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Bayesian Participatory-Based Decision Analysis: An Evolutionary, Adaptive Formalism for Integrated Analysis of Complex Challenges to Social-Ecological Systems Sustainability

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Abstract

This dissertation responds to the need for integration between researchers and decision-makers who are dealing with complex social-ecological system sustainability and decision-making challenges. To this end, we propose a new approach, called Bayesian Participatory-based Decision Analysis (BPDA), which makes use of graphical causal maps and Bayesian networks to facilitate integration at the appropriate scales and levels of descriptions. The BPDA approach is not a predictive approach, but rather, caters for a wide range of future scenarios in anticipation of the need to adapt to unforeseeable changes as they occur. We argue that the graphical causal models and Bayesian networks constitute an evolutionary, adaptive formalism for integrating research and decision-making for sustainable development. The approach was implemented in a number of different interdisciplinary case studies that were concerned with social-ecological system scale challenges and problems, culminating in a study where the approach was implemented with decision-makers in Government. This dissertation introduces the BPDA approach, and shows how the approach helps identify critical cross-scale and cross-sector linkages and sensitivities, and addresses critical requirements for understanding system resilience and adaptive capacity.

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Keywords: sustainability, transdisciplinarity, complexity, hyperstructures, case studies, social-ecological systems, decision-makers, multi-scale, complex adaptive systems, self-organisation.

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Vanya Gastrow, the undying love of my life who has continually brought me back to reality so beautifully throughout this process and before. Every member of my family, as you have all contributed to who I am, but especially my father, who has played a key role in the development of my ideas. All my friends - I am nothing without you.

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“The masterwork is unknown, only the work is known, knowable. The master is the head, the capital, the reserve, the stock and the source, the beginning, the bounty. It lies in the intermediary interstices between manifestations of work. No one can produce a work without labouring in this sheer sheeting cascade from which now and then arises a form. One must swim in language and sink, as though lost, in its noise, if a proof or a poem that is dense is to be born. The work is made of forms, the masterwork is a formless fount of forms, the work is made of time, the masterwork is the source of times, the work is a confident chord, the masterwork trembles with noise. He who does not hear this noise has never composed any sonatas. The masterwork never stops rustling and calling. Everything can be found in this matrix, nothing is in this matrix; one could call it smooth, one could call it chaotic, a laminar waterfall or clouds storm-crossed, a crowd. What are called phenomena alone are known and knowable, avatars of a secret remote proteus emerge from the clamorous sea. Visible and beautiful are the dispersed tableaux; beneath the green serge veil, lies the well. Empty, full, will we ever know? When there is an infinity of dispersed information in the well, it is really the same well as if it were devoid of information.”

Michel Serres (Genesis 1982 - 1998)

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1. Overview of Dissertation	13
1.1 Introduction.....	13
1.1.1 The Need for Sustainability.....	13
1.1.2 Social-Ecological Systems	15
1.1.3 The Emerging Discourse on Sustainability	17
1.1.4 Transdisciplinarity.....	18
1.1.5 Complexity, Self-Organisation and Emergence	19
1.1.6 Implications for Case Study Research of Social-Ecological Systems	22
1.1.7 Research Goals: Methodological and Analytical Considerations.....	23
1.1.8 Research Contribution.....	27
1.1.9 Outline of Dissertation.....	30
2. The Basics: Complexity Theory & Social-Ecological Systems Sustainability	33
2.1 Sustainability: Strategy-Making, Scenario Planning and Adaptive Management	33
2.2 Scenarios, Projections, Causality & Conditionality.....	37
2.3 A New ‘Science’ for Sustainability?	39
2.3.1 The Need for a New Approach: Systems & Complexity.....	39
2.3.2 Transdisciplinarity: The Need for Shared Knowledge.....	49
2.3.2.1 “Undecideability”: A Necessary Evil	52
2.3.2.2 Transdisciplinarity & Complexity.....	53
2.3.3 Resilience, Adaptive Cycles & Panarchy	54
2.4 Complexity & Hierarchy: Emergence & Hyperstructures.....	60
2.4.1 Emergence & Hierarchy: An Unholy Mix	60
2.4.2 Emergence, Learning & Hyperstructures.....	62
2.4.3 The Case for Heterarchy	66
3. Bayesian Networks and Graphical Causal Models as Hyperstructures for Social-Ecological Systems	69
3.1 Capturing Shared Knowledge in Ontology’s.....	69
3.1.1 Modelling Social-Ecological Systems: Requirements for Ontologies.....	69
3.1.1.1 Learning, Causality & Classification	70
3.1.1.2 Alternative Conceptual Schema’s & Causality	72
3.2 What are Bayesian Networks and Graphical Causal Maps?	75
3.3 Bayesian Networks as Hyperstructures & Requirements for Social-Ecological Systems	79
3.3.1 Multi-Participatory Process Facilitation:	80
3.3.2 Learning, Conditionality and Causality	80
3.3.3 Addressing the Complexity of Social-Ecological Systems as Multi-Agent Systems.....	81
3.4 Why Bayesian Networks & Graphical Causal Maps?	82
3.4.1 Conditionality, Causality & Organisation	82
3.4.2 Contrary Views and Sets of Evidence	84
3.4.3 Learning: Observations & Interventions.....	85
3.4.4 Complexity: Scale, Non-Linearity, Adaptive Capacity & Resilience	85

3.4.5	Participatory Process Facilitation	86
3.5	Summary.....	88
4.	Research Methodology: Strategy & Design Considerations	
	91	
4.1	Background: A Review of Research & Decision-Support Tools for Sustainability	
	92	
4.1.1	Scenario Planning & Participatory Processes for Modelling Multiple Futures	92
4.1.2	Modelling the Complexity of Social-Ecological Systems.....	94
4.1.2.1	Modelling Complexity: Hierarchy & the Multi-Agent System	94
4.1.2.2	The Role of Narrative: Multiple Perspectives.....	99
4.1.3	Case Study Research: Strategies & Methodologies.....	101
4.2	Proposed Case Study Research Strategy	109
4.3	Aims of single and cross-case study analysis.....	115
4.3.1	Testing Specific Requirements for Social-Ecological Systems.....	115
4.3.2	Summary of Methodological and Analytical Objectives.....	120
4.3.2.1	Integration Across Scales	121
4.3.2.2	Integration Across Disciplines and Sectors.....	121
4.3.2.3	Facilitating Transdisciplinarity Research	122
4.3.2.4	Developing New Indices.....	123
4.3.2.5	Incorporating Non-Linear Effects	123
4.3.2.6	Resilience & Adaptive Capacity: Critical Limits & Thresholds	124
4.3.2.7	Decision Support for Adaptive Management.....	124
4.3.2.8	Supporting the Future Integration of Manual and Automatic Engineering.....	125
5.	Modelling Methodology: Hyperstructures for Case Study	
	Research on Social-Ecological Systems	127
5.1	Overview: Methodological Framework for Reasoning using Graphical Causal Models & Bayesian Networks.....	128
5.1.1	Facilitating Interdisciplinary Problem Formulation, Review & Validation of Case Study Inputs, Outputs, Conclusions & Recommendations	132
5.1.1.1	Initial Phase: Problem Formulation and Research Design:	132
5.1.1.2	Feedback Phase: Review of Case Study Outputs, Conclusions and Recommendations	135
5.1.2	Formulating Hyperstructures: Bayesian Models & Graphical Causal Models	137
5.1.3	Detailed Embedded Unit & System Analysis	139
5.2	Formulating Hyperstructures: Graphical Causal Models & Bayesian Networks	141
5.2.1	Formulating Graphical Causal Models.....	142
5.2.2	Formulating & Populating Bayesian Networks	145
5.2.3	Developing New Indices	153
5.2.4	Sensitivity Analysis & Running Scenarios.....	153
5.2.5	Interpreting Model Results & Making Recommendations	155
5.2.6	Enabling Learning & Reasoning with Hyperstructures	155
6.	Case Studies: Single Case Analyses.....	157
6.1	Incomati Catchment – Maputo Bay Study.....	160

6.2	National Scale Model: Climate Change - Irrigated Agriculture	175
6.3	National Scale Model: Climate Change – Biofuels Production.....	182
6.4	Magisterial District Scales: Nelspruit & Mbombela.....	195
6.4.1	Water-Based Household Informal and Subsistence Activities Module:	205
6.4.2	Biodiversity Intactness Module:	207
6.4.3	The Nelspruit Bayesian Model:.....	207
6.5	Province: Western Cape.....	210
6.5.1	Description of General Scenarios A- I	225
6.5.2	Results for Projected Short, Medium and Long Term Growth Scenarios A - I.....	231
6.5.3	Description: Short Term (Less Growth) Scenarios	236
6.5.4	Results: Projected Short Term “Less-Growth” Trajectories.....	240
6.5.5	Determining Climate Change Related Thresholds on Provincial Multi-Sector Growth	242
6.5.6	General Results Summary: Western Cape Study.....	248
6.5.6.1	Summary of Water Use	248
6.5.6.2	Summary of Energy Use	249
6.5.6.3	Summary of Employment.....	250
6.5.6.4	Summary of CO2 Emissions.....	251
6.5.6.5	Summary of Residential Energy, Water Use & Household Income.....	251
6.5.6.6	NOX Emissions.....	252
6.5.6.7	Solid Waste.....	252
6.5.6.8	General Summary.....	252
6.5.7	Brief Discussion: What did we Learn?	257
6.5.7.1	Participatory Processes	257
6.5.7.2	Massive Scale-Ability	258
6.5.7.3	Integration Across Sectors	258
6.5.7.4	Critical Limits, Thresholds & Resilience.....	258
6.5.7.5	Adaptive Capacity.....	259
6.6	Facilitation Using Graphical Causal Maps.....	261
6.6.1	Cholera Study.....	261
6.6.1.1	Divergence Phase	271
6.6.1.2	Convergence.....	279
6.6.1.3	What Did We Learn?	283
6.6.2	Gauteng Urban Growth Study: Built Environment	284
7.	BPDA & Cross-Case Analysis & Discussion	287
7.1	Integration across Scales.....	291
7.2	Integrative Modelling across Disciplines & Sectors using Bayesian Networks .	293
7.3	Developing New Indices & Embedded Units	295
7.4	Facilitating and Enabling Transdisciplinarity	296
7.5	Incorporating Non-Linearity.....	298
7.6	Resilience & Adaptive Capacity.....	299
7.7	Critical Limits & Thresholds.....	300
7.8	Monitoring & Multiple Futures.....	301
7.9	Choosing Connectors or Integrators.....	302
7.10	Participatory Process Facilitation.....	304
7.11	Decision Support for Adaptive Management.....	310

8.	BPDA & Case Study Research.....	313
8.1	Case Study Research Design Considerations.....	314
8.1.1	Introduction: Purpose of Research Design.....	314
8.1.2	Components of Research Design.....	316
8.1.3	Evaluation, Validity & Causality.....	318
8.2	Implementation Considerations of the Research Strategy.....	322
8.2.1	Conceptualising the Study.....	322
8.2.2	Pattern-Matching.....	326
8.2.3	Rival Explanations as Patterns.....	327
8.2.4	Explanation Building.....	329
8.2.5	Third Strategy – Time Series Analysis.....	330
8.2.6	Chronologies.....	331
8.2.7	Lesser Analytical Modes of Analysis: Embedded Units, Repeated Observations & Case Surveys.....	332
9.	Frameworks for Future Development of BPDA Approach	333
9.1	Introduction.....	333
9.2	Social-Ecological System Integration: Conceptual Frameworks Used in Case Studies 335	
9.2.1	Human, Manufactured and Natural Capitals of Social-Ecological System.....	337
9.2.2	Total Economic Value.....	342
9.3	Manual and Automatic Engineering of Emergence Revisited.....	346
9.3.1	Manual Engineering of Emergence.....	346
9.3.2	Automatic Engineering of Emergence.....	348
9.3.3	Converging Manual & Automatic Engineering.....	349
9.4	Can Bayesian Hyperstructures Support Dynamic Systems and Agent-Based Models 351	
9.4.1	Bayesian Hyperstructures: Incorporating Dynamic Systems and Agent-Based Models.....	351
9.4.2	Visualising Real-Time Evolution of System in Heterarchical Framework.....	354
9.5	Shared Understanding for Decision-Support in Adaptive Management	360
9.5.1	Understanding Resilience using Agents and Ontology's.....	360
9.5.2	Understanding Agency, Resilience & Adaptive Management.....	365
9.5.3	Accommodating Values, Beliefs, Norms & Behaviours.....	368
9.5.4	Representing Multiple Mental Models of High Uncertainty Decision-Making Scenarios.....	373
10.	Summary and Conclusions	375
11.	References	379
12.	Appendix A: Cholera Study	401

13.	Appendix B: Urban Growth in Gauteng – Sub-Module Illustrations & Descriptions	411
14.	Appendix C: Western Cape Provincial Model – Individual Modules	423
15.	Appendix D: Mbombela Model Sub-System Modules .	449
16.	Appendix E	473

University Of Cape Town

University Of Cape Town

1. Overview of Dissertation

1.1 Introduction

1.1.1 The Need for Sustainability

We are living in a new era of human development, where the long-term sustainability of human and ecological systems is under increasing pressure from global and local change effects. Notable changes are occurring in the growth and decline of the populations of humans and other species, in the rates of social and economic globalisation, and in the rates of change in the decline of the earth's natural support systems (Holling, Gunderson & Ludwig, 2002; Lubchenco, 1998; Malhotra, 1999). Variations in climate and the global economy are also occurring more suddenly and at faster rates than experienced in recent human history. Consequently, traditional leadership and management approaches often fail to adapt quickly enough to the fast pace of changes (Malhotra, 1999) (Folke et al., 2005; Malhotra, 1999, Perlas, 2000).

Moreover, *decisions* and *actions* taken toward sustainability are increasingly thwarted by externalities. As global systems become more interconnected, actions taken in one area or sector can have disastrous effects on the sustainability of other areas and sectors. According to Folke et al. (2005); "human activities have become globally interconnected and intensified through new technology, capital markets and systems of governance, with decisions in one place influencing people elsewhere."

Therefore, decision-making for sustainable development in the 21st Century is faced with the critical challenge of adapting to the increasing *rates of change* and *inter-connectivity* between human, natural and technological systems. These factors, taken together, are having increasingly noticeable effects on both developed and developing nations alike (Lubchenco, 1998).

It is widely acknowledged that historical approaches towards human development and ecological resource exploitation haven't and will not prove effective

in reducing the immense and pervasive human pressures that are being placed on earths' ecologically driven life support systems (Burns & Weaver, 2008; Holling et al., 2002; Lubchenco, 1998; Malhotra, 1999; Stern, 2000; Van Kerkhoff & Lebel, 2006). It is unlikely that more of the same approach will lead to the sustainability of human and ecological systems and their critical interdependencies. As a result higher levels of uncertainty are being faced in both leadership and management levels in organizations than ever before (Folke et al., 2005; Folke et al., 2002, Malhotra, 1999; Max-Neef, 2005; Pahl-Wostl, 2007), and are searching for frameworks that enhance broader understanding of social-ecological systems (Anderies, Jansen & Ostrom, 2004).

According to Van der Sluijs (2007) the failure of traditional management approaches in coping with these new challenges is also due to “imperfect understanding of the complex systems involved”. When the collective behaviour of decision-makers lacks overall coordination, they can often act in conflicting ways that bring pressure on the ability of the system to sustain itself. Socio-economic and ecological systems are interconnected at different scales and levels of description¹. They have multiple nested or embedded sub-systems, many of which are complex in nature and adaptive themselves (Levin, 2006). Socio-economic systems in particular are constantly adapting and changing by virtue of their ability to *self-organise* at the *individual* and *collective* level (i.e. as groups (Ehrlich & Levin, 2005)), and to evolve according to socio-cultural norms (Ehrlich & Levin, 2005, Stern, 2000). Therefore, these groups and individuals can, through their individual behaviours, bring about *reflexivity*² at the whole system scale i.e. emergent behaviours or ‘emergent higher order structure’ (Ehrlich & Levin, 2005). The *self-organisation* and *reflexivity* of social systems places difficult methodological demands on case study research of social-ecological systems and on decision-makers seeking to ensure sustainability (Folke et al., 2005).

¹ According to Ingram (2007), “‘scale’, is the spatial, temporal quantitative or analytical dimension used to measure and study any phenomenon, and ‘level’ is the unit of analysis that is located at different positions on a scale.” (Gibson et al, 2000; Cash et al, 2006)”. *Panarchy* is the term used to describe the interconnectedness that exists *across* scales within a social-ecological system.

² Reflexivity, is used here to describe how behaviour, at the individual level can be informed by a variety of considerations (e.g. values, norms), and as such, gives rise to behavioural responses of which the individual may not be directly aware (i.e. to act reflexively or without thought). These responses may be similar or dissimilar at the group level, leading to emergence at the system scale.

Ensuring the sustainability of current human development trajectories in the fast changing political, environmental and social context of the 21st Century will therefore require decision-makers to; (1) be self-reflexive³, (2) be able to adapt to unforeseeable changes and faster rates of change, and (3) to cope with an increasingly inter-connected set of developmental problems and challenges that spans across sectors and institutions.

Enabling sustainability necessitates that researchers and decision-makers deal with socio-economic and ecological systems as integrated 'whole' systems. This has led to the introduction of the term 'social-ecological systems' or 'socio-ecological systems' by a growing body of researchers involved in research for sustainability (Holling et al., 2002).

1.1.2 Social-Ecological Systems

Social-ecological systems are real-world, multi-scale, complex adaptive systems (Folke et al., 2005; Levin, 2006). The dependence of social-ecological systems on emerging social, economic, ecological and technological dynamics means that social-ecological systems are often more dependent on *current context* than *historical context* i.e. due to the faster rates of change in economy, ecology and society (Folke et al., 2002; Folke et al., 2005; Gregory & Oerlemans, 2009; Holling, 2004; Kates & Clarke, 1996; Kates & Dasgupta, 2007; Malhotra, 1999).

The use of the term 'social-ecological system' does not imply that there is a universal theory of social-ecological systems. A social-ecological system is also complex in that it can be defined differently, and from different perspectives, depending on the context of inquiry. Disciplinary fragmentation in the research of social-ecological system scale problems results in 'tunnel vision' and consequently, fragmented decision-making and actions in the governance and management of

³ The term 'self-reflexive' is used here in the same sense that it is used in action research methodologies i.e. reflecting the need for researchers and decision-makers to be aware of their own value positions and how they may contribute to the dominance of adverse effects in relation to the

social-ecological systems (Folke et al., 2002; Holling et al., 2002, pp .24). Hence, to some extent, the term ‘social-ecological systems’ has emerged from the need to overcome the limitations and dominance of “partial truths” (Holling, Gunderson & Ludwig, 2002, pp. 24) in research and decision-making for sustainability. The dominance of partial truths (or alternatively; partial perspectives) often results in *conflicting actions* in different spheres of governance, management and research, to the detriment of the sustainability of social-ecological systems as a whole.

Enabling the sustainability of social-ecological systems necessitates that researchers and decision-makers can collectively self-organise to address unforeseen changes in a self-reflexive manner and can transcend the limitations of partial-perspectives. One of the key reasons for introducing the collective term ‘social-ecological systems’ is to help engender a *shared understanding* of sustainability challenges, that can translate into more effective and coordinated actions towards sustainability across different scales and levels of governance.

Where the sustainability of social-ecological systems is concerned, there is a particular need to understand the ‘resilience’ of the system in different scenarios. The *resilience* of social-ecological systems results from its’ *adaptive capacity*, i.e. the ability of adaptive agents to *self-organise* in relation to each other and the external environment; and in such a manner that the system stays within its internal critical limits and thresholds (Walker et al, 2004). When self-organisation occurs in this way the system’s global behaviour, internal structure and processes do not undergo fundamental changes, and the system is regarded as stable or ‘resilient’ in relation to its’ environment (Walker et al, 2004).

sustainability of the ‘whole’ system. Note that this term should not be confused with the use of the term ‘reflexivity’ in the text.

1.1.3

The Emerging Discourse on Sustainability

As outlined earlier, the need for new ways of achieving sustainability is the key challenge of our era. The notion and question of sustainability engages a wide range of theories, experts, sectors, methodologies and schemes for observation and intervention in a quest to enable decisions towards sustainability to be made.

In response, a new discourse is emerging regarding the role of science in realising and actualising sustainability (Clarke et al., 2004; Holling et al., 2002; Lubchenco, 1998, Stern, 2000; Van Kerkhoff & Lebel, 2006). A diverse array of social and natural science research strategies can be used to arrive at very different conclusions about what actions are necessary to remedy a particular situation. The broad challenge is appreciating and understanding the multiplicity of futures the system may have, and putting in place research and management strategies to strengthen the adaptive capacity of the system. This requires employing conceptual frameworks that are capable of coping with what emerges out of a range of possible futures, including the unexpected or surprising (Clarke, Crutzen & Schellnhuber, 2004; Holling, Gunderson & Ludwig., 2002; Holling, 2004; Folke et al., 2002; Malhotra, 1999; Peterson et al., 2003).

In this new discourse, two new areas of research have emerged as critical for providing the understanding that is required to make decisions and take actions in support of sustainability:

1. *Observing the “whole” - multiple perspectives:* The first critical area from which surprises emanates is from the “fragmentation” in perspectives and a consequent fragmentation in decision-making, often leading to unintended, unforeseen and undesired impacts on the sustainability of social-ecological systems. This fragmentation in perspectives and actions is a result of traditional disciplinary and institutional limitations, which prevent a researcher or decision-maker from making decisions (about how they study and evaluate the system and consequently decide to act) that relate to whole system sustainability (Folke, 2002; Holling et al., 2002).

2. *Understanding the causal relationships amongst the behaviour of the “parts” and behaviour of the “whole” - the multi-agent system:* We need to understand how social and ecological systems are nested and inter-linked, what their critical limits and thresholds are, and how these linkages affect the sustainability of the whole ‘social-ecological’ system in different scenarios. Here it is crucial that the role of multiple agents within the system can be visualised and understood by decision-makers, as sustainability is critically dependent on their interactions. This is especially so where cross-scale and cross-sector linkages are concerned (Holling et al., 2002).

In summary, research and decision-making for the sustainability of social-ecological systems are currently hampered at global, regional and local scales by two types of fragmentation (Holling et al., 2002); (1) the inability of researchers to effectively integrate beyond disciplinary boundaries to address the *complexity* of social-ecological systems as *integrated wholes*, and (2) the *fragmentation in decisions and actions* taken by decision-makers in social-ecological systems.

The former (1) is a critical area of focus for complexity theory, which is mainly concerned with self-organisation and emergence in multi-agent systems. The latter (2) is a critical area of focus for emerging thinking on *transdisciplinarity*, which is concerned with the inability of monodisciplinary approaches to deal with complex real-world phenomena, events and systems.

1.1.4 Transdisciplinarity

Research processes attempting to deal with the sustainability of social-ecological systems must necessarily engage with the “political processes of decision-making and change” through the processes of “learning, participation, integration, learning and negotiation” (Van Kerkhoff & Lebel, 2006). The current era of human development therefore requires more from the natural and social sciences than they have provided in recent history (Clarke et al., 2004; Ehrlich & Levin, 2005; Holling,

Gunderson & Ludwig, 2002; Lubchenco, 1998; Starzomski, 2004; Stern, 2000; Van Kerkhoff & Lebel, 2006). It calls for science to transcend its disciplinary and epistemological boundaries in order to help deal with the key global “problematiques” facing humankind (Max-Neef, 2006).

According to Max-Neef (2005) the call to transdisciplinarity is a response to the need to understand real-world phenomena; such as those involving the sustainability of natural resources, war, water, globalisation, forced migration, poverty and inequality. Transdisciplinarity requires researchers to find “a different manner of seeing the world, more systemic and more holistic”. It also, by necessity, must engage with the *complexity* of real-world systems (Max-Neef, 2005).

According to Max-Neef (2005) *transdisciplinarity* also requires an understanding of *complexity*. As already outlined in the previous section, both are key concepts for enabling research for sustainability of social-ecological systems.

1.1.5 Complexity, Self-Organisation and Emergence

“The multiple as such. Here’s a set undefined by elements or boundaries. Locally, it is not individuated; globally, it is not summed up. So it’s neither a flock, nor a school, nor a heap, nor a swarm, nor a herd, nor a pack. It is not an aggregate; it is not discrete. It’s a bit viscous perhaps. A lake under the mist, the sea, a white plain, background noise, the murmur of a crowd, time. I have no idea, or am dimly aware, where its individual sites may be. I’ve no notion of its points, very little idea of its bearings. I have only the feeblest conception of its internal interactions, the lengthiness and entanglement of its connections and relations, only the vaguest idea of its environment. It invades the space or it fades out, takes a place, either gives it up or creates it, by its essentially unpredictable movement. Am I immersed in this multiple, am I, or am I not a part of it? Its edge a pseudopod takes me and leaves me. I hear the sound and

I lose it, I have only fragmentary information on this multiplicity.
(Serres, 1998).

In the preceding sections we have introduced and elaborated on the role of self-organisation and emergence as central themes in the governance and management of social-ecological systems. We also noted the fragmentation of perspectives (or lack of shared understanding) by agents in social-ecological systems often thwarts sustainability. The inability of system actors to comprehend the systemic effects of their decisions and actions, results in the emergence of collective behaviours that are not sustainable (Holling et al., 2002). Here complexity theory is especially relevant.

Complexity theory is a theory that is primarily concerned with the *multi-agent system* (Heylighen et al., 2007); systems with adaptive agents which self-organise (Ashby, 1962) at individual and group level in relation to their environments. Self-organisation, as an *ontological* phenomenon, occurs as a result of interactions between agents themselves and agents and their environments. These interactions “comprise a complex set of causal relationships” (Potgieter, 2004). Self-organisation as an *epistemological* phenomenon varies with the “graining” or “levels” of observation or description implemented on the system (Gershenson & Heylighen, 2003).

Similarly the concept of emergence, or ‘surprise’ in complex, adaptive systems has both ontological and epistemological origins, respectively:

Emergence, in the first case, is due to the lower-level dynamics that are responsible for generating collective behaviour (Baas & Emmeche, 1997, in Potgieter 2004, p.10), and this is indeed the case for social-ecological systems, which “are complex, adaptive systems” (Cilliers, 2008; Levin 2006). Human and natural (or social and ecological) systems are inseparable, open systems (Gillaume et al. 2004), the whole of which must necessarily be sustainable. As already discussed, the ‘whole’ social-ecological system has emergent properties due to the dynamic behaviour of self-organizing agents. These agents enable system level adaptations to be innovated (Levin, 2006). In this sense, emergence results from the reflexivity and

self-organisation of agents within the system and their collective actions (Ehrlich & Levin, 2005; Folke et al., 2002, Stern, 2000; Van Kerkhoff & Lebel, 2006).

Emergence, in the second case, results because no one ‘fragmented perspective’ alone (Holling et al., 2002; Islam et al., 2006; Allenby, 2006) can satisfactorily reflect or explain the nature of the ‘whole’ system as a shared phenomenon amongst people. In complexity theory the concept of ‘perceptual emergence’ (Islam et al., 2006) puts forward the idea that emergence results because no single perspective can adequately account for the full complexity of real-world systems i.e. there will always be surprises because our models cannot fully replicate complex reality (Cilliers, 2001/2008). The ‘whole’ in this case is the elusive, emergent product of different perspectives (Islam et al., 2006) or “ways of looking” at the system, and how it is self-organized (Gershenson & Heylighen, 2003). Islam et al. (2006) argue that there is no single ‘objective’ “whole system” that exists as a metaphysical entity. No single interpretation of a complex whole can adequately represent it, and hence no universal theory can exist for the analysis or description of complex, adaptive systems (Cilliers, 2008; Holling et al., 2002; Van der Sluijs, 2007).

Emergence, as observed in complex systems therefore occurs “relative to a model” (Cariani, 1991, in Potgieter 2004, p.10). In this sense, all complex adaptive systems “maintain internal models, consisting of *hyperstructures* representing “regularities” in the information about the system’s environment and its own interaction with that environment. Hyperstructures are higher-order structures or “emergent phenomena” that emerge from the collective behaviour of agents. Complex adaptive systems use these hyperstructures to act in the real world (Gell-Mann, 1994) (Holland, 1995)” (Potgieter 2004, p1, emphasis added: italics). Hyperstructures must necessarily be adaptive and flexible enough to incorporate new evidence in order to cope with emergence. Emergence ‘relative to a model’ (Cariani, 1991), in this case, constitutes observed deviations from the models that constitute these hyperstructures (see section 2.4.2). Our ways of observing, interpreting and analysing complex events and systems are therefore always subject to revision in fast changing contexts i.e. our ‘models’ of systems are never fully correct, and emergence occurs when our observations don’t agree with our models of a phenomena or event.

1.1.6

Implications for Case Study Research of Social-Ecological Systems

In summary of the key points, understanding and coping with emergence in social-ecological systems is concerned with; (1) the *multiple perspectives* of what constitutes the ‘whole’ social-ecological system in relation to context, (2) *complexity and reflexivity*; how its constituent ‘parts’ and adaptive agents are inter-related and can adapt to bring about different social-ecological system behaviours, and (3) the real-world *context* in which the social-ecological system is located and the context of inquiry.

As already discussed in the preceding sections, social-ecological systems are complex, adaptive systems (Levin, 2006). Decisions and behaviours resulting from the values, beliefs and norms of human actors in the system (Stern, 2000) leads to the emergence of higher order structure in these systems (Ehrlich & Levin, 2005). This higher order structure is indivisible from its context. It is too complex to be exhaustively formulated from a *top-down* general set of rules - and too variational and expansive to be described exclusively from *bottom-up* parsimonious approaches.

We can only obtain a resolved understanding of a social-ecological system when it is viewed in its *context*, and the particular purpose (or question) for which the system has been formulated⁴. We also explained earlier how real-world complex adaptive systems such as social-ecological systems are dynamically changing systems and depend strongly on the *current context* for analysis and interpretation of system behaviours (Malhotra, 1999). The relevance of the historical behaviour of these systems fades when compared to the influence of current contextual factors (Malhotra, 1999). The sensitivity of the currently observed behavioural trajectory of the system is more likely to sway with the influences in its environment that are currently significant. While system ‘memory’ is important in understanding the evolution of the system, it does not exclusively govern the behaviour of the system as it journeys through changing external and internal contexts.

⁴ The purpose for which a question is constructed is as important as the question itself.

In the case of social-ecological systems the ways in which the complex causal relationships underlying self-organisation can be envisaged may differ substantially between researchers and decision-makers from different disciplines and sectors. Explanation of existing behaviours and changes in a social-ecological system cannot be achieved through a single case study. Each case study can be represented by a different model or set of hyperstructures ‘explaining’ the phenomena. Identifying regularities (hyperstructures) necessitates democratic sharing of perspectives on the system as a whole, and its constituent embedded units (or sub-systems and / or agents). Within a single case study the analysis of embedded units (and / or agents) will be bound by the context of that particular case study. Hyperstructures representing the internal models of social-ecological systems may therefore differ significantly within a case study, and between case studies of the same system or event.

1.1.7 Research Goals: Methodological and Analytical Considerations

The need for more cooperative, collective governance of resources, while desired, is thwarted by *fragmentation*, as outlined earlier in this chapter. It is therefore clear that there is a need for ways of bringing about *shared understanding* across disciplines, sectors and levels of governance. An ‘action research’ approach is required, where researchers and decision-makers can be enabled towards more *self-reflexive* programmes of research, decision-making and implementation.

The goal of this dissertation is therefore to introduce a complexity based modelling framework that helps integrate case study analyses, and can help engender shared understanding amongst researchers and decision-makers that are concerned with the challenge of sustainability of social-ecological systems.

We use hyperstructures to engender shared understanding. Shared understanding, in the context of this dissertation, is achieved when researchers and decision-makers from different disciplines and sectors reach a common understanding *of the causal relationships amongst the behaviour of the “parts” and behaviour of the “whole”*. This allows them to be more self-reflexive in their analyses and decision-

making, and can contribute significantly to helping bring about more sustainable decisions and actions.

Generally speaking, social-ecological systems and the question of sustainability are themselves both quantitatively and qualitatively complex i.e. at various scales and levels of description, respectively (Ingram, 2007). *In this dissertation, we contend that the nature of the problem must dictate the means of inquiry, and not the other way round.* Since social-ecological systems are complex, adaptive systems (Levin, 2006), it stands to reason that an adaptive formalism is required. This formalism should also be able to accommodate complexity and uncertainty, and help provide a ‘whole’ systems perspective on social-ecological systems. At the philosophical level, this dissertation proposes and tests the notion that Bayesian probability theory, enabled by software interface technology, can serve as a *formalism* that can satisfy these requirements, at least in part.

As a formalism, Bayesian networks do not dictate the completeness or consistency of any model formulated using Bayesian networks, except in two aspects; that of *conditionality*, and of *causality*. In the BPDA approach, these are the only two conditions we impose in engendering shared understanding in multi-participant programmes.

We argue that the BPDA approach provides a framework for informing collective actions and interventions in social-ecological systems. It is intended to assist in bringing about better coordinated collective governance and management programmes across sectors and disciplines. We contend that the BPDA approach, if intelligently applied, can help assist in arriving at reliable, verifiable, valid models of SES’s. Furthermore, we propose that these models can help engender shared understanding between researchers and decision-makers because they rely on a basic and intuitive understanding of the principles of causality and conditionality to share understanding.

To this end, this dissertation argues and tests the proposition that a combination of graphical causal models and Bayesian networks provides an open, heterarchical framework of reasoning that can be used as *hyperstructures* to maintain

the internal models of inter- and transdisciplinary case studies of complex adaptive social-ecological systems.

Graphical causal maps and Bayesian networks are used as hyperstructures to formulate and maintain the internal models around which the case studies are designed and conducted. These hyperstructures are collections of overlapping and non-overlapping models which represent regularities in observed information in the systems environment, and in regularities in its interactions (e.g. interventions) with that environment. We evaluate the ability of these hyperstructures to support complex decision-making challenges in social-ecological systems. Bayesian networks have recently been used in other studies to address issues concerning sustainability such as Baran & Jantunen (2004), Borsuk, Stow & Rehow (2004) and Bromley et al. (2005).

The emphasis in this dissertation is on conducting a number of *case studies* of complex, interdisciplinary social-ecological systems problems facing researchers. Every case study is an instance of some higher order structure and can be represented by a group of hyperstructures. These case studies were conducted at different scales and levels of description, and deal with a variety of research questions pertaining to complex social-ecological systems. The case studies were incrementally built up to include greater complexity and variations in scale and levels of description.

The scales of governance that the case studies dealt with were the magisterial district, municipality, provincial and national scales. The variety of research questions explored in individual case studies ranged from; catchment-coastal interactions, rural-urban ecosystem benefit flows, the effect of climate change effects on agriculture and evaluating the potential for biofuels production, to the environmental causes of cholera. In the penultimate case study, an interdisciplinary review team worked with decision-makers to review a provincial level strategy for climate change in the Western Cape, South Africa. This involved evaluating climate change effects and inter-related consequences on food, energy and water sectors, and assessing climate-related provincial multi-sector growth limitations.

In order to test the BPDA approach incrementally, we systematically built up the complexity of hyperstructures for social-ecological system in terms of scale and the number of embedded units involved in conducting each case study. The case studies were conducted using interdisciplinary workshops that were facilitated by using graphical causal maps and Bayesian networks to articulate system interdependencies. They were used to capture cause-and-effect relationships. These hyperstructures are a representation of the *shared knowledge* in interdisciplinary case studies, and may consist of overlapping and non-overlapping explanations. In this way the internal models are maintained by a multi-participant and interdisciplinary group that is engaged in a process of adapting to emergence, whether through learning (i.e. the introduction of new evidence), or through changes in the real-world context.

The learning process is dependent on how well the approach proposed and tested in this dissertation (i.e. the BPDA approach) can accommodate emergence and surprise or ‘deviations from a model’ (Cariani, 1991, in Potgieter 2004, p.10). Understanding and modelling the complexity of social-ecological systems also depends on how well the proposed approach can be employed in dealing with some of the complex features of social-ecological systems, such as; *non-linearity, cross-scale effects, cross-sector and remote effects, thresholds and critical limits, adaptive capacity, participatory processes* and *new evidence* representing significant changes in the *current context* of the system.

Understanding and researching the resilience of a social-ecological system as a whole (Holling et al., 2002) requires a broad understanding of several factors. These are firstly, to obtain an understanding of the *adaptive capacity* of the system in a variety of ‘what-if’ scenarios. Secondly, to identify what the critical variables for *observation* and *intervention* in the system are. Thirdly, to understand the critical limits and thresholds which provide cross-scale stability and sustainability of social-ecological systems.

We use Bayesian hyperstructures to obtain an understanding of social-ecological system thresholds and adaptive capacity in different ‘what-if’ scenarios. Both observations and interventions of system behaviours can be employed in the progressive modification of Bayesian hyperstructures (Meder, Hagmayer &

Waldmann, 2005). Bayesian hyperstructures can therefore be used to help identify and differentiate between *observational* and *interventional* variables. As such, they can play a critical role in decision-making and *adaptive management* towards sustainability of social-ecological systems by helping decision-makers collectively understand; (a) *what to observe*, and (b) *where to intervene* in the system, in different what-if scenarios.

We show how the approach can be used to help decision-makers consider the consequences of a potential decision on other parts or sectors of the system, and on the sustainability of the system as a whole, in a variety of what-if scenarios. We also show how the approach can be used to help adapt models used in decision-making to reflect changes occurring in the real-world context, and thereby to support efforts in adaptive management of social-ecological systems.

Cross-case analysis is used to evaluate the extent to which graphical causal models and Bayesian networks can be used to; (1) *understand complexity and resilience* (in particular, to model the critical limits and thresholds of non-linear and cross-scale interactions in social-ecological systems), (2) to *facilitate transdisciplinarity* (i.e. to support democratic, inter-research participatory process management, dialogue and sharing of different opinions, views and causal models of reasoning), and (3) to *support decision-making*.

1.1.8 Research Contribution

The key research contributions of this dissertation lies in; (1) introducing a new approach (i.e. the BPDA approach) for conducting cross-disciplinary, multi-participant case studies of social-ecological systems using a combination of graphical causal models and Bayesian networks to maintain the internal models of case studies. The uniqueness in our approach lies in pulling together a multiplicity of views that are held on “single reality” to achieve a shared understanding of emergence. (2) In laying the foundations for the future development of the approach i.e. to accommodate near-real time adaptability using agent-based Bayesian models for decision-support research, and (3) in proposing how the approach could be abstracted

to support concepts in resilience theory, and to accommodate more general classes of case studies of complex systems.

These contributions are outlined in more detail below:

1. The approach proposed in this dissertation (i.e. the BPDA approach) is tested in a variety of social-ecological system case studies and cross-case analysis is conducted to assess the strengths and weaknesses of the approach in; (a) dealing with the complexity of social-ecological systems, (b) its suitability for supporting case study research on social-ecological systems, and (c) for supporting complex decision-making challenges concerning the sustainability of social-ecological systems.
2. A framework is proposed, which conceptually illustrates how the approach can be extended (in future research) to accommodate near-real time inputs to the hyperstructures, and be used to support decision-making for the sustainability of social-ecological systems.
3. A third contribution of this dissertation is that we show how the BPDA approach can be used to elucidate and complement concepts in resilience theory, such as the adaptive cycle, and can be generalised to address case studies of broader classes of complex systems (not exhaustively), or other classes of complex systems that are akin to social-ecological systems.

At the philosophical core of this dissertation, Bayesian probability theory is being suggested as an *alternative and complementary* formalism to traditional systems formalisms (e.g. dynamic systems models (Bennet, Cumming & Peterson, 2005)) in the study of social-ecological systems. We locate Bayesian probability theory in a larger participatory-based framework (i.e. BPDA). The overall contribution of this dissertation lies in evaluating the extent to which Bayesian probability theory can be applied to social-ecological scale problems. In particular, we assess the extent to which the BPDA approach can be used to elucidate complexity, engender shared understanding, and can be adapted to accommodate real-world changes as they occur.

We argue that; as an approach for integrating between disciplines, and creating shared understanding between researchers and decision-makers, the BPDA approach yields a wider range of benefits than traditional approaches. This is because the BPDA approach can be implemented to accommodate the key elements of complexity theory, transdisciplinarity and resilience theory in addressing case studies into social-ecological systems. These are all critical areas of research that must necessarily be taken into account in the study of social-ecological system scale problems. In this dissertation, we show how the BPDA approach can be used to satisfy these critical areas, as we evaluate the extent of its applicability in a range of case studies.

As far as economic theory is concerned, the BPDA approach is located within the Schumpertarian or ‘evolutionary’ theory of economics and development. Our contribution is to propose a formalism that is adaptive and heterarchical in that it allows for the co-evolution of categories, conditionalities and causalities. We do not propose a new theory of economics or development. Rather we propose a formalism that allows for theoretical considerations to be made that remains governed by the particular context of inquiry. As such, we argue that the BPDA approach is a basis on which to develop context-governed, adaptable models that support integration, and enables an evolutionary economics-based perspective to be maintained on critical issues that affect sustainable development. While we test the BPDA approach in case studies that mainly deal with the challenges of sustainability through the ‘lens’ of social-ecological systems, we envisage that in the future it can be broadened to support a range of development studies that require an evolutionary approach. As such, the BPDA approach has the potential to provide a valuable contribution to the field of evolutionary economics and the emerging ‘resilience theory’ of social-ecological systems (Gunderson & Holling, 2002).

1.1.9

Outline of Dissertation

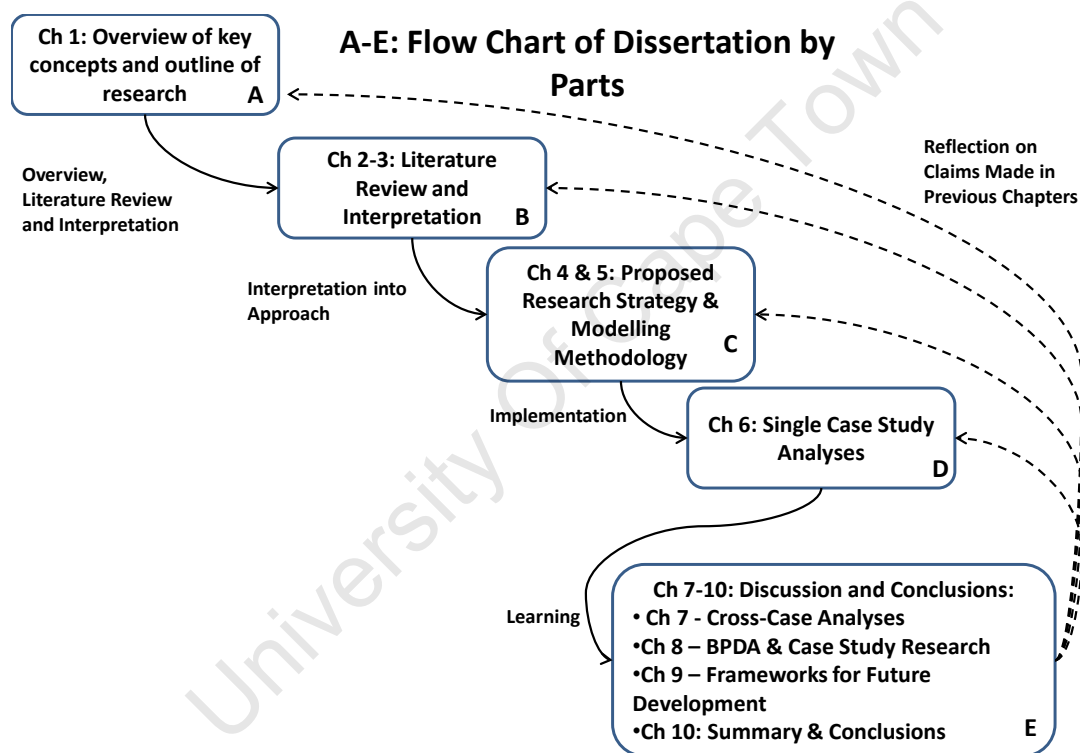


Figure 1: Flow Chart of Dissertation in Parts A to E.

A broad outline of the parts of this dissertation is illustrated above in Figure 1. As illustrated, chapters 1 to 3 and parts of chapter 4 constitute the literature review of this dissertation. However, some concepts are reviewed in more detail in later chapters where detailed interpretation and discussions of case studies conducted in this dissertation are made. Chapter 2 outlines the key concepts concerning sustainability, transdisciplinarity, complexity, heterarchy. The requirements for

representing shared knowledge of social-ecological systems, and the use of ontology's is also outlined in Chapter 2.

Chapter 3 makes the case for using graphical causal models and Bayesian networks as hyperstructures in maintaining the internal models for case studies of social-ecological systems. These hyperstructures can also play a role in integrating research and decision-making activities, and provide an adaptive framework to support adaptive management.

Chapter 4 reviews research and decision-support approaches for dealing with the sustainability of social-ecological systems (scenario planning, adaptive management, modelling & case study research), and proposes a research strategy for dealing with social-ecological system scale sustainability challenges.

Chapter 5 discusses the facilitation of case study research using hyperstructures, and links the role of hyperstructures to the key requirements of case study research and design. It proposes a research strategy and research design for this dissertation, and outlines the aims of single and cross-case analysis for the case studies conducted in this dissertation in support of the goal of this dissertation. It also details the modelling methodology used in this dissertation, which makes use of Bayesian networks and graphical causal models as hyperstructures for case study management of social-ecological systems. Implementation considerations are also outlined in this section.

Chapter 6 constitute the case study outlines for this dissertation. Chapter 6 introduces and discusses the individual case studies conducted in support of this dissertation, and outlines the key elements of learning obtained from each case study in respect of the aims and goals of cross-case analysis for this dissertation. Chapter 6 also deals with case studies that were conducted using only graphical causal maps to facilitate interdisciplinary research and cooperation through integrated causal modelling.

Chapters 7, 8, 9 and 10 constitute the discussion sections of this dissertation. Chapter 7 presents the cross-case case study analyses, and interprets the results in

terms of requirements established for the BPDA approach in this dissertation. Cross-case comparison is made here; each factor for cross-case analysis is evaluated and discussed. It contains a discussion of the methodology proposed in this dissertation, and evaluates its effectiveness in coping with the requirements of modelling complex social-ecological systems.

Chapter 8 discusses in detail how the BPDA approach satisfies the requirements for case study research. A conceptual framework is motivated in Chapter 9, which shows how this approach could support agent-based modelling for decision-support in adaptive governance and management of social-ecological systems.

In the conclusion (Chapter 10), a summary of key insights regarding the strengths and the weaknesses of the approach are outlined.

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2. The Basics: Complexity Theory & Social-Ecological Systems Sustainability

2.1 Sustainability: Strategy-Making, Scenario Planning and Adaptive Management

... the concept and practise of sustainable development as a guiding institutional principle, as concrete policy goal, and as focus of political struggle remains salient in confronting the multiple challenges of this new global order. Yet how sustainable development is conceptualized and practised hinges crucially on ... the willingness of scholars and practitioners to embrace a plurality of epistemological and normative perspectives on sustainability ... embracing pluralism provides a way out of the ideological and epistemological straightjackets that deter more cohesive and politically effective interpretations of sustainable development. (Sneddon, Howarth & Norgaard, 2006)

The term '*sustainable development*', in the broadest sense, refers to the sustainability of socio-economic systems, ecological resources and ecosystem services from this generation to the next (and beyond). Since its inception in the Brundlandt Report (also known as Our Common Future) in 1987, the term 'sustainable development' has its fair share of critics. One of the founders of systems theory, Stafford Beer (1992) referred to the term 'sustainable development' as a "*misnomer*", because it brings together incompatible ideas; that of sustainability, and that of development. Beer argues that the rapid pace of human and economic development, such as population expansion and economic growth, leaves little space for the more long-term goals of sustainability. Sustainability may require a slowing down of the rapid pace of human development. Short term goals would necessarily have to be sacrificed where they conflicted with long-term needs. Beer (1992) states it more strongly; "Out of 'political correctness', no one talks about the exploitation of either nature or indigenous peoples any more. They talk instead about 'sustainable

development' - but there is no such thing. Not only can development not be sustained; even the existing fabric cannot be sustained any longer.”

In the current, highly competitive, global economic climate, survive-ability of human development and enterprise depends on making effective short-term adjustments to foreseeable and unforeseeable changes as they occur (Folke et al., 2005). It has become more difficult to envisage long-term sustainability in the context of highly variable short-term changes in organisational and governance systems that often cannot be predicted, but only reacted or adapted to (Malhotra, 1999). If sustainable development is conceptualised as development that is sensitive to the needs of future generations, this ‘short-termism’ can have disastrous effects (Beer, 1992). In the race to satisfy human needs in the short term in a highly competitive global socio-economy, our current rates of development are placing a large cost on future generations. Simply put, future generations will have to invest a great deal into the rejuvenation of ecological system functions and processes in order to obtain the same services that we currently benefit from.

In some cases, these ecosystem services may disappear entirely, for example, due to rapid human expansion or climate change effects (Lubchenco, 1998). The availability of natural resources such as freshwater resources are threatened by multiple factors, not all of which are within the direct control of those that are immediately affected by it. Sustainability, in this case, depends on the ability of human beings to plan for and adapt to foreseen and unforeseen changes as they occur. In this sense, adaptability and adaptive capacity is a critical requirement for the sustainability of social systems in relation to ecological systems, and vice versa (Folke et al., 2002).

However, adaptability is hampered by the lack of coordination of governance and institutional organisations. The failure to realise more sustainable human development activities in recent history can be put down to “*ineffective institutions and a general lack of political will of governments and citizens at multiple scales*” (Sneddon et al., 2006). Sustainable development is therefore an institutional and organizational challenge at multiple scales, which requires strategy-making at various levels of governance and management within social-ecological systems.

Strategy-making is about asking the right questions about the future and having appropriate strategies to deal with the multiplicity of futures that may unfold (Peterson, Cumming & Carpenter, 2003). It involves handling real-world contexts that have varying levels of uncertainty. Strategy, broadly speaking, has two schools of thought which are located at different ends of the decision-making spectrum because they handle different levels of uncertainty, namely *strategic leadership* and *strategic management*.

At the one end, *strategic leadership* is often confronted with irreducible and uncontrollable uncertainties of a system that can be *observed but not directly influenced* by strategy-makers. Strategic leadership (in this context) is focussed on framing the right questions, and building institutional or organizational capacity to adapt or react to *unforeseeable* changing circumstances which lie beyond the control of strategy-makers. The general perception usually held at this level of strategy-making is that there is little point trying to obtain a predictive, measureable analytical framework of the system because ‘things will emerge’ over time (Malhotra, 1999).

At the other end of the spectrum, *strategic management* is usually more concerned with *measurables* that can be *observed* and *interventions* that can be *implemented* and *adapted*. Where strategic management is concerned the reliance on measurables is a direct consequence of the need for accountability within management hierarchies. Management accountability is often interpreted as the need for measureable results and accounts of management processes. Often, strategy-makers at management levels have the attitude that ‘can’t manage what they can’t measure’. At this end of the spectrum a more ‘scientific’ approach to strategy-making is implemented because the availability of measured evidence means that traditional science and statistical methods can be applied to the data. Policy-making is usually an activity associated with strategic leadership based approaches, whereas implementation of policy is performed with strategic management based approaches.

The same governance-management tensions are apparent in the strategic approaches used for social-ecological systems i.e. the two strategy making approaches that are currently used for social-ecological systems sustainability questions.

Adaptive governance (strategic leadership) makes use of scenario planning exercises to cope with high levels of uncertainty and predictability (Folke et al., 2005). In this domain, system actors have little or no influence upon the greater system forces they are subject to, and can only *observe* changes as they occur. *Scenario planning* entails envisioning and discussing system futures and possible adaptation options through facilitated dialogues and interactions (Peterson et al., 2003). Generally the accounts are structured in a story-telling framework where narrative and dialogue are central to ensuring rigour. Scenario planning is a tool to handle questions about the future in a robust framework that is open to various levels of critique. It creates a space for conversation and learning to occur (Peterson et al., 2003), increasing the ability of strategy-makers (system actors, stakeholders, system users) to cooperatively adapt to uncontrollable changes.

Adaptive management (Walters, 1986) is distinguished from scenario planning in that it permits *observations and interventions* to be made upon the system (Peterson et al., 2003) and deals with a more controllable range of issues than scenario planning does.

Strategy-making for social-ecological systems is concerned with two types of *learning processes*. In *scenario planning* the learning process is restricted to learning from *observations* because the action(s) of strategy-makers upon the system brings about negligible influence at 'whole' systems level. Rather, scenario planning is concerned with merging a broader spectrum of quantitative and qualitative information to stimulate people into new insights about the system or problem they are concerned with. In *adaptive (co)management*, the learning occurs from *observations and interventions* made upon the system. Management interventions have an influence upon the system and bring about observable effects that can be learnt from. Scenario planning and adaptive management operate at different levels of uncertainty and predictability. Scenario planning draws on observational information whereas adaptive management makes use of both observations and interventions of the system. Learning from both *observations* and *interventions* is therefore a self-evident requirement for dealing with social-ecological systems.

2.2 Scenarios, Projections, Causality & Conditionality

So far we've discussed scenario planning, but the issue of what a scenario *is* deserves some attention. So what is a scenario? Peterson et al. (2003) define a scenario as a 'structured account of a possible future'. In this case of scenario planning this structure often takes the form of *narrative* and *dialogue*. So how do we formulate a "structured account of a possible future", or a scenario? This question is intimately concerned with prediction, forecasts and projections (Peterson et al., 2003). Prediction has different interpretations, but it can be defined as "the best possible estimate of future conditions". A forecast is a "best possible estimate from a particular method, model or individual". Projections are made when a 'prediction' is "heavily dependent on assumptions about drivers and may have unknown, imprecise or unspecified probabilities. Projections lead to "if this, then that" statements (MacCracken, 2001)" (Peterson et al., 2003). Thus, a scenario as a structured account of a possible future relies on causality to express predictions. Moreover, these causal relationships are *conditional* upon a set of assumptions:

Whereas scientists understand that **predictions are conditional probabilistic statements**, nonscientists often understand them as things that will happen no matter what they do (Sarewits et al., 2000; MacCracken, 2001). (Peterson et al., 2003, emphasis added: bold)

To summarise, a structured account of a scenario involves several key features. Causality is the logic used to express predictions. This causality is conditional upon a set of assumptions about system controls, functions and processes. In addition, information gleaned from both observations and interventions are used to learn about and iteratively improve the 'structured account' of the scenario.

Three "*fundamental, interacting problems*" (Carpenter, 2001; Peterson et al., 2003) are associated with ecological predictions; *uncertainty*, *contingency* and *reflexivity*. Where complex systems are concerned, uncertainties in models and their results are often "*not rigorously evaluated*" (Peterson et al., 2003). Where forecasts are concerned the future system state may have very different multiple futures, each

with equal probability of occurring. Contingency refers to the dependence of ecological predictions on unpredictable drivers. Human behaviour is given as an example of this (Peterson et al., 2003). Reflexivity is concerned with *dynamic feedback* due to actors (or agents) within the system acting upon individually and collectively held perceptions about the future. This dynamic feedback has a significant effect on critical thresholds, system functions and controls of the system. Reflexivity scuppers prediction, because it is concerned with how actors within the system may change their behaviour in response to predictions that are ‘taken seriously’, thereby changing the evolution of the system. Reflexivity can bring about self-fulfilling prophecies. For example, panic-buying of petroleum often increases where perceptions of looming fuel shortages are held, resulting in exactly the kind of crisis (low fuel supply at service points) that people individually attempt to avert by buying more than they usually would.

According to Peterson et al. (2003) predictions, forecasts and projections fall in the realm of “*the probable*”, while scenarios deal with “*the possible*”. While this distinction can be made for the purposes of distinguishing between the roles of scenario planning and adaptive management, there exists a *continuum* between the functions of strategic leadership and adaptive management of social-ecological systems. Adaptive governance (Folke et al., 2005) and adaptive management may generally be considered as being more concerned with strategic leadership and strategic management roles, respectively. Both processes must interact effectively to engender system resilience and adaptive capacity to change (Folke et al., 2005). Adaptive governance has come to represent alternatives to “conventional top-down government control, including collaboration, partnerships, and networks” (Folke et al., 2005).

Issues of legitimacy and accountability are often stressed in the literature on governance ... and good governance of ecosystems has been interpreted as solving the trilemma characterised by tensions between effectiveness, participation and legitimacy. (Folke et al., 2005)

Legitimacy and accountability are key requirements for adaptive governance and management programmes. Therefore, how we evaluate (or verify and validate) adaptive governance and management programmes is critical to the levels of confidence we associate with them. Accordingly Bellamy et al., state the importance of validity (verification) and reliability (validation) in the evaluation of such programmes (Bellamy, Walker, McDonald & Syme 2001, p. 408). Furthermore Van Kerkhoff & Lebel emphasise that evaluation also relies on participation (Van Kerkhoff & Lebel, 2006; Peter et al., 2008). Evaluation necessitates *participation* as a mechanism for evaluating the *reliability* upon which assumptions and evidence pertaining to a particular scenario is contingent.

2.3 **A New ‘Science’ for Sustainability?**

2.3.1 **The Need for a New Approach: Systems & Complexity**

What may be sustainable in a human or ecological system alone, researched and managed by itself, does not necessarily ensure sustainability at the whole system scale. Research and management strategies that follow this type of approach often fail to produce sustainable actions in social-ecological systems due to fragmented knowledge and consequent decision-making by key human actors within the social-ecological system (Holling, Gunderson & Ludwig, 2002, pp.8).

In a chapter entitled “*In quest of a theory of adaptive change*” Holling, Gunderson & Ludwig (2002, pp.19) summarises the key elements of the quest for a research strategy for social-ecological systems as;

In our quest, we would like to discover ways to integrate and extend existing theory to achieve a requisite level of simplicity, just complex enough to capture and explain the behaviours we see. Those include explanations of discontinuous patterns in space, time and structure and explanations for how novelty emerges, is suppressed, or is entrained. For prescriptive purposes we also seek adaptive ways to deal with surprise and the unpredictable. We

concentrate on adaptive approaches that do not smother opportunity, in contrast to control approaches that presume that knowledge is sufficient and that consequences of policy implementation are unpredictable.

The quest to “integrate and extend existing theory” is not unique to the research that is conducted on social-ecological systems, and the challenge of sustainability of these systems (Lubchenco, 1998; Allen, 2005). Inter and trans-disciplinarity and coping with emergence are the key requirements for solving problems in many different arenas of research and practise, especially where complex, adaptive systems are the subject of interest (Holling, 2004; Max-Neef, 2005; Starzomski et al., 2004). It is a quest that is shared by many researchers, in many different disciplines, who have come to share the view that real-world complex systems requires interdisciplinary and transdisciplinary approaches in order to appropriately address the complexity of the real-world system or problem that confronts them (Cilliers, 2008; Holling, Gunderson & Ludwig, 2002; Max Neef, 2005). In particular, social-ecological systems exhibit emergent behaviour; requiring *adaptive learning* approaches to research (Folke, 2005; Van Kerkhoff & Lebel, 2006) in order to cope with uncertainty and surprising, discontinuous behaviour.

Van Kerkhoff & Lebel (2006) relate the need for natural scientists to migrate towards social science based ‘action research’ methodologies in order to increase their relevance at the levels of political negotiation and decision-making. In relation to linking theory and practise in the social sciences through action research, Gustavson (2001, p.17) states that: “*most proponents of action research argue that theory alone has little power to create change and that there is a need for a more complex interplay between theory and practise*” (Gustavson, 2001, p.17). Similarly, research and decision-making for sustainable development of social-ecological systems are presented with the challenge of “*linking knowledge and action*” (Van Kerkhoff & Lebel, 2006) and that actions for sustainable development must necessarily engage with a combination of “*scientific, social and political knowledge and judgements*”. Van Kerkhoff & Lebel (2006) review the theories and strategies that have come about or into use in response to this challenge across the categories of “*participation, integration, learning and negotiation*”, and emphasize the need for a “*system-wide*”

perspective that covers multiple scales and remote effects on sectors/groups beyond those directly affected by decisions made in social-ecological systems.

As a consequence of this challenge, researchers have great difficulty in negotiating the multiple dimensions that formulating sustainable actions requires, and in working effectively with decision-makers, stakeholders and system users to implement actions. Van Kerkhoff & Lebel (2006) take the view that “*the authority of research emerges from the interaction of the research processes with the political processes of decision-making and change*”. They then identify theories and strategies for addressing the goal of linking knowledge to actions for sustainability, which involve learning, participation, cooperation and negotiation. Any research paradigm that seeks to become relevant in the arena of decision-making, must necessarily engage with the fact that social-ecological systems are complex, adaptive systems (Levin, 2006), which self-organise, and *also* require an interdisciplinary, sometimes transdisciplinary approach towards research (Max-Neef, 2005).

In summary, sustainability research necessarily engages a broad range of issues and factors and requires an open approach towards methodologies, as methodologies are used where they ‘fit’ a problem and its context of application appropriately. Such research efforts must necessarily be sensitive to *real-world changes* and events, and how they occur in the *current context* (Folke et al., 2002; Folke et al., 2005; Malhotra, 1999). A researcher may have to interact with a wide range of experts from different disciplinary orientations in order to obtain a balanced and fair understanding of the problem from a whole social-ecological systems perspective. It may also require that the researcher consults with stakeholders and system users directly in order to obtain contextually reliable and verifiable information. Finally, a researcher in sustainable development seeking to deal with complex, integrative problems should aspire to enabling a true *transdisciplinary* approach towards knowledge (Max-Neef, 2005), where a democratic, unbiased study can emerge from the various understandings of the system, even if they contain conflicting positions and assumptions. This is an important development in theory, and has emerged in order to avoid the dominance of “partial truths” (Holling et al., 2002, p.19) or partial perspectives from developing within the research effort. Normative views are therefore significant where research and decision-making for the

sustainability of social-ecological systems is concerned, and an awareness of normative frameworks employed in both are required of the researchers involved.

In the next few sections of this chapter a more detailed account is given of the need for such an approach and the philosophical, conceptual and methodological issues that are involved in implementing such an approach. It is meant to introduce the reader into the range of background issues that have a bearing on the content of this dissertation. The challenge of reconciling the epistemological and ontological differences between the social and natural sciences is the subject of the next part of this section.

Even in ‘purer’ sciences, however, since Kuhn (1970) it has been reasonably accepted that science, as a human activity, necessarily reflects its time and place in many ways, and to that extent is not a ‘purely objective’ activity. Moreover, science and engineering are self-selective processes, in that those who choose to pursue such professions as opposed to, say, law or economics or crime, choose to do so for a number of reasons, many of which are not ‘objective’ in the usual sense (such as, for example, status, employment opportunities, desire to create a better world, and the like). The context within which science occurs, and individual scientists self-select, therefore, is heavily normative. (Allenby, 2006)

It is widely recognised that even the ‘pure’ sciences involve both objective and normative components in the ‘identification and formulation of hypotheses’ (Allenby, 2006; Kuhn, 1970) that can be tested for ‘falsifiability’⁵. Moreover, where the overlap of academic disciplines is further strained by having to accommodate non-academic discourse; the balance between normative and objective inquiry can sway between these two aspects as the context changes. This is also the case with adaptive governance and co-management programmes for sustainable development.

What we call ‘science’ is often a matter of worldviews and paradigms. Science advances through changes in paradigms (Kuhn, 1970). In particular, when

⁵ The author has coined the term ‘falsifiability’ for ease of use in the sentence.

we insist that science provides *objective* knowledge we assume that we are not a part of creating the reality we observe, or attribute *meaning* to. In this view (the Cartesian⁶ worldview), reality occurs and we observe it. From this, various interpretations can be tested against one another and consensus reached about which theory (or theories) best fit our observations and understanding. In this way we refine theories until they approximate reality. In the classical sciences, these ‘refinements’ are believed to be achievable through observation of known, measurable indicators. That is why science has long enjoyed a privileged position amongst disciplines. The very use of the word ‘science’ itself lends credibility to insights that are made using its methods and techniques of observation and analysis. Science relies on ‘repeatability’ and testability. Experiments and observations are repeated to ensure that ‘objectivity’ of the hypothesis is ensured. Hypotheses are repeatedly tested for consistency of results. The idea that an objective reality can be interpreted is seductive because it implies that deterministic predictability and control over natural systems is possible. However, what we call ‘science’ is often tied up with what we want science to be and reflects our worldview(s) of reality to some degree.

When the science of social-ecological systems is considered, however, the ethical and ‘scientific’ considerations of human and natural systems must be merged. It is necessary for this kind of science to bridge disciplinary, institutional and socio-economic boundaries in order to deal with the level of complexity of social-ecological systems appropriately. It is clear that ‘objective’ scientific knowledge is useless in the real-world context unless a further step is taken to integrate the interpretation of objectively determined scientific ‘facts’ with its context (Van Kerkhoff & Lebel, 2006). This view mirrors movements towards holism in the philosophy of governance in the 20th and 21st century (e.g. Smuts, 1926). The need for holism is also the basis

⁶ Descartes proposed that the mind and body were two distinct, separate entities. This forms the roots for subject-object separation that underlies human-nature dualism. He also proposed that reductionism should lie at the core of rational scientific inquiry. The Cartesian worldview lies at the basis of reductionism, which in turn lies at the core of scientific determinism - the successes of which led to the dominance of science since the 18th century. There are many critiques of the Cartesian worldview, from the time of its inception until now.

on which the need for transdisciplinarity can be proposed, for example, in dealing with global scale problems Max-Neef⁷ (2005). Three key areas for enabling an ethical idea, which goes beyond the reach of pure 'objective' scientific knowledge, are identified by Gandhi (1968); *self-awareness*, *knowledge representation* and *taking action*. When it comes to social-ecological systems, the awareness and representation of knowledge is a key step towards formulating and taking actions for sustainable change, especially at different levels of organisation and decision-making within social-ecological systems. A more distributed intelligence is therefore required for better whole systems coordination and sustainability.

... the process of consciously generating and spreading sustainable ideas may be termed sustainable governance. The process that leads to sustainable governance is management of sustainable change. (Lamberts, 2006)

In this dissertation, adaptive governance and adaptive management (Folke et al., 2005) are viewed as complementary processes which need to interact in order to bring about successful results at various levels and scales of involvement. As already discussed, adaptive governance refers to the higher level functions of policy and decision-making at larger scales, whereas adaptive management is concerned with practical implementation of intervention and monitoring programmes. Both require effective and transparent participation in order to legitimise the eventual approach taken towards the problem. However, for the purposes of this dissertation, a clear distinction between the two is not necessary, as the dissertation aims to deal with both simultaneously and to facilitate interaction between both.

Therefore, dealing with the awareness and representation of knowledge generated firstly from the facilitation of interdisciplinary and cross-boundary dialogue, and secondly from scientific models, simulations, experiments and observations, are key requirements for ensuring good adaptive management and governance. In summary, the challenge of social-ecological systems sustainability is

⁷ *Transdisciplinarity* (Max-Neef, 2005) must be enabled in order to deal with the problematics of social-ecological systems. The domain of transdisciplinarity, according to Max-Neef (2005) is tangled up with ideas of 'what is', 'what we can do', 'what we want to do' and 'what we ought to do' i.e.

not just an analytical one; it also involves the realms of governance and management. The parties or actors involved in these functions are influenced by the values, beliefs and norms that they bring to the analysis of a problem and the decisions that are made about how to deal with it. The worldviews, assumptions and observations that underlie their (often different) ways of thinking and acting has, in reality, a significant effect on social-ecological system resilience. We are required to understand the conditionality upon which causal relationships are inferred, and predictions made is required. An approach for dealing with sustainability challenges must necessarily engage with this level of knowledge representation in order to stimulate the emergence of new knowledge i.e. knowledge that could be regarded as transdisciplinary in nature.

The term 'sustainability' can be interpreted in many ways, depending on the perspective from which sustainability is being interpreted. An ecologist might lean towards assessing the sustainability of ecological systems in response to human pressures, whereas a politician might focus on the sustainability of human communities and 'ways of life' in response to increasing ecological crises or uncontrollable ecological changes (e.g. climate change and natural disasters). If the ecologist had a natural science background, she may by virtue of the security of her training tend towards a predisposition for using measurable evidence rather than qualitative evidence. A politician, however, might instead seek to gauge perceptions through participation with various actors at different levels in the system. Therefore, adaptive governance and management programmes may tend to 'pull' in different directions, depending on how hard and soft factors combine to impact upon the specific goals of the programme.

Where adaptive co-management is concerned, normative, value-based problematics are found to be as important as objective scientific analyses and experiments (Levin, 2005; Stern, 2000; Van Kerkhoff & Lebel, 2006). Moreover, it has become necessary to overcome the dominance of *partial perspectives* (Gunderson & Holling, 2002) in dealing the social-ecological systems sustainability. These multi and interdisciplinary approaches attempt to deal with the research problem through

transdisciplinarity engages with empirical, purposive, normative and value (ethical) levels (see later

jointly defining the overall research problem, but by resorting exclusively to traditional disciplinary approaches in addressing specific questions. This often leads to fragmented mono-disciplinary research outputs and evaluations which are ‘stapled’ together, but don’t address the problem at whole systems level sufficiently. It is widely acknowledged that a more holistic, systems-based view of social-ecological systems is desirable (Allenby, 2006; Gunderson & Holling, 2002; Levin, 2006; Starzomski et al., 2004). Both normative and objective inquiries become relevant in different measures where research attempts to engage the ‘political processes of decision-making and change’ (Stern, 2000).

This is not without conflicts in values and beliefs about the ‘universality’ or ‘context specificity’ of rules, procedures and principles that can be formulated for such systems. This is especially so where the formulation and implementation of policy, law and legislature are concerned; critical elements of governance and management. For example, regarding the application of legal principles, rules and procedures, Isaiah Berlin (1969) writes that:

... since some values may conflict intrinsically, the very notion that a pattern must in principle be discoverable in which they are all rendered harmonious is founded on a false a priori view of what the world is like. If ... the human condition is such that men cannot always avoid choices ... (this is) for one central reason ... namely, that ends collide; that one cannot have everything ... Even those who are aware of the complex texture of experience, of what is not reducible to generalisation or capable of computation, can, in the end, justify their decisions only by their coherence with some over-all pattern of a desirable form of personal or social life, of which they may become fully conscious, it may be, when faced with the need to resolve conflicts of this kind. If this seems vague, it is so of necessity.

This view provides a good parallel insight into the nature of the problem being faced by adaptive governance and management practitioners and researchers, and legislators. Berlin acknowledges the limitations of pure calculable rationale as a basis

text on transdisciplinarity in section 2.3.2).

for the formulation universally applicable rules and procedures when considerations regarding human agency become important. There is lively debate amongst researchers and practitioners about whether research into ‘social-ecological systems’ can be defined as ‘science’ or ‘scientific field’ (Allenby, 2006) in itself, but these debates often focus on narrow definitions of science (Lubchenco, 1998; Holling et al., 2002; Holling, 2004).

The Cartesian view on the ‘method’ of scientific inquiry and the mind-body problem, have had a profound effect on how human-nature interactions are scientifically articulated, explored and analysed. It is widely recognised as the overriding normative epistemological and ontological background underlying the natural and social sciences. It has been posed by some authors that the fragmentation of disciplines is a consequence of Cartesian reductionism (Capra, 1997; Cilliers, 2008; Max-Neef 2005; Hodgson, 1993). It is responsible for the prevalence of ‘partial perspectives’ which now needs to be overcome. The normative foundation of traditional natural and social sciences needs reconsideration where complex, integrated systems are concerned (Max-Neef, 2005). To view social-ecological system through absolute objective or normative filters is to *not* acknowledge the complexity of practically dealing with real-world social-ecological systems sustainability challenges. However, social-ecological systems theory as a way of thinking and doing is recognised as a necessary tool for dealing with the real-world complexity of social-ecological systems challenges.

A framework is needed for how we describe human-nature (and other) relationships within a single social-ecological system. One method to approach the complexity of systems is, for example, found in the work of Descartes. To Descartes, everything in the material world obeyed mechanistic laws and could be reduced to ‘atomic’ components. At the core of his method is the idea that from decomposing a system and analysing its components the behaviour of the whole could be understood. Though this reductionist method has been very successfully in the basic sciences, for example, in physics, biology and chemistry, it has its shortcomings when it comes to social-ecological systems because it fails even at the level of dealing with ecosystem complexity alone, as stated by Gillaume et al. (2004) “A reductionist approach fails in modelling such mutual interactions and feedback processes.”

Hodgson (1993) reaches a similar conclusion when critiquing the roots of the epistemological basis of economics:

Contrary to Descartes, we ‘cannot begin from complete doubt. We must begin with all the prejudices which we actually have.’ Peirce (1934, p.156) ... The search for knowledge ... is a social endeavour, in which we inevitably rely on both the recent work of others and on the undersigned, mysterious and sometimes unsatisfactory conventions of usage and meaning that have been built up over centuries. (Hodgson, 2003, p.15)

In particular, it fails when complex systems exhibit emergent properties which result from the interaction of its parts: ‘*systemic properties are destroyed when a system is dissected into isolated elements*’ (Capra, 1996/7). In this case, the conceptual framework of reductionism is not any longer appropriate since higher level (emergent) properties of the system cannot be analysed from giving a rigorous description of the behaviour of its parts.

An alternative view to the classic reductionist approach is provided by systems theory, general systems theory (Le Moigne, 1994) and complexity theory (Heylighen, Cilliers & Gershenson, 2007⁸). In particular, these theories stress the importance of the interconnectedness of complex systems entities. This results in emergent properties which cannot be analysed by decomposing the system. Complexity theory views all entities in a system as system *agents*. A complexity-based analysis of a system must acknowledge the different levels of description in which a system can be understood. The existence of emergent properties arising in complex systems has the immediate consequence that within a particular scientific discipline, a proper analysis of a system must acknowledge the fact that higher level properties cannot always be reduced to lower level descriptions.

⁸ Where, complexity theory is the theory of complex, adaptive systems.

Moreover, an adequate analysis of complex systems might also require the consideration of different conceptual frameworks *across* scientific disciplines. Researchers from different disciplines may have different non-overlapping *and* overlapping conceptual schemes. For example, HIV and AIDS are research subjects in both medicine and epidemiology, though they take different perspectives on the issue (i.e. describing the development of AIDS versus investigating the spread of the disease among individuals). From a systems perspective, two types of systems are involved, which are also characterised by different boundaries. A physician investigates the causal mechanisms *within* a biological system (i.e. the human body) whose boundaries are defined in biological terms. In contrast, the epidemiologist whose goal is to understand the spread of the disease also needs to take into account social factors (e.g. pertinent to the context people live in). The inclusion of this perspective is crucial because the disease spreads by interaction (e.g. sexual intercourse) among the individuals. As a consequence, the system investigated by the epidemiologist might be characterised more by specific social and political circumstances, or norms and values inherent in the prevailing discourse around HIV in South Africa (e.g. in investigating the spread of HIV in South Africa or in a certain community). The epidemiologist has to grapple with the greater influence of individual and collective agency within the system to adequately understand how and why the disease spreads at the observed rates. It cannot be understood from analysing data about the spread of infection alone.

2.3.2 Transdisciplinarity: The Need for Shared Knowledge

Transdisciplinarity is a term which is used to describe many kinds of interdisciplinary cooperation. The interpretation of transdisciplinarity used in this dissertation was proposed by Nobel laureate for economics Max-Neef (2005). He outlined a framework in which transdisciplinarity could be visualised and conceptualised, as shown in Figure 2. The reason for his proposal was to outline a framework for transdisciplinarity that could practically help deal with the main ‘problematiques’ of the century. These problematiques include the sustainability of natural resources, forced migration, poverty, war, water, globalisation global and cyber terrorism etc.

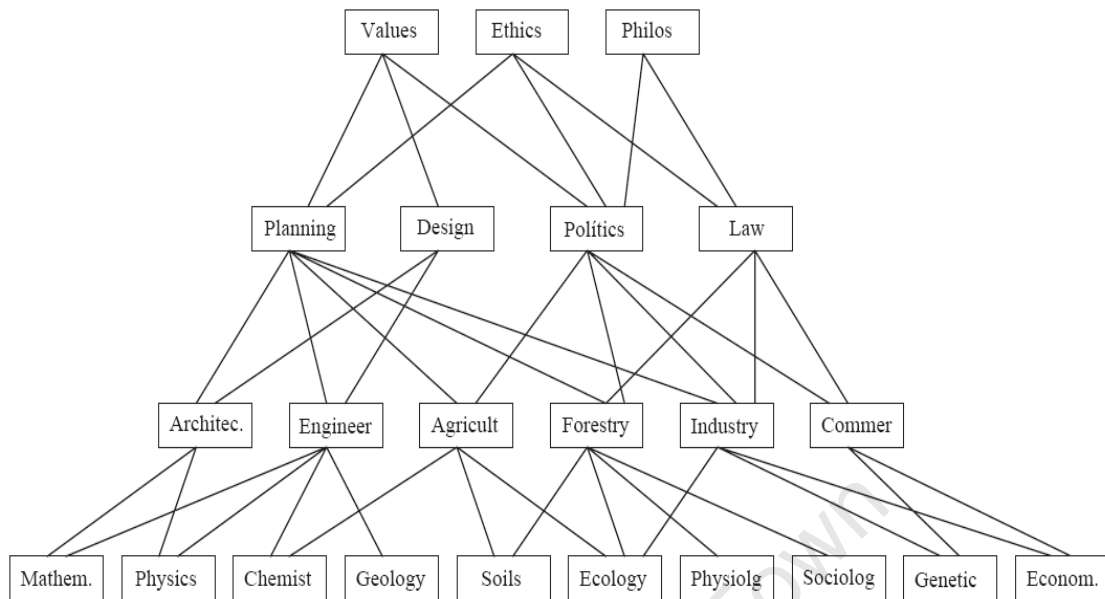


Figure 2: Transdisciplinarity: “Transdiscipline. Reading the graph from bottom to top, the lower level refers to what exists. The second level to what we are capable of doing. The third to what we want to do. And finally, the top level refers to what we must do, or rather, how to do what we want to do. In other words, we travel from an empirical level, towards a purposive or pragmatic level, continuing to a normative level, and finishing at a value level. Any multiple vertical relations including all four levels, defines a transdisciplinary action.” Max-Neef (2005: Graph 3)

A framework for transdisciplinarity is presented in Figure 2 (Max-Neef, 2005) with a detailed caption. *Transdisciplinarity* (Max-Neef, 2005) must be enabled in order to deal with the integrative, real-world problematiques facing humankind. The domain of transdisciplinarity, according to Max-Neef (2005) is tangled up with ideas of ‘what is’, ‘what we can do’, ‘what we want to do’ and ‘what we ought to do’ i.e. transdisciplinarity engages with empirical, purposive, normative and value (ethical) levels. A “*transdisciplinary action*” is an action which traverses vertical and horizontal levels (see Figure 2) in order to address a question (Max-Neef, 2005). It therefore stands to reason that a *process* that allows researchers to operate at all levels of Max-Neef’s (2001) hierarchy in Figure 2 is required in order for transdisciplinarity to *emerge*.

Max-Neef suggests two possible classes of transdisciplinarity; weak and strong transdisciplinarity. Weak transdisciplinarity “can be applied following traditional methods and logic, and is essentially practical”, while strong transdisciplinarity requires a great deal more i.e. it, “represents an epistemological challenge that introduces a kind of quantum logic (Nicolescu, 2000), as a substitute for linear logic, and breaks with the assumption of a single reality.” The basis of strong transdisciplinarity, according to Max-Neef (2005), includes three basic pillars, namely, “Levels of Reality; the Axiom of the Included Middle; and Complexity”, as three “Three Laws of Transdisciplinarity”. He concludes that ‘strong’ transdisciplinarity is “still in the making, thus representing an unfinished scientific programme that offers fascinating possibilities for advanced reflection and research”.

In the context of this dissertation, which is concerned with sustainability, transdisciplinarity must negotiate a wide range of issues and sectors. It is therefore necessarily concerned with overlap of power, ethics, philosophy with the value, normative, purposive and empirical levels of reality. The added attractiveness of Max-Neef’s framework (2005) is that socio-political features such as power can be located within and across different levels, from the empirical to value levels of reality. There are actors from various power domains that can be located at different levels of influence and organisation. The issue of global sustainability is tied to governance, civil society and business power structures (Perlas, 2002). Participatory efforts towards sustainable decision-making often involve a wide range of researchers, stakeholders, decision-makers and system users. Transdisciplinarity, in some sense, is not an end in itself, but emerges from the participation, interaction, dialogue, negotiation and evidence-based research conducted around a subject.

In order to enable strong transdisciplinarity for social-ecological systems as complex adaptive systems, we have to cater for the multiplicity of views that are held on a single reality. Moreover, two more distinctions are required where social-ecological systems are concerned; that of *undecideability* and *complexity*. These are reviewed in the next two sub-sections:

“So I asked Derrida; what’s the difference between an undecideable and the impossible? He thought for a bit and replied, ‘Well that’s an undecideable!’” John Comaroff (2007, private communication, anecdotal)

The ‘included middle’ makes a good comparison to the ‘undecideable’ in political processes of decision-making as described by Derrida (1992);

“The undecideable is not merely the oscillation or the tension between two decisions, it is the experience of that which, though heterogeneous, foreign to the order of the calculable and the rule, is still obliged — it is of obligation that we must speak — to give itself up to the impossible decision, while taking account of law and rules. A decision that didn’t go through the ordeal of the undecideable would not be a free decision, it would only be the programmable application or unfolding of a calculable process.” In Banisch (2002).

A political decision made without the consideration of *undecideables* would be achieved through applying a set of rules as though they defined reality perfectly (Derrida, 1992). Engaging effectively with the political processes of decision-making and change as researchers of social-ecological systems therefore requires acknowledging and dealing with the inherent undecideability which accompanies political decision-making. According to Nicolescu (2000), “ Transdisciplinarity is the transgression of duality (;) opposing binary pairs: subject/object, subjectivity/objectivity, matter/consciousness, nature/divine, simplicity/complexity, reductionism/holism, diversity/unity”. The incontrovertible presence of undecideables in political decision-making introduces uncertainty, and highlights the need to transcend philosophical dualism.

In the context of sustainability, undecideability emerges from contrary views, and/or contrary sets of evidence. This usually emerges from the variety of worldviews, value and belief systems held by participants and stakeholders. That is, it

emerges from attempting to maintain the diversity of belief systems involved in taking a decision. This emergent undecideability is due, in large part, to the limitations of being able to reconcile 'partial perspectives' and consequent fragmented decision-making. In this sense, undecideability also occurs (at another level) with respect to the limitations of understanding and prediction, and with respect to emergence in systems behaviours.

Both contrary views and contrary sets of evidence involve learning from observation and/or intervention. It is entirely plausible that some views and explanations may converge, while others may diverge over time in a process of learning and interacting with a particular social-ecological system. Even legal loopholes may be considered undecideables, and are a good illustration of the power of undecideables in making critical decisions. Taxonomic uncertainty, in the case of legal loopholes, provides spaces of uncertainty that can be exploited for reasons of prosecution or defence of a charge of crime.

2.3.2.2 **Transdisciplinarity & Complexity**

It is also necessary that in order for transdisciplinarity to be enabled, an appreciation and understanding of complexity is required (Max-Neef 2005). Transdisciplinarity is concerned with real-world contexts and problems, where traditional approaches no longer find appropriate application. Transdisciplinarity as articulated by Max-Neef (2005) is concerned with integrating across the empirical, normative, purposive and value levels of reality (see Figure 2), and must therefore negotiate complex issues related to scale, agency, context and interconnectedness.

It is of this necessity that integration between disciplines has become an imperative. As previously outlined, complexity theory is concerned with multi-agent systems where adaptive agents self-organise and bring about emergent behaviours. As such, complexity theory has great relevance for transdisciplinarity in social-ecological systems research, especially where resilience theory is concerned.

2.3.3

Resilience, Adaptive Cycles & Panarchy

Buzz Hollings initial formulation of the concept of resilience was established upon the developments in computer based chaos simulations. These revealed that systems that followed deterministic rules could break down in their ability to make absolute deterministic predictions and behaved unpredictably and chaotically under specific conditions. However, even when behaviours were highly unpredictable they were bounded; they did not exhibit truly random behaviour. This prompted a large amount of interest in analysing how systems with critical non-linear relationships evolved. In order to obtain better understanding of the various 'stability regimes' in which these systems could exist, they were analysed in phase space. Phase space is where multiple attractors represent the various 'solution states' in which the system may exist. The idea of a system being able to exist in multiple stable states is being used in adaptive management of ecosystems; especially where lakes, grasslands, savannahs, rangelands etc. have been the subject of interest (Witten, 2001), and social-ecological systems themselves have been the subject of interest (Gunderson & Holling, 2002; Peterson et al., 2003).

A system's resilience is tested by emergence. There is a critical difference between the concept of resilience as understood in engineering, when compared with how the concept of resilience is interpreted when referring social-ecological systems. With engineering systems, resilience refers to the capacity of a system to remain in equilibrium. Complex adaptive systems find stability *far away from equilibrium*, through their ability to self-organise through non-linear controls such as reinforcing and dampening feedback loops.

Social-ecological systems *also* maintain themselves in stability far away from equilibrium through networked feedback mechanisms with different order effects. Social-ecological systems are complex, and therefore, the concept of stability used in chaos theory was adapted to reflect the stability basin, or 'attractor' of social ecological systems, where the depth and width of an attractor which would describe a stable social-ecological system state. There are five interconnected factors with which resilience theorists are concerned; latitude, precariousness, connectedness, rigidity and potential (Gunderson & Holling, 2002). These can be used to describe

the potential for innovation (or adaptive capacity), stability conditions and interdependencies of a social-ecological system.

It can be argued that resilience theory has found easier implementation in the study of the complexity of biophysical ecosystems than social systems. It yields a collection of metaphors however, which provide a basis for an evolutionary approach towards social-ecological systems and it is acknowledged that the theory of resilience itself is expected to evolve. The concept of resilience has evolved since its conception and is now defined on the resilience website as:

Ecosystem resilience is the capacity of an ecosystem to tolerate disturbance without collapsing into a qualitatively different state that is controlled by a different set of processes. (www.resalliance.org)

Note that the definition above implicitly recognises that there are multiple stability regimes that a social-ecological system can revert to. Resilience is a concept with many possible definitions, some of which are listed here (Gunderson, 2000; www.resalliance.org):

- “The amount of change the system can undergo and still retain the same controls on function and structure.
- The degree to which the system is capable of self-organization.
- The ability to build and increase the capacity for learning and adaptation.”

According to Walker et al. (2004), resilience is the “capacity of a system to absorb disturbance and re-organise while undergoing change so as to retain essentially the same function, structure, identity and feedback”.

Walker et al. (2004) go further and includes the factor of ‘identity’ in the definition and interpretation of the concept of resilience. The ‘identity’ of a social-ecological system may be characterised using another metaphoric analytical tool; *the*

adaptive cycle. The different phases of an adaptive cycle provide a useful conceptual framework for visualising different stability regimes of social-ecological systems.

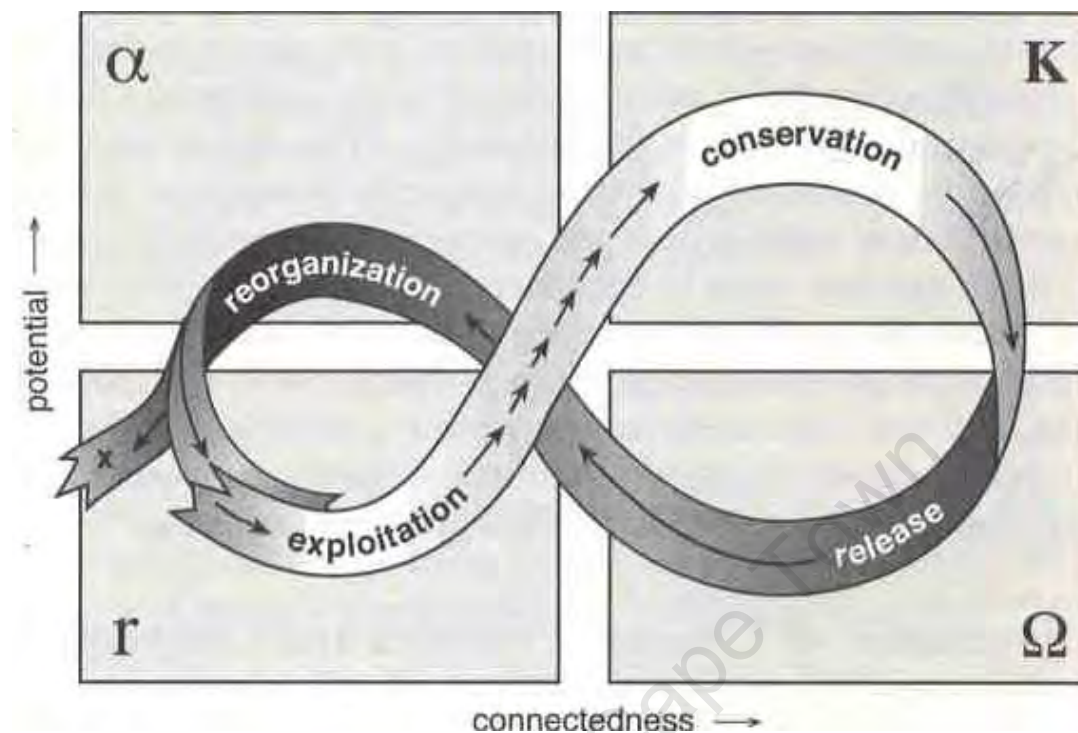


Figure 3: Theoretical Phases of an Adaptive Cycle (Holling, 2004)

The phases of an adaptive cycle are used to describe four phases of a system evolution (see Figure 3 and Table 1). These phases of system evolution are used to identify the state of evolution in which a system may reside.

A social-ecological system can be stable in a number of different system states. Four broad states of self-organisation have been identified for social-ecological systems; growth, conservation, breakdown and renewal (Holling, 2004). Together, and in that respective order, they constitute an adaptive cycle (see Figure 3 and Table 1). Social-ecological systems are dynamic, and the states of stable self-organisation, in the context of an adaptive cycle, are ultimately transitory and can more appropriately be regarded as phases. A social-ecological system may be resilient in any one of these phases. Hence resilience is not always desirable, and the challenge of decision-makers may lie in increasing resilience or bringing about significant changes to the state of the system i.e. adaptively managing the system into a more desirable phase, for example from breakdown (release) to renewal (reorganisation) as illustrated in Figure 3. The adaptive cycle does not imply that a system has to

conform to the evolutionary path in a strict sense and go through each phase sequentially. It uses the concept of evolutionary phases to help identify system properties like resilience and connectedness. In this view of social-ecological systems a system is identifiable as having some kind of ‘organization’ by virtue of the system existing in one of the phases of an adaptive cycle.

Table 1:

Description of Phases of the Adaptive Cycle

r-Phase: (Exploitation phase)	Resilience high, connectedness low, innovation high, capitalisation of resources, relationships consolidated but flexible.
K-Phase (Conservation phase)	Resilience low, connectedness high & rigid, innovation low, large capital base, processes optimize but rigidity increases to such a degree that if external shocks to the system are too frequent, or too asymmetric, then the vulnerability of the system increases (and conversely resilience decreases) until ...
Omega-Phase (Release phase)	Resilience very low, connections broken, regulatory feedbacks weaken, resources released and strong destabilizing feedbacks develop, transient state where uncertainty is high and the system is subject to regular periods of chaos. In this phase self-organization may take a very destructive and resilient, if undesired, form in human social systems.
Alpha-phase (Reorganization phase)	Resilience increasing, loose connectivity, capital more available, unexpected reorganizations to minimize losses, innovation tested by short chaotic periods.

Panarchy (Holling, Gunderson & Peterson, 2002) may be visualized as an aggregation of sub-systems (embedded units) and super systems all in particular phases of the adaptive cycle individually, but related through cross-scale effects that are governed by the context of application (see Figure 4). It is a view that stresses the importance of causal influences between adaptive cycles (and underlying processes) occurring at various scales.

One of the key aims of viewing social-ecological systems as a panarchy of adaptive cycles related through cross-scale influences is to overcome the partial disciplinary perspectives often used to evaluate the social-ecological system interface. This leads to disciplinary bias in multi-disciplinary efforts and unbiased collation of partial perspectives in inter-disciplinary efforts (i.e. without an understanding of the

sensitivities of cross-disciplinary and cross-scale influences). If we picture the adaptive cycles constituting the panarchy in Figure 4, there are a variety of interactions that come to mind, for example; what is the effect if one sub-system, such as agriculture, is in a particular phase, say, the 'r' or exploitative phase. What then would be the cross-scale effects on other sectors such as food production, water, human health, etc? If food production, or human health is already in a vulnerable phase (such as the release phase), then one could expect an overall improvement in the system due to the agricultural sector growth. If the food production, water and human health are in the conservative phase (K-phase) then more noticeable improvements in these sectors can be expected as long as stability is maintained in the environment. However, if real-world changes exceed their capacity to adapt as top-heavy, capital intensive, rigid systems, then they will become increasingly vulnerable. It is therefore possible to consider a range of cross-scale effects between sub-systems and embedded units in different phases of the adaptive cycle, and with different combinatorial outcomes.

The concept 'panarchy' (Gunderson & Holling, 2002) is therefore a useful tool for visualising multi-scale system dynamics; a global system is identifiable as consisting of a number of systems, each of which may be in some phase of the adaptive cycle. It stresses the role of processes and inter-relationships in constituting a system that evolves, or which can evolve, over time, spatially, or in phase space etc. Resilience of whole social-ecological systems is thought to be brought about by cross-scale dependencies in the system. Biodiversity, for example, increases resilience by strengthening and broadening the number of inter-relationships between species and ecosystem functions (Peterson et al., 1998). Resilience theory therefore indicates that we need to account for cross-scale and intra-scale influences in estimating system resilience.

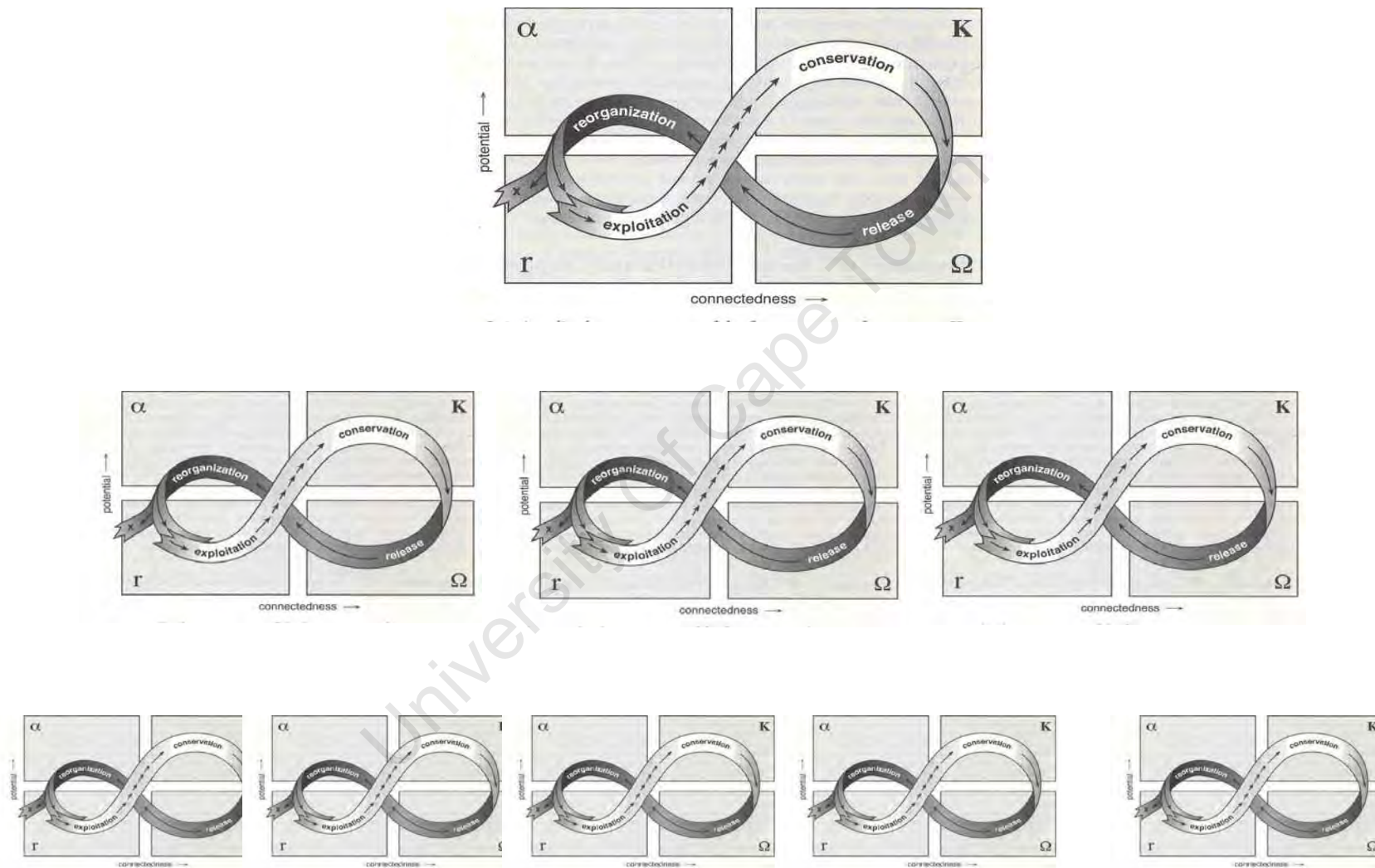


Figure 4: Panarchy of Adaptive Cycles Related Through Cross-Scale Influences

2.4 Complexity & Hierarchy: Emergence & Hyperstructures

2.4.1 Emergence & Hierarchy: An Unholy Mix

There are many interpretations of the concept of emergence, but they are all primarily concerned with coping with the unexpected behaviours and events. As already outlined, emergence is the concept that the behaviour of real-world systems will always deviate from model-based predictions because no model can fully represent the real-world system without replicating it. Absolute predictability is difficult for systems that are governed by complex agent-driven behaviours. In this sense, emergence is that which observationally (*perceptually or empirically*) disconfirms our hypotheses regarding the structure, content, processes and behaviour of systems. The description given by Ashby (1962) of observer-subject relationality below, has relevance for the concept of emergence:

The real world gives the subset of what is; the product space represents the uncertainty of the observer. The product space may therefore change if the observer changes; and two observers may legitimately use different product spaces within which to record the same subset of actual events in some actual thing. The “constraint” is thus a relation between observer and thing; the properties of any particular constraint will depend on both the real thing and on the observer. (Ashby, 1962, pp. 258)

Earlier we stated that Islam et al. (2006) take the view that emergence is due to observer-subject relationality and call this “*perceptual emergence*”. They attack the concept of “*absolute emergence*”, that is, of a whole which is absolute and distinct from its parts as a singular ‘thing’. Perceptual emergence takes the view that emergence results because the whole can be many things to many different observers, depending on the perspective taken on the system. The conceptual framework that is

used to 'observe' or 'interact' with a system is thus critical to what is considered emergent, that is, in the sense where emergence is interpreted as deviation from a model (Cariani, 1991, in Potgieter, 2004, p.10).

So how are conceptual frameworks constituted and organised? Concepts are usually grouped in terms of classification and hierarchy. A hierarchy of subsystems/agents is different from a hierarchy of concepts, in that the structure into which subsystems/agents are arranged in the former, constitute an organization i.e. of a system. Conceptual hierarchies, in contrast, depend heavily on the taxonomic classification criteria that are used to evaluate the system. For social-ecological systems these classification criteria are in turn derived differently, according to the underlying institutional and epistemological perspectives (e.g. disciplinary, political or civil) taken on the system

Classical universal and taxonomic hierarchies can be derived from arranging a taxonomy of conceptual classifications (or classes) into super and sub-classes. Concepts are often *defined* in terms of a hierarchy. These are definitional hierarchies, where if one concept class is present so is its super and sub-classes. One does not cause another, except in defining one another i.e. it is a conceptual, and not a dynamic scheme. There are no driver-response relationships between classes, objects and attributes. The hierarchy of concepts, classes and states is rigid, and in some sense absolute, where definitional (or taxonomic) hierarchies are concerned.

Scientific categorization schemes are numerous and are designed for a variety of purposes. Universal taxonomies are constrained by hierarchical classification schemas. A hierarchy is not allowed to evolve with context in a non-linear fashion. Rather, the taxonomy and hierarchy is viewed as existing independently of the context in which it is applied and is therefore universally applicable in all contexts⁹. The idea

⁹ The view that universal classification systems, taxonomies and models exist is based on the assumption that there is a reducible 'essence' to which the classification, function and behaviour of a system can be attributed. Philosophically, this reflects a perspective that reality is reducible to an ultimate 'truth'. This is consistent with the perspective emanating from Cartesianism and becomes problematic as more complex, dynamic systems are considered for analysis.

of hierarchy is useful where; systems are well-understood, only slight variations occur from historical behaviour, and change is incremental. Hierarchies do not cater for complex, adaptive systems where non-linear, often irreversible and non-repeatable changes occur, as occurs in real-world systems. We require an approach that can go beyond interpreting behavioural change using fixed hierarchies and having expectations of linear change. *We need an approach that can cope with complex, adaptive 'heterarchical' changes in the hierarchical organisation and taxonomy of systems in relation to sub-systems and their environment.* Therefore, an evolutionary and interdisciplinary approach towards understanding systems is needed; one which goes beyond traditional, monodisciplinary classification systems and hierarchies, while accommodating them at the same time.

2.4.2 Emergence, Learning & Hyperstructures

Emergence is the critical feature of complex, adaptive systems. Emergence implies holism, where a phenomena, event, object, agent or system displays features and behaviours that cannot be explained by simply summing up its constituent parts. According to Minsky (1988, in Potgieter 2004) holism can be described as “a lack of understanding (of an observer) due to the unexpected emergence of a phenomena that had not seemed inherent in the system components, showing that a whole is more than the sum of its parts”. Emergence is inherent in our perceptual experience of system level behaviours and their self-organisation (Islam et al., 2006). Our ways of seeing, or lenses and filters we impose upon what we observe restricts our ability to fully observe the whole, even though we have a sense of it, and our part in it. This is the cornerstone of subject-object inseparability as it relates to complexity theory, and to social-ecological systems sustainability.

According to Ronald, Sipper & Capcarrere (1999, in Potgieter, 2004) a test for emergence can be conducted in terms of “*design, observation and surprise* of a system designer and a system observer (which could be the same), as follows:

1. Design: The system has been constructed by the designer, by describing local interactions between components (e.g. artificial creatures and elements of the environment), in a language L1.
2. Observation: The observer is fully aware of the design, but describes global behaviours and properties of the running system, over a period of time, using a language L2.
3. Surprise: The language of design L1 and the language of observation L2 are distinct, and the causal link between the elementary interactions programmed in L1, and the behaviours observed in L2 is non-obvious to the observer – who therefore experiences surprise. In other words, there is a cognitive dissonance between the observer’s mental image of the system’s design stated in L1 and his contemporaneous observation of the systems behaviour stated in L2.”

The design-observation-surprise loop represents an incremental process of adaptive learning. When studying simple phenomena we expect to reach greater levels of predictability and certainty regarding its internal structure over iterations of the design-observation-surprise loop, and to converge in understanding over the phenomena. With complex phenomena such as social-ecological systems the changes in the current real-world context of the system can have a large influence upon the observed system level behaviours. In the case of complex adaptive systems iterations over the design-observation-surprise loop have to deal with real-time emergence. The iterations over the design-observation-surprise loop yield ongoing divergence and convergence of multiple explanations of real-world phenomena. This presents a challenge of Sisyphus proportions for software approaches and ontology’s aiming to support adaptive learning.

To recap, hyperstructures are “emergent higher order structures” or “emergent explanations” (Baas & Emmeche, 1997, in Potgieter, 2004). They are used “for explanation and understanding” by “separating regularities from randomness in its input stream” (Gell-Mann, 1994, in Potgieter, 2004). As such, hyperstructures constitute the internal model of a complex adaptive system, and emergence can then

simply be understood as deviations identified in the “input stream” from what is expected. Indeed, this is known as “Emergence, Relative to a Model” (Cariani 1991, in Potgieter, 2004). With *heterarchical* hyperstructures, ‘hierarchy’ is allowed to emerge, that is, in relation to context; where function and authority are determined.

Emergent software engineering refers to the continuous process of adapting the hyperstructures to accommodate new regularities in the input stream. The hyperstructures can be adapted manually through human interventions, or automatically. **Manual emergent engineering** is a very cumbersome process requiring constant involvement from the human software engineer. In **automatic emergent engineering**, the hyperstructures are adaptive and able to evolve, eliminating the need for human intervention. (Potgieter, 2004: Emphasis added: bold)

The internal models (sets of) of complex, adaptive systems are maintained by hyperstructures, which can constitute a variety of “*schemas*” (Gell-Mann, 1994), consisting of overlapping and non-overlapping explanations of a phenomena that can be verified or vice versa by remaining sensitive to deviations from regularities in its input stream. Learning, where complex adaptive systems are concerned therefore involves adaptively managing hyperstructures in relation to a multiplicity of factors in its environment and internal structure, and is hence demanding and often bewildering.

Economists also encounter the limitations of economic theory when attempting to address the adaptive nature of social aspect of economic systems. In response to this, the economist, Alfred North Whitehead promoted an organicist philosophy of economics. In this view:

In an organicist ontology, relations between entities are internal rather than external, and the essential characteristics of any element **are outcomes or relations with other entities**. This relates to the central question in social theory as to whether or not structure may be represented simply as the property of the interactions between given individuals. Organicism denies that individuals may be treated as elemental or immutable building blocks of

analysis. Just as society cannot exist without individuals, the individual does not exist prior to the social reality. Individuals both constitute, and are constituted by, society. The organicist does not deny this, but insists that individuality itself is a **social phenomenon**. Hodgson (1993, p. 11)

Hodgson's reference to an organicist ontology reflects a desire to link adaptive self-organisation of a system its internal structure and in relation to its environment. De Wit refers to the need for "*multiple learning loop frameworks*" (De Wit, 2001, p. 159-161) for adaptive research in support of economic policymaking for complex environmental problems. These learning loops involve watching, thinking, doing and feeling. Two loops are required (De Wit, 2001);

In loop I ..., the policy process loop, the focus would be more on the physical and more practical aspects of group processes and facilitation, while loop II ..., the theoretical learning loop, would be more cognitive, focussing on applications on economic theories on the environment and public policies.

These learning loops constitute complex, adaptive frameworks of learning that can adjust with changes in understanding and in the real-world context in which a problem or system is located. Hyperstructures, in this context, would be used to maintain verification and validation of *assumptions* regarding self-organisation of the system's internal structure, and in relation to its environment in a real-world context.

Visualising and understanding how overlapping and non-overlapping explanations can be managed in a joint framework towards adaptiveness and degrees of understanding involves employing a non-hierarchical representation of the internal organisation, and the interactions between the system and its greater environment. This is explored further in the next section, where the concept of heterarchy is introduced to help address this need.

2.4.3 The Case for Heterarchy

Heterarchy is defined by Heylighen, Joslyn & Turchin (2001) as, “a form of organization resembling a network or **fishnet**. Authority is determined by knowledge and function.” Heterarchy is a useful concept for engaging with systems, one that invokes visualisations of a ‘flattened’ relativist framework, which ‘unflattens’ itself when applied in context. The concept of heterarchy finds application in many diverse fields where traditional hierarchies do not fit the problem context. For example, Kintz (2004) takes the view that a better understanding of Mayan socio-economic and cultural organization and spatial and temporal household variability can be obtained by using mechanisms to interpret both hierarchical and heterarchical organizational arrangements¹⁰. Kintz (2004) outlines the historical and current definitions of heterarchy as a concept for self-organization:

... According to the Principia Cybernetica (Heylighen et al. 2003), heterarchy in its modern usage refers to an organizational structure that operates as a network rather than topdown hierarchical management, with decision making based on uncertainty and the person at the apex unable to compile or comprehend all the facts necessary to make a decision. Decision making is **decentralized**, focused and occurring where knowledge is located. (Kintz, 2004, emphasis added: bold)

Where social-ecological systems are concerned, fragmented decision-making occurs because decision-making is distributed throughout the system without shared understanding and/or explicit incentives for cooperative governance. Predictive models are destined to fail at predicting the behaviour of social-ecological systems because intelligence and decision-making is distributed throughout the social-ecological system through agents, and is closely linked to the current real-world context. Their reflexivity ensures that there will always be emergence in social-ecological systems.

¹⁰ “Hierarchy and heterarchy are suggested as organizational principles that reflect the variability characteristic of the Maya households past and present” (Kintz 2004).

Elements of global behaviour are also distributed throughout the system. Where social-ecological systems are concerned, adaptive cycles are distributed at different scales and levels of the system, and together, these adaptive cycles constitute a “*panarchy*” (Holling, Gunderson & Peterson, 2002). As explained earlier, the concept of ‘panarchy’ allows a system to be defined in terms of adaptive cycles and the inter-relationships (intra-scale, cross-scale) between them. Panarchy represents a process-based view of the system where a flexible hierarchical organization of concepts/subsystems/agents is required for social-ecological systems. Due to their rich interconnectedness at multiple scales social-ecological systems, remote effects can often lead to significant emergent behaviours. This has implications for what kind of hierarchy is relevant for modelling social-ecological systems. Fixed or absolute hierarchies that can be derived for social-ecological systems aren’t feasible because social-ecological systems are agent-based complex, adaptive systems, for which a more adaptive kind of ‘hierarchy’ (i.e. a heterarchy) is required.

In social-ecological systems, the question becomes one of how do we adapt to real world contexts? *A heterarchy is a complex adaptive hierarchy.* Heterarchy serves this purpose well, as it is essentially a flexible hierarchy, where both conceptual and sub-system/agent hierarchies change. In the approach proposed in this dissertation it is argued that, proceeding from a heterarchical perspective on the system, more insight can be obtained regarding the cross-scale effects within a social, ecological system and between its’ environment. Top-down and bottom-up reasoning are jointly required to arrive at an understanding of a complex system, and for modelling a complex adaptive system (Richardson 2002).

Every system contains subsystems, while being contained in one or more supersystems. Thus, it forms part of a hierarchy which extends upwards towards ever larger wholes, and downwards towards ever smaller parts (de Rosnay, 1979) ... Systems theory considers both directions, the downward direction of reduction or analysis, and the upward direction of holism or emergence, as equally important for understanding the true nature of the system. It does not deny the utility of the analytical method, but complements it by adding the integrative method, which considers the system in the broader

context of its relations with other systems together with which it forms a supersystem. (Heylighen, Cilliers & Gershenson, 2007)

Top-down and bottom-up descriptions of systems constrain each other. The challenge for social-ecological systems is to develop a methodology which allows the flexible exploration of relationships between sub-system components and agents. Moreover the methodology should be restricted by universal hierarchies, but should remain open to factors that have greater contextual relevance than historical context or fixed rules. Heterarchy is an appropriate concept for studying emergence in social-ecological systems. Emergence, in the case of social-ecological systems, results from self-organisation of adaptive agents in relation to each other and the external environment where intelligence is *distributed* throughout the system and no fixed hierarchy is maintained over a long period of time. The concept of heterarchy accommodates emergence by allowing for changes in hierarchical arrangement and classification of concepts in relation to their contextual relevance at a particular moment in time. Learning and adapting to change is the key element of the approach we desire. So how do we represent knowledge heterarchically? Some key concepts are introduced in the next chapter.

3. **Bayesian Networks and Graphical Causal Models as Hyperstructures for Social-Ecological Systems**

3.1 **Capturing Shared Knowledge in Ontology's**

3.1.1 **Modelling Social-Ecological Systems: Requirements for Ontologies**

An ontology is defined by Gruber (1995) as a 'specification of a conceptualisation' or a 'description of concepts and relationships, which if it is to be shared; requires a 'commitment to use a shared vocabulary' to express different views on the same domain.

Knowledge regarding the scope and goals of sub-systems integration can be captured using software ontologies¹¹. Ontologies are symbolic reasoning languages (consisting of objects, entities, classes, and attributes) that are used to help integrate software-based models (Helsper & Van der Gaag, 2002). The word 'ontology' has a different interpretation in computer science from its use in the discipline of philosophy. In computer science, ontologies are used to help reason, understand and share knowledge between users and makers of software systems. This shared understanding is used as a basis for collaboration on software engineering design and implementation during software development. Ontologies that focus more on taxonomic (classification) of sub-systems tend to be more hierarchical, whereas ontologies that place emphasis on defining and keeping track of system interdependencies tend to be have more flexible, adaptable hierarchies.

In the context of sustainable development and adaptive governance and management programmes a shared understanding is required to enable a more

¹¹ Where reference is made to philosophical ontology in this dissertation it will be clarified in the text through the context of its use.

transdisciplinary approach towards problem solving. Ontologies provide a way to visualise concepts, definitions, inter-relationships and agency between interdisciplinary and multi-participant action-research based programmes. They may also help identify mechanisms and sensitivities that are key to understanding system behaviours. Moreover, ontologies can provide a way to adapt shared understanding and sub-system agent and/or model configuration as real-world changes occur, or understanding of the system changes with new insights. This is a key feature of the approach proposed in this dissertation because coping with ‘emergence’ or the surprises that occur when real-world system behaviours deviate from the software and mental models. This is also an essential requirement for dealing with the challenge of assisting with adaptive management through action-based research.

In order to achieve this, the formulation of system understanding (in terms of interdependencies between sub-systems and/or agents) must depart from a static hierarchical perspective. This brings into question how knowledge and decision-making is formulated at the cognitive level of human awareness i.e. how do we learn and make decisions about the world before we are ‘trained’ into disciplinary perspectives?

3.1.1.1

Learning, Causality & Classification

“Causal laws, such as the fact that smoking causes heart disease, can only be noticed on the basis of events that are categorized (e.g., events of smoking and cases of heart disease). Without such categories causal laws neither could be detected nor could causal knowledge be applied to new cases. Thus, causal knowledge not only affects the creation of categories, it also presupposes already existing categories for the description of causes and effects.”(Waldmann & Hagmayer, 2006)

Human beings observe the world by making causal inferences about events that are observed to be “*contiguous*” in space and time (Hume, 1739, in Meder, 2006, p.6). They also make decisions from information based on the causal relationships that they ‘think’ explains the observations they make (Waldmann & Hagmayer, 2006).

Causality, it seems, is central to how we learn about and make decisions about information i.e. how we generate *knowledge* from *information*. It is also central to how organization between sub-system components (and/or agents) is perceived to exist.

The philosopher, Sir David Hume (Hume, 1739, in Meder, 2006, p.6), viewed causality as essential for understanding the world around us, even though he did not assert that events and things are *necessarily* causally interrelated in the world around us. Causality is a key component of how we learn and reason about the world around us; its events, systems and sub-systems. We observe events and infer causal relationships and intervene on systems on the basis of this understanding.

Learning involves categorisation and causality, and the emergence of causalities and categories in a process of learning are closely inter-related. In a broad sense, they are co-evolving and give rise to one another. There is a dynamic interaction and the co-evolution of categories and causality is ongoing. However, there is a tendency to rely on memory and established causalities and categorisation until there is a clear non-overlap, at which point new categories are made (Waldmann & Hagmayer, 2006). In order to provide a clear understanding of how Waldmann & Hagmayer (2006) arrived at their conclusions regarding the relationship between causal inference and categorisation, a detailed explanation is provided below:

According to the dynamic theory modification hypothesis, the choice of a reference class is a more flexible process than envisaged by the perceptual learning hypothesis, and is guided by both bottom-up and top-down factors. We hypothesize that the decision between old and new categories is driven by intuitive theories about the domain (top-down) and by a tendency to be parsimonious (bottom-up). As for the bottom-up component, we believe that in general people are reluctant to induce several competing category systems in parallel even though parsimony may come at the cost of suboptimal predictability. If maximizing predictability was the main goal of category learning (see Anderson, 1991; Lien & Cheng, 2000) people should tend to induce a new category system for each target feature or target causal effect they are trying to predict (these category systems may overlap, of course). Old

categories are in most cases not as predictive as new ones that could be induced from scratch. However, we believe that people try to minimize the number of alternative categorical schemes whenever possible. As long as the old categories allow us to make sufficiently satisfying predictions, people should have a tendency to continue to use them. ... Thus, we expect to see a general tendency to use old categorical schemes whenever they have at least some predictive value. In contrast, when the categories and the target effect seem hard to interrelate, then people may decide to **abandon the old categories and induce new ones** that are better suited for the **current context** of discovery ... Indirect empirical support for this hypothesis comes from a number of studies using paradigms different from ours ... Lassaline (1996) has supported this hypothesis by showing that undergraduates were more likely to project a new property when the categories share a common cause of the property (see also Rehder & Hastie, 2004; Sloman, 1994). (Waldmann & Hagmayer, 2006, emphasis added: bold)

Categories (or taxonomies) play a critical role in the development of theories of all systems, whether they are theories of the natural sciences, philosophies, social theories and even indigenous knowledge. Categories are essential frameworks because they create a shared language for shared understanding amongst people, who may relate to and influence the system in a variety of ways, based on a variety of value systems. Categorisation is indivisible from the causalities that are known, observed or intuited by the observers of the system. Where categories and causal dependencies evolve during a process of learning about or system, or whether they emerge as real-world changes in the current context, an approach is needed that can cater for a flexible, evolving hierarchy. It is for this reason that we identify the need to enable learning with a heterarchical framework of reasoning.

3.1.1.2

Alternative Conceptual Schema's & Causality

A promising model of pluralism can be forged from understanding that causal models are abstractions that will always remain idealizations. By making simplifying assumptions regarding the non-interference of other

potential causes, causal models describe only what would be expected in idealized circumstances (Levins, 1968). This conception of theories helps to explain how it can be that models of different causal factors qua models do not directly conflict. However, even if the models may be jointly consistent in the application of models to the explanation of a concrete case, conflict can arise. In actual cases, **multiple causes** are likely to be present, and interact, and other local elements may also contribute to a specific causal history. Thus in explanation, models of variant possible contributing factors must be integrated to yield the correct description of the actual **constellation of causes and conditions** that brought about the event to be explained. (Mitchell, 2004, emphasis added: bold)

Waldmann & Hagmayer (2006) note that both philosophers and historians of science have “evidence that alternative categorizations are not only a theoretical possibility, but also a practical reality”, such as the observation that “Kuhn’s (1962) concept of scientific paradigms can be reconstructed as denoting categorical schemes (see Hacking, 1993; Thagard, 1999)”. Indeed, according to Sorokine et al. (2005), there exists “an infinite number of descriptions of the world with a potentially infinite number of statistical regularities entailed by these descriptions”. They also highlight that “many philosophers have argued that there are alternative conceptual schemes that can be used to describe reality and that truth is a joint function of reality and the conceptual scheme being used to describe states of affairs in the world (see Dupré, 1993; Goodman, 1978; Hacking, 2000; Nozick, 2001; Putnam, 1987).” The clear conclusion Sorokine et al. (2005) arrive at is that this view implies that “*the causal relations we see in the world will depend on the categorical schemes we use to describe causes and effects.*” Waldmann and Hagmayer (2006) show that the converse is also true. A process of co-creation and hence co-evolution is therefore at work between causal and taxonomic knowledge.

Causal models that seek to separate regularities from randomness necessarily rely on the omission of a group or set of potential causes in order to construct an idealised ‘laboratory’ for modelling (Mitchell, 2004). Therefore, the existence of alternative causal models is always possible, and where complex systems are

concerned; probable. Researchers investigating different levels or scales of system understanding can conceivably construct a range of causal models that may overlap or not. There are often necessary and justifiable conflicts between views of how causal relationships function at sub-system and whole system scales, and at different levels of description. Modelling without integration amongst the mental models in the minds of the researchers (including decision-makers and stakeholders in the case of adaptive management programmes) does not bring about true transdisciplinarity. An approach for dealing with social-ecological systems must take into account the different perspectives, hypotheses and causal models of the system structure, function and behaviour, and incorporate a wide range of evidence and case studies.

In the next section we explore the use of graphical causal models and Bayesian networks as hyperstructures for integration of case study research on social-ecological systems sustainability. In the BPDA approach the dominance of partial perspectives (Holling, Gunderson & Ludwig, 2002) in research and adaptive management of social-ecological systems is subverted by utilising a framework in which multiple representations of system understanding can be formulated, tested and adapted. This is achieved using hyperstructures consisting of graphical causal maps and Bayesian networks, which is explored in more detail in the next section.

What are Bayesian Networks and Graphical Causal Maps?

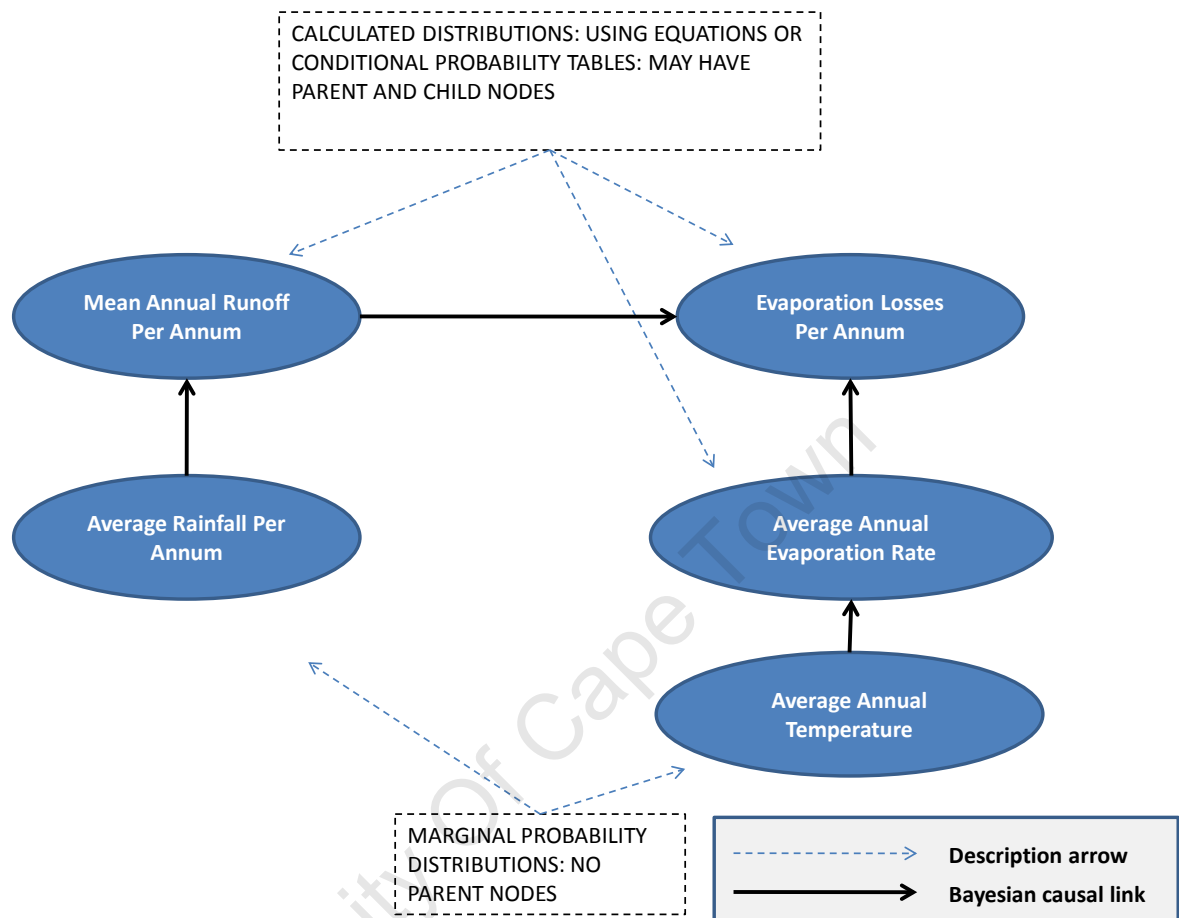


Figure 5: Example of Bayesian Network Nodes: Related through conditional causal links.

A Bayesian network is a directed acyclic graph (DAG) that consists of a set of variables (or nodes) that can be linked by cause-effect directional links (see Figure 5 & Figure 6). These cause-effect links are linked by parent and child node. Parent nodes (e.g. “average rainfall per annum and “average annual temperature”): see Figure 5) have marginal distributions, and have no parents themselves, while child nodes (e.g. “mean annual runoff”, “average annual evaporation rate”, and “evaporation losses per annum”: see Figure 5) and child nodes. Their interdependencies are formulated in terms of “the conditional probabilities that a node can have given the values of the parent nodes (Pearl, 1988; Dechter, 1996)” (Potgieter, 2004, p. 21). Each node represents a system variable, often a variable about which the quantity is uncertain. Each variable can be described by “a finite set of mutually exclusive propositions, called states” (Potgieter 2004, p. 21). Each node or variable is characterised by a

probabilistic distribution over these states (see Figure 6). These states can take a variety of forms; from numeric intervals (see Figure 6) to qualitative states such as ‘acceptable, unacceptable, or neither’.

Bayesian networks use conditional probability tables (or matrices) to relate parent and child nodes to each other (Dechter, 1996; Pearl, 1988, in Potgieter 2004, p.22). These conditional probability tables can be automatically generated by relating nodes with *equations*, or they can be manually composed using *expert judgement* (see section 5.2.2 later in text: Figure 12 and Figure 13). Nodes characterised by marginal probability distributions (compare Figure 5 and Figure 6) are those nodes that don’t have any parents and have no posterior distributions (e.g. the area of maize under cultivation at a particular moment in time is known and can be formulated as a sole input itself). Child nodes have distributions which are calculated using equations, such as the nodes shown in Figure 6, which have numeric intervals for states, over which a probability distribution is calculated through inference. They may also be formulated using other states, using expert opinion and consultation to formulate the conditional probability tables and verify and validate their sources.

Scenario-based inference can be conducted using Bayesian networks. A combination of parent nodes can be assigned to a particular state reflecting the scenario. The Bayesian model is ‘run’ or propagated, and the changes in output variable probability distributions can be assessed. As explained in Potgieter (2004) inference is conducted using Bayes Rule; “Bayesian inference is the process of calculating the posterior probability of a hypothesis H (involving a set of query variables) given some observed event (assignment of values of a set of evidence variables e)”:

$$P(H | e) = P(e)P(H)/P(e)$$

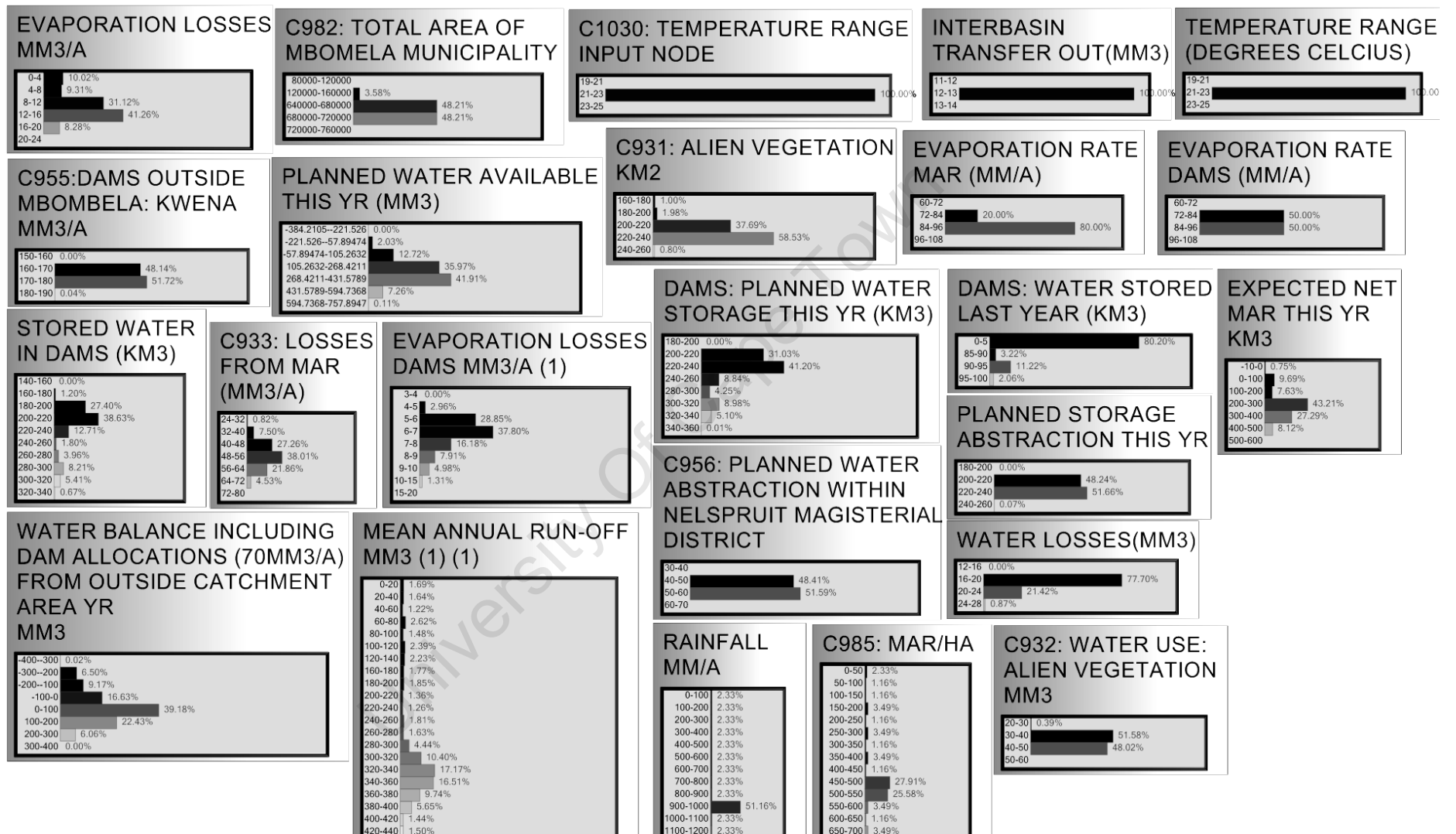


Figure 6: Example of Bayesian Network Nodes: With populated states that are related through equations and conditional probability tables for water module in Mbombela study (see Figure 13 & Figure 27).

As outlined earlier in section 2.4.2, Bayesian networks can be static or dynamic (Potgieter, 2004, p. 24). Dynamic Bayesian networks can be used to incorporate variables which change over time. When these changes are automatically updated it is referred to as *automatic engineering of emergence*. In this sense, this dissertation is mainly concerned with static Bayesian networks, which are manually updated by consultation with an interdisciplinary research group and/or decision-makers (i.e. *manual engineering of emergence*) (Potgieter, 2004, p. 4, 8-19). Manual engineering of emergence is also used to effect changes to the Bayesian network because reasoning with Bayesian networks for social-ecological systems involves testing a variety of what-if scenarios that are agreed upon by the interdisciplinary research group.

When formulating the Bayesian model and updating the model with changes, the qualitative reasoning which underlies conditionality can be expressed and captured using graphical causal maps (Helsper & van der Gaag, 2002). In this dissertation, causal graphical causal maps are formulated using a combination of ontology's of directional arcs proposed by Helsper & Van der Gaag (2002) and Nadkarnay & Shenoy (see later: section 5.2.1: Figure 11). The causal ontology used to describe the causal relationships consists of initiating, enabling, resulting and definitional arcs. These can be used to conceptualise and formulate the Bayesian networks in a trace-able, reviewable manner (Helsper & Van der Gaag, 2002). We make use of the ontology for Bayesian networks formulated by Helsper & Van der Haag (2002) and expand it to include elements of an ontology for Bayesian networks that was formulated by Nadkarni & Shenoy (2004), namely; one that indicates positive and negative relationships (see Figure 11 later in section 5.2.1). The graphical causal maps are formulated using a specialised software interface, wherein a wide variety of information can be trace-ably captured. Information and evidence from case studies, histories, archival information, surveys, empirical and modelled outputs, and publications can be captured in support of the reasoning (or conditionality) for the existence of causal relationships that are reflected in the Bayesian model. Alternative perspectives can be captured and catered for in this manner, providing a flexible explanatory and descriptive framework for integration of hypotheses, sub-systems (embedded units), and / or models and simulations. This constitutes the BPDA approach as proposed in this dissertation.

3.3 **Bayesian Networks as Hyperstructures & Requirements for Social-Ecological Systems**

Beliefs are formed as a “distillation of sensory experiences” during a process in which the actual experiences are learnt in terms of averages, weights or qualitative relationships that are used to determine future actions (Pearl, 1988). Bayesian networks (also called Bayesian belief networks or causal networks) provide the ideal formalism to express these probabilistic regularities. These networks encode beliefs and causal relationships between beliefs and provide a formalism for reasoning about **partial beliefs under conditions of uncertainty** (Pearl, 1988). A complex adaptive system can use a Bayesian network as a probabilistic model of what the emergent effects are of certain interactions and behaviours in response to certain environmental states (the causes). Such a causal model can then be queried by an arbitration process to decide which action(s) are most relevant given a certain state of the environment. Bayesian networks are therefore ideally suited to be used as hyperstructures in the internal models of complex systems Potgieter (2004: P18, emphasis added: bold).

This dissertation, and this section, deals with why graphical causal models and Bayesian networks are suitable for use as hyperstructures for integrating, testing and maintaining the ‘internal models’ of social-ecological systems that are used in case study research. A variety of requirements, specific to the qualities of social-ecological systems must be taken into account, but first, we can draw on previous research which addresses the role of Bayesian networks as hyperstructures for complex adaptive systems in general (Potgieter, 2004, p. 18, 28-30):

This dissertation argues that a heterarchical approach towards social-ecological systems is a necessary **departure** point for multi-power and interdisciplinary cooperation and for modeling complex adaptive systems. Potgieter (2004) argues that

Bayesian networks can be used as hyperstructures for managing the internal models of complex systems, and illustrates why in detail. We know that Bayesian networks can be used as hyperstructures for complex, adaptive systems in *general* (Potgieter, 2004, p.37-38). In this section, we provide reasons why Bayesian networks and graphical causal models are suitable for use as hyperstructures to maintain the internal models of *social-ecological systems*. In order to address the needs of supporting multi-participatory research for decision support social-ecological systems, several areas can be identified as critical areas for hyperstructures that are required to deal with the complexity of social-ecological systems. They relate directly the broad requirements for coping with; multiple perspectives, the multi-agent system and the real-world context. These areas are outlined in the next few sub-sections:

3.3.1 Multi-Participatory Process Facilitation:

The sustainability of social-ecological systems requires the integration of research and decision-making across scales, sectors and different levels of organisation and decision-making or influence. This is characterised by *contrary views* and *contrary sets of evidence*. This leads to differences of opinion and *undecideability* in decision-making for sustainability that need to be shared and tested. Two issues are critical requirements for conducting case study research and decision support for social-ecological systems, while taking into account contrary views and sets of evidence; (1) how well these contrary views and sets of evidence match the *real-world context*, and (2) to what extent *observations* and *interventions* can be designed to test these contrary views and accompanying sets of evidence, respectively.

3.3.2 Learning, Conditionality and Causality

The process of learning involves iteratively articulating, testing, refuting and validating contrary views and sets of evidence arranged into *hypotheses*. Learning involves categorising information and identifying patterns of influence between different categories. As outlined earlier, according to Hume, *causality* is a critical

element affecting how we reason about what we observe in the world. We infer that causal connections are present when we are able to provide reasoning for why and how events that appear contiguous in space and time are causally linked. Causality is therefore a critical element in identifying patterns from observations. Moreover, causality is closely linked to categories that are inferred by people, and vice versa i.e. categories and causalities *co-evolve*.

Causality and categorization co-evolves when social-ecological systems are observed and analysed in their real-world contexts. Causal relations and categorisation may change, depending on the context of application. This context is embedded in the *conditionalities* assigned to causal relationships. Hence, a flexible, adaptive, heterarchical approach that can accommodate bottom-up and top-down reasoning and an analytical capability to interrogate these conditional relationships is required.

Moreover, quantitative and qualitative (interpretive) considerations must be made when dealing with complex adaptive social-ecological systems in real-world contexts. An analytical capability for modelling and simulating complex systems must be capable of integrating both sources of information (Richardson, 2002). Hence, it must be able to accommodate social science methodologies such as action research, mixed methodologies and *narrative* approaches into *case study research* for social-ecological systems. It must also be capable of integrating evidence from different sources of information and disciplines.

3.3.3 Addressing the Complexity of Social-Ecological Systems as Multi-Agent Systems

At the same time, the *quantitative analytical* requirements of a capability for modelling and simulating complex social-ecological systems must be satisfied. The critical elements of dealing with the complexity of social-ecological systems relate to *non-linearity, feedback, scale* and *emergence*. Distributed decision-making, actions and feedback at multiple scales within a social-ecological system leads to the

emergence of behaviours that are recognizable as *systemic*. Efforts to promote the sustainability of social-ecological systems are concerned with the adaptive governance and adaptive management of social-ecological systems. Understanding the *adaptive capacity* of social-ecological systems requires gaining insight into the resilience and stability conditions of a social-ecological system. At a quantitative, analytical level this translates into the need for our approach to be able to incorporate non-linearity and feedback effects, and to help identify and verify *critical limits* and *thresholds* under a variety of future and current scenarios.

3.4 **Why Bayesian Networks & Graphical Causal Maps?**

This section expands on the aforementioned areas and explain what features of Bayesian and graphical causal models/maps are identified, which indicates their suitability for meeting the requirements outlined above (i.e. for hyperstructures that can deal with the complexity of social-ecological systems). Their suitability for these purposes are tested later in this dissertation through case study analysis conducted in support of this dissertation, the results of which are presented and discussed in later sections.

3.4.1 **Conditionality, Causality & Organisation**

Ashby (1962), in his exploration of conditionality, states that “as soon as the relation between two entities A and B becomes conditional on C’s value or state then a necessary component of “organization” is present” and therefore concludes that the, “theory of organizations is partly co-extensive with the theory of functions of more than one variable” (Ashby, 1962)’. Conditionality, as outlined by Ashby (1962) is therefore a prerequisite for organisation to be present between a set of entities or agents.

Conditional dependence and independence is the basis of Bayesian network theory and constitutes the underlying foundation of the probabilistic method of

analysis it conducts on variables. Graphical causal models *and* Bayesian networks employ conditional dependence as a basic rule which governs the articulation of causal system interdependencies. Conversely, conditional independence signifies that no direct causal dependence can be made between two agents or sub-system components. Causal conditional dependence, in particular is a way of probing the degree of organization of a system. This view is reinforced by Ashby (1962), who states that;

The treatment of “conditionality” (whether by functions or many variables, by correlation analysis, by uncertainty analysis, or by other ways) makes us realize that the essential idea is that there is first a product space – that of the possibilities – within which some subset of points indicates the actualities. This way of looking at “conditionality” makes us realise that it is quite related to that of “communication”; and it is, of course, quite plausible that we should define parts as being “organized” when “communication (in some generalised sense) occurs between them. (Again the natural converse is that of independence, which represents non-communication.)

Taxonomy and classifications that are chosen to represent a system rely heavily on the assumptions that are assumed to govern causal relationships in the system. As explained earlier in section 3.1.1.1, classifications are founded upon causal assumptions, which are conditionality-based (if this, then that) and vice versa. Graphical causal maps and Bayesian networks also allow definitional relationships to be incorporated into the framework (Helsper & Van der Gaag, 2002). A classification of an entity, process or concept is also sometimes implicit in the causal *conditionality* underlying why it exists in a particular context.

Both Bayesian networks and graphical causal maps can be manually adapted (using a specialist, customised software interface) to reflect changes in a complex system as they are observed or learnt. As such, we felt that they would also be suitable for dealing with systems where categories and causalities may change, whether over a process of learning, or from observations of the current real-world context in which the system is located. In this dissertation, we assert and test the idea

that they can serve as hyperstructures for maintaining the internal models of complex systems in a heterarchical manner (i.e. adapting relative hierarchy in response to contextual changes as they unfold). We test the ability of graphical causal models and Bayesian networks as a framework for characterising the extent of organisation of social-ecological systems in particular problem contexts.

3.4.2 Contrary Views and Sets of Evidence

The heterarchical approach enabled by Bayesian networks and graphical causal maps, when used as hyperstructures; provides a framework in which categories and causal relationships can be re-arranged to accommodate different causal models of the same phenomenon. Helsper & Van Der Gaag (2002) show how different causal models can be formulated using an ontology to formulate different graphical causal maps for factors contributing to cancer of the oesophagus. They used the causal ontology to describe the causal relationships that underlie different hypotheses or explanations (causal models) of system structure and behaviour. The customized software used in this dissertation to formulate graphical causal maps enables a virtual library of information pertaining to causal linkages to be formulated and stored in a methodical, trace-able manner where necessary. In this way, contrary sets of evidence can be compared and case studies designed to investigate the different causal linkages in a shared framework of understanding which allows them to interrogate each other's interpretations and evidence. Contrary views are maintained and verified by further directed research, creating a process of learning and consensus building amongst interdisciplinary groups. This is a critical element for dealing with research and decision-making for social-ecological system sustainability, which is further tested in this dissertation through case study analysis conducted in later sections.

The approach taken towards *undecideability* in this dissertation involves elucidating the context around undecideability in decision-making. The transparency of beliefs which underlie the graphical causal and Bayesian belief models is facilitated by a software based approach that is used for interdisciplinary cooperation, workshops and model integration. This helps *elucidate* the undecideability between different levels and scales of involvement in social-ecological systems, from the local to

macro-scales of governance and economics. This does not mean that it will resolve undecideability, but rather that it will help engender shared understanding of undecideability.

3.4.3 Learning: Observations & Interventions

Graphical causal maps and Bayesian networks enable a probabilistic reasoning framework of overlapping categories that are not strictly structured in a bottom-up or top-down fashion (Potgieter, 2004, p. 32). Inference with Bayesian networks can support top-down and bottom-up reasoning, and a combination of both. It also helps understand what is observable (can be monitored) and what can be intervened upon, and allows for causal relationships and categories to evolve (Meder et al., 2005). For these reasons, we felt that Bayesian networks were suitable for the role of providing a heterarchical framework for reasoning, where issues of scale do not restrict top-down and bottom-up inference.

Quantitative and qualitative evidence can be incorporated into a Bayesian network. Graphical causal maps themselves constitute qualitative frameworks of reasoning. Graphical causal maps help interrogate conditionality between system variables. When graphical causal maps are used in combination with Bayesian network, they can provide trace-ability of reasoning in processes of formulating different conceptual causal models of a system or phenomenon (Helsper & Van der Gaag, 2002).

3.4.4 Complexity: Scale, Non-Linearity, Adaptive Capacity & Resilience

Bayesian networks consist of variables or nodes that are described by probabilistic states. These states can be discrete or continuous. Nodes can be related to each other through any kind of linear or non-linear equation describing their conditional causal inter-relationship. By incorporating these non-linear effects, it stands to reason that cumulative thresholds and critical limits will also be reflected in

the outputs of Bayesian networks when run in different scenarios, as long as they are correctly conceived and are evidence-based. This understanding of critical limits and thresholds, in different scenarios, is the basis for understanding the stability conditions and resilience of the system in different scenarios, and may therefore contribute to understanding the general adaptive capacity of the system. The reasoning provided here is tested in more detail in the case studies conducted later in this dissertation.

3.4.5 Participatory Process Facilitation

We propose and argue that causal or cause and effect (driver-response) based articulation of system interdependencies using graphical causal maps and/or Bayesian networks, serves as an effective mechanism for facilitating constructive dialogue and debate around social-ecological system futures.

Traditional associative learning theories only deal with observations (Meder, Waldmann & Hagmayer, 2005). However, Bayesian networks provide an opportunity to integrate learning from both observational and interventional inputs in a single framework (Meder et al., 2005) in which they can be evaluated and compared. The Bayesian approach can also incorporate and elucidate probabilistic uncertainty, and can be adapted to reflect complex changes as they occur i.e. serve as hyperstructures (Potgieter, 2004). For these reasons, we propose that adaptive governance based on observation-based learning from scenario planning, and adaptive management based on observation and interaction-based learning can be integrated in a single framework using Bayesian networks and graphical causal models.

Other frameworks for analysing the resilience and robustness of social-ecological systems place emphasis on uncovering the content of variables (e.g. fast or slow varying variables (Bennet, Cummings & Peterson, 2005) or key drivers (Anderies et al., 2004)). However, they usually lack an explicit means of analyzing interdependencies between sub-system entities (and/or agents). In particular, computer-based systems for elucidating, analyzing and critiquing complexity-based approaches are scant in the literature. This is true of analytical frameworks for

complexity in general (Vellupillai, 2003). Scenario planning generally involves soft-system methodologies whereas dynamic systems and agent-based models are used when finer scale understanding of systems is required at a more manageable scale. However, the processes are usually distinct and the integration is managed mainly in the minds of researchers. Usually, the project leader of interdisciplinary teams is the only one to have a complete understanding of how integration was conducted in the project. The approach proposed in this dissertation aims to facilitate a more integrated, evaluate-able integration of strategic management (high level uncertainty) with adaptive management (lower level uncertainty) enabled by computer-based model integration.

Bayesian networks are increasingly finding use in application to environmental management research (Clarke, 2005). Some deal with participatory process management and stakeholder participation (Baran & Jantunen, 2004). Others are concerned with integrating detailed high-resolution models of environmental phenomena for decision support (e.g. estuarine eutrophication (Borsuk, Stow & Reckhow, 2004) to detailed ecological systems (Clark, 2005). This doctoral dissertation is concerned with proposing an approach for supporting transdisciplinary research for adaptive governance and adaptive management programmes. Participation is enabled by a software platform that makes use of graphical causal maps and Bayesian networks. Graphical causal maps and Bayesian networks are used to visualise and express predictions as conditional causal dependencies in a probabilistic modelling framework.

We envisage that the additional advantage gained by enabling an understanding of critical observational and interventional variables will prove of great use in adaptive management programmes, that is; (1) in coping with emergence in decision-making programmes (i.e. enabling adaptive management), and, (2) in identifying areas of undecideability and gaps in knowledge to guide case study research on an ongoing basis.

As previously outlined, where self-organization occurs; different sub-system level drivers up to system level significance according to their contextual significance as the system evolves with collective and individual agent observations, decision-

making and intervention. We propose that managing a changing system within a heterarchical framework as proposed in this dissertation (i.e. using graphical causal maps and Bayesian networks as hyperstructures) which can keep track of changes as they occur, may provide a valuable contribution to the facilitation of multi-participatory adaptive management programmes. The approach proposed in this dissertation therefore aims to keep researchers focussed on both emerging system level behaviours, and bottom-up sub-system level interactions, in a single qualitative analytical framework. In this dissertation, we therefore test the degree to which uncertainty due to ‘contingency’ can be evaluated and scrutinised in multi-participatory research and decision-making programmes using the proposed approach.

3.5 **Summary**

It is not just that we lack the methodologies for understanding the complexity of the systems that industrial ecology purports to treat. It is deeper than that. We lack the language to not just express the relationships, (but) the system structure and behaviour, and even perhaps to perceive them. (Allenby, 2006)

We respond to the need articulated by Allenby (2006) by proposing an approach which can help facilitate a shared understanding of the description of system interdependencies amongst diverse participants in adaptive co-management programmes. For the purposes of this dissertation, the approach is named the “Bayesian Participatory-Based Decision Analysis”, as has already been referred to in the text of this dissertation as the “BPDA approach”.

We propose a framework (i.e. BPDA) for the articulation of social-ecological system dependencies and self-organization in a framework consisting in a shared ontology between participants in multi-participant and interdisciplinary cooperation. Graphical causal maps, Bayesian networks, systems models and agent based models are referred to as hyperstructures, which are used to understand and reason about system sensitivities and dependencies. The collective set of hyperstructures serves as the ‘shared ontology’ or ‘shared specification of the conceptualisation’ of the social-

ecological system linkages describing sub-model integration in research efforts. This conceptual framework is integrated by a software enabled Bayesian modelling framework which helps visualise the articulated framework of model sensitivities and adaptive responses mechanisms in a heterarchical framework of causal dependencies. The graphical causal models (and Bayesian nets) are used in different phases of model development to help visualise and create shared understanding about causal system interdependencies. Simply put, simple graphical causal models are used to facilitate the dialogue between participants, and focus the dialogue around the causalities underlying hypotheses making and testing.

To summarise our reasoning about the use of Bayesian networks, several factors are outlined:

Bayes rule is a statistical rule based on conditional dependence between parent and child variables (or Bayesian nodes). In this dissertation, the articulation and visualisation of causal conditional dependence relationships is used to probe the 'organization' of systems, and the potential for self-organization of the system under different conditions. Graphical causal maps and Bayesian networks provide a causality-based framework for reasoning. We contend that this framework enables a simple and human-intuitive framework for reasoning about drivers, responses, influences, interdependencies, constraints, thresholds and limits of the system in relation to its sub-systems.

Bayesian approaches also consider any system entity as a set of states, with rules and laws governing its behaviour. Therefore, our reasoning follows that multi-scale systems and cross-scale effects can be represented using Bayesian Belief networks because every Bayesian entity, agent or 'node' is described in terms of states. These states can be used to represent different scales. Drivers and responses are elucidated in a heterarchy of causal relations. Moreover, as already outlined, Bayesian networks allow for both observational and interventional based learning to be facilitated by a single graphical causal model (Meder et al., 2005).

We propose that the Bayesian framework allows for understanding of categories and causal relationships between members of these categories to be jointly

understood and adapted by an interdisciplinary research group. It also enables new categories and causal relationships to be incorporated into the framework and adapted as new understanding or events unfold. In this way, new indices can be developed and monitoring programmes put in place to assess how well these indices perform as mechanisms for increasing understanding of the adaptive capacity, and hence resilience of the system; by helping understand critical limits and thresholds.

In this dissertation, a heterarchical framework (where overlapping categories are not strictly structured in a bottom-up or top-down fashion) is used in case studies of social-ecological systems to facilitate shared understanding amongst researchers, decision-makers and users of (and in) these systems. Coping with emergence is a matter of understanding how top-down and bottom-up understandings of system diverge. We therefore contend that the heterarchical organisation of concepts and agents into a causal driver-response framework provides a more flexible, adaptive conceptual foundation for the exploring the self-organisation of social-ecological systems.

In the BPDA approach causal models help visualise the various types of driver-response influences. Over time, a hierarchy of how system entities (agents/sub-systems) influence one another emerges from a facilitated participatory dialogue conducted around the structure and sensitivity of the causal model entities. This hierarchy may be derived purely from the context in which the system exists. It is not restricted by the universally applicable definitions of terms, concepts and relationships. Rather, definitions of concepts, agent roles and behaviours emerge from a shared, contextual understanding of causal system influences.

In respect of social-ecological systems, many different processes are brought to bear on research, strategy-making, decision-making and adaptive management as tools for understanding and coping with emergence. These are described in the next section.

4. **Research Methodology: Strategy & Design Considerations**

“So once I started having thoughts like this, everything began looking different to me. To my eyes, this system I was observing, this ‘trial’¹² thing itself, began to take on the appearance of some special, weird creature.”

“Wierd creature?”

“Like, say, an octopus. A giant octopus living way down deep at the bottom of the ocean. It has this tremendously powerful life force, a bunch of long, undulating legs, and it’s heading somewhere, moving through the darkness of the ocean. I’m sitting there listening to these trials, and all I can see in my head is this creature. It takes on all kinds of different shapes – sometimes it’s ‘the nation’, and sometimes it’s ‘the law,’ and sometimes it takes on shapes that are more difficult and dangerous than that. You can try cutting off its legs, but they just keep growing back. Nobody can kill it. It’s too strong, and it lives too far down in the ocean. Nobody knows where its heart is. What I felt then was a deep terror. And a kind of hopelessness, a feeling that I could never run away from this thing, no matter how far I went. And this creature, this thing, doesn’t give a dam I’m me or you’re you. In its presence, all human beings lose their names and faces. We all turn into signs, into numbers.”

Murakami (2008, pp.97-98, anecdotal)

4.1 **Background: A Review of Research & Decision-Support Tools for Sustainability**

Before the research methodology considerations made in this dissertation can be presented, there are several background areas of research that must be shared with the reader. These background areas are concerned with approaches that are already in existence and use in dealing with complex social-ecological system problems, even though they may be better suited to either social or ecological systems respectively. In this section we discuss approaches that are used in support of sustainable development programmes. These involve the use of narrative accounts in scenario planning, modelling complex social-ecological systems and case study approaches. These are discussed in more detail in the following sections.

4.1.1 **Scenario Planning & Participatory Processes for Modelling Multiple Futures**

Human beings are well adapted to living with the complexity of real-world challenges that they face. Humans have the unique ability to conduct a dialogue around system interdependencies and sensitivities, which involves considering the softer and harder aspects at hand in order to reach a decision about how to respond to undesirable system behaviours. Humans are also able to predict the possible future states of systems under different scenarios through dialogue involving a wide range of discourses. Analyses of power, culture and gender have proved powerful tools for understanding and influencing the evolution of social norms at different scales and levels of description used to understand socio-political systems. These require a more nuanced understanding of context, and top-down universality may be difficult to obtain where such bottom-up richness of systems largely influences whole-system level behaviours. Information overload and ‘too much objectivity’ (Allenby, 2006) further hinder the ability of human beings to comprehend the complexity of systems.

¹² Referring to law trials in general.

In unlocking this complexity, Allenby (2006) states that; “*narrative is the key to dealing with complexity without compromise*”.

On a daily basis human beings navigate uncertain futures by using a mixture of normative and objective judgements to adapt to or influence their environment. Narrative, or ‘story telling’ is an essential element of dialogue, and is “inherently interdisciplinary” (Riessman, 1993). It “extends the interpretive in the social sciences” (Riessman, 1993). Both are powerful conceptual modelling tools that are used to rationalise objective and subjective elements of the argument being considered (Riessman, 1993). More importantly, predictability (and its limits) is garnered through dialogue and conversation where the adaptation of social-ecological systems is concerned. We survive real-world emergence through adaptation from agent-driven self-organization, and predictions drawn from problem solving conversations which draw on a diverse range of participating agents. A modelling approach which seeks to *enhance the dialogue* amongst participants in adaptive co-management efforts is more likely to have an impact upon the “political processes of decision-making and change” as required by Van Kerkhoff & Lebel (2006). This is because dialogue is the main analytical tool employed in adaptive governance and adaptive co-management programmes and is hence a significant ‘soft’ element which can improve or hinder system resilience.

As already explained, scenario planning and adaptive management are ways of coping with uncertainty through participation and dialogue (Peterson et al., 2003). Prediction is always limited by the set of assumptions underlying it. Where models of social-ecological systems are concerned the formulation of model structure and the sensitivities of interdependent variables are dependent on a variety of perceptions and interpretations. The level of uncertainty associated with model-based assessments may range considerably depending on the level of understanding, historical knowledge and availability of empirical data. Often, rigorous assessment of the uncertainties in understanding the sensitivities of critical systems interdependencies necessitates a dialogue that involves participants from a relevant but diverse set of worldviews. Scenario planning embraces uncertainty by analysing problem contexts using multi-participatory dialogue (often facilitated by soft systems methods) as a means of ‘modelling’ historical, current and future system states and interpreting

different perspectives within the dialogue space. Quantitative and qualitative (Peterson et al., 2003) information, whether subjectively assessed or objectively measured may be integrated to serve the purposes of prediction, forecasting and projections in scenario planning. This makes scenario-planning suitable for dealing with the reflexivity of social-ecological systems, which adapt and change as human and other agents self-organise to ward off perceived future threats or to adapt to current uncontrollable external pressures.

4.1.2 Modelling the Complexity of Social-Ecological Systems

4.1.2.1 Modelling Complexity: Hierarchy & the Multi-Agent System

Ecosystems and social-ecological systems are open systems (Cilliers, 2008). They are complex, multi-scale systems (Gillaume et al., 2004), where the “*organism complex*” is inseparable from the environment, with which they “*form one physical system*” (Tansley, 1935, in Guillaume et al., 2004). General systems theory views systems as a “*set of interacting elements which are characterised by the following aspects: mutual dependence ... emergence of organisations ... (and) feedback processes*” (Le Moigne, 1994, in Guillaume, 2004). Ecosystems (and social-ecological systems) also satisfy this definition. Therefore, they can be regarded as subsets of complex social-ecological systems. Hierarchical systems organization is generated from the iterative and recursive action of the processes that lead to emergence of “*new entities*” (Gillaume et al., 2004). Guillaume et al. (2004) take the view that an adapted description, SOHOS or Self-Organized Holarchic Open Systems (Koestler and Smythies, 1969), must be taken on ecosystems (though the authors are more concerned with aquatic ecosystems in particular).

According to Guillaume et al. (2004), “a holarchy is a non-directional hierarchy in which the members are called a holon”. Ecosystems as holarchic systems may have different levels of description and scales of observation, intervention and analysis¹³. These multiple scales of interaction are ‘crossed by fluxes (mass transport or energy)

¹³ Levels and scales of description are distinguished in Ingram (2007).

which dynamically structure them'. If the ecosystems concept is broadened to that of a social-ecological system, then the multiple levels of description may also be said to be dynamically structured by the conceptual, normative, performative and constative factors that underlie the conceptualisation of the different levels of description (by actors within the system). The interaction between these actors (or agents) may be modelled using rule-based approaches. In this approach, entities (or agents) 'and their behaviour are described by a set of rules'. Dynamic, agent-based simulations are often used to generate these behaviours and identify system thresholds and derive system laws where possible. With law-based modelling approaches, which are more classical, 'The level of description is always global with global variables on which we apply the equations of the model'. (Gillaume et al., 2004)

Gillaume et al. (2004) advocate a 'mixed-model' approach where laws and rule-based approaches are used complementarily. Using this approach an "ecosystem could be globally described as a set of ecosystems states", individuals as individual states and population as population states. Each element of the model is therefore considered as a set of states. In this respect, the compatibility of Bayesian networks with this requirement is obvious. As explained in the previous chapter, Bayesian networks are a state-based probabilistic formalism, and can serve as hyperstructures which are heterarchically adapted (as outlined in section 3.4). Moreover, quantitative and qualitative reasoning can be used to formulate and populate a Bayesian network. In addition to this Bayesian networks as hyperstructures for social-ecological systems will also have to accommodate non-linearity, feedback, and providing and understanding of resilience through critical limits and thresholds, is a necessary requirement for modelling social-ecological systems.

However, complexity, is also related to decision-making, in particular, negotiating the undecidable decision. Indeed, Zellmer et al. (2006) relate a similar view, that; "complexity arises when there is no paradigm, when critical decisions are left unmade". Predictive modelling of complex systems are often to no avail in these situations, and models, in general are limited by the assumptions that govern the fundamental causalities, conditionalities, constraints and parameters of the model in question. This is more robustly stated by Beer (1992):

But here's the rub. In programming a computer, one needs a model. Models are provided by brains. Models are necessarily massive variety attenuators, because they select only those aspects of the world that are relevant to the model's purpose. Worse still, the models adopted are not the best that we can provide: they are consensual models put in place and held together by ideologies.

Zellmer et al. (2006) recant their earlier position that “measureable characteristics” of what makes a system complex could be determined. Indeed, they suggested a range of characteristics of complex systems in earlier work (Allen et al., 1999, McCormick et al., 2004), that in retrospect, was in fact reducing a complex system to classes of simple “things”. They assert that this is the standard approach towards complexity and hierarchy in general. Simplifying a system is the role of modelling. The benefit of models is that help make explicit assumptions that underlie the simplifications that have to be made to formulate a model and the possible consequences of the assumptions in different scenarios. Models help simplify and share understanding of systems. Zellmer et al. (2006) explore what simplification means in this context:

A system is simple when the observer has decided on the following distinctions: What is: structure versus behaviour; rate-independent versus rate dependent; meaningful change versus mere dynamics, discrete versus continuous? ... Before simplicity, there is complexity.

According to (Zellmer et al., 2006), law based models tend towards universality because they are independent of structure and dependent on rate. Rule-based models, however, “*are the* observer’s contribution what is observed, that which arises because of explicit observer decisions.” Rules are therefore a record of how the observer defines the boundaries of a model, and, “the model becomes the rules for equivalence” (Zellmer et al., 2006)

The issue of categorisation or taxonomy occurs whenever an equivalence class that underlies model construction, is uncovered; “underpinning every model is an

equivalence class¹⁴”. The aim of research is to find the basis of equivalence in observed entities, the reason for the patterns we recognize’. The identification of ‘equivalence’ is then a matter of identifying the essence of a particular entity or phenomenon. This is where ‘observer-subject relationality’ throws a spanner into the works; namely that the unique interpretation of experience into narrative and other models of reality are also important.

Often, a singular essence of a particular entity or phenomenon cannot be satisfi-ably or rigorously determined. The notion of essence itself is challenged by Zellmer et al. (2006), who conclude that “essence is undefineable and linked to the definitions that fix the level of analysis”. The complexity of ‘essence’ lies in the fact that upward and downward causation is involved in the level of analysis of the equivalence class and because it is inseparable from the participation of the observer. The notion of ‘essence’ is subverted when its relationship to the equivalence class is determined in contradictory ways by when utilizing downward (top-down) or upward (bottom-up) directions of analysis. This is illustrated with the use of examples in Zellmer et al. (2006).

Essence and self-organization¹⁵ are therefore relegated, in some sense, to the as the entities used to describe them, lying between both the realm of the observer and undefinable ‘other’ as defined by Zellmer et al. (2006). When scientists or researchers identify a model, the model defines an equivalence class, and further research endeavours relate to testing and verifying (i.e. through various analytical and observational methods) whether old and newly identified entities belong to this class. According to Zellmer et al. (2006) “this act closes the loop of model building: assignment to a class and verification of membership”. After a model that articulates system structure (in one way or another) has been formulated, the measurement phase of research can begin (Zellmer et al., 2006). The key objectives of this phase are to identify the scale and type of entity. Where social-ecological systems are concerned

¹⁴ This is consistent with the view that an entity or individual instantiates a class for ecosystems. (Allenby, 2006).

¹⁵ With self-organisation, multiple understandings (that may agree in areas or disagree completely) can be derived about whether the system is self-organizing or disorganizing.

a variety of other factors need to be taken into account when addressing the complexity of modelling these systems (e.g non-linearity, scale, emergence, thresholds and critical limits). However, no complex system can be modelled exhaustively, that is, it is not reproducible in infinite detail (Cilliers, 2001; Cilliers, 2008; Richardson, 2002).

Zellmer et al. (2006) summarise their position on modelling by stating that “any unified account is lacking, because it fails to capture the contradictions and complementarity”. Moreover, there are no ‘correct’ or ‘incorrect’ models, “so long as what they posit follows logically”. The issue of scale is important for formal models as they are usually constituted by a set of “scaling rules, like the laws of aerodynamics”, and are hence themselves scale independent. On the issue of modelling, Zellmer concludes that *“the point of all this encoding and decoding (into the world of observation) is an attempt to link the causal entailment in material systems to the logical entailment of the model.”*

This ‘causal entailment’ often results from differences in downward and upward directions of causal logic. Causality occurs both in the conceptual domain and the dynamic domain of interacting entities. With taxonomies, causality may be identified where the presence of an individual or entity instantiates a class. A model and entities of a model, may therefore instantiate a hierarchy of classes. This hierarchy of classes is difficult to fix into universal laws for complex systems because the ‘essence’ changes with different understandings and perceptions of what the ‘essence’ of the system constitutes. Downward and upward directions of analysis reveal contradictions in agreement over what constitutes a particular class in terms of a singular essence. Indeed, other systems theorists agree;

... the concept of emergent property receives a more solid definition via the ideas of constraint and downward causation. Systems that through their coupling form a supersystem are constrained: they can no longer act as if they are independent from the others; the supersystem imposes a certain coherence or coordination on its components. This means that not only is the behavior of the whole determined by the properties of its parts (“upwards causation”), but the behavior of the parts is to some degree

constrained by the properties of the whole (“downward causation” (Campbell, 1974)). (Heylighen, Cilliers & Gershenson, 2007)

Hence, there is more to what makes social-ecological systems complex. Social-ecological systems are not just what our models are able to represent in law and rule-based models, which are abstract simplified understandings of system interdependencies. What makes a system complex is its fundamental inability to be characterised within a *single* scientific (or other) paradigm (Zellmer et al., 2006). This is an identifiable crisis of invoking “a duality between the observer and the observed” (Zellmer et al., 2006) - or the Cartesian *observer* and *subject*.

4.1.2.2 **The Role of Narrative: Multiple Perspectives**

Zellmer et al. (2006) take a constructivist philosophical approach and make use of the concept of “the other”, as “that which arises above and beyond the choices and decisions of the observer”. They go on to say that “the things in the other are not only undefined, they are undefinable”, and that their approach towards dealing with the ‘other’ is through the use of narrative, “where the observer’s knowledge and understanding is constructed by interaction with experience (Piaget, 1963)” (Zellmer et al., 2006).

Zellmer et al. (2006) therefore introduce the idea of the narrative as a means of modelling that can “rise above” formal law and rule based models because *the narrative “is still in business” when formal models break down*. The authors make a comparison between the irreducible attractor, which still exhibits identifiable form, and the process of an unfolding narrative, that may contain contradictory factors but still have form and still functions when causality or taxonomy breaks down.

The narrative is “an expression ... of the values that are shifting as the story unfolds”. It is therefore a complex model itself because it “works at a higher level of analysis, and transcends the model”. Most importantly:

Narrative can still apply when the model is driven into contradiction, because it is about the decisions of the narrator, not some internally consistent representation as occurs in the model (Zellmer et al., 2006).

The value of incorporating the narrative into scientific enquiry is also stressed in other studies (Cilliers, 2008). Most notably, Cilliers identifies the inclusion of the narrative into the body of science as a crucial need (i.e. from a complexity theory perspective), and one that would engender useful and beneficial academic enquiry.

Narrative can be converted into an evaluable conditional, taxonomical, and hierarchical framework using causality and Bayesian networks (hyperstructures) as a means for expressing system interdependencies, be they taxonomic or influence-based. Although it can never completely capture the narrative, or help predict how the narrative would unfold over time, it can nevertheless provide a valuable aid to understanding how changes in understanding evolve, by adapting the causal models to reflect changes in basic understanding. We propose that the BPDA approach can be used as a tool around which the narrative can be tested. Zellmer argues for a different perspective of the usefulness of science in relation to the narrative. The narrative serves as the higher level of complex modelling that engenders shared understanding for decision-making, as stated;

The point of science is not prediction. Rather, the undeniable power of science comes from its capacity to get us convinced that we are all seeing the same thing, at least if we adherents to the same paradigm, the same story. Prediction makes the story convincing. (Zellmer et al., 2006)

By extending scientific enquiry into the realm of the narrative more effectively, science can start to participate in complexity based systems research more usefully. We therefore recognise the importance of narrative, as a social science methodology in the negotiation of the role of science in decision-making. Accordingly, we therefore embrace the role of dialogue, discussion, narrative as constituents of learning, participation, negotiation and cooperation as required by Van Kerkhoff & Lebel (2006).

The power of narratives, as with the power of myths, is their capacity to rise above contradiction, when the juxtaposition of large disparate issues is given meaning. Zellmer et al. (2006)

The “undefine-able” realm is “out there” (Zellmer, 2006), because it is indivisible from how the many observers understand it. This leads to the inevitable influence of the undecideable upon decision-making. The realm of ‘the other’ is viewed by Zellmer et al., 2006, as consisting of undefineables, impossible to understand in terms of a single essence. ‘Undecideability’ in decision-making is the natural consequence of such a situation.

Narrative is also a critical mechanism for elucidating and resolving the inevitable undecideable decisions that attempts at sustainability must necessarily face. We respond to the need for research to engage at the level of political decision-making by adopting the narrative as a tool for conducting multi-participatory engagements. In this dissertation we achieve this by employing participation to capture contradictions in the narrative in causal models as a way of engendering shared understanding, and dealing with conflicts in understanding within the greater frameworks of understanding that help constitute perceptions of sustainability challenges in social-ecological systems.

4.1.3 Case Study Research: Strategies & Methodologies

April (1994) draws on a number of sources to compile a comparison of research traditions in the social sciences as outlined in detail in Table 2. These research traditions show that a range of approaches can be brought to bear on social systems that lie outside of the scope of the natural sciences. In this dissertation, we focus more deliberately on enabling case study research in developing the BPDA approach, as case study research can serve as an integrative framework for insights and conclusions drawn from other research traditions, and can accommodate a wide

range of data and information sources as will be outlined in more detail later (Yin, 1984).

Table 2:

Comparison of Research Traditions (April, 1994: pp.84)

Comparison of Research Traditions					
Key Design Elements	Biography	Phenomenology	Grounded Theory	Ethnography	Case Study
Theory Used. Before & After	Both—before & after study	Before study	During & after study	Before study	Both—before & after study
Focus of the Study: Themes/Goals	Stories; Epiphanies; oral/life history; individual	Phenomenological stated; description; meanings; essence	Grounded theory stated; generate theory; develop; processes; propositions	Ethnography stated; cultural; behavioural; culture theme and portraits	Bounded, entities; single or cross comparisons; investigates “how”/“why” on processes, events, and individuals
Data Collection: --Analysis focus	--Individual	--Multiple individuals with experience on phenomenon	--Multiple individuals who have participated or acted upon a central phenomenon	--Members of a culture; a group or individuals representing shared culture	-Bounded investigation of a process, system, program; or multiple individuals
-Sample selection	--Person dependent: availability; a critical case; politically important	--Criterion sample, i.e. people sharing same phenomenon	-- homogeneous sample; theory based sample	--A cultural group to which one is a sample; “stranger” or “representative” sample	--Finding case(s); similar; maximum variation;
--Information collected	--Documents; archival material; journalistic — informal chats	--Interviews: up to 10 people	--Mostly interviews with 20-30 people to build theory	--Participant observations; interviews; artifacts; documents	--Documents’ records; interviews; observations; artifacts
--Common Issues	--Access to materials; authenticity and/or verifiability of account	--Bracketing one’s personal views; logistics of interviewing	--Interviewing issues, e.g., logistics, openness	--Field issues, e.g., reflexivity, reciprocity, “going native”, deception	--Interviewing and observing similar to other traditions
Data Analysis --Classifying	--Identify stories, epiphanies, context materials	--Identify lists of statements with meaning to individuals; group statements to meaning units	--Engage in axial and open coding for context, strategies, consequences	--Analyse data for themes and recurring patterns	--Use categorical aggregation; establish patterns of categories
--Interpreting	--Theorize—developing patterns and meanings	--Textural description of event; how it was experienced; its essence	--Selective coding; develop conditional matrix	--Interpret and make sense of findings	--Use direct interpretation; develop naturalistic generalizations
Sources: Creswell (1994); input from: Yin (1984), Stake (1995); Patton (1990); Denzin & Lincoln (2000)					

According to Yin (1984), “the core contribution of research is to create relationships between actors, and arenas where they can meet in democratic dialogue.” (Yin, 1984, p.xxxii), and that “unless two people can relate in a democratic way to each other, no new ideas, no just causes, or indeed any science, be it social or other, is possible” (Yin, 1984, p.25). Research into complex social-ecological scale problems usually involves working with an cross-disciplinary team, rather than a single researcher to address the various dimensions of the social-ecological system research questions being posed. As such, it requires a researcher to go beyond pure quantitative research methods, and to embrace a less theoretical and more practical, investigative stance towards research. Indeed in case study research, “the need to balance adaptiveness with rigor but not rigidity – cannot be overemphasized”. (Yin, 1984, p.x)

The goal is not merely to obtain historical information of key variables and to develop an understanding of the causal and correlative relationships in order to fit them to a classical model that will enable us to predict the future of a social-ecological system. Social-ecological systems can have multiple futures, as they can adapt or re-organise internally into different stable (and sometimes unstable) states because they are complex, adaptive systems (Levin, 2006; Holling et al., 2002). The future is an emergent property of the complex, adaptive, self-organisation of social-ecological systems, and cannot be predicted from mere historical knowledge of the system. The researcher must therefore also engage deeply with the current context of a social-ecological problem (and across disciplines), and in this sense, each study of a social-ecological system is in some ways *unique*, and a case study in its own right because it is so heavily influenced by context (historical, and especially current). It is not guaranteed that the case study itself will be generalise-able to larger scales, or levels of description and abstraction towards theoretical universality. Rather, the emphasis is on elucidating the rich influence of context, and how it relates to the research question; a link that must constantly be maintained by the researcher through a variety of interactions with experts from substantially different disciplinary perspectives and information assimilation and data gathering efforts.

Various research strategies and designs have been employed in the different, traditionally distinct academic disciplines, to address their respective disciplinary

methodological requirements. Generally, research is a strategy for increasing learning and understanding about a system, phenomenon, case, object, subject or concept that is of interest, that is; to a researcher, group of researchers, society, governance organisations and the like. According to Checkland (1985), this involves three elements; “(a) some linked ideas in a framework, (b) a way of applying these ideas in a methodology, and (c) an application area (Checkland, 1985)” (Flood, 2001, p. 135). In a chapter assessing the relationships between systems thinking and action research, Flood states that, “after employing a methodology there is reflection on what has been learned about the three elements. Modifications might be called for.” (Flood, 2001, p. 135). Research is therefore an *adaptive, evolutionary and iterative* process of learning and testing hypotheses and understanding about a phenomena, problem, context, situation, event, object, subject, process etc., that is, anything that is of interest to a researcher or group of researchers.

As already argued in this dissertation, social-ecological systems are complex, adaptive systems (Levin, 2006) by virtue of their ability to self-organise in different and sometimes unique ways, in relation to their context. Research into social-ecological systems therefore requires a strategy for research that matches the nature of social-ecological systems. In particular, we require a strategy that helps build the capability to iteratively improve understanding of the adaptive capacity of the system. According to Yin (1984, p. 17), research strategies constitute a wide variety of approaches towards addressing research questions, for example: ‘case studies, experiments, surveys, histories and the analysis of archival information’. Each research strategy is ‘a different way of collecting and analyzing empirical evidence’, and ‘can be used for all three purposes – exploratory, descriptive, or explanatory’ (Yin, 1984, p. 16).

The most appropriate research strategy to match a particular research question depends on how well or badly three conditions can be satisfied by each research strategy i.e. the “ 1) type of research question, 2) extent of control over actual behavioural events, and 3) degree of focus on contemporary as opposed to historical events’). These three conditions distinguish the different strategies, and not any hierarchy between them (Yin, 1984, p. 16).

Yin lists the types of research questions as “exploratory, explanatory and descriptive” (Yin, 1984, p. 13, 17, 18, 19). In most research into social-ecological systems, all three may be required (and often are) in addressing the broader goal of a research group. However, where research is conducted with the specific aim of addressing issues of sustainability (for decision-makers or decision-making audiences), the ultimate aim of the inquiry is to provide some kind of explanatory model or understanding that can be used to consider different strategies for addressing possible multiple futures of the system.

Social-ecological systems contain many actors (decision-makers, stakeholders, system users) at different levels and scales of influence in the system. However, due to the rich influence of context on social-ecological systems, the extent of control over actual behavioural events is rather limited, being restricted to interventions and observations (or monitoring). Moreover, it is not always helpful to focus purely on understanding the *historical* evolution of the system in the hope of obtaining a predictive model of the system. Social-ecological systems self-organise and adapt in often unpredictable ways, depending on the influence of current context, and the systems’ vulnerability to externalities that are beyond their control (e.g. global and regional economics). The adaptive co-management of social-ecological systems needs to be understood in terms of how its *present context* comes to bear upon the *present ‘state’* of the system, however that may be defined, hence the need for approaches based on action-research principles (Van Kerkhoff & Lebel, 2006; Malhotra, 1999).

According to Yin, “Research questions have both *substance* (what is the study about?), and *form* (is it a “who”, “what”, “where”, “how much”, “how many”, “how” or “why” question?)” (Yin, 1984, p. 19). This encompasses a broad range of possibilities all of which may find application in research into social-ecological systems. Due to the nuanced and complex influence of context on social-ecological systems, they often need to be studied and understood on a case-by-case basis. Moreover, while general models are useful, they do not provide a definitive or explanatory understanding of the ‘real’ ontological social-ecological system when located in its context. This is true of both social and ecological systems alone too. Research into, and decision-making about social-ecological systems, generally suffers

from fragmentation in perspectives (disciplinary or otherwise) and their accompanying 'partial truths' (Holling, Gunderson & Ludwig., 2002, p.19). According to Flood (2001, p.136), "the socio-ecological perspective takes the open systems principle as its intellectual framework of ideas ... a system is defined by the 'system principle (i.e. the organizing principle), which can be used to characterise the intra- and inter-relationships existing in and between a system and its environment. These relationships are referred to as 'lawful relationships' reflecting the view that systems and individuals are capable of knowing their environments ...". They are therefore useful in themselves as 'modellers' of complex events and situations.

What is required for research into social-ecological systems is an open systems approach that is inclusive, representative and transparent to whatever methodological problem best suits the particular nature of the problem or case that needs to be solved. That is, we require an approach that; encourages interdisciplinary understanding to grow and to be iteratively tested, can adequately account for the understanding of self-organisation in the system, can adapt to new problem contexts, and can be broadened to include and share understanding with decision-makers, users and stakeholders (Flood, 2001, pp.136; Holling, Gunderson & Ludwig, 2002).

In discussing moving beyond 'fragmentation' in his chapter on the 'relationship of 'systems thinking' to action research', Flood (2001) states that complexity theory is a new form of systemic thinking which offers a systemic logic that accepts that reality can never be fully modelled or understood in its infinite detail, due the "vastness of interrelationships and emergence in which people are immersed". As previously mentioned, in addressing the issue of self-organisation Gershenson & Heylighen (2003) argue that self-organisation depends on the levels or 'graining' of description used to formulate an understanding of a system. Soft systems thinking is complementary in this regard, as it sees "reality as the creative construction of human beings (Jackson, 1991)", takes a subjective position on knowledge and meaning, and is "firmly linked to interpretive theory" in this way. Soft systems thinking, "generates and works with an evolving appreciation of people's points of view and intentions." (Flood, 2001, pp.137)

This does not discount dynamic systems models; “Systems models, or indeed any other model may be employed in a heuristic fashion to see if they generate insight and assist in the construction process. With soft systems thinking, however, models must never be taken as representations of reality. Each model is employed like a pair of spectacles through which we can look at and interpret reality ... systems models are likely to be particularly useful in achieving meaningful understanding” (Flood, 2001, p. 138).

In a recent book chapter entitled, “complexity theory as a general framework for sustainability science”, Cilliers (2008, p.39) argues for an explanatory framework “which makes explicit why these problems are so difficult”, rather than a predictive, exhaustively descriptive framework “that will generate foolproof methods for dealing with complex problems”. By understanding complex systems better, we can devise better measures for dealing with them (Cilliers, 2008, p. 40), but there are limits to understanding that must be acknowledged. This is especially the case where scientific knowledge is concerned, that is, in dealing with the full realm of considerations regarding ‘values’ and ‘perceptions’ that become important in dealing with the issue of sustainability of social-ecological systems (Stern, 2000).

Cillier’s highlights the distinction that Morin (2007) makes between “*restricted complexity*” and “*general complexity*” (Cilliers, 2008, p. 42-43). Restricted complexity characterises the research spaces in which mathematical and statistical computer models are employed to characterise complex phenomena, and which recognises ‘interdisciplinary potentialities’. However, due to an underlying quest for universalism or “laws of complexity”, these approaches fall within the paradigm of classical science. General complexity “is not merely a methodology” but, “involves a fundamental rethink of what knowledge is” (Cilliers, 2008, p. 43). It requires “that one tries to comprehend the relations between the whole and the parts”, as a way of substituting the for reductionist principle of classical science. According to Cilliers (2008, p. 43), maintaining distinction, but establishing the relation, is suggested by Morin (2007, p. 18-20) as an improvement on the classical science principle of disjunction. Morin does not argue for relativism, nor for “a “generality” which is naively holistic or vague”. Universal determinism, the third principle of classical science (Cilliers, 2001, p. 32), is subverted by the rich influence of context,

where distinctions between classes are always “contextualised within a set of relationships”.

Cilliers (2001, p. 45) proposes that if one “follows an open research strategy – a strategy which is open to new insights as well as to its own limitations” then it is possible to develop a better understanding of both the epistemological complexity and ontological complexity (Cilliers, 2001, p. 44). He stresses that there is good reason to pursue both with a good understanding of the limitations of descriptive and explanatory models of complex systems¹⁶. Cilliers goes further to state it is important to bring together the knowledge and meaning created through restricted complexity-based approaches (which are generally more akin to ‘hard’ systems approaches), and general complexity-based approaches (that are more akin to open, soft systems approaches). This must be achieved in a manner which; supports an adaptive stance towards learning and understanding, recognises the multiple dimensions involved in the soft systems perspective, and “is brave enough to think the uncomfortable consequences of its insights through to the end” (Cilliers, 2001, p. 43).

While a list of characteristics of a complex system can be listed (e.g. Cilliers (2001, pp. 45)), it is important to note that complex social-ecological systems do not necessarily have to be exhibiting overt complexity in its behaviours at all times. Rather, social-ecological systems can be in different phases (some stable, some unstable) for different periods of time, depending on factors which can be explained using metaphorical frameworks such as the adaptive cycle (Holling & Gunderson, 2002, pp. 27-28, 34-35).

Cilliers’ notes that “when there are a lot of simultaneous, non-linear interactions, it soon becomes impossible to keep track of causal relationships between components”, and that due to the non-linearity of interactions, were “incompressible”. However, Holling et al. (2002) state that despite the vast interrelatedness of social-ecological systems; complex behaviour can usually be understood by understanding a handful of key variables - and presumably their causal relations. For example, a system may appear complicated until a few factors combine, rendering the system in a

complex, often catastrophic state, as is common in disasters and disastrous mechanical failures which emerge from a combination of errors and factors specific to the context.

The critical issue for any research strategy dealing with complex social-ecological systems is not in keeping track of causal relations between components in an exhaustive framework. Rather, the task is to harness all forms of knowledge and understanding on the case being researched into a framework that is useful in helping identify the critical relationships, interdependences and key variables and factors that are of concern or interest in that they give rise to complex behaviour(s). The aim of the BPDA approach is in finding the appropriate scales of analysis, levels of description, constraints and inter-relationship sensitivities that are required to research and model the social-ecological system challenge. In the BPDA approach, this, as a research objective, is more important than modelling the entire system exhaustively.

4.2 Proposed Case Study Research Strategy

The view taken in this dissertation regarding modelling - is that modelling the complexity of social-ecological systems is *not* about replicating the system exhaustively in all its complexity. Rather it is about being able to arrive at an understanding of complex phenomena and behaviours using any and all appropriate methodologies in combination, according to the needs of the study. The modelling approach proposed and tested in this dissertation deliberately enables a *heterarchical* framework of reasoning for conducting *open systems* research. Both ‘soft’ and ‘hard’ systems approaches are brought together in a unique way in this dissertation, in order to better coordinate between processes underlying decision-making and research - towards better mutual effectiveness.

A claim that has been laid in this dissertation is that a heterarchical framework of reasoning enables the democratic evaluation of system variables in relation to the context and the topic of the study, where variables “rise to authority depending on

¹⁶ Formulating explanatory and descriptive models of reasoning are the core elements behind case study research methodologies, especially conceptualizing the study (see later in text section : Yin, 1984: P100)

their form and function” (Heylighen, Joslyn & Turchin, 2001) in relation to the problem or issue being studied. The concept of heterarchy therefore subverts the traditional idea of hierarchies as ‘nested’ (Cilliers, 2001, pp. 49) and allows for the possibility of relationships that cut ‘across hierarchies’ in different ways, depending on the context. It is comparable with the concept of ‘panarchy’ (Holling, Gunderson & Peterson, 2002, pp. 74-76) that has been introduced in resilience theory in order to enable an understanding of cross-scale relationships between nested *cycles* (i.e. adaptive cycles) in an open framework. However, the concept of heterarchy is more generalised. Moreover, in this framework, the boundaries that are defined remain “simultaneously a function of the activity of the system itself, and a product of the strategy of description involved” (Cilliers, 2001, pp. 47), and can remain open, yet bounded for the purposes of analysis of a particular scenario or situation.

In this doctoral dissertation, the focus was mainly on; (1) establishing whether graphical causal maps and Bayesian networks could be used in conjunction with facilitated open-systems participatory processes for researchers to establish a shared model and understanding of a social-ecological system, and (2) whether meaningful and useful results could be obtained from the Bayesian models. The Bayesian models serve as the integrator of the extent of reliable shared knowledge of the systems causal structure, its sensitivities and thresholds. These were obtained from data, empirical knowledge and/or well defined and constrained sub-system models.

This necessarily engages both the realms of ‘restricted complexity’ and ‘general complexity’ based (Cilliers, 2008; Morin, 2007) research and decision-support approaches. In this dissertation, both these realms are linked by the heterarchical framework of reasoning consisting of graphical causal maps and Bayesian networks, as outlined in Figure 7. Methodologies employed in restricted complexity approaches are usually more quantitative, empirical, and mathematical and statistical. Methodologies employed in general complexity approaches utilise softer facilitation techniques for knowledge building, and require more qualitative, interpretive analysis, interpretation and evaluation of the role of context in evaluating the system, such as participatory process facilitation.

These two levels of ‘modelling’ (i.e. modelling with mental models and modelling with mathematical and statistical models) are critical components of enabling the link between knowledge and action as far as sustainability of social-ecological systems is concerned, and generally where complex systems modelling is concerned. A key goal of this dissertation is exploring the effectiveness of using a heterarchical, causal framework of reasoning to bring these softer and harder systems thinking approaches into closer alignment. The aim of this is to enable closer alignment between research and decision-making for the sustainability of social-ecological systems. The manner and extent to which restricted complexity and general complexity-based approaches are used, depends on what the requirements of the particular case study being investigated dictates is necessary to arrive at reliable conclusions and recommendations of a social-ecological system. The process outlined in Figure 7 is therefore implemented to varying degrees in each case study undertaken in this doctoral dissertation.

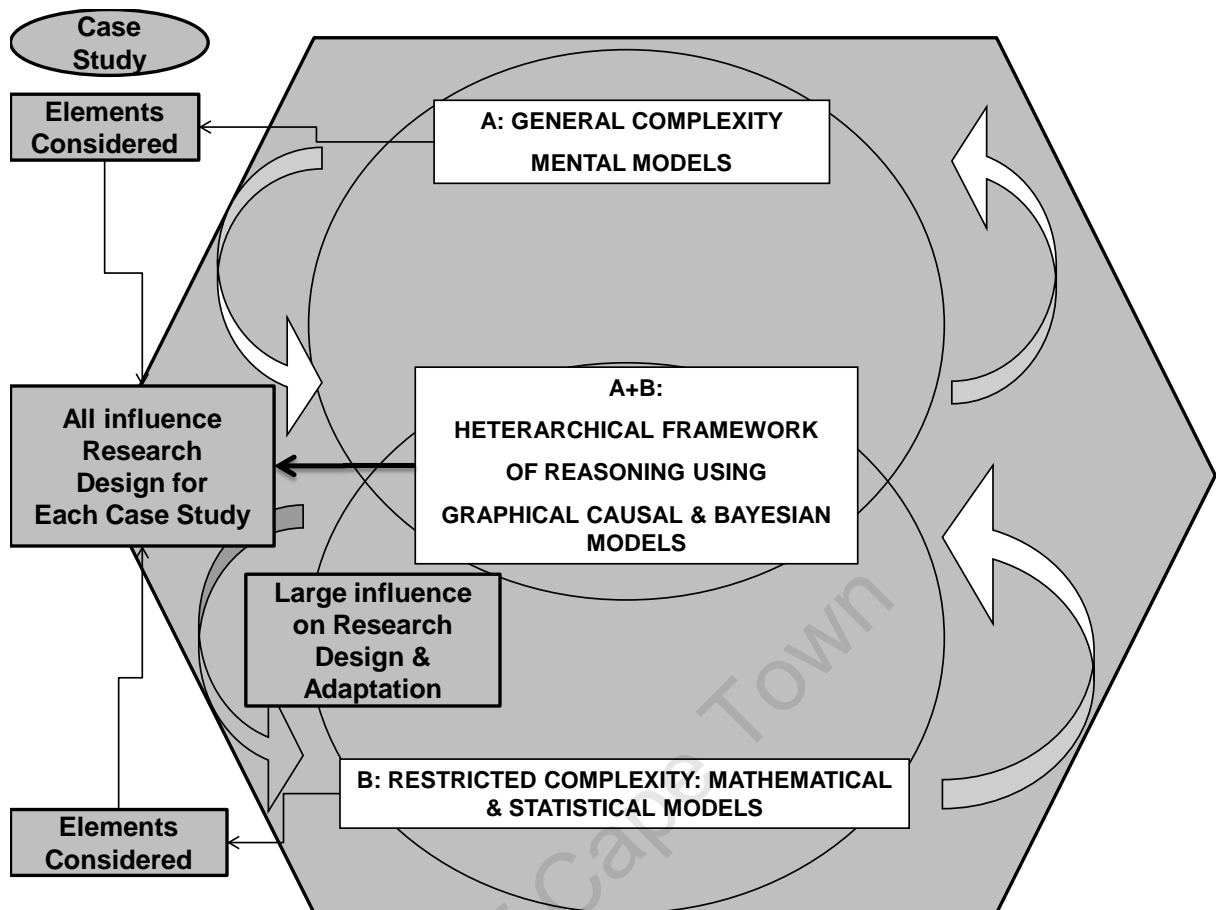


Figure 7: BPDA & Complexity: How soft general complexity approaches are combined with harder, more empirical restricted complexity approaches towards modelling social-ecological systems.

The modelling approach that is core to this dissertation helps hinge the research design effectively between both processes and to quickly adapt the research design as changes in understanding unfold or as real-world events change the system considerably. It is shown in Figure 7, and can be briefly described as consisting of three broad areas of developing understanding:

- A: General complexity approaches that are more qualitative and interpretive processes of reasoning about complexity.
- B: Restricted complexity approaches are more quantitative, empirical, mathematical and statistical processes of reasoning
- A + B: A heterarchical framework of reasoning that uses graphical causal maps and Bayesian networks as a device for verifying mutual understanding between the two processes i.e. qualitative and

quantitative processes of reasoning involved in evaluation and decision-making social-ecological systems and complex systems in general.

- This framework has a large influence on research design, as it enables full traceability of the adaptations made to the research design as new understanding is obtained, or as changes occur in the real world system that require re-orientation of the research design (see Figure 7).

This dissertation does not present any framework for the unification of theories but deals with the interface between disciplines in a context-based open systems approach where a heterarchical view of the system can be taken. Each social-ecological system is seen as a case study in its own right, and any generalizable conclusions that emerge from the cross-case comparison would be of benefit, but this is not the sole intention of this approach.

In this dissertation, eight case studies were undertaken (see chapter 6) of social-ecological system problems facing interdisciplinary research teams in order to explore the extent to which the methodology could find application in modelling complex social-ecological systems. Each study had its own specific objectives, but fitted the profile required for testing the modelling approach proposed in this dissertation. The case studies were incrementally undertaken and the complexity of case studies were built up as more insight and understanding was gained into the implementation of the soft and hard systems modelling approaches, through application in various research cases. The case studies were incrementally built up to handle greater levels of scale, level of description, integration and shared understanding between disciplines, interdisciplinary participatory process management, and decision-maker engagement. Careful considerations have to be made regarding the characterising, planning and implementing of effective 'case studies' of social-ecological systems. This is dealt with in detail in chapter 7, after the case studies, so the BPDA approach could be assessed in terms of its value in addressing critical aspects of internal and external case study validity and present critical learning points that emerged from implementing BPDA.

For the purposes of this dissertation, case study as a research strategy is taken to be a valid research strategy for dealing with social-ecological systems, and as a general framework for research design, because it is essentially an open systems methodology, which encourages the use of multiple sources of evidence (Yin, 1984, pp. 20, 23). As such, it can provide a framework to help integrate the outputs of general complexity (more qualitative, interpretive) and restricted complexity (more quantitative, empirical) exercises undertaken in support of the case study.

A misconception regarding the role of case study's as traditionally understood and used in research is that the case study was not seen as a separate research strategy in itself, but was seen as part of one or more of the phases of research strategies (Yin, 1984, pp. 13). Yin asserts that case studies constitute a research strategy that is distinct from other research strategies such as 'experiments, surveys, histories and the analysis of archival information' (Yin, 1984, pp. 13). The case study as a research strategy is defined by Yin (1984, pp. 23) as "an empirical inquiry that:

- Investigates a phenomenon in its real-life context, when
- The boundaries between phenomenon and context are not clearly evident, and in which,
- Multiple sources of evidence are used."

Yin states that "In general, case studies are the preferred strategy when, "how" or "why" questions are being posed, when the investigator has little control over events, and when the focus is on a contemporary phenomena within some real-life context. Such "explanatory" case studies also can be complemented by two other types – "exploratory" and "descriptive" case studies." (Yin, 1984, p: 13)

Case studies are used in different real-world research areas, for example: strategy-making, policy-making and policy implementation guidelines, planning and planning research, organisational and management studies, psychology, sociology, and the political and social sciences (pp. 13). Case studies are often essential inputs into evaluation and planning research outputs to decision-makers, stakeholders, system users and the general public. In a sense, an adaptive management programme

is itself an ongoing a case study for decision-makers involved in the programme, as it involves learning, participating, integrating, observing and intervening in a system that is characterised by emergence.

Yin (1984, pp. 24) states that case studies can both include, and be “limited to quantitative evidence” and that the difference “between quantitative and qualitative evidence does not distinguish the various research strategies”. Where social-ecological systems are concerned, a mix of qualitative and quantitative evidence is often necessary to different degrees. This mix depends on the nature of the research question or problem. All of the stated research strategies come into play in dealing with the problem of sustainability of social-ecological systems, that is; according to Yin’s (1984, pp. 13) categories of research strategies (i.e. including case studies, experiments, surveys, histories, and analysis of archival evidence). However, the integrative nature of the case study as a research strategy, which has the strength of being able to accommodate multiple sources of evidence, deal with a “real-life context”, where the “boundaries are not clearly evident”. This makes it a compatible and suitable research strategy for dealing with a broad range of social-ecological systems problems and research questions. Case study approaches fundamentally underlie research and decision-making on sustainability of social-ecological systems. The case study research strategy was therefore used as a basis for investigating the claims made for the modelling methodology proposed in this dissertation.

4.3 Aims of single and cross-case study analysis

4.3.1 Testing Specific Requirements for Social-Ecological Systems

Modeling and simulations play a large role in advancing our understanding of human and ecological systems and the relationships between them. However, it is increasingly becoming more recognized as an aid to understanding the adaptive capacity of a social-ecological system under a variety of projected system future scenarios - rather than providing a accurate predictions of the possible futures decision-makers may face. The processes involved in formulating future scenarios

and projected system futures necessarily involves; (1) a degree of scenario planning and participatory process facilitation (Peterson et al., 2003; Richardson, 2002), and (2) integration of models representing sub-system components (and agents) at appropriate scales and levels of description (Bennet et al., 2003; Richardson, 2002).

The value of participatory processes, such as scenario planning (Peterson et al., 2003) cannot be underestimated as a means of modeling complex system futures. According to Richardson (2002), “The (nonlinear) modeling process is regarded as an ongoing dialectic between stakeholders (modelers, users, customer, decision makers, etc.)”. Non-linearities in complex systems are often best elucidated through a qualitative modeling process involving dialogue and exchange, indicating that human beings are very capable of using their mental models to get a grasp of the complexity of the challenges they are faced with. Model integration is necessary in order to enable researchers to determine thresholds, critical limits and key intervention and monitoring points (or variables). These points are determined in support of characterizing the adaptive capacity of the social-ecological system in question more thoroughly and rigorously.

Model integration, however, is often constrained by pragmatic bottom-up considerations such as availability of data, and availability of models (Richardson, 2002). More subtly, it is constrained by the soft interactions and qualitative (or subjective) judgements that are made amongst researchers in deciding on how integration will be performed. Richardson states that “it is essential that quantitative methods be incorporated into a qualitative (nonlinear) analytical framework ... so that linear application of non-linear models is avoided”, revealing the need for a qualitative framework of integration that can accommodate non-linearity. In modeling complex systems, affording appropriate attention and scrutiny to the process of modeling is as important, if not more important, than the computer-based model(s) that are being used to understand system behaviours (Richardson, 2002).

Predictive models of complex systems often fail to produce sufficiently adaptive decision-support systems and results that are useful to decision-makers when unforeseeable changes occur. Predictive modeling approaches often result in integration of models and simulations to service a rather small set of future scenarios.

As such, predictive approaches are difficult and tedious to adapt when real-world changes occur. These may be changes in understanding, or changes in the system context due to real world changes to the system (whether internal or external influences occur). Behavioural models are designed to improve understanding of a complex system in an iterative manner, which calls for extensive adaptability of the modeling framework in order to be able to handle a variety of scenarios, complete with drivers, constraints and responses. Richardson (2002) cites Kolman et al. (1997), who states the challenge of behavioural modeling well, “[a]n ideal tool for social science inquiry would combine the flexibility of qualitative theory with the rigor of mathematics. But the flexibility comes at the cost of rigor.” Richardson therefore prescribes a “healthy skepticism” of these (behavioural) frameworks. In this dissertation, the proposed BPDA methodology is tested and evaluated in a series of case studies to establish whether it, and to what extent, it satisfies the need for a complexity based approach towards modeling complex social-ecological systems.

Predictive, more quantitative approaches towards research and problem-solving tend to be mainly bottom-up, to draw on theoretical frameworks, and to collect evidence ‘objectively’ in support or denial of these theoretical frameworks – while qualitative, interpretive approaches are more subjective and tend to emphasize the role of the context in which the research problem is situated (April, 1994). Top-down research and decision-support inquiries into social-ecological systems often involve a range of qualitative modeling approaches such as scenario planning (Peterson et al., 2003). The dichotomy between quantitative and qualitative approaches (April, 1994, see Table 3.1) is useful for understanding the processes involved in investigating a research question (or set of research questions). However, quantitative and qualitative processes of reasoning both play a part, to varying degrees, in supporting the construction of a model of any complex system. This is especially so where computer simulations of complex systems are concerned (Richardson, 2002).

Where social-ecological systems are concerned, the challenge involves tying the research problem closely to the context in which the problem is situated and trying to prevent the fragmentation that results in research and decision-making as a result of partial disciplinary and sectoral perspectives (Holling, Gunderson & Ludwig, 2002,

pp. 19). This necessitates the engagement of *both* qualitative (mainly top-down) and bottom-up (mainly quantitative) research approaches in order to maintain a *shared awareness* of the *apriori* assumptions that inform model development. Moreover, according to Holling, Gunderson & Ludwig (2002), “What are needed are alternative hypotheses and specific predictions that can be tested empirically” revealing the additional need for flexible modeling frameworks that can adapt to different hypotheses and a variety of scenarios.

This invokes the need for a flexible modelling methodology (as described in the previous chapter), where non-linearity, quantitative and qualitative information, and cross-scale interactions are accommodated. All elements of reasoning are required to hinge a complex problem to its context; both qualitative and quantitative. Arguments that focus on which approach is superior often deter from the purpose of research into complex problems; which is to acknowledge as far as is appropriate and relevant, the full complexity of the problem being faced. The focus of this dissertation is not an argument for attempting to exhaustively model a complex problem or system. Rather we propose an approach for employing both qualitative and quantitative processes of reasoning in conjunction with each other to arrive at a reliable and valid model and shared understanding of a social-ecological system. That is; it is valid in relation to the problem that is being addressed and researched, and it reflects the *extent* of shared understanding of the system.

It is inevitable that different, often conflicting views are held about how to approach such complex problems in research and decision support. This often results in ‘causal ambiguity’, as previously outlined, where different causal models can seem to exhibit the same behavior or phenomenon (Helsper & Van der Gaag, 2002). Different causal pathways of logic and reasoning can apply to the same situation, even at the disciplinary level, for example, in medical diagnoses of cancer (Helsper & van der Gaag, 2002). A critical element of research into complex systems involves acknowledging such differences and creating a shared understanding of why participants in research or decision-making programs may differ in opinion about; (1) which methodology to employ, (2) what is causing what in a system (including ‘causal ambiguity’ or ‘causal confounds’ (Meder et al., 2006)) and (3) what steps to

take to remedy the problem in adaptive governance and adaptive management programs.

A fact that often remains unacknowledged when more traditional bottom-up approaches towards modeling are employed is that they employ a degree of subjectivity. This subjectivity lies in the decisions (judgements) that are made in defining system structure and configuring system constraints, parameters and functions. Equally, more qualitative or interpretive top-down approaches often employ evidence gleaned from bottom-up research to make sense out of the problem and complex system. The apriori assumptions that are made in both quantitative and qualitative modeling efforts often go unrecorded and remain untraceable, especially where convergence between different views is 'forced' to some extent, by pragmatic decisions made earlier on in the research effort. This is especially the case where the tendency of researchers is to rigidly employ only readily available data and models as a basis for the research integration effort in conceptualizing how they can address the problem.

In general, models and modeling of complex, adaptive systems, including social-ecological systems, (Levin, 2006) are constrained by the underlying apriori assumptions that are made during model formulation and implementation. These apriori assumptions inform the different, often conflicting opinions or mental models that are held regarding the complexity of the system or problem. Exposing these differing apriori assumptions and creating a shared understanding of them is critical to transcending multi and inter-disciplinary approaches towards research. Moreover, it is a critical requirement if a transdisciplinary understanding of the system, context and problem are to emerge from a research effort that aims to support decision-making about social-ecological systems. To this end, the research methodology explored and tested in this dissertation (i.e. BPDA) aims to provide a framework for integration that aims to achieve several aims. Firstly, to harness both qualitative and quantitative approaches appropriately. Secondly, to help bridge the gap between these generally top-down and bottom-up approaches, and thirdly, to provide a framework to catalyze shared understanding in research efforts that support decision-making in social-ecological systems, and in other systems where appropriate.

Richardson observes that models and simulations of systems that are complex in nature should not be built from the bottom-up purely from pragmatic considerations regarding available tools and information (Richardson, 2002). Bottom-up approaches are more appropriate when a very good understanding of the system is available to researchers, and the linkages between subsystem components are well understood. The modeling approach developed in this dissertation provides a way to integrate participatory processes with interdisciplinary cases studies and models and simulations for social-ecological systems to be built and adapted iteratively. That is, in both a top-down and bottom-up manner.

4.3.2 Summary of Methodological and Analytical Objectives

To summarise; in this dissertation, we are testing if this approach helps produce verifiable, reproducible results for single case studies into social-ecological systems that illustrates the usefulness of the approach. However, we are also testing whether the approach can deal with a spread of case studies that characterise the range of challenges of research and decision-making in social-ecological systems. Then we interpret what generalizations can be made from cross-case comparison regarding the approach taken in this dissertation and present findings and conclusions.

In doing so, the approach must first satisfy the requirements of case study methodology research and design as described in detail the preceding sections to this section, and summarised in Table 19 (see later in section 8.1.3). Each social-ecological system case study's requirements, as determined from the outline in the previous sections, must be individually met by the approach proposed in this dissertation. This includes ensuring validity of the single case studies in addressing their individual objectives through the variety of mechanisms proposed in the previous sections for addressing construct, internal and external validity, and reliability (as outlined later in Table 19). A variety of mechanisms are brought to bear, and in combination, upon individual case studies through the BPDA modelling approach as proposed in this dissertation, and as outlined and detailed in the next chapter i.e. chapter 5.

However, that is not the end of analysis. The methodological framework proposed in this dissertation was applied in a number of case studies for the purpose of identifying whether the approach served the cause of modelling for decision support in social-ecological systems sustainability across a range of social-ecological systems research requirements. Over all the case studies conducted there are several key priority application areas in which the implementation of the approach was tested. These were specific requirements that must be satisfied in order to support the central aims of the approach of this dissertation i.e. to be able to use modelling for decision-support in sustainable development of social-ecological systems. The latter issues discussed in regard to cross-case analysis are important for the goals of this dissertation as a whole and as such will form a critical component of the discussion section of this dissertation. Listed in the next few sections (i.e. 4.3.2.1 to 4.3.2.8), are the application areas that were tested and evaluated in this dissertation i.e. to what extent can the methodology help as outlined in the next few sections:

4.3.2.1 **Integration Across Scales**

The prevalence of cross-scale and remote effects in social-ecological systems is a critical element of its complexity. To some degree, its openness as a system allows for externalities to become significant drivers of social-ecological system behaviour under certain conditions. Therefore, it is essential that cross-scale effects be explicitly conceptualised and empirically evaluated where possible in a methodology or formalism that seeks to model social-ecological system interactions as it is critical for an understanding of system resilience and vulnerability (Holling, Gunderson & Peterson, 2002, pp. 75; Peterson, Allen & Holling, 1998).

4.3.2.2 **Integration Across Disciplines and Sectors**

The major global ‘problematiques’ (Max-Neef, 2005) affecting humanity today (e.g. poverty, forced migration, water, climate change) are of a highly integrated nature, and require integration between disciplines. Many of these

problematiques are also directly or indirectly concerned with social-ecological system sustainability. The fragmented response to complex problems of such a highly integrated nature is deemed to be due to a deeper fragmentation that lies between traditional disciplines and sectors. In particular, this fragmentation is due to their respective ways of understanding these problems, and the translation of these differences into the worldviews of stakeholders, users and decision-makers in a multi-institutional governance system (Folke et al., 2002; Folke et al., 2005; Holling et al., 2002, pp. 19, Stern, 2000; Van Kerkhoff & Lebel, 2006).

In response, participatory processes have emerged at all levels of research and decision-making in attempts to set up adaptive management programmes for social-ecological systems sustainability. Participatory process facilitation requires close attention when dealing with inter-disciplinary and transdisciplinary case studies. In this respect, we view shared understanding as the first step towards more cooperative governance.

4.3.2.3 **Facilitating Transdisciplinarity Research**

The value of transdisciplinarity (Max-Neef, 2005) is increasingly being appreciated in areas where the types of problems being dealt with demand a more integrated response. This response must consider a diversity of views and manages to transcend disciplinary boundaries in solving the problem. There is no recipe for transdisciplinarity, although Max-Neef (2005) does put forward a framework which can be used to enable transdisciplinarity (Figure 2). The requirement for transdisciplinarity, from a modelling perspective, requires an open systems approach to be followed. Any transdisciplinarity that occurs will emerge from an unbiased consideration of the various systems that come to bear on a social-ecological systems problem. As such, maintaining and accommodating conflicting views, and preventing the dominance of a single disciplinary framework from subsuming the research effort is a paramount requirement of any methodology that hopes to deal with social-ecological systems from a transdisciplinary perspective.

4.3.2.4 **Developing New Indices**

Where there are gaps in understanding, it is sometimes possible to establish a conceptual framework to assess a measurable index or set of indices that is tailored to suit a specific context. Any rigorous *analytical* transdisciplinary research framework will be required to gear itself around adaptively improving understanding of system indices. Indeed, this constitutes a critical requirement for identifying and monitoring emergent system level behaviours. It would also be of use in developing monitoring and evaluation programmes, and can help guide research effort allocation, and an iterative migration towards a better understanding of system behaviours. In complex systems, where the basket of measures required to understand the particular behaviour or phenomenon may change, models are required to be adaptive enough to include and reflect these changes in a trace-able manner.

4.3.2.5 **Incorporating Non-Linear Effects**

Non-linearity is a critical feature of complex systems (Richardson, 2002), and usually involves non-linear interdependencies including positive and negative feedback and feed-forward relationships. Non-linear relationships usually lead to faster rates of change or sometimes abrupt changes (such as step functions, or abrupt changes in system state) between the variables that are non-linearly related. Non-linearity has implications for how the critical limits and thresholds of a system will evolve under different scenarios, and as such; is a critical and requisite feature for the modelling of complex, adaptive social-ecological systems. As a rule, when dealing with complex systems, statistical linearization should be employed only when it is clearly understood what complexity is lost in the linearization, and what assumptions have been made in the linearization of certain functions. Statistical distributions usually contain non-linearity's in the line wings of the distribution, that is, non-linear effects are usually lower probability events, and under 'normal' conditions do not dominate the statistical distribution. However, under different driver scenarios the non-linear effects can come to dominate the distribution and produce unexpected behaviours such as runaway feedback effects.

4.3.2.6 **Resilience & Adaptive Capacity: Critical Limits & Thresholds**

Understanding the linear and non-linear thresholds and critical limits of a system leads to a better characterisation of the resilience of a system under different conditions. Changes of state in a system result from non-linear variation in the dynamics of variables in the system. However, for open social-ecological systems a change of state can often result from a purely anthropocentric perspective on the system, and the 'state' of a system is purely defined with respect to the research question being posed. As such, understanding how indicators of changes in the system state occur and evolve usually consists of observing how thresholds and critical limits of the defined set of system variables, which taken together, loosely describes the system state.

A better understanding of what the observational and interventional variables are in a system, and which critical linkages can be measured or intervened upon, constitutes a key requirement for understanding the adaptive capacity of a social-ecological system. Moreover, understanding the human elements behind agency and self-organisation (e.g. community, institutional) also plays a critical role in characterising the resilience and adaptive capacity of a social-ecological system.

4.3.2.7 **Decision Support for Adaptive Management**

Adaptive management is mainly concerned with understanding and improving the adaptive capacity of systems to cope with unpredictable and emergent challenges. As such, adaptive management requires a broad, yet critical understanding of system interdependencies, thresholds and critical limits and its vulnerability to remote effects and externalities. Moreover, adaptive management requires a flexible and adaptive supporting framework of research, models and methodologies that can all be employed, where relevant, to a particular emergent problem that is facing decision-makers at a particular moment in time, and that they may face in the future. Involving decision-makers in research, and vice-versa, requires that a shared understanding is

obtained of the system in question that reflects the views, opinions and evidence of all participants appropriately (i.e. as jointly agreed) in the research programme. .

4.3.2.8 **Supporting the Future Integration of Manual and Automatic Engineering**

In traditional modelling, human intellect and experience was used to identify patterns of behaviour from data and used to construct models (manual engineering of emergence), whereas non-traditional techniques can be used to ‘learn’ model structure from raw data. Bayesian networks can also be used to automatically learn both model structure and classifications from data (automatic engineering of emergence), and to verify the causalities that underlie hypotheses and models of systems. In complex systems, spurious correlations can sometimes be established from correlative techniques, and even learnt structure needs to be validated by some kind of causal model that explains and describes what the logical basis is for the relationship. As such, both manual and automatic processes of engineering must necessarily be brought together if a system is to be understood in near real-time. How this may be achieved is discussed later in this document in section 9.3.3, which presents a conceptual framework showing how manual and automatic engineering of emergence can be integrated.

University Of Cape Town

5. **Modelling Methodology: Hyperstructures for Case Study Research on Social-Ecological Systems**

So how can such an integrative framework for modeling complex social-ecological problems be appropriately conceived, explored and developed? In this chapter we will detail the modelling methodology that is proposed in this dissertation, and show how it is designed to cater for the critical elements of case study research strategies as outlined in the previous chapter.

The aim of this section is to provide a detailed description of the approach, and to highlight precisely where, in the phases of the modeling approach, the various requirements are met, and present a rationale for these claims (in sections 5.1 and 5.2). Later, in the case study section will show how the various requirements were met in practice, through individual case studies and cross-case analysis.

5.1 Overview: Methodological Framework for Reasoning using Graphical Causal Models & Bayesian Networks

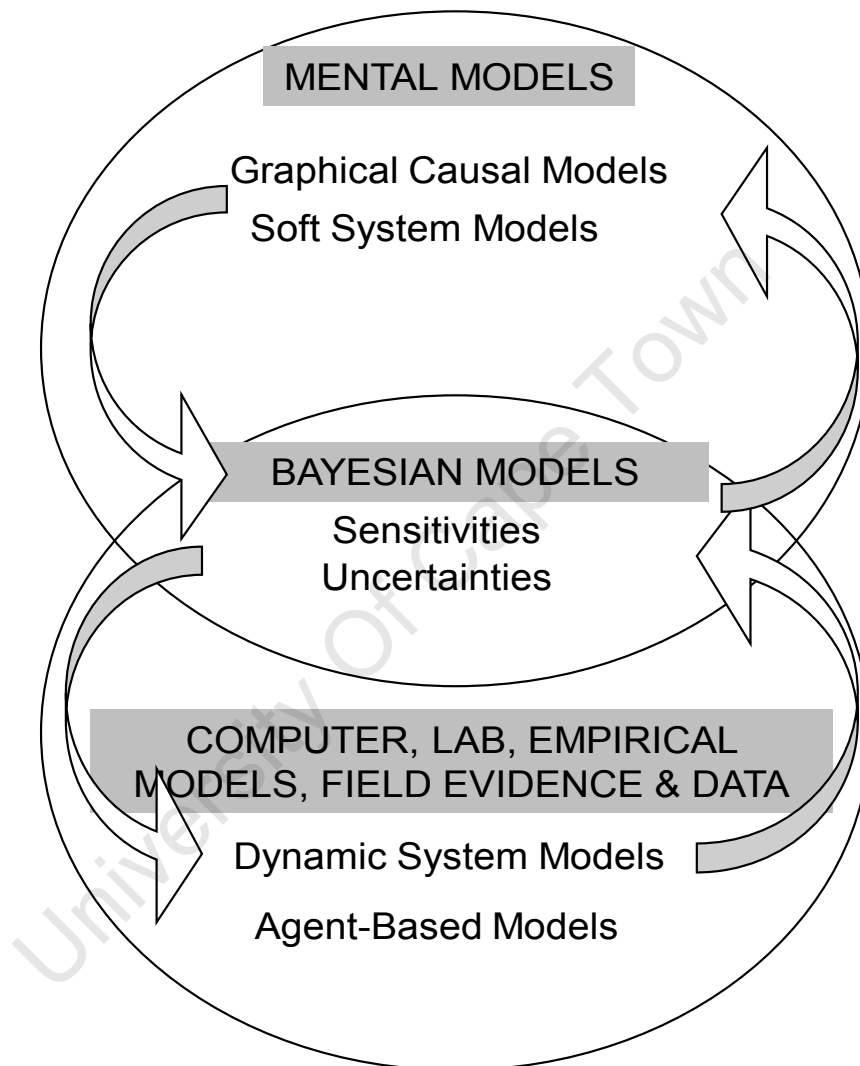


Figure 8: The BPDA Approach: Simple illustration of proposed modelling methodology for complex social-ecological systems.

The simplest illustration of the methodological process proposed in this dissertation is shown in Figure 8, which shows a conceptual model of how the processes involving top-down mental modeling of a complex problem is linked to bottom-up research involving laboratory research, computer models, empirical and theoretical models, and samples of field evidence and data. These two areas are

characterized by the need for methodologies that stem from a generalized complexity, and restricted complexity perspective, respectively, as shown in Figure 7. It is a three stage process that consists of the following phases, which are sequential at the outset of research, but which gradually become more overlapped during the course of the research effort:

1. Phase One: Interdisciplinary participatory processes were facilitated using open-systems approaches (e.g. concept mapping, scenario planning (Peterson et al., 2003) and in those listed in chapter 8 (Yin, 1984, pp. 100), discussion, debate, scrutiny), to characterize the research problem in terms of its critical concepts and hypotheses. As a facilitative tool, the mental models of participants are captured in soft systems models and graphical causal models to establish the causal relationships that underlie key hypotheses that are made by individual participants or the group itself.
2. Phase Two: In phase two chains of evidence are formalized into probabilistic relationships. The outputs of the soft, open systems approach are then used to formulate and used to formulate and populate Bayesian models with evidence. These are combined with graphical causal maps in a software interface, which are then used as an integrating framework to interrogate and model bottom-up sub-system integration of embedded units within each case study.
3. Phase Three: By conducting more focused quantitative modeling and research on the critical gaps in understanding of the overall system, embedded systems and the relationships between them, the outputs can then be used to re-constrain the Bayesian models and mental models through managing feedback of information and learning to phase two and phase one. In this way, an iterative process of learning is enabled. This process of learning can be referred to as a “multiple learning loop framework” (De Wit, 2001). De Wit identifies multiple learning loop frameworks as the overarching essential requirement for enabling sustainability in economic decision-making.

Research that has been conducted in this dissertation has involved establishing and testing the process in Figure 8, and the extent to which it enables and ensures the

validity and reliability of case studies and cross-case comparison into social-ecological systems; in the following two general ways:

- Interdisciplinary systems development and collaboration for case study research of social-ecological systems:
 - Establish a software enabled process of workshop collaboration for hypotheses development and interdisciplinary systems definition, enabled by graphical causal models, which supports the formulation and development of probabilistic Bayesian models.
- Modelling and simulation for complex adaptive social-ecological systems:
 - Satisfying requirements for a complexity based modelling approach for social-ecological systems.
 - Elucidating causal mechanisms for adaptive capacity and increased resilience of social-ecological systems.

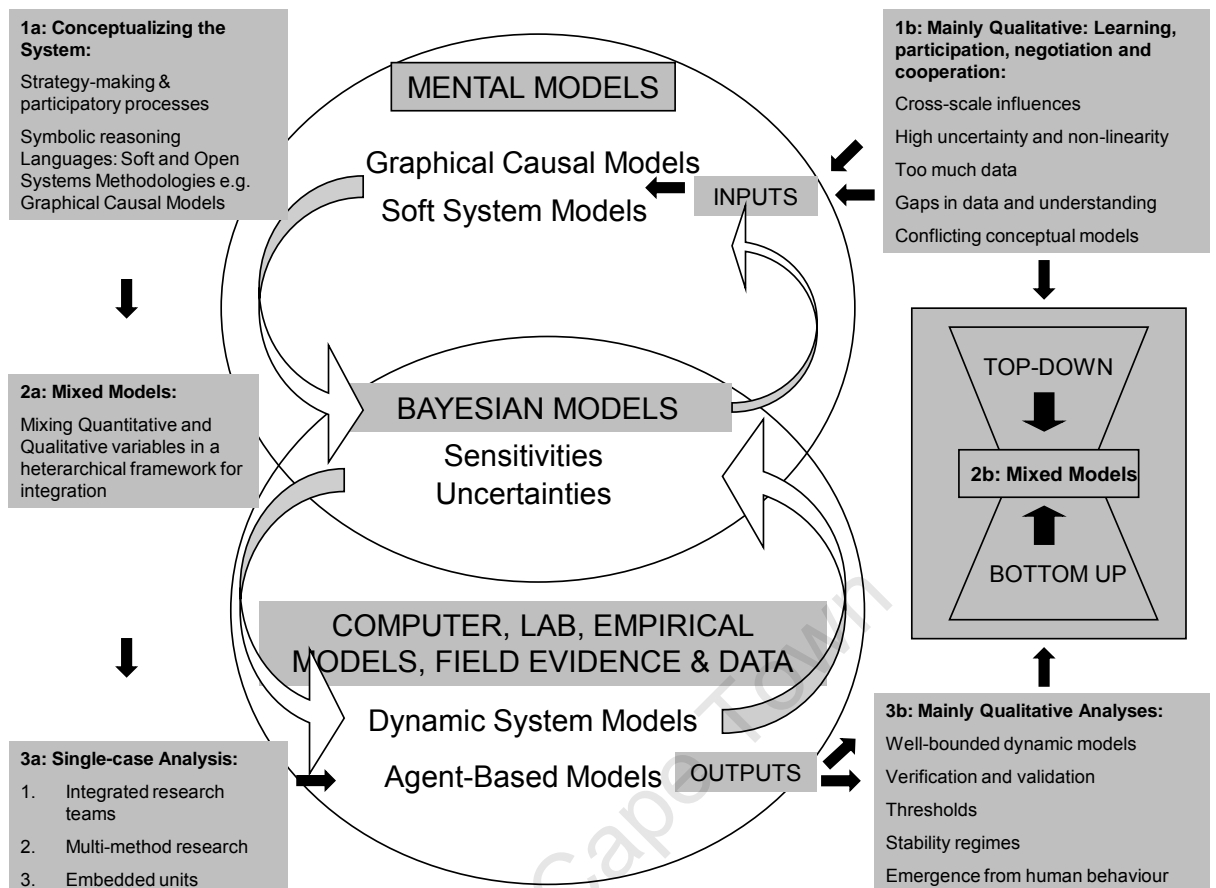


Figure 9: BPDA Illustrated: Detailed description of integrative modelling approach proposed in this dissertation

The methodology proposed in this dissertation outlines a process for model integration, as illustrated in Figure 9. The methodology employs the use of graphical causal models and Bayesian networks as hyperstructures for integration between top-down and bottom-up directions of system inquiry (see Figure 9: 2a & 2b). The methodology (in this dissertation) proposes and tests the idea that Bayesian hyperstructures can help as translators of the gap between mental modeling and software/research based modeling.

The methodological process outlined in Figure 7 & Figure 9 can be described in 3 broad phases (as outlined earlier), which interact with each other iteratively as new understanding emerges from the research-based participatory processes and the engagement of participants. These three broad processes are outlined below in the next three sections (i.e. 5.1.1, 5.1.2 & 5.1.3).

5.1.1 Facilitating Interdisciplinary Problem Formulation, Review & Validation of Case Study Inputs, Outputs, Conclusions & Recommendations

5.1.1.1 Initial Phase: Problem Formulation and Research Design:

In this phase of the research approach, interdisciplinary workshops are facilitated using open systems approaches, in order to establish a widely reflective view on the critical issues that the individual case study should be concerned with. In keeping with the spirit of an 'open systems approach' the boundaries of the study are not set in place upfront, at the outset of the study, by imposing any general or specific theoretical framework upon the study. Rather, participant researchers from different disciplines are given the choice of how they would like to proceed to describe the system and the problem set they are concerned with, and how they are related. Often, elements of other approaches are used. This includes scenario planning (Peterson et al., 2003) which involves envisaging multiple possible futures. It also involves case study conceptualization techniques (see section 8.2.1)). Case study research, in turn involves classifying and grouping factors, system components (or embedded units) and identifying the critical relationships that underlie key hypotheses regarding the system phenomena or behavior under investigation.

Sometimes, broad integrative conceptual frameworks are used for framing the key issues of the study. These frameworks, such as Total Economic Value (TEV: see later section 9.2.2 for more detail) are used only where they appropriately fit the context and purposes of the study. The frameworks help initiate classification, grouping, clustering and ordering of information and evidence. Skilled facilitation techniques are required for managing such interdisciplinary processes. This necessitates the ability to allow the process to emerge from the interactions amongst the various individuals. This helps establish trust between participants and promotes consensus and buy-in to the process of problem formulation and system definition itself. This early phase of problem formulation and research design process focuses

on establishing a shared understanding of what the study's questions and propositions are, and start exploring the units of analysis that will be necessary to address the "questions" and test the "propositions" of the study (see section 8.1.2: Yin 1984, pp. 29).

In the next phase of problem formulation and research design a better understanding of the "units of analysis", "the logic linking data to its propositions" and the "criteria for interpreting the findings" are rigorously established (see section 8.1.2: Yin 1984, pp. 29). Knowledge and shared understanding is captured using symbolic reasoning languages such as soft and open systems methodologies (e.g. graphical causal models and dynamic systems models to explain hypotheses or opinions about causality in the social-ecological system). The methodologies are used to facilitate a basic understanding, from which a 'straw dog' graphical causal model of the system can be composed; one which although likely oversimplified, stimulates interdisciplinary scrutiny of the model, and helps initiate the process of modeling using graphical causal mapping. In this phase, the key hypotheses are expressed through making graphical causal maps of the chains of variables (and their causal interactions) that underlie the hypotheses (explanatory), or to reflect the extent of knowledge of system (descriptive).

In this phase, the embedded units are detailed in relation to the objectives of research detailed at the whole system level and scale as more and more causal influences are articulated during model formulation. The units of analysis at whole system scale are related to the scale that is required of the embedded units as model formulation unfolds iteratively. For each causal chain in the model, suitable evidence of the causal relationship must be provided in the participatory workshops, and recorded in the software-based graphical user interface that is used to formulate the graphical causal maps. The software graphical user interface allows for versioning such that older iterations can be reviewed by the multi-participant group, and re-scrutinized to improve learning. A library of evidence for each causal chain in the model is thus established. Where there are overlapping or non-overlapping (rival) explanations these are recorded, the evidence is presented and the research team decides whether a rival hypothesis is strong enough to warrant further research and

investigation. Examples of this will be given in the section on formulating graphical causal models (see section 5.2.1), and in the section on case studies (see chapter 6).

Already, in this initial phase of research design, it becomes critical to envisage the multiple system futures that the social-ecological system is faced with, that the main research questions relate to. Establishing the context of inquiry, the boundaries of the study, and a preliminary understanding of the critical linkages to be studied requires many iterations. Anywhere from one to three workshops may be necessary to obtain consensus in this phase of case study research and an interdisciplinary team or reference group is set up to support the study. This phase involves mainly qualitative analyses of the system, and considering multiple system futures and influential and sometimes unpredictable externalities. The key issues that are constantly reflected upon in this phase involve staying focussed on identifying:

- Core hypotheses and underlying causal chains of evidence.
- Relevant cross-scale influences (Gunderson & Holling, 2002).
- Variables that are linked with high uncertainty and non-linearity to other variables.
- Gaps in data and understanding.
- Conflicting conceptual models and data sets.
- Recording multiple sets of interface in graphical causal modelling software graphical user interface.

In this phase, participants become intimate with the whole system, including data sources, inputs, outputs, causal logic, hypotheses etc. The foundations for pattern matching exercises to be conducted in later phases of the study are set up in this phase, where explanatory causal chains of evidence are articulated and tested by the interdisciplinary team and embedded units are identified for further investigation.

5.1.1.2 **Feedback Phase: Review of Case Study Outputs, Conclusions and Recommendations**

The interdisciplinary team or reference group that is set up to support the study also serves a role as an interdisciplinary review mechanism. They review the outputs conducted from more model and data-oriented research processes conducted in the 'restricted complexity' phase of research on the approach (see Figure 7). The interdisciplinary team formulates the research design and reviews results from implementation of the design in areas that have been determined to be critical to furthering understanding. This usually involves paying closer attention to the dynamics of various embedded units and their critical interdependencies. Here, explanation building is conducted using graphical causal maps, where overlapping or non-overlapping rival explanations are identified. These are verified through iterations of research by the broader research groups as the latter phases of the approach unfold. The evaluation requirements for pattern-matching (see 10.2.2) are implemented in this phase of the approach. It also in this phase that the results of Bayesian model runs (that correspond to different scenarios), and each causal chain underlying the results, is evaluated by the interdisciplinary review team.

ADAPTIVE MANAGEMENT DECISION SUPPORT PROCESS

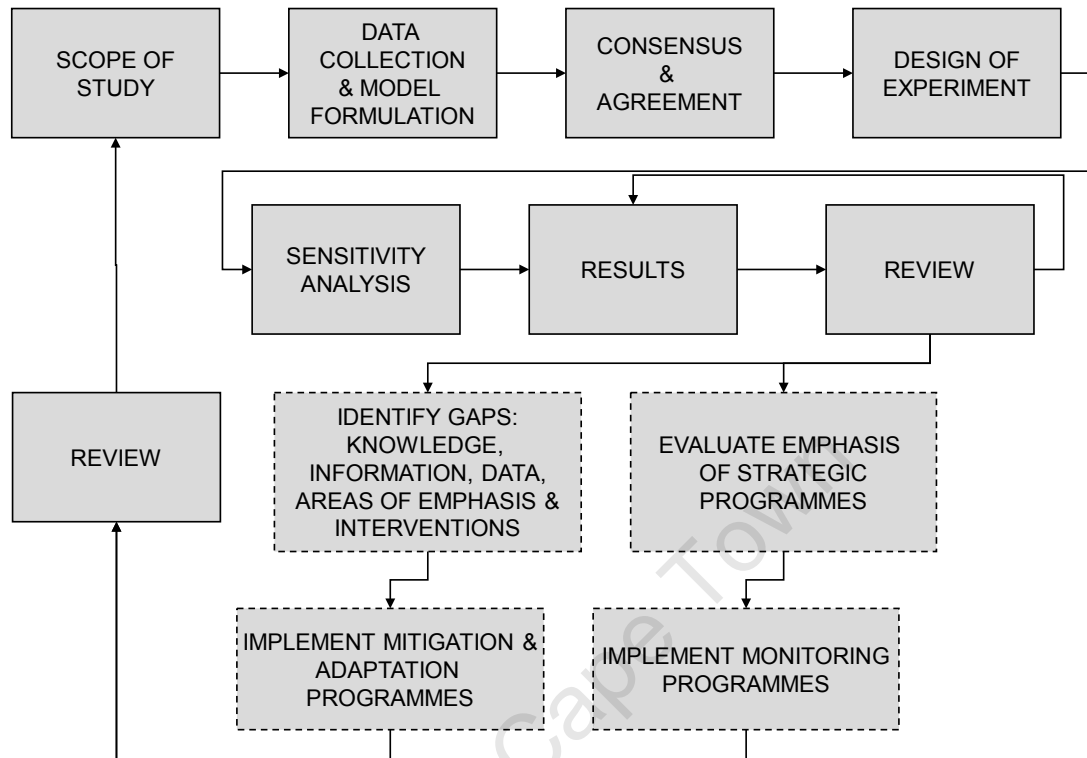


Figure 10: Decision-Support Process: Illustration of how methodology is employed in support of an adaptive management programme, in this case, the Western Cape Climate Change Strategy and Action Plan.

The interdisciplinary team also plays a key role in formulating and reviewing the overall results of the study, and any possible recommendations that are made as a result of the findings of the study. In decision-maker consultation, the symbolic reasoning languages can also be used to facilitate the processes of verifying the shared knowledge and understanding that underlies learning, participation, negotiation and cooperation (Van Kerkhoff & Lebel, 2006). We can also use symbolic reasoning languages to facilitate research processes that engage with the “political processes of decision-making and change” that are required for action-based research into social-ecological systems (Van Kerkhoff & Lebel, 2006). The review group plays a key role in interactions with the decision-maker. Mutual reviews and workshops between the review group and the decision-makers builds understanding and confidence in that the outcomes of the study as they are tested in both arenas. Any “analytical generalization” that results from the study should therefore be tested through both

empirical means and qualitative (interpretive) means of inquiry across disciplines and methodologies. That is the perspective taken in this dissertation.

Supporting adaptive management with modelling requires that process is in place for managing the various stages of participation and research, as illustrated in Figure 9, and requires that process is in place for managing the various stages of participation and research, (see Figure 10).

The illustrated process was implemented in support of the Western Cape Climate Change Strategy and Action Plan (CCSAPWC, 2007). This was a case study in which the BPDA methodology was applied (see section 6.5 for more details). It involved conducting an integrated review of a variety of provincial strategies in order to assess decision-making challenges. It also involved conducting scenario based strategy development with decision-makers regarding options for implementation, and adaptation.

5.1.2 Formulating Hyperstructures: Bayesian Models & Graphical Causal Models

This phase of research involves using the graphical causal models derived in the previous phase to populate Bayesian networks, which match the same causal structure. The chains of evidence established and recorded in the software interface are researched and the results are used to populate the Bayesian networks with probabilities and constraints obtained from the restricted complexity based phase. This phase involves using multiple research methodologies to investigate and scrutinise embedded research units and key system intra- and inter-relationships more closely in the third phase of the approach. At the same time, qualitative judgements that are made concerning the fundamental assumptions about key relationships and variables that are made in the study play a large role in arriving at a more complete understanding of the social-ecological system in its current context.

We argue that when graphical causal models and Bayesian networks are brought together, as they have been in the software interface, they become

'hyperstructures' themselves. The iterative, adaptive ability of the hyperstructures provide two avenues of adaptation. Firstly, through information and evidence obtained from emerging from qualitative analysis of causalities identified by the interdisciplinary group in the study. Secondly from evidence obtained from more quantitative analysis of embedded units and their inter-relationships. These are used to help formulate the system constituents and interdependencies in relation to a particular problem. The quantitative foundation for explanation building and pattern-matching as outlined in Yin (1984) is set up in this phase of the approach, when Bayesian networks are populated with probabilities and the model is run in different scenarios and each causal chain is evaluated in the context of a scenario. Causal chronologies are verified through empirical and modeling-based evidence and from qualitative assessment by an interdisciplinary research group or review team.

The overarching and extensive role of the hyperstructure serving a dual role as an interface for social-ecological systems complexity modelling, and for an interface between arenas of generalised and restricted complexity, involves:

- a. Managing mixed models: Mixing quantitative and qualitatively deduced information resulting from multiple research methods in a heterarchical framework for integration.
- b. Managing between the top-down and bottom-up interfaces of research using Bayesian networks as a framework for model integration, with a particular emphasis on resilience & adaptive capacity, through helping with:
 - i. Understanding monitoring and intervention points for adaptive governance and management.
 - ii. Understanding thresholds, stability regimes and transitions between system states.
 - iii. Understanding and adapting to emergence and reflexivity of systems.
 - iv. Overcoming partial perspectives, fragmentation, 'causal ambiguity' and undecideability.

In summary, we contend that graphical causal maps provide a heterarchical causality-based framework for interdisciplinary interaction. The hyperstructures enable a simple and human-intuitive framework for reasoning about drivers, responses, influences, interdependencies, constraints, thresholds and limits of the system in question. The heterarchical approach provides a framework in which categories always overlap, even if causal models do not. The heterarchy of graphical causal maps and Bayesian networks enable a framework of overlapping categories that are not strictly structured in a bottom-up or top-down fashion.

We propose and test whether the causality-based articulation of system interdependencies serves as an effective mechanism for facilitating constructive dialogue and debate around social-ecological system futures. A causality-based articulation also allows for causal relationships and categories to co-evolve (Meder et al., 2005); a feature that is in concert with the concept of heterarchy.

Moreover, as previously outlined, Bayesian networks also offer the benefit of integrating both observational and interventional learning in a single framework. As such, they can be used to differentiate between what is observable (can be monitored) and what can be intervened upon (influenced).

5.1.3 Detailed Embedded Unit & System Analysis

In this phase of research computer, laboratory, empirical models, and case study field surveys and evidence and data are brought to bear on investigating the often complex relationships within and between embedded units, and externalities such as climate change (e.g. temperature and rainfall variations) and global change effects (e.g. demand changes, growth). These methodologies can be employed because the case study is well bounded and directed, due to the activities conducted in the previous two phases of the approach.

While this phase of research involves pursuing well-bounded problems, embedded units themselves can have complex underlying relationships and complexity occurs at all scales and levels of description in social-ecological systems.

The more complex the question; the more insight is required into the degree of self-organization that is required to understand the system, especially where social-ecological systems are concerned. The key elements of complexity, such as self-organisation and non-linearity, can occur at various scales and levels of description that is applied to a complex, social-ecological system. The techniques for dealing with them are well understood at the disciplinary level, as most embedded units usually reflect sub-system components that fall recognizably within disciplinary boundaries. For example there are complexities in economics that are articulated through economic theory, as there are complexities in engineering and ecology articulated through the language of their disciplines. They themselves often require the individual effort of whole research teams to solve in themselves and are characterized by the following features:

1. Case analysis conducted from:
 - a. Integrated research teams,
 - b. Multi-method research, and
 - c. Embedded units, and

2. Evidence is gathered from bottom-up quantitative and empirical analysis using:
 - a. Well-bounded dynamic models
 - b. Observation and measurement
 - c. Time series analysis
 - d. Surveys and case study investigation
 - e. Thresholds and stability regimes

Time series analysis is usually conducted in this phase of research, and can include observation (monitoring, measuring), the use of models and simulations, or facilitated participatory processes where the system 'history' is uncovered (in particular, rural participatory processes: Cundill, 2008, pp. 548-549). Some time series data is used to perform validation on model integration through forecasting or hind-casting methods. Time series data also helps identify and validate chronology, even though the actual causal linkages underlying the chronology may not always be apparent in correlation analyses. In addition, existing surveys may be used or new

ones conducted in this phase of research, which involves more detailed investigation and research into the key interdependencies, embedded units and variables that are thought to underlie system level research questions.

Detailed system analyses or studies of any kind, both qualitative and quantitative, can be used in this phase of research, including detailed, high resolution dynamic systems (and other) models of embedded units. Models of embedded units can also be complex and adaptive, but their boundaries are understood more clearly. Therefore, the study of them are regarded to lie within the realm of “restricted complexity” based approaches for the purposes of this dissertation, where the complexity of embedded units can sometimes rival that of the whole system itself. Often, the proverbial ‘devil in the detail’ is a complexity hidden or latent within an embedded unit until the conditions for its emergence arises. Even well-bounded, well understood systems can display complex, unpredictable behavior and these can reasonably be regarded to lie within the realm of “restricted complexity”.

5.2 **Formulating Hyperstructures: Graphical Causal Models & Bayesian Networks**

As already discussed Bayesian networks and graphical causal models allow for both *quantitative* and *qualitative* variables to be inter-related in a causal framework. In this dissertation they are used to integrate results from case study research, and more detailed dynamic sub-systems models. These are mainly used to understand bottom-up system dynamics. From a purely numerical perspective a larger number of variables (both quantitative and qualitative) can be included in our hyperstructures. From systems perspective, a greater variety of causal sub-system interdependencies is captured using a graphical causal mapping framework especially because different types of causal interdependencies are accommodated.

5.2.1 Formulating Graphical Causal Models

In the conceptual systems development phase system definition is conceived (mentally modelled), verified and tested with the Bayesian network and knowledge engineering language derived for this purpose. In this phase only a mixture of quantitative and qualitative information is available. This is conducted during the early phases of research in order to obtain joint consensus on the interdisciplinary model being used in the conceptual system development phase. In the conceptual system development phase of the research process the key consideration of the approach is to **investigate alternative causal structures** representing the various influence linkages.

The implementation of causal structure of variables and conditionally dependent and independent relationships is tested by a Bayesian Network (BN) modelling exercise, depending on the complexity of the modelling effort and the degree to which sensitivities within the system are understood. Dealing with multiple influence linkages is emphasised as it enables system scientists and decision-makers to consider multiple scenarios and futures. Building chains of evidence is the key objective. Sources of evidence are recorded in the software-based graphical user interface and are later used to populate Bayesian networks with probabilities.

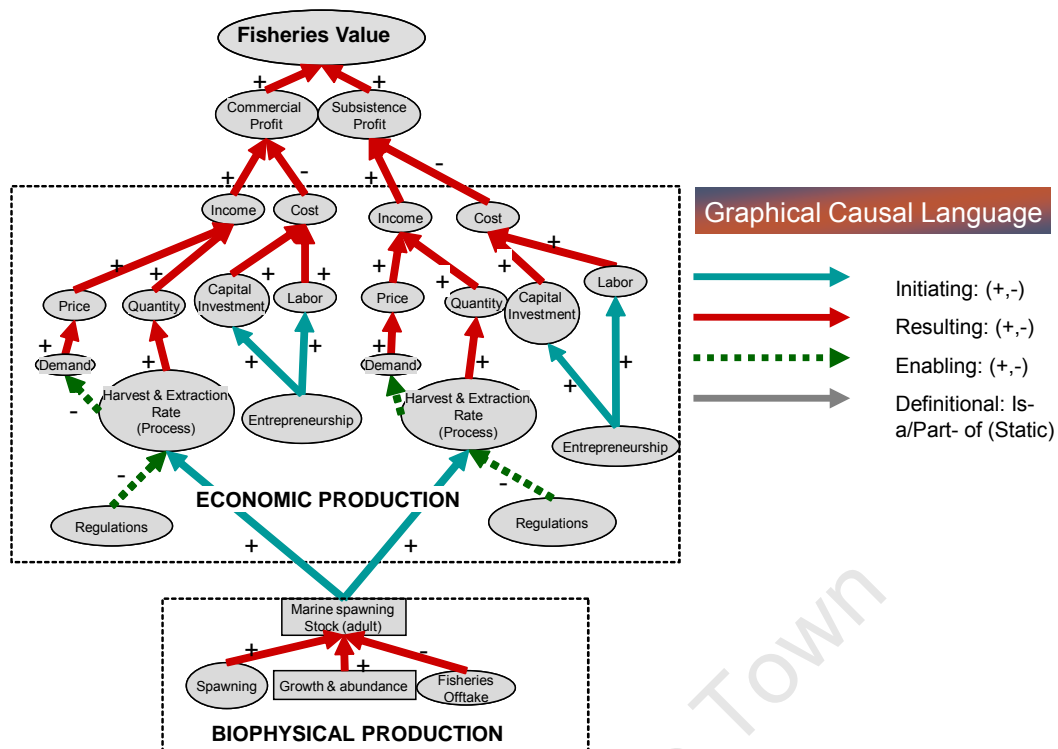


Figure 11: Example of Graphical Causal Model: Prawn Fisheries Production in Maputo Bay

An illustration of an economic model of prawn fisheries in Maputo Bay derived using the knowledge engineering language is shown in Figure 11 (this model was derived in interdisciplinary workshops as part of a larger coupled catchment-coastal ecosystem; see Figure 15). The approach uses elements of knowledge engineering languages developed from different perspectives (Helsper & Van der Haag, 2002; Nadkarni & Shenoy, 2004). They are drawn as visual arcs preceding the construction of Bayesian networks and enables easier conceptualisation of cause and effect influence relationships through a variety of relationships. This way of defining the influence linkages between drivers and responses is more intuitive and readily understandable than most ‘cause and effect’ (Helsper and Van der Haag, 2002) type descriptions which are too general and don’t capture the nature of the influence relationship adequately. These are defined as influences of the type:

- Initiating arc: a dynamic cause which initiates an effect.
- Resulting arc: a dynamic cause which results in an effect.
- Enabling arc: a dynamic cause which enables an effect.
- Definitional arc: a static cause which defines an effect.

- Initiating and Enabling arc: a cause which initiates an effect and also enables it by maintaining the relationship.
- User-Defined: This provides flexibility for evolution of the knowledge engineering language.

The user may further define these influences having a positive or negative effect (Nadkarni & Shenoy, 2004):

- A positive (+) symbol next to a linkage indicates that a *positive* influence occurs where an increase in the influencing variable increases the influenced variable. Positive feedback may be represented in this way.
- A negative (-) symbol next to a linkage indicates that a *negative* influence occurs where an increase in the influencing variable decreases the influenced variable. Negative feedback may be represented in this way.
 - For example, a negative enabling arc is a disabling arc: a dynamic cause which disables an effect.

These relationships can therefore be used to represent the effect of positive and feedback using feed-forward relationships in a causal influence structure, from one instance in time to the next i.e chronologically. Characterising these relationships with probabilities can be conducted using data or expert judgement, as shown in the next section. All arcs are influence relationships, bound by cause and effect. If an arc exists between two variables then those variables are said to be conditionally dependent and vice versa. An arc thus represents a conditionally dependent linkage between two variables, which can be tested within a greater framework of linkages and variables. The nodes are either objects or processes which may be assigned subclasses of attributes. These attributes are valuable for interpretation into probabilistic states for Bayesian networks.

5.2.2 Formulating & Populating Bayesian Networks

To summarise the qualities of Bayesian networks as discussed in this dissertation, Bayesian networks contain a variety of Bayesian nodes (or variables) that are inter-related through conditional causal relationships. A parent node influences a child node, which in turn may become a parent node for another child node. Characterising and constraining Bayesian networks for the purpose of modelling can be achieved using a variety of information sources. The Bayesian propagation algorithm ensures that each probability distribution can be added, subtracted, multiplied, etc. Parent and child nodes can therefore be related through equations (drawn from detailed sub-models or empirical evidence), or conditional probability tables (drawn from expert opinion). Both qualitative and quantitative information can therefore be incorporated into the nodes (or variables) of a Bayesian model.

In the case studies conducted in this dissertation, characterising a Bayesian network with probabilities most often involved establishing a baseline state of the system that matches the current state of the system, or averaged over some time period such as a year, with the current or closest year used as the baseline. The marginal distributions (i.e. parent nodes without parent nodes), in particular, usually reflect measured evidence about the current state of the variables, and with all resultant distributions peaking at the current value (as estimated from reliable, recent data or evidence of the variable). When these distributions match observed evidence and data, their reliability is verified. This necessitates a degree of sensitivity analyses during the process of constructing conditional causal linkages between variables.

As far as social-ecological systems are concerned, we are more concerned with the current context of the system than its history. If the underlying dynamics of the current system matches that of a previous period in history, then its standard deviation may offer some relevant information (i.e. to the current decision-making context). However, we are often concerned with problems where the historical dynamics behaviour of the system does not match current trends. In these cases, historical standard deviations and other estimates of uncertainty and correlation often do not adequately provide a predictive understanding of the system. For example, we may be concerned with the area of maize under cultivation and may draw on several

recent surveys to estimate the current value. The uncertainty, in this case, is with respect to the accuracy of our knowledge of the area currently under maize, and no precise predictions can be obtained from historical data in this respect. Decision-making and circumstance are responsible for the area of maize under cultivation, and not history.

Generally speaking, two types of evidence can be used i.e. quantitative and qualitative.

Quantitative information about probabilities and equations that link variables in a Bayesian network can be drawn from empirical and modelled evidence that help characterise the probability distributions of Bayesian nodes. Academic publications, census data, expert consultation, case studies, and a variety of other sources can be used to help characterise the probability distributions of Bayesian networks with quantitative information regarding marginal probabilities and equations (e.g. non-linear, exponential, linear and other) that describe the causal relationships between parent and child nodes, especially their thresholds and critical limits.

Qualitative information regarding the relationship between nodes can be characterised using conditional probability tables (CPTs). CPTs allow an expert or a group of experts to prescribe what function (linear, non-linear, exponential, etc) the relationships between two or more variables. There are no known limits (to the knowledge of this author) to the types of algebraic functions that can be related using either CPTs or equations in a Bayesian modelling framework. By way of illustration, Figure 12 and Figure 13 show how non-linear functions can be composed in a CPT using a complex equation to prescribe the non-linearity of the relationship. In both the aforementioned figures, the x-axis describes what percentage of the total area of a chosen location falls under protected area and light use area, respectively. The y-axis in each figure describes the biodiversity intactness index measure that correlates to the area under protected and light use respectively. As protected area increases, the biodiversity intactness index increases. As light use area increases, the biodiversity intactness index decreases, but at a lower rate than if the area was degraded, for example. The CPTs can also be populated in the same way without using equations, but rather facilitating experts to hypothesise the shape of the curve from considering

the matrix describing the CPT in a step-by-step fashion. Where-ever expert opinion is used to characterise a Bayesian network, that part of the network is treated as groups of hypotheses that need to be tested against empirical data. The sensitivity of the non-linear inter-relationships in particular, must be established through verification against empirically bounded, well-defined models of the system or embedded units, or against empirical measurements.

The conditional probability tables of the variables that constitute the models formulated in this dissertation are very long in size, due to the large number of states that were attributed to parent variables and the child variable itself. Two illustrative examples of conditional probability tables in the water module of the Mbombela model are shown in Appendix D, from Figure 96 to Figure 109. These probability tables were included to give the reader an idea of what they are constituted of. Due to their large size, it was not possible to include every probability table of every case study conducted in this dissertation. And neither is that the intention where verification is concerned. To remind the reader, we are more concerned with the sensitivities of output variables to input variables, that is, in specific scenarios. In this way, every scenario is verified using the sensitivities of output variables, over a range of input variable values. This is a more reliable way of ensuring that what results from the propagation of CPT values through the network is valid for the specific scenario in which it is being used. Sensitivity analyses can be conducted at every node in a causal pathway, allowing for thorough and complete sensitivity analysis. Most of the CPTs are governed by equations relating their input variables. As such, they are governed by the Bayesian rule, and we can trust that the CPTs are correctly constituted. It is only marginal variables for which the CPTs must be correct, but this is easily verified using the figures given in the appendices of this dissertation because all marginal probabilities are exactly the same as they appear in the CPTs. That is, the marginal probability distributions are exactly the same as their CPTs. CPTs only become complicated when they have input nodes. In this sense, the reader does not need to view the CPTs where marginal input probabilities are concerned, the probability distributions are sufficient as provided.

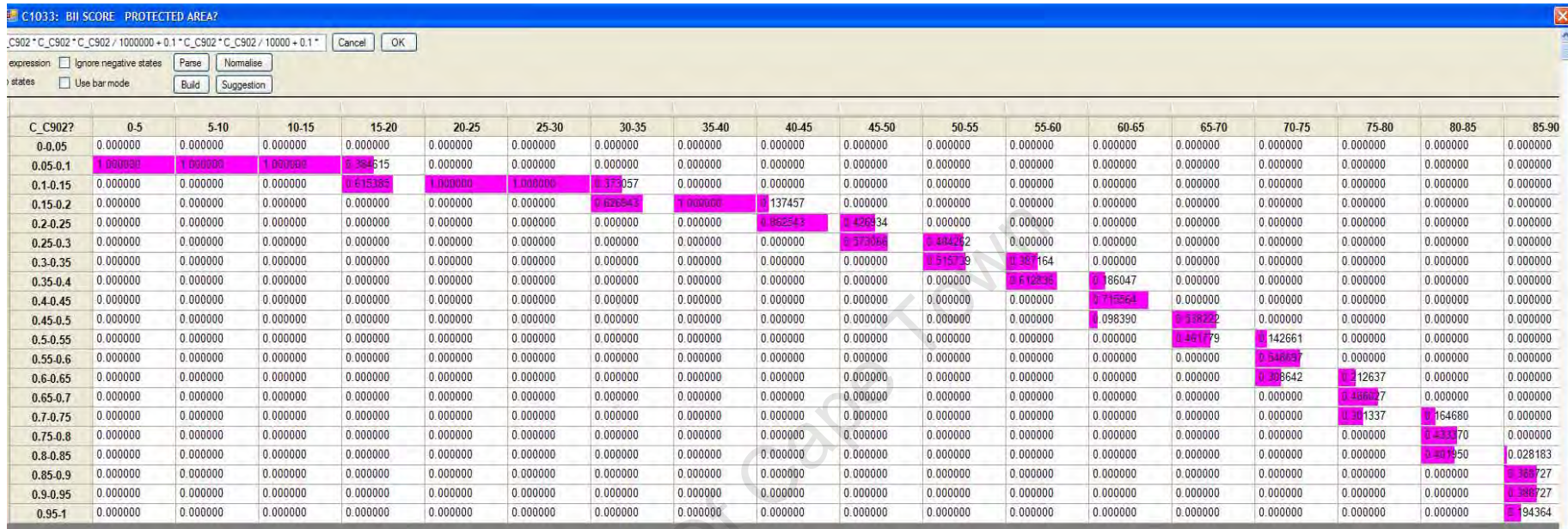


Figure 12: Non-linear Positive Amplification between Two Variables

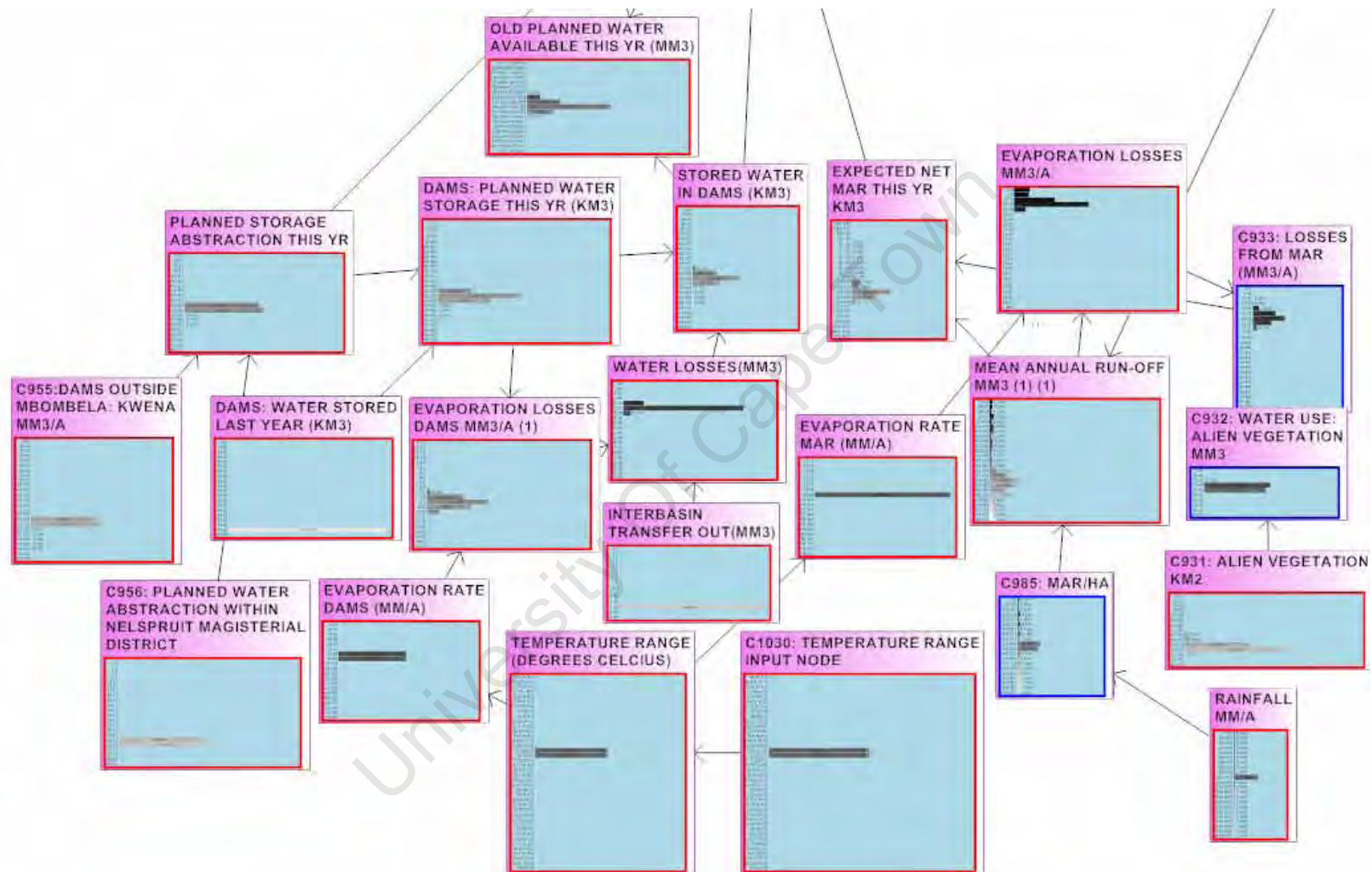


Figure 14: Example of the Customised Software Interface; Water Module for Mbombela Case Study (see section 6.3): for detailed illustration of individual nodes and probability distributions see Figure 5.

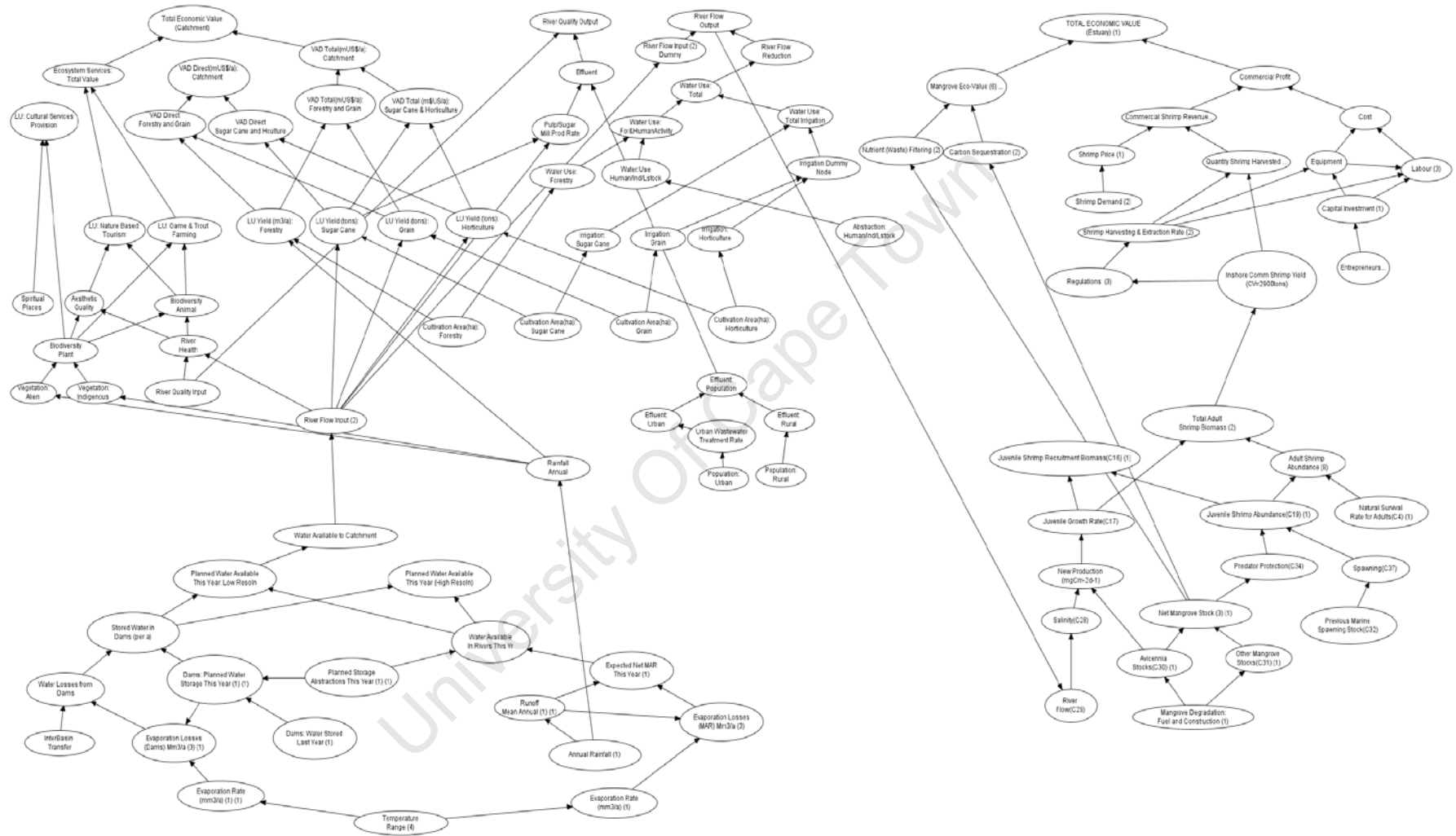


Figure 15: Illustration of Bayesian Model Linking Incomati Catchment and Maputo Bay Shrimp Biophysical Production & Fisheries Production.

A software interface (named Sisyphus: see Peter C, 2008, pp. 493-494) (see Figure 14) has been developed to facilitate the graphical causal modelling language and process during interdisciplinary workshops. During each case study, assumptions underlying relationships, functions, thresholds, parameters are recorded using the software interface. Agreements and disagreements amongst experts and literature sources are also recorded, so different views of system integration can be tested. In the phases of development where quantitative and qualitative variables are mixed using Bayesian networks, the Bayesian networks are derived from best available information and expertise. Data and information sources used to characterise probabilities the network are captured in the graphical causal modelling software. Full traceability of underlying assumptions, sources of information etc. are provided for review and scrutiny to participants during a particular case study in order to help engender a shared understanding of different ways of thinking about a phenomenon or behaviour. An example of a case study in this dissertation is shown in a Bayesian model in Figure 15. It represents the causal influence of catchment activities in the Incomati Catchment of South Africa on Maputo Bay in Mozambique. Note that Figure 11 and Figure 14 may be identified as sub-system components in the right half of Figure 15, illustrating the degree of modularity and reuse-ability of embedded units that is enabled through using a Bayesian approach.

Bayesian network software interfaces, in general, enable a linkage, module or drivers and responses to be added, deleted or changed without having to reconstitute the entire model. The Bayesian approach enables the derivation and quantification of causal influences representing the system for different contexts or scenarios. The knowledge engineering language (when converted into an object orientated software platform) ensures that the modularity, reuse-ability, trace-ability and upgrade-ability of the Bayesian models involved is appropriately ensured and accommodated at the input-output causal level. In addition, the correct variable sensitivities required of the Bayesian effort are preserved. This approach enables a 'learning model' approach (see section 5.2.6); one that can evolve with a long term interdisciplinary effort supported by modular, incremental testing and

validation. In systems and software engineering there is often a need to underlie the use of a particular methodology in research efforts with a systems language or ‘knowledge engineering language’. This enables easier management of changes in understanding of the mental model being built by the group of experts.

5.2.3 Developing New Indices

When characterising a Bayesian network with equations or conditional probability tables (CPTs) and populating it with probabilities, there are often areas of the model about which there is poor understanding and data, and which has not been studied a great enough depth to provide any useful empirical information. This is where the role of CPTs is greatest. It allows for experts to debate the nature of a function (linear, non-linear, etc) and to create the function using the CPT framework. The CPT framework basically provides a matrix of comparison in which a function, relating two or more nodes, can be hypothesized. This hypothetical function can then be tested by more focussed and detailed modelling and research and monitoring efforts, that is, in more quantitative bottom-up studies where possible. In this way, a hypothetical, contextual index or set of indices can be iteratively tested, and knowledge of the ‘gaps in understanding’ can be better characterised and understood. The development of new indices such as direct and total value add and the biodiversity intactness index were explored in the case studies conducted in this dissertation and are discussed in detail in the case studies later on.

5.2.4 Sensitivity Analysis & Running Scenarios

Sensitivity analysis involves testing the sensitivity of one variable against another variable, or a group of variables i.e. deviations from the baseline established in section 5.2.2 are tested in various scenarios and verified by an interdisciplinary group who use expert opinion, empirical evidence, data and theoretical models to help characterise the Bayesian network. In this

dissertation, the dependency of the variable being tested, that is, to its parent variables; is managed and tested using Bayesian networks. As long as there is a causal chain of conditional dependencies between two or more variables the driver-response sensitivity of these variables can then be assessed and validated against empirical evidence or expert opinion, using a Bayesian network.

Where Bayesian networks are used in assessing a particular scenario, the driver and response relationships being evaluated must be specifically verified and validated for that particular scenario. In other words, a full sensitivity analysis is conducted for each scenario that is run, in order to ensure that the scenario itself is valid, and that conclusions can be reliably made from the run. This is critical where a mix of empirical and expert judgement is used to characterise the probabilities and relationships between variables in a Bayesian network. The boundaries of application of a model must always be thoroughly ensured and how it relates to the context of application must be verified.

The software interface allows for exhaustive sensitivity analysis of driver-response relationships included in the model (as long as they are conditionally related through some causal chain). Often, the sensitivities of a wide range of responses are tested to a particular driver, in order to ensure that the 'basket of measures' that are used for that scenario react in ways that are verifiable and validate-able. In the process of sensitivity analysis, knowledge of key non-linear relationships, their thresholds and critical system limits are established and shared. These are usually identified as causal chains are tested for their sensitivities and iteratively verified by the interdisciplinary group, and drawn into the arena of generalised complexity for review and analysis, especially where model results from scenario runs are concerned.

5.2.5 Interpreting Model Results & Making Recommendations

Establishing the sensitivities quantitatively is but one part of the process of sensitivity analysis and verification and validation of the model. There are many contextual factors that must be interpreted appropriately in running the model and evaluating its results. In the case of social-ecological systems this requires the close participation of the interdisciplinary group in interpreting the results of any inference run that is conducted using the Bayesian network. Model results can easily be misinterpreted if they are located within an argument that makes incorrect assumptions about the context of application. For example, a threshold that might be fixed in one context of application, might not be fixed in another context; and because the models are not exhaustive in terms of the causal relations that constitutes it, additional contextual considerations can play a critical role in interpretation.

Moreover, each scenario must be independently verified in terms of the quantitative logic applied to the scenario, and the quantitative evidence reflected in the probabilities of the model. It therefore becomes critical that the interdisciplinary team or reference group that is involved in the study play a part in the interpretation. The multiple dimensions of social-ecological systems extend beyond our ability to exhaustively model them (Cilliers, 2008, pp. 40). For each context of interpretation there may be critical assumptions upon which interpretation of results is conducted, which must be made explicit so that the interpretive elements of explaining model results are incorporated in the outputs of the study.

5.2.6 Enabling Learning & Reasoning with Hyperstructures

In this dissertation, the combination of graphical causal maps and Bayesian networks provides the user with the dual ability to; (1) scrutinise data and information that underlies causal linkages (this information may be qualitative or quantitative, but is usually mainly qualitative as it is interpreted

in context), and (2) to verify and test the quantitative basis upon which the model has been constructed, by conducting a sensitivity analysis upon key variables. It also allows for the processes of generalised and restricted complexity research to overlap and merge and support an iterative “multiple-learning-loop framework” (de Wit, 2001) learning process that requires adaptability. This is a model that seeks to cope with emergence as that behaviour which *deviates from a model*.

A key feature that supports learning is that the heterarchical causal framework allows for categories and causalities to emerge from a process of co-creation during learning, and that this can be captured, shared and scrutinized in the framework of reasoning. This process of co-created causality and taxonomy lies at the heart of the concept of heterarchy enabled in the approach in this dissertation.

As has been observed by Waldmann & Hagmayer (2006) in psychological experimentation, these constitute critical elements of explanation building or theory-forming. As these categories emerge, and are updated and reflected in the hyperstructures (e.g. through new indices); a framework of learning is enabled. In this framework critical interdependencies (non-linearity, thresholds, critical limits), cross-sector sensitivities and the difference between observational and interventional variables can be adapted and shared as new understanding emerges. This allows for the resilience of the system to be characterised; using an understanding of what cross-sector interdependencies, non-linearities, thresholds and critical limits exist. Through identifying and understanding the role of observational and interventional variables (Meder, 2005) in the context of these system features, these in turn can be used to obtain an understanding of the adaptive capacity of the system.

6. Case Studies: Single Case Analyses

In this section a narrative is provided of the case studies conducted in support of this dissertation. The single case studies range from case studies in which the full BPDA approach was implemented, to ones where only parts of the BPDA approach were implemented. In chapter 7 we conduct cross-case analyses, and in chapter 8 we assess how the approach addresses the elements of cross-case analysis that are required to test the approach proposed in this dissertation (i.e. BPDA).

The case studies conducted in this dissertation were closely co-produced with the cross-disciplinary teams and team members. This is illustrated in the number of joint publications and research reports that resulted from close collaboration and specific team members in the consolidation phases of the case studies. In the case of the Incomati-Maputo catchment case study, Peter, Monteiro and de Wit (2007) collaborated on writing up the study. The national irrigated agriculture - climate change case study was published by Musango & Peter (2007). The consequent case study on how climate change might impact on biofuel production targets was co-written for conference presentation by Peter, Musango & de Lange (2007). This was revised to reflect the new biofuels production target and later published by Peter, Musango & de Lange (2009). Lastly, the cholera case study was captured in a CSIR report by Peter et al. (2007*).

That is, the scientific foundations, foundational assumptions and evidence for the case studies were already published elsewhere when writing this dissertation, and it served no purpose to repeat the same information to the reader, except where information was relevant to the objectives of this dissertation. We considered including some of the publications and reports of studies as appendices to this dissertation, but due to word and size limitations, and the copyrights associated with the publications, we were unable to do so. Rather, priority was given in this dissertation to articulating the nature of the

case studies through a clear case study narrative, and highlighting the key issues that were explored in each, and what was learnt from each case study.

While the case studies are supported by evidence published elsewhere, the aim of our analysis in this dissertation is not to repeat these case studies but rather to link the studies to the claims made about the ability of the BPDA approach in this dissertation. In each case study, we tabulate the key learning points of the case study in relation to the claims that were made regarding the ability of the approach. These are later integrated in cross-case analyses. The reader is therefore advised to consult the publications and reports listed here for more details regarding the specific assumptions that were made in each study, and the conclusions of the study.

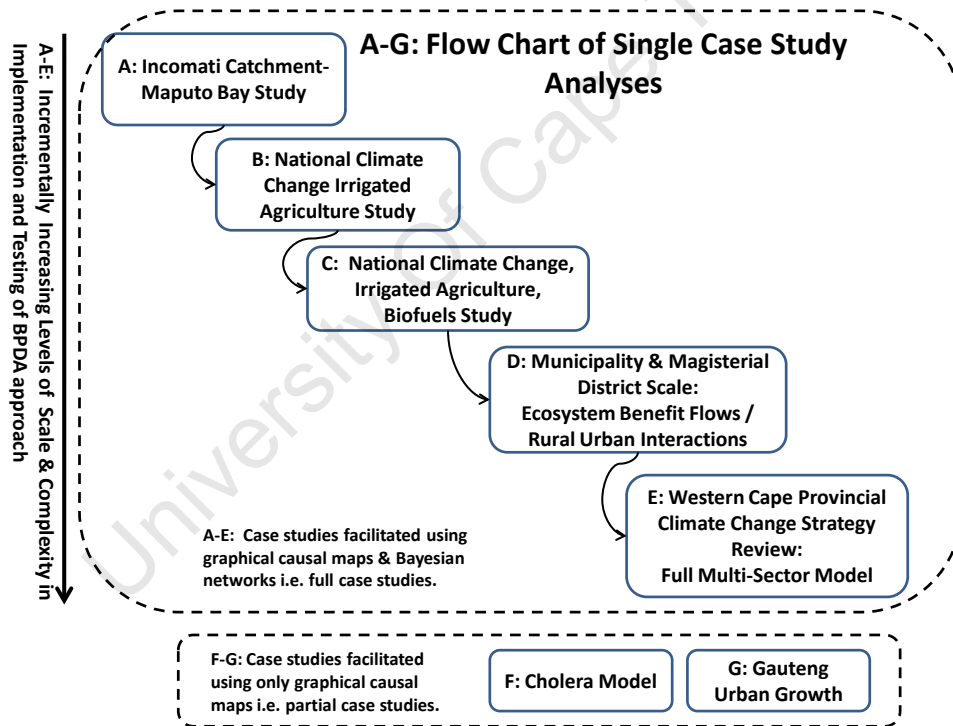


Figure 16: Flow Chart of Single Case Study Analyses

A flow chart of single case studies conducted in chapter 6 is shown in Figure 16. It also shows the order in which case studies in this dissertation were incrementally developed in order to negotiate issues of scale and complexity. The single case studies incrementally grow and test the scope and flexibility of the approach to accommodate; (1) an increasing number of

embedded units (and consequently; an increasing number of variables), and (2) to provide valuable understanding of cross-scale and cross-sector linkages at different scales of integration (regional, national, magisterial district, municipality, provincial), analysis and decision-making.

The earlier case studies conducted in support of this dissertation made use of a few embedded units (agricultural land-use production models, water use and water availability models, sectors such as fisheries (e.g. shrimp biophysical and economic production models) in model formulation and analysis for development of social-ecological systems. In later case studies, this was extended to include a range of embedded units. The embedded units integrated in later case studies includes biodiversity intactness index, GDP, GGP, employment, CO₂ emissions, solid waste, air pollution/noxious gases, household informal activities, manufacturing, energy and water production and savings, etc.

A strong thread that runs through most (but not all) the case studies was the need to deal with climate change related scenarios, and how they affect social-ecological systems sustainability. The author of this dissertation has been closely involved in climate change adaptation research for the past six years, and therefore, this topical area of research heavily influenced the case studies conducted in this dissertation. However, the case studies were always focussed on a broad range of critical issues, and were not restricted to assessing climate change related scenarios alone.

At the same time, the single case studies allowed for an incremental understanding to be built around participatory process management of cross-disciplinary research, facilitated using graphical causal maps and Bayesian networks.

The penultimate case study involves working with government decision-makers in the Department of Environmental Assessment and Development Planning (DEADP) in the Western Cape Government of South Africa in 2008. It also shows how the limits to provincial growth can be

determined with respect to climate – related effects on water availability and energy consumption in a variety of future economic growth scenarios, and at the social-ecological system scale.

6.1 Incomati Catchment – Maputo Bay Study

This case study was the first undertaken in support of the BPDA approach proposed in this dissertation. At the time, we were mainly concerned with testing the BPDA approach's ability to link economic and biophysical systems, and for this case study in particular; linking land-use changes in the catchment to changes in shrimp productivity at the coast. We were also concerned with the ability of the approach to cope with challenges of interdisciplinary research into socio-economic and biophysical systems challenges and problems. In that context, this case study served as a learning point for all subsequent case studies conducted in this dissertation. We learnt that the approach could be used to integrate across the economics-biophysics interface, cope with issues of non-linearity, scale and aggregation. We also showed that two sectors (agriculture in the Incomati catchment and shrimp fisheries in Maputo Bay) could be inter-related through the biophysical systems underlying them, and has the potential for supporting decisions made at the regional economic scale.

We used the results of a 3 year interdisciplinary research project named Catchment2Coast (Monteiro & Mathews, 2003), which was conducted into the linkages between the Incomati catchment (which runs from South Africa to Maputo Bay in Mocambique). The Catchment2Coast project was an EU funded project involving several teams of international researchers from the UK (England, Scotland), Portugal, South Africa, Swaziland and Mocambique. In its initial phases, this case study was developed and presented during the last year of the Catchment2Coast project. Some of the researchers from the Catchment2Coast project were involved in the case study presented here throughout its entire evolution, including close collaboration and supervision of the project leader Dr Pedro Monteiro (CSIR), who is originally from

Maputo and had a deep understanding of the context of the study, and how the multidisciplinary modelling project had integrated its various models to obtain its results. The author also received a great deal of support from Vivek Naidoo (CSIR) who conducted the hydrological modelling component of the Catchment2Coast project using the Soils, Water, Air and Temperature (SWAT), and Dr Pete Ashton (CSIR), who is a widely recognised expert with over 25 years of research experience into the Incomati catchment. Dr Ashton played a key role in providing data and verifying the Bayesian model that was eventually formulated in a series of day-long workshops. His input was invaluable, as it played a key role in determining where the emphasis of the model should lie in terms of land-use and catchment activities. Professor Martin de Wit (then CSIR, now de Wit Sustainable Options Pty Ltd) is an economist who collaborated with the author on the case study and helped guide the study significantly by introducing the use of the conceptual framework (Total Economic Value – see later in this section), which enabled us to construct the link between the biophysical and economic systems that the model was concerned with.

Maputo is heavily dependent, economically, on its shrimp fisheries. The Catchment2Coast project linked river flow features of the Incomati catchment to its downstream effects on coastal ecosystem productivity. In particular, the project explored the effects of reduced water in-flow to Maputo Bay on the shrimp biophysical and economic systems (through a significant proxy indicator - P Indicus - of shrimp productivity in Maputo Bay (Monteiro, 2007)).

The Catchment2Coast study explored critical inter and intra system linkages using historical evidence, GIS data, detailed modelling and fieldwork to develop biophysical and economic models. This was used to develop a **decision support tool**, which integrated the various models and scenarios explored in the research project, and was verified against data hindcasted over a ten-year period. However, this decision support tool, which relied on integrating detailed numerical models and simulations, was only able to be used in a small set of scenarios, namely, those explored for the purposes of the

research project. Also, if significant changes were to come about in the system, which weren't catered for in the original studies around which the project and decision support tool were orientated, then a great deal of re-work and expense would be required by researchers in order to provide decision support. This raised the question of how a flexible framework for integration of the various embedded units in the study could be established. These allowed for a broad range of scenarios to be tested, and which could be adapted to reflect real-world changes as they unfold.

We explored conceptual frameworks for integrating between biophysical and economic systems, and developed a Bayesian network of these linkages between catchment and coast. We used the conceptual framework of Total Economic Value (TEV) (Blignaut & de Wit 2004) as a first level of integration of economic and biophysical systems, with a long-term view to dealing with more complex social-ecological systems (TEV is explained in more detail in section 9.2.2). According to Blignaut & de Wit (2004) TEV necessitates the consideration of a broader range of variables. These range from; "life support services (regulatory and structural functions), human development support services (recreational, cultural, spiritual), sources (renewable and non-renewable) and sinks (pollution and waste absorption)." This framework is illustrated, in part, in Figure 17, that is; direct and indirect use values are outlined, while non-use values such as existence and bequest values are not illustrated.

The concept classes identified in Figure 17 were then used to explore a wide range of TEV – related services for a coastal ecosystem, as shown in Figure 18. The conceptual frameworks shown in Figure 17 and Figure 18 were both used to stimulate discussion between an interdisciplinary workshop group, and to formulate graphical causal maps Figure 19 and Figure 20, which shows the Incomati-Maputo Bay model at various stages of development, before it is eventually formalised into a Bayesian model using a software interface, as shown in Figure 21.

Graphical causal models were used to facilitate a series of workshops where the linkages were determined, verified and validated or substantiated.

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Total Economic Value

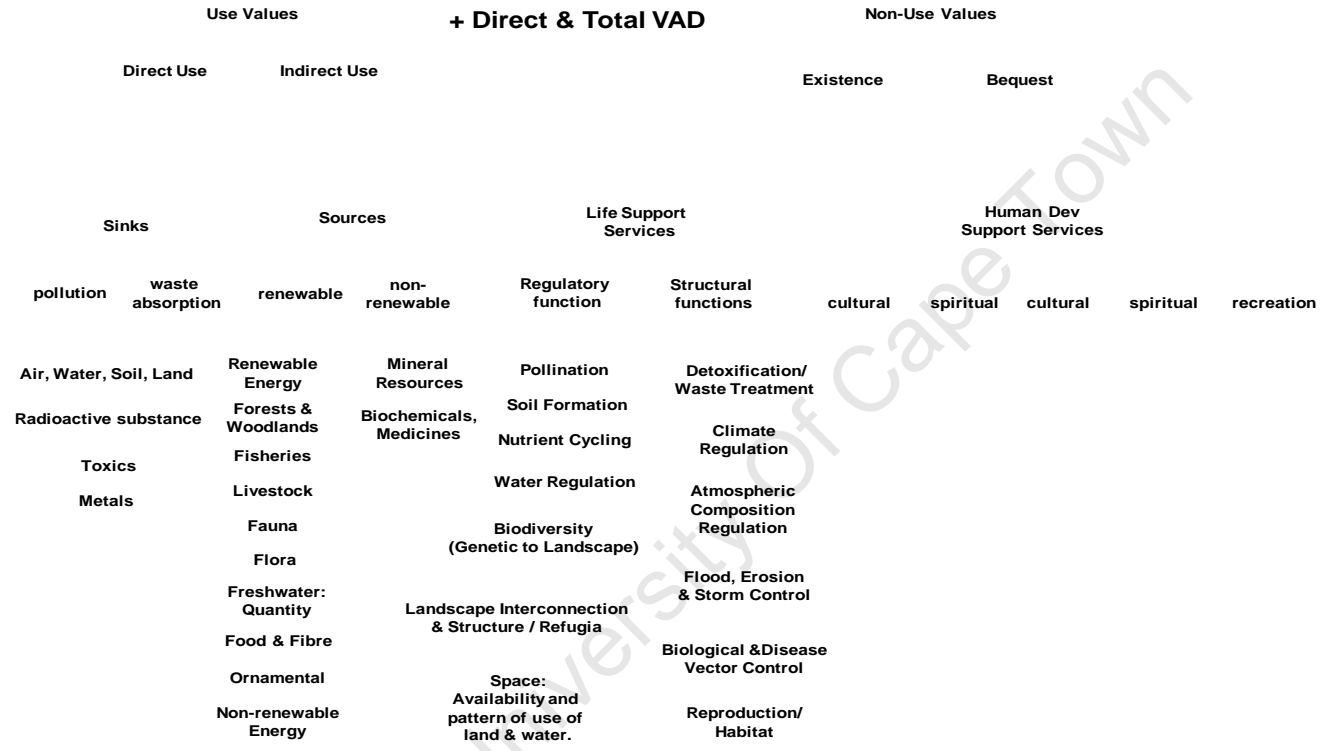


Figure 17: Illustration of Total Economic Value Conceptual Framework

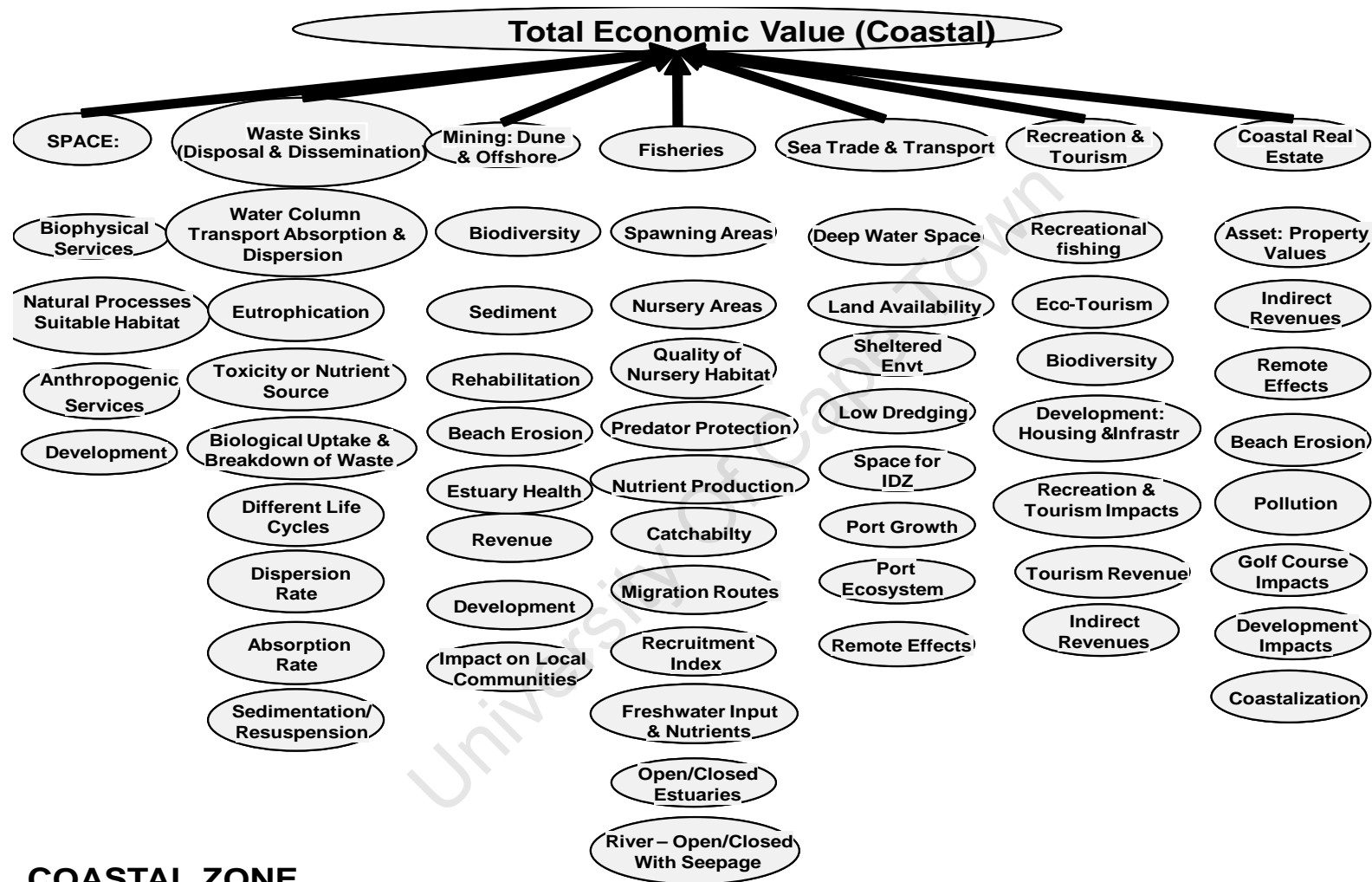


Figure 18: Using TEV Framework to Select Salient Factors for a Coastal System

Formulating Bayesian Models Using Graphical Causal Maps

We made use of the knowledge engineering language outlined in section 5.2.1. The language is comprised of initiating, enabling, resulting and definitional arcs to represent driver response relationships, and positive and negative signs to indicate positive and negative amplification between parent and child nodes. We used our customised Bayesian software interface, which allows the user to compose graphical causal maps before converting them into Bayesian networks. As previously explained, this software capability captures information around nodes and linkages to be characterised and recorded for review and evaluation. This can be conducted by both the internal interdisciplinary workshop team, and experts external to the study.

The Incomati Catchment – Maputo Bay model is shown at different levels of abstraction in Figure 19 and Figure 20. The Incomati Catchment – Maputo Bay system was treated as a single aggregated basin. Ecosystem services and land-uses, and shrimp biophysical and economic production; are distinguished in Figure 19 and developed to further detail in Figure 20. The causal chains, in a sense, represent hypotheses about how the system is integrated, and may be formulated and characterised from correlation – based studies, expert opinion, historical and archival evidence, survey information and case studies. The structure of the model was verified and validated by a team consisting of field experts with long term knowledge and experience of the area and against the results of the Catchment2Coast study.

The causal links constituting the structure of the model we formulated were characterised using; expert judgement, a variety of sources of information containing empirical, qualitative, numerical and simulated outputs from publications (Sengo et al., 2004; Hassan, 2003, Janse van Rensburg, 2001; Nkomo & van der Zaag, 2003) and internal reports from government departs such as the Department of Water Affairs and Forestry’s ‘State of the River Reports’ and CSIR Natural Resource and Environment data records and reports. We used and consulted the models that were developed during the

Catchment2Coast project. These included a detailed catchment hydrology models using the Soils, Water, Air, Temperature (SWAT), and a decision support tool (DELFT3D) which integrated the various sub-systems or 'embedded units' of the system. Moreover, the overall results of the 3 year multidisciplinary project Catchment2Coast were also used to characterise the baseline probability distributions of the Incomati Catchment – Maputo Bay Model. For areas in the catchment, known and modelled sources of information were used to characterise data for river flow, rainfall, temperature abstraction types and related volumes, inter-basin transfers and water quality.

TEV was used as an integrative framework, and two new indices were introduced, relating to the direct and total economic value add to water by various agricultural (land-use) crop production types (e.g. maize, wheat, sugar cane). Direct and total economic value add were estimated using conversion factors established in a study by Hassan (2003) on the Crocodile Catchment, a major constituent catchment of the Incomati. We used the same conversion factors for horticulture as for grain, as there was no precedent in the study. This provided, at a very coarse level, the distinction between micro and macro-economic levels of impact.

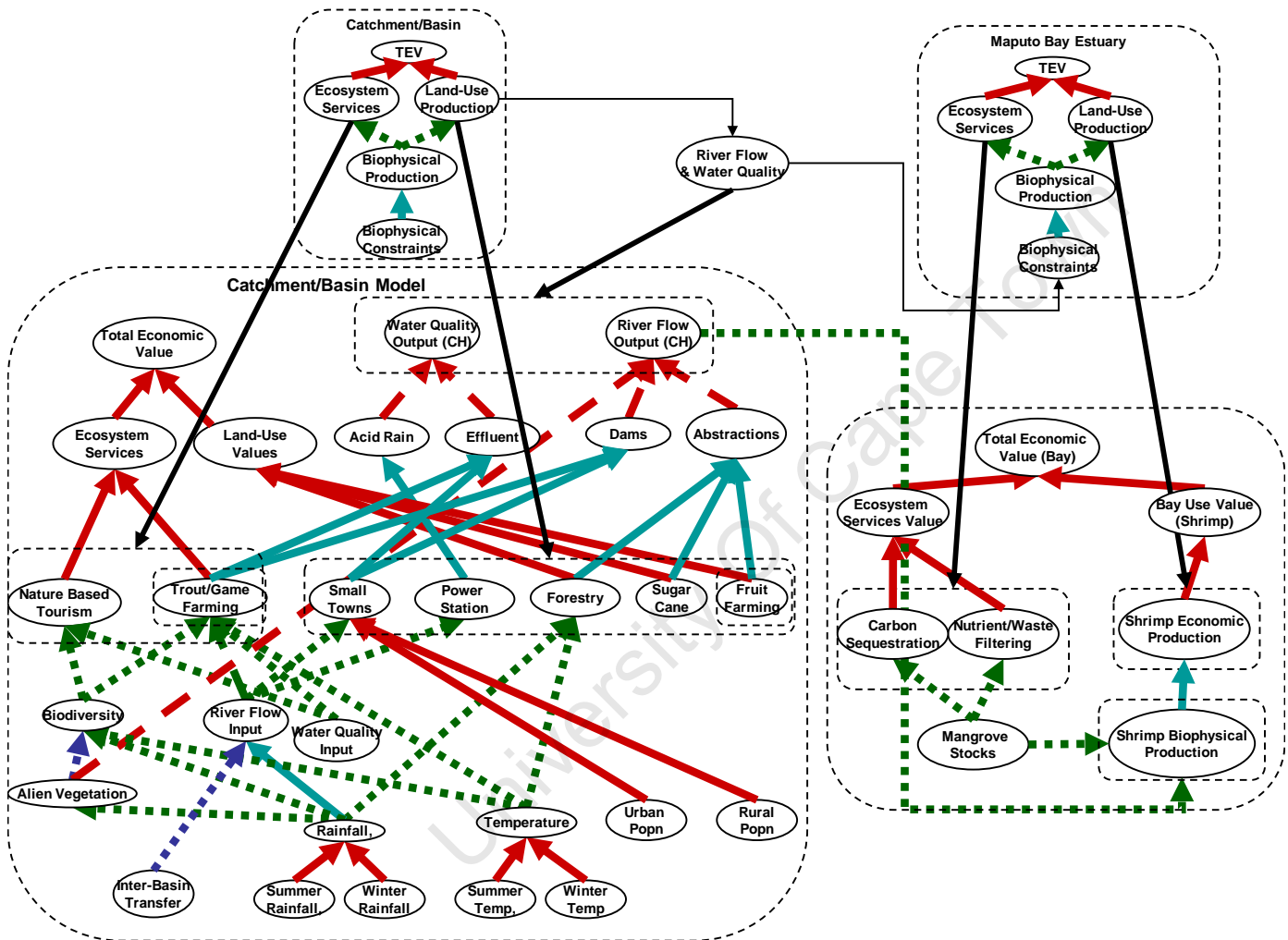


Figure 19: Model Linking Catchment to Maputo Bay - First Level Conceptual Model

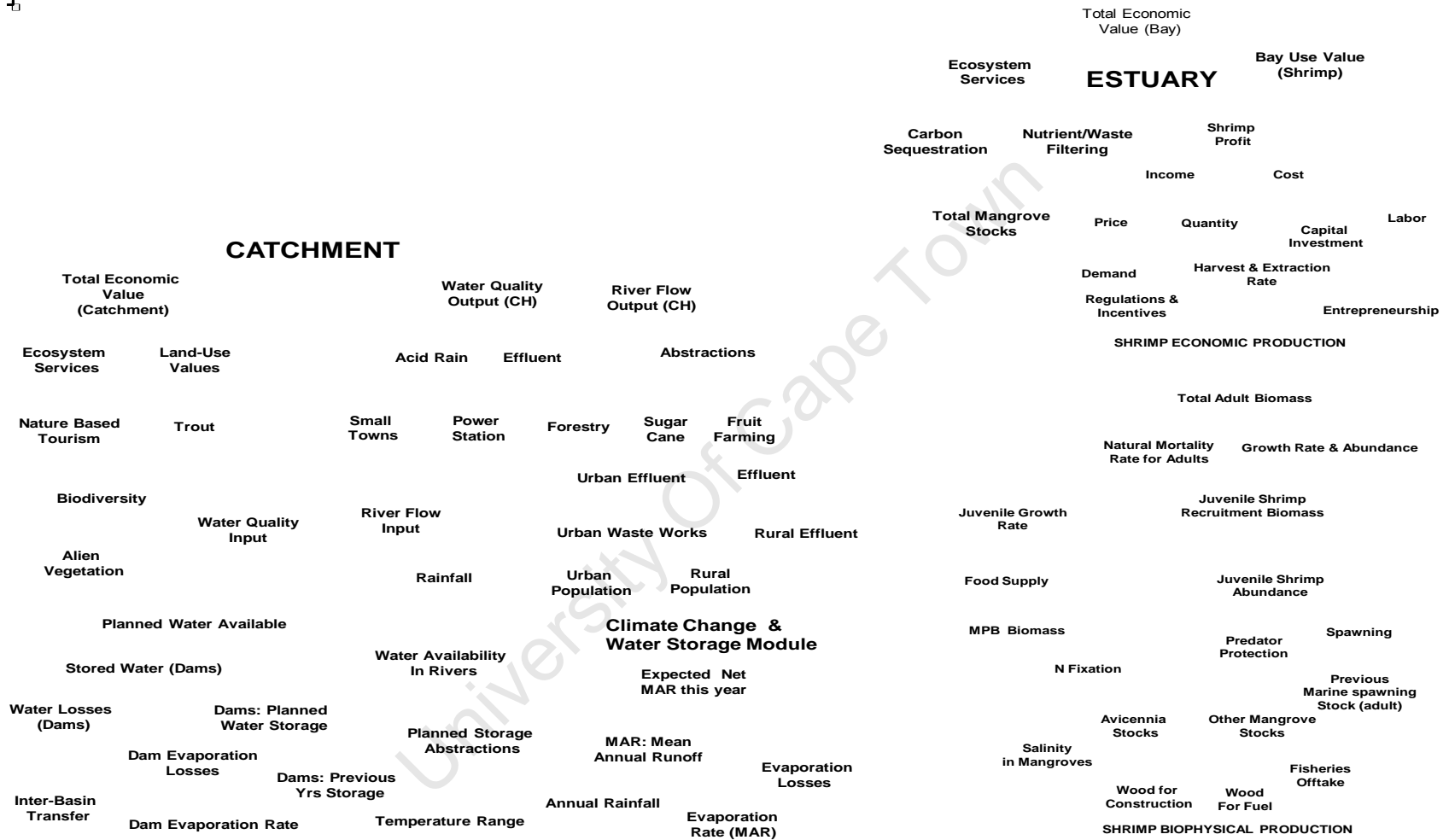


Figure 20: Bayesian Network Linking Catchment Land-Uses to Biophysical and Economic Consequences on Maputo Bay Estuary

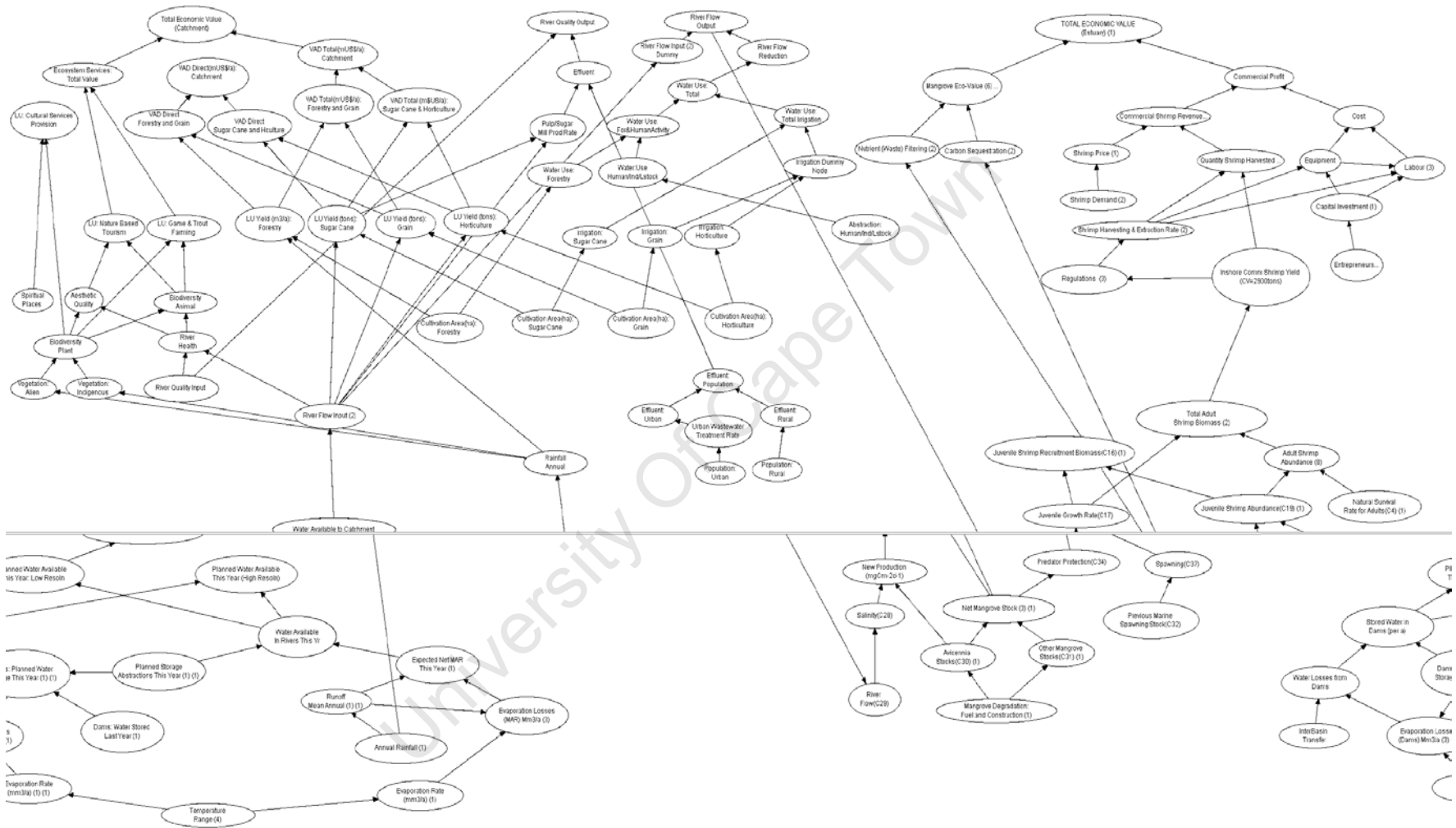


Figure 21: The Incomati-Maputo Bay Model as Formulated in a Bayesian Software Interface. It contains a knowledge capturing facility for all nodes and arcs.

Having constituted and formulated a Bayesian model, sensitivity analyses was conducted on the Incomati Catchment – Maputo Bay model to ensure robustness of the model structure in general. Where a particular scenario is concerned, the full range of driver-response relationships used in the scenario must be verified. Calibrating the model to represent a scenario depends, in some part on the qualitative judgements underlying the causal hypotheses made in formulating the model structure.

This model explored integration at cumulative regional scales, and scenarios were designed to explore three key questions, namely (Peter et al., 2007, in prep for resubmission):

1. “What type of agro-development strategies would best ensure that international water sharing obligations will be met?”
2. How would projected climate change effects impact on water availability in the catchment and at the coast?
3. Optimising local activities in relation to systems level dependencies. How can shrimp fishery production be optimised in relation to its biophysical and economic production system?”

The scenarios in which the model was used related directly to the above questions, and focussed on (respectively);

1. Exploring different land-use development strategies, in particular, assessing the difference between ‘one-on-one’ trade-off’s in agro-production against moderate combinations of agricultural land-use.
2. Exploring sensitivity to climate change effects on rainfall and temperature, and the relationships between water catchment output to Mocambique and (1) dam storage practises within the catchment and (2) the level of water intensive land-use activities conducted in the catchment.

3. Exploring the sensitivities of multiple biophysical drivers on shrimp production. For example river flow, salinity, spawning, juvenile food production from mature *Avicennia* mangrove stocks. This is because of microbes that are attached to mature *Avicennia* mangroves, which are responsible for the production of juvenile food production or 'macrophytobenthos'. These were related in our model to produce an estimate of adult shrimp biomass production for Maputo Bay (Monteiro, 2007).

The results of the study show that:

1. More nuanced combinations of land-use changes can provide the same, if not better overall system level effects.
2. When planning for water resource planning so that international water sharing agreements are met, it is important that the inter-relationships between dam storage practises, slight changes in rainfall and temperature, various land-use combinations, evaporation from stored water and mean annual runoff must be considered in unison. The results showed that a good rainfall year could still result in significant stored water shortages if annual temperatures were higher. Adaptations that may result from climate-related water shortages, involving increasing water storage capacity (e.g. through dams) would prove ineffective should these conditions exist.
3. Multiple biophysical and economic factors can impact on shrimp fisheries and shrimp biophysical production. These were explored using the Incomati – Maputo Bay Model, and the study showed that the tendency to emphasize one factor above others without considering the causal chain between factors could be overcome by creating a shared understanding of the sensitivity of these linkages between participant disciplinary experts.

The study was used to explore how the BPDA approach could be used to provide an integrated understanding of catchment – coastal linkages. It was also to explore the range of possibilities that the approach would unleash, and the new directions of research that would emerge as a result of the learning conducted in this study. For example, incorporating non-linearity into Bayesian networks proved easier than anticipated and exciting possibilities emerged for representing known or speculated feedback effects using Bayesian networks.

Table 3:

Critical Learning Points for BPDA in Incomati-Maputo Bay Case Study

Critical Learning Points (BPDA)	Description
Cross-scale	Regional scale effects are evaluated at an aggregated scale in this case study. This was achieved by linking land-use activities upstream in the Incomati catchment to its downstream impacts in Maputo Bay.
Cross-sector	Regional scale economic interactions, mediated by biophysical system services, and human impacts on land-use changes upstream were evaluated in this case study. This proved encouraging, in the sense that it would be possible to build larger models, and with greater numbers of embedded units that represent different sectors or biophysical systems.
Non-linearity	A variety of non-linear relationships were incorporated into the model, for example, including water availability – crop production relationships, salinity and new production, and various others (see Figure 21).
Critical Limits & Thresholds	The resultant sensitivities of variable interdependencies and were verified against known data and expert opinion for the model in general, and for each scenario in particular.
New Indices	We evaluate total economic value by introducing economic value-add indices and a value for ecosystem services (see Figure 21).

Participation	A range of workshop and one-on-one sessions were conducted to formulate, populate and verify the model involving the aforementioned participants in groups, or as individuals, at various stages of the case study. The initial learning we obtained regarding participation in this regard was simply that through detailed inspection of causal linkages, researchers from different disciplines could contribute to building a shared picture of the system.
Decision Support	The Bayesian model formulated for this case study proved effective at coping with a much larger range of scenarios (and adaptations) than the highly detailed Delft3D model could.

This study served as an initial point of learning for this dissertation, and the methodology employed in this case study was expanded, in later case studies, to include a wider variety of system components and measures for analysis. As such, while the study provided useful results, the learning that emerged from later case studies, for example, regarding estimating system resilience in future scenarios through establishing scenario-based critical limits and thresholds, was yet to be revealed to its full extent.

6.2 National Scale Model: Climate Change - Irrigated Agriculture

In this case study, we developed an understanding of the linkages between water, climate and irrigated agricultural land-use requirements by developing a Bayesian network of these linkages. We assessed the ability of the BPDA approach to model at the national cumulative scale of integration i.e. of water requirements versus water availability for irrigated crop production, and the respective sensitivity of water availability (storage and rainfall) to climate related changes in temperature and annual rainfall.

We formulated an understanding of the national scale model using graphical causal maps and Bayesian networks (Musango & Peter, 2007). We re-used the model structure formula of the Incomati Catchment – Maputo Bay Model, formulated in the previous case study, to assess the impacts of climate change on irrigated agriculture in South Africa. The study was an interdisciplinary collaboration between the author and a resource/agricultural economist (Musango & Peter, 2007).

Agricultural production in South Africa consists of a developed commercial sector, and a large number of subsistence-based farming homesteads and communities. The percentage of GDP contributed by the agricultural sector has dropped steadily since the 1930's, that is, from 20% to less than 7% in the 1990's. Cyclical droughts are a regular occurrence in the agricultural sectors of South Africa, which calls into question the increased vulnerability of the agricultural sector to possible climate change effects, and their combined effect in different scenarios.

The prospect of using the Bayesian approach to assess climate change related effects on land-use adaptations, discussed in the previous case study, begged further investigation. This is due to several concerns. Firstly, the topical nature of climate change as a global concern, the lack of research into human adaptation to climate change (Reilly, 1999) in developing countries and secondly, inaction at the national scale of decision-making in South Africa,

which is a water-scarce country (Mendelsohn et al., 2000). We envisaged that a cumulative framework in which a variety of what-if's relating to land-use combinations in different climate change scenarios can be tested at the national scale, and that this would prove a valuable decision support tool for land-use adaptation planning for climate change, in particular, agricultural land-use planning (i.e. Musango & Peter, 2007).

We formulated the model in such a way that we could simultaneously test the potential total and direct value add at the national scale in two ways. Firstly, as projected from a proposed land-use strategy for agriculture without considering climate change effects, and secondly, considering the same strategy with climate change effects (see Figure 22).

The same economic multipliers derived by Hassan (2003) were used to establish the baseline probabilities of the Climate Change – Irrigated Agriculture Model. The water use amounts for various water intensive land-use activities that were obtained from a study on the Incomati Basin by Sengo et al. (2004). The model was also populated using known crop yields and related incomes as outlined in Aquastat (FAO, 2005). An illustration of some nodes in the populated model is shown in Figure 23.

In this study, we developed a better understanding of how to model the sensitivity of different land-use combinations to a range of climate change scenarios; as forecast by IPCC based Global Climate Model (GCMs) projections (Midgeley, 2005).

We ran the model in a series of scenarios that deal with projected climate related changes in rainfall and temperature. We increased temperature by 3°C and tested a variety of scenarios related to rainfall, and the extent and combinations of different types of irrigated agriculture in South Africa (Musango & Peter, 2007).

The sensitivity of irrigated agricultural practises to climate change effects on rainfall, temperature, water storage were determined for a variety of scenarios, as outlined in Musango & Peter (2007).

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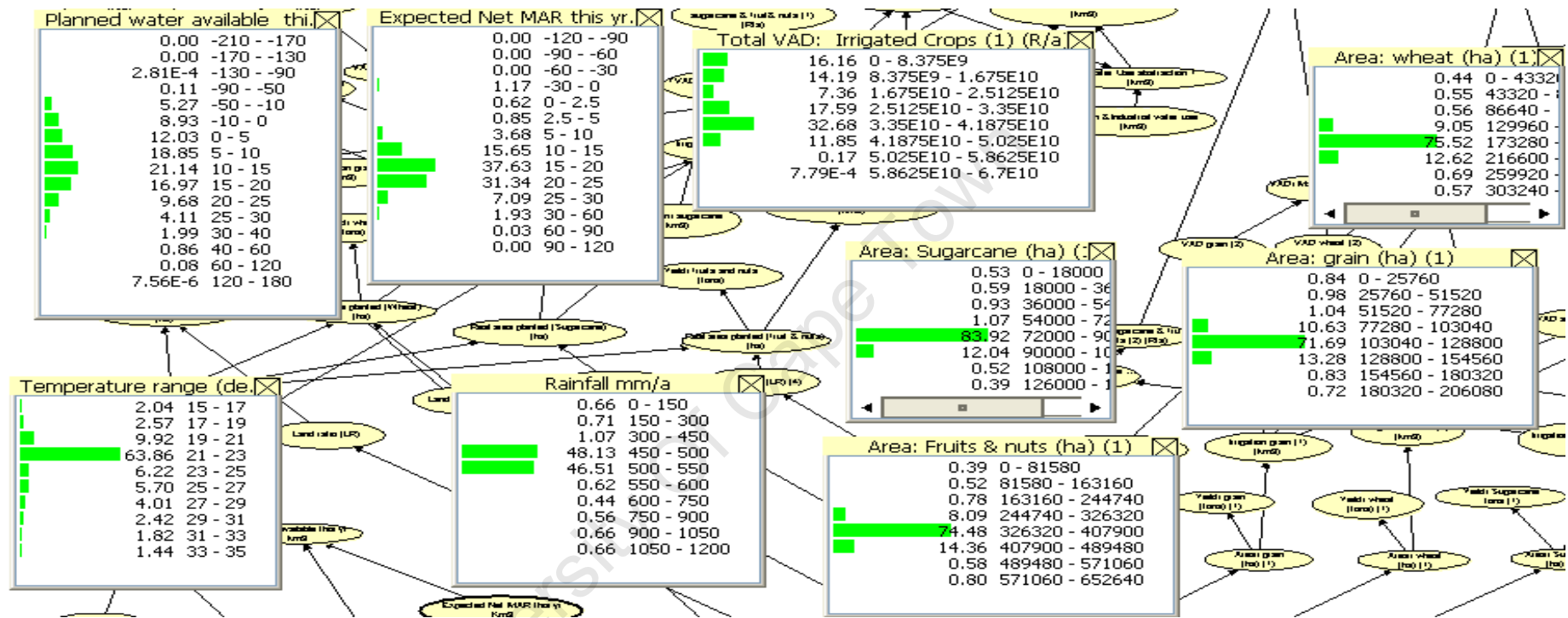


Figure 23: Bayesian network Constructed for South African Agriculture

In the scenarios conducted in this study we found that in order to increase the resilience of the national agricultural system to climate change under climate change related conditions the following measures would have to be considered, and in combination (Musango & Peter, 2007):

1. Reduce inter-basin transfers slightly
2. Store more water in dams.
3. Increase area under fruit and nut cultivation by 160% of current value.
4. Maintain area under wheat, grain and sugar-cane cultivation at current levels.

This study showed how embedded units formulated in a previous study (Incomati-Maputo Bay), could be *adapted* at the national scale to model the cumulative effects of climate change related variables on irrigated agriculture. The study mainly focussed on demonstrating how adaption measures could be formulated using the BPDA approach and the Climate Change – Irrigated Agriculture Model and no significant predictive conclusions were formulated. Rather, this study explored the usefulness of the approach in providing an integrated understanding of a larger scale system and the methods developed in this study would be further expanded in later case studies. The learning engendered in this case study for the purposes of the BPDA approach is summarised in Table 4, as shown below.

Table 4:

Critical Learning Points for BPDA from National Scale Climate Change – Irrigated Agriculture Case Study

Critical Learning Points (BPDA)	Description
Cross-scale	National scale effects are evaluated at an aggregated scale in this case study. This involved aggregating certain relationships at the national scale, and relating them in a verifiable manner. The global cross-scale effect of climate

	change upon the water and (consequently) agricultural sectors is also conducted, thereby linking effects at the global and regional scale to the national scale capacity for agricultural production.
Cross-sector	The agriculture and water sectors are related at a national scale in this case study, and furthermore, linked to potential climate change effects.
Non-linearity	A variety of non-linear relationships were incorporated into the model, for example, including water availability – crop production relationships.
Critical Limits & Thresholds	We learnt that we could use the model to get an understanding of critical limits and thresholds in different climate change and agricultural land-use scenarios.
New Indices	We evaluate total economic value by introducing economic value-add indices, including direct value add and total value add – in order to get a feel for the economic impact of land-use activities in relation to water at local and national scales, respectively.
Adaptability	We were able to adapt the model formulated at regional scale for a catchment (see previous case study) to deal with questions of agriculture at a national scale, and in a different context i.e. assessing the possible impact of climate change effects on different land-use adaptation scenarios.
Decision Support	The Bayesian model formulated for this case study proved effective at coping with a large combinatorial range of climate change and agricultural land-use adaptations scenarios. The learning from this case study was presented at a local conference and published in a local journal, as an initial starting point for testing our understanding that the BPDA approach that could enhance decision-support.

6.3 National Scale Model: Climate Change – Biofuels Production

The Draft National Biofuels Industrial Strategy (DME, 2007) was announced in South Africa in 2007 by the Department of Minerals and Energy (DME). This brought into question the possible effects of this intervention on food crop production, and hence, food security in South Africa. This case study therefore presented the opportunity to assess the flexibility of the approach BPDA to adapt to real-world strategic changes as they are announced (Peter et al., 2007) and developed. Moreover, our research goal was informed by emerging concerns that biofuels production may threaten food security, as evidenced in the United States of America (MIT Technology Review, 2007), where biofuels production in the Midwest has led to competition between buyers of biofuel feedstock and food producers. Moreover, there were growing concerns regarding the linkages between biofuels production and global food security. In South Africa, the perception amongst dairy farmers was that the increases in prices of animal feedstock were driven by the competition for maize for bioethanol production in the US. This study explored the importance of considering the linkages between biofuels production, and other sectors such as the food and water sectors, under a variety of projected climate change and land-use change scenarios.

In this case study, the author collaborated mainly with two agricultural economists, namely, Ms Josephine Musango and Dr Willem de Lange. We formulated a model to explore the linkages between food and energy production, and water availability, under projected climate change scenarios. We re-used the model formulated in the previous study (see section 6.2). In this case study, we tested the flexibility of the BPDA approach to accommodate the new biofuels strategy into the modelling framework developed in the previous case study (see section 6.2) as a new embedded unit, and thereby demonstrating how an existing model can be modified and/or changed in order to assess a new, emerging development strategy at the national scale.

We conducted a study that involved formulating an embedded unit for biofuels production and linking production to agricultural yield, and water availability in South Africa. The model is cumulative, and does not reflect spatial changes and how they may affect crops, and aggregates at the national scale.

We adapted the model from the previous study to include a biofuels production module, which we linked to the irrigated agricultural sector. We re-constrained and re-parametrised the model at the national scale. We used a variety of information sources and options, elicited in cross-disciplinary participatory workshops that were held to guide the research effort and to validate the model structure and parametrisation.

Four basic modules compose the model (see Figure 24 taken from Peter et al., 2009, In Press), namely:

1. a & b: Economics modules that calculate the economic value add to water that is created through food-based agriculture. Two economics modules are used; one which includes the effect of climate changes, and another which excludes the effect of climate changes, so that immediate comparisons can be made when the model is run.
2. c: A biofuels production module, which allows the user to select the percentage of cultivated crops that can be dedicated as biofuels feedstock, and assess levels of biodiesel and bioethanol production.
3. d: A water availability module, which allows the user to set different levels of water storage, annual temperature and rainfall, inter-basin transfers

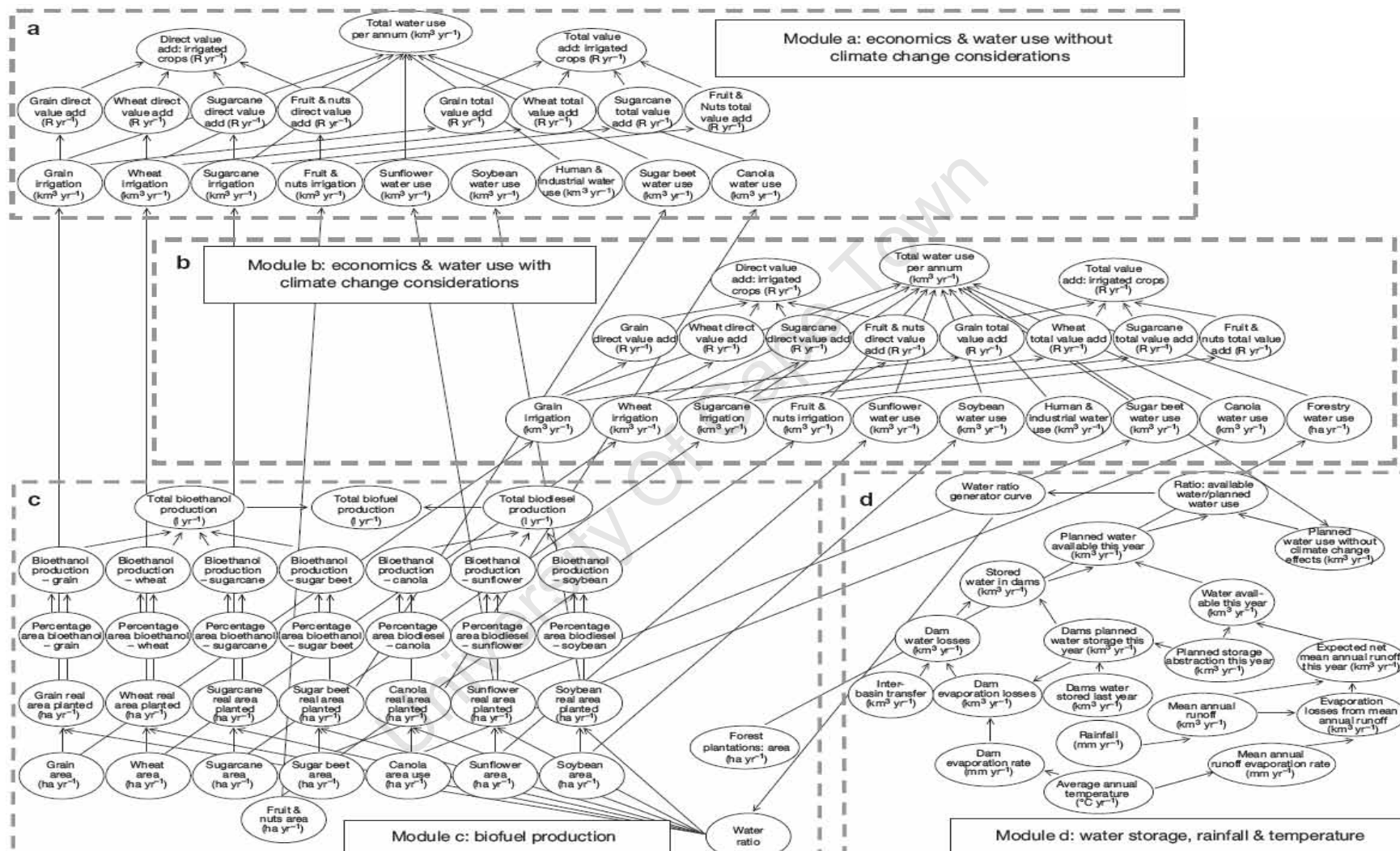


Figure 24: Detailed Illustration of Climate Change - Biofuels Bayesian Model: Including four constituent modules a-d (in Peter et al., 2009, In Press).

A diverse array of information sources were solicited in cross-disciplinary participatory workshops and used in this study. We used the economic multipliers derived by Hassan for the crocodile catchment as a baseline indicator of the value-add to water by individual crop production per unit. We estimated multipliers for those crops for which there was no information regarding economic value add to water i.e. using expert opinion. A feasibility study (Lemmer, 2006) for a bio-ethanol production plant was used to constrain some of the crop-biofuel production relationships. Dam evaporation rates were obtained from CSIR records and reports, and information about current irrigation levels was obtained from FAO (2005). The model parameters and constraints were verified in interdisciplinary workshops and with individual experts in one-on-one interactions conducted at the later stages of the study.

Sensitivity analysis was also conducted over the range of scenarios conducted in the study. The sensitivity of response variables chosen for a particular scenario are tested over the full range of driver variable states, producing graphs. This provides easy verification of critical limits and thresholds. In this way, for each scenario, driver and response variable inter-relationships and sensitivities are verified and validated against known information and expert knowledge.

We ran the model in a variety of land-use combinations and climate change projection based scenarios and assessed the resilience of the national industrial biofuels strategy in terms of the crop-types that have been identified for use as biofuel feedstock. In the first study (i.e. Peter et al., 2007) we tested the feasibility of meeting the targets proposed by the Draft National Industrial Biofuels Strategy (2007), that is, that biofuels production capability could be established by 2013 that would see biofuel production at 4.5% of national fuel production (DME, 2006).

A number of crops were proposed for cultivation, including maize, soya beans, sunflowers and sugar cane. These were tested in a variety of scenarios, only one of which was presented in the study by Peter et al. (2007)

for the purposes of illustrating the effectiveness of the approach in assessing the levels of surplus agricultural production that would be required to meet the national biofuels production targets. It was clear from the study that larger surpluses would be required under climate change conditions than envisaged by the Draft National Industrial Biofuels Strategy.

After presenting the study at a conference in Fiji (Peter et al., 2007), we re-worked the study for submission in a special edition of the *Journal of Climate Research*. In the interim period, during which the study was under review by the journal, the national biofuels strategy was finalised (DME, 2007). This finalised strategy contained significant changes from the draft strategy; namely; the overall target was slashed to 2% of national petroleum production, maize and jatropha were excluded from the strategy (citing concerns over food security) and new biofuel crops were announced as potential feedstock candidates. These included sugar cane, sugar beet, biodiesel sunflower, canola and soy beans. These crops are intended to be grown in the short term by small scale farmers in the former rural homelands such as the Eastern Cape (KPMG, 2007), under dryland conditions. Therefore, the land-use strategies and scenarios were amended to reflect these changes in the study, mid-way through submission (Peter et al., 2009, In Press), to reflect the changes that had been made to the strategy.

The final study (Peter et al., 2009, In Press) drew on two scenarios that were selected from a range of scenarios that were explored. This range was conducted by incrementally increasing the growth area of each crop, and establishing what levels of growth are required at the system scale in order to meet the national biofuels production target. We chose two scenarios which met the national target and tested their resilience to climate change related changes in rainfall and temperature, to illustrate the usefulness of the approach in determining the robustness of a particular strategy, given a range of future scenarios. We therefore tested the resilience of these strategies over a range of annual rainfall and temperature, in order to determine where limits to growth may lie. This was consistent with climate change related forecasts and projections made by the IPCC (2008) and drawn from global climate change

models (GCMs). They make forecasts and projections for 2099, and simple linear regression of these trends is not representative of the ways in which climate change related effects are expected to unfold. The IPCC (2008) acknowledges this, and warns scientists that considering a range of changes, which can occur on faster timescales in the short and long term is more appropriate for this type of system and problem. Indeed, recent research have shown that rates of glacial melt are faster than originally thought (Gregory & Oerlemans, Nature, 2009).

We tested the two scenarios (and the land-use combinations they were based on) for their critical limits in relation to temperature and rainfall by testing iterative, incremental combinations of both. In this way, we were able to establish an understanding of what the limits to growth were for a particular strategy i.e. under which climate change scenario was it resilient, and conversely vulnerable, respectively. This is shown in Table 6, which is taken from Peter et al. (2009: In Press). It shows how two biofuels production strategies (i.e. 1 & 2) respond to increasing temperatures (a-d) over the annual rainfall range, as outlined in Peter et al. (2009, In Press):

The average annual temperature is raised in 1⁰ Celsius increments; from the average 22⁰ (no increase in annual temperature) to 26⁰ Celsius in each consecutive row in Table 6; where total biofuels, biodiesel and bioethanol production in response to rainfall at each temperature is shown. Meeting a total biofuels production of approximately 400 million litres per annum would require higher and higher annual rainfall to achieve, and the point at which rainfall meets the requirements of the agricultural land-use strategy is clearly shown to change from row to row.

In this way we are able to determine the critical limits and thresholds of the ability of a system to sustain growth under a variety of different climate change – related scenarios.

This study showed also that we can change and adapt not only a model, but our lines of inquiry into the same study as real-world changes occur. Using the BPDA approach, we were able to follow and analyse the strategy from its draft to final form, as the changes were made, illustrating the usefulness of the approach to decision-makers and researchers alike, in linking their analyses to changing, real-world contexts. In short, we were able to assess a strategy dynamically as it was changed, demonstrating the usefulness of the approach in supporting decision-making in changing real-world contexts. The study achieved this primarily through providing an understanding of the resilience through visualising critical limits and thresholds in a variety of possible future climate change scenarios (especially with respect to changes in rainfall, temperature and water storage).

In summary, in this case study we used the BPDA approach to successfully adapt to changing ideas and decisions about how a strategy is implemented at the national scale, in this case, for biofuels production. This study has been published in the *Journal of Climate Research* (Peter et al., 2009, In Press). We adapted previous study, which was presented at a conference in Fiji (Peter et al., 2007) to assess national biofuels strategy based on draft biofuels strategy. The first submission of paper had to be revised with new scenarios as the national biofuels strategy was finalised and significant changes were made to it in the period between first submission of our manuscript and receiving the reviewers' comments. These are detailed later in the cross-case analysis, but are also summarised in Table 5 below.

Table 5:

Critical Learning Points for BPDA approach from Climate Change – Biofuels Production Case Study

Critical Learning Points (BPDA)	Description
Cross-scale	National scale effects are evaluated at an aggregated scale in this case study. This involved aggregating certain relationships at the national scale, and relating them in a verifiable manner. The global cross-scale effect of climate change upon the water and (consequently) agricultural sectors is also conducted, thereby linking effects at the global and regional scale to the national scale capacity for agricultural production, and hence biofuels production.
Cross-sector	The agriculture, energy (biofuels) and water sectors are all directly inter-related in this case study, increasing the complexity of this case study from the previous. Through limits imposed on the available surplus agricultural production we were hence also able to get an understanding of how food security might consequently be affected.
Non-linearity	A variety of non-linear relationships were incorporated into the model.
Critical Limits & Thresholds	We determine the limits to biofuels production in different projected climate change scenarios, and we could evaluate a variety of different land-use strategies to find more a more nuanced, balanced options for production of biofuels using a range of crops, beyond those considered in the official strategy.
Adaptability	We were able to adapt the model formulated at national scale to assess climate change – irrigated agriculture interdependencies (in the previous case study) to assess the national strategy for biofuels production in relation to agriculture, to assess the possible impact of climate change effects on different land-use adaptation scenarios. Thereafter, as the national industrial biofuels strategy was finalised from

	<p>draft form, significant changes were made, which we were able to incorporate in a short amount of time, as described earlier in this section.</p>
Decision Support	<p>The Bayesian model formulated for this case study proved effective at coping with a large combinatorial range of climate change and agricultural land-use adaptations scenarios, and relating agricultural production to possible biofuels production alternatives. The learning from this case study was presented at an international conference in Fiji, and was later published in an international journal (Climate Research). This served to further establish the idea that the BPDA approach that could be used to enhance decision-support in social-ecological systems.</p>

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Table 6

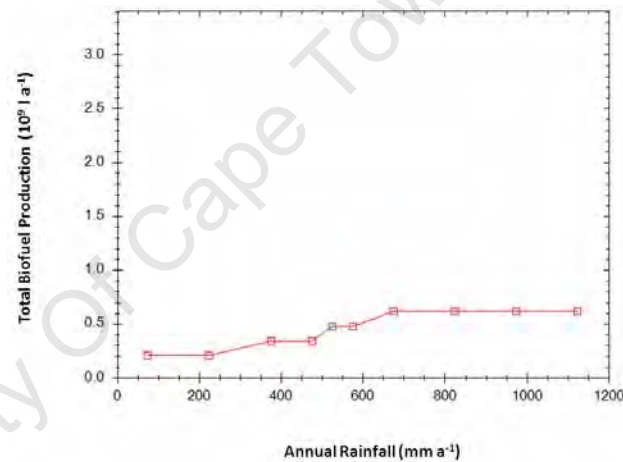
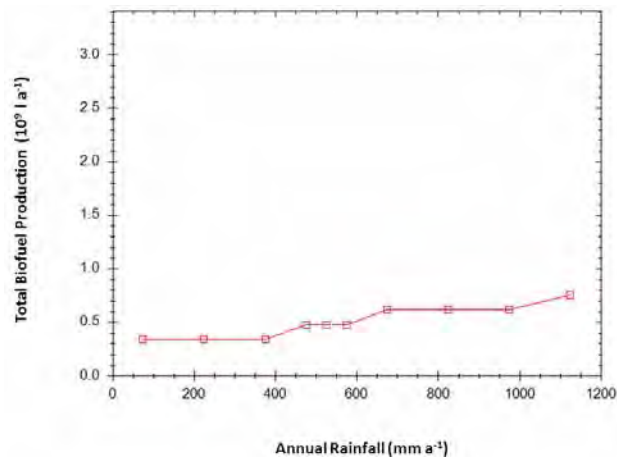
Land - Use Strategy 1 and 2: Compared Over a Temperature Range from 22⁰C to 27⁰C (see: Peter et al., 2009, In Press).

Strategy 1

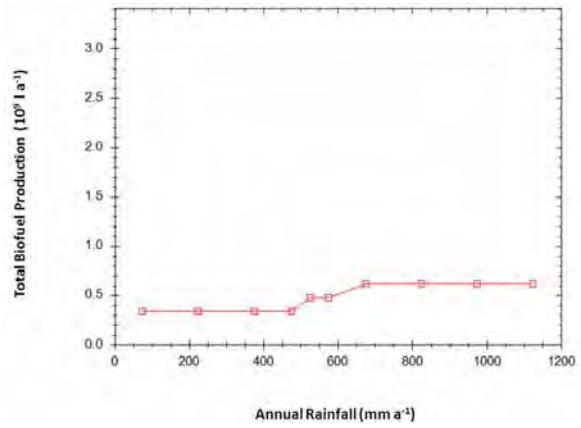
Strategy 2

1a: 22⁰C

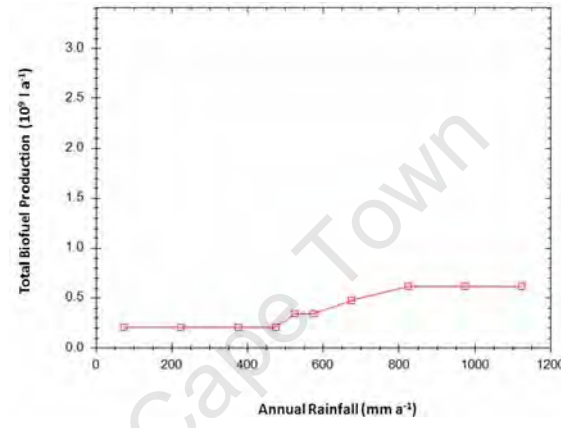
2a: 22⁰C



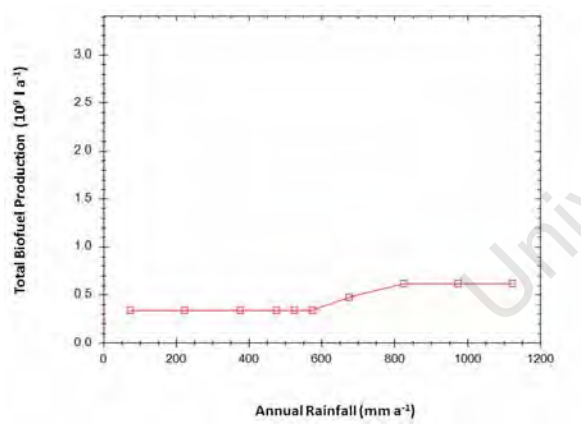
1b: 23⁰C



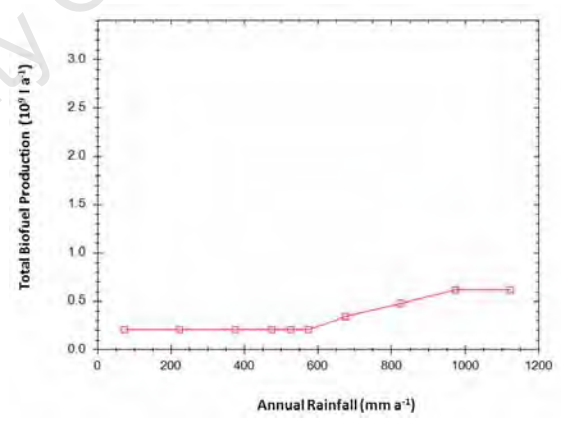
2b: 23⁰C



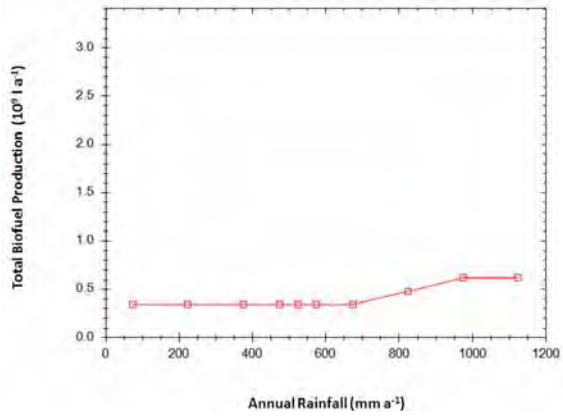
1c: 24⁰C



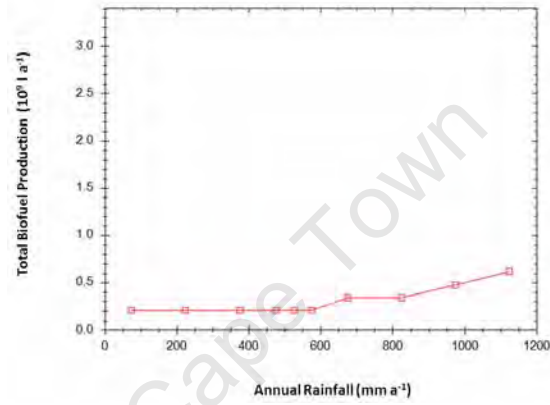
2c: 24⁰C



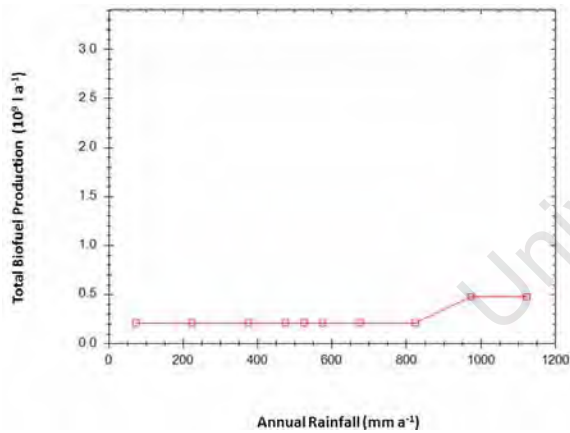
1d: 25⁰C



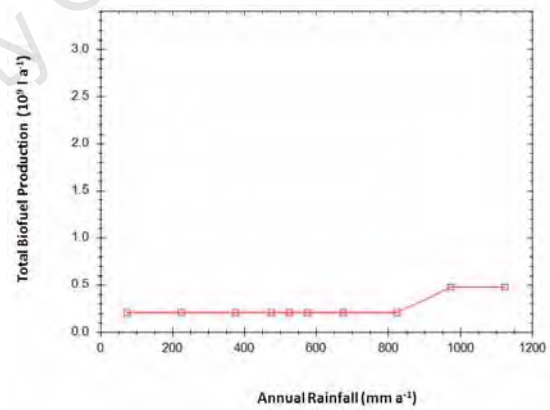
2d: 25⁰C



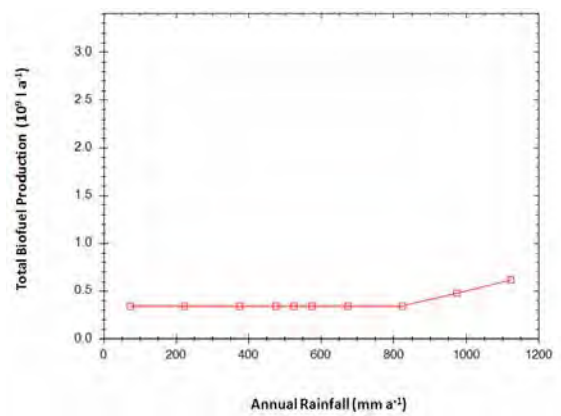
1e: 26⁰C



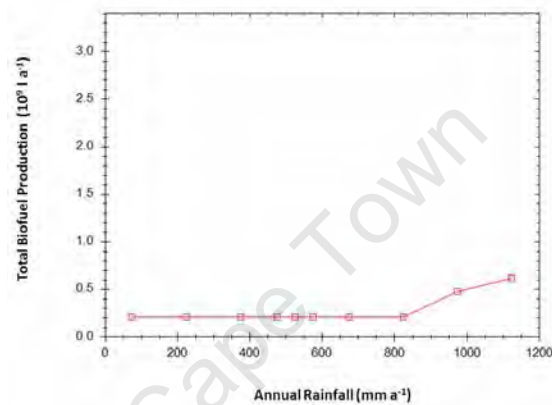
2e: 26⁰C



1f: 27⁰C



2f: 27⁰C



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6.4 Magisterial District Scales: Nelspruit & Mbombela

This study leveraged learning obtained from a two-year interdisciplinary Strategic Review Panel (CSIR) funded research project, and was conducted in close collaboration with Dr David Le Maitre of the Ecosystems and Biodiversity Unit at CSIR. In addition, Dr Belinda Reyers was involved in developing an understanding of the Biodiversity Intactness Index (BII), and provided data for the formulation of the BII module. The project researched the ecosystem benefit flows in the Incomati Water Management System (WMA), which lies in the Mpumalanga Province of South Africa (see Figure 25). Ecosystem benefit flows include both actual flows of materials, and flows of cash and other types of human benefits. We focussed on the Mbombela Local Municipality, as this is the scale at which local government decision-making and implementation occurs, in particular through Integrated Development Plans (IDPs). We learnt that we could adapt the BPDA approach to deal with a different contextual view of social-ecological systems i.e. one that was concerned with rural-urban benefit flows and ecosystem services. We also learnt that we could build a model at municipality scale (which is the scale of decision-making implementation in South Africa), using the learning obtained from previous case studies conducted at the national scale.

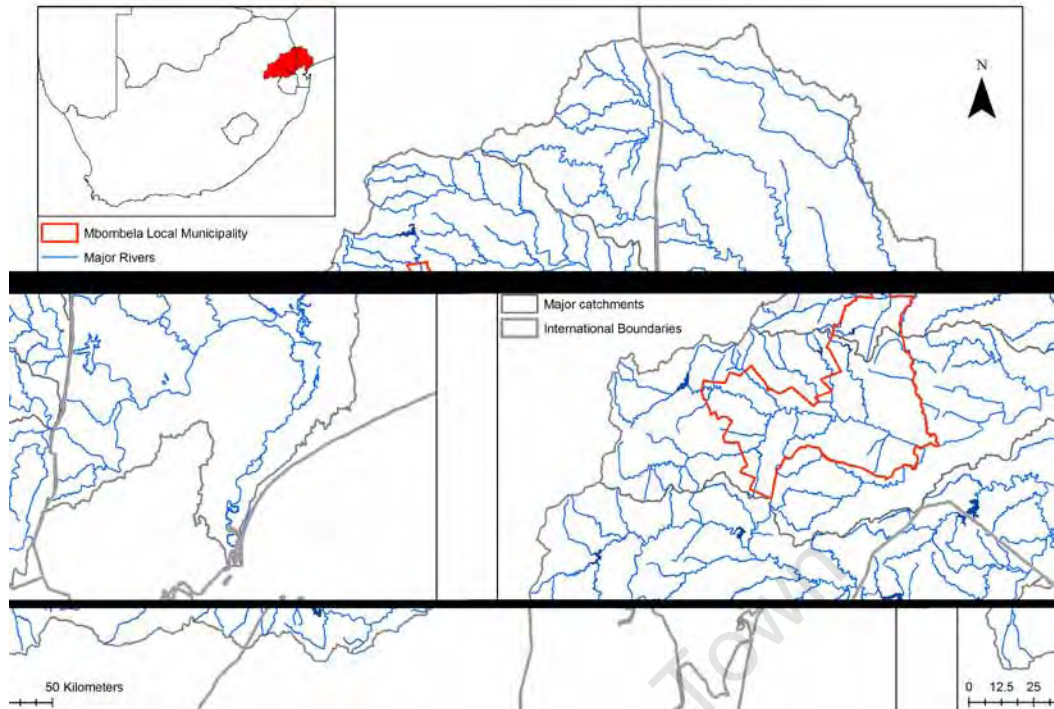


Figure 25: Mombela Map 1: Incomati catchment and Mbombela local municipality showing the major sub-catchments of the Komati, Crocodile and Sabie Rivers and the international boundaries. South African sub-catchment data and designations include Swaziland but end at the Mozambican border (Courtesy of Le Maitre).

This case study focussed on the Mbombela Local Municipality because it is an area with high densities of rural populations, situated around Nelspruit, which is a fast-growing hub of economic activity, migrant labour, trade and transport situated in a fast-growing economic corridor (i.e. from Johannesburg in South Africa to Maputo in Mocambique). The Mbombela Local Municipality consists of three magisterial districts, namely; Nelspruit, White River and Nsikazi (see Figure 26).

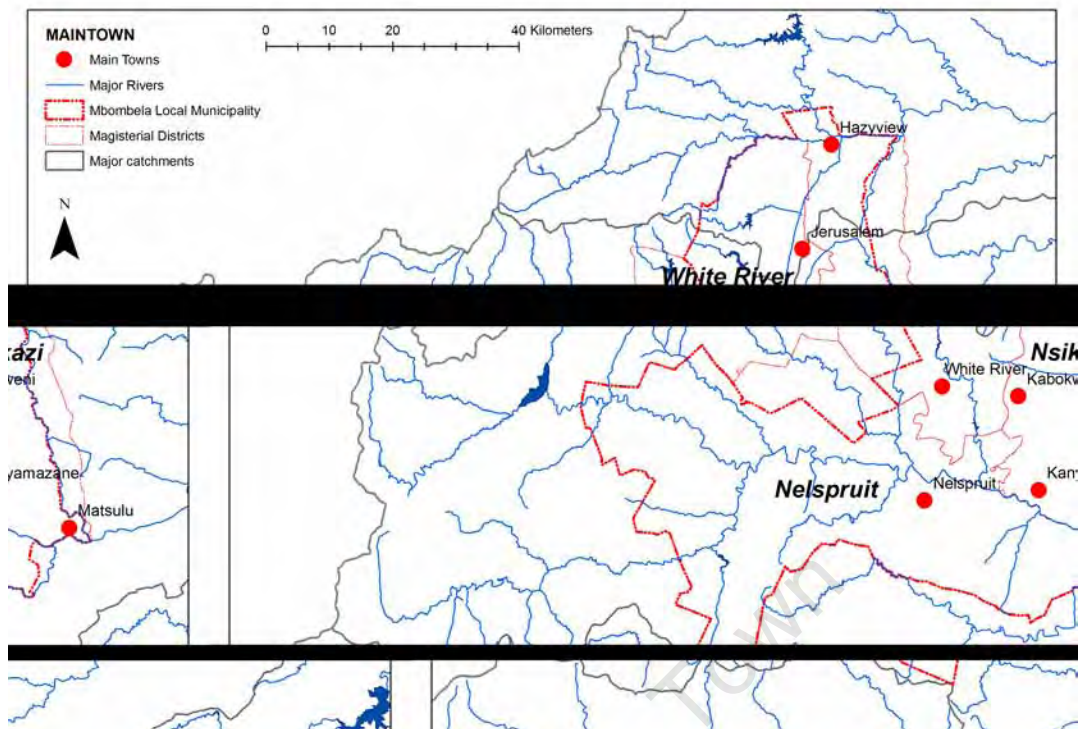


Figure 26: Mbombela Map 2: The Mbombela Local Municipality showing the magisterial districts (*italics*) and major towns. The magisterial districts are still used as the basis for reporting social and economic statistics although they are not the units for local governance, socio-economic management and development planning (Courtesy of Le Maitre).

We used research and expertise from the Ecosystem Benefit Flows Project, and conducted cross-disciplinary participatory workshops over a two-year period to formulate an understanding of ecosystem benefit flows (i.e. identifying sources, sinks and flows) using graphical causal maps and Bayesian networks using members of the project, which was led and coordinated by Dr David Le Maitre.

The results of 2-year Ecosystem Benefit Flows study and other sources of knowledge were used for informing integration and formulation of graphical causal maps and Bayesian models. Economic, biophysical and social analyses were integrated in this study, through interdisciplinary workshops and consultations with individual experts over a two-year period. A cross-disciplinary group that was small but diverse was used to rigorously

verify model formulation, characterisation and parametrisation. This included GIS, spatial planners, resource economists, hydrologists and social scientists, and various individual experts at the CSIR.

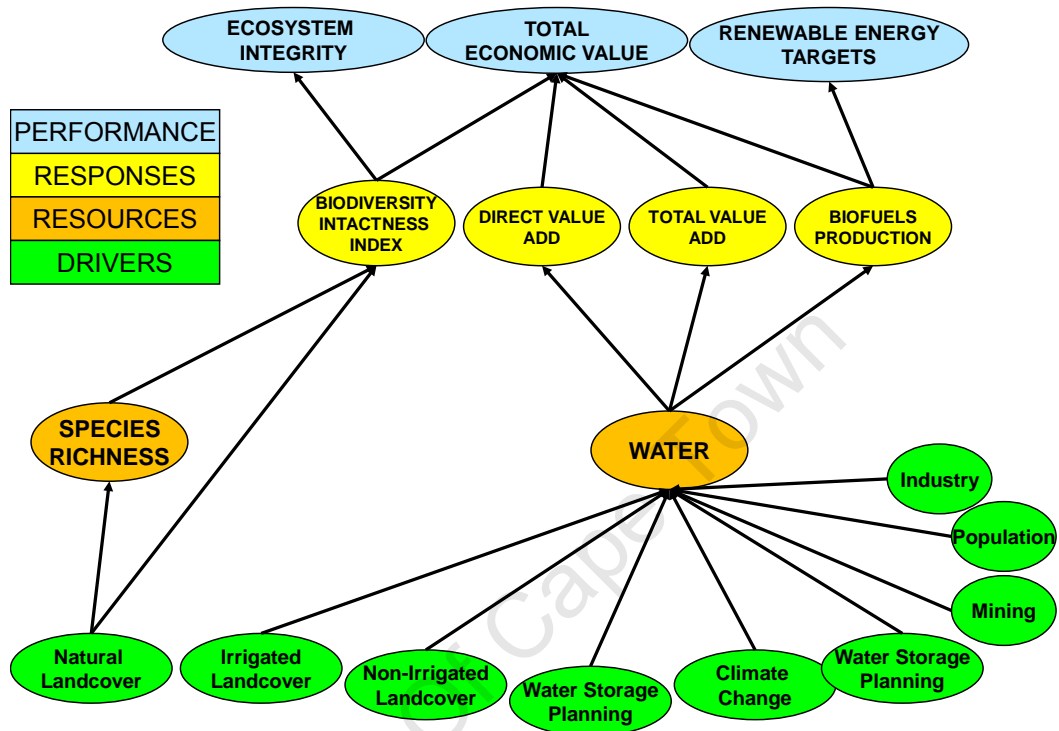


Figure 27: Conceptual Illustration of the Bayesian Network Model for the Mbombela Local Municipality: The arrows represent influences and causes and directions of interactions not flows of material goods or information.

A set of guiding questions (“what are the key ecosystem benefit flows, where are they going to? ... (and) are benefits being equitably shared?”), and a high-level model (see Figure 27) were used to stimulate the process of model formulation. The study focussed mainly on water related services as a point of integration and crop production because there was a bias of existing expertise in this area and they are critical ecosystem services. However, while the framework for relating water availability and agro-production was used in previous case studies, here it was expanded to include a variety of new embedded units, and associated measures of performance (see Figure 28). This includes modules for dryland and irrigated agriculture, irrigated and

dryland biofuel production modules, forestry mining and industry water use, sugar mill water use, population water use, biodiversity intactness index, household water-based subsistence and informal activities and a water storage, rainfall and temperature module (see Figure 28). For example, the water availability module in Figure 28 is shown in Figure 29, is extended to include a wide range of driver variables; for example, the impact of alien plant coverage is taken into account in this case study, a slight, but significant improvement upon the previous water availability modules used in previous studies.

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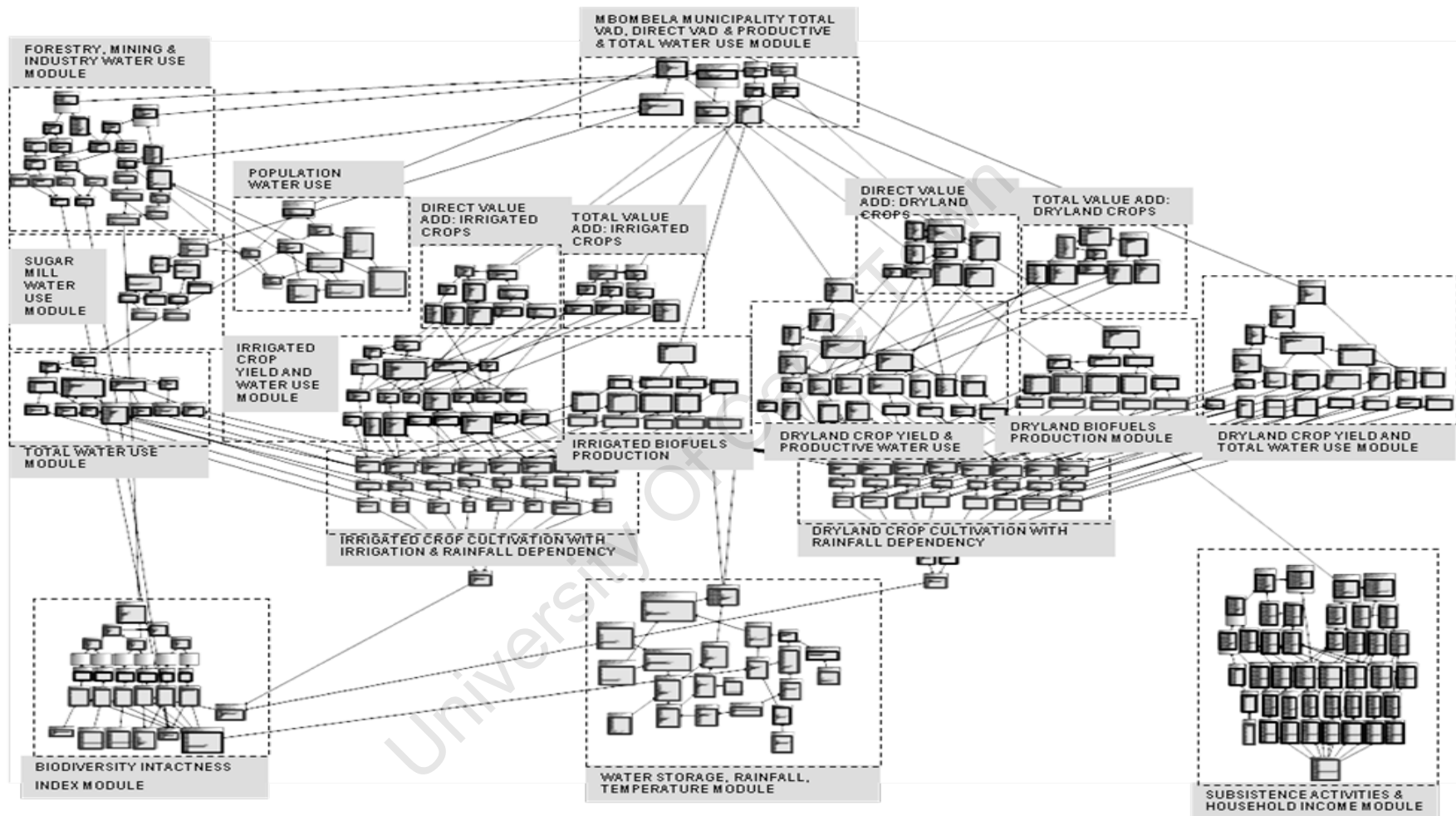


Figure 28: Full Bayesian Model for the Mbombela Local Municipality with Embedded Units: The Modules are shown in More Detail in Appendix C.

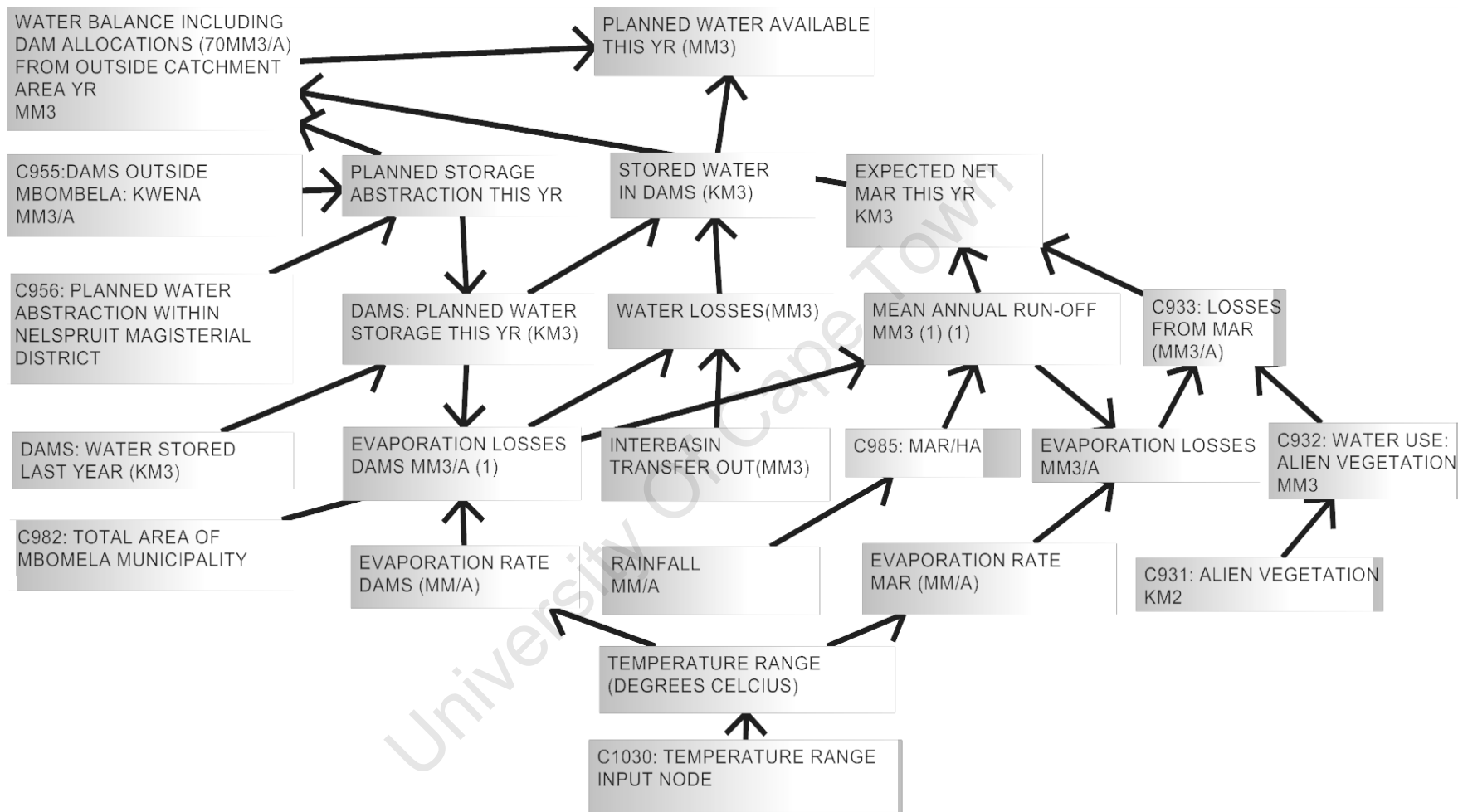


Figure 29: Planned Water Available (PWA): As the aggregate outcome of the various factors which determine water availability.

We focussed on identifying and characterising existing ecosystem benefit flows, and assessing the future state of ecosystem benefit flows, given a set of development and climate change scenarios. In this case study, it is necessary to provide more detail regarding the individual scenarios that were used, in order to ensure that the reader is able to interpret and appreciate the results that are presented later in this section while keeping in mind the context informing the study.

The scenarios take the following sequence. First the sensitivity of production of the system to current levels of human development activities to rainfall was established. This acted as a baseline for the Mbombela Bayesian Model i.e. against which other scenarios were compared. We then assessed the sensitivity of production to rainfall under different conditions of economic growth and development from the current baseline. Lastly, we increased annual average temperatures for the region over a range to test the sensitivity of production to evaporation and moisture stress. Through sensitivity analyses we were able to identify the optimal rainfall and temperature ranges, for sustainable growth conditions to continue.

The set of scenarios A-D from the study are listed below. These scenarios were developed by Peter & Le Maitre joint case study in 2008:

- “Scenario A: Vary mean annual rainfall from 0 mm to 1770 mm per annum – 100 % below the mean to 181 % above the mean (i.e. 975mm/a). All sectors are kept at current levels of productivity.
- Scenario B: The level of economic activity in each sector is increased by 10% except forestry which has already been limited by law to an allowable water-use. This is intended to be a medium to long-term growth strategy for the Mbombela magisterial district that could feasibly deliver the provincial growth required by ASGISA at the national

scale (i.e. 6%) in the short term. Urban centres in provinces need to achieve a benchmark of 10 percent growth in order to achieve the provincial targets in general across South Africa.

- Scenario C: Scenario B plus an increase in the mean annual temperature by 4°C. Regional climate change model predictions predict an average temperature increase of 2-3°C, but this scenario provides an extreme conditions test for temperature.
- Scenario D: The total planned water available (PWA) to the catchment, which aggregates the effect of rainfall, temperature, water storage, evaporation losses and alien plants, is varied from -210 to 493 Mm³/a per annum – 276 % above the average at approximately 178 Mm³/a per annum. The model makes allowance for evaporation losses and water demand by alien plants to become so large that a negative value can be derived for planned water available. As far as the model is concerned, the negative values are treated as a 0 state input to child nodes (responses) of the planned water available variable”.

The results for scenarios A – D are shown in part, in Figure 30, of which column 1 is illustrated in greater detail in Figure 31 in order to provide more detail for the reader. The rainfall ranges over which direct and total value add can be ensured are shown in the dashed regions outlined in Figure 30 and Figure 31. These indicate the rainfall ranges over which scenarios A-D are feasible, given the variations in temperature and other variables in the individual scenarios A-D, as listed above. Scenario C tests an extreme climate change scenario, where a mean annual temperature of 4°C is applied to scenario B.

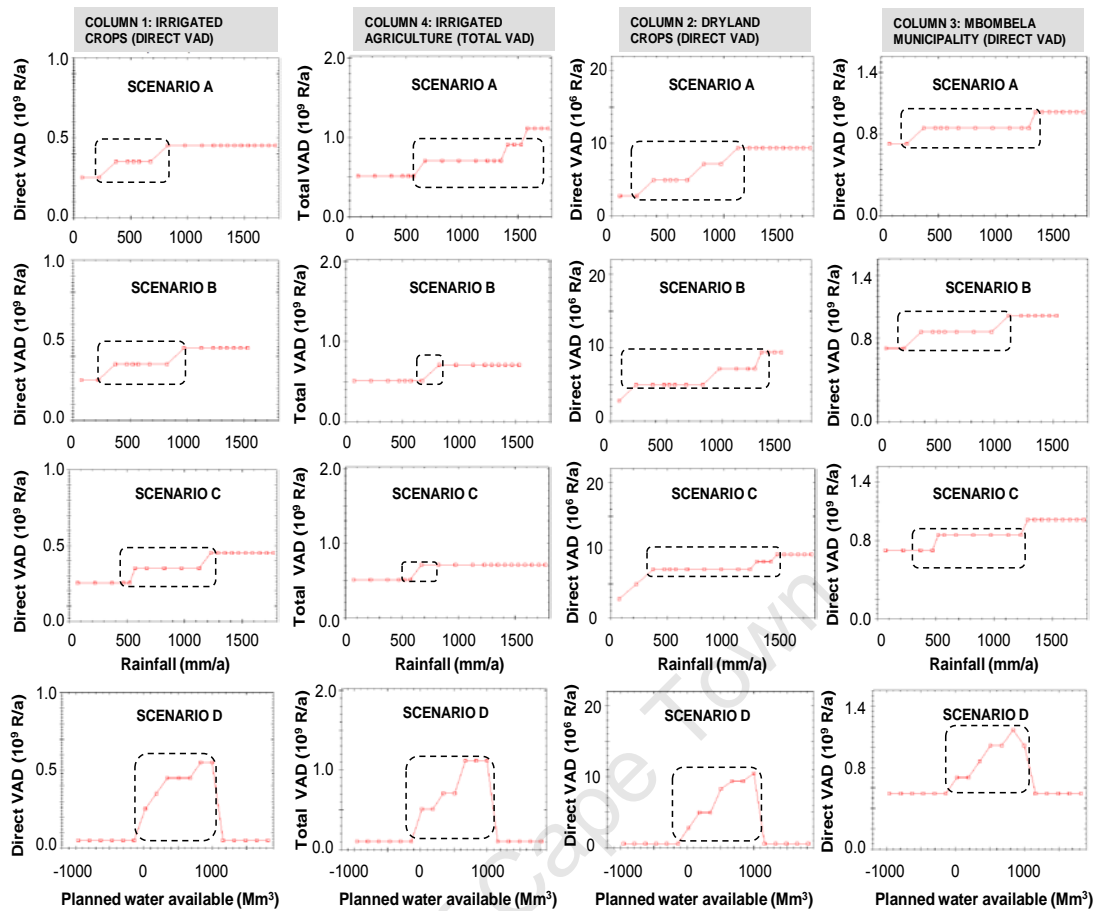
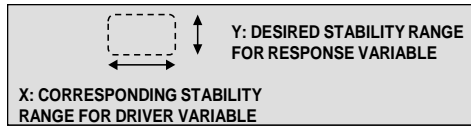


Figure 30: Results 1: Figure illustrating results for scenarios A to D, with the dotted boxes indicating the ranges which maintain the system in a desired state.

For the purposes of this dissertation, the key results of this case study relate to how critical limits can be visualised using the Bayesian interface (as shown in Figure 29 and Figure 30), and used to establish an idea of the **resilience** of a system in a variety of different scenarios. Cross-sector driver and response effects can be tested in a variety of scenarios, and the users of the BPDA approach obtain an understanding of system behaviours, limits and thresholds in a variety of circumstances, thus ‘getting a feel’ for system resilience.



Scenario A - see Figure 6: All sector productivities at current value – evaluating current sensitivity of system to variations in annual rainfall given the current temperature scenario

Scenario B – see Figure 7: Sensitivity of system level productivity to rainfall under growth conditions where every sector except forestry has been increased by approximately 10% growth

Scenario C – see Figure 8: Sensitivity of water-intensive production (esp agriculture) to rainfall, with critical stable growth regimes approximately characterized, with average temperature increased by 4 degrees at roughly 10 percent growth in each sector except forestry

Scenario D – see Figure 9: Sensitivity of production to water availability in the catchment, with stability regimes generally characterized (i.e. with rough interpolation at roughly 10 percent growth in each sector (except forestry).

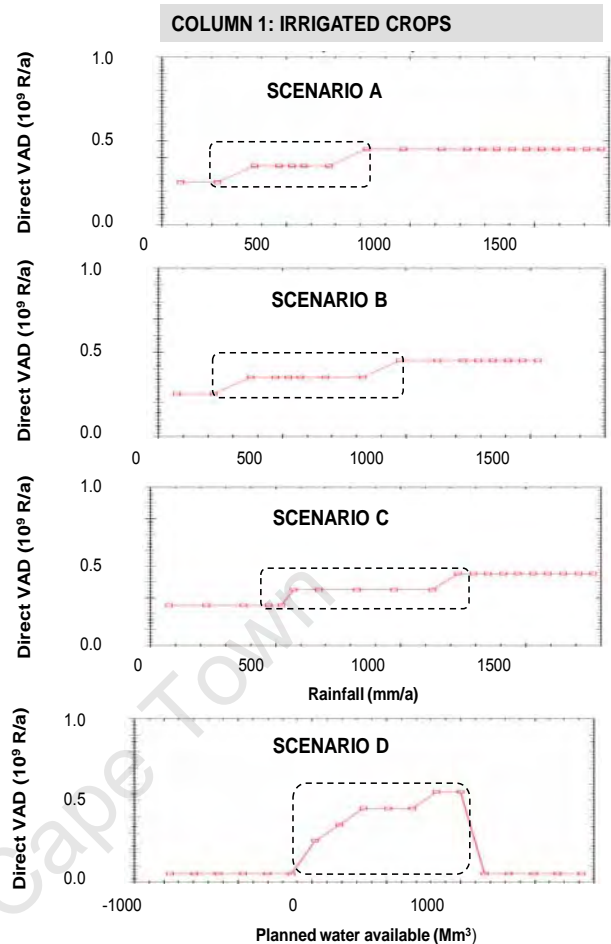


Figure 31: Results 1 in Detail: Results of scenarios A to D, illustrated with hypothetical desired ranges and thresholds within which system variables must remain in order to provide provide system level stability.

The other significant aspects of this study are related to the new sub-modules or embedded units that were introduced into the basic Bayesian framework that has informed previous case studies.

6.4.1 Water-Based Household Informal and Subsistence Activities Module:

A study by de Mendiguren Castresana (2003) focussed on identifying and quantifying the value add to water from household informal and subsistence activities such as brewing, construction, hair salons, livestock farming (goats and cattle), fruit and vegetable farming and ice block making.

In the effort to model cross-sector linkages pertaining to ecosystem benefit flows between rural and urban areas composing Nelspruit magisterial district, we made use of the de Mendiguren Castresana (2003).

The de Mendiguren Castresana study was conducted on the Bushbuckridge area, which is located very near Mbombela, and is a very similar to the densely populated rural areas in Mbombela. We formulated a Bayesian model for the Mbombela Local Municipality (i.e. based on an understanding of rural-urban households in Mbombela) to assess the benefit of subsidising water to low-income households in order to promote household and informal activity productivity. This provides a significantly different view of water as a mechanism for poverty alleviation from that taken through a 'trick-down economics' view, where water is subsidized to large industries and the socio-economic benefits are felt through employment and remuneration, and creating a value chain of activities associated with the primary industry.

In this case study, returns on water subsidized development schemes for promoting resilience of rural-scale informal and household economies can be compared with returns on water used in industry and farming (in terms of employment and remuneration). The study found that given the profile of rural and informal households in the Mbombela Local Municipality R7500 per annum could be added per household for an average household water use ranging from 20-30 m³.a⁻¹. This translates to direct household earnings at low-income levels of R800 million per annum for the Mbombela Local Municipality, at a cost of 3.1 Mm³.a⁻¹; a trivial cost in terms of the total water use of Mbombela, which is around 350 Mm³.a⁻¹.

In the Mbombela Municipality Bayesian Model, the view enabled by the household income module allows for trade-offs and benefits to be considered at both top-down and bottom-up levels of decision-making regarding how ecosystem benefits can be used to stimulate economy and alleviate poverty. In one sense, a key benefit is being able to contemplate

assess interventions at different levels in the system, within and between embedded units or sub-modules contained in the larger model.

6.4.2 Biodiversity Intactness Module:

We also developed a framework for biodiversity intactness index (BII) based on a study conducted by Scholes & Biggs (2005), which showed how biodiversity intactness could be estimated using expert elicited sensitivities regarding land-use change types. We used this study to formulate a Bayesian Biodiversity Intactness Module, and tested it in a range of scenarios. Each land-use change scenario can potentially be related to a change in biodiversity intactness. The usefulness of formulating this module in the case study is not only in the analytical results obtained from it. The case study helped us understand how expert opinion can be obtained and interpreted into the Bayesian network for BII estimation by making use of conditional probability tables (as shown and illustrated earlier in section 5.2.2 , and as explained in 5.2.3), resulting in a Bayesian framework that enables a multiplicity of possible scenarios to be tested.

6.4.3 The Nelspruit Bayesian Model:

In order to test the scale-ability of the BPDA approach, we applied the model framework to one of the constituent magisterial districts of the Mbombela, namely; the magisterial district of Nelspruit. The same causal structure that was used for Mbombela can be used for a smaller area of decision-making and monitoring, i.e. the magisterial district level. We intended to test whether the approach would prove useful at both larger and smaller scales of integration. However, this proved to be a matter that was more dependent on the ability of Bayesian network software to be able to cope with massive scale-ability in models. However, funding limitations constrained the study in pursuing a massive model, which linked the magisterial district to the municipal level of decision making. The issue of massive scale-ability is thoroughly addressed in the next case study, which is

the final and penultimate case study involving using Bayesian networks, in this dissertation.

The overall learning engendered in this case study is summarised below in Table 7.

Table 7:

Critical Learning for BPDA Approach from Mbombela Case Study

Critical Learning Points (BPDA)	Description
Cross-scale	Here we adapt our understanding at the national scale to formulate a model at the municipality scale. This is the scale on which Integrated Development Plans (IDPs) are planned and implemented in South Africa, and constitutes a critical decision-making scale. Within this municipality scale model we were also able to assess informal economic activities at the household scale. We then formulated a model at the Magisterial district scale, namely the Nelspruit Magisterial District, with a view to linking these different scale models in future research.
Cross-sector	In this case study we explored how water-related ecosystem benefit flows relates rural, per-urban and urban populations, through the formal and informal economic sectors.
New Indices	We formulated two new models; namely the informal household economic activities module, and the biodiversity intactness index module, thereby broadening the extent of indices from the previous case study.
Resilience and Adaptive Capacity	In this case study we derived critical limits and thresholds as in the previous case study, and learnt that by establishing these in a range of scenarios a characterisation and understanding of system resilience could be obtained, in the context of a variety of land-use and household adaptations.
Adaptability	We also adapted the learning from previous studies to a new context of inquiry. We were more concerned with introducing indices through developing an understanding of

	rural household level informal economics and BII, and with agricultural and other land-use activities.
Decision Support	We also showed that the BPDA approach can be employed to assess various scales of decision-making and influence i.e. municipality, magisterial district and household scales.

University Of Cape Town

6.5 Province: Western Cape

The opportunity to deal with the issue of massive scale-ability of Bayesian models, and their usefulness at large decision-making scales emerged with this case study, which is the penultimate case study in which the BPDA approach was *fully* applied. We learnt that the BPDA approach could be implemented at massive scale, and could integrate across a wide range of interdependent sectors. The project involved reviewing the climate change strategy of the Western Cape Province in relation to other sub-sectoral strategies (e.g. water, energy, transport, and a large range for formal and informal economic sectors). The CSIR review team included Dr Alex Weaver, Dr Mike Burns, Dr Michelle Audoin, Dr Willem de Lange, Ms Josephine Musango and Dr David Le Maitre. The decision-makers included from provincial government were; the director Mark Gordon, and deputy directors Dr Dennis Laidler and Victor Nicholson. The various heads of provincial government in other areas were also briefed, in presentations, of recommendations that emerged as a result of the review.

In this case study we embarked upon a project to support decision-making at the provincial scale, working with the Western Cape Government's Department of Environmental Assessment and Development Planning (DEADP). The author was approached by DEADP to perform a review of their recently finalised Climate Change Strategy and Action Plan for the Western Cape (CCSAPWC, 2007), which identified adaptation and mitigation response programmes, and particular focus areas as outlined in Table 8 below (CCSAPWC, 2007). We proposed implementing the BPDA approach in support of the review. The project involved a collaboration between the author, as a senior researcher of the CSIR and Complex Adaptive Systems Pty Ltd, a local research-based SME that built the software interface in earlier collaborations with the CSIR. This collaboration was necessary in order to develop the software to be able to handle a large number of variables and

embedded units in a single Bayesian model, and to ensure that the challenge of massive scale-ability could be realised

The Western Cape Climate Change Strategy and Action Plan (CCSAPWC, 2007) was the outcome of a large multidisciplinary study and interactions between participants in a range of very large stakeholder participation processes. The process that was followed in producing the strategy attempted to solicit expertise, opinions and insight from as broad a range of the private, public and civil society sectors. The main outcome of the strategy was to establish adaptation and mitigation programmes with a range of areas of focus, as outlined in Table 8. These areas of focus were determined as those that would best address the key linkages and gaps in knowledge that would bring about sustainable growth in the short, medium and long-term.

Table 8

Description of Climate Change Adaptation and Mitigation Programmes Proposed by CCSAPWC (2008)

Programme Type	Name of Programme	Focus Areas of Programme
Adaptation response strategy and programmes:	Integrated Water Management Programme:	<ol style="list-style-type: none"> 1. Conserving wetlands, estuaries and rivers. 2. Establish and implement the ecological reserve. 3. Foster science/environmental/government dialogue. 4. Systems maintenance and repairs. 5. Strengthen resilience against 1:100 year drought. 6. Establish uninterrupted water conservancy targets. 7. Increase water efficiency through pricing strategies. 8. Research areas: demand, cost benefit of irrigation efficiency and profitability.
	Climate Change, weather research and information programme:	<ol style="list-style-type: none"> 1. Weather stations. 2. Foster science/environmental/government dialogue. 3. Research irrigation efficiency. 4. Research pest sensitivity to climate change. 5. Increase number of Air Quality stations; integrate other data – e.g. traffic.

	Land Stewardship and Livelihoods Programme:	<p>Establish clear linkages between land stewardship, livelihoods and the economy:</p> <p>Land Stewardship:</p> <ol style="list-style-type: none"> 1. Effective land usage and land care. 2. Protect, maintain and enhance natural resources.
Mitigation response strategy and programmes:	Energy, transport, waste and air quality management programme:	<ol style="list-style-type: none"> 1. Reduce Carbon footprint. 2. Air quality monitoring. 3. Waste management, energy conversion and recycling initiatives 4. Develop the provincial renewable resources. 5. Energy efficiency – drive targets, incentivise through pricing strategies. 6. Develop provincial industry and innovations – electric car, SWH, installation capacity. 7. Transport fuel replacement. 8. Household fuel replacement.

The concern that decision-makers expressed is that; (1) there were a number of different proposed interventions and they desired a way of knowing where to focus their efforts and funding to create impact, (2) they were concerned with the alignment of the strategy with other provincial departmental strategies and proposed interventions that were being implemented, such as:

1. The Ikapa Growth and Development Strategy (IKAPA GDS, 2008),
2. The Sustainable Energy Strategy for the Western Cape (SESWC, 2007),
3. The Western Cape Sustainable Development Implementation Plan (WCSSDIP, 2007), and
4. The Western Cape Water Supply Reconciliation Strategy Study (WCWSSRSS, 2007).

A key challenge of this case study was to ensure that the alignment between the focal areas of programmes proposed in the climate change strategy (CCSAPWC, 2007) and various interventions proposed in the abovementioned strategies (e.g. water and energy), could be tested in an integrated modelling framework representing the Western Cape Province system.

The sustainable energy strategy for the Western Cape (SESWC, 2007) is but one strategy with which the climate change strategy (CCSAPWC, 2007) must align, but it is presented here because it was of critical importance to the climate change strategy (CCSAPWC, 2007). The energy strategy for the Western Cape suggests a number of strategic interventions that could be used in combination to reduce energy consumption and emissions from the various sectors, as outlined in Table 9 below (SESWC, 2007). A number of energy savings are proposed, which focus on savings in the transport, industrial, commercial, governmental and residential sectors.

Table 9

Proposed Energy Savings Interventions Proposed in SESWC (2007)

Sector	Energy Use (% of Total Energy Consumption in Western Cape)	Proposed Interventions (SESWC 2007)
Transport	Uses 34 % of total energy consumption	<ol style="list-style-type: none"> 1. Model shift from private (reduce by 25 %) to public transport (increased to 75 %). 2. Taxi shift to diesel (100 % of taxis). 3. Switch to Biodiesel: 15 % of diesel market.
Industry	Uses 46 % of total energy consumption, produces 48 % of emissions:	<ol style="list-style-type: none"> 1. Energy efficiency. 2. Fuel Switching – half of thermal energy to be supplied by natural gas instead of coal.
Commerce & Government	4 % of total energy consumption.	<ol style="list-style-type: none"> 1. Lighting (CFL replacement). 2. Heating Ventilation and Cooling
Residential	% of energy supply and produces 15% of CO ₂ emissions	<ol style="list-style-type: none"> 1. Solar Water Heaters: 15 % replacement. 2. CFL – 100%. 3. Energy efficient new households.
Buildings	Energy efficiency of buildings e.g. ceilings	No clear proposed interventions

Of key concern to the implementation programmes proposed in the western cape climate change strategy and action plan (CCSAPWC, 2008) is whether the proposed savings as outlined in the sustainable energy strategy of the Western Cape (SESWC, 2007) are aligned, or will act in a complementary way.

The proposed interventions are shown in Table 9. The energy strategy also proposes options for increasing the energy supply of the Western Cape:

1. Coal generated electricity.
2. Nuclear Energy.
3. Natural Gas.
4. Wind energy.
5. Biomass.
6. Solar radiation.
7. Wave power.
8. Waste.
9. Hydropower.

Another critical concern revolved around the fundamental assumptions made in supporting studies of the CCSAPWC (2008) regarding climate change effects, and how they would unfold in the short and medium terms. As mentioned before, global climate change models make projections for 2099, as that is the resolution at which they are currently capable of providing reliable sensitivity at for global and regional climate change simulations. The economic projections used in formulating the CCSAPWC (2008) were based on a linear projection, backwards from 2099, of climate change effects such as changes in rainfall and temperature. As acknowledged by the IPCC (2008) such linear projections are unlikely to provide reliable and resilient human adaptations in the short and medium term. This is because more drastic changes and higher variability generally characterise the forecasted trends that global climate change models show in future scenarios (IPCC, 2008).

Therefore, it was necessary to test the resilience of growth and development in the Western Cape Province over a range of climate change scenarios, instead of basing an understanding of resilience on a simple linear regression of trends, backward from 2099.

Two processes, which form the core of the BPDA approach proposed in this dissertation, were tested in this penultimate case study, namely; (1) participatory processes between decision-makers and cross-disciplinary research groups, and (2) model-based integration across disciplines, sectors, programmes and strategic foci of respective strategies.

We conducted a review process, which included participatory process facilitation with both decision-makers and cross-disciplinary researchers. The review process, which included a series of workshops with and between decision-makers and researchers, is shown in Figure 32. The DEADP provincial government decision-makers played a role in the model development and verification at various stages of the review. The general focus of outcomes of the review focus on; (1) identifying gaps in knowledge, information and data about critical linkages (especially cross-sector) in the Western Cape Province, and (2) evaluating whether the emphasis of the strategic adaptation and mitigation programmes that have been set in place, is appropriately focussed on linkages that will make the desired impact on sustainability of growth, development and ecological integrity in the Western Cape Province.

Process Description

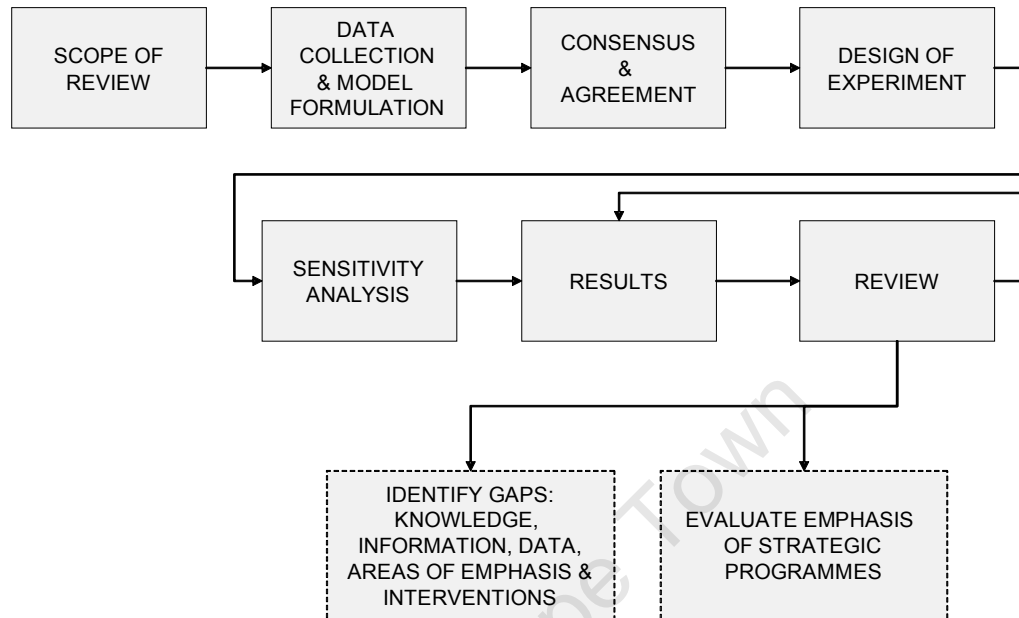


Figure 32: BPDA Review Process Western Cape: The process undertaken to perform the review, which involved a series of client consultations and review team workshops.

The Western Cape Bayesian Model is shown in broad outline in Figure 33. The model extends the models formulated in previous case studies to include a wide variety of diverse sectors of the Western Cape Province, and at various levels of detail. These include; irrigated and dryland agriculture, livestock, tourism, transport, informal and SMME sector, construction, manufacturing, water-based household subsistence and informal activities, transport, energy and water. Some of these modules have been included in Appendix C, so that the reader can conveniently familiarise themselves with the illustrations while reading the text.

We made use of known sector productivities for 2004-2005 were used to establish a core set of measures of performance for each of these sectors. The top system level measures of performance of the model include; noxious gases (VOC, PM10, PM2.5, SO₂, NO_x), solid waste, CO₂ emissions, water and energy consumption, Gross Domestic Product (GDP), Gross Geographic

Product (GGP) and Employment. These are formulated according to the classes in which the information was obtained, and therefore involves a degree of aggregation. However, reliable information was available regarding historical and current ratios and expert judgement was employed in verifying these aggregations.

Irrigated and dryland agriculture modules were formulated in order to assess their water use levels in different scenarios, value add to water per crop type and yield, and total value add per crop type and yield. Crop yields are constrained to be sensitive to their water requirements by a generalised relationship, and will not meet full production under less than optimal water supply conditions (or alternatively, excessive water saturation conditions).

The total hectares' under agricultural cultivation is set to current levels. Energy use for irrigation constitutes a significant share of farm-scale expenses and is also calculated in the model.

The livestock, tourism, informal and SMME sector, construction and manufacturing modules, were formulated according to the level of aggregated data available on the sector, and what was available in the literature at the time.

The water and energy modules constitute the core modules around which all other sectors were integrated in formulating the Western Cape Bayesian Model. The information and data sources used to populate the water and energy modules include a wide variety of known data and embedded sub-modules to assess for example; savings options, the impact of changes in climate related variables on water and energy.

The Bayesian energy module calculates the electrical energy production of the Western Cape according to a permutation of a range of productions options ranging from coal, new coal, nuclear, new nuclear, PBMR, gas turbine, wind, ocean, solar to wind energy production. It also

takes into account backup options, savings in demand side management measures and household fuel replacement.

The water module aggregates the water supply over the entire Western Cape, a cumulative aggregation of catchments within the Western Cape. The water availability module is largely generic, and contains a variety of drivers, of which average rainfall and temperature are mainly used.

Lastly, the transport module was formulated and populated according to the availability of reliable information regarding; the number of vehicles, their average mileage per annum, and associated emissions, depending on the type of fuel used (petrol or diesel). The transport module also allows some of the transport sector emissions savings actions to be tested, such as fuel switching and passenger switching, respectively.

Current state of electricity production includes savings from adaptation measures, and with mitigation and backup options.

To summarise, the system level measures of performance included in the Western Cape Bayesian Model includes the following top-level measures of performance (see Appendix C for detailed illustrations of embedded units or sub-systems):

1. GDP,
2. GGP,
3. Employment & unemployment,
4. CO₂ emissions,
5. Noxious gas emissions (NOX, VOC, SO₂, etc.),
6. GHG emissions,
7. Water use and potential for savings,
8. Energy use and potential for savings,
9. Household informal and subsistence activities,
10. Pollution and waste loads (solid and air),
11. Biodiversity intactness index (heuristic)

Significant sub-system level measures of performance include:

- Planned water abstraction and storage, and,
- Water Module: Including evaporation losses - from mean annual runoff (MAR) and dams.

The sub-system level drivers, contained within embedded units that are catered for in the model are indeed numerous in the case of each module and may be viewed in more detail Appendix C.

It is worth noting that a linear extrapolation between water and energy deficit in production when compared to demand, is used to determine losses to sectors. This broad simplification is used to illustrate the extent of variation that occurs, rather than to predict actual measures (for example, exactly how much GDP might reduce as a consequence of water and energy shortages).

The climate change scenarios conducted in this case study are consistent with the linear projections adopted in the CCSAPWC (2007), and in the growth scenarios adopted in IPCC (2008) predictions.

We take linear projections as a point of departure from which variations should be assessed. Since we are more concerned with the variation in the supply and demand of energy, the value of such an analysis is in estimating the impact of water and energy shortages, in this case, with linear projections serving as a baseline for analysis.

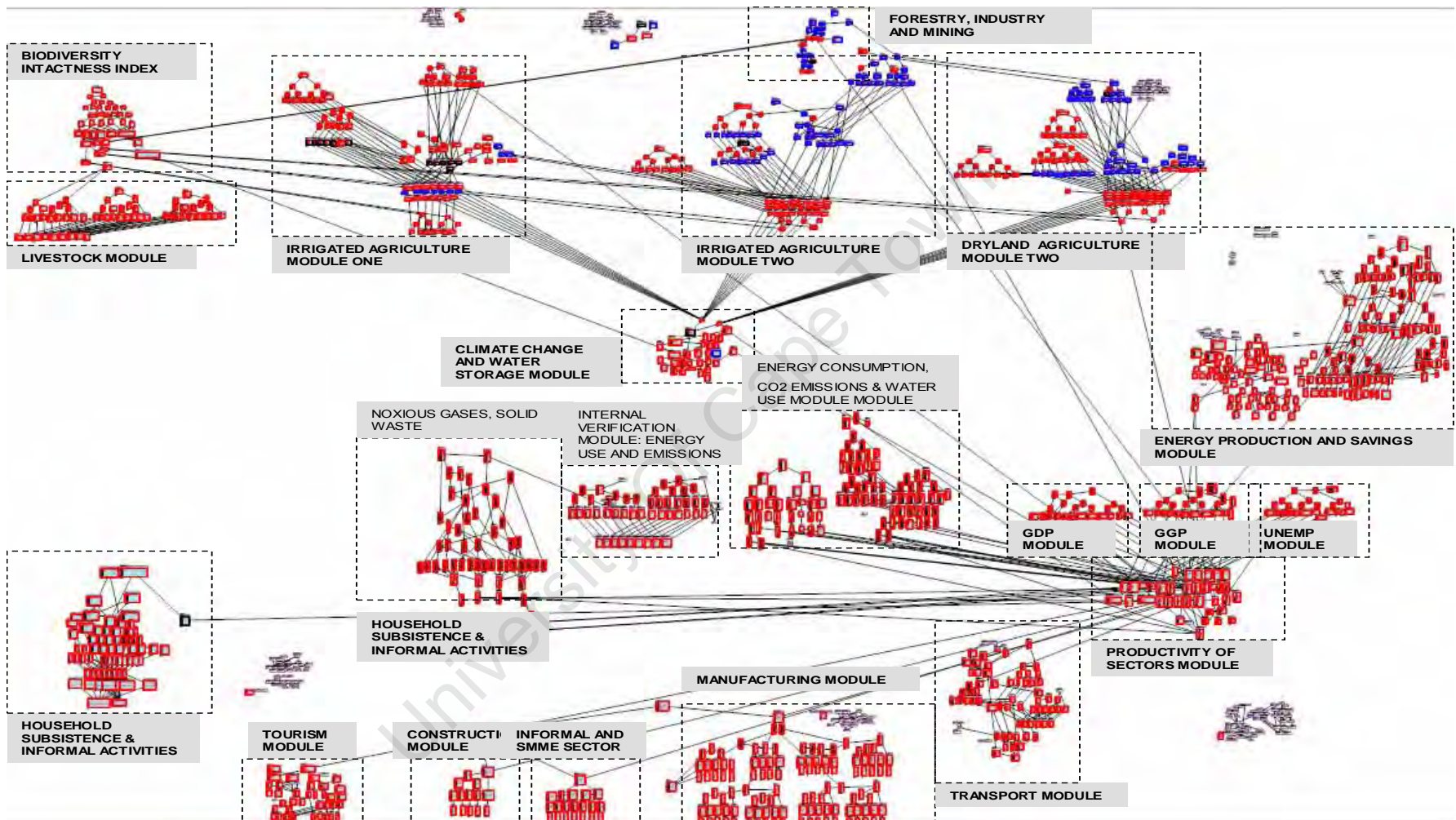


Figure 33: Illustration of Modules in the Western Cape Bayesian Model (CSIR & CAS Pty Ltd): Selected module causal maps shown in Appendix B.

The Bayesian model was formulated to evaluate the following areas of concern, paraphrased from the Review of the Western Cape Climate Change Strategy & Action Plan (RCCSAPWC, Peter, 2008):

1. Establishing an integrated understanding of the ‘current’ or baseline state of the Western Cape Provincial system based on 2003-2005 statistics. This scenario forms the baseline for comparison for the scenarios that reflect growth within sectors constituting the Western Cape Province socio-economic base.
2. Evaluating water and energy sector related limitations of the Western Cape Province in scenarios with equal growth of sectors (i.e. all sectors except agriculture, forestry and fishing).
3. Evaluating scenarios that reflect lower levels of growth than at the levels projected by supporting studies of growth (guidelines were drawn RCCSAPWC (Peter, 2008), and from information used as guidelines from source material (which includes: WCTT, 2005; WCTB, 2007; SESWC, 2007; TSB, 2005/6; WCSER, 2003; IKAPA GDS, 2008; WCWSSRSS, 2007). These were discussed and reviewed by the review team and in consultations with DEADP.
4. Evaluating scenarios that grow sectors at approximately the same levels as projected by supporting studies of growth in the short term (5 years), but decreased from short term growth projections in the medium (10 years) and long term scenarios (guidelines were drawn from source material in: WCTT, 2005; WCTB, 2007; SESWC, 2007; TSB, 2005/6; WCSER, 2003; IKAPA GDS, 2008; WCWSSRSS, 2007; CCSAPWC, 2007). These were discussed and reviewed by the review team and in consultations with DEADP.”
5. Evaluating the sensitivity of the water availability to the Western Cape provincial system to increases in temperature across different rainfall ranges as outlined in the climate change strategy and action plan (CCSAPWC, 2007), based on projections from global climate

change models published by the International Panel for Climate Change (IPCC, 2008).

6. Testing the potential of combining backup electricity production alternatives and demand side management of electricity such as residential electricity use in the Western Cape.
7. Testing different energy production scenarios i.e. combinations of renewable and no-renewable energy production strategies for short, medium and long term stability of the Western Cape provincial system.
8. Testing the sensitivity of these energy production scenarios to temperature induced transmission losses on lines that range about 1800km away from the Western Cape, using an average loss estimate of 10% (losses vary between 8-20%; CCSAPWC, 2007).
9. Testing transport fuel use and emission savings options against short, medium and long term growth scenarios for the transport sector. The savings options include, switching fuel use to diesel, a possible switch from private to public transportation.
10. Testing household income for informal and rural households generated through water-based informal and subsistence household activity income generation activities such as hair salons, fruit trees, vegetable cultivation, brewing).
11. Tourism – assess possible growth of tourism sector.
12. Agriculture - identify efficiency measures and possible growth strategies.

The results of this study are too long to be shown in complete detail in this dissertation. Key excerpts from the RCCSAPWC (2008), containing a detailed description of scenarios and general descriptions of results are outlined in Appendix A

The full results of this study can be viewed by the reader in the Review of the Western Cape Climate Change Strategy and Action Plan (RCCSAPWC, 2008), and are too elaborate and detailed to be presented in this dissertation in

full. Rather, the results of the study are summarised in this section, as they are outlined in (RCCSAPWC, 2008).

The scenarios conducted for the study were both intended to test limits and to identify levels of water and energy savings that will be required for growth in the future, if the current strategy is pursued. This can then be compared against IPCC rainfall reductions and temperature variations, and used as a basis for discussion, interactively in the workshops.

6.5.1 Description of General Scenarios A- I

The study first assessed the current, baseline conditions and used this to verify the constraints of the Western Cape Bayesian Model. We then assessed system level responses to a range of possible growth trajectories (90-130%) associated with each variable. Thereafter we evaluated different combinations of growth in different sectors; in order to find out which combinations of sectoral growth conditions provide resilience to climate change effects. This was conducted in a fashion similar to that conducted in the previous case study (i.e. the Mbombela case study).

Scenarios A-I (see **Table 10**) deal with a range of short, medium and long-term scenarios that were chosen after many model runs to test various assumptions in the western cape climate change strategy (CCSAPWC, 2008) about the emphasis of programmes, interventions and the future sustainability of the Western Cape Province. Projected growth scenarios were drawn from a number of studies and from expert judgements, and climate change scenarios were aligned to the scenarios results of GCM models as published by the International Panel for Climate Change (IPCC, 2008). Scenarios A-I are described briefly in **Table 10**. These descriptions are elaborately detailed in **Table 11**, and the results of scenarios A-I are presented in **Table 12**.

Table 10

Description of Scenarios A - I: Western Cape Province (excerpts from RCCSAPWC 2008)

A	Short term growth per annum – 5yrs. Growth of Tertiary Sectors (% growth from current values).	Finance, real estate and business, Tourism, Informal sector and SMMEs, construction and manufacturing are the lead growth sectors. Other sectors (e.g. agriculture) are left at 0 or 1% growth from current growth.
B	Short term– 5yrs. Growth of tertiary, agro-forestry, manufacturing and other sectors.	This scenario is the same as scenario A, except that agriculture, forestry and fishing and other producers is grown by 5% from its current value.
C	Short term growth– 5yrs.	Growth as in scenario B with 5% decrease in agro-forestry and fishing (i.e. more water and energy efficient) (% growth from current values).
D	D: Short term growth– 5yrs.	Scenario D: Growth as in scenario C with additional 5% decrease in alien plant cover (which results in additional water savings to the system).
F	F: Short term growth – 5yrs.	Scenario F: Higher short term growth of selected sectors with 15% alien plant cover removal, agroforestry water and energy efficiency reduced by 15% (% growth from current values), and mining reduced by 5%.

G	G: Medium term projected growth 10yrs.	Scenario G: Growth of tertiary sectors increased to almost double the short term growth levels, with agro-forestry efficiencies implemented in scenario F; alien plant clearance increased to 15%, and agriculture, forestry and fishing decreased by 15%, , and mining reduced by 5%; resulting in more water and energy savings in the medium to long-term.
H	Long term growth per annum – 20yrs (% growth from current values).	Growth of tertiary sectors and general govt increased substantially to represent long-term growth. Savings are the same as in scenario G (aliens, agroforestry and fishing, and mining).
I	Long term growth per annum – Scenario I 20 yrs (% growth from current values).	Increase growth substantially from scenario H: including general govt, community, social and personal services, construction and household income.

Table 11:

Specifications for Short, Medium and Long-Term Growth of Tertiary Sectors - Estimated Conservatively from Projected Growth Levels

SCENARIO	A	B	C	D	F	G	H	I
SECTOR PRODUCTIVITY DRIVERS (% growth from current values)	Short term growth per annum – 5yrs: Scenario A: Growth of Tertiary Sectors (% growth from current values)	Short term– 5yrs: Scenario B: Growth of tertiary, agro-forestry, manufacturing and other sectors (% growth from current values)	Short term growth– 5yrs: Scenario C: Growth as in scenario B with 5% decrease in agro-forestry and other sectors (i.e. more water and energy efficient) (% growth from current values)	Short term growth– 5yrs: Scenario D: Growth as in scenario C with 5% decrease in alien plant cover (% growth from current values)	Short term growth – 5yrs: Scenario F: Higher short term growth of selected sectors with 20% alien plant cover removal and agro-forestry water and energy efficiency reduced by 15% (% growth from current values)	Medium term projected growth 10yrs: Scenario G: Growth of tertiary sectors with agro-forestry efficiencies implemented in scenario F (% growth from current values).	Long term growth per annum – Scenario H 20yrs (% growth from current values)	Long term growth per annum – Scenario I 20yrs(% growth from current values)
HOUSEHOLD INCOME	9	9	9	9	9	9	22.5	47.5
FINANCE, REAL	37.5	37.5	37.5	37.5	22.5	47.5	95	95

ESTATE AND BUSINESS								
TOURISM	32.5	32.5	32.5	32.5	17.5	42.5	95	95
INFORMAL SECTOR & SMMES	22.5	22.5	22.5	22.5	22.5	42.5	95	95
TRANSPORT	22.5	22.5	22.5	22.5	7	7	17.5	17.5
CONSTRUCTION	37.5	37.5	37.5	37.5	9	17.5	32.5	47.5
MANUFACTURING	17.5	17.5	17.5	17.5	22.5	22.5	55	75
WATER & ELECTRICITY	1	1	1	1	1	5	9	9
AGRICULTURE, FORESTRY & FISHING	Initial State: 0	5	-5	-5	-15	-15	-15	-15
AGRICULTURE	1	5	-5	-5	-15	-15	-15	-15
FORESTRY	1	5	-5	-5	-15	-15	-15	-15
OTHER PRODUCERS	1	5	5	5	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0
GENERAL GOVERNMENT	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	5	9	17.5	47.5
COMMUNITY, SOCIAL & PERSONAL SERVICES	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	17.5	47.5
MINING	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	-5	-5	-5	0

	0	0		0				
ALIEN PLANT COVER	Initial State: 0	Initial State: 0	Initial State: 0	-5	-15	-15	-15	-55
TAXES LESS SUBSIDIES ON PRODUCTS	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	Initial State: 0	17.5

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6.5.2 Results for Projected Short, Medium and Long Term Growth Scenarios A - I

The results for short, medium and long-term growth projections are shown in Table 12. These scenarios were both intended to test limits and to identify levels of water and energy savings that will be required for growth in the future, if the current strategy is pursued and forecasted levels of growth become a reality. This can then be compared against IPCC rainfall reductions and temperature variations, and was used as a basis for discussion, interactively in the review workshops. This is shown in more detail in Table 14 in (RCCSAPWC, 2008).

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Table 12:

Western Cape Province: Results for Scenarios A-I

Scenario	Sector Configuration for Scenario
A	<p>In this scenario, GDP growth is expected to increase from approximately R199Bn to R243.7Bn (roughly 22.5% increase from current GDP), but water and electricity supply (which contains both current energy supply limitations and the contribution of projected energy savings and demand side management interventions) is too low to maintain expected growth, and will affect GDP adversely. Without any additional interventions or demand side adaptation to water and energy shortages, whether from the consumer, business owner, industry or government, growth will not be possible under current conditions.</p> <p>Water use is between 2444-2580 Mm³a⁻¹, approximately 15% more than currently provided.</p> <p>Energy use is between 78.706-83.078Bn kwha⁻¹</p> <ul style="list-style-type: none"> • Electricity required is 24.59-25.95Bn kwha⁻¹, approximately 19% more than current capacity, including projected energy related savings and backup power options, can provide.
B	<p>Same as scenario C, with increase in agriculture, forestry and fishing activities.</p> <p>GDP is approximately around R224.7Bn.</p> <p>Water use increases to between 2580-2715 Mm³a⁻¹, approximately 17% more than currently provided.</p> <p>Energy use is between 78.705Bn kwha⁻¹</p> <ul style="list-style-type: none"> • Electricity required between 24.59-25.95 kwha⁻¹, approximately 19% more than current capacity,

	including projected energy related savings and backup power options, can provide.
C	<p>Growth as in scenario B with 5% decrease in agriculture, forestry and fishing.</p> <p>The reduction in these sectors is intended to reflect savings in energy and water use through greater efficiency (i.e. resulting in 5% savings, rather than just a simple decrease in production. The agricultural sector, in particular, will show great sensitivity to climate change effects on water supply, and efficiency measures will have to be taken, in any event, in the long-term, to preserve the value and contribution of the agricultural sector to employment and export of produce in the Western Cape, but it's water dependence will require resilience in the long term in through adaptation and mitigation measures towards more efficient water use in agriculture and forestry activities..</p> <p>GDP remains unchanged from scenario B.</p> <p>Water required/use decreases to between 2308 Mm³a⁻¹-2444 Mm³a⁻¹ due to savings. 8% less water is currently produced in the system than is required.</p> <p>Energy usage and electricity requirement is approximately the same as in scenario B.</p>
D	<p>Growth as in scenario C with 5% decrease in alien plant cover (percentage growth from current values).</p> <p>Growth as in scenario C with 5% decrease in agriculture, forestry and fishing and 5% clearance of alien plants.</p> <p>Energy usage and electricity requirement remains unchanged.</p> <p>Water use remains largely unchanged, with alien plant clearance as an intervention. It stands to reason that the</p>

	alien plant clearance programme alone will not provide sufficient water savings in the short term under scenarios A-D.
F	<p>In this scenario, more even growth of sectors, with higher savings from agriculture, forestry and fishing, and alien plant clearance programmes. Higher short term growth of selected sectors (manufacturing, informal sectors and SMES) and lower short term growth in finance, insurance, real estate and business and tourism, with 20% alien plant cover removal and agro-forestry water and energy efficiency reduced by 15% (percentage growth from current values).</p> <p>Both energy and water use is significantly decreased in this approach:</p> <ul style="list-style-type: none"> ▪ Water required ($\sim 2172 \text{ Mm}^3\text{a}^{-1}$) is brought within range of current water available in the system ($2200 \text{ Mm}^3\text{a}^{-1}$). ▪ Electricity required ($\sim 21.86\text{-}23.22\text{Bn kwha}^{-1}$).
G	<p>Growth of tertiary sectors with agro-forestry efficiencies implemented in scenario F (% growth from current values).</p> <p>Water use lies between $2172\text{-}2308 \text{ Mm}^3\text{a}^{-1}$</p> <p>Electricity requirement lies between $23.22\text{-}24.59\text{Bn kwha}^{-1}$</p>
H	Long term growth of tertiary sectors with 15% water and energy efficiency imposed on agriculture and forestry, and 15% alien plant clearance

	<p>Projected GDP lies between R249.9Bn-R265.25Bn, approximately 30% increase in GDP from current value.</p> <p>Water use remains low, between 2172-2308 Mm³a⁻¹</p> <p>Electricity requirement lies between 25.96-27.32Bn kwha⁻¹</p> <p>This long-term scenario is achievable as its water and energy requirements can foreseeably be met in the future.</p>
I	<p>Long term growth of tertiary sectors with 15% water and energy efficiency imposed on agriculture and forestry, and 55% alien plant clearance.</p> <p>Projected GDP lies between R312.85Bn-R325.44Bn, approximately 30% increase in GDP from current value.</p> <p>Water use remains low, between 2172-2308 Mm³a⁻¹</p> <p>Electricity requirement lies between 25.96-27.32Bn kwha⁻¹</p>

6.5.3 Description: Short Term (Less Growth) Scenarios

Towards the end of this case study, the global financial collapse of 2008 occurred. This brought the projected growth scenarios being considered by the study into question. For the 'less growth' scenarios, the rates of growth into the short term future were generally reduced, as sustained growth of high performing sectors at their current levels cannot be assured in the current 2009 global financial crisis. Rather, lower estimates of growth were used, in order to help explore how short term growth targets may be achieved in limited growth scenarios. The purpose of introducing these scenarios into the study were to adapt the study to the changing real-world context with which it was concerned, to address the feasibility of lower levels of growth than expected. By effecting changes midway through the execution of the project, the flexibility of the BPDA approach is also tested in a real-world decision-making context, where significant changes can occur at any time that require re-formulating and adapting an implementation strategy.

Three scenarios, referred to as “B LESS GROWTH, C LESS GROWTH and D LESS GROWTH”, explore possible scenarios for development with savings in agriculture and alien plant removal. Current state of electricity production includes savings from adaptation measures, and with mitigation and backup options. The specifications of B LESS GROWTH, C LESS GROWTH and D LESS GROWTH in the short term (5yrs) are shown briefly in **Table 13** and in elaborate detail in **Table 14**, while the results are recorded in **Table 15** (excerpts from RCCSAPWC 2008).

Table 13:

Less Growth Scenario Brief Descriptions

SCENARIO	DESCRIPTION
B LESS GROWTH	B LESS GROWTH: Lower rates of overall growth in the short term in tertiary, agro-forestry and manufacturing sectors – intended to probe system limits to low growth. In this scenario, finance & investment, manufacturing and construction lead growth while agriculture, forestry and fishing are grown by 5%.
C LESS GROWTH	C LESS GROWTH: Lower rates of overall growth as in scenario B with 5% decrease in agro-forestry and 5 % decrease in alien plant cover. In this scenario, by lowering the productivity of agro-forestry and fishing, and reducing alien plant cover by 5%, less water and energy is used in the system, and is reflected in the energy produced/energy required ratios in the tables. This does not imply that agriculture should be curtailed in production, but rather that more efficient methods of water and energy use in this sector could have major impact on the other water and energy dependent sectors. GDP, GGP and employment ‘after’ measurements are therefore lower estimates too.
D LESS GROWTH	D LESS GROWTH: Growth as in scenario C LESS GROWTH with 15% decrease in agriculture productivity and 15% decrease in alien plant cover. Again, this reduction is intended to reflect possible savings in water that could be achieved through increasing efficiency of agricultural water use and alien plant clearance programmes in the short term.

Table 14

Detailed Specifications for Short Term Growth of Tertiary Sectors, at Much Less than Projected Growth Levels.

SCENARIO	B LESS GROWTH	C LESS GROWTH	D LESS GROWTH
SECTOR PRODUCTIVITY DRIVERS (% growth from current values)	Short term– 5yrs: Scenario B: Lower rates of overall growth in short term: tertiary, agro-forestry, manufacturing and other sectors (% growth from current values)	Short term growth– 5yrs: Scenario C: Lower rates of overall growth as in scenario B with 5% decrease in agro-forestry and 5% decrease in alien plant cover (i.e. more water and energy efficient system) (% growth from current values)	Short term growth– 5yrs: Scenario D: Growth as in scenario C with 15% decrease in agriculture (or water and energy use of agriculture) and alien plant cover (% growth from current values)
HOUSEHOLD INCOME	9	9	9
FINANCE, REAL ESTATE AND BUSINESS	17.5	17.5	17.5
TOURISM	7	7	7
INFORMAL SECTOR & SMMES	7	5	7
TRANSPORT	7	7	7
CONSTRUCTION	9	9	9
MANUFACTURING	17.5	17.5	17.5
WATER &	1	1	1

ELECTRICITY			
AGRICULTURE, FORESTRY & FISHING	5	-7	-15
AGRICULTURE	5	-5	-15
FORESTRY	5	-5	-15
OTHER PRODUCERS	5	5	5
GENERAL GOVERNMENT	1	1	1
COMMUNITY, SOCIAL & PERSONAL SERVICES	5	5	5
MINING	Initial State: 0	Initial State: 0	Initial State: 0
ALIEN PLANT COVER	1	-5	-15
TAXES LESS SUBSIDIES ON PRODUCTS	Initial State: 0	Initial State: 0	Initial State: 0

6.5.4 Results: Projected Short Term “Less-Growth” Trajectories

The results indicate that 5% water and energy efficiency in agriculture combined with alien plant clearance can provide a significant proportion of the required water savings in the short term, while a 10-15% savings in agriculture in combination with alien plant clearance programmes will increase the resilience of the system to water supply, under current rainfall and temperature conditions.

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Table 15:

Results for Less Growth Scenario Brief Descriptions

SCENARIO	DESCRIPTION
B LESS GROWTH	In this scenario, water use ($\sim 2,580,137,000 \text{ Mm}^3 \text{ a}^{-1}$) is significantly more than the available water ($2,200,000,000 \text{ Mm}^3 \text{ a}^{-1}$), and only 85% of water requirements can be met, while 96% of energy requirements can be met.
C LESS GROWTH	Lower rates of overall growth as in scenario B with 5% decrease in agro-forestry and 5 % decrease in alien plant cover. In this scenario, by lowering the productivity of agro-forestry and fishing, and reducing alien plant cover by 5%, less water (92% of requirements met) and energy (96% of requirements met) is used in the system, and is reflected in the energy produced/energy required ratios in the tables. This does not imply that agriculture should be curtailed in production, but rather that more efficient methods of water and energy use in this sector could have major impact on the other water and energy dependent sectors. GDP, GGP and employment ‘after’ measurements are therefore lower estimates too.
D LESS GROWTH	Growth as in scenario C LESS GROWTH with 15% decrease in agriculture productivity and 15% decrease in alien plant cover. Water requirements are met up to 98%, while 96% of energy requirements are met.

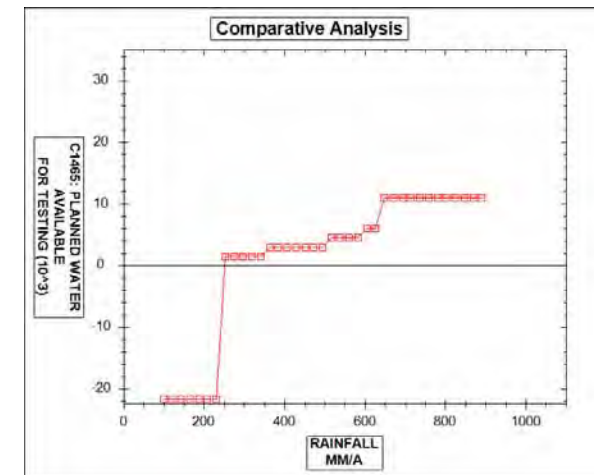
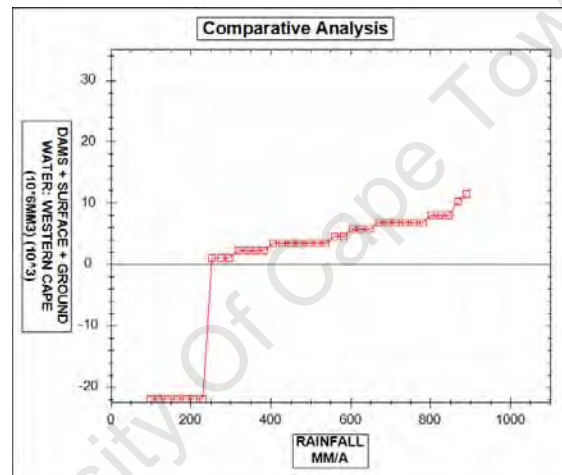
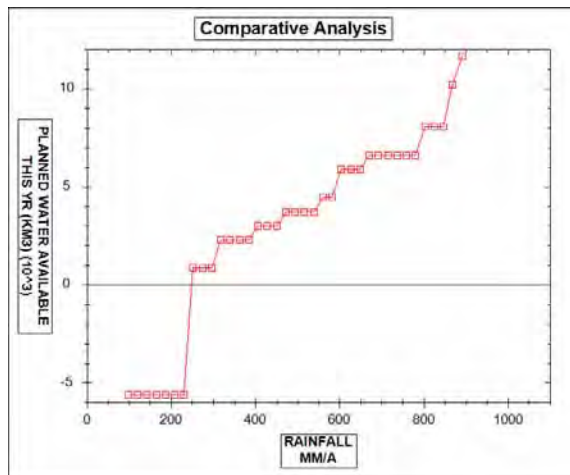
6.5.5 Determining Climate Change Related Thresholds on Provincial Multi-Sector Growth

The results shown in Table 16, show thresholds for water and energy usage in various scenarios, which allows us to assess and discuss the possible impacts of projected climate change effects in the future as prescribed in GCM models (IPCC, 2008). As temperature is increased, the average rainfall required to meet the desired production increases. This is shown in **Table 16**, where in each new row the temperature is raised by 1 degree Celsius. The effectiveness of the Berg water management scheme has been assessed (results not shown here, but included in CD of results), but showed no significant improved resilience to climate changes in rainfall and temperature. Overall the model indicates that a change of just 1 degree Celsius (average temperature) significantly affects the water available to the Western Cape, due to high evaporation rates, and the large amounts of dammed water that might be necessary to meet future demand.

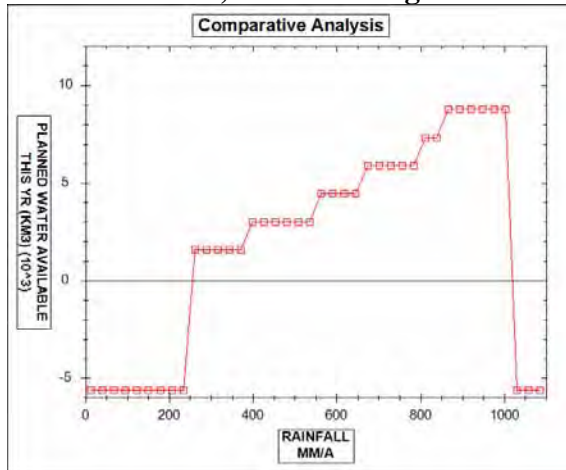
Table 16:

Total Water Available Measured by 3 Output Variables at Current to Increasing Temperatures, over the Rainfall Range 0-1100mm Per Annum

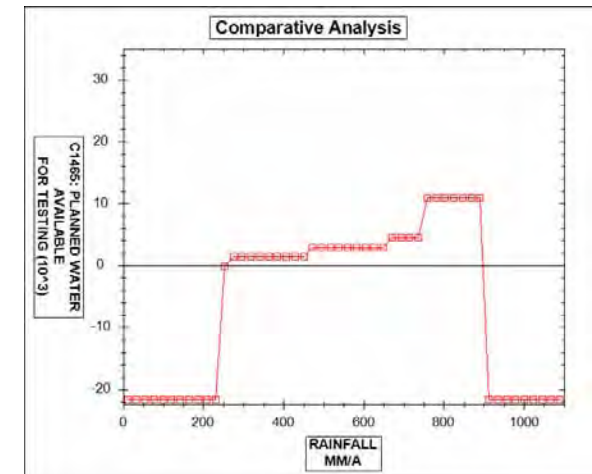
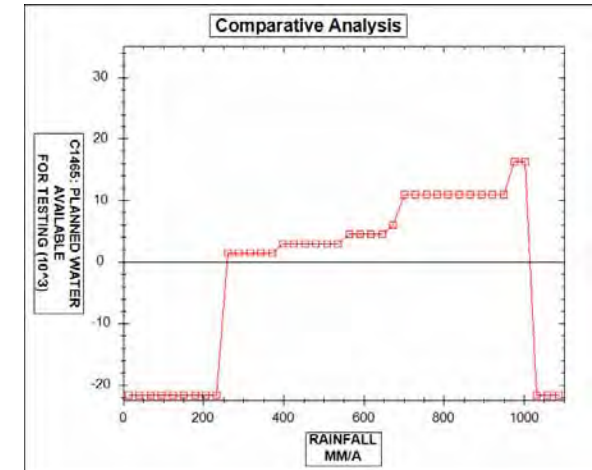
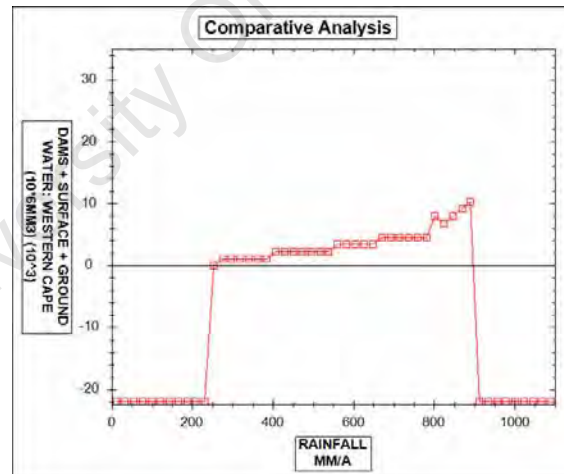
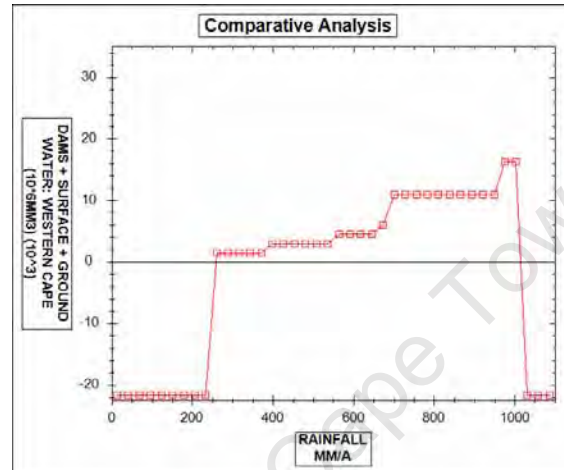
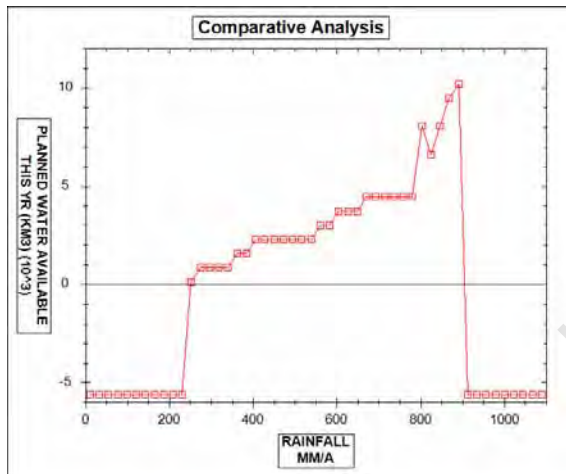
Initial State: R varied, T = 21 deg C



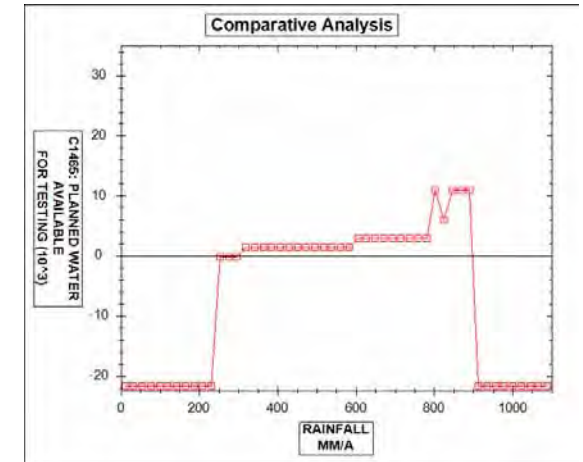
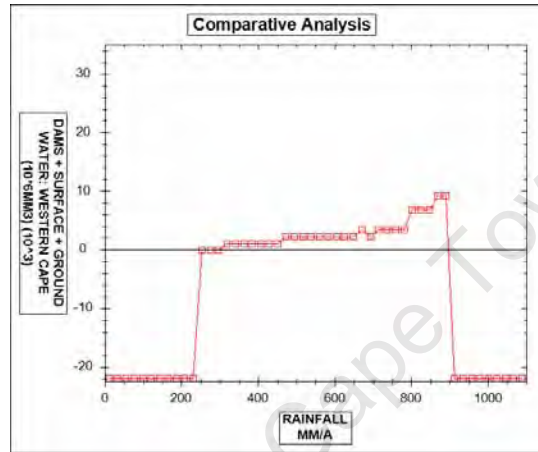
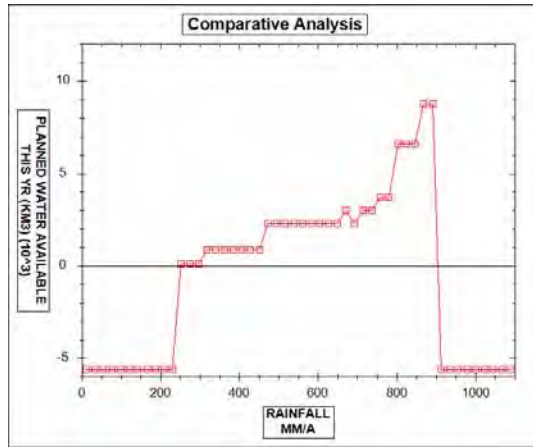
R varied, T = 21.75 deg C



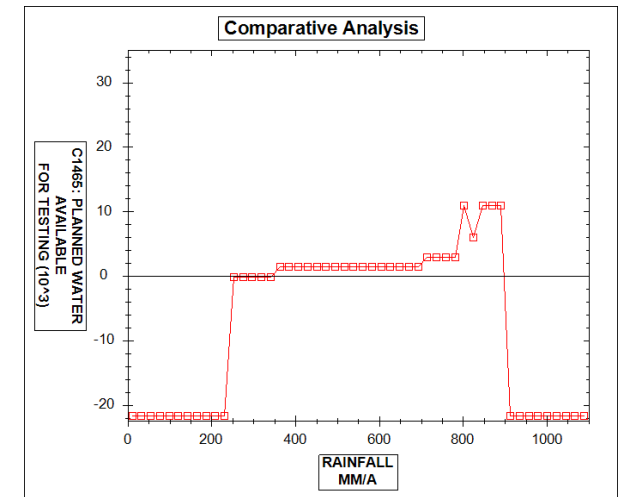
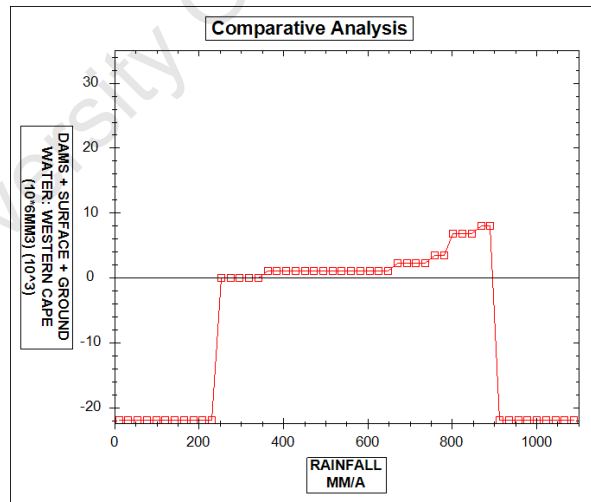
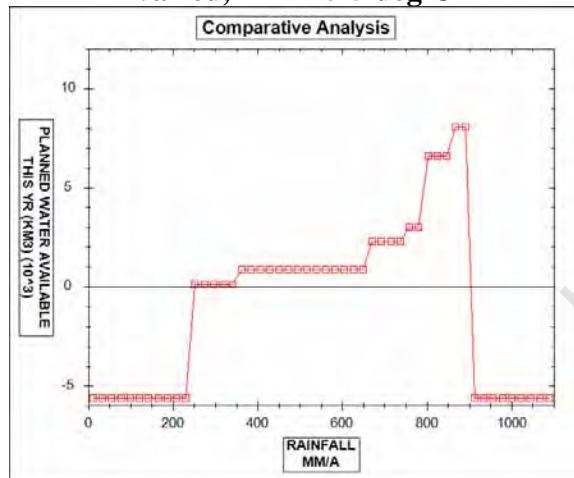
R varied, T = 22.75 deg C



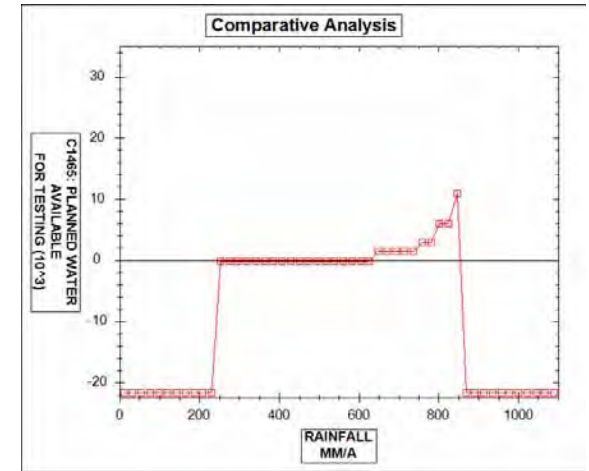
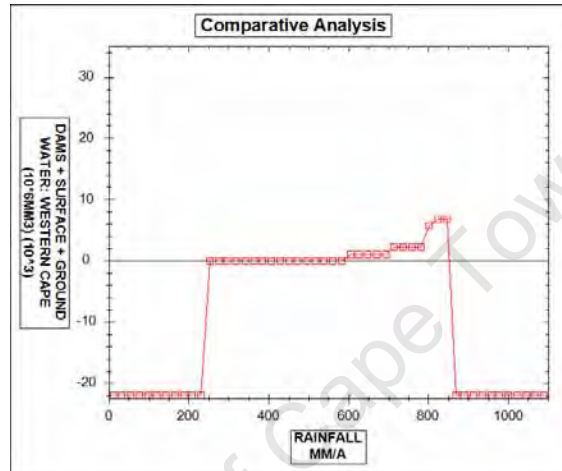
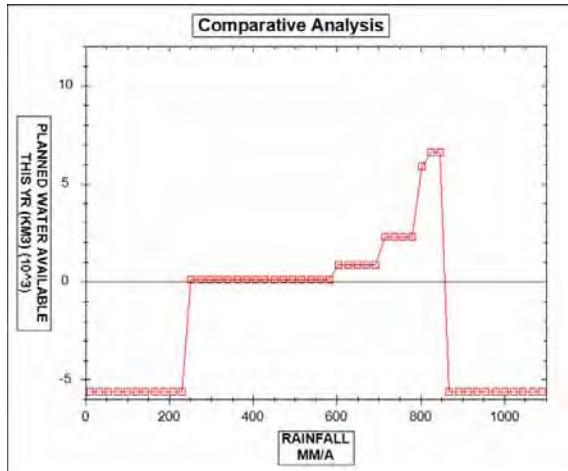
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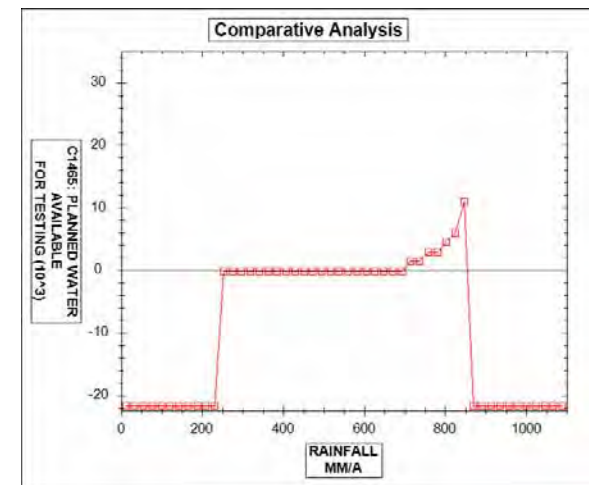
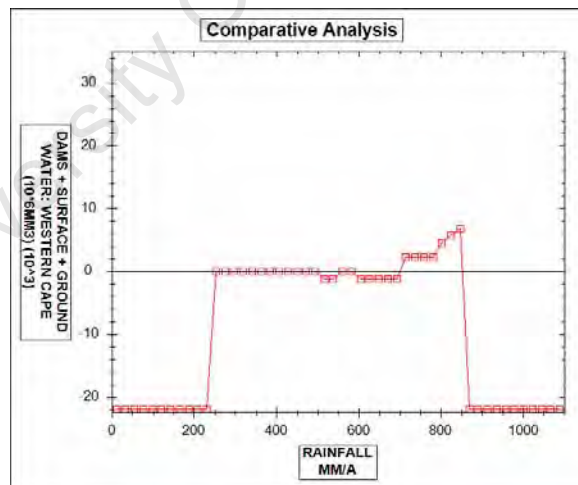
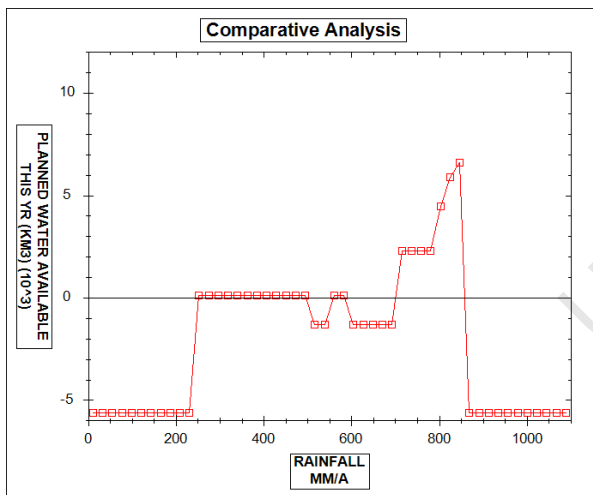
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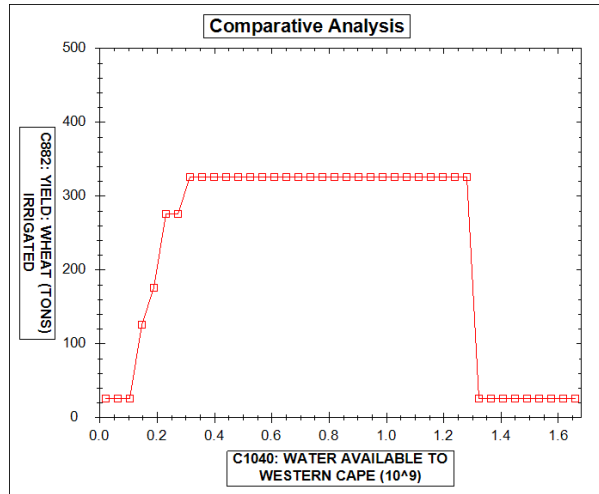
R varied, T = 25.75 deg C



R varied, T = 26.75 deg C



Example: Crop Sensitivity



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6.5.6 General Results Summary: Western Cape Study

As already mentioned, these results are presented in detail in Table 14 in the review of the Western Cape climate change strategy and action plan (RCCSAPWC, 2008). Please refer to this report for more detailed analysis and discussion. We summarise the results from this report in this section, as outlined below.

6.5.6.1 Summary of Water Use

Water use can be brought within range of current water availability if efficiency interventions in agriculture and alien plant removal are implemented. The vulnerability of current water availability to climate change effects deserves continued attention and monitoring. In the long-term, water use can be brought within range of current water availability limits, as shown in scenarios A-I but this requires that the linear growth trend in water demand be met with appropriate interventions to prevent growth.

To some degree this aim can be met by water use efficiency increases that have been identified and suggested in the climate strategy (e.g. savings in the residential, commerce, industry and government sectors) in the short term. However, medium and long term savings would require that continual improvement of water use efficiency becomes a part of strategic planning of sectors and legacy equipment and infrastructure replacement and upgrade programmes. This is already the case for the City of Cape Town (CCT). Most reviewers were of the opinion that efficiency management constitutes a temporary solution and that growth in demand will eventually cancel efficiency gains, so a programme of continual, iterative efficiency improvement across all sectors is necessary in the medium to long term future.

In most of the scenarios (A-I) considered in this review, the order of water users from largest to smallest is agricultural, urban, alien and afforestation related water use. Agricultural and urban water use are the largest, but agricultural water use is approximately double that of urban water use. This is the case for all catchments in the Western Cape apart from the Berg water catchment; where urban use of water outstrips agricultural use. The pressing issue concerning urban water use is that potable water is required for human use in the residential, commercial and industrial sectors. Population increase may increase water demand and the need for wastewater treatment plants, should adverse water supply conditions occur due to climate related changes in rainfall and temperature.

6.5.6.2 **Summary of Energy Use**

In most of the scenarios (A-I) considered in this review, the order of energy users from largest to smallest is industrial, transport, residential, agriculture and mining energy use. Total energy use ranges from 69.91Bn kwha⁻¹ - 87.45Bn kwha⁻¹. F is the lowest energy usage scenario in the long-term.

As far as energy is concerned, industry and transport are the biggest energy users in all scenarios, but residential energy use levels are significantly high and the residential sector is a good candidate for mitigation and adaptation measures to save energy to be taken up. The growth of the provincial economy (which is especially dependent on industry and tertiary sector development in the future) might be severely adversely affected by energy shortages.

To some degree, required savings can be met by energy use efficiency measures that have been identified and suggested (e.g. savings in the residential, transport, commerce, industry and government sectors) in the short term. However, medium and long term savings would require that continual improvement of energy use efficiency becomes a part of strategic

planning of sectors and legacy equipment and infrastructure replacement and upgrade programmes. To some degree, energy efficiency of current technologies look set to increase, as energy and fuel costs have risen globally providing the incentive to develop new cleaner, more energy and water efficient technologies and infrastructures.

An increase in energy efficiency in the transport, government and agricultural sector can be achieved using some of the mechanisms available (such as switching to public transport, and taxi switch to diesel fuel use) but in the medium and long term, the ability to meet energy requirements will increasingly depend on how energy use demand evolves into the future. It is foreseeable that a linear growth rate (such as 3% in the case of water) when applied to the electrical energy, cannot be met in the future without considerable start-up and operating costs for new electricity production be established. Backup options provide considerable resilience to energy demand increases, but aren't available all year round as a supply option.

6.5.6.3 **Summary of Employment**

Employment may be increased from approximately 1.4 to 2.1 million, if the condition that growth of these sectors would linearly increase employment in them is assumed. The largest to smallest employing sectors in the Western Cape are Finance, Insurance, Real Estate and Business; Manufacturing, Wholesale, Retail Trade and Accommodation; General Government and Agro-forestry and Fishing, respectively.

The agricultural sector is a large employer of people who fall in the minimum wage and lower income groups in the Western Cape. It is likely that due to the large water use of this sector that employment in the agricultural sector may become adversely affected in the future. Increases in extreme events may compound the stability of employment in this sector, where seasonal work is often dependent on the reliability of harvests. Extreme

events such as flooding, fire and pest explosion conditions are more difficult to plan for and predict, and agriculture is especially vulnerable to these conditions. Drought may be easier to predict as understanding of the sensitivity of El Nino and La Nina cycles in relation to climate change effects, becomes more apparent over time.

6.5.6.4 **Summary of CO2 Emissions**

Carbon emissions lie between 6 and 21% more than current levels of emission across scenarios A-I. In these scenarios, efficiency requirements could be balanced by requiring a mandatory minimum of 5% reduction or efficiency improvement in low to medium level energy users. This can be implemented while imposing increasing levels of energy efficiency into the medium and long-term for high-energy using industries, so that improvements might be made as legacy equipment is replaced.

Carbon emissions per sector from largest to smallest per sector may be listed as; Industry; Transport; Residential; Commerce and Government; Agriculture and Mining, respectively. Carbon efficiency measures constitute a critical element of climate change adaptation programmes, and carbon credits as a mechanism for change now has the support of the global political and scientific communities as a key point of focus if the human contribution to climate change effects is to be minimised.

6.5.6.5 **Summary of Residential Energy, Water Use & Household Income**

Household energy and water use is 9% for scenarios A-F, and increased to 22.5 and 47.5% for scenarios H and I respectively. The lower rates of growth reflect a degree of growth that can be tolerated in terms of residential energy and water use-age levels.

6.5.6.6 **NOX Emissions**

Total noxious emissions increase from approximately 285 000 - 550 000 in scenarios A-I. Transport, commerce and the residential sector contribute the most, in general to VOC, PM10, PM2.5, SO3 and NO_x emissions (collectively termed as noxious emissions in this report).

6.5.6.7 **Solid Waste**

Solid waste increases from approximately 3m tons per annum to 3.7m tons per annum in scenarios A-I. The largest to smallest sources of solid waste in the Western Cape are the residential sector, commercial sector, industrial sector, gardens and builders. It is clear that the residential sector is by far the largest contributor and consequently the most likely suitable candidate for mitigation and adaptation measures to be effected. Recycling of residential solid waste will need to include more sectors of society in the Western Cape in order to be effective in combating solid waste. Residential recycling of paper, glass and plastic waste also provides valuable opportunities for green small businesses and green collar government employment to be developed into the future, and can play a significant role in reducing the landfill requirements of the Western Cape annual solid waste output.

6.5.6.8 **General Summary**

The residential sector is a significantly cross-cutting sector in terms of energy use, water use, solid waste and CO₂ emissions to justify its inclusion as a target for both adaptation and mitigation programmes in the short, medium and long-term. In the scenarios used for the review (A-I), the growth of the household sector is restricted to 9% in the short term and medium, and 22.5% and 47.5% in the long term. In reality, the growth of energy use, water use, solid waste and CO₂ emission output from the residential sector is increasing at higher rates of growth than used in the

scenarios; which deliberately restrict growth in order to obtain growth scenarios that remain resilient to water and energy supply limitations that could result from climate change effects. That is, we deliberately restricted growth in order to obtain growth scenarios that remain resilient to water and energy supply limitations that could result from climate change effects.

The priority areas that have been identified for development within the adaptation and response programmes through the process conducted in this review are listed below:

1. Agricultural water efficiency regulation
2. Alien plant clearance programme
3. Residential & Urban energy use
4. Residential solid waste
5. Transport & Emissions
6. Finance & Investment

The residential sector is a significantly cross-cutting sector in terms of energy use, water use, solid waste and CO₂ emissions to justify its inclusion as a target for both adaptation and mitigation programmes in the short, medium and long-term. In the scenarios used for the review (A-I), the growth of the household sector is restricted to 9% in the short term and medium, and 22.5% and 47.5% in the long term. In reality, the growth of energy use, water use, solid waste and CO₂ emission output from the residential sector is increasing at higher rates of growth than used in the scenarios.

The energy strategy for the Western Cape suggests a number of strategic interventions that could be used in combination to reduce energy consumption and emissions from the various sectors (SESWC, 2007). In this review, scenarios were run with sectors at lower levels of growth, reflecting savings in energy as outlined in the results. From these results, adequate savings could be made in electricity use, fuel use and emissions if these efficiency criteria could be introduced in the medium to long term:

1. Transport: reduced by 10-15%
2. Industry: reduced by 15 %
3. Commerce and Government: reduced by 9-15 % of total energy consumption
4. Residential: reduced by 9% - 25%
5. Agriculture: reduced by 10-15%
6. Energy efficiency of buildings e.g commerce and industry: reduced by 5-10%

This is consistent with an overall 15% efficiency target for all sectors by 2014, although realistically achievable by most sectors in the medium to long term. Maintenance of technology and replacement of legacy equipment occurs over medium to long term cycles; hence these targets are more likely achievable in the medium to long term.

In the analysis of electrical energy production alternatives conducted in this review we tested various combinations of renewable and non-renewable future options. We also evaluated their energy and emission output, and cost of production as possible propositions for increasing the energy supply of the Western Cape. This need should inform research into a multiple sources of supply of electrical energy, and should become a key element of developing the provincial resources in an innovative and multi-faceted manner. The decentralisation of energy production is viewed as a likely possibility under climate change conditions, especially where rising fuel costs are concerned.

The energy losses resulting from the effect of temperature on transmission lines from coal-fired plants in Mpumalanga was shown in the review to be significant enough to be the subject of research and technological innovation to support resilience to climate change.

A general comment on the mitigation and adaptation programmes is that there is no clear programme to deal with the social impacts

of climate change, especially at the lower income level households and informal settlements. Climate change can exacerbate social conditions such as poverty and unemployment. The failure of subsistence and agricultural activities in a climate of rising food, household energy and transport prices, etc. can have severe effects at the household level and it might require a dedicated programme, with an interdisciplinary approach and structure, in order to be effective.

The study also included a detailed but in-exhaustive list of the types of issues that have emerged as significant gaps in understanding, or actions that could help increase resilience to climate change in the Western Cape. These included:

1. Understanding local effects of wind, rain and temperature relationships and how crops, biodiversity and ecological integrity may be affected at local scale.
2. The response of crops and biodiversity to pest and alien species explosions under climate change induced climatic changes such as: droughts, floods, storms, fires, pests and alien invasive species.
3. Generally, for all sectors, sectoral water and energy use statistics and studies into sector sensitivities to water and energy shortages is required.
4. Programmes for buffering low income households and informal settlements from the effects of climate change and helping increase household resilience.
5. There are also complex hydrological and water quality issues surrounding making any predictions regarding climate change and water pollution loading levels.

6. Tariff planning for water and energy requires a better understanding of sector dependencies, and should be determined through inclusive processes involving debate, discussion, negotiation and dialogue.
7. The sensitivity of the tourism to climate change related effects such as extreme events, water and energy shortages, potential sea level rise still needs to be more clearly determined before any reliable conclusions can be reached regarding the sector and how growth may be affected in the future. In addition, more research into understanding the difference between ecotourism vs non ecotourism activities. A significant driver of change, as addressed in the analysis is the potential increase in long-haul flight expenses due to increased jet fuel prices and possible carbon taxation.
8. As far as the transport sector is concerned a few valid concerns threaten any strategy for load-shifting from private passenger to public transport. The key issues involve establishing safety and security and reliability in the transport sector using innovative mechanisms that help improve the quality of life of people using the service.

Identifying gaps in knowledge and understanding informing the basis of strategy-making was a key requirement of decision-makers and was an explicit aim of the review. The detailed analyses conducted in this case study was very well received by the decision-makers for whom the study was conducted i.e. the provincial government (DEADP).

6.5.7 Brief Discussion: What did we Learn?

The challenges involved in realising this project were manifold, involving; (1) participatory process facilitation: facilitating a participatory process involving both decision-makers and researchers from different disciplines, (2) modelling at massive scale: ensuring that the software interface could cope with a large model constituted by a variety of detailed embedded units, (3) using the model and participatory workshop processes to perform a review which integrated across sectors, government department strategies, (4) determining the critical limits and thresholds to growth in the Western Cape in relation to energy and water supply and (5) obtaining an understanding of system resilience from cross-comparison between scenarios, and (6) coping with real-world contexts and changes.

6.5.7.1 Participatory Processes

By the time this case study was undertaken, the author had been involved in facilitating participatory processes with graphical causal maps and Bayesian networks for over seven years as a full time researcher at the CSIR. We therefore understood the requirements better and put a great deal of effort into planning for participatory processes. Even with this degree of preparation, participatory processes between decision-makers and researchers aren't always guaranteed to flow smoothly because each problem context is different. Moreover, what may have worked with one group of researchers or decision-makers can often prove unsuitable for researchers and decision-makers who are located in a different context.

For that reason, the primary responsibilities as far as facilitation is concerned are; (1) to focus the group on defining their problem(s) clearly, (2) to ensure that equal and democratic participation occurs, (3) that a reasonable understanding of system components and key causalities are obtained, and (4) to remember that each process will customise itself around the problem and people who are participating.

6.5.7.2 **Massive Scale-Ability**

Ensuring massive scale-ability in Bayesian models introduced software challenges that were iteratively resolved over the course of the project. Of more concern, was whether a probabilistic framework would experience an ‘overload’ of sensitivities, resulting in too much noise and not enough sensitivity to reach conclusions using the model. While this should ostensibly not be the case, it was still a valid concern where large multiplicitous systems, models and simulations are concerned. Ensuring that cross-scale and other sensitivities are verified and validated appropriately remains the task of the main case study investigator, who can draw on a broad interdisciplinary review group to help with verification and validation of model structure, constraints and outputs. In this case it is clear that the BPDA approach is scale-able to massive scale (approximately 1500 variables) and still produces meaningful results from scenario-based sensitivity analyses.

6.5.7.3 **Integration Across Sectors**

In this study, the water and energy sectors as integrators to all other sectors, as they were the primary resources, the limitation of which the study was mainly concerned with. The challenge of linking every sector to the water and energy sectors with known reliable information on sensitivities was overcome by drawing on a wide range of information and expertise to arrive at an understanding of these relationships.

6.5.7.4 **Critical Limits, Thresholds & Resilience**

The approach can be used to assess the limits to growth of the provincial system in a variety of sector growth, land-use and climate change scenarios. As shown in this case study, the ‘resilience’ of the system can be determined from building up a history of the critical limits and thresholds in a variety of scenarios, thereby obtaining an understanding of the range of limits and hence resilience of the system.

6.5.7.5 Adaptive Capacity

The ability of the BPDA approach to support adaptive management and decision-making was tested, when real-world changes that occurred towards the end of the project, namely; the 2008 economic recession. We were able to quickly adapt our analysis by running new scenarios. While this may seem trivial, the ability of large complex simulations to be quickly adapted to address new scenarios is often impossible. The BPDA approach allows for a wide range of scenarios to be run and verified due to the flexibility and modularity of Bayesian models. Even introducing new embedded units or adapting internal relationships of embedded units becomes almost as simple as ‘cut and paste’ task. Most traditional models and simulations are primarily integrated around a set of scenarios that the integration is hoped to address, and are usually adapted only with great time and expense. Coping with multiple futures, that is, dealing with systems that aren’t necessarily predictable, requires approaches that ensure flexibility at the structural and parametrisation levels of modelling, so that models can be quickly adapted to cope with newly unfolding contexts.

Overall, the critical learning points for BPDA in the Western Cape Climate Strategy Review Case Study are outlined in Table 17.

Table 17:

Critical Learning for BPDA from Western Province Case Study

Critical Learning Points (BPDA)	Description
Cross-scale	Here we adapt our understanding at the national, municipality and magisterial district scales to formulate a detailed model at the provincial scale. We learnt that the BPDA approach could be used to inter-relate a wide range of sectors as embedded units that were formulated in great detail. Interventions at different scales in the system and embedded sub-systems, and

	influences at different scale (e.g. climate change) can be assessed.
Cross-sector	A large variety of sectors were included in the model, and we were able to inter-relate these models in ways that questions at the whole systems scale could be answered in relation to changes in rates of growth in these sectors, in relation to climate change. In each sector or embedded unit, sub-scale interventions (e.g. for savings in water, energy or emissions) were also implemented where possible.
New Indices	A broad range of indices can be evaluated alongside one another using the BPDA approach. This is clearly illustrated in this case study, and has been discussed earlier in the text.
Resilience and Adaptive Capacity	We derived critical limits and thresholds in a range of different scenarios, and were able to evaluate various sector-growth combinations in relation to one another using the BPDA approach.
Adaptability	At the end of this case study the financial collapse prompted a re-assessment of the possible growth of the Western Cape in the short-term. We were able to accommodate these changes easily, and provide support to decision-makers nonetheless.
Participation	In this case study, we used the BPDA approach to facilitate the processes of interaction between decision-makers in provincial government, and a cross-disciplinary research and review team.
Decision Support	In this case study we showed that the BPDA approach can be extended to support decision-making at the provincial scale in great detail, including a wide range of sectors, themselves modelled in great detail. The BPDA approach can provide an understanding of system resilience by revealing the system level thresholds and critical limits across a range of different projected scenarios. It can also help evaluate different adaptation options in response to these scenarios. As such, the value of the BPDA approach in decision-making is self-evident.

6.6 Facilitation Using Graphical Causal Maps

Graphical causal maps are used to facilitate explanation building, pattern matching and using rival patterns as explanations in formulating an interdisciplinary case study research design. In the two case studies presented in this section, no Bayesian networks were built. The purpose of these studies was to assist two different cross-disciplinary research projects to integrate their research plans and understanding using graphical causal maps. As such, these case studies focussed purely on facilitating an inter-disciplinary learning, participation, negotiation and cooperation at the level of cross-disciplinary research projects concerned with social-ecological systems problems.

6.6.1 Cholera Study

This study involved assisting a cross-disciplinary CSIR SRP project that was concerned with biophysical drivers of cholera in the environment. The project sought to explain observed correlations between, for example, observed lagged correlations between high rainfall and high temperatures, and peaks in the rate of first infection to human beings, as recorded at clinics. Interdisciplinary workshops were conducted with the full host of Cholera SRP project participants, but mainly including Dr Stephan Woodborne, Dr Marna van der Merwe, Martella du Preez, Wouter le Roux, Mr Graham von Maltitz, and Dr Sally Archibald during the whole sequence of workshops. The full list of participants in the project included:

Micro-biologists:

- Martella du preez
- Wouter le Roux

Modellers and data analysts:

- Marna van der Merwe (spectral and time series analysis using neural networks and principles from chaos theory).
- Frans van den Bergh (spectral analysis).
- Stephan Woodborne (wavelet analysis).
- Marc Pienaar (wavelet analysis).
- Graham von Maltitz.
- Renee Koen (stats - time series analysis).
- Jenny Holloway (stats -time series analysis).
- Chris Elphinstone (stats -time series analysis).
- Bongani Majeke (satellite data analysis).
- Christo Wittle (UCT - oceanography: satellite data)
- Tarron Lamont (UCT - oceanography: satellite dataChris Elphinstone (stats)

A variety of research disciplines were brought to bear on the problem of understanding the environmental causes of cholera, including; epidemiologists, marine scientists, estuarine specialists, statisticians, sediment scientists and a few participants with general analytical skills. The methodologies employed in the project ranged from; using alternative techniques such as wavelet analysis to identify hidden frequency patterns in noisy data, offshore and estuarine sampling and analysis, using GIS information and models, sediment sampling and analysis, applying traditional statistical methods to identify patterns in complex data sets (i.e. purely from data), and various other smaller supporting studies.

However, the main challenge of the cholera SRP project at this stage was the need to create a shared understanding between different project sub-groups of the different hypotheses and system linkages they were actively researching. The aim of this study was to use graphical causal maps to facilitate and catalyse the emergence of shared understanding that the project required in order to successfully integrate their research efforts.

We used graphical causal maps to explore the full range of causalities that researchers felt could feasibly explain their observations, in a process of hypotheses building, facilitated by building graphical causal maps.

This study focussed completely on the effectiveness of graphical causal maps as facilitators of interdisciplinary research, particularly in a biophysics-intensive epidemiological problem.

A week of workshops involving the Cholera project team were held at the team's offices at the CSIR in Pretoria (South Africa), where we formulated graphical causal maps to match the main or key hypotheses that were being investigated in the project.

A 'straw dog' model was composed (see Figure 34) in order to help stimulate discussion amongst the full cross-disciplinary project team during the workshops in which they would be composing graphical causal maps.

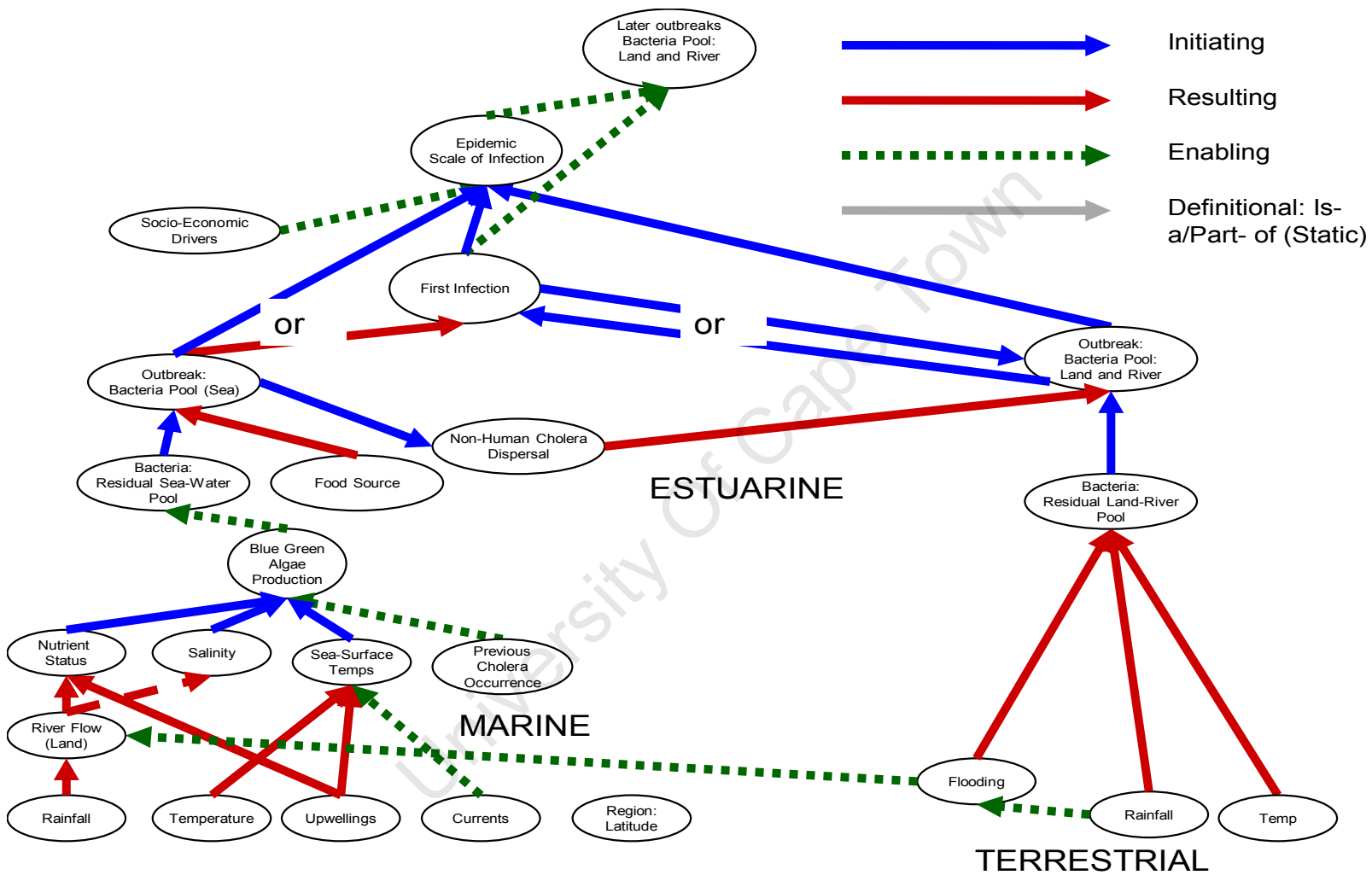


Figure 34: Cholera ‘Strawdog’ Model of Environmental Causes: The shared ontology is illustrated in a very simple graphical causal map relating biophysical sub-system components as drivers of cholera peaks in the environment.

The main hypotheses that had developed during the Cholera focussed on several areas and are listed here (excerpts from Peter, 2007*)

1. **“Marine Hypotheses:** Cholera forms in the near-shore environment when conditions for blue-green algal blooms are good, providing an environment for cholera hosting and food production. Cholera is then transported to the land by advective sea currents into bays and estuaries, or by hosts and carriers of cholera (fish, birds, larvae, fishermen, crustaceans etc.).
2. **Estuarine Hypothesis:** The less turbid estuarine environment has algal blooms and mangroves (N-fixation) which could also provide an appropriate environment for cholera reproduction.
3. **Terrestrial Hypotheses:** Cholera is resident on land and awaits the right conditions for rapid bacterial reproduction to occur and may be triggered by a combination of:
 - a. High temperatures, high rainfall and large amounts of standing water (wetland conditions) or by flooding (river flow):
 - i. Exposure – contaminants washed into drinking water and direct contact with humans, and/or
 - ii. A bloom cycle for algae and cholera is initiated leading to rapid cholera production and higher infection rates.
4. Change in water tables upriver is experienced more drastically at the coast, raising groundwater levels and more exposure to cholera from pit latrines etc. to occur.
5. **Terrestrial-Marine Link Sub-Hypotheses:** Link between river and marine/estuarine cholera production (1) occurs through:
 - a. River impact on salinity in estuary and nearshore environment – lower salinity drives cholera production.
 - b. River impact on nutrient loads in estuary and nearshore environment – algal blooms provide a habitat or iron in system acts as a driver.

- c. This river impact could be directly into the estuary or may occur north of the estuary via huge outflows observed from the Zambezi river – high nutrient loads and may link to nearshore advection of sediment/nutrients in chlorophyll a remote sensing data.
6. **Human causes of spread of cholera** (socio-economic conditions play a role i.e. 33):
- a. Hypotheses may focus around whether 30a or 32 plays a stronger role i.e. human spread of disease or more cholera bacteria in the environment through biophysical processes. To some extent, both play a role but it is important to understand which driver is more significant under certain conditions and why.”

The linkages that are thought to underlie these general hypotheses were tabulated as part of a pre-planning phase of development, as shown in **Table 18** in more detail. These were then used to formulate the graphical causal map in Figure 35, where every link that is numbered corresponds to a description in Table 18.

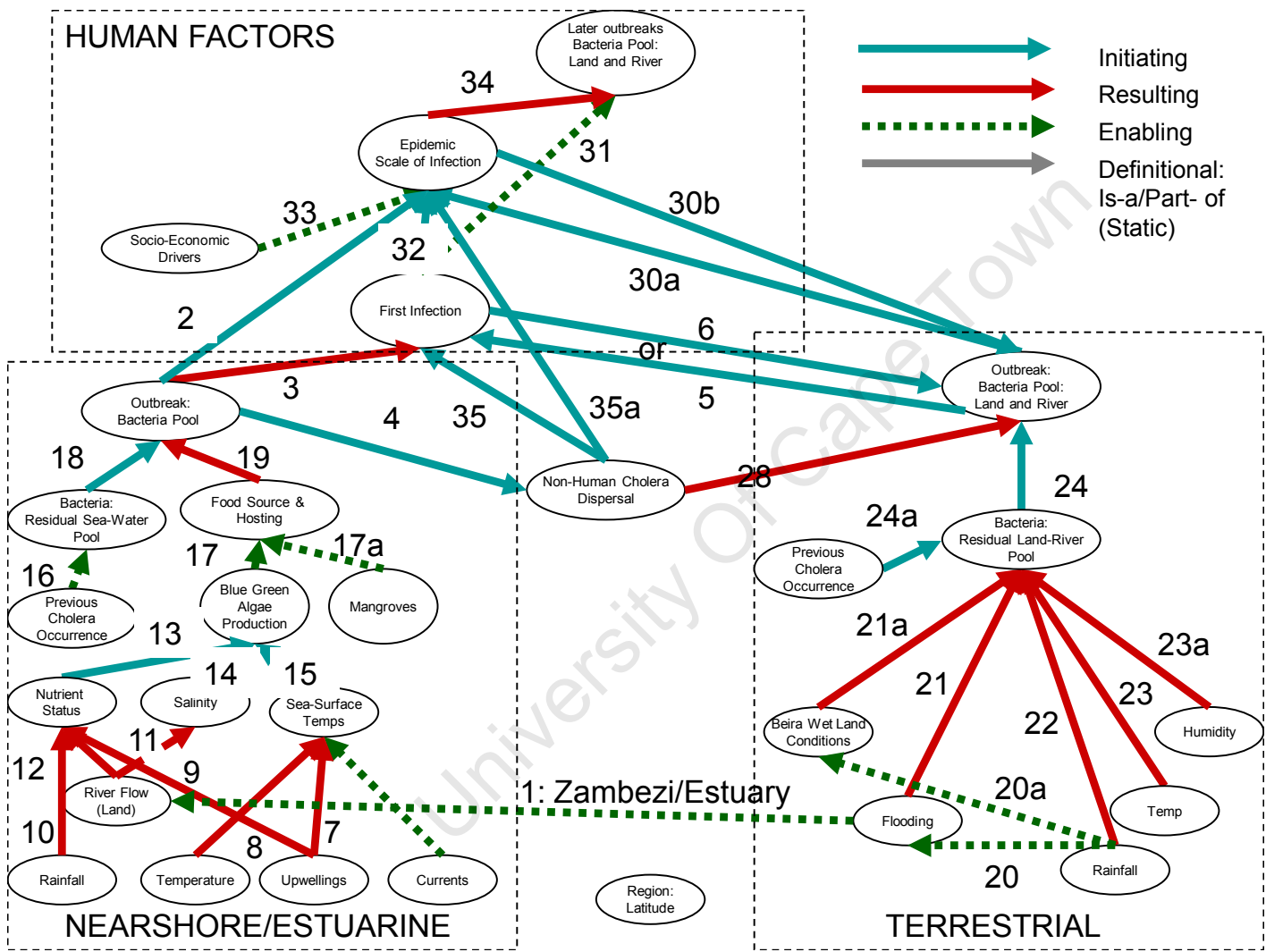


Figure 35: Cholera Model 1 of Environmental Causes: Graphical Causal Model for Cholera Origin Hypotheses

At this point of the study we were ready to delve into formulating detailed causal maps of embedded units corresponding to the main hypotheses, from the outlines provided in Table 18 and Figure 35. This unfolded as two distinct phases of explanation and hypotheses building; namely, a phase of divergence and a phase of convergence, respectively. The divergent phase involved delving into specific hypotheses that 'reside' within the embedded units that specific project sub-teams were concerned with (e.g. sediment). The convergent phase emerged from a shared understanding between participants of the various hypotheses and embedded units that informed hypotheses that were held within the project team

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Table 18

Description of Linkages Displayed in Figure 35

#	Description of Linkage, Assumptions, etc.
1	Link between river and marine/estuarine cholera production: either through nutrient load or impact on salinity (flow) through rivers running directly into the estuary, or through the Zambezi north of the estuary impacting on nearshore processes.
2	Critical amount of cholera bacteria in environment leads to overall epidemic from sea: seems unlikely to be a strong link given the amount of water that needs to be consumed for infection to occur. Weak link.
3&4	Strong link assumed between sea-water bacterial pool to first infection. The key questions are whether it occurs through: <ul style="list-style-type: none"> • Contact with water. • 4: Contact with food sources (fish, crab, shrimp, etc.).
5	Outbreak on land leads to first infection.
6	People contaminate water sources leading to land and river bacterial pools.
7&8	Upwellings contributing to sea surface temperature and nutrient loading – not significant for this case study.
9	Ambient temperature variations induce critical temperature variations with seasonal changes.
10	Direct Rainfall (Estuary/Sea) may contribute nutrients.
11	River Flow impacts on nutrients through runoff.
12	River flow impacts on salinity through runoff: how does salinity gradient in estuary respond to seasons/tides?
13,14,15	Nutrients, Salinity and Sea Surface Temp are assumed to initiate blue-green algae production in nearshore or estuarine environment.
16	Previous occurrence of cholera leaves a residual in system which waits until the conditions are right to multiply.
17&17a	17: Blue-green algal blooms provide environment for cholera to host and feed, resulting in a bacterial pool of cholera. 17a: Perhaps mangroves may provide the environment for cholera to be hosted and feed (N fixation also performed by mangroves).
18&19	Residual bacterial pool (18) provided with food source and host (19) results in a outbreak of bacteria in a pool.
20&20a	Terrestrial rainfall leading to flooding (20) or sustained wet conditions over land (20a).

21&21a	Flooding or sustained wet overland conditions leads.
22-24a	Conditions for outbreak of cholera bacterial pool over land – 2 main avenues; through river or sustained wet overland conditions.
24	Outbreak of cholera over land in river or wet overland areas. Comments: host and food source not clearly stipulated if a bloom cycle initiates cholera production.
31	First infection enables later outbreaks but is a weaker link than 34.
32&33	Human vector for spread of cholera (socio-economic conditions play a role i.e. 33). Hypotheses may focus around whether 30a or 32 plays a stronger role i.e. human spread of disease or more cholera bacteria in the environment through biophysical processes. To some extent, both play a role but it is important to understand which driver is more significant under certain conditions and why.
30a&30b	Possible bidirectional influences considered between outbreaks of bacterial pool on land: temporal question about what comes first; 30b or 6 and how strong are these linkages if relevant. This assumes the marine/estuarine hypotheses holds for first infection.
34	Later outbreaks on land result from epidemic spread of cholera through human beings. A whole chain of feedback effects to the human system may be modelled here but require consideration of socio-economic drivers more clearly.

When the process of formulating graphical causal maps was initiated, it required that the hypotheses that had been posed earlier be articulated in terms of the causal chain of events upon which the hypotheses were based. Project team sub-groups and members had previously tended to focus their attention either on the sub-system domain on which they had most expertise, or on macro-scale evaluations of correlation based evidence on data sets.

When the participants were forced to make causal inferences explicit in a graphical framework, a cross-conversation was initiated between the micro-scale and macro-scale observations of the system. Team members started to co-operate over 'finding the link' which may substantiate one or both of their hypotheses on the problem.

However, during the divergence phase they still remained focussed mainly on the sub-system 'parts' or embedded units where they held greatest expertise for hypotheses making. A host of divergent hypotheses, each described by a complete causal structure was formulated during interdisciplinary workshops where they were exposed to scrutiny of the whole team. These resulted in five different graphical causal models as shown in Figure 36, Figure 37, Figure 38, Figure 39, & Figure 40. Each graphical causal model corresponds to an embedded unit, upon which a series of hypotheses are made. The modules are called:

1. The Sediment Hypotheses Module (see Figure 36):
 - a. This is the hypothesis that cholera is endemic to aquatic sediments, and that two mechanisms can be identified for amplifying and distributing cholera in sediment. Temperature is the main amplifier of the sediment reservoir, while turbation is the distributing amplifier - and brings it into the area where

people are exposed to it. Runoff may act as a contributing distributor.

2. The Pond Hypotheses Module (see Figure 37).

a. We assume cholera doesn't survive dry-land conditions. However, it may lie latent or dormant in ponds and generally where-ever standing water is found.

3. The River Hypotheses Module (see Figure 38)

a. There are two hypotheses regarding cholera concentration changes, that is; (1) that both zooplankton and phytoplankton play a role as nutrient sources and carriers (see arc A: Figure 38), (2), that the nutrient source alone leads to changes in cholera concentration (see arc B: Figure 38), or (3) both A & B drive cholera concentration in combination (see arc C in: Figure 38 i.e. all 3 edges).

4. The Sea Hypotheses Module (see Figure 39)

a. Here, we tested published opinions on biophysical sources of cholera (Bangladesh, Bay of Bengal). The first sea hypothesis is essentially that zooplankton serves as a host for cholera, and that cholera multiplies in large amounts in large-scale offshore marine algal blooms.

b. This still leaves the requirement for a mechanism for transport of cholera to humans, for example, through contaminating drinking water near the sea when sea-surface rises occurs.

c. The second sea hypothesis related to sediment on seabed as a reservoir where cholera concentrates, and can be amplified in zooplankton through high nutrient availability.

5. The Human Epidemic Hypotheses Module (see Figure 40)

a. There are many socio-economic (and behavioural) factors affecting cholera transmission, including what people eat and drink and vulnerability – and softer aspects such as access to running water, electricity, radio communication, clinics and primary healthcare, etc. The core focus of the cholera SRP project was on the environmental causes of cholera, and as such, the project was only concerned with social transmission of cholera in as far as it involved the system features they were researching. Therefore, we did not build an elaborate model of causes and effects, but rather focussed on obtaining a general characterisation of the diversity of drivers and responses involved in social transmission of cholera.

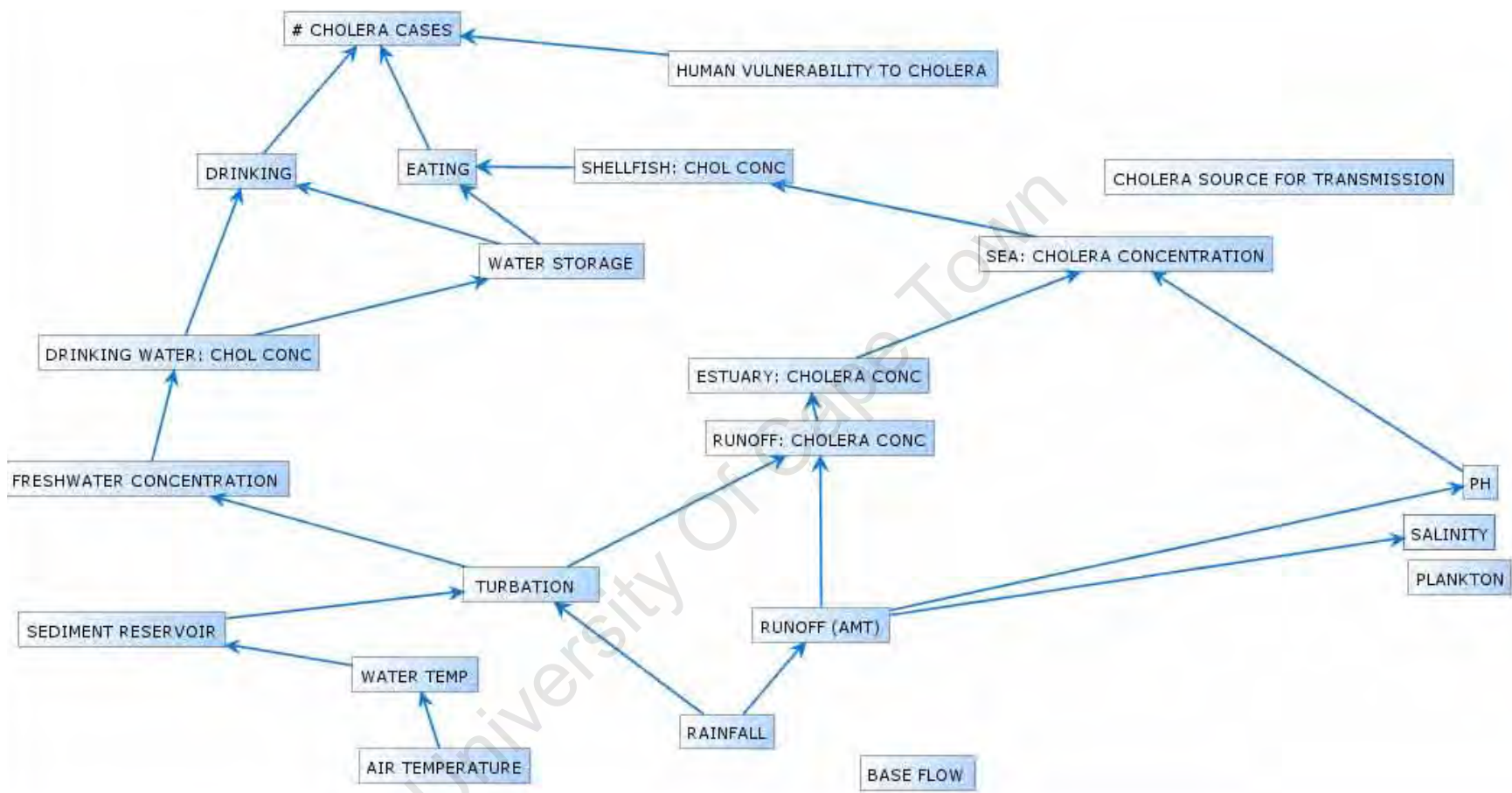


Figure 36: Sediment Hypothesis

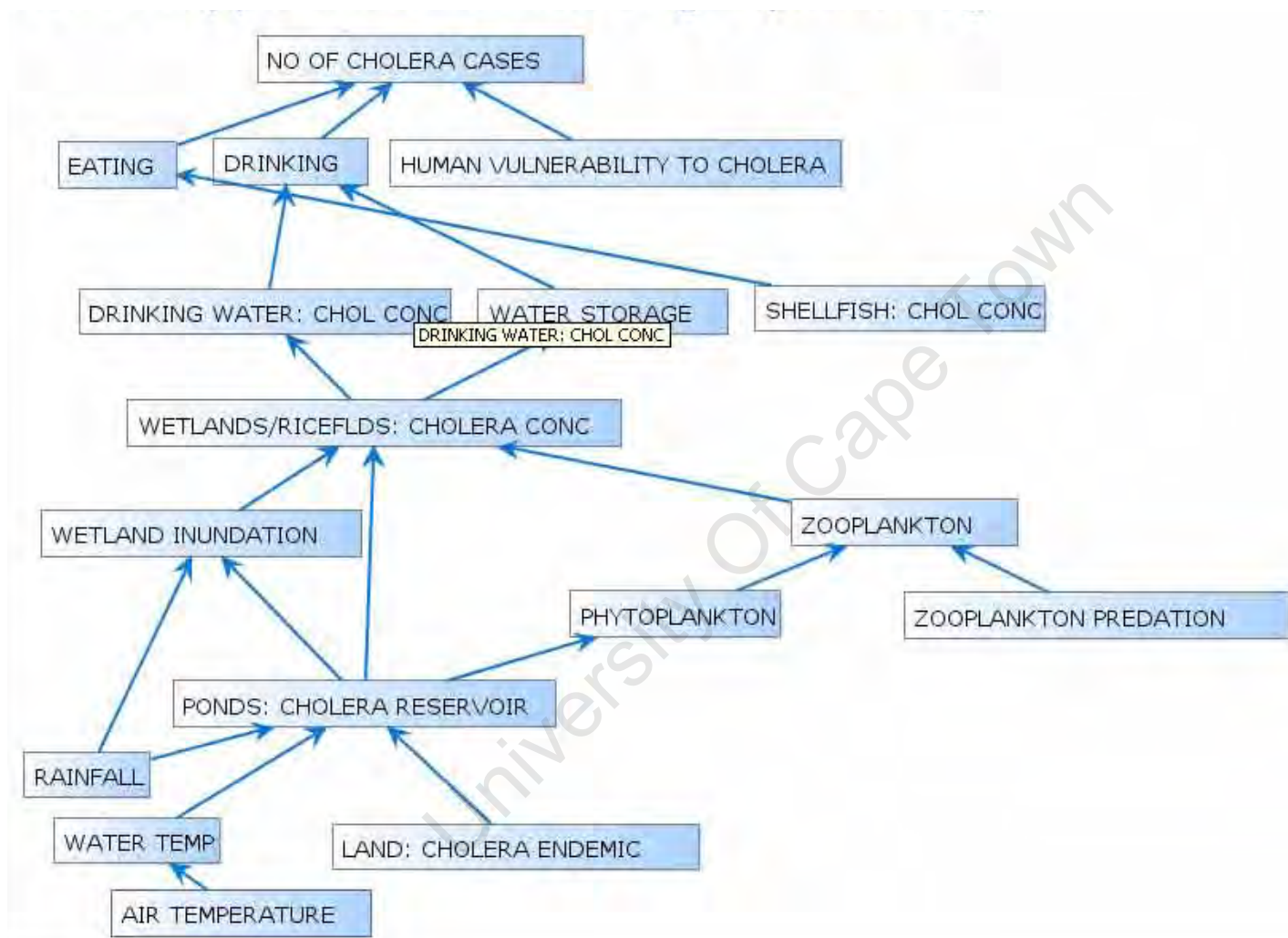


Figure 37: Pond Hypotheses Model

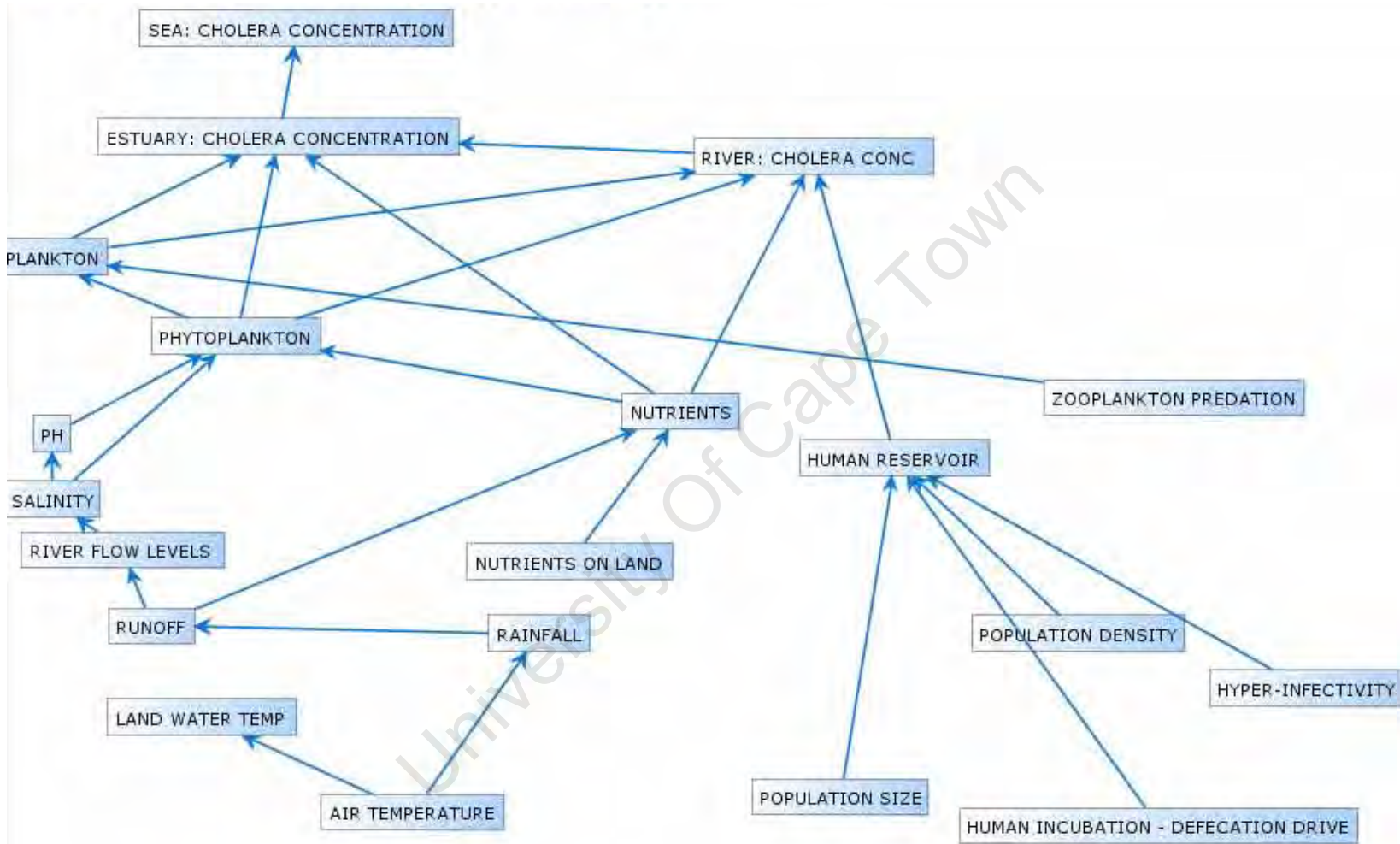


Figure 38: River Hypotheses Model

Sea Hypotheses [Expanded]

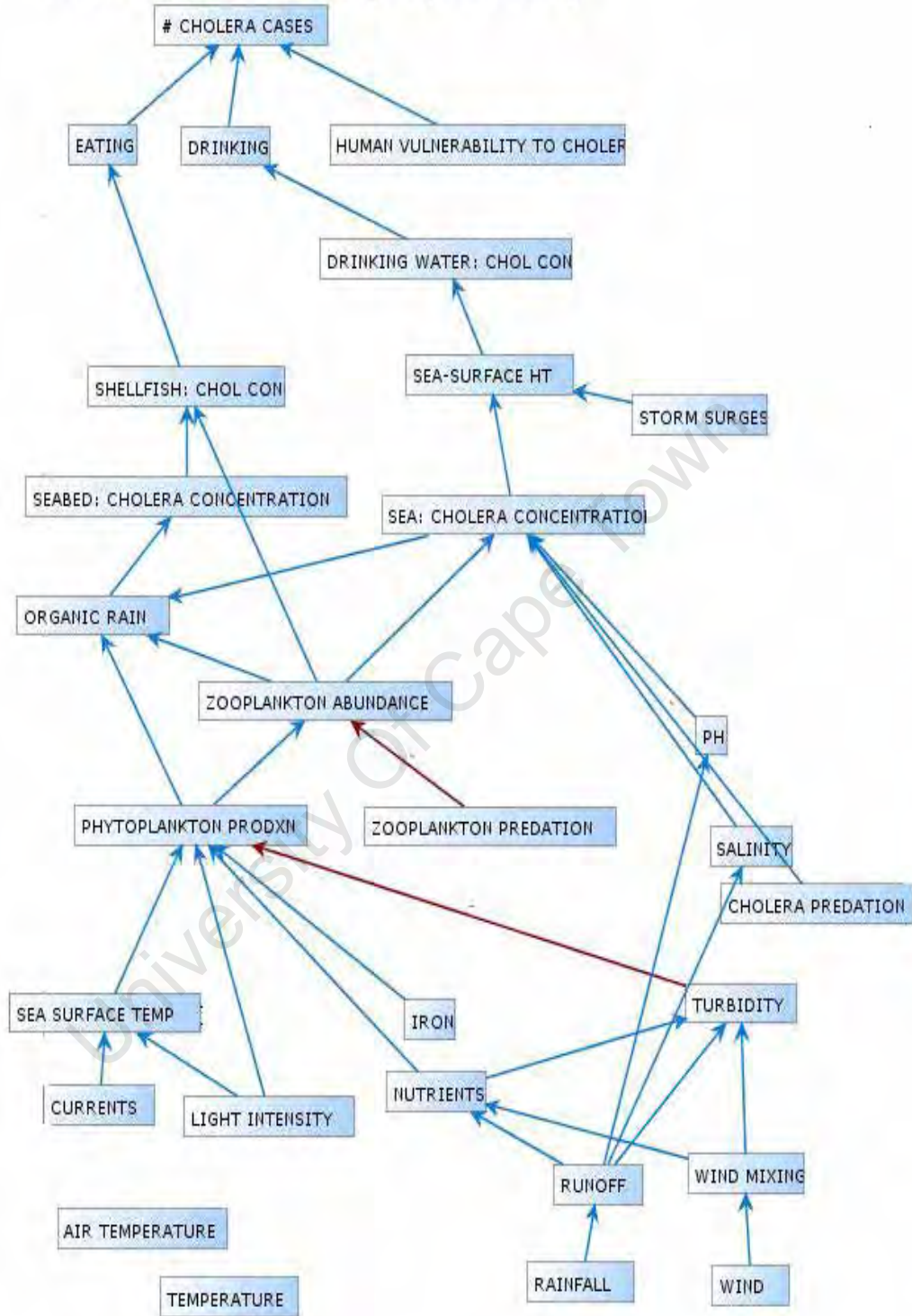


Figure 39: Sea Hypotheses Model: “Cholera Predation”

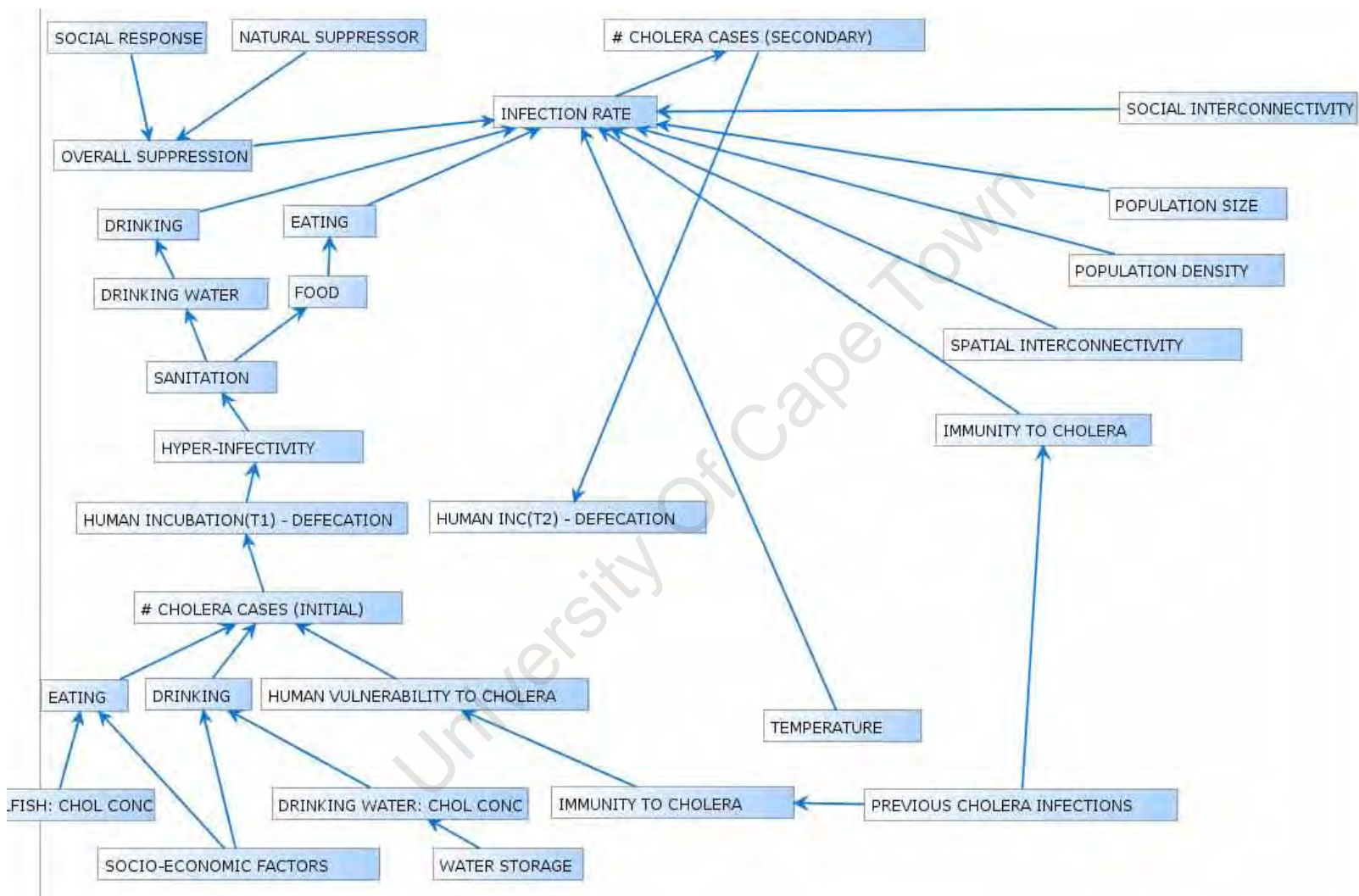


Figure 40: Human Epidemic Hypotheses

An interesting development occurred during the project that is worth mentioning in this dissertation. The Cholera project team decided to ‘take a step back’ so they could work out how they wanted to engage with the graphical causal methodology themselves. They then developed a vocabulary or terminology for understanding the causal linkages in the system, which they identified as reservoirs, amplification mechanisms, exposure mechanisms, general transmission mechanisms and long and short term de-amplification mechanisms – see Table 20 in Appendix A: Cholera Study. What is striking about the terminology they used is that it illustrates how a ‘systems level’ understanding of the system (i.e. dynamic systems theory; involving stocks, flows, leads and lags) emerged from the contemplation of causal linkages. The ‘amplification’ and ‘de-amplification’ mechanisms that the team identified are direct matches to positive and negative feedback effects in dynamic systems theory. The reservoirs are the ‘stocks’, and exposure and transmission mechanisms involve ‘flows’. This is important because it emphasizes the compatibility of a causal hyperstructure based approach with other soft system methodologies (Checkland & Scholes, 1990) and dynamic systems models. The BPDA approach allows for flexible evolution of hierarchy, definition and terminology within a framework in which shared understanding can be engendered.

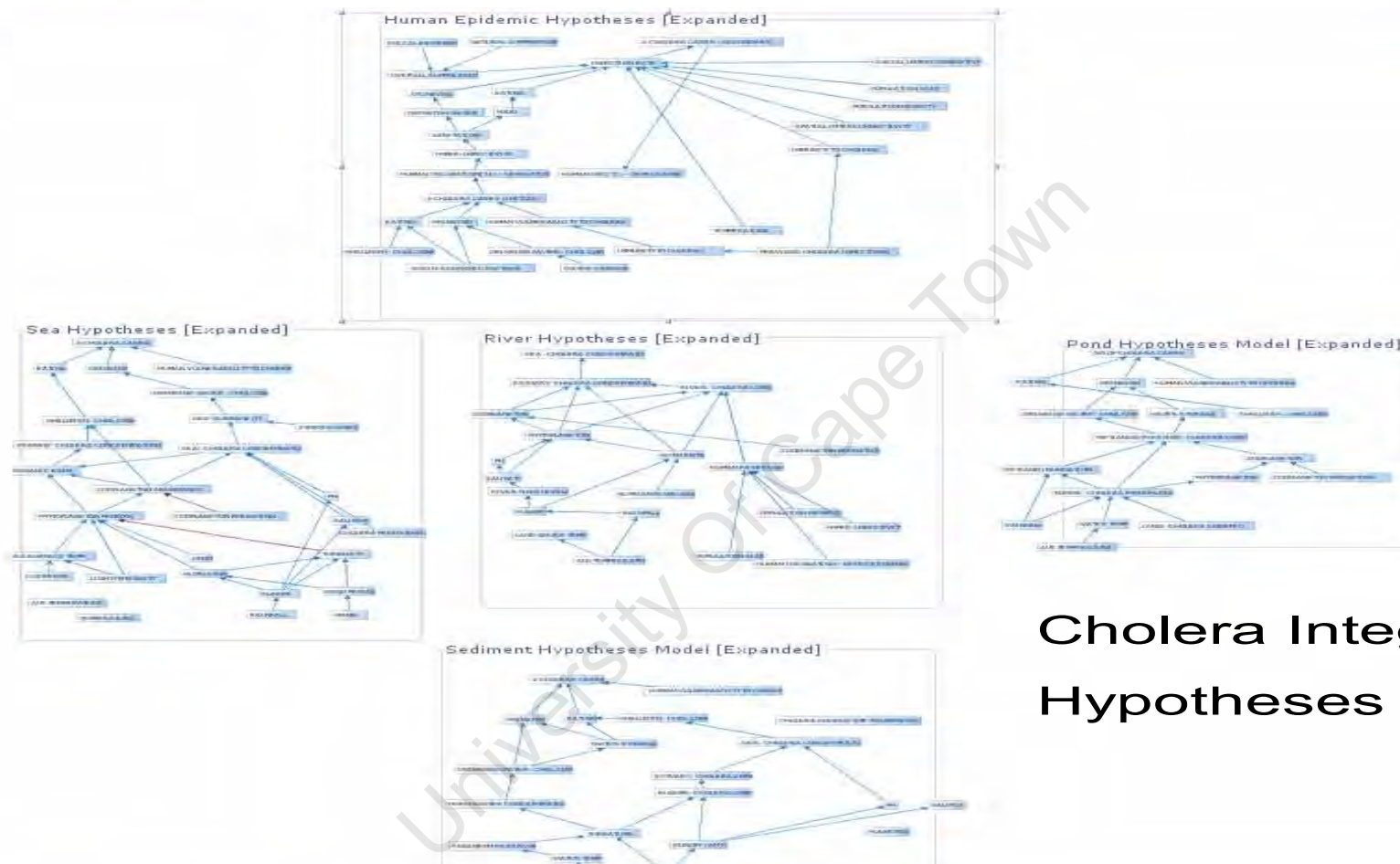
6.6.1.2 **Convergence**

In the previous phase, the focus of workshop participants remained mainly on sub-systems or embedded units of study. While they were able to help share understanding of each other’s respective hypotheses, they had not yet started to make insights into possible hypotheses that existed between the respective embedded units, at the whole social-ecological system scale.

However, when the model was displayed to the participants as displayed in Figure 41, where the various sub-modules are shown together, this began to facilitate a different level of shared understanding between them. Researchers started to make hypotheses based on linkages between different

embedded units (usually corresponding with areas of expertise). By considering inter-relationships between various hypotheses models (linked to sub-system level components), the participants were able to consider the linkages between previously non-overlapping models. They made full use of the terminology and vocabulary developed earlier in the study to communicate, interrogate and debate how the embedded units might be linked. Reservoirs, amplification and transmission mechanisms of different types were explored to identify cross-system linkages and intra-scale linkages within embedded units.

In this phase the team viewed each model in relation to each other while making system level hypotheses. Each sub-hypotheses model was able to fit to each others' causal structures to formulate system level hypotheses. A variety of different linkages could be envisaged. At this stage maximum cooperation amongst researchers was achieved, as they explored system level hypotheses with the comfortable knowledge that their sub-system level hypotheses were still being included and addressed. For example, in Figure 42, we illustrate how a sub-system component such as 'sediment' from one embedded unit may be linked to others supporting system level hypotheses making. Issues regarding sediment could then be viewed as possibly underlying the hypotheses made regarding other system components (rivers, ponds, etc.). In this way, the research project was facilitated towards a greater, systems level understanding of their system.



Cholera Integrated Hypotheses Model

Figure 41: Figure Illustrating the Various Hypotheses Modules in a Single Framework: Hypotheses focussed on different sub-system components (sea, rivers, sediment, ponds) and human agents.

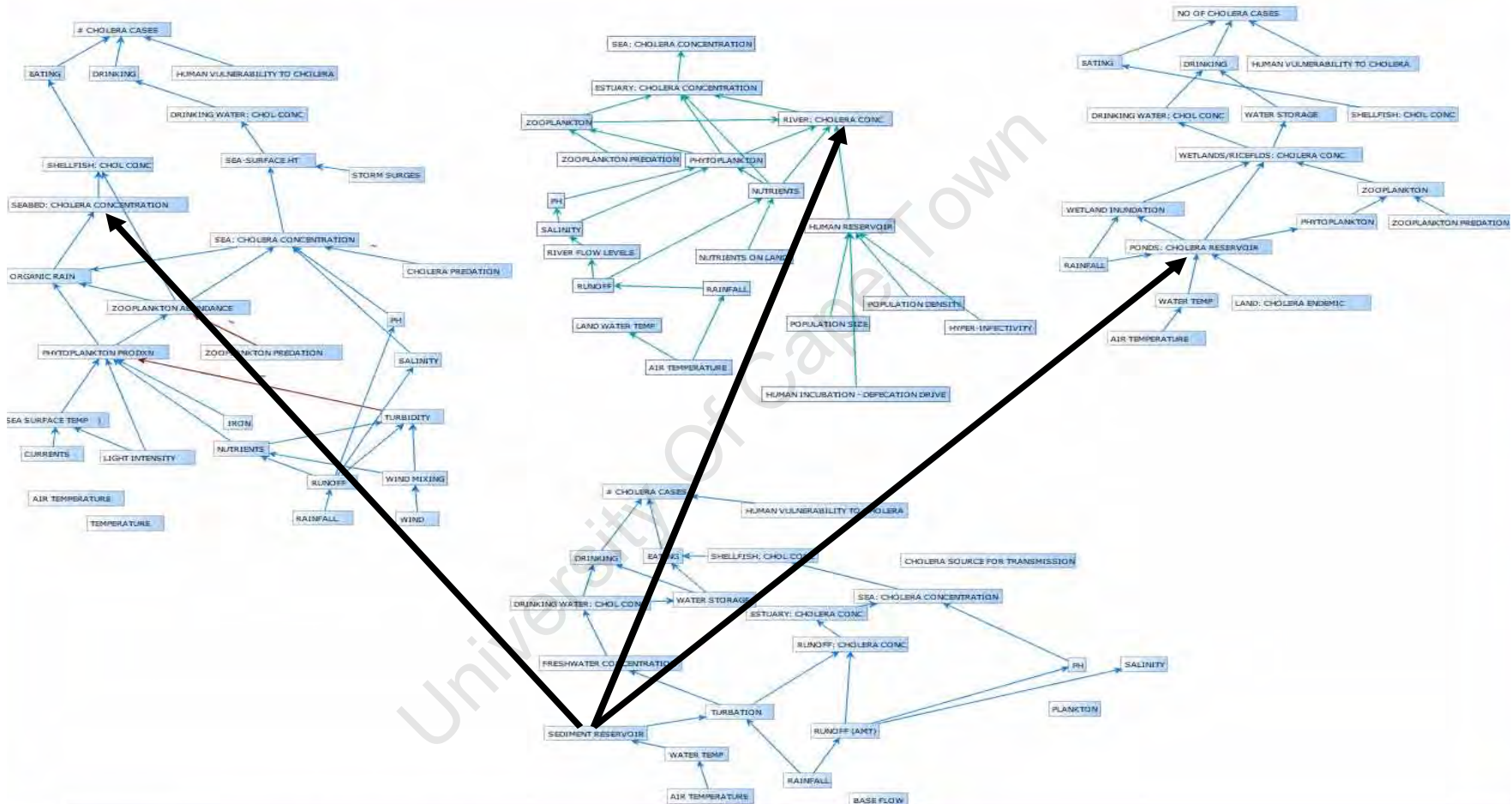


Figure 42: Making System Level Hypotheses: Researchers identified that the ‘Sediment Hypotheses Model’ could be linked to sea, riverine and terrestrial sub-system components, and were able to articulate hypotheses using causal linkages.

In this study we observed how a diverse cross-disciplinary project team, consisting of sub-groups of experts with specific disciplinary expertise, could arrive at a shared understanding of the various hypotheses and embedded units being researched in the study, and how they are or might be related.

Graphical causal maps are especially suited to explanation building as they force the process of hypotheses making into specifying causal relationships, and allowing the rest of the project team to interrogate their decision-making.

The project team were able to ‘take ownership’ of the BPDA approach, and developed their own vocabulary for explaining system level features and effects such as stocks, flows, leads, lags and feedback, and used this vocabulary increasingly as the workshop exercises unfolded.

As each “hypotheses module” was formulated, the project team dug out research publications, articles, books, computer models, presentations and data to support the hypotheses they tendered. These sources of information, and explanatory notes were captured in the graphical user interface, and provide a record of thinking that can serve as a transparent, trace-able record of the thinking that informs the research design of the project.

Perhaps the most significant outcome of this case study is that the team broke through to systems level understanding – reflected in system level hypotheses formulation after workshops. Whereas before workshops there was fragmented embedded unit level competing hypotheses that were being pursued by researchers, after these workshops researchers identified significant relationships between embedded units and formulated system level hypotheses. This system level understanding emerged from a rigorous multi-

participant interrogation of the causalities underlying the key research hypotheses.

6.6.2 Gauteng Urban Growth Study: Built Environment

This study was undertaken in two two-day workshops with a research group in the CSIR Built Environment division which focuses mainly on planning and implementation in the built environment. It was mainly concerned with the issue of urban growth in Gauteng, the main economic province of South Africa, in which the city of Johannesburg is located. The aim of this study was to explore the linkages between the different sectors in Gauteng and assess, at a cumulative scale, the impact of growth on various limiting resources, such as water and energy.

We held a series of two workshops with the research group to help establish a baseline causal model of how sectors are limited and inter-related through different levels of, for example; economic, population and transport growth.

In this study, the research group took ownership of the participatory process, and used their extensive experience with such processes to explore the full range of system components and inter-relationships.

We then used the information collected at the workshop, and our experience with building embedded sub-system modules to formulate graphical causal maps to articulate the critical interdependencies between embedded units. We followed a similar process as was undertaken in the Cholera project, and put together a preliminary graphical causal model of how urban growth in Gauteng might be modelled using a Bayesian network. This is shown in Figure 43, where a number of sectors are shown as embedded units or sub-modules, as detailed in chapter 13; appendix B.

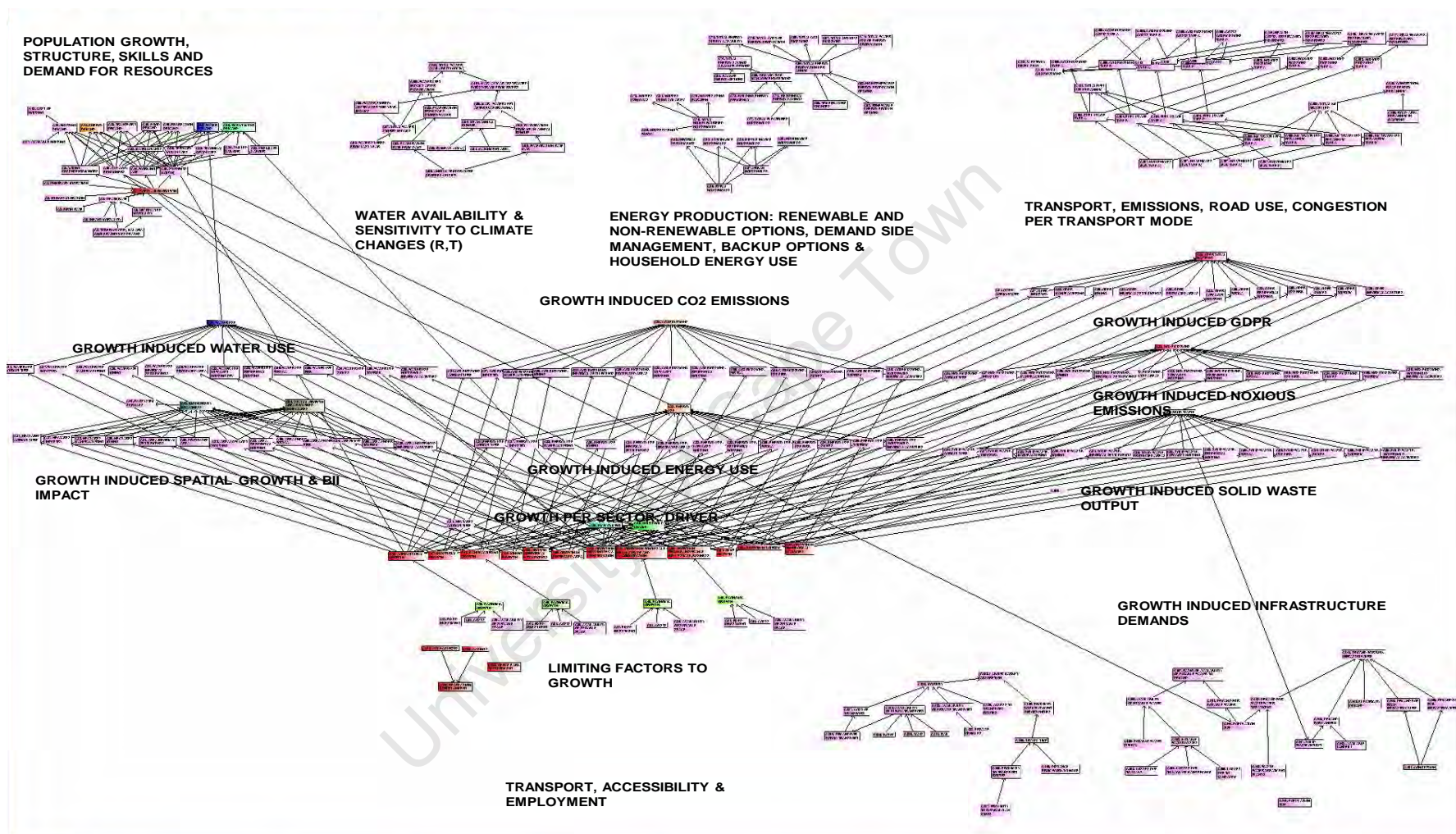


Figure 43: Gauteng Urban Growth Model: All modules are shown

A graphical causal framework for inter-related causes and effects for the City of Gauteng is shown in Figure 43. Various sector-based models can be formulated by scrutinising driver and response measures needed to answer broadly scoped and detailed questions. The model and sub-models shown here are not exhaustively formulated and are mere illustrations of how sector-based models can be constructed in an adaptive modelling framework, and linked in different ways to answer system level questions regarding cumulative effects. At this stage, the model is exclusively focussed on cumulative effects, but models can be developed for smaller or larger spatial regions which can be interconnected using the outputs of more detailed systems dynamics and agent based models that focus on the dynamics and reflexivity of the social-ecological system.

This model was only developed to a preliminary stage, as the time period allocated for the study was short. The key learning revolved not around urban growth in Gauteng, but rather about what the key requirements for participatory processes involving a wide range of disciplinary considerations, involves. The level of awareness required for a researcher employing the BPDA approach is such that the researcher will have to be able to adapt to new and different ways of viewing and characterising an issue or problem. The ability to 'thrive' in the often chaotic environment of participatory workshops by being able to 'let go' and trust how the process unfolds, is essential. A process that is too tightly or too loosely prescribed and managed leads the researcher to encounter resistance from the research group concerned.

7. **BPDA & Cross-Case Analysis & Discussion**

The extent of collaboration that resulted from using the BPDA approach is evidenced in the number of co-authored interdisciplinary publications that resulted from the study. The author also collaborated extensively on the *conceptual* development of the BPDA approach, as evidenced in the early conference publication by Peter, Potgieter & Monteiro (2007). However, as the author gained more insight into the conceptual foundations of the BPDA approach during the course of this PhD, a single authored book chapter was published, i.e. Peter (2008), which detailed the fundamental principles underlying the approach, even though it had not been given the name BPDA yet. That is, the BPDA approach underwent refinement as we engaged with case studies of increasing complexity in terms of scale and number of variables and embedded units, and in terms of progressively more inclusive participatory processes.

When we first considered what methodology we could employ to test the BPDA approach, we settled on a case study based approach. We therefore decided to take 'slices' of social-ecological system interfaces, progressively increasing the slices in complexity, scale of application, number variables and embedded units, number of states of individual variables, number of cross-disciplinary participants, eventually working up to large scale models and interfacing with decision-makers. We progressively increased the scale and complexity of case studies in order to build up our understanding of how to formulate, test and verify Bayesian models and how to employ them effectively in scenario planning.

In addition, the Sisyphus software was developed in parallel, and the development cycle was closely tied to the order in which case studies were developed. That is, we had to consider the development cycles of the software in developing the case studies, as the software was increasingly being pushed to higher levels of computational complexity, as more variables and interdependencies were introduced with every successive case study.

Moreover, starting off with smaller case studies also allowed us to progressively learn and engage with the nuances involved in participatory process management.

As we progressed through each case study, which originated from a range of ongoing CSIR projects and programmes of research, we learnt how suited the BPDA approach was to ensuring rigour, robustness, internal and external validity of social-ecological system case studies. Even though an open systems approach was taken towards cross-disciplinary workshop facilitation in each case study (i.e. each group was able to design its own way of using the BPDA approach, depending on what the problem demanded), when participants got to the stage where they were speaking the 'language' of causality, (i.e. building, interrogating and debating hypotheses using graphical causal maps and eventually, Bayesian networks), the power of the approach in dealing with contradictions and creating shared understanding became clear to participants. From thereon, workshops usually became highly constructive debates around the fundamental assumptions governing key hypotheses around which their interdisciplinary case studies were oriented.

Perhaps the key observation that emerged from engaging a wide set of case studies and problem spaces is that the BPDA approach is flexible enough to act as an integrator of more general classes of case studies than that conducted on social-ecological systems. Where case study integration is concerned, hypothesis formulation necessitates articulating and scrutinizing causal interdependencies in the system in question, and this is where the BPDA approach is strongest. The approach does not impose any strict top-down conceptual frameworks, and therein lies its strength. It only prescribes that hypotheses and system interdependencies be visualised as conditional causalities. This frees up the BPDA approach to find application independently of the specific context of inquiry of a particular study.

Whether BPDA can be effectively employed in all classes of case studies, however, is contentious. Indeed, for some case studies, such as those involving deep and textured ethnographies, an approach such as BPDA may

be of no use at all, because the objective of the study is to arrive at subjective conclusions through an embedded experience, and not necessarily to build hypotheses and test them.

From conception to conclusion, each case study benefited greatly from using the BPDA approach (whether in full or not) in terms of achieving shared understanding that did not exist before the study. Different problem sets and contexts were encountered in different case studies, and by cross-disciplinary teams from varying ends of the methodological spectrum. In general, both tacit and explicit knowledge was generated through navigating the sequence of case studies. The tacit elements relate to know-how and experiential learning that was engendered regarding technical aspects involved in building Bayesian networks, and to facilitating participatory processes between researchers, decision-makers, and combinations of both. The tacit elements can only be obtained from 'doing', and as such, the BPDA approach will require the same of anyone who wants to implement BPDA.

Consequently, the role of the author also grew and evolved with the case studies as learning increased. The author's key role in conducting the case studies was, in broad terms:

Firstly, to facilitate disciplinary interaction in participatory processes (this will be discussed in more detail later in this chapter). Secondly, the author played a central role in; model formulation, construction, population and verification, running scenarios, conducting preliminary analysis and coordinating the feedback from multiple participants to revise scenarios and analyses. The author was at the core of integrating analyses and writing up most of the research. Thirdly, the author conceived of, and played a close supervisory role in the development of the Sisyphus software and worked closely with the local based SME Complex Adaptive Systems Pty Ltd to develop the design to its full potential.

The authors role evolved from playing a very central role in the initial case studies, to gradually playing more of a background, facilitator role in the

final case studies. This initial learning curve was exponential, because the detailed nuances of how to employ the approach in different problem spaces was not yet clearly understood. However, as the author became more confident through the progression of diverse encounters, in case studies with different disciplinary emphases, participants and methodological contributions, a personal store of know-how developed, admittedly, mainly to the benefit of the author. However, the intention of the BPDA approach is not to educate participants about how to build Bayesian networks. Rather, the purpose of the BPDA approach is to introduce them to integrated hypothesis-building, to participate in formulating a shared understanding of systemic interdependencies, and in a sense, to enable them to engage with Bayesian networks without becoming Bayesian experts. It is most likely that a newcomer to implementing the BPDA approach in the role of the author will embark upon a similar exponential learning curve in learning to engage with the technical, detailed aspects of both Bayesian network model development and participatory process management.

So far, we have dealt with what we learnt about the role of the BPDA approach in case study research, that is, in supporting and enhancing case study as a research methodology. The key learning points that arose from implementing the BPDA approach in case study research are carefully detailed in chapter 8. We also discussed the role of the author, as it emerged through the series of case studies that were performed.

For the remainder of this chapter, cross-case comparison is made in respect of the key factors that were identified as necessary for dealing with the complexity of social-ecological systems, as articulated earlier in this dissertation. Here, we summarise the overall learning that was gained through conducting the single case studies. We attempt to isolate its particular advantages for supporting case study research into social-ecological systems challenges that are concerned with sustainability. We base this on the learning

that was summarised for each full¹⁷ case study (i.e. in Table 3, Table 4, Table 5, Table 7, and Table 17). The conclusions that are drawn regarding the critical factors that this dissertation aimed to test regarding the range of capabilities of the BPDA approach are made on the basis of the conclusions that were reached in the aforementioned list of tables. These tables examine to what extent the BPDA approach was successful in addressing a specific list of factors for each full case study. A summary table, estimating the degree to which required factors were addressed (on a scale of 1-5) in each case study is shown in Appendix E, Table 21. These factors are accounted for in the next sections of this chapter, where more detailed explanation is given in respect of each.

7.1 **Integration across Scales**

The case studies show that the BPDA approach can be used to model systems at the key decision-making scales in South Africa, namely; magisterial district, municipality, provincial, national and regional scales of integration can be supported at cumulative scales. Although we did not explore linking models at, for example; the magisterial district scale, with municipal or provincial scales, the Western Cape Province Bayesian Model illustrates that it is indeed possible to integrate across different levels of decision-making using a large number of embedded units.

We progressively included more embedded units in successive case studies, broadening the scope of research and modelling in terms of providing meaningful sensitivity analysis with increasing complexity and scale. The Western Cape case study illustrates that intra-scale (within embedded units) and cross-scale (between embedded units) sensitivities can be evaluated within the Bayesian framework at massive scale (in terms of numbers of variables

¹⁷ Tables were only drawn up for the first five of the case studies presented in this dissertation. This is because the remaining two did not involve using the full BPDA approach, where Bayesian networks are built and used as part of the process. The last two case studies are only relevant in so far as they interrogate the ability of graphical causal models to help orientate hypothesis-making in participatory processes for complex social-ecological systems.

and scope of system). This allows researchers and decision-makers to evaluate interventions within a sector, or to evaluate regulations between sectors.

In all case the full case studies embedded units were detailed at different scales and at different levels of influence in relation to the broader system. It is not difficult to envisage cross-scale influences using the BPDA approach, because cross-scale influences are treated alongside all other causal interdependencies as 'equals'. The Bayesian hyperstructures make no distinction between an intra-scale and inter-scale effect. We can visualise these interdependencies clearly using the BPDA approach, and the software based visualisation makes all causal dependencies clear to the participant.

There is no limit to the amount of detail that can be developed within embedded units, except software memory limitations. In general, each Bayesian node can be expanded into a more detailed model. This is achieved with ease using Bayesian hyperstructures, as evidenced in the progression from the simple Incomati-Maputo Bay case study to the Western Cape Province climate change study. We were able to develop a more detailed system understanding with each new, increasingly complex, case study. We also designed the Sisyphus software to run over a computer LAN so that we could distribute processing as the models became larger and more detailed. In theory there is no limit to the integration of embedded units at different scales.

Lastly, the number of states that the Sisyphus software can handle in individual variables simultaneously is very large compared to other Bayesian network software interfaces. We had variables with up to 60 states, included in some of the models. This is because at the whole systems level, we were testing the system under extreme driver ranges, and the variables needed more states in order to be able to vary across these ranges themselves. Thus, in terms of fine-scale testing of driver changes, the software that was developed in support of the BPDA approach proved exceptional and provided a deeper level of flexibility, and system response to fine changes in driver values could be tested in scenarios.

In summary, the BPDA approach works well for integrating across scales and levels of detail. However, as employed in the case studies in this dissertation, the BPDA approach was applied mainly at cumulative scales. It remains questionable to what level of precision and accuracy Bayesian networks can be employed in more dynamic, spatial models, such as transport, but they can certainly link to and collect probabilistic output from more detailed models. Implementing Bayesian networks at finer spatial and temporal scales remains an ongoing subject of research for the author, and is also an area of focus in other recent efforts that use Bayesian networks to address sustainability questions (e.g. Baran & Jantunen, 2004; Borsuk et al, 2004, Bromley et al, 2005).

7.2 **Integrative Modelling across Disciplines & Sectors using Bayesian Networks**

From a modelling perspective, we began our case studies by relating the human development and economic components to the biophysical components of a system (Incomati catchment – Maputo bay case study). This included the water, agriculture, mining, population, shrimp fisheries sectors. In later case studies, this was progressively built up to include an increasing number of sectors such as water, energy, manufacturing, tourism, household informal activities, etc. We incrementally built up to greater levels of complexity and included more embedded units as each single case study unfolded.

The case studies covered a variety of inter-disciplinary research group facilitation workshops that were concerned with social-ecological systems scale issues, and the BPDA approach proved useful in facilitating interdisciplinary researcher (and ultimately decision-maker) interactions. It achieved this by enabling researchers and decision-makers to engage with the core assumptions around how the research was integrated to address the questions they were interested in. Cross-disciplinary workshop facilitation is difficult, and we used a variety of soft mechanisms to improve communication

and understanding. At the outset of workshops, orienting participants around the BPDA approach often proved slow and laboured. However, once participants started to make and interrogate causal linkages and causal chains to explain their hypotheses, they would begin to appreciate the value that the approach brought to their integration efforts.

In modelling terms, each sector is 'represented', in a sense, by the inclusion of an embedded unit representing it. Moreover, its cross-scale and inter-sector dependencies are also made explicit through the integration of embedded units in graphical causal models and Bayesian networks. This allows sector representation, or analysis by proxy sector representation. This is because we can envisage sector interventions within a sector, and between sectors, and test them in scenarios.

As far as eliciting expert opinion the BPDA approach worked well to extract causal structure. However, where conditional probability tables were extremely large it was difficult to populate them one step at a time. It required a deeper understanding of how to use equations to generate distributions, which could then be adapted by experts. Thus, anyone attempting to implement the BPDA approach by solely eliciting expert-generated CPTs will take a long time to build case studies at the scales and levels of detail that were conducted in this dissertation. The added benefit of using equations to generate the CPTs before experts analyse and interrogate them, is that the participants are automatically forced to start thinking about the equations, and hence, can design research to improve understanding of the nature of these relationships from an early stage in the research effort.

The core strength of the BPDA approach in integrative modelling is simply in its capacity to help *visualise* cross-sector and cross-disciplinary interactions. In this respect, the software-based approach to employing graphical causal maps and Bayesian networks has enormous advantages over paper based processes. It allows for careful contemplation of the fundamental assumptions that underlies sector integration in the model. Some disciplinary experts are sector based. For example, those working in water will be more

concerned about water and how it relates to other sectors in the model, and likewise with those working in energy or conservation of the environment. Accordingly, these disciplinary experts orientate their analyses around the sector they are concerned with. With the BPDA approach however, they benefit from interdisciplinary views on how their sector inter-relates with other sectors, and are able to participate in constructing a shared understanding of their role in the system, whether from a research or decision-support perspective.

7.3 **Developing New Indices & Embedded Units**

We also increased the number of indices for top-level measures of performance included in the model(s) over the course of our research. We began our case studies by calculating simple indices such as water availability, water use and direct and total economic value-add. We increased the number of indices per model as we included new embedded units in each new case study, to suit its particular needs. Our penultimate case study (Western Cape) had top level indices that included; five different noxious gas emissions, total energy use, total water use, total energy availability, total water availability, CO₂ emissions, Gross Domestic Product (GDP), Gross Geographic Product (GGP), solid waste, and waste-water abstraction from population pressure.

Moreover, *within* each embedded unit there are useful indices that have been formulated for each model, particular to its needs. For example in the Western Cape case study; the tourism module has indices ranging from the number of tourists from different countries to the revenue obtained from each, and relevant totals. On the other hand, the energy production module contains a range of indices ranging from total energy production, total CO₂ emissions, total water use and total cost of energy production. Thus, indices can be set up at multiple scales, simultaneously within the Bayesian framework.

Moreover, due to the large numbers of variables included in a single case study model, and at different scales, we can design different *sets of*

indicators, and different *aggregate indicators*, to suit the particular research question and context of inquiry at hand. This is of critical importance and a main benefit of the BPDA approach. Users can use different sets of indicators to help explore and explain different system level behaviours.

Indices must also be able to evolve and change if required; with the insights that unfold as the research effort progresses, and with changing real-world events. Here, the BPDA approach is at its strongest. Bayesian hyperstructures can easily be updated with new information, and simple 'cut and paste' type of tasks characterise the modelling activity involved. The BPDA framework allows us to model large numbers of variables and their interdependencies. The inherent uncertainty in social-ecological systems, due to their dense intra and inter-connectedness, implies that there is little point trying to predictive its future behaviour more and more accurately. The BPDA approach can accommodate a large number of variables because of its suitability to handling information that is uncertain. Bayesian networks are designed for reasoning with uncertainty and they serve their purpose in the BPDA approach here extremely well. The flexibility afforded by Bayesian networks comes at a small cost in certainty (Bayesian networks model causalities to between 10 and 20% uncertainty), but this lies within the inherent uncertainty of the system itself, and as such is not really a trade off.

In summary, the hyperstructures, which consist of graphical causal maps and Bayesian networks can be easily adapted to include new indices and embedded units, depending on the quality of information available in formulating the index. Indices can be adaptively monitored and new indices can be added and developed within the framework.

7.4 **Facilitating and Enabling Transdisciplinarity**

Often, when contemplating the causal relationships using graphical causal maps or Bayesian networks participants are able to postulate the existence of new relationships and indices. The very fact that the

hyperstructure based approach enables a flexible, adaptive, non-hierarchical modelling framework where new indices can be developed alongside old indices means that transdisciplinarity, at an analytical level, becomes a real possibility.

Moreover, the very insistence on expressing hypotheses at the causal level, where different overlapping and non-overlapping explanations can be developed for a system, phenomena or event, encourages a more democratic exchange of views. The facilitated graphical causal mapping and Bayesian network formulation exercises rid inter-disciplinary dialogues of opaqueness and lack of shared understanding because it employs the visual expression of causal relationships as a basic language for communication between different disciplinary and other experts.

The range of different hypotheses that can be tested within a single model is astounding. Moreover, we can develop contrary and different understandings of the system by expressing the causal linkages to formulate different views, whether these views are overlapping or non-overlapping. This shared understanding forms a good basis for transdisciplinarity to emerge.

Moreover, for transdisciplinarity to occur in practise, the issue of creating a shared language to address context-specific observations and deductions must be addressed. That is, the integrating formalism must be 'open' enough to allow for different top-down and bottom up frameworks to be incorporated, and for the shared language to evolve as and when disciplinary participants have new insights and find new terms to describe them. In practise, the BPDA approach makes no restrictions on how participants engage with it except in stipulating causality and conditionality. Earlier in this dissertation we described how taxonomies (i.e. classifications) and causalities co-evolve. This was indeed the case in the cholera case study, where after first engaging with graphical causal maps, the team 'took a step back' and formulated their own set of terms and classifications, as tabulated in Appendix A. They intuited a set of terms that resembled systems dynamics terms such

as stocks, flows, leads and lags, which were all consequently encoded into graphical causal models.

The hyperstructures employed in all the case studies progressively increased in detail or scale, and embedded units were added or deleted as their relevance to the particular case study dictated. This allowed for the exploration of different ideas of how embedded units are inter-related in relation to system level behaviours, and the core benefit of the BPDA approach as far as transdisciplinarity is concerned is the shared understanding it helps set up, which can then serve as a basis for new knowledge and understanding to *emerge* (i.e. from a set of transdisciplinary actions (Max-Neef, 2005)). In short, the BPDA approach provides a valuable framework for sharing and managing the evolution of new knowledge, as it emerges, and in this sense is suited to supporting transdisciplinarity.

7.5 **Incorporating Non-Linearity**

In all the case studies presented in this dissertation a wide variety of linear and non-linear relationships are incorporated into the models using equations or conditional probability tables to relate parent and child nodes. What is important, is that these non-linearity's show up at the correct sensitivities at the output end of the model, especially where full sensitivity analyses were conducted for each scenario. This distinguishes the BPDA approach apart from other MCDA type approaches, where 'linearising' the system is a procedural requirement for the underlying statistics. Feedback and feed forward effects can be incorporated as probabilistic relationships (not dynamic) that are easily understood, and can be debated by a variety of disciplinary experts due to the simple manner in which sensitivity analyses are presented. In all the full case studies presented in this dissertation, extensive sensitivity analyses were conducted between different combinations of variables.

In conventional maximum likelihood approaches, where system predictions are desired, the probability distributions governing their behaviour 'linearise out' the lower probabilities in the line wings of the statistical distribution, and with that, these often non-linear second and third order effects are lost or ignored in the resulting analyses. This is not the case in the BPDA approach, where the full probability distributions are preserved in the Bayesian models. In the BPDA approach, a low probability 'state' is set to a higher value, its effect immediately shows up in the system level behaviours (i.e. after inference). If an underlying non-linearity is associated with the lower probability state in relation system level behavioural response, then this shows up in inference and sensitivity analyses conducted over a range of inference tests. This is automated in the Sisyphus software, where the user can set the scenario and let the inference run over a series of driver ranges, after which graphs are automatically generated and posted to the screen. In all the full case studies conducted in this dissertation these non-linear relationships formed the basis of recommendations regarding system extremes, as they dictated where system level thresholds and critical limits lay. This understanding is critical for decision-making, and the BPDA approach is especially suited to this by virtue of it being based on Bayesian networks.

7.6 Resilience & Adaptive Capacity

The resilience of a system is essentially its ability to withstand a wide variety of changes which lie outside of its control, by adapting its internal structure, organisation and processes (Walker et al., 2004). It is self-evident that the resilience of system to one particular scenario does not characterise its resilience in another scenario. In order to build up an understanding of resilience there is a need to build up an understanding of the critical limits and thresholds of a system in different scenarios. The resilience alliance therefore maintains an online database of thresholds in order to support future research into the resilience of social-ecological systems (see www.resalliance.org).

This was also our approach, and as in all the complete single case studies we were able to test the resilience of the social-ecological system in question by conducting a wide range of ‘what-if’ future scenarios and possible adaptations. Being able to characterise the resilience through an understanding of critical limits and thresholds within embedded units, and between embedded units, across a wide range of scenarios goes some way towards characterising system resilience and adaptive capacity because cross-scale and cross-sector sensitivities are made explicit.

Moreover, because the BPDA framework is not solely a predictive tool, with maximum likelihood pretensions, but a probabilistic tool, we could adapt the models and frameworks to suit changing real-world circumstances, as in the case of the biofuels case studies. That is, Bayesian models of the kind formulated using the BPDA approach, are more flexible, and in this respect BPDA suits efforts that are oriented towards *adaptive* governance and management of social-ecological systems.

7.7 Critical Limits & Thresholds

The Bayesian network approach, and by implication the BPDA approach, is a probability theory based approach, and is therefore able to incorporate known or hypothesized linear and non-linear relationships into its modelling framework. A variety of critical limits and thresholds are derived in the case studies, in particular with respect to climate change related effects, water and energy availability, limits to levels of economic and population growth, etc.

Moreover, as explained earlier, non-linear effects, which usually dominate at lower probability ranges in the probability distribution of a said variable, emerge as significant drivers of system level critical limits and thresholds, as they themselves are located in the extremes as 'low probability' events. Therefore, in generating a realistic understanding of critical limits and thresholds of a system under a wide range of scenario permutations the BPDA

approach is exceptional. In each case study, the critical limits and thresholds that emerged from sensitivity analysis 'made sense' to everyone who was involved in the study, and could be verified against other models, empirical evidence or external expert opinion.

In all cases, the limits and thresholds that were obtained using the BPDA approach in all case studies agreed well with known thresholds and expected limits. Moreover, they were all verified by expert interrogation. In the case of the Western Cape climate change case study, the limits and thresholds served as recommendations to the provincial government and were vetted by decision-makers. These limits and thresholds, when understood in terms of the range of scenarios in which they were generated, help build understanding of system resilience in different contexts. The ability of the BPDA approach to produce sensible and understandable graphs showing where critical limits lie, and what threshold values exist at the whole system level makes it of significant importance to adaptive management efforts, in which research is often playing catch-up with decision-makers. In summary, non-linear relationships and critical limits and thresholds are sensitively handled using the BPDA approach, and the approach thus has the potential to provide great value to sustainability efforts.

7.8 **Monitoring & Multiple Futures**

A wide range of scenarios can be tested using the BPDA approach due to the flexibility provided by the models, and because they include embedded units at various scales and levels of description in the models. We also showed how a model could be adapted to incorporate real-world changes that directly affected the cross-disciplinary research efforts. Dealing with a vast range of futures is a strength that Bayesian network models have over predictive models of large integrated systems. Predictive models are usually constrained to handle only a few, selected scenarios, and if major changes occur predictive models require a great deal more effort to rework and re-constrain for use.

Bayesian networks contain and make explicit different observational and interventional variables. This is a critical feature in that an understanding of where to monitor and where to intervene in a system are among the key concerns of most hands-on managers and decision-makers dealing with complex social-ecological scale system problems. A knowledge of which variables can be measured, and which can be intervened upon, is required in order to design monitoring regimes and interventions for sustainable development, and to design cross-disciplinary research and case studies into social-ecological systems. We have shown how this functionality can be translated into meaningful decision support in the case studies conducted in this dissertation with suggestions made in publications and reports to decision-makers about 'gaps' in monitoring and measurement. The Hegelian mindset that what cannot be measured cannot be managed, means that where gaps aren't identified, huge problems can grow and appear as if by surprise. The BPDA approach proved very successful at identifying gaps in monitoring and intervention, especially where cross-sector and cross-scale dependencies were concerned, for example; in the climate change - irrigated agriculture and biofuels case studies, and Western Cape Province case studies, critical inter-sector and cross-scale influences would have been ignored if the BPDA approach had not been implied. Moreover, in a changing world, monitoring requirements may change, and the flexibility of the BPDA approach ensures that the model can be adapted with minimal effort to address changing circumstances.

7.9 **Choosing Connectors or Integrators**

System connectors or integrators (as they are referred to in this dissertation) usually consists of the critical resources that are shared between sectors or users. Water and energy are good examples of system connectors where climate change considerations are made on human development scenarios. For example, water and energy availability, shortages and allocations can have significant effects on the ability of human and natural

systems sustainability precisely because it enables and supplies a multiplicity of sectors. The choice of connector(s) depends critically on the key questions and the context in which those questions are asked – for example; the carbon cycle could also be considered a connector or systems integrator if a system is considered within the full scope of its carbon cycle.

It is critical that the choice of system integrators is well defined and relevant to the key questions being explored. Often the system integrators can be assessed and determined easily at the outset of the study. However, it is often the case that as system formulation is underway (i.e. graphical causal models and Bayesian networks are being built) it becomes clear what role the connectors play in integrating across sectors. Moreover, an understanding of the key integrating sectors can also emerge from multiple participants engaging with the processes of graphical causal and Bayesian modelling. In the graphical causal modelling and Bayesian network formulation phases it is important to allow a full discussion of how system connectors are inter-related with sub-system level drivers, responses and constraints. In this respect the visualisation capabilities of the Sisyphus software help facilitate a deeper understanding of system connectors or integrators and the issues of scale and aggregation that are associated with them.

Moreover, the role that connectors or integrators play as loci of integration for other embedded units (or sectors) can change depending on the research question and the context of inquiry. Here, the main benefit of the BPDA approach is its flexibility, which allows the user to change how the connector, or locus of integration, is inter-related in the model. As the emphasis of analysis changes, and different research questions are brought to bear on the system, different sub-system influences become relevant. In one context water may act as the integrator, whereas in another context energy may act as the integrator. Catering for this flexibility is critical, and the BPDA approach is especially suited to the flexible management of system integrators, whether they be whole sectors, sub-sectors, or embedded units and sub-units, respectively.

7.10 Participatory Process Facilitation

Participatory processes are required for research and decision-making for sustainability of social-ecological systems because actualising sustainability involves negotiating, cooperating, participating and learning (Van Kerkhoff & Lebel, 2006). This requires that a shared understanding is engendered between researchers from different disciplines, and between the decision-makers, system users and actors from different sectors, spheres of governance, spheres of influence.

In the case studies conducted in this dissertation, we mainly conducted workshops at the outset of projects, and then worked with individuals and smaller expert groups to formulate, verify and validate embedded units specific to their discipline. The graphical causal maps and Bayesian networks helped keep the smaller groups focussed on their particular ‘research module’ while keeping in mind its relationship(s) with the rest of the system.

One irrefutable feature of participatory process is “hypothesis deadlock” and associated undecideability in research and decision-making for sustainability. The challenge of transdisciplinarity is the requirement for context-based integration at various scales of analysis, observation and intervention, and value systems, and allowing for the emergence of new knowledge and understanding regarding how sustainable options can be determined. Hyperstructures are especially suited to dealing with conflicting hypotheses because hyperstructures can contain a set of conflicting hypotheses about a complex system at the same time, in anticipation of its behaviour observed from in a variety of historical and current case studies, and behaviours projected in future scenarios.

In each case study, graphical causal maps are used for explanation building, pattern matching and identifying and testing rival explanations. This ensures that conditional dependence between variables is stipulated, justified and verified between cross-disciplinary workshop participants. This ensures a rigorous level of ‘democratic’ interaction between participants in formulating and adapting the research design over the duration of the study.

There are major differences between various expert groups and how they engage with the methodology. Therefore, the main facilitator must remain open to adaptation on the spot. How different expert groups create different classifications schemas and terminologies to help them better understand their problem or system (e.g. cholera study), differs from group to group. There is no single formalised approach that an a practitioner of the BPDA approach can rely on to facilitate workshops. However, there are a set of guidelines that have been identified from the case studies conducted in this dissertation which may prove useful. They include:

1. Ensuring sufficient preparation and background knowledge of the problem context before planning and executing workshops. The scope of the case study may vary significantly, and anywhere between two days to two weeks of workshops may be necessary.
2. Being able to envision how previous models and sub-modules may be brought to bear on the case in question, or how they may be adapted or customised to fit a different problem context, for example, by intelligently re-using the structure of a previously formulated model.
3. Preparing ‘straw dog’ models with one or two of the workshop participants before a workshop, to use as a point of engagement for workshop participants. Usually, the straw dog acts more as an antagonistic stimulus, and participants critique the straw dog, and then formulate their own models. The straw dog, however, introduces the problem and the approach to workshop participants upfront.
4. Having examples of other graphical causal map and Bayesian network – based case studies on hand for participants to familiarize themselves with the BPDA approach.

5. Focussing the participants on the core research questions and key hypotheses that their study is concerned with, identifying the overarching causalities and identifying system components or embedded units that are relevant to the study.
6. Calling on participants to break into groups to formulate their hypotheses using graphical causal maps and presenting this to the rest of the group, where, in turn, they get to critique each other's ideas.
7. Remaining observant of participant and inter-participant behaviours, being able to break non-constructive side-dialogues and ensure that participants who tend to fade to the background in the presence of more dominant participants are afforded a chance to share their views.
8. However, allowing for changes of direction in how the participatory process unfolds is also required. To some extent, the sensitivity that is required to recognise when a change of direction is necessary, and does not necessarily constitute a diversion, cannot be taught. It is acquired through experience with actively working with cross-disciplinary workshops and participatory processes involving researchers, stakeholders and decision-makers alike.
9. In the rare cases where a participant is obstructive, to the point of sabotaging the process from moving forward it is best to handle the situation directly, and give the participant the choice to leave, or in very drastic circumstances, to ask the participant to leave.
10. Remain sensitive to the need for contemplation. There are many occasions within a single participatory workshop where the phenomenon of 'analysis-paralysis' arises, purely because too much information and too many ideas are being sounded too quickly for a systematic evaluation to be made on the spot. It is desirable to have body and food breaks regularly, and to have half-day workshops instead of full-day workshops, where participants can reflect overnight about progress made during the day.

The main goal of participatory processes is creating the shared understanding that can serve as basis for constructive learning, participation, negotiation and cooperation, and there is no formula or process that will

ensure this kind of convergence. The usefulness of the BPDA approach lies in that it uses causality as a 'common language' between participants. Moreover the visual software interface removes the need for participants to fully understand complex mathematical and statistical theory, but keeps them focussed on the core linkages and embedded units they are concerned with, and how they relate to others in the system being researched.

The role of the author, in regard to facilitating participatory processes, begs further inquiry. Generally, the author was engaged in real-world projects as a senior researcher at the CSIR, and the case studies presented in this dissertation were located in these projects. The key role that the author played was being the 'glue' between decision-makers, between researchers from different disciplines, and between both, to various degrees in the case studies. The role of facilitator required that the author develop and refine the ability to shed personal bias and disciplinary 'clothing' in the various interactions that the case studies required. As a 'glue' to interaction the author engaged in facilitating day to week long workshops, summarising and collating information from day to day, and hour to hour, to follow the process of knowledge construction that emerged in the case studies.

Additionally, the author was responsible for designing, formulating, populating, verifying and validating all the models that were used in the case studies in this dissertation. At each stage of model construction the author either conducted one-on-one sessions, group sessions or large workshops to validate and verify the functions, relationships and sensitivities that the model outputs revealed. In all case studies, the author was acting in a professional capacity, which required building trust, sincerity and honesty in all interactions. The more open the author remained to different points of view, the more people were able to share their views. To summarise, the author's role involved acting more as a facilitator than a consensus builder i.e. through patient negotiation, cooperation and participation.

The role of the interdisciplinary teams involved more than just helping frame and compose Bayesian network models. They played a critical role in

formulating, verifying and validating the causal structure, sensitivities and scenario runs that were conducted in the case studies. That is, they played a key role in ensuring the validity, rigour and robustness of case studies. Moreover, they often 'took control' of the process as the particular case study desired, and as their collective consensus dictated, and the author needed to remain sensitive of the needs of the group in relation to the process they were engaging in. The key learning point in this regard is that the need for an 'open' systems approach is required in the initial phases of implementing the BPDA approach with a cross-disciplinary team. The only conditions that BPDA imposes in the final stages of model formulation are that of causality and conditionality. Hypothesis forming and testing is therefore a key element of the BPDA approach and the facilitator and group need to remain sensitive to hypotheses that emerge, or can be inferred from the discussions conducted in workshops, whether explicit or embedded in narratives, debates and dialogues.

One of the key learning points revolved around hypothesis deadlock or 'analysis-paralysis'. Over time, it became apparent that whenever deadlock ensued, a breakthrough was not far off. It required having the patience to work through the various conflicting positions, and reach shared understanding. That then served as a basis for discussion and revision. In all, deadlock mostly turned into opportunity, and revealed the most salient and critical perspectives on key factors of interest to all and sundry participating in the workshops.

As each case study unfolded, we learnt more about coping with issues of scale, non-linearity, larger numbers of embedded units, challenges of aggregation. We learnt that the BPDA approach can be scaled up or down as far as cumulative effects are concerned, without losing any complexity, but as yet, they cannot easily be employed to assess spatial dynamics at fine scale. This does not mean that Bayesian networks are incapable of providing this kind of analysis, merely that this was not the focus of the case studies conducted in this dissertation. Later, in chapter 9, we explore how both spatial and temporal frameworks can be established for Bayesian networks, drawing on current trends in research.

As far as the decision-maker and inter-disciplinary team experiences are concerned, the BPDA approach was highly appreciated as a mechanism for increasing shared understanding between them. Participants would often relate that they 'saw the value of the process' in one way or another, and would stick with it. Stephan Woodborne, of the Cholera case study, in a moment of revelation exclaimed, "I have never done science this way before!". In the Western Cape Government case study, the key decision-maker, Dennis Laidler stressed the need for continued implementation of the BPDA approach in decision-making in government, writing in recommendation to his superiors, "this report should not languish on a shelf somewhere." In all, even sceptics usually relented their initial positions after embarking on a process of joint exploration facilitated using the BPDA approach.

In these cases the knowledge was co-produced and in some cases, peer reviewed for publication. The extent of collaboration is displayed in the *joint* publication of the papers and research reports that resulted from the case studies, as detailed at the beginning of this chapter. Even the conceptual foundations of the approach was formulated with the input of many participants.

Two of the project teams (cholera case study team¹⁸ and catchment2coast team¹⁹) were awarded for outstanding interdisciplinary collaboration and innovative, cross-boundary research by the CSIR. It is due to the research environment provided by the CSIR that the author was able to conduct such extensive interdisciplinary workshops, and to be able to conduct one-on-one engagements with a wide variety of experts. The CSIR is heavily concerned with integration, as it serves a joint research and application agenda, and must engage with real-world problems. Hence, the CSIR

¹⁸ CSIR Natural Resources and the Environment Excellence Awards 2007: Cholera Team: For outstanding contribution by a team.

¹⁹ CSIR Environmentek Awards 2005: Catchment2Coast: Cross-Boundary Team Award: For demonstrating the ability to successfully undertake a complex, multidisciplinary project requiring close cooperation between teams from different organisations with diverse operational cultures, resulting in effective and innovative outputs.

supported and heavily funded most stages of the research conducted in this dissertation. A sense of exploration and discovery accompanied most case study research efforts, and this is in no small part due to the environment cultivated at the CSIR. The open-minded but critical environment created by the CSIR served as fertile ground for exploring and refining the BPDA approach.

7.11 **Decision Support for Adaptive Management**

The case studies conducted in support of this dissertation gradually built up towards working with decision-makers, and in the penultimate case study on the Western Cape province the BPDA approach was used in a collaboration with decision-makers who were faced with real-world decision-making challenges. Not only did the BPDA approach help create shared understanding between decision-makers and researchers, it also helped them communicate their concerns, disagreements and ideas with each other more clearly than in the absence of the approach.

In the Western Cape case study the BPDA approach was employed with decision-makers and was used to make recommendations to the provincial government of the Western Cape Department of Environmental Assessment and Development Planning. The decision-makers found the Bayesian models intriguing, and engaged directly with interrogating the causal structure, underlying assumptions, validity of evidence used to constrain marginal conditional probability distributions, the equations used to inter-relate nodes and the sensitivity analyses outputs. They helped design scenarios and often, we were able to test scenarios on the spot to help frame the discussion. The input of decision-makers was critical to orienting the study. Often, decision-makers spend many hours in dialogue, conversation and debate, where they 'model' complex multiple futures using their experience and ability to envisage the future, including surprise and the unexpected (that is, the low probability 'externalities that are often omitted in scenario planning exercises, but which increasingly have to feature in

decision-maker planning). They found the BPDA approach extremely useful in two aspects. Firstly, in helping them understand how researchers envisaged the integration of the system in a particular problem context. Secondly, they found that the approach helped them interrogate such a wide variety of possible future system trajectories and intervention and observation devices, that they were able to test their differing, often sector based understandings of future trajectories and suggested interventions.

The BPDA approach yields hyperstructures that are flexible, non-hierarchical and adaptive. As shown in the biofuels case study, and the Western Cape province case study, unfolding real-world changes can be quickly incorporated. Moreover, the wide range of what-if's and scenarios afforded by using the BPDA approach makes it suitable for supporting scenario-planning processes before, during and after implementation of a strategy. The BPDA approach can, in a sense, follow the decision-makers needs in a transparent, traceable, verifiable manner. It enables 'on the spot' sensitivity analysis and link interrogation in participatory workshops, and can easily be adapted to reflect changing circumstances.

The value of employing a probabilistic approach in dealing with the complexity of social-ecological systems is uncannily similar to the role of probability theory in dealing with the 'particle zoo' in quantum physics. It allows a variety of alternative permutations to be jointly considered within a probabilistic evaluative (not predictive) framework. There is no absolute predictability, only the ability to understand the variety of potential outcomes of a system. As we have consistently argued in this thesis, the BPDA approach to modelling complex, real-world systems is far more valuable due to the heavy dependence of these systems on changes in the *current context*. The current context is itself emerging and hence changing, and hence the BPDA approach is designed to incorporate a large number of variables simultaneously so that a variety of alternative future scenarios can be catered for as they unfold. This is in contradiction to approaches that deal with systems that are heavily reliant on historical context - where hind-casted and forecasted models dominate the methodologies for researching and

understanding these systems. Where relevant, the BPDA approach makes use of historical information and hind casted models - as in the case of the Incomati-Maputo case study, where models that hind casted over ten years were used as a basis for constraining relationships in the Incomati-Maputo Bay model. However, the BPDA approach is not constrained in the same way as maximum likelihood based approaches are to the need for historical data, because of its emphasis on current context.

All the case studies conducted in this dissertation involved exploring inter sector and cross-disciplinary linkages. This was also reflected in the outputs of the case studies. Where findings and recommendations were concerned, they were usually focussed on cross-sector and cross-disciplinary linkages. The focus of the Western Cape study was to review how well the Western Cape climate change strategy integrated with other provincial level strategies on economic growth, water, energy and waste, and this is where the BPDA approach proved most successful and provoked the most enthusiastic response from decision-makers in the Western Cape provincial government.

8. **BPDA & Case Study Research**

In the previous chapter we discussed the use of the BPDA approach to support the requirements for modelling the sustainability of complex social-ecological systems. In the BPDA approach, as proposed in this dissertation, we used graphical causal maps and Bayesian models as hyperstructures for managing the internal models of a complex, interdisciplinary social-ecological system case studies concerned with system scale sustainability.

In every phase of case study research design, and implementation discussed in the next two sections, we make the case for using hyperstructures to facilitate shared understanding between researchers from different disciplinary backgrounds and decision-makers on case studies in general, but not without exception.

Earlier, we argued that the BPDA approach can be used to strengthen coordination in case study research of complex, interdisciplinary problems in general. We now draw on the learning engendered in conducting individual case studies of social-ecological systems and the cross-case analyses presented in the previous section to explain why the BPDA approach is suited to supporting interdisciplinary case studies involving complex systems. In this section we discuss how the BPDA approach plays a role in merging more analytical natural science based methodologies with social science based case study methodologies.

8.1 Case Study Research Design Considerations

8.1.1 Introduction: Purpose of Research Design

Case study research design is not a trivial undertaking – more so if multiple case studies are being used (Yin, 1984, pp. 22). This dissertation engages a wide range of research strategies in a series of case studies that are mainly quantitative, structural and behavioural in nature. Qualitative interpretation is used to formulate a descriptive and exploratory modelling framework that is formulated solely in the context of the question being asked and the system being investigated. Many of the case studies in this dissertation were conducted using multiple-case embedded research designs (Yin, 1984, pp. 42) because each case study has more than one unit of analysis. The uppermost unit of analysis is the social-ecological system itself, when analysed in a particular context and scenario. However, a variety of sub-units of analysis (embedded case studies) play a critical role in helping assess system level behaviour at the social-ecological system level.

According to Yin the four applications of case studies are:

- “to *explain* the causal links in real life interventions that are too complex for the survey or experimental strategies.”
- “to *describe* the real-life context in which an intervention has occurred.”
- “[that] an evaluation can benefit, again in descriptive model, from an illustrative case study ... of the intervention itself.
- “[that] the case study may be used to *explore* those situations in which an intervention being evaluated has no clear, single set of outcomes.”

In this dissertation, the proposed modelling approach specifically focuses on; explaining causal linkages, describing the context, formulating a

descriptive model of the intervention, and exploring the combinatorial²⁰ outcomes (Richardson, 2002) of an intervention, or set of interventions in different scenarios. These four application areas of case studies match the critical requirements of research for the sustainability of social-ecological systems.

An open systems approach is used to support case study design and development and the models formulated and used to assess scenarios are qualitative in the sense that it attempts to “avoid any prior commitments to any theoretical model” (Yin, 1984, pp. 25) i.e. causal linkages aren't bounded by any generic or theoretical frameworks but are tied to the context of interpretation in which they are determined. The modelling approach employed in this dissertation provides trace-ability of changing understanding regarding causal linkages and provides a framework for validation and verification as adaptation occurs. The hyperstructures allow for both the interrogation of the qualitative judgements underlying causal linkages - and the empirical, quantitative and theoretical (equations) evidence used in populating the sensitivities between variables in the Bayesian models formulated from the basis of graphical causal maps. Hyperstructures, as used and defined in this dissertation, offer a framework that helps bridge the divide between the use of models (using quantifiables as inputs and outputs) and the qualitative interpretation of the results of these models (using expert interdisciplinary groups).

The purposes of a research design are to ensure that the evidence addresses the initial research questions, and to ensure that logic behind collecting and interpreting evidence (Yin, 1984, pp. 29) is maintained correctly (especially in conceiving of the causal chains of evidence (Yin, 1984, pp. 28)) in an iterative process of learning. In defining what a research design is, Yin (1984, pp. 28) calls on two writers, who “have described a research design as a plan that guides the investigator in the process of

²⁰ Combinatorial here refers to the overlapping and non-overlapping explanations, and equifinal and non-equifinal outcomes referred to later in the text (see sections 10.2.2, 10.2.3 & 10.2.4 for further explanation of terms).

collecting, analyzing, and interpreting observations. It is a *logical model of proof* that allows the researcher to draw inferences concerning causal relations among the variables under investigation. The research design also defines the domain of generalizability, that is, whether the obtained interpretations can be generalized to a larger population or to different situations (Nachmias and Nachmias, 1976 pp77-78; emphasis added) (Yin, 1984, pp. 28).” Research can also be thought of as a “blueprint of research” which addresses “at least four problems: what questions to study, what data are relevant, what data to collect, and how to analyze the results (see Philliber, Schwab, & Samsloss, 1980)” (Yin, 1984, pp. 29).

Research designs go through many iterative phases of verification before being finalised and even then may have to be revised during the study itself. This dissertation showcases a modelling approach (BPDA) that helps manage this process of revising the case study research design by elucidating and revising the causal chains of events or influences that are envisaged to underlie the key hypotheses that address the research questions.

8.1.2 Components of Research Design

According to Yin (1984, pp. 29), “For case studies, five components of a research design are especially important:

- 1) a study’s questions;
- 2) its propositions, if any;
- 3) its unit(s) of analysis;
- 4) the logic linking the data to the propositions; and
- 5) the criteria for interpreting the findings.”

For social-ecological systems, to formulate a case study design according to the list of components shown above engages both general complexity based approaches and restricted complexity based approaches. The first two components, “a study’s questions” and “its propositions” require

more qualitative, interpretive reasoning between different disciplines in order to define these components adequately for a social-ecological system case study i.e. a general complexity-based approach. Determining the “units of analysis” and “the logic linking data to the propositions” requires a more restricted complexity-based approach as it relates to formulating and testing the critical boundaries, variables and interdependencies in the system, while the “criteria for interpreting the findings” necessarily engages with a general complexity based approach in order to ‘make sense’ of the studies outputs and findings. In considering the components of a case study in the context of social-ecological systems, the observation can be made that general complexity is in a sense, required for both ‘opening’ and ‘closing’ the research process. General complexity serves as a filter to the inputs and outputs of the case study investigation of a social-ecological system and serves to frame and give context to the overall study (i.e. its ‘outer’ boundaries or interface with reality), while restricted complexity represents the ‘inner’ boundaries of the case study investigation.

The modelling approach caters for all components (1-5) of a case study design in detail, because it merges general complexity approaches with restricted complexity (Cilliers, 2008; Morin, 2007) approaches in a single modelling framework or ‘hyperstructure’ from which shared understanding can be encouraged and engendered. The story of evidence behind every causal link is independently verified in the process of formulating the graphical causal models and performing sensitivity analysis when verifying the Bayesian networks. The strength of this approach is primarily focussed at managing the joint understanding of the five components of case studies into social-ecological systems, in particular, and can be used in other systems problems in general, to varying degrees of usefulness.

8.1.3 Evaluation, Validity & Causality

The critical issue in most decision support for sustainability is evaluation (Peter C, 2008, pp. 472) to ensure validity, that is; of assumptions, models, evidence, conclusions and recommendations. Where adaptive co-management of social-ecological systems is concerned the need for systems evaluation in support of ensuring validity is stressed by Bellamy, Walker, McDonald & Syme (2001, pp. 408, in Peter C, 2008, pp. 473), who identify that “evaluation in natural resource management policy has been neglected and a substantial gap is emerging between theory and practise”. Operating in the space between theory and practise is where case study research is most effective. However, according to Yin (1984, pp. 37) those who are critical of case study research mostly highlight cases where “a case study investigator fails to develop a sufficiently operational set of measures and that “subjective” judgements are used to collect the data”. Yin therefore suggests that two steps are requisite for any case study investigator (Yin, 1984, pp. 37):

1. “Select the specific types of changes that are to be studied (in relation to the original objectives of the study) and
2. Demonstrate that the selected measures of these changes do indeed reflect the specific types of change that have been selected.”

Case studies rely on “analytical generalisation” instead of statistical generalisation (Yin 1984, pp. 39). Therefore, ensuring the logic behind building hypotheses and models, and collecting evidence to test them is a critical element of ensuring the validity of the research and evaluation of case studies. Building robustness in a case study requires that the causal chains of logic and evidence suitably address the particular research question or set of questions that is under investigation. As outlined earlier, causality is critical to our understanding of the world. According to Hume (1739/2000) we observe events that are contiguous in space and time and infer causal relations that explain our observations, even if they do not necessarily have to exist, according to Hume, in the real world. Even pure correlative evidence undergoes scepticism in research circles if there is no causal explanation for

the correlation. As previously highlighted, causality is a critical issue, and is the basis upon which lack of detailed scientific evidence has been exploited, for example; by pro-smoking legal lobbies. Causality is the basis upon which research validity rests. Even if correlative evidence is brought before a researcher, it is useless unless it provides a causal explanation of how or why a particular phenomena exists, because without an understanding of the causal relationship one would not be able to express any understanding of why a particular relationship exists, except for personal intuition. Validity for a case study or set of studies requires reliability, in the sense that research should be repeatable upon the same set of evidence on the system. This is reflected in the tests Yin (Kidder, 1981, pp. 7-8, in Yin, 1984, P36) identifies as critical for ensuring case study research design (also shown in Table 19):

- “Construct validity: establishing correct operational measures for the concepts being studied;
- Internal validity (for explanatory or causal studies only, and not for descriptive or exploratory studies): establishing a causal relationship, whereby certain conditions are shown to lead to other conditions, as distinguished from spurious relationships;
- External validity: establishing the domain to which a study’s findings can be generalized; and
- Reliability: demonstrating that the operations of a study – such as the data collection procedures – can be repeated, with the same results.”

Theoretical generalisation, however, requires acting on the *same and different* sets of evidence in order to establish the extent to which a particular model can be abstracted to higher levels of generality or universalism. This ensures applicability across a broader context, usually at different scales of levels of description.

Table 19:

Four Tests for Research Design (Table taken from Yin, 1984, pp. 36)

Tests	Case Study Tactic	Phase of Research in Which Tactic Occurs
Construct validity	Use multiple sources of evidence Establish chain of evidence Have key informants review draft case study report	Data collection Data collection Composition
Internal validity	Do pattern matching Do explanation building Do time-series analysis	Data analysis (all)
External validity	Use replication logic in multiple case studies	Research Design
Reliability	Use case study protocol Develop case study data base	Data collection (all)

The case study tactics involved in ensuring validity are outlined in Table 19, and includes the phases of research in which each tactic is used. The modelling methodology proposed in this dissertation (BPDA) addresses each aspect of validity outlined in explicitly, and enables shared understanding of these aspects amongst interdisciplinary research groups.

Six sources of evidence can be collected when conducting case studies (Yin, 1984) i.e. documentation (Yin, 1984, pp. 79), archival records (Yin, 1984, pp. 81), interviews (Yin, 1984, pp. 82), direct observation (Yin, 1984, pp. 85), participant observation (Yin, 1984, pp. 86) and physical artefacts (Yin, 1984, pp. 87). Three principles of data collection apply (Yin, 1984, pp. 89):

- Using multiple sources of evidence (Yin, 1984, pp. 90)
- Creating a case study data base (Yin, 1984, pp. 92)
- Maintaining a chain of evidence (Yin, 1984, pp. 96)

It is at the heart of the processes of construct validity and data collection, as outlined above, that the graphical causal map & Bayesian network hyperstructure comes into its own. Casual chains of evidence are visualised, made explicit, shared and interrogated by an interdisciplinary research team. The hyperstructures help; maintain the chain of evidence, adaptively maintain changes in thinking and understanding of the system, and provide a linked data base that allows access to the sources of evidence used. It acts as a visual representation of shared knowledge and understanding of the causal chains of evidence being constructed in the research effort and acts as a library of information about the key assumptions and core evidence that is used to formulate the model.

8.2 Implementation Considerations of the Research Strategy

8.2.1 Conceptualising the Study

“too many times, the investigators start case studies without having the foggiest notion about how the evidence is to be analyzed” (Yin, 1984).

In discussing the desired skills of case study investigator – Yin stresses that a senior researcher is required for such an undertaking and not merely a research assistant who is sent out to collect data. The case study investigator must have a requisite understanding and appreciation of qualitative judgements that are necessary in order to guide the quantitative surveys or evidence-gathering. In this dissertation, research that was conducted with a variety of interdisciplinary teams, consisting of senior researchers with requisite knowledge and experience of case study areas and material, some with several decades of fieldwork conducted in the case study areas. Each researcher that contributed to case study development was specifically chosen to ensure the validity of embedded units that are included in the models i.e. validity of their causal structures.

The case studies conducted in this doctoral dissertation rarely involved any visits to any particular ‘site’ or spatial location. Rather, experts from various disciplines, with expert knowledge of these particular sites, were sought out. They were included in formulating and verifying the model in interdisciplinary workshops, and screening the model outputs and conclusions and recommendations that were made. All of the studies, except two (i.e. no Bayesian models were built for the cholera & gauteng urban growth case studies), involved gathering extensive quantitative data and evidence in order to populate the Bayesian model with probabilities.

Finding a ‘starting point’ for researching a complex social-ecological system problem can be difficult. Research questions and hypotheses can often seem to be endless in interdisciplinary workshops that are held to ‘frame the study’ at the outset of research, as different views emerge regarding the overall goals of the study, and where specific research questions and hypotheses are concerned. Often no descriptive framework and clear theoretical propositions can be made, precisely because of the complexity of the system and the focus of research (which is usually integrative in nature if it is linked to a question of sustainability of the system). An *open systems* approach is required in this phase of research, as researchers need time to explore the domain of factors, variables and relationships that characterise the social-ecological system (or any case study) that is under investigation. In this phase of research where little is known or understood about the system as a whole Yin (1984, pp. 119) suggests that, “In the absence of a strategy based on theoretical propositions or a basic descriptive framework the investigator is encouraged to “play with data” in a preliminary sense, as a prelude to developing a systematic sense of what is worth analyzing and how it should be analyzed.”

This may involve the use of various types of analytical techniques, and in the study in this dissertation; the inclusion of facilitation approaches for interdisciplinary participatory processes. For case studies, Yin (1984, pp. 100) lists some of the techniques:

- “Putting information into different arrays;
- Making a matrix of categories and placing the evidence within such categories;
- Creating data displays –flow charts and other devices – for examining the data
- Tabulating the frequency of different events;
- Examining the complexity of such tabulations and their relationships by calculating second order numbers such as means and variances; and
- Putting information in chronological order or using some other temporal scheme”

These forms of knowledge sharing suit the facilitation of scenario planning and interdisciplinary research processes well, as they allow for many degrees of flexibility in providing a description of the system. These techniques may all be used alone, and in combination, to varying degrees of effectiveness in interpreting the problem, system and context appropriately. It is also appropriate to allow for flexibility in the chronology of implementation, that is, to match different phases of problem solving to appropriate knowledge facilitation techniques.

One of the findings of this dissertation is that where the interaction between multiple participants, from different disciplines is facilitated through the use of these techniques, an open systems approach often works best. That is, we should allow the group itself to choose what approaches (or combination of approaches) work best for characterising the particular problem and system that is under scrutiny, and allowing the full expression of views and opinions of the group. The aim of this process is to give the group enough room to allow for reliably scrutinized research questions, and hypotheses, explanations and propositions to be obtained. The process also aims to help researchers to select the appropriate techniques from those available to them, in order begin the analytic phase of case study research with a well defined idea of the how the study is bounded.

A critical element of the analytic phase involves ruling out ‘alternative interpretations’ (Yin, 1984, pp. 100. Yin identifies two strategies for the analytic phase of case studies where theoretical propositions and a description for the case study exists, or have been developed:

- “Relying on theoretical propositions” (Yin, 1984, pp. 100):
 - To formulate an understanding of, ‘a set of research questions, reviews of the literature, and new insights’ that led to the propositions.

- Developing a case study description (Yin, 1984, pp. 101):
 - When theoretical propositions are absent “A second general analytic strategy is to develop a descriptive framework for organizing the case study”.

These two approaches basically consist in formulating an explanatory and descriptive model respectively, in order to help rule out alternative explanations. Yin states that the case study description strategy is “less preferable” presumably because of the perception that too many levels of detail might be generated in a case study description.

In this dissertation we take a systems approach. A systems description is seen as a facilitative framework for developing and testing theoretical propositions. In particular, the heterarchical framework used in the modelling approach enables the interrogation, monitoring, and testing of theoretical propositions that are made within the causal framework of reasoning. The graphical causal maps, and Bayesian networks which constitute the heterarchical framework of reasoning has a descriptive role, and also helps reason about the various causal linkages that may underlie observed behaviours. It can be easily adapted with changes in understanding, to reflect new, emerging shared understanding of the system, and can be employed in an iterative process of learning and reasoning about a social-ecological system. It also plays a critical role in the analytic phase of research, because it serves as an integrative framework that reflects shared understanding and is the quantitative basis upon which the study is being conducted.

When a general analytic strategy has been established and implemented, Yin identifies several ‘specific analytic strategies’ that can be used. These include; “pattern-matching, explanation building and time series analysis,” which are deemed as “effective ways of laying the groundwork for high quality case studies,” and “incomplete ways of doing case study analysis”, which includes; “analyzing embedded units, making repeated observations, and doing case surveys”. The incomplete strategies “must be

used in conjunction with one of the other techniques in order to have an effective analysis” (Yin 1984, pp. 119).

The dominant modes of analysis, according to Yin (1984, pp. 103) for ensuring internal and external validity of the case study research are described in the next few section (see sections 8.2.2 to 8.2.7):

8.2.2 Pattern-Matching

According to Yin (1984, pp. 103), pattern-matching is “one of the most desirable strategies” for dealing with case studies. Pattern-matching compares “an empirically based pattern with a predicted one (or with several alternative predictions)”. Coincident patterns strengthen the internal validity of the case study by verifying whether “the patterns may be related to the dependent or independent variables of study (or both)”. For descriptive studies the “predicted pattern of specific variables” must be defined “prior to data collection”.

Pattern matching is an element of the BPDA approach as the approach is used to validate and establish reliable shared understanding of ‘chains of evidence’ in the formulation of Bayesian models and graphical causal maps (or hyperstructure). Dependent and independent variables and conditional dependencies are clearly articulated and visualised in the approach. The proposed approach brings together descriptive and explanatory approaches by providing, and the description is iteratively adapted as new explanations or more precise explanations are obtained through learning and participation.

Pattern-matching also includes using “non-equivalent variables as a pattern”. Yin cites Cook & Campbell (1979, pp. 118) who introduce a “non-equivalent, dependent variables design” where “According to this design, an experiment or quasi-experiment may have multiple dependent variables – that is, a variety of outcomes. If, for each outcome, the initially predicted values have been found, and at the same time alternative “patterns” of predicted

values (including those deriving from methodological artefacts or “threats” to validity) have not been found, strong causal inferences can be made”.

One of the main strengths of the proposed approach is that it uses hyperstructures to assess a variety of equifinal and non-equifinal outcomes from changes in underlying (Richardson, 2002) relationships, where different combinations of system drivers can yield the same overall global system behaviour in the case of equifinality, and where they yield different global system behaviours in the case of non-equifinality. The BPDA approach makes these equifinal and non-equifinal combinations explicit, so that they can be tested for validity through interdisciplinary scrutiny. These may be underlaid by overlapping and/or non-overlapping descriptive and explanatory models. In this manner, explanations can be verified, eliminated or researched further, and gaps in knowledge can be identified and targeted.

Using the BPDA approach, hyperstructures consisting of Bayesian networks and graphical causal models are used to represent the shared understanding of the system by the interdisciplinary group. They enable a more informed level of interdisciplinary inquiry to be conducted into the social-ecological system. This involves the use of the probabilistic Bayesian model in evaluating a large range of conditional causal sensitivities that are believed to underlie real social ecological system behaviours, functions and relationships by the interdisciplinary group, in different scenarios. *Pattern-matching* is conducted at this stage, where model outputs are compared against observed evidence, model outputs, empirical evidence or expert opinions regarding the causal links (and its various inter-linkages) under question in the study.

8.2.3 Rival Explanations as Patterns

Using rival explanations (Yin, 1984, pp. 105) as a strategy for analysis involves eliminating rival explanations which can be considered “threats to validity” (Yin, 1984, pp. 105-106). If the explanation was applied across

multiple case studies with the same results, then the goal of “literal replication” would have been accomplished across cases, and the validity of the explanation could be considered stronger. The goal of “theoretical replication” requires the explanation to be tried on a second group of cases, and to fail “due to predictably different circumstances”.

The key characteristic of rival explanations, as discussed by Yin, is that “each involves a pattern of variables that is mutually exclusive: If one explanation is to be valid, the others cannot be.” He goes on to state that, “This means that the presence of certain independent variables (predicted by one explanation) precludes the absence of other independent variables predicted by a rival explanation. The independent variables may involve several or many different types of characteristics or events, each assessed with different measures and instruments.”

Rival and alternative explanations of the same phenomenon are rife in both social theories and ecological theories, not to mention where they are linked. Even diseases such as cancer, can result from different causal pathways (Helsper & Van der Gaag, 2002) involving the same, and sometimes different variables. There are often overlapping and non-overlapping causal logical pathways that can provide an explanation for complex phenomena (Richardson, 2002). In Yin’s estimation, “The concern of the case study analysis, however, is with the overall pattern of results and the degree to which a pattern match(es) the predicted one”.

The BPDA approach, in particular the use of Bayesian networks and graphical causal maps as hyperstructures, enables each causal chain of evidence, underlying each explanation, hypothesis or proposition of the social-ecological system phenomenon to be assessed fairly against all others. Moreover, overlapping and non-overlapping explanations can be considered, and the causalities underlying them can be scrutinised fairly by all participants in the study, through facilitated interaction using the software interface developed for the purposes of supporting the research conducted in this dissertation. The hyperstructures serve as an integrative framework for

reasoning about existing and emerging patterns of observed and projected behaviours.

8.2.4 Explanation Building

Yin (1984, pp. 107) calls explanation building ‘a special type of pattern matching’ and states that “to “explain” a phenomenon is to stipulate *a set of causal links* about it.” Explanation building involves arriving at a final explanation only as a “result of a series of iterations” (Yin, 1984), and has historically mainly been conducted in “narrative form” in case study research. In the approach proposed in this dissertation, using graphical causal maps and Bayesian networks for facilitated interdisciplinary explanation-building extends and strengthens the narrative story-telling conducted within the dialogue conducted amongst participants. This is because the BPDA approach maintains the focus on the precise causalities underlying explanations that are proposed to explain a phenomena, problem or behaviour.

While it is true that “in most studies, the links may be complex and difficult to measure in any precise manner” (Yin, 1984) the Bayesian framework allows for using qualitative expert opinion to quantify conditional causal relationships between variables by using conditional probability tables to describe the relationship (see later in text– section 5.2.2). These (CPTs) allow for completely hypothetical propositions to be qualified (relationally) and quantified (even in the absence of data). The BPDA approach plays a critical role in the explanation building phase of a case study; which undergoes more iteration at the outset of the study than later. By focussing explanation building into a causal framework, different explanations can be made explicit. These inform the research design plans, and these explanations are tested during implementation. This process can be used iteratively to improve the research design as the study unfolds.

Understanding causality lies at the foundation of explanation building because “the casual links may reflect critical insights into public policy

process or into social science theory. The public policy propositions, if correct, can lead to recommendations for future policy actions; the social science propositions, if correct, can lead to major contributions to theory-building.” (Yin, 1984, pp. 107). The BDPA approach enables a full probabilistic framework, complete with interventional and observational variables; that can guide research and decision-making.

8.2.5 Third Strategy – Time Series Analysis

Simple and complex time series are critical where case studies of systems with memory are conducted, and allow for patterns (e.g. seasonal, cyclic) to be identified, and act as a stimulus for hypothesis building. For example, in a study exploring the environmental causes of cholera, cited later in this dissertation (see section 6.6.1), it was observed that cholera peaks seemed to correlate strongly with rainfall highs, after a lag period. This stimulated a great deal of thinking, discussion and theorizing about the causal linkages through which this relationship might be working, and various research areas and linkages were identified relating to various embedded units or relationships between them.

In the case studies in this dissertation, historical time series evidence was used to characterise relationships only where they were relevant to the context and scenarios being considered. The judgement involved in using historical time series analysis relies on the context in which the time series analysis finds application. For example, if seasonal variations are observed over the duration of a yearly period, then those seasonal variations are not accounted for if the model aggregates at the annual scale, and must be considered at a different temporal scale. The BPDA approach yields models that can adapt to different temporal and spatial scales of analysis are of great use when dealing with multiple-scale systems with significant cross-scale effects, such as social-ecological systems.

8.2.6 Chronologies

Chronology must necessarily be compared with an explanatory theory which “specifies one or more of the following conditions:

- Some events must always occur before other events, with the reverse sequence being impossible;
- Some events must always be followed by other events, on a contingency basis;
- Some events can only follow other events after a prespecified passage of time; or
- Certain time periods in a case study may be marked by classes of events that differ substantially from those of other time periods” (Yin, 1984, pp. 113).

Chronology involves specifying sequences of events, some fixed, lags, and temporal changes in classes of events. The heterarchical approach adopted in this dissertation helps manage these changes in classes of event, as classes “rise to authority based on form and function” (Heylighen et al., 2001) as understanding changes, or as the system changes due to real-world events, and the case study must adapt to incorporate these changes.

Chronology is clearly articulated and tested in the hyperstructures that are used as the basis of the modelling approach in this dissertation, in particular, a causal chronology. This causal chronology is more generalised than spatial and temporal causality, but does not exclude them. Moreover, the heterarchical approach taken in this dissertation, based on causality; is bolstered by the observations by Waldmann & Hagmayer (2006) that causality and taxonomy are co-producing.

8.2.7 Lesser Analytical Modes of Analysis: Embedded Units, Repeated Observations & Case Surveys

Amongst the ‘lesser modes of analysis’, or “incomplete ways of doing case study analysis” (Yin, 1984, pp. 119) Yin, includes embedded unit analysis, repeated observations and the case survey approach. Embedded analysis refers to a case where embedded units within a case study, or system, require propositions internal to the embedded unit to be tested in order to support the hypotheses made about the inter-relationships between embedded units, and how this results in global system behaviour (Yin, 1984, pp. 115).

The embedded units may be constructed with evidence from a variety of sources including, “survey analysis, economic analysis, historical analysis, or even operations research”. The BPDA approach is particularly strong at embedded unit analysis, especially due to its scale-ability; where many embedded units (or sub-units) can be constructed, if it is deemed necessary for the research effort. In this dissertation, all the case studies conducted into social-ecological systems required extensive sub-system or embedded unit analysis, in order to trace the root causes of global system unit analysis to their independent sources (i.e. independent variables or marginal probabilities in a Bayesian sense).

Repeated observations are also used in case studies conducted in this dissertation where they find relevance to a particular problem context. No individual case study investigators were sent into a particular region or area to investigate phenomena or collect data. Rather, due to the highly integrated nature of social-ecological systems many sources of survey data were used in combination, as outlined earlier in this section. Using the BPDA approach the appropriate scales and levels of integration of embedded units are appropriately maintained.

9. Frameworks for Future Development of BPDA Approach

9.1 Introduction

As already outlined in great detail in this dissertation the need for *evaluation* in adaptive management for sustainable development is especially critical (Plummer & Armitage, 2007), that is, in an era where unprecedented rates of change are being experienced, in terms of economy, society and environment on local and global scales (Holling et al., 2002; Lubchenco, 1998). Plummer & Armitage (2007) cite Bellamny et al., (2001, pp. 408), on the need for systems evaluation; “evaluation is fundamental to identifying change, supporting an adaptive approach that is flexible enough to meet the challenge of change, and enabling progressive learning at individual, community, institutional, and policy levels. However, evaluation in natural resource management policy has been neglected and a substantial gap is emerging between theory and practise.”

Making decisions about changing real-world systems and challenges, especially where development is concerned, requires that appropriate forms of verification and validation (or evaluation) are used to ensure that decisions are made upon the best available information. Moreover, we are required to ensure that these decisions are informed by the most recent developments in the current context, in order to help ensure effective implementation. Traditional scientific techniques, which aim for providing predictability, and are based on historical knowledge of the system, are sometimes called into question where decision-making for sustainability is concerned. As a result, the importance of participation is stressed by Van der Sluijs (2007), who states that “the traditional dominance of ‘hard fact’ over ‘soft values’ has been inverted: hard policy decisions may have to be made, based on soft facts”, in particular, because due to the “many uncertainties, traditional science is not able to sufficiently legitimize the drastic steps that may be needed to deal with

complex risks.” This uncertainty is associated with the reflexivity of human systems, in particular, the inability to predict exactly how decision-making may aggregate from the individual to the collective levels, and behaviours often emerge as surprises (Holling, 1986; Kates & Clarke, 1996).

We contend that research and modelling that serves to play a useful role in decision-support for development are required to have the flexibility to trace-able adapt to and appropriately reflect the multiple levels of stability, re-organisation and disorganisation of real-world systems, in a shared model of understanding that is used for directing research and supporting decisions (Peter, 2008).

In this section, we motivate a conceptual framework of ideas, which shows how the BPDA approach can be developed in the future. This involves several areas in which the approach can be developed further, as outlined in more detail in the sections in this chapter, as listed below, respectively:

1. We outline a variety of conceptual frameworks can be used to facilitate top-down and bottom-up system definition (see section 9.2).
2. To migrate towards ‘mixed’ Bayesian model-based hyperstructures (Peter C, 2008) that are both manually supervised (i.e. formulated by the user), and which learn from real-time data-bases automatically (where trends and patterns are identified by algorithms rather than the user) (see section 9.3),
3. To illustrate how the Bayesian hyperstructures proposed in this dissertation can be extended to include a variety of different systems and taxonomic ontology’s within its causal framework (see section 9.4),
4. To help articulate and share understanding of areas where researchers and decision-makers are faced with the enigma of the undecided-able, where different overlapping and non-overlapping hypotheses or explanations of a particular phenomena, or reasoning behind a decision, bring about deadlock (see section 9.4.2),

5. What implications the BPDA approach has for helping researchers and decision-makers understand social-ecological system resilience, adaptive cycles and cross-scale effects (see section 9.5), and,
6. To help visualise system interdependencies in near-real time and support the research and decision-making challenges that face sustainability efforts (see section 9.5).

It must be stressed that the subject matter dealt with in this section is mainly conceptual in nature and remains the subject of ongoing and future research.

9.2 Social-Ecological System Integration: Conceptual Frameworks Used in Case Studies

There are no definitive top-down frameworks for formulating a social-ecological system mapping or model, because the study of complex social-ecological system problems is often richly contextual. Generic models generally don't find purchase with researchers and decision-makers alike, especially when held up to scrutiny with respect to the context in which the model is applied. The purpose of top-down frameworks, in the context of maintaining the sustainability of social-ecological systems, is generally to ensure that a *system-wide* perspective is maintained when identifying and formulating the systemic problems facing researchers, decision-makers, users and stakeholders who are concerned with overall social-ecological system sustainability.

In particular, most systems-based top-down approaches towards modelling complex behaviour place great emphasis on understanding the nature of critical interdependencies and cross-scale system linkages that drive overall system behaviour. This does not negate the development of detailed sub-system models, but places emphasis on how these models inter-relate to answer different questions regarding the systemic behaviours of the system in different contexts. However, it should be noted that systems level behaviours

often can only be understood from a detailed sub-system level understanding where specific interactions (e.g. positive feedback, which can lead to non-linearity and runaway behaviours). Therefore, a top-down approach is never completely 'top-down'. It often involves drawing on detailed sub-system level knowledge to assist the participant in exchanging views and understanding of the system. Here, the purpose of the top-down approach must be emphasised; it is to prevent the dominance of a single sub-system (often disciplinary) i.e. in taking over the primary research goal. The top-down approach, in short, is intended to keep participants focussed upon the big picture, and to draw on details from sub-system level understanding as appropriate and required for the problem and context being studied.

In the next few sections a series of top-down frameworks that were used, to varying degrees, in formulating graphical causal models and Bayesian networks for the case studies conducted for this dissertation, are outlined and discussed. They include; human, manufactured and natural capital, Total Economic Value (TEV) and the development of indices such as direct and total value add to a resource such as water or energy through human-activities, to the biodiversity intactness index (BII). These frameworks are illustrative, and are by no means intended to be interpreted as an exhaustive framework for top-down definition of a social-ecological system. Rather, the conceptual frameworks are discussed and critiqued so that the reader will obtain some insight into them, and how they can be applied to conceptualise social-ecological systems as whole systems for top-down strategic governance and management imperatives. These top-down frameworks are used flexibly to enable an open systems approach, where no single framework influences the boundaries of the study. Rather, frameworks can be used or discarded as fits the nature of the problem appropriately in terms of levels of description and scale.

Some of the frameworks that were used as top-down conceptual frameworks for system definition in case studies, are outlined in the next few sections.

9.2.1 Human, Manufactured and Natural Capitals of Social-Ecological System

Human, manufactured and natural capitals (Costanza & Daly, 1992) provide a useful framework with which to characterise a social-ecological system. It is not an exhaustive framework however, as it does not consider the various flows between capitals (or stocks) explicitly. In order to enable a framework that explicitly considers human, manufactured and natural capitals in systems oriented formulation and design methodology, it must necessarily be extended to include the important influences and interdependencies in the system between the capitals themselves, and other driving factors that affect social-ecological system resilience under various scenarios.

Natural capital is a useful concept, as it often contains the resource bases from which human and manufactured capitals are derived. Water and energy are examples of two such sectors, that are supported by and enabled by ecosystems, and which have an impact on ecosystems. Natural capital is a stock, from which flows of natural income into various human and manufactured capital stocks originate. The value of the concept of natural capital (for the purposes of conceptualising sustainable development) over utility is that; “Utility cannot be bequeathed, but natural capital can be” (Costanza & Daly, 1992). From a systems or complexity perspective, the value in understanding natural capital from this perspective is that actions (on stocks and key linkages between these stocks) can be taken to preserve the integrity of crucial natural capital stocks for the use of future generations (Costanza & Daly, 1992), without having to worry about how future generations choose to make use of it. It helps enable a more sensible approach to the issue of sustainability, rather than judging the future by the current socio-economy and way of life, and its living standards, and projecting historical or current values, norms, beliefs and behaviours on future generations. In this small way, the natural capital approach helps to cope with the undecideability regarding the lifestyle of future generations; something

that is impossible to accurately imagine or predict, and hence to decide upon, even though a decision has to be made.

The question of evaluating natural capital necessarily engages a broader range of social-ecological system issues. At some times natural capital may be a renewable service provider such as an 'ecosystem' for example. The consideration of an entire 'ecosystem' as a stock in itself is not entirely problematic, but it can be challenged by those who would feel the word 'system' implies that it contains stocks, flows, leads and lags and should be considered precisely as that. Simply allocating an economic value (or an indicator such as species count) to natural capital, and regarding that measurement as an aggregated measure of the 'stock' of natural capital, is inadequate for understanding resilience – precisely because it does not address the issue of ecosystem integrity, and hence its sustainability. The concept of natural capital, used alone or in isolation, would constitute a limited top-down conceptual framework because while it acknowledges whole system complexity (e.g. of ecosystems) it provides no new way of interpreting natural capital alongside human and manufactured capitals in a whole systems perspective. Since the inception of this concept however, other ideas about dealing with the social-ecological system in its entirety has evolved as a very genuine response to the demands of scientists, policy-makers, decision-makers and stakeholders alike (e.g. Ehrlich & Levin, 2005; Gunderson & Holling, 2002; Lubchenco, 1998; Stern, 2000; Levin, 2006; Van Kerkhoff & Lebel, 2006).

The trend towards integration is also a result of changes in the global socio-economy and climate. Some of the value provided by this approach is for dealing with social-ecological systems (e.g. transdisciplinarity, complexity, resilience, climate change, institutional and stakeholder approaches). Placing natural capital alongside human and manufactured capitals in an appropriate social-ecological systems framework (i.e. one that addresses the central questions we are concerned with) might prove a valuable approach towards formulating key system interdependencies (see Figure 44 & Figure 45) to support integration efforts.

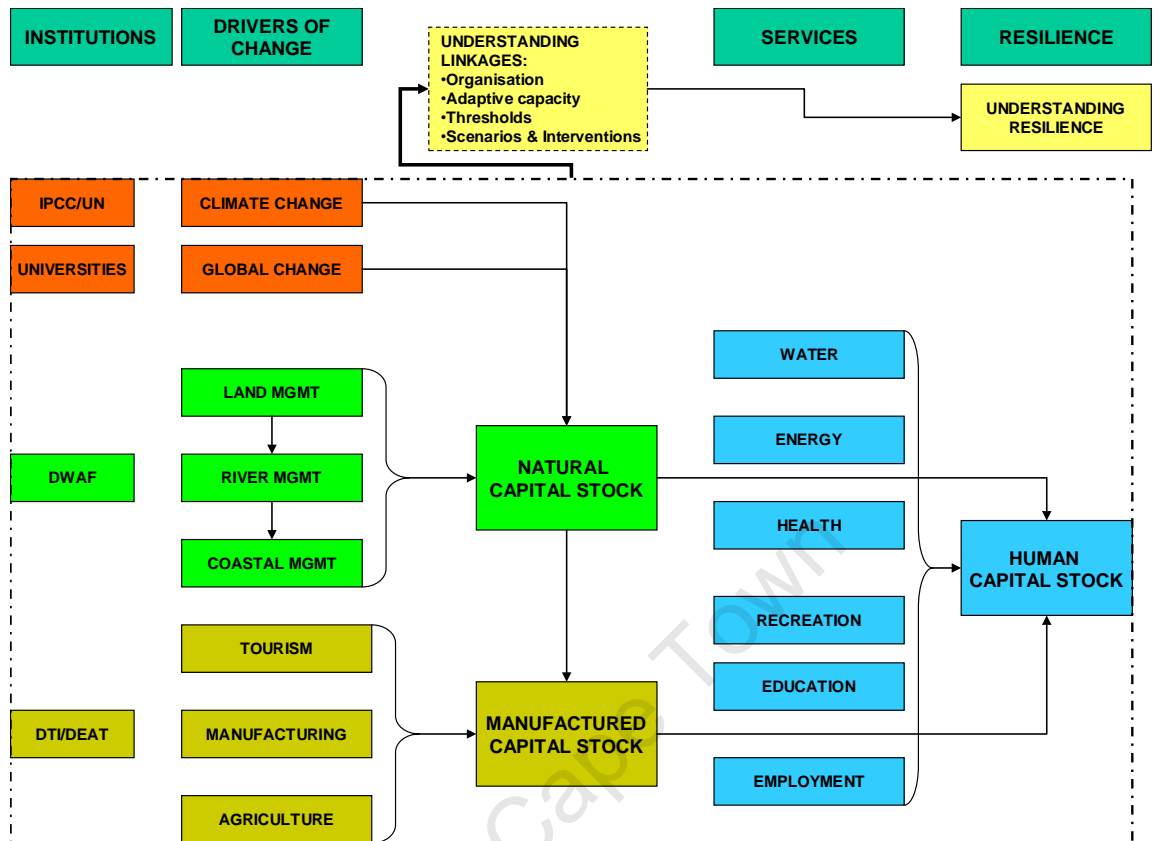


Figure 44: Conceptual Map for System Integration

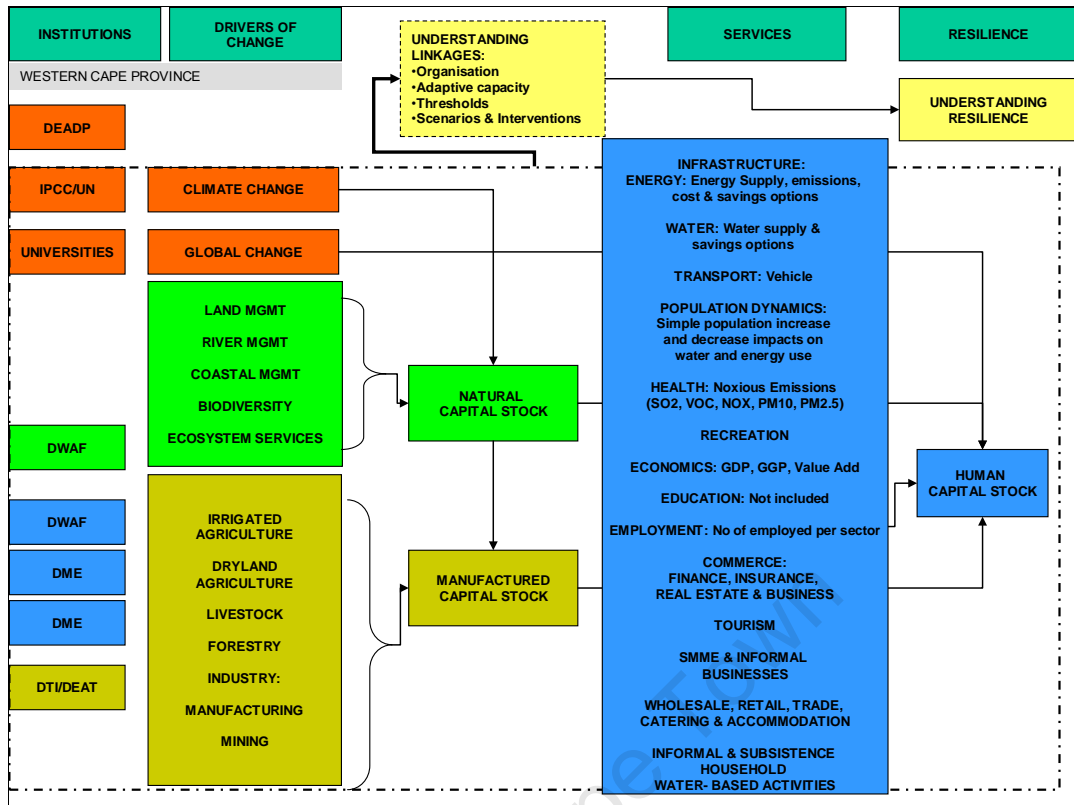


Figure 45: Implementation of Conceptual Map: Using conceptual map to map out the areas of concern in the social-ecological system by considering human, manufactured and natural capital stocks for the Western Cape Case Study.

The natural, human and manufactured capital stocks of the Western Cape Province in South Africa are outlined and detailed (not exhaustively) in Figure 44 and Figure 45. The illustration is not exhaustive but attempts to capture some of the key factors and issues that could be related to natural, human and manufactured capital. These illustrations show how we could use descriptions of natural, human and manufactured capital as a starting point to outline the institutions involved and consider the key drivers of social-ecological system change and sectors and services that could be related to human and manufactured capital stock and resilience. From an illustration such as Figure 45, we can detail the key system components, stocks, flows, etc and then compose a graphical causal model of the system helping initiate an understanding of how the system is inter-linked.

Multi-participatory workshops with strategic planning and graphical causal mapping exercises can be used to help understand the ‘linkages’

between social, economic and natural systems - in order to migrate to a more holistic understanding of the system. Linkages, or interdependencies, are important for several reasons:

1. By understanding linkages we get a better idea of where we can intervene or act in a system, and where we can't (i.e. distinguishing between observational and interventional variables).
2. Understanding the linkages or interdependencies at whole system scale will help us answer the question; "what are the key system interdependencies that constitute the resilience of the system in different scenarios?"

Populating a Bayesian network with probabilities from both quantitative (empirical, detailed sub-system models) and qualitative (expert opinion using conditional probability tables) would help us start to identify the key sensitivities of the integrated system, as we currently understand them. As demonstrated in the case studies, we could then build upon this understanding in an iterative manner through discussion and/or workshops when we review progress on the project. Dynamic systems models can then be built after we've identified critical areas of sensitivity within the system and decide to probe their function and processes deeper. In future, we could feed back the results of these higher resolution dynamic systems (or other e.g. GIS) models to the Bayesian network and estimate the scale influence of improving understanding of those particular parts (chosen to represent natural, human or manufactured capital) of the system. It is entirely feasible to use this framework in two ways; firstly, as a top-down conceptual framework from which detailed embedded units could be constructed for a system that services decision-making over the wide range of areas that are required to be managed (e.g. land management, etc.), and secondly, for getting to grips with the full scope of requirements that we identified in this dissertation as necessary for treating social-ecological systems as complex adaptive systems.

9.2.2 Total Economic Value

The framework for natural, human and manufactured capitals itself is insufficient, however, for the purpose of discovering system interdependencies. Therefore, the consideration of additional evaluative frameworks are needed in order to obtain the context specific sub-system level definition required for Bayesian models, especially in terms of cause and effect relationships (including flows such as ecosystem services).

In most case studies conducted in this dissertation, Total Economic Value (TEV) (Blignaut & de Wit, 2004) is used as a conceptual framework to inform the articulation of social-ecological system benefits in most case studies attempted. It must be stressed that TEV is not necessarily useful as an indicator, but as an evaluative framework for articulating, considering and understanding social-ecological system benefits, and creating a shared understanding of cross-system interdependencies. Neither is it exhaustively applied to each case study system, but is customised to suit the problem at hand and the context in which the problem is located.

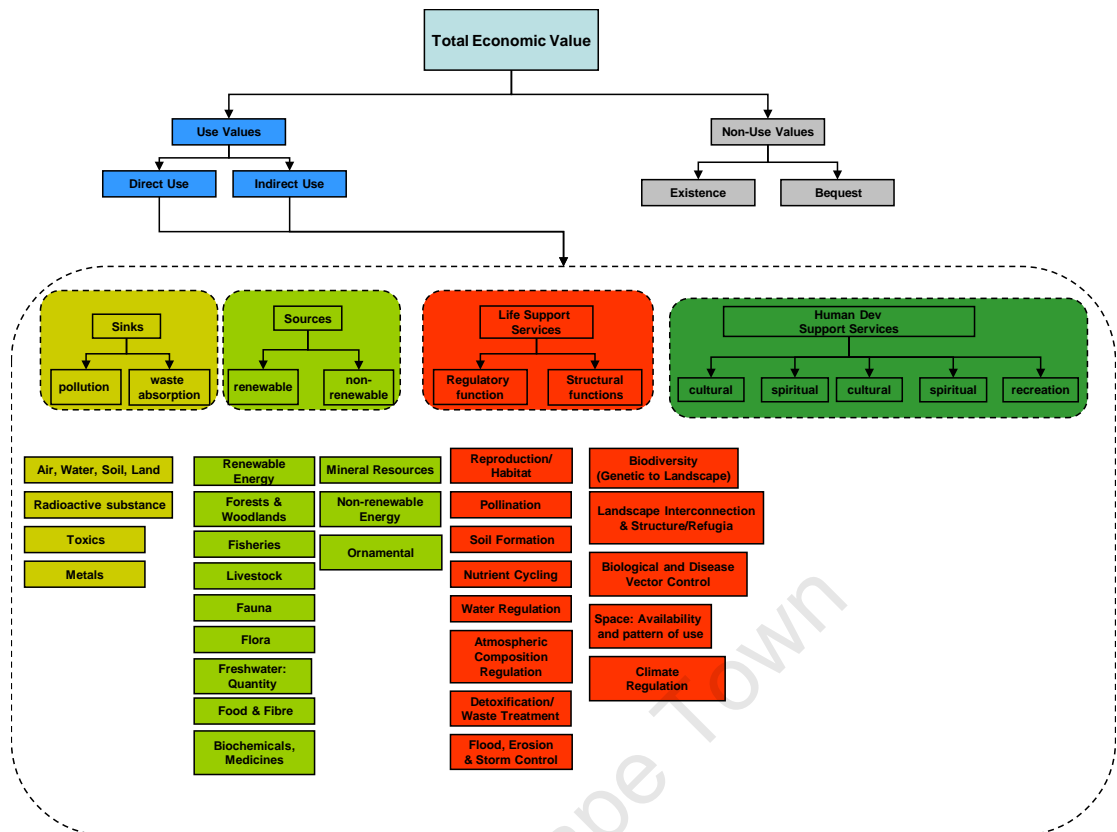


Figure 46: Total Economic Value Framework for Considering Ecosystem Services.

The top-down derivation of the social-ecological interface is in relation to Total Economic Value (TEV). Total Economic Value (TEV) necessitates the consideration of a broad range of ecosystem services (see Figure 46, or Blignaut & de Wit, 2004):

- “Life Support Services (regulatory and structural functions)
- Human Dev Support Services (recreation, cultural, spiritual)
- Sources (renewable and non-renewable)
- Sinks (pollution and waste absorption)”

The following description of TEV was formulated in private communication with Prof Martin de Wit, while developing the methodology proposed in this dissertation in a case study. The following interpretation was co-written with De Wit during case study development. We wrote in support of the use of

TEV as a top-down conceptual systems framework for engaging with social-ecological systems²¹:

“The concept of TEV (Blignaut & De Wit, 2004) goes beyond the dominant neo-classical economic value system, enabling the economic value of biophysical services provided by coastal ecosystem to be expressed. This can be achieved using both market prices and estimated values where markets do not exist. In particular, TEV can be used as a concept to differentiate the values of biophysical services provided to commercial and artisanal/subsistence economies. The concept of TEV facilitates a discussion on the economically most important goods and services provided within a particular system, whether it is the provision of water, the assimilation of waste or providing attributes for recreation to name a few. This has the following benefits:

- Trade-Off Analysis: Locally optimised activities (e.g. a commercially optimised agricultural production process) can then be evaluated in relation to other important ecosystem activities and services at ecosystem scale. This will inform a decision on trade-offs between economic and biophysical goods and services at a broader ecosystem scale, rather than the local scale only. It therefore provides a mechanism to deal with ever-increasing importance of off-site externalities of a particular economic process on other ecosystem services and human actors.
- Gaps in knowledge, partnerships or competencies can be developed where a linkage(s) is not well enough understood but is seen as crucial to the systems behaviour. As a strategic concept, TEV is expected, at least initially, to be broad enough to accommodate a constructive debate between various disciplines during the systems formulation phase of modelling. Using an open framework such as TEV enables the science base to be continually built upon and improved as

²¹ The text in quotes was co-written with Martin de Wit for a paper, but we dropped this part in the

investigation into the economics-biophysics interface continues.

TEV does not provide an exhaustive framework for interpretation of social-ecological systems and is used merely to engage the interface and is viewed as a flexible and adaptable framework that can conceptually evolve over time to include other measurement systems.”

final submission. It has been included here because it describes the role of TEV rather well.

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9.3 Manual and Automatic Engineering of Emergence Revisited

In this section we discuss how the BPDA approach could, in the future, support both manual and emergent engineering of emergence. We present a rationale for how the BPDA approach can be developed in the future, and what direction(s) must be taken in terms of methodologies. We explore and explain how using hyperstructures that are enabled by agent-based Bayesian models can be used to provide decision-support in adaptive governance and management of social-ecological systems.

The purposes of bringing these two processes together are; (1) to provide a new level of cross-verification (Peter C, 2008) of large, complex, interdisciplinary models for decision-making, one that involves enabling all participants to grasp the basic logic of the model i.e. causality, and (2) to ensure a development path for the BPDA approach that will facilitate the development of decision-support models towards near real-time and real-time decision-support frameworks.

9.3.1 Manual Engineering of Emergence

In this dissertation, manual engineering of emergence was conducted at two levels; (1) between cross-disciplinary research group participants, and (2) between researchers and decision-makers. This was mainly conducted in interdisciplinary workshops, supplemented by one-on-one interactions with experts with specialist disciplinary knowledge (to be scrutinised later by the multi-participant group). In this way, each causal relationship in every embedded unit was verified and validated by more than one participant. Each embedded unit underwent a series of sensitivity analyses to ensure its validity in the scenarios in which it was employed.

We used soft facilitation techniques in participatory workshops in order to formulate a heterarchical, causality-based formulation of system interdependencies using the BPDA approach. It involved interdisciplinary workshops between researchers and decision-makers. Although there were no opportunities to work directly with stakeholders in the case studies conducted in this dissertation, there is room for adapting how the BPDA approach is implemented in different participatory processes that involve stakeholder participation. While the BPDA approach engages the use of different conceptual frameworks for stimulating reasoning between workshop participants, the main purpose of participatory process facilitation is ultimately to stimulate learning, dialogue, negotiation, participation, debate and cooperation. This is with the ultimate goal of creating shared understanding and shared awareness of decision-making contexts amongst participants. To this end, the softer aspects of facilitating participatory processes take precedence in any workshop exercise.

The BPDA approach enables both researchers from different disciplines and decision-makers obtain a shared understanding of how the social-ecological system is integrated at the level of research-based models, and can interrogate the fundamental assumptions upon which the causal relationships that constitute the model are founded. In this way, the participatory process enables a strong platform for verification of the Bayesian hyperstructures that are used in decision-support models that are constituted using the BPDA approach. This is critical where the issue of evaluation in adaptive management programmes is concerned. The fundamental assumptions governing the detailed intra-relations of sub-units can be scrutinised by an informed and experienced decision-maker. The software interface enables an easy-to-understand view of causal relationships, and the fundamental assumptions governing these relationships are transparent and trace-able.

In almost all of the case studies conducted in this dissertation, the Bayesian models were flexible enough that they could be adapted to suit

consequent studies, and to incorporate new information pertaining to the particular context of the new study.

9.3.2 Automatic Engineering of Emergence

The case studies in this dissertation did not involve any automatic learning from data. Data and information was interpreted and used to manually formulate hyperstructures consisting of graphical causal maps and Bayesian networks. However, it is possible that in the future, the BPDA approach might be extended to include automatic learning from real-time databases such as weather, rainfall, temperature, pricing, demand indices, etc. through automatic learning from on-line data feeds. In the case of the BPDA approach, the key requirement is a computational Bayesian framework with the ability to cope with a large number of variables (or nodes), each with a large number of discrete states over which its probability distribution is comprised in conditional probability tables.

As far as temporal reasoning is concerned, recent developments in the application of Bayesian networks yield a measure of hope. Osunmakinde (2009) has developed a framework in his PhD for dealing with 'evolving dynamic Bayesian networks'. Osunmakinde & Bagula (2009) have applied temporal probabilistic reasoning for emergent situational awareness that is generated without any input from domain experts. The BPDA approach has much simpler requirements for temporal reasoning. It will involve linking to historical and real-time or near real-time databases and/or empirical and numerical models. It does not require the higher level reasoning that is required for situational awareness. Automatic engineering can already be used to learn from other models, in particular, high resolution models of embedded units (for example, in Borsuk et al., 2004), which often have complex data sets of their own to interpret, if every variable is taken into account in the model.

It is therefore feasible that the BPDA approach can, in the future, be developed to incorporate automatic learning from real-time data feeds because

it helps researchers and decision-makers distinguish between observational and interventional variables. In this way, observational variables (new and old) can be identified and monitoring programmes can be put in place, which can be used to update Bayesian network sensitivities over time.

9.3.3 Converging Manual & Automatic Engineering

It is doubtful that pure automatic engineering techniques could produce the complex models formulated in the case studies conducted in this dissertation. Generating Bayesian models such as those formulated in this dissertation requires verification and validation by *human beings*, so that a complex system can be integrated in order to address a particular problem context.

The long term view for the BPDA approach is that both processes of manual and automatic engineering can be combined in a single software framework, although this is beyond the scope of this dissertation. The BaBe framework (illustrated in Figure 47), a patented agent-based Bayesian engine, holds some promise in this regard. As illustrated in the figure, the Babe contains three levels of agents, which can be grouped to form agencies, in a heterarchical manner. Real-time feeder agents are feeds that can be distributed at remote sources (e.g. real-time databases) to collect streamed data. Reasoning agents are agents which 'reason' using rules, logical models, deductive models and inference based models to make decisions about information that is collected by real-time feeder agents. Competence agents lie at a higher level of decision-making within the framework and can make decisions or 'intervene' upon the system, using a fair level of intelligence, currently. This framework is still under development but we envisage that in future, the BPDA approach will provide the capability to provide near real-time decision support.

Sisyphus OMT Phase III

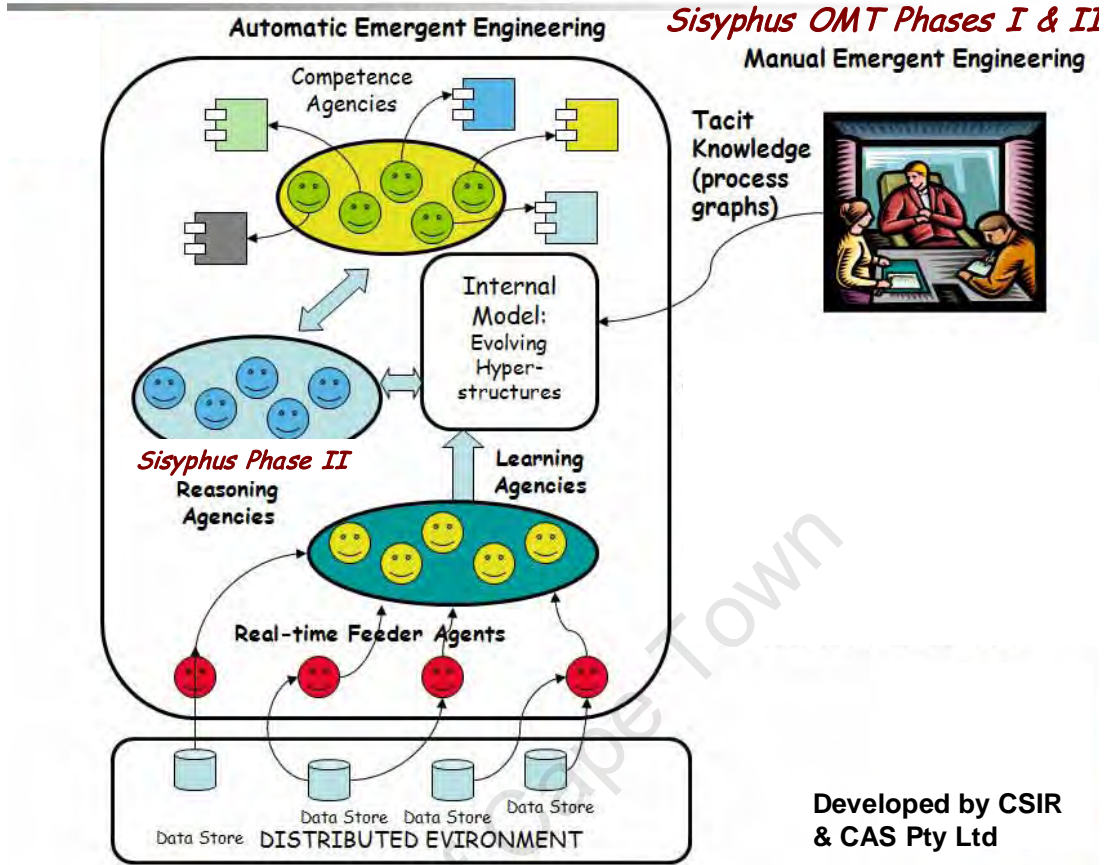


Figure 47: Sisyphus Software Structure: Sisyphus is enabled by the BaBe (Bayesian behavioural) framework of feeder, learning, reasoning and competence agents (Peter C, 2008: from Potgieter, 2005)

9.4 Can Bayesian Hyperstructures Support Dynamic Systems and Agent-Based Models

9.4.1 Bayesian Hyperstructures: Incorporating Dynamic Systems and Agent-Based Models

The information contained in the graphical causal models and underlying the sensitivities exhibited by Bayesian networks helps define the requirements for dynamic systems and agent based models. System feedbacks are determined and resilience stability regimes and thresholds may be derived and compared against empirical data and expert opinion. High resolution numerical modelling, observational data and evidence and explicit feedback modelling and analysis may be used to verify interdisciplinary hypotheses.

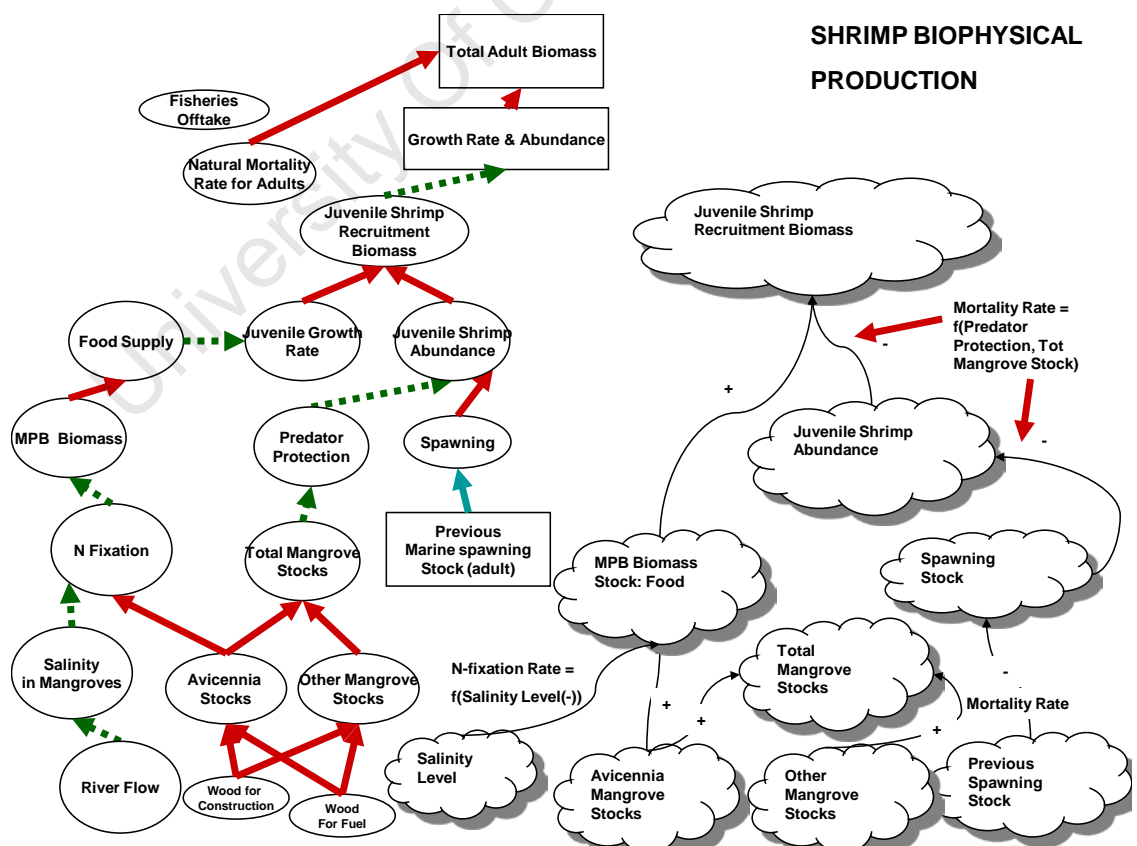


Figure 48: How Dynamic Systems Models are Derived Using Bayesian Networks

The BPDA approach is not restricted to the limitations of systems models; which are based on defining stocks, flows, leads and lags of the system. In dynamic systems models, flows define the interaction between variables whereas in Bayesian and graphical causal models causal relations (initiating, resulting, enabling, defining and combinations thereof) are used to articulate interactions between variables. In the graphical causal model (and Bayesian nets), stocks and flows are defined as variables linked by causal relations (or influences) and are linked to variables that may not be 'assessable' using measurements (e.g. aesthetic judgements, which may only be subjectively assessable).

In Figure 48, a systems diagram consisting of stocks and flows are derived from a graphical causal model. Note how rates are defined in relation to the variables considered in the Bayesian network e.g. nitrogen fixation rate is expressed as a function of salinity levels, which in turn is a function of river flow. The top-down interpretation of the system is therefore derived from a perspective that considers a wider range of variables in a trace-able fashion, some of which are qualitatively defined.

However, the language of systems theory; stocks, flows, leads and lags does not adequately account for the full spectrum of causal inter-relationships that may exist between social-ecological systems processes, actors/agents, components, functions, values etc. The information contained in the graphical causal models and the sensitivities exhibited by Bayesian networks helps define the requirements for dynamic systems and agent based models. System feedbacks can be determined and resilience stability regimes and thresholds may be derived and compared against empirical data and expert opinion. High resolution numerical modelling, observational data and evidence and explicit feedback modelling and analysis may be used to verify interdisciplinary hypotheses that are tendered in explanation of observed behaviours and correlations.

Agent based models require a good understanding of the rules under which an agent may be programmed. Defining the system from a perspective

of causal influences made explicit in causal maps (such as in the BPDA approach), therefore provides a useful framework for definition of agent and agent environments. The different causal paths of influence available to an agent; to respond to - or affect the system is made explicit. Agent environment can be described in terms of the causal mechanisms available to the agent to intervene upon, and helps understand how what is observed is causally related to these points of intervention.

Using the BPDA approach more avenues of influence available to an agent is made explicit than when using traditional soft system methodologies. For example, different possible response strategies may be devised from an integrated view of the system and a greater variety of system interventions for an agent may be conceived. For instance, the strategy of an agricultural manager may be played out against that of water, energy and forestry managers. The agricultural manager may discover that managing within the constraints of the agricultural sector alone may be an insufficient strategy. The influence of the agricultural manager in other key sectors may in fact be equally necessary for survival of the agricultural sector. Moreover traditional management controls within the agricultural sector may be assessed and a greater number of leverage points within the system elucidated through sensitivity analysis.

Using agents, other high resolution models and data sets can be directly linked to the Bayesian framework, which can integrate these inputs and a broader framework. In this way more detailed spatial and temporal trends can be accommodated in the network. Learning and reasoning is performed in terms of learning from historical data and characterizing the probability distributions and uncertainty associated with variables - which can be extended to include real-time data feeds and inputs in future.

The strength of computer-based Bayesian models is that they can be made dynamic in several ways. Spatial, temporal and agent-based dynamics may be assessed using the Bayesian methodology; all of which are important for social-ecological system complexity. In future it is hoped that some

progress will be made towards exploring how agents can potentially be used for learning, reasoning and decision-making in the system - and to represent decision-making sub-systems and people that have a significant influence on the system.

9.4.2 Visualising Real-Time Evolution of System in Heterarchical Framework

The heterarchical hyperstructure argued for in the BPDA approach is an adaptive hyperstructure. As such, it can be adapted to reflect real-world changes that influence the system in question at different scales and levels of inquiry. In particular, the hyperstructures used in the BPDA approach enable both upward and downward directions of systems analysis (i.e. the downward direction of analysis or reductionism, and the upward direction of holism or emergence (Peter 2008, pp. 487). In this dissertation, we showed how a heterarchical hyperstructure based approach (i.e. BPDA) is employed as a mechanism for ensuring democratic interaction between disciplines and guiding cross-disciplinary research and case studies into large-scale social-ecological systems.

In this dissertation we used Bayesian networks and graphical causal maps as hyperstructures that helped understand and reason about system sensitivities and dependencies in a variety of case studies relating to social-ecological systems problems. For each case study, a set of hyperstructures can be used to help create shared understanding that bridges disciplinary divides and focuses and orients participatory research and decision-making processes. In the future, we aim to extend the BPDA methodology by making full use of the BaBe agent-based Bayesian behavioural modelling framework to enable distributed real-time data feeds, in order to provide near real-time modelling for decision support.

The causal ‘fishnet’ enabled by graphical causal maps and Bayesian networks, provide a framework in which the evolution of causal influence sensitivities can be illustrated, as shown in Figure 49, where agents (in red) are

assigned (i.e. learning, reasoning and competence agents) to real-time or near real-time databases, and automatically update the sensitivities in the Bayesian network, as shown by the white causal chains in Figure 50 and Figure 51. Different causal chains may then rise to significance in the hierarchy as sensitivities are automatically updated from information drawn from real-time or near-real time data feeds.

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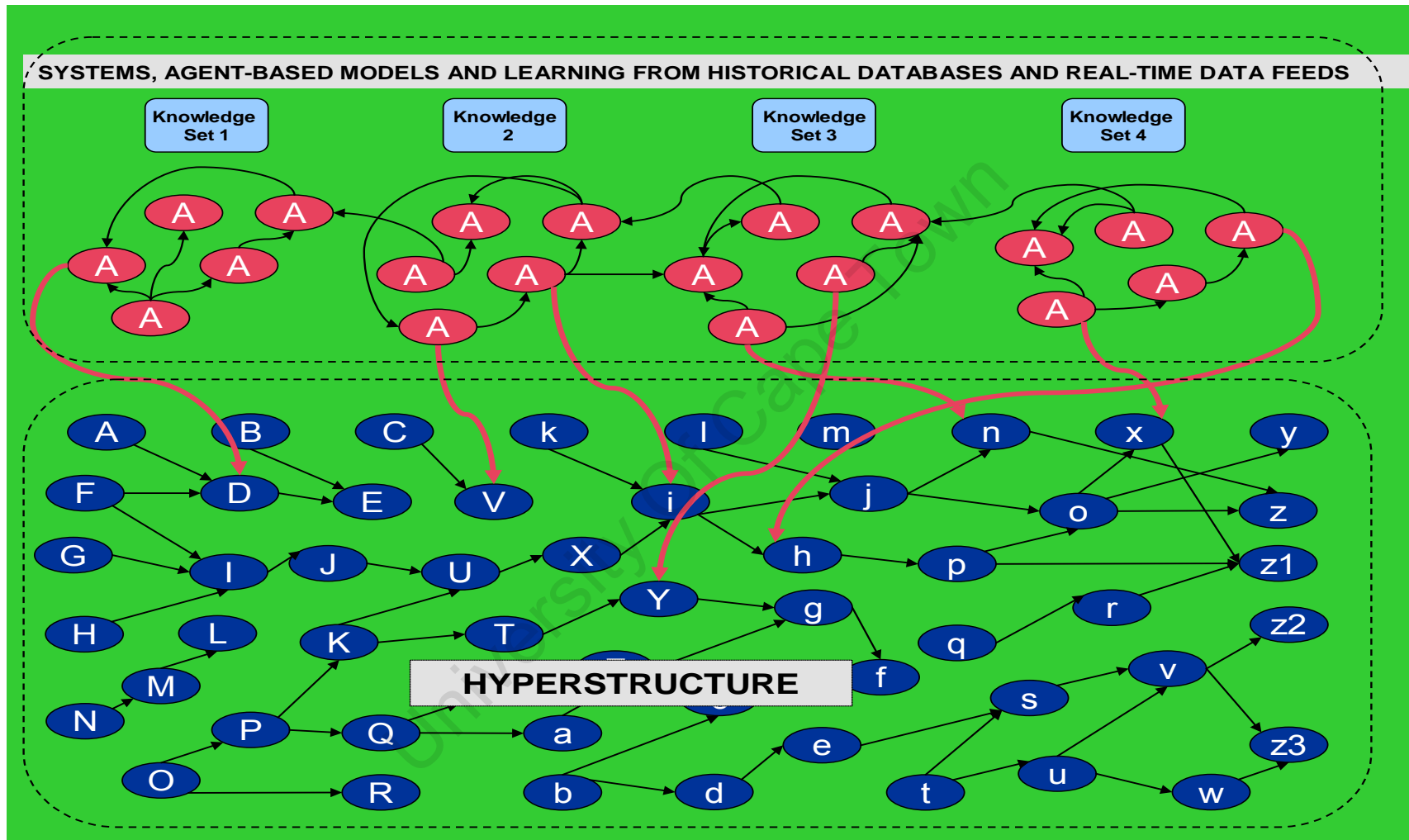


Figure 49: Heterarchical Causal Framework for Visualising System Evolution in Real-Time (Peter 2008)



SYSTEMS, AGENT-BASED MODELS AND LEARNING FROM HISTORICAL DATABASES AND REAL-TIME DATA FEEDS

Knowledge Set 1 Knowledge 2 Knowledge Set 3 Knowledge Set 4

EVOLVING HYPERSTRUCTURE

SYSTEMS, AGENT-BASED MODELS AND LEARNING FROM HISTORICAL DATABASES AND REAL-TIME DATA FEEDS

Knowledge Set 1 Knowledge 2 Knowledge Set 3 Knowledge Set 4

EVOLVING HYPERSTRUCTURE

A

B

Figure 50: Heterarchical Causal Framework for Visualising System Evolution in Real-Time A & B

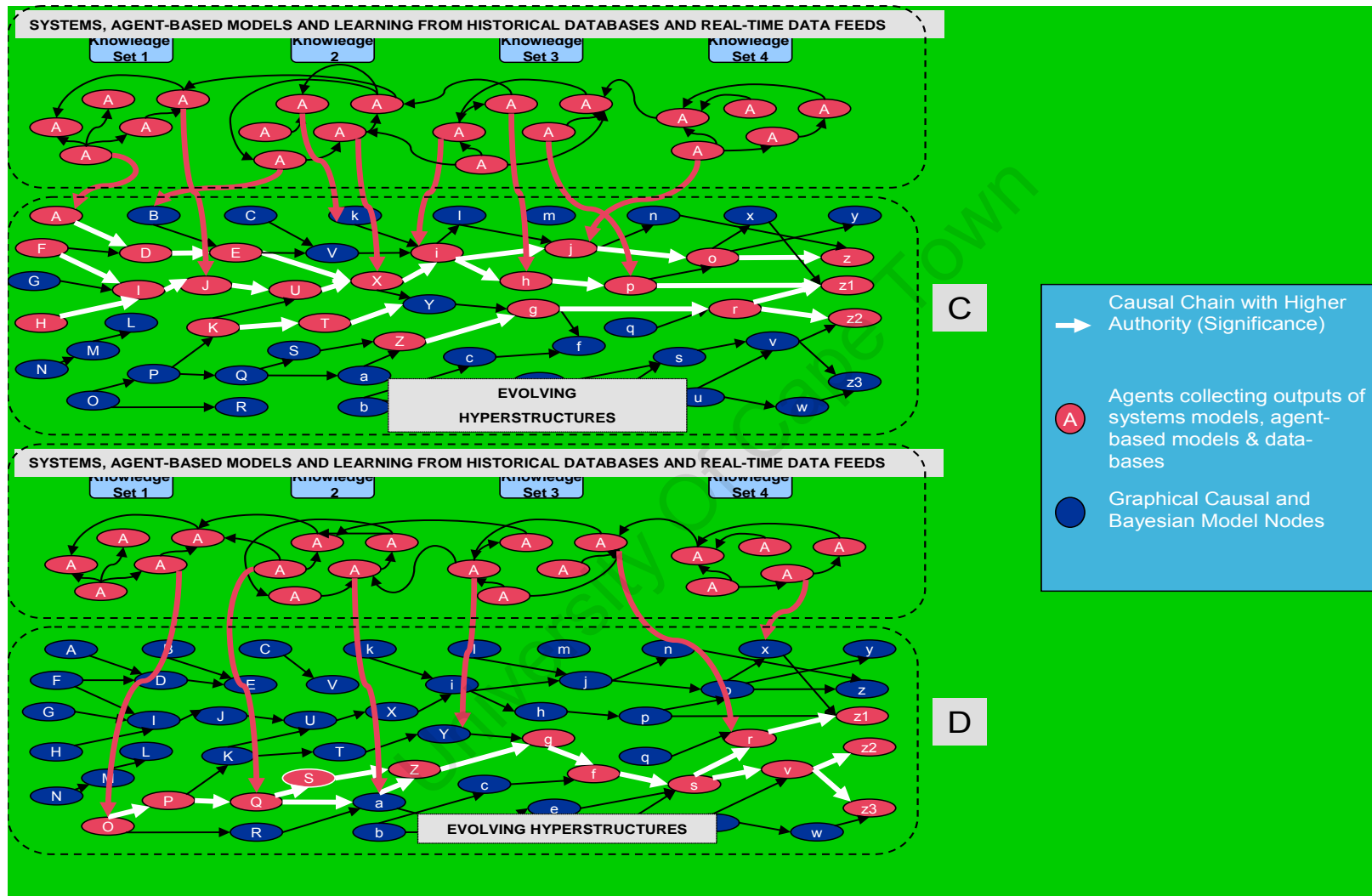


Figure 51: Hierarchical Causal Framework for Visualising System Evolution in Real-Time: C & D

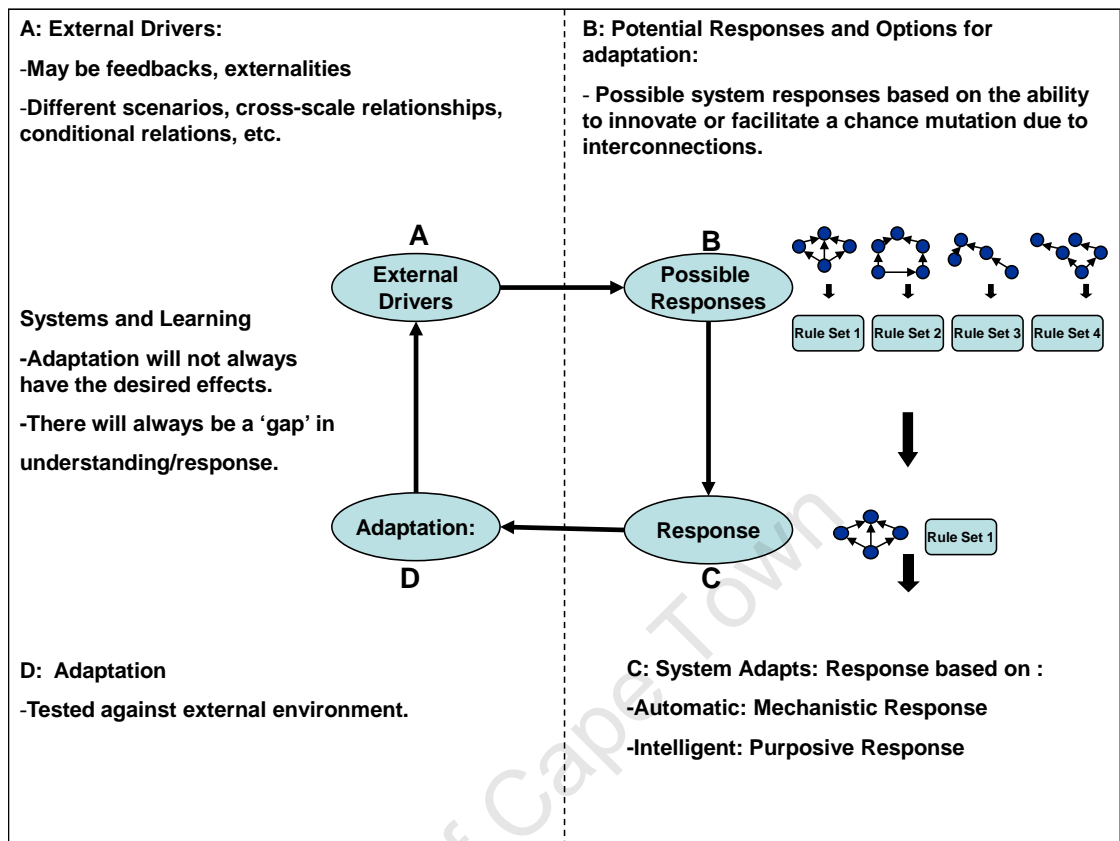


Figure 52: The Dynamic Chain of Cause and Effect Relationships that Binds a System to its Environment of Systems

Deriving causal models of social-ecological system inter-relatedness makes explicit the various causal relationships between a defined system and its external environment. In Figure 52, a social-ecological system is viewed as having a variety of possible responses (B) to an external influence (A). The eventual response (C) may or may not lead to an adaptation (D) which helps mitigate the undesired external influence (A). This may be interpreted within a research framework as the conceptualisation of various scenarios (A), possible strategies or responses (B), and a way of testing whether these responses result in the appropriate adaptations (C and D).

For example, a variety of hypotheses may exist to explain eutrophication of a lake, which is densely settled by humans. However, researchers and stakeholders may disagree on the required responses to the eutrophication problem both at the biophysical and socio-economic system

levels. An integrated response strategy may integrate community intervention strategies, legal strategies, policy development strategies and biophysical systems monitoring strategies.

The BPDA approach, as proposed, will support the representation and testing of these diverse hypotheses and facilitate interdisciplinary scrutiny of the general research integration strategy, and the integration of computer models with empirical data and fieldwork (sampling or case study's). These may be used to obtain better understanding of system stability regimes and resilience before an adaptation (or set of them) may be implemented.

9.5 Shared Understanding for Decision-Support in Adaptive Management

9.5.1 Understanding Resilience using Agents and Ontology's

This dissertation is generally concerned with stimulating and understanding resilience for improved adaptive governance and management sustainability programmes:

1. Stimulating *actual* resilience of the system through strengthening dialogue and cooperation amongst adaptive governance and management programme participants. We make use of metaphors and conceptual tools from resilience theory, such as *resilience*, *the adaptive cycle*, *panarchy* and *cross-scale* interactions to obtain better mutual understanding of the goals, objectives and opinions of various system users and stakeholders. Through exploring this in a multi-participant process, we enable a more 'shared' understanding of the desired and undesired system states to be obtained by participants. In a sense, a shared understanding or collective 'self-awareness' is encouraged through a focused, facilitated dialogue. In particular, a more shared understanding of the diverse beliefs, value systems and normative

views (as required by many authors including Ehrlich & Levin, 2006, Max-Neef, 2005; Stern, 2000) may be obtained using the approach (see later in section 9.5.3).

2. Improving the *understanding* of resilience by elucidating perceived and measured thresholds, critical interdependencies (e.g. non-linear feedbacks) within and between embedded units (e.g. cross-scale) in relation in different future scenarios. The aim of the approach is to create a better shared understanding of the mechanisms of resilience and test this understanding through high-resolution sub-system models, empirical observations and tests, and dynamic systems and agent-based models.

These two aspects are *coupled* to each other in bringing about better collective adaptive governance and management. Implicit to this view is the idea that as shared understanding increases amongst the variety of researchers, stakeholders and users involved in adaptive governance and management programmes, so does the actual resilience of the system. Converting tacitly held knowledge to explicit, shared knowledge boosts the effectiveness of the social-network in question to overcome barriers and adapt to new challenges.

Causality is used to constrain the dialogue, but also to stimulate it. The shared understanding of system interdependencies, critical thresholds and agent-behaviours is visualised and elucidated in graphical causal models. In this dissertation, it is claimed that the traditional soft systems language of systems theory (i.e. stocks, flows, leads and lags) does not account for the full spectrum of causal inter-relationships that may exist between social-ecological systems processes, actors/agents, components, functions, values etc.

The approach proposed and tested in this dissertation aims to use causal modelling to overcome the limitations of traditional systems theory approaches (Checkland & Scholes, 1990) in facilitating the type of transdisciplinary research and interaction for adaptive management. The BPDA approach is based on using graphical causal maps and Bayesian

networks to facilitate interdisciplinary cooperation and dialogue. We know that Bayesian networks can dynamically integrate with historical and real-time databases, so we envisage that in the future, we will be able to make use of Bayesian agents to provide near real-time or even real-time spatio-temporal analysis of thresholds and stability regimes. Moreover, we will be able to test a wide variety of different understandings of projected future social-ecological system sustainability scenarios, as the BPDA approach can accommodate different causal explanations, and a wide range of single variable (or node) states (i.e. corresponding to the scale that is required of the variable for analysis)..

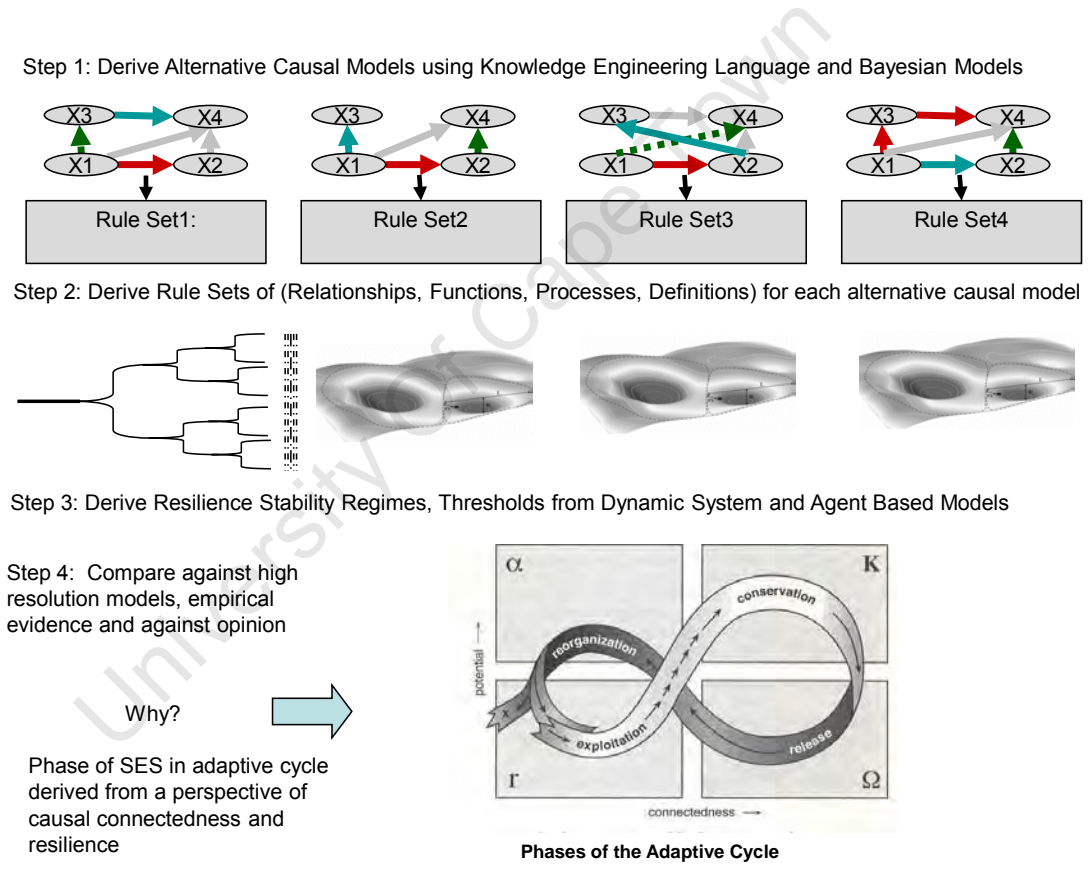


Figure 53: Deriving Dynamic System and Agent Based Models from Bayesian Nets and Graphical Causal Models: Using rule sets to understand adaptive capacity.

In our approach, both non-overlapping as well as overlapping hypotheses models are accommodated explored by deriving alternative graphical causal models and Bayesian networks to represent various system definitions between interdisciplinary experts. This also helps define the

boundaries between variables that can be modeled in mathematical and probabilistic fashion and those which are so subjective as to remove them from quantifiable analysis.

The graphical causal models are software enabled to record descriptions of the functional/mathematical 'rule-set' of each alternative causal structure using parameters and thresholds based on state-based descriptions as inputs to dynamic modelling and simulations (see Figure 53). Dynamic systems models may then be derived from parameters, thresholds and functions interpreted from the alternative causal Bayesian models. Dynamic system models may be used to obtain stability regimes i.e. multiple stable states and thresholds of embedded sub-system unit. Comparing the resultant thresholds and stability regimes against historical and current empirical evidence and observation enables more traceable and rigorous verification of which mental model(s) best describes the system. Various rule sets can be tested in this way against models, empirical data and expert opinion. This understanding can be used in integration at the 'whole' system. This, in turn, can be used to help establish a shared understanding of resilience (in terms of threshold and critical limits) at the 'whole' systems scale and level of description employed for analysis.

Where convergence between observed evidence and modeled behaviours are found more confidence in the assumptions underlying the correct model is obtained. Where disagreement is observed, the underlying causal chain of sensitivities (and assumptions) can be analysed and tested in a step-wise manner. The models therefore provide a verification capability that can be used to engender deeper understanding of system sensitivities.

Through an iterative learning cycle it is hoped that a better context governed understanding of the interconnectedness, resilience and stability regimes of the social-ecological system may be obtained. Context refers to historical and current state of the system, itself an emergent of the evolution of interactions over time. Through this iterative learning process it is possible to:

1. Improve understanding of resilience through dynamic systems analysis and agent based modeling.
2. Improve understanding of causal interconnectedness of the system variables and between agents,
3. Improve understanding of system sensitivities and iteratively improve them.
4. Reduce uncertainty in system variables,
5. Migrate modelling to agent-based techniques, and finally,
6. Furnish a coherent set of reasoning underlying the relationships, sensitivities and uncertainties regarding system variables.

The phases of an adaptive cycle are defined by different combinations of potential, resilience and connectedness, which change along the axes of an adaptive cycle. Identifying which phase of an adaptive cycle a system may be in is a valuable, sometimes critical input to adaptive management plans. The factors mentioned in the list above may be used to inform the reasoning behind which phase of the adaptive cycle the social-ecological system being researched most likely resides in at present, and perhaps which phase it has been in the past. Moreover, the traceability of the process enables easier verification of the entire process of interdisciplinary cooperation and model integration planning. This is achieved precisely through elucidating and testing the:

- Causal interconnectedness of the social-ecological system components and agents, and the,
- Resilience of overlapping and non-overlapping models of explanation.

Resilience theory views the evolution of social-ecological systems as consisting of a four phase cycle i.e. the adaptive cycle. The four phases are characterised by differences in resilience and connectedness as explained earlier in this dissertation.

Resilience theory indicates that we need to account for cross-scale and intra-scale influences. These are causal driver-response relationships of all

kinds; any change in a variable that produces a change in a variable which is conditionally dependent upon it must be accounted for.

The BPDA approach attempts to link the conceptualised connectedness envisaged by a crossdisciplinary group (i.e. the shared understanding) to the stability (and instability) regimes of the system. It also aims to provide full trace-ability of the underlying assumptions and logic thereof. The aim of the approach is thus to provide a better way of understanding connectedness and resilience of a social-ecological system. In doing so the evolutionary phase of the adaptive cycle in which a social-ecological system is said to exist will be trace-ably identified and verified. That is, by using the software enabled Bayesian knowledge engineering language and by Bayesian sensitivity analysis, dynamic systems modelling, respectively.

Knowledge of which phase of an adaptive cycle a social-ecological system is regarded to currently exist is of key importance in conceptualising, planning and implementing adaptive management strategies. An approach such as the BPDA approach has the potential to facilitate trace-able iterative learning as a system evolves through different phases of an adaptive cycle. It may therefore prove valuable in the adaptive management of social-ecological systems.

9.5.2 Understanding Agency, Resilience & Adaptive Management

One of the key advantages of the BPDA approach is that it can be used to help establish which phase of an adaptive cycle a social-ecological system may be in at a particular moment in time. Moreover, through scenario-based testing of different interventions, it can also help envision how to either; keep the social-ecological system in a particular phase (e.g. conservation), or migrate it from one phase to another (.e.g from exploitation to conservation: see Figure 54). Correctly understanding and classifying a social-ecological system in terms of the phases of an adaptive cycle requires in-depth

knowledge of cross-scale and intra-scale sensitivities and of critical limits and thresholds.

The BPDA approach is especially suited to this as the Bayesian hyperstructures helps to distinguish cross-scale effects and to identify where interventions can be made, and where only observations can be made. This helps put in place monitoring systems for early warning and guides researchers and decision-makers as to the system-level effects of interventions at any particular level within the system, and in a variety of future scenarios. This has the potential to benefit decision-makers in dealing with adaptation at multiple scales of governance.

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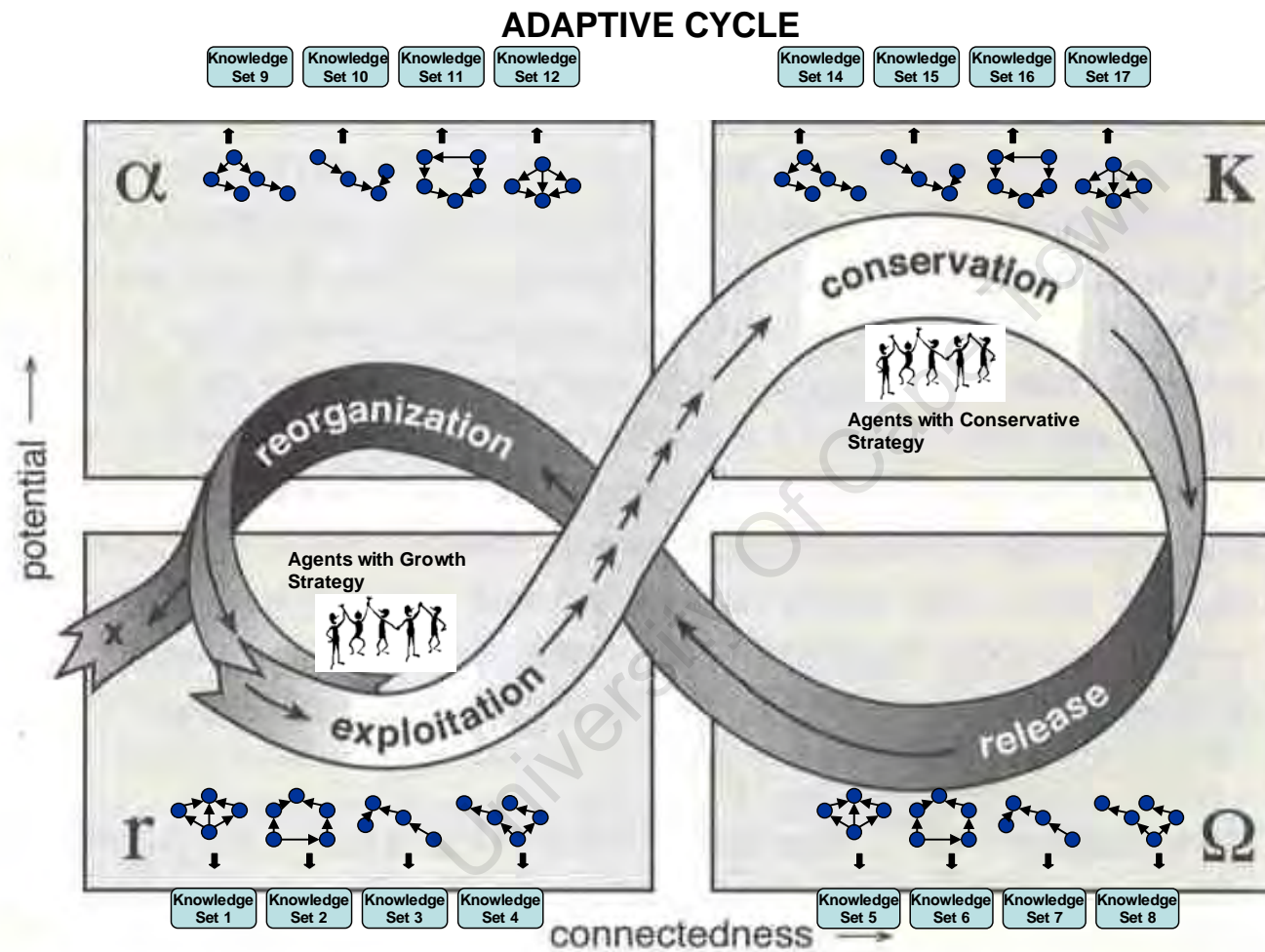


Figure 54: Resilience, Agency and the Adaptive Cycle: Adapted from Peter (2008)

9.5.3 Accommodating Values, Beliefs, Norms & Behaviours

Establishing the required norms and behaviours that are required for sustainable decision-making and actions, requires understanding the ‘nature and origin of filters’ (Peter, 2008, in Clarke, 2003) in order to formulate actions that bring about sustainability. The BPDA approach allows for multiple hypotheses and levels of description to be formulated, precisely in order to facilitate learning, participation, negotiation and cooperation at all decision-making levels and across sectors.

In this section we deal with the future of the BPDA approach in accommodating the higher level frameworks of reasoning used by agents and actors in the system i.e. within a framework of values, beliefs, norms and behaviours. The rationale for this is shown in Figure 55 (which is detailed at length in Peter (2008, pp. 496-498), and can be summarised as follows, in reference to Figure 55. The BPDA approach, if extended to include full agent-based modelling, will be able to follow the complex analytical chain from A – E, as shown in Figure 55, thereby aligning with the requirements for elucidating, understanding and analysing the various elements of the VBN chain. That is, we are not testing predictions about how norms and behaviours will evolve; we merely test what possible norms and behaviours may exist, or may result from a set of decisions and actions or interventions. We suggest that the five phases listed below serve as a future framework in which we can envisage extending the BPDA approach to accommodate the values, beliefs and norms of agents or system actors, all in aid of obtaining a deeper understanding of the ‘rule sets’ governing agent decision-making and behaviours.

- A. Phase A involves using participatory workshops to formulate shared understanding amongst workshop participants. The BPDA approach can accommodate a wide variety of top-down frameworks (e.g. TEV, human, manufactured and natural capitals),

and allows for new indices to be determined and verified. Most importantly, it allows for exchange of views and creating the shared understanding and transparency that is required for adaptive management processes to yield successful coordinated programmes that bring about the desired results.

- B. Graphical causal maps and Bayesian networks are used to capture the belief structure underlying the model and the constraints, parameters and equations underlying the belief structure, respectively.
- C. Phase C involves assessing what effect the belief structures formulated in step B may have on the required, observed and projected norms. This can be conducted in discussions between cross-disciplinary workshop participants.
- D. Phase D involves using rule sets for the norms, and the knowledge of decision-maker constraints (such as the distinction between observational and interventional variables, and knowledge of cross-sector and cross-scale effects) to formulate an understanding of agent environments and constraints. In addition to using Bayesian inference to derive critical limits and thresholds, in future, it is envisaged that virtual agents could play out scenarios and help refine understanding of their effect on critical limits and thresholds. In this way a variety of different possible adaptations can be tested, at a variety of different levels of detail and scale.
- E. Phase E involves coping with emergence or surprise. We have already shown how the hyperstructures can be manually updated (or adapted) to accommodate unexpected real-world changes in the case studies conducted in this dissertation. In future, we would like to develop the automatic engineering of emergence i.e. where real-time data-bases (e.g. weather, stock prices) are monitored by agents, and used to automatically update the hyperstructures as

changes unfold, as shown in the previous sections (see Figure 50 & Figure 51). By obtaining a deeper understanding of system agents and actors we aim to model their roles in social-ecological systems more appropriately.

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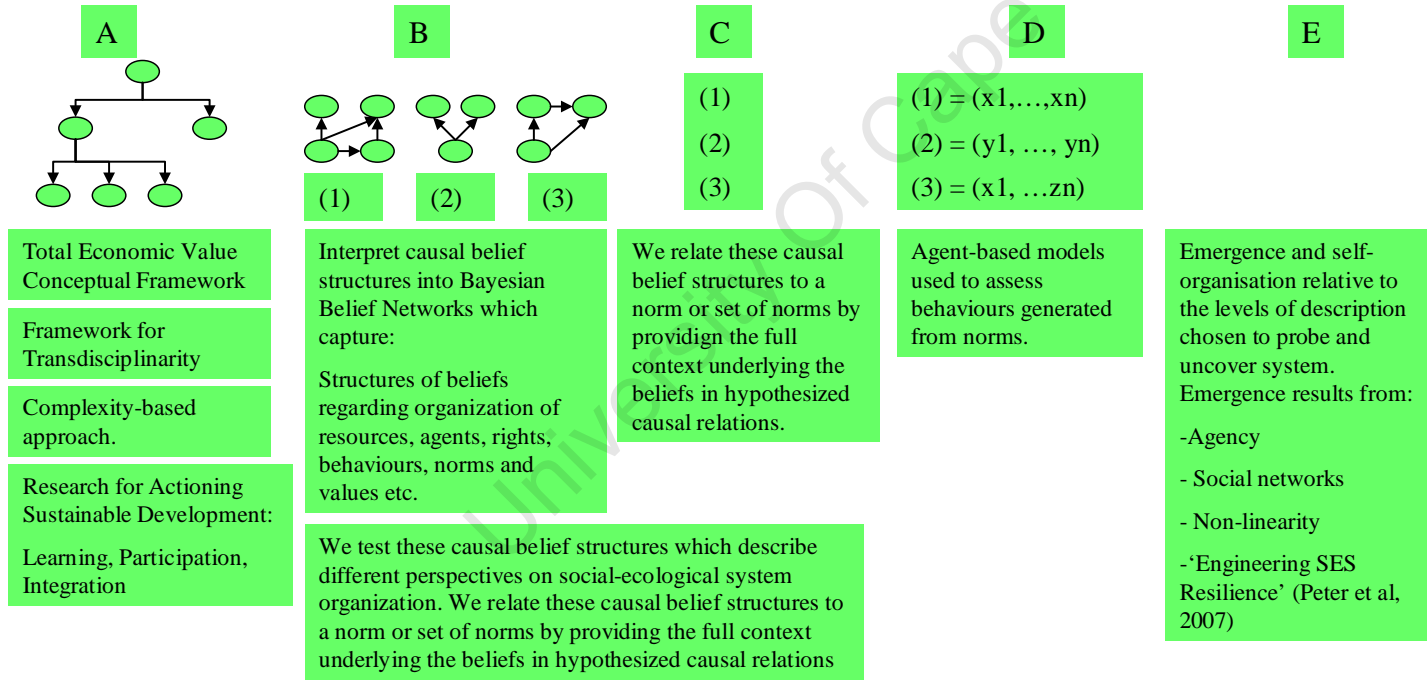
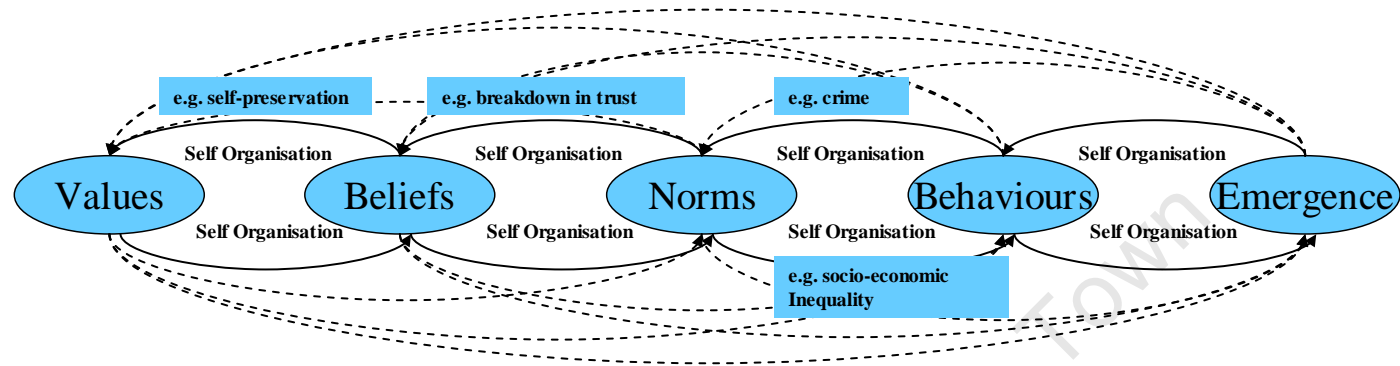


Figure 55: Framework for Adaptive Management of Social-Ecological Systems (Peter C 2008: adapted from Stern 2002)

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9.5.4 Representing Multiple Mental Models of High Uncertainty Decision-Making Scenarios

The BPDA approach also helps elucidate and articulate the complex linkages, sensitivities, thresholds and scales and the underlying framework of assumptions that is required to elucidate the spaces in which decision-making is considered 'decideable' and 'undecideable'.

In Figure 56 a description is given of a situation where a decision-making strategy of one ecosystem user may conflict with others and it is unclear which strategy should be adopted. In these cases a simple binary proposition isn't helpful for decision-making; there is no clear 'yes' or 'no' decision. Alternative causal models can be used to represent the various mental models of the multiple stakeholder and decision-maker group. In the BPDA approach graphical causal maps and Bayesian nets are used to derive probabilistic models representing the sensitivities of causal influences. These, in turn may be used to derive different rule sets for competing proposed responses. These rule sets can be used to compose scenarios in Bayesian networks and the results can be tested against cross-disciplinary scrutiny, real-world evidence over time, validating or invalidating some explanations above others. While this may not address the full range and complexity of agent behaviours, it is nonetheless a valuable complementary framework that can be broadened, in future, to help define agents in terms of rule sets, constraints, boundary conditions and extent of influence. This could feasibly be used to better assess roles and responsibilities where collective actions are concerned in much the same way agent-based simulations are used for decision-making today, but with more cross-disciplinary rigour and trace-ability around agent characterisation.

How we deal with undecidability i.e. elucidating context in which undecidability emerges

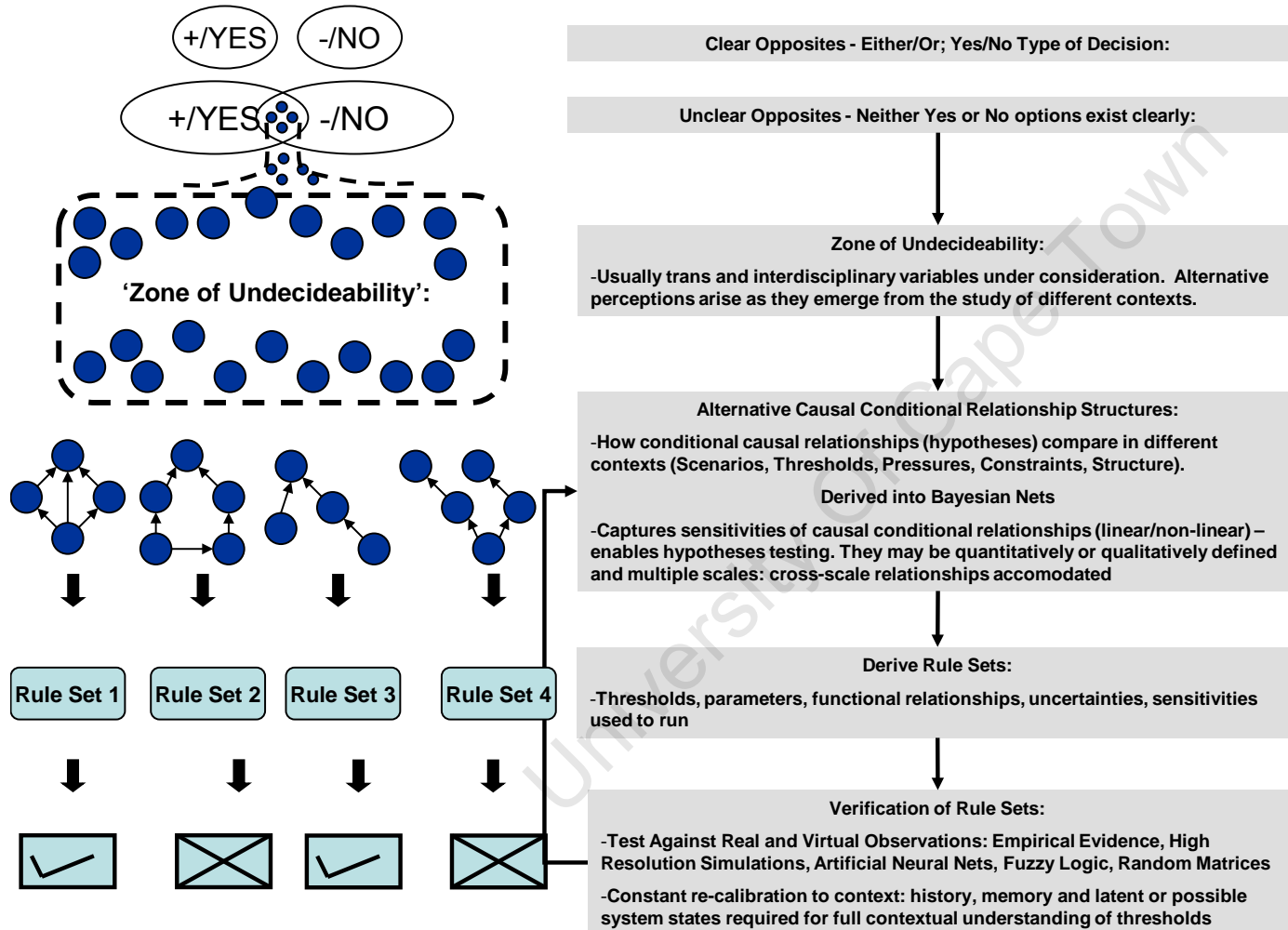


Figure 56: How we Deal with Undecidability: We elucidating context in which undecidability emerges

10. **Summary and Conclusions**

To summarise, in this dissertation we showed that the BPDA approach is a complexity-based approach for dealing with the challenge of integration in social-ecological systems research, that is; research that has the ultimate purpose of supporting sustainable development research and adaptive management programmes. A great deal of effort was made in this dissertation to develop and test an approach that had practical value, but which was also soundly grounded in complexity theory. As such, this dissertation draws heavily on philosophical concepts for its foundation, but also devotes a great deal of attention to implementing and testing the approach through a series of case studies that incrementally increased in complexity.

However, throughout this dissertation, it is acknowledged that there is no single approach or methodology that can sufficiently cope with a system in all its real-world complexity. That is, the BPDA approach does not seek to model systems exhaustively but aims to keep the contextually relevant variables continually present in the analytical space that forms the basis for shared understanding.

As a general framework for dealing with the complex challenges facing attempts at sustainable development the BPDA approach has enormous potential for application, and in a variety of problem domains. We have argued for future avenues of development that could extend that approach beyond its current capacity to support decision-making i.e. to near real-time and real-time simulation.

The hyperstructures serve as a quantitative interface for pattern-matching between conceptualised and observed or modelled empirical understandings of the social-ecological system problem under study. Moreover, the distinction between observational and interventional variables is made evident in a Bayesian network (Meder, 2005; Waldmann & Hagmayer, 2005), and categories can evolve as understanding of causal relationships unfolds (Waldmann & Hagmayer, 2006). This provides a critical insight into the differences between what needs to be measured, and what needs to be acted upon. As such it provides a valuable research and

decision-making framework. Monitoring programmes and intervention programmes (e.g. adaptation and mitigation) can be set up with a clear understanding of the boundaries of knowledge regarding the system and what needs to be done to obtain a better understanding of the system over time. We have shown how this is achievable in the case studies conducted in support of this dissertation.

Our broad conclusions regarding the BPDA approach is that; (1) hyperstructures provide a causality-based framework for interdisciplinary interaction and thereby enable a simple and human-intuitive framework for reasoning, and (2) that this includes reasoning about drivers, responses, influences, interdependencies, constraints, thresholds and limits of the ‘whole’ system in relation to its sub-systems in a *joint* bottom-up and top-down framework. Hyperstructures are also an effective mechanism for facilitating constructive dialogue and debate around social-ecological system futures and engendering shared understanding. Bayesian networks, in particular, offer the benefit of integrating both observational and interventional learning in a single framework, while maintaining the distinction between them. It also helps understand what is observable (can be monitored) and what can be intervened upon (influenced), and allows for causal relationships and categories to evolve. The heterarchical approach provides a framework in which categories always overlap, even if causal models do not. The heterarchy of graphical causal maps and Bayesian networks enable a framework of overlapping categories that are not strictly structured in a bottom-up or top-down fashion. The BPDA approach also provides a methodological framework that is largely un-restricted by disciplinary boundaries, scale and non-linearity. As such, the BPDA approach accommodates a wide range of the requirements for conducting research into social-ecological systems i.e. from the perspective of the emerging theories of complexity and resilience.

As demonstrated in this dissertation, the BPDA approach is one way to provide an unbiased framework in which different disciplinary perspectives can be shared, scrutinised, integrated into a research design, and tested, and adapted as new understanding unfolds. It provides a democratic framework for testing hypotheses evidence and opinions; regarding the question of what leads to system behaviours of concern in the study. It therefore satisfies the requirements set out by de Wit (2001) in a PhD dissertation. De Wit (2001) emphasized the role of “multiple-loop learning

frameworks” (2001, pp. 154) for advancing towards merging theory with practise in the arena of “economic policy making for complex and dynamic environmental problems”.

The BPDA approach is a new way of integrating between researchers themselves, and researchers, decision-makers and stakeholders tasked with ensuring sustainable development, and requiring adaptive management approaches. The BPDA approach has its own limitations, but its strengths are sufficient to provide a valuable contribution to the field of sustainability. Some of these limitations can feasibly be dealt with in the future (as outlined in the previous section). The BPDA approach can be implemented in a number of different areas of research and may be generalised to deal with case studies in general, although not exhaustively.

The BPDA approach also has a clear direction for future development, where it can be extended to deal with greater levels of decision-making, and research and modelling integration challenges. It has not been explored to its full potential in this dissertation. However, even as presented and tested in this dissertation, the BPDA approach provides a new and hopefully valuable contribution to the field of sustainability research. It also integrates well with historical and newly emerging theories that attempt to shed light on the complexity of social-ecological systems (e.g. resilience theory) and sustainable development (e.g. action research). We intend to build on the research conducted in this dissertation, and to extend the BPDA framework, as far as is valuable, in respect of its potential to help visualise cross-sectoral development and sustainability of economic development in terms of its resource relationships.

In conclusion, as a formalism, graphical causal maps and Bayesian networks satisfy all the requirements for modelling the complexity of social-ecological systems at a bio-physical level that were identified in this dissertation. We showed how, by using the BPDA approach, the challenges of dealing with scale and non-linearity, for example, can be overcome. Moreover, it helps engender shared understanding between diverse participants in research programmes. We also showed how, in theory, the approach could be extended in future to accommodate full agent-based support for near real-time and real-time simulations.

In the BPDA approach the hyperstructures are heterarchical. These hyperstructures therefore constitute an adaptive, evolutionary formalism. We explained how we think that the approach could, in future, be expanded to learn from data sources in real-time or near real-time, and play an even greater role in decision support. While we can only speculate as to the future of the BPDA approach, the approach, as applied to social-ecological systems, provides valuable insights that can be extended to help provide a more inclusive, and evolutionary perspective of economic systems in relation to the key challenge of economic development. That is, that economic development does not occur in isolation and involves social and ecological systems perspectives to be included in order for sustainability to be realised. Moreover, nuances regarding the balance between the development trajectories of different sectors can be more important for ensuring whole system sustainability in relation to the available resource base.

The BPDA approach, by accommodating embedded units and variables at massive scale, enables a wide range of future scenarios and adaptation options to be envisaged and tested. This is in contrast to predictive modelling approaches, which seek to predict future system trajectories. By allowing for a greater number and variety of system variables to be analysed, a more varied analysis can be conducted around, for example; balancing multi-sectoral growth in relation to a range of forecasted and projected resource limitations. As such, the BPDA approach is not a theory of development or economics, but rather it seeks to provide a formalism to match a model to its particular context in an adaptive manner. Heterarchy ensures that an evolutionary perspective is maintained.

The BPDA approach enables a shared understanding of a complex, adaptive system to be maintained, while it is adapted and changed. As such, it has the potential to contribute to a variety of problems and case studies that researchers' and decision-makers may be concerned with currently, and in the future.

11. References

- Allen, T.F.H., Tainter, J.A., Hoekstra, T.W. (1999). Supply-side sustainability. *Syst. Res. Behav. Sci.*, 16 (5), 403–427.
- Allen, T.F.H., Zellmer, A.J., Wuennenberg, C. (2005). The loss of narrative. In Cuddington, K., Beisner, B.E. (Eds.), *Ecological Paradigms Lost: Routes to Theory Change*. Academic Press, New York, pp. 333–370.
- Allenby, B. (2006). The ontologies of industrial ecology? [electronic version]. *Progress in Industrial Ecology*, 3 (1-2), 28-40.
- Anderies, J.M., Janssen, M.A., Ostrom, E. (2004). A framework to analyse the robustness of social-ecological systems from an institutional perspective [electronic version]. *Ecology & Society*, 9(1), 18, URL: <http://www.ecologyandsociety.org/vol9/iss1/art18/>.
- Anderson, J. R. (1991). The adaptive nature of human categorization. *Psychological Review*, 98, 409-429.
- April, K. (2004). *A Resource-Based View of the Firm: Integrating The Role of IT as a Strategic Resource: An Empirical Study of South African Personal Financial Services Firms: 1999-2003*. Unpublished PhD Dissertation, Graduate School of Business, University of Cape Town & Templeton College, University of Oxford, August 2004, pp. 1 - 531.
- Ashby, W.R. (1962). Principles of the self-organizing system [electronic version]. In Von Foerster H. & Zopf, Jr, G.W. (Eds.), *The principles of self-organization: Transactions of the University of Illinois Symposium*, London, Pergamon Press, pp. 255-278.

- Ashby W. R. (1964). *An Introduction to Cybernetics* [electronic version]. Methuen, London, 1964.
- Ashby, F. G., Waldron, E. M., Lee, W. W., & Berkman, A. (2001). Suboptimality in human categorization and identification [electronic version]. *Journal of Experimental Psychology: General*, 130, 77-96.
- Ashton, P. J. (2002). Avoiding conflicts over Africa's water [electronic version]. *Ambio*, 31(3), 236- 242.
- Baas, N. A., & Emmeche, C. (1997). On emergence and explanation. *Intellectica*, 25, 67-83. Retrieved March 22, 2001, from <http://www.nbi.dk/~emmeche/coPubl/97d.NABCE/ExplEmer.html>
- Banisch, M. (2002). Derrida, Schmitt and the essence of the political [electronic version]. *Refereed paper presented as part of the Political Theory Stream Jubilee Conference of the Australasian Political Studies Association, Australian National University, Canberra, Australia.*
- Baran, E., Jantunen, T. (2004) Stakeholder consultation for Bayesian decision support systems in environmental management. *Proceedings of the Regional Conference on Ecological and Environmental Modeling (ECOMOD 2004), Universiti Sains Malaysia, 15-16 September 2004, Penang, Malaysia.*
- Beer, S. (1992). World in Torment [electronic version]. URL: http://www.ototsky.mgn.ru/it/papers/world_in_torment.pdf
- Bennet, E.M., Cumming, G.S., & Peterson, G.D. (2005). A systems model approach to determining resilience surrogates for case studies [electronic version]. *Ecosystems*, 8, 1-14.
- Berlin, I. (1969). *Four Essays on Liberty*. Oxford: Oxford University Press.

- Bijker, W.E., Hughes, T.P. & Pinch, T. (Eds.) (1997). *The Social Construction of Technological Systems*. Cambridge, MIT Press.
- Blignaut, J., & de Wit, M.P. (2004). *Sustainable options: Development lessons from applied environmental economics*. Cape Town: University of Cape Town Press.
- Boulding, K. E. (1956). General systems theory – the skeleton of science. *Management Science*, 2(3), 197-264.
- Borsuk, M. E., Stow, C. A. and Reckhow, K. H. (2004). A Bayesian network of eutrophication models for synthesis, prediction and uncertainty analysis, *Ecological Modelling*, ISSN 0304-3800, 173, 219-239.
- Bromley J., Jackson N. A., Clymer O. J., Giacomello A. M., Jensen F. V. (2005). The use of Hugin to develop Bayesian networks as an aid to integrated water resource planning, *Environmental Modelling and Software*, 20, 231-242.
- Carpenter, S. R. (2002). Ecological Futures: Building an ecology of the long now, *Ecology*, 83, 2069–2083.
- Campbell, D. T. (1974). Downward causation in hierarchically organized biological systems. In Ayala F.J., & Dobzhansky T. (Eds.) *Studies in the Philosophy of Biology*, New York, Macmillan.
- Cash, D.W.W., Adger, W.N., Berkes, F., Garden, P., Lebel, L., Olsson, P., Pritchard, L., & Young, O. (2006). Scale and cross-scale dynamics: governance and information in a multilevel world [electronic copy]. *Ecology and Society*, 11(2), 8.

- Clarke, K. (2003). The limits of simplicity: toward geocomputational honesty in urban modelling. *Proceedings of the 7th International Conference on Geocomputation, Southampton, UK.*
- Clark, K. (2005). Why environmental scientists are becoming Bayesians. *Ecology Letters*, 8, 2–14.
- Clarke, K., Crutzen, P.J., & Schellnhuber, H.J. (2004). Science for global sustainability: Towards a new paradigm. In Schellnhuber, H.J., Crutzen, P.J., Clark, W.C., Claussen, M. & Held, H. (Eds.), *Earth system analysis for sustainability*, Cambridge MA: M.I.T. Press, pp. 1-28.
- Capra, F. (1997). *The web of life* (2nd ed). Great Britain, Flamingo.
- Cariani, P. (1991). A review of emergence and artificial life. In Langton, C., Taylor, C., Farmer, J. & Rasmussen, S. (Eds.), *Artificial Life II*, Vol. X of *Santa Fe Institute Studies in the Sciences of Complexity*, Addison-Wesley, Reading, pp. 775-797.
- CCSAPWC (2007). A Climate change strategy and action plan for the Western Cape: Final, Department of Environmental Affairs and Planning, Western Province, South Africa.
- Checkland, P.B. (1985). From optimising to learning: a development of systems thinking for the 1990s [electronic version]. *Journal of Operational Research Society*, 36, 757-767.
- Checkland, P.B., & Scholes, J. (1990). *Soft systems methodology in action*. Wiley, Chichester.

- Cilliers, P. (2001). Boundaries, hierarchies and networks in complex systems. *International Journal of Innovation Management*, 179-186.
- Cilliers, P. (2008). Complexity theory as a general framework for sustainability science. In Burns, M. & Weaver, A. (Eds), *Exploring sustainability science: A Southern African perspective* (1st ed). Stellenbosch, Sun Press, pp. 39-57.
- Cook, T.D., & Campbell, D.T. (1979). *Quasi-experimentation: Design and analysis for field settings*, Chicago, Illinois, Rand McNally.
- Costanza, R., & Daly, H.E. (1992). Natural capital and sustainable development [electronic version]. *Conservation Biology*, 6(1), 37-46.
- Cundill, G. (2008). Adaptive co-management under resource-poor conditions. In A. Weaver, & M. Burns (Eds), *Exploring Sustainability Science: A Southern African Perspective*, Stellenbosch, SUN Press, pp. 471-505.
- Dawid, A. P. (2002). Influence diagrams for causal modelling and influence. *International Statistical Review*, ISSN 0306-7734, 70 (2): 161–189.
- Derrida, J. (1992). 'Force of law: "The mystical foundation" of authority', in D. Cornell, In Rosenfeld, M., & Carlson D. (Eds.), *Deconstruction and the Possibility of Justice*, New York: Routledge.
- Dechter, R. (1996). Bucket elimination: A unifying framework for probabilistic inference [electronic version]. *Uncertainty in Artificial Intelligence*, 196, 211-219.
- de Mendiguren Castresana, J.C.P. (2003). Productive uses of water at the household level: evidence from Bushbuckridge, South Africa. *International Symposium*

on Water, Poverty and Productive uses of Water and the Household Level, 21-22 January, Muldersdrift, South Africa.

de Rosnay J. (1979). *The macroscope: a new world scientific system*, HarperCollins.

De Wit, M., (2001). *Economic policy making for complex and dynamic environmental problems: A conceptual framework*. Unpublished doctoral dissertation, Department of Commerce, University of Pretoria, South Africa.

DME (2006). Draft biofuels industrial strategy of the Republic of South Africa. Department of Minerals and Energy, South Africa.

DME (2007) Biofuels industrial strategy of the Republic of South Africa. Department of Minerals and Energy, South Africa.

Dupré, J. (1993). *The disorder of things: Metaphysical foundations of the disunity of science*. Cambridge MA, Harvard University Press.

Ehrlich, P.R., & Levin, S.A. (2005). The evolution of norms [electronic version]. *Public Library of Science Biology*, 6, 943-948.

Food and Agricultural Organisation (FAO) (2005). Aquastat: FAO's Information System on Water and Agriculture. www.fao.org/ag/agl/aglw/aquastat/countries/south_africa/index.stm

Flood, R.L. (2001). The relation of systems thinking to action research. In Reason, P. & Bradbury, H. (Eds.), *Handbook of Action Research*. London, Sage Publications Ltd, pp. 133-144.

Folke, C., Hahn, T., Olsson, P., & Norberg, J. (2005). Adaptive governance of social-ecological systems. *Annu. Rev. Environ. Resour.*, 30, 441-473.

Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C.S., Walker, B., Bengtsson, J., Berkes, F., Colding, J., Danell, K., Falkenmark, M., Gordon, L.,

- Kasperson, R., Kautsky, N., Kinzig, A., Levin, S., Maler, K-G., Moberg, F., Ohlsson, L., Olsson, P., Ostrom, E., Reid, W., Rockstrom, J., Savenije, H., & Svedin, U. (2002). Resilience and Sustainable Development: Building Adaptive Capacity in a World of Transformations, International Council for Science, *ICSU Series on Science for Sustainable Development*, 3.
- Gandhi, M., K. In Narayan S. (Ed.) (1968). *The selected works of Mahatma Gandhi: Satyagraha in South Africa*. Ahmedabad: The Navajivan Trust.
- Gell-Mann, M. (1994). *The quark and the jaguar*. New York: W H Freeman & Co.
- Gibson, C.C., Ostrom, E., & Ahn, T.K. (2000). The concept of scale and the human dimensions of global change: a survey. *Ecological Economics*, 32, 217-239.
- Gillaume, P., Tranouez, P., Bertelle, C., Olivier, D., Lerebourg, S. (2004). *Methodology for holarchic ecosystem model based on ontological tool*. In ESMc'2004 Conf., Paris (France), October 2004.
- Glymour, C. N. (2001). *The minds arrows: Bayes nets and graphical causal models in psychology*, ISBN 0262072203.
- Glymour, Clark, Spirtes, P., and Scheines, R. (1993). *Thinking things through*, M.I.T. Press.
- Gunderson, L. H. (2000). Ecological resilience – in theory and application, *Annual Review of Ecology and Systematics*, ISSN 0066-4162, 31, 425-39.
- Gunderson, L.H., & Holling C.S. (Eds.). (2002). *Panarchy: Understanding transformations in human and natural systems*, Washington DC, Island Press.
- Gruber, T. R. (1995). Toward principles for the design of ontologies used for knowledge sharing. *International Journal of Human-Computer Studies*, ISSN 1071-5819.

- Gustavson, B. (2001). Theory and practise the mediating discourse. In Reason, P. & Bradbury, H. (Eds.), *Handbook of Action Research*. London, Sage Publications Ltd, pp.17-26.
- Gershenson, C., & Heylighen, F. (2003). When can we call a system self-organizing? [electronic version]. In Banzhaf, W. Christaller, T. Dittrich, P., Kim, J.T., & Ziegler, J. (Eds.) *Advances in artificial life, 7th European conference. Dortmund*. Springer, pp. 606-614.
- Goodman, N. (1978). *Ways of worldmaking*. Indianapolis IND, Harvester Press.
- Gregory, J.M., & Oerlemans, J. (2009). Simulated future sea-level rise due to glacier melt based on regionally and seasonally resolved temperature changes. *Nature*, 391, 474-476.
- Hassan, R.M., (2003). Economy-wide benefits from water-intensive industries in South Africa: quasi-input–output analysis of the contribution of irrigation agriculture and cultivated plantations in the Crocodile River catchment, *Development Southern Africa*, 20, 2
- Hacking, I. (2000). *The social construction of what*. Cambridge, MA: Harvard University Press.
- Heylighen, F., Cilliers, P., & Gershenson, C. (2007). Complexity and philosophy. In Blogg, J., & Geyer, R (Eds), *Complexity, science and society*. Oxford: Radcliffe Publishing.
- Heylighen, F., Joslyn, C., & Turchin, V. (2001). Principia cybernetic web [online]. URL: <http://pcp.lanl.gov/>. (Last accessed March 18 2002 – in Potgieter 2004).
- Helsper, E.M., & Van der Gaag, L.C. (2002). Building Bayesian networks through ontologies. In van Harmelen, F. (Ed.), *Proceedings of the 15th European conference on artificial intelligence. Amsterdam*. IOS Press, pp. 680-684.

- Hodgson, G. M. (1993) *Economics and Evolution: Bringing Life Back Into Economics*. University Of Michigan Press & Polity Press.
- Holland, J.H. (1995). *Hidden order: how adaptation builds complexity*. Reading MA: Addison-Wesley.
- Holling, C.S., Gunderson, L.H., & Ludwig, D. (2002). In quest of a theory of adaptive change. In L.H. Gunderson, & C.S. Holling (Eds.), *Panarchy: Understanding transformations in human and natural systems*. Washington DC, Island Press, pp. 3-24.
- Holling, C.S., & Gunderson, L.H. (2002). Resilience and adaptive cycles. In Gunderson, L.H., & Holling C.S. (Eds.), *Panarchy: Understanding transformations in human and natural systems*. (25-62), Washington DC, Island Press.
- Holling, C.S., Gunderson, L.H., & Peterson, G.D. (2002). Sustainability and panarchies. In L.H. Gunderson, & C.S. Holling (Eds.), *Panarchy: Understanding transformations in human and natural systems*. Washington DC, Island Press, pp. 63-102.
- Holling, C. S. (2004). From complex regions to complex worlds, *Ecology and Society*, 9 (1): 11
- Hume, D. (1739/2000). *A treatise of human nature*. Oxford, Oxford University Press.
- IKAPA GDS (2008). The Ikapa Growth and Development Strategy, Serves as a White Paper for the Western Cape, Provincial Gazette Extraordinary 6500, Province of the Western Cape [electronic version].
- Ingram, J. (2007). Spatial and temporal scales and levels in human systems: some examples in the context of food security. *Presented at Regional Expert*

Meeting, IPCC TGICA Expert Meeting Integrating Analysis of Regional Climate Change and Response Options, 20-22 June 2007, Nadi, Fiji.

IPCC (2008). (Eds) Bates, B., Kundzewicz, Z.W., Wu, S., Palutikof, J., Climate Change and Water, Intergovernmental Panel on Climate Change Technical Paper VI, WMO, UNEP [electronic version].

Islam, G., Zyphur, M., J., Beal, D., J. (2006). Can a whole be greater than the sum of its parts? A critical appraisal of “emergence”, *IBMEC Working Paper - WPE – 11 – 2006, Sao Paulo: IBMEC.*

Jackson, M.C. (1991). *Systems methodology for the management sciences*. New York, Plenum.

Janse van Rensburg, J., Gorgens, AHM, (2001). Komati Basin: Juxtaposing conflicting water resource interests via a water resources systems model. *Tenth South African National Hydrology Symposium, 26-28 September 2001.*

Kates, R. W., & Clarke, W. C. (1996). Expecting the unexpected. *Environment*, 38 (2), 6-11.

Kates, R. W., & Dasgupta, P. (2007). African poverty: A grand challenge for sustainability science, *PNAS*, 104 (43), 16747-16750.

Kintz, E. R. (2004). Considering the ties that bind: Kinship, marriage, household and territory among the Maya [electronic version]. *Ancient Mesoamerica*, 15, 149-158.

Koestler, A. and Smythies, J. (1969). *Beyond reductionism*. Hutchinson.

Kolman, K., Miller, J.H., & Page, S. (1997). Computational political economy. In W.B. Arthur, S.N. Durlauf, & D.A. Lane (Eds.), *The economy as an evolving complex system II*. Reading MA, Addison-Wesley, pp 463.

- Kuhn, T. S. (1962). *Structure of scientific revolutions*. Chicago, ILL: Chicago University Press.
- Kuhn T. S. (1970). *The structure of scientific revolutions*. Chicago: Chicago University Press.
- Lamberts, S.W.J. (2006). *Adaptive networks: the governance for sustainable development* [electronic version]. Netherlands, Eburon Publishers.
- Lemmer, W. (2006). Bio-ethanol production in the Western Cape: value adding to winter cereal through ethanol, DDGS, and CO₂ production. Department of Agriculture, Western Cape.
- Levin, S.A. (2006). Learning to live in a global commons: Socio-economic challenges for a sustainable environment [electronic version]. *Ecological Research Special Feature*, 21, 328-333.
- Levins, R. (1968). *Evolution in changing environments*. Princeton, Princeton University Press.
- Lien, Y., & Cheng, P. W. (2000). Distinguishing genuine from spurious causes: A coherence hypothesis. *Cognitive Psychology*, 40, 87-137.
- Lubchenco, J. (1998). Entering the century of the environment: A new social contract for science [electronic version]. *Science*, 279, 491-497.
- MacCracken, M. (2001). Prediction versus projection: forecast versus possibility. *WeatherZine*, 26, URL: <http://sciencepolicy.colorado.edu/zine/archives/1-29/26/index.html>
- Max-Neef, M. A. (1991). *Human Scale Development*. New York & London, APEX Press.

- Max-Neef, M.A. (2005). *Foundations of transdisciplinarity* [electronic version]. *Ecological Economics*, 53, 5-16.
- Malhotra, Y. (1999). Toward a knowledge ecology for organizational white-waters [electronic version]. *Knowledge Management*, 2(6), 18-21.
- McCormick, R.J., Zellmer, A.J., Allen, T.F.H. (2004). Type, scale, and adaptive narrative: keeping models of salmon, toxicology and risk alive to the world. In Kapustka, L.A., Gilbraith, H., Luxon, M., Biddinger, G.R. (Eds.), *Landscape Ecology and Wildlife Habitat Evaluation: Critical Information for Ecological Risk Assessment, Land-Use Management Activities, and Biodiversity Enhancement Practices*. ASTM STP 1458, ASTM International, West Conshohocken, PA.
- Meder, B., Hagmayer, Y., & Waldmann, M.R. (2005). Doing after seeing [electronic version]. In Bara B.G., Barsalou L., & Bucciarelli M. (Eds.), *The Proceedings of the Twenty Seventh Annual Conference of the Cognitive Science Society*, Mahwah NJ, Erlbaum, pp. 1461-1466.
- Meder, B., Hagmayer, Y., Waldmann, M.R. (2006). Understanding the causal logic of confounds. In R. Sun, & N. Miyake (Eds), *Proceedings of the Twenty Eighth Annual Conference of the Cognitive Science Society*, pp. 1461-1466.
- Mendelsohn, R., Dinar A. and Dalfelt A. (2000). Climate change impacts on African agriculture, Centre for Environmental Economics and Policy in Africa.
- Midgley, G.F., Chapman, R.A., Hewitson, B., Johnston, P., de Wit M., Ziervogel, G., Mukheibir, P., van Niekerk, L., Tadross, M., van Wilgen, B.W., Kgope, B., Morant, P.D., Theron, A., Scholes, R.J., Forsyth, G.G. (2005). A Status Quo, Vulnerability and Adaptation Assessment of the Physical and Socio-economic Effects of Climate Change in the Western

Cape. Report to the Western Cape Government, Cape Town, South Africa. CSIR Report No. ENV-S-C 2005-073, Stellenbosch.

MIT Technology Review (2007) Ethanol demand threatens food prices.
www.technologyreview.com/Energy/18173/ (accessed Feb 13, 2009)

Mitchell S. D. (2004) Why integrative pluralism? [electronic version]. In Richardson, K.A., Goldstein, J.A., Allen, P.M., & Snowden D (Eds.), *E:CO Special Double Issue*, 6 (1-2), 81-89. Mansfield MA, ISCE Publishing.

Minsky, M. (1988). *The Society of Mind* (1st ed). New York: Simon & Schuster.

Monteiro, P. M. S. and Mathews, S. (2003). Catchment2Coast: Making the link between coastal resource variability and river input, *South African Journal of Science*, 99.

Monteiro, P.M.S., A. Pascall, N. Machava, J.L. Graça, E. André, (2007). Biogeochemical characteristics of a tropical mangrove in a nutrient poor river – coastal system. Council for Scientific and Industrial Research, In prep for Estuarine, Coastal and Shelf Science in April 2007, ftp://ftp.cordis.europa.eu/pub/inco/docs/coastal2/22_cat_2002_10059catchment_en.pdf .

Morin, E. (2007). Restricted complexity, general complexity. In Gershenson, C., Aerts, D. & Edmonds, B. (Eds.) *Worldviews, science and us: Philosophy and complexity*. Singapore. World Scientific, pp. 5-29.

Mukheibir P., Sparks, D., 2003. Water resource management and climate change in South Africa: Visions, driving factors and sustainable development indicators, April 2003, Report for Phase I of the Sustainable Development

and Climate Change project, Energy and Development Research Centre (EDRC), University of Cape Town.

Murakami, H. (2008). *After dark*. Vintage Books (First Published as “Afutadaku” by Kodansha, Tokyo in 2004).

Musango, J., & Peter, C. (2007). A Bayesian approach towards facilitating climate change adaptation research on the South African agricultural sector. *South African Journal of Agricultural Economics*, 46(2), 245-259.

Nadkarni, S. & Shenoy. P. (2004). A causal mapping approach to constructing Bayesian networks [electronic version]. *Decision Support Systems*, 38, 259-281.

Nicolescu, B. (2000). *Levels of reality as a source of quantum indeterminacy*. In F. Tito Arecchi F. T. (Ed.). Roma: Determinismo e complessit`a, Fondazione Nova Spes and Armando Editore, 2000, pp. 127-158.

Nkomo, S., Van der Zaag, P. (2003). Equitable water allocation in a heavily committed international catchment area: the case of the Komati Catchment, 15th – 17th October, 2003, 4th WaterNet/WARFSA Annual Symposium: Water, Science, Technology and Policy: Convergence and Action by all, Gabarone.

Nozick, R. (2001). *Invariances: The structure of the objective world*. Cambridge, MA: Harvard University Press.

- Osunmakinde, Isaac (2009) *Computational intelligent systems: Evolving dynamic Bayesian networks*. Unpublished doctoral dissertation, Department of Computer Science, University of Cape Town.
- Osunmakinde, I O and A Bagula (2009) Emergent future situation awareness: A temporal probabilistic reasoning in the absence of domain experts. In Kolehmainen et al., M. , (Eds.) *Proceedings ICANNGA 2009* 5495, pages 340-349.
- Pahl-Wostl, C. (2007). The implications of complexity for integrated resource management [electronic version]. *Environmental Modelling and Software*, 22, 561-569.
- Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference* (2nd ed). San Mateo, USA, Morgan Kauffman Publishers.
- Perlas, N. (2000). *Shaping globalization: civil society, cultural power and threefolding*. Co-published by the Centre for Alternative Development Studies & The Novalis Press. Cape Town, Falcon Press.
- Peter, C. Potgieter, A.G.E., Monteiro P.M.S. (2007). Engineering social-ecological system resilience. In Kay, R. & Richardson, K.A. (Eds.), *Building and Sustaining Resilience in Complex Organizations, Pre-proceedings of the 1st international workshop on complexity and organizational resilience*, MA, ISCE Publishing, MA, pp.35-64.
- Peter, C., Meder, B., von Maltitz, G., van der Merwe, M., (2007*). *Analysing Analysis! A Study of Causal Reasoning for Complex Biophysical Problem-*

Solving and Hypotheses Making, Council for Scientific and Industrial Research, GWDS Number: Pretorial General, 143891.

Peter, C., Monteiro, P., M., S. De Wit, M. (2007). Understanding the socio-ecological complexity of water allocation in coupled river – coastal systems: A Bayesian approach for linking the Incomati Catchment & Maputo Bay systems, *Journal of Ecological Economics*, provisionally accepted Nov 2007 (In Prep for resubmission).

Peter, C., Musango, J. K., De Lange, W. (2007). Case study of national climate change, water storage, irrigated agriculture and biofuel - food security relationships: Using Bayesian networks to model the impact of climate change scenarios on biofuels production from irrigated agriculture – analyzing water, energy and food sector interdependencies. Presented at Regional Expert Meeting, *IPCC TGICA Expert Meeting Integrating Analysis of Regional Climate Change and Response Options*, 20-22 June 2007, Nadi, Fiji.

Peter, C. (2008). Complexity based modeling for sustainability and resilience of social-ecological systems. In A. Weaver, & M. Burns (Eds), *Exploring Sustainability Science: A Southern African Perspective*, Stellenbosch, SUN Press, pp. 471-505.

Peter, C., de Lange, W., Musango, J.K., April, K., Potgieter, A.G.E. (2009). Applying Bayesian modelling to assess climate change impacts on biofuel production, *Climate Research*, (Accepted September 2009: In Press).

- Peirce, C. S. (1934). *Collected papers of Charles Sanders Peirce*, Volume 5. Charles Hartshorne, C. and Paul Weiss, P, (Eds.). Cambridge, Mass, Harvard University Press, pp. 156.
- Pepper, S.C. (1926). Emergence. *The Journal of Philosophy*, 23(9), 241-245.
- Peterson, G.D., Allen, C.R., & Holling, C.S. (1998). Ecological resilience, biodiversity and scale [electronic version]. *Ecosystems*, 1, 6-18.
- Peterson, G.D., Cumming, G.S., & Carpenter, S.R. (2003). Scenario planning: a tool for conservation in an uncertain world [electronic version]. *Conservation Biology*, 17(2), 358-366.
- Piaget, J., 1963. *The origins of intelligence in children*. New York, W.W. Norton & Company, Inc.
- Plummer, R. & Armitage, D. (2007). A resilience-based framework for evaluating adaptive co-management: Linking ecology, economics and society in a complex world [electronic version]. *Ecological Economics*, 61, 62-74.
- Potgieter, A.E.G. (2004). *The engineering of emergence in complex adaptive systems*. Unpublished doctoral dissertation, Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, South Africa.
- Putnam, H. (1975). The meaning of "meaning". In H. Putnam, *Mind, language, and reality*. *Philosophical papers* (Vol. 2, pp. 215-271). London, Cambridge University Press.
- Putnam, H. (1987). *The many faces of realism*. LaSalle, ILL: Open Court.
- RCCSAPWC (2008). Analytical Review of Western Cape Climate Change Strategy and Action Plan: Water and Energy as Integrators. By Peter C., Council for Scientific & Industrial Resources, Natural Resources and Environment,

Sustainability Science Group, for Department of Environmental Assessment and Development Planning, Western Cape Provincial Government, South Africa. Report number PTA General #174799.

Reilly J (1999). What does climate change mean for agriculture in developing countries? A Comment on Mendelsohn and Dinar [electronic version]. *The World Bank Research Observer*, 14(2), 295-305.

Rehder, B., & Hastie, R. (2004). Category coherence and category-based property induction. *Cognition*, 91, 113-153.

Richardson, K.A. (2002). On the limits of bottom-up computer simulation: Towards a nonlinear modelling culture [electronic version]. *Proceedings of the 36th Hawaii International Conference on System Sciences, 7-10 January, 2003 Hawaii, California*, IEEE Computer Society.

Richardson, K. A. (2005). Systems theory and complexity: Part 3, *E:CO Emergence, Complexity and Organisation*, ISCE Research, 7, 104-1144.

Richardson, K.A., & Cilliers, P. (2001). What is complexity science? A view from different directions [electronic version]. *Special Issue of Emergence*, 3(1), 5-22.

Riessman, C.K. (1993). Narrative analysis. *Qualitative Research Methods Series 30: A Sage University Paper*, London, SAGE publications.

Ronald, E.M.A., Sipper, M., & Capcarrère, M.S. (1999). Design, observation, surprise! A test of emergence, *Artificial Life*, 5 (3): 225-239.

Sarewitz, D., Pielke, R. A., & Byerly, R. (2000). *Prediction: science, decision making, and the future of nature*. Washington D.C., Island Press.

SDIP (2007). Sustainable Development Implementation Plan [electronic version], Environmental Evaluation Unit, Incite Sustainability.

- SESWC (2007). Sustainable Energy Strategy for the Western Cape: Draft Summary Document [electronic version], Department of Environmental Affairs and Planning.
- Sengo, D.J., Kachapila, A., van der Zaag, P., Mul, M. and Nkomo, S, (2004). Valuing environmental water pulses into the Incomati estuary: key to achieving equitable and sustainable utilisation of transboundary waters. *Presented at the 5th Waternet/WARFSA Symposium, 'Integrated Water Resources Management and the Millenium Development Goals: Managing water for peace and prosperity', 2-4 November, Windhoek.*
- Serres, M. (1995/1982). *Genesis*. USA: University of Michigan Press. James, G. & Nielson J. (translators). Originally published in French by Editions Grasset et Fasquelle (1982).
- Skyttner, L. (2001). *General systems theory: Ideas and applications*. River Edge, NJ, World Scientific, ISBN 9810241755.
- Slovan, S. A. (1994). When explanations compete: The role of explanatory coherence on judgments of likelihood. *Cognition*, 52, 1-21.
- Smuts, J. C. (1926). *Holism and Evolution*, MacMillan.
- Sneddon, C., Howarth, R.B., & Norgaard, R.B. (2006). Sustainable development in a post-Brundtland world [electronic version]. *Ecological Economics*, 57, 2, 253-268.
- Sorokine et al., (2005). Ontological Investigation of Ecosystem Hierarchies and Formal Theory for Multi-scale Ecosystem Classifications [electronic version]. *Geoinformatica*, 10, 313-335.
- Spirtes, P., Glymour, C. and Scheines, P. (1993). *Causation, prediction, and search*. New York, Springer-Verlag.

Starzomski, B. M., Cardinale, B. J., Dunne, J. A., Hillery, M. J., Holt, C. A., Krawchuk, M. A, Lage, M., McMahon, S. and Melnychuk, M. C. (2004). Contemporary visions of progress in ecology and thoughts for the future, *Ecology and Society*, ISSN 1708-3087, 9 (1), 14. URL: <http://www.ecologyandsociety.org/vol9/iss1/art14>. (Last accessed 15 Nov 2007).

Statistics South Africa (2004). Provincial Profile 2004, Western Cape, South Africa.

Stern, P.C. (2000). Toward a coherent theory of environmentally significant behaviour [electronic version]. *Journal of Social Issues*, 5(3), 407-424.

Strategy Study, Department of Water Affairs and Forestry, Directorate: National Water Resource Planning.

Tansley, A. (1935). The use and abuse of vegetational concepts and terms. *Ecology*, 16(3), 299.

Thagard, P. (1999). *How scientists explain disease*. Princeton, NJ: Princeton University Press.

TIA, 29 August 2002. Tripartite Interim Agreement between Mocambique, South Africa and Swaziland for cooperation on the protection and sustainable utilisation of water resources of the Incomati and Maputo watercourses, Johannesburg.

TSB (2005/6). Tourism Sector Brief [electronic version], WESGRO, URL: <http://www.wesgro.co.za/publications/publications.asp?CatId=14>

Van der Sluijs, J.P. (2007). Uncertainty and precaution in environmental management: insights from UPEM conference [electronic version]. *Environmental Modelling and Software*, 22, 590-598.

- Van Kerkhoff, L., & Lebel, L. (2006). Linking knowledge and action for sustainable development [electronic version]. *Annual Review of Environmental Resources*, 31, 445-477.
- Vellupillai, K. V. (2003). Economics and the complexity vision: chimerical partners or Elysian Adventurers? [electronic version]. Dept of Economics, National University of Ireland, Galway & Dept of Economics, University of Trento, Italy: September 29.
- Waldmann, M.R., & Hagmayer, Y. (2005). Seeing versus doing: Two modes of accessing causal knowledge [electronic version]. *Journal of Experimental Psychology: Memory, Learning and Cognition*, 31(2), 216-227.
- Waldmann, M.R., & Hagmayer, Y. (2006). *Categories and causality: The neglected direction* [electronic version]. *Cognitive Psychology*, 53, 27-58.
- Walker, B., Holling, C.S., Carpenter, C.R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social-ecological systems. *Ecology & Society*, 9(2), 5, URL: <http://www.ecologyandsociety.org/vol9/iss2/art5>
- Walters, C. J. (1986). *Adaptive management of renewable resources*. New York, Macmillan.
- Wegener, M. (1994). Operational urban models: State of the art, *Journal of the American Planning Association*, 60 (1), 17-30.
- Witten G. Q. & Richardson F. D. (2001). Managing arid and semi-arid rangelands accounting for the variability of key factors over space and time [electronic version]. *Arid Zone Ecology Forum, Calitzdorp, September 5-7*.
- WC SER (2003). Socio Economic Review [electronic version], Western Cape Provincial Treasury.

WCSSDIP (2007). The Western Cape Sustainable Development Implementation Plan [electronic version].

WCTB (2007). Western Cape Tourism Barometer, v1:1, The Provincial Tourism Intelligence Source [electronic version].

WCTT (2005). Western Cape Trade Trends: An Analysis of Trends in Western Cape merchandise trade between 2000 and 2004 [electronic version], WESGRO.

WCWSSRSS (2007). Western Cape Water Supply System Reconciliation [electronic version]. Department of Water Affairs and Forestry, Directorate: National Water Resource Planning.

Weaver, W. (1948). Science and complexity [electronic version]. *American Scientist*, 36, 536-544.

Yin, R.K, (1984). *Case study research: Design and methods*. London. Sage Publications Ltd.

Zellmer, A.J., Allen, T.F.H, Kesseboehmer K., 2006, The nature of ecological complexity: A protocol for building the narrative [electronic version]. *Ecological Complexity*, 3, 171-182.

12. **Appendix A: Cholera Study**

A sample of the classification schema that was designed and used in the cholera case study is shown in Table 20. It shows how the schema that was chosen by the cholera team was used to explore systemic interdependencies. The team evaluated the pros and cons of mechanisms that cause cholera, and determined test criteria that could lead to an understanding of which causal relationships would form the core hypotheses. The mechanisms were conceptualised as 'reservoirs, amplifiers, de-amplifiers and transmission mechanisms'. These match system level definitions extremely well, being a metaphoric framework for 'stocks, flows, leads and lags' as they are traditionally understood in systems theory.

Table 20:

Sample of Tables Used to Explore Pros and Cons of Hypotheses for 'Reservoirs, Amplifiers, Transmission and Exposure Mechanisms' of Cholera

1° Reservoir	PROS	CONS	Test Criteria
Sea Sediment (Nearshore and Offshore)	<p>1 - Documented evidence of cholera being able to survive in coral sea-beds (ref: NeryBelle Perez-Rosas & Terry C Hazen: In situ survival of Vibrio Cholera and ... in tropical choral reefs, 1988).</p> <p>2 - Temporal Occurrence of Vibrio Species and Aeromonas Hydrophila in Estuarine Sediments (Leslee A Williams and Paul A LaRock, 1985).</p> <p>3 – Cholera can survive through re-arrangement on a cellular level to low nutrient (food) supply (Ref: Effect of Nutrient Deprivation on Lipid, Carbohydrate, DNA, RNA and Protein levels in Vibrio Cholera (Mary A Hood et</p>	<p>1 - Sea: coral reefs off Beira are far away and may not influence cholera infections</p> <ul style="list-style-type: none"> - Inland outbreaks sometimes occur before coastal outbreaks <p>2 – Patchy records of cholera in sediments</p> <ul style="list-style-type: none"> - High concentrations of cholera is associated with flocc (incomplete description). <p>Pure saltwater would lie outside the preferred salinity band but the survival range is 0-45% and they may survive for other reasons (nutrients) and may have adaptive mechanisms.</p>	<ul style="list-style-type: none"> - Locate cholera in sediment during all seasons. - To start testing marine molluscs.

	al., 1986).		
Sea Sediment (Nearshore and Offshore): Amplification mechanisms	PROS	CONS	Test Criteria
Temperature driven multiplication of bacteria in the sediment.	<ul style="list-style-type: none"> - Based on simple correlation between temperature and cholera incidences. - Sea water is hotter in summer: water column temperature. 	<ul style="list-style-type: none"> - Tests for drivers are complicated by the possibility of multiple factors being involved in amplification. - Sediment amplification on it's own can't explain an outbreak – there has to be a vector or transmission mechanism. - Air temperature is measured on land, which is the basis of our correlation. Does this hold in the sea case? 	<ul style="list-style-type: none"> - Do controlled experiments at sites (or labs) on sediment (heat them up and measure response). - Test water column temperatures near sediment (lower

			<p>layers of water column).</p> <ul style="list-style-type: none"> - General: Test whether cholera is always a summertime disease (see Eastern Cape data).
<p>Plankton Precipitation: Phytoplankton/Zooplankton decay and settling on sea-floor (flow)</p>	<ul style="list-style-type: none"> - There seems to be a link between chitin and cholera (Ref1: Caldwell (link to climate change and copepods; Bartlett DH and Azam F, Chitin Cholera and Competence, Science Vol 310, 2005 Dec). - Competing for food paper (need to find): peak in cholera lagged significantly after plankton peak. - Paper on plankton & rain. - 	<ul style="list-style-type: none"> - There is evidence that cholera also multiplies when unattached to a host. 	<p>Experimental proof of amplification through addition of chitin or detritus (as substrate).</p>

Sea-Water Column: Amplification mechanism	PROS	CONS	Test Criteria
Amplification mechanism (Land)	PROS	CONS	Test Criteria
Exposure Mechanisms (Sea)	PROS	CONS	Test Criteria
Sea water ingestion	Direct exposure to sea water (20ml on average is swallowed (Wouter Ref). A toxic dose may result from one copepod (INSERT REF)).	Many people who have cholera are not exposed to sea-water.	- Gender exposure (men are predominantly fishermen). - Distance from Coast.
Shellfish/Finfish	<ul style="list-style-type: none"> - Cholera has affinity for chitin (see REF). - May multiply when attached to chitin (boom). - Sea Sediment link: Higher concentrations of cholera on the seabed would give shellfish etc a higher exposure to cholera. Would 	- Major contaminations occur in KZN with very low dependency on fish or shellfish.	

	also explain 'lag' effect between algae and cholera cases (Bangladesh).		
General Transmission Mechanisms	Proc	Cons	Test Criteria
Contamination of food by humans	-Contamination of food through poor hygiene practises or availability of clean water (washing dishes, vegetables) may result in cholera transmission.	-Would only apply to food that's uncooked. -Would not explain seasonality of cholera cases and this is a serious problem.	
Exposure Mechanisms (Land)	PROS	CONS	Test Criteria
Drinking Water	- Well recognised transmission hypothesis - Cholera cases seem to be rare in places of good quality water reticulation - Boiling drinking water to prevent cholera is a well established practise (INSERT REF) - Wells are predominantly dark and have	- We haven't detected cholera in Beira's drinking water. However, our sample is too low (one well). - Columns of pure water seem to have low infectivity. We haven't found cholera in the wells, limited numbers in standing water.	- Test for cholera in drinking water.

	still water which might not hold plankton and bacteria (cholera might exist in the sediment but not in the water column).		
Copepods in drinking water	<ul style="list-style-type: none"> - Simple filtering of drinking water through sari cloth significantly reduces cholera outbreaks (INSERT REF). - Seems to be no debate about cholera being found on copepods 		<ul style="list-style-type: none"> - Test for cholera on copepods (land) - Does cholera occur in water sources that have a basic filtering (e.g. groundwater)
De-amplification (Short Term)	PROS	CONS	Test Criteria
Iron	1. The toxogenic strain of cholera survives twice as long if iron is in the environment (REF: Marna van der Merwe).		Test for iron where we find cholera?
Temperature	- Strong evidence that temperature both enables and disables cholera	<ul style="list-style-type: none"> - Questionable whether temperature is a trigger mechanism or rather provides a suitable environment. - Endemic and Introduced? 	- Test literature for evidence whether the cholera cycle is due to 'introduction' of cholera to

			<p>an area e.g. polluted well in London. Presume human influence.</p> <ul style="list-style-type: none"> - In the endemic case, the amplification mechanism is of more importance - If temperature is a key driver then the duration of outbreaks should change in cooler environments (can be tested): <ul style="list-style-type: none"> -- Inland to coast --Towards equator
Salinity	<ul style="list-style-type: none"> - Below a certain salinity cholera does not thrive and multiply - However, cholera survives over a large salinity range 	- No evidence that salinity is a major driver of cholera density and seems to play more of a role in providing an ‘enabling environment’ for cholera.	- Test for direct correlation between salinity and cholera density
De-amplification (Long	PROS	CONS	Test Criteria

Term)			
Viral Predation	Very high concentration of viruses in stools of patients as they recover (INSERT REF: Graham) seems to coincide with reduction in cholera bacteria.	- Why then, does Stephens temperature driven model give good results?	Test parameters with classic predator-prey model and compare with literature.
Immunity (natural)	Human populations develop immunity to cholera with exposure. This holds for the 01 strain. (INSERT Ref: Mercedes-Pascall)	However, for the 0139 strain, no immunity seems to develop over a generation.	<ul style="list-style-type: none"> - Find out whether a cholera patient can get cholera twice in the same season. - Test for longer term cycles of immunity - Test for impacts on demography of cases -- Places where once off cases of cholera exist should have a different demography of

			cholera cases.
Human-induced Immunity (vaccine)	Human adaptation responses – vaccines, etc which may last 2 years.	There is evidence to suggest that cholera dies off through its own natural cycle and remains unaffected by human interventions to prevent the spread of the disease.	

University Of Cape Town

13. **Appendix B: Urban Growth in Gauteng – Sub-Module Illustrations & Descriptions**

Graphical causal models were used to formulate hypotheses and causal interdependencies throughout the case studies conducted in this dissertation. In this section, some of the sub-modules that constitute the model for urban growth in Gauteng are presented for the benefit of closer inspection by the reader. Each figure is accompanied by a detailed caption, which explains the sub-module being illustrated. These graphical causal models are conceptual, and were not developed to the stage where they were populated with probabilities. This study remains a focus of ongoing research, and the opportunity has now emerged to apply this model in support of the City of Joburg, and is the subject of ongoing conversations between the author and the City of Joburg.

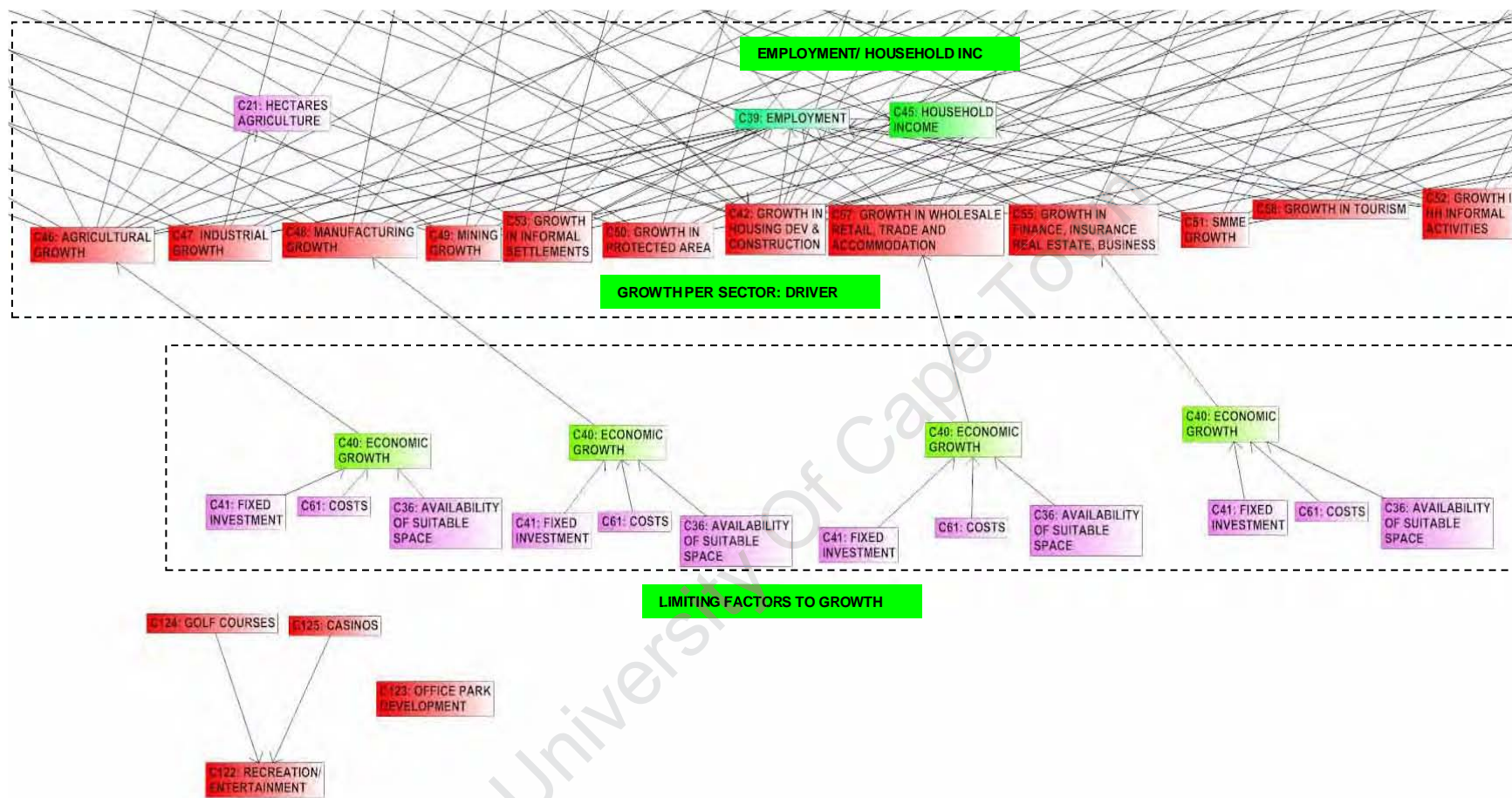


Figure 57: The growth potential for various sectoral land-uses are shown in this model (Figure 57), and a baseline can be established for growth in terms of the current state of productivity (of emissions, GDP, water use, etc) from which growth can be inferred, keeping in mind whether the relationships are linear, non-linear, exponential or otherwise. The potential for growth is explored in the ‘limiting factors to growth’ module, where a few ‘token’ factors are shown (e.g. costs, fixed investment and availability of suitable space). These are not yet exhaustively developed, and are shown for illustration. For example, the agricultural sector can be developed into a full sub-module including the full range of crops, livestock, etc.

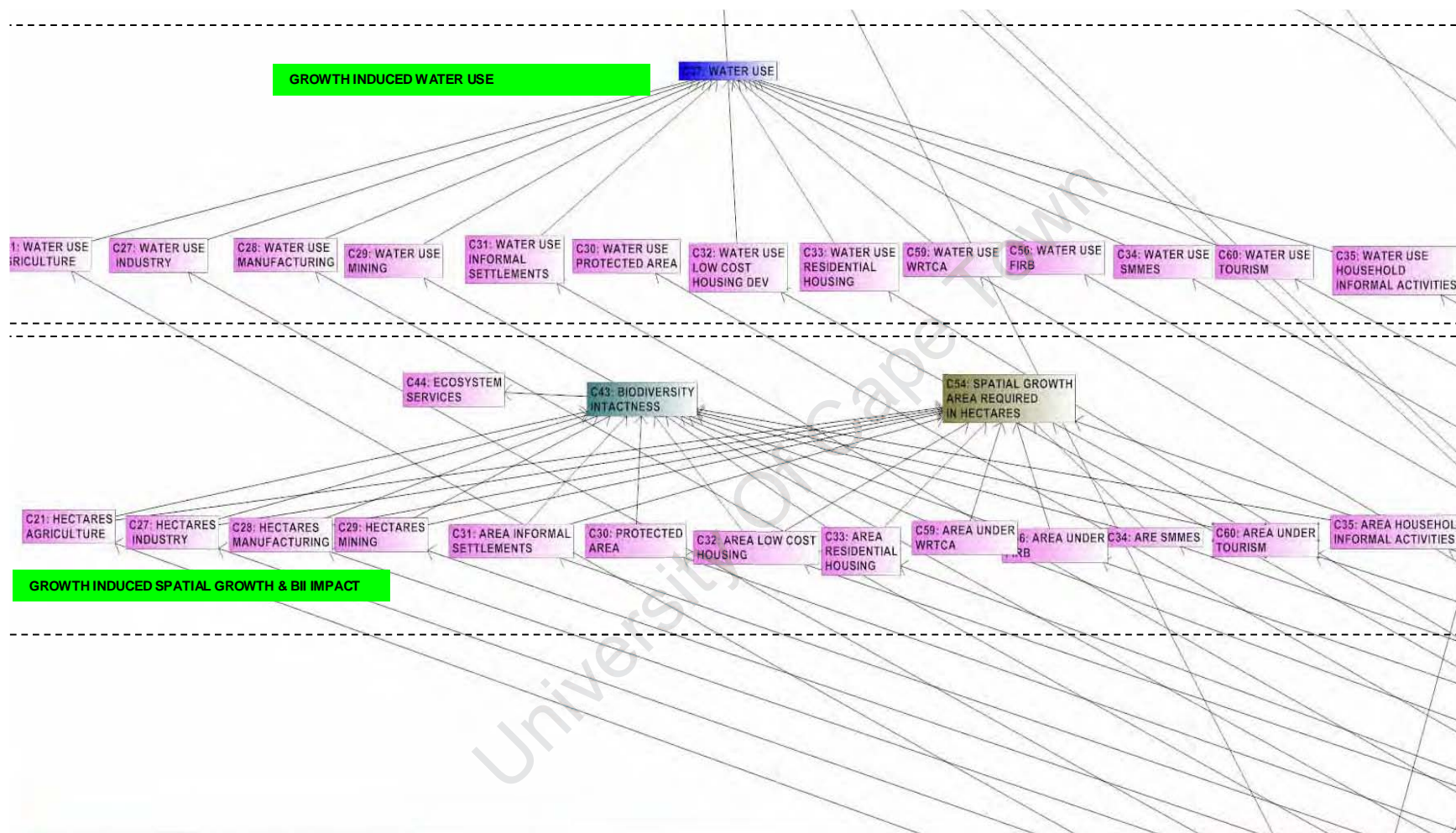


Figure 58: From an understanding of what the spatial requirements are for a particular land-use, we can project how much spatial area would be required (cumulatively and per land-use) to satisfy certain growth conditions. This information can also be used to estimate the impact of growth and development on the biodiversity intactness index/indices (Figure 58).

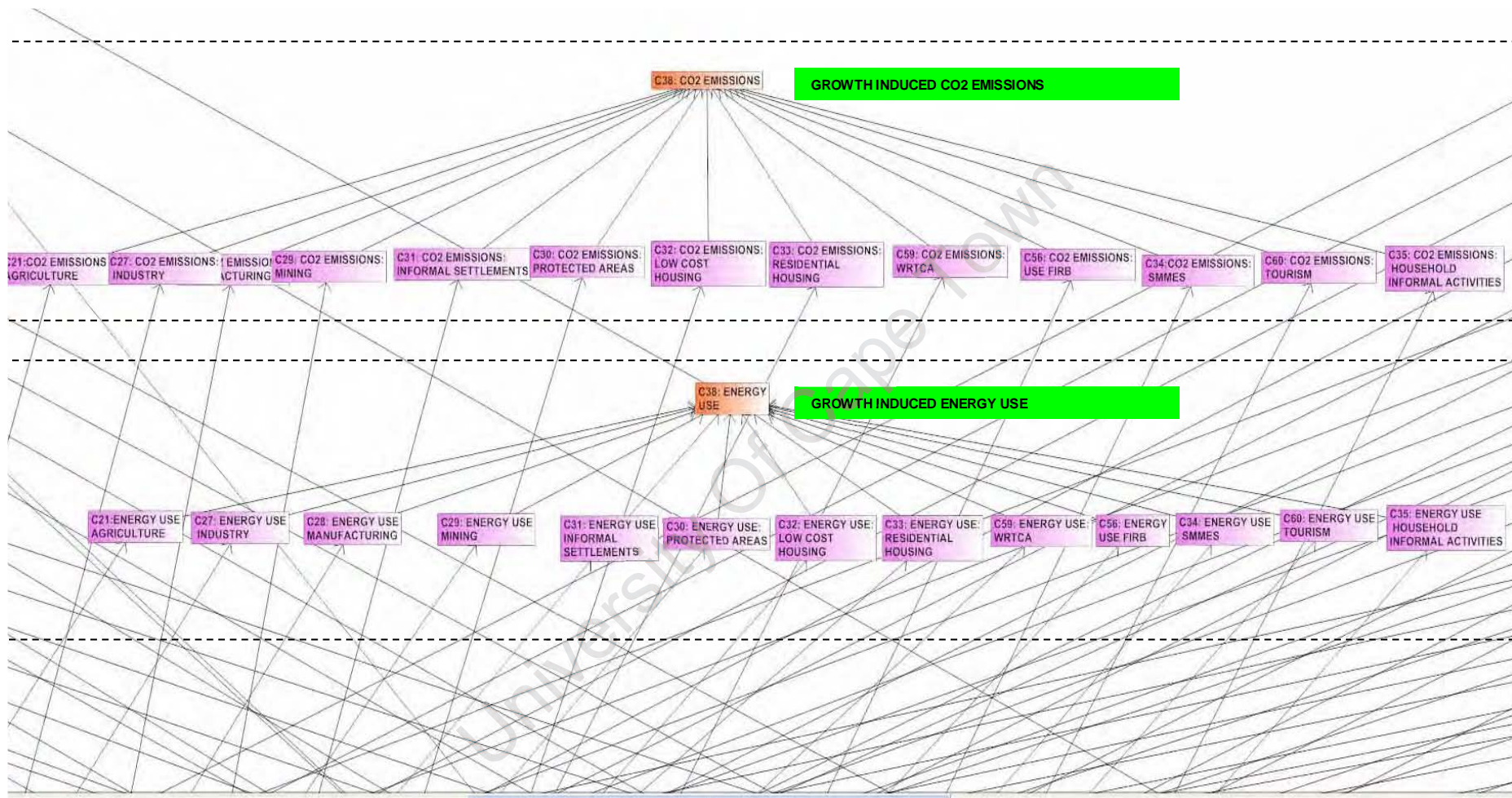


Figure 59: Using reliable sector and sub-sector related energy requirement and CO2 emission data, we can estimate the impact of growth and development on the cumulative CO2 and energy usage at a cumulative system scale (Figure 59).

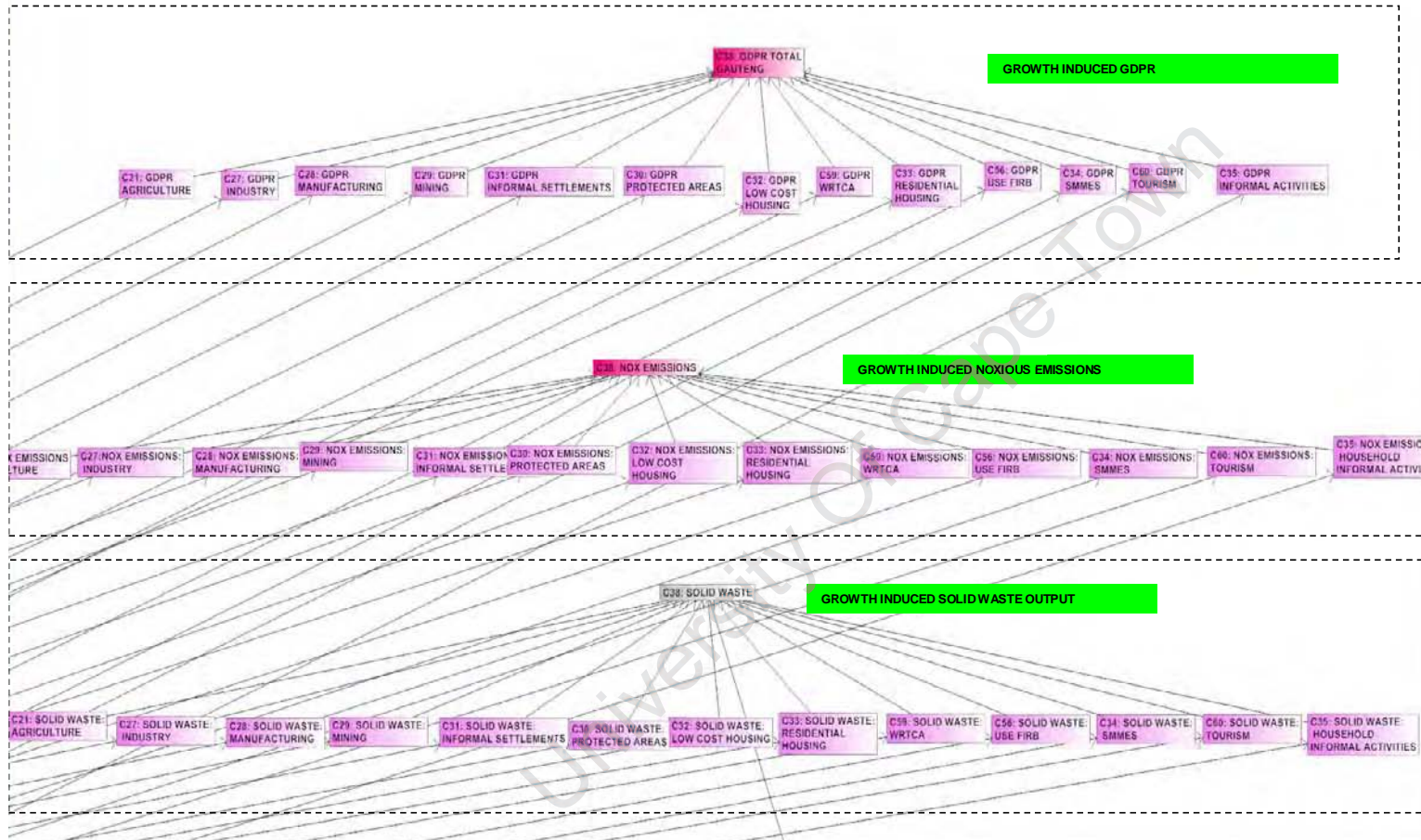


Figure 60: Growth induced GDP, solid waste and noxious emissions can also be calculated from reliable sector and sub-sector data, and related to a set of growth and development scenarios. However, these data sets are usually collected according to different classes, and verification will be needed where aggregations of classes shown above are made.

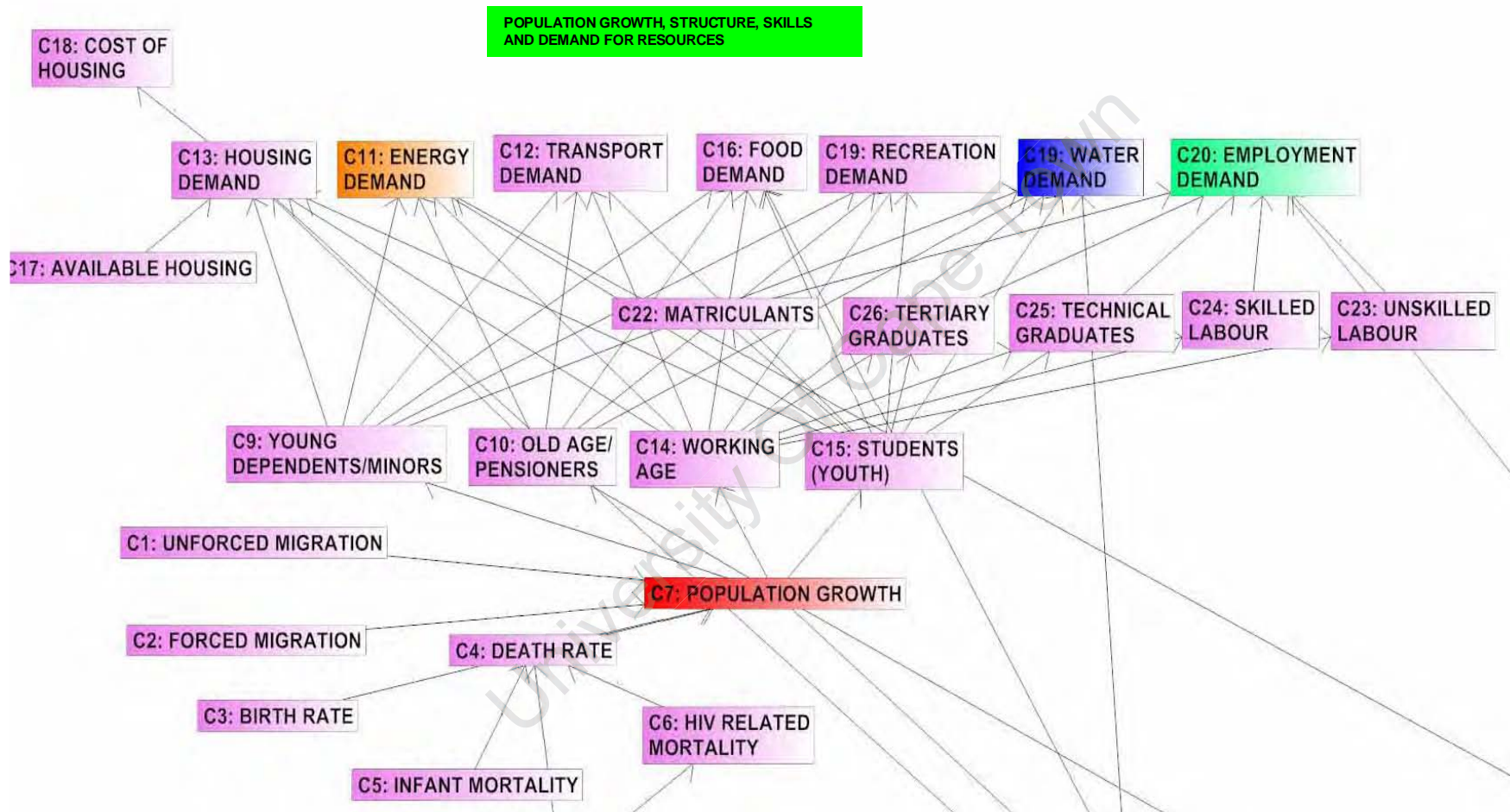


Figure 61: This module illustrates how causal relationships related to population growth may be explored. The details of the model are not exhaustive or definitive at this stage and are simplified. This module may be used to explore the links between population growth, the age pyramid and the skills base of Gauteng

WATER AVAILABILITY & SENSITIVITY TO CLIMATE CHANGES (R,T)

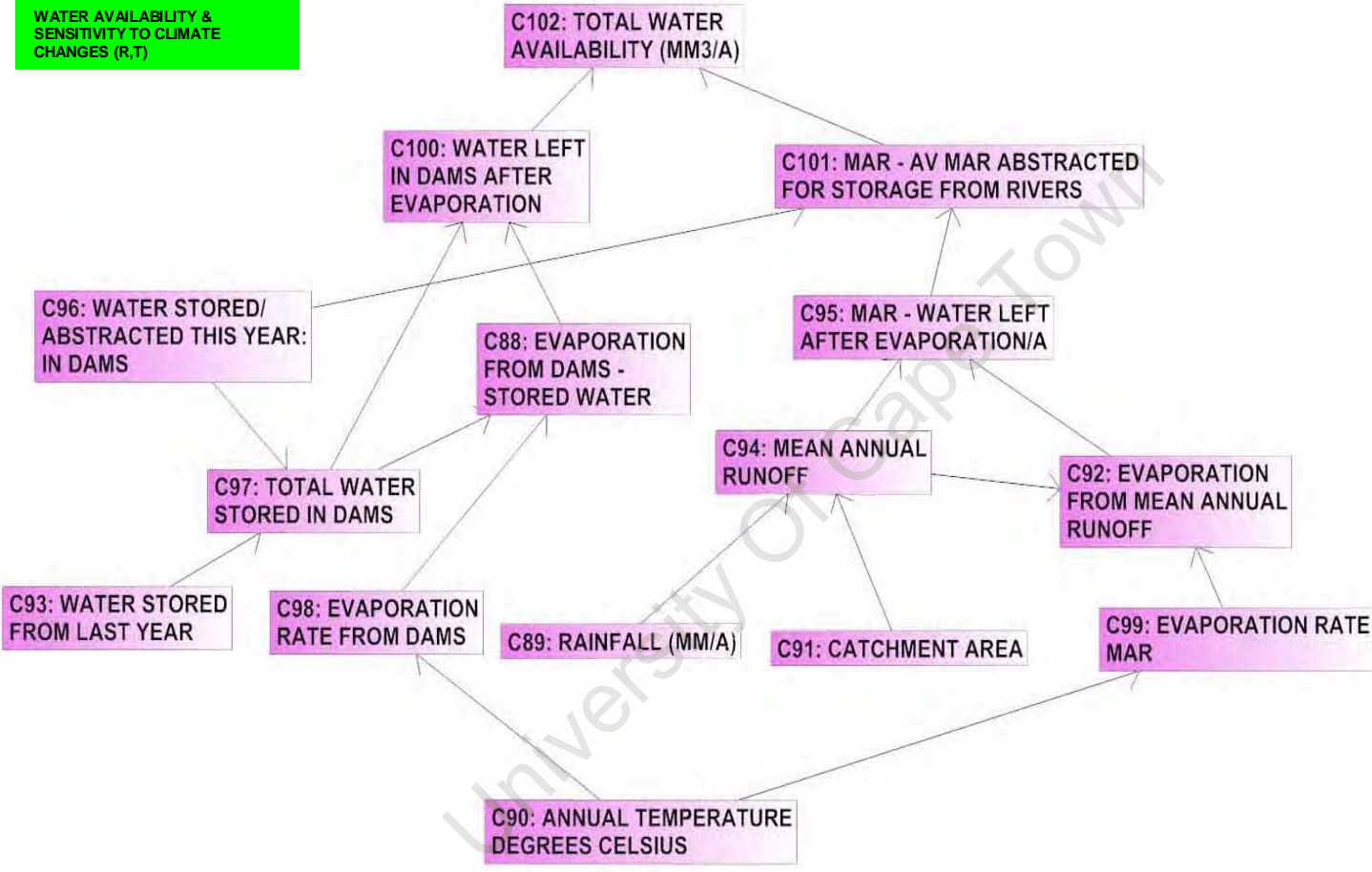


Figure 62: This is an illustrated model of how the total water available to the Gauteng system may be assessed, either at a cumulative scale, or at a catchment scale, even including remote water sources. Rainfall and temperature, water storage regimes (dams and planned construction of dams), water use by alien plants, return flows, etc.

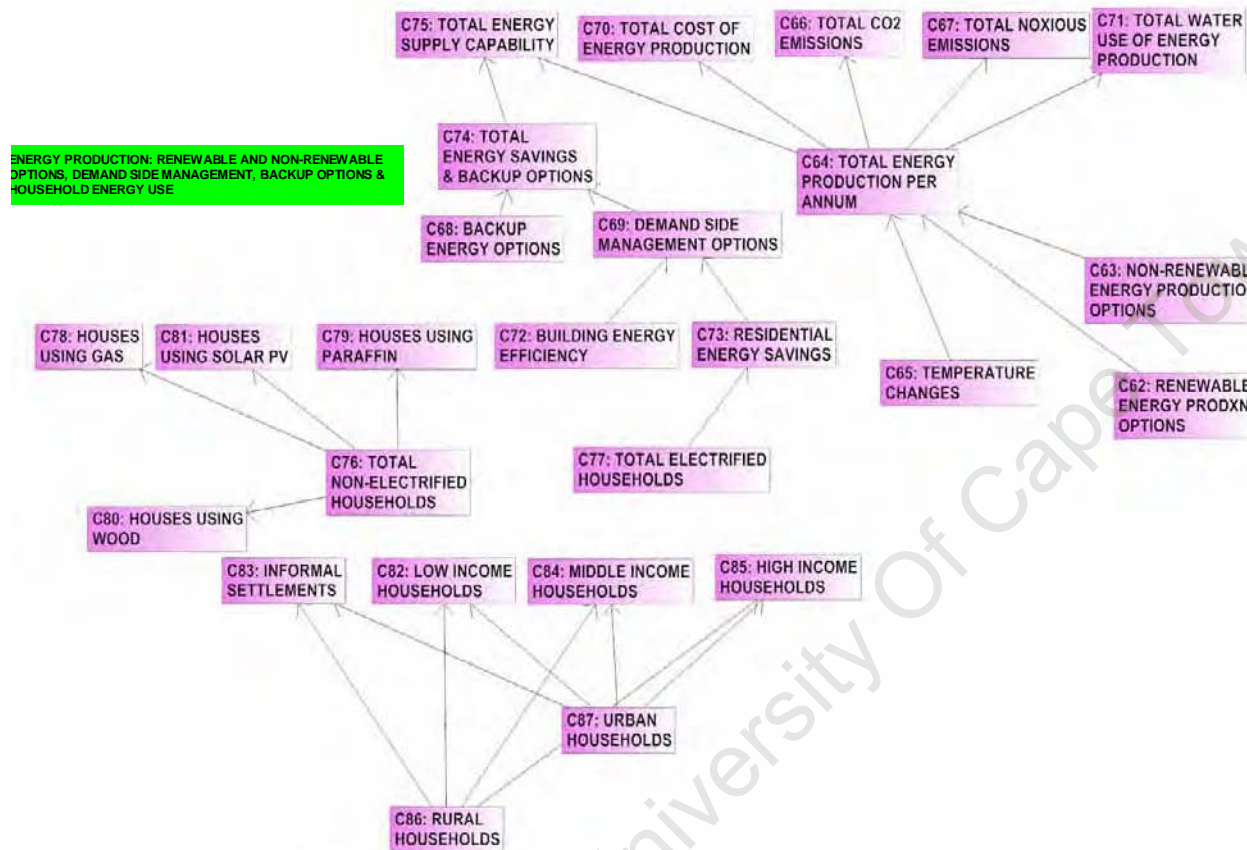


Figure 63: This module shows how a range of non-renewable (e.g. nuclear, coal, gas, new nuclear, new coal, clean coal) and renewable (e.g. hydropower, wind, ocean, solar thermal, solar pv) can be used to estimate total energy availability to Gauteng, total water use, total cost of energy production per kwh, total CO2 emissions and possibly total noxious emissions. In addition, a range of demand side management energy savings (residential, buildings, loadshedding) can be estimated, utilising % savings and planned savings (even projected savings due to tariff increases, or other measures). Household energy dependence and usages can also be determined, because total electrified and non-electrified households can be detailed and assessed in different scenarios. Energy use profiles of households can also be detailed, and paraffin use levels estimated and evaluated against LPG and other fuel-switching options that have less emissions and are more stable (in terms of volatility) and less likely to give rise to fires in informal settlements.

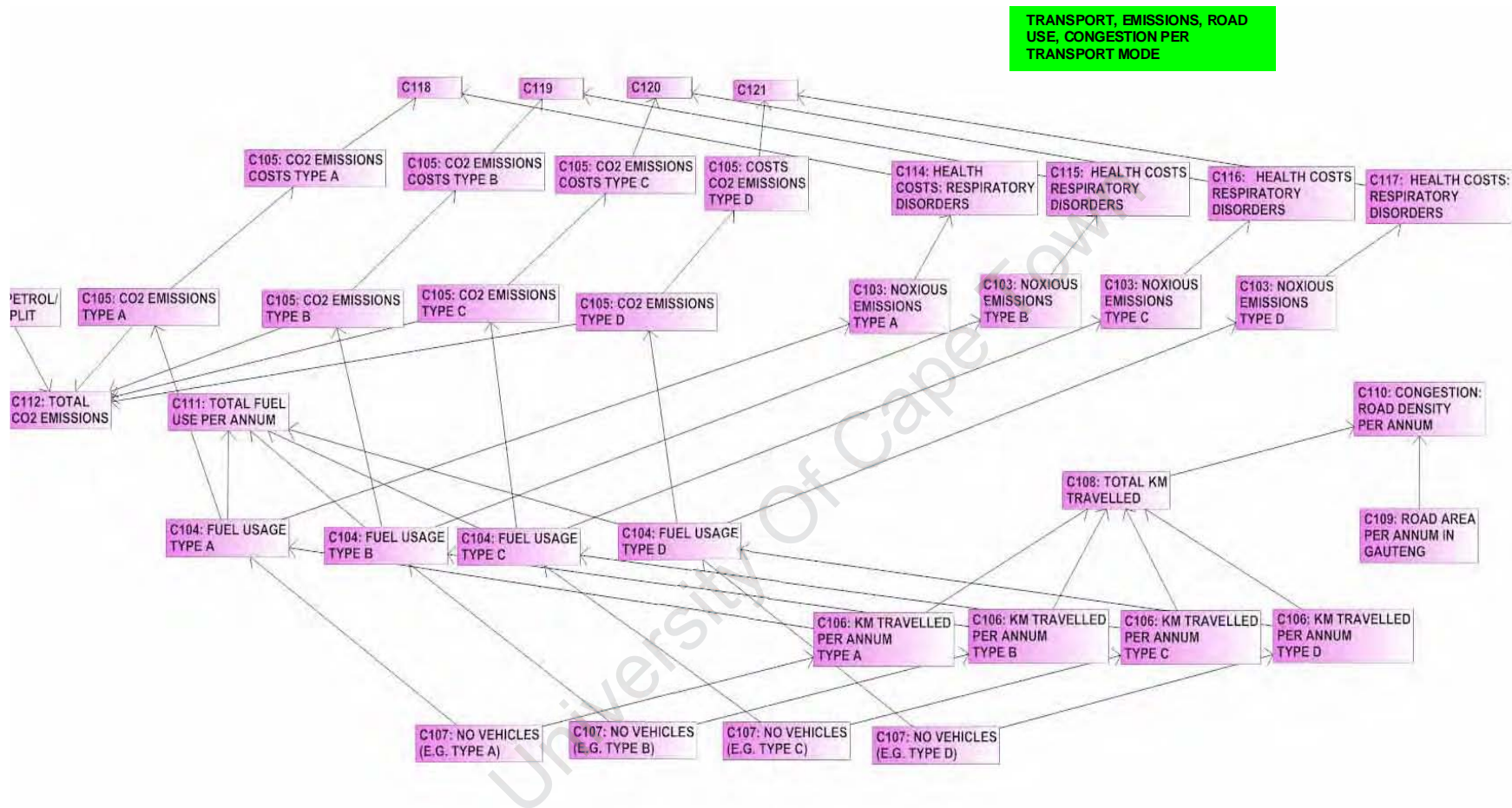


Figure 64: The module of transport above shows how a modal framework can be established for testing a variety of scenarios of transport mode loads, total km travelled per annum, congestion (at a cumulative load scale) mode related and total CO2 emissions. A theoretical framework for exploring transport – noxious emission indices can also be included, and used to guide research into more specific concerns regarding noxious emissions and health (if required).

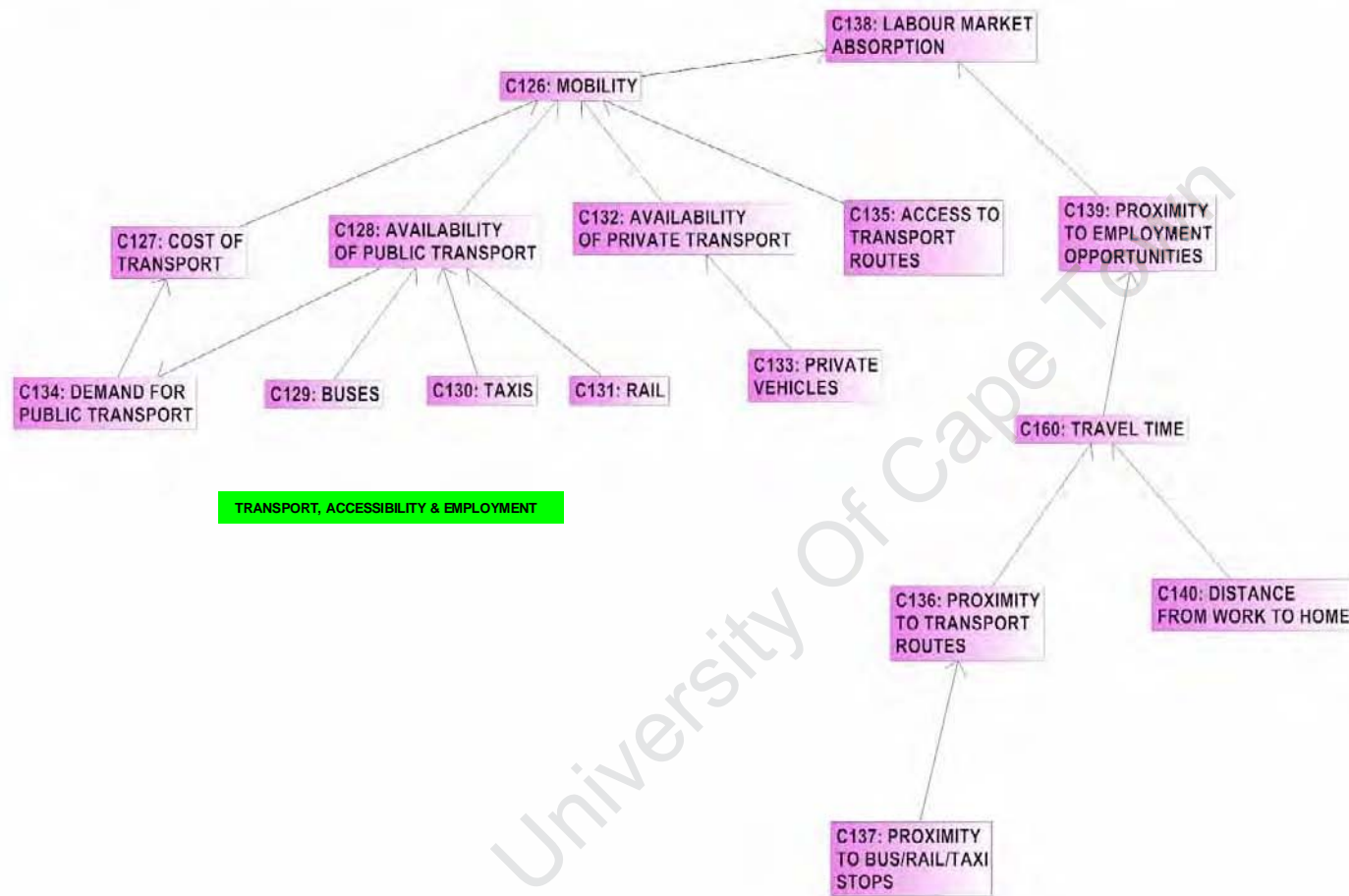


Figure 65: This module was established to explore the question “3. How will increased access and mobility impact on labour market absorption?” and may be linked to the transport module where different modes (bus, taxi) will be included. The aim of this module is to explore the links between increased working age population, accessibility to areas of employment, demand for public transport and its availability. Making the link to labour market absorption will be theoretical at this stage. Perhaps this module would be more relevant if developed at smaller scales within the Gauteng area.

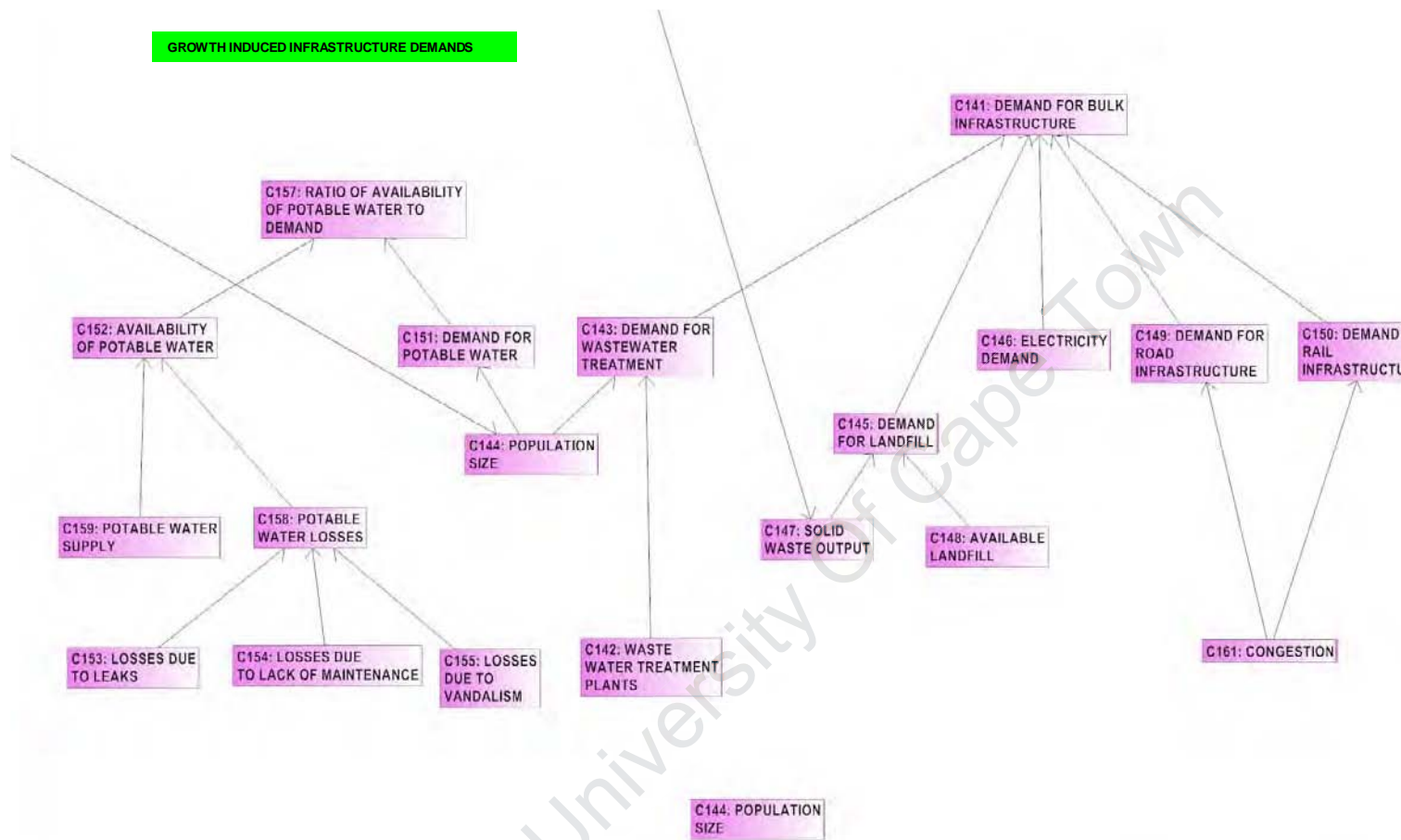


Figure 66: This module as a sketchy attempt to show how the demand for bulk infrastructure can be explored. This module will need to be developed more thoroughly (as will many others) with a user group, who can help identify critical linkages of concern with respect to the demand and provision of bulk infrastructure. Currently, we explored the availability and demand for potable water (and losses), land-fill demand (which can be related to the growth induced solid waste module), electricity demand (which can be related to the population growth and sectoral, land-use growth rates. Demand for road infrastructure can be related to the transport module congestion variable, and population growth can be related to the demand for wastewater plants.

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14. **Appendix C: Western Cape Provincial Model – Individual Modules**

The models shown in this section are fully functioning Bayesian models that have been populated with the large range of data sources that were used in the review of the Western Cape climate change strategy and action plan (RCCSAPWC, 2008). It is not feasible or useful to display every CPT and relationship that was used in formulating and constructing the model in this dissertation due to the large number of variables and states used in Bayesian nodes and the resulting large CPTs. The software serves the purpose of carrying this record. Moreover, detailed appendices of sensitivity analyses and scenario runs are presented in the review (RCCSAPWC, 2008), and should be referred to for more information, where the reader may be interested in specific model outputs, and how they were generated - full probability distributions, sensitivities and analyses are presented in the review. An appendix of approximately 200 pages of results were tabulated, graphed and presented, on a scenario by scenario basis in the review (RCCSAPWC, 2008), and the appendices are too large to be included in this doctoral dissertation. The reader is advised to refer to the review for a more detailed and nuanced review of the actual figures and probabilities that were generated in each range of scenario runs for the sole reason that the review itself focus's heavily on the analytical elements of the study and links the recommendations to the analysis and model outputs with a great deal of clarity.

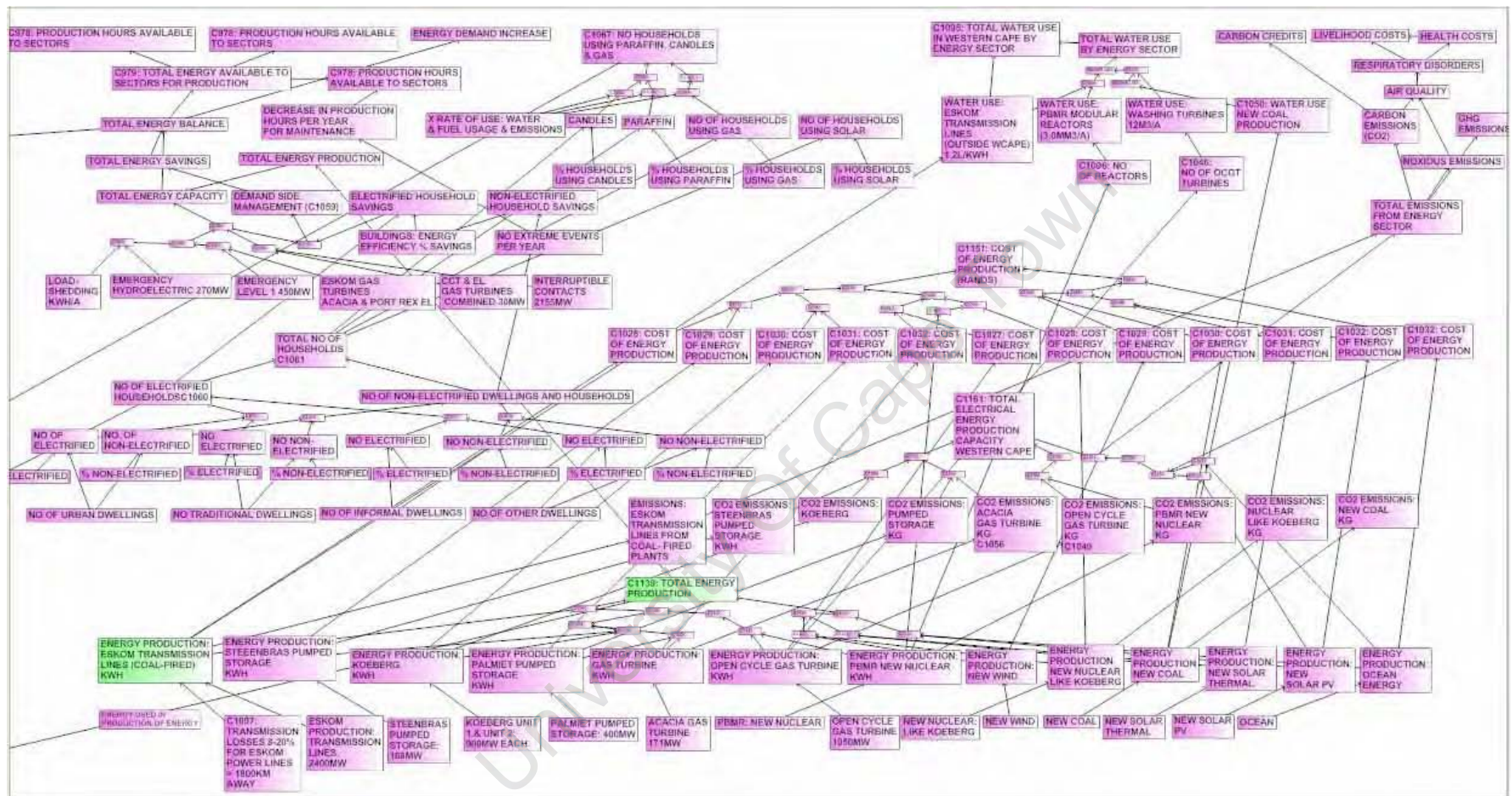


Figure 67: Illustrated causal model of Energy Production, Savings, Demand Side Management & Backup Options for Electricity Supply: Including Renewable and Non-Renewable Energy Production Options. Cost, Water Use, Energy Production and CO2 Emissions are calculated. This energy module was formulated and populated in compliance with the information and data in which classes were available. Total electricity production from a variety of sources, and in various combinations, can be tested in the model. The sensitivity to temperature changes on electricity production is included, and cost of production, water use and carbon

emission counts are calculated for different electricity production combinations. The effects of increased rates of household electrification is also catered for. Lastly, backup options for electricity supply that already exist in the Western Cape system are included, and the feasibility of demand side management, including loadshedding options, is provided for.

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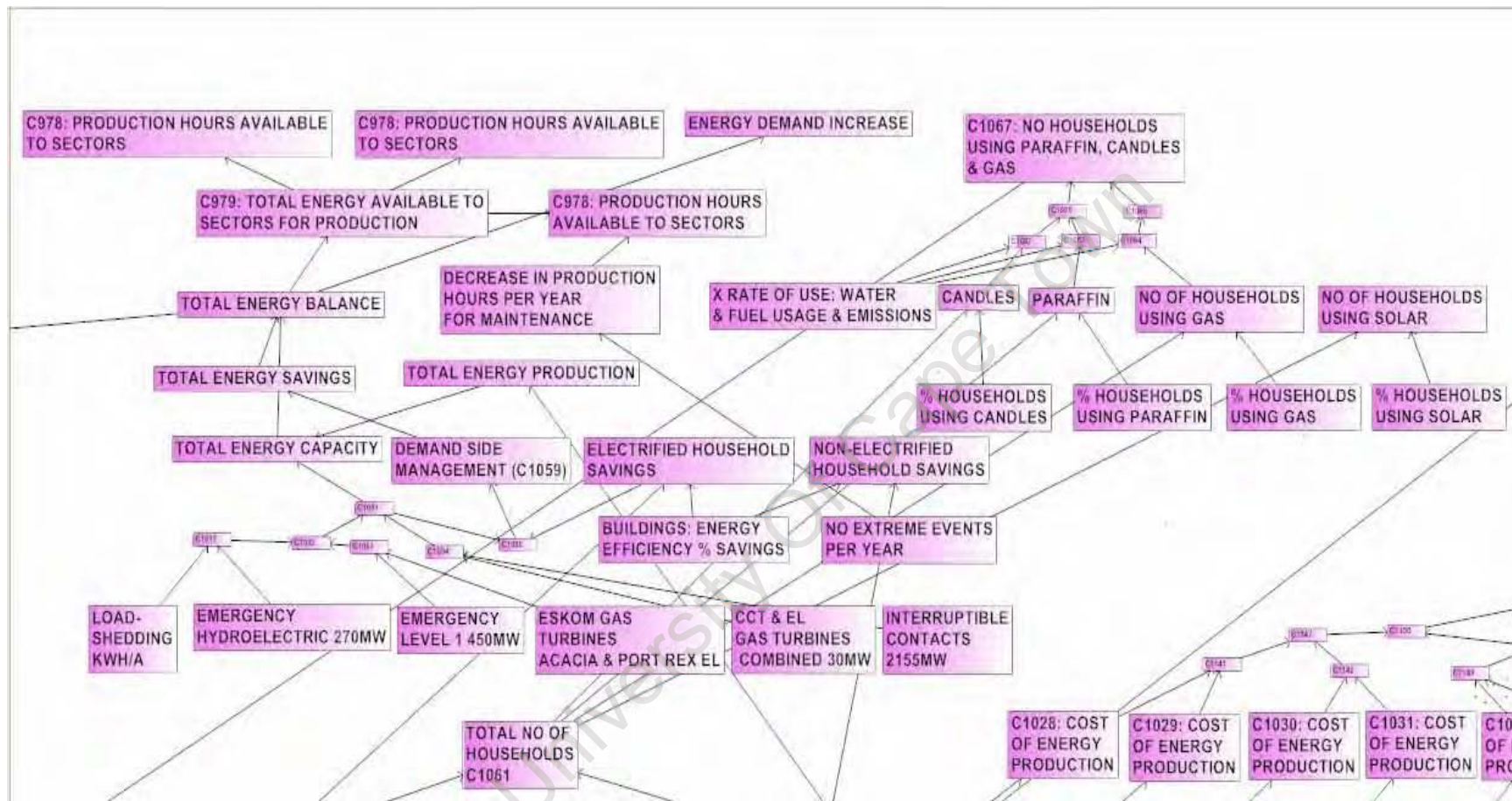


Figure 68: Sub-Module of Energy Production Module - Backup and Demand Side Management Options. The sub-module for backup and demand side management of energy systems caters for a range of backup options, and the user can experiment with different permutations. Efficiency of buildings and residences is also catered for.

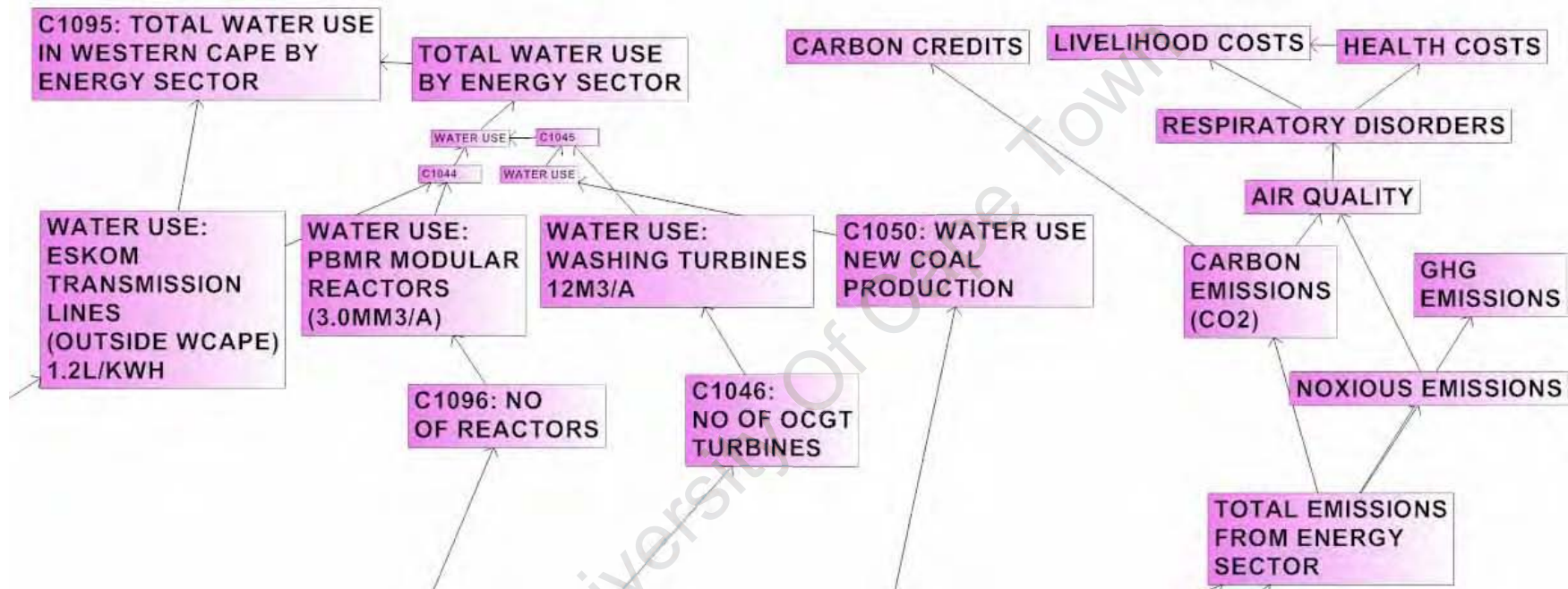


Figure 69: Water Use for Energy Production Module and CO2 emissions calculations. Potential Indices for Air Quality and Respiratory Disorders are also Shown.

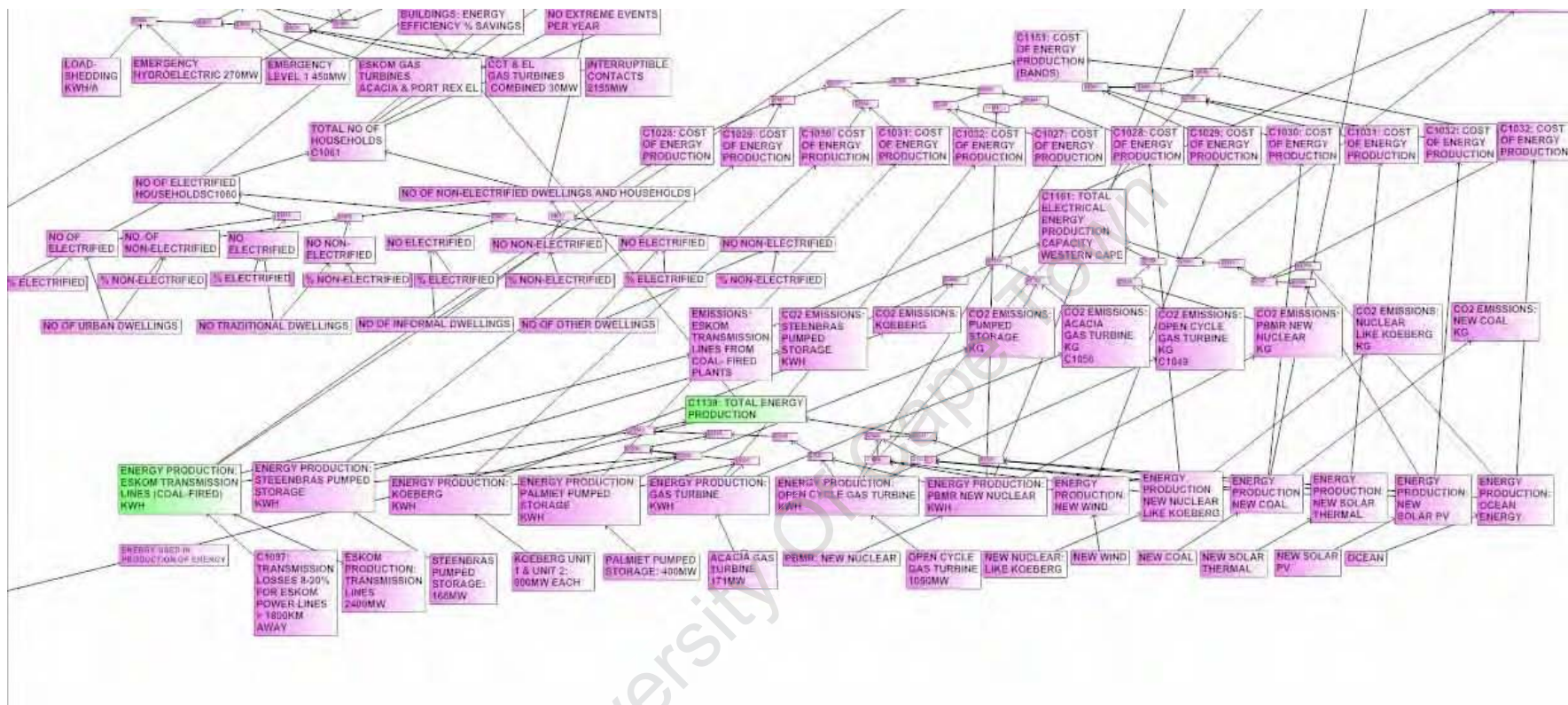


Figure 70: A Range of Renewable and Non-Renewable Electricity Production Options are Illustrated. In this module the user can experiment with and test a variety of combinations and permutations of renewable and non-renewable electricity production options. The carbon emissions, water use, and cost of production are also calculated for each scenario. Moreover, the growth in electrified households can also be tested over a range of projected possible futures.

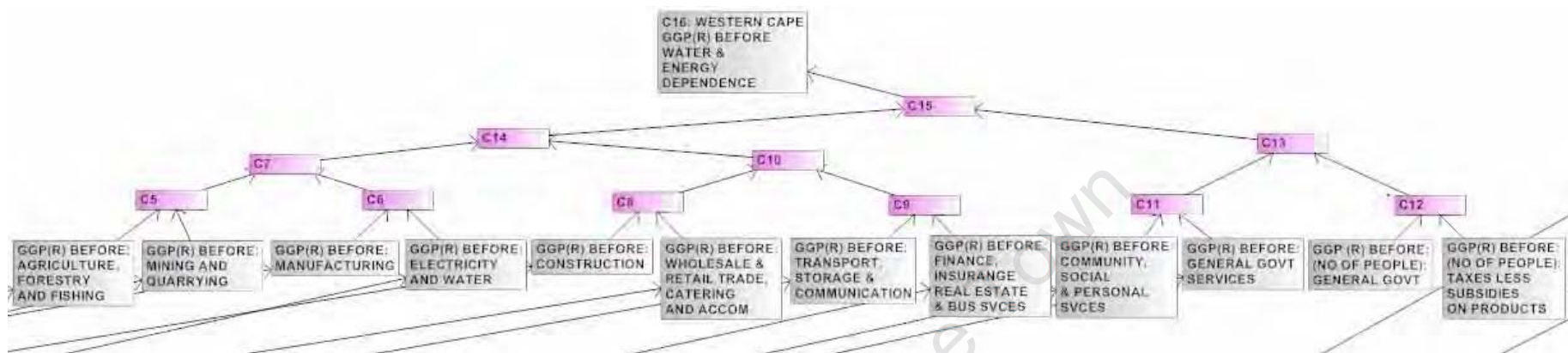


Figure 71: Illustration of Provincial Gross Geographical Product (GGP) Drivers Included in Western Cape Provincial Model. In particular, the sub-module here calculates the potential GGP for the Western Cape, if energy and water limitations are not taken into account. This is compared with another replicate module, but where energy and water limitations are taken into account.

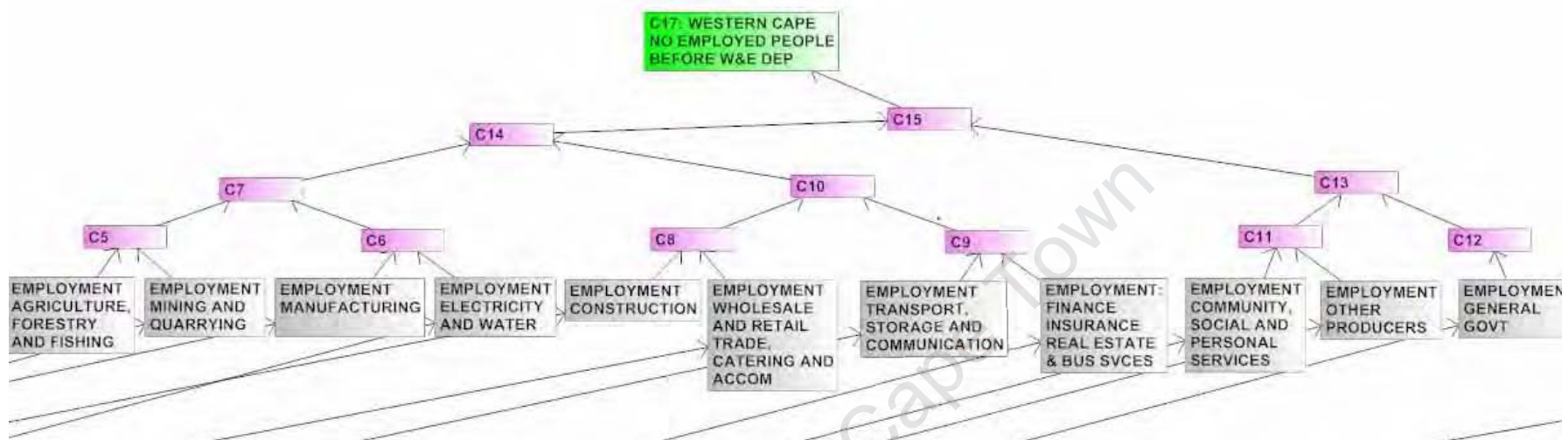


Figure 72: Illustration of Employment Sector Drivers Included in Western Cape Provincial Model. In this model the user can assess how projected or envisaged changes in sector levels of growth and production will affect employment in the Western Cape. The user can experiment with different combinations of multi-sector growth and assess possible changes in employment, given current employment rates in the sectors. This is compared with another replicate module, but where energy and water limitations are taken into account.

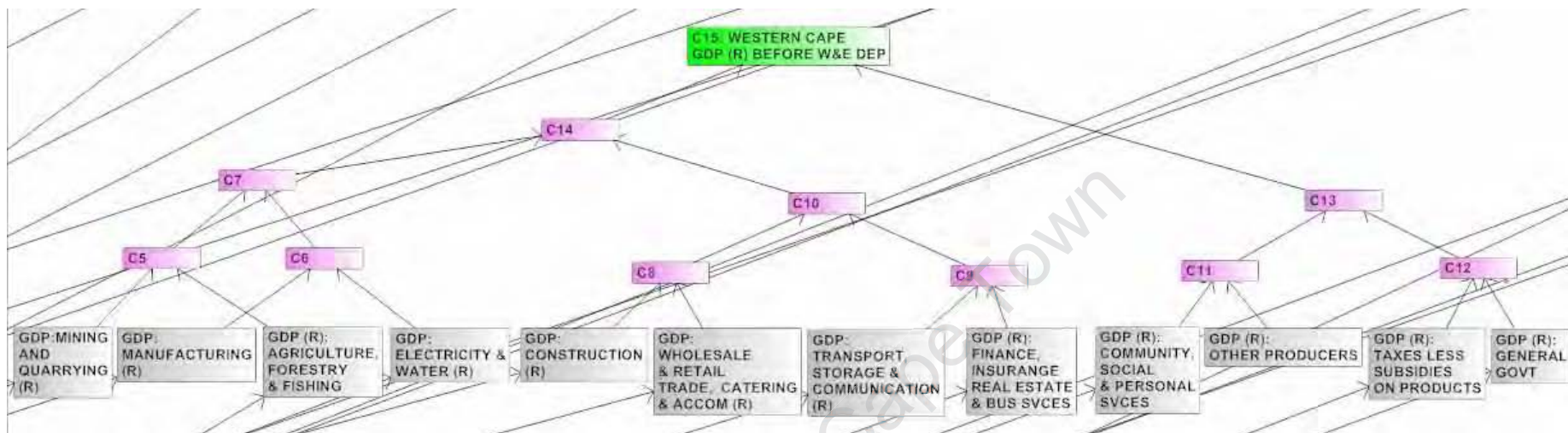


Figure 73: Illustration of Provincial Gross Domestic Product (GDP) Drivers Included in Western Cape Provincial Model. In particular, the sub-module here calculates the potential GDP for the Western Cape, if energy and water limitations are not taken into account. This is compared with another module, where limitations are taken into account. This is compared with another replicate module, but where energy and water limitations are taken into account.

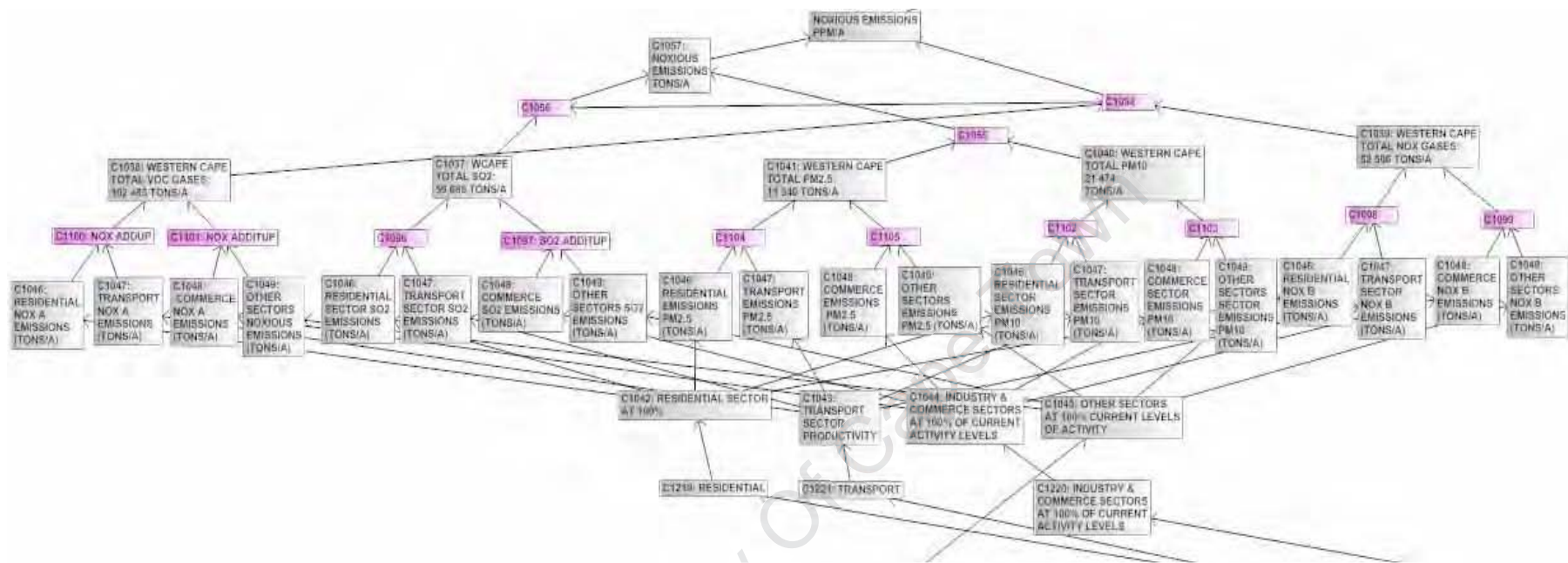


Figure 74: Illustration of Noxious Emissions Drivers Included in Western Cape Provincial Model. Multi-sector sources of noxious emission levels are calculated in this model, according to their current rates of emission. The user can experiment with how changes in sector growth may affect noxious emissions, should sectors continue to emit at their current levels. In this way, interventions can be envisaged and designed for encouraging or regulating sector compliance to lower levels give their current and projected rates of growth.

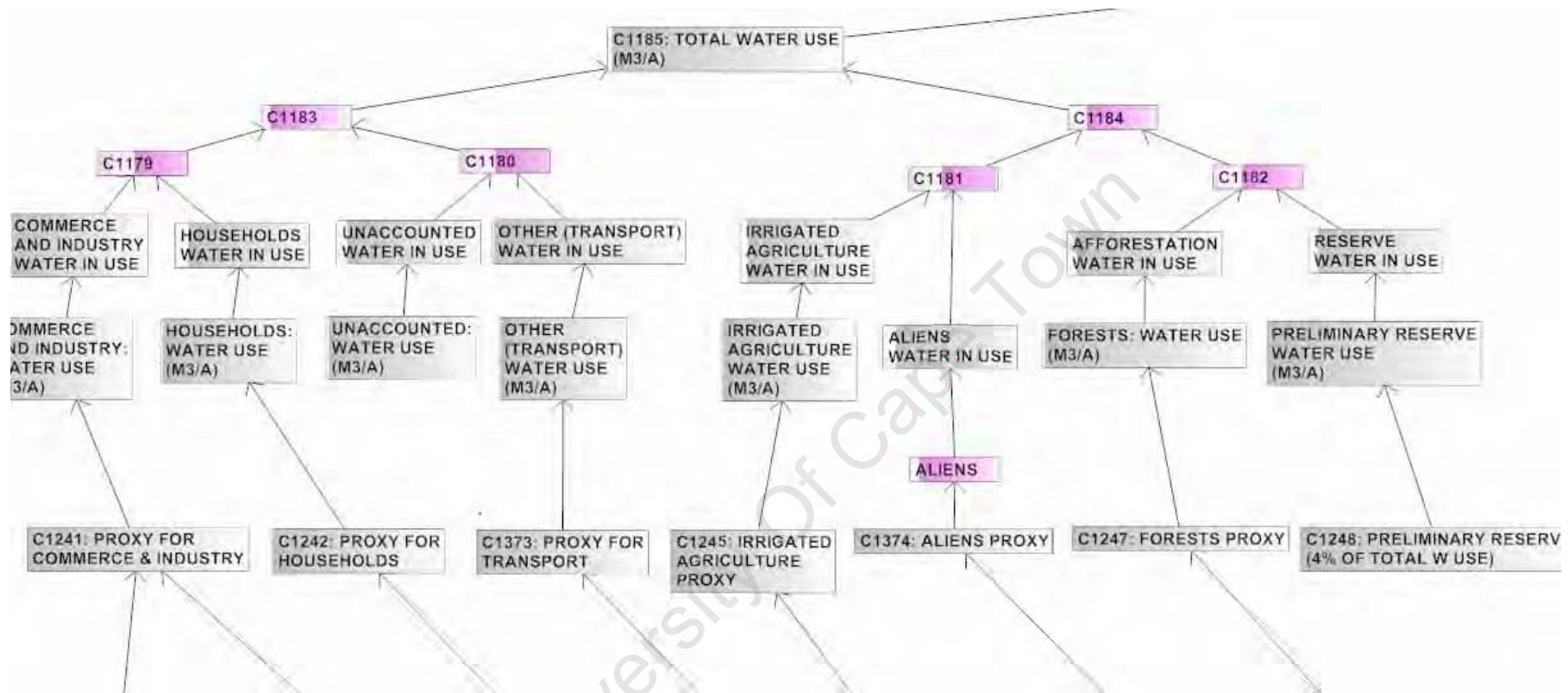


Figure 75: Illustration of Provincial Water Use Drivers Included in Western Cape Provincial Model. Water use levels for different sectors are used to calculate the total water use for the province given levels of growth of sectors. The user can also assess how interventions effective interventions such as alien clearance, reduced non-indigenous afforestation and interventions in the transport, household, agricultural, commercial and industrial sectors play out against each other in terms of total water use.

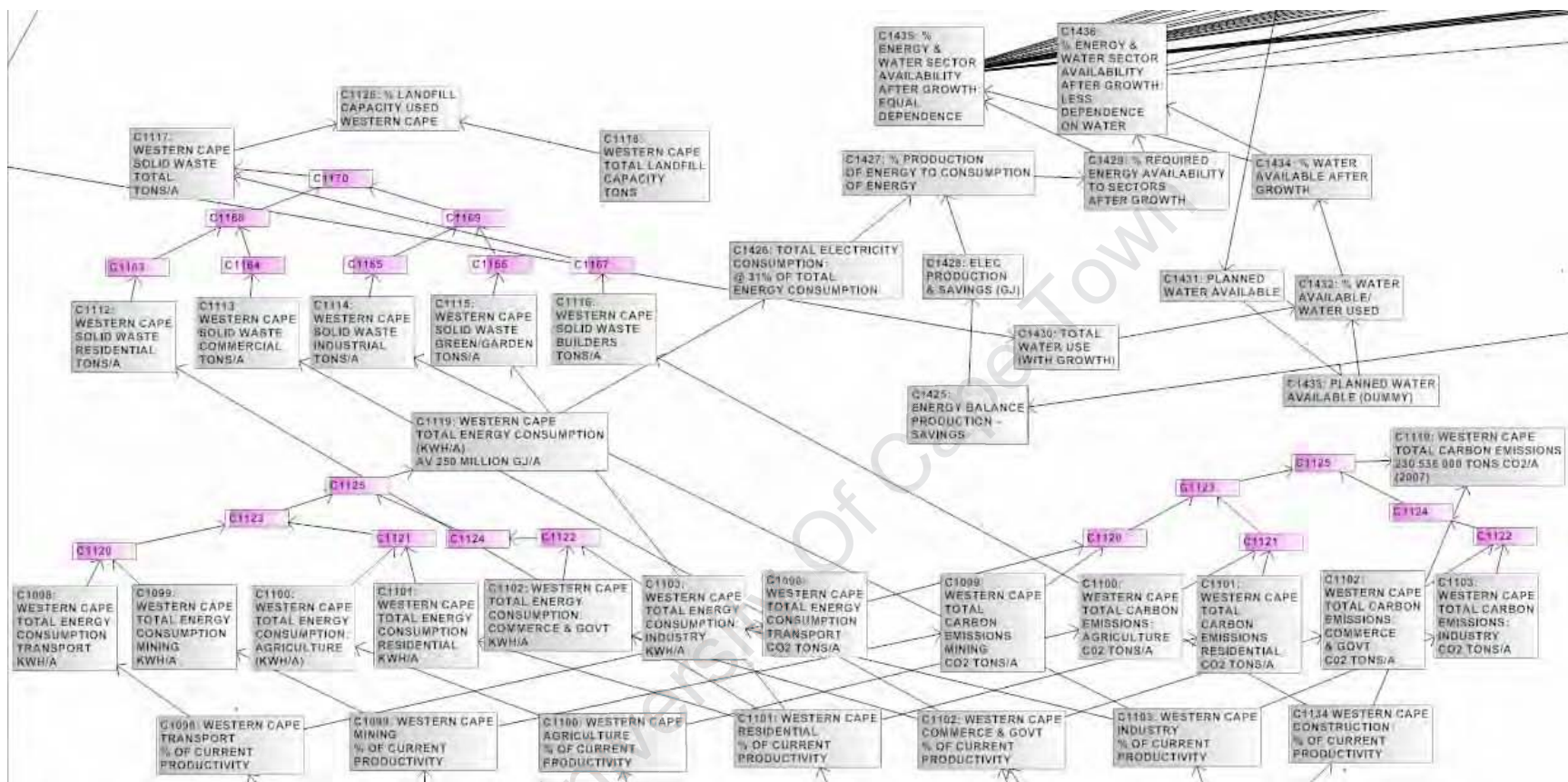


Figure 76: Illustration of Solid Waste, Energy Consumption, Water Consumption and Carbon Emission Modules in Western Cape Provincial Model. Solid waste, energy and water consumption and carbon emissions are calculated in terms of their sector contributions. This includes transport, mining, agriculture, residential, commercial, industry and construction sectors. The user has the flexibility to test different rates of sector growth against solid waste output, water consumption and carbon emission footprints, according to their current rates of sector consumption or production.

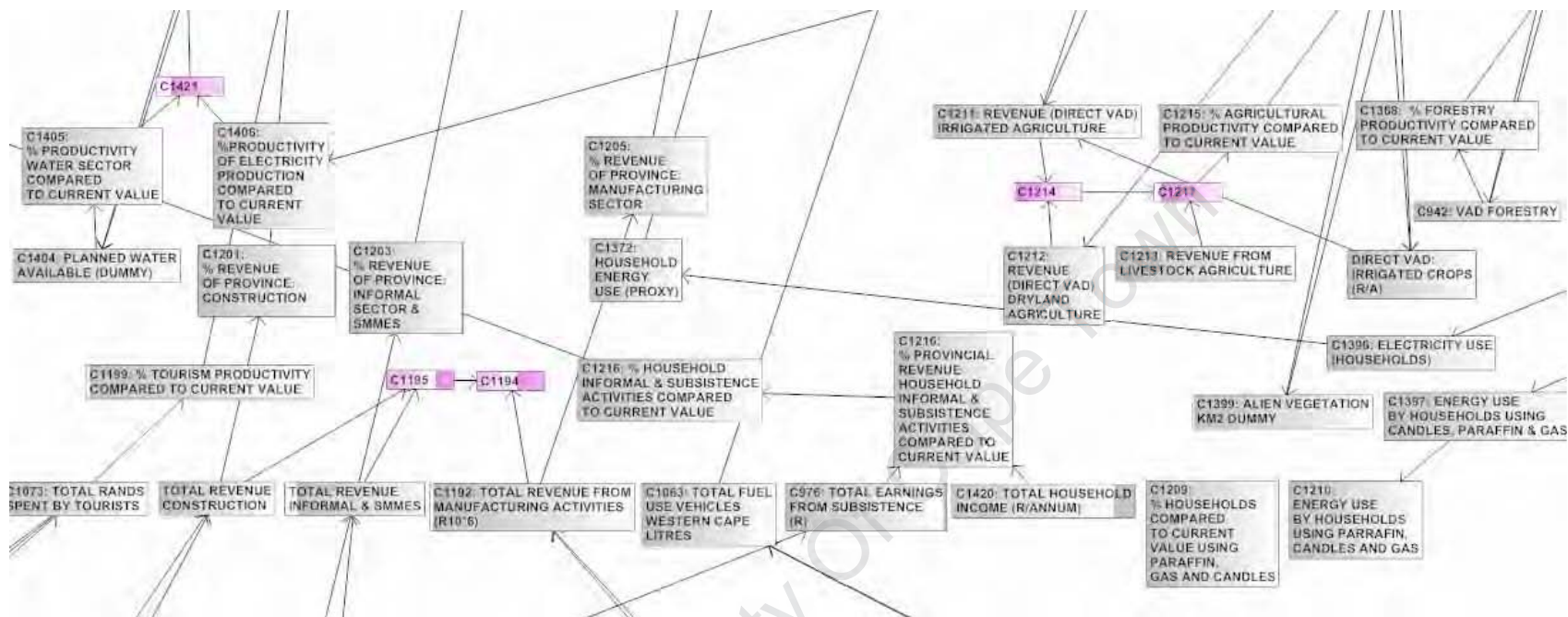


Figure 77: Integrator Module for Western Cape Bayesian Module: These variables are aggregated from embedded modules and combined in known weighted ratios to assess responses in systems level measures of performance e.g. GDP, GGP, etc. Some classes were aggregated in order to fit into the classes of available data and information that was available on the output (i.e. measure of performance) end. Careful considerations were given to how these aggregations were made, and as far as possible it was based on actual estimates of their percentage contributions to the cause-effect relationships that drive the measure of performance modules.

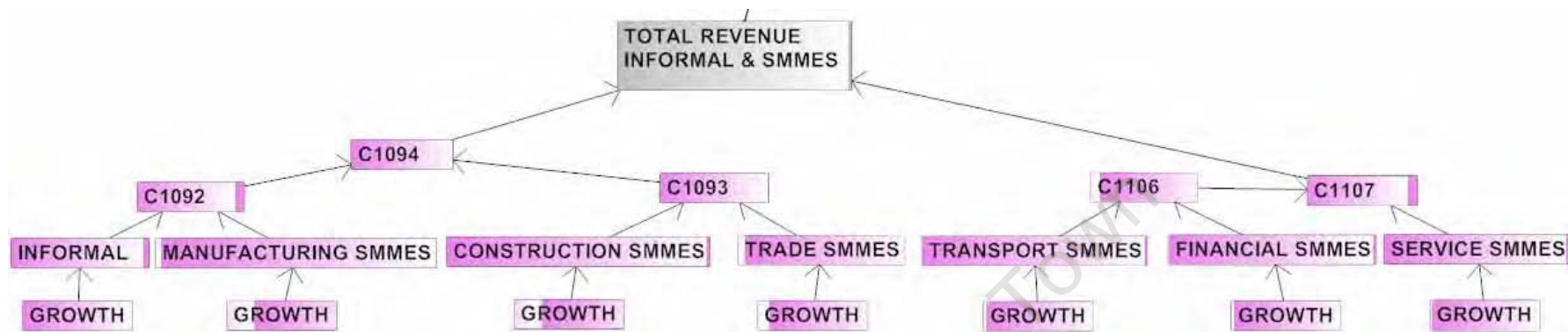


Figure 78: Illustration of Informal Sector & SMME Drivers Included in Western Cape Provincial Model. The total revenue generated by the informal sector, and by SMMEs can be assessed across different projected growth scenarios, according to their current rates of revenue generation. This model is extremely useful in understanding micro-economic changes, and if more data is collected, this can be developed into a very detailed model of the informal and SMME sectors, which is of critical importance in understanding the Western Cape and South African economies, where dual economic activities are at work and are equally important to understand.

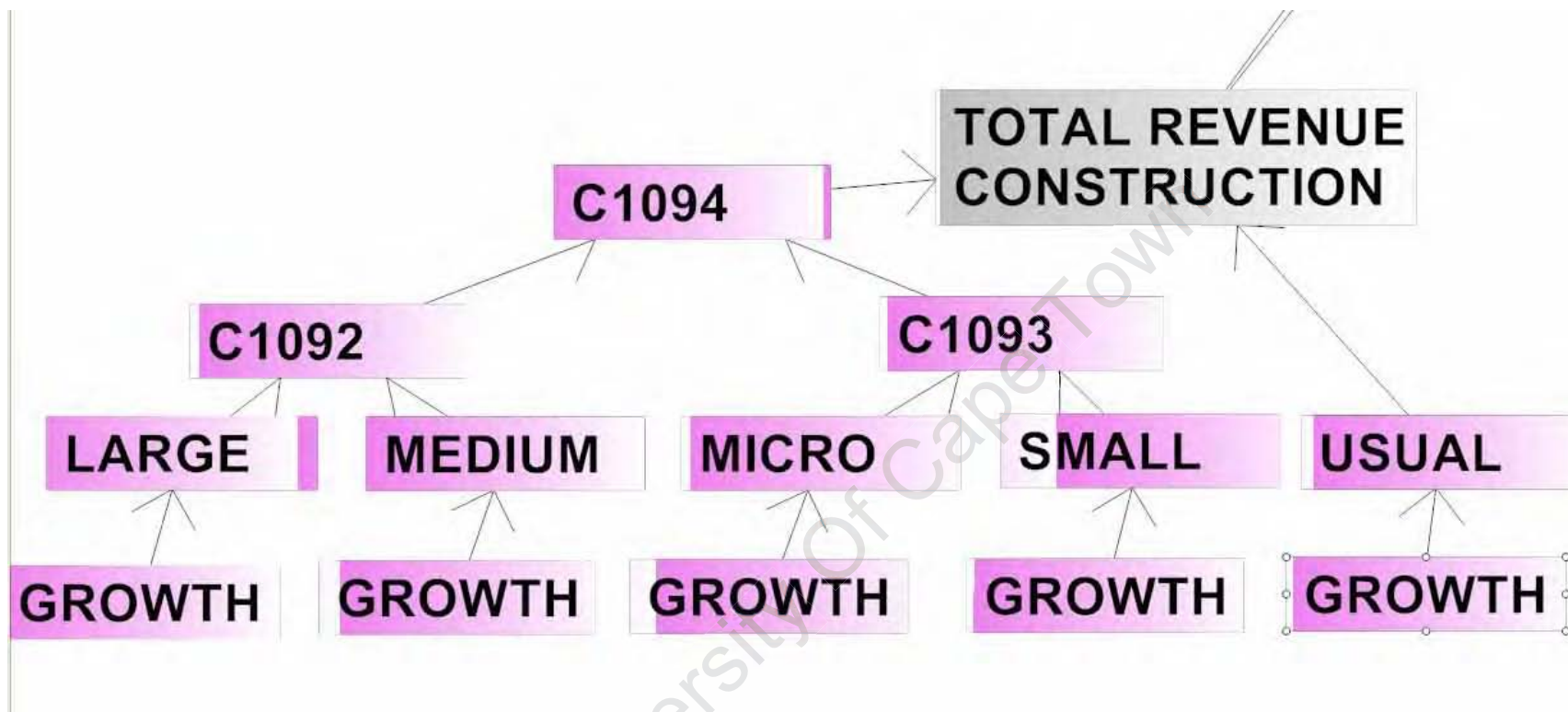


Figure 79: Illustration of Construction Sector Drivers Breakdown Included in Western Cape Provincial Model. The model is formulated according to the classes provided in the available data and information on the construction industry. The classes (large, medium, micro, small and usual) can be expanded as more in depth information and research becomes available on the construction sector. As it stands, the user can experiment with different rates of growth in the sector, according to the provided classes, at current rates of revenue production. Improved efficiencies in production, leading to cost savings, can also be assessed, but indirectly at this stage.

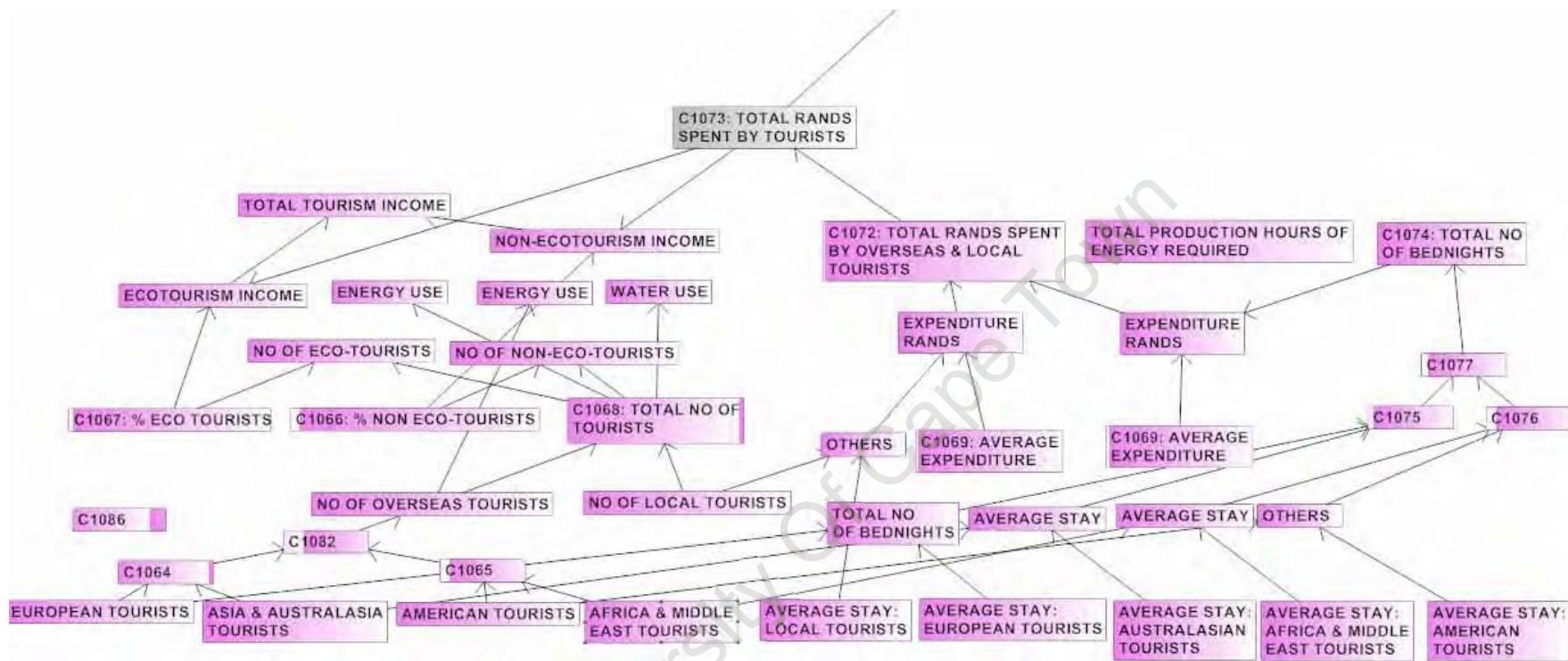


Figure 80: Illustration of Provincial Tourism Sector Drivers Included in Western Cape Provincial Model. The tourism module calculates the total revenue (approximate) generated from stays for tourists from Europe, Asia and Australia, America, Africa and the Middle East, and locally. The user can vary a range of factors including, visitor numbers from particular parts of the world and locally, their average stay, average expenditure. A small conceptual model that can assess the benefits of eco-tourism versus non eco-tourism is also included, but presently, its use is restricted to assessing what the water and energy savings levels should be set at for eco-tourism efforts, so that significant benefits are obtained.

employment in the formal sector. It is of increasing importance in South Africa to address the issue of benefits derived from services. The model was constructed according to the classes in which data and information have been made available.

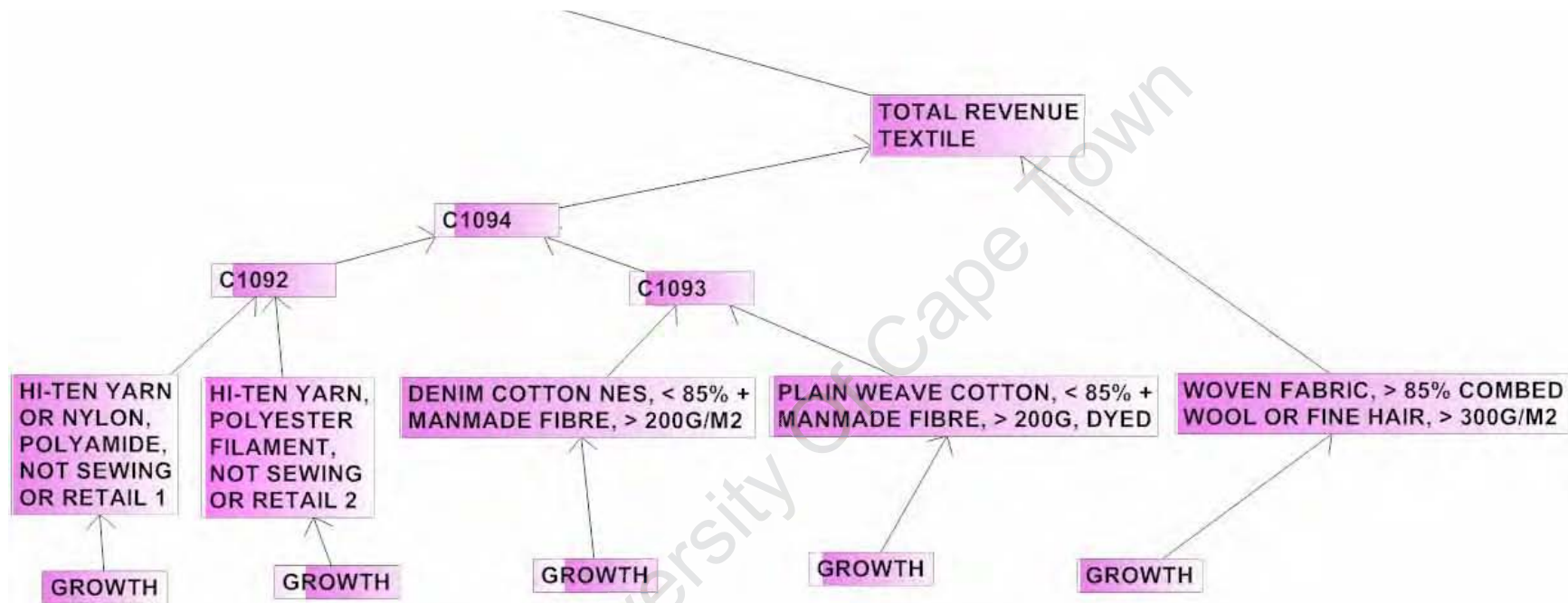


Figure 82: Illustration of Textile Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different textile making operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according to the classes in which data and information have been made available.

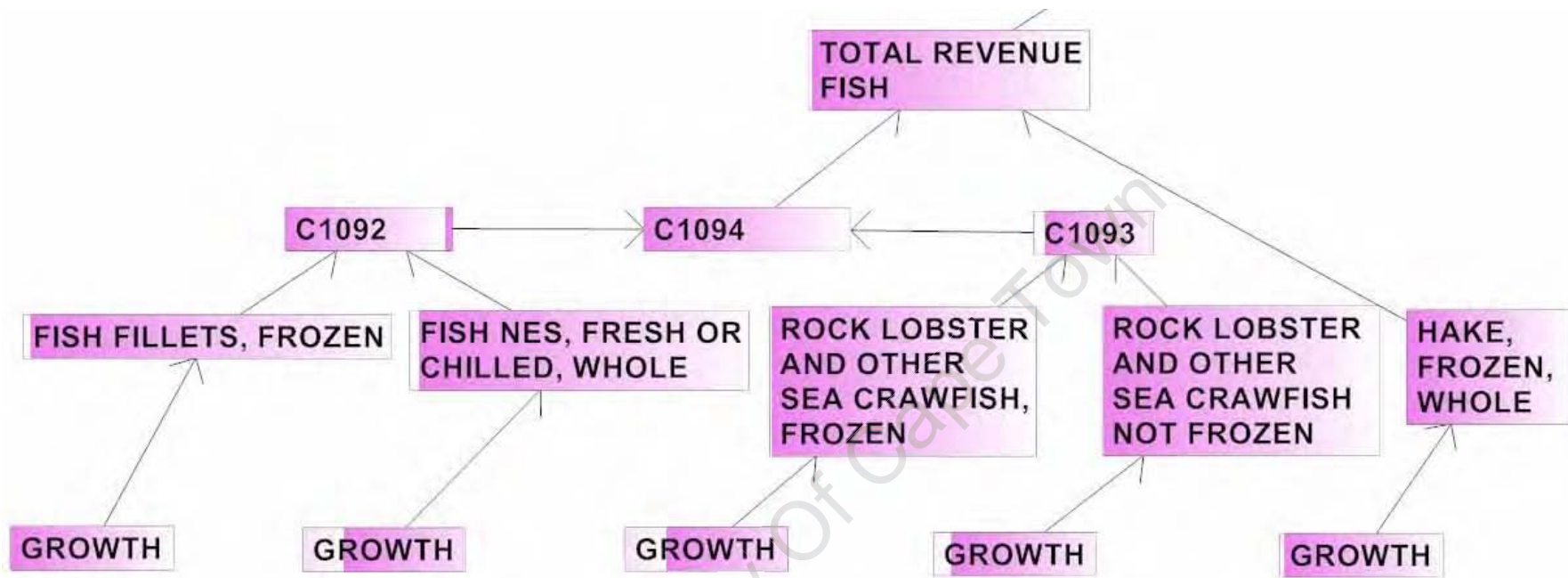


Figure 83: Illustration of Fish Products Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different fisheries operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

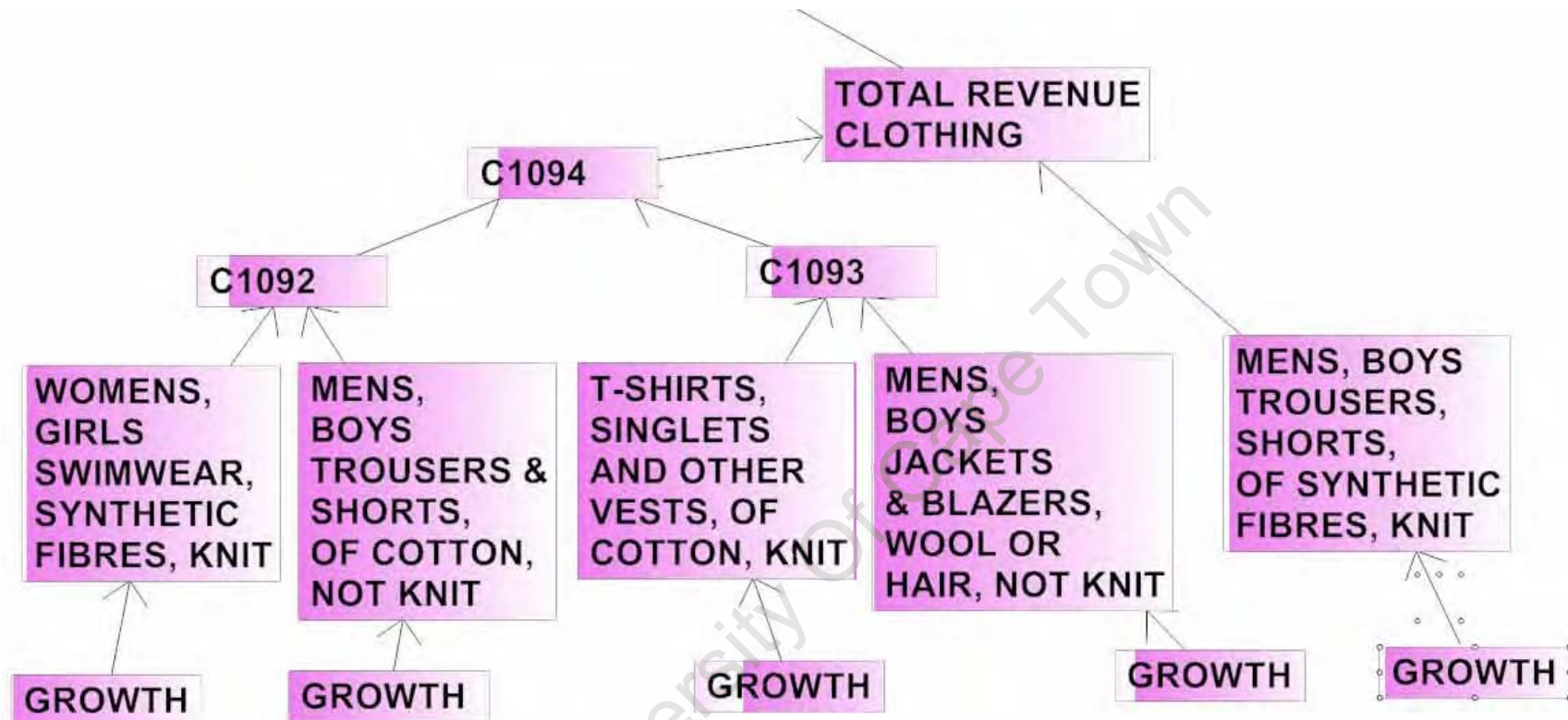


Figure 84: Illustration of Clothing Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different clothing operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

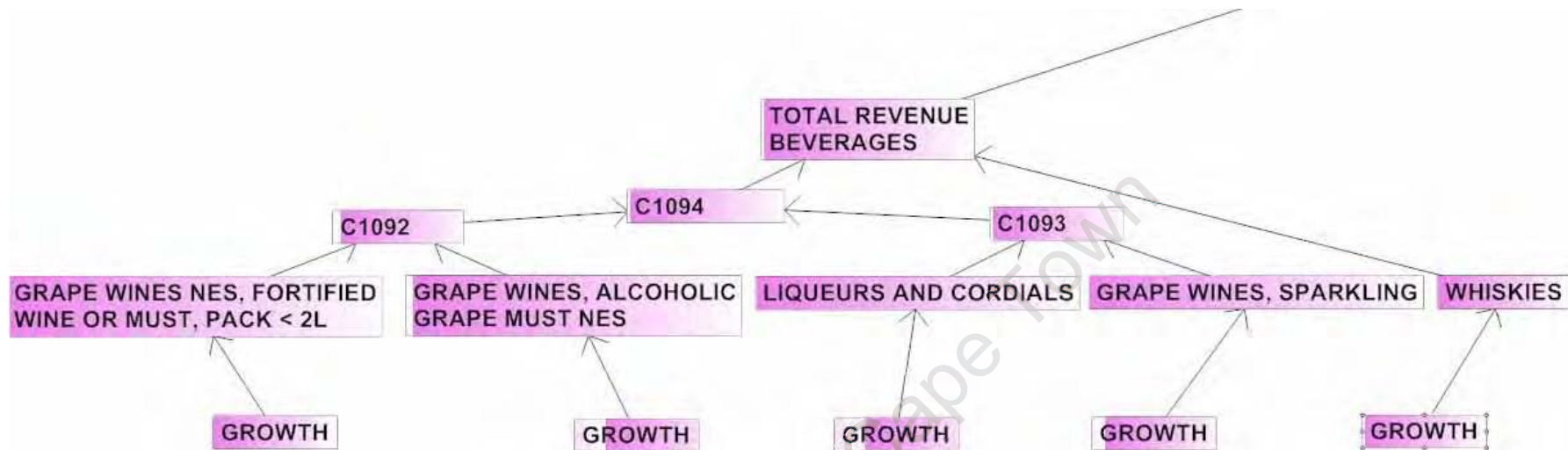


Figure 85: Illustration of Beverages Sub-Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different alcoholic beverage operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

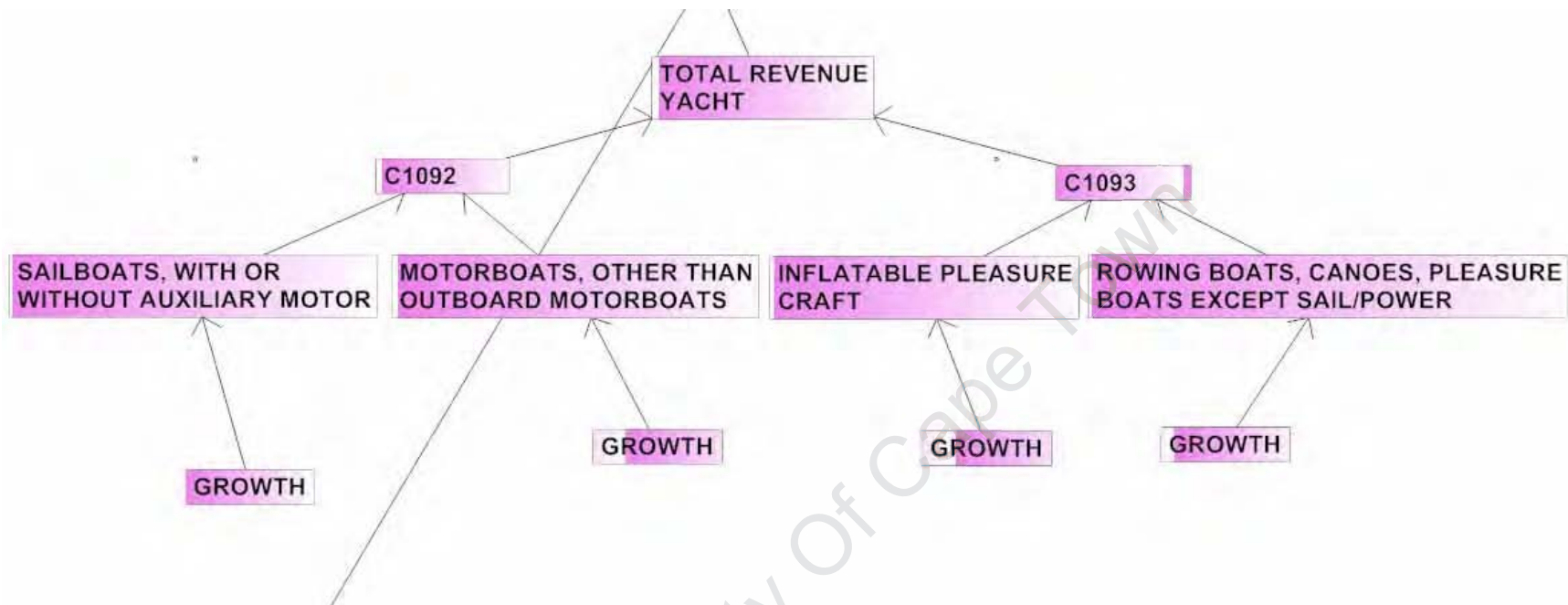


Figure 86: Illustration of Yacht & Boating Sub-Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different boating and yachting operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

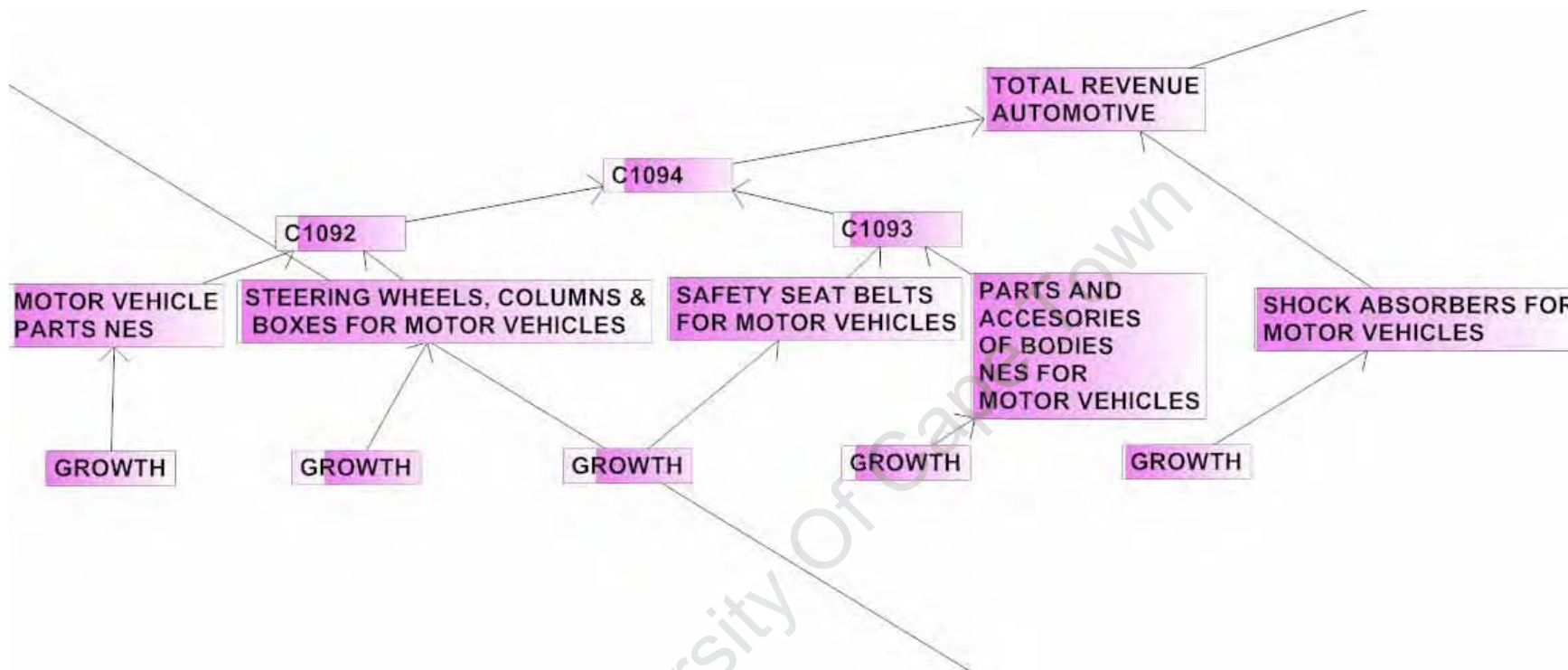


Figure 87: Illustration of Automotive Production Sub-Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different motoring operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

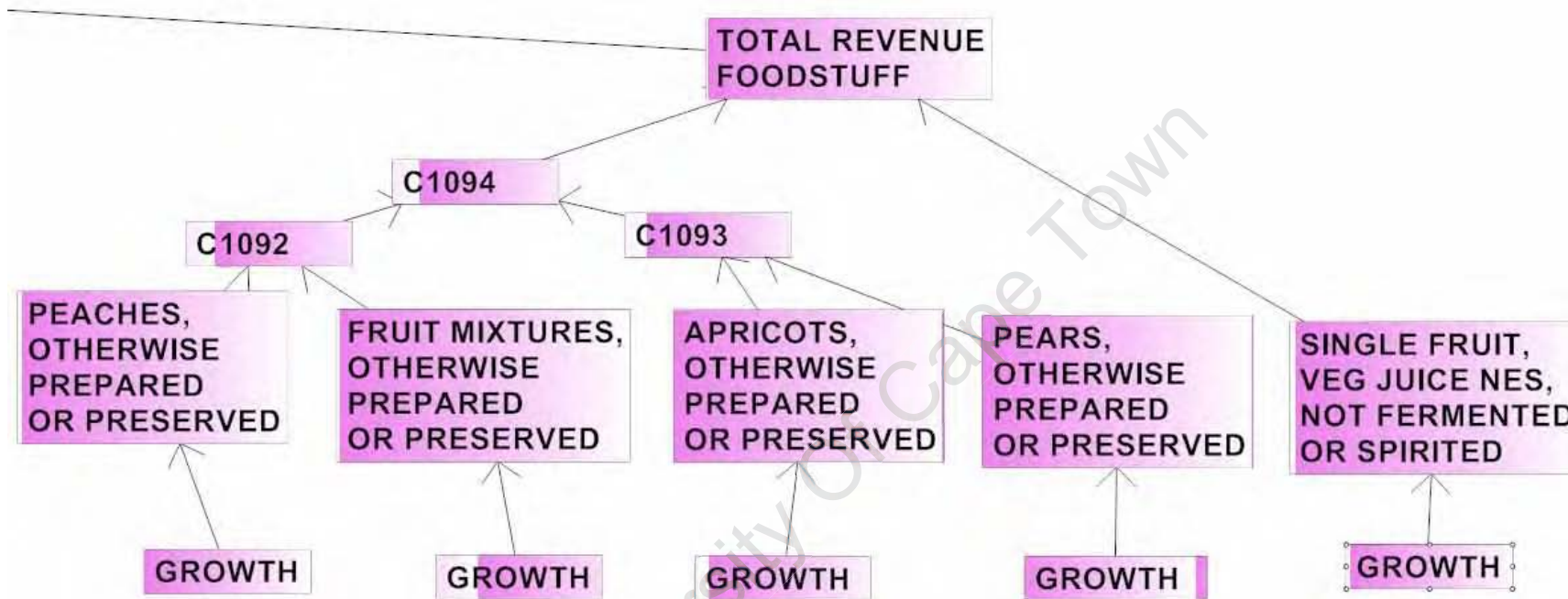


Figure 88: Illustration of Foodstuff Sub-Module in Manufacturing Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different fruit production operations that are currently underway in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available.

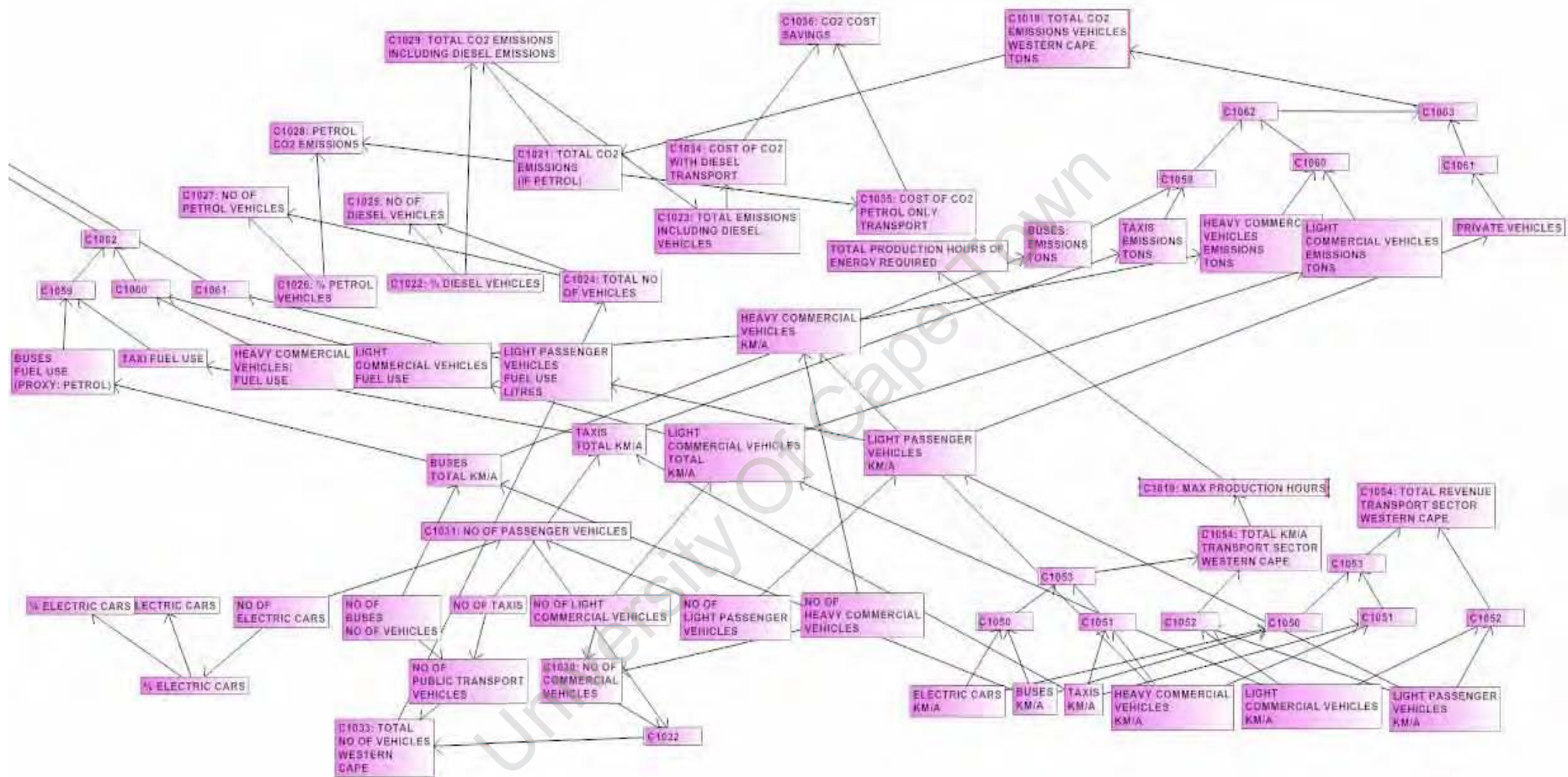


Figure 89: Illustration of Transport Module – Western Cape Province Bayesian Model. The user can experiment with detailed changes in growth in the different vehicle classes that are present in the Western Cape, according to their current revenue contribution rates. The model was constructed according the classes in which data and information have been made available. The user can experiment with different permutations of projected vehicle growth and road use patterns, and compare this with emission outputs. The model also caters for new and different classes of vehicles such as electric cars. The user can experiment with switching from private to public transport, and from petrol to diesel and biodiesel.

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15. **Appendix D: Mbombela Model Sub-System Modules**

In this section, the Mbombela model is shown in various parts. Thereafter, the conditional probability tables of two variables are shown as examples to the reader. These were chosen from the water module of the Mbombela model. These modules match their 'kin' as embedded units in other case studies as far as causal structure is concerned (however contextual changes may cause them to differ slightly), but their main differences lie in the equations used (their particular weighted relationships) and the marginal probabilities, which naturally have to be changed with the new context of application of the model.

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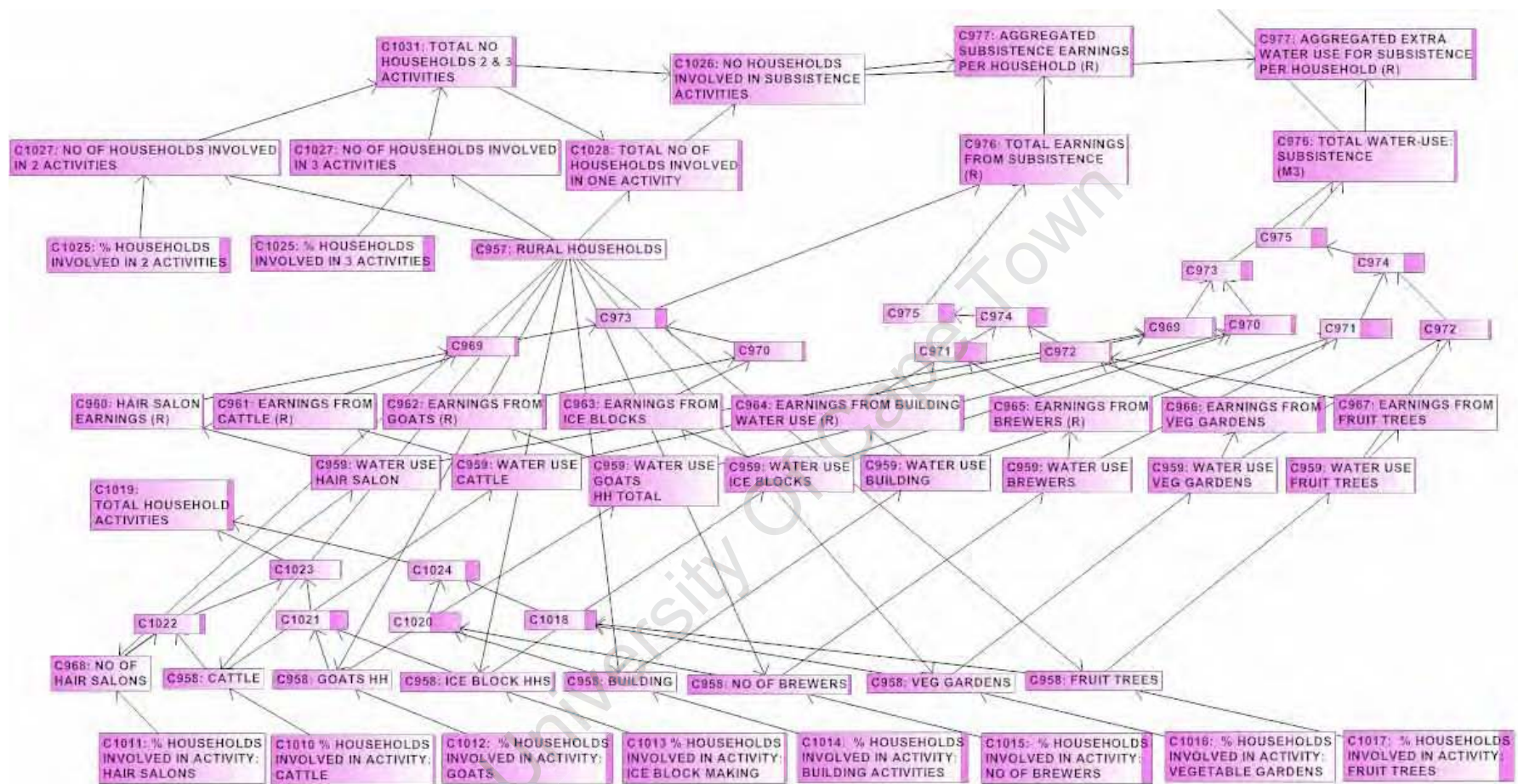


Figure 90: Causal Schematic Illustration of Water-Based Household Activities Model for Bushbuckridge Region Applied to Mbombela Municipality, which is nearby the Bushbuckridge Region (de Mendiguren Castresana, 2003). This model has been explained in the previous appendix.

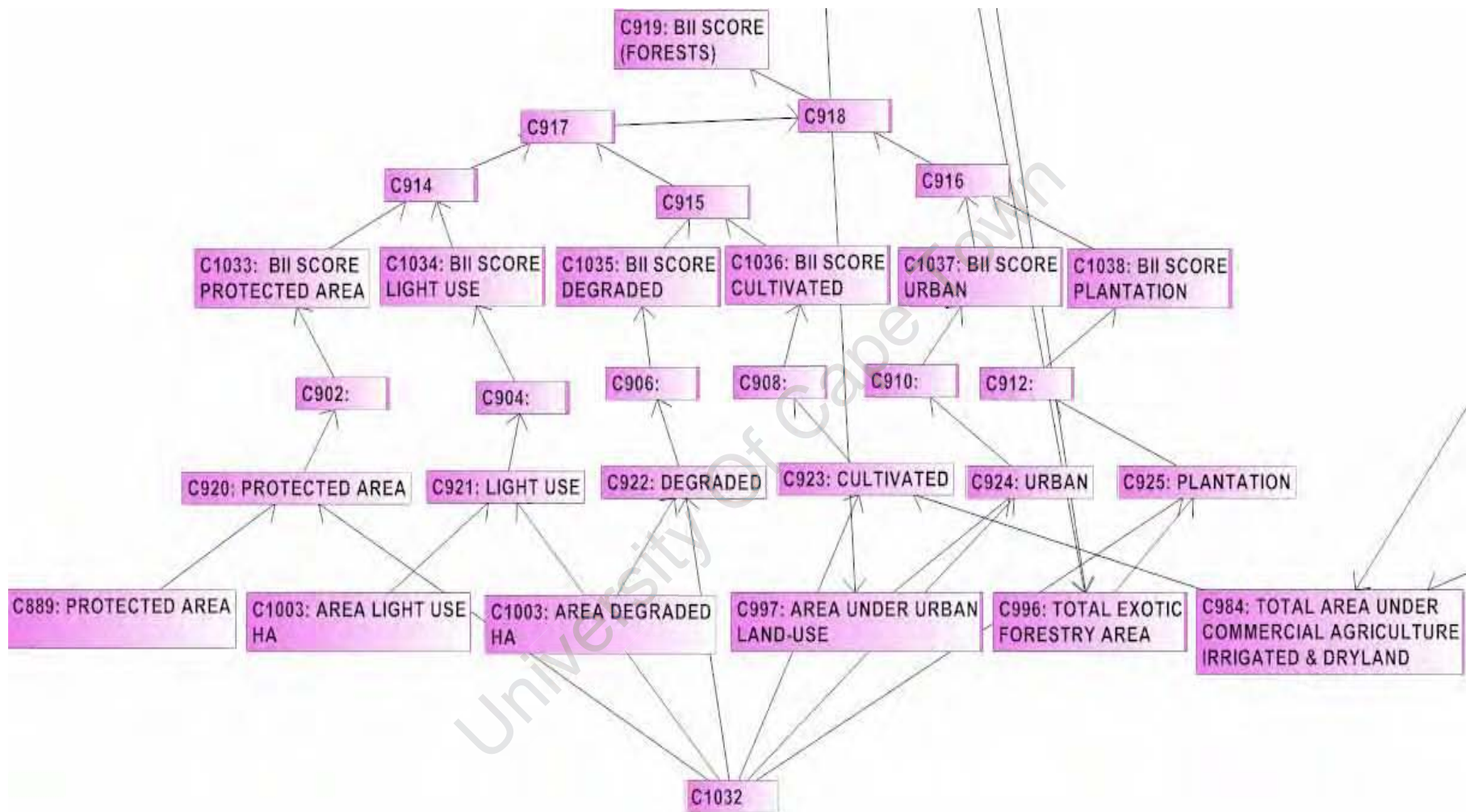


Figure 91: Biodiversity Intactness Index Module for Mbombela: A Generic Module That Can Be Adapted for Different Contexts. In this model, the biodiversity intactness index for the Western Cape is shown. It is still a conceptual model however, as the specific sensitivities of the Western Cape ecosystem, as a whole, have

not been researched yet. Currently, the model is constrained by probabilities that were obtained from ongoing research efforts on South Africa in general, and at a large, aggregative scale. Only in the Mbombela and Nelspruit models were the BII modules correctly constrained, as they were based on evidence from studies conducted on BII in the Incomati catchment. However, even as constrained, the BII, as a relative indicator, is a useful and interesting filter through which to envisage large scale changes in land use. In particular, it provides a very useful way of assessing how changes in land-use affect biodiversity at large scales.

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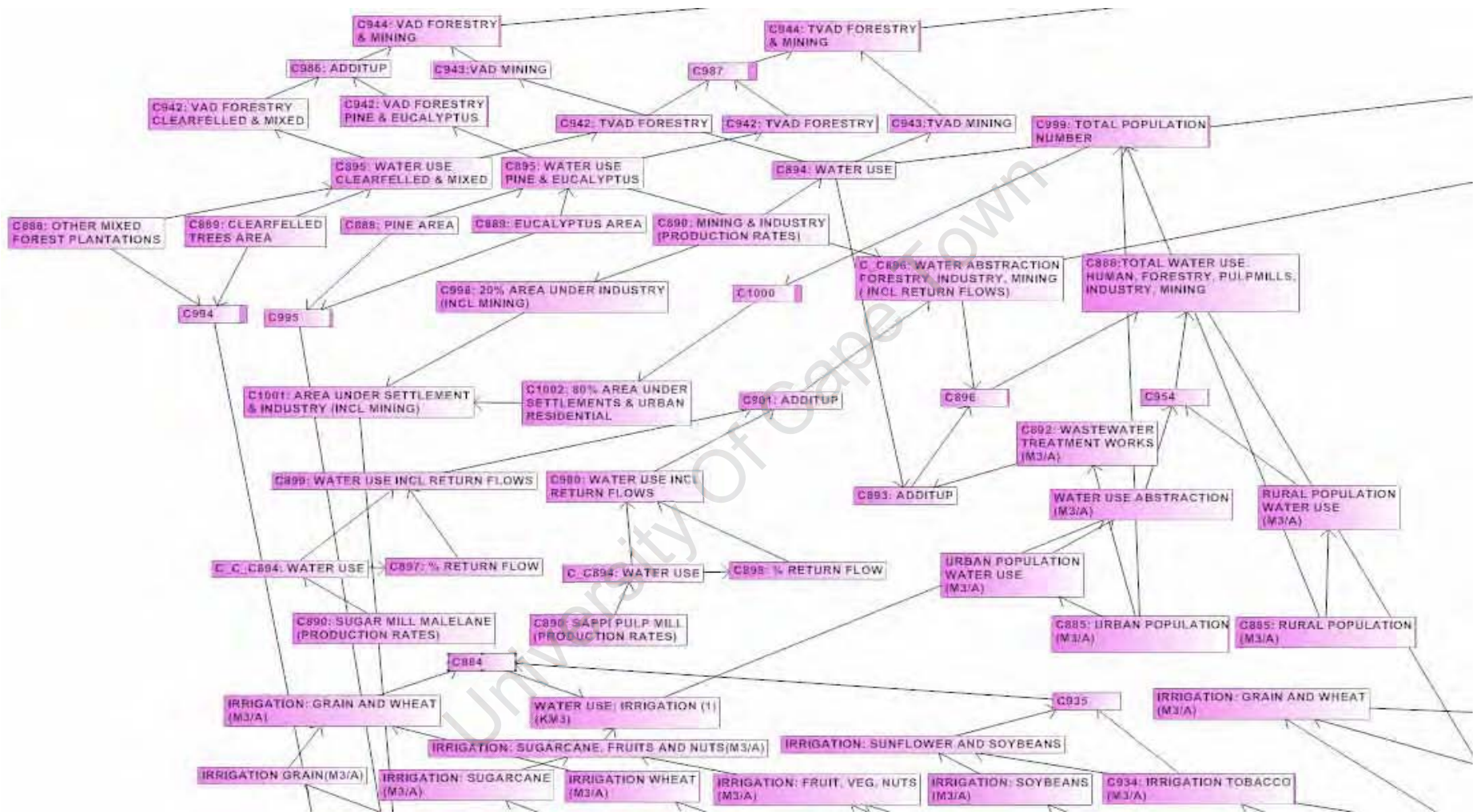


Figure 92: Causal Schematic Diagram of Total Water Use Module: In this module, the total water use from all sectors is aggregated, including return flows from pulp mills, water use of forestry and the direct and total value add associated with these water intensive activities. Urban population water use is differentiated from that of rural population, allowing for more flexibility in running scenarios with different interventions.

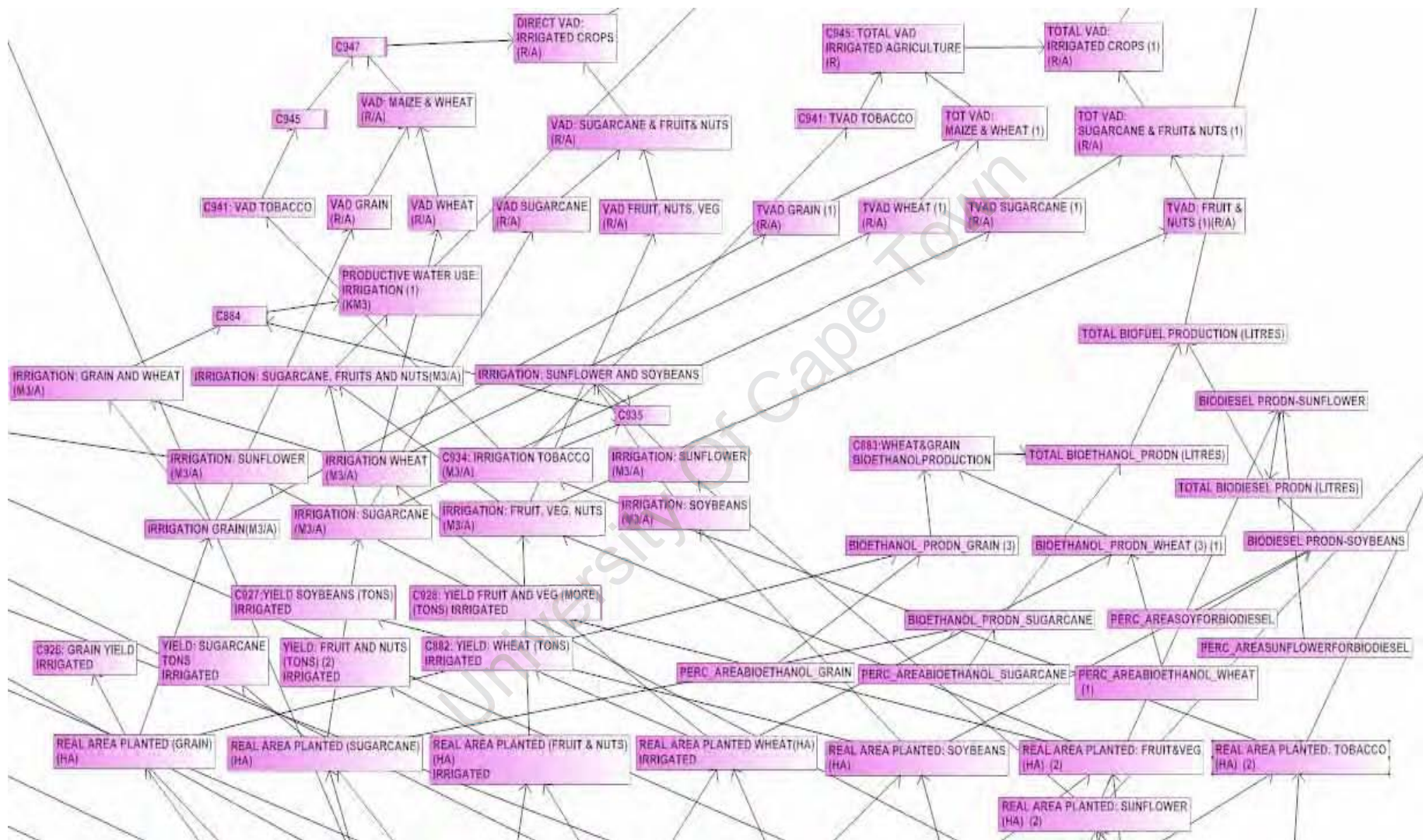


Figure 93: Schematic of Irrigated Agriculture Module: Mbombela Municipality Bayesian Model.

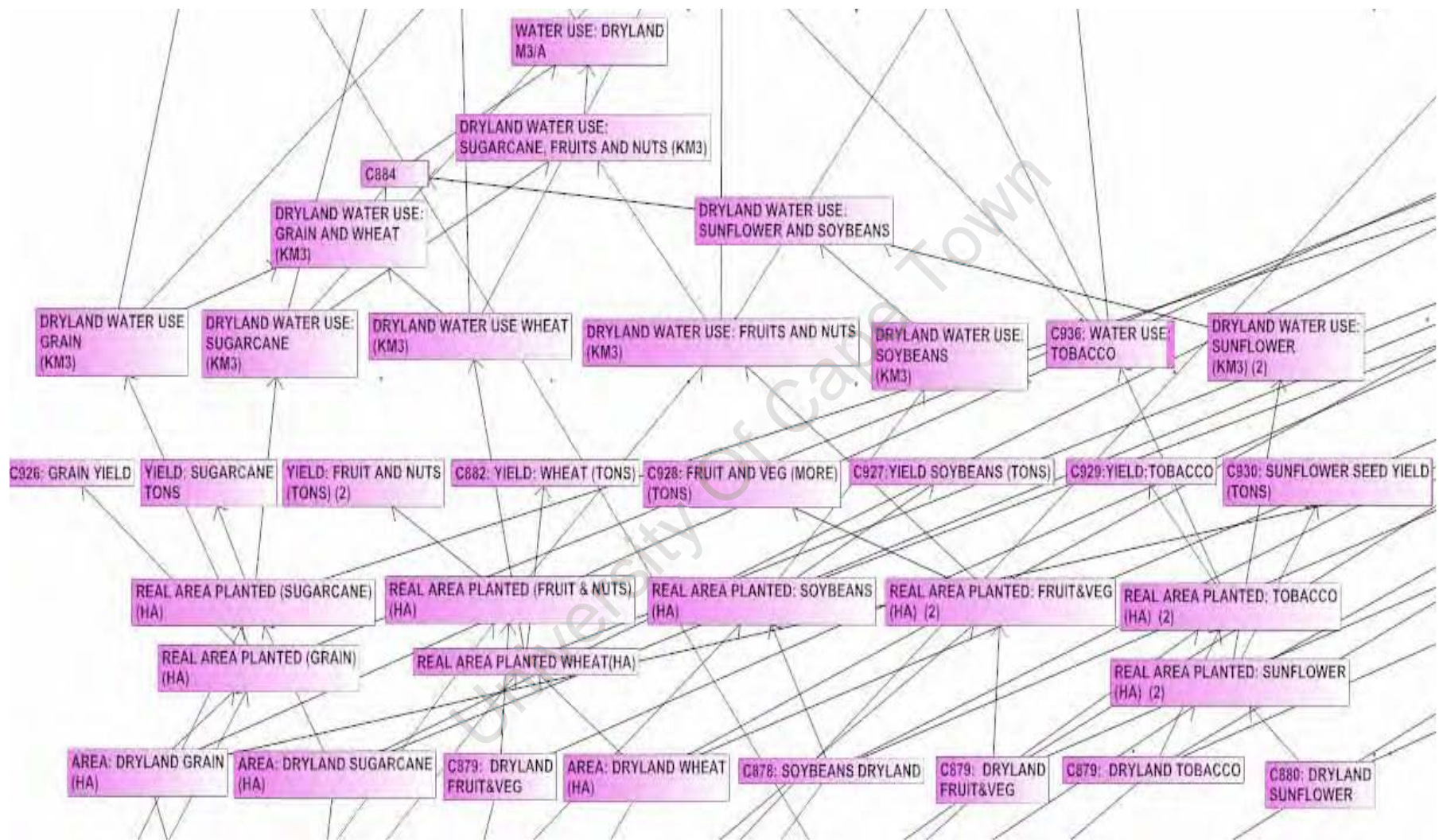


Figure 94: Schematic of Dryland Agriculture Module: Mbombela Municipality Bayesian Model. Irrigated agricultural activities, as conducted in the Western Cape, are catered for in this module. In particular, crop choice changes can be assessed against different water regime requirements, and evaluated further against projected changes in water supply in the future.

In the next part of this appendix, we show some examples of conditional probability tables. These tables were drawn from the water module of the Mbombela model. As can clearly be seen, the feasibility of illustrating every probability table is low because of the sheer size of conditional probability tables. Instead, we present a number of slides of the same probability table, to help the user understand how conditional probability tables are generated by the software.

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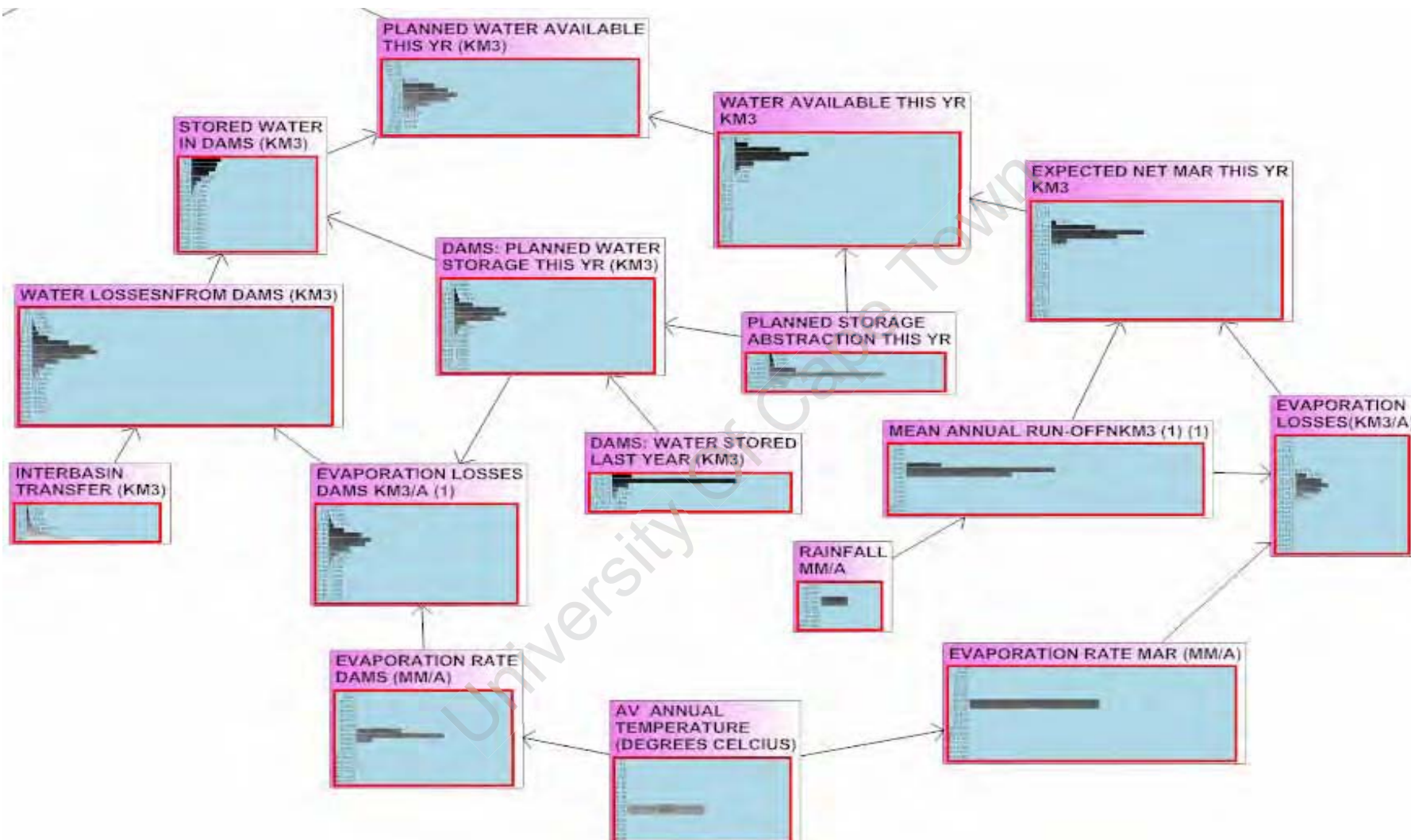


Figure 95: Schematic of Water Availability Module: Mbombela Municipality Bayesian Model

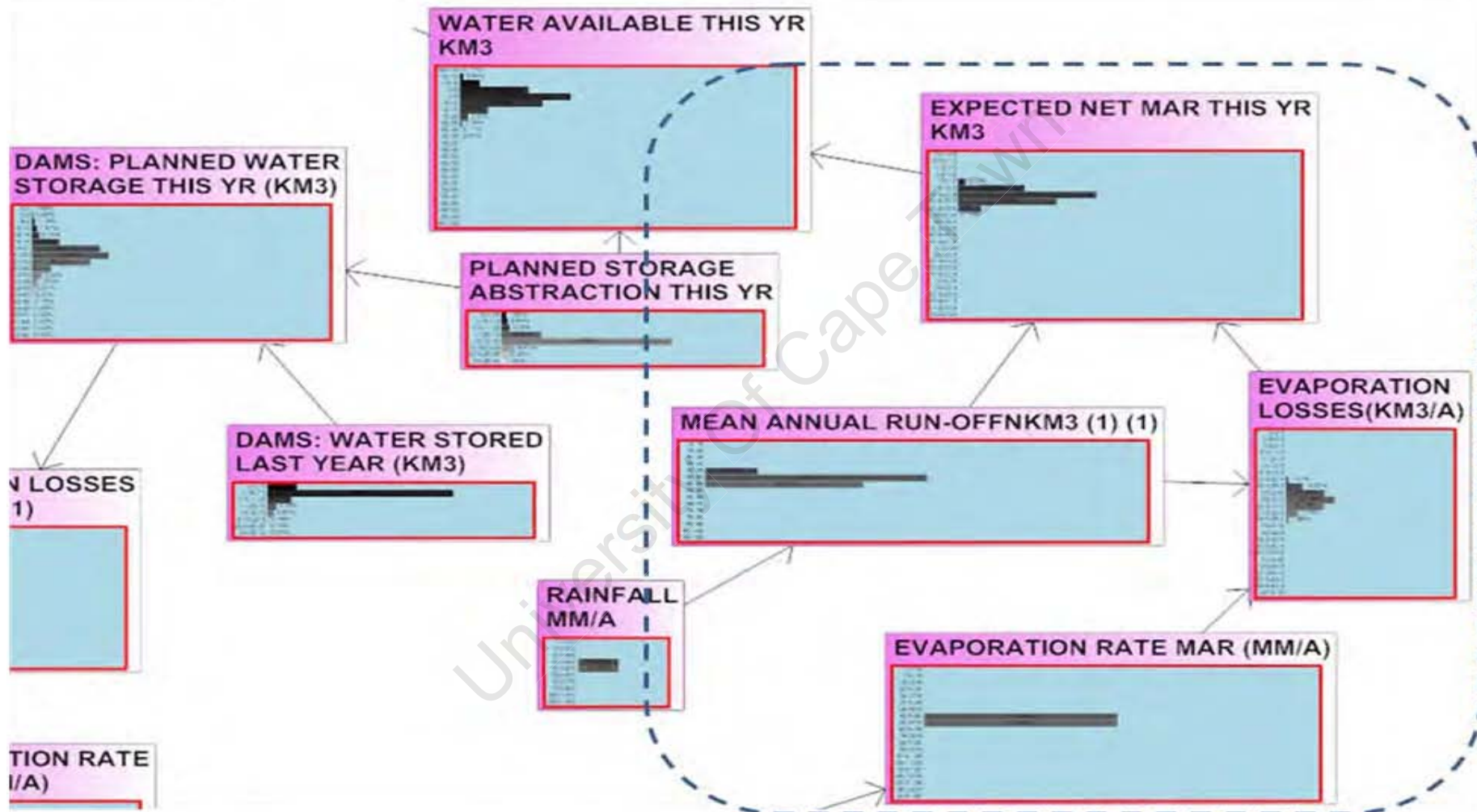


Figure 96: Schematic of Water Availability Module - Highlighted Section: Mbombela Municipality Bayesian Model. Mean Annual Runoff (MAR) and Expected Net MAR were selected for illustrating CPTs.

C1_1_1?	0-150	150-300	300-450	450-500	500-550	550-600	600-750	750-900	900-1050	1050-1200
0-15	1.000000	0.026971	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
15-30	0.000000	0.973029	0.053942	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
30-35	0.000000	0.000000	0.342324	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
35-40	0.000000	0.000000	0.342324	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
40-45	0.000000	0.000000	0.261411	0.242739	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
45-50	0.000000	0.000000	0.000000	0.757261	0.269710	0.000000	0.000000	0.000000	0.000000	0.000000
50-55	0.000000	0.000000	0.000000	0.000000	0.730291	0.296681	0.000000	0.000000	0.000000	0.000000
55-60	0.000000	0.000000	0.000000	0.000000	0.000000	0.703320	0.107884	0.000000	0.000000	0.000000
60-65	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.342324	0.000000	0.000000	0.000000
65-70	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.342324	0.000000	0.000000	0.000000
70-75	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.207469	0.134855	0.000000	0.000000
75-80	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.342324	0.000000	0.000000
80-90	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.522822	0.161826	0.000000
90-105	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.838174	0.188797
105-120	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.811203

Figure 97: Conditional Probability Table of Marginal Probability - Mean Annual Runoff. Variable C1_1_1 is the 'rainfall' variable.

In this section we illustrate the conditional probability tables of the variables shown in Figure 96, Figure 97. The marginal probability table of the mean annual runoff variable is shown in Figure 98. It has one input node i.e. C1_1_1 or rainfall. However, when considering the conditional probability table of the expected net mean annual runoff, which has two input nodes, an extremely long probability table is generated. As shown

in Figure 99 to Figure 108, the conditional probability table spans the whole range of C31_1_1 - the 'Evaporation Losses' variable, which runs until the 100th percentile. Conditional probability tables were not included in full in this dissertation, for this reason.

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EXPECTED NET MAR THIS YRKM3?													
Use expression <input type="checkbox"/> Ignore negative states <input type="checkbox"/> Parse <input type="button" value="Parse"/> Normalse <input type="button" value="Normalse"/>													
Auto states <input type="checkbox"/> Use bar mode <input type="checkbox"/> Build <input type="button" value="Build"/> Suggestion <input type="button" value="Suggestion"/>													
C31_1_1?	0-2.8												
C24_1_1?	0-15	15-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	
-10-5.6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
-5.6-1.2	0.089888	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
-1.2-3.2	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
3.2-7.6	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
7.6-12	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
12-16.4	0.168539	0.235955	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
16.4-20.8	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
20.8-25.2	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25.2-29.6	0.000000	0.247191	0.307692	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
29.6-34	0.000000	0.022472	0.564103	0.230769	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
34-38.4	0.000000	0.000000	0.128205	0.564103	0.153846	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
38.4-42.8	0.000000	0.000000	0.000000	0.205128	0.564103	0.076923	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
42.8-47.2	0.000000	0.000000	0.000000	0.000000	0.282051	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
47.2-51.6	0.000000	0.000000	0.000000	0.000000	0.000000	0.358974	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
51.6-56	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.435897	0.487180	0.000000	0.000000	0.000000	0.000000	0.000000
56-60.4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.512821	0.410256	0.000000	0.000000	0.000000	0.000000
60.4-64.8	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.333333	0.000000	0.000000	0.000000
64.8-69.2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.025641	0.564103	0.256410	0.000000	0.000000
69.2-73.6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.102564	0.564103	0.179487	0.000000
73.6-78	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.179487	0.564103	0.256410
78-82.4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.256410	0.000000
82.4-86.8	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
86.8-91.2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
91.2-95.6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
95.6-100	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 98: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 1

EXPECTED NET MAR THIS YRKM3?													
			2.8-5.6										
80-90	90-105	105-120	0-15	15-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.247191	0.146067	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.011236	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.247191	0.102564	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.112360	0.564103	0.025641	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.333333	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.410256	0.512821	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.487180	0.435897	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.358974	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.282051	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.076923	0.564103	0.205128	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.153846	0.564103	0.128205	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.230769	0.564103	0.051282
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.307692	0.564103
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.384615
0.062500	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.250000	0.312500	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 99: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 2

EXPECTED NET MAR THIS YRKM3?													
70-75	75-80	80-90	90-105	105-120	5.6-8.4		30-35	35-40	40-45	45-50	50-55	55-60	
					0-15	15-30							
0.000000	0.000000	0.000000	0.000000	0.000000	0.157303	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.056180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.101124	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.202247	0.461539	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.538462	0.384615	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.307692	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.051282	0.564103	0.230769	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.128205	0.564103	0.153846	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.205128	0.564103	0.076923	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.282051	0.564103	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.358974	0.564
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.435
0.051282	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.384615	0.538462	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.461539	0.281250	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.343750	0.153846	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.031250	0.282051	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.282051	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.282051	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000

Figure 100: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 3

EXPECTED NET MAR THIS YRKM3?												
55-60	60-65	65-70	70-75	75-80	80-90	90-105	105-120	8.4-11.2 0-15	15-30	30-35	35-40	40-45
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.265060	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.265060	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.265060	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.204819	0.213483	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.256410	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.044944	0.564103	0.179487	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.179487	0.564103	0.102564
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.256410	0.564103
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.025
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.410
0.076923	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.358974	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.435897	0.487180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.512821	0.410256	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.564103	0.333333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.025641	0.564103	0.156250	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.102564	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.044944	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.156250	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.213483	1.000000	0.000000	0.000000	0.000000	0.000000	0.000

Figure 101: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 4

EXPECTED NET MAR THIS YRKM3?													
40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	80-90	90-105	105-120	14-16.8 0-15	15-30	
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.400000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.400000	0.033708	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.200000	0.247191	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.224719	0.410000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.025000
0.461539	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.538462	0.384615	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.564103	0.307692	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.051282	0.564103	0.230769	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.128205	0.564103	0.153846	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.205128	0.564103	0.076923	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.282051	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.358974	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.435897	0.487180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.512821	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.112360	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.062500	0.247191	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.022222	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.146067	0.488889	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.488889	0.000000	0.000000	0.000000

Figure 102: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 5

EXPECTED NET MAR THIS YRKM3?													
75-80	80-90	90-105	105-120	14-16.8	0-15	15-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65
0.000000	0.000000	0.000000	0.000000	0.400000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.400000	0.033708	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.200000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.224719	0.410256	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.333333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.025641	0.564103	0.256410	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.102564	0.564103	0.179487	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.179487	0.564103	0.102564	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.256410	0.564103	0.025641	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.333333	0.564103	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.410256	0.512821	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.487180	0.435000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.487180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.512821	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.343750	0.112360	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.062500	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.247191	0.022222	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.146067	0.488889	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.488889	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 103: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 5

EXPECTED NET MAR THIS YRKM3?													
60-65	65-70	70-75	75-80	80-90	90-105	105-120	16.8-19.6 0-15	15-30	30-35	35-40	40-45	45-50	5
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.536585	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.463415	0.191011	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.205128	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.067416	0.564103	0.128205	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.230769	0.564103	0.051282	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.307692	0.564103	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.384615	0.538462	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.461539	0.461539
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.538462
0.512821	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.487180	0.435897	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.564103	0.358974	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.564103	0.282051	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.076923	0.564103	0.125000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.153846	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.343750	0.022472	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.187500	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.235955	0.254237	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.372881	0.372881	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.372881	0.372881	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 104: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 6

EXPECTED NET MAR THIS YRKM3?												
40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	80-90	90-105	105-120	19.6-22.4	15-30
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.814815	0.101124
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.185185	0.247191
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.157303
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103
0.051282	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.384615	0.538462	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.461539	0.461539	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.538462	0.384615	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.564103	0.307692	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.051282	0.564103	0.230769	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.128205	0.564103	0.153846	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.205128	0.564103	0.076923	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.282051	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.358974	0.343750	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.312500	0.179775	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.095890	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078652	0.301370	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.301370	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.301370	0.000000	0.000000

Figure 105: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 6

EXPECTED NET MAR THIS YRKM3?													
19.6-22.4													
0-15	15-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75	75-80	80-90	9
0.814815	0.101124	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.185185	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.157303	0.564103	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.435897	0.487180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.512821	0.410256	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.564103	0.333333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.025641	0.564103	0.256410	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.102564	0.564103	0.179487	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.179487	0.564103	0.102564	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.256410	0.564103	0.025641	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.333333	0.564103	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.410256	0.512821	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.487180	0.435897	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.218750	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.343750	0.0891
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.093750	0.247
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.168
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 106: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 7

EXPECTED NET MAR THIS YRKM3?													
			22.4-25.2										
80-90	90-105	105-120	0-15	15-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65	65-70	7
0.000000	0.000000	0.000000	1.000000	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.250000	0.358974	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.282051	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.076923	0.564103	0.205128	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.153846	0.564103	0.128205	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.230769	0.564103	0.051282	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.307692	0.564103	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.384615	0.538462	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.461539	0.461539	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.538462	0.384615	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564103	0.307
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.051282	0.564
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.128:
0.218750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.343750	0.089888	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.093750	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.168539	0.241379	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.252874	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.252874	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.252874	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000

Figure 107: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 7. C31_1_1 continues until the 100th percentile.

EXPECTED NET MAR THIS YRKM3?														
60-65	65-70	70-75	75-80	80-90	90-105	105-120	25.2-28	0-15	15-30	30-35	35-40	40-45	45-50	!
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.297297	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.297297	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.297297	0.153846	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.108108	0.564103	0.076923	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.282051	0.564103	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.358974	0.564103	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.435897	0.487180	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.512821	0.410
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.564
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.025
0.461539	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.538462	0.384615	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.564103	0.307692	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.051282	0.564103	0.230769	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.128205	0.564103	0.093750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.205128	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.343750	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.218750	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.146067	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.011236	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.247191	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.112360	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000

Figure 108: Conditional Probability Table - Evaporation Net Mean Annual Runoff. Variable C31_1_1 is the 'Evaporation Losses' variable, and variable C24_1_1 is the Mean Annual Runoff list. Slide number 7. C31_1_1 continues until the 100th percentile. C31_1_1 continues until the 100th percentile. As can be seen from the sequence of slides, the CPTs are too exhaustive in length to be incorporated in full.

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16. Appendix E

Table 21:

Table Illustrating Factors of Increasing Complexity as Addressed by Single Case Studies. A score of 1-5 has been used to estimate the degree to which each case study engaged with the full range of factors. This helps illustrate the matrix of complex challenges, as they were engaged with each successive case study.

Case Study	Cross-Scale Effects	Cross-Sector Effects	New Indices	Resilience & Adaptive Capacity	Adaptability	Participatory Processes	Decision Support
Incomati-Maputo Catchment2Coast Study	1	1	1	1	1	1	1
Climate Change - Irrigated Agriculture Study	2	2	2	2	2	2	2
Climate Change - Irrigated Agriculture - Biofuels Study	3	3	3	4	3.5	4	4

Magisterial District Scales: Nelspruit & Mbombela Scales	3.5	4	3.5	4	4	3	3
Western Cape Province Climate Change Strategy Review	5	5	5	5	5	4.5	4.5

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