PREDICTING RECRUITMENT IN SOUTH AFRICAN ANCHOVY: Analysis of an expert system approach, and the incorporation of probabilistic reasoning.

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DECLARATION

This dissertation reports the results of research which I carried out in the Marine Biology Research Institute, Zoology Department, at the University of Cape Town. It has not been submitted for any other degree or examination at any other university. Most of the data that are presented were obtained from unpublished reports of the Sea Fisheries Research Institute, Department of Environment Affairs, or from published studies, and are referenced as such. All opinions expressed, unless otherwise acknowledged, are my own. Any technical and other assistance which I received is fully acknowledged.

Signed 1/9/95

Jan L. Korrûbel

For my parents,
for that second chance in 1987.

In the space of one hundred and seventy-six years the Lower Mississippi has shortened itself two hundred and forty-two miles. That is an average of a trifle over one mile and a third per year. Therefore, any calm person, who is not blind or idiotic, can see that, in the Old Oolitic Silurian Period, just a million years ago next November, the Lower Mississippi River was upward of one million three hundred thousand miles long, and stuck out over the Gulf of Mexico like a fishing rod. And by the same token, any person can see that seven hundred and forty two years from now the Lower Mississippi will be only a mile and three-quarters long, and Cairo and New Orleans will have joined their streets together, and be plodding comfortably along under a single mayor and a mutual board of aldermen.

There is something fascinating about science. One gets such wholesale returns of conjecture from such a trifling investment of fact.

Mark Twain,
"Life on the Mississippi" (1883)

CONTENTS

ABSTRACT

KORRûBEL, J. L. 1995. Predicting recruitment in South African anchovy: Analysis of an expert system approach and the incorporation of probabilistic reasoning. M.Sc. Dissertation, Marine Biology Research Institute, Zoology Department, University of Cape Town, 7700 Rondebosch, South Africa.

Commercial pelagic fisheries contend with high levels of risk and uncertainty associated with the exploitation of environmentally dependent resources. Two kinds of models are seen as a necessary part of the scientific effort. Detailed models of controlling mechanisms provide field workers and experimentalists with a consistency check on research findings, while some form of inference about future outcomes of possible actions is required for decision making.

Forecasts serve a critical purpose for decision-makers. The need for a predictive system in the South African pelagic fishery stems from the pressure applied by both the scientific and fishing communities for an accurate assessment of the initial Total Allowable Catch (TAC). For the purpose of predicting recruitment in clupeoids, perhaps only a simplified model requiring little computing time will be necessary. The aim of this study is to determine the feasibility of using an 'expert system' and expert techniques for decision support for those decision-makers undertaking initial TAC assessments for the South African anchovy, *Engraulis capensis*, fishery. The systems described here would be used to enhance generation of the initial anchovy TAC, which is set early in the year at or just before the commencement of fishing, before the year's recruitment of 0-year old fish, an important component of the catch, is known.

Pre-fishing season environmental and biological information is used to make a forecast about expected recruitment. Of the many environmental variables which, may potentially give an indication of future recruitment, a subset of eight variables was identified and shortlisted for possible inclusion in an expert system. On the basis of these influencing factors, forecasting anchovy recruitment is tackled in two ways: deterministically, using simple regression and correlation analysis and an expert system shell to develop a set of rule-based expert systems; and probabilistically, implementing subjective probability assessments (obtained from workshops conducted for personnel concerned with the South African pelagic fishery), and Bayesian probability equations, to calculate the probability that anchovy recruitment would be below the observed median.

The deterministic rule-based model simply predicts whether below average recruitment will be observed (or not). By reducing the number of variables to obtain the "best" and simplest combination, and calibrating the rules, it was possible to obtain correct predictions of below average recruitment for all years in the recruitment time-series.

For the probabilistic system, the eight influencing factors investigated for the deterministic system were further reduced, on the basis of data availability, to a subset of four variables that are thought to allow numerical forecasting of recruitment in anchovy. Subjective probabilities of events were extracted from a select group of experts by means of workshops and a questionnaire, and compared to probabilities extracted from time-series data. Close inspection of the subjective data revealed that the expert assessed probabilities were inconsistent with the axioms of probability, temporarily ruling out application of a custom-built 'probability calculator'. Linear (Goal) programming methods and personal re-assessment of the subjective data were then employed to obtain a consistent dataset. From these re-assessed data, it is possible to obtain correct predictions of below average recruitment for all years in the recruitment time-series.

The ability of these models to correctly predict fluctuations in recruitment, supports the use of such systems as decision-support tools in fisheries management.

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It has been said that formulating good linear programming models is an art bordering on a science. In this respect, I must thank Professor Theo Stewart (Department of Statistical Sciences, UCT) for his artistic abilities in identifying my inconsistency problem as a LP application, and for formulating the appropriate LP model. Special thanks also go to the following for help with their probabilistic and statistical know-how: the new friends I established through the *sci.stat.** Internet newsgroups, in particular Professor Vicki Bier (Department of Industrial Engineering, University of Wisconsin-Madison) and Professor Bob

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Recruitment prediction has been an elusive and seemingly unobtainable goal, with no entirely satisfactory general approach yet available

Frank (1991)

Chapter 1

INTRODUCTION

1.1 BACKGROUND

Managers and scientists are often concerned with the impact of perturbations on populations (Kope and Botsford 1988), and in particular, are usually involved in comparing choices and making decisions (Alexander 1981). This process of comparison necessarily involves some form of forecast or prediction (Walters 1993), or participation in the production of forecasts. Managers and scientists are however, generally reluctant to make predictions.

In an attempt to cope with the uncertainties in environment and recruitment, there are a number of approaches which can be used to aid decision makers in the management of a particular resource. Holling (1973) proposed a qualitative approach to management that "would emphasize the need to keep options open". This philosophy is expressed as "adaptive management" which treats management actions as experiments that can later be modified from experience (Holling 1978, Walters 1986). Another approach is to use quantitative mathematical models to simulate a random world. Starfield and Bleloch (1983), Starfield, Adams and Bleloch (1985), Starfield and Louw (1986) and Starfield (1990) discuss the utility of qualitative models in building models for systems that are assumed to be well understood, but difficult to measure quantitatively.

Qualitative models may be used as tools for using subjective information about a system that conventional modelling techniques have difficulty in using. Such a management strategy accepts uncertainty as a fundamental characteristic of complex ecosystems, and from this perspective, the goal of management shifts from quantitative prediction to judicious management (Bottom, Jones, Rodgers and Brown 1993) - requiring an integration of technical analysis and human experience to find solutions (Francis 1990).

1.2 VARIABLE RECRUITMENT AND THE PROBLEMS FOR MANAGEMENT

Almost all marine fish stocks experience a wide range of variability in the strength of successive year-classes - variability in recruitment is assumed to be the primary source of uncertainty in most fisheries (Csirke 1980; Doubleday 1985). The term recruitment has been used in several senses: the surviving number of a cohort of year class which enter the fishery; the number of a specific stage colonising a nursery; and, the process of growing and surviving to a fishable (or other) size or stage. This dissertation uses recruitment in the latter sense, defined by Bakun (1985) as:

> "*the quantity of younger fish surviving the various egg, larval, juvenile, etc., stages to reach a size at which they become susceptible to fishing gear and thus begin to be sampled by the fishery*".

The central question for fisheries management is therefore "What controls interannual variation in recruitment?" or alternatively, "What regulates interannual variation in recruitment?". At first glance, one might assume that these questions are one and the same; Miller (1994) however, points out that there is a distinction - controlling means generating interannual variability, while regulating means reducing interannual variability. A controlling factor must therefore vary interannually in order to generate interannual variability in recruitment. One of the problems in fisheries management is to determine what causes (controls) interannual variability; i.e. to gain the ability to predict strong and weak year classes.

Pelagic fishes, particularly clupeoids, form the basis of many important commercial fisheries; hence fluctuations in fish abundance are of much concern to the fishing industry. Our present inability to predict environmental anomalies and their effects on fish mean that fishing quotas cannot be adjusted in a prescriptive manner (Shelton 1984); consequently managers have to develop strategies which allow "coexistence" with this uncertainty (Hilborn 1987).

Commercial fisheries have usually pursued a policy of maximizing economic yield. A negative trade-off is that management policies that maximize average yield also tend to result in a large variation of yield (Quinn, Fagen and Zheng 1990). Essentially, good management should be able to take advantage of higher than average biomass in the stock as one or more strong year classes passes through the fishery, as well as protect the stock when biomass is low. It is extremely difficult for management to calculate a quota that is considered reasonable by all parties interested in a particular stock - users (that is, the fishermen, and other parties at the marketing level) operate under economic constraints, while those with preservation in mind, are simply concerned about the magnitude of the quota (Getz, Francis and Swartzman 1987) and its subsequent effect on the stock. Ludwig, Hilborn and Walters (1993) propose that

> "*we shall never attain ... consensus concerning the systems that are being exploited*".

In view of the 'classic' surprises and failures over the years, perhaps this reaction is understandable. Management policies that maximize average yield usually attempt to drive the population close to the most productive level as quickly as possible. At this level, these populations are very sensitive to environmental variation (Quinn *et al.* 1990). They cite the 'fixed escapement' policy as a typical example of a maximum harvest strategy. A management procedure closely approximating constant escapement was implemented in the South African anchovy fishery in 1987 but was changed to a constant proportion procedure in 1991, subsequent to the fall in the anchovy population in 1989 and 1990 (Cochrane and Starfield 1992).

Previous studies attempting to identify causal mechanisms behind the variability in recruitment have used recruitment indices estimated by virtual population analyses (VPA) (Lapointe, Peterman and Rothschild 1992). Lapointe *et al.* document that the failure of VPA to account for interannual variability in the true adult natural mortality, "results in recruitment estimates that are more variable than true recruitment". They point out that this increased variance in the estimated recruitment decreases the power to detect correlations that might actually exist between recruitment and environmental factors. Furthermore, they explain that

> " *... just as finding a significant correlation is insignificant evidence for the existence of some causal relationship between the abundance of recruits and an environmental factor (due to potential spurious correlations; ...), failing to find a significant relationship is also insignificant evidence for the nonexistence of a relationship because the power of such correlation tests may be low ...*".

The value of short-term forecasts of recruitment variation has been clearly demonstrated by Walters (1989) and Cochrane and Starfield (1992). There have been a number of different approaches to the prediction of recruitment in fisheries management. For example: Lochner (1980) describes the modelling of fish populations in terms of electrical engineering principles; Evans and Rice (1988) present evidence that when predicting recruitment, the recruitment indices are better presented as a probability distribution, and not a single number; Frank (1991) proposed the use of meristic variation (fluctuations in vertebral counts), caused by changes in temperature, to predict recruitment variation; Adams, Seddon and Van Heezik (1992) assessed the potential of using seabirds as indicators and predictors of change in commercially important fish species; and Bloomer, Cochrane and Field (1994) used the fundamental physical indices of sea surface temperature and wind to predict recruitment.

The use of environmental factors as aids in understanding the causes of variability of fish distributions and recruitment rates, and the furnishing of more accurate predictions based on this understanding, has been questioned by Walters and Collie (1988); they claim that improved prediction is often impossible because environmental factors are not predictable - even if fish responses are. Walters (1984), Butterworth (1989), and Butterworth, Punt, Bergh and Borchers (1992) have criticized ecological programmes attempting to elucidate recruitment-environment relationships, for not providing much information useful to management. It has also been pointed out that the cumulative error associated with the measurement of environmental factors results in relationships that have broad confidence intervals (Miller, Crowder, Rice and Marshall 1988; Pepin 1991). In order to achieve an understanding of the mechanisms that determine overall survival, there is a need to develop a perspective that integrates information from several levels (Crowder, Rice, Miller and Marschall 1992). However, if fish responses to specific anomalies are predictable, then by monitoring the environment and picking up the advent of these anomalies, as well as making use of the information resident in the assembly of researchers, we may be able to predict the response of the fish (in terms of, for example, spawning and recruitment).

1.3 OBJECTIVES AND KEY QUESTIONS OF THIS RESEARCH

1.3.1 General Objectives of this Study

Bakun (1985) and Anderson (1988) reviewed the hypotheses concerning the regulation of recruitment success. Although the role of the environment has been much emphasized in answering queries about fluctuations in pelagic stocks (see Kawasaki, Tanaka, Toba and Taniguchi 1991), in general, researchers acknowledge that no single, clearly defined variable is responsible for determining year-class success (Sharp, Csirke and Garcia 1983; Anderson 1988; Campbell and Graham 1991).

This dissertation deals with identifying and selecting a subset of environmental and population parameters thought to play important roles in regulating recruitment in the South African anchovy, *Engraulis capensis* Gilchrist; and to develop models or sets of rules which will predict/forecast departures from median recruitment. These models or sets of rules will then be synthesized into expert systems which may be used to arrive at qualitative and semi-quantitative forecasts of future anchovy recruitment success.

In this dissertation, a non-technical, information systems focus will be adopted. This is reflected in the minimal attention devoted to discussing general expert system principles, terminology, historic developments, design issues and programming techniques. These topics are discussed fully in the many expert system textbooks and guides (see Hayes-Roth, Waterman and Lenat 1983; Jackson 1986; Waterman 1986; Carden 1987, 1988; Pedersen 1989; for a review of expert system development tools see Mackerle 1989). Discussion will thus concentrate on the decision support aspects of such a system.

1.3.2 Relevance of this Research to the South African Fisheries Context

In the existing management procedure for the South African anchovy, an initial Total Allowable Catch (TAC) is set at the start of the commercial fishing season in January, before the year's recruitment of 0-year-old fish (an important component of the catch; Bergh 1986) is known. The TAC is estimated, as is described later, from the estimate of spawner biomass (obtained in November) and by assuming that recruitment of 0-year-old fish will be equal to the observed long-term median. The TAC may be revised in May or June, after the actual recruitment has been acoustically estimated. This procedure incorporates a risk that, if recruitment is below the median, the stock could be adversely depleted before the results from the recruitment survey justify the January TAC.

This research endeavors to provide information at an earlier stage than at present, on recruitment in the southern Benguela anchovy stock by looking at selected environmental and population parameters. It is envisaged that by being able to forecast success or failure in anchovy recruitment for the forthcoming season, the procedure of setting the TAC for the forthcoming commercial harvesting season can be enhanced (Cochrane and Starfield 1992).

This project is not the first to attempt development of a management tool incorporating environmental parameters for the South African pelagic fishery (see Wickens and Field 1990), nor is it the first attempt at predicting recruitment in South African anchovy (see Bloomer *et al.* 1994). From an academic point of view however, this research can be seen as a progression of other South African theoretical and quantitative research in fisheries management (Bergh and Butterworth 1987; Butterworth and Bergh 1993; Butterworth, De Oliveira and Cochrane, in prep.). Additionally, this dissertation details the first local survey of expert opinion with respect to the recruitment problem, and it is hoped that it will serve as a basis to evaluate future developments in the expert and decision support system area in South African fisheries management. South Africa is, in general, at a relatively high level in terms of computer technology (Van Belle 1992). Management could therefore take immediate advantage of expert and decision support systems. A further important consideration motivating this research is the keen competition for resources in the light of South Africa being a developing country (Bergh and Barkai 1993).

1.3.3 Key Questions in this Study

(1) What is already known about expert and decision support systems and probabilistic reasoning, that is relevant to the project objectives?

(2) What models or rules are currently available concerning the regulation of recruitment in marine clupeoids?

(3) What new insights into the factors controlling the events in the recruitment process can be incorporated into an expert system?

(4) What procedures or variables play the key roles in regulating model output?

(5) Can a valid system for forecasting clupeoid recruitment success be developed from (2), (3) and (4) above?

(6) Does the incorporation of probabilistic reasoning improve predictive capabilities?

I scan modern fisheries mathematics with awe, and a large degree of incomprehension

Beverton (1983)

Chapter 2

ECOSYSTEM MODELLING

2.1 INTRODUCTION

Resource management at the ecosystem level is complicated by the inability to forecast accurately ecological responses to perturbation - not only must they understand which environmental/biological factors deserve attention during a decision process, but they must also determine how these factors interact to produce outcomes each with different consequences. Additionally, the managers knowledge about this complex environment must be integrated into the analysis in a way that facilitates the choice of an appropriate course of action. This chapter is a general discussion of ecosystem modelling as a management tool. Particular attention is paid to expert and decision support systems, and the incorporation of probabilistic reasoning into such systems. Expert systems are also discussed in the context of decision support systems. For the purposes of this dissertation, the term *expert system* has been adopted to encompass both expert and decision support systems - except where separation of the terms is required for clarity - and is also used to describe the systems developed later.

2.2 MECHANISTIC vs. NON-MECHANISTIC MODELS

The most general classification of modelling approaches distinguishes between mechanistic and non-mechanistic models. Essentially, if it is thought that enough is known about the system under investigation to be able to suggest a formal description, then the model under development is following a mechanistic (either deterministic or probabilistic) approach. If, on the other hand, there is poor understanding of why the system behaves as it does, a non-mechanistic (statistical) approach may be necessary to derive the required information.

Two kinds of models are seen as a necessary part of the scientific effort: detailed *simulation models* of controlling mechanisms provide field workers and experimentalists with research directions, while *forecasting* serves a critical purpose for decision-makers and managers (Duinaker and Baskerville 1986). Decision making, by definition, requires some form of inference about future outcomes of present actions (Walters 1986); Bunn and Wright (1991) review some of the controversies in the relative value of judgemental and statistical forecasting methods.

Simulations on a computer remove the problems associated with experimentation on real resources because:

- the consequences of the application of what might prove to be poor management to a real resource may be highly undesirable; "resources" can only be rendered extinct - and resurrected - on a computer;
- the state of the resource under investigation in known exactly at all times to the analyst;
- each simulation requires only a little computer time (usually in the order of a couple of minutes) to carry out.

The issue for the scientist is not whether to 'model', but rather how to go about the modelling (Walters 1993). There is a prevailing viewpoint that the statistical approach is more reliable (Ludwig *et al.* 1993). Uncertainty has however, forced many modellers to opt for a probability distribution around a result, rather than a single figure. The approach most frequently used for this purpose is Monte-Carlo simulation (Punt 1992).

Two important advantages result from assumptions embedded in standard statistical procedures: the ability to construct confidence limits, and the ability to test hypotheses. However, when data of a dynamic nature are lumped into static measures, these virtues are believed to be of dubious value - Shaffer and Cahoon (1987) assert that in any standard statistical analysis, distinct bits of unusual information are blended into overall effects, masking the true behaviour of the system.

Unlike standard statistical analysis, 'entropy data analysis' analyses data in 'states and 'substates' (Jones 1985a, 1985b, 1985c, 1986). Variables are free to act and interact in combinations suggested by the data - structure is "discovered", not assumed by a mathematical or statistical model (Shaffer and Cahoon 1987; Shaffer 1988). This form of analysis serves to elucidate how the constituent components within a system act and interact to produce variation, without making any distributional assumptions.

K-systems analysis (KSA) is a maximum entropy stepwise regression that employs events rather than variables as its fundamental unit (Shaffer 1988). KSA isolates important events, whether periodic or aperiodic, and this is event driven rather than time driven - stepwise KSA is designed to isolate the minimum number of events which account for a maximal portion of the behaviour of a dependent variable (Shaffer 1988). In addition to the stepwise analysis, KSA may be used to develop predictive models (Shaffer 1988).

Collopy and Armstrong (1992) and Bloomer *et al.* (1994) examine the feasibility of rule-based forecasting, a procedure that applies forecasting expertise and domain knowledge to produce forecasts according to features in the data. With rule-based forecasting, one can apply expertise about forecasting methods and domain knowledge that are appropriate to the conditions of the time-series.

Ryan and Smith (1985) point out that it is often the case that many models cannot be completed due to imperfect knowledge. Resource managers however, need enhanced tools to help them keep ahead. The aim of this study is to investigate the mechanistic approach, using expert system and probabilistic techniques to forecast recruitment success in the South African anchovy resource. The system envisaged would be useful for decision support by resource managers undertaking forecasts of anchovy recruitment.

2.3 THE ROLE OF ARTIFICIAL INTELLIGENCE IN MANAGEMENT

Unlike the traditional computer simulation models that have become so widespread in management, artificial intelligence (that is expert systems and expert system technology) has played only a small role in research (Plant and Stone 1991). Where the primary role of simulation models in research has been the mathematical statement of hypotheses, the expert system is more of an application tool than a research tool. This application role presents several obstacles to the successful adoption of expert systems in a management environment. A simulation model can be considered a success simply if it works, that is if it performs its simulation function. However, it has been suggested that an expert system cannot be considered successful just because it works correctly; it must be employed by its intended users, or its development will be an empty gesture (Plant and Stone 1991).

The field of artificial intelligence has been dominated primarily by large expert systems; however, they demonstrated that expert systems have important practical applications (Starfield *et al.* 1985). Expert systems are best suited to problems which resist [pure] deterministic solutions, but are compliant to solution by experts (Davis and Nanninga 1985). Such systems are designed to substitute for a human expert, or multiple experts, when such expertise is in short supply (Starfield and Bleloch 1983).

Expert systems are intended to act as 'consultants', on a specific task, to individuals or groups who lack the expertise in the problem domain (Spiegelhalter 1986). An expert system provides a consistent answer to a specific problem, and should be updated and revised to preserve its accuracy (Ryan and Smith 1985). Essentially then, if a problem needs to be solved and an expert is unavailable, a computer program like an expert system may offer the best alternative. Of course, it rests on the developer of the system to make it the best possible substitute for the human expert - without necessarily imitating human functioning (Loehle 1987).

Much specialist information exists in researchers from the environmental, oceanographic and marine biology disciplines. A large proportion of this knowledge is not in a form suitable to be used directly for management purposes (Silvert 1989); however, it may constitute real and valuable information that should be utilized (Hilborn 1992). Consequently, when developing an expert system, it is valid for the developer to ask the human expert to formalize the rules by which the system in question operates; science is, after all, a search for the rules that describe the way nature behaves (Rykiel 1989). There are numerous problems in the resource management field which cannot be easily or appropriately analyzed - many management problems, especially those dealing with the environment, are characterized by imprecision. Usually, both qualitative and quantitative information associated with several criteria needs to be systematically considered when evaluating alternatives (Wenger and Rong 1987). Unfortunately, one of the major problems to emerge from the construction of expert systems is the 'bottleneck' of extracting knowledge from the experts; experts often find it difficult to express, in exact rules, what they think they know to be the case (Muggleton 1990, Liang 1992).

Also, there is a marked gap between the demands placed on forecasting and the results that forecasting techniques can actually provide (Zimmer 1984).

In summary, there is a need to centralize expertise and to have it easily accessible to potential users. The basis for rational management, of a fishery for example, is an up-to-date forecast of changes in the abundance of the exploited population; this permits selection of an optimal strategy. An expert system, designed to assist the decision-maker by implementing the accumulated quantitative and qualitative data into a forecasting system, could address these needs. More importantly, such a system formalizes the steps and logic used to arrive at a conclusion - mistakes can later be used to improve the system. Hence an expert system can be viewed, *inter alia*, as a scientific hypothesis.

2.4 EXPERT AND DECISION SUPPORT SYSTEMS

2.4.1 Definition of Expert Systems

Expert systems are computer-based models, developed to mimic the way a human expert reasons. As with many scientific disciplines, there is some difficulty in establishing a satisfactory definition. The classic definition of an expert system is that proposed by Feigenbaum (Giarratano and Riley 1989):

> "[An expert system is] *an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution*".

Many other more technically phrased definitions are available in the literature, however, the following definition of expert systems by Turban (1990) has been selected for the purposes of this dissertation because it is readily understood:

> ***"Expert systems will be understood to be computerized advisory programs that attempt to imitate or substitute reasoning processes and knowledge of experts in solving ... problems".***

A final remark concerns the term *knowledge-based system*: it appears to be treated in the literature as a synonym for expert system (see use thereof in Davis 1986 and Plant and Stone 1991), and is readily confused with 'knowledge base' (explained later in section 2.4.4). In this dissertation, the term 'knowledge-based system' has therefore been avoided.

2.4.2 Expert Systems as Decision Support Systems

Since most expert systems provide support for decision-makers, every expert system can be seen as a decision support system in the wider sense. The perceived linkage between expert systems and decision support systems is such that the topic requires that a brief overview of the issues be given here. This is particularly relevant because the systems discussed later tend to lean more toward decision support than "true" expert systems.

In the information systems literature, the term decision support system has acquired a slightly more specific meaning:

> "*A decision support system is a computer-based system used by managers as an aid to decision making in semi-structured decision tasks through direct interaction with data and models*" (Benbasat and Nault 1990).

The important elements in this definition are i) the use of decision support systems is limited to managers and managerial environments, and ii) decisions are made using (raw) data directly as input. The main reason for this distinction from expert systems is that the problems of management are usually much wider and shallower than that of most "true" expert systems (Sprague and Watson 1986; Kim and Courtney 1988).

2.4.3 Similarities and Differences

Kopcso, Pipino and Rybolt (1988) explain:

> "*Inevitably, the question arises: Is an expert system a decision support system? There are a number of differences [...]. Expert systems deal with problems whose scope is narrow and relatively well defined. The system incorporates a set of rules and heuristics that are repeatedly used in the solution of the problem. The rules and relationships change with experience. Typically, an expert system has the ability to explain why it reached a conclusion. In contrast, a decision support system is intended to operate in a broader and more diverse decision environment. It*

should be usable for ad hoc problems but usually does not incorporate a facility for explanation".

As defined above, expert and decision support systems appear quite distinct. In reality however, the difference between the two is one of nomenclature more than of structure. Upon closer inspection, large areas of overlap are revealed; for example, both systems have an inferencing mechanism, although a different emphasis may be given to exactly how the inferencing is done: more heuristically (logically) in expert systems as opposed to more mathematically in decision support systems (Finlay 1990). The major differences between decision support systems and expert systems are tabled in Tables 2.1 and 2.2.

	DSS	ES
Objective	Assist human	Replicate (mimic) human and replace him/her
Who makes the decision?	The human	The system
Major orientation	Decision making	Transfer of expertise (human-machine-human)
Query direction	Human queries the machine	Machine queries the human
Clients	Individual and/or group users	Individual user
Manipulation	Numerical	Symbolics
Problem area	Complex, integrated, wide	Narrow domain
Data-Base	Factual knowledge	Procedural and factual knowledge

Table 2.1: The differences between decision support (DSS) and expert systems (ES) (from Sprague and Watson 1986, p. 141).

The relationships between expert and decision support systems have been much discussed in the literature - the contribution these two technologies have made to each other are deliberated by Benchimol, Lévine and Pomerol (1987). For an original approach, see Holtzman (1989) who offers a useful framework for deciding on the most appropriate technology.

2.4.4 Structure of Expert Systems

The three traditional components of an expert or decision support system are:

- the *knowledge base* which contains the rules (logic) and facts (statements) about the problem;

- the *inference engine* (the 'brain') draws conclusions, makes recommendations and motivates actions based on the information supplied by the user and the information stored in the knowledge base; and
- the *user interface*, or shell, which is the mechanism through which communication between the expert system and the user takes place.

Dimension	Decision Support Systems	Expert Systems
Applications	Long-range strategic planning, complex integrated problem areas	Diagnosis, strategic planning, internal control planning, maintenance strategies. Narrow domain
Focus	Decisions, flexibility, user-friendliness	Inferencing, Transfer of expertise
Database	Database management systems, interactive access, factual knowledge	Procedural and factual knowledge; knowledge base (facts, rules)
Decision Capabilities	Semistructured problems, integrated OR models, blend of judgment and structured support capabilities	The system makes complex decisions, unstructured; use of rules (heuristics)
Manipulation	Numerical	Symbolic
Type of information	Information to support specific decisions	Advice and Explanations
Highest organizational level served	Top management	Top management and specialists
Impetus	Effectiveness	Effectiveness and expediency

Table 2.2: Comparison of attributes between decision support and expert systems (abbreviated from Turban 1990, p. 18).

2.5 UNCERTAINTY AND FORECASTING

2.5.1 Background

Knowledge is usually assumed to be able to fit into rules; in mathematical reasoning, every conclusion must follow from previous information (Stefik, Aikins, Balzar, Benoit, Birnbaum, Hayes-Roth and Sacerdoti 1983a). Although many decisions may be made straightforwardly, many others are too difficult to be prescribed in any simple manner; Szolovits and Pauker (1978, in Neapolitan 1990) state that exact decisions are not possible because the world is too complex. In the simplest case however, no doubt may be expressed when making a decision. In reality, there may be considerable uncertainty about any one decision; virtually any decision making situation in management involves some degree of uncertainty (Plant and Stone 1991; Hilborn 1992). Decision-makers and managers need to act in spite of the lack of facts and knowledge.

Fox (1986) states that uncertainty in expert systems manifests itself in the following places: *data/facts* can be uncertain, *interpretations* can be unreliable, and *rules* can be rough and ready. Plant and Stone (1991) categorize the following forms of uncertainty:

User uncertainty occurs when the user is uncertain of the correct response to the expert systems prompt;

Rule uncertainty involves the introduction of uncertainty into a rule in the rule base, for example: even if the rule involves a precise conclusion with complete certainty, the fact that the antecedents are not known with complete certainty should prevent the conclusion from being made with complete certainty; and

Vagueness is a concept related to uncertainty. Plant and Stone (1991) consider rules that beg the question of the defining terms to be vague. They explain the difference between vagueness and uncertainty with the following example. Consider the vague statement "John is tall". A more mathematical statement of this assertion is "John is a member of the set of tall men". If John's height is seven feet, then this statement is clearly true, and the relationship to the set of tall men is strong. If John's height is five feet however, the statement is false, and there is no relationship whatsoever to the set of tall men. Suppose however, that John is six feet tall. In this case John has some degree of membership in the set of tall men, but the relationship is not as strong as that if John were seven feet tall.

Although most commercial expert system shells usually have a built in capacity for dealing with uncertainty (Kopcso *et al.* 1988), there is no universally accepted method of dealing with uncertainty (for an excellent introduction, see Cooke 1991). When solving problems and making judgements, people - experts included - sometimes use methods different from those of formal mathematical reasoning. However, decision-makers and researchers usually require the judgements to be numerical (e.g. 80% or 4:1 chance) rather than linguistic (e.g. very likely) (Wallsten, Budescu and Zwick 1993). It is argued (von Winterfeldt and Edwards 1986) that numerical expressions are precise, unambiguous communications, while natural language is vague, subject to different interpretations by different people, and cannot be assessed in the same way as numerical expressions (Beyeth-Marom 1982).

There are four basic approaches that have been suggested for the representation of uncertainty in expert systems. These methods are: Bayesian probability theory (e.g. Lindley 1987), Dempster-Shafer theory of evidence (Dempster 1968; Shafer 1987; Caselton and Luo 1994), fuzzy logic (Zadeh 1983), and certainty factors (Shortliffe and Buchanan 1975).
Bayesian theory is viewed as the "Established Church" for dealing with uncertainty (Plant and Stone 1991). One of the appealing features of Bayesian analysis is that its procedures are, in most cases, practical and relatively simple as compared to other approaches (Caselton and Luo 1992), and based on familiar notions of probability. In recent times however, Japanese companies have popularized fuzzy logic by using it to direct electrical appliances; and other investigators are finding that fuzzy models are more useful than standard mathematical ones (Kosko and Isaka 1993). I explore both avenues after a brief definition and explanation of probability.

2.5.2 **Definition of Probability**

The earliest ideas in the theory of probability arose to deal with various problems in the mathematics of gambling, where a probability can be usefully defined as the frequency of a specified outcome in a long series of identical trials. At the heart of probability theory, we find the classical definition of Laplace (1951, cited by Neapolitan 1990):

> *"The theory of chance consists in reducing all the events of some kind to a certain number of cases equally possible, that is to say, such as we may be equally undecided in regard to their existence, and in determining the number of cases favorable to the event whose probability is sought. The ratio of this number to that of all the cases possible is the measure of the probability"*.

Neapolitan (1990) is interested in the association of real numbers with propositions to represent uncertainty. He explains that

> "... *we are concerned with the determination of a method for assigning real numbers to represent our uncertainty ..., and of a calculus for manipulating these real numbers (and therefore change our certainty) as evidence is accumulated*".

Probabilities are numbers between 0 and 1 (Steele and Torrie 1980). Statisticians indicate precisely how probable or improbable an event is by assigning a higher value (closer to 1) if a contemplated event is more probable, and a lower value (closer to 0) if the contemplated event is improbable; 1 means that the contemplated event is certain and 0 means that it is impossible. For example: Let C stand for any particular conclusion. Suppose a rule, r_1, implies C with strength 0.8, while another rule, r_2, implies C with strength 0.2. We have:

$$r_1(C) = 0.8 \quad \text{and} \quad r_2(C) = 0.2.$$

We define a probability space, $\varnothing$, and let $\varnothing$ be the exhaustive set of all possibilities (alternatives). In this example, lets say that $\varnothing$ contains only two possibilities, C and $\neg C$ [NOT C]. Using probability theory, it is necessary that the sum of the 'strengths' assigned to the members of $\varnothing$ be equal to 1. Therefore, for each of the rules r_1 and r_2, we have:

$$r_1(\{C\}) + r_1(\{\neg C\}) = 1$$
$$\text{and,} \quad r_2(\{C\}) + r_2(\{\neg C\}) = 1.$$

An important point to note is that each rule (that is r_1 and r_2) contains evidence for C ($\{C\}$), *and evidence against it* ($\{\neg C\}$), i.e.:

$$r_1(\{C\}) = r_2(\{\neg C\}) = 0.8$$
$$\text{and,} \quad r_2(\{C\}) = r_1(\{\neg C\}) = 0.2.$$

Traditionally, when a probability space is created, all probabilities which are based on the initial information are called *a priori* probabilities since, by definition, *a priori* means 'independent of experience' (James and James 1966). A more modern term for an *a priori* probability is prior probability. Probabilities based on additional information are usually called conditional probabilities. All probabilities are conditional on some information (Neapolitan 1990) - whether the conditioning information is explicit, implicit or unspecified is immaterial, it always exists. To avoid confusion, Von Winterfeldt and Edwards (1986) recommend that the term conditional probability be avoided unless it is useful to specify some particular conditionalization, because as Neapolitan (1990) explains, a conditional probability in one space can be a prior probability in another space (the new probability space being based on the additional information). The subsequent or revised probability - based on the additional information - is therefore usually called the posterior or total probability.

2.5.3 Bayesian Probability Theory

This section deals only with a few relevant aspects of Bayesian analysis. For a more thorough introduction to Bayesian analysis and its applications see De Finetti (1970) and Berger (1985).

There are essentially two extremes in interpretation of probability in the Bayesian scheme: the 'classical', or *frequentist*, interpretation and the 'degree of belief', or *subjectivist*, interpretation. Both interpretations are assumed to obey the same mathematical rules.

The strict *frequentist* interpretation defines the probability $P(\mathrm{A})$ of an event A in terms of repeatable experiments. Suppose an experiment whose probable outcomes are A and ¬A (NOT A) are repeated over and over again (e.g. the classic tossing of a coin, where the probable outcomes are heads, and ¬heads, i.e. tails). As the experiment is repeated, the fraction of times that the outcome A (e.g. heads) is observed approaches some number that is defined to be $P(\mathrm{A})$. These objective numbers represent the relative frequencies of the occurrence of an event.

To the extreme frequentist, numerical probabilities have meaning only in the case of an experiment that can be repeated, and there exists a number, accurate to "100+ digits", to describe the result (Neapolitan 1990). (S)he would claim that any probability (s)he is forced to assign (at gun point, of course!), is a probability based on past experiences (Neapolitan 1990). However, an extreme frequentist can never know the precise values of his/her objective probabilities (to "100+ digits" that is); (s)he can only obtain estimates and confidence intervals (Neapolitan 1990).

The strict *subjectivist* interpretation of probability is the value that a 'rational person' would associate with the probability that A is true (or that the outcome of a particular experiment will be A). The probability is a measure of plausibility of a hypothesis or proposition - the uncertainty simply represents one's *degree of belief* in the statement, relative to the evidence at hand. Subjective, or judgementally assessed, probability works with statements or experiments for which the concept of an infinite number of repetitions is either difficult or meaningless (Plant and Stone 1991) - for example, a geologist might ask: "What is the probability of an earthquake, given certain precursory seismic signals?". Obviously, it is not possible to calculate this probability by performing many trials under identical conditions. The extreme subjectivist does not deny that probabilities generated through repeated experimentation exist, but rather denies the assumption that objective probabilities are adequate to describe events (Neapolitan 1990).

Non-extreme frequentists and non-extreme subjectivists are not bound to these conclusions. The non-extreme frequentist realizes that decisions must be made in some situations where uncertainties are not represented by relative frequencies; i.e. (s)he can embrace the usefulness of subjectivist theory while still maintaining that some probabilities are best conceived as being objective; and, non-extreme subjectivists do not deny the existence of objective probabilities (Neapolitan 1990).

The foundation of Bayesian statistics is a theorem proved by the Reverend Thomas Bayes, an English clergyman and amateur mathematician, in 1761, the year of his death; the proof was published posthumously (Bayes 1763). Bayes' theorem is usually written as follows (this version of the theorem from Von Winterfeldt and Edwards 1986):

$$P(\mathrm{H}|\mathrm{E}) = \frac{P(\mathrm{H}) \bullet P(\mathrm{E}|\mathrm{H})}{P(\mathrm{E})}, \qquad (2.1)$$

where:

$P(\mathrm{H}|\mathrm{E})$, called the *posterior* (or total) probability, represents the probability that hypothesis H is true given the evidence E;

P(H), called the *prior* probability, represents the probability that hypothesis H would be observed, prior to learning the evidence E;

P(E|H), called the *likelihood*, represents the probability that evidence E would be available given that hypothesis H were true; and

P(E), called the *marginal* probability, represents the probability that evidence E would be observed, independent of whether or not the hypothesis H is true.

Assuming there is enough data, the prior, likelihood and marginal probabilities can easily be estimated. They may also be elicited from experts.

Suppose now that some new information I comes to our attention. Bayes' theorem also explains how to modify our beliefs in the light of this new information; i.e., a way of incorporating the new data into our present understanding. To include the new information, we can now state Bayes' theorem as follows (from Jefferys and Berger 1992):

$$P(\mathrm{H}|\mathrm{E}\&\mathrm{I}) = \frac{P(\mathrm{H}|\mathrm{E}) \bullet P(\mathrm{I}|\mathrm{H}\&\mathrm{E})}{P(\mathrm{I}|\mathrm{E})} . \tag{2.2}$$

This equation can be used to calculate P(H|E&I), that is the posterior probability that hypothesis H is true, given both the original evidence E and the new information I. As explained previously, three factors enter into the calculation:

P(H|E) is the *prior* probability, in other words the probability of H given the initial evidence E (note that previously, we calculated this as the posterior probability in the first-order equation but it enters this equation as a prior probability);

P(I|H&E) is the *likelihood*, the probability of observing the new information I, given the initial evidence E and the knowledge that H is true; and

P(I|E) is the *marginal* probability, the total probability of observing the new information I, given the evidence for E, and whether or not if the hypothesis turns out to be true.

Suppose now that another new piece of information J comes to our attention. Bayes' theorem also explains how to modify our beliefs in the light of this new information. To include the new information, we can now state Bayes' theorem as follows (T. Stewart, Department of Mathematics and Statistics, UCT, pers. comm.):

$$P(\mathrm{H}|\mathrm{E\&I\&J}) = \frac{P(\mathrm{H}|\mathrm{E\&I}) \bullet P(\mathrm{J}|\mathrm{H\&E\&I})}{P(\mathrm{J}|\mathrm{E\&I})} . \tag{2.3}$$

This equation can be used to calculate $P(\mathrm{H}|\mathrm{I\&E\&J})$, that is the posterior probability that hypothesis H is true, given the original evidence E and both new pieces of information I and J. As before, three factors enter into the calculation and their definitions follow from equation 2.2.

A common difficulty experienced with Bayes' rule is the large amount of data needed to determine the prior probabilities and likelihoods (Stefik, Aikins, Balzar, Benoit, Birnbaum, Hayes-Roth and Sarcedoti 1983b); in most applications not all of the inputs required by the Bayesian probability analyses are available (Lindley 1990, Mosteller and Youtz 1990). In particular, the likelihoods and marginal probabilities, especially where a large number of variables are involved, may be difficult - if not impossible - to estimate.

2.5.4 **Fuzzy Logic**

Fuzzy logic is an outgrowth of the theory of fuzzy sets, developed by Zadeh (1965). The concept comes from the simple observation that nothing is exactly what it appears to be - the original purpose of fuzzy set theory was to model vagueness (or fuzziness), as opposed to uncertainty (Spiegelhalter 1986). For a clear discussion of the distinction between fuzziness and probability, see Gaines (1978).

The key concept of fuzzy logic is that "everything is a matter of degree" (Kosko and Isaka 1993). They explain that the difference between classical logic and fuzzy logic is something Aristotle called 'the law of the excluded middle'. In standard set theory, an object does or does not belong to a particular set; there is no middle ground - it *must* belong to only one set. Sets that are fuzzy, or multivalent, break the law of the excluded middle - but only to some degree. Items belong only *partially* to a fuzzy set. They belong to more than one set. Returning to the example of John's height: if John is five feet tall, he would clearly fall into 'set of short men'; if John is seven feet tall, he would clearly fall into 'set of tall men'. The distinction blurs somewhat if John is six feet tall - he may be considered partially short and partially tall. In this case John has some degree of membership to both sets - in essence, a fuzzy set.

Unlike computers, humans have common sense that enables them to reason in a world where things are only partially true. The human brain can reason with vague assertions or claims that involve uncertainties or value judgments: "The air is cool", or "That speed is fast". Fuzzy logic manipulates such vague concepts. Zadeh (1983) suggests that "fuzzy logic provides a natural conceptual framework for knowledge representation and inference from knowledge bases which are incomplete, imprecise, or not totally reliable".

There are rules for combining possibilities analogous to those for combining probabilities. Zadeh's method involves the use of "possibility theory", which is the fuzzy analog of probability theory. By using the fuzzy combining rules, which involve minimization and maximization rather than multiplication and division, the representation of uncertainty can be calculated (Plant and Stone 1991). It has however, been said "The literature on fuzzy logic is vast, complicated, and somewhat obscure" (Lindley 1985, p13).

For an introduction on building and implementing a fuzzy system see Kosko and Isaka (1993). The Achilles heel of a fuzzy system is in the generation of its rules. Most fuzzy systems built to date have been control systems with few variables and few rules - almost all systems rely on rules supplied by an expert. Knowledge engineers then engage in a lengthy process of tuning those rules and the fuzzy sets to prevent the system converging on an inappropriate solution. The challenge is to tackle large-scale, nonlinear systems with many variables - yet, it is quite probable that there are no experts to describe such systems.

2.5.5 The Reverend Bayes vs. Fuzzy Logic

Statistical theorists, zealous in their belief in one method of calculating uncertainty, display an astounding lack of tolerance for other methods - those who favour the Bayesian approach tend to dismiss any other method of dealing with uncertainty. The debate over the superiority of various methods provides plenty of reading for making comparisons; much of it highly mathematical.

Since Bayesian theory is firmly rooted in probability theory and considered to be "The Established Church", focus is placed on Bayesianism, determining whether and to what extent other theories overcome the difficulties experienced with Bayes' theorem.

Objections to Bayesianism may generally be divided into two categories: i) theoretical questions on the ability of probability theory to adequately represent the process of decision making; and, ii) practical questions on successfully implementing a Bayesian scheme to solve a real problem.

The first category essentially addresses whether probabilities are suitable for describing subjective uncertainty. In the case of the frequency-based definition of probability, a person can do experiments and experimentally show that the axioms of probability correspond well with observations. However, is this statement true for subjective probability as well? Frequentists argue that inference should be based on observed data, and that alone; subjectivity can introduce bias. The debate between frequentists and subjectivists is now an ancient one (see Poirier 1988; Rust, Pagan and Geweke 1988). The connection between the subjective and frequentist interpretations of probability is the assumption that both obey the same mathematical rules. In other words, do people, when asked to assign numbers to their degrees of belief in statements and then combine them in ways that can be modelled probabilistically, arrive at the appropriate probability without the aid of experimentation and calculation as dictated by the frequentists? Unfortunately, there is evidence that they do not (see Plant and Stone 1991, p75-76). Humans have been shown, through both mathematical reasoning and psychological experimentation, to be poor decision-makers in matters involving uncertainty (Tversky and Kahneman 1974; Sanders 1992). See Kopcso *et al.* (1988) for a comparison of the way humans and commercially available expert system shells deal with uncertainty. The Bayesian's response to this criticism is "So what?" The point of Bayesian analysis is to improve upon human judgement, not to imitate it - Bayes' Law is supposed to be a guide to making more rational, consistent and defensible decisions (Hobbs 1994). In reality, it is possible to turn the frequentists argument upside down and assert that evolution favors individuals that are able to successfully deal with the rigors of living in an uncertain environment. Most described statistical experiments involve precisely defined numerical probabilities, so it is fair to ask how frequently (outside the realms of gambling and finance) such numerical situations are actually encountered in "the real world". It can be argued that the results do not demonstrate that humans are poor at dealing with risk and uncertainty - rather, they demonstrate that *untrained* humans are poor at dealing with risk and uncertainty when it is presented in a numerical form (Plant and Stone 1991).

So, while Bayesian methods for dealing with uncertainty exist, their implementation faces theoretical and practical difficulties. How then, are we to deal with uncertainty?

At first glance, fuzzy logic appears to hold the answer - it requires less data and places fewer restrictions on the form of the data than does Bayes' theorem. However, fuzzy logic is a theory of *vagueness* that is being applied to problems in *uncertainty*; it cannot address the theoretical issue of representation of the human reasoning process anymore adequately than Bayes' theorem (Plant and Stone 1991). In addition, fuzzy logic suffers from the same dependence on numerical data of possibly suspect origin as does Bayes' theorem.

Plant and Stone (1991) suggest three other alternatives to deal with this discouraging situation. The first is to develop the knowledge base in such a way as to mimic the actual process of human reasoning; the designer of the expert system can attempt to arrange the logic of the rules to match the approach taken by the user. Expert systems can often deal successfully with uncertainty by emulating the manner in which the human expert deals with it (Plant and Stone 1991). The second alternative, appropriate for situations in which the resources for completing the task are inadequate, is to proceed with a numerical representation of uncertainty, but to use simple *ad hoc* formulas. Plant and Stone (1991) explain that in many applications the most appropriate output from an expert system is simply a listing of all the possibilities together with some coarse classification of the probability of each. The third alternative is to actually use a formal system such as one based on Bayes' theorem. Such an approach is justifiable if the process involves numerically represented uncertainty, as would be the case if the data are available to provide values for the priors and likelihoods.

In promoting the frequentist approach, Neapolitan (1990) argues that although humans may not reason numerically, they reason in terms of the frequencies of events which they experience. He outlines some of the advantages of staying with the frequentist approach: i) we can obtain objective probabilities from information in a database and from time-series *and*, if necessary, augment these probabilities subjectively with data obtained from experts, and ii) if probabilities are given a frequency interpretation, we can substantiate their accuracy as and when more data become available. In the case where we cannot get good frequentist probabilities, investigations by Ben-Basset *et al.* (1980, in Neapolitan 1991) reveal that even some apparently poor probabilities may be good enough to yield accurate results - they show that, in cases where indications are that the numbers are not as good as may be hoped, they may still be good enough to use. They conclude:

> "*.....Bayesian models tolerate large deviations in the prior and conditional probabilities. That is, even rough estimates for which qualitative expressions such as 'rare', 'frequent', and 'probable' serve as guidelines may be accurate enough to result in the recommendation of the correct decision*".

Note that the conclusions of Ben-Basset *et al.* (1980, in Neapolitan 1990) are not a license to plug in any dubious probabilities, rather we should always get the best possible numbers we can; after all, a practicing decision analyst will generally attempt to obtain probabilities from individuals with the most relevant expertise about the events of interest. The point made here is that initial probabilities can always be refined at a later stage in the development process as more information comes to light.

In summary, Bayesian analysis provides a mechanism to incorporate diverse types of data, historical experience, as well as using prior information not previously incorporated into other methods. Although awkward when many parameters are unknown, current trends suggest that Bayesian methods have an important future role in stock assessment (Hilborn 1992), and the provision of management advice (Rosenberg, Fogarty, Sissenwine, Beddington and Shepherd 1993). Bayesian analysis has been used in fisheries applications (Fried and Hilborn 1988; Sainsbury 1988; Thompson 1992; see also the introduction in Hilborn, Pikitch and McAllister 1994), is currently used in the assessments of several fisheries in South Africa (K. Cochrane, Sea Fisheries Research Institute, pers. comm.), and has also been used by the International Whaling Commission (IWC) in a number of their assessments (Raftery, Turet and Zeh 1988).

It is a truism to say that fish production ultimately depends on physical factors ..., and there is little doubt that variation in these factors is somehow involved in the fluctuations that most stocks exhibit

Walters and Collie (1988)

Chapter 3

THE SOUTHERN BENGUELA ECOSYSTEM

3.1 INTRODUCTION

The Benguela System is one of the world's four major eastern boundary current regions dominated by coastal upwelling. It is bounded in the north by the warm Angola Current (at about 16°S) and in the south by the Agulhas Retroflection (at about 35°S) (Shannon 1985). The system is effectively divided into three sections by a strong, perennial center of upwelling in the vicinity of Lüderitz (27°S) (Agenbag and Shannon 1988).

This chapter deals with the environmental factors currently thought to affect the spawning and subsequent recruitment success of the Cape anchovy (*Engraulis capensis*) of the southern Benguela system; accordingly the processes described in this section will be limited to that area of the southeast Atlantic defined as the southern Benguela region by Shannon (1985), viz. the area between 31° S and 35° S. As anchovy spawn on the Agulhas Bank, the centre of which extends to about 36° S and about 21° E, this area has also been included (Figure 3.1).

3.2 GROSS ENVIRONMENTAL VARIABILITY AND COMPLEXITY

Deducing the factors controlling recruitment success in pelagic fish has been of concern to both the fishing industry and fisheries scientists; many attempts have been made to correlate environmental fluctuations to reproductive success of pelagic fish (i.e. recruitment). Previous studies have directed attention toward three classes of environmental processes considered to be likely regulators of recruitment in pelagic fish in upwelling areas: food, and food availability, and transport of eggs and larvae; upwelling is believed to be a linkage between these processes (Bakun 1985).

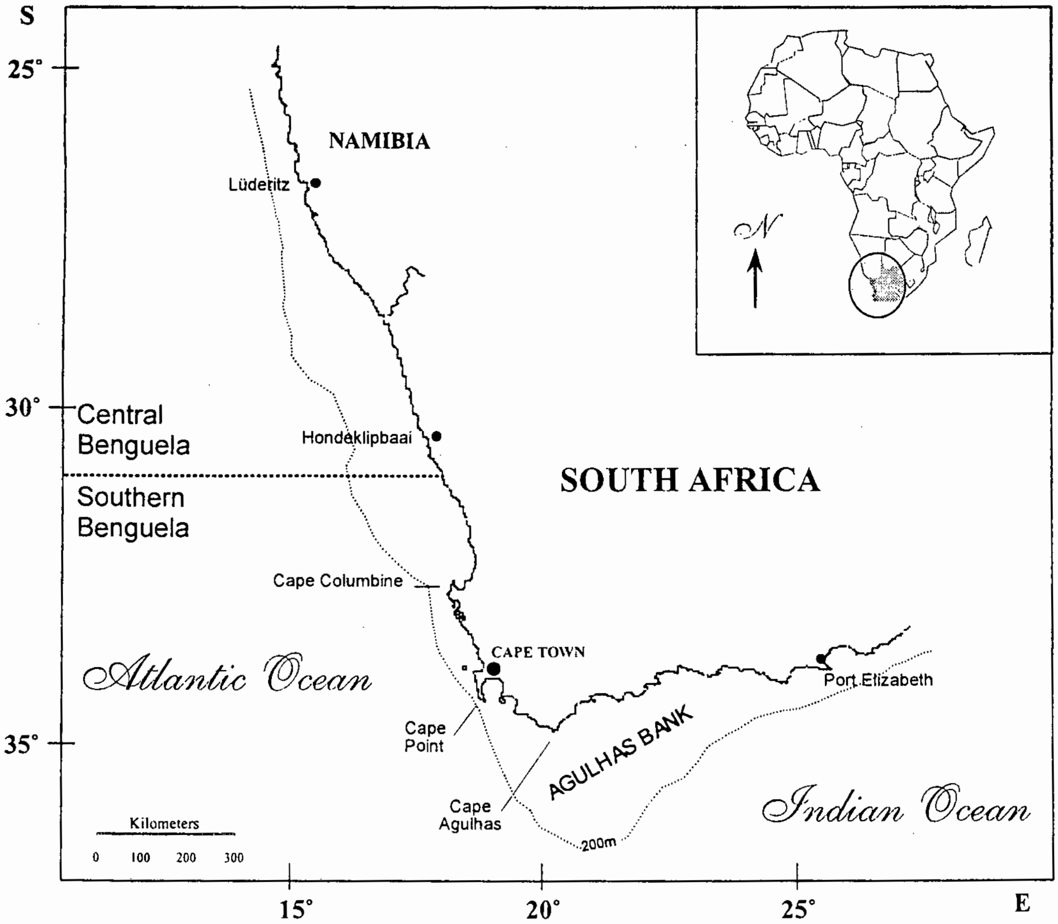


Figure 3.1: The Benguela ecosystem, with areas as defined by Shannon (1985).

The major upwelling regions of the oceans are notable for high levels of primary organic production and massive fish stocks (Bakun and Parrish 1982; see Crawford 1987; Silvert and Crawford 1987; Lluch-Belda, Crawford, Kawasaki, MacCall, Parrish, Schwartzelose and Smith 1989, for descriptions of, and comparisons among these systems). This has led to the belief that fish abundance is dependent on the maintenance of organic production by upwelling processes, and that variations in upwelling, with its many ramifications, may induce stock fluctuations.

Pelagic fish have several requirements in order to build up large populations. Essentially, these requirements include high plankton productivity and standing stocks for feeding and sustained serial spawning (such as found on shallow continental shelves and upwelling regions); warm, stable surface waters for successful development of eggs and larvae and first-feeding of newly hatched larvae; and a transport system to move larvae to suitable feeding grounds (Bakun and Parrish 1982). It has become clear that a number of factors, primarily environmental, play a dynamic role in the early life history of pelagic fishes (see Dahlberg 1979; Blaxter and Hunter 1982; Cruickshank 1990; Le Clus 1990; Campbell and Graham 1991; Castro and Cowen 1991; Jenkins, Young and Davis 1991; Pepin 1991; Brander and Hurley 1992; Fogarty 1993; Mann 1993). However, this does not exclude other factors such as predation, cannibalism and dominance of other species as potentially important regulating mechanisms (see Alderdice and Hourston 1985; Valdéz, Shelton, Armstrong and Field 1987; Campbell and Graham 1991; Valdéz Szeinveld 1990; Laevastu and Bax 1991; Valdéz Szeinveld and Cochrane 1992; Crawford, Underhill, Raubenheimer, Dyer and Märtin 1992; Rice, Miller, Rose, Crowder, Marschall, Trebitz and DeAngelis 1993; Daan 1980; Skud 1982; Korrûbel 1992; Shelton 1992).

With the aim of improving the understanding of variability in pelagic fish, fishery biologists have recently focused attention on the early life history of fish because the early life stages are thought to be the most susceptible to changes in the environment (Shelton 1984; Smith 1985; Peterman, Bradford, Lo and Methot 1988; Armstrong and Shelton 1990). Hjort (1914, 1926) was one of the first to recognize the importance of differential larval mortality giving rise to variable recruitment. One may infer that mortality must be heavy between the egg stage and maturity because pelagic fish typically reproduce by means of repeated spawning (iteroparity), releasing large numbers of eggs into the environment over a protracted spawning season (Shelton 1986). Iteroparity is a potential 'bet hedging' trait in clupeoid fishes (Shelton 1987).

It is important to recognize the differences in scale, both of time and space, on which the various physical/environmental factors influence the biological processes (see Mann and Lazier 1991; Mann 1992), and ultimately affect recruitment (Bakun and Parrish 1982). A distinction must be made between rapid (short-term, perhaps seasonal) and persistent (long-term) changes in the environment - events acting at different periodicities affect the biota in different ways (Armstrong and Shelton 1990), and should be detectable in the population (Waldron, Armstrong and Prosch 1989). The work of Waldron, Armstrong and Roel (1992) reveals that the average rates of growth of juvenile anchovy caught within restricted localities and periods of time are highly variable.

Wind and coastal upwelling are undeniably related; the main coastal upwelling areas are located on the eastern boundaries of the oceans where equatorward trade winds induce offshore Ekman transport (Nelson 1992). Wind driven

upwelling is a feature along the entire West Coast of South Africa (Kamstra 1985, Jury 1985, Taunton-Clark 1985), and is considered to be the dominant short-term variable driving upwelling in the Benguela system (Shannon 1985). In the classical Ekman scheme, the magnitude of the offshore transport in the upper ocean layer is considered to be an indication of the amount of water upwelled along the coast (Bakun 1973, in Cury and Roy 1989).
Wind also plays a role in influencing the thermal structure of the water column - in the Benguela system, winds along the West Coast are seasonally favourable for the upwelling of cold, nutrient-rich water. This stimulates phytoplankton growth and drives the food chain (Cochrane, James, Mitchell-Innes, Pitcher, Verheye and Walker 1993). On a short (seasonal) scale, a shorter than normal period of offshore winds may cause weakened nutrient upwelling and thus a reduction in plankton blooms, leading to possible starvation for the larval stages of pelagic fish (Huntsman and Barber 1977, Armstrong and Thomas 1989). Alternatively, "Lasker Events" - strong local winds causing increased turbulence and inducing mixing of the thermocline, thereby breaking up plankton aggregations - affect the concentration of food items for pelagic larvae and increase larval mortality (Lasker 1978, 1981, 1985; Lasker and Zweifel 1978; Peterman and Bradford 1987; Wroblowski and Richman 1987; Wroblowski, Richman and Mellor 1989). Lasker's hypothesis has been subject to some criticism and alternative explanations. Kiørboe and Nielsen (1990) observe that turbulent mixing actually introduces new nitrogen into the euphotic zone, stimulating copepod reproduction and so increasing the supply of food for first-feeding larvae.

It has also recently been suggested that small-scale turbulence can play an important role when assessing the encounter rates between planktonic predators and their prey (MacKenzie and Leggett 1991, 1993). Rothschild and Osborne (1988) showed that zooplankton feeding rates may be underestimated by failure to consider turbulent motion when estimating the potential encounter frequency between predators and prey. Sundby and Fossum (1990) found that during periods when winds were 6 $m.s^{-1}$, feeding rates of cod larvae increased two-fold compared to periods when winds were only 2 $m.s^{-1}$. MacKenzie, Leggett and Peters (1990) found that wild populations of larval fish feed at rates higher than would be predicted from laboratory studies (in which turbulence is absent or reduced). Bloomer *et al.* (1994) found a strong positive correlation between recruitment and wind velocity. These studies suggest that contact rates, and hence feeding rates of zooplankton and larval fish, may be increased through the action of favourable levels of small-scale turbulence.

Variations in upwelling may also underlie the patterns generated by the short-scale turbulence mechanism (Bakun and Parrish 1982). Upwelling, and its associated offshore transport, may be a favorable factor on long time and broad spatial scales; for example, upwelling prior to the spawning season and upstream of the spawning grounds ensures a good nutrient supply to the water column and subsequent adequate food concentrations for the arrival of first-feeding larvae. The importance of food availability for larvae led Cushing (1975, 1990) to formulate the "match-mismatch" hypothesis. The match and mismatch relates to the coincidence of spawning time with the appropriate components in the food cycle.

The offshore transport component may be unfavorable at specific moments in time and space; for example, a longer than normal period of offshore winds acting at the precise time and location when eggs and larvae are present in the water column, may cause increased egg and larval drift out into oceanic waters (Bakun and Parrish 1982) - resulting in offshore advective loss of these eggs and larvae (Boyd, Taunton-Clark and Oberholster 1992). Hutchings and Nelson (1985) have suggested that wind anomalies need to persist for at least 3-4 months in order to affect recruitment in pelagic fish; however such prolonged anomalies are rare in the southern Benguela region (L. Hutchings, Sea Fisheries Research Institute, pers. comm.).

Armstrong and Shelton (1990) believe that it may be insufficient to only consider clupeoid life-history styles in the context of 'predictable/unpredictable', or 'stable/unstable' environmental conditions. They assert that environmental variation affecting the critical developmental stages of the species concerned should be considered in more detail since changes in the environment giving rise to even small negative changes in juvenile mortality, could lead to catastrophic effects for a commercial fishery. Several studies suggest that relatively small reductions in mean growth rate during the early life history may cause cohort survival to decrease by one to two orders of magnitude simply by prolonging the period of vulnerability to mortality sources (Chambers and Leggett 1987; Houde 1987, 1989; Pepin 1990). This has been suggested for the South African anchovy:

> "*a decline in average growth rate from 0.4 to 0.3 mm.d*$^{-1}$ *would result in a drop in the mean length of 200-day-old fish from 80 to 60 mm. [...]. A fixed commercial catch quota comprising mainly juvenile anchovy would therefore result in a more than doubling of the fishing mortality, increasing the risk of undesirable levels of stock depletion*" (Waldron *et al.* 1989).

Thus, as local environmental parameters differ spatially and temporally, so larval survival can sometimes be positively or negatively correlated with these parameters. There are many examples in the literature of correlations between environmental factors and changes in fish stocks. However, these correlations frequently hold for a few years only before breaking down.

The theory of and 'optimal environmental window' for upwelling regions (Cury and Roy 1989) suggests that by optimising local constraints, pelagic fish can maximise recruitment. This hypothesis suggests that for Ekman-type upwelling ecosystems, there is an optimum wind mixing level in the stable upper layers of the ocean, and therefore an optimal level of upwelling intensity. Roy, Cury and Kifani (1992) suggest that a dome-shaped relationship exists between recruitment success and wind intensity (Figure 3.2).

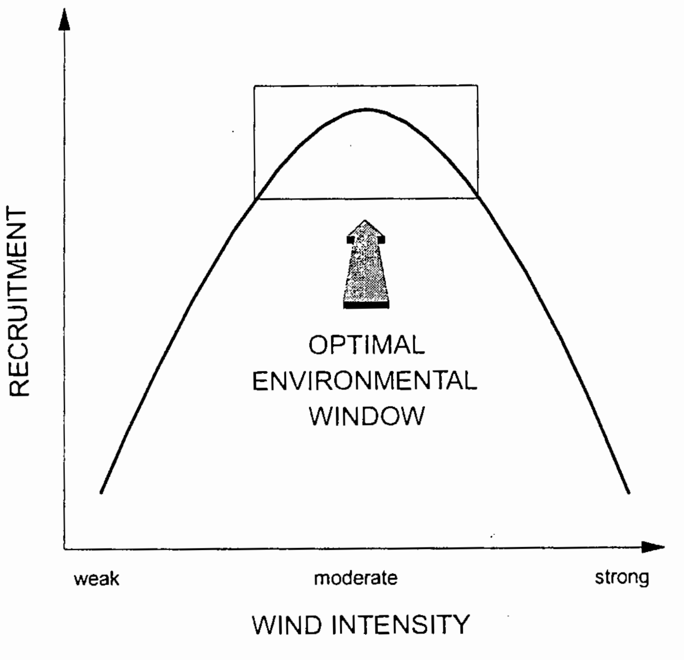


Figure 3.2: The theoretical relationship between recruitment and environmental factors in upwelling areas (from Roy *et al.* 1992).

Roy *et al.* (1992) explain:

> "*On the left side of the curve, wind and upwelling intensities are weak to moderate; enhanced food production or increased encounter rate between larvae and food particles as a result of small-scale turbulence may then be beneficial for survival of larvae. On the right side of the curve, upwelling is strong, and wind-mixing and offshore transport are then the detrimental factors*".

In summary, it is believed that in an upwelling system characterized by pulsed primary production and wind-induced turbulent mixing and offshore Ekman transport, the multiple spawning behaviour of clupeoid fishes reduces the potentially wide fluctuations in reproductive success. The various clupeoid fishes appear to have adopted iteroparity to cope with the problem of environmental variability, thereby ensuring maximal egg and larval survival (Shelton 1987).

3.3 CAPE ANCHOVY IN THE SOUTHERN BENGUELA REGION

The requirements for pelagic fish (as defined by Bakun and Parrish 1982) are satisfied off the South African coast by the Benguela upwelling zone, the Agulhas Bank and the Cape Columbine frontal jet current (Figure 3.3) (Hutchings and Nelson 1985).

Marine environmental variability has important consequences for the biota in the Benguela region (Crawford, Shannon and Pollock 1987; Crawford, Siegfried, Shannon, Villacastin-Herrero and Underhill 1990; Shannon, Crawford, Pollock, Hutchings, Boyd, Taunton-Clark, Badenhorst, Melville-Smith, Augustyn, Cochrane, Hampton, Nelson, Japp and Tarr 1992). The southern Benguela pelagic ecosystem is characterized by variable physical forcing (Shannon 1989; Shannon and Agenbag 1990) at time scales from hours to decades (Shelton 1989). A number of environmental cycles are clearly apparent in the Benguela ecosystem (Taunton-Clark and Shannon 1988). A recent investigation suggests that the environment plays a large role in these fluctuations (Anon. 1991). Natural selection however, implies that the reproductive strategies observed in large populations of pelagic fish represent successful accommodation to the most crucial environmental factors (Bakun Parrish 1982; Shannon, Crawford, Brundrit and Underhill 1988).

Anders (1965), appears to be the first to make observations on anchovy spawning off the South African coast. Well defined age-specific, seasonal patterns of distribution and availability have been found for pelagic fish off South Africa's Western Cape coast (Crawford 1980). Hampton (1987, 1992) gives detailed information on the distribution and abundance of anchovy off South Africa. The major spawning ground for anchovy is on the Agulhas Bank, while the main nursery grounds for the young are along the West Coast (Crawford *et al.* 1987) (Figure 3.3).

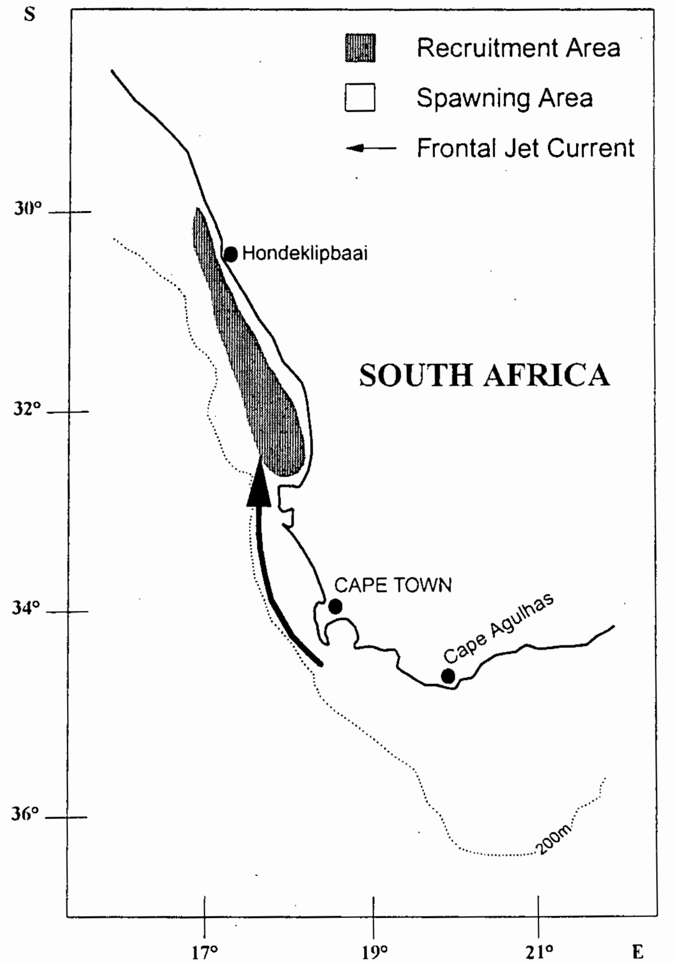


Figure 3.3: The southern Benguela ecosystem, with areas of most intense spawning and recruitment, with transport from one to the other by means of a frontal jet current (after Shelton and Hutchings 1982).

Spawning in Cape anchovy, *Engraulis capensis*, is largely confined to the period October to January in the area extending east of Cape Point down to Cape Agulhas (Shelton 1981, 1986). Eggs, larvae and pre-recruits are carried from the spawning grounds to the recruitment area in a north-westerly direction by the prevailing currents; pre-recruits (2-4 cm in length) are widespread offshore along the West Coast shelf region, from where they presumably migrate or are passively moved shorewards (Hutchings 1992), before beginning a return migration back to the spawning grounds (Crawford *et al.* 1987). During this return migration, the 0-year old fish recruit to the fishery, with peak recruitment in approximately May/June, a period six months after the peak in egg production (Shelton 1981). It is important to note that the commercial fishery targets predominantly migrating 0-year olds; catches consist almost entirely of 0-year old fish (Bergh 1986; Cochrane, Hampton and Roel 1991). The anchovy fishery is thus dependent on annual recruitment, rendering it highly susceptible to recruitment failure.

In an attempt to ascertain the major factors affecting the Cape anchovy in the southern Benguela region, attention will be directed toward processes thought to be likely regulators of recruitment success: that is, food and food availability, both preceding spawning and during spawning, and transport of eggs and larvae from the spawning grounds to the recruitment area. Upwelling, a third factor considered by Bakun (1985), is implicated in egg and larval transport, and will also be discussed.

3.3.1 **Food and Food Availability**

The anchovy, a facultative filter-feeder, practices size-selective omnivory throughout its life (James 1987). Migrating down in the coastal zone along the West Coast, juvenile anchovy consume phyto- and zooplankton. The mode of feeding (particulate- or filter-feeding) and the consumption rate are determined largely by the concentration and size spectrum of food particles in the water column (James and Findlay 1989); these vary considerably in response to upwelling and stabilization of the water column (Pitcher, Brown and Mitchell-Innes 1992). It is energetically more advantageous for anchovies to feed on large food items (James and Findlay 1989), and in this way, the fish may acquire the bulk of their food by size-selective feeding on the largest available particles. It is vital that the surviving juveniles (future spawners) build up condition while on their migration down the West Coast so that they may begin producing eggs shortly after reaching the spawning grounds on the western Agulhas Bank. If the recruits encounter marginal feeding conditions over the duration of their migration, they will arrive on the spawning grounds in poor condition, first having to gain condition before spawning can begin, or reach a certain size for maturity to occur (L. Hutchings, Sea Fisheries Research Institute, pers. comm.).

Shannon and Field (1985) state that it was widely thought that food is not a limiting factor for pelagic fish in the southern Benguela system; the view expressed is that there is an obvious excess of phytoplankton production in the system. However, it has been suggested (Shannon and Henry 1983) that food may be limiting for pelagic fish in the Benguela system. Daily ingestion rates (wet mass ratio) for *E. capensis* are estimated by James and Findlay (1989) to lie in the range 3.46 to 4.32 per cent (mean 3.76%) of the body mass, demonstrating that under average conditions anchovy could fulfill their daily requirement in the southern Benguela system. The biomass of each year class of anchovy can therefore be expected to increase through the larval and juvenile stages because somatic growth exceeds the rate of mortality (Armstrong, James and Valdéz Szeinveld 1991). However, as a result of the high variability in a strongly pulsed upwelling system such as the southern Benguela, the probability of "match-mismatch" phenomena is greatly increased. For example: newly upwelled water supplies nutrients for phytoplankton growth (on the order of 4-10 days), which are prey for the slower growing zooplankton (on the order of 20-60 days), which in turn are prey for even slower growing anchovy (6-18 months) (J. Field, Marine Biology Research Institute, pers. comm.).

The Agulhas Bank supports a large population of planktivorous pelagic fish during the summer months (Roel, Hewitson, Kerstan and Hampton 1994; Armstrong *et al.* 1991). Parrish, Bakun, Husby and Nelson (1983) presume that the stability of the water over the Agulhas Bank during the spawning season could allow for high concentrations of food suitable for anchovy; indeed, Shelton and Hutchings (1990) note the presence of food-enriched layers of the Agulhas Bank during the spawning season. Good feeding conditions for the adults on the spawning grounds are vital to maintain condition in order to sustain serial spawning over the 3-4 month spawning season, and prevent gonad atresia. On the western Agulhas Bank however, zooplankton biomass appears to be subject to severe fish predation, and may drop to below the level necessary to maintain spawning in anchovy (Verheye, Hutchings, Huggett, Carter, Peterson and Painting 1994): low standing stocks of zooplankton (<0.5 g C m^{-2}), primarily the large copepod *Calanus agulhensis*, are observed on the western Agulhas Bank when dense concentrations of anchovy occur (implying a predatory impact by the spawning adult fish; Hutchings 1994).

3.3.2 **Transport of Eggs and Larvae, and Upwelling**

To reach the recruitment grounds on the West Coast, anchovy eggs and larvae depend on some method of transportation from the spawning grounds. Ample evidence exists for the presence of a seasonal jet current (the "Good Hope Jet" of Bang and Andrews 1974), rounding Cape Point from the western Agulhas Bank and moving northwards past Cape Columbine (Shelton and Hutchings 1982; Nelson and Hutchings 1983) (Figure 3.4). The jet current is stronger in summer than in winter (Bang and Andrews 1974), coinciding with the period of anchovy spawning on the western Agulhas Bank. Transects of the jet current show the presence of both anchovy eggs and larvae (Shelton and Hutchings 1990).

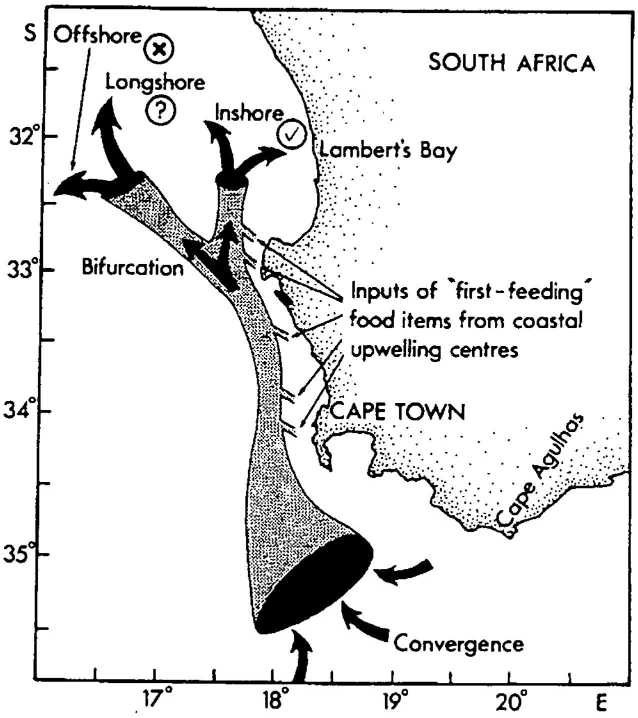


Figure 3.4: Model of anchovy egg and larval transport from the western Agulhas Bank to the West Coast, showing convergence of the Bank, inputs of particles suitable for first-feeding larvae from coastal upwelling centers, and the bifurcation of the frontal jet system near Cape Columbine (from Hutchings 1992).

A comparative study of seasonality and geography of ocean transport and fish reproductive strategies has indicated a general pattern of avoidance of intense offshore flow conditions in the reproductive habits of coastal fish stocks (Parrish, Nelson and Bakun 1981). However, bifurcation of the jet current near Cape Columbine (Shannon 1985; Boyd *et al.* 1992), probably separates eggs and larvae into those entering the nearshore environment along the West Coast immediately (✓), later (?), or perhaps never (X) (see Figure 3.4). Even though the jet current normally follows the shelf-edge, limiting the offshore extent of larval drift (Shelton and Hutchings 1990), the bifurcation is considered to be a potential source of considerable loss of anchovy reproductive products (Hutchings 1992).

Moreover, any changes in the movement of Agulhas water into the southeast Atlantic may adversely affect the transport of spawning products (Boyd and Shillington 1994); particularly if Agulhas Rings occur in close proximity to the coast and either divert the jet current offshore (Shillington, Hutchings, Probyn, Waldron and Peterson 1992) beyond the outer edge of the West Coast shelf and into the oligotrophic waters of the "oceanic desert", or extract frontal water and actually prevent the return of this water - laden with spawning products - to the shelf region (Duncombe Rae 1991; Duncombe Rae, Boyd and Crawford 1992).

Shelton and Hutchings (1990) have shown conclusively that both anchovy eggs and larvae are associated with the upwelling frontal zone. For first-feeding larvae entrained in the jet current during transport, an adequate food supply is assured - results of a study by Armstrong, Mitchell-Innes, Verheye-Dua, Waldron and Hutchings (1987) show that copepod eggs and young stages (nauplii and copepodites) also accumulate in the vicinity of the jet current; Hutchings (1992) suggests a mechanism for the input of food particles from centres of upwelling into the jet current (see Figure 3.4).

Public agencies are very keen on amassing statistics
- they collect them, add them,
raise them to the nth power,
take the cube root and prepare wonderful diagrams.

But what you must never forget,
is that every one of those figures
comes in the first instance from the village watchman,
who just puts down what he damn pleases.

Sir Josiah Stamp

Chapter 4

DATA AND ASSUMPTIONS

4.1 INTRODUCTION

The major problem in predicting recruitment in the South African anchovy, or any fish for that matter, is obtaining acceptably accurate estimates of the biological and environmental factors thought to impact the recruitment process for possible association with recruitment. Also, only limited recruitment data are available, from no earlier than 1984, when objective estimates of anchovy biomass and recruitment were first obtained. The models discussed later are therefore limited to using those biological and environmental factors having time-series corresponding to the recruitment estimates, primarily those presently monitored by the Sea Fisheries Research Institute (SFRI). However, note was also taken of other factors not monitored by the SFRI, but considered to be potentially important. This chapter describes the data and their origins, and the assumptions surrounding the relationships of the environmental and biological factors to recruitment.

Shipborne acoustic surveys of clupeoid spawner and recruit biomass off the South African coast have been undertaken aboard the F.R.S. *Africana* and F.R.S. *Algoa* (June 1995) by the Sea Fisheries Research Institute, in November and May/June/July respectively, since 1984 (Hampton 1987).

Although other pelagic species are encountered, the November ('spawner biomass') survey, is primarily aimed at estimating the spawning biomass of Cape anchovy (*Engraulis capensis*), midway through the peak of the spawning season, and sardine (*Sardinops sagax*). In addition, this survey monitors a number of biological and environmental parameters suspected of influencing the recruitment process. The November survey provides most of the biological and environmental data on which a recruitment forecast (for the following year) could be made.

An (austral) autumn/winter 'recruit' survey takes place sufficiently later (in the period May to July), ensuring that the bulk of the recruits are acoustically detectable (at caudal lengths of 5cm, that is about 3 months old; Prosch 1986), and close inshore. This survey is aimed at estimating the biomass and mean fish density of recruits, viz. the recruitment strength from the preceding spawning season. Random samples of fish are taken from each trawl for age estimation and for the purposes of calculating the birthdate distribution (Waldron *et al.* 1989, 1992, and Waldron 1994).

Each survey is undertaken along a stratified random grid, usually with four or five strata. Within each of these strata, a number of lines, randomly spaced and at right angles to the shore, are surveyed. Each line is devided into 5 or 10 nautical mile intervals (for spawning and recruit surveys respectively), with sampling taking place at the beginning and end of each interval. The lines extend from as close to shore as the ship is able to approach (usually within one nautical mile), to the point at which no further fish eggs (spawning surveys), or fish (recruit surveys), are encountered. Each cruise usually surveys approximately 35 lines and samples over 350 stations (see Hampton 1987 for a detailed description of the survey methods).

4.2 ESTIMATION OF RECRUITMENT STRENGTH

Two estimates of recruitment strength are obtained each year. The first is the actual measurement of the abundance of recruits, on the west and partially on the south coast, obtained from the mid year acoustic survey. The survey results show a fluctuation in the biomass of recruits, with a minimum of 109 thousand tons recorded in 1994 to a maximum of 575 thousand tons recorded in 1987 (Figure 4.1).

The second estimate is obtained in hindsight from the time-series of adult spawner biomass and recruit survey results, which are used in a Bayes-like estimation procedure incorporating fishing mortality and natural mortality, to estimate the number of recruits available to the fishery at the beginning of the year by back-calculation. The application of the estimation procedure is described in Bergh and Butterworth (1987) and Butterworth and Bergh (1993). During the period over which the spawners and recruits have been surveyed, the estimated number of recruits produced per year has ranged from a minimum of

134.2 billion individuals in 1989 to a maximum of 538.9 billion individuals in 1991 (Figure 4.2).

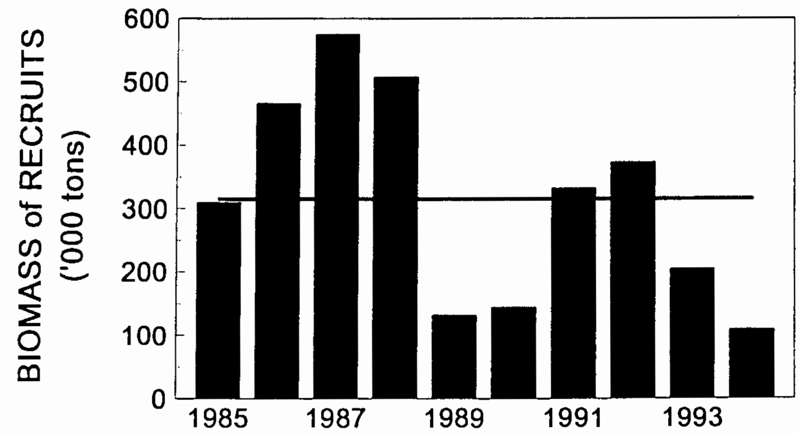


Figure 4.1: Biomass of recruits for the Cape anchovy, *Engraulis capensis*, from the mid-year recruit surveys 1985-1994. The horizontal line indicates the overall mean. Data from Sea Fisheries Research Institute (unpublished).

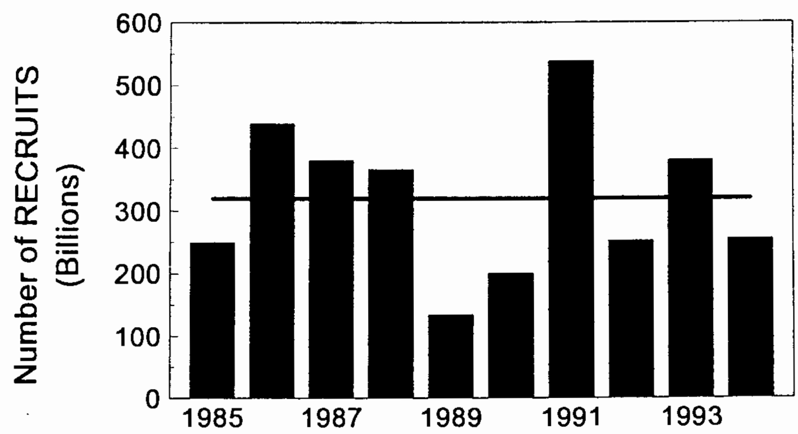


Figure 4.2: Estimated number of recruits, from the estimation procedure, for Cape anchovy, *Engraulis capensis*, 1985-1994. The horizontal line indicates the overall mean. Data from Sea Fisheries Research Institute (unpublished).

On average, the two time-series above correspond very well. If we take the respective means of these recruitment indices, and assume that values above the mean indicate periods of above average recruitment, we can say that the periods 1986-1988 inclusive and 1991 had above average recruitment, while the years 1985, 1989-1990 and 1994 are periods of below average recruitment. There is some disagreement however, for the years 1992 and 1993 - the 'biomass index' suggests above average recruitment for 1992 and below average recruitment for 1993, while the 'number index' suggests the opposite. It has been suggested that fishing mortality may be responsible for this discrepancy. Fishing commences in mid-January on adult fish available from the November-December spawning aggregation. Recruits however, only become available to the fishery some 4 months later. In essence then, only 1 to 2 months of fishing can take place on recruits between the November spawner survey and the mid-year recruit survey. In 1992 the biomass of recruits was above average, suggesting that above average recruitment was about to follow. Also, the mean individual mass of the recruits was above average (Table 4.1), suggesting that spawning had taken place early on in the season. It is possible that fishing mortality could reduce the number of recruits before the recruit survey took place, but as explained above, this is unlikely. In addition, the mean individual mass of the recruits in 1993 - the lowest on record (Table 4.1) - suggests that spawning occurred substantially later than usual. This would have resulted in late recruitment to the fishery, and little or no recruit fishing mortality prior to the recruit survey. An alternative suggestion for this discrepancy is that the recruits were "missing" from the west coast survey area during the time of the recruit survey - presumably there was delayed migration and they were still on the south coast - and therefore not surveyed.

YEAR	BIOMASS ('000t)	INDIVIDUAL MASS (g)	NUMBERS (billions)
1985	310	3.96	78.28
1986	466	4.48	104.02
1987	575	5.82	98.80
1988	508	4.35	116.78
1989	132	5.25	25.14
1990	144	3.17	46.00
1991	332	5.34	62.17
1992	373	4.50	82.89
1993	204	1.93	105.62
1994	109	4.28	25.47

Table 4.1: Anchovy recruitment estimates from the mid-year acoustic surveys, 1985-1994. Data from Sea Fisheries Research Institute (unpublished).

It has been found that the biomass figure from the mid-year recruit survey, back-calculated to January in the same manner as in the estimation procedure, on average under-estimates the estimation procedure by a factor of 0.72 (Cochrane and Starfield 1992). The estimate from the estimation procedure (numbers of recruits) is therefore considered to be the more reliable index and is the estimate used in this study to judge years of below average recruitment.

4.3 CHOICE OF VARIABLES

Local scientists from the Sea Fisheries Research Institute and the Zoology Department, University of Cape Town, considered to be experts in various aspects of the pelagic fishery, were invited to attend workshops with respect to providing their insight into the possibilities surrounding the forecasting of recruitment in South African pelagic fish stocks (a list of participants may be found in Appendix 1). An initial workshop was held to extract from the experts, a list of possible predictors of pelagic fish recruitment. As a collective, the experts were asked to subjectively put forward factors - biological and environmental - that they felt could possibly serve as predictors for anchovy recruitment. The following list was produced:

- the presence of small and large (*phyto*)plankton cells on the west coast - as an indicator of food for zooplankton,
- a starvation index for the spawning fish on the spawning grounds,
- a (direct) condition index of the spawners,
- level of egg production,
- some index of wind stress,
- some index of the activity of the Cape Columbine Jet Current,
- commercial oil yield (as an indicator of fish condition),
- sea surface temperature (SST) (in the spawning and transport areas),
- distance offshore of the 16° isotherm at Cape Columbine,
- incidence of alpha oocyte (gonad) atresia in (female) anchovy, and
- incidence of phenomena associated with El Niño - Southern Oscillation (ENSO).

However, to consider any one variable useful as a predictor of recruitment for a prospective management scheme, it is thought that the variable must:

- show a clear cyclical pattern which is repeated on an annual basis, with suitable differences between the highest and lowest values,

- be available before the start of the fishing season (i.e. in January), and
- be relatively easy to obtain and use.

The predictors were then reviewed individually and the initial list revised on the basis of data availability and ease of monitoring. A few of the variables suggested are not being monitored at present but were earmarked as being important for future research and monitoring programs.

These are:

- presence of small and large (phyto)plankton cells on the west coast,
- (direct) condition index of spawners, and
- the activity of the Cape Columbine Jet Current.

From this initial workshop, it emerged that the experts considered the following indices/processes to be the most significant criteria governing successful spawning and recruitment:

- the size and condition of the fish in the spawner stock (i.e. readiness/fitness to spawn) upon their arrival on the spawning banks,
- an index of spawning success,
- an index of food availability for the spawners while resident on the spawning banks, and
- an index of egg and larval transport success.

These variables are assumed to influence recruitment via the relationships described below.

4.3.1 Size and Condition of the Spawners:

The overall result from each November survey is an estimate of the total biomass and length structure of the anchovy and sardine populations.

Size

ASSUMPTION: the presence of small fish (i.e. immature fish not yet ready to spawn) suggests that delayed spawning took place, resulting in decreased egg production at the "correct time" (i.e. in the optimal window). This may lead to increased mortality of eggs and larvae as they fall outside of the optimal period, increasing the chance of below average recruitment.

EXPLANATION: It is important to be able to separate recruits (0-year fish) from adults (1+ year fish). This is usually done by assuming that all fish shorter than 10.5cm in total length are recruits - this is consistent with the observed growth rate of the South African anchovy (Prosch 1986). Recruits are assumed to have lower spawning capabilities than adults.

Condition

Until now, a direct index of the condition of the spawner stock as the spawners arrive on the spawning grounds (western Agulhas Bank) has not been obtained. The variable used to obtain an indirect index of fish condition is the average annual commercial oil yield.

ASSUMPTION: low oil content of recruits suggests poor energy reserves for fish coming onto the spawning grounds which results in reduced early egg production, and also an increased probability of non-sustained egg production and increases the chance of below average recruitment (Figure 4.3).

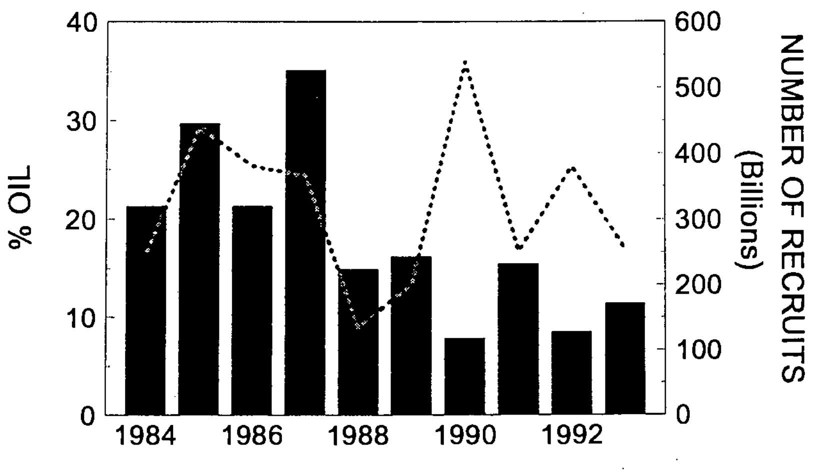


Figure 4.3: The oil yield obtained by the pelagic fishing industry as a percentage of the fish meal produced in the reduction process, 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals) for Cape anchovy, *Engraulis capensis*, for the following year. Data from Stuttaford (1994) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: The oil parameter is the average annual oil yield obtained from the commercial fisheries (for all pelagic species combined) over the fishing season *prior* to spawning (Schülein, Crawford and Underhill 1991). Oil yields are available at the end of the commercial fishing season - unfortunately this is approximately August of each year (F. Schülein, Sea Fisheries Research Institute, pers. comm.), and therefore does not overlap the start of the spawning season. Nevertheless, it is assumed that the average annual oil yield can be used as a 'condition factor', giving one an indication of the 'fitness' of the spawners before they arrive on the western Agulhas Bank to spawn. The condition that the fish are in when they arrive on the spawning grounds is considered to be a major factor regulating sustained egg production (L. Hutchings, Sea Fisheries Research Institute, pers. comm.).

4.3.2 **Food Availability on the Spawning Grounds:**

Copepods have been shown to be the primary source of nutrition for the Cape anchovy (James 1987, and James and Findlay 1989). During the November survey, a CalCOFI Vertical Egg Tow (CalVET) net haul (Smith, Flerx and Hewitt 1985) is undertaken at each sampling station, from 200m depth or 5m from the bottom, whichever is less, to the surface. From 1988, a vertical Bongo net (mesh size = 200μm), has been combined with the CalVET net assembly (Cochrane and Hutchings 1992). The Bongo net samples are used to estimate the biomass and species composition of the mesozooplankton. From these data, an index expressing the amount of food available to the spawning fish is calculated. This index, expressed as the percentage of "starvation stations", records the number of individual sampling stations where anchovy were food-limited; that is, those sampling stations with a biomass of copepods, and their estimated daily production for that day, less than the maintenance ration for the standing stock of anchovy (based on the assumption that anchovy ingest 2% of their body mass per day - James 1987, and James and Findlay 1989). This index gives an indication whether reproduction in anchovy will be food limited (Peterson, Hutchings, Huggett, and Largier 1992).

Starvation Index

ASSUMPTION: A large percentage of "starvation stations" suggests that less food is available than required by the spawning fish in the spawning area which results in a reduction in spawning ability (and reduced probability of sustained spawning) and increases the chance of below average recruitment (Figure 4.4).

EXPLANATION: The possibility that anchovy spawners can be food-limited is suggested by historical data - Pillar (1986) showed evidence for reduced biomass of zooplankton over the main anchovy spawning area (the western Agulhas Bank) during 1977/78.

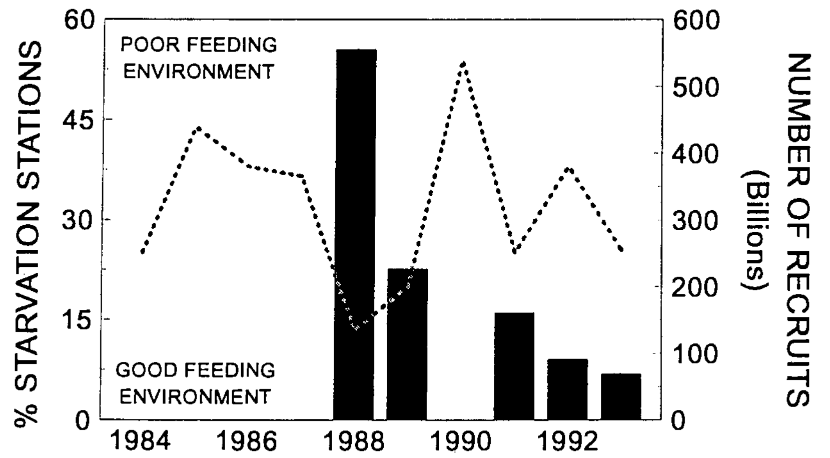


Figure 4.4: Percentage "starvation stations" encountered during the November Spawner Biomass survey, 1988-1993 (note: there are no data for 1984-1987; 1990 is zero). The broken line (···) indicates estimated recruitment (billions of individuals) for Cape anchovy, *Engraulis capensis*, for the following year. Data from Verheye and Hutchings (1994).

Food availability is considered to be a factor regulating sustained egg production by the spawner stock; a large percentage of "starvation stations" on the spawning grounds is considered to decrease the probability of sustained spawning. This has more serious implications if the fish arrive on the spawning banks in poor condition (low commercial oil yields should forecast this). Should this occur, sustained spawning may however still be achieved by the availability of food: i.e. a small percentage of "starvation stations", thereby allowing the spawning anchovy to meet their daily maintenance requirements and increase their level of egg production.

4.3.3 **Spawning Success:**

During the November survey, success (or failure) of spawning is estimated by two different approaches: mean daily egg production per unit area, and the proportion of females undergoing alpha oocyte (gonad) atresia (the degeneration of developing eggs within the ovary).

A CalVET net haul is undertaken at each sampling station, from 200m depth or 5m from the bottom, whichever is less, to the surface. The CalVET net sample

is used to estimate anchovy egg abundance at the time of the survey. Additional data are collected on the November surveys for the estimation of the number of eggs in the water, the batch fecundity and spawning fraction of the females and the mean female mass in the spawning populations (Cochrane and Hutchings 1992). The age of the eggs collected during the survey is estimated, and the abundance at age is used to estimate egg mortality. The above parameters yield an estimate of the mean daily egg production per unit area (Cochrane and Hutchings 1992). For an in depth discussion of the egg production method, the reader is referred to Shelton, Armstrong and Roel (1993).
The percentage atresia is estimated from the ovaries of females collected during the survey (Melo 1994a,b).

Mean Daily Egg Production

ASSUMPTION: reduced egg production by the spawners results in fewer eggs available for hatching and subsequent development, thereby increasing the chance of below average recruitment (Figure 4.5).

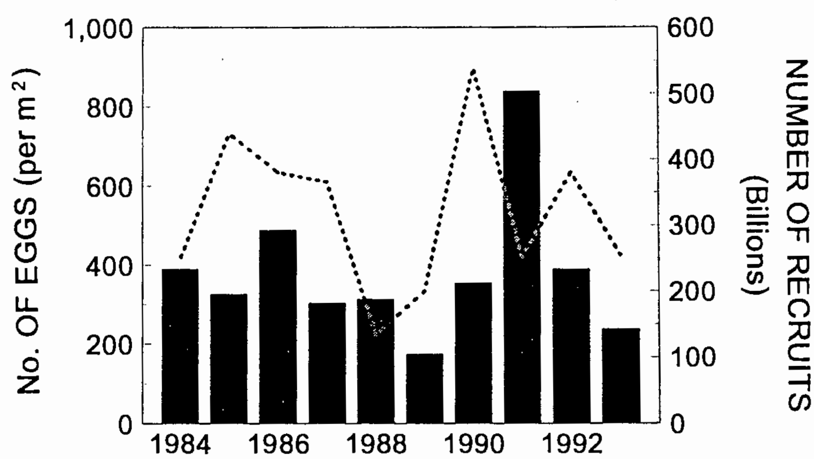


Figure 4.5: Mean daily egg production for Cape anchovy, *Engraulis capensis*, 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals) for the following year. Data from B. Roel-Payne (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: Reduced egg production is assumed to result in relatively few offspring at the start of the recruitment process, thus increasing the probability of fewer recruits. Also, using egg production as a predictor of recruitment, is one step shorter in the causal chain than the classical stock-recruitment relationship.

Incidence of Alpha Oocyte Atresia

ASSUMPTION: Increased frequency of alpha oocyte atresia will result in reduced egg production, causing a reduced number of eggs available to develop into recruits and thereby increasing the chance of below average recruitment (Figure 4.6).

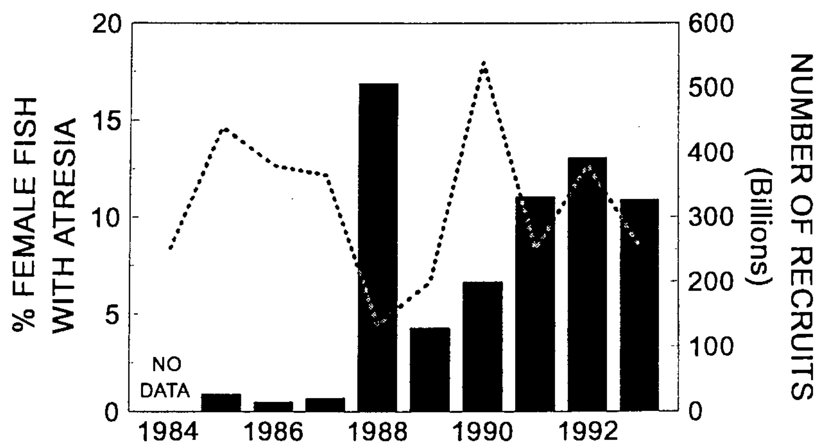


Figure 4.6: Percentage female Cape anchovy, *Engraulis capensis*, with alpha oocyte atresia during the November Spawner Biomass survey, 1985-1993 (note: there is no datum for 1984). The broken line (···) indicates estimated recruitment (billions of individuals), for the following year. Data from Melo (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: Successful spawning is dependent on the amount of energy available for reproduction - resorption of gonad material takes place if there are inadequate energy reserves available for oocyte maturation - which is dependent on the prevailing condition of the spawning fish. In stage 1 or alpha (α) stage oocyte atresia, the entire oocyte (including the yolk, if present) is resorbed, leaving only the follicular layers (Hunter and Macewicz 1985). Atretic conditions can result from poor feeding conditions (starvation), low water temperature, and "a host of other variables" (Hunter and Macewicz 1985). Smaller females also show higher rates of ovarian atresia than larger females (Hunter and Macewicz 1985).

Historically (pre 1988), there appears to have been little alpha oocyte atresia in the South African anchovy; only between 0.5-1.0% of females examined during the spawning seasons of 1985-87 showed signs of atresia (Melo 1994a) - this is considered "normal" (Y. Melo, Sea Fisheries Research Institute, pers. comm.). Atresia of the gonads usually only becomes marked as the spawning season draws to a close (February - March) and the remaining advanced oocytes are resorbed (Melo 1994a,b). However, anchovy showing alpha stage oocyte atresia during the spawning season have only a 50% probability of spawning (Melo 1994a,b). This suggests that if a significant number of females is affected, a substantial lowering in egg production may be expected and hence a reduction in the subsequent recruitment.

4.3.4 **Egg and Larval Transport Success:**

In addition to physical and biological conditions within the spawning (and nursery) areas, the role of wind and currents in transporting eggs and small larvae is thought to be of considerable importance in regulating recruitment (see Parrish *et al.* 1981; Bakun and Parrish 1982; Parrish *et al.* 1983; Lasker 1985). Wind is considered to be the dominant short-term variable driving upwelling and currents in the southern Benguela system (Shannon 1985), and it has been suggested to play a role in recruitment of the South African anchovy (Shelton and Hutchings 1982, 1990; Hutchings and Nelson 1985; Boyd *et al.* 1992; Hutchings 1992).

Since the eggs and larvae of the anchovy are most abundant in the upper layers of the water column, reversals in the direction of their transport are subject to changes in wind direction (Shelton and Hutchings 1982). The predominant wind directions in the southern Benguela are south-easterly and north-westerly. Southerly winds enhance upwelling on the west coast of South Africa, and are thought to increase offshore transport of eggs and young pelagic larvae, thereby increasing losses of these spawning products to the offshore environment. Westerly winds reduce upwelling on the west coast, and are thought to reduce losses of pelagic eggs and larvae by offshore transport. Monthly accumulated wind displacements to the south and west are measured at a station at Cape Point, latitude 34.5°S (Hutchings and Taunton-Clark 1990). Each value in the time-series, is the total cumulative windrun for that month, less the averaged windrun from 1960 (J. Taunton-Clark, Sea Fisheries Research Institute, pers. comm.).

Since 1990, Acoustic Doppler Current Profiler (ADCP) measurements have been undertaken at most of the sampling stations during the November survey (Boyd *et al.* 1992). Information on current strength and direction should assist in identifying any abnormal losses of eggs and larvae to the offshore environment. Although the time-series is short, simulation modelling of the transport process (L. J. Shannon 1995) is showing some important results (Boyd, Schülein, L. V. Shannon, Taunton-Clark 1994; Boyd and L. J. Shannon 1995).

The distance offshore of the 16°C isotherm at latitude 33°S (Cape Columbine), will give an indication of the extent of upwelling, and hence, productivity in this region (Shannon and Pillar 1986). Additionally, the thermal structure of the water column is potentially important; sea surface temperature in the spawning and transport areas play a significant role in regulating spawning and hatching success.

It has been suggested (Anon. 1991) that the 1989 decline in the anchovy biomass was caused by recruitment failure as a result of unfavourable environmental conditions, that is, "*substantial changes in the large-scale meteorology and oceanic oceanography*", which prevailed during the 1988/89 spawning season. This appears to correspond with a Southern Oscillation event. The El Niño-Southern Oscillation (ENSO) is a large scale ocean-atmosphere occurrence that extends over the whole Pacific and may be important as its effects globally are numerous; manifestations have been detected worldwide (Derr and Slutz 1994). A commonly used method to monitor the ENSO is the Southern Oscillation Index (SOI), which represents the sea-level atmospheric pressure difference between Tahiti and Darwin (Australia). The index is calculated as the difference, Tahiti minus Darwin, of the standardised monthly pressure anomalies. Negative anomalies are termed El Niño while positive pressure are termed La Niña, also known as "anti-El Niño" (Kerr 1988).

Index of Wind Stress

ASSUMPTION: high incidence of southerly winds during the spawning season suggests strong turbulence and offshore advection of the west coast surface water (and bifurcation of Cape Columbine jet current [Hutchings 1992]), resulting in strong upwelling and wind-mixing, and a large loss of spawning products and larvae to the offshore environment, thereby increasing the chance of below average recruitment (Figure 4.7).

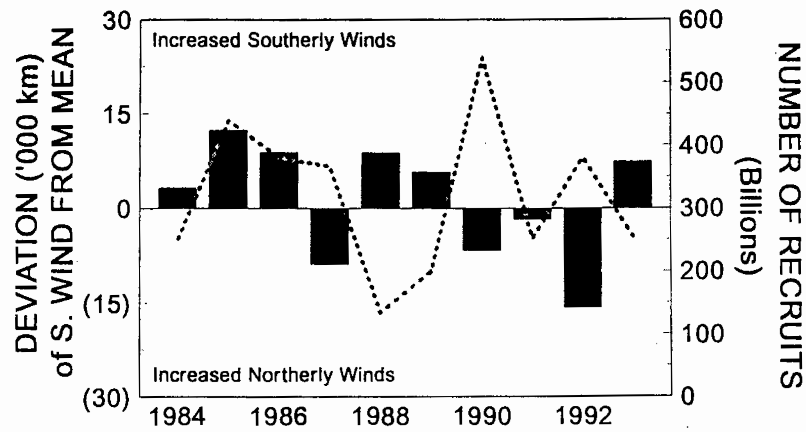


Figure 4.7: Cape Point north-south windrun anomaly, averaged over October-December 1984-1993 (deviation in '000km from the mean). Positive values indicate a stronger southerly component. The broken line (···) indicates estimated recruitment (billions of individuals) for Cape anchovy, *Engraulis capensis*, for the following year. Data from J. Taunton-Clark (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: The 'optimal environmental window' hypothesis for upwelling regions, suggests that there is relationship between wind and pelagic fish recruitment; i.e. optimum winds exist such that there is sufficient upwelling, enhanced food production or increased encounter rate between larvae and food particles, and offshore transport is not detrimental (Cury and Roy 1989).

The cumulative windrun showed considerable variability over the period of interest. If the phenomenon of egg and larval transport is of considerable importance in regulating recruitment of clupeoids, it is important to be able to detect abnormally large egg and larval losses through offshore transport. The accumulated southerly wind displacement is assumed to give an indication of the amount of offshore transport. The sum of departures from the long-term mean for the period October to December (in the preceding year) is used.

Distance Offshore of the 16°C Isotherm at Cape Columbine

ASSUMPTION: 16°C isotherm close inshore (weak southerly winds and hence reduced upwelling) results in little or no food production in nursery area for developing larvae (and also weak operation of Cape Columbine jet current) suggesting slower growth and higher mortality of juvenile fish (and also reduced transport success), thereby increasing the chance of below average recruitment (Figure 4.8).

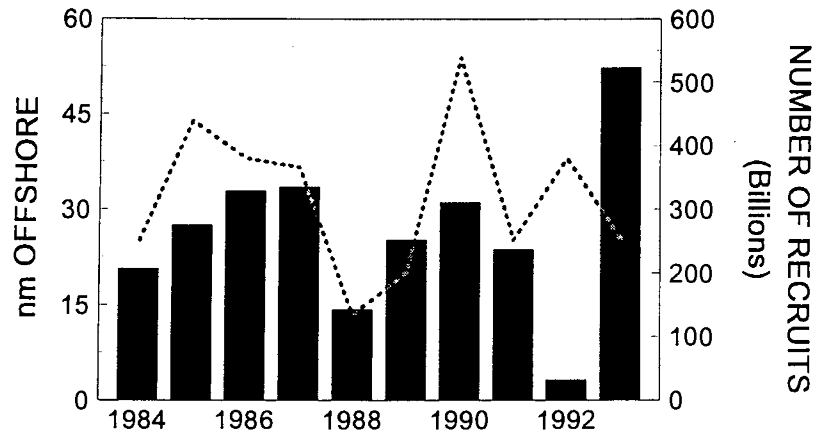


Figure 4.8: Distance offshore of the 16°C isotherm, averaged for October-December 1984-1993 (distance in nautical miles, nm). The broken line (···) indicates estimated recruitment (billions of individuals) for Cape anchovy, *Engraulis capensis*, for the following year. Data from J. Agenbag (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: The mean distance offshore of the 16°C isotherm over the period November and December at Cape Columbine (33°S), is assumed to give an indication of the intensity of the south/south easterly winds, and hence the upwelling in the area bordering the transport and nursery/recruitment zones.
The 16°C isotherm far offshore indicates intense offshore (southerly) winds and powerful operation of the Cape Columbine Jet current, contributing to improved egg and larval transport, leading to above average recruitment.
Alternatively, the 16°C isotherm close inshore is assumed to indicate reduced southerly wind stress, and weak operation of the Cape Columbine Jet current, contributing to reduced transport success and below average recruitment.

Sea Surface Temperature (SST) (in the Spawning and Transport Area)

ASSUMPTION: Cold water in the spawning area suggests that there is a reduced area suitable for spawning resulting in reduced spawning, thereby increasing the chance of below average recruitment. Also, cold water in the transport area results in increased mortality of eggs and larvae, thereby increasing the chance of below average recruitment (Figure 4.9).

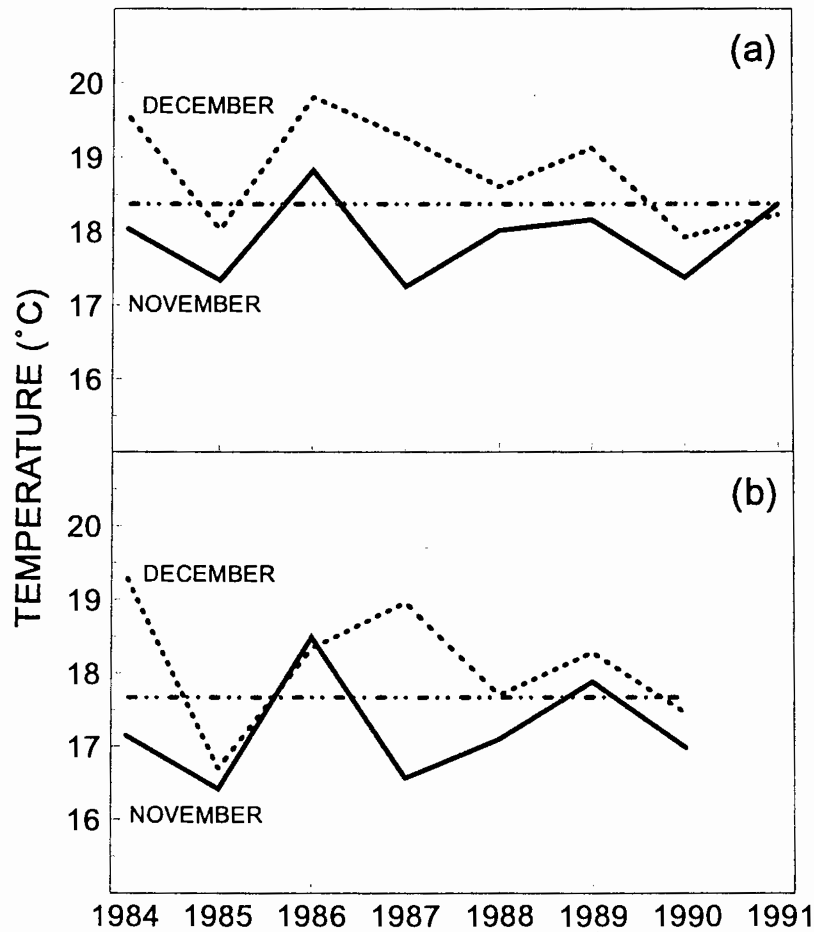


Figure 4.9: Monthly mean sea surface temperatures (°C) for November (-) and December (···) 1984-1991, in (a) the spawning area (Agulhas Bank; 18°30'-21°00'E and 36°S to the coast), and (b) the egg and larval transport area (Cape Point to Cape Columbine; 32°45'-34°30'S and 17°E to the coast). The horizontal broken line (·-··) indicates the overall mean. Data from the South African Data Center for Oceanography (SADCO).

EXPLANATION: Temperature has a substantial influence on growth and development in pelagic fish (Pepin 1991). Physiologically, anchovy growth is temperature dependent with an "environmental window" - the lower lethal limit for development of eggs and larvae in South African anchovy is 14°C, while 24°C appears to be the maximum, with an optimum between 17 and 17.5°C (Reid 1967; Baird and Geldenhuys 1973; Shelton, Boyd and Armstrong 1985; Crawford *et al.* 1987). Anchovy appear to spawn only in areas of optimal temperature. On this basis, 16 and 20°C have been chosen as the upper and lower limits for optimal temperature, with temperatures below 16°C and above 20°C being sub-optimal.

Incidence of El Niño - Southern Oscillation (ENSO) Events

ASSUMPTIONS: La Niña (anti-El Niño) enhances "summer" conditions (i.e. increases south/south-easterly winds) resulting in increased upwelling and offshore advection of the west coast surface water (16°C isotherm very far offshore) with possible bifurcation of the Cape Columbine jet current, thereby increasing the loss of spawning products and larvae to the offshore environment and increasing the chance of below average recruitment:
El Niño enhances "winter" conditions (i.e. reduces south/south-easterly winds) resulting in weaker upwelling (16°C isotherm close inshore) and weaker operation (non-bifurcation) of the Cape Columbine jet current, thereby increasing transport success and the chance of average/above average recruitment (Figure 4.10).

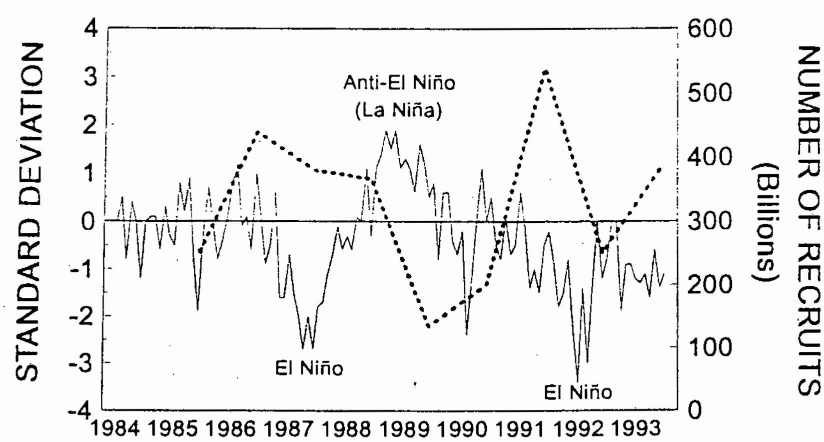


Figure 4.10: The Southern Oscillation Index (SOI). The broken line (···) indicates estimated recruitment (billions of individuals) for Cape anchovy, *Engraulis capensis*. Data from Kousky, Bell and Kopman (1984-93) and Sea Fisheries Research Institute (unpublished).

EXPLANATION: It is apparent that intermittent, meso- to large-scale environmental fluctuations have a pronounced effect on a broad spectrum of local marine species (Shannon *et al.* 1992). There is increasing evidence to suggest that ENSO events have an effect on climatic and oceanic variability, not only in the southern hemisphere (Horel and Wallace 1981; Van Loon and Madden 1981; Pan and Oort 1983), but off the African sub-continent (Walker and Taunton-Clark 1983; Walker, Taunton-Clark and Pugh 1984; Lindesay, Harrison and Haffner 1986; Preston-Whyte and Tyson 1988; Taunton-Clark and Kamstra 1988). Figure 4.11 is a summary of possible relationships which may account for correlations between the SOI and anchovy recruitment. For detailed descriptions of the El Niño, La Niña and the Southern Oscillation phenomenon, see Philander (1983, 1990).

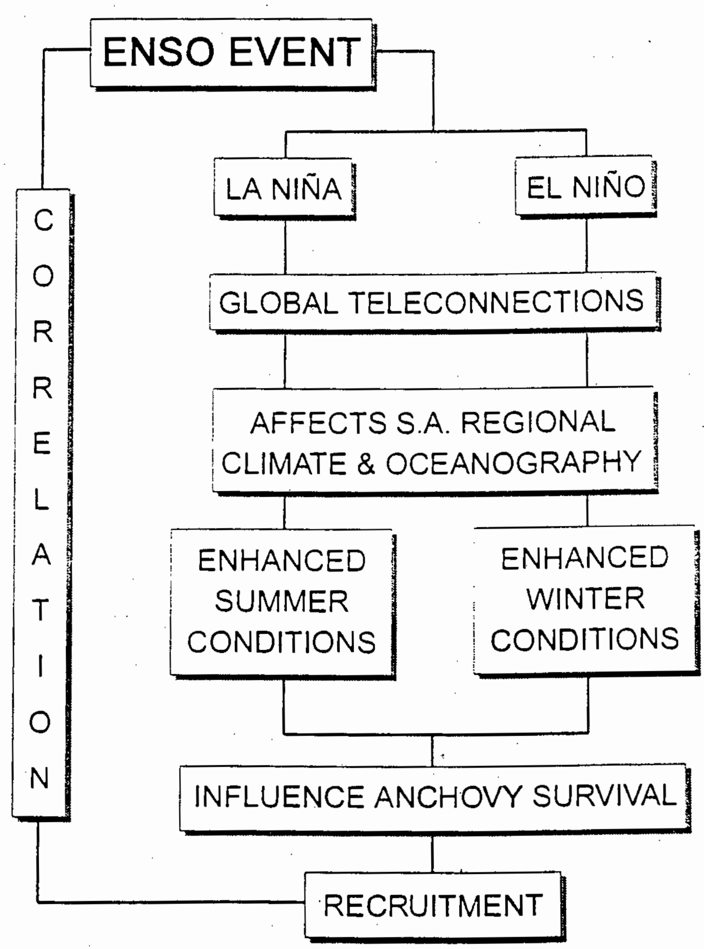


Figure 4.11: Theoretical model showing the possible relationships between ENSO events and the fluctuations in anchovy recruitment (modified from Roberts and Sauer 1995).

4.4 VARIABLES TO BE USED IN THE DETERMINISTIC SYSTEM

The following list of variables to be used in the deterministic model (see Chapter 5):

- level of egg production,
- some index of wind stress,
- commercial oil yield of recruits,
- a starvation index for spawning fish on the western Agulhas Bank,

The following variables, suggested in the workshops, are also to be investigated:

- spawning and transport area sea surface temperature,
- distance offshore of the 16° isotherm at Cape Columbine,
- incidence of alpha oocyte atresia, and
- incidence of El Niño - Southern Oscillation (ENSO) events.

4.5 VARIABLES TO BE USED IN THE PROBABILISTIC SYSTEM

Due to the difficulties associated with estimating probabilities, three variables were considered to be a practical maximum for a first attempt at a probabilistic system (see Chapter 6). The list of variables proposed for the deterministic expert system was trimmed on the basis of data availability to yield the following list of four variables that are, at present, thought the most likely to allow numerical forecasting of recruitment in the South Africa anchovy:

- egg production,
- index of wind stress,
- commercial oil yield (of recruits), and
- a starvation index for spawning fish on the western Agulhas Bank.

It was decided however, that all four of the selected variables warranted probabilistic investigation and should be considered for the forecasting system(s). It was therefore proposed that two (comparative) systems be constructed with three variables each. The following combinations of variables were suggested:

(1)	Commercial Oil Yield Egg Production Starvation Index	(2)	Commercial Oil Yield Egg Production Index of Wind Stress

4.6 DEFINING THRESHOLDS

Many processes can be adequately described by two parameters of a probability distribution - the mean and the variance; one measures the central position of the distribution and the other measures its breadth. However, many biological problems concern extremes in variables (e.g. highest temperature, lowest yield) rather than their central tendencies - i.e. the average is not the relevant parameter, but the extreme (maximum or minimum) is. Gaines and Denny (1993) have shown that accurate predictions can be made from certain short-term data that are unusual in that they contain extreme events. Using the assumptions outlined in Section 4.3 above, further decisions therefore need to be made on quantitative thresholds for those variables under examination. These thresholds define whether or not individual data points in the time-series of a particular variable can be considered "extreme" - defined here as having a negative impact on recruitment.

4.6.1 Annual Commercial Oil:Meal Ratio

In order to calculate an oil yield threshold, commercial pelagic fish catch and processing data (see Appendix 2, Table A2.1) were obtained from Stuttaford (1991). These catch and processing figures are only available as total annual tonnages, so the data are complicated by the fact that the totals for fish meal and oil are for all pelagic species combined. Lantern fish (*Lampanyctodes hectoris*), have a very high oil content (Anon. 1986) and can represent up to 10% of the total pelagic catch. Other pelagic species recorded by Stuttaford (1991) include pilchard (*Sardinops sagax*), Cape horse mackerel (*Trachurus trachurus*) and Cape round herring (*Etrumeus whiteheadi*). Therefore, as a base-case, only data for the years where anchovy comprised 50% or more of the total pelagic catch (Appendix 2, Table A2.2) were considered for the calculation of the oil yield threshold. Data sets further refined (consisting of the years where the anchovy catch comprised 65% and over, 75% and over and 80% and over of the total pelagic catch) were also considered (Appendix 2, Tables A2.3, A2.4, A2.5 respectively). Mean values, ± 1 standard deviation, were calculated for the individual sets of data (Table 4.2).

Low oil yields are assumed to indicate poor condition in the spawners. We are therefore interested in the lower deviations; as these values ranged from 18.5% to 20.6% (Table 4.2) with a mean of 19.7%, a threshold of 20% is proposed.

% ANCHOVY	NO. OF OBS.	MEAN OIL:MEAL (%)	STD. DEVIATION	
			- 1 S.D.	+ 1 S.D.
50+	21	26.2	*18.5*	33.9
65+	13	27.6	*19.6*	35.6
75+	9	29.1	*20.6*	37.6
80+	5	28.7	*20.1*	37.3

Table 4.2: Mean commercial oil:meal ratios (± 1 standard deviation, S.D.) for the South African pelagic fish catch (1964-1990), where anchovy comprised 50% or more, 65% or more, 75% or more and 80% or more of the total pelagic catch. The number of observations, out of a possible 27, in each category is also shown.

This threshold therefore informs one that oil:meal ratios falling below this value are to be considered harmful to recruitment, and indicative of poor condition in the spawners, thereby increasing the chance of below average recruitment.

4.6.2 **Mean Daily Egg Production**

The daily egg production times-series for the period 1984-1993 was analyzed for corresponding peaks and troughs in recruitment (Table 4.3).

The data are extremely variable; egg production values for anchovy ranged from a peak of 840 eggs.m^{-2} in 1992, to a low of 174 eggs.m^{-2} in 1989 (Table 4.3). In general, it is assumed that low recruitment will result from low egg production. However, recruitment is not correlated to egg production ($r = 0.03$, $n = 10$, $P > 0.25$). If however, we remove the outlier (low) 1992 recruitment estimate (Table 4.3), the correlation improves ($r = 0.43$, $n = 9$, $P < 0.1$). Stronger still however, is the relationship between egg production and recruitment from the previous year ($r = 0.72$, $n = 9$, $P < 0.005$). We have the classical "chicken or the egg" conundrum. Essentially then, it appears that setting a threshold level for egg production is problematical. Calculating the mean of the full 10-year egg production time-series yields $\bar{x} = 381.5$ eggs.m^{-2}; excluding the 1992 recruitment yields $\bar{x} = 330.6$ eggs.m^{-2}.

YEAR (t)	DAILY EGG PRODUCTION	R (t+1)
1984	389.4	248.9
1985	326.5	439.1
1986	487.6	380
1987	303.7	365.7
1988	313.7	134.2
1989	174	200.4
1990	354	538.9
1991	840	251.6
1992	389	380.4
1993	237.4	254.7

Table 4.3: Daily egg production (eggs.m^{-2}) for Cape anchovy, *Engraulis capensis*, recorded during the November spawner biomass surveys (1984-1993). Estimated recruitment (R, billions of individuals) is shown for the succeeding year (t+1). Data B. Roel-Payne (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

If we can assume that low egg production results in reduced recruitment, we are again interested in the lower value to set a threshold sufficiently low such that values falling below the threshold has a good probability of forecasting below average recruitment. It is proposed therefore that the threshold be set at 300 eggs.m^{-2}. To date, egg production figures below this threshold have all resulted in below average recruitment (Table 4.3).

4.6.3 Index of Wind Stress

The cumulative Cape Point north-south windrun anomaly, measured over October to December each year, for the period 1984-1992, was analyzed for corresponding peaks and troughs in recruitment (Table 4.4). To detect the likelihood of abnormally high losses of anchovy eggs and larvae through offshore transport on the west coast of South Africa, special attention is given to the southerly wind component.

The winds showed considerable variability over the period of study. Strong southerly windruns are apparent for 1988 and '93 coinciding with below average recruitment in the following year.

YEAR (*t*)	**CUMULATIVE N-S WINDRUN**	**R** (*t*+1)
1984	3.3	248.9
1985	12.4	439.1
1986	8.8	380
1987	-8.9	365.7
1988	8.8	134.2
1989	5.8	200.4
1990	-6.8	538.9
1991	-1.8	251.6
1992	-15.9	380.4
1993	7.4	254.7

Table 4.4: Cape Point north-south windrun anomaly (deviation in '000 km from mean), averaged for the period October-December 1984-1992. Positive values signify a stronger southerly wind component. Estimated recruitment (R, billions of individuals) for Cape anchovy, *Engraulis capensis*, is shown for the following year (*t*+1). Data from J. Taunton-Clark (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

Weakening the relationship however, are southerly windruns of greater and equal strength in 1985 and '86, which were followed by above average recruitment in 1986 and 1987 respectively (Table 4.4); the data suggesting only a possible relationship between southerly winds and recruitment ($r = -0.36$, $n = 10$, $P < 0.25$). Calculating the mean of the southerly windrun anomalies, yielded an average cumulative anomaly of 7750 km. As a threshold value, this is considered to be too high to be informative: windrun values for 1985, '89 and '93 are lower than the threshold (Table 4.4), yet all correspond with below average recruitment. It is proposed therefore that the threshold for the southerly windrun anomaly be set at 5000 km. That is, a cumulative southerly windrun for the period Oct-Dec, greater than the threshold value indicates poor egg and larval transport conditions, thereby increasing the chance of below average recruitment.

4.6.4 **Percentage "Starvation Stations"**

The time-series of the annual estimates of the percentage "starvation stations" is short, data only having being recorded from 1988 (Table 4.5). There is however, a good correlation between percentage "starvation stations" on the spawning ground and the succeeding recruitment ($r = -0.77$, $n = 6$, $P < 0.025$).

YEAR (t)	PERCENTAGE STARV. ST'NS	R (t+1)
1988	55.5	134.2
1989	22.7	200.4
1990	0	538.9
1991	16.1	251.6
1992	9.1	380.4
1993	6.9	254.7

Table 4.5: Percentage "starvation stations" recorded during November spawner biomass surveys (1988 - 1993). Estimated recruitment (R, billions of individuals) for Cape anchovy, *Engraulis capensis*, is shown for the following year (*t*+1). Data from Verheye and Hutchings (1994) and Sea Fisheries Research Institute (unpublished).

1988 proved to be very anomalous, with 55.5% of stations sampled on the November survey recorded as being food-limiting for anchovy; succeeding values range from 0% to 22.7%. Recruitment in 1989 was severely reduced, the lowest level recorded to date. With a 50% decrease in the recorded percentage of "starvation stations" from 1988 to 1989, recruitment in 1990 recovered, but was still considered to be below average.

The mean percentage "starvation stations" for the time-series is calculated to be 22.1% (±17.6%). Discussion in the workshops dismissed this value as a viable threshold, and the value 30% was decided upon. That is, a percentage "starvation stations" value greater than this threshold indicates poor feeding conditions on the spawning ground (thereby increasing the chance of below average recruitment).

When you have eliminated the impossible,
whatever remains, however improbable,
must be the truth.

Shelock Holmes
(A. Conan Doyle)

Chapter 5

DETERMINISTIC EXPERT SYSTEMS

5.1 INTRODUCTION

The aim of this chapter is to assemble a set of deterministic rules linking anchovy recruitment to selected biological and environmental variables (indicators) believed to reflect recruitment in the South African anchovy, *Engraulis capensis*, and then incorporate those rules into a simple expert system. This model may then be used to simulate a variety of "IF (condition) - THEN (conclusion)" scenarios and qualitatively forecast the occurrence of below average recruitment, in a deterministic manner, for each of these scenarios.

This chapter is structured as follows: descriptions of the expert system development tool, knowledge-base design, and the consultation procedure are followed by descriptions of the systems developed for this dissertation (including discussion of new data specific to later systems). The results from testing the systems follow, with discussion on tuning the models.

5.2 DEVELOPMENT TOOL

Of the many expert system building tools (or 'shells') examined for this project, the shell selected for this modelling exercise is "WinEXP® - a Small Expert System for Windows". WinEXP® is the MS-WINDOWS® version of a shell designed for developing simple expert systems on MS/PC-DOS® computers (see Adams 1985; Starfield *et al.* 1985 for a description of the early, DOS-based, version of the expert system shell).

WinEXP® falls into the category of 'Production Expert Systems'. Production, or rule-based expert systems, are systems in which knowledge is stored in production rules. A production rule is a rule of the type:

IF *A* THEN *C*;

that is, IF condition *A* is fulfilled, THEN conclusion *C* is assumed to hold true. The IF determines the applicability of the rule to the situation under analysis and the THEN describes the action to be performed if the rule is applied.

Some benefits of using production systems include (Hayes-Roth 1985):

- They are easy to construct,
- They provide an easy way to furnish explanations,
- New rules may be easily added with little disturbance to the rest of the system.

One drawback is that production systems cannot cope efficiently with very large rule files (Pau 1986). Rule-based systems are however, thought to be the best approach for formalizing and codifying problem-solving expertise (Hayes-Roth *et al.* 1983).

Reasons for choosing WinEXP®:

- The software is available (almost) free of charge,
- It is suitable for use on any IBM® microcomputer (or compatible) running MS/PC-DOS® and MS-WINDOWS®, or an APPLE® Power Macintosh® capable of running SoftWINDOWS®, and is therefore fully portable across the most common working platforms,
- It has a "*WHY*" facility that allows the user to inquire into the reasoning behind a specific question/decision,
- It has a "*TRAIL*" facility that allows the user to trace the flow of logic through the questions (and their answers) to the final decision (forecast/prediction),
- It has a built in editor which makes for ease of coding, editing and de-bugging the rules and decisions that form the knowledge-base.

WinEXP® does not however, have any probabilistic reasoning mechanism or any weighting evaluation scheme unlike most high-level commercial expert system shells (see Kopcso *et al.* 1988).

5.3 KNOWLEDGE BASE DESIGN

The IF part of production rules can have multiple conditions, for example:

IF *A* and *B* [and/or....] THEN *C*,
(if conditions *A* and *B* are met, then conclusion *C* holds true)

IF *A* or *B* [and/or....] THEN *C*,
(if either condition *A* or *B* is met, then conclusion *C* holds true).

A convenient aid for encoding knowledge into production rules is a decision table (Walters and Hilborn 1976; Walters 1986; Hilborn and Walters 1992). A decision table lays out all possible combinations of the variables, along with the conclusion (decision/forecast) specific to that particular combination. Tables 5.1 and 5.2 show the variable combinations and the resulting decisions (forecast), for the two 3-variable and the 4-variable deterministic systems respectively. Note how the decision table increases in size by merely adding another variable - very large tables (lots of variables generate many combinations), become unmanageable.

The questions put to the user by the systems are designed to extract information on whether certain data can be considered as having a negative impact on recruitment (or otherwise show an association with below average recruitment). The questions and possible answers are therefore based on the assumptions and thresholds outlined in Chapter 4; for example, the question and possible answers for oil yield are:

Question:

Is the commercial OIL:MEAL RATIO low?

Possible Answers:

YES (i.e. < 20% oil:meal ratio)
NO (i.e. > 20% oil:meal ratio)
Unsure / No data available

The questions are similar for the other variables, viz. daily egg production, percentage "starvation stations" and cumulative N-S windrun.

VARIABLES			DECISIONS				
Low Oil	Low Eggs	Strong S. Winds	Chance of B. A. R.			A / AA	Unsure
		High % S.St'ns	V. Likely	Likely	Possible	R'ment	
N.D.	N.D.	N.D.					♦
X	X	X				♦	
✓	X	X			♦		
X	✓	X			♦		
X	X	✓			♦		
✓	✓	X		♦			
✓	X	✓		♦			
X	✓	✓		♦			
✓	✓	✓	♦				

Table 5.1: Decision table for the two 'base-case' 3-variable deterministic expert systems. Variables are unweighted. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the decision. N.D. = No Data. Only the simplest case is shown for the "No Data" scenario.

VARIABLES				DECISIONS				
Low Oil	Low Eggs	Strong S. Winds	High % S. St'ns	Chance of B. A. R.			A / AA R'ment	Unsure
				V. Likely	Likely	Possible		
N.D.	N.D.	N.D.	N.D.					♦
X	X	X	X				♦	
✓	X	X	X			♦		
X	✓	X	X			♦		
X	X	✓	X			♦		
X	X	X	✓			♦		
✓	✓	X	X		♦			
✓	X	✓	X		♦			
✓	X	X	✓		♦			
X	✓	✓	X		♦			
X	✓	X	✓		♦			
X	X	✓	✓		♦			
✓	✓	✓	X	♦				
✓	✓	X	✓	♦				
✓	X	✓	✓	♦				
X	✓	✓	✓	♦				
✓	✓	✓	✓	♦				

Table 5.2: Decision table for the 'base-case' 4-variable deterministic expert system. Variables are unweighted. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the decision. N.D. = No Data. Only the simplest case is shown for the "No Data" scenario.

So that conservative measures can be applied when setting the Total Allowable Catch (TAC), we are primarily interested in forecasting a forthcoming below average recruitment event; recruitment that is expected to be average, or above average can be treated as before. The information required from the expert systems should therefore tell us whether to expect below average recruitment or not, hence forecasts need only be of the order:

UNSURE
- i.e. unable to make forecast

AVERAGE / ABOVE AVERAGE RECRUITMENT
- i.e. no chance of Below Average Recruitment

BELOW AVERAGE RECRUITMENT
- i.e. Below Average Recruitment will be observed

However, with such a system, there is no way to measure the confidence we might have in a below average recruitment forecast. To generate an end result that will be more informative to the user of such a system, it was decided split the single below average recruitment forecast into a logical sequence of three categories, increasing in confidence. In this way, we can recognise below average recruitment forecasts that are imminently usable (and those that are not). We break the single below average recruitment forecast into the following three categories:

BELOW AVERAGE RECRUITMENT
- *Possible*
- *Likely*
- *Very Likely*

To make the distinction between the categories of below average recruitment forecasts, a simple ratio is implemented. It is assumed that only the variables used in the systems play a role in regulating recruitment; then, within each system, for each particular scenario, the ratio of the number of variables thought to be impacting recruitment, divided by the total number of variables used in the system, is used to compute which category of below average recruitment should be forecast. If up to one third of the number of variables are believed to be impacting recruitment, the forecast will be *Possible* Below Average Recruitment; between one and two thirds of the variables impacting will result in a *Likely* Below Average Recruitment forecast; while greater than two thirds of the variables impacting will result in a *Very Likely* Below Average Recruitment forecast. The forecasts deemed imminently usable are:

BELOW AVERAGE RECRUITMENT
- *Likely*
- *Very Likely*

In the unweighted-variable systems, each variable carries equal weight and plays an equal part in the decision process. The category of below average recruitment that is forecast is therefore decided on a presence-absence percentage basis (see Tables 5.1 and 5.2). In the weighted-variable systems, each variable does not play an equal part in the decision-making process. The particular category of the below average recruitment forecast is also decided on a presence-absence percentage basis - but in this case, a simple weighting-factor is applied to give more weight to variables considered to have greater impact in the recruitment process (Table 5.3).

5.4 THE CONSULTATION PROCEDURE

To begin a new consultation, the user must first load the relevant knowledge base (KB), and then choose '*Ask*' (or 'Run - Query' from the main menu) to begin the consultation. At this stage the expert system engine checks the KB and reports any errors in logic. If the KB fails this check, WinEXP will take the user to the offending rule so that corrections can be made. If the KB passes scrutiny, the '*Question*' window appears and the consultation starts. Using the questions in the KB, the system now asks the user (decision-maker) for information (specific to that KB). When it comes to answering the system's queries, the user has three options to choose from - '*Yes*', '*No*' or '*Unsure/No data available*'. If the user has the information required, he/she obviously chooses either '*Yes*' or '*No*' in answer to the question; if the user does not have information, or is uncertain about the answer, the '*Unsure/No data available*' option should be chosen. The user must however choose one of these three options in order to continue to the next question.

There are an number of options available to the user at any stage of the consultation:

- '*Abort*' - this aborts the current KB immediately, and returns the user to the expert system engine,

VARIABLES				DECISIONS				
Low Oil	Low Eggs	Strong S. Winds	High % S. St'ns	Chance of B. A. R.			A / AA R'ment	Unsure
				V. Likely	Likely	Possible		
N.D.	N.D.	N.D.	N.D.					♦
X	X	X	X				♦	
✓	X	X	X			♦		
X	✓	X	X			♦		
X	X	✓	X			♦		
X	X	X	✓		♦			
✓	✓	X	X		♦			
✓	X	✓	X		♦			
✓	X	X	✓	♦				
X	✓	✓	X		♦			
X	✓	X	✓		♦			
X	X	✓	✓	♦				
✓	✓	✓	X		♦			
✓	✓	X	✓	♦				
✓	X	✓	✓	♦				
X	✓	✓	✓	♦				
✓	✓	✓	✓	♦				

Table 5.3: Decision table for the 'base-case' 4-variable deterministic expert system. Variables are weighted according to impact on recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the decision. N.D. = No Data. Only the simplest case is shown for the "No Data" scenario.

- *'Why'* - this opens the *'Explanation'* window and may be used to inquire about the line of reasoning; this is essentially a help facility that explains to the user why a particular question is being asked (or why a particular decision has been reached), and
- *'Trail'* - this may be used to show the user the trace, up to the current point, of questions asked and answers answered. The window also shows any decisions that have been reached up to that point, and those that cannot possibly be reached.

Once the system has no further questions, it uses the information it has extracted from the user to formulate the decision (forecast) and presents the decision (forecast) in a *'Decision Reached'* window. As before, the *'Why'* option is available so that the user can inquire as to the reasoning behind the decision. The user also has the option of looking for additional decisions - this allows the expert system engine to evaluate any additional rules in the KB that have not been considered.

5.5 EXPERT SYSTEM DESCRIPTIONS

A number of different deterministic expert systems were developed for this study. What follows is a description of each, with additional discussion outlining system specifics.

5.5.1 3-Variable 'Base-Case' Systems

Two 'base case' (unweighted variable) systems using 3-variables each were constructed. Both systems incorporate the same base pair of variables, viz. oil:meal ratio and daily egg production (data available for the period 1984-1993), and a discrete third variable: the *'Wind'* system uses the cumulative Cape Point N-S windrun anomaly (data available for the period 1984-1992), and the *'Food'* system uses percentage "starvation stations" (data only available for the period 1988-1993).

5.5.2 4-Variable Systems

Three systems using all four variables under investigation (viz. oil:meal ratio, egg production, cumulative N-S windrun and percentage "starvation stations") were constructed: as before, an unweighted variable system was used as the 'base-case'; in addition, a simple weighting mechanism was devised for a weighted-variable system; while the third system investigates using "fuzzy logic" by incorporating fuzzy thresholds - that is, threshold values with a percentage variation.

Unweighted-Variable ('Base-Case') System

Due to there being no data on percentage "starvation stations" for the years 1984-1987, the unweighted variable ("base case") system required some engineering: recruitment forecasts prior to 1988 are generated with the 3-variable *'Wind'* system, and amalgamated with the 4-variable forecasts for 1989-1994 to construct a forecasting system for the duration of the recruitment time-series (1985-1994).

Weighted-Variable Systems

Rule-based expert systems can have a built in capacity of dealing with uncertainty: if the knowledge is partial or uncertain, it is considered effective to have a (numerical) weighting factor attached to each rule (Hayes-Roth *et al.* 1983; Stefik *et al.* 1983b; Pedersen 1989) and a mechanism which will combine these weights in a realistic way (Stefik *et al.* 1983b, Shafer 1987).

In order to rank the variables for weighting, it was believed important to consider the sequence in which the variables come into play in the process of recruitment. To this end, the recruitment process was broken down into sub-processes, representing specific stages within the recruitment process as a whole (Figure 5.1). Analysis of the individual time-series however, and (subjective) opinions expressed during workshops, revealed that the variables may be ranked not necessarily in the order in which they occur, but according to their *contribution* to the recruitment process. In this weighting exercise, greater emphasis is placed on variables that are considered to play a greater role in the process of recruitment - clearly, some variables are more important to the recruitment process than others.

In general, the number of recruits in any one year is a function of the number of eggs produced during the preceding spawning season and the survival of those eggs through to fish of recruiting age. The numbers of eggs produced is a function of the spawning success of the adults, determined by the "spawning fitness" of the adults and the availability of food on the spawning grounds. Egg and larval survival is a function of the species population density in relation to the carrying capacity (density-dependent component) and other density-independent factors like successful transport to the nursery area.

Rothschild, Osborn, Dickey and Farmer (1989) maintain that egg production accounts for a large proportion of recruitment variability in many fishes, and that poor egg production cannot result in good recruitment however favourable the environmental conditions. However, clupeoids typically reproduce by means of repeatedly spawning (iteroparity) large numbers of eggs over an extended spawning season (Shelton 1986, Shelton 1987), and was first noted as a potential bet-hedging trait in clupeoid fishes (Shelton 1987). On average, only two offspring need to survive to maturity during the life span of each adult female in order to replace the population (assuming an equal ratio of females and males are produced) - and as a consequence, egg production carries minimal weight in this exercise.

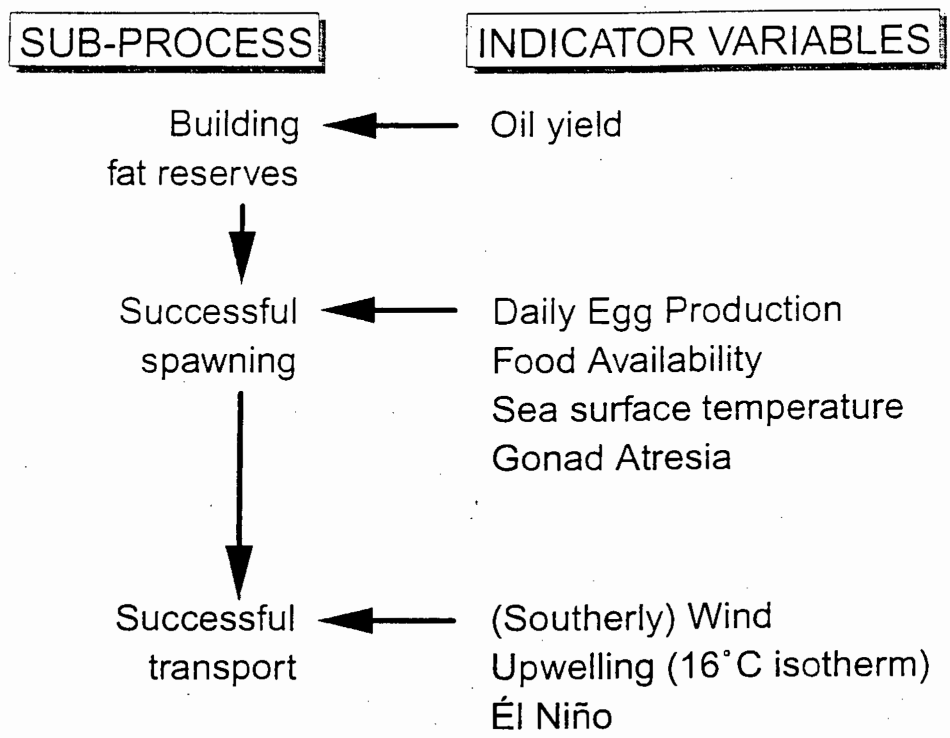


Figure 5.1: Conceptual model of the major sub-processes, and their indicator variables, within the process of pelagic fish recruitment.

The commercial oil:meal ratio gives us an indication of the condition (i.e. readiness to spawn) of the pre-adult fish prior to their arrival on the spawning ground, while the wind index gives an indication of the success of the transport of the spawning products. If condition (that is, oil:meal ratio) of recruits is high, we assume that spawning begins immediately, and if there is a low southerly wind index, offshore losses of the spawning products is assumed to be reduced, followed by successful transport of these products to the recruitment grounds. If condition of recruits is low, we assume that spawning cannot begin immediately and will be delayed until sufficient reserves have been acquired assuming that food is readily available. Hence, it appears that prior condition and successful transport are not essential conditions for spawning success, while the availability of food on the spawning grounds is crucial.

Based on the preceding logic, we can now rank the variables in ascending order of importance, attach an arbitrary numerical weighting factor to each of the variables:

Egg Production	-	1
Oil:Meal ratio -and- Wind Index	-	2
Food Index	-	3

The weighting factor acts as a multiplier - when the variable is used in the decision-making process, it brings with it additional "weight" (if any) generated by multiplying it by the weighting factor - a variable with a weighting factor of 3, carries 3 times its own weight; while a variable with a weighting factor of 1, carries only its own weight. In this way, emphasis is placed on the variables considered to have a greater impact on the recruitment process. As before, the sum of the variables (now including their additional weights) is assumed to explain recruitment; decisions are made on a presence-absence percentage basis as before.

Although egg production is a direct measure of recruitment potential (while the other variables just indicate conditions [for spawning, survival and transport]), egg production receives a low weighting factor for the following reasons. The egg production time-series reveals that the lowest egg production (174 eggs.m^{-2} in 1989), does not correspond to the lowest estimated recruitment (see Table 4.3). It can therefore be argued that measuring a large number of eggs during the November Spawner survey does not necessarily indicate a forthcoming average/above average recruitment event. Additionally, the egg production estimates are based only a single month's sampling (usually November) out of the five month spawning season (October to February) - if spawning is later than "usual", sampling early in the season will miss the bulk of the eggs and the estimate will be an underestimation.

"Fuzzy" System

Further analysis of the variable time-series revealed that perhaps the current thresholds are not accurately isolating the extreme values in the time-series, but are also including some values that ought not to be considered detrimental to recruitment (or do not accurately reflect forthcoming below average recruitment). These investigations led to the formulation of a "fuzzy threshold" - that is, the current threshold value is employed, but with an allowed variation (a certain percentage of the threshold). The area covered by this "fuzzy threshold" determines the average case - data points falling in this fuzzy area, are treated as average, and are not used in the decision process. Data points falling outside the area may then be assumed to be truly extreme and used as possible indicators of below average recruitment in the decision process. It is expected that by incorporating this fuzzy component, certain "borderline" values in the variable time-series would be excluded from the decision process, thereby improving forecast accuracy.

In an effort to establish whether a fuzzy-type threshold would be able to reconcile forecasts with the recruitment time-series, further investigations were undertaken to discover just how large the threshold variability would have to be. Figures 5.2 and 5.3 show the time-series for the individual variables with the fuzzy threshold, the variability being ±10% and ±20% of the threshold value respectively.

The data for the 1985 and '86 N-S wind anomaly are the highest on record (Figure 5.4) - indicating the possibility of large advective losses of spawning products and reduced transport success. However, recruitment was not considered to be below average in 1986 and '87 (see Figure 4.2). To achieve the goal of a fuzzy area incorporating the 1985 and 1986 values, a variability of some ±150% added to the current threshold value would be required. This is, of course, totally unrealistic, as such a value incorporates the entire range of southerly windrun values, imparting no information to the decision process.

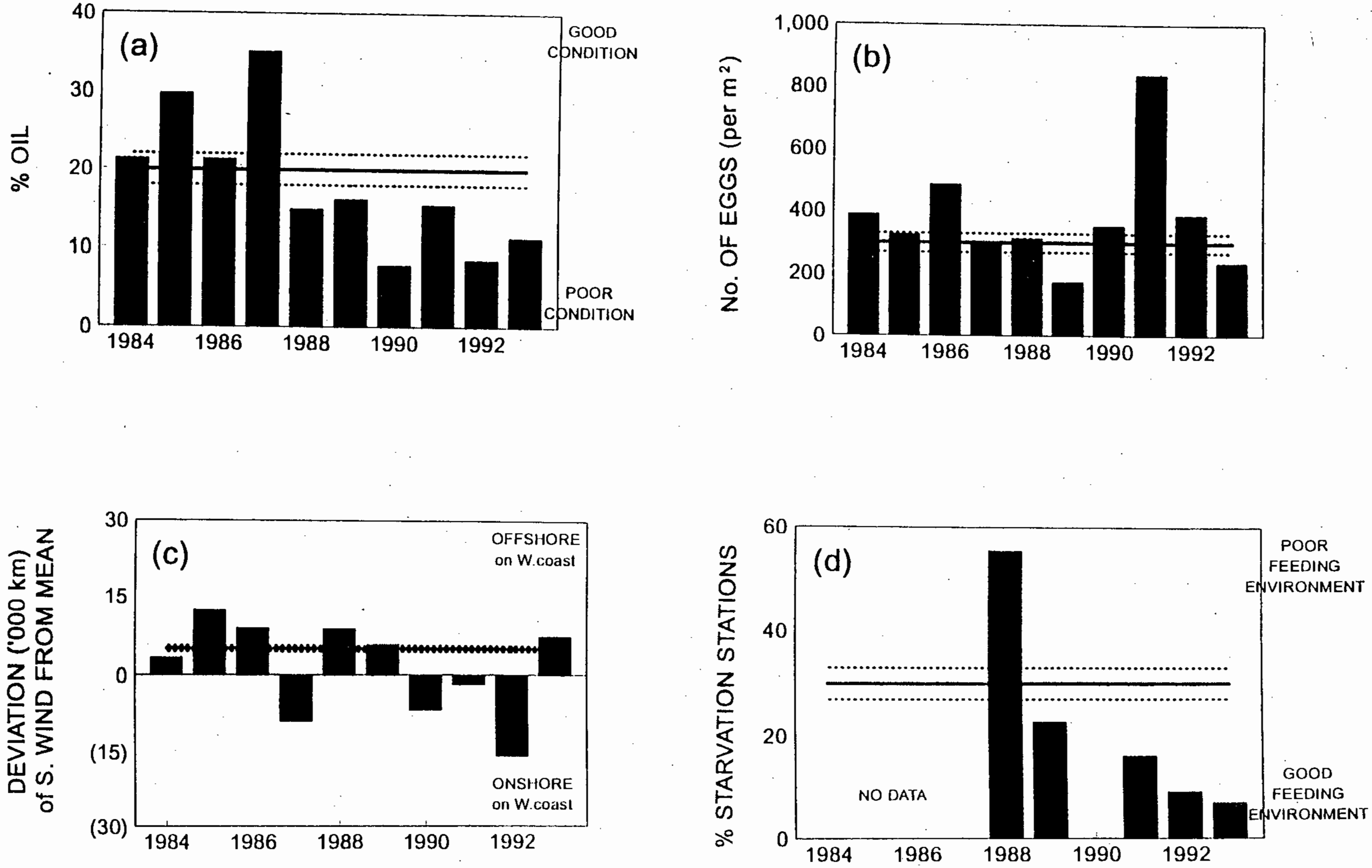


Figure 5.2: Individual time series for (a) oil yield, (b) egg production, (c) N-S wind anomaly, and (d) % starvation stations. The horizontal line (-) indicates the threshold value, and the broken line (···) indicates the fuzzy threshold at ±10%.

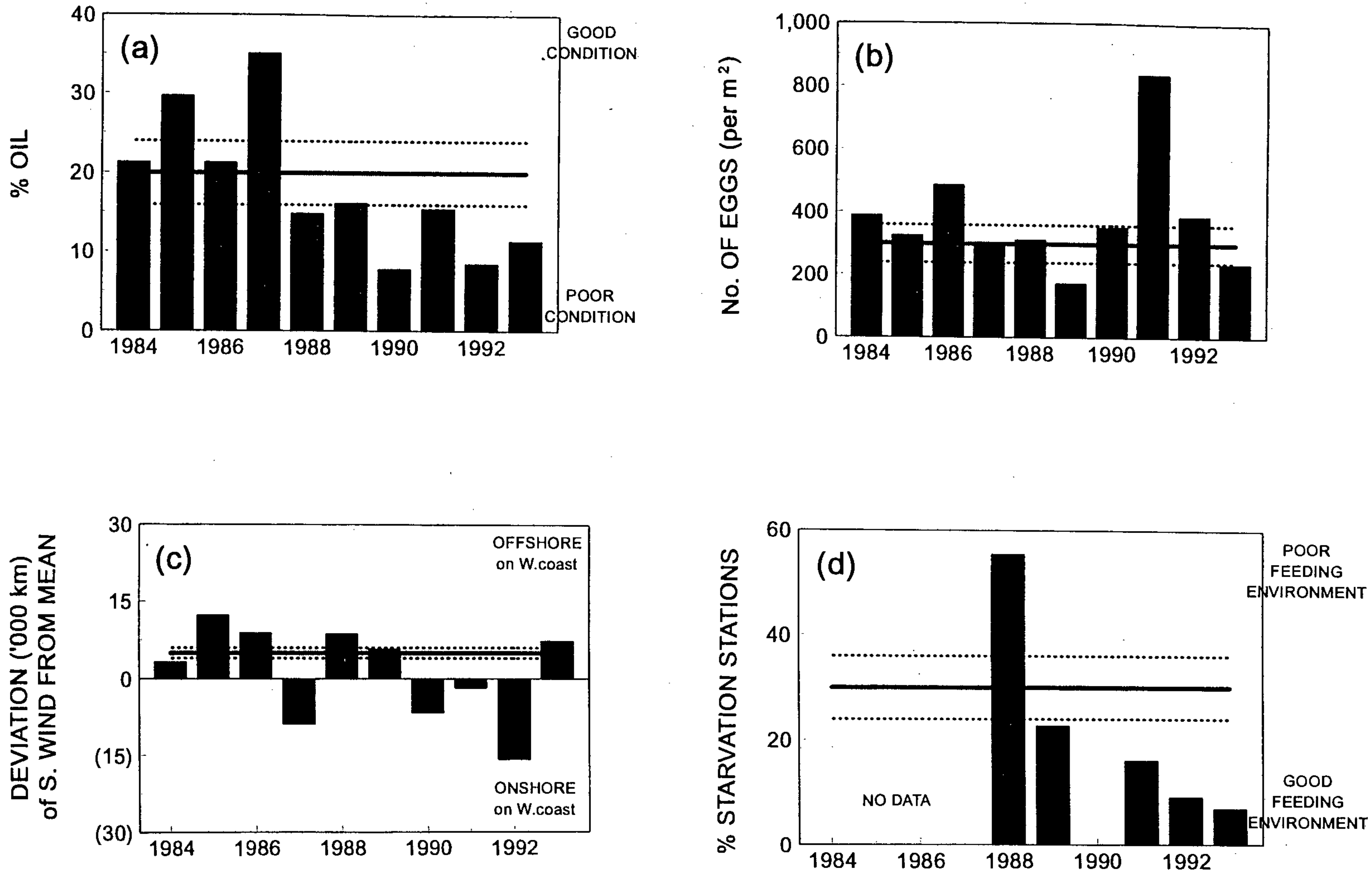


Figure 5.3: Individual time series for (a) oil yield, (b) egg production, (c) N-S wind anomaly, and (d) % starvation stations. The horizontal line (-) indicates the threshold value, and the broken line (···) indicates the fuzzy threshold at ±20%.

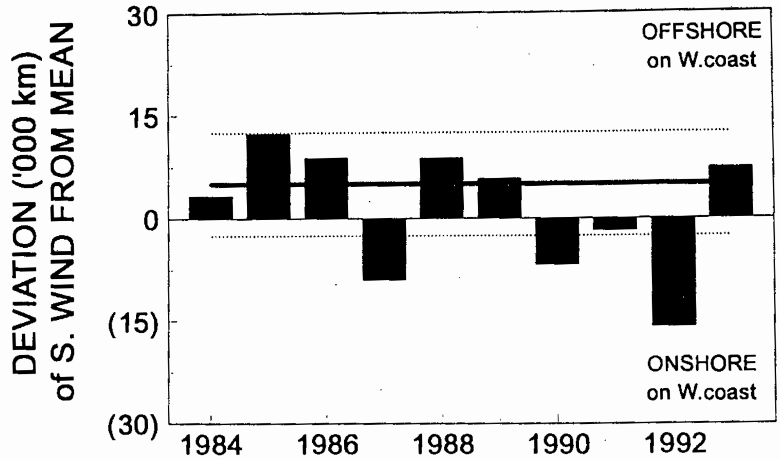


Figure 5.4: Cape Point N-S windrun anomaly (1984-1993), averaged for the period October-December (deviation in '000 km from mean). Positive values signify a stronger southerly wind component. The horizontal lines indicate the threshold value (-) and the allowable variation of ±150% (···). Data from J. Taunton-Clark (Sea Fisheries Research Institute, pers. comm.).

The data for the 1990 and 1992 oil yields are the lowest on record (Figure 5.5). To achieve the goal of a fuzzy threshold incorporating the 1990 and 1992 values, a variability of some 65% must be added to the current threshold value. This is again totally unrealistic, as it includes all the data points bar one, again imparting no information to the decision process (Figure 5.5).

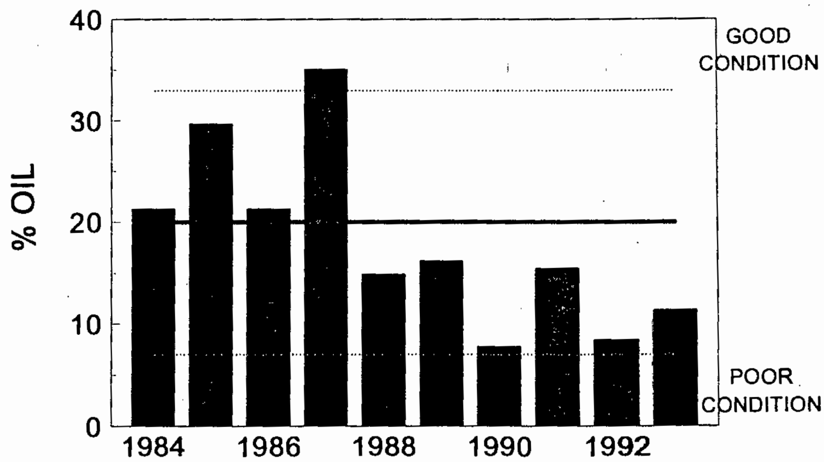


Figure 5.5: Commercial annual oil:meal ratios for the South African pelagic fish catch (1984-1990). The horizontal lines indicate the overall mean (-) and the allowed variation (···). Data from Stuttaford (1994) and Sea Fisheries Research Institute (unpublished).

5.5.3 **More Variables?**

Additional variables earmarked for possible inclusion in a multi-variable deterministic system are:

- sea surface temperature (in the spawning and transport area),
- distance offshore of the 16° isotherm at Cape Columbine,
- incidence of alpha oocyte atresia, and
- incidence of Southern Oscillation (SO) events.

Although earmarked, these variables have not as yet been investigated in terms of their forecasting abilities - this is now discussed.

Sea Surface Temperature (SST) (in the Spawning and Transport Area)

Mean monthly SST's from the anchovy spawning ground (Agulhas Bank; 18°30'-21°00'E and 36°S to the coast) and egg and larval transport area (Cape Point to Cape Columbine; 32°45'-34°30'S and 17°E to the coast), are shown in Figure 5.6 (a) and (b) respectively.

As outlined previously, optimal temperatures for anchovy spawning and hatching are in the range 16 to 20°C. Figure 5.6 (a) and (b) show that temperatures (monthly means) fell within these boundaries over the period of interest - mean values are 18.4°C and 17.7°C respectively - giving no clear indication of their effects on recruits. Therefore, it would appear that, for the period of interest, temperature in the spawning and transport areas cannot be called sub-optimal, and can be rejected as an influencing factor.

Temperatures in the west coast transport area were however, higher than expected. As this is where the greatest upwelling takes place, temperatures were expected to be cooler. It is suggested that the usually cool temperatures found in this region are moderated by the influx of warm water from the western Agulhas Bank, where a frontal jet sets up over the (summer) spawning season, drawing water of optimal temperature along with the developing anchovy eggs and larvae off the western Agulhas Bank (Largier, Chapman, Peterson and Swart 1992); temperature fluctuations in the spawning area are also experienced in the transport area (Figure 5.6 (a) and (b)).

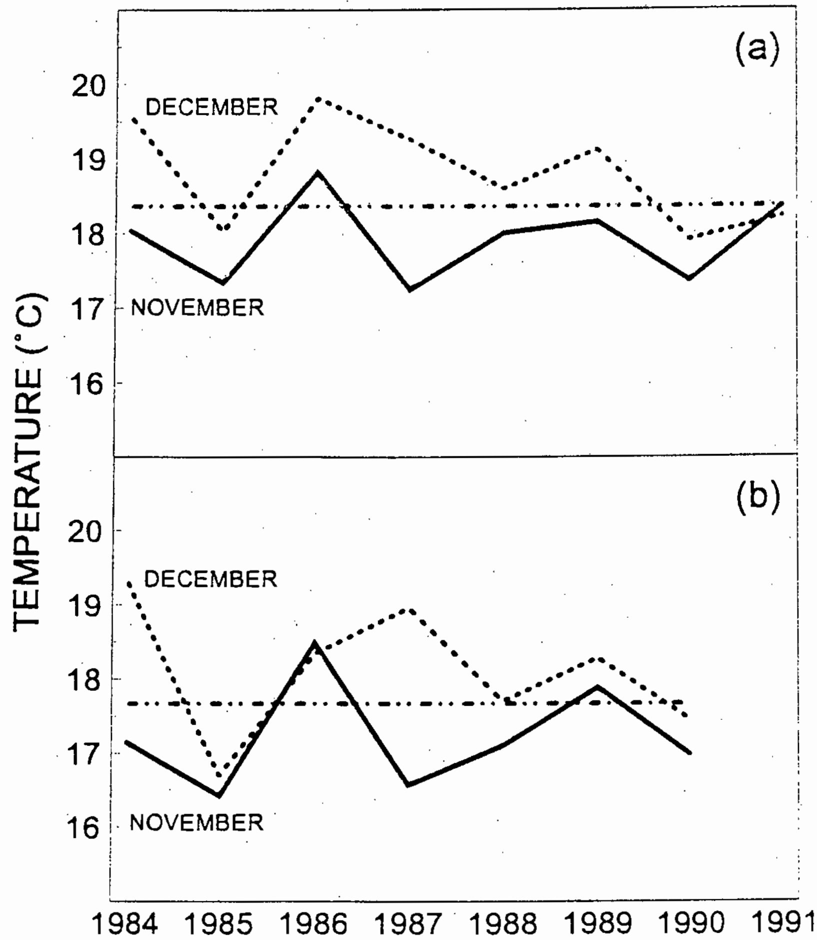


Figure 5.6 Sea surface temperatures (monthly averages, °C) for November (-) and December (···) 1984-1991, in (a) the spawning area (Agulhas Bank), and (b) the egg and larval transport area (Cape Point to Cape Columbine). The horizontal broken line (·-·-·) indicates the overall mean. Data from the South African Data Center for Oceanography (SADCO).

Francis (1993) found that SST explained some 94% of the variability in year-class strength in New Zealand snapper *Pagrus auratus*. In the current dataset however, there is no strong relationship between anchovy recruitment and SST in either the spawning ($r = -0.44$, $P < 0.25$, $n = 8$) or transport areas ($r = -0.38$, $P < 0.25$, $n = 7$). Due to small r values above, it was decided not to include this SST into the model at the present time.

Distance Offshore of the 16°C Isotherm at Cape Columbine

The distance offshore of the 16°C isotherm on the west coast of South Africa at 33°S (Cape Columbine), clearly shows some of the trends apparent in the estimated recruitment data; fluctuations in the distance offshore of the 16°C isotherm appear to be followed by the trends in estimated recruitment (Figure 5.7).

The distance offshore of the 16°C isotherm showed some variability over the period 1984-1991, values ranged between 14.3 and 33.5 nautical miles offshore. This was followed by two extreme fluctuations in 1992 and 1993, a short distance offshore of 3.2 nautical miles and a great distance of 52.3 nautical miles respectively. The mean distance offshore for the period 1984-1993 is 26 nautical miles (Figure 5.7).

Upon closer inspection, the relationship between distance offshore of the 16°C isotherm and recruitment is not what it seems to be ($r = 0.12$, $P > 0.25$, $n = 10$). In general however, it appears that below average recruitment is preceded by the isotherm being close inshore, while above average recruitment is preceded by the isotherm being far offshore. In contrast to this observed relationship, the below average distance of 3.2 nautical miles in 1992 was followed by above average recruitment, and the above average distance of 52.3 nautical miles of 1993 was followed by below average recruitment.

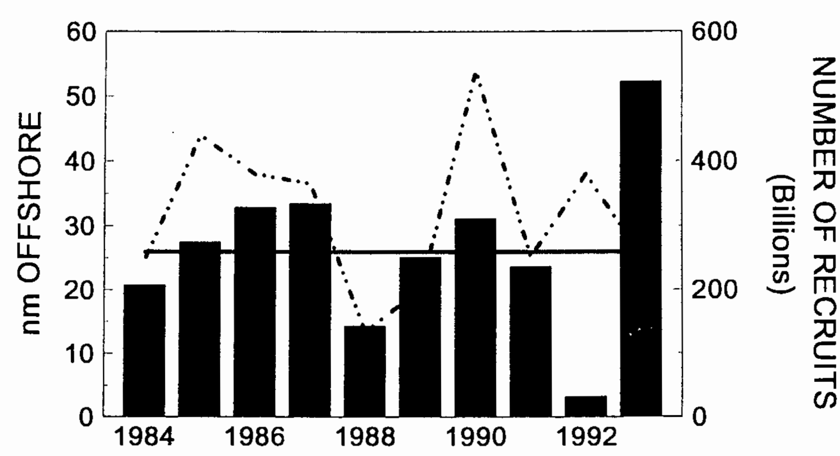


Figure 5.7: Combined monthly average distance offshore (nautical miles, nm), October-December 1984-1993, of the 16°C isotherm at Cape Columbine. The horizontal line (-) indicates the overall mean. The broken line (-···-) indicates estimated recruitment (billions of individuals) for the following year. Data from J. Agenbag (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

The association of anchovy eggs with the thermal front, and water of *ca.* 16°C, is shown in Figure 5.8 (the close association of the frontal zone hydrography and the eggs and early larvae of anchovy, suggest microscale events are important in determining survival of larvae during the transport phase [L. Hutchings. Sea Fisheries Research Institute, pers. comm.]).

It was expected that a relationship would be apparent between the distance offshore of the 16°C isotherm and offshore wind stress (on the west coast, i.e. southerly winds) . Intense upwelling - as a result of strong offshore winds - will result in the 16°C isotherm being far offshore, carrying the anchovy eggs and larvae with it, thereby increasing the chance of losing these spawning products as a result of offshore advective processes. Less intense upwelling - as a result of weak southerly winds, or strong northerly winds - will result in the 16°C isotherm being close inshore, thereby decreasing the chance of losing these spawning products. This relationship is not apparent ($r = 0.10$, $P > 0.25$, $n = 6$).

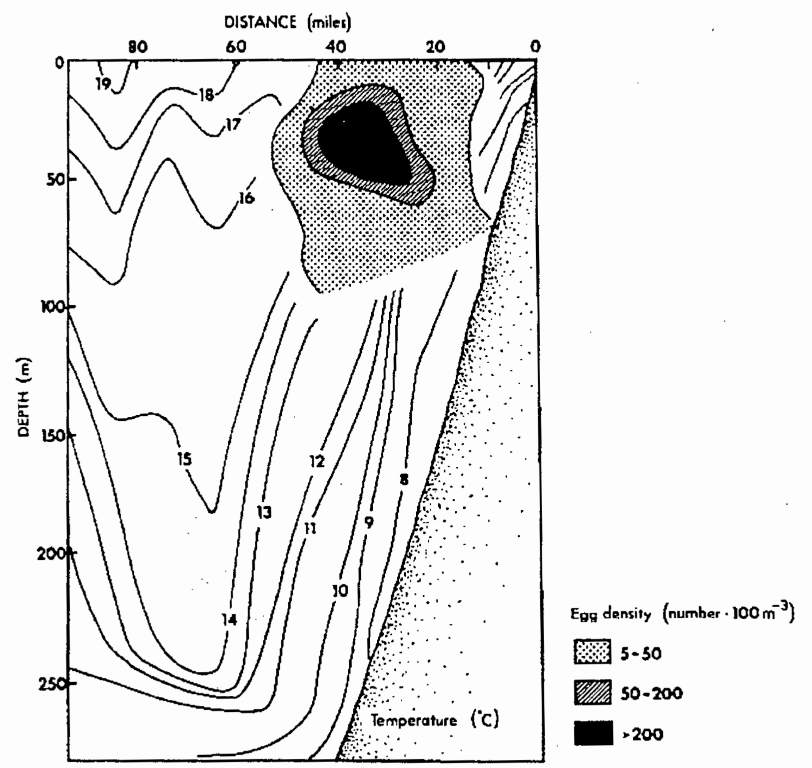


Figure 5.8: Association of anchovy eggs with the isotherms of the frontal region off the south-western Cape; egg concentrations superimposed over the isotherms (modified from Shelton and Hutchings 1990).

It is suggested that for successful transport of spawning products from the western Agulhas Bank to the west coast recruitment grounds, at least some southerly wind is necessary to start the upwelling process and drive the jet current - essentially, the classic optimal environmental window (see Figure 3.2).

As a consequence, the 16°C isotherm will appear some distance offshore. Additionally, little upwelling does not allow for sufficient primary production (Shannon and Pillar 1986) and hence poorer feeding for first-feeding larvae.

Even though a relationship may not be statistically apparent, by using the mean distance offshore of 26 nautical miles as the threshold value, the forecasting ability of the 16°C isotherm dataset appears to be quite sound; distances close inshore - below the mean - may be considered detrimental to recruitment, and indicate poor conditions for larval transport/survival (thereby increasing the chances of below average recruitment). As is the case with the optimal window concept, too much of anything is also detrimental, so the 52.3 nautical mile value recorded in 1993 is also likely to be detrimental to recruitment, most probably indicating extensive loss of eggs and larvae through offshore advective processes.

Incidence of Alpha Oocyte Atresia

Evidence exists for a relationship between the percentage female anchovy with atresia and recruitment ($r = -0.52$, $P < 0.10$, $n = 9$). The most obvious datum in the percentage atresia time-series is, of course, that of 1988, in which a record 17% of female fish were observed to have alpha-stage oocyte atresia concurrent with a dramatic drop in anchovy recruitment (Figure 5.9).

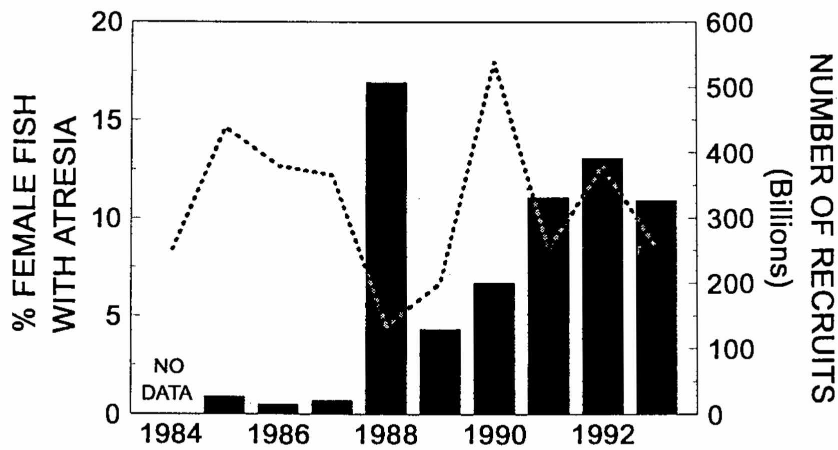


Figure 5.9: Percentage of female Cape anchovy, *Engraulis capensis*, showing alpha oocyte atresia, 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals) for the following year. Data from Y. Melo (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

Unfortunately, data on gonad resorbtion were not recorded in 1984, thereby leaving open to speculation the possibility of a link to the below average recruitment value estimated for 1985. Under 'normal' circumstances, a low percentage of atresia, *ca.* 1-2%, is not uncommon; values above this threshold should, however, indicate that poor spawning (with a following drop in recruitment) is about to follow (Y. Melo, Sea Fisheries Research Institute, pers. comm.). This proposed relationship breaks down after 1988 however, where for all subsequent years the percentage atresia is recorded as being greater than 1-2%; values for 1989-1993 range between *ca.* 4-13% (mean value *ca.* 9%).

In general, it is assumed that lower incidence of atresia in the female anchovy should be followed by above average recruitment, while higher incidence should be followed by below average recruitment. In order to use percentage atresia for forecasting of recruitment, a threshold value is required that meets these expectations. The value of 1 or 2% suggested by Melo is obviously too low; all the atresia data subsequent to 1988 suggests below average recruitment, which is not the case. However, if we use the mean value of the 1989-1993 data (i.e. 9%) as the threshold value, there is a suggestion of the expected relationship (Figure 5.10).

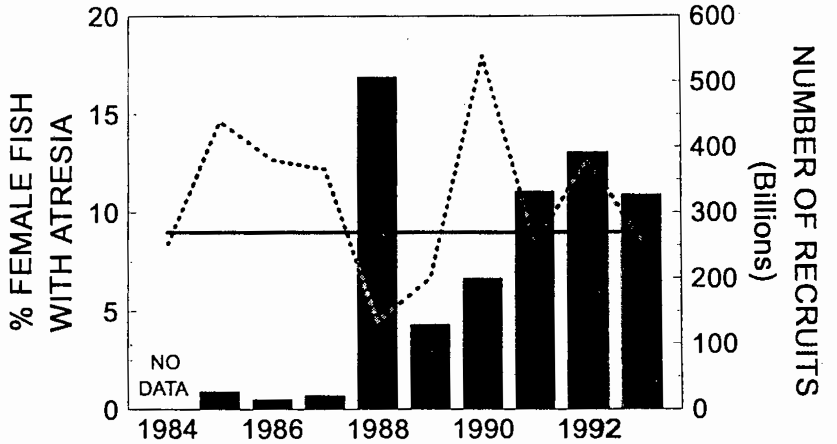


Figure 5.10: Percentage of female Cape anchovy, *Engraulis capensis*, showing alpha oocyte atresia, 1984-1993. The horizontal line (-) indicates the proposed threshold. The broken line (···) indicates estimated recruitment (billions of individuals) for the following year. Data from Y. Melo (Sea Fisheries Research Institute, pers. comm.) and Sea Fisheries Research Institute (unpublished).

Breaking down this relationship however, is the below median percentage atresia of *ca.* 4% in 1989 being followed by below average recruitment, and the above median percentage atresia of *ca.* 13% in 1992 being followed by above average recruitment. It has been suggested that perhaps a bias exists in the measurements of alpha oocyte atresia. Prior to 1988, the percentage alpha oocyte atresia might well have been low, and therefore difficult to recognise without adequate experience. In 1988, with atresia being found in some 17% of the female population, experience was gained in the recognition of atresia. In subsequent years, atresia was more easily recognised - hence the higher percentages post-1988. The scientist involved in these analyses, denies this possibility however (Y. Melo, Sea Fisheries Research Institute, pers. comm.).

El Niño - Southern Oscillation (ENSO) Events

Fluctuations in the estimated recruitment time-series, although alternate in amplitude, appear to follow the trends in the Southern Oscillation Index (SOI) (Figure 5.11). In general, fluctuations of positive amplitude in the SOI, e.g. the La Niña (Anti-El Niño) of 1988-1989, coincide with below average recruitment, while fluctuations of negative amplitude, e.g. the El Niños of 1987 and 1991, coincide with above average recruitment.

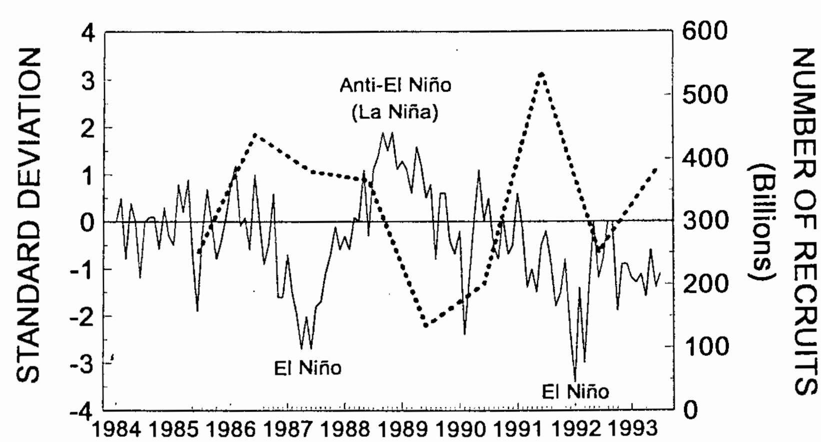


Figure 5.11: The Southern Oscillation Index (SOI), 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals). Data from Kousky *et. al.* (1984-93) and Sea Fisheries Research Institute (unpublished).

It has been reported that there is about a 6-month lag between a temperature switch in the tropical Pacific, and its effect globally (Kerr 1988). Figures 5.12

(a) and (b) show the SOI with estimated recruitment lagged at 6 months and 1 year respectively; it would appear that the lag of 6 months is approximately of the correct order.

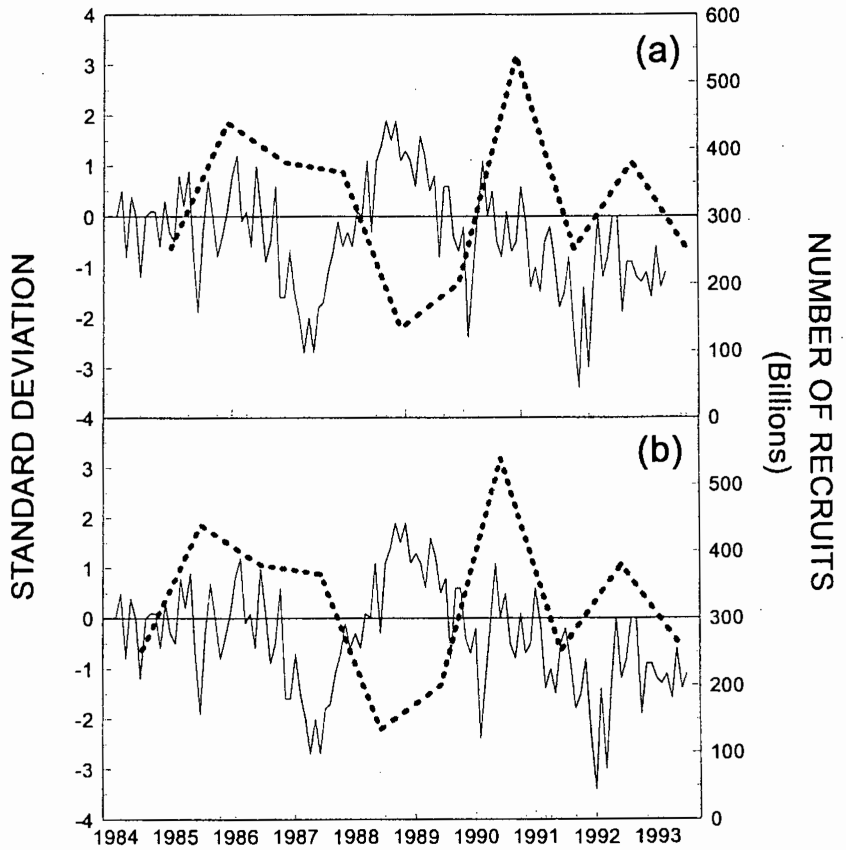


Figure 5.12: The Southern Oscillation Index (SOI), 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals) with (a) 6 month lag, and (b) 1 year lag. Data from Kousky *et. al.* (1984-93) and Sea Fisheries Research Institute (unpublished).

It is believed that ENSO phenomena can be used as a holistic index of environmental conditions in the southern Benguela, i.e. an ENSO event (that is, La Niña or El Niño), affects the climate and oceanography in a specific way, with a tendency to enhance either "summer" or "winter" conditions respectively (see Figure 4.12). Furthermore, it is expected that these processes relate to the concept of the dome-shaped curve of the environmental window (see Figure 3.2) - too little, or too much, being detrimental to recruitment.

The assumptions are that El Niño, by enhancing "winter" conditions (i.e. reducing "summer" conditions), is beneficial to the recruitment process because southerly wind stress (a summer phenomenon) is reduced along with the possibility of advective loss of spawning products; La Niña on the other hand, by enhancing "summer" conditions, is detrimental to the recruitment process because of increased southerly wind stress (to levels detrimental to recruitment). With these assumptions in mind, threshold deviations for La Niña and El Niño were assigned (the data for the SOI time-series may be found in Appendix 1). The assumption that El Niño, by reducing "summer" conditions, is beneficial to recruitment appears to hold: compartment (1) of Figure 5.13 shows that the El Niño of 1987 (maximum deviation of -2.7) held no major impact for recruitment. The assumption that La Niña, by enhancing "summer" conditions, is detrimental to recruitment also appears to hold: compartment (2) of Figure 5.13 shows that the La Niña of 1988-89 (maximum deviation of 1.9) had a major impact on recruitment.

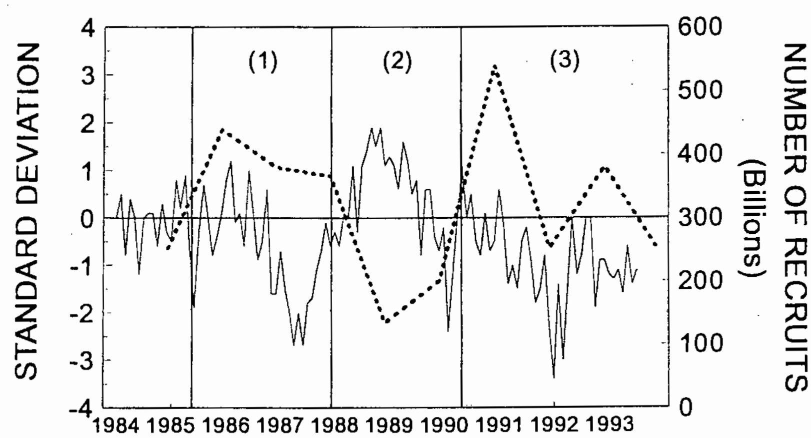


Figure 5.13: The Southern Oscillation Index (SOI), 1984-1993. The broken line (···) indicates estimated recruitment (billions of individuals), lagged by 6 months. The labeled compartments are referred to in the text. Data from Kousky *et al.* (1984-93) and Sea Fisheries Research Institute (unpublished).

There are other points of interest: the series of positive deviations (ranging from 0.6 to 1.2) in 1986, coincide with a decrease in estimated recruitment (Figure 5.13 - compartment (1)); and the downward trend in deviation leading to the El Niño of 1992 (maximum deviation of -3.4), coincides with the below average recruitment estimate for 1992.

The environmental window concept therefore appears to apply. It appears that an El Niño with deviation less than -3 is beneficial to recruitment, while an El Niño of deviation greater than -3 is detrimental to recruitment by over-enhancing "winter" conditions. The La Niña (positive) fluctuations of 1986, appear to negatively impact recruitment; we assume therefore that La Niñas of deviation greater than 0.5 appear to be detrimental to recruitment.

5.6 TESTING THE 'BASE-CASE' EXPERT SYSTEMS

The objective of these expert systems is to forecast qualitatively annual recruitment success for Cape anchovy, *Engraulis capensis*. These 'base-case' systems use the basic set of four variables believed to be capable of forecasting recruitment, as proposed at the workshops (see Chapter 4). Three systems were developed: two systems using three variables each, and the third incorporating all four variables into a single system. The systems forecasting abilities are tested by comparing forecasts against the existing time-series of estimated Cape anchovy recruitment (1985-1993). Note that the year for which the forecast is made, refers to the year succeeding that in which the data are collected. The results for these systems are shown comparatively in Table 5.4. Detailed results from these, and all the subsequent systems, are also to be found in Appendix 3).

At the time of building and testing the systems, data were only available up to 1992. The 1993 data, and the 1994 recruitment estimate, were not yet available, so when the 1993 data became available, a "real" forecast was tendered for 1994. A complete set of data was not available for 1994, so no forecast was made for recruitment in 1995.

5.6.1 3-Variable Systems

The 'WIND' System

With the exception of 1985 and 1988, below average recruitment, is forecast for all years, 1985-1994; the confidence of the below average recruitment forecast varies from 'possible' to 'very likely' (Table 5.4). As below average recruitment is recorded to have occurred in 1985, '89, '90 and '92, the system therefore makes correct forecasts for 1989, '90 and '92 (the forecast for 1992 being unusable however, for lack of confidence - see section 5.3). The forecast of average/above average recruitment made for 1985, and the below average recruitment forecasts made for 1991 and '93, are in disagreement with the recruitment estimate time-series: below average and average/above average recruitment is recorded to have occurred for these years respectively.

YEAR	ESTIMATED RECRUITMENT	FORECAST BY 'BASE-CASE' SYSTEM....		
		3-variable 'Wind'	3-variable 'Food'	4-variable
1985	Below Average	A/AA Recruitment	No Data	A/AA Recruitment
1986	A/AA	B.A.R - Possible	No Data	B.A.R - Possible
1987	A/AA	B.A.R - Possible	No Data	B.A.R - Possible
1988	A/AA	A/AA Recruitment	No Data	A/AA Recruitment
1989	Below Average	B.A.R - Likely	B.A.R - Likely	B.A.R - Very Likely
1990	Below Average	B.A.R - Very Likely	B.A.R - Likely	B.A.R - Very Likely
1991	A/AA	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1992	Below Average	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1993	A/AA	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1994	Below Average	B.A.R. - Very Likely	B.A.R. - Likely	B.A.R. - Very Likely

Table 5.4: Comparative forecast table for the three 'base-case' deterministic expert systems. Variables are unweighted. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. The first four forecasts in the 4-variable column are those from the 3-variable 'Wind' system.

As mentioned above, the 1994 recruitment estimate was not yet available, so a "real" forecast (not hindcast) of below average recruitment - 'very likely' chance - was tendered. When the estimate was later made available, the forecast of below average recruitment was justified. Detailed results are shown in Appendix 3, Table A3.1.

The 'FOOD' System

Data on percentage "starvation stations" were not collected prior to 1988, hence forecasts using this 3-variable system only begin at 1989. Below average recruitment, is forecast for all years, 1989-1993; the confidence of the below average recruitment forecast varies from 'possible' to 'likely' (see Table 5.4). As below average recruitment is recorded to have occurred in 1989, '90 and '92, the system forecasts correctly for these years (the forecast for 1992 is again unusable). In 1991 and '93 however, average/above average recruitment is recorded to have occurred, contradicting the below average recruitment forecasts made for these years.

A "real" forecast of below average recruitment - 'likely' chance - was tendered for 1994. When the recruitment estimate was later made available, it was found that the forecast was justified - note however, the decrease in confidence from the previous system. Detailed results are shown in Appendix 3, Table A3.2.

5.6.2 **4-Variable System**

Unfortunately, data on percentage "starvation stations" were not collected prior to 1988, therefore forecasts from the 4-variable system only begin at 1989. For continuity however, the 4-variable forecasts are joined on to those generated by the 3-variable 'Wind' system (1985-1988), so that a forecast is presented for each year of the recruitment time-series.

Except for 1985 and 1988, in which average/above average recruitment is forecast, below average recruitment is forecast for all years; the confidence of the below average recruitment forecast varies from 'possible' to 'very likely' (see Table 5.4). The system therefore makes correct forecasts for the years 1989, '90 and '92 (due to lack of confidence, the 1992 forecast is again unusable however). Forecasts contradicting the recruitment time-series are: 1985, average/above average recruitment forecast but below average recruitment observed; 1986, '87, '91 and '93, below average recruitment forecast but average/above average recruitment observed.

A "real" forecast of below average recruitment - 'very likely' chance - was tendered for 1994. When the estimate was later made available, it was found that the forecast was justified - note the increase in confidence from the previous system. Detailed results are shown in Appendix 3, Table A3.3.

5.6.3 **Summary**

Due to the percentage "starvation station" time-series becoming available only much later than the other variables, forecasts generated by the three 'base-case' systems can only be compared over the period 1989-1994 (see Table 5.4). All three systems give the same forecasts for this period - only the confidence of the below average recruitment forecasts differs. Of the three 'base-case' systems, the forecasts generated by the 3-variable *'Food'* system were the least confident, while the 4-variable system generated the most confident forecasts. Due to the short forecast time-series and the lack of confidence in the 3-variable *'Food'* system, discussion will center on the two systems that provide forecasts for the entire recruitment time-series (1985-1994); i.e. the 3-variable *'Wind'* system and the 4-variable system.

The below average recruitment forecasts generated by both these systems agree with the estimated below average recruitment for all years in the recruitment time-series, except one. 1985 is recorded as a below average recruitment year, while the expert systems both forecast average/above average recruitment. These systems also forecast below average recruitment for some years in which average/above average recruitment is estimated to have occurred, viz. 1986-'87, 1991 and 1993. These forecasts are however, all made with "Possible" confidence and, as decided previously, are not immediately usable in decision-making. It is important to note that the expert systems are built upon basic assumptions detailing the recruitment process (outlined in Chapter 3); it has been suggested that these incorrect forecasts are due to violations of these basic assumptions. In 1986 and '87, due to an intrusion of Agulhas Bank water onto the West Coast (L. Hutchings, Sea Fisheries Research Institute, pers. comm.), spawning took place on the West Coast (Figure 5.14). As the larvae were therefore already on the West Coast, no transport to the recruitment grounds (an assumption for successful recruitment) was needed.

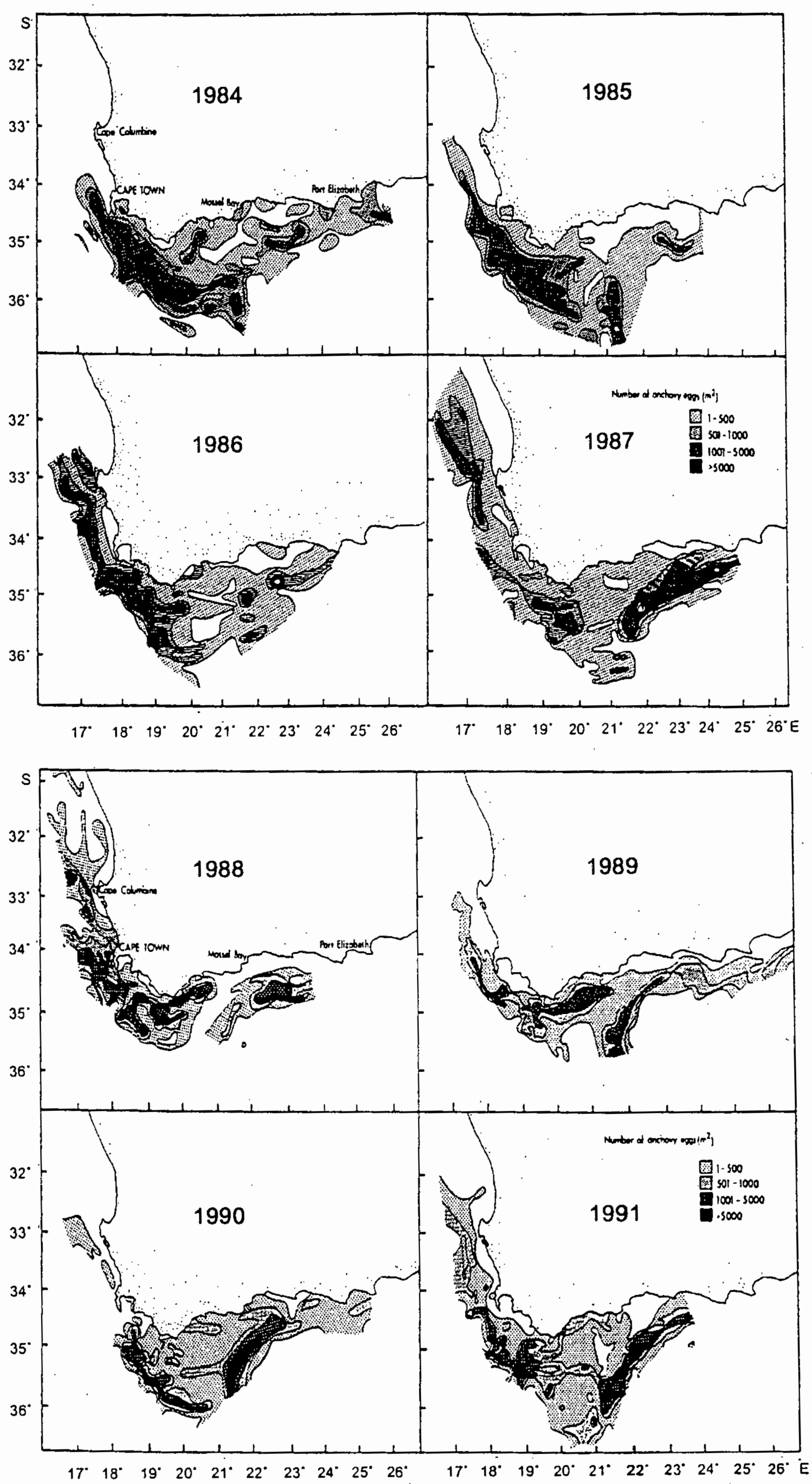


Figure 5.14: Distribution of anchovy eggs from the November Spawner Biomass cruises of 1984-1991 (from Roel *et al.* 1994).

However, an above threshold southerly windrun was also recorded in 1986 (Tables 3.1, 3.3; Appendix 3), necessitating a forecast of possible below average recruitment because there is a good chance of losing eggs and larvae through offshore advective processes. In 1990, high concentrations of anchovy eggs were found on the eastern Agulhas Bank (Figure 5.14), violating the assumption that for successful recruitment on the west coast of South Africa, anchovy spawn on the western Agulhas Bank (see Figure 3.4). Although unrecorded, it has been suggested that average/above average recruitment occurred on the south coast (L. Hutchings, Sea Fisheries Research Institute, pers. comm.). In 1993, the estimated number of recruits was high, but the biomass of recruits was low (see Figures 41 and 4.2 respectively), probably indicating that spawning took place much later than assumed.

5.7 TUNING THE 'BASE-CASE' EXPERT SYSTEMS

Failure of the above models to correctly forecast recruitment for all years necessitates further investigation: what changes can be made in order to obtain a closer agreement between the predicted and observed recruitment? Since the 4-variable model gave the best results, all attempts at tuning will be applied to this system. The methods undertaken for tuning the model are:

- differential weighting of the variables;
- using "fuzzy" thresholds; and
- adding, and eliminating, variables.

These methods examine the response of the chosen model to changes in the structure of the system and changes in the variables, and may be seen as a sensitivity analysis. The results generated by the tuning process are shown in Tables 5.5, 5.6 and 5.7.

5.7.1 Weighted-Variable System

This system is identical to the above 4-variable system, except that the variables are now differentially weighted according to their perceived impact on recruitment (as explained in section 5.5.2 above). Weighting the variables makes no difference to the output however - the results are exactly the same as those generated by the unweighted 4-variable system and are not shown here (see Table 5.4). Detailed results are shown in Appendix 3, Table A3.4.

It is however, believed that as not all variables will have the same impact on recruitment, the differential weighting of variables is an important component of the system. All subsequent systems therefore maintain this element of the tuning process, and although not explicitly referred to as such, are weighted-variable systems.

5.7.2 "Fuzzy" System

As explained above (see section 5.5.2), it is believed that perhaps the current thresholds are not accurately isolating the extreme values in the time-series, but are also including some values that ought not to be considered detrimental to recruitment. "Fuzzy" thresholds were not successful in correcting the forecasts however - thresholds "fuzzy" at ±10% and ±20% made absolutely no changes to the forecasting ability of the system; results are the same as those for the 'base-case' 4-variable system (see Table 5.4). Essentially then, it would appear that a "fuzzy" threshold of the type applied here, is not able to reconcile the forecasts with the historical time-series of estimated recruitment. Detailed results for the "fuzzy" systems are shown in Appendix 3, Tables A3.5 and A3.6 respectively.

Both "fuzzy" systems correctly forecast below average recruitment for 1994; the forecast being made with less certainty by the ±20% system (Appendix 3, Tables A3.5 and A3.6). This is as a result of the ±20% "fuzzy" threshold incorporating the 1993 southerly windrun datum and reducing the number of variables playing a role in the decision process. This therefore reduces the confidence with which the forecast can be made.

5.7.3 Adding and Eliminating Variables

The expert systems built so far all incorrectly forecast "Possible" below average recruitment for the majority of these average/above average years (except 1988). In most cases, the erroneous forecast is caused by the presence of a single variable generating the below average recruitment forecast. It is suggested that generally, two or more indicator variables crossing their respective thresholds are required for a reliable below average recruitment prediction. This is unobtainable with the current variable set. Further investigations explore the possibility of using other indicator variables to correct the erroneous forecasts, so that predicted recruitment is in agreement with observed recruitment.

Distance Offshore of the 16°C Isotherm

Three separate systems incorporate the distance offshore of the 16°C isotherm time-series: as a first attempt, the 16°C isotherm data were merely added to the existing 4-variable weighted system to create a 5-variable system; in two other systems, the 16°C isotherm dataset was used to respectively replace the oil yield (16-4A) and N-S wind anomaly time-series (16_4B). The results are shown in Table 5.5. Note that because of the lack of data for "starvation stations" for the period 1984-1987, the 1985-1988 forecasts are based on those 4 variables for which data are available, viz. oil yield, egg production, N-S wind anomaly and the distance offshore of the 16°C isotherm.

For the 5-variable system, the 16°C isotherm dataset falls into the same class of indicator as the N-S wind anomaly data, and therefore carries a weight of 2 (see Section 5.5.2, Figure 5.1). With the addition of the 16°C isotherm data, the results are the best so far and show certain improvement over the original 4-variable system. For 1985, the system now correctly forecasts below average recruitment (although in reality, "Possible" confidence makes the forecast unusable), and confidence is improved in the 1992 below average recruitment forecast. Detailed results are shown in Appendix 3, Table A3.7

Further tuning of this system was attempted by alternately replacing the oil yield and N-S wind anomaly data with the 16°C isotherm data, and returning to a 4-variable system. The forecasting abilities of these two new systems, however, offer little improvement on the 5-variable system. In these individual systems, 50% of the erroneous forecasts are corrected, but at a cost to the confidence in the below average recruitment forecast of 1992, thereby rendering this forecast unusable. System 16_4A corrects forecasts for 1991 and 1993, while System 16_4B corrects forecasts for 1986 and 1987 (detailed results are shown in Appendix 3, Tables A3.8 and A3.9 respectively). The 5-variable weighted system remains the best system so far.

YEAR	ESTIMATED RECRUITMENT	FORECAST BY SYSTEM....		
		16°C - 5-variable	16_4A	16_4B
1985	Below Average	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1986	A/AA	B.A.R - Possible	B.A.R - Possible	A/AA Recruitment
1987	A/AA	B.A.R - Possible	B.A.R - Possible	A/AA Recruitment
1988	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1989	Below Average	B.A.R - Very Likely	B.A.R - Very Likely	B.A.R - Very Likely
1990	Below Average	B.A.R - Very Likely	B.A.R - Very Likely	B.A.R - Very Likely
1991	A/AA	B.A.R - Possible	A/AA Recruitment	B.A.R - Possible
1992	Below Average	B.A.R - Likely	B.A.R - Possible	B.A.R - Possible
1993	A/AA	B.A.R - Possible	A/AA Recruitment	B.A.R - Possible
1994	Below Average	B.A.R. - Likely	B.A.R. - Very Likely	B.A.R. - Very Likely

Table 5.5: Comparative forecast table generated by deterministic expert systems incorporating the distance offshore of the 16°C isotherm time series. Systems 16_4A and 16_4B refer to 4-variable systems in which the oil yield and N-S windrun data have been respectively replaced by the 16°C isotherm data. The variables are weighted according to their impact on recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average.

Incidence of Alpha Oocyte Atresia

Four separate forecasting systems incorporate the percentage gonad atresia data: as a first attempt, the atresia data were merely added to the existing 5-variable weighted system to create a 6-variable system; attempts at tuning this system reduced this to two 5-variable systems in which the oil yield (Atresia_5A) and N-S windrun data (Atresia_5B) were respectively replaced by the atresia data; and finally, these systems were further distilled to create a 4-variable system in which the oil yield and N-S windrun data were together replaced by the atresia data. With respect to the weighting of the variables, percentage gonad atresia falls into the same class of indicator as the oil yield and therefore carries a weight of 2 (see Section 5.5.2; Figure 5.1).

The results are shown in Table 5.6. Note that due to the lack of both percentage "starvation station" and atresia data for 1984, the 1985 forecast is based on the 4 variables for which there are data. Similarly, due to the lack of percentage "starvation station" data for 1985-1987, the 1986-1988 forecasts are based on the 5 variables for which there are data. Detailed results are shown in Appendix 3, Table A3.10.

Unfortunately, the results for the 6-variable system show no improvements over that of the 5-variable system (see Table 5.6). Although itself a problematical dataset (missing datum for 1984 and conflicting datum for 1992), the atresia time-series contains fewer conflicting data points than either of the oil yield and N-S wind anomaly time-series. Improved forecast accuracy was obtained from tuning this system by alternately replacing the oil yield and N-S wind with atresia, and reverting to 5-variable systems (see Table 5.6, detailed results are shown in Appendix 3, Tables 3.11 and 3.12). The best results however, were obtained from a 4-variable system, constructed by simultaneously replacing both oil yield and N-S wind with atresia (see Table 5.6; detailed results are shown in Appendix 3, Table A3.13). Removing these two indicators (and replacing them with atresia), corrects all but one of the previous erroneous forecasts - for 1993, this system forecasts "Possible" below average recruitment (unusable forecast anyway), whereas the observed recruitment is average/above average.

YEAR	ESTIMATED RECRUITMENT	FORECAST BY SYSTEM....			
		Atresia - 6-variable	Atresia_5A	Atresia_5B	Atresia - 4-variable
1985	Below Average	B.A.R - Possible	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1986	A/AA	B.A.R - Possible	B.A.R - Possible	A/AA Recruitment	A/AA Recruitment
1987	A/AA	B.A.R - Possible	B.A.R - Possible	A/AA Recruitment	A/AA Recruitment
1988	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1989	Below Average	B.A.R - Very Likely	B.A.R - Very Likely	B.A.R - Very Likely	B.A.R - Very Likely
1990	Below Average	B.A.R - Very Likely	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1991	A/AA	B.A.R - Possible	A/AA Recruitment	B.A.R - Possible	A/AA Recruitment
1992	Below Average	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1993	A/AA	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1994	Below Average	B.A.R. - Likely	B.A.R. - Likely	B.A.R. - Very Likely	B.A.R. - Likely

Table 5.6: Comparative forecast table generated by deterministic expert systems incorporating the percentage gonad atresia time series. Systems Atresia_5A and Atresia_5B refer to 5-variable systems in which the oil yield and N-S windrun data have been respectively replaced by the atresia data. The 4-variable system refers to a system in which both the oil yield and N-S windrun data have been replaced by the atresia data. The variables are weighted according to their impact on recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average.

Incidence of El Niño-Southern Oscillation (ENSO) Events

Two separate 5-variable systems, respectively incorporating La Niña and ENSO events, were formed from the previous best 4-variable system. With respect to the weighting of the variables, both the La Niña and ENSO events fall into the same class of indicator as the N-S windrun and therefore carries a weight of 2 (see Section 5.5.2, Figure 5.1). The results are shown in Table 5.7.

Unfortunately, adding either the La Niña or ENSO data makes no improvements to the forecasting abilities of the previous best 4-variable system. The results are exactly the same (Table 5.7). Detailed results are also shown in Appendix 3, Tables A3.14 and A3.15 respectively.

Everything

Final investigations revolved around creating systems incorporating all the indicators currently at our disposal. Unfortunately, the results from these 7-variable systems suffer from the conflicting data in the oil yield and N-S windrun time-series, and no improvements were obtained. The results are not shown here (see Appendix 3, Tables A3.16 and A3.17).

YEAR	ESTIMATED RECRUITMENT	FORECAST BY SYSTEM....		
		Atresia - 4-variable	La Niña - 5-variable	ENSO - 5-variable
1985	Below Average	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1986	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1987	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1988	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1989	Below Average	B.A.R - Very Likely	B.A.R - Very Likely	B.A.R - Very Likely
1990	Below Average	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1991	A/AA	A/AA Recruitment	A/AA Recruitment	A/AA Recruitment
1992	Below Average	B.A.R - Likely	B.A.R - Likely	B.A.R - Likely
1993	A/AA	B.A.R - Possible	B.A.R - Possible	B.A.R - Possible
1994	Below Average	B.A.R. - Likely	B.A.R. - Likely	B.A.R. - Likely

Table 5.7: Comparative forecast table generated by the previous best 4-variable deterministic expert system, and the La Niña and ENSO 5-variable systems. The variables are weighted according to their impact on recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average.

5.8 EXPLORING FOR THE SIMPLEST (BEST) SYSTEM

A number of the above systems had problems with erroneous forecasts - these problems centered around the data points in the time-series of specific indicators, notably the oil yield and N-S windrun anomaly. These time-series contain data that incorrectly indicate an upcoming below average recruitment event. The only systems to correct this problem were those that, alternatively and then simultaneously, replaced the oil yield and N-S windrun anomaly, effectively removing the conflicting data.

In moving toward the ultimate goal of a system that uses the minimum of data, i.e. good economy, yet still correctly forecasts anchovy recruitment, the 4-variable atresia system gave the best performance (see Table 5.6). However, the lack of percentage "starvation station" data for the period 1984-1987 restricts this system to using only 3 variables to generate forecasts for this period. It is perhaps worthwhile to replace this indicator with one that has the full data complement. The most feasible indicator appears to be ENSO. We therefore have the following 4-variable differentially weighted system, with data over the entire recruitment time-series:

- Egg Production,
- Distance offshore of the 16°C Isotherm,
- Percentage Atresia, and
- El Niño-Southern Oscillation (ENSO) events.

Table 5.8 and Figure 5.15 shows the forecasting abilities of this system (detailed results are shown in Appendix 3, Table A3.18).

The forecasts generated by this final expert system are a definite improvement, even on the previous best 4-variable 'atresia' system. Of note are the greater confidence in the forecasts of below average recruitment for the 1990, '92 and '94. There is only one incorrect forecast: 1993, where "Possible" below average recruitment is forecast, contradicting the observed average/above average recruitment. This forecast is believed to be unusable.

The complete WinEXP rule-base for this system is presented in Appendix 4.

YEAR	ESTIMATED RECRUITMENT	FORECAST BEST - 4-variable
1985	Below Average	B.A.R - Likely
1986	A/AA	A/AA Recruitment
1987	A/AA	A/AA Recruitment
1988	A/AA	A/AA Recruitment
1989	Below Average	B.A.R - Very Likely
1990	Below Average	B.A.R - Very Likely
1991	A/AA	A/AA Recruitment
1992	Below Average	B.A.R - Very Likely
1993	A/AA	B.A.R - Possible
1994	Below Average	B.A.R. - Very Likely

Table 5.8: Forecast table generated by the 'best' 4-variable deterministic expert system. The variables are weighted according to their impact on recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average Recruitment.

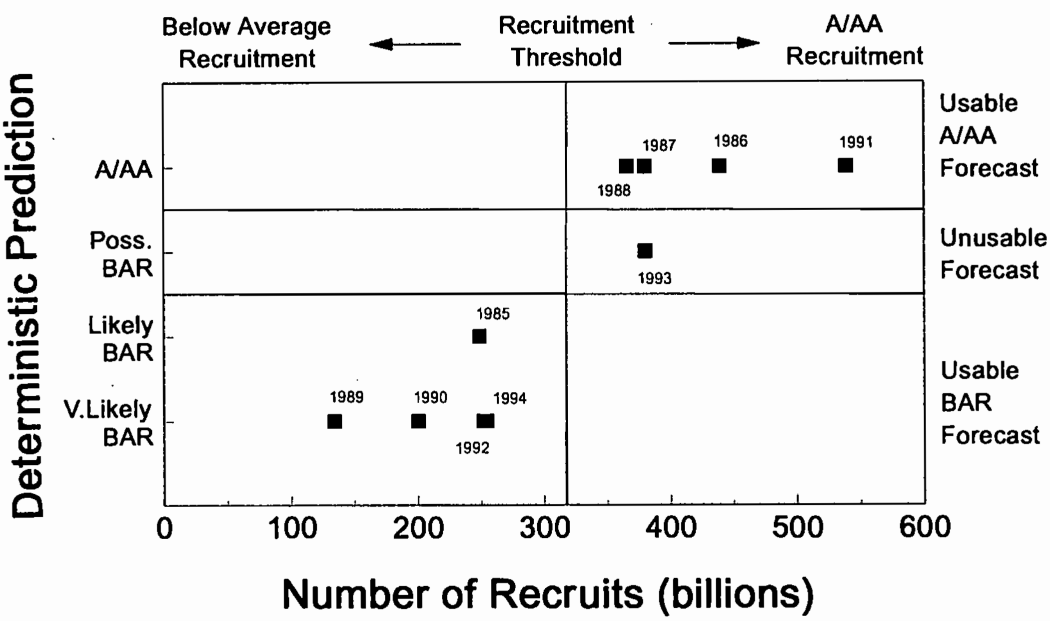


Figure 5.15: Graphical representation of the forecasts generated by the 'best' 4-variable deterministic expert system. The variables are weighted according to their impact on recruitment. The shaded area is the area of interest, delineated by the thresholds for usable/unusable forecasts and below average/average/above average recruitment. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average Recruitment.

5.9 SUMMARY

The models described here highlight some of the many factors believed to play a role in the recruitment of the South African anchovy, *Engraulis capensis*. In the quest for the simplest "best" system, the development of the final expert system went through several revealing phases, each giving new insight into the recruitment problem. One notable result is that essentially the same forecasts (with varying degrees of confidence), may be obtained with a variety of systems. By using as many variables as possible, we may minimize the likelihood of erroneous or unusable forecasts. Such systems are worth investigating and may even be preferable, but in the interests of economy, the fewer the number of variables that require monitoring, the better.

It is believed that the data presently collected over the anchovy spawning season on the Spawner Biomass survey, coupled with current knowledge of the Benguela pelagic system, is sufficient to provide a qualitative forecast of below average recruitment by January of the recruitment year. There is of course a need to further validate the model before such a forecasting system can be used with confidence in a fisheries management environment.

... there comes a time in the mangement process,
... the moment of truth, of realization
that no information exists ...

Pope (1980)

Chapter 6

PROBABILISTIC EXPERT SYSTEMS

6.1 INTRODUCTION

This chapter describes the methods used for a Bayesian probability model for forecasting recruitment in the South African anchovy resource, and the results from generated from the application of the model. Pre-fishing season environmental and biological information is used to make a probabilistic forecast about the forthcoming seasons expected recruitment.

6.2 MODEL CONSTRUCTION

In contrast to the deterministic forecasting system, the probabilistic system has the objective of quantitatively estimating the probability of below average anchovy recruitment, rather than the ordinal approach (possible, likely, very likely) explored in Chapter 5. Many software houses now offer inexpensive shells allowing a user to build his/her own expert system. The user fills in his/her own rules, and supplies "certainty factors" without really being told what they might mean. Of the many expert system shells examined for this project, none had the capability to handle "true" Bayesian probabilities. The closest, and a system perhaps worthy of later investigation, is VP-EXPERT® 3.0, a rule-based expert system development tool (Paperback Software International 1989), that uses numerical confidence factors similar to assigning probabilities.

It was decided, however, that to implement Bayes' theorem (see section 2.6.4), an individual system would have to be developed. This was achieved using TURBO Pascal®. It is pointed out, however, that the intention was not to build a fully-fledged expert system shell like those found in the commercial arena, but rather to create a simple system, for the specific objectives of this dissertation - essentially, a "calculation-engine" implementing the Bayesian equations to calculate posterior probabilities.

Quantifying the probability of below average anchovy recruitment is achieved by iteratively combining, in a step-wise manner, the probabilities and likelihoods associated with those variables believed to be a force in regulating anchovy recruitment. If we let

> BAR = below average recruitment, and
> I = a particular indicator variable related to BAR in a defined way (see Chapter 4),

then by Bayes' theorem, we can calculate the probability of below average recruitment, $P(\mathrm{BAR})$, given specific information about this indicator variable, as follows (see section 2.5.3):

$$P(\mathrm{BAR}|\mathrm{I}) = \frac{P(\mathrm{BAR}) \cdot P(\mathrm{I}|\mathrm{BAR})}{P(\mathrm{I})}. \tag{6.1}$$

Suppose now that some new information on another indicator variable, *J*, comes to our attention. Bayes' theorem explains how to incorporate the new data into our present understanding. We can now state Bayes' theorem to include the new information:

$$P(\mathrm{BAR}|\mathrm{I\&J}) = \frac{\boldsymbol{P(\mathrm{BAR}|\mathrm{I})} \cdot P(\mathrm{J}|\mathrm{BAR\&I})}{P(\mathrm{J}|\mathrm{I})}. \tag{6.2}$$

Note how the output from 1st-order probability equation 6.1, that is $P(\mathrm{BAR}|\mathrm{I})$, becomes an input to the 2nd-order probability equation 6.2.

Suppose now that data for a third indicator variable, *K*, comes to our attention. Bayes' theorem again explains how to incorporate the new information:

$$P(\mathrm{BAR}|\mathrm{I\&J\&K}) = \frac{\boldsymbol{P(\mathrm{BAR}|\mathrm{I\&J})} \cdot P(\mathrm{K}|\mathrm{BAR\&I\&J})}{P(\mathrm{K}|\mathrm{I\&J})}. \tag{6.3}$$

Similarly, when taking the third variable into consideration, the output from the 2nd-order equation (6.2), that is $P(\mathrm{BAR}|\mathrm{I\&J})$, becomes an input into the 3rd-order equation (6.3).

The complete Turbo PASCAL® source code in which the above equations are implemented, can be found in Appendix 5.

6.3 THE CONSULTATION PROCEDURE

To start the program, type "PROBABLY" at the MS-DOS® prompt and press <ENTER>. The user will then be presented with the introductory screen (Figure 6.1).

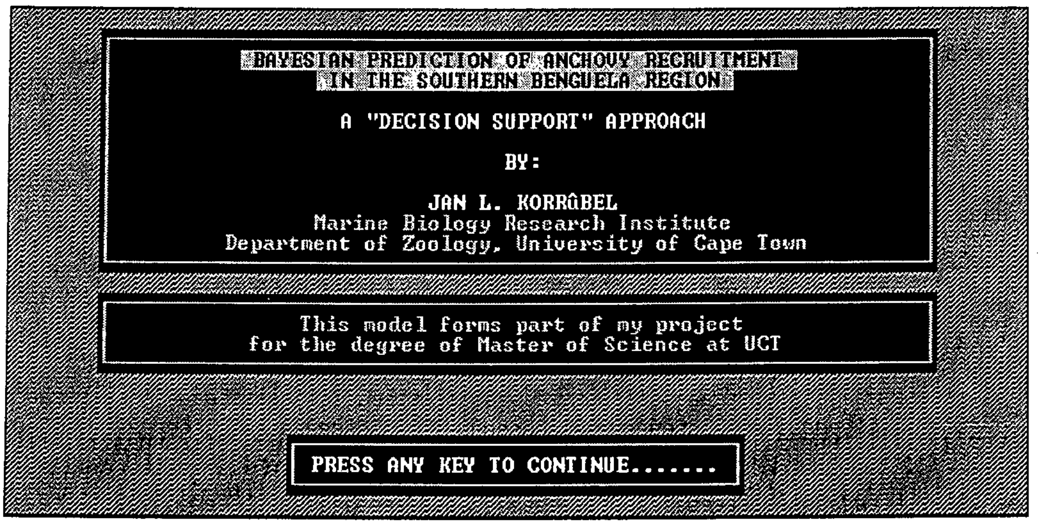


Figure 6.1: Introductory screen from *Probably.*

To begin a new consultation the user must first confirm which set of variables is to be used in the run - this is accomplished by choosing 'Get Questionnaire Data' from the Main Menu (Figure 6.2).

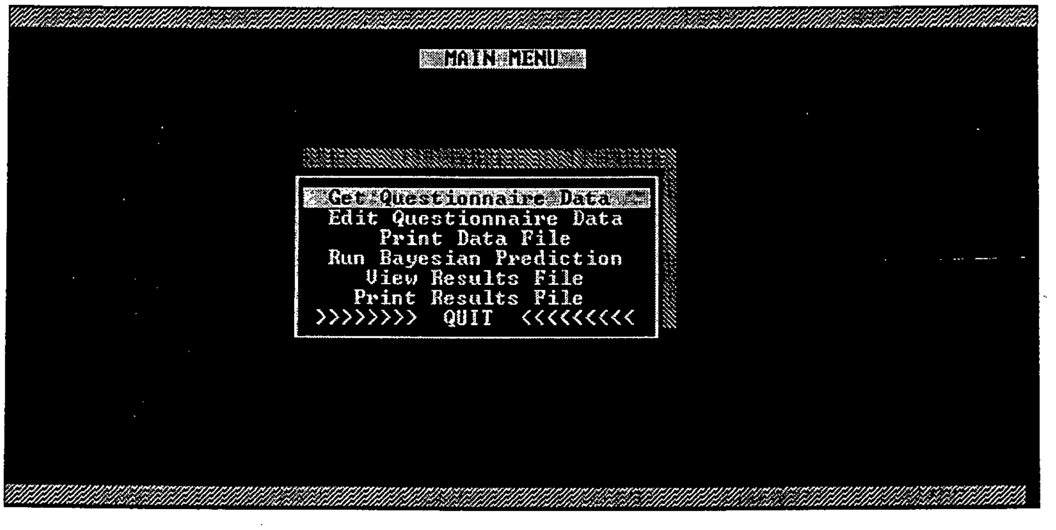


Figure 6.2: Main Menu screen from *Probably.*

The user is presented with a screen from which either the '(W)ind' or '(F)ood' system is to be chosen, by pressing either 'W' or 'F' (Figure 6.3).

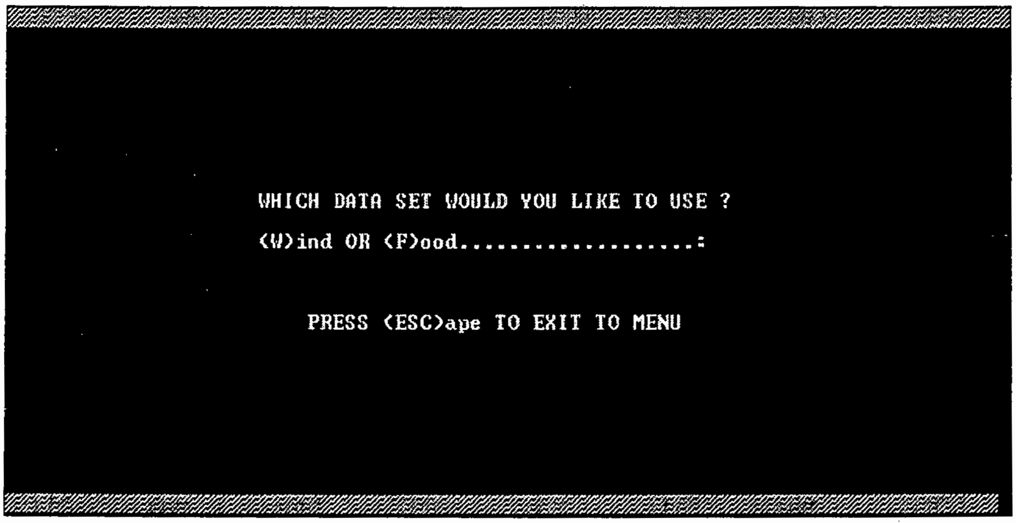
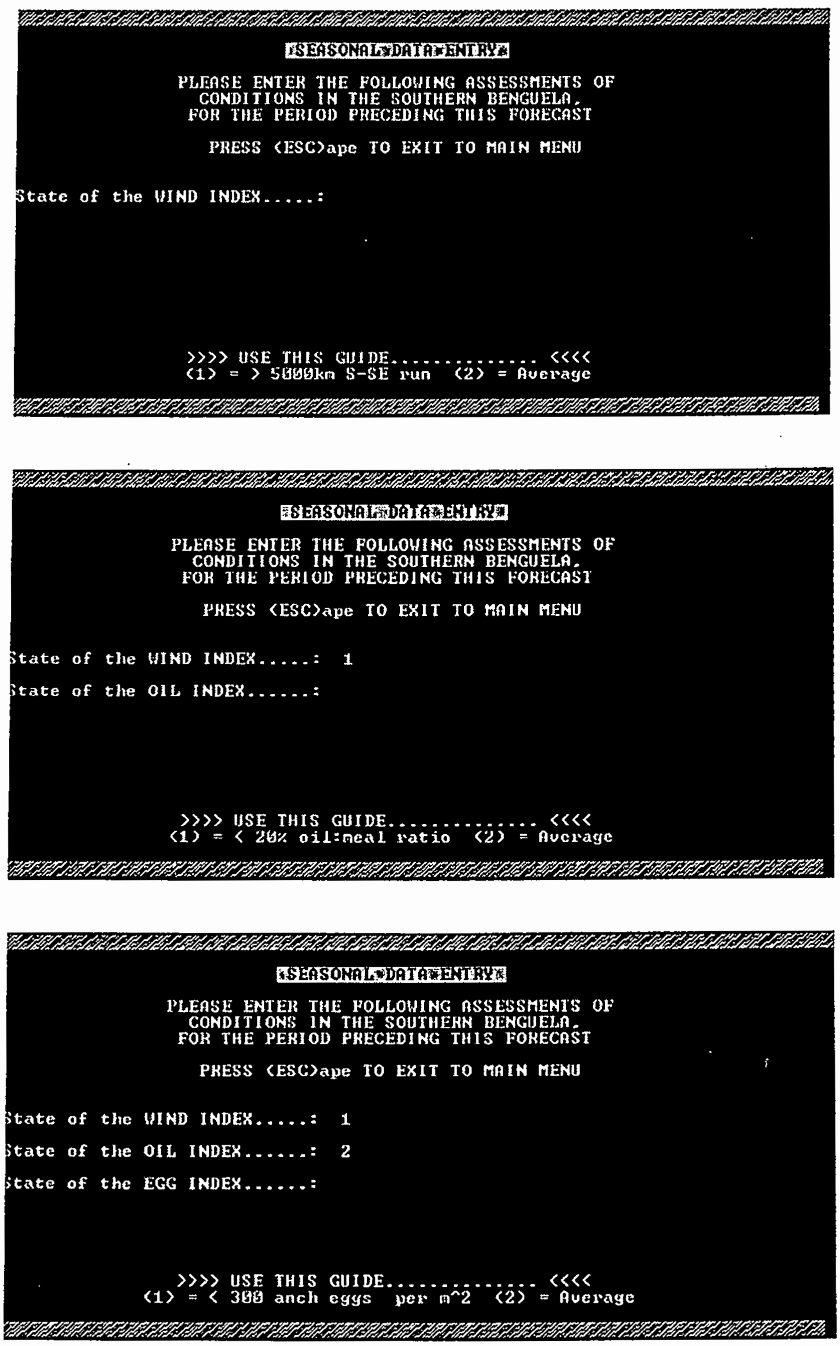


Figure 6.3: Choosing which dataset to run.

Once the user's choice has been established, the system loads from disk the respective data file containing the priors and likelihoods. Once the data file has been loaded, the system returns to the Main Menu - at which stage the user may edit the data file (modify priors for example), print a hardcopy of the data file or run a prediction. The choices to view or print a results file are obviously not available at this stage, as no results file has been created.

To run a prediction, the user chooses 'Run Bayesian Prediction' from the Main Menu. The user is presented with a 'question and answer' screen, through which (s)he is prompted to communicate the status of the variables under examination. The user is guided by threshold values which appear at the bottom of the screen (Figure 6.4). After the user has entered the required parameters, the system does the calculations, writes the results to two separate files, and returns the user to the main menu. At this time the user can view the forecast result - held in the file 'FINAL.OUT' - on the computer screen or print a hardcopy for later perusal. This file contains the final probability of below average recruitment and the scenario, explaining the variables involved in that particular forecast. A second, more detailed, results file - 'BAYES.OUT' - contains the output probabilities from the various stages in the calculation process, presented in sequential order; that is, the probability of below average recruitment calculated from a single variable, followed by the probability of below average recruitment calculated from two variables (and the various combinations), followed by the probability of below average recruitment calculated from three variables (and combinations). Note that if the data file remain unchanged between runs, the contents of the results file 'BAYES.OUT', will also not change - the final probability of below average recruitment is merely drawn from this file and output to 'FINAL.OUT' along with the justification.



(a)

(b)

(c)

Figure 6.4: The data entry screen for a prediction using the 'wind' system, where the user is asked to describe the state of (a) the wind index, (b) the oil index, and (c) the egg production index.

6.4 THE INPUTS

As mentioned above (see section 4.5), one of the tasks tackled by the workshops held to discuss the forecasting of recruitment in the South African anchovy, was to define which variables are, at present, thought to be most likely to allow *numerical* forecasting. They are:

- egg production,
- index of wind stress,
- commercial oil yield, and
- a starvation index for spawning fish on the western Agulhas Bank.

The use of three variables (and all their associated combinations!) was considered to be a practical maximum for a first attempt at a probabilistic system - it was envisaged that obtaining the probabilities would be the major hurdle to overcome; an acceptable goal would be to obtain 2nd-order probabilities. However, it was decided that all four of the selected variables warranted investigation and should be considered. It was therefore proposed that two (comparative) systems be constructed with three variables each. The following combinations of variables were used:

(1)	Oil Yield	(2)	Oil Yield
	Egg Production		Egg Production
	Index of Wind Stress		Starvation Index

6.5 OBTAINING THE INPUTS

In most applications of Bayesian probability theory, not all the inputs required by the Bayesian equation are readily available (Lindley 1990, Mosteller and Youtz 1990). For this exercise, prior probabilities are required for *low* annual oil yield, *low* daily egg production, *strong* southerly winds and *high* percentage "starvation stations", and likelihoods for their many combinations. Before these could be determined, the threshold values defining these states had to be defined (see Chapter 4, section 4.6).

There are two approaches that might be applied to obtain the required inputs: the use of empirical frequency data (i.e. the 'real' data), and probabilities judgementally assessed by experts in the field. Both approaches are examined here.

6.5.1 **Empirical Data:**

If one has enough data, or one does not have experts supplying the probabilities, one might at first assess the frequency approach for extracting the required data from the available time series.

The values for P(BAR) and P(I) - the prior and marginal probabilities respectively - can be obtained from a table of frequencies (Table 6.1), using the following equation:

$$P(\text{Variable}) = \frac{\begin{array}{c}\text{no. of times the variable falls}\\ \text{above / below the threshold value}\end{array}}{\begin{array}{c}\text{total number of years}\\ \text{in the time series}\end{array}} \tag{6.4}$$

YEAR (t)	**VARIABLES**			
	Low Oil	**Low Eggs**	**Strong S. Wind**	**High % S. St'ns**
1984				N.D.
1985			✓	N.D.
1986			✓	N.D.
1987		✓		N.D.
1988	✓		✓	✓
1989	✓	✓	✓	
1990	✓			
1991	✓			
1992	✓			
1993	✓	✓	✓	

Table 6.1: Frequency table showing the incidence (✓) of Low Oil:Meal Ratio, Low Egg Production, Strong Southerly Winds and High Percentage ""Starvation Stations"" for the period 1984-1993. N.D. = No Data. Data from the Sea Fisheries Research Institute (unpublished).

The value for $P(\mathrm{I}|\mathrm{BAR})$ - the likelihood - can be given (approximately) by:

$$P(\mathrm{I}|\mathrm{BAR}) = \frac{\text{no. of times the influencing variable I preceeds a BAR event}}{\text{total no. of times BAR is present in the time series}} . \tag{6.5}$$

Although the time series shown in Table 6.1 are considered too short to be of any real value in obtaining reliable probabilities, the attempt is made nonetheless to extract the required priors and likelihoods using the above equations (the calculations are presented in Appendix 6).

6.5.2 **Expert Opinion:**

Local scientists from the Sea Fisheries Research Institute and the Zoology Department, University of Cape Town (see list in Appendix 1), considered to be experts in various aspects of the South African pelagic fishery, were invited to attend workshops to provide their insights into the possibility of forecasting recruitment in the South African anchovy, *Engraulis capensis*.

It was outlined that, as a starting point, all the indicator variables used in the probabilistic model would be defined as having a prior probability of 0.33. That is, there is a 33% chance that any variable would be in one of the following three 'states': 'detrimental to recruitment', 'average', or 'not detrimental to recruitment'. This 0.33 prior probability was then put before the experts and discussed further with respect to the perceived frequency of below average recruitment and the probability of extreme events associated with the chosen variables. If it was anticipated that below average recruitment, or any extreme event associated with the indicator variables, occurs more or less frequently than prescribed by the 0.33 prior, then a new prior probability (respectively larger or smaller than 0.33) was decided upon by the group.

Furthermore, a questionnaire was designed to obtain additional subjective information (the likelihoods) as required by the Bayesian equations. A series of hypotheses and assumptions relating recruitment and the selected indicator variables was assembled, and then questions formulated in an attempt to quantify these relationships. It should be noted that these relationships were not presented to the group as fact - if a respondent felt that their hypothesis/es differed from any of those presented, space was provided on the questionnaire for them to present their argument(s). In order to prevent any bias at the individual question level, the wording was kept identical for all questions.

As one of the aims of the questionnaire was to obtain the scientists' personal insights into the recruitment forecasting problem, it was asked of the group that they not discuss the worksheet with any of their colleagues. That is, each individual was to use his/her own knowledge of the pelagic ecosystem and its inter-relationships to decide what the "answers" should be.

Budescu, Weinberg and Wallsten (1988) and Rapoport, Erev and Cohen (1990) report that when respondents are allowed to select answers (probabilities) freely, the answers (probabilities) may vary enormously among individuals. As a stabilizing measure, Hamm (1991) suggests that when (subjective) probabilities are required from experts, they be allowed to select from a fixed list. The answer sheet was drawn up in the form of a "chance spectrum" - respondents chose from a fixed number of columns, and placed their mark in the column which they thought best represented the chance of occurrence of a particular event. The columns, seven in all, described the ranges 0-10%, 11-30%, 31-49%, 51-70%, 71-90% and 91-100% (note that in order to force a decision from the respondents and not have them "sit on the fence", the 50% ["no confidence"] category was not included). In addition, the columns were labeled with descriptive names; for example, the 11-30% column was labeled 'Poor' (chance of occurrence), while the 91-100% column was labeled 'Excellent' (chance of occurrence). The idea here is to associate natural language 'anchor phrases' with a specific range of probabilities, in order to guide the respondents in placing their information (Hamm 1991). The ranges are easily converted to probabilities; the median of the range was used as the probability representative for a particular column.

In addition, an extra column was added, in which the respondents could place a mark if they felt they were giving an answer that wasn't in their domain of knowledge - questionnaires containing such marks were excluded from the analysis, but were useful indicators for gauging the respondents' overall knowledge. A total of 36 questionnaires was despatched. Some 31 out of the 36 questionnaires went to local scientists; the remaining 5 went to scientists overseas whom the author believed would have enough of a working knowledge of the Benguela system to complete the questionnaire.

The questionnaire was structured as follows:

Section 1:	Aim, Introduction, Hypotheses and Assumptions
Section 2:	Space for Respondents Alternative Hypotheses
Section 3:	Probabilities from one variable (14 questions)
Section 4:	Probabilities from two variables (16 questions)
Section 5:	Probabilities from three variables (6 questions)
Section 6:	Answer sheet

A copy of the questionnaire is presented in Appendix 7.

6.6 RESULTANT PRIORS AND LIKELIHOODS

References to the probabilities are in abbreviated form. A complete list of the abbreviations used is given in Appendix 8.

6.6.1 Priors

The prior probability of event E, *P*(E), is the probability ascribed to observing event E. The empirical priors (calculated from the time-series using equation 6.4), and the expert assessed priors - assessed with reference to the thresholds determined in Chapter 4 - are shown in Table 6.2. With the exception of oil yield and egg production, the priors obtained from these two methods compared favourably.

PRIOR PROBABILITY	PRIORS FROM:	
	EMPIRICAL DATA	EXPERT DATA
P(BAR)	0.44	0.33
P(LO)	0.60	0.15
P(LE)	0.33	0.10
P(HSW)	0.55	0.40
P(HSS)	0.17	0.15

Table 6.2: Empirical data and expert assessed prior probabilities of Below Average Recruitment *P*(BAR), Low Oil *P*(LO), Low Egg production *P*(LE), High Southerly Winds *P*(HSW) and High percentage "Starvation Stations" *P*(HSS).

6.6.2 **Likelihoods**

Empirical Data

A successful attempt was made to calculate some 1st-order likelihoods from the empirical time-series (see Appendix 6), the results of which are shown in Table 6.3. These were however, the only 1st-order likelihoods to be extracted from the time-series. No 2nd-order likelihoods were calculated. The length of the dataset is too short to get reliable likelihoods involving multiple variables. Further attempts to obtain multi-variable likelihoods via this method were abandoned.

Questionnaire/Workshop Response

Of the 36 questionnaires despatched, 26 (72%) were returned. Of the returned questionnaires, 22 were from local experts, 4 from overseas.

Of the 26 returned questionnaires, 19 respondents (17 local and 2 overseas) answered all the questions. Of the remaining 7 respondents, 4 (all local) answered some of the questions, explaining that the remaining questions were out of their domain; the other 3 respondents (1 local and 2 overseas) answered no questions at all, choosing instead to return the questionnaire with comments and suggestions only. Of interest is the fact that only 5 of the 26 respondents accepted the questionnaire unconditionally, answering all the questions and making no comments with respect to the hypotheses; the rest of the questionnaires were returned with comments and suggestions.

Analysis of the questionnaire was undertaken by assembling the responses from the 19 respondents who had answered all the questions - these were grouped to produce frequency distributions, examples of which are shown in Figures 6.5 and 6.6(a). Figure 6.5 illustrates the case when a majority of the respondents were in agreement as to the probability (likelihood) for a specific question: there is a clear mode - the 71-90% category is favoured over the other categories. On the other hand, Figure 6.6(a) illustrates the form of the frequency distribution that is obtained for a question in which there is no clear consensus - note the spread of opinion across the range of categories.

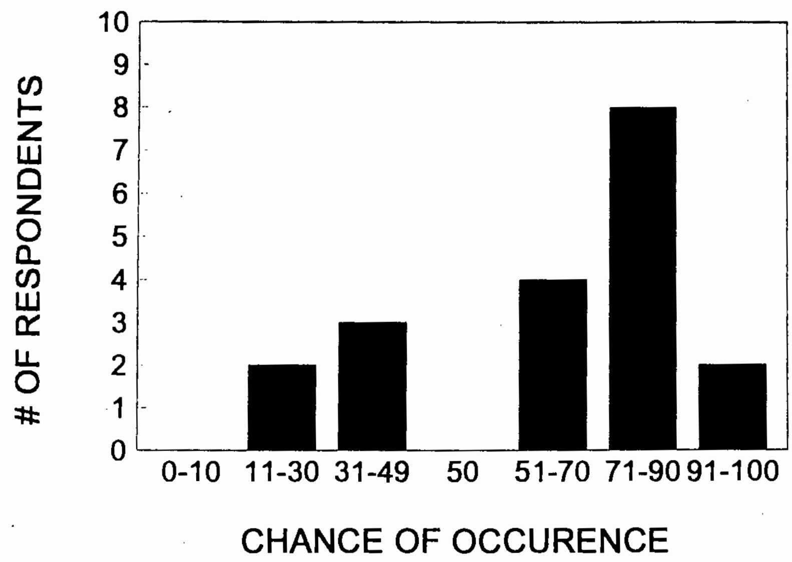


Figure 6.5: Frequency distribution for any question in the questionnaire in which there is a clearly favoured category.

The answer (that is, the likelihood) to any of the questions may easily be obtained if all the questions yielded frequency distributions as shown in Figure 6.5. Obtaining the "answer" however, from a distribution like that shown in Figure 6.6(a) is obviously somewhat more problematical. In order to extract the required information, it was decided to combine categories in these problematic distributions. The number of categories was at first decreased to 3 (from a total of 7), and then further reduced to 2 (Figure 6.6).

In most cases, reducing the number of categories to 3 allows one to immediately distinguish on which side of the 50% "no confidence" line the expert consensus lies, and no further reduction in categories is necessary. In some cases however, as in the example shown in Figure 6.6(a), the greatest consensus lies in the 31-70% "multi-category" (Figure 6.6(b)) - and because the "multi-category" now spans the 50% "no confidence" line, this gives one no further information above that of the original frequency distribution (Figure 6.6(a)). In such a case, further reducing the number of classes (down to 2), allows one to decide which side of the 50% "no confidence" line is favoured - in the example, this is clearly in the 0-49% range (Figure 6.6(c)). This would therefore guide one to put the datum from this example question into the original 31-49% category. This approach does however, still suffer from the fact there was no clear consensus on the answer, and is inherently uncertain. The final questionnaire likelihoods are given, in worksheet form, in Appendix 9.

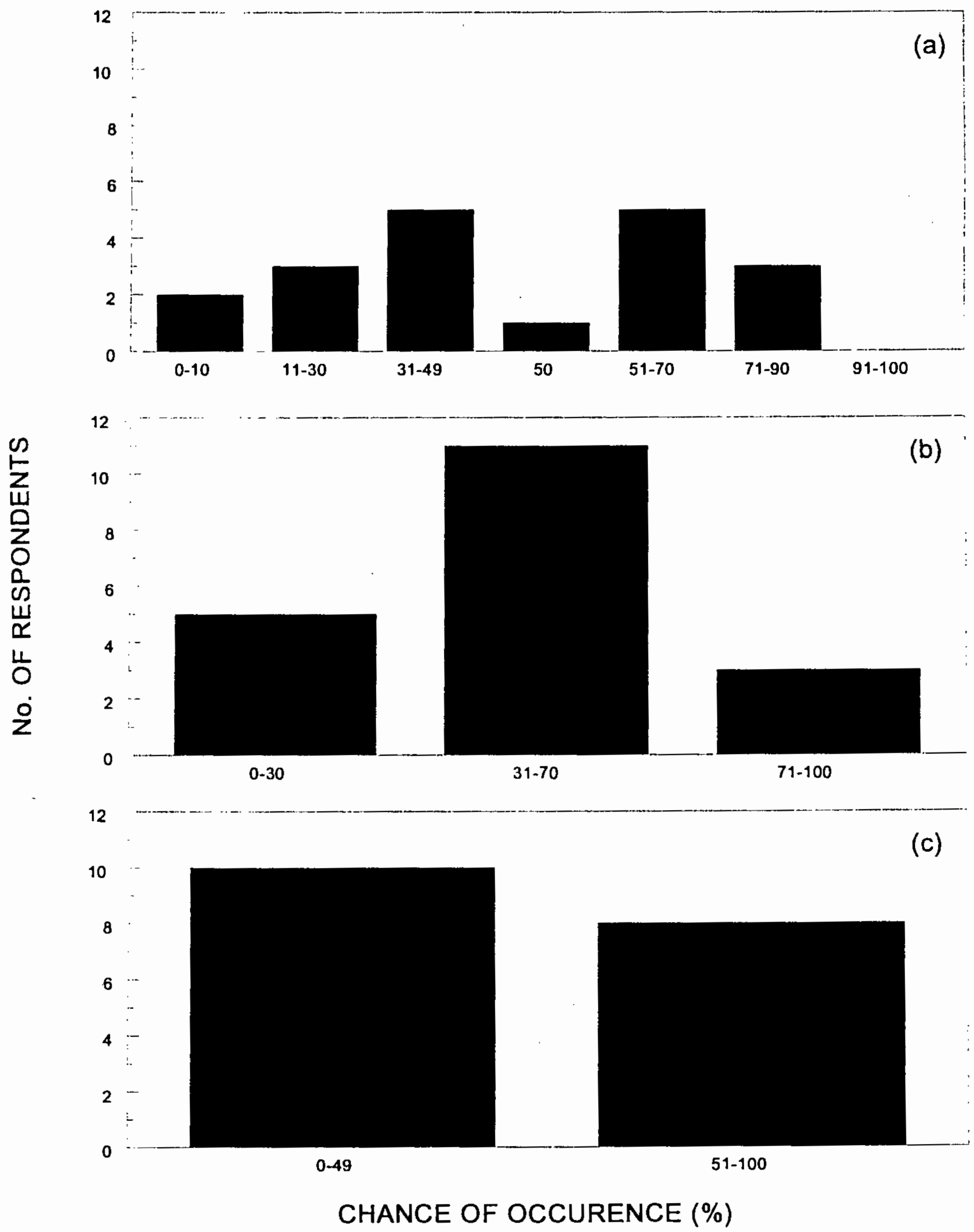


Figure 6.6: Frequency distribution for a hypothetical question showing (a) the full range of 7 categories where there is no clearly favoured category, (b) the number of categories reduced to 3 and, (c) the number of categories reduced to 2.

The questionnaire likelihoods corresponding to those extracted from the empirical data, are shown in Table 6.3.

LIKELIHOOD	LIKELIHOODS FROM:	
	EMPIRICAL DATA	EXPERT DATA
P(LO|BAR)	0.75	0.40
P(LE|BAR)	0.25	0.40
P(HSW|BAR)	0.50	0.60
P(HSS|BAR)	0.25	0.60

Table 6.3: Empirical data and expert assessed 1st-order likelihoods for the probability of finding Low Oil (LO), Low Egg production (LE), strong Southerly Winds (HSW) and High percentage of "Starvation Stations" (HSS), associated with a Below Average Recruitment (BAR) event.

The empirical and expert assessed likelihoods are quite distinct. The only probability to show some affinity between the two groups is $P(\text{HSW}|\text{BAR})$, the probability of having observed strong southerly winds, given that a below average recruitment event is taking place. There are two possible explanations for the differences: one is that the empirical time-series is too short to extract reliable probabilities, resulting in probabilities that are unnaturally high or low; while the other is that the experts are being conservative - the fact that the set of indicator variables were hand picked by the same group of experts currently assessing the probabilities should be borne in mind.

6.7 NECESSARY CONDITIONS FOR DATA CONSISTENCY

Although many subjective probability responses appear quite reasonable, they are often inconsistent with probability axioms (Moskowitz and Sarin 1983). Wallsten *et al.* (1993) point out that overconfidence on the part of the experts is usually to blame. Errors in data can have a serious effect on inferences (Gaba and Winkler 1992), and it is usually only after careful analysis that the inconsistencies come to light. Moskowitz and Sarin (1983) outline necessary and sufficient conditions that a 1st-order likelihood, such as $P(\text{I}|\text{BAR})$, must satisfy in order to be consistent with the probability axioms.

These are:

$$P(\mathrm{I}|\mathrm{BAR}) \leq 1, \tag{i}$$

$$P(\mathrm{I}|\mathrm{BAR}) \leq \frac{P(\mathrm{I})}{P(\mathrm{BAR})}, \tag{ii}$$

(implicated in this violation is that the posterior probability, $P(\mathrm{BAR}|\mathrm{I})$, would be greater than 1)

$$P(\mathrm{I}|\mathrm{BAR}) \geq \frac{P(\mathrm{I}) + P(\mathrm{BAR}) - 1}{P(\mathrm{BAR})}, \text{ and} \tag{iii}$$

$$P(\mathrm{I}|\mathrm{BAR}) \geq 0. \tag{iv}$$

Although the study by Moskowitz and Sarin (1983) deals only with the assessment of pairwise (1st-order) probabilities like the one above, they go further and explain the more complex assessment for higher ordered probabilities. They explain that there are problems associated with the bounding of higher ordered probabilities, and they show that the assessment of prior probabilities and 1st-order likelihoods may often be sufficient (in other words, if the priors and 1st-order likelihoods are inconsistent, other higher order data in the set are just as likely to be inconsistent too).

The probabilities obtained from the empirical data all satisfy the above conditions (Table 6.4), and can therefore be said to be consistent (see Appendix 10 for the calculations). Such is not the case however, for the expert, subjectively assessed, probabilities - Moskowitz and Sarin's condition (ii) is violated in two cases (see Appendix 10 for calculations), and the resultant posterior probability is greater than 1 (Table 6.4).

Moskowitz and Sarin (1983) believe that the violation of consistency is merely a symptom for lack of proper understanding of the concept of probability. Sanders (1992) and Wright, Stokes and Dyer (1994) point out that probability judgements, based on pre-conceived causal theories connecting events, may be biased in "various poorly understood ways"; for example, people do not take proper account of new evidence, which results in poor revision of probabilities when new information is received.

POSTERIOR PROBABILITY	PROBABILITIES FROM:	
	EMPIRICAL DATA	EXPERT DATA
P(BAR|LO)	0.55	0.88
P(BAR|LE)	0.33	1.32
P(BAR|HSW)	0.40	0.50
P(BAR|HSS)	0.65	1.32

Table 6.4: Probabilities of below average recruitment (BAR), given the fact that either Low Oil (LO), Low Egg production (LE), High (strong) Southerly Winds (HSW) and High percentage of Starvation Stations (HSS), has been found to occur, as calculated from the empirical and expert assessed data. The probabilities in the shaded boxes, being greater than 1, are inconsistent with the axioms of probability.

Although the questionnaire introduced and explained the concept of probability, it is suggested that at current levels of understanding, the experts are not acting in a probabilistic manner. It would therefore be virtually impossible to get consistent probabilities from the current group of experts. From this it can be seen that the difficulty with the subjective approach lies not in the mathematics, but in obtaining valid estimates of the required probabilities from the experts. We could dispense with the idea of obtaining expert assessed probabilities, but for the problem that we do not have enough empirical data with which to calculate the required probabilities. Of interest now is whether the inconsistencies in the expert assessed probabilities are sufficiently small, such that the probabilities are still able to yield useful information.

6.8 REFORMULATING THE PROBLEM

Much of the literature dealing with inconsistency in subjective assessments of probability, deals with the prevention of inconsistency before the fact, but no mention is made of how to rectify probabilities that are already inconsistent. It is however, a simple enough task to force consistency in the expert assessed probabilities. For example: the probability of below average recruitment being caused by low egg production, *P*(BAR|LE), was calculated to be 1.32 (see Table 6.4).

This results from:

$$P(\text{BAR}|\text{LE}) = \frac{P(\text{BAR}) \bullet P(\text{LE}|\text{BAR})}{P(\text{LE})}$$

$$= \frac{(0.33) \bullet (0.40)}{(0.10)}$$

$$= 1.32$$

The subjective probability estimates involved here are, of course, the prior probability of below average recruitment P(BAR), the likelihood of low eggs being found during a below average recruitment event P(LE|BAR), and the prior probability of low egg production P(LE) - any, or even all, of these probabilities could be the source of the inconsistency. As mentioned previously, condition (ii) of Moskowitz and Sarin's consistency checks was violated, i.e.:

$$P(\text{LE}|\text{BAR}) \leq \frac{P(\text{LE})}{P(\text{BAR})},$$

that is:

$$0.40 \leq \frac{0.10}{0.33} = 0.30.$$

To remedy the situation, we might argue for, and apply any one of the following assumptions to achieve consistency:

a) P(BAR) and P(LE) are correct, P(LE|BAR) is incorrect; therefore:

$$x = \frac{0.10}{0.33}; \text{ where } x, \text{ that is } P(\text{BAR}|\text{LE}), = 0.30$$

b) P(LE|BAR) and P(BAR) are correct, P(LE) is incorrect; therefore:

$$0.40 = \frac{x}{0.33}; \text{ where } x, \text{ that is } P(\text{BAR}), = 0.13$$

c) P(LE|BAR) and P(LE) are correct, P(BAR) is incorrect; therefore:

$$0.40 = \frac{0.10}{x}; \text{ where } x, \text{ that is } P(\text{LE}), = 0.25$$

Note of course, that if we accept either assumptions (b) or (c), that is that the priors $P(\text{BAR})$ or $P(\text{LE})$ are incorrect, this would have serious implications for the problem as a whole, necessitating further consistency checks wherever these two priors are used in subsequent calculations. Note also, that the above assumptions apply to the other inconsistent probability, $P(\text{BAR}|\text{HSS})$, the probability of below average recruitment as a result of a high percentage of "starvation stations".

However, assuming we accept any of the above assumptions (a), (b) or (c), and correct the corresponding variable accordingly, we will achieve consistency such that:

$$P(\text{LE}|\text{BAR}) = \frac{P(\text{LE})}{P(\text{BAR})} \text{ and/or } P(\text{HSS}|\text{BAR}) = \frac{P(\text{HSS})}{P(\text{BAR})}.$$

Fulfilling the minimum requirements for consistency is rather uninformative, as it results in the posterior probabilities, $P(\text{BAR}|\text{LE})$ and $P(\text{BAR}|\text{HSS})$, being equal to 1; i.e. below average recruitment will result (with a certainty of 1) when we have either a low egg production event or a high percentage of "starvation stations" in the spawning area, respectively.

As mentioned above, not only one, but two, or even all three of the subjective estimates may be erroneous, and the "true answer" may be somewhere inbetween. We require a new set of probabilities, such that they comply not only with the minimum requirements for consistency, but preferably fall within these minimum requirements. Given this practical problem, we can now see that there are several correct formulations of the problem.

6.9 RE-EVALUATING THE PROBABILITIES

Judgementally assessed probabilities can be thought of as a combination of signal and noise. The signal is that based on the respondents' experience and knowledge, while the noise (or error), results from mistaken beliefs, misleading or irrelevant experience, inconsistencies and biases that reduce accuracy (Stewart 1987). What has been shown in the section above, is that the noise currently overrides the signal, resulting in inconsistency. The challenge is to separate the signal from the noise, and in so doing, obtain the most consistent set of probabilities.

One method for re-evaluating forecasts (probabilities) is the Delphi Technique. Linstone and Turoff (1975) describe the Delphi as "... a method for structuring a group communication process so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem".

The "classical" Delphi, involves the following steps (from Martino 1983 and Twiss 1992):

1) A questionnaire is drawn up, regarding the occurrence of events in a specific area of interest (respondents may be asked to assign probabilities to their forecasts).
2) The questionnaire is circulated to a group of respondents, who have been selected for their expertise in the area of interest. The respondents are asked to individually answer the questions without consultation (a Delphi exercise is usually conducted by mail or computerised conference to preserve the anonymity of the respondents).
3) The moderator summarizes the individual answers (probabilities) into a single set, and computes the median and the upper and lower quartiles for each forecast.
4) The respondents receive a new questionnaire listing the events and the medians and quartiles from the previous round. They are asked to prepare new forecasts, and if their forecasts fall outside the upper and lower quartile boundaries, to provide reasons for their forecasts.
5) The moderator again summarizes the forecasts - and the reasons - and prepares a revised questionnaire.
6) The respondents receive the new questionnaire and are asked to take the reasons into account when preparing a new forecast. The median forecasts for each event from this (third) round are the final forecasts (the Delphi is usually completed in three rounds, although additional rounds may sometimes be thought to be desirable; if it is intended to proceed to additional rounds, the respondents are again requested to make further comments).

Objections to the Delphi technique are reviewed in Stewart (1987). A major criticism is its tendency to produce a false appearance of consensus among the respondents. Bardecki (1984) points out that measures of central tendency (e.g. medians), are powerful anchors that tend to narrow the range of responses in future rounds. He concludes that "...unless the individual has great assurance and the issue is of considerable importance, there is reason to believe that any consensus will be, at least in part, a result of assimilative pressure rather than any "true education". Chan (1982) notes that consensus may represent "collective bias rather than wisdom". The Delphi technique therefore appears to be subject to unwanted influences on individual judgements. The extent of the influence on the results is dependent on the respondents and the problem (Stewart 1987). It would seem therefore that the Delphi technique is not acceptable for serious forecasting.

Many problems in which a single alternative must be chosen from many potential alternatives involve multiple objectives (Evans 1984). Multiple criteria decision making (MCDM) is one way of considering multiple objectives explicitly and simultaneously in a mathematical programming framework. Mathematical programming is an attractive methodology as it enables the decision-maker to determine optimal values for variables.

In the analysis of any MCDM problem, the analyst has essentially two possible approaches from which to choose (Stewart 1984). He/she can either:

(i) interact with the decision-maker(s), and allow him/her (them) to reveal preferences gradually by means of choices or value judgements expressed through comparison with actual decision alternatives; or
(ii) obtain some measure of preferences, and then solve a conventional optimization problem.

A wide variety of MCDM methods have been developed and a number of reviews have appeared; for example the books of Goicoechea, Hansen and Duckstein (1982) and Steuer (1986), as well as articles such as those by Evans (1984), Rosenthal (1985) and Stewart (1992). The problem itself determines which approach is appropriate to it. However, by the very nature of the decision process, there is an increasing emphasis on interactive methods. Approach (i) has been explored in the context of setting catch quotas for pelagic fish management by Stewart (1988). He concentrates on three methods in all of which the responses required from the user are in the form of goals or aspiration levels. We can apply this train of thought to our current problem: we already have some measure of preference - the expert assessed probabilities obtained from the questionnaire, and the probabilities obtained from the empirical data - these can be used as goals. All that is required now is to solve a conventional optimization problem (Approach (ii)). Of course, we could make use of the interactive methods described in Stewart (1988), but time constraints forced us to limit our considerations.

6.10 OPTIMIZATION WITH LINEAR (GOAL) PROGRAMMING

Much of statistics is concerned with making a prediction based on a set of data. Usually the prediction is chosen so that it minimizes the squared forecast error - classical least squares estimation finds the prediction formula which minimizes the sum of squared differences between the observed and the prediction (Schrage 1986). Linear programming (LP) can be used for linear regression in much the same way that least squares is used. However, it provides a very powerful tool if one wishes to use other measures of goodness-of-fit, such as mean absolute error or maximum absolute error instead of squared error in determining the prediction.

LP was originally developed to solve strategic planning problems for the U.S. Airforce during World War II (Dykstra 1984); since then its been used in the areas of business, economics, engineering and natural resources (primarily in forestry, agricultural applications). However, LP has seldom been used in managerial modelling of renewable natural resource systems - this has primarily been the field of more dynamic techniques such as simulation models (for exceptions see Everitt, Sonntag, Puterman and Whalen 1978; and examples in Starfield and Bleloch 1986).

A LP model is essentially composed of two parts: a linear objective function (a function in which the exponents of the variables is zero or one, and in which there are no products of variables; Sousa-Rodriguez 1966), and a set of linear constraints. The purpose of LP is to optimize (maximize or minimize) the objective function, subject to a specific set of constraints. The solution is the set of values for the variables that satisfies all the constraints and maximizes (or minimizes) the objective function.

The standard LP problem is defined as follows (Cooper and Steinberg 1970):

$$\text{Maximize/Minimize} \quad z = \sum_{j=1}^{n} c_j x_j \quad \text{(the objective function)} \tag{6.6}$$

subject to (the constraints):

$$\sum_{j=1}^{n} a_{ij} x_j \ (<=>) \ b_i \qquad \text{for } i = 1, 2, \ldots, m$$

$$x_j \geq 0 \qquad \text{for } j = 1, 2, \ldots, n.$$

where

z	= maximum or minimum value
c_j	= objective function coefficient
x_j	= decision variables
n	= number of decision variables
a_{ij}	= constraint coefficient
b_i	= constant
m	= number of constraints.

Let us now introduce our problem, which will be useful in illustrating the various concepts. We presently have a set of expert assessed probabilities that are inconsistent with the axioms of probability, and as such, cannot currently be used. We require a new set of consistent probabilities and have identified LP as an appropriate tool to solve the problem. In the interests of parsimony, we now incorporate all four driving variables into a single system. instead of developing two separate models each incorporating three driving variables as before.

We define decision variables (probabilities of specific events) of the form:

$$P_{RXYZJ}$$

where the symbols R, X, Y, Z, J designate the events of Below Average Recruitment. Low (commercial) Oil Yield. Low Daily Egg Production, High (strong) Southerly Wind. and High percentage of Starvation Stations.

The events exist only in two states; that is, above or below some threshold value. We use binary notation - each event takes on values 0 or 1, to signify this, For example, the probability of observing LowEgg Production, would be defined as:

$$P_{00100}$$

and the probability of observing Low Egg Production, Low (commercial) Oil Yield and a High Percentage of Starvation Stations, would be defined as:

$$P_{01101}$$

This results in $n = 2^5$ decision variables. The axioms of probability require the following constraints:

- the 32 probabilities must sum to one

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{RXYZJ} = 1, \text{ and}$$

- the individual probabilities must all lie in the range zero to one

$$0 \le P_{RXYZJ} \le \ .$$

We now need to examine the possible objectives. Essentially, we can immediately identify 32 objectives - maximize (or minimize) the individual probabilities (there are others of course, but suppose the current set applies), viz.

1. maximize (or minimize) $z_1 = P_{00000}$

.

.

32. maximize (or minimize) $z_{32} = P_{11111}$

We now have a multi-objective formulation - how do we find a good answer? One way to start, would be to solve the series of LPs, in each of which we maximize (or minimize, as the case may be) the single objective; i.e. in the first LP, maximize or minimize z_1 subject to the constraints: in the second, maximize or minimize z_2 subject to these same constraints; etc. It is useful to construct a table (the "payoff table") of the values obtained for each z_k, as we optimize each one in turn. We obtain the following payoff table if we individually maximize each z_k:

OBJECTIVE BEING MAXIMIZED	**VALUES OBTAINED FOR:**							
	z_1	z_2	.	.	.	.	z_{31}	z_{32}
z_1	1	0	0	0	0	0	0	0
z_2	0	1	0	0	0	0	0	0
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
z_{31}	0	0	0	0	0	0	1	0
z_{32}	0	0	0	0	0	0	0	1

Table 6.5: Payoff table showing results from maximizing each z_k in the example outlined above.

There are however, problems associated with ordinary LP. In Table 6.5, note that the variable being maximized goes to 1, while the remaining variables go to 0. The tendency toward extremes is self-evident. The mathematics may be consistent and hence mathematically correct, but the problem the mathematics solves may not be the problem we want to solve. LPs, by their very nature, tend always to rush off to extremes, which is seldom what a decision maker actually wants (Stewart 1995). Also, in real life, we may not be able to always ensure that the constraints remain fixed, accepting perhaps that one of the constraints would drop temporarily below some minimum. The standard LP formulation has no such flexibility, and when the LP cannot satisfy this condition, it tells us that the solution is infeasible. Additionally, the fact that LPs allow only one criterion for determining the optimal strategy is considered a major weakness (Bottoms and Bartlett 1975). There are two ways around this rigidity - one is to be subtle in the way the LP model is formulated, and the other is to make use of extensions of LP that allow more flexibility in setting up the constraints (Stewart 1995).

Linear Programming with multiple objectives, or Linear Goal Programming (LGP), is an extension of LP with considerably more flexibility. What makes it especially attractive are the following two features (Starfield and Bleloch 1986):

- LGP allows for more than one objective function to be considered simultaneously in the formulation of the model, and perhaps more importantly,
- LGP permits what were previously regarded as "fixed" constraints to be loosely formulated as goals that are desirable (but no longer essential).

The objective is to model the true aims of the decision maker in a simple manner, but in such a way that LP can be used to find the best compromise available between the (possibly) conflicting goals. Instead of the single well-defined objective, we define p new variables z_k for $k = 1, 2, ..., p$, each representing performance in terms of a specific decision making objective, by appending the following equality constraints (Stewart 1995):

$$z_k - \sum_{j=1}^{n} c_{kj} x_j = 0 \qquad \text{for } k = 1, 2, ..., p. \tag{6.7}$$

We can represent this idea formally in terms of goal values for each objective (Stewart 1995). We specify goals g_k for $k = 1, 2, ..., p$, one for each objective. The intention is that instead of maximizing (or minimizing) each z_k, we will only try to increase (or decrease) its value towards the goal g_k. We define deviation values, d_k, which we shall attempt to minimize. If z_k is a maximizing objective (where d_k now represents the deviation below the desired goal, and will be 0 in any solution in which $z_k \geq g_k$), we introduce the constraint:

$$z_k + d_k \geq g_k.$$

Alternatively, if z_k is a minimizing objective (where d_k now represents the deviation above the desired goal, and will be 0 in any solution in which $z_k \leq g_k$), the following constraint applies:

$$z_k - d_k \leq g_k$$

Note how we have replaced some of our constraints by a new objective expressed in terms of deviations from these constraints, and how the new objective aims to minimize the extent to which we violate the replaced constraints. However, we still want to maximize (or minimize) z_k: we therefore have more than one objective. Essentially, multi-objective programming approaches seek to find a simultaneous compromise among the various goals. Clearly, if there exists such a solution in which the deviational variables are all zero, then all goals are met. More realistically, it will not be possible to drive all the deviations to zero.

The most direct approach, termed *Archimedean Goal Programming*, is to create an aggregate weighted sum of deviations, $\sum_{k=1}^{p} w_k d_k$, as a minimizing objective (Stewart 1995). The LP still tends to generate extreme solutions, although not as seriously as before. Thus the use of goals and deviational variables has moved towards more balanced solutions, but not ideally (Stewart 1995).

In *Pre-emptive Goal Programming*, the idea is to rank the objectives in a priority order. The algorithm then attempts to minimize the deviational variable on the first (most important) goal, and then fixes it at the optimal value obtained (hopefully zero) for all subsequent iterations, i.e. as a further constraint. The second most important deviational variable is then minimized, and its value fixed in a similar fashion. This is repeated for each objective in turn, until no further freedom remains. In most cases priority ordering seems to be the exception, rather than the rule: there is no goal so important that one would not give up a little on it in order to achieve large gains elsewhere (Stewart 1995).

A useful alternative to either Archimedean or pre-emptive GP, is *Tchebycheff (or Min-Max) Goal Programming*. We weight the deviations as before, but focus on the worst current under-achievement; i.e. the maximum of all the $w_k d_k$ terms (Stewart 1995). We need to introduce another variable, say Δ, together with the constraints $\Delta \geq w_k d_k$ for each k. We then minimize Δ. In effect, what we are doing is to minimize the maximum value of $w_k d_k$, calculated across all goals (Stewart 1995).

Sometimes however, our aim is not to maximize (or minimize), but to strive toward some desirable target. With *Tchebycheff aggregation*, we have again some objective z_k and an associated goal g_k, but rather than minimizing over- or under-deviations, we want our objective z_k as close to the goal g_k as possible. A convenient measure of closeness is the absolute difference $|z_k - g_k|$. We now define two deviational variables, d_k^+ and d_k^-, representing deviation above and below the target respectively. These are linked to the constraint:

$$z_k + d_k^+ - d_k^- = g_k$$

If we include a weighted sum of d_k^+ and d_k^- in our overall minimizing objective, then for any set of values for the other variables in the problem, at least one of d_k^+ and d_k^- will go to zero. The other variable will then take on the value $|z_k - g_k|$ (Stewart 1995). For objectives of this nature, the weighted deviational variable $w_k d_k$ is replaced by $w_k^+ d_k^+ + w_k^- d_k^-$.

The formulation above can be adapted to several kinds of specific problems. If, for example, over-achievement of a goal is acceptable, the over-deviation variables (d_k^+) can be dropped. If over-achievement of a goal is actually desirable, the w_k^+ weight can be made negative, which would move the solution toward over-achievement because the objective function is minimized.

To return to our problem: the aim is to choose a new set of probabilities that are consistent with the axioms of probability. Using the current inconsistent (expert assessed) information (as goals *not constraints*), we opt for the concept of deviational variables and Tchebycheff aggregation.

As before, we have decision variables (probabilities) of the form P_{RXYZJ} with the constraints:

- the 32 probabilities must sum to one

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{RXYZJ} = 1,$$

where: R = Below Average Recruitment. X = Low (commercial) Oil Yield, Y = Low Daily Egg Production, Z = High (strong) Southerly Wind, and J = High percentage of Starvation Stations.

- the individual probabilities must all lie in the range zero to one

$$0 \le P_{RXYZJ} \le 1.$$

We now re-examine the objectives. If we had no information at all, we could assume that the probabilities of all 32 individual events in the activity space would be equal. We therefore have:

$$\text{any} \quad P_{RXYZJ} = \frac{1}{32};$$

that is, any of the 32 possible events has a small but equal (0.03125%) chance of occurrence. This is, of course, the simplest, most uninformative, case. In reality, not all the probabilities will be the same - some events will have a greater chance of occurrence than others; some events, although highly unlikely, may even have a probability of zero. Previously, we tried to obtain this information by extracting subjective probabilities from a group of experts, but found that we could not use their information successfully. We assume however, that although inconsistent, we can still use the expert information to indicate the chance of occurrence of events *relative to each other*, and can use this information to drive the LP.

We define the following objectives:

1. Get each *Prior/Marginal Probability*, $P(\mathrm{A})$, as close to the expert estimated probability, $\overline{P(\mathrm{A})}$, with a measure of the deviation:

e.g. $P(\mathrm{R})$ = Probability of Below Average Recruitment:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} \cdot P_{1XYZJ} - d_R^- + d_R^+ = \overline{P(\mathrm{R})} = 0.44$$

2. Get each *1st-order conditional Probability*, $P(\mathrm{A|B})$, as close to the expert estimated probability, $\overline{P(\mathrm{A|B})}$, with a measure of the deviation:

   e.g. $P(\mathrm{R|X})$ = Probability of Below Average Recruitment given there is Low Oil Yield:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(R|X)}\}P_{11YZJ}-\overline{P(R|X)}\}P_{01YZJ}]-d^{-}_{R|X}+d^{+}_{R|X}=0$$

3. Get each *2nd-order conditional Probability*, $P(\mathrm{A|B\&C})$, as close to the expert estimated probability, $\overline{P(\mathrm{A|B\&C})}$, with a measure of the deviation:

   e.g. $P(\mathrm{R|X,Y})$ = Probability of Below Average Recruitment given there is Low Oil Yield and Low Egg Production:

$$\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(R|X,Y)}\}P_{111ZJ}-\overline{P(R|X,Y)}\}P_{011ZJ}]-d^{-}_{R|X,Y}+d^{+}_{R|X,Y}=0$$

   Note that although the questionnaire contained questions pertaining to 3rd-order probabilities, they are considered tenuous and unreliable at best, and are therefore not used as goal values when applying the LP.

4. Minimize Δ - i.e. minimize the maximum value of d_k, calculated across all goals (Stewart 1995), and the absolute deviations between the expert assessed and LP-generated probabilities - such that:

   $\Delta - P_{RXYZJ} \geq 0.03125$ for all 32 possible P_{RXYZJ}

   By setting the goal at ≥ 0.03125, we try to prevent the LP returning probabilities of zero.

   $\Delta - d^{-}_{A} - d^{+}_{A} \geq 0$ for all priors;
   for all A = R, X, Y, Z, J

   $\Delta - d^{-}_{A|B} - d^{+}_{A|B} \geq 0$ for all 1st-order conditioning;
   for all combinations of A, B = R, X, Y, Z, J

   $\Delta - d^{-}_{A|B,C} - d^{+}_{A|B,C} \geq 0$ for all 2nd-order conditioning;
   for all combinations of A, B, C = R, X, Y, Z, J

Minimization of Δ thus yields a minimum absolute deviation solution from the expert assessments. The complete LP formulation, is presented in Appendix 11.

6.11 SOLVING LPs WITH LINDO®

The solving of an LP requires a large number of calculations and is purely mechanical, and is therefore best performed by a computer. The software used here is LINDO® (an acronym for **L**inear, **IN**teractive, **D**iscrete **O**ptimizer) for MS/PC-DOS® computers (Schrage 1986, 1991, 1993). LINDO® solves linear, integer and quadratic programs entered in natural form. It is command oriented (rather than menu oriented), so for small LPs, LINDO® allows a user to interactively input an LP formulation, solve it, assess the correctiveness of the formulation based on the solutions and then quickly make modifications and repeat the process. For larger LPs, LINDO® allows the use of an input file (in the traditional form of a LP matrix), which can be run in batch mode. For users wishing to design customised systems in which LP is just one part of a larger problem solving process, LINDO® has a modular design, so that most of the features can be accessed via subroutine calls from non-LINDO® software.

The possible outcomes resulting from solving a LP with LINDO® are shown in Figure 6.8.

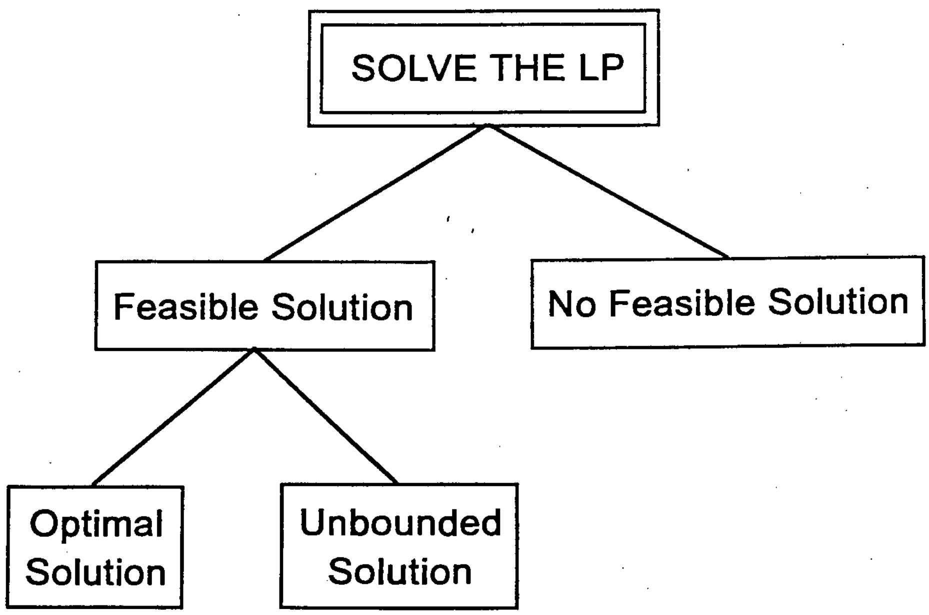


Figure 6.8: Solution outcomes when solving a LP with LINDO® (redrawn from Schrage 1986).

For a properly formulated LP, the leftmost path will be taken. The solution procedure will first attempt to find a feasible solution, i.e. a solution which simultaneously satisfies all constraints (but does not necessarily maximize the objective function). The rightmost "No Feasible Solution" will be taken if the formulation has been too demanding; that is, two or more constraints cannot be satisfied simultaneously. A simple example is the pair of constraints $x \leq 2$ and $x \geq 3$ - the nonexistence of a feasible solution does not depend on the objective function, but solely on these constraints. If a feasible solution has been found, the procedure then attempts to find an optimal solution. If the "Unbounded Solution" termination occurs, it implies that the formulation admits the impractical result that an infinite number of solutions are possible. A more practical conclusion is that an important constraint has been omitted (Schrage 1986).

The complete input matrix, in LINDO® format, is presented in Appendix 12.

6.11.1 Re-organising the LINDO® Output

The LP formulation described above calculates optimal values for the 32 decision variables. The LINDO® output file consists of the LP estimated values for the individual P_{RXYZJ}, along with the values for the deviational variables (an example of the output file is presented in Appendix 12). In order to obtain the final posterior probabilities, these estimated values need to be aggregated. Instead of doing these summations longhand, a program was written to accomplish this (the TURBO Pascal® source code is presented in Appendix 13).

The equations used to calculate the final (LP assessed) posterior probabilities are shown below:

(i) For each prior (marginal) probability:

e.g. P(R) = Probability of Below Average Recruitment

$$P(\mathrm{R}) = \sum_{X=0}^{1} \sum_{Y=0}^{1} \sum_{Z=0}^{1} \sum_{J=0}^{1} P_{1XYZJ}$$

As a consistency check, the following formula was also used:

$$P(\mathrm{R}) = \overline{P(\mathrm{R})} + d_R^- - d_R^+$$

where $\overline{P(\mathrm{R})}$ is the expert estimated value.

(ii) For each 1st-order posterior (conditional) probability:

e.g. $P(\mathrm{R}|\mathrm{X})$ = Probability of Below Average Recruitment given that there is Low (commercial) Oil Yield

$$P(\mathrm{R}|\mathrm{X}) = \frac{P(\mathrm{R}\&\mathrm{X})}{P(\mathrm{X})} = \frac{\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{11YZJ}}{\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{R1YZJ}}$$

As a consistency check, the following formula was also used:

$$P(\mathrm{R}|\mathrm{X}) = \overline{P(\mathrm{R}|\mathrm{X})} + \frac{d^-_{R|X} - d^+_{R|X}}{P(\mathrm{X})}$$

where $\overline{P(\mathrm{R}|\mathrm{X})}$ is the expert estimated value,

and $P(\mathrm{X}) = \sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{R1YZJ}$.

(iii) For each 2nd-order posterior (conditional) probability:

e.g. $P(\mathrm{R}|\mathrm{X}\&\mathrm{Y})$ = Probability of Below Average Recruitment given that there is Low (commercial) Oil Yield *and* Low Daily Egg Production

$$P(\mathrm{R}|\mathrm{X}\&\mathrm{Y}) = \frac{P(\mathrm{R}\&\mathrm{X}\&\mathrm{Y})}{P(\mathrm{X}\&\mathrm{Y})} = \frac{\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{111ZJ}}{\sum_{R=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{R11ZJ}}.$$

As a consistency check, the following formula was also used:

$$P(\mathrm{R}|\mathrm{X}\&\mathrm{Y}) = \overline{P(\mathrm{R}|\mathrm{X}\&\mathrm{Y})} + \frac{d^-_{R|XY} - d^+_{R|XY}}{\sum_{R=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{R11ZJ}}.$$

(iv) For each 3rd-order posterior (conditional) probability:

e.g. *P*(R|X&Y&Z) = Probability of Below Average Recruitment given that there is Low (commercial) Oil Yield *and* Low Daily Egg Production *and* High (strong) Southerly Wind

$$P(\mathrm{R}|\mathrm{X\&Y\&Z}) = \frac{P(\mathrm{R\&X\&Y\&Z})}{P(\mathrm{X\&Y\&Z})} = \frac{\sum_{J=0}^{1} \cdot P_{111J}}{\sum_{R=0}^{1}\sum_{J=0}^{1} \cdot P_{R11J}}.$$

Note that there is no consistency check. We did not use the expert assessed 3rd-order probabilities as goal values, and therefore there are no deviational variables.

(v) For the fourth-order posterior probability:

e.g. *P*(R|X&Y&Z&J) = Probability of Below Average Recruitment given that there is Low (commercial) Oil Yield *and* Low Daily Egg Production *and* High (strong) Southerly Wind *and* a High Percentage of Starvation Stations

$$P(\mathrm{R}|\mathrm{X\&Y\&Z\&J}) = \frac{P(\mathrm{R\&X\&Y\&Z\&J})}{P(\mathrm{X\&Y\&Z\&J})} = \frac{P_{1111}}{\sum_{R=0}^{1} \cdot P_{R111}}.$$

An example of the output file generated by this program, may also be found in Appendix 13.

6.12 APPLYING THE LGP MODEL

As with any manipulation of data, the time-honoured adage of "garbage in, garbage out" applies - realistic LPs require large amounts of data (Schrage 1986). Unfortunately, data are expensive to collect, so we are usually forced to make use of less data than we would like, and in many cases, data in which we have less than complete confidence.

Three basic experiments were applied to the probability datasets using the LGP formulation above.

The basic experiments are:

i) use the full set of judgementally assessed probabilities - from the priors through to the 2nd-order conditionals; or use a subset of the data:

ii) use the priors and the 1st-order conditionals only (exclude the 2nd-order conditionals), or even

iii) use just the priors (exclude both the 2nd-order and 1st-order conditionals.)

These experiments, which we will call Exp-I, Exp-II and Exp-III respectively, are easily applied to the expert assessed probabilities. For the set of empirical probabilities however, experiment (i) cannot be applied because we don't have all the data; we are therefore left with implementing experiments (ii) and (iii).

6.12.1 **Analysis of the Expert Assessed Probabilities**

The three experiments listed above were conducted using the LGP with the expert assessed data. Table 6.6. summarizes the results obtained for the main items of interest; that is, the posterior probabilities of below average recruitment. Complete tables of results, comparing the entire dataset of expert assessed probabilities with the LGP estimated probabilities, are presented in Appendix 14 (Tables A14.1 - A14.5).

"Optimal" solutions are possible for all three experiments. The results generated by Exp-I however, are not be as reasonable as we might have hoped. Immediately noticeable are the 'Undefined' estimates (Table 6.6). These indicate that the combination of constraints and goals in Exp-I is too restricting for the LGP. The solution process actually ignores some of the goals - resulting in a number of zero estimates for the likelihoods (see Appendix 14, Tables A14.1 - A14.5). In the final probability calculations (see section 6.11.1), a number of the denominators are zero, hence the 'Undefined' result. These particular probabilities cannot be estimated under the present regime. Also, we have what appears to be a "nonsense" estimates. For example, the LGP estimates $P(\text{BAR}|\text{LE\&HSW})$, the probability of below average recruitment given that there is low egg production and strong southerly winds, to be 0.10. This value however, is nowhere near the range of probabilities estimated for the other 2nd-order posterior probabilities (Table 6.6).

POSTERIOR PROBABILITY	EXPERT DATA	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR | LO	0.88	0.68	0.68	0.64
BAR | LE	1.32	0.59	0.72	0.50
BAR | HSW	0.50	0.49	0.49	0.55
BAR | HSS	1.32	0.74	0.86	0.64
BAR | LO&LE	**	0.64	0.78	0.50
BAR | LO&HSW	**	0.77	0.62	0.50
BAR | LO&HSS	**	1.00	0.50	0.72
BAR | LE&HSW	**	0.10	0.50	0.50
BAR | LE&HSS	**	1.00	0.66	0.50
BAR | HSW&HSS	**	0.66	0.91	0.50
BAR|LO&LE&HSW	**	Undefined	0.50	0.50
BAR|LO&LE&HSS	**	1.00	0.50	0.50
BAR|LO&HSW&HSS	**	1.00	0.50	0.50
BAR|LE&HSW&HSS	**	1.00	0.50	0.50
BAR|LO&LE&HSW&HSS	**	Undefined	0.50	0.50

Table 6.6: Posterior probabilities of below average recruitment estimated by the linear (goal) programming model, using as input the expert assessed dataset. Results from three experiments, Exp-I, Exp-II and Exp-III, are compared to probabilities calculated from the expert data (where available). In column Exp-I are the results obtained by using the full dataset of priors to 2nd-order conditionals as goals, in column Exp-II are the results from using the priors and 1st-order conditionals only, and in column Exp-III are the results from using the priors only. (**) indicates that there are no expert data to compare the LGP estimates with, and that goal values were not specified when running the LGP (the shaded values were not used as goals; they are included merely for comparison). See Appendix 8 for the probability abbreviations.

No such problems were encountered with experiments II and III. By decreasing the number of constraints and goals, the LGP is given much freedom. As a result, there are no 'Undefined' or "nonsense" estimates. Note however, the sharp increase in the 0.50 "No Confidence" estimates from Exp-I to Exp-III.

6.12.2 Analysis of the Empirical Probabilities

The two experiments listed above were conducted using the LGP with the empirical data. Table 6.7 summarizes the results obtained for the main items of interest; that is, the posterior probabilities of below average recruitment. Complete tables of results, comparing the entire dataset of empirical probabilities (where available) with the LGP estimated probabilities, are presented in Appendix 14 (Tables A14.6 - A14.10).

POSTERIOR PROBABILITY	EMPIRICAL ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR | LO	0.55	0.59	0.58
BAR | LE	0.33	0.27	0.29
BAR | HSW	0.40	0.40	0.52
BAR | HSS	0.65	0.54	0.50
BAR | LO&LE	**	0.18	0.20
BAR | LO&HSW	**	0.47	0.52
BAR | LO&HSS	**	0.58	0.50
BAR | LE&HSW	**	0.18	0.20
BAR | LE&HSS	**	0.50	0.50
BAR | HSW&HSS	**	0.50	0.50
BAR|LO&LE&HSW	**	0.11	0.13
BAR|LO&LE&HSS	**	0.50	0.50
BAR|LO&HSW&HSS	**	0.50	0.50
BAR|LE&HSW&HSS	**	0.50	0.50
BAR|LO&LE&HSW&HSS	**	0.50	0.50

Table 6.7: Posterior probabilities of below average recruitment estimated by the linear (goal) programming model, using as input the empirical dataset. Results from two experiments, Exp-II and Exp-III, are compared to empirically assessed probabilities (where available). In column Exp-II are the results from using the priors and 1st-order conditionals as goals, and in column Exp-III are the results from using the priors only. (**) indicates that there are no empirical data to compare with the LGP estimates, and that goal values were not specified when running the LGP. See Appendix 8 for the probability abbreviations.

"Optimal" solutions are also possible with the empirical data. The reduced number of constraints and goals with Exp-II and Exp-III allow the LP more freedom; as a result, there are no 'Undefined' or "nonsense" estimates. Note again, the large number of 0.50 "No Confidence" estimates.

6.12.3 Comparing the Experiments

Table 6.8 quantitatively assesses the results of the experiments with the expert data and the empirical data.

EXPERIMENT	GOALS	'UNDEFINED' ESTIMATES	0.50 ESTIMATES
	EXPERT DATA		
Exp-I	37 goals in total: 78% goal failure	9	None
Exp-II	25 goals in total: 56% goal failure	None	19
Exp-III	5 goals in total: 20% goal failure	None	41
	EMPIRICAL DATA		
Exp-II	13 goals in total: 15% goal failure	None	19
Exp-III	5 goals in total: All goals attained	None	36

Table 6.8: Comparison of the LGP experiments on the expert and empirical probability datasets. Failure to attain the goal value is recognised when the LGP estimate falls outside the range ±10% of the goal value.

In Exp-I with the expert data, the LGP was severely constrained by the full set of 37 goals. This can be seen by the high percentage failure to attain goals, and the presence of 'Undefined' estimates. Exp-II and Exp-III saw a decrease in the number of goals - relaxing control allows the LGP more freedom to fit a solution, resulting in lower goal failure rates and more importantly, no 'Undefined' estimates. This relaxation of control has however, also had the unfortunate consequence of many probabilities equilibrating to the same value -

note the increase 0.50 estimates. These probabilities are not useful to decision making.

6.13 REVISING THE INPUT

A major advantage of the mathematical programming approach is its flexibility. With minor modifications to the input matrix, additional runs can be activated, and after analysing the results, questions quickly answered. The unsatisfactory results above prompted a close inspection of the probability data.

The basic assumptions underlying this research are the following. When a datum for an indicator variable lies above (or below - as the case may be) its threshold value, there is a detrimental impact on recruitment; and when a number of variables are acting in phase - the combined effect is an *monotonic* (combined) detrimental impact on recruitment - the indicator variables were specifically chosen because of their perceived link to recruitment. In other words, any information received, confirming the occurrence of an event detrimental to recruitment must add confidence to the posterior probability of below average recruitment. In the case where there is no indication that such an event is going to take place, no confidence is added. More importantly, it is assumed that confidence is not decreased. This assumption is derived from the fact that a January recruitment prediction would be made from data that are annual averages, or have been collected in a "snap-shot" fashion during a single, short research survey. Even if the November survery showed no indication of events detrimental to recruitment, it is still considered impossible to say with any certainty that the probability of below average recuitment should be decreased from the *a priori* level - conditions may change immediately after the survey!
In essence then, once the value of a posterior probability of below average recruitment (conditional on some information) has been set, it can either move closer to 1 when new *monotonic* information is received, or remain the same when *neutral* information is received - the value never decreases back toward 0.

This assumption may not hold for other problems of course. A simple example illustrates this. Let us assume that the (prior) probability of observing rain on any particular day, P(Rain), is 0.30 (30% chance of occurrence). We receive some new information - the sky is overcast. The revised probability in the light of this new information - the probability of observing rain when the sky is overcast, P(Rain|Overcast sky), might now increase to 0.75 (75% chance of occurrence), because the information is *monotonic* - dark skies indicate the possibility of rain and adds to our confidence in observing rain later. Assume now, that the new information reveals that rather than overcast, the sky is not overcast. If we had no further information, the revised probability of observing rain when the sky is not overcast, *P*(Rain|No overcast sky), would not remain at the *a priori* level of 0.30 because the information is *negative.* The fact that the sky is not overcast doesn't add to our confidence in observing rain.

Many of the expert assessed probabilities do not conform to the *monotonic* information assumption explained above. In revising a posterior probability in the light of new information, the experts fail to take into consideration the value previously held by that probability. Furthermore, a close inspection of the expert dataset revealed some 'spurious' probabilities that necessitated specific re-evaluation. An example is the probability of Low Egg Production given that there is a High percentage of Starvation Stations (on the spawning grounds), LE|HSS: the data gathered from the returned questionnaires suggested a value of 0.05 (i.e. a 5% chance of occurrence) be assigned to this probability. However, in the light of the suggestions by Peterson *et al.* (1992) that anchovy spawning can be food-limited, this probability is considered conservative in the extreme, and should be revised. It was decided therefore to re-assess the entire probability dataset, and on the basis of the *monotonic* information assumption, revise probabilities where it was deemed necessary. The arguments for re-assigning the probabilities, and the complete revised dataset, compared with the expert and empirically assessed probabilities, is presented in Appendix 15 (Tables A15.1 - A15.5)

6.13.1 **Revising the Prior Probabilities**

Since collaboration is common in many judgement situations, decision-makers frequently obtain conflicting information from a number of different sources - they are then faced with the problem of reconciling the options (Clemen and Winkler 1993).

The combining of predictions, including probability forecasts, has received considerable attention in recent years; for reviews of the literature, see Genest and Zideck (1986) and Clemen (1989). The underlying rationale is that additional information will lead to better decisions - often a second opinion will more or less confirm the initial judgement, but on occasion, may pick up on different cues that lead to a another course of action. Taking averages from two or more sources is one way of representing, in probabilistic terms, the notion of getting a second, third, or fourth, opinion (Winkler and Poses 1993). The theoretical effectiveness of optimally combining forecasts is described by Clemen and Winkler (1985). Increasing forecast accuracy by combining probabilities from two or more sources has been successfully demonstrated: Clemen and Winkler (1987) analyzed combinations of probabilities of precipitation and showed that improved accuracy could be obtained by combining two probability forecasts; and in Poses, Winkler, Scott and Copare (1990), survival probabilities from two inexperienced physicians were averaged, resulting in a probability as accurate as that provided by a more experienced physician. Brannen, Godfrey and Goetter (1989) combined probabilities of survival from an experienced physician and from a model - the combined probability outperformed the model but not the physician. Essentially then, obtaining multiple forecasts and combining them can, in some instances, lead to improved forecasting performance. Winkler and Poses (1993) believe that simple averages of forecasts work just as well as fancier combining methods.

The revised prior probabilities, obtained by combining and averaging the existing expert and empirical assessments, are shown in Table 6.9.

PRIOR PROBABILITY	EXPERT ASSESSMENT	EMPIRICAL ASSESSMENT	REVISED VALUE
P(BAR)	0.33	0.44	0.39
P(LO)	0.15	0.60	0.38
P(LE)	0.10	0.33	0.22
P(HSW)	0.40	0.55	0.48
P(HSS)	0.15	0.17	0.16

Table 6.9: Revised prior probabilities of below average recruitment (BAR), Low Oil (LO), Low Egg production (LE), High (strong) Southerly Winds (HSW) and High percentage of Starvation Stations (HSS), calculated by combining and averaging the existing expert and empirical assessments.

Even though the process of combining and averaging tones down extreme probabilities, a simple unweighted average was considered sufficient. Winkler and Poses (1993) report that even though performance increases as the number of data sources increases, attempts to improve upon equally weighted combinations with differential weighting, may lead only to small improvements, if at all. This is consistent with the general results in the combining-forecasts literature - equal weights are robust and preferable.

6.13.2 Revising the Posterior and Conditional Probabilities

Having undertaken the preceding LGP estimations, it is now suggested that, for the problem being addressed, it is inappropriate to specify as goals the posterior probabilities of below average recruitment, and use the LGP to drive the results toward them. These are afterall, the values that we are attempting to calculate from the data, not decide beforehand. These goals were therefore removed.

6.13.3 New Results

Table 6.10 summarizes the solutions for the main items of interest - the posterior probabilities of below average recruitment. Complete tables of solutions, comparing the revised probabilities with the LP estimated probabilities, may be found in Appendix 15 (Tables A15.1 - A15.5).

The results from the current estimation are much improved over any previously obtained. In an earlier experiment, using as input the expert assessed probabilities, the results contained some nine "undefined" probabilities; believed to be due to an impossible regime of constraints and goals. The current input matrix however, produces no "undefined" probabilities (see Appendix 15, Tables A15.1 - A15.5) - clearly, the revised set of constraints and goals is much improved.

A few posterior probabilities do not adhere to the *monotonic* information assumption (Table 6.10). The 2nd-order probabilities, *P*(BAR|LO&HSW) - the probability of observing below average recruitment given that there has been a low (commercial) oil yield and that there is strong southerly wind over the egg and larval transport area; *P*(BAR|LO&HSS) - probability of observing below average recruitment given that there has been a low (commercial) oil yield and that there is a high percentage of "starvation stations" on the spawning grounds; and *P*(BAR|HSW&HSS) - the probability of observing below average recruitment given that there is strong southerly wind over the egg and larval transport area and that there is a high percentage of "starvation stations" on the spawning grounds), were assessed to be 0.50, 0.68 and 0.68 respectively. Applying the *monotonic* information assumption, their respective 1st-order probabilities tell us that we would expect minimum values of 0.53, 0.72 and 0.72 (Table 6.10). What this probably indicates, is that some conditional probabilities are probably subject to (human) estimation error, resulting in the posterior probability not being estimated correctly by the LGP.

POSTERIOR PROBABILITY	LP ASSESSMENT
BAR | LO	0.53
BAR | LE	0.66
BAR | HSW	0.37
BAR | HSS	0.72
BAR | LO&LE	0.77
BAR | LO&HSW	***0.50*** (0.53)
BAR | LO&HSS	***0.68*** (0.72)
BAR | LE&HSW	0.72
BAR | LE&HSS	0.72
BAR | HSW&HSS	***0.68*** *(0.72)*
BAR|LO&LE&HSW	0.81
BAR|LO&LE&HSS	0.77
BAR|LO&HSW&HSS	0.77
BAR|LE&HSW&HSS	0.77
BAR|LO&LE&HSW&HSS	0.85

Table 6.10: Posterior probabilities of below average recruitment estimated by the linear (goal) programming model, using as input the revised dataset (incorporating probabilities up to 2nd-order level). Where a probability does not satisfy the *monotonic* information assumption, the minimum expected value is indicated alongside. See Appendix 8 for the probability abbreviations.

The remainder of the results are as expected. The prior probability of observing below average recruitment was set at 0.37. Any new information received, informing us of the occurrence of an event detrimental to recruitment, serves to add confidence (i.e. move closer to 1) to the revised posterior probability of below average recruitment in the light of this new information.

The 1st-order posterior probabilities (the probability of below average recruitment when only one indicator is active), indicate the perceived scale of impact (relative to each other), on recruitment (Table 6.11). From these results, we can rank the indicators in ascending order of importance:

N-S windrun anomaly
Annual (commercial) Oil:Meal ratio
Egg Production
Percentage of "Starvation Stations"

The current ranking differs from that proposed in Chapter 5 for applying differential weighting.

PRIOR PROBABILITY	POSTERIOR PROBABILITY of BAR
$P(\text{BAR}) = 0.37$	
$P(\text{HSW}) = 0.50$	$P(\text{BAR}\mid\text{HSW}) = 0.37$
$P(\text{LO}) = 0.37$	$P(\text{BAR}\mid\text{LO}) = 0.53$
$P(\text{LE}) = 0.20$	$P(\text{BAR}\mid\text{LE}) = 0.66$
$P(\text{HSS}) = 0.18$	$P(\text{BAR}\mid\text{HSS}) = 0.72$

Table 6.11: Linear (goal) programming estimated prior probabilities of below average recruitment (BAR), High (strong) Southerly Winds (HSW), Low Oil Yield (LO), Low Egg production. (LE), and High percentage of Starvation Stations (HSS), and posterior probability of observing below average recruitment on the occurrence of these events.

Note also, that the scale of the impact on recruitment by a particular indicator is proportional to the inverse of the frequency of occurrence of that indicator; i.e. the more frequently an event is perceived to occur, the less its impact on recruitment (Table 6.11).

6.13.4 **Prediction Performance**

The ultimate objective of this modelling exercise is to correctly predict, with a high degree of certainty, when a below average recruitment (BAR) event is about to take place (using the data gathered during the pelagic Spawner Biomass research cruise, in the month preceding the forecast). Ideally, the forecast should take place before the setting of the anchovy Total Allowable Catch (TAC) in January, thereby reducing the risk of setting an inappropriate TAC. Probabilities of observing a below average recruitment event in any one year, assuming that we have information on the selected influencing variables, are shown in Table 6.12.

Predicted below average recruitment compares favourably with the historical time-series of observed recruitment. Theoretically, the greater the number of indicators "active" in any one year, the greater the probability of below average recruitment. The years in which below average recruitment was forecast with the greatest confidence, viz. 1989, '90 and '94, have all indicators affecting recruitment, but one. For most years however, the forecast is generated on the basis of a single indicator in the "active" state (i.e. above or below the threshold value, as the case may be) - a tenuous situation at the best of times. The variables N-S windrun anomaly and (commercial) oil yield, indicators of egg and larval transport success and spawner condition (before they arrive on the spawning grounds) respectively, are most commonly observed solo. A forecast based solely on the presence of strong southerly winds, generates a revised probability of below average recruitment of 0.37 - no improvement on the 0.37 below average recruitment probability. A forecast based solely on low annual commercial oil yield, generates a revised probability of below average recruitment of 0.53. Due to the lack of percentage starvation station data for the period 1984-1987, two results are open to speculation. The probability of observing below average recruitment in 1985 and 1988 is 0.37. This is the unrevised prior probability of observing below average recruitment, since none of the other three indicators display a negative impact on recruitment. However, had there been a high percentage of "starvation stations" recorded on the spawning grounds in either of these years, the prior probability of below average recruitment would be revised to 0.72 (Table 6.12). For 1985, this would confirm the observed below average recruitment. Similarly for 1988, such conjecture would forecast below average recruitment with a certainty of 0.72 - 1988 is however, a year in which below average recruitment was not observed (SFRI, unpublished data).

DATA YEAR	INFLUENCING FACTORS				LGP PROBABILITY OF BELOW AVERAGE RECRUITMENT	FORECAST YEAR
	Low Oil	Low Eggs	Strong S. Wind	High % Starv. Stn's		
1984				N.D.	0.37	1985 *
1985			✓	N.D.	0.37	1986
1986			✓	N.D.	0.37	1987
1987				N.D.	0.37	1988
1988	✓		✓	✓	0.77	1989 *
1989	✓	✓	✓		0.81	1990 *
1990	✓				0.53	1991
1991	✓				0.53	1992 *
1992	✓				0.53	1993
1993	✓	✓	✓		0.81	1994 *

Table 6.12: Forecast table showing indicator presence/absence in the years the data were collected (1984-1993), and the LGP estimated probability of below average recruitment for each of the following years (1985-1994). Forecast years marked (*) indicate years in which below average recruitment was observed. ✓ = Influencing variable "active".

6.13.5 **Discussion**

Pelagic fish typically reproduce by means of repeatedly spawning (iteroparity) large numbers of eggs into the environment over the spawning season (Shelton 1986, 1987), and was first noted as a potential bet-hedging trait in clupeoid fishes (Shelton 1987). Since large numbers of eggs are produced, one may infer that mortality must be high between the egg stage and maturity, because on average, only two offspring need to survive to maturity during the lifespan of each female in order to replace the population (assuming an equal ratio of females and males).

The results presented above reflect the life history traits displayed by anchovy in the southern Benguela system. By frequently spawning large numbers of eggs over the spawning season, anchovy buffer the mortality and are thus better adapted to frequent small-scale events (e.g. wind) impacting recruitment. While wind is considered one of the dominant factors affecting anchovy recruitment (Bloomer *et al.* 1994), the present study suggests that southerly wind is the least important of the four factors investigated. Although the most frequent of the four indicators (prior probability of observing strong southerly wind = 0.50), if we observe strong southerly winds over the egg and larval transport area, it is estimated that there is a below average chance (probability of 0.37) that below average recruitment will also be observed. It has been suggested (Shannon, Crawford and Duffy 1984), that a wind anomaly likely to influence anchovy dynamics would have to prevail for several months. Hutchings and Nelson (1985) conclude that a 3-4 month wind anomaly would be needed to "upset" anchovy recruitment, and that such prolonged events are rare in the southern Benguela system.

Of the four factors investigated in the present study, a high percentage of "starvation stations" on the spawning grounds is thought to have the greatest impact on recruitment. Although an infrequent occurrence (prior probability of observing a high percentage of "starvation stations" = 0.18), whenever poor feeding conditions for the spawners is observed, it is estimated that there is an above average chance (probability of 0.72) that below average recruitment will also be observed. Ecologically, this would result from the link between maintenance of daily ration and the output of eggs.

The LGP probabilistic system provides a consistent set of probability data, which can be used to quantitatively forecast anchovy recruitment success. The ability of the model to provide an index of recruitment success and, at least partially, support the observed recruitment is shown in Figure 6.7.

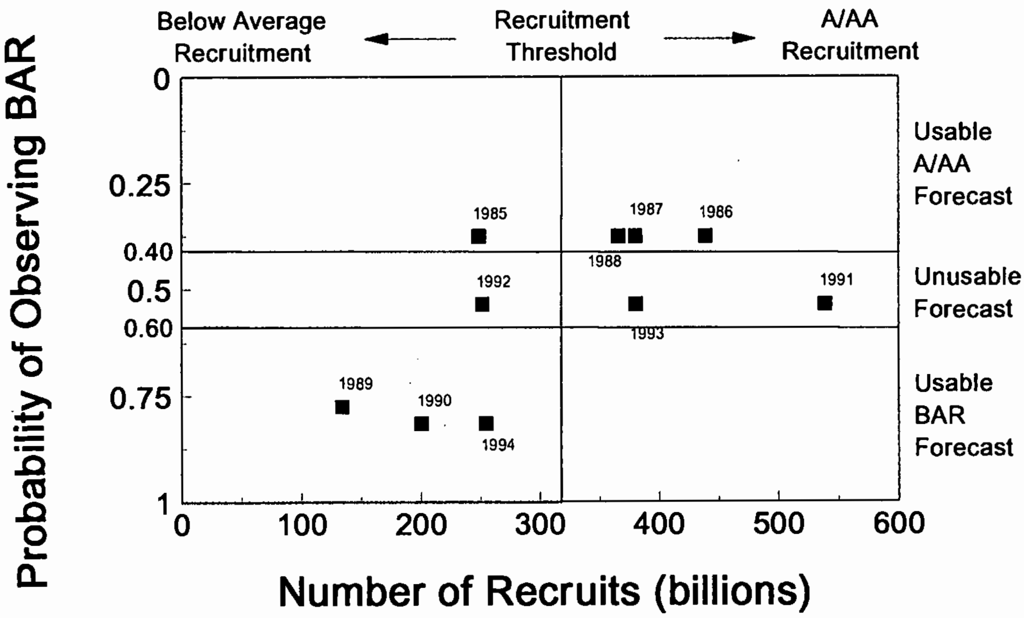


Figure 6.7: Graphical representation of the forecasts generated by the LGP probabilistic system. The shaded area is the area of interest, delineated by the thresholds for usable/unusable forecasts and below average/average or above average recruitment. Note that the probability scale has been reversed. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average Recruitment.

Comparison with the observed recruitment demonstrates that although advances have been made in elucidating the factors influencing the recruitment process for use in forecasting, there are clearly some inconsistencies in the results. Above average recruitment forecasts for 1985 and 1992 (although themselves insubstantial and usable), do not corroborate the observed recruitment, and reflect the generally tenuous nature of existing knowledge.

6.14 SUMMARY

The development of a recruitment prediction system, based on the axioms of probability, was proposed. To obtain the inputs required by the probability equations, two datasets were assembled: empirical probabilities extracted as frequency data from the time-series of the indicator variables and observed recruitment, and subjective probabilities extracted by questionnaire from selected experts in the field of pelagic fisheries (both local and international).

Initial attempts concentrated on the development of two comparative probabilistic systems, each using three variables. The systems were each to use a common base-pair of variables (annual commercial oil:meal ratio and daily egg production; available for the period 1984-1993), and a discrete third variable: the "*Wind*" system was to use the Cape Point N-S windrun anomaly time-series (available for 1984-1993), and the "*Food*" system was to use the percentage "starvation stations" time-series (data only available for 1988-1993). The forecasts of below average recruitment resulting from these systems were to be compared to the historic time-series of estimated recruitment (data available for 1984-1993). However, close inspection of the data revealed that the subjective data (expert assessed probabilities) were inconsistent with the axioms of probability, and unusable in their initial state.

Linear programming (LP) methods - and in particular, a special case of LP, linear goal programming (LGP) - were employed to obtain a subjective dataset consistent with the probability axioms. With LGP, obtaining a consistent dataset proved easy enough. Based on various experiments however, the probabilities that arose were deemed unsatisfactory. The experts probabilities were re-assessed in conjunction with the empirical probabilities, and subject to the LGP model yielding much improved results.

The research described in this chapter highlights the problems associated with extracting reliable numerical data for such dynamic variables. It is suggested that at the present time, the empirical time-series of the indicator variables under investigation, are too short for the generation of reliable prior probabilities and likelihoods. Furthermore, it is suggested that because the present study also primarily forecasts existing facts, well after the fact has taken place, the probabilities and likelihoods arising from this study are more confident than what they might be under "real time" forecasting. Expert opinion, although extremely useful for gaining insight into the recruitment problem, was inconsistent and apparently overconfident. Overall, the performance of the probabilistic system was not as reliable as that of the deterministic system developed in Chapter 5. The opinion therefore, is that it would be sensible to consider the probabilities of below average recruitment as worst-case scenarios, and imprudent to use the model for management purposes before some substantial improvements in forecasting ability have been made.

"Marine fisheries science has long acted as if the size of stocks depended solely on the extent to which they were fished. That stocks were also influenced by other species in their ecosystems and by environmental change has only recently become widely accepted."

Warren S. Wooster
(preface to Glantz 1994)

Chapter 7

DISCUSSION AND CONCLUSION

Most populations (including those of pelagic fish) are characterized by large natural variability in stock levels (May 1989); it has been suggested that "*ecological systems contain the seeds of chaos*" (Berryman and Millstein 1989). Although overexploitation has taken its toll on some important marine resources, the environment is believed to play a large role in the fluctuations of fish stocks (see Glantz 1994). Due to commercial interests, short term fluctuations in pelagic fish stocks are of considerable interest and as a consequence, the need for scientific knowledge to manage this exploitation has grown.

One of the goals of ecology is to derive general principles which serve as the basis for understanding the functioning of whole systems. Understanding what controls recruitment success in pelagic fish has been investigated extensively (Wooster and Bailey 1989), yet evidence for a single dominant effect is limited and results of investigations tend to be controversial and subjective:

> "*Recruitment is the result of a complex interaction of many processes, no one of which is truly dominant*" (Campbell and Graham 1991).

Empirical attempts to relate recruitment to environment have thus not been very successful, partly due to the short time series available for analysis (Bakun 1985). The use of mathematical models for simulation is but one approach in an attempt to cope with uncertainties in environment and recruitment. Models also allow one to partly sidestep the issue of limited data - from what data are available, output may be generated within set constraints.

This study has endeavored to provide qualitative and quantitative information to managers on anchovy recruitment success at an earlier stage than is presently possible. By linking Cape anchovy (*Engraulis capensis*) recruitment to environmental and biological influencing factors, expert systems were constructed to forecast departures from median recruitment - specifically, those departures below the median. Two approaches were undertaken: a rule-based deterministic expert system and Bayesian probabilistic reasoning. Although the deterministic system is not the first to attempt forecasting anchovy recruitment, the probabilistic system is a first attempt at quantitatively estimating the confidence which can be placed in a prediction.

7.1 IMPORTANT FINDINGS

The Cape anchovy is a relatively short-lived species and recruitment in any one year has a marked impact on the population biomass (Cochrane and Hutchings 1992). Recruitment is however, not correlated to the spawner biomass of the previous November ($r = 0.24$, $n = 10$, $P > 0.25$), which represented the parent stock. The highest recruitment recorded (1991) was generated by the lowest spawner biomass (1990) (Figure 7.1).

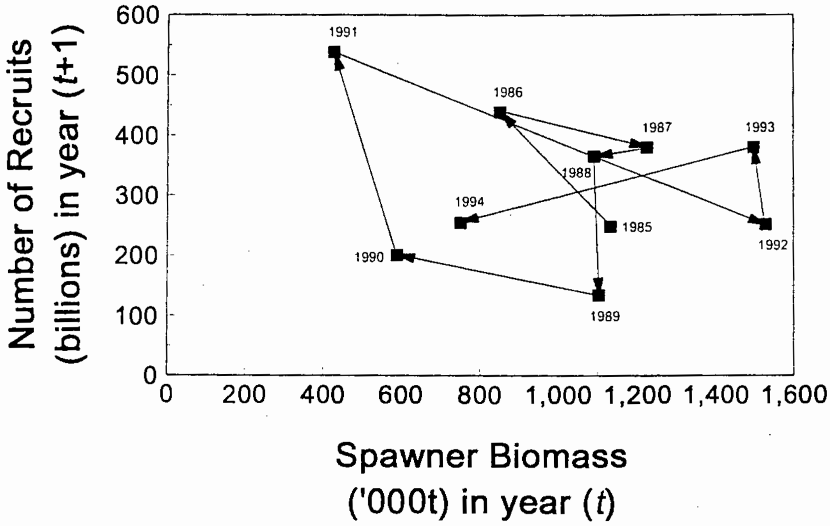


Figure 7.1: Relationship between recruitment and November spawner biomass of the previous year for Cape anchovy, *Engraulis capensis*. Numbers at the datapoints refer to the year of the recruitment estimate.

A number of variables were identified as possible influencing factors on, and indicators of, recruitment in anchovy. A subset of these factors was selected (in particular, those currently being monitored) and used to formulate rules to predict below average recruitment. These rules were synthesized and then developed into the deterministic and probabilistic systems. The models' predictions were compared to the historical time-series of observed recruitment.

7.1.1 The Deterministic System

A number of deterministic models, incorporating a variety of variables thought to be possible predictors of anchovy recruitment, were constructed and tuned using time-series data for 1984 - 1992 (recruitment data for 1985 - 1993); the 1993 time-series data were not yet available. Threshold levels were developed so that reliable indicators of below average recruitment might be obtained. Trial models included experiments with between three and seven variables, differential weighting of the variables and "fuzzy" thresholds. A successful combination was found in a differentially weighted model incorporating the following four variables:

- Egg production by spawning anchovy
- Distance offshore of the 16° Isotherm
- Percentage female gonad atresia, and
- El Niño-Southern Oscillation (ENSO) events.

The utility of this expert system is demonstrated in Figure 7.2 - the model correctly forecasts fluctuations in recruitment for all years in the time-series of observed (estimated) recruitment (1985 - 1993). When the 1993 time-series data became available, a "real" forecast of below average recruitment was tendered for 1994. When the estimate was later made available, the forecast was seen to be justified. Unfortunately, a complete set of data was not available for 1994, so no forecast was tendered for recruitment in 1995.

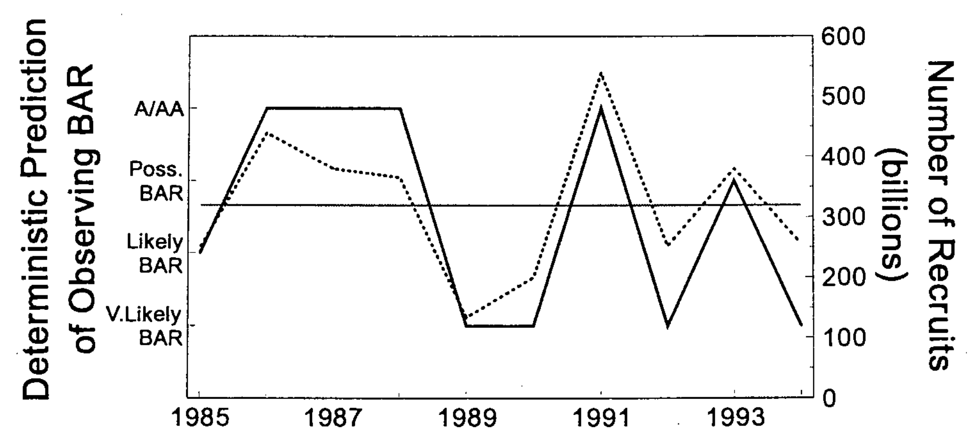


Figure 7.2: Observed (···) and predicted (-) recruitment, as forecast by the deterministic expert system. Median recruitment is shown by the horizontal line. Recruitment data from Sea Fisheries Research Institute (unpublished).

The results obtained from this system are extremely encouraging. It is therefore suggested that this expert system be updated as new information becomes available.

7.1.2 **The Probabilistic System**

Through the implementation of the threshold values developed for the deterministic expert system, empirical and subjective probabilities - i.e. frequencies of occurrence of influencing variables - were respectively extracted from time-series data, and by questionnaire from a selected group of experts. The probabilities relate the following four influencing factors to anchovy recruitment:

- Egg production by spawning anchovy
- Average annual (commercial) oil:meal ratio
- N-S windrun anomaly, and
- Percentage "starvation stations" .

The initial proposal of building two comparable Bayesian probabilistic systems, each generating forecasts of below average recruitment based on data for three influencing factors, was revised after it was discovered that the expert assessed (subjective) probabilities were not consistent with the axioms of probability. Linear goal programming (LGP) was implemented to construct a more consistent set of subjective probabilities, and to extend the limited dataset of empirical probabilities. An additional advantage of the LGP model was that all four influencing factors could now be used simultaneously to compute the probability of observing below average recruitment. The empirical and subjective probability datasets were initially used independently to drive the LGP model. However, these experiments yielded unsatisfactory results, necessitating re-assessment of the data. In constructing a single "best" dataset, the empirical and expert assessed probabilities were averaged, re-assessed and re-assigned where necessary (see Chapter 6, section 6.12). Posterior probabilities of observing below average recruitment were then computed by the LGP model using these revised data (Figure 7.3).

As a first attempt at probabilistically quantifying the confidence of a prediction of anchovy recruitment, the results obtained from this system are extremely encouraging. This system does not however, perform quite as well as the deterministic system described above.

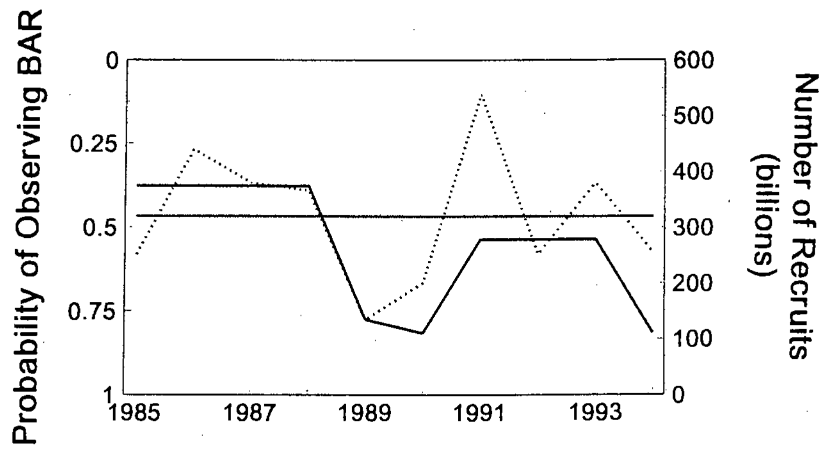


Figure 7.3: Observed (···) and predicted (-) recruitment, as forecast by the LGP probabilistic system. Median recruitment is shown by the horizontal line. Note that the probability scale is reversed. Recruitment data from Sea Fisheries Research Institute (unpublished). BAR = Below Average Recruitment.

The tenuous nature of the probability data renders this system inadequate for conclusive application at this stage. Future extensions of this model would benefit if longer time-series were available, allowing a more robust probabilistic assessment.

7.1.3 **Comparing the Systems**

The predictions from the two forecasting systems compare well with the time-series of observed recruitment. Thresholds were developed to distill usable forecasts (i.e. forecasts for which we have a large degree of confidence) from those that are not (see Chapter 5, section ??, and Chapter 6, section ??). After the application of these thresholds, the predictions generated by the deterministic system fare better against the time-series of observed recruitment than those from the probabilistic system. It is disconcerting that there is a large probability of observing below average recruitment in some of the LGP estimated 1st-order posterior probabilities. This is however, almost certainly a result of overconfidence on the part of the experts, a well known feature of subjective probability assessments (Wallsten *et al.* 1993).

In general, the results comply with the suggestions of Shelton (1986, 1987): in a variable environment, the anchovy are better adapted to events that occur frequently, and poorly adapted to "anomalies" of less frequent occurrence.

These "anomalous" events appear to have a greater impact on recruitment. Examination of the 1st-order posterior probabilities generated by the revised LGP model demonstrated that the scale of the impact on recruitment by a particular influencing variable, is proportional to the inverse of the frequency of occurrence of the variable (see Chapter 6, Table 6.11). Also, the deterministic system that generated the best results was constructed largely with variables that are infrequent in their occurrence, but which severely impact recruitment when they do occur.

The results need to be viewed in the light of the following reservations. It should be borne in mind that the bulk of the data are recorded during a single research cruise, lasting perhaps one month out of the spawning season that may last as long as four months. The annual research cruise is planned so that sampling normally coincides with the peak of the spawning season, when the factors thought to affect recruitment are presumably having the greatest effect. Shelton (1986, 1987) makes a case for "bet-hedging"; i.e. "the spreading of risk over both time and space in order to maximize survival, growth and reproduction". It is entirely feasible that after recording factors pointing toward a below average recruitment event, spawning may improve to such an extent (i.e. the factors affecting spawning recover), that average to above average recruitment is attainable. Encouraging as the results are, it would be prudent to consider the forecasts of below average recruitment presented here, as "worst-case" scenarios. There is therefore the need to update and test the systems when new data become available.

7.2 LIMITATIONS OF THIS RESEARCH

It is recognized that the information presented here cannot be regarded as all inclusive, for the following reasons. Most researchers have "pet" hypotheses and "pet" indicators that they believe explain the impact of environmental variability on recruitment success in pelagic fish. This exercise is no different - the factors selected for this study were "hand-picked" by a group of experts, and therefore reflect their interests and the trends currently foremost in their thinking. Experts from only two local institutions, the Sea Fisheries Research Institute (SFRI), and the Zoology Department, University of Cape Town (UCT), were targeted for this research. These two institutions already work in close co-operation, possibly narrowing the range of opinions. Also, fishermen are often ignored in fisheries management, as was the case in this exercise. It is believed that skippers have a "good feel" for the relationship between fish and the environment, and almost certainly have their own subjective "instincts" for what is happening with the fish population; Hilborn (1985) argues that understanding fishermen's behaviour is the key to successful fisheries management. Fishermen may yet prove to be an untapped resource of subjective data.

The most obvious limitation of this exercise has already been mentioned - the fact that a January prediction would be made from data that are annual averages, or have been collected in a "snap-shot" fashion during a single research survey. The lack of empirical data in the forms of longer time-series seriously hampers the ability to extract realistic probabilities and likelihoods.

The Benguela Ecology Programme (BEP) recently initiated a new Sardine and Anchovy Recruitment Prediction (SARP) programme involving scientists at the Sea Fisheries Research Institute (SFRI) and the University of Cape Town (UCT) (Painting 1993). Research surveys (of anchovy) are undertaken every month during the summer spawning season (from September to March) to determine within season variability in spawner stock size, fish condition, egg production rates and other factors (e.g. food concentrations). Recruits captured six months later during the annual autumn/winter recruit survey are aged to determine birth-date distributions, which may then be related back to the variability observed during the spawning season.

The SARP datasets (of which there are currently two - each comprising seven monthly datasets from the individual surveys) are potentially an excellent basis for forecasting within season recruitment success. As the monthly survey data become available, the new information can be used to forecast within season recruitment success one month at a time.

In a study by Patwardhan and Small (1992), a formal method was developed for using evidence to systematically update probability distributions for parameters of an existing model as additional information is obtained. For the SARP dataset, this would be on a monthly basis, as the new information is collected. The model, using the updated probability distributions of its parameters, can then be used to make predictions (in the article by Patwardhan and Small, predicting sea level rise). Eventually taking all the monthly forecasts into consideration, a single "best" estimate of recruitment success may be formulated (see also Fried and Hilborn 1988).

The successful technique employed in this research to obtain a consistent set of probabilities from those generated by the experts, was linear (goal) programming. The goals for this exercise, were specified precisely from the probabilities generated by the experts. Ignizio (1982) documents and briefly reviews the fuzzy goal programming approach, a special form of goal programming, in which goals need not be fixed. This approach addresses an issue of some importance - imprecision in the determination of the goals. This issue indeed came to the fore in the current research, and was dealt with by a process of combining and averaging distinct goals, and personal re-assessment. It is suggested that fuzzy goal programming may be an alternative route, worthy of investigation.

7.3 FORECASTING SYSTEMS: PROS AND CONS

Forecasting is based on the use of data from the past, and rules for relating those data to the future. The validity of forecasting methods may be evaluated on their "track records" - a good track record for a forecasting method can give some degree of confidence in it. However, since the accuracy of a forecast is usually only known after the fact, there is no way to know ahead of time if a given method is going to fail. It is therefore necessary to evaluate alternative forecasts prior to making decisions; many forecasts are therefore (correctly) used only as decision support information (Martino 1987). If a method should fail, research after the fact should therefore include systematic studies which look for specific reasons for the failure. Once the reasons for failure have been identified, the decision-makers can attempt to recognize additional occurrences of similar situations, and so recognise the potential for failure again, and improve the rules.

Even so, forecasting systems need to make certain, sometimes dubious, assumptions that may be the cause of their downfall. For example: one of the fundamental assumptions of the forecasting systems presented above, is that if the datum for a specific influencing factor indicates that the factor is impacting recruitment (the datum falls either above or below the threshold value, whatever the case may be), recruitment *will* be considered to be impacted by the system.

The deterministic system provides a simple compartmentalized "Yes/No" prediction of whether below average recruitment will be observed, and even if there is only one variable impacting on recruitment, the below average recruitment forecast will be generated. However, the potential influence of environmental factors on the recruitment success of pelagic fish appears to be strongly buffered in the southern Benguela region (Hutchings and Nelson 1985), and it would be fortunate indeed if we can place such certainty on whether below average recruitment will be observed. The threshold however, allows us to distinguish between forecasts that we may have more confidence in (and are imminently usable), and those that are not. A major feature of the probabilistic approach is that it provides not only a "Yes/No" answer to whether below average recruitment will be observed, but also a quantitative degree to which the forecast should be believed. For example, if the probability of observing below average recruitment is 0.10, we should feel quite confident in saying that we will not observe below average recruitment (even though there is a 10% chance that we might); if on the other hand, the probability of observing below average recruitment is 0.90, we should feel quite confident in saying that we will observe below average recruitment (even though there is a 10% chance that we might not). Overall, such a system, when successfully developed, would allow decision-makers to evaluate the various risks (biological, social and economic) associated with any management choice and hence arrive at the optimum solution.

There are of course, other pros and cons. A big point in favour of a deterministic system, is its data requirements: no data beyond the selection of the influencing factors and the specification of critical thresholds are required for the formalization of the rule base. For a probabilistic system however, it has been pointed out that a common difficulty is the large amount of data needed to determine realistic prior probabilities and likelihoods. This was indeed found to be a problem when extracting the required priors and likelihoods from the empirical data; the time-series for these data are very short (only 10 data points in all), hardly satisfactory for the estimation of realistic probabilities. When it was found that the empirical data were lacking, a route for extracting subjective probabilities from a select group of experts by means of a questionnaire was followed. The results indicated that a number of the respondents had difficulty with the concept of assigning probabilities to events, especially when it came to assigning probabilities/likelihoods to events involving more than one factor. Furthermore, one of the respondents commented that the use of descriptive names in the quantitative 'chance of occurrence' categories was confusing - what was described as a 'poor' chance of occurrence, was in fact to him, a 'good' chance of occurrence (on the whole though, it appears as if the descriptive names were more of a help than a hindrance).

Both systems lend themselves to the process of re-evaluation. If, for example, a user was unsatisfied with the way in which a particular question was asked or rule was formulated (deterministic system), or unsatisfied with a particular probability or likelihood (probabilistic system), modifications are easily incorporated.

As long as a forecasting system forecasts below average recruitment, it will always be conservative in terms of biological risk. The system can therefore only really be wrong from a biological perspective when a forecast of average/above average recruitment is made when below average recruitment is observed - a situation which could potentially lead to overexploitation. The problem however, is the negative impact such "correct" forecasts would have on the fishery, and the associated social and economic fronts. The real question therefore, is: are these approaches, or a particular one, an improvement on the assumption of average recruitment currently used in the assessment procedure (Butterworth and Bergh 1993, Cochrane and Starfield 1992)?

In this exercise, although we are actually hindcasting (forecasting an existing time-series), the experts are dealing with a real forecast situation. This contrasts with many previous studies in which uncertainty regarding existing facts is of little or no interest (e.g. the probability that the distance from Seattle to Mexico City is greater than the distance from Stockholm to Cairo - see Wright and Wisudha 1982). While promising, the fact that the deterministic system attaches only a qualitative degree of confidence to its predictions, essentially lacks the rigor required for a management tool. By assessing the major impacts on recruitment of anchovy, and placing a quantitative (subjective) figure on a particular factors impact on recruitment, the experts are "putting their money where their mouth is". The probabilistic system with its quantitative forecast, is the desired approach. Both need to be tested, and proven, over a number of years, before being employed as a decision aid. Nevertheless, it is believed that both these systems are a definite improvement over the far removed assumption of average recruitment. Although the deterministic system currently outperforms the probabilistic system, as the time-series data are extended it is believed that the probabilistic system will eventually outperform the deterministic system.

Mine eyes have seen the glory of the Reverend Thomas Bayes,
He is stamping out strict frequentists and their incoherent ways,
He has raised his mighty army at the Hotel Las Fuentas,
His troops are marching on.

Glory, Glory, Probability
Glory, Glory, Subjectivity
Glory, Glory, on to infinity
His troops are marching on!

P.R. Freeman and A. O'Hagan

In: *Bayesian Statistics 2*, Bernard, J.M.; DeGroot, M.H.; Lindley, D.V. & A.F.M. Smith (Eds). Elsevier, Amsterdam. Recited at the final dinner (at the Hotel Las Fuentas) of the Second Valencia International Meeting, September 6-10, 1983.

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APPENDICES

Appendix 1

LIST OF PARTCIPATING EXPERTS

Universty of Cape Town - Zoology Department:

Professor John Field
Dr. Patti Wickens
Ms Éva Plagányi

Universty of Cape Town - Oceanography Department:

Professor Geoff Brundrit
Dr Mark Jury

Sea Fisheries Research Institute:

Professor Vere Shannon
Dr Kevern Cochrane
Dr Larry Hutchings
Dr Kobus Agenbag
Dr Awie Badenhorst
Dr Alan Boyd
Dr Penny Brown
Dr Rob Crawford
Dr Grev Nelson
Dr Suzanne Painting
Dr Grant Pitcher
Dr Hans Verheye
Mr Geoff Bailey
Mr Simon Bloomer
Ms Jenny Huggett
Ms Beatriz Payne
Mr Anthony Richardson
Mr Fritz Schülein
Mr John Taunton-Clark
Mr Carl Van der Lingen

Foreign:

Professor Paul Smith	Southwest Fisheries Center National Marine Fisheries Service, La Jolla
Professor Tony Starfield	Department of Ecology and Behavioural Biology University of Minnesota, Minneapolis
Dr Coleen Moloney	Department of Wildlife and Fisheries Research University of California, Davis
Dr Andre Punt	Fisheries Research Institute University of Washington, Seattle
Dr Peter Shelton	Department of Fisheries and Oceans St. Johns, Newfoundland

Appendix 2

SOME DATA AND THRESHOLD CALCULATIONS

A2.1 OIL YIELD

Tables begin overside.

YEAR (Fishing Period)	Anchovy Catch	Total Pelagic Catch	Percent Anchovy	Fish Meal	Fish Oil	Oil:Meal Ratio
1990 (Jan 15 - Oct 20)	150100	259343	57.9	54354	4253	**7.8**
1989 (Feb 1 - Aug 31)	294153	404317	72.8	93606	15175	**16.2**
1988 (Jan 15 - Nov 5)	569815	672113	84.8	156073	23359	**15.0**
1987 (Jan 15 - Sep 30)	596015	667884	89.2	155015	54462	**35.1**
1986 (Jan 15 - Dec 15)	303816	388399	78.2	90721	19292	**21.3**
1985 (Jan 15 - Dec 15)	272662	380036	71.7	86364	25692	**29.7**
1984 (Jan 15 - Jul 15, Oct 1 - Dec 15)	268552	345551	77.7	79819	17029	**21.3**
1983 (Jan 15 - Jun 30, Oct 15-Dec 15)	240185	376486	63.8	90157	24415	**27.1**
1982 (Jan 1 - Aug 31)	306161	377003	81.2	90771	24702	**27.2**
1981 (Jan 1 - Aug 31)	292039	379176	77.0	89482	34532	**38.6**
1980 (Jan 1 - Aug 31)	322644	381422	84.6	91269	33611	**36.8**
1979 (Jan 1 - Aug 31)	304167	381151	79.8	90677	33510	**37.0**
1978 (Jan 1 - Aug 31)	247670	379569	65.3	93126	27945	**30.0**
1977 (Jan 1 - Aug 31)	247228	356441	69.4	88507	18579	**21.0**
1976 (Jan 1 - Aug 31)	235621	404251	58.3	102144	26822	**26.3**
1975 (Jan 1 - Aug 31)	256773	407360	63.0	97783	22470	**23.0**
1974 (Jan 1 - Aug 9)	349027	400513	87.1	90045	26500	**29.4**
1973 (Jan 1 - Aug 31)	283861	453027	62.7	98445	29118	**29.6**
1972 (Jan 1 - Aug 4)	281254	436426	64.4	96902	27316	**28.2**
1971 (Jan 1 - Aug 31)	184825	326143	56.7	74279	16503	**22.2**
1970 (Jan 1 - Aug 31)	215387	370300	58.2	80299	22007	**27.4**
1969 (Jan 1 - Aug 31)	170352	357827	47.6	80006	20181	**25.2**
1968 (Jan 1 - Sep 15)	170019	372323	45.7	86476	15939	**18.4**
1967 (Jan 1 - Sep 30)	273250	632505	43.2	115791	17646	**15.2**
1966 (Jan 1 - Sep 30)	156823	408843	38.4	94617	12823	**13.6**
1965	208603	512363	40.7	112602	23477	**20.8**
1964	94919	430348	22.1	98705	22208	**22.5**

Table A2.1: Annual South African pelagic fish catch (all years) showing total anchovy and pelagic catch, percentage of the total catch that was anchovy, total fish meal and oil produced and the oil:meal ratio. Raw fish, meal and oil are in tons. Data from Stuttaford (1991).

YEAR (Fishing Period)	Anchovy Catch	Total Pelagic Catch	Percent Anchovy	Fish Meal	Fish Oil	Oil:Meal Ratio
1990 (Jan 15 - Oct 20)	150100	259343	57.9	54354	4253	**7.8**
1989 (Feb 1 - Aug 31)	294153	404317	72.8	93606	15175	**16.2**
1988 (Jan 15 - Nov 5)	569815	672113	84.8	156073	23359	**15.0**
1987 (Jan 15 - Sep 30)	596015	667884	89.2	155015	54462	**35.1**
1986 (Jan 15 - Dec 15)	303816	388399	78.2	90721	19292	**21.3**
1985 (Jan 15 - Dec 15)	272662	380036	71.7	86364	25692	**29.7**
1984 (Jan 15 - Jul 15, Oct 1 - Dec 15)	268552	345551	77.7	79819	17029	**21.3**
1983 (Jan 15 - Jun 30, Oct 15-Dec 15)	240185	376486	63.8	90157	24415	**27.1**
1982 (Jan 1 - Aug 31)	306161	377003	81.2	90771	24702	**27.2**
1981 (Jan 1 - Aug 31)	292039	379176	77.0	89482	34532	**38.6**
1980 (Jan 1 - Aug 31)	322644	381422	84.6	91269	33611	**36.8**
1979 (Jan 1 - Aug 31)	304167	381151	79.8	90677	33510	**37.0**
1978 (Jan 1 - Aug 31)	247670	379569	65.3	93126	27945	**30.0**
1977 (Jan 1 - Aug 31)	247228	356441	69.4	88507	18579	**21.0**
1976 (Jan 1 - Aug 31)	235621	404251	58.3	102144	26822	**26.3**
1975 (Jan 1 - Aug 31)	256773	407360	63.0	97783	22470	**23.0**
1974 (Jan 1 - Aug 9)	349027	400513	87.1	90045	26500	**29.4**
1973 (Jan 1 - Aug 31)	283861	453027	62.7	98445	29118	**29.6**
1972 (Jan 1 - Aug 4)	281254	436426	64.4	96902	27316	**28.2**
1971 (Jan 1 - Aug 31)	184825	326143	56.7	74279	16503	**22.2**
1970 (Jan 1 - Aug 31)	215387	370300	58.2	80299	22007	**27.4**
Mean						**26.2**
Std. Deviation						**7.7**
Lower Bound						**18.5**
Upper Bound						**33.9**

Table A2.2: Annual South African pelagic fish catch showing total anchovy and pelagic catch, where the percentage of the total catch that was anchovy is 50% or more, total fish meal and oil produced and the oil:meal ratio. The mean oil:meal ratio, with std. deviation and lower and upper bounds, is also shown. Raw fish, meal and oil are in tons. Data from Stuttaford (1991).

YEAR (Fishing Period)	Anchovy Catch	Total Pelagic Catch	Percent Anchovy	Fish Meal	Fish Oil	Oil:Meal Ratio
1989 (Feb 1 - Aug 31)	294153	404317	72.8	93606	15175	**16.2**
1988 (Jan 15 - Nov 5)	569815	672113	84.8	156073	23359	**15.0**
1987 (Jan 15 - Sep 30)	596015	667884	89.2	155015	54462	**35.1**
1986 (Jan 15 - Dec 15)	303816	388399	78.2	90721	19292	**21.3**
1985 (Jan 15 - Dec 15)	272662	380036	71.7	86364	25692	**29.7**
1984 (Jan 15 - Jul 15, Oct 1 - Dec 15)	268552	345551	77.7	79819	17029	**21.3**
1982 (Jan 1 - Aug 31)	306161	377003	81.2	90771	24702	**27.2**
1981 (Jan 1 - Aug 31)	292039	379176	77.0	89482	34532	**38.6**
1980 (Jan 1 - Aug 31)	322644	381422	84.6	91269	33611	**36.8**
1979 (Jan 1 - Aug 31)	304167	381151	79.8	90677	33510	**37.0**
1978 (Jan 1 - Aug 31)	247670	379569	65.3	93126	27945	**30.0**
1977 (Jan 1 - Aug 31)	247228	356441	69.4	88507	18579	**21.0**
1974 (Jan 1 - Aug 9)	349027	400513	87.1	90045	26500	**29.4**
Mean						**27.6**
Std. Deviation						**8.0**
Lower Bound						**19.6**
Upper Bound						**35.6**

Table A2.3: Annual South African pelagic fish catch showing total anchovy and pelagic catch, where the percentage of the total catch that was anchovy is 65% or more, total fish meal and oil produced and the oil:meal ratio. The mean oil:meal ratio, with std. deviation and lower and upper bounds, is also shown. Raw fish, meal and oil are in tons. Data from Stuttaford (1991).

YEAR (Fishing Period)	Anchovy Catch	Total Pelagic Catch	Percent Anchovy	Fish Meal	Fish Oil	Oil:Meal Ratio
1988 (Jan 15 - Nov 5)	569815	672113	84.8	156073	23359	**15.0**
1987 (Jan 15 - Sep 30)	596015	667884	89.2	155015	54462	**35.1**
1986 (Jan 15 - Dec 15)	303816	388399	78.2	90721	19292	**21.3**
1984 (Jan 15 - Jul 15, Oct 1 - Dec 15)	268552	345551	77.7	79819	17029	**21.3**
1982 (Jan 1 - Aug 31)	306161	377003	81.2	90771	24702	**27.2**
1981 (Jan 1 - Aug 31)	292039	379176	77.0	89482	34532	**38.6**
1980 (Jan 1 - Aug 31)	322644	381422	84.6	91269	33611	**36.8**
1979 (Jan 1 - Aug 31)	304167	381151	79.8	90677	33510	**37.0**
1974 (Jan 1 - Aug 9)	349027	400513	87.1	90045	26500	**29.4**
Mean						**29.1**
Std. Deviation						**8.5**
Lower Bound						**20.6**
Upper Bound						**37.6**

Table A2.4: Annual South African pelagic fish catch showing total anchovy and pelagic catch, where the percentage of the total catch that was anchovy is 75% or more, total fish meal and oil produced and the oil:meal ratio. The mean oil:meal ratio, with std. deviation and lower and upper bounds, is also shown. Raw fish, meal and oil are in tons. Data from Stuttaford (1991).

YEAR (Fishing Period)	Anchovy Catch	Total Pelagic Catch	Percent Anchovy	Fish Meal	Fish Oil	Oil:Meal Ratio
1988 (Jan 15 - Nov 5)	569815	672113	84.8	156073	23359	**15.0**
1987 (Jan 15 - Sep 30)	596015	667884	89.2	155015	54462	**35.1**
1982 (Jan 1 - Aug 31)	306161	377003	81.2	90771	24702	**27.2**
1980 (Jan 1 - Aug 31)	322644	381422	84.6	91269	33611	**36.8**
1974 (Jan 1 - Aug 9)	349027	400513	87.1	90045	26500	**29.4**
Mean						**28.7**
Std. Deviation						**8.6**
Lower Bound						**20.1**
Upper Bound						**37.3**

Table A2.5: Annual South African pelagic fish catch showing total anchovy and pelagic catch, where the percentage of the total catch that was anchovy is 80% or more, total fish meal and oil produced and the oil:meal ratio. The mean oil:meal ratio, with std. deviation and lower and upper bounds, is also shown. Raw fish, meal and oil are in tons. Data from Stuttaford (1991).

A2.2 TRENBERTHS SOUTHERN OSCILLATION INDEX

The following data - monthly averages for the Southern Oscillation Index, 1984-1993 - were extracted from Kousky, Bell and Kopman (1984-1993).

YEAR	MONTH	INDEX	YEAR	MONTH	INDEX
1984	January	0	1986	January	0.8
	February	0.5		February	1.2
	March	-0.8		March	-0.1
	April	0.4		April	0.1
	May	0		May	-0.6
	June	-1.2		June	1
	July	0		July	0.1
	August	0.1		August	-0.9
	September	0.1		September	-0.5
	October	-0.6		October	0.6
	November	0.3		November	-1.6
	December	-0.3		December	-1.6
1985	January	-0.5	1987	January	-0.7
	February	0.8		February	-1.5
	March	0.2		March	-2
	April	0.9		April	-2.7
	May	-0.7		May	-2
	June	-1.9		June	-2.7
	July	-0.3		July	-1.8
	August	0.7		August	-1.7
	September	0		September	-1.1
	October	-0.8		October	-0.7
	November	-0.4		November	-0.1
	December	0.1		December	-0.6

Table continues overside......

YEAR	MONTH	INDEX	YEAR	MONTH	INDEX
1988	January	-0.3	1991	January	0.6
	February	-0.6		February	-0.1
	March	0.1		March	-1.4
	April	0		April	-1
	May	1.1		May	-1.5
	June	-0.3		June	-0.5
	July	1.1		July	-0.2
	August	1.4		August	-0.9
	September	1.9		September	-1.8
	October	1.5		October	-1.5
	November	1.9		November	-0.8
	December	1.1		December	-2.3
1989	January	1.3	1992	January	-3.4
	February	1.1		February	-1.4
	March	0.6		March	-3
	April	1.6		April	-1.4
	May	1.2		May	0
	June	0.5		June	-1.2
	July	0.8		July	-0.8
	August	-0.8		August	0
	September	0.6		September	0
	October	0.6		October	-1.9
	November	-0.4		November	-0.9
	December	-0.7		December	-0.9
1990	January	-0.2	1993	January	-1.2
	February	-2.4		February	-1.3
	March	-1.2		March	-1.1
	April	0		April	-1.6
	May	1.1		May	-0.6
	June	0		June	-1.4
	July	0.5		July	-1.1
	August	-0.5			
	September	-0.8			
	October	0.1			
	November	-0.7			
	December	-0.5			

Appendix 3

DETERMINISTIC SYSTEM RESULTS

Tables begin overside.

YEAR	VARIABLES			FORECAST			
	Low Oil	Low Eggs	High S. Wind	Chance of B. A. R. V. Likely	Chance of B. A. R. Likely	Chance of B. A. R. Possible	A / AA R'ment
1984 (*)	X	X	X				♦
1985	X	X	✓			♦	
1986	X	X	✓			♦	
1987	X	X	X				♦
1988 (*)	✓	X	✓		♦		
1989 (*)	✓	✓	✓	♦			
1990	✓	X	X			♦	
1991 (*)	✓	X	X			♦	
1992	✓	X	X			♦	
1993 (*)	✓	✓	✓	♦			

Table A3.1: Forecast table for the 'base-case' 3-variable 'WIND' deterministic expert system. Variables are unweighted. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast.

YEAR	VARIABLES			FORECAST			
	Low Oil	Low Eggs	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
				V. Likely	Likely	Possible	
1984 (*)	X	X	N.D.				
1985	X	X	N.D.				
1986	X	X	N.D.				
1987	X	X	N.D.				
1988 (*)	✓	X	✓		♦		
1989 (*)	✓	✓	X		♦		
1990	✓	X	X			♦	
1991 (*)	✓	X	X			♦	
1992	✓	X	X			♦	
1993 (*)	✓	✓	X		♦		

Table A3.2: Forecast table for the 'base-case' 3-variable 'FOOD' deterministic expert system. Variables are unweighted. Years marked (*) indicate that below average recruitment was estimated to be observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Chance of B. A. R. V. Likely	Likely	Possible	A / AA R'ment
1984 (*)	X	X	X	N.D.				♦
1985	X	X	✓	N.D.			♦	
1986	X	X	✓	N.D.			♦	
1987	X	X	X	N.D.				♦
1988 (*)	✓	X	✓	✓	♦			
1989 (*)	✓	✓	✓	X	♦			
1990	✓	X	X	X			♦	
1991 (*)	✓	X	X	X			♦	
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	✓	X	♦			

Table A3.3: Forecast table for the 'base-case' 4-variable 'WIND and FOOD' deterministic expert system. Variables are unweighted. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	X	X	X	N.D.				♦
1985	X	X	✓	N.D.			♦	
1986	X	X	✓	N.D.			♦	
1987	X	X	X	N.D.				♦
1988 (*)	✓	X	✓	✓	♦			
1989 (*)	✓	✓	✓	X		♦		
1990	✓	X	X	X			♦	
1991 (*)	✓	X	X	X			♦	
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	✓	X	♦			

Table A3.4: Forecast table for the 4-variable 'WIND and FOOD' deterministic expert system. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	FUZZY	X	X	N.D.				♦
1985	X	FUZZY	✓	N.D.			♦	
1986	FUZZY	X	✓	N.D.			♦	
1987	X	FUZZY	X	N.D.				♦
1988 (*)	✓	FUZZY	✓	✓	♦			
1989 (*)	✓	✓	✓	X		♦		
1990	✓	X	X	X			♦	
1991 (*)	✓	X	X	X			♦	
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	✓	X	♦			

Table A3.5: Forecast table for the 4-variable 'WIND and FOOD' deterministic expert system. The threshold is fuzzy at ±10%. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. FUZZY = Variable falls into the fuzzy threshold area. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	FUZZY	X	X	N.D.				♦
1985	X	FUZZY	✓	N.D.			♦	
1986	FUZZY	X	✓	N.D.			♦	
1987	X	FUZZY	X	N.D.				♦
1988 (*)	✓	FUZZY	✓	✓	♦			
1989 (*)	FUZZY	✓	✓	X		♦		
1990	✓	FUZZY	X	X			♦	
1991 (*)	✓	X	X	X			♦	
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	X	X		♦		

Table A3.6: Forecast table for the 4-variable 'WIND and FOOD' deterministic expert system. The threshold is fuzzy at ±20%. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. FUZZY = Variable falls into the fuzzy threshold area. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES					FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Far 16°C Isotherm	Chance of B.A. R.			A / AA R'ment
						V. Likely	Likely	Possible	
1984 (*)	X	X	X	N.D.	✓			♦	
1985	X	X	✓	N.D.	X			♦	
1986	X	X	✓	N.D.	X			♦	
1987	X	X	X	N.D.	X				♦
1988 (*)	✓	X	✓	✓	✓	♦			
1989 (*)	✓	✓	✓	X	✓	♦			
1990	✓	X	X	X	X			♦	
1991 (*)	✓	X	X	X	✓		♦		
1992	✓	X	X	X	X			♦	
1993 (*)	✓	✓	X	X	✓		♦		

Table A3.7: Forecast table for the 5-variable deterministic expert system. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Far 16°C Isotherm	Low Eggs	Strong S. Wind	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	✓	X	X	N.D.			♦	
1985	X	X	✓	N.D.			♦	
1986	X	X	✓	N.D.			♦	
1987	X	X	X	N.D.				♦
1988 (*)	✓	X	✓	✓	♦			
1989 (*)	✓	✓	✓	X	♦			
1990	X	X	X	X				♦
1991 (*)	✓	X	X	X			♦	
1992	X	X	X	X				♦
1993 (*)	✓	✓	✓	X	♦			

Table A3.8: Forecast table for the 4-variable deterministic expert system in which oil yield has been replaced by the 16°C isotherm. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Oil	Low Eggs	Far 16°C Isotherm	High % S. St'ns	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	X	X	✓	N.D.			♦	
1985	X	X	X	N.D.				♦
1986	X	X	X	N.D.				♦
1987	X	X	X	N.D.				♦
1988 (*)	✓	X	✓	✓	♦			
1989 (*)	✓	✓	✓	X	♦			
1990	✓	X	X	X			♦	
1991 (*)	✓	X	✓	X			♦	
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	✓	X	♦			

Table A3.9: Forecast table for the 4-variable deterministic expert system in which the N-S wind anomaly has been replaced by the 16°C isotherm. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES						FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Far 16°C Isotherm	High % Atresia	Chance of B. A. R.			A / AA R'ment
							V. Likely	Likely	Possible	
1984 (*)	X	X	X	N.D.	✓	N.D.			♦	
1985	X	X	✓	N.D.	X	X			♦	
1986	X	X	✓	N.D.	X	X			♦	
1987	X	X	X	N.D.	X	X				♦
1988 (*)	✓	X	✓	✓	✓	✓	♦			
1989 (*)	✓	✓	✓	X	✓	X	♦			
1990	✓	X	X	X	X	X			♦	
1991 (*)	✓	X	X	X	✓	✓		♦		
1992	✓	X	X	X	X	✓			♦	
1993 (*)	✓	✓	X	X	✓	✓		♦		

Table A3.10: Forecast table for the 6-variable deterministic expert system. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES					FORECAST			
	High % Atresia	Low Eggs	Strong S. Wind	High % S. St'ns	Far 16°C Isotherm	Chance of B. A. R.			A / AA R'ment
						V. Likely	Likely	Possible	
1984 (*)	N.D.	X	X	N.D.	✓		♦		
1985	X	X	✓	N.D.	X			♦	
1986	X	X	✓	N.D.	X			♦	
1987	X	X	X	N.D.	X				♦
1988 (*)	✓	X	✓	✓	✓	♦			
1989 (*)	X	✓	✓	X	✓		♦		
1990	X	X	X	X	X				♦
1991 (*)	✓	X	X	X	✓		♦		
1992	✓	X	X	X	X			♦	
1993 (*)	✓	✓	X	X	✓		♦		

Table A3.11: Forecast table for the 5-variable deterministic expert system in which oil yield has been replaced by atresia. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES					FORECAST			
	Low Oil	Low Eggs	High % Atresia	High % S. St'ns	Far 16°C Isotherm	Chance of B. A. R.			A / AA R'ment
						V. Likely	Likely	Possible	
1984 (*)	X	X	N.D.	N.D.	✓		♦		
1985	X	X	X	N.D.	X				♦
1986	X	X	X	N.D.	X				♦
1987	X	X	X	N.D.	X				♦
1988 (*)	✓	X	✓	✓	✓	♦			
1989 (*)	✓	✓	X	X	✓		♦		
1990	✓	X	X	X	X			♦	
1991 (*)	✓	X	✓	X	✓		♦		
1992	✓	X	✓	X	X			♦	
1993 (*)	✓	✓	✓	X	✓	♦			

Table A3.12: Forecast table for the 5-variable deterministic expert system in which N-S wind anomaly has been replaced by atresia. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	Low Eggs	High % Atresia	High % S. St'ns	Far 16°C Isotherm	Chance of B. A. R. V. Likely	Likely	Possible	A / AA R'ment
1984 (*)	X	N.D.	N.D.	✓		♦		
1985	X	X	N.D.	X				♦
1986	X	X	N.D.	X				♦
1987	X	X	N.D.	X				♦
1988 (*)	X	✓	✓	✓	♦			
1989 (*)	✓	X	X	✓		♦		
1990	X	X	X	X				♦
1991 (*)	X	✓	X	✓		♦		
1992	X	✓	X	X			♦	
1993 (*)	✓	✓	X	✓	♦			

Table A3.13: Forecast table for the 4-variable deterministic expert system in which both oil yield and the N-S wind anomaly have been replaced by atresia. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES					FORECAST			
	Low Eggs	High % Atresia	High % S. St'ns	Far 16°C Isotherm	La Niña	Chance of B. A. R.			A / AA R'ment
						V. Likely	Likely	Possible	
1984 (*)	X	N.D.	N.D.	✓	X		♦		
1985	X	X	N.D.	X	X				♦
1986	X	X	N.D.	X	X				♦
1987	X	X	N.D.	X	X				♦
1988 (*)	X	✓	✓	✓	✓	♦			
1989 (*)	✓	X	X	✓	✓		♦		
1990	X	X	X	X	X				♦
1991 (*)	X	✓	X	✓	X		♦		
1992	X	✓	X	X	X			♦	
1993 (*)	✓	✓	X	✓	X		♦		

Table A3.14: Forecast table for the 5-variable deterministic expert system in which both oil yield and the N-S wind anomaly have been replaced by atresia, and the La Niña time series added. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES					FORECAST			
	Low Eggs	High % Atresia	High % S. St'ns	Far 16°C Isotherm	Severe ENSO	Chance of B. A. R.			A / AA R'ment
						V. Likely	Likely	Possible	
1984 (*)	X	N.D.	N.D.	✓	X		♦		
1985	X	X	N.D.	X	X				♦
1986	X	X	N.D.	X	X				♦
1987	X	X	N.D.	X	X				♦
1988 (*)	X	✓	✓	✓	✓	♦			
1989 (*)	✓	X	X	✓	✓		♦		
1990	X	X	X	X	X				♦
1991 (*)	X	✓	X	✓	✓		♦		
1992	X	✓	X	X	X			♦	
1993 (*)	✓	✓	X	✓	X		♦		

Table A3.15: Forecast table for the 5-variable deterministic expert system in which both oil yield and the N-S wind anomaly have been replaced by atresia, and the ENSO time series added. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES							FORECAST			
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Far 16°C Isotherm	High % Atresia	La Niña	Chance of B. A. R.			A / AA R'ment
								V. Likely	Likely	Possible	
1984 (*)	X	X	X	N.D.	✓	N.D.	X			♦	
1985	X	X	✓	N.D.	X	X	X			♦	
1986	X	X	✓	N.D.	X	X	X			♦	
1987	X	X	X	N.D.	X	X	X				♦
1988 (*)	✓	X	✓	✓	✓	✓	✓	♦			
1989 (*)	✓	✓	✓	X	✓	X	✓	♦			
1990	✓	X	X	X	X	X	X			♦	
1991 (*)	✓	X	X	X	✓	✓	X		♦		
1992	✓	X	X	X	X	✓	X			♦	
1993 (*)	✓	✓	X	X	✓	✓	X		♦		

Table A3.16: Forecast table for a 7-variable deterministic expert system incorporating La Niña. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES							FORECAST			
								Chance of B. A. R.			A / AA
	Low Oil	Low Eggs	Strong S. Wind	High % S. St'ns	Far 16°C Isotherm	High % Atresia	Severe ENSO	V. Likely	Likely	Possible	R'ment
1984 (*)	X	X	X	N.D.	✓	N.D.	X			♦	
1985	X	X	✓	N.D.	X	X	X			♦	
1986	X	X	✓	N.D.	X	X	X			♦	
1987	X	X	X	N.D.	X	X	X				♦
1988 (*)	✓	X	✓	✓	✓	✓	✓	♦			
1989 (*)	✓	✓	✓	X	✓	X	✓	♦			
1990	✓	X	X	X	X	X	X			♦	
1991 (*)	✓	X	X	X	✓	✓	✓		♦		
1992	✓	X	X	X	X	✓	X			♦	
1993 (*)	✓	✓	X	X	✓	✓	X		♦		

Table A3.17: Forecast table for a 7-variable deterministic expert system, incorporating ENSO. Variables are weighted according to impact on recruitment. Years marked (*) indicate that below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", and ♦ marks the forecast. N.D. = No Data.

YEAR	VARIABLES				FORECAST			
	High % Atresia	Low Eggs	Severe ENSO	Far 16°C Isotherm	Chance of B. A. R.			A / AA R'ment
					V. Likely	Likely	Possible	
1984 (*)	N.D.	X	X	✓		♦		
1985	X	X	X	X				♦
1986	X	X	X	X				♦
1987	X	X	X	X				♦
1988 (*)	✓	X	✓	✓	♦			
1989 (*)	X	✓	✓	✓	♦			
1990	X	X	X	X				♦
1991 (*)	✓	X	✓	✓	♦			
1992	✓	X	X	X			♦	
1993 (*)	✓	✓	X	✓	♦			

Table A3.18: Forecast table for the 4-variable deterministic expert system in which oil yield and N-S wind anomaly have been replaced by atresia and ENSO. Variables are weighted according to impact on recruitment. Years marked (*) indicate below average recruitment was estimated to have been observed in the following year. B.A.R. = Below Average Recruitment. A/AA = Average/Above Average. X = Variable not "extreme", ✓ = Variable "extreme", ♦ marks the forecast, and YES/NO denotes whether or not the forecast agrees with the historical time series of estimated below average recruitment. N.D. = No Data.

Appendix 4

DETERMINISTIC MODEL RULEBASE

The rulebase presented below is (almost) what can be expected as output after getting WinEXP© to print a hardcopy - the format has been altered slightly so that it is easier to follow the logic.

Context ' TOWARDS PREDICTION OF RECRUITMENT IN PELAGIC FISH:
Analysis of an expert system approach

Jan L. Korrubel
Marine Biology Research Institute
University of Cape Town
September 1994

This knowledge base endeavors to provide information, at an earlier stage than at present, on recruitment in the southern Benguela anchovy stock. It is envisaged that by being able to make an ordinal forecast about anchovy recruitment for the forthcoming season, the procedure of setting the total allowable catch (TAC) for the forthcoming commercial harvesting season, can be enhanced.

This system bases its forecast on the following variables:

DAILY EGG PRODUCTION
DISTANCE OFFSHORE OF THE 16 deg.C ISOTHERM
PERCENTAGE ALPHA OOCYTE ATRESIA
El Nino-Southern Oscillation (ENSO)

This system uses a simple method to weight the variables.
See M.Sc. dissertation (1995) for details.

D1: 'The forecast is:
BELOW AVERAGE Recruitment - Very Likely'

D2: 'The forecast is:
BELOW AVERAGE Recruitment - Likely'

D3: 'The forecast is:
BELOW AVERAGE Recruitment - Possible'

D4: 'The forecast is:
AVERAGE / ABOVE AVERAGE Recruitment'

D5: 'The forecast is:
UNABLE TO MAKE DECISION'

Q1: 'Is the DISTANCE OFFSHORE OF THE 16 deg.C ISOTHERM great?'
Why 'HYPOTHESIS:
==> isotherm far offshore = intense upwelling = cold water close inshore and high incidence of S/SE winds = increased egg mortality and increased loss of eggs and larve to offshore advective processes

EXPLANATION:
Upwelling that is too intense - as a result of strong S/SE winds - will result in the 16 deg.C isotherm being far offshore. Pelagic fish eggs and larve are associated with the thermal front, thereby increasing the chances of loss of eggs and larvae to offshore advective processes.
This also indicates the presence of cold newly upwelled water, close inshore, increasing the egg the mortality.
'

A 1 'YES (i.e. > 26 nautical miles offshore)'
2 'NO (i.e. < 26 nautical miles offshore)'
3 'Unsure / No data available'

Q2: 'Is the level of DAILY EGG PRODUCTION low?'
Why 'HYPOTHESIS:
==> low egg production = low numbers of eggs available for hatching and subsequent development.

EXPLANATION:
Essentially, low egg production means a relatively low number of offspring at an early stage in the recruitment process, thus increasing the chances of a low number of recruits.
The mean daily egg production per unit area is an essential parameter in the egg production method of biomass determination; a plot of recruitment on egg production gives some indication of a postive relationship.

Also, egg production as a forecaster is one step shorter in the causal chain than the stock:recruitment relationship.
'

A 1 'YES (i.e. < 300 eggs per m^2)'
2 'NO (i.e. > 300 eggs per m^2)'
3 'Unsure / No data available'

Q3: 'Is the percentage of fish with ALPHA GONAD ATRESIA high?'
Why 'HYPOTHESIS:
==> High percentage of atresia = reduced number of successfully spawning fish = reduced number of eggs.

EXPLANATION:
Essentially, high atresia means that a relatively low number of fish are successfully spawning. In turn, this indicates a reduction in the number of possible offspring at an early stage in the recruitment process, thus increasing the chances of below average recruitment.
'

A 1 'YES (i.e. > 10% of female fish show atresia)'
2 'NO (i.e. < 10% of female fish show atresia)'
3 'Unsure / No data available'

Q4: 'Are we currently in an EXTREME ENSO event?'
Why 'HYPOTHESIS:
La Nina ==> enhanced "summer" conditions = increased S/SE (offshore) winds = 16 deg.C isotherm far offshore = high incidence of offshore advection of surface waters.
El Nino ==> enhanced "winter" conditions = reduced S/Se winds = wek operation of Cape Columbine Jet current = reduced transport success.

EXPLANATION:
It is apparent that intermittant meso- to large-scale environmental fluctuations have an effect on marine species. An ENSO event, that is El Nino or La Nina, through global "teleconnections", affects the regional climate and oceangraphy, enhancing "winter" and "summer" conditions; each influencing pelagic fish survival and impacting recruitment.
'

A 1 'YES (i.e. conditions indicate El Nino or La Nina)'
2 'NO (i.e. conditions do not indicate El Nino or La Nina)'
3 'Unsure / No data available'

Rule1
Why 'You have input that all four variables, 16 deg.C ISOTHERM, DAILY EGG PRODUCTION, % GONAD ATRESIA and ENSO appear to be extreme.'
IF q1a1 and q2a1 and q3a1 and q4a1 THEN D1

Rule2
Why 'You have input that all four variables,16 deg.C ISOTHERM, DAILY EGG PRODUCTION, % GONAD ATRESIA and ENSO appear to be 'normal'.'
IF q1a2 and q2a2 and q3a2 and q4a2 THEN D4

Rule3
Why 'You have input that you have no information / data on all four variables, 16 deg.C ISOTHERM, DAILY EGG PRODUCTION, % GONAD ATRESIA and ENSO. No forecast can be made.'
IF q1a3 and q2a3 and q3a3 and q4a3 THEN D5

Rule4
Why 'You have input that only one of the four variables, 16 deg.C ISOTHERM, appears to be extreme.
DAILY EGG PRODUCTION, % GONAD ATRESIA and ENSO do not play a role in this decision.'
IF q1a1 and (q2a2 or q2a3) and (q3a2 or q3a3) and (q4a2 or q4a3) THEN D3

Rule5
Why 'You have input that only one of the four variables, DAILY EGG PRODUCTION, appears to be extreme.
16 deg.C ISOTHERM, % GONAD ATRESIA and ENSO do not play a role in this decision.'
IF (q1a2 or q1a3) and q2a1 and (q3a2 or q3a3) and (q4a2 or q4a3) THEN D3

Rule6
Why 'You have input that only one of the four variables, % GONAD ATRESIA, appears to be extreme.
16 deg.C ISOTHERM, DAILY EGG PRODUCTION and ENSO do not play a role in this decision.'
IF (q1a2 or q1a3) and (q2a2 or q2a3) and q3a1 and (q4a2 or q4a3) THEN D3

Rule7
Why 'You have input that only one of the four variables, the ENSO, appears to be extreme.
16 deg.C ISOTHERM, DAILY EGG PRODUCTION and % GONAD ATRESIA do not play a role in this decision.'

IF (q1a2 or q1a3) and (q2a2 or q2a3) and (q3a2 or q3a3) and q4a1 THEN D3

Rule8
Why 'You have input that two of the four variables, 16 deg.C ISOTHERM and DAILY EGG PRODUCTION, appear to be extreme.
% GONAD ATRESIA and ENSO do not play a role in this decision.'
IF q1a1 and q2a1 and (q3a2 or q3a3) and (q4a2 or q4a3) THEN D2

Rule9
Why 'You have input that two of the four variables, 16 deg.C ISOTHERM and % GONAD ATRESIA, appear to be extreme.
DAILY EGG PRODUCTION and ENSO do not play a role in this decision.'
IF q1a1 and (q2a2 or q2a3) and q3a1 and (q4a2 or q4a3) THEN D2

Rule10
Why 'You have input that two of the four variables, 16 deg.C ISOTHERM and ENSO, appear to be extreme.
DAILY EGG PRODUCTION and % GONAD ATRESIA do not play a role in this decision.'
IF q1a1 and (q2a2 or q2a3) and (q3a2 or q3a3) and q4a1 THEN D2

Rule11
Why 'You have input that two of the four variables, DAILY EGG PRODUCTION and % GONAD ATRESIA, appear to be extreme.
16 deg.C ISOTHERM and ENSO do not play a role in this decision.'
IF (q1a2 or q1a3) and q2a1 and q3a1 and (q4a2 or q4a3) THEN D2

Rule12
Why 'You have input that two of the four variables, DAILY EGG PRODUCTION and ENSO, appear to be extreme.
16 deg.C ISOTHERM and % GONAD ATRESIA do not play a role in this decision.'
IF (q1a2 or q1a3) and q2a1 and (q3a2 or q3a3) and q4a1 THEN D2

Rule13
Why 'You have input that two of the four variables, % GONAD ATRESIA and ENSO, appear to be extreme.
16 deg.C ISOTHERM and DAILY EGG PRODUCTION do not play a role in this decision.'
IF (q1a2 or q1a3) and (q2a2 or q2a3) and q3a1 and q4a1 THEN D2

Rule14
Why 'You have input that three of the four variables, 16 deg.C ISOTHERM, DAILY EGG PRODUCTION and % GONAD ATRESIA, appear to be extreme.

The ENSO does not play a role in this decision.'
IF q1a1 and q2a1 and q3a1 and (q4a2 or q4a3) THEN D1

Rule15
Why 'You have input that three of the four variables, 16 deg.C ISOTHERM, DAILY EGG PRODUCTION and ENSO, appear to be extreme.
% GONAD ATRESIA does not play a role in this decision.'
IF q1a1 and q2a1 and (q3a2 or q3a3) and q4a1 THEN D1

Rule16
Why 'You have input that three of the four variables, 16 deg.C ISOTHERM, % GONAD ATRESIA and ENSO, appear to be extreme.
DAILY EGG PRODUCTION does not play a role in this decision.'
IF q1a1 and (q2a2 or q2a3) and q3a1 and q4a1 THEN D1

Rule17
Why 'You have input that three of the four variables, DAILY EGG PRODUCTION, % GONAD ATRESIA and ENSO appear to be extreme.
The 16 deg.C ISOTHERM does not play a role in this decision.'
IF (q1a2 or q1a3) and q2a1 and q3a1 and q4a1 THEN D1

Appendix 5

SOURCE CODE FOR PROBABILITY "CALCULATOR"

The code below consists of the TURBO Pascal® source for the main program, *PROBABLY*, and two UNIT files, *MENUUNIT* and *WINUNIT*.

PROGRAM Probably

```
{ | Written with TURBO PASCAL Version 6.0 / Borland PASCAL 7.0
  |
  | BY:   JAN L. KORRûBEL - Marine Biology Research Institute (MBRI)
  |                         Department of Zoology
  |                         University of Cape Town
  |
  | DATE: Aug/Sept '92
  |       January '93 ('user-friendly' version)
  |       August '93  ('user-friendlier' version)
  |
  | This program is .... blurb
  |
  | A useful, 'reader-friendly' text in developing Bayes' equation has
  |   been:
  |   Von Winterfeldt, D. and Edwards, W.  1986.  Decision analysis and
  |      behavioural research.  Cambridge University Press, Cambridge
  |      (Massachussetts).
  |
  |                         ********************
  |
  | This model forms part of my project on an "expert system" for BEP and
  |   SFRI and forms the basis for the degree of Master of Science at the
  |   University of Cape Town.
  |
  | Supervisors:  Professor John G. Field (MBRI),
  |               Dr Kevern L. Cochrane (SFRI),
  |           and Dr Larry Hutchings (SFRI).
  |
  |                         ********************
}

{$M 8000,0,8000} { Set up stack size to 8K and heap (i.e. free memory) to a
                   minimum of 0K and a maximim of 8K.  This allows me
```

```
                    enough memory to run a separate editor (TED.COM) using
                    the DOS unit EXEC procedure (instead of writing my own
                    editor).
                    NOTE: this appears to work only under DOS and not if
                    you're running TURBO Pascal under WINDOWS.  If this
                    program crashes, it's due to TED being called too
                    many times.  WINDOWS doesn't release the memory, and you
                    eventually run out of memory.  That's WINDOWS for you...
                    Set the heap (the 3rd number in the sequence) to a
                    larger value e.g. 10000, and recompile the program.}

PROGRAM Probably;

{$R+}                { Turn on Range Checking - just checks that all
                       variables lie in the ranges defined for them
                       - rather useful ! }

(* {$IFDEF CPU87}    { Check if hardware has a math coprocessor }
{$N+}                { If YES (my 486 has one.....), use it     }
{$ELSE}              { ELSE                                     }
{$N+}
{$E+}                { Use mathco emulation library routines    }
{$ENDIF} *)

USES
   CRT,         { Uses the screen }
   MenuUnit,    { Uses MenuUnit.TPU unit for making bounce-bar menus }
   WinUnit,     { Uses WinUnit.TPU for making fast windows & frames }
   DOS;         { Uses DOS.TPU to make a call to the DOS command line }

CONST
   MaxWinWidth    = 80;    { Maximum screen width }
   ProbabilityMax = 1.00;  { Probability maximum }

{  Set all constant values common to both systems, so that reading of the
     data file is specific to the application: WIND or STARVATION }


VAR
{
  Gyppo Global Variables - accessable throughout the entire program
                         - easier than having to pass parameters!!

 'Abbreviations:  BAR  - Below Average Recruitment
                  LO   - Low Oil Content
                  LE   - Low Egg Production
                  HW   - High southerly wind index
                  LF   - Low food index
                  XTRA - Ad hoc variable for either HW or LF depending on
                           which data set is being run.
}
   { Priors }
   BARP,                  { BAR Prior }
   BARPNorm,              { BAR Prior - Assuming normal distribution }
   LOP,                   { LO Prior }
   LEP,                   { LE Prior }
   XTRAP,                 { XTRA variable Prior - either Wind or Food }
   { Subjective probablities for 1 variable }
   LOBAR,                 { P of LO | BAR }
```

```
    LEBAR,                  { P of LE | BAR }
    XTRABAR,                { P of XTRA | BAR }
    { Subjective probablities for 2 variables }
    LOBARXTRA,              { P of LO | BAR & XTRA }
    LOXTRA,                 { P of LO | XTRA }
    LOBARLE,                { P of LO | BAR & LE }
    LOLE,                   { P of LO | LE }
    LEBARXTRA,              { P of LE | BAR & XTRA }
    LEXTRA,                 { P of LE | XTRA }
    LEBARLO,                { P of LE | BAR & LO }
    LELO,                   { P of LE | LO }
    XTRABARLO,              { P of XTRA | BAR & LO }
    XTRALO,                 { P of XTRA | LO }
    XTRABARLE,              { P of XTRA | BAR & LE }
    XTRALE,                 { P of XTRA | LE }
    { Subjective probablities for 3 variables }
    LEBARXTRALO,            { P of LE | BAR & XTRA & LO }
    LELOXTRA,               { P of LE | LO & XTRA }
    LOBARXTRALE,            { P of LO | BAR & XTRA & LE }
    LOLEXTRA,               { P of LO | LE & XTRA }
    LEBARLOXTRA,            { P of LE | BAR & LO & XTRA }
    LEXTRALO,               { P of LE | XTRA & LO }
    LOBARLEXTRA,            { P of LO | BAR & LE & XTRA }
    LOXTRALE,               { P of LO | XTRA & LE }
    XTRABARLOLE,            { P of XTRA | BAR & LO & LE }
    XTRALELO,               { P of XTRA | LE & LO }
    XTRABARLELO,            { P of XTRA | BAR & LE & LO }
    XTRALOLE      : REAL;   { P of XTRA | LO & LE }

    NormallyDistributed,      { Set to TRUE iff using 'normal' BAR prior }
    DataLoaded,               { Set to TRUE iff a data set has been loaded }
    UsingWindData,            { Set to TRUE iff WIND data set is loaded }
    DataGenerated : BOOLEAN;  { Set to TRUE iff a Bayes run has been done }

    WindIndex,              {}
    FoodIndex,              {} { Categorical indeces of the state of the }
    OilIndex,               {} { variables }
    EggIndex       : CHAR;  {}

{--------------------------------------------------------------------------}
{
    This procedure centers a given string on a given line.  The procedure
      takes into account if the screen is less than 80 characters wide.
}

PROCEDURE Center( WinWidth, LineNum : INTEGER; Str : STRING );

VAR
    WinCenter : INTEGER;

BEGIN
    IF WinWidth < MaxWinWidth
      THEN
        WinCenter := WinWidth DIV 2
      ELSE
        WinCenter := MaxWinWidth DIV 2;
    GOTOXY( WinCenter - ( LENGTH(Str) DIV 2 ), LineNum );
    WRITE( Str );
END;  { of PROCEDURE Center }
```

```
{---------------------------------------------------------------------}
{
  This procedure makes a title page introducing the model.

  Procedures called:  FillWin  ]
                      FrameWin ]] defined in UNIT WinUnit.
                      Center
}

PROCEDURE Title_Page;

VAR
   Scrap : CHAR;  { Scrap variable to dump a keypress to }

BEGIN
   {
    Clear the screen and initialize the character attribute
   }
   CLRSCR;
   NORMVIDEO;
   {
    Do the background shading
   }
   WINDOW( 1,1,80,25 );
   FillWin( #178, LIGHTGRAY + BLACK * 16 );
   {
    Main Title box - with details
   }
   WINDOW( 8,2,73,13 );
   FrameWin( '', SingleFrame, LightGray, LightGray );
   CLRSCR;
   TEXTATTR := $70;  { Set text to reverse video }
   Center( 66, 1, ' BAYESIAN PREDICTION OF ANCHOVY RECRUITMENT ' );
   Center( 66, 2, ' IN THE SOUTHERN BENGUELA REGION ' );
   NORMVIDEO;
   HIGHVIDEO;  { Set text to bold, AFTER setting normal text  }
   Center( 66, 4, 'A "DECISION SUPPORT" APPROACH' );
   Center( 66, 6, 'BY:' );
   Center( 66, 8, 'JAN L. KORR-BEL' );
   LOWVIDEO;
   Center( 66, 9, 'Marine Biology Research Institute' );
   Center( 66, 10, 'Department of Zoology, University of Cape Town' );

   {
    If CPU87 supported, then say so.
   }
   {$IFOPT N+}
   WINDOW( 8,14,73,17 );
   FrameWin( '', SingleFrame, LightGray, LightGray );
   CLRSCR;
   Center( 66, 1, 'This model forms part of my project' );
   Center( 66, 2, 'for the degree of Master of Science at UCT' );
   WINDOW( 26,19,55,21 );
   FrameWin( '', SingleFrame, LightGray, LightGray );
   CLRSCR;
   HIGHVIDEO;
   WRITE( ' >>>> CPU87  SUPPORTED <<<<' );
   LOWVIDEO;
```

```
    {
     If no CPU87, then space things out a bit.
    }
    {$ELSE}
    WINDOW( 8,15,73,18 );
    FrameWin( '', SingleFrame, LightGray, LightGray );
    CLRSCR;
    Center( 66, 1, 'This model forms part of my project' );
    Center( 66, 2, 'for the degree of Master of Science at UCT' );
    {$ENDIF}  { of checking for CPU87 }

    {
     Final box.....
    }
    WINDOW( 23,22,58,24 );
    FrameWin( '', SingleFrame, LightGray, LightGray );
    CLRSCR;
    HIGHVIDEO;
    WRITE( ' PRESS ANY KEY TO CONTINUE.......' );
    NORMVIDEO;
    REPEAT UNTIL KEYPRESSED;
    {
     This is to clean out the keyboard buffer, otherwise the keypress is
     saved and echoed to the next screen.  This may be problematic,
     especially if the keypress is an <ENTER>.
    }
    Scrap := READKEY;
    {
     Clear out the screen
    }
    WINDOW( 1,1,80,25 );    { This 'windows' whole screen }
    CLRSCR;
END;  { of PROCEDURE Title_Page }

{-----------------------------------------------------------------------}
{
   Depending on user input, this procedure gets the input data from the
   data files:  WindFile.DAT (Wind dataset) or FoodFile.DAT (Starve
   dataset).  The output file CHECK.OUT can be used to cross-check that all
   input has been received correctly during the reading process.

   Procedure called:  Center
}

PROCEDURE GetFileData( DataFile : CHAR );

VAR
   InFile,                        { Data Input File - 'INFILE.DAT' }
   CheckFile  : TEXT;             { Data Checking File - 'CHECK.OUT' }
   TextLine   : STRING[ 75 ];     { Arb Line of Text in Datafile }
   i          : INTEGER;          { Arb counter variable }


BEGIN
   {
    Which data file to get?  Also set up the cross-checking file.
   }
   CLRSCR;
```

```
IF DataFile = 'W'
   THEN
      BEGIN
         UsingWindData := TRUE;
         Center( 80, 12, 'GETTING Wind DATA SET.........' );
         DELAY( 1000 );
         ASSIGN( InFile, 'A:\Wind.DAT' );
         RESET( InFile );
         ASSIGN( CheckFile, 'A:\WCheck.OUT' );
         REWRITE( CheckFile );
         CLRSCR;
      END
   ELSE
      BEGIN
         UsingWindData := FALSE;
         Center( 80, 12, 'GETTING Food DATA SET.......' );
         DELAY( 1000 );
         ASSIGN( InFile, 'A:\Food.DAT' );
         RESET( InFile );
         ASSIGN( CheckFile, 'A:\FCheck.OUT' );
         REWRITE( CheckFile );
         CLRSCR;
      END;
{
 Unfortunately have to do this manually because there are a number of
    different variables to be read.
}
FOR i := 1 TO 4 DO        { Dump first 4 comment lines from data file }
   BEGIN
      READLN( InFile, TextLine );
      WRITELN( CheckFile, TextLine );
   END;

{
 Five PRIORS, each with comment line
}
READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, BARP );
WRITELN( CheckFile, BARP:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, BARPNorm );
WRITELN( CheckFile, BARPNorm:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOP );
WRITELN( CheckFile, LOP:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRAP );
WRITELN( CheckFile, XTRAP:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEP );
```

```
WRITELN( CheckFile, LEP:5:3 );
{
 Two comment lines in datafile
 THEN: One-Way (frequentist) data, each with comment line
}
FOR i := 1 TO 2 DO
   BEGIN
      READLN( InFile, TextLine );
      WRITELN( CheckFile, TextLine );
   END;

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOBAR );
WRITELN( CheckFile, LOBAR:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRABAR );
WRITELN( CheckFile, XTRABAR:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEBAR );
WRITELN( CheckFile, LEBAR:5:3 );

{
 Arb comment line
 THEN: Two-Way (subjective) data, each with comment line
}
READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRABARLO );
WRITELN( CheckFile, XTRABARLO:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRALO );
WRITELN( CheckFile, XTRALO:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOBARXTRA );
WRITELN( CheckFile, LOBARXTRA:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOXTRA );
WRITELN( CheckFile, LOXTRA:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRABARLE );
WRITELN( CheckFile, XTRABARLE:5:3 );

READLN( InFile, TextLine );
```

```
WRITELN( CheckFile, TextLine );
READLN( InFile, XTRALE );
WRITELN( CheckFile, XTRALE:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEBARXTRA );
WRITELN( CheckFile, LEBARXTRA:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEXTRA );
WRITELN( CheckFile, LEXTRA:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOBARLE );
WRITELN( CheckFile, LOBARLE:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOLE );
WRITELN( CheckFile, LOLE:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEBARLO );
WRITELN( CheckFile, LEBARLO:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LELO );
WRITELN( CheckFile, LELO:5:3 );

{
 Arb comment line
 THEN: Three-Way (subjective) data, each with comment line
}
READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LEBARXTRALO );
WRITELN( CheckFile, LEBARXTRALO:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LELOXTRA );
WRITELN( CheckFile, LELOXTRA:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOBARXTRALE );
WRITELN( CheckFile, LOBARXTRALE:5:3 );

READLN( InFile, TextLine );
WRITELN( CheckFile, TextLine );
READLN( InFile, LOLEXTRA );
```

```
    WRITELN( CheckFile, LOLEXTRA:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, LEBARLOXTRA );
    WRITELN( CheckFile, LEBARLOXTRA:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, LEXTRALO );
    WRITELN( CheckFile, LEXTRALO:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, XTRABARLOLE );
    WRITELN( CheckFile, XTRABARLOLE:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, XTRALELO );
    WRITELN( CheckFile, XTRALELO:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, LOBARLEXTRA );
    WRITELN( CheckFile, LOBARLEXTRA:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, LOXTRALE );
    WRITELN( CheckFile, LOXTRALE:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, XTRABARLELO );
    WRITELN( CheckFile, XTRABARLELO:5:3 );

    READLN( InFile, TextLine );
    WRITELN( CheckFile, TextLine );
    READLN( InFile, XTRALOLE );
    WRITELN( CheckFile, XTRALOLE:5:3 );

    {
     Close Up - DATA In/Output Files No Longer Necessary
    }
    CLOSE( InFile );
    CLOSE( CheckFile );

    {
     Set the 'DataLoaded' booloean to TRUE - Data has now been loaded
    }
    DataLoaded := TRUE;

END;  { of PROCEDURE GetFileData }

{------------------------------------------------------------------------}
{
   This procedure gets the qualitative data from last year, for scheduling
      the printout process.
```

```
   Easier to use global variables than to pass parameters:
      WindIndex
      OilIndex
      EggIndex
      FoodIndex
}

PROCEDURE GetLastYear;

VAR
   Scrap : CHAR;              { Scrap variable to dump a keypress to }

BEGIN
   WINDOW( 1,2,80,24 );
   CLRSCR;
   TEXTATTR := $70;  { Set text to reverse video }
   Center( 80, 2, ' SEASONAL DATA ENTRY ');
   NORMVIDEO;
   Center( 80, 4, 'PLEASE ENTER THE FOLLOWING ASSESSMENTS OF' );
   Center( 80, 5, 'CONDITIONS IN THE SOUTHERN BENGUELA,' );
   Center( 80, 6, 'FOR THE PERIOD PRECEDING THIS FORECAST' );
   Center( 80, 8, 'PRESS (ESC)ape TO EXIT TO MAIN MENU' );
   HIGHVIDEO;
   NORMVIDEO;
   IF UsingWindData
      THEN
         BEGIN { wind dataset collection }
            Center( 80, 21, '>>>> USE THIS GUIDE.............. <<<<');
            Center( 80, 22, '    (1) = > 5000km S-SE run  (2) = Average');
            GOTOXY ( 5,11 );
            WRITE ( 'State of the WIND INDEX.....:  ');
            REPEAT
               WindIndex := READKEY;
            UNTIL WindIndex IN [ '1', '2', #27 ];
            IF WindIndex = #27  { ESCape key }
               THEN
                  { Do Nothing - exit to Main Menu }
               ELSE
                  BEGIN
                     WRITE ( WindIndex );
                     Center( 80, 22, '  (1) = < 20% oil:meal ratio  (2) =
Average  ');
                     GOTOXY ( 5,13 );
                     WRITE ( 'State of the OIL INDEX......:  ');
                     REPEAT
                        OilIndex := READKEY;
                     UNTIL OilIndex IN [ '1', '2', #27 ];
                     IF OilIndex = #27  { ESCape key }
                        THEN
                           { Do Nothing - exit to Main Menu }
                        ELSE
                           BEGIN
                              WRITE ( OilIndex );
                              Center( 80, 22, '(1) = < 300 anch eggs  per
m^2  (2) = Average');
                              GOTOXY ( 5,15 );
                              WRITE ( 'State of the EGG INDEX......:  ');
                              REPEAT
```

```
                              EggIndex := READKEY;
                           UNTIL EggIndex IN [ '1', '2', #27 ];
                           WRITE ( EggIndex );
                        END;
               END;
      END { wind dataset }
   ELSE
      BEGIN { food dataset collection }
         Center( 80, 21, '>>>> USE THIS GUIDE.............. <<<<');
         Center( 80, 22, '(1) = > 30% starvation stations  (2) =
Average');
         GOTOXY ( 5,12 );
         WRITE ( 'State of the FOOD INDEX.....:  ');
         REPEAT
            FoodIndex := READKEY;
         UNTIL FoodIndex IN [ '1', '2', #27 ];
         IF FoodIndex = #27  { ESCape key }
            THEN
               { Do Nothing - Just exit to Main Menu }
            ELSE
               BEGIN
                  WRITE ( FoodIndex );
                  Center( 80, 22, '   (1) = < 20% oil:meal ratio  (2) =
Average   ');
                  GOTOXY ( 5,14 );
                  WRITE ( 'State of the OIL INDEX......:  ');
                  REPEAT
                     OilIndex := READKEY;
                  UNTIL OilIndex IN [ '1', '2', #27 ];
                  IF OilIndex = #27  { ESCape key }
                     THEN
                        { Do Nothing - Just exit to Main Menu }
                     ELSE
                        BEGIN
                           WRITE ( OilIndex );
                           Center( 80, 22, ' (1) = < 300 anch eggs  per
m^2  (2) = Average ');
                           GOTOXY ( 5,16 );
                           WRITE ( 'State of the EGG INDEX......:  ');
                           REPEAT
                              EggIndex := READKEY;
                           UNTIL EggIndex IN [ '1', '2', #27 ];
                           WRITE ( EggIndex );
                        END;
               END;
      END; { food dataset }
END; { of PROCEDURE GetLastYear }

{-----------------------------------------------------------------------}
{
   This procedure gets the explanations from the text files and outputs
   them to the output file.
}

PROCEDURE GetExplanation( TF, EF : STRING );

VAR
  OneLine : STRING[80];
  ToFile,
```

```
  EFile    : TEXT;


BEGIN
   ASSIGN( ToFile, TF );
   APPEND( ToFile );
   ASSIGN( EFile, EF );
   RESET( EFile );

   WHILE NOT EOF( EFile ) DO
      BEGIN
          READLN( Efile, OneLine );
          WRITELN( ToFile, OneLine );
      END;

   CLOSE( ToFile );
   CLOSE( EFile );

END; { of PROCEDURE GetExplanation }

{---------------------------------------------------------------------------}
{
   This procedure takes the probability data from file and computes the
      posterior probability given the priors.
   The form of Bayes' equation used here is given in Von Winterfeldt and
      Edwards, p.138.

   Explanation of Variables:

   PRIOR is the prior probability of the thing we are looking at (Note: it
      is a conditional probability - it is the probability of the thing we
      are looking at BEFORE learning about the evidence);
   EVIDENCEOBSERVED is the probability that the evidence would be observed
      if the observation on the thing we are looking at were TRUE.
   EVIDENCEPRIOR is the prior probability of there being the evidence we
      are looking for; it is also a conditional probability.
   POSTERIOR is, of course, the probablity of the thing we are looking at
      i.e. AFTER we have learned the evidence.
}

FUNCTION Posterior ( Prior, EvidenceObserved, EvidencePrior : REAL ) :
REAL;

BEGIN
   Posterior := ( Prior * EvidenceObserved ) / EvidencePrior;
END;  { of FUNCTION Posterior }

{---------------------------------------------------------------------------}
{
    This procedure does the calculating of the posterior probabilities, and
      the output to the file 'Bayes.OUT'.

    Function called: Posterior
}

PROCEDURE Bayes;

VAR
   OutFile,             { Output File - 'BAYES.OUT' }
```

```
   OutFile2   : TEXT;   { Output File2 - 'FINAL.OUT' }
   {
    The following probabilities are those calculated by this procedure
    The required priors have already been defined and read in as global
vars
    XTRA = the other exchangeable parameter: food or wind
   }
   { 1 Effect }
   PBARLE,                  { P(BAR) | LE }
   PBARLO,                  { P(BAR) | LO }
   PBARXTRA,                { P(BAR) | XTRA }
   { 2 Effects }
   PBARLOXTRA,              { P(BAR) | LO & XTRA }
   PBARXTRALO,              { P(BAR) | XTRA & Low Oil }
   PBARLEXTRA,              { P(BAR) | LE & XTRA }
   PBARXTRALE,              { P(BAR) | XTRA & LE }
   PBARLELO,                { P(BAR) | LE & LO }
   PBARLOLE,                { P(BAR) | LO & LE }
   { 3 Effects }
   PBARXTRALOLE,            { P(BAR) | XTRA & LO & LE }
   PBARXTRALELO,            { P(BAR) | XTRA & LE & LO }
   PBARLOXTRALE,            { P(BAR) | LO & XTRA & LE }
   PBARLOLEXTRA,            { P(BAR) | LO & LE & XTRA }
   PBARLEXTRALO,            { P(BAR) | LE & XTRA & LO }
   PBARLELOXTRA   : REAL;   { P(BAR) | LE & LO & XTRA }

   TAverage       : REAL;   { Total Average }


BEGIN
   {
    Open output files, check booleans and intialize variables
   }
   ASSIGN( OutFile, 'A:\Bayes.OUT' );
   REWRITE( OutFile );
   ASSIGN( OutFile2, 'A:\Final.OUT' );
   REWRITE( OutFile2 );

   IF NormallyDistributed
      THEN
         BARP := BARPNorm;
   IF UsingWindData
      THEN
         BEGIN
            WRITELN( OutFile, '*****************************************' );
            WRITELN( OutFile, '*****  FISHFINDER:  WIND DataSet   ******' );
            WRITELN( OutFile, '*****************************************' );
            WRITELN( Outfile );
            WRITELN( OutFile2, '****************************************' );
            WRITELN( OutFile2, '*****  FISHFINDER:  WIND DataSet  *****' );
            WRITELN( OutFile2, '****************************************' );
            WRITELN( Outfile2 );

         END
      ELSE
         BEGIN
            WRITELN( OutFile, '*****************************************' );
            WRITELN( OutFile, '*****  FISHFINDER:  FOOD DataSet *******' );
            WRITELN( OutFile, '*****************************************' );
```

```
          WRITELN( Outfile );
          WRITELN( OutFile2, '****************************************' );
          WRITELN( OutFile2, '*****  FISHFINDER:  FOOD DataSet ******' );
          WRITELN( OutFile2, '****************************************' );
          WRITELN( Outfile2 );
       END;
TAverage := 0.0;

{
 Do the P(BAR) for 1 effect
 -------------------------
}
WRITELN( OutFile );
WRITELN( OutFile, 'P(BAR) for single effects.....................' );
WRITELN( OutFile );
{
 (1) P(BAR) given XTRA variable
}
PBARXTRA := Posterior( BARP, XTRABAR, XTRAP );
IF PBARXTRA > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
IF UsingWindData
   THEN
      WRITELN( OutFile, 'PBAR | High Wind:              ', PBARXTRA:5:2 )
   ELSE
      WRITELN( OutFile, 'PBAR | High Starvation Index:', PBARXTRA:5:2 );

{
 (2) P(BAR) given Low Oil
}
PBARLO := Posterior( BARP, LOBAR, LOP );
IF PBARLO > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
WRITELN( OutFile, 'PBAR | Low Oil:                  ', PBARLO:5:2 );

{
 (3) P(BAR) given Low Egg Production
}
PBARLE := Posterior( BARP, LEBAR, LEP );
IF PBARLE > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
WRITELN( OutFile, 'PBAR | Low Egg Production:       ', PBARLE:5:2 );
WRITELN( OutFile );

{
 Do the P(BAR) for 2 effects (and combinations!)
 ----------------------------------------------
}
WRITELN( OutFile, 'P(BAR) for 2-combination effects................' );
WRITELN( OutFile );
{
 (1) P(BAR) given Low Oil AND XTRA
     P(BAR) given XTRA AND Low Oil
}
PBARLOXTRA := Posterior( PBARLO, XTRABARLO, XTRALO );
IF PBARLOXTRA > ProbabilityMax
```

```
    THEN
       WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
 IF UsingWindData
    THEN
       WRITELN( OutFile, 'PBAR | Low Oil & High Wind: ', PBARLOXTRA:5:2 )
    ELSE
       WRITELN( OutFile, 'PBAR | Low Oil & High Starvation Index:  ', +
           PBARLOXTRA:5:2 );

 PBARXTRALO := Posterior( PBARXTRA, LOBARXTRA, LOXTRA );
 IF PBARXTRALO > ProbabilityMax
    THEN
       WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
 IF UsingWindData
    THEN
       WRITELN( OutFile, 'PBAR | High Wind & Low Oil: ', PBARXTRALO:5:2 )
    ELSE
       WRITELN( OutFile, 'PBAR | High Starvation Index & Low Oil:  ', +
           PBARXTRALO:5:2 );

 WRITELN( OutFile, 'Average --------------------------------', +
    (PBARLOXTRA + PBARXTRALO)/2:5:2 );

 {
  (2) P(BAR) given Low Eggs AND XTRA
      P(BAR) given XTRA AND Low Eggs
 }
 PBARLEXTRA := Posterior( PBARLE, XTRABARLE, XTRALE );
 IF PBARLEXTRA > ProbabilityMax
    THEN
       WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
 IF UsingWindData
    THEN
       WRITELN( OutFile, 'PBAR | Low Eggs & High Wind:', PBARLEXTRA:5:2 )
    ELSE
       WRITELN( OutFile, 'PBAR | Low Eggs & High Starvation Index: ', +
           PBARLEXTRA:5:2 );

 PBARXTRALE := Posterior( PBARXTRA, LEBARXTRA, LEXTRA );
 IF PBARXTRALE > ProbabilityMax
    THEN
       WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
 IF UsingWindData
    THEN
       WRITELN( OutFile, 'PBAR | High Wind & Low Eggs:', PBARXTRALE:5:2 )
    ELSE
       WRITELN( OutFile, 'PBAR | High Starvation Index & Low Eggs: ', +
           PBARXTRALE:5:2 );

 WRITELN( OutFile, 'Average --------------------------------', +
    (PBARLEXTRA + PBARXTRALE)/2:5:2 );

 {
  (3) P(BAR) given Low Eggs AND Low Oil
      P(BAR) given Low Oil AND Low Eggs
 }
 PBARLELO := Posterior( PBARLE, LOBARLE, LOLE );
 IF PBARLELO > ProbabilityMax
    THEN
```

```
        WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
   WRITELN( OutFile, 'PBAR | Low Eggs & Low Oil:          ', PBARLELO:5:2 );

   PBARLOLE := Posterior( PBARLO, LEBARLO, LELO );
   IF PBARLOLE > ProbabilityMax
      THEN
         WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
   WRITELN( OutFile, 'PBAR | Low Oil & Low Eggs:          ', PBARLOLE:5:2 );

   WRITELN( OutFile, 'Average --------------------------------', +
      (PBARLELO + PBARLOLE)/2:5:2 );

   WRITELN( OutFile );

   {
    Do the P(BAR) for 3 effects (and combinations!)
    ----------------------------------------------
   }
   WRITELN( OutFile, 'P(BAR) for 3-combination effects................' );
   WRITELN( OutFile );

   {
    (1) P(BAR) given XTRA AND Low Oil AND Low Eggs
        P(BAR) given XTRA AND Low Eggs AND Low Oil
   }
   PBARXTRALOLE := Posterior( PBARXTRALO, LEBARXTRALO, LELOXTRA );
   IF PBARXTRALOLE > ProbabilityMax
      THEN
         WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
   IF UsingWindData
      THEN
         WRITELN( OutFile, 'PBAR | HW and LO and LE: ', PBARXTRALOLE:5:2 )
      ELSE
         WRITELN( OutFile, 'PBAR | HSI and LO and LE:', PBARXTRALOLE:5:2 );

   PBARXTRALELO := Posterior( PBARXTRALE, LOBARXTRALE, LOLEXTRA );
   IF PBARXTRALELO > ProbabilityMax
      THEN
         WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
   IF UsingWindData
      THEN
         WRITELN( OutFile, 'PBAR | HW and LE and LO:', PBARXTRALELO:5:2 )
      ELSE
         WRITELN( OutFile, 'PBAR | HSI and LE and LO:', PBARXTRALELO:5:2 );

   WRITELN( OutFile, 'Average --------------------------------', +
      (PBARXTRALOLE + PBARXTRALELO)/2:5:2 );
   TAverage := TAverage + (PBARXTRALOLE + PBARXTRALELO);

   {
    (2) P(BAR) given Low Oil AND XTRA AND Low Eggs
        P(BAR) given Low Oil AND Low Eggs AND XTRA
   }
   PBARLOXTRALE := Posterior( PBARLOXTRA, LEBARLOXTRA, LEXTRALO );
   IF PBARLOXTRALE > ProbabilityMax
      THEN
         WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
   IF UsingWindData
      THEN
```

```
      WRITELN( OutFile, 'PBAR | LO and HW and LE:', PBARLOXTRALE:5:2 )
   ELSE
      WRITELN( OutFile, 'PBAR | LO and HSI and LE:', PBARLOXTRALE:5:2 );

PBARLOLEXTRA := Posterior( PBARLOLE, XTRABARLOLE, XTRALELO );
IF PBARLOLEXTRA > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
IF UsingWindData
   THEN
      WRITELN( OutFile, 'PBAR | LO and LE and HW:', PBARLOLEXTRA:5:2 )
   ELSE
      WRITELN( OutFile, 'PBAR | LO and LE and HSI:', PBARLOLEXTRA:5:2 );

WRITELN( OutFile, 'Average --------------------------------', +
   (PBARLOXTRALE + PBARLOLEXTRA)/2:5:2 );
TAverage := TAverage + (PBARLOXTRALE + PBARLOLEXTRA);

{
 (3) P(BAR) given Low Eggs AND XTRA AND Low Oil
     P(BAR) given Low Eggs AND Low Oil AND XTRA
}
PBARLEXTRALO := Posterior( PBARLEXTRA, LOBARLEXTRA, LOXTRALE );
IF PBARLEXTRALO > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
IF UsingWindData
   THEN
      WRITELN( OutFile, 'PBAR | LE and HW and LO:', PBARLEXTRALO:5:2 )
   ELSE
      WRITELN( OutFile, 'PBAR | LE and HSI and LO:', PBARLEXTRALO:5:2 );

PBARLELOXTRA := Posterior( PBARLELO, XTRABARLELO, XTRALOLE );
IF PBARLELOXTRA > ProbabilityMax
   THEN
      WRITELN( OutFile, 'ERROR !! - PMax exceeded' );
IF UsingWindData
   THEN
      WRITELN( OutFile, 'PBAR | LE and LO and HW:', PBARLELOXTRA:5:2 )
   ELSE
      WRITELN( OutFile, 'PBAR | LE and LO and HSI:', PBARLELOXTRA:5:2 );

WRITELN( OutFile, 'Average --------------------------------', +
   (PBARLEXTRALO + PBARLELOXTRA)/2:5:2 );
TAverage := TAverage + (PBARLEXTRALO + PBARLELOXTRA);

WRITELN( OutFile );
WRITELN( OutFile, 'TOTAL AVERAGE (3-Way)--------------------', +
   TAverage/6:5:2);

{
 Close Up - 'Bayes' Output Files No Longer Necessary
}
CLOSE( OutFile );

{
 Now do the results printout:
 ----------------------------
}
```

```
IF UsingWindData
   THEN
      BEGIN
         IF (WindIndex = '1') AND (OilIndex = '2') AND (EggIndex = '2')
            THEN
               BEGIN
                  WRITELN( OutFile2, 'PBAR | High Wind:', PBARXTRA:5:2);
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'WindOnly.EXP' );
               END;
         IF (OilIndex = '1') AND (WindIndex = '2') AND (EggIndex = '2')
            THEN
               BEGIN
                  WRITELN( OutFile2, 'PBAR | Low Oil: ', PBARLO:5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'OilOnly.EXP' );
               END;
         IF (EggIndex = '1') AND (WindIndex = '2') AND (OilIndex = '2')
            THEN
               BEGIN
                  WRITELN( OutFile2, 'PBAR | Low Eggs: ', PBARLE:5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'EggsOnly.EXP' );
               END;
         IF (WindIndex = '1') AND (OilIndex = '1') AND (EggIndex = '2')
            THEN
               BEGIN
                  WRITE( OutFile2, 'PBAR | High Wind & Low Oil: ');
                  WRITELN( OutFile2, ((PBARXTRALO+PBARLOXTRA)/2):5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'WindOil.EXP' );
               END;
         IF (WindIndex = '1') AND (EggIndex = '1') AND (OilIndex = '2')
            THEN
               BEGIN
                  WRITE( OutFile2, 'PBAR | High Wind & Low Eggs: ');
                  WRITELN( OutFile2, ((PBARXTRALE+PBARLEXTRA)/2):5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'WindEggs.EXP' );
               END;
         IF (OilIndex = '1') AND (EggIndex = '1') AND (WindIndex = '2')
            THEN
               BEGIN
                  WRITE( OutFile2, 'PBAR | Low Oil & Low Eggs: ');
                  WRITELN( OutFile2, ((PBARLOLE+PBARLELO)/2):5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'OilEggs.EXP' );
```

```
            END;
      IF (WindIndex = '1') AND (OilIndex = '1') AND (EggIndex = '1')
         THEN
            BEGIN
               WRITE( OutFile2, 'PBAR | High Wind & Low Oil & Low +
                  Eggs: ');
               WRITELN( OutFile2, (TAverage/6):5:2 );
               {
                Append the explanation to the output file
               }
               GetExplanation ( 'Final.OUT', 'WdOilEgg.EXP' );
            END;
   END
ELSE  { Using food data }
   BEGIN
      IF (FoodIndex = '1') AND (OilIndex = '2') AND (EggIndex = '2')
         THEN
            BEGIN
               WRITELN( OutFile2, 'PBAR | Low Food:', PBARXTRA:5:2 );
               {
                Append the explanation to the output file
               }
               GetExplanation ( 'Final.OUT', 'FoodOnly.EXP' );
            END;
      IF (OilIndex = '1') AND (FoodIndex = '2') AND (EggIndex = '2')
         THEN
            BEGIN
               WRITELN( OutFile2, 'PBAR | Low Oil: ', PBARLO:5:2 );
               {
                Append the explanation to the output file
               }
               GetExplanation ( 'Final.OUT', 'OilOnly.EXP' );
            END;
      IF (EggIndex = '1') AND (FoodIndex = '2') AND (OilIndex = '2')
         THEN
            BEGIN
               WRITELN( OutFile2, 'PBAR | Low Eggs: ', PBARLE:5:2 );
               {
                Append the explanation to the output file
               }
               GetExplanation ( 'Final.OUT', 'EggsOnly.EXP' );
            END;
      IF (FoodIndex = '1') AND (OilIndex = '1') AND (EggIndex = '2')
         THEN
            BEGIN
               WRITE( OutFile2, 'PBAR | Low Food & Low Oil: ');
               WRITELN( OutFile2, ((PBARXTRALO+PBARLOXTRA)/2):5:2 );
               {
                Append the explanation to the output file
               }
               GetExplanation ( 'Final.OUT', 'FoodOil.EXP' );
            END;
      IF (FoodIndex = '1') AND (EggIndex = '1') AND (OilIndex = '2')
         THEN
            BEGIN
               WRITE( OutFile2, 'PBAR | Low Food & Low Eggs: ');
               WRITELN( OutFile2, ((PBARXTRALE+PBARLEXTRA)/2):5:2 );
               {
                Append the explanation to the output file
```

```
                  }
                  GetExplanation ( 'Final.OUT', 'FoodEggs.EXP' );
               END;
         IF (OilIndex = '1') AND (EggIndex = '1') AND (FoodIndex = '2')
            THEN
               BEGIN
                  WRITE( OutFile2, 'PBAR | Low Oil & Low Eggs: ');
                  WRITELN( OutFile2, ((PBARLOLE+PBARLELO)/2):5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'OilEggs.EXP' );
               END;
         IF (FoodIndex = '1') AND (OilIndex = '1') AND (EggIndex = '1')
            THEN
               BEGIN
                  WRITE( OutFile2, 'PBAR | Low Food & Low Oil & Low +
                     Eggs: ');
                  WRITELN( OutFile2, (TAverage/6):5:2 );
                  {
                   Append the explanation to the output file
                  }
                  GetExplanation ( 'Final.OUT', 'FdOilEgg.EXP' );
               END
      END; { of ELSE }

   CLOSE ( Outfile2);

END;  { of PROCEDURE Bayes }

{---------------------------------------------------------------------------}
{
   This procedure offers the user a choice of data input method: manually
      or by calling up a predefined dataset.
   This procedure also allows the user to edit/view and print the data and
      results files.  The editor, TED.COM, and MS-DOS utility, PRINT.EXE,
      are used for this.

   NOTE:  This procedure uses the MS-DOS procedure PRINT.EXE (from DOS
      version 5.0 to automatically print a data/results file.  PRINT.EXE
      must be installed before attempting to run this option.  You can add
      the line PRINT /d:LPT1 to your AUTOEXEC.BAT and then reboot your
      machine. Alternatively, just type the same at the DOS commnad line
      before running this program.
      NOTE also that PRINT.EXE is specific to the version of DOS, so if you
      are not running DOS version 5.0, ensure that your version of
      PRINT.EXE is in the same subdirectory as the program.

      Procedures called:  Init       ]
                          AddPrompt  ]] Defined in UNIT MenuUnit.TPU
                          GetChoice  ]
                          Center
                          GetFileData
                          Bayes
}

PROCEDURE MainMenu;

VAR
```

```
   Choice,                 { Answer variable for bounce bar menu }
   i         : INTEGER;    { Counter variable }
   BBM       : BBMenu;     { Menu driver is in MenuUnit.TPU UNIT }
   DataSet,                { Answer variable for which data set to use }
   Scrap     : CHAR;       { Scrap answer variable }

BEGIN
   {
   Variable initialization
   }
   Choice := 0;
   WHILE Choice <> 7 DO
      BEGIN
         GOTOXY( 1,1 );
         FOR i := 1 to 80 DO
            WRITE( #178 );
         GOTOXY( 1,25 );
         FOR i := 1 to 79 DO
            WRITE( #178 );
         GOTOXY( 33,3 );
         TEXTATTR := $70;  { Set reverse video text }
         WRITE( '  MAIN MENU  ' );
         NORMVIDEO;
         BBM.Init( 24, 10, 27 );
{         BBM.AddPrompt( '    Get Primary Dataset' );
         BBM.AddPrompt( '   Edit Primary Dataset' );
}        BBM.AddPrompt( '  Get Questionnaire Data' );
         BBM.AddPrompt( '  Edit Questionnaire Data' );
         BBM.AddPrompt( '      Print Data File' );
         BBM.AddPrompt( '  Run Bayesian Prediction' );
         BBM.AddPrompt( '     View Results File' );
         BBM.AddPrompt( '    Print Results File');
         BBM.AddPrompt( ' >>>>>>>>  QUIT  <<<<<<<<<' );
         Choice := BBM.GetChoice;
         GOTOXY( 1, 23 );
         CASE Choice OF
            1 : BEGIN
                   WINDOW( 1,2,80,24 );
                   CLRSCR;
                   Center( 80, 9, 'WHICH DATA SET WOULD YOU LIKE TO USE?');
                   Center( 80, 11, '(W)ind OR (F)ood...................:');
                   Center( 80, 15, 'PRESS (ESC)ape TO EXIT TO MENU' );
                   REPEAT
                      DataSet := READKEY;
                   UNTIL DataSet IN [ 'w', 'W', 'f', 'F', #27 ];
                   IF DataSet = #27  { ESCape key }
                      THEN
                         { Do Nothing }
                      ELSE
                         IF DataSet IN [ 'w', 'W' ]
                            THEN
                               GetFileData( 'W' )
                            ELSE
                               GetFileData( 'F' );
                   WINDOW( 1,1,80,25 );
                   CLRSCR;
                END; { of CASE 1 }
            2 : BEGIN
                   IF DataLoaded
```

```
                THEN  { EDIT THE LOADED DATA FILE }
                   IF UsingWindData
                      THEN
                         BEGIN
                            EXEC( 'TED.COM', 'Wind.Dat' );
                            GetFileData( 'W' );
                         END
                      ELSE
                         BEGIN
                            EXEC( 'TED.COM', 'Food.Dat' );
                            GetFileData( 'F' );
                         END
                ELSE  { GIVE ERROR MESSAGE }
                   BEGIN
                      WINDOW( 1,2,80,24 );
                      CLRSCR;
                      Center( 80, 11, 'YOU MUST FIRST LOAD A DATA');
                      Center( 80, 13, 'SET BEFORE TRYING TO EDIT!');
                      DELAY( 2000 );
                      WINDOW( 1,1,80,25 );
                      CLRSCR;
                   END;
          END; { of CASE 2 }
      3 : BEGIN
             IF DataLoaded
                THEN  { PRINT DATA FILE }
                   IF UsingWindData
                      THEN
                         EXEC( 'PRINT.EXE', 'Wind.Dat' )
                      ELSE
                         EXEC( 'PRINT.EXE', 'Food.Dat' )
                ELSE  { GIVE ERROR MESSAGE }
                   BEGIN
                      WINDOW( 1,2,80,24 );
                      CLRSCR;
                      Center( 80, 11, 'YOU MUST FIRST LOAD A DATA');
                      Center( 80, 13, 'SET BEFORE TRYING TO PRINT!');
                      DELAY( 2000 );
                      WINDOW( 1,1,80,25 );
                      CLRSCR;
                   END;
          END; { of CASE 3 }
      4 : BEGIN
             IF DataLoaded
                THEN
                   BEGIN
                      GetLastYear;
                      Center( 80, 21, '                                   ' );
                      Center( 80, 22, 'PRESS ANY KEY TO CONTINUE.' );
                      REPEAT UNTIL KEYPRESSED;
                      Scrap := READKEY;
                      IF Scrap = #27
                         THEN
                            { Do nothing }
                         ELSE
                            BEGIN
                               WINDOW( 1,2,80,24 );
                               CLRSCR;
                               Center( 80, 12, 'CALCULATING......' );
```

```
                        Bayes;
                        DELAY( 1000 );
                        WINDOW( 1,1,80,25 );
                        CLRSCR;
                        DataGenerated := TRUE;
                      END;
                END
             ELSE
                BEGIN
                   WINDOW( 1,2,80,24 );
                   CLRSCR;
                   Center( 80, 11, 'YOU MUST FIRST LOAD THE +
                      QUESTIONNAIRE');
                   Center( 80, 13, 'DATA BEFORE RUNNING THE' );
                   Center( 80, 15, 'BAYES CALCULATION !!');
                   DELAY( 2000 );
                   WINDOW( 1,1,80,25 );
                   CLRSCR;
                END;
    END; { of CASE 4 }
5 : BEGIN
       IF DataGenerated
          THEN  { VIEW RESULTS FILE }
             BEGIN
                EXEC( 'TED.COM', 'Final.OUT' );
                CLRSCR;
             END
          ELSE  { GIVE ERROR MESSAGE }
             BEGIN
                WINDOW( 1,2,80,24 );
                CLRSCR;
                Center( 80, 11, 'YOU MUST FIRST GENERATE A +
                   RESULTS');
                Center( 80, 13, 'FILE BEFORE TRYING TO VIEW +
                   IT !!');
                DELAY( 2000 );
                WINDOW( 1,1,80,25 );
                CLRSCR;
             END;
    END; { of CASE 5 }
6 : BEGIN
       IF DataGenerated
          THEN  { PRINT RESULTS FILE }
             EXEC( 'PRINT.EXE', 'Bayes.Out' )
          ELSE  { GIVE ERROR MESSAGE }
             BEGIN
                WINDOW( 1,2,80,24 );
                CLRSCR;
                Center( 80, 11, 'YOU MUST FIRST GENERATE A +
                   RESULTS');
                Center( 80, 13, 'FILE BEFORE TRYING TO PRINT +
                   !!');
                DELAY( 2000 );
                WINDOW( 1,1,80,25 );
                CLRSCR;
             END;
    END; { of CASE 6 }
7 : BEGIN
       WINDOW( 1,2,80,24 );
```

```
                  CLRSCR;
                  WINDOW( 22,11,58,15 );
                  FrameWin( '', DoubleFrame, LightGray, LightGray );
                  CLRSCR;
                  Center( 36, 1, '>>>>  QUITTING  <<<<' );
                  Center( 36, 3, 'Thank you for using FISHFINDER !!' );
                  DELAY( 1000 );
                  WINDOW( 1,1,80,25 );
                  CLRSCR;
                  EXIT;
               END;
         END;  { of CASE 7 }
      END;  { of WHILE }
   BBM.Done;

END;  { of PROCEDURE MainMenu }

{---------------------------------------------------------------------}
{
    This procedure sets up the global booleans.
}

PROCEDURE Initialize;

BEGIN
   NormallyDistributed := TRUE;
   DataLoaded := FALSE;
   DataGenerated := FALSE;
END;  { of Procedure Initialize }

{************************** MAIN PROCEDURE ******************************}

BEGIN

   Initialize;

   Title_Page;

   MainMenu;

END.  { of PROGRAM }

{****************************>>>>>><<<<<<******************************}
```

UNIT MenuUnit

```
{ | Compiled under TURBO Pascal Version 7.0
  |
  | This code was copied from the LANGUAGES editorial in PC Magazine (USA
  |    edition of September 24, 1991 (a full explanation of how the menu
  |    system works is to be found there too).
  | The original code was written by Yasir Liaqat Ullah of Peshawar,
  |    Pakistan and revamped to be object oriented by Trudy Neuhaus of PC
  |    Magazine.
  |
  | Modified by Jan L. Korrûbel for inclusion in program PROBABLY
  | September '92
}

UNIT MenuUnit;

INTERFACE

USES
   CRT;  { Uses the screen }

CONST
   MaxMsgLen   = 60;
   ScreenWidth = 80;

   EnterKey    = $000D;   EscKey   = $001B;
   HomeKey     = $4700;   EndKey   = $4F00;
   LeftKey     = $4B00;   RightKey = $4D00;
   DownKey     = $5000;   UpKey    = $4800;

TYPE
   MessageString = STRING[ MaxMsgLen ];
   EntryPointer  = ^EntryType;

   EntryType = OBJECT
         Prev, Next            : EntryPointer;
         XCor, YCor, ChoiceNo  : INTEGER;
         Message               : MessageString;
         CONSTRUCTOR Init( iPr, iNx    : EntryPointer;
                           iX, iY, iC  : INTEGER;
                           iM          : MessageString );
         PROCEDURE Draw( Selected : BOOLEAN );
         FUNCTION GetChoice : INTEGER;
      END;

   BBMenu = OBJECT
         XCor, YCor, TextWidth, Choices : INTEGER;
         FirstEntry, CurrentEntry       : EntryPointer;
         CONSTRUCTOR Init( iX, iY, iW : INTEGER );
         DESTRUCTOR Done;
         PROCEDURE AddPrompt( iM : MessageString );
         PROCEDURE Draw;
         FUNCTION GetChoice : INTEGER;
      END;


IMPLEMENTATION
```

```
CONSTRUCTOR BBMenu.Init( iX, iY, iW : INTEGER );

BEGIN
   XCor      := iX;
   YCor      := iY;
   TextWidth := iW;
   IF TextWidth > MaxMsgLen
      THEN
         TextWidth := MaxMsgLen;
   IF ( XCor + TextWidth ) > ScreenWidth
      THEN
         TextWidth := ScreenWidth - XCor;
   FirstEntry := NIL;
   Choices := 0;
END;  { of CONSTRUCTOR BBMenu.Init }


DESTRUCTOR BBMenu.Done;

BEGIN
   IF FirstEntry <> NIL
      THEN
         BEGIN
            FirstEntry^.Prev^.Next := NIL;
            REPEAT
               CurrentEntry := FirstEntry;
               FirstEntry := FirstEntry^.Next;
               DISPOSE( CurrentEntry );
            UNTIL FirstEntry = NIL;
         END;
END;  { of DESTRUCTOR BBMenu.Done }


PROCEDURE BBMenu.AddPrompt(iM : MessageString);

VAR
   EP : EntryPointer;

BEGIN
   INC( Choices );
   FILLCHAR( iM [ LENGTH( iM ) + 1 ], TextWidth - LENGTH( iM ), ' ' );
   iM[ 0 ] := CHAR( TextWidth );
   IF FirstEntry = NIL
      THEN
         BEGIN
            FirstEntry := NEW(EntryPointer, Init( NIL,
                                                  NIL,
                                                  XCor,
                                                  YCOR + Choices - 1,
                                                  Choices,
                                                  iM ) );
            FirstEntry^.Next := FirstEntry;
            FirstEntry^.Prev := FirstEntry;
         END
      ELSE
         BEGIN
            EP := NEW( EntryPointer, Init( FirstEntry^.Prev,
                                           FirstEntry,
```

```
                                                    XCor,
                                                    YCor + Choices - 1,
                                                    Choices,
                                                    iM ) );
            FirstEntry^.Prev^.Next := EP;
            FirstEntry^.Prev       := EP;
         END;
END;  { of PROCEDURE BBMenu.AddPrompt }


PROCEDURE BBMenu.Draw;

VAR
   Row, Column : BYTE;

BEGIN
   GOTOXY( XCor - 1, YCor - 1 );
   WRITE( #218 );
   FOR Column := 1 TO TextWidth DO
      WRITE( #196 );
   WRITE( #191 );
   GOTOXY( XCor, YCor - 2 );
   WRITE( #176 );
   FOR Column := 1 TO TextWidth DO
      WRITE( #176 );
   WRITE( #176 );
   FOR Row := YCor TO ( YCor + Choices - 1 ) DO
      BEGIN
         GOTOXY( XCor - 1, Row );
         WRITE( #179 );
         GOTOXY( XCor + TextWidth, Row );
         WRITE( #179 );
         WRITE( #176 );
         GOTOXY( XCor + TextWidth + 1, Row - 1 );
         WRITE( #176 );
      END;
   GOTOXY( XCor - 1, YCor + Choices );
   WRITE( #192 );
   FOR Column := 1 TO TextWidth DO
      WRITE( #196 );
   WRITE( #217 );
   LOWVIDEO;
   CurrentEntry := FirstEntry;
   REPEAT
      CurrentEntry^.Draw( FALSE );
      CurrentEntry := CurrentEntry^.Next;
   UNTIL CurrentEntry = FirstEntry;
END;  { of Procedure BBMenu.Draw }


FUNCTION BBMenu.GetChoice : INTEGER;

VAR
   SaveX, SaveY : INTEGER;
   Finished     : BOOLEAN;
   InChar       : CHAR;
   InWord       : WORD;

BEGIN
```

```
   SaveX := WHEREX;
   SaveY := WHEREY;
   Draw;
   Finished := FALSE;
   REPEAT
      CurrentEntry^.Draw( TRUE );
      InChar := READKEY;
      IF ( InChar = #0 ) AND KEYPRESSED
         THEN
            BEGIN
               InChar := READKEY;
               INWord := WORD( InChar ) SHL 8;
            END
         ELSE
            InWord := ORD( InChar );
      CurrentEntry^.Draw( False );
      CASE InWord OF
         LeftKey, UpKey     : CurrentEntry := CurrentEntry^.Prev;
         RightKey, DownKey : CurrentEntry := CurrentEntry^.Next;
         HomeKey            : CurrentEntry := FirstEntry;
         EndKey             : CurrentEntry := FirstEntry^.Prev;
         EscKey             : BEGIN
                                 Finished  := TRUE;
                                 GetChoice := 0;
                              END;
         EnterKey           : BEGIN
                                 Finished  := TRUE;
                                 GetChoice := CurrentEntry^.GetChoice;
                              END;
      END; { of CASE }
   UNTIL Finished;
   GOTOXY( SaveX, SaveY );
END;  { of FUNCTION BBMenu.Getchoice }


CONSTRUCTOR EntryType.Init( iPr, iNx    : EntryPointer;
                            iX, iY, iC : INTEGER;
                            iM          : MessageString );

BEGIN
   Prev     := iPr;
   Next     := iNx;
   XCor     := iX;
   YCor     := iY;
   ChoiceNo := iC;
   Message  := iM;
END;  { of CONSTRUCTOR EntryType.Init }


PROCEDURE EntryType.Draw( Selected : BOOLEAN );

BEGIN
   IF Selected
      THEN
         TEXTATTR := $70    { Set bounce bar to reverse video }
      ELSE
         NORMVIDEO;  { Can also say TEXTATTR := $07, sets normal text }
   GOTOXY( XCor, YCor );
   WRITE( Message );
```

```
END;  { of PROCEDURE EntryType.Draw }


FUNCTION EntryType.GetChoice : INTEGER;

BEGIN
   GetChoice := ChoiceNo;
END;  { of FUNCTION EntryType.GetChoice }


END.  { of UNIT MenuUnit }
```

UNIT WinUnit

```
{************************************************************************}
{                                                                        }
{   TURBO PASCAL Version 6.0                                             }
{   Window Interface Unit                                                }
{                                                                        }
{   Copyright (C) 1989,90 Borland International                          }
{                                                                        }
{   Modified by Jan L. Korrûbel (September 1992) for PROGRAM Probably.   }
{                                                                        }
{************************************************************************}

UNIT WinUnit;

INTERFACE

USES
   CRT,   { Use the screen UNIT }
   DOS;   { Use the DOS UNIT - for the INTR procedure for cursor control }

TYPE
   TitleStr    = STRING[ 63 ];                 { Window title string }
   FrameChars = ARRAY[ 1..8 ] OF CHAR;         { Window frame characters }

   WinState    = RECORD                        { Window state record }
                    WindMin, WindMax : WORD;
                    WhereX, WhereY,
                    TextAttr         : BYTE;
                 END;

CONST
   SingleFrame : FrameChars = '┌─┐││└─┘'; { Standard frame character sets }
   DoubleFrame : FrameChars = '╔═╗║║╚═╝'; { for single and double borders }


{ Direct write routines }

PROCEDURE WriteStr( X, Y : BYTE;
                    S    : String;
                    Attr : BYTE );

PROCEDURE WriteChar( X, Y, Count : BYTE;
                     Ch          : CHAR;
                     Attr        : BYTE );


{ Window handling routines }

PROCEDURE FillWin( Ch : CHAR; Attr : BYTE );

PROCEDURE ReadWin( VAR Buf );

PROCEDURE WriteWin( VAR Buf );

FUNCTION  WinSize : WORD;

PROCEDURE SaveWin( VAR W : WinState );
```

```
PROCEDURE RestoreWin( VAR W : WinState );

PROCEDURE FrameWin( Title                  : TitleStr;
                    VAR Frame              : FrameChars;
                    TitleAttr, FrameAttr : BYTE );

PROCEDURE UnFrameWin;

PROCEDURE BlinkText;

PROCEDURE NoCursor;


IMPLEMENTATION

{$L WinUnit}  { Link in the external WinUnit.OBJ }

{These following procedures/functions are all in the external WinUnit.OBJ}

PROCEDURE WriteStr( X, Y : BYTE;
                    S    : STRING;
                    Attr : BYTE ); EXTERNAL;

PROCEDURE WriteChar( X, Y, Count : BYTE;
                     Ch          : CHAR;
                     Attr        : BYTE ); EXTERNAL;

PROCEDURE FillWin( Ch   : Char;
                   Attr : BYTE ); EXTERNAL;

PROCEDURE WriteWin( VAR Buf ); EXTERNAL;

PROCEDURE ReadWin( VAR Buf ); EXTERNAL;

FUNCTION WinSize : WORD; EXTERNAL;


PROCEDURE SaveWin( VAR W : WinState );

BEGIN
   W.WindMin   := WindMin;
   W.WindMax   := WindMax;
   W.WhereX    := WHEREX;
   W.WhereY    := WHEREY;
   W.TextAttr := TEXTATTR;
END;


PROCEDURE RestoreWin( VAR W : WinState );

BEGIN
   WindMin  := W.WindMin;
   WindMax  := W.WindMax;
   GOTOXY( W.WhereX, W.WhereY );
   TEXTATTR := W.TextAttr;
END;
```

```
PROCEDURE FrameWin( Title                   : TitleStr;
                    VAR Frame               : FrameChars;
                    TitleAttr, FrameAttr : BYTE );

VAR
  W, H, Y: WORD;

BEGIN
  W := LO( WindMax ) - LO( WindMin ) + 1;
  H := HI( WindMax ) - HI( WindMin ) + 1;
  WriteChar( 1, 1, 1, Frame[ 1 ], FrameAttr );
  WriteChar( 2, 1, W - 2, Frame[ 2 ], FrameAttr );
  WriteChar( W, 1, 1, Frame[ 3 ], FrameAttr );
  IF LENGTH( Title ) > W - 2
     THEN
        Title[ 0 ] := CHR( W - 2 );
  WriteStr( ( W - LENGTH( Title ) ) SHR 1 + 1, 1, Title, TitleAttr );
  FOR Y := 2 TO H - 1 DO
     BEGIN
        WriteChar( 1, Y, 1, Frame[ 4 ], FrameAttr );
        WriteChar( W, Y, 1, Frame[ 5 ], FrameAttr );
     END;
  WriteChar( 1, H, 1, Frame[ 6 ], FrameAttr );
  WriteChar( 2, H, W - 2, Frame[ 7 ], FrameAttr );
  WriteChar( W, H, 1, Frame[ 8 ], FrameAttr );
  INC( WindMin, $0101 );
  DEC( WindMax, $0101 );
END;


PROCEDURE UnFrameWin;

BEGIN
  DEC( WindMin, $0101 );
  INC( WindMax, $0101 );
END;


{
    These procedures set the screen text attributes.
    Inherent TURBO Pascal text procedures in use are:
          TEXTCOLOR      - can set text color
          TEXTBACKGROUND - can set background screen color
}

PROCEDURE ReverseVideo;

BEGIN
   TEXTCOLOR( BLACK );
   TEXTBACKGROUND( WHITE );
END;


PROCEDURE BlinkText;

BEGIN
   TEXTCOLOR( WHITE + BLINK );
END;
```

```
{
   These procedures use DOS interrupt 16, service 1, to set the cursor.
   Register AH is set to 1 (register AL should be 0) and if the curser is
      to dissappear, bit 5 of register CH should be set (see the Registers
      TYPE definition below - defined in the DOS UNIT).

   Registers  = RECORD
                   CASE INTEGER OF
                      0: ( AX,BX,CX,DX,BP,SI,DI,DS,ES,FLAGS : WORD );
                      1: ( AL,AH,BL,BH,CL,CH,DL,DH          : BYTE );
                   END;
}

PROCEDURE NoCursor;

VAR
   Regs : Registers;

BEGIN
   Regs.AH := 1;     {Need to set the service required - i.e. 1, to effect}
   Regs.AL := 0;     {    the change when interupt 16 is called.          }
   Regs.CH := 32;    { Set CH bit 5 to 32 to supress cursor }
   INTR( 16, Regs );{ Now call interrupt 16 with the required changes }
END;

END.  { of UNIT WinUnit }
```

Appendix 6

ESTIMATION OF PRIORS AND LIKELIHOODS FROM EMPIRICAL DATA

Calculations begin overside.

P(BAR) - Probability of Below Average Recruitment

NOTE: At the time of calculations, the estimated recruitment time series extended only to 1993; the 1994 estimate only became available later, and is used to validate the model.

If we assume that estimated recruitment values below the overall mean (327.58 billion individuals) indicate a "below average recruitment" event (see data for years 1985, '89, '90 and '92 - Figure A6.1) then the probability of below average recruitment, *P*(*BAR*), is that number of years in which the recruitment index is below the mean devided by the number of years in the available time series.

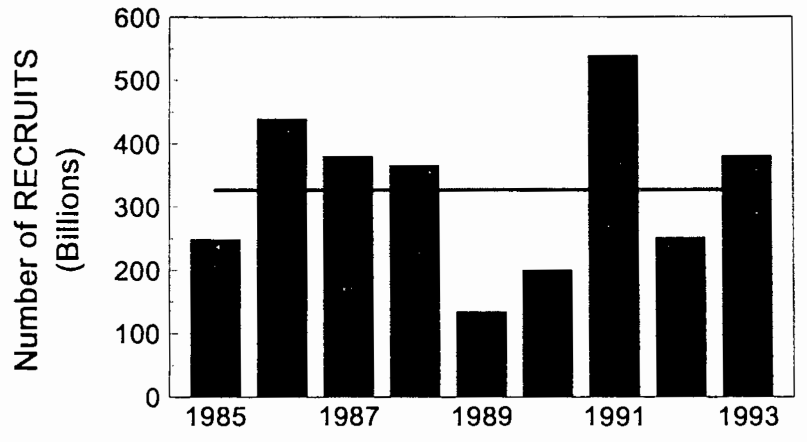

Figure A6.1: Estimated number of recruits for the South African anchovy, *Engraulis capensis*, 1985-1993. The horizontal line (-) indicates the overall mean. Data from Sea Fisheries Research Institute (unpublished).

Therefore:

$$P(BAR) = \frac{\text{no. of times the recruitment falls below the mean value}}{\text{total no. of years in the time series}}$$

$$P(BAR) = \frac{4}{9}$$
$$= 0.44$$

P(LO) - Probability of Low Oil Yield

If we assume that commercial oil yield values below the threshold value of 20% (see section 4.6) indicate low fat reserves in the fish (spawners), then the probability of Low Oil, *P*(*LO*), is that number of years in which the oil yield is below the threshold devided by the number of years in the available time series (see data for 1988 through '93 in Figure A6.2).

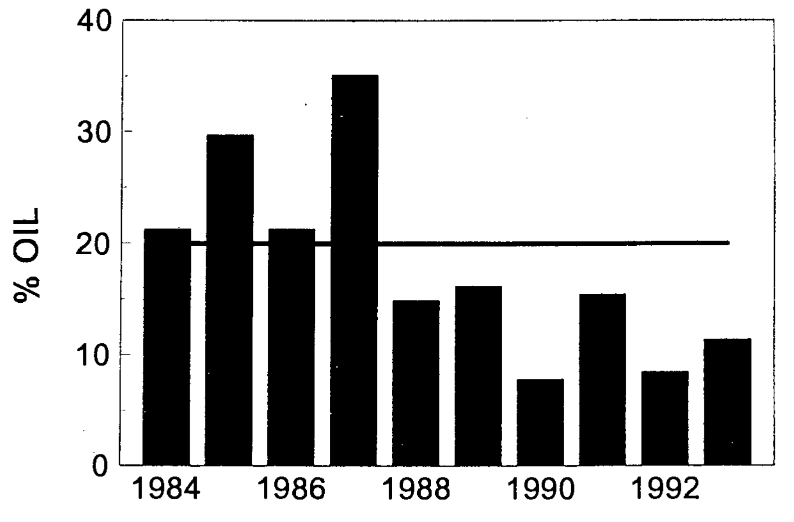

Figure A6.2: Mean annual commercial oil:meal ratios for the South African anchovy, *Engraulis capensis*, 1984-1993. The horizontal line (-) indicates the threshold value. Data from Sea Fisheries Research Institute (unpublished).

Therefore:

$$P(LO) = \frac{\text{no. of times the oil yield is below the threshold value}}{\text{total no. of years in the time series}}$$

$$P(LO) = \frac{6}{10}$$
$$= 0.60$$

P(LE) - Probability of Low Daily Egg Production

If we assume that values for daily egg production below the threshold value of 300 eggs.m^{-2} (see section 4.6) are indicative of poor spawning success, then the probability of Low (number of) Eggs, *P(LE)*, is that number of years in which the daily egg production is below the threshold devided by the number of years in the available time series (see data for 1987, '89 and '93 in Figure A6.3).

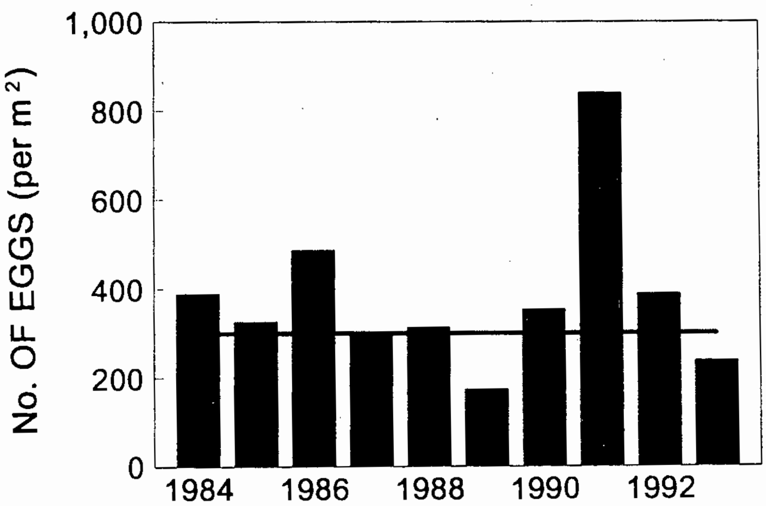

Figure A6.3: Mean daily egg production for the South African anchovy, *Engraulis capensis*, during the November Spawner Biomass cruise, 1984-1993. The horizontal line (-) indicates the threshold value. Data from Sea Fisheries Research Institute (unpublished).

Therefore:

$$P(LE) = \frac{\text{no. of times daily egg production is below the threshold value}}{\text{total no. of years in the time series}}$$

$$P(LE) = \frac{3}{9} = 0.33$$

P(HSW) - Probability of Strong Southerly Winds

If we assume that values for accumulated monthly southerly windrun above the threshold value of 5000 km (see section 4.6) are indicative of enhanced offshore transport and an increase in the loss of spawning products, then the probability of High Southerly Winds, *P(HSW)*, is that number of years in which the southerly windrun is above the threshold devided by the number of years in the available time series (see data for 1985, '86, '88, '89 and '93 in Figure A6.4).

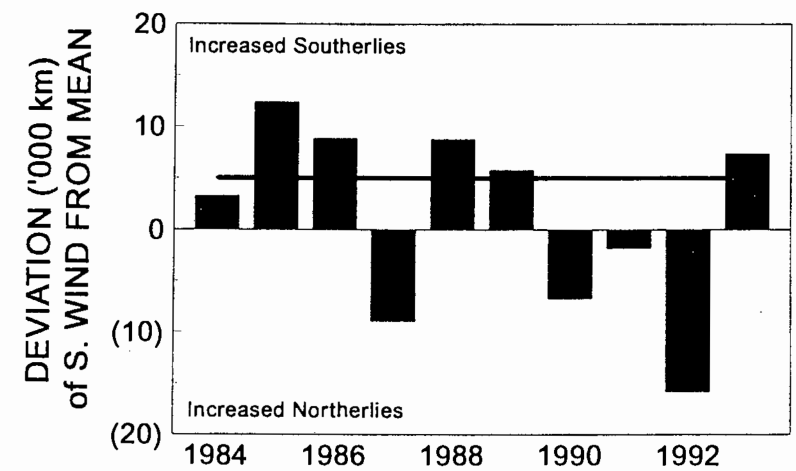

Figure A6.4: Cape Point N-S windrun anomaly, averaged over October-December 1984-1993 (deviation in '000 km from the mean). Positive values indicate a stronger southerly component to the winds. The horizontal line (-) indicates the threshold value. Data from Sea Fisheries Research Institute (unpublished).

Therefore:

$$P(HSW) = \frac{\text{no. of times the southerly wind stress is above the threshold value}}{\text{total no. of years in the time series}}$$

$$P(HSW) = \frac{5}{9}$$
$$= 0.55$$

P(HSW) - Probability of High Starvation Stations

If we assume that values for % starvation stations above the threshold value of 30% (see section 4.6) indicate of poor feeding conditions for spawning anchovy, then the probability of High Starvation Stations, *P*(*HSS*), is that number of years in which the oil yield is above the threshold devided by the number of years in the available time series (see data for 1988 in Figure A6.5).

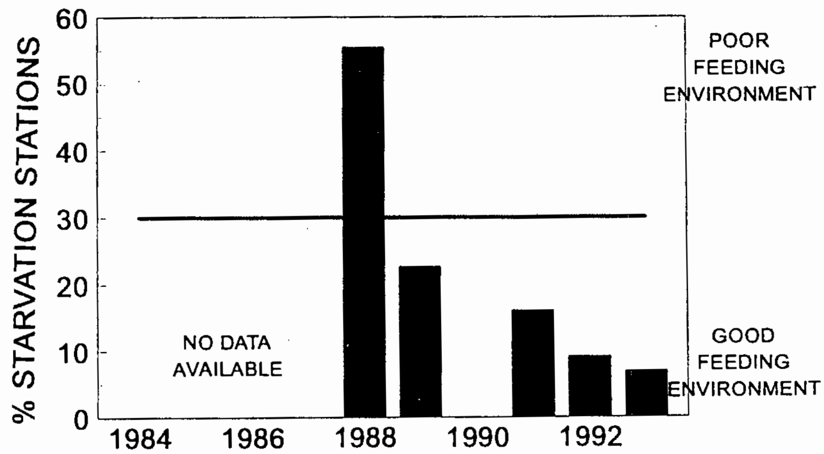

Figure A6.5: Percentage starvation stations encountered during the November Spawner Biomass cruise, 1988-1993. Postive values indicate a poor feeding environment for the spawning fish. The horizontal line (-) indicates the threshold value. Data from Sea Fisheries Research Institute (unpublished).

Therefore:

$$P(HSS) = \frac{\text{no. of times the \% starvation stations is above the threshold value}}{\text{total no. of years in the time series}}$$

$$P(HSS) = \frac{1}{6} = 0.17$$

P(LO|BAR) - Likelihood of Low Oil Yield, given that fact that there is Below Average Recruitment

Given the fact that there is a known below average recruitment event in any one year, the probability of this being preceded by low oil yield in the previous season, *P*(LO|BAR), may be calculated from the time series of oil yield and estimated recruitment (see Figure A6.6).

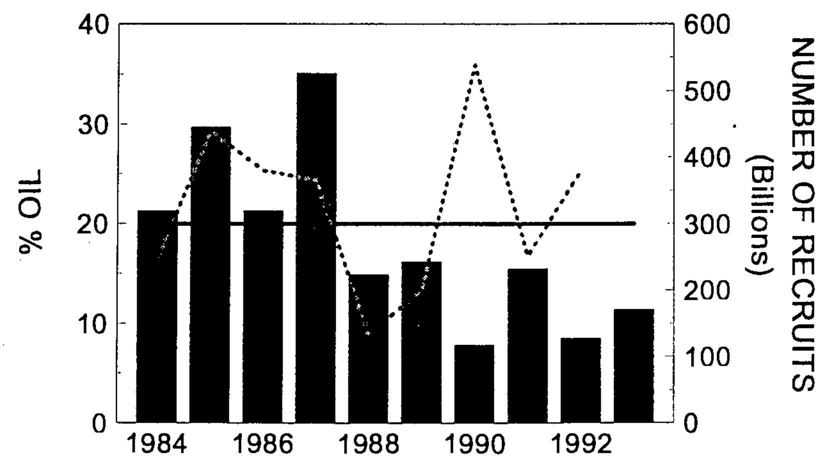

Figure A6.6: Mean annual commercial oil:meal ratio in relation to estimated recruitment (···) in the following year for the South African anchovy, *Engraulis capensis.* The horizontal line (-) indicates the oil yield threshold value. Data from Sea Fisheries Research Institute (unpublished).

$$\text{i.e.:} \quad P(\text{LO}|\text{BAR}) = \frac{\text{no. of times LO preceeds a BAR event}}{\text{total no. of years BAR is present in the time series}}$$

$$P(\text{LO}|\text{BAR}) = \frac{3}{4}$$

$$= 0.75$$

P(LE|BAR) - Likelihood of Low Egg Production, given that fact that there is Below Average Recruitment

Given the fact that there is a known below average recruitment event in any one year, the probability of this being preceded by low egg production in the previous season, *P*(LE|BAR), may be calculated from the time series of egg production and estimated recruitment (see Figure A6.7).

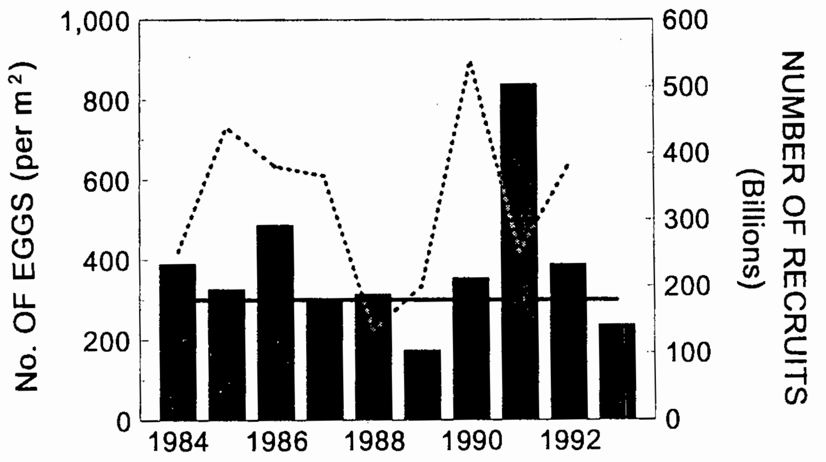

Figure A6.7: Daily Egg Production in relation to estimated recruitment (···) in the *following year* for the South African anchovy, *Engraulis capensis*. The horizontal line (-) indicates the egg production threshold value. Data from Sea Fisheries Research Institute (unpublished).

$$P(\mathrm{LE}|\mathrm{BAR}) = \frac{\text{no. of times LE preceeds a BAR event}}{\text{total no. of years BAR is present in the time series}}$$

$$P(\mathrm{LE}|\mathrm{BAR}) = \frac{1}{4}$$

$$= 0.25$$

P(HSW|BAR) - Likelihood of High (incidence of) Southerly Winds, given that fact that there is Below Average Recruitment

Given the fact that there is a known below average recruitment event in any one year, the probability of this being preceded by high southerly winds in the previous season, *P*(HSW|BAR), may be calculated from the time series of the N-S Wind Anomaly and estimated recruitment (see Figure A6.8).

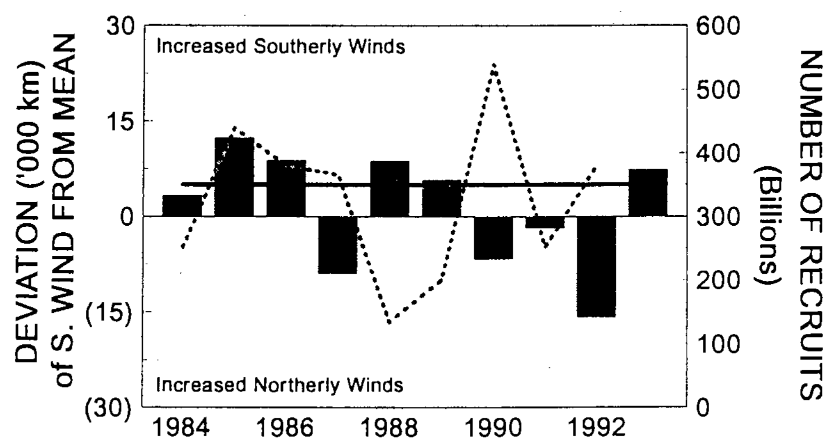

Figure A6.8: N-S windrun anomalies at Cape Point in relation to estimated recruitment (···) in the *following year* for the South African anchovy, *Engraulis capensis*. The horizontal line (-) indicates the southerly windrun threshold value. Data from Sea Fisheries Research Institute (unpublished).

$$P(\text{HSW}|\text{BAR}) = \frac{\text{no. of times HSW preceeds a BAR event}}{\text{total no. of years BAR is present in the time series}}$$

$$P(\text{HSW}|\text{BAR}) = \frac{2}{4}$$

$$= 0.50$$

P(HSS|BAR) - Likelihood of High (incidence of) Starvation Stations, given that fact that there is Below Average Recruitment

Given the fact that there is a known below average recruitment event in any one year, the probability of this being preceded by high starvation stations in the previous season, *P*(HSS|BAR), may be calculated from the time series of percentage starvation stations and estimated recruitment (see Figure A6.9).

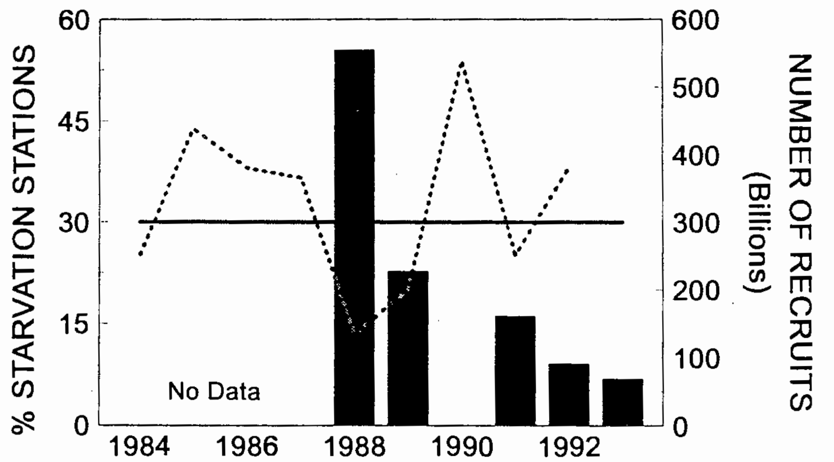

Figure A6.9: Percentage Starvation Stations in relation to estimated recruitment (···) in the *following year* for the South African anchovy, *Engraulis capensis*. The horizontal line (-) indicates the percentage starvation station threshold value. Data from Sea Fisheries Research Institute (unpublished).

$$P(\mathrm{HSS}|\mathrm{BAR}) = \frac{\text{no. of times HSS preceeds a BAR event}}{\text{total no. of years BAR is present in the time series}}$$

$$P(\mathrm{HSS}|\mathrm{BAR}) = \frac{1}{3}$$

$$= 0.33$$

SUMMARY:

PROBABILITY	EMPIRICAL PRIOR
P(BAR)	0.44
P(LO)	0.60
P(LE)	0.33
P(HSW)	0.55
P(HSS)	0.17

Table A6.1: Empirical prior probabilities of Below Average Recruitment *P*(BAR), Low Oil *P*(LO), Low Eggs *P*(LE), High Southerly Winds *P*(HSW) and High Starvation Stations *P*(HSS), obtained from the time series.

LIKELIHOOD	EMPIRICAL LIKELIHOOD
P(LO|BAR)	0.75
P(LE|BAR)	0.25
P(HSW|BAR)	0.50
P(HSS|BAR)	0.33

Table A6.2: Empirical likelihoods for the probability of finding Low Oil (LO), Low Eggs (LE), High Southerly Winds (HSW) and High Starvation Stations (HSS), preceding a Below Average Recruitment (BAR) event.

P(LO|BAR & LE) - Probability of Low Oil, given that fact that there is Below Average Recruitment *and* Low Eggs

Given the fact that there is known below average recruitment *and* low egg production in any one year, the probability of this being preceded by low oil yields in the previous season, *P*(LO|BAR&LE), may be calculated from the time series of percentage starvation stations and estimated recruitment (see Figure A6.10).

P(LE|BAR & LO) - Probability of Low Eggs, given that fact that there is Below Average Recruitment *and* Low Oil

Similarly, given the fact that there is known below average recruitment *and* low oil yield in any one year, the probability of this being preceded by low egg production in the previous season, *P*(LE|BAR&LO), may be calculated from the time series of percentage starvation stations and estimated recruitment (see Figure A6.10).

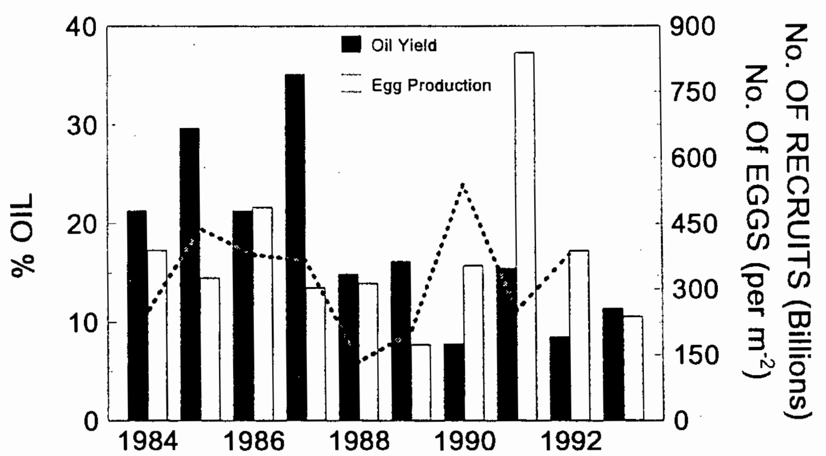

Figure A6.10: Oil yield and daily egg production in relation to estimated recruitment (···) in the *following year* for the South African anchovy, *Engraulis capensis*. Data from Sea Fisheries Research Institute (unpublished).

$$P(\text{LE}|\text{BAR\&LO}) = \frac{\begin{array}{c}\text{no. of times LE corresponds}\\ \text{with a BAR\& LO event}\end{array}}{\begin{array}{c}\text{total no. of years BAR\& LO is}\\ \text{present in the time series}\end{array}}$$

$$P(\text{LE}|\text{BAR\&LO}) = \frac{1}{3}$$

$$= 0.33$$

Also:

$$P(\text{LO}|\text{BAR\&LE}) = \frac{\text{no. of times LO corresponds with a BAR\& LE event}}{\text{total no. of years BAR\& LE is present in the time series}}$$

$$P(\text{LO}|\text{BAR\&LE}) = \frac{1}{1}$$

$$= 1.00$$

Clearly, it would appear that the time series over which the variables extend is too short to get reliable likelihoods from, and that further attention to this method of obtaining likelihoods is futile.

Appendix 7

PROBABILITY QUESTIONNAIRE

Questionnaire begins overside.

Oil Yield:

Hypothesis: low oil content (oil:meal ratio < 20%) = low energy reserves for fish coming onto the spawning grounds = low early egg production (and also perhaps non-sustained egg production) = below average recruitment.

NOTE: The oil parameter is the *average* oil yield obtained over the fishing season *prior* to spawning (oil yields are available until approximately August in any one year). It is assumed that oil yield can be used as a 'condition factor', giving one an indication of the 'fitness' of the spawner animals *before* and when they arrive on the Agulhas Bank to spawn - the condition that the fish are in when they arrive on the spawning grounds is considered to be a major factor regulating sustained egg production.

Southerly Winds at Cape Point:

Hypothesis: high incidence of southerly winds at Cape Point (total deviation from long-term mean between October and December > 5000 km) = high offshore advection of surface water on the west coast = high loss of spawning products and larvae to the offshore environment = below average recruitment.

NOTE: The phenomenon of egg and larval transport is widely thought to be of considerable importance in regulating recruitment of clupeoids; hence, it is important to be able to detect abnormally high egg and larval losses through offshore transport. The accumulated wind displacement from the south should give some indication of the amount of offshore transport. The sum of departures from the long-term mean for the period October to March each year is used.

Egg Production:

Hypothesis: low egg production (daily production < 300 eggs m^{-2}) = low numbers of eggs (available for hatching and subsequent development) = below average recruitment.

NOTE: The mean daily egg production per unit area is an essential parameter in the egg production method of biomass determination; a plot of recruitment on egg production gives some indication of a positive relationship. Essentially, low egg production means a relatively low number of offspring at an early stage in the recruitment process, thus increasing the probability of a low number of recruits.

% Starvation Stations:

Hypothesis: A high percentage of 'starvation stations' (>30%) = less food available than required by the spawning fish in the spawning area = reduced spawning ability (and reduced probability of sustained spawning) = increased chances of below average recruitment.

NOTE: Food availability is considered to be a factor regulating sustained egg production by the spawner stock; a large percentage of starvation stations on the spawning grounds is considered to decrease the probability of sustained spawning.

It should be noted that these hypotheses/relationships *do not have to be accepted as fact.* If your own hypothesis(es) differ from any presented above, then state them clearly (space is provided) and work out the probabilities according to *your own* hypotheses. It is asked that you do not discuss this worksheet with any of your colleagues. *It is for you, from what you know about the pelagic ecosystem and it's inter-relationships, to decide what you expect the answers to be.*

Please also note that in all cases you are being asked to consider the probabilities associated with events occurring during the recruitment process in a given period, and the resulting recruitment. Thus, for example, if you are told that recruitment was below average and are asked for the probability that egg production was low, the question refers to the egg production during the just completed spawning season which gave rise to the present below average recruitment.

It is not expected that you will *know all* the answers - the point here is that initial probabilities can always be refined at a later stage (as more information becomes available) - BUT we want the best possible numbers we can get. Therefore, answer *ALL* the questions, but if you feel strongly that the question (and your answer) is not in the domain of your knowledge, place a mark in the extra column provided (column marked **).

YOUR ALTERNATE HYPOTHESES

'OIL YIELD HYPOTHESIS'

'CAPE POINT SOUTHERLY WIND HYPOTHESIS'

'EGG PRODUCTION HYPOTHESIS'

'STARVATION STATION HYPOTHESIS'

PROBABILITIES FROM ONE VARIABLE

1-1 *High Wind Index | BELOW AVERAGE RECRUITMENT*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT is observed, a HIGH WIND INDEX will *also* be observed?

1-2 *High Wind Index | Low Eggs*
What is the chance that, in the same recruitment process as LOW EGGS is observed, a HIGH WIND INDEX will *also* be observed?

1-3 *High Wind Index | Low Oil*
What is the chance that, in the same recruitment process as LOW OIL is observed, a HIGH WIND INDEX will *also* be observed?

1-4 *Low Eggs | BELOW AVERAGE RECRUITMENT*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT is observed, LOW EGGS will *also* be observed?

1-5 *Low Eggs | High Wind Index*
What is the chance that, in the same recruitment process as a HIGH WIND INDEX is observed, LOW EGGS will *also* be observed?

1-6 *Low Eggs | Low Oil*
What is the chance that, in the same recruitment process as LOW OIL is observed, LOW EGGS will *also* be observed?

1-7 *Low Eggs | High % Starvation Stations*
What is the chance that, in the same recruitment process as HIGH % STARVATION STATIONS is observed, LOW EGGS will *also* be observed?

1-8 *Low Oil | BELOW AVERAGE RECRUITMENT*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT is observed, LOW OIL will *also* be observed?

1-9 *Low Oil | High wind index*
What is the chance that, in the same recruitment process as HIGH WIND INDEX is observed, LOW OIL will *also* be observed?

1-10 *Low Oil | Low Eggs*
What is the chance that, in the same recruitment process as LOW EGGS is observed, LOW OIL will *also* be observed?

1-11 *Low Oil | High % Starvation Stations*
What is the chance that, in the same recruitment process as HIGH % STARVATION STATIONS is observed, LOW OIL will *also* be observed?

1-12 *High % Starvation Stations | BELOW AVERAGE RECRUITMENT*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT is observed, HIGH % STARVATION STATIONS will *also* be observed?

1-13 *High % Starvation Stations | Low Eggs*
What is the chance that, in the same recruitment process as LOW EGGS is observed, HIGH % STARVATION STATIONS will *also* be observed?

1-14 *High % Starvation Stations | Low Oil*
What is the chance that, in the same recruitment process as LOW OIL is observed, HIGH % STARVATION STATIONS will *also* be observed?

PROBABILITIES FROM TWO VARIABLES

2-1 *High Wind Index | BELOW AVERAGE RECRUITMENT and Low Eggs*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW EGGS are observed, a HIGH WIND INDEX will *also* be observed?

2-2 *High Wind Index | BELOW AVERAGE RECRUITMENT and Low Oil*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL are observed, a HIGH WIND INDEX will *also* be observed?

2-3 *High Wind Index | Low Eggs and Low Oil*
What is the chance that, in the same recruitment process as LOW EGGS *and* LOW OIL are observed, a HIGH WIND INDEX will *also* be observed?

2-4 *Low Eggs | BELOW AVERAGE RECRUITMENT and High Wind Index*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH WIND INDEX are observed, LOW EGGS will *also* be observed?

2-5 *Low Eggs | BELOW AVERAGE RECRUITMENT and Low Oil*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL are observed, LOW EGGS will *also* be observed?

2-6 *Low Eggs | BELOW AVERAGE RECRUITMENT and High % Starvation Stations*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH % STARVATION STATIONS are observed, LOW EGGS will *also* be observed?

2-7 *Low Eggs | High Wind Index and Low Oil*
What is the chance that, in the same recruitment process as HIGH WIND INDEX *and* LOW OIL are observed, LOW EGGS will *also* be observed?

2-8 *Low Eggs | Low Oil and High % Starvation Stations*
What is the chance that, in the same recruitment process as LOW OIL *and* HIGH % STARVATION STATIONS are observed, LOW EGGS will *also* be observed?

2-9 *Low Oil | BELOW AVERAGE RECRUITMENT and High Wind Index*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH WIND INDEX are observed, LOW OIL will *also* be observed?

2-10 *Low Oil | BELOW AVERAGE RECRUITMENT and Low Eggs*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW EGGS are observed, LOW OIL will *also* be observed?

2-11 *Low Oil | BELOW AVERAGE RECRUITMENT and High % Starvation Stations*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH % STARVATION STATIONS are observed, LOW OIL will *also* be observed?

2-12 *Low Oil | High Wind Index and Low Eggs*
What is the chance that, in the same recruitment process as HIGH WIND INDEX *and* LOW EGGS are observed, LOW OIL will *also* be observed?

2-13 *Low Oil | Low Eggs and High % Starvation Stations*
What is the chance that, in the same recruitment process as LOW EGGS *and* HIGH % STARVATION STATIONS are observed, LOW OIL will *also* be observed?

2-14 *High % Starvation Stations | BELOW AVERAGE RECRUITMENT and Low Eggs*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW EGGS are observed, HIGH % STARVATION STATIONS will *also* be observed?

2-15 *High % Starvation Stations | BELOW AVERAGE RECRUITMENT and Low Oil*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL are observed, HIGH % STARVATION STATIONS will *also* be observed?

2-16 *High % Starvation Stations | Low Eggs and Low Oil*
What is the chance that, in the same recruitment process as LOW EGGS *and* LOW OIL are observed, HIGH % STARVATION STATIONS will *also* be observed?

PROBABILITIES FROM THREE VARIABLES

3-1 *High Wind Index | BELOW AVERAGE RECRUITMENT and Low Oil and Low Eggs*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL *and* LOW EGGS are observed, a HIGH WIND INDEX will *also* be observed?

3-2 *Low Eggs | BELOW AVERAGE RECRUITMENT and High Wind Index and Low Oil*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH WIND INDEX *and* LOW OIL are observed, LOW EGGS will *also* be observed?

3-3 *Low Eggs | BELOW AVERAGE RECRUITMENT and Low Oil and High % Starvation Stations*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL *and* HIGH % STARVATION STATIONS are observed, LOW EGGS will *also* be observed?

3-4 *Low Oil | BELOW AVERAGE RECRUITMENT and High Wind Index and Low Eggs*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* HIGH WIND INDEX *and* LOW EGGS are observed, LOW OIL will *also* be observed?

3-5 *Low Oil | BELOW AVERAGE RECRUITMENT and Low Eggs and High % Starvation Stations*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW EGGS *and* HIGH % STARVATION STATIONS are observed, LOW OIL will *also* be observed?

3-6 *High % Starvation Stations | BELOW AVERAGE RECRUITMENT and Low Eggs and Low Oil*
What is the chance that, in the same recruitment process as BELOW AVERAGE RECRUITMENT *and* LOW OIL *and* LOW EGGS are observed, HIGH % STARVATION STATIONS will *also* be observed?

	CHANCE OF OCCURRENCE						
P(A)	0-10% *None*	11-30% *Poor*	31-49% *B.Avg.*	51-70% *A.Avg.*	71-90% *Good*	91-100% *Excellent*	**
1-1							
1-2							
1-3							
1-4							
1-5							
1-6							
1-7							
1-8							
1-9							
1-10							
1-11							
1-12							
1-13							
1-14							
2-1							
2-2							
2-3							
2-4							
2-5							
2-6							
2-7							
2-8							
2-9							
2-10							
2-11							
2-12							
2-13							
2-14							
2-15							
2-16							
3-1							
3-2							
3-3							
3-4							
3-5							
3-6							

Appendix 8

GLOSSARY OF PROBABILITY ABBREVIATIONS USED IN THE TEXT

A8.1 PRIOR PROBABILITIES:

P(BAR)	-	probability of below average recruitment
P(LO)	-	probability of low oil yield
P(LE)	-	probability of low daily egg production
P(HSW)	-	probability of high (strong) southerly windrun
P(HSS)	-	probability of high % starvation stations

A8.2 1st-ORDER POSTERIOR PROBABILITIES:

P(BAR|LO)
- probability of below average recruitment given that low annual commercial oil yield has been observed

P(BAR|LE)
- probability of below average recruitment given that low daily egg production has been observed

P(BAR|HSW)
- probability of below average recruitment given that a high southerly windrun, for the period Oct-Dec, has been observed

P(BAR|HSS)
- probability of below average recruitment given that a high percentage of starvation stations has been observed

A8.3 2nd-ORDER POSTERIOR PROBABILITIES:

P(BAR|LO&LE)

- probability of below average recruitment given that low annual commercial oil yield *and* low daily egg production have been observed

P(BAR|LO&HSW)

- probability of below average recruitment given that low annual commercial oil yield *and* a high southerly windrun, for the period Oct-Dec, have been observed

P(BAR|LO&HSS)

- probability of below average recruitment given that low annual commercial oil yield *and* a high southerly windrun, for the period Oct-Dec, have been observed

P(BAR|LE&HSW)

- probability of below average recruitment given that low daily egg production *and* a high southerly windrun, for the period Oct-Dec, have been observed

P(BAR|LE&HSS)

- probability of below average recruitment given that low daily egg production *and* a high percentage of starvation stations have been observed

P(BAR|HSW&HSS)

- probability of below average recruitment given that high southerly windrun *and* a high percentage of starvation stations have been observed

A8.3 3rd-ORDER POSTERIOR PROBABILITIES:

P(BAR|LO&LE&HSW)

- probability of below average recruitment given that low annual commercial oil yield *and* low daily egg production *and* a high southerly windrun, for the period Oct-Dec, have been observed

P(BAR|LO&LE&HSS)

- probability of below average recruitment given that low annual commercial oil yield *and* low daily egg production *and* a high percentage of starvation stations have been observed

P(BAR|LO&HSW&HSS)

- probability of below average recruitment given that low annual commercial oil yield *and* a high southerly windrun, for the period Oct-Dec, *and* a high percentage of starvation stations have been observed

A8.4 4th-ORDER POSTERIOR PROBABILITY:

P(BAR|LO&LE&HSW&HSS)

- probability of below average recruitment given that low annual commercial oil yield *and* low daily egg production *and* a high southerly windrun, for the period Oct-Dec, *and* a high percentage of starvation stations have been observed

Appendix 9

EXPERT ASSESSED PROBABILITIES

The numbered probabilities *P*(A), *viz.* 1-X, 2-X, and 3-X, refer to the questions in the questionnaire found in Appendix 7.

The resultant probabilities - for use in the Bayesian equations - are the means of the columns, e.g. for the 0-10% column, the probability used in the calculations is 0.5; for the 51-70% column, the probability used in the calculations is 0.6.

	CHANCE OF OCCURRENCE						
P(A)	0-10% *None*	11-30% *Poor*	31-49% *B.Avg.*	50%	51-70% *A.Avg.*	71-90% *Good*	91-100% *Excellent*
1-1					X		
1-2			X				
1-3			X				
1-4			X				
1-5	X						
1-6			X				
1-7	X						
1-8			X				
1-9		X					
1-10			X				
1-11		X					
1-12					X		
1-13		X					
1-14	X						
2-1			X				
2-2			X				
2-3			X				
2-4		X					
2-5					X		
2-6				X	→X		
2-7			X				
2-8				X	→X		
2-9		X					
2-10					X		
2-11					X		
2-12			X				
2-13			X				
2-14			X				
2-15			X				
2-16	X						
3-1			X		X		
3-2					X		
3-3					X		
3-4					X		
3-5					X		
3-6			X				

Appendix 10

DATA CONSISTENCY ANALYSIS

Moskowitz and Sarin (1983) outline necessary and sufficient conditions that likelihoods, such as *P*(I|BAR), must satisfy in order to be consistent with the axioms of probability (see Chapter 6, section 6.7).

A10.1 INVESTIGATING THE CONSISTENCY OF THE EMPIRICAL 1ST-ORDER PROBABILITIES:

First-order probabilities obtained from the empirical data - as calculated in Appendix 8 - are shown in Table A10.1

PRIOR PROBABILITY	EMPIRICAL PRIOR	LIKELIHOOD	EMPIRICAL LIKELIHOOD
P(BAR)	0.44		
P(LO)	0.60	*P*(LO|BAR)	0.75
P(LE)	0.33	*P*(LE|BAR)	0.25
P(HSW)	0.55	*P*(HSW|BAR)	0.50
P(HSS)	0.17	*P*(HSS|BAR)	0.25

Table A10.1: Empirical data prior probabilities for Below Average Recruitment *P*(BAR), Low Oil (yield) *P*(LO), Low Egg production *P*(LE), High (strong) Southerly Winds *P*(HSW) and High percentage "Starvation Stations" *P*(HSS), and first-order likelihoods (see Appendix 8 for abbreviations).

The results of the consistency analysis are shown in Table A10.2.

		CONDITIONS FOR DATA CONSISTENCY			
LIKELIHOOD $P(\mathrm{I}\vert\mathrm{BAR})$	**EMPIRICAL DATA**	$P(\mathrm{I}\vert\mathrm{BAR}) \leq 1$	$P(\mathrm{I}\vert\mathrm{BAR}) \leq \frac{P(\mathrm{I})}{P(\mathrm{BAR})}$	$P(\mathrm{I}\vert\mathrm{BAR}) \geq \frac{P(\mathrm{I})+P(\mathrm{BAR})-1}{P(\mathrm{BAR})}$	$P(\mathrm{I}\vert\mathrm{BAR}) \geq 0$
$P(\mathrm{LO}\vert\mathrm{BAR})$	0.75	$0.75 \leq 1$	$0.75 \leq 1.50$	$0.75 \geq 0.09$	$0.75 \geq 0$
$P(\mathrm{LE}\vert\mathrm{BAR})$	0.25	$0.25 \leq 1$	$0.25 \leq 0.75$	$0.25 \geq -0.52$	$0.25 \geq 0$
$P(\mathrm{HSW}\vert\mathrm{BAR})$	0.50	$0.50 \leq 1$	$0.50 \leq 1.25$	$0.50 \geq -0.02$	$0.50 \geq 0$
$P(\mathrm{HSS}\vert\mathrm{BAR})$	0.25	$0.25 \leq 1$	$0.25 \leq 0.39$	$0.25 \geq -0.08$	$0.25 \geq 0$

Table A10.2: Consistency table for the empirical data likelihhoods, showing that the likelihoods satisfy all the conditions for consistency with the axioms of probability (as outlined by Moskowitz and Sarin 1983). See Table A10.1 for the values of *P*(BAR), *P*(LO), *P*(LE), *P*(HSW) and P(HSS), and Appendix 8 for abbreviations.

A10.2 INVESTIGATING THE CONSISTENCY OF THE EXPERT 1ST-ORDER PROBABILITIES:

First-order probabilities obtained from the experts are shown in Table A10.1.

PRIOR PROBABILITY	EXPERT PRIOR	LIKELIHOOD	EXPERT LIKELIHOOD
P(BAR)	0.33		
P(LO)	0.15	*P*(LO|BAR)	0.40
P(LE)	0.10	*P*(LE|BAR)	0.40
P(HSW)	0.40	*P*(HSW|BAR)	0.60
P(HSS)	0.15	*P*(HSS|BAR)	0.60

Table A10.3: Expert data prior probabilities for Below Average Recruitment *P*(BAR), Low Oil (yield) *P*(LO), Low Egg production *P*(LE), High (strong) Southerly Winds *P*(HSW) and High percentage "Starvation Stations" *P*(HSS), and first-order likelihoods (see Appendix 8 for abbreviations).

The results of the consistency investigations are shown in Table A10.4.

LIKELIHOOD $P(\mathrm{I}\mid\mathrm{BAR})$	EXPERT DATA	CONDITIONS FOR DATA CONSISTENCY			
		$P(\mathrm{I}\mid\mathrm{BAR}) \leq 1$	$P(\mathrm{I}\mid\mathrm{BAR}) \leq \frac{P(\mathrm{I})}{P(\mathrm{BAR})}$	$P(\mathrm{I}\mid\mathrm{BAR}) \geq \frac{P(\mathrm{I})+P(\mathrm{BAR})-1}{P(\mathrm{BAR})}$	$P(\mathrm{I}\mid\mathrm{BAR}) \geq 0$
$P(\mathrm{LO}\mid\mathrm{BAR})$	0.40	$0.40 \leq 1$	$0.40 \leq 0.45$	$0.40 \geq -1.58$	$0.40 \geq 0$
$P(\mathrm{LE}\mid\mathrm{BAR})$	0.40	$0.40 \leq 1$	$0.40 \leq 0.30$	$0.40 \geq -1.72$	$0.40 \geq 0$
$P(\mathrm{HSW}\mid\mathrm{BAR})$	0.60	$0.60 \leq 1$	$0.60 \leq 1.21$	$0.60 \geq -0.82$	$0.60 \geq 0$
$P(\mathrm{HSS}\mid\mathrm{BAR})$	0.60	$0.60 \leq 1$	$0.60 \leq 0.45$	$0.60 \geq -1.58$	$0.60 \geq 0$

Table A10.4: Consistency table for the expert data likelihhoods, showing that the likelihoods satisfy all the conditions for consistency with the axioms of probability (as outlined by Moskowitz and Sarin 1983). The shaded values indicate that a the condition is violated. See Table A10.3 for the values of *P*(BAR), *P*(LO), *P*(LE), *P*(HSW) and P(HSS), and Appendix 8 for abbreviations.

Appendix 11

FORMALIZATION OF THE LINEAR (GOAL) PROGRAMMING MODEL

The problem is to choose probabilities, based on the current inconsistant expert information, that are consistant with the axioms of probability. We opt for the concept of deviational variables and Tchebycheff aggregation, with Δ minimised by LP.

The decision variables are the 32 probabilities emanating from all possible combinations of:

R $\equiv$ Below Average Recruitment
X $\equiv$ Low (commercial) Oil Yield
Y $\equiv$ Low Daily Egg Production
Z $\equiv$ High (strong) Southerly Wind Index
J $\equiv$ High percentage of Starvation Stations

And take the form:

P_{RXYZJ} where R, X, Y, Z, J = 0 or 1

The only constraint is axiomatic; the 32 probabilities must sum to 1:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} P_{RXYZJ} = 1$$

(most LP computer programs assume the all variables are constrained to be non-negative, so the constraint that the individual $P_{RXYZJ} \geq 0$ is unnecessary).

Although inconsistant, we would like to be able to use the information we got from the experts as goals at which to aim for. A number of objectives were defined as follows:

(i) *For each prior/marginal probability, we would like to get as close to the expert estimated probability, with a measure of the deviation. We are trying to achieve:*

$$P(\mathrm{A}) = \overline{P(\mathrm{A})}$$

where $P(\mathrm{A})$ *and* $\overline{P(\mathrm{A})}$ *are the LP and expert assessed values respectively.*

$P(\mathrm{R}) \equiv$ Probability of Below Average Recruitment:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} \cdot P_{1XYZJ} - d_R^- + d_R^+ = \overline{P(R)}$$

$P(\mathrm{X}) \equiv$ Probability of Low (commercial) Oil Yield:

$$\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} \cdot P_{R1YZJ} - d_X^- + d_X^+ = \overline{P(X)}$$

$P(\mathrm{Y}) \equiv$ Probability of Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1} \cdot P_{RX1ZJ} - d_Y^- + d_Y^+ = \overline{P(Y)}$$

$P(\mathrm{Z}) \equiv$ Probability of High (strong) Southerly Winds:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{J=0}^{1} \cdot P_{RXY1J} - d_Z^- + d_Z^+ = \overline{P(Z)}$$

$P(\mathrm{J}) \equiv$ Probability of a High Percentage of Starvation Stations:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1} \cdot P_{RXYZ1} - d_J^- + d_J^+ = \overline{P(J)}$$

(ii) *For each first-order posterior and conditional probability, we would like to get as close to the expert estimated probability, with a measure of the deviation. We use a slightly different formulation to that for the prior/marginals above; we are however, still trying to achieve:*

$$P(\mathrm{A}|\mathrm{B}) = \overline{P(\mathrm{A}|\mathrm{B})}$$

where $P(\text{A}|\text{B})$ *and* $\overline{P(\text{A}|\text{B})}$ *are the LP and expert assessed values respectively. This equates to:*

$$\sum_{R=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1} P_{R1CD} = \overline{P(A|B)}.\sum_{R=0}^{1}\sum_{A=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1} P_{RACD}$$

$$= \overline{P(A|B)}.\sum_{R=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1}[P_{R0CD} + P_{R1CD}]$$

$$i.e. \quad \sum_{R=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1}[P_{R1CD} - \overline{P(A|B)}\{P_{R0CD} + P_{R1CD}\}] - d^{-}_{A|B} + d^{+}_{A|B} = 0$$

$$\sum_{R=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1}[P_{R1CD} - \overline{P(A|B)}\,P_{R0CD} - \overline{P(A|B)}\,P_{R1CD}] - d^{-}_{A|B} + d^{+}_{A|B} = 0$$

$$\sum_{R=0}^{1}\sum_{C=0}^{1}\sum_{D=0}^{1}[\{1 - \overline{P(A|B)}\}\,P_{R1CD} - \overline{P(A|B)}\,P_{R0CD}] - d^{-}_{A|B} + d^{+}_{A|B} = 0$$

$P(\text{R}|\text{X}) \equiv$ Probability of Below Average Recruitment given there is Low (commercial) Oil Yield:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1 - \overline{P(R|X)}\}\,P_{11YZJ} - \overline{P(R|X)}\,P_{01YZJ}] - d^{-}_{R|X} + d^{+}_{R|X} = 0$$

$P(\text{R}|\text{Y}) \equiv$ Probability of Below Average Recruitment given there is Low Daily Egg Production:

$$\sum_{X=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1 - \overline{P(R|Y)}\}\,P_{1X1ZJ} - \overline{P(R|Y)}\,P_{0X1ZJ}] - d^{-}_{R|Y} + d^{+}_{R|Y} = 0$$

$P(\text{R}|\text{Z}) \equiv$ Probability of Below Average Recruitment given there is High (strong) Southerly Winds:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1 - \overline{P(R|Z)}\}\,P_{1XY1J} - \overline{P(R|Z)}\,P_{0XY1J}] - d^{-}_{R|Z} + d^{+}_{R|Z} = 0$$

$P(\text{R}|\text{J}) \equiv$ Probability of Below Average Recruitment given there is a High Percentage of Starvation Stations:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1 - \overline{P(R|J)}\}\,P_{1XYZ1} - \overline{P(R|J)}\,P_{0XYZ1}] - d^{-}_{R|J} + d^{+}_{R|J} = 0$$

P(X|R) ≡ Probability of Low (commercial) Oil Yield given there is Below Average Recruitment:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|R)}\}P_{11YZJ}-\overline{P(X|R)}P_{10YZJ}]-d^{-}_{X|R}+d^{+}_{X|R}=0$$

P(X|Y) ≡ Probability of Low (commercial) Oil Yield given there is Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|Y)}\}P_{R11ZJ}-\overline{P(X|Y)}P_{R01ZJ}]-d^{-}_{X|Y}+d^{+}_{X|Y}=0$$

P(X|Z) ≡ Probability of Low (commercial) Oil Yield given there is High (strong) Southerly Winds:

$$\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|Z)}\}P_{R1Y1J}-\overline{P(X|Z)}P_{R0Y1J}]-d^{-}_{X|Z}+d^{+}_{X|Z}=0$$

P(X|J) ≡ Probability of Low (commercial) Oil Yield given there is a High Percentage of Starvation Stations:

$$\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(X|J)}\}P_{R1YZ1}-\overline{P(X|J)}P_{R0YZ1}]-d^{-}_{X|J}+d^{+}_{X|J}=0$$

P(Y|R) ≡ Probability of Low Daily Egg Production given there is Below Average Recruitment:

$$\sum_{X=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|R)}\}P_{1X1ZJ}-\overline{P(Y|R)}P_{1X0ZJ}]-d^{-}_{Y|R}+d^{+}_{Y|R}=0$$

P(Y|X) ≡ Probability of Low Daily Egg Production given there is Low (commercial) Oil Yield:

$$\sum_{R=0}^{1}\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|X)}\}P_{R11ZJ}-\overline{P(Y|X)}P_{R10ZJ}]-d^{-}_{Y|X}+d^{+}_{Y|X}=0$$

P(Y|Z) ≡ Probability of Low Daily Egg Production given there is High (strong) Southerly Winds:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|Z)}\}P_{RX11J}-\overline{P(Y|Z)}P_{RX01J}]-d^{-}_{Y|Z}+d^{+}_{Y|Z}=0$$

P(Y|J) ≡ Probability of Low Daily Egg Production given there is a High Percentage of Starvation Stations:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(Y|J)}\}P_{RXYZ1}-\overline{P(Y|J)}P_{RX0Z1}]-d_{Y|J}^{-}+d_{Y|J}^{+}=0$$

P(Z|R) ≡ Probability of High (strong) Southerly Winds given there is Below Average Recruitment:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|R)}\}P_{1XY1J}-\overline{P(Z|R)}P_{1XY0J}]-d_{Z|R}^{-}+d_{Z|R}^{+}=0$$

P(Z|X) ≡ Probability of High (strong) Southerly Winds given there is Low (commercial) Oil Yield:

$$\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|X)}\}P_{R1Y1J}-\overline{P(Z|X)}P_{R1Y0J}]-d_{Z|X}^{-}+d_{Z|X}^{+}=0$$

P(Z|Y) ≡ Probability of High (strong) Southerly Winds given there is Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|Y)}\}P_{RX11J}-\overline{P(Z|Y)}P_{RX10J}]-d_{Z|Y}^{-}+d_{Z|Y}^{+}=0$$

P(Z|J) ≡ Probability of High (strong) Southerly Winds given there is a High Percentage of Starvation Stations:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}[\{1-\overline{P(Z|J)}\}P_{RXY11}-\overline{P(Z|J)}P_{RXY01}]-d_{Z|J}^{-}+d_{Z|J}^{+}=0$$

P(J|R) ≡ Probability of a High Percentage of Starvation Stations given there is Below Average Recruitment:

$$\sum_{X=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|R)}\}P_{1XYZ1}-\overline{P(J|R)}P_{1XYZ0}]-d_{J|R}^{-}+d_{J|R}^{+}=0$$

P(J|X) ≡ Probability of a High Percentage of Starvation Stations given there is Low (commercial) Oil Yield:

$$\sum_{R=0}^{1}\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|X)}\}P_{R1YZ1}-\overline{P(J|X)}P_{R1YZ0}]-d_{J|X}^{-}+d_{J|X}^{+}=0$$

P(J|Y) ≡ Probability of a High Percentage of Starvation Stations given there is Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|Y)}\}P_{RX1Z1}-\overline{P(J|Y)}P_{RX1Z0}]-d^-_{J|Y}+d^+_{J|Y}=0$$

P(J|Z) ≡ Probability of a High Percentage of Starvation Stations given there is High (strong) Southerly Winds:

$$\sum_{R=0}^{1}\sum_{X=0}^{1}\sum_{Y=0}^{1}[\{1-\overline{P(J|Z)}\}P_{RXY11}-\overline{P(J|Z)}P_{RXY01}]-d^-_{J|Z}+d^+_{J|Z}=0$$

(iii) *For each second-order conditional probability, we would like to get as close to the expert estimated probability, with a measure of the deviation. We use the same formulation as for the first-order conditionals: ($\overline{P(A|BC)}$ is the expert estimated value)*

P(R|X,Y) ≡ Probability of Below Average Recruitment given there is Low Oil (commercial) Yield and Low Daily Egg Production:

$$\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(R|X,Y)}\}P_{11ZJ}-\overline{P(R|X,Y)}P_{01ZJ}]-d^-_{R|X,Y}+d^+_{R|X,Y}=0$$

P(R|X,Z) ≡ Probability of Below Average Recruitment given there is Low Oil (commercial) Yield and High (strong) Southerly Wind:

$$\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(R|X,Z)}\}P_{11Y1J}-\overline{P(R|X,Z)}P_{01Y1J}]-d^-_{R|X,Z}+d^+_{R|X,Z}=0$$

P(R|X,J) ≡ Probability of Below Average Recruitment given there is Low Oil (commercial) Yield and High Percentage Starvation Stations:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(R|X,J)}\}P_{11YZ1}-\overline{P(R|X,J)}P_{01YZ1}]-d^-_{R|X,J}+d^+_{R|X,J}=0$$

P(R|Y,Z) ≡ Probability of Below Average Recruitment given there is Low Daily Egg Production and High (strong) Southerly Wind:

$$\sum_{X=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(R|Y,Z)}\}P_{1X11J}-\overline{P(R|Y,Z)}P_{0X11J}]-d^-_{R|Y,Z}+d^+_{R|Y,Z}=0$$

P(R|Y,J) ≡ Probability of Below Average Recruitment given there is Low Daily Egg Production and High Percentage Starvation Stations:

$$\sum_{X=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(R|Y,J)}\}P_{1X1Z1}-\overline{P(R|Y,J)}P_{0X1Z1}]-d^{-}_{R|Y,J}+d^{+}_{R|Y,J}=0$$

P(X|R,Y) ≡ Probability of Low (commercial) Oil Yield given that there is Below Average Recruitment and Low Daily Egg Production:

$$\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|R,Y)}\}P_{111ZJ}-\overline{P(X|R,Y)}P_{101ZJ}]-d^{-}_{X|R,Y}+d^{+}_{X|R,Y}=0$$

P(X|R,Z) ≡ Probability of Low (commercial) Oil Yield given that there is Below Average Recruitment and High (strong) Southerly Wind:

$$\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|R,Z)}\}P_{11Y1J}-\overline{P(X|R,Z)}P_{10Y1J}]-d^{-}_{X|R,Z}+d^{+}_{X|R,Z}=0$$

P(X|R,J) ≡ Probability of Low (commercial) Oil Yield given that there is Below Average Recruitment and High Percentage Starvation Stations:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(X|R,J)}\}P_{11YZ1}-\overline{P(X|R,J)}P_{10YZ1}]-d^{-}_{X|R,J}+d^{+}_{X|R,J}=0$$

P(X|Y,Z) ≡ Probability of Low (commercial) Oil Yield given that there is Low Daily Egg Production and High (strong) Southerly Wind:

$$\sum_{R=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(X|Y,Z)}\}P_{R111J}-\overline{P(X|Y,Z)}P_{R011J}]-d^{-}_{X|Y,Z}+d^{+}_{X|Y,Z}=0$$

P(X|Y,J) ≡ Probability of Low (commercial) Oil Yield given that there is Probability of Daily Egg Production and High Percentage Starvation Stations:

$$\sum_{R=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(X|Y,J)}\}P_{R11Z1}-\overline{P(X|Y,J)}P_{R01Z1}]-d^{-}_{X|Y,J}+d^{+}_{X|Y,J}=0$$

P(Y|R,X) ≡ Probability of Low Daily Egg Production given that there is Below Average Recruitment and Low (commercial) Oil Yield:

$$\sum_{Z=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|R,X)}\}P_{111ZJ}-\overline{P(Y|R,X)}P_{110ZJ}]-d^{-}_{Y|R,X}+d^{+}_{Y|R,X}=0$$

P(Y|R,Z) ≡ Probability of Low Daily Egg Production given that there is Below Average Recruitment and High (strong) Southerly Wind:

$$\sum_{X=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|R,Z)}\}P_{1X11J}-\overline{P(Y|R,Z)}P_{1X01J}]-d^-_{Y|R,Z}+d^+_{Y|R,Z}=0$$

P(Y|R,J) ≡ Probability of Low Daily Egg Production given that there is Below Average Recruitment and High Percentage of Starvation Stations:

$$\sum_{X=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(Y|R,J)}\}P_{1X1Z1}-\overline{P(Y|R,J)}P_{1X0Z1}]-d^-_{Y|R,J}+d^+_{Y|R,J}=0$$

P(Y|X,Z) ≡ Probability of Daily Egg Production given that there is Low (commercial) Oil Yield and High (strong) Southerly Wind:

$$\sum_{R=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Y|X,Z)}\}P_{R111J}-\overline{P(Y|X,Z)}P_{R011J}]-d^-_{Y|X,Z}+d^+_{Y|X,Z}=0$$

P(Y|X,J) ≡ Probability of Daily Egg Production given that there is Low (commercial) Oil Yield and High Percentage Starvation Stations:

$$\sum_{R=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(Y|X,J)}\}P_{R11Z1}-\overline{P(Y|X,J)}P_{R01Z1}]-d^-_{Y|X,J}+d^+_{Y|X,J}=0$$

P(Z|R,X) ≡ Probability of High (strong) Southerly Wind given that there is Below Average Recruitment and Low (commercial) Oil Yield:

$$\sum_{Y=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|R,X)}\}P_{11Y1J}-\overline{P(Z|R,X)}P_{11Y0J}]-d^-_{Z|R,X}+d^+_{Z|R,X}=0$$

P(Z|R,Y) ≡ Probability of High (strong) Southerly Wind given that there is Below Average Recruitment and Low Daily Egg Production:

$$\sum_{X=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|R,Y)}\}P_{1X11J}-\overline{P(Z|R,Y)}P_{1X10J}]-d^-_{Z|R,Y}+d^+_{Z|R,Y}=0$$

P(Z|X,Y) ≡ Probability of High (strong) Southerly Wind given that there is Low (commercial) Oil Yield and Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{J=0}^{1}[\{1-\overline{P(Z|X,Y)}\}P_{R111J}-\overline{P(Z|X,Y)}P_{R110J}]-d^-_{Z|X,Y}+d^+_{Z|X,Y}=0$$

P(J|R,X) ≡ Probability of High Percentage Starvation Stations given that there is Below Average Recruitment an
d Low (commercial) Oil Yield:

$$\sum_{Y=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|R,X)}\}P_{11YZ1}-\overline{P(J|R,X)}P_{11YZ0}]-d^{-}_{J|R,X}+d^{+}_{J|R,X}=0$$

P(J|R,Y) ≡ Probability of High Percentage Starvation Stations given that there is Below Average Recruitment and Low Daily Egg Production:

$$\sum_{X=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|R,Y)}\}P_{1X1Z1}-\overline{P(J|R,Y)}P_{1X1Z0}]-d^{-}_{J|R,Y}+d^{+}_{J|R,Y}=0$$

P(J|X,Y) ≡ Probability of High Percentage Starvation Stations given that there is Low (commercial) Oil Yield and Low Daily Egg Production:

$$\sum_{R=0}^{1}\sum_{Z=0}^{1}[\{1-\overline{P(J|X,Y)}\}P_{R11Z1}-\overline{P(J|X,Y)}P_{R11Z0}]-d^{-}_{J|X,Y}+d^{+}_{J|X,Y}=0$$

(iv) *Minimise the absolute difference between the expert assessed probability and the LP assessed probability, Δ, such that:*

$\Delta + P_{RXYZJ} \geq 0.03125$ for all 32 combinations of R, X, Y, Z, J = 0 and 1

$\Delta - d^{-}_{x} - d^{+}_{x} \geq 0$ for all priors; x = R, X, Y, Z, J

$\Delta - d^{-}_{x|y} - d^{+}_{x|y} \geq 0$ for all first-order conditioning, for all combinations of x, y = R, X, Y, Z, J

$\Delta - d^{-}_{x|y,z} - d^{+}_{x|y,z} \geq 0$ for all second-order conditioning, for all combinations of x, y, z = R, X, Y, Z, J

Appendix 12

THE LINDO® INPUT MATRIX AND EXAMPLE OF LINDO® OUTPUT FILE

A12.1 LINDO® INPUT MATRIX

```
!*****************************************************
! 2nd Order Conditionals - EXPERT DATA - JLK REVISED
!**************************************=============
!
! Probabilities are of the form: P_RXYZJ, where 0 and 1 reflect "Off"
! and "On" status for each variable for all combinations......
!
! Define:  R = Below Average Recruitment
!          X = Low Commercial Oil Yield
!          Y = Low Daily Egg Production
!          Z = High (strong) Southerly Winds
!          J = High % Starvation Stations
!
!          dM - negative deviation
!          dP - positive deviation
!          D  - absolute deviation of current probabilities from
!               being consistant with the constraints
!
MIN D
SUBJECT TO
!
!-------------------------------------------------------------
!                The sum of all 32 probabilities must equal 1
!-------------------------------------------------------------
!
SUM) P_00000 + P_00001 + P_00011 + P_00101 + P_01001 + P_00111 +
     P_01011 + P_01101 + P_01111 + P_00010 + P_00110 + P_01010 +
     P_01110 + P_00100 + P_01100 + P_01000 + P_10000 + P_10001 +
     P_10011 + P_10101 + P_11001 + P_10111 + P_11011 + P_11101 +
     P_11111 + P_10010 + P_10110 + P_11010 + P_11110 + P_10100 +
     P_11100 + P_11000 = 1.00
!
!-------------------------------------------------------------
!                         The priors (marginals)
!-------------------------------------------------------------
!
1)   P_10000 + P_10001 + P_10011 + P_10101 + P_11001 + P_10111 +
     P_11011 + P_11101 + P_11111 + P_10010 + P_10110 + P_11010 +
     P_11110 + P_10100 + P_11100 + P_11000 - dM_R + dP_R = 0.39
2)   P_01001 + P_01011 + P_01101 + P_01111 + P_01010 + P_01110 +
```

```
      P_01100 + P_01000 + P_11001 + P_11011 + P_11101 + P_11111 +
      P_11010 + P_11110 + P_11100 + P_11000 - dM_X + dP_X = 0.38
  3)  P_00101 + P_00111 + P_01101 + P_01111 + P_00110 + P_01110 +
      P_00100 + P_01100 + P_10101 + P_10111 + P_11101 + P_11111 +
      P_10110 + P_11110 + P_10100 + P_11100 - dM_Y + dP_Y = 0.22
  4)  P_00011 + P_00111 + P_01011 + P_01111 + P_00010 + P_00110 +
      P_01010 + P_01110 + P_10011 + P_10111 + P_11011 + P_11111 +
      P_10010 + P_10110 + P_11010 + P_11110 - dM_Z + dP_Z = 0.48
  5)  P_00001 + P_00011 + P_00101 + P_01001 + P_00111 + P_01011 +
      P_01101 + P_01111 + P_10001 + P_10011 + P_10101 + P_11001 +
      P_10111 + P_11011 + P_11101 + P_11111 - dM_J + dP_J = 0.16
 !
 !-------------------------------------------------------------------
 !                       First order conditioning
 !-------------------------------------------------------------------
 !
 !
 !6) Skip: no goal for P(BAR|LO)
 !
 !
 !7) Skip: no goal for P(BAR|LE)
 !
 !
 !8) Skip: no goal for P(BAR|HSW)
 !
 !
 !9) Skip: no goal for P(BAR|HSS)
 !
 !-------------------------------------------------------------------
 10)  0.42P_11001 + 0.42P_11011 + 0.42P_11101 + 0.42P_11111 +
      0.42P_11010 + 0.42P_11110 + 0.42P_11100 + 0.42P_11000 -
      0.58P_10000 - 0.58P_10001 - 0.58P_10011 - 0.58P_10101 -
      0.58P_10111 - 0.58P_10010 - 0.58P_10110 - 0.58P_10100 -
      dM_X_R + dP_X_R = 0
 11)  0.40P_01101 + 0.40P_01111 + 0.40P_01110 + 0.40P_01100 +
      0.40P_11101 + 0.40P_11111 + 0.40P_11110 + 0.40P_11100 -
      0.60P_00101 - 0.60P_00111 - 0.60P_00110 - 0.60P_00100 -
      0.60P_10101 - 0.60P_10111 - 0.60P_10110 - 0.60P_10100 -
      dM_X_Y + dP_X_Y = 0
 12)  0.60P_01011 + 0.60P_01111 + 0.60P_01010 + 0.60P_01110 +
      0.60P_11011 + 0.60P_11111 + 0.60P_11010 + 0.60P_11110 -
      0.40P_00011 - 0.40P_00111 - 0.40P_00010 - 0.40P_00110 -
      0.40P_10011 - 0.40P_10111 - 0.40P_10010 - 0.40P_10110 -
      dM_X_Z + dP_X_Z = 0
 13)  0.60P_01001 + 0.60P_01011 + 0.60P_01101 + 0.60P_01111 +
      0.60P_11001 + 0.60P_11011 + 0.60P_11101 + 0.60P_11111 -
      0.40P_00001 - 0.40P_00011 - 0.40P_00101 - 0.40P_00111 -
      0.40P_10001 - 0.40P_10011 - 0.40P_10101 - 0.40P_10111 -
      dM_X_J + dP_X_J = 0
 !-------------------------------------------------------------------
 14)  0.67P_10101 + 0.67P_10111 + 0.67P_11101 + 0.67P_11111 +
      0.67P_10110 + 0.67P_11110 + 0.67P_10100 + 0.67P_11100 -
      0.33P_10000 - 0.33P_10001 - 0.33P_10011 - 0.33P_11001 -
      0.33P_11011 - 0.33P_10010 - 0.33P_11010 - 0.33P_11000 -
      dM_Y_R + dP_Y_R = 0
 15)  0.60P_01101 + 0.60P_01111 + 0.60P_01110 + 0.60P_01100 +
      0.60P_11101 + 0.60P_11111 + 0.60P_11110 + 0.60P_11100 -
      0.40P_11001 - 0.40P_11011 - 0.40P_11010 - 0.40P_11000 -
      0.40P_01001 - 0.40P_01011 - 0.40P_01010 - 0.40P_01000 -
      dM_Y_X + dP_Y_X = 0
```

```
16)  0.80P_00111 + 0.80P_01111 + 0.80P_00110 + 0.80P_01110 +
     0.80P_10111 + 0.80P_11111 + 0.80P_10110 + 0.80P_11110 -
     0.20P_00011 - 0.20P_01011 - 0.20P_00010 - 0.20P_01010 -
     0.20P_10011 - 0.20P_11011 - 0.20P_10010 - 0.20P_11010 -
     dM_Y_Z + dP_Y_Z = 0
17)  0.60P_00101 + 0.60P_00111 + 0.60P_01101 + 0.60P_01111 +
     0.60P_10101 + 0.60P_10111 + 0.60P_11101 + 0.60P_11111 -
     0.40P_00001 - 0.40P_00011 - 0.40P_01001 - 0.40P_01011 -
     0.40P_10001 - 0.40P_10011 - 0.40P_11001 - 0.40P_11011 -
     dM_Y_J + dP_Y_J = 0
!--------------------------------------------------------------------
18)  0.45P_10011 + 0.40P_10111 + 0.45P_11011 + 0.45P_11111 +
     0.45P_10010 + 0.45P_10110 + 0.45P_11010 + 0.45P_11110 -
     0.55P_10000 - 0.55P_10001 - 0.55P_10101 - 0.55P_11001 -
     0.55P_11101 - 0.55P_10100 - 0.55P_11100 - 0.55P_11000 -
     dM_Z_R + dP_Z_R = 0
19)  0.52P_01011 + 0.52P_01111 + 0.52P_01010 + 0.52P_01110 +
     0.52P_11011 + 0.52P_11111 + 0.52P_11010 + 0.52P_11110 -
     0.48P_11001 - 0.48P_11101 - 0.48P_11100 - 0.48P_11000 -
     0.48P_01001 - 0.48P_01101 - 0.48P_01100 - 0.48P_01000 -
     dM_Z_X + dP_Z_X = 0
20)  0.52P_00111 + 0.52P_01111 + 0.52P_00110 + 0.52P_01110 +
     0.52P_10111 + 0.52P_11111 + 0.52P_10110 + 0.52P_11110 -
     0.48P_00101 - 0.48P_01101 - 0.48P_00100 - 0.48P_01100 -
     0.48P_10101 - 0.48P_11101 - 0.48P_10100 - 0.48P_11100 -
     dM_Z_Y + dP_Z_Y = 0
21)  0.52P_00111 + 0.52P_01111 + 0.52P_00011 + 0.52P_01011 +
     0.52P_10111 + 0.52P_11111 + 0.52P_10011 + 0.52P_11011 -
     0.48P_00101 - 0.48P_01101 - 0.48P_00001 - 0.48P_01001 -
     0.48P_10101 - 0.48P_11101 - 0.48P_10001 - 0.48P_11001 -
     dM_Z_J + dP_Z_J = 0
!--------------------------------------------------------------------
22)  0.57P_10001 + 0.57P_10011 + 0.57P_10101 + 0.57P_11001 +
     0.57P_10111 + 0.57P_11011 + 0.57P_11101 + 0.57P_11111 -
     0.43P_10000 - 0.43P_10010 - 0.43P_10110 - 0.43P_11010 -
     0.43P_11110 - 0.43P_10100 - 0.43P_11100 - 0.43P_11000 -
     dM_J_R + dP_J_R = 0
23)  0.80P_01001 + 0.80P_01011 + 0.80P_01101 + 0.80P_01111 +
     0.80P_11001 + 0.80P_11011 + 0.80P_11101 + 0.80P_11111 -
     0.20P_11010 - 0.20P_11110 - 0.20P_11100 - 0.20P_11000 -
     0.20P_01010 - 0.20P_01110 - 0.20P_01100 - 0.20P_01000 -
     dM_J_X + dP_J_X = 0
24)  0.40P_00101 + 0.40P_00111 + 0.40P_01101 + 0.40P_01111 +
     0.40P_10101 + 0.40P_10111 + 0.40P_11101 + 0.40P_11111 -
     0.60P_00110 - 0.60P_01110 - 0.60P_00100 - 0.60P_01100 -
     0.60P_10110 - 0.60P_11110 - 0.60P_10100 - 0.60P_11100 -
     dM_J_Y + dP_J_Y = 0
25)  0.80P_00011 + 0.80P_00111 + 0.80P_01011 + 0.80P_01111 +
     0.80P_10011 + 0.80P_10111 + 0.80P_11011 + 0.80P_11111 -
     0.20P_00010 - 0.20P_00110 - 0.20P_01010 - 0.20P_01110 -
     0.20P_10010 - 0.20P_10110 - 0.20P_11010 - 0.20P_11110 -
     dM_J_Z + dP_J_Z = 0
!--------------------------------------------------------------------
!                      Second order conditioning
!--------------------------------------------------------------------
!
!26)  Skip: no goal for P(BAR|LO,LE)
!
!27)  Skip: no goal for P(BAR|LO,HSW)
!
```

```
!28)  Skip: no goal for P(BAR|LO,HSS)
!
!29)  Skip: no goal for P(BAR|LE,HSW)
!
!30)  Skip: no goal for P(BAR|LE,HSS)
!
!-----------------------------------------------------------------------
31)  0.40P_11100 + 0.40P_11110 + 0.40P_11101 + 0.40P_11111 -
     0.60P_10100 - 0.60P_10110 - 0.60P_10101 - 0.60P_10111 -
     dM_X_RY + dP_X_RY = 0
32)  0.40P_11010 + 0.40P_11110 + 0.40P_11011 + 0.40P_11111 -
     0.60P_10010 - 0.60P_10110 - 0.60P_10011 - 0.60P_10111 -
     dM_X_RZ + dP_X_RZ = 0
33)  0.40P_11001 + 0.40P_11101 + 0.40P_11011 + 0.40P_11111 -
     0.60P_10001 - 0.60P_10101 - 0.60P_10011 - 0.60P_10111 -
     dM_X_RJ + dP_X_RJ = 0
34)  0.40P_01110 + 0.40P_11110 + 0.40P_01111 + 0.40P_11111 -
     0.60P_00110 - 0.60P_10110 - 0.60P_00111 - 0.60P_10111 -
     dM_X_YZ + dP_X_YZ = 0
35)  0.40P_01101 + 0.40P_11101 + 0.40P_01111 + 0.40P_11111 -
     0.60P_00101 - 0.60P_10101 - 0.60P_00111 - 0.60P_10111 -
     dM_X_YJ + dP_X_YJ = 0
36)  0.60P_01011 + 0.60P_11011 + 0.60P_01111 + 0.60P_11111 -
     0.40P_00011 - 0.40P_10011 - 0.40P_00111 - 0.40P_10111 -
     dM_X_ZJ + dP_X_ZJ = 0
!-----------------------------------------------------------------------
37)  0.40P_11100 + 0.40P_11110 + 0.40P_11101 + 0.40P_11111 -
     0.60P_11000 - 0.60P_11010 - 0.60P_11001 - 0.60P_11011 -
     dM_Y_RX + dP_Y_RX = 0
38)  0.67P_10110 + 0.67P_11110 + 0.67P_10111 + 0.67P_11111 -
     0.33P_10010 - 0.33P_11010 - 0.33P_10011 - 0.33P_11011 -
     dM_Y_RZ + dP_Y_RZ = 0
39)  0.40P_10101 + 0.40P_11101 + 0.40P_10111 + 0.40P_11111 -
     0.60P_10001 - 0.60P_11001 - 0.60P_10011 - 0.60P_11011 -
     dM_Y_RJ + dP_Y_RJ = 0
40)  0.60P_01110 + 0.60P_11110 + 0.60P_01111 + 0.60P_11111 -
     0.40P_01010 - 0.40P_11010 - 0.40P_01011 - 0.40P_11011 -
     dM_Y_XZ + dP_Y_XZ = 0
41)  0.40P_01101 + 0.40P_11101 + 0.40P_01111 + 0.40P_11111 -
     0.60P_01001 - 0.60P_11001 - 0.60P_01011 - 0.60P_11011 -
     dM_Y_XJ + dP_Y_XJ = 0
42)  0.60P_00111 + 0.60P_10111 + 0.60P_01111 + 0.60P_11111 -
     0.40P_00011 - 0.40P_10011 - 0.40P_01011 - 0.40P_11011 -
     dM_Y_ZJ + dP_Y_ZJ = 0
!-----------------------------------------------------------------------
43)  0.45P_11010 + 0.45P_11110 + 0.45P_11011 + 0.45P_11111 -
     0.55P_11000 - 0.55P_11100 - 0.55P_11001 - 0.55P_11101 -
     dM_Z_RX + dP_Z_RX = 0
44)  0.45P_10110 + 0.45P_11110 + 0.45P_10111 + 0.45P_11111 -
     0.55P_10100 - 0.55P_11100 - 0.55P_10101 - 0.55P_11101 -
     dM_Z_RY + dP_Z_RY = 0
45)  0.45P_10011 + 0.45P_11011 + 0.45P_10111 + 0.45P_11111 -
     0.55P_10001 - 0.55P_11001 - 0.55P_10101 - 0.55P_11101 -
     dM_Z_RJ + dP_Z_RJ = 0
46)  0.52P_01110 + 0.52P_11110 + 0.52P_01111 + 0.52P_11111 -
     0.48P_01100 - 0.48P_11100 - 0.48P_01101 - 0.48P_11101 -
     dM_Z_XY + dP_Z_XY = 0
47)  0.52P_01011 + 0.52P_11011 + 0.52P_01111 + 0.52P_11111 -
     0.48P_01001 - 0.48P_11001 - 0.48P_01101 - 0.48P_11101 -
     dM_Z_XJ + dP_Z_XJ = 0
```

```
48)    0.52P_00111 + 0.52P_10111 + 0.52P_01111 + 0.52P_11111 -
       0.48P_00101 - 0.48P_10101 - 0.48P_01101 - 0.48P_11101 -
       dM_Z_YJ + dP_Z_YJ = 0
!-----------------------------------------------------------------
49)    0.57P_11001 + 0.57P_11101 + 0.57P_11011 + 0.57P_11111 -
       0.43P_11000 - 0.43P_11100 - 0.43P_11010 - 0.43P_11110 -
       dM_J_RX + dP_J_RX = 0
50)    0.40P_10101 + 0.40P_11101 + 0.40P_10111 + 0.40P_11111 -
       0.60P_10100 - 0.60P_11100 - 0.60P_10110 - 0.60P_11110 -
       dM_J_RY + dP_J_RY = 0
51)    0.57P_10011 + 0.57P_11011 + 0.57P_10111 + 0.57P_11111 -
       0.43P_10010 - 0.43P_11010 - 0.43P_10110 - 0.43P_11110 -
       dM_J_RZ + dP_J_RZ = 0
52)    0.40P_01101 + 0.40P_11101 + 0.40P_01111 + 0.40P_11111 -
       0.60P_01100 - 0.60P_11100 - 0.60P_01110 - 0.60P_11110 -
       dM_J_XY + dP_J_XY = 0
53)    0.80P_01011 + 0.80P_11011 + 0.80P_01111 + 0.80P_11111 -
       0.20P_01010 - 0.20P_11010 - 0.20P_01110 - 0.20P_11110 -
       dM_J_XZ + dP_J_XZ = 0
54)    0.40P_00111 + 0.40P_10111 + 0.40P_01111 + 0.40P_11111 -
       0.60P_00110 - 0.60P_10110 - 0.60P_01110 - 0.60P_11110 -
       dM_J_YZ + dP_J_YZ = 0
!-----------------------------------------------------------------
!              Goals for the individual probabilities (1/32)
!-----------------------------------------------------------------
!
55)    D + P_00000 >= 0.03125
56)    D + P_00001 >= 0.03125
57)    D + P_00011 >= 0.03125
58)    D + P_00101 >= 0.03125
59)    D + P_01001 >= 0.03125
60)    D + P_00111 >= 0.03125
61)    D + P_01011 >= 0.03125
62)    D + P_01101 >= 0.03125
63)    D + P_01111 >= 0.03125
64)    D + P_00010 >= 0.03125
65)    D + P_00110 >= 0.03125
66)    D + P_01010 >= 0.03125
67)    D + P_01110 >= 0.03125
68)    D + P_00100 >= 0.03125
69)    D + P_01100 >= 0.03125
70)    D + P_01000 >= 0.03125
71)    D + P_10000 >= 0.03125
72)    D + P_10001 >= 0.03125
73)    D + P_10011 >= 0.03125
74)    D + P_10101 >= 0.03125
75)    D + P_11001 >= 0.03125
76)    D + P_10111 >= 0.03125
77)    D + P_11011 >= 0.03125
78)    D + P_11101 >= 0.03125
79)    D + P_11111 >= 0.03125
80)    D + P_10010 >= 0.03125
81)    D + P_10110 >= 0.03125
82)    D + P_11010 >= 0.03125
83)    D + P_11110 >= 0.03125
84)    D + P_10100 >= 0.03125
85)    D + P_11100 >= 0.03125
86)    D + P_11000 >= 0.03125
!
```

```
!-------------------------------------------------------------------
!                   Deviationals for Priors (marginals)
!-------------------------------------------------------------------
!
87)  D - dM_R - dP_R >= 0
88)  D - dM_X - dP_X >= 0
89)  D - dM_Y - dP_Y >= 0
90)  D - dM_Z - dP_Z >= 0
91)  D - dM_J - dP_J >= 0
!
!-------------------------------------------------------------------
!              Deviationals for First order conditionals
!-------------------------------------------------------------------
!
92)  D - dM_R_X - dP_R_X >= 0
93)  D - dM_R_Y - dP_R_Y >= 0
94)  D - dM_R_Z - dP_R_Z >= 0
95)  D - dM_R_J - dP_R_J >= 0
!-------------------------------------------------------------------
96)  D - dM_X_R - dP_X_R >= 0
97)  D - dM_X_Y - dP_X_Y >= 0
98)  D - dM_X_Z - dP_X_Z >= 0
99)  D - dM_X_J - dP_X_J >= 0
!-------------------------------------------------------------------
100) D - dM_Y_R - dP_Y_R >= 0
101) D - dM_Y_X - dP_Y_X >= 0
102) D - dM_Y_Z - dP_Y_Z >= 0
103) D - dM_Y_J - dP_Y_J >= 0
!-------------------------------------------------------------------
104) D - dM_Z_R - dP_Z_R >= 0
105) D - dM_Z_X - dP_Z_X >= 0
106) D - dM_Z_Y - dP_Z_Y >= 0
107) D - dM_Z_J - dP_Z_J >= 0
!-------------------------------------------------------------------
108) D - dM_J_R - dP_J_R >= 0
109) D - dM_J_X - dP_J_X >= 0
110) D - dM_J_Y - dP_J_Y >= 0
111) D - dM_J_Z - dP_J_Z >= 0
!
!-------------------------------------------------------------------
!             Deviationals for Second order conditionals
!-------------------------------------------------------------------
!
112) D - dM_X_RY - dP_X_RY >= 0
113) D - dM_X_RZ - dP_X_RZ >= 0
114) D - dM_X_RJ - dP_X_RJ >= 0
115) D - dM_X_YZ - dP_X_YZ >= 0
116) D - dM_X_YJ - dP_X_YJ >= 0
117) D - dM_X_ZJ - dP_X_ZJ >= 0
!-------------------------------------------------------------------
118) D - dM_Y_RX - dP_Y_RX >= 0
119) D - dM_Y_RZ - dP_Y_RZ >= 0
120) D - dM_Y_RJ - dP_Y_RJ >= 0
121) D - dM_Y_XZ - dP_Y_XZ >= 0
122) D - dM_Y_XJ - dP_Y_XJ >= 0
123) D - dM_Y_ZJ - dP_Y_ZJ >= 0
!-------------------------------------------------------------------
124) D - dM_Z_RX - dP_Z_RX >= 0
125) D - dM_Z_RY - dP_Z_RY >= 0
126) D - dM_Z_RJ - dP_Z_RJ >= 0
```

```
127) D - dM_Z_XY - dP_Z_XY >= 0
128) D - dM_Z_XJ - dP_Z_XJ >= 0
129) D - dM_Z_YJ - dP_Z_YJ >= 0
!-------------------------------------------------------------------
130) D - dM_J_RX - dP_J_RX >= 0
131) D - dM_J_RY - dP_J_RY >= 0
132) D - dM_J_RZ - dP_J_RZ >= 0
133) D - dM_J_XY - dP_J_XY >= 0
134) D - dM_J_XZ - dP_J_XZ >= 0
135) D - dM_J_YZ - dP_J_YZ >= 0
!-------------------------------------------------------------------
END
```

A12.2 LINDO® OUTPUT FILE

```
 LP OPTIMUM FOUND AT STEP    248

        OBJECTIVE FUNCTION VALUE

        1)      0.2470757E-01

  VARIABLE        VALUE          REDUCED COST
         D         0.024708          0.000000
   P_00000         0.203973          0.000000
   P_00001         0.006542          0.000000
   P_00011         0.006542          0.000000
   P_00101         0.006542          0.000000
   P_01001         0.006542          0.000000
   P_00111         0.006542          0.000000
   P_01011         0.006542          0.000000
   P_01101         0.006542          0.000000
   P_01111         0.006542          0.000000
   P_00010         0.208332          0.000000
   P_00110         0.006542          0.000000
   P_01010         0.069959          0.000000
   P_01110         0.006542          0.000000
   P_00100         0.021560          0.000000
   P_01100         0.006542          0.000000
   P_01000         0.058917          0.000000
   P_10000         0.008504          0.000000
   P_10001         0.046443          0.000000
   P_10011         0.006542          0.000000
   P_10101         0.017069          0.000000
   P_11001         0.006542          0.000000
   P_10111         0.006542          0.000000
   P_11011         0.006542          0.000000
   P_11101         0.006542          0.000000
   P_11111         0.036145          0.000000
   P_10010         0.079945          0.000000
   P_10110         0.006542          0.000000
   P_11010         0.026561          0.000000
   P_11110         0.018341          0.000000
   P_10100         0.006542          0.000000
   P_11100         0.030211          0.000000
   P_11000         0.056276          0.000000
      DM_R         0.000000          0.082454
      DP_R         0.024708          0.000000
      DM_X         0.000000          0.000000
      DP_X         0.024708          0.000000
      DM_Y         0.000000          0.000000
      DP_Y         0.024708          0.000000
      DM_Z         0.024708          0.000000
      DP_Z         0.000000          0.000000
      DM_J         0.024708          0.000000
      DP_J         0.000000          0.191755
    DM_X_R         0.000000          0.000000
    DP_X_R         0.024708          0.000000
    DM_X_Y         0.012471          0.000000
    DP_X_Y         0.012237          0.000000
    DM_X_Z         0.000000          0.000000
    DP_X_Z         0.024708          0.000000
    DM_X_J         0.016383          0.000000
```

DP_X_J	0.008324	0.000000
DM_Y_R	0.007389	0.000000
DP_Y_R	0.000000	0.000000
DM_Y_X	0.000000	0.000000
DP_Y_X	0.024708	0.000000
DM_Y_Z	0.008753	0.000000
DP_Y_Z	0.015954	0.000000
DM_Y_J	0.018585	0.000000
DP_Y_J	0.000000	0.000000
DM_Z_R	0.005316	0.000000
DP_Z_R	0.019392	0.000000
DM_Z_X	0.015671	0.000000
DP_Z_X	0.009036	0.000000
DM_Z_Y	0.000000	0.000000
DP_Z_Y	0.000000	0.000000
DM_Z_J	0.000000	0.000000
DP_Z_J	0.006718	0.000000
DM_J_R	0.000000	0.191755
DP_J_R	0.024708	0.000000
DM_J_X	0.017795	0.000000
DP_J_X	0.006912	0.000000
DM_J_Y	0.000000	0.000000
DP_J_Y	0.024708	0.000000
DM_J_Z	0.002854	0.000000
DP_J_Z	0.021854	0.000000
DM_X_RY	0.019593	0.000000
DP_X_RY	0.005115	0.000000
DM_X_RZ	0.000000	0.000000
DP_X_RZ	0.024708	0.000000
DM_X_RJ	0.000529	0.000000
DP_X_RJ	0.024178	0.000000
DM_X_YZ	0.018017	0.000000
DP_X_YZ	0.006691	0.000000
DM_X_YJ	0.012499	0.000000
DP_X_YJ	0.012208	0.000000
DM_X_ZJ	0.023851	0.000000
DP_X_ZJ	0.000856	0.000000
DM_Y_RX	0.001825	0.000000
DP_Y_RX	0.022883	0.000000
DM_Y_RZ	0.015257	0.000000
DP_Y_RZ	0.009450	0.000000
DM_Y_RJ	0.000000	0.000000
DP_Y_RJ	0.013123	0.000000
DM_Y_XZ	0.010704	0.000000
DP_Y_XZ	0.014004	0.000000
DM_Y_XJ	0.015657	0.000000
DP_Y_XJ	0.009050	0.000000
DM_Y_ZJ	0.023851	0.000000
DP_Y_ZJ	0.000856	0.000000
DM_Z_RX	0.000000	0.000000
DP_Z_RX	0.015349	0.000000
DM_Z_RY	0.010957	0.000000
DP_Z_RY	0.013751	0.000000
DM_Z_RJ	0.000000	0.000000
DP_Z_RJ	0.017030	0.000000
DM_Z_XY	0.017961	0.000000
DP_Z_XY	0.006747	0.000000
DM_Z_XJ	0.020574	0.000000
DP_Z_XJ	0.004134	0.000000
DM_Z_YJ	0.018048	0.000000

DP_Z_YJ	0.006660	0.000000
DM_J_RX	0.000000	0.000000
DP_J_RX	0.024708	0.000000
DM_J_RY	0.007122	0.000000
DP_J_RY	0.017585	0.000000
DM_J_RZ	0.000000	0.000000
DP_J_RZ	0.024708	0.000000
DM_J_XY	0.005017	0.000000
DP_J_XY	0.019691	0.000000
DM_J_XZ	0.022522	0.000000
DP_J_XZ	0.002185	0.000000
DM_J_YZ	0.000000	0.000000
DP_J_YZ	0.000472	0.000000
DM_R_X	0.000000	0.000000
DP_R_X	0.000000	0.000000
DM_R_Y	0.000000	0.000000
DP_R_Y	0.000000	0.000000
DM_R_Z	0.000000	0.000000
DP_R_Z	0.000000	0.000000
DM_R_J	0.000000	0.000000
DP_R_J	0.000000	0.000000

ROW	SLACK OR SURPLUS	DUAL PRICES
SUM)	0.000000	0.000000
1)	0.000000	-0.041227
2)	0.000000	0.000000
3)	0.000000	0.000000
4)	0.000000	0.000000
5)	0.000000	0.095877
10)	0.000000	0.000000
11)	0.000000	0.000000
12)	0.000000	0.000000
13)	0.000000	0.000000
14)	0.000000	0.000000
15)	0.000000	0.000000
16)	0.000000	0.000000
17)	0.000000	0.000000
18)	0.000000	0.000000
19)	0.000000	0.000000
20)	0.000000	0.000000
21)	0.000000	0.000000
22)	0.000000	-0.095877
23)	0.000000	0.000000
24)	0.000000	0.000000
25)	0.000000	0.000000
31)	0.000000	0.000000
32)	0.000000	0.000000
33)	0.000000	0.000000
34)	0.000000	0.000000
35)	0.000000	0.000000
36)	0.000000	0.000000
37)	0.000000	0.000000
38)	0.000000	0.000000
39)	0.000000	0.000000
40)	0.000000	0.000000
41)	0.000000	0.000000
42)	0.000000	0.000000
43)	0.000000	0.000000
44)	0.000000	0.000000

45)	0.000000	0.000000
46)	0.000000	0.000000
47)	0.000000	0.000000
48)	0.000000	0.000000
49)	0.000000	0.000000
50)	0.000000	0.000000
51)	0.000000	0.000000
52)	0.000000	0.000000
53)	0.000000	0.000000
54)	0.000000	0.000000
55)	0.197430	0.000000
56)	0.000000	-0.095877
57)	0.000000	-0.095877
58)	0.000000	-0.095877
59)	0.000000	-0.095877
60)	0.000000	-0.095877
61)	0.000000	-0.095877
62)	0.000000	-0.095877
63)	0.000000	-0.095877
64)	0.201790	0.000000
65)	0.000000	0.000000
66)	0.063416	0.000000
67)	0.000000	0.000000
68)	0.015018	0.000000
69)	0.000000	0.000000
70)	0.052375	0.000000
71)	0.001962	0.000000
72)	0.039900	0.000000
73)	0.000000	0.000000
74)	0.010526	0.000000
75)	0.000000	0.000000
76)	0.000000	0.000000
77)	0.000000	0.000000
78)	0.000000	0.000000
79)	0.029602	0.000000
80)	0.073403	0.000000
81)	0.000000	0.000000
82)	0.020019	0.000000
83)	0.011799	0.000000
84)	0.000000	0.000000
85)	0.023669	0.000000
86)	0.049734	0.000000
87)	0.000000	-0.041227
88)	0.000000	0.000000
89)	0.000000	0.000000
90)	0.000000	0.000000
91)	0.000000	-0.095877
92)	0.024708	0.000000
93)	0.024708	0.000000
94)	0.024708	0.000000
95)	0.024708	0.000000
96)	0.000000	0.000000
97)	0.000000	0.000000
98)	0.000000	0.000000
99)	0.000000	0.000000
100)	0.017319	0.000000
101)	0.000000	0.000000
102)	0.000000	0.000000
103)	0.006123	0.000000
104)	0.000000	0.000000

105)	0.000000	0.000000
106)	0.024708	0.000000
107)	0.017990	0.000000
108)	0.000000	-0.095877
109)	0.000000	0.000000
110)	0.000000	0.000000
111)	0.000000	0.000000
112)	0.000000	0.000000
113)	0.000000	0.000000
114)	0.000000	0.000000
115)	0.000000	0.000000
116)	0.000000	0.000000
117)	0.000000	0.000000
118)	0.000000	0.000000
119)	0.000000	0.000000
120)	0.011585	0.000000
121)	0.000000	0.000000
122)	0.000000	0.000000
123)	0.000000	0.000000
124)	0.009358	0.000000
125)	0.000000	0.000000
126)	0.007677	0.000000
127)	0.000000	0.000000
128)	0.000000	0.000000
129)	0.000000	0.000000
130)	0.000000	0.000000
131)	0.000000	0.000000
132)	0.000000	0.000000
133)	0.000000	0.000000
134)	0.000000	0.000000
135)	0.024235	0.000000

NO. ITERATIONS= 248

Appendix 13

SOURCE CODE FOR PROGRAM TO READ AND CONVERT LINDO® OUTPUT FILE, AND EXAMPLE OF CONVERTED OUTPUT FILE

A13.1 LINDO® OUTPUT FILE CONVERSION PROGRAM

The code below list the TURBO Pascal® source for the program, *CALCULATE_LINDO_OUTPUT*, that reads the LINDO® output file, and calculates the final output probabilities (posterior probabilities and likelihoods) from their component bits (saves LOTS of time over doing doing it by hand and calculator.....). The program assumes the existance of an input file, INPUT.TXT, in the correct format - that is, a single column of figures (modified LINDO® output file) - each number corresponding to a particular LINDO® variable, which are read in specific order.

```
{ |  Written in TURBO PASCAL Version 7.0
  |
  |  BY:   JAN L. KORRUBEL - Marine Biology Research Institute (MBRI)
  |                         Department of Zoology
  |                         University of Cape Town
  |
  |  DATE: June '95
  |
  |  This program does the reading of my LINDO output files, and the
  |     calculating of the final probabilities.  You didn't really think
  |     I was going to do all that by hand did you.....???
  |
  |                        *********************
  |                      SECOND-ORDER CONDITIONALS
  |                        *********************
  |                         JLK REVISED DATASET
  |                        *********************
}
```

```
PROGRAM Calculate_LINDO_Output_JLKREV;

VAR
{
  Gyppo Global Variables - accessable throughout the entire program
                         - easier than having to pass parameters!!

  Abbreviations:  dM -- Minus and Plus Deviational Variables
                  dP /        for the LP
                  R  - Below Average Recruitment
                  X  - Low Oil Content
                  Y  - Low Egg Production
                  Z  - High southerly wind index
                  J  - High % Starvation Stations (Low food index)
}
   { All 32 Possible Probabilities }
   P_00000, P_00001, P_00011, P_00101, P_01001, P_00111,
   P_01011, P_01101, P_01111, P_00010, P_00110, P_01010,
   P_01110, P_00100, P_01100, P_01000,
   P_10000, P_10001, P_10011, P_10101, P_11001, P_10111,
   P_11011, P_11101, P_11111, P_10010, P_10110, P_11010,
   P_11110, P_10100, P_11100, P_11000,

   { Deviational Variables on the Priors}
   DM_R, DP_R,  { MINUS and PLUS deviations for Recruitment }
   DM_X, DP_X,  { MINUS and PLUS deviations for Oil Yield }
   DM_Y, DP_Y,  { MINUS and PLUS deviations for Egg Production }
   DM_Z, DP_Z,  { MINUS and PLUS deviations for Southerly Wind Index }
   DM_J, DP_J,  { MINUS and PLUS deviations for Starvation Stations }

   { Deviational Variables on the First-Order Conditionals }
   DM_X_R, DP_X_R, DM_X_Y, DP_X_Y, DM_X_Z, DP_X_Z, DM_X_J, DP_X_J,
   DM_Y_R, DP_Y_R, DM_Y_X, DP_Y_X, DM_Y_Z, DP_Y_Z, DM_Y_J, DP_Y_J,
   DM_Z_R, DP_Z_R, DM_Z_X, DP_Z_X, DM_Z_Y, DP_Z_Y, DM_Z_J, DP_Z_J,
   DM_J_R, DP_J_R, DM_J_X, DP_J_X, DM_J_Y, DP_J_Y, DM_J_Z, DP_J_Z,

   { Deviational Variables on the Second-Order Conditionals }
   DM_X_RY, DP_X_RY, DM_X_RZ, DP_X_RZ, DM_X_RJ, DP_X_RJ,
   DM_X_YZ, DP_X_YZ, DM_X_YJ, DP_X_YJ, DM_X_ZJ, DP_X_ZJ,

   DM_Y_RX, DP_Y_RX, DM_Y_RZ, DP_Y_RZ, DM_Y_RJ, DP_Y_RJ,
   DM_Y_XZ, DP_Y_XZ, DM_Y_XJ, DP_Y_XJ, DM_Y_ZJ, DP_Y_ZJ,

   DM_Z_RX, DP_Z_RX, DM_Z_RY, DP_Z_RY, DM_Z_RJ, DP_Z_RJ,
   DM_Z_XY, DP_Z_XY, DM_Z_XJ, DP_Z_XJ, DM_Z_YJ, DP_Z_YJ,

   DM_J_RX, DP_J_RX, DM_J_RY, DP_J_RY, DM_J_RZ, DP_J_RZ,
   DM_J_XY, DP_J_XY, DM_J_XZ, DP_J_XZ, DM_J_YZ, DP_J_YZ

   : REAL;

{---------------------------------------------------------------------}
{
   The output file CHECK.OUT can be used to cross-check that all input has
     been received correctly during the reading process.

}

PROCEDURE Get_Data;
```

```
VAR
   InFile,                    { Data Input File }
   CheckFile : TEXT;          { Data Checking File }

BEGIN
   {
    Open Input and Check Files 'Input.TXT' and 'Check.OUT'
   }
   ASSIGN( InFile, 'C:\LINDO\Revised.TXT' );
   RESET( InFile );
   ASSIGN( CheckFile, 'C:\LINDO\Chk_Rev.OUT' );
   REWRITE( CheckFile );
   {
    Prefer to do the read manually, because there are so many different
       variables to be read.
   }
   {
    Read all 32 Probabilities and dump them to Check.OUT
   }
   READLN( InFile, P_00000 );
   WRITELN( CheckFile, 'P_00000 =', P_00000:10:6 );
   READLN( InFile, P_00001 );
   WRITELN( CheckFile, 'P_00001 =', P_00001:10:6 );
   READLN( InFile, P_00011 );
   WRITELN( CheckFile, 'P_00011 =', P_00011:10:6 );
   READLN( InFile, P_00101 );
   WRITELN( CheckFile, 'P_00101 =', P_00101:10:6 );
   READLN( InFile, P_01001 );
   WRITELN( CheckFile, 'P_01001 =', P_01001:10:6 );
   READLN( InFile, P_00111 );
   WRITELN( CheckFile, 'P_00111 =', P_00111:10:6 );
   READLN( InFile, P_01011 );
   WRITELN( CheckFile, 'P_01011 =', P_01011:10:6 );
   READLN( InFile, P_01101 );
   WRITELN( CheckFile, 'P_01101 =', P_01101:10:6 );
   READLN( InFile, P_01111 );
   WRITELN( CheckFile, 'P_01111 =', P_01111:10:6 );
   READLN( InFile, P_00010 );
   WRITELN( CheckFile, 'P_00010 =', P_00010:10:6 );
   READLN( InFile, P_00110 );
   WRITELN( CheckFile, 'P_00110 =', P_00110:10:6 );
   READLN( InFile, P_01010 );
   WRITELN( CheckFile, 'P_01010 =', P_01010:10:6 );
   READLN( InFile, P_01110 );
   WRITELN( CheckFile, 'P_01110 =', P_01110:10:6 );
   READLN( InFile, P_00100 );
   WRITELN( CheckFile, 'P_00100 =', P_00100:10:6 );
   READLN( InFile, P_01100 );
   WRITELN( CheckFile, 'P_01100 =', P_01100:10:6 );
   READLN( InFile, P_01000 );
   WRITELN( CheckFile, 'P_01000 =', P_01000:10:6 );
   READLN( InFile, P_10000 );
   WRITELN( CheckFile, 'P_10000 =', P_10000:10:6 );
   READLN( InFile, P_10001 );
   WRITELN( CheckFile, 'P_10001 =', P_10001:10:6 );
   READLN( InFile, P_10011 );
   WRITELN( CheckFile, 'P_10011 =', P_10011:10:6 );
   READLN( InFile, P_10101 );
   WRITELN( CheckFile, 'P_10101 =', P_10101:10:6 );
   READLN( InFile, P_11001 );
```

```
WRITELN( CheckFile, 'P_11001 =', P_11001:10:6 );
READLN( InFile, P_10111 );
WRITELN( CheckFile, 'P_10111 =', P_10111:10:6 );
READLN( InFile, P_11011 );
WRITELN( CheckFile, 'P_11011 =', P_11011:10:6 );
READLN( InFile, P_11101 );
WRITELN( CheckFile, 'P_11101 =', P_11101:10:6 );
READLN( InFile, P_11111 );
WRITELN( CheckFile, 'P_11111 =', P_11111:10:6 );
READLN( InFile, P_10010 );
WRITELN( CheckFile, 'P_10010 =', P_10010:10:6 );
READLN( InFile, P_10110 );
WRITELN( CheckFile, 'P_10110 =', P_10110:10:6 );
READLN( InFile, P_11010 );
WRITELN( CheckFile, 'P_11010 =', P_11010:10:6 );
READLN( InFile, P_11110 );
WRITELN( CheckFile, 'P_11110 =', P_11110:10:6 );
READLN( InFile, P_10100 );
WRITELN( CheckFile, 'P_10100 =', P_10100:10:6 );
READLN( InFile, P_11100 );
WRITELN( CheckFile, 'P_11100 =', P_11100:10:6 );
READLN( InFile, P_11000 );
WRITELN( CheckFile, 'P_11000 =', P_11000:10:6 );

{
 Now Read the Deviational Variables on the Priors/Marginals
}
READLN( InFile, DM_R );
WRITELN( CheckFile, DM_R:10:6 );
READLN( InFile, DP_R );
WRITELN( CheckFile, DP_R:10:6 );
READLN( InFile, DM_X );
WRITELN( CheckFile, DM_X:10:6 );
READLN( InFile, DP_X );
WRITELN( CheckFile, DP_X:10:6 );
READLN( InFile, DM_Y );
WRITELN( CheckFile, DM_Y:10:6 );
READLN( InFile, DP_Y );
WRITELN( CheckFile, DP_Y:10:6 );
READLN( InFile, DM_Z );
WRITELN( CheckFile, DM_Z:10:6 );
READLN( InFile, DP_Z );
WRITELN( CheckFile, DP_Z:10:6 );
READLN( InFile, DM_J );
WRITELN( CheckFile, DM_J:10:6 );
READLN( InFile, DP_J );
WRITELN( CheckFile, DP_J:10:6 );

{
 Now Read the Deviational Variables for the 1st-Order Conditionals
}

{ No deviationals for 1st-Order Posteriors R_* }

READLN( InFile, DM_X_R );
WRITELN( CheckFile, DM_X_R:10:6 );
READLN( InFile, DP_X_R );
WRITELN( CheckFile, DP_X_R:10:6 );
READLN( InFile, DM_X_Y );
WRITELN( CheckFile, DM_X_Y:10:6 );
```

```
READLN( InFile, DP_X_Y );
WRITELN( CheckFile, DP_X_Y:10:6 );
READLN( InFile, DM_X_Z );
WRITELN( CheckFile, DM_X_Z:10:6 );
READLN( InFile, DP_X_Z );
WRITELN( CheckFile, DP_X_Z:10:6 );
READLN( InFile, DM_X_J );
WRITELN( CheckFile, DM_X_J:10:6 );
READLN( InFile, DP_X_J );
WRITELN( CheckFile, DP_X_J:10:6 );

READLN( InFile, DM_Y_R );
WRITELN( CheckFile, DM_Y_R:10:6 );
READLN( InFile, DP_Y_R );
WRITELN( CheckFile, DP_Y_R:10:6 );
READLN( InFile, DM_Y_X );
WRITELN( CheckFile, DM_Y_X:10:6 );
READLN( InFile, DP_Y_X );
WRITELN( CheckFile, DP_Y_X:10:6 );
READLN( InFile, DM_Y_Z );
WRITELN( CheckFile, DM_Y_Z:10:6 );
READLN( InFile, DP_Y_Z );
WRITELN( CheckFile, DP_Y_Z:10:6 );
READLN( InFile, DM_Y_J );
WRITELN( CheckFile, DM_Y_J:10:6 );
READLN( InFile, DP_Y_J );
WRITELN( CheckFile, DP_Y_J:10:6 );

READLN( InFile, DM_Z_R );
WRITELN( CheckFile, DM_Z_R:10:6 );
READLN( InFile, DP_Z_R );
WRITELN( CheckFile, DP_Z_R:10:6 );
READLN( InFile, DM_Z_X );
WRITELN( CheckFile, DM_Z_X:10:6 );
READLN( InFile, DP_Z_X );
WRITELN( CheckFile, DP_Z_X:10:6 );
READLN( InFile, DM_Z_Y );
WRITELN( CheckFile, DM_Z_Y:10:6 );
READLN( InFile, DP_Z_Y );
WRITELN( CheckFile, DP_Z_Y:10:6 );
READLN( InFile, DM_Z_J );
WRITELN( CheckFile, DM_Z_J:10:6 );
READLN( InFile, DP_Z_J );
WRITELN( CheckFile, DP_Z_J:10:6 );

READLN( InFile, DM_J_R );
WRITELN( CheckFile, DM_J_R:10:6 );
READLN( InFile, DP_J_R );
WRITELN( CheckFile, DP_J_R:10:6 );
READLN( InFile, DM_J_X );
WRITELN( CheckFile, DM_J_X:10:6 );
READLN( InFile, DP_J_X );
WRITELN( CheckFile, DP_J_X:10:6 );
READLN( InFile, DM_J_Y );
WRITELN( CheckFile, DM_J_Y:10:6 );
READLN( InFile, DP_J_Y );
WRITELN( CheckFile, DP_J_Y:10:6 );
READLN( InFile, DM_J_Z );
WRITELN( CheckFile, DM_J_Z:10:6 );
READLN( InFile, DP_J_Z );
```

```
WRITELN( CheckFile, DP_J_Z:10:6 );

{
 Now Read the Deviational Variables for the 2nd-Order Conditionals
}

{ No deviationals for 2nd-Order Posteriors: R_** }

READLN( InFile, DM_X_RY );
WRITELN( CheckFile, DM_X_RY:10:6 );
READLN( InFile, DP_X_RY );
WRITELN( CheckFile, DP_X_RY:10:6 );
READLN( InFile, DM_X_RZ );
WRITELN( CheckFile, DM_X_RZ:10:6 );
READLN( InFile, DP_X_RZ );
WRITELN( CheckFile, DP_X_RZ:10:6 );
READLN( InFile, DM_X_RJ );
WRITELN( CheckFile, DM_X_RJ:10:6 );
READLN( InFile, DP_X_RJ );
WRITELN( CheckFile, DP_X_RJ:10:6 );
READLN( InFile, DM_X_YZ );
WRITELN( CheckFile, DM_X_YZ:10:6 );
READLN( InFile, DP_X_YZ );
WRITELN( CheckFile, DP_X_YZ:10:6 );
READLN( InFile, DM_X_YJ );
WRITELN( CheckFile, DM_X_YJ:10:6 );
READLN( InFile, DP_X_YJ );
WRITELN( CheckFile, DP_X_YJ:10:6 );
READLN( InFile, DM_X_ZJ );
WRITELN( CheckFile, DM_X_ZJ:10:6 );
READLN( InFile, DP_X_ZJ );
WRITELN( CheckFile, DP_X_ZJ:10:6 );

READLN( InFile, DM_Y_RX );
WRITELN( CheckFile, DM_Y_RX:10:6 );
READLN( InFile, DP_Y_RX );
WRITELN( CheckFile, DP_Y_RX:10:6 );
READLN( InFile, DM_Y_RZ );
WRITELN( CheckFile, DM_Y_RZ:10:6 );
READLN( InFile, DP_Y_RZ );
WRITELN( CheckFile, DP_Y_RZ:10:6 );
READLN( InFile, DM_Y_RJ );
WRITELN( CheckFile, DM_Y_RJ:10:6 );
READLN( InFile, DP_Y_RJ );
WRITELN( CheckFile, DP_Y_RJ:10:6 );
READLN( InFile, DM_Y_XZ );
WRITELN( CheckFile, DM_Y_XZ:10:6 );
READLN( InFile, DP_Y_XZ );
WRITELN( CheckFile, DP_Y_XZ:10:6 );
READLN( InFile, DM_Y_XJ );
WRITELN( CheckFile, DM_Y_XJ:10:6 );
READLN( InFile, DP_Y_XJ );
WRITELN( CheckFile, DP_Y_XJ:10:6 );
READLN( InFile, DM_Y_ZJ );
WRITELN( CheckFile, DM_Y_ZJ:10:6 );
READLN( InFile, DP_Y_ZJ );
WRITELN( CheckFile, DP_Y_ZJ:10:6 );

READLN( InFile, DM_Z_RX );
WRITELN( CheckFile, DM_Z_RX:10:6 );
```

```
    READLN( InFile, DP_Z_RX );
    WRITELN( CheckFile, DP_Z_RX:10:6 );
    READLN( InFile, DM_Z_RY );
    WRITELN( CheckFile, DM_Z_RY:10:6 );
    READLN( InFile, DP_Z_RY );
    WRITELN( CheckFile, DP_Z_RY:10:6 );
    READLN( InFile, DM_Z_RJ );
    WRITELN( CheckFile, DM_Z_RJ:10:6 );
    READLN( InFile, DP_Z_RJ );
    WRITELN( CheckFile, DP_Z_RJ:10:6 );
    READLN( InFile, DM_Z_XY );
    WRITELN( CheckFile, DM_Z_XY:10:6 );
    READLN( InFile, DP_Z_XY );
    WRITELN( CheckFile, DP_Z_XY:10:6 );
    READLN( InFile, DM_Z_XJ );
    WRITELN( CheckFile, DM_Z_XJ:10:6 );
    READLN( InFile, DP_Z_XJ );
    WRITELN( CheckFile, DP_Z_XJ:10:6 );
    READLN( InFile, DM_Z_YJ );
    WRITELN( CheckFile, DM_Z_YJ:10:6 );
    READLN( InFile, DP_Z_YJ );
    WRITELN( CheckFile, DP_Z_YJ:10:6 );

    READLN( InFile, DM_J_RX );
    WRITELN( CheckFile, DM_J_RX:10:6 );
    READLN( InFile, DP_J_RX );
    WRITELN( CheckFile, DP_J_RX:10:6 );
    READLN( InFile, DM_J_RY );
    WRITELN( CheckFile, DM_J_RY:10:6 );
    READLN( InFile, DP_J_RY );
    WRITELN( CheckFile, DP_J_RY:10:6 );
    READLN( InFile, DM_J_RZ );
    WRITELN( CheckFile, DM_J_RZ:10:6 );
    READLN( InFile, DP_J_RZ );
    WRITELN( CheckFile, DP_J_RZ:10:6 );
    READLN( InFile, DM_J_XY );
    WRITELN( CheckFile, DM_J_XY:10:6 );
    READLN( InFile, DP_J_XY );
    WRITELN( CheckFile, DP_J_XY:10:6 );
    READLN( InFile, DM_J_XZ );
    WRITELN( CheckFile, DM_J_XZ:10:6 );
    READLN( InFile, DP_J_XZ );
    WRITELN( CheckFile, DP_J_XZ:10:6 );
    READLN( InFile, DM_J_YZ );
    WRITELN( CheckFile, DM_J_YZ:10:6 );
    READLN( InFile, DP_J_YZ );
    WRITELN( CheckFile, DP_J_YZ:10:6 );

    {
     Close Up - In/Output Files No Longer Necessary
    }
    CLOSE( InFile );
    CLOSE( CheckFile );

END;  { of PROCEDURE GetFileData }

{------------------------------------------------------------------------}
{
   This procedure does the respective calculations for the 1st-Order
      probabilities.
```

```
}

PROCEDURE Calculate_Probabilities_1;

VAR
   OutFile : TEXT;          { Data Output File }

   { Priors/Marginals }
   BARP,                    { BAR Prior }
   LOP,                     { LO Prior }
   LEP,                     { LE Prior }
   HSWP,                    { HSW Prior }
   HSSP,                    { HSS Prior }

   { 1st-Order Posteriors and Conditionals }
   BARLO,                   { BAR | LO }
   BARLE,                   { BAR | LE }
   BARHSW,                  { BAR | HSW }
   BARHSS,                  { BAR | HSS }
   LOBAR,                   { LO | BAR }
   LOLE,                    { LO | LE }
   LOHSW,                   { LO | HSW }
   LOHSS,                   { LO | HSS }
   LEBAR,                   { LE | BAR }
   LELO,                    { LE | LO }
   LEHSW,                   { LE | HSW }
   LEHSS,                   { LE | HSS }
   HSWBAR,                  { HSW | BAR }
   HSWLO,                   { HSW | LO }
   HSWLE,                   { HSW | LE }
   HSWHSS,                  { HSW | HSS }
   HSSBAR,                  { HSS | BAR }
   HSSLO,                   { HSS | LO }
   HSSLE,                   { HSS | LE }
   HSSHSW,                  { HSS | HSW }

   FORCONSISTANCY : REAL;  { Temporary variable }

BEGIN
   {
    Open output file
   }
   ASSIGN( OutFile, 'C:\LINDO\LP_Rev.OUT' );
   REWRITE( OutFile );
   {
    Write Header to Output File...
   }
   WRITELN( OutFile, '********************************************' );
   WRITELN( OutFile, '      LP CALCULATED PROABABILITIES' );
   WRITELN( OutFile, '      USING 2nd-ORDER CONDITIONALS' );
   WRITELN( OutFile, '********************************************' );
   WRITELN( OutFile, '           JLK Revised Dataset' );
   WRITELN( OutFile, '********************************************' );
   WRITELN( Outfile );
   {
    Calculate the Priors/Marginals from their component bits
   }
   WRITELN( OutFile );
   WRITELN( OutFile, '>>>>>  PRIOR/MARGINALS  <<<<<<<<<<<<<<<<<<<<<<<<<<');
   WRITELN( OutFile );
```

```
{ Below Average Recruitment Prior }
BARP := P_10000 + P_10001 + P_10011 + P_10101 + P_11001 + P_10111 +
        P_11011 + P_11101 + P_11111 + P_10010 + P_10110 + P_11010 +
        P_11110 + P_10100 + P_11100 + P_11000;
WRITELN( OutFile, ' P(BAR) =', BARP:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.39');
WRITELN( OutFile, 'MINUS Deviation is:', dM_R:10:6);
WRITELN( OutFile, ' PLUS Deviation is:', dP_R:10:6);
WRITELN( OutFile );

{ Low Oil Yield Prior }
LOP := P_01001 + P_01011 + P_01101 + P_01111 + P_01010 + P_01110 +
       P_01100 + P_01000 + P_11001 + P_11011 + P_11101 + P_11111 +
       P_11010 + P_11110 + P_11100 + P_11000;
WRITELN( OutFile, ' P(LO) =', LOP:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.38');
WRITELN( OutFile, 'MINUS Deviation is:', dM_X:10:6);
WRITELN( OutFile, ' PLUS Deviation is:', dP_X:10:6);
WRITELN( OutFile );

{ Low Egg Production Prior }
LEP := P_00101 + P_00111 + P_01101 + P_01111 + P_00110 + P_01110 +
       P_00100 + P_01100 + P_10101 + P_10111 + P_11101 + P_11111 +
       P_10110 + P_11110 + P_10100 + P_11100;
WRITELN( OutFile, ' P(LE) =', LEP:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.22');
WRITELN( OutFile, 'MINUS Deviation is:', dM_Y:10:6);
WRITELN( OutFile, ' PLUS Deviation is:', dP_Y:10:6);
WRITELN( OutFile );

{High (strong) Southerly Wind Prior }
HSWP := P_00011 + P_00111 + P_01011 + P_01111 + P_00010 + P_00110 +
        P_01010 + P_01110 + P_10011 + P_10111 + P_11011 + P_11111 +
        P_10010 + P_10110 + P_11010 + P_11110;
WRITELN( OutFile, ' P(HSW) =', HSWP:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.48');
WRITELN( OutFile, 'MINUS Deviation is:', dM_Z:10:6);
WRITELN( OutFile, ' PLUS Deviation is:', dP_Z:10:6);
WRITELN( OutFile );

{ High % Starvation Stations Prior }
HSSP := P_00001 + P_00011 + P_00101 + P_01001 + P_00111 + P_01011 +
        P_01101 + P_01111 + P_10001 + P_10011 + P_10101 + P_11001 +
        P_10111 + P_11011 + P_11101 + P_11111;
WRITELN( OutFile, ' P(HSS) =', HSSP:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.16');
WRITELN( OutFile, 'MINUS Deviation is:', dM_J:10:6);
WRITELN( OutFile, ' PLUS Deviation is:', dP_J:10:6);
WRITELN( OutFile );

{
 Calculate the 1st-Order Posteriors and Conditionals from their
    component bits
}
WRITELN( OutFile );
WRITELN( OutFile, '>>>>>  1st-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<');
WRITELN( OutFile );

{ P(BAR|LO) = P(BAR&LO)/P(LO) }
```

```
BARLO := (P_11001 + P_11011 + P_11101 + P_11111 +
          P_11010 + P_11110 + P_11100 + P_11000)/LOP;
WRITELN( OutFile, ' P(BAR|LO) =', BARLO:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'JLK estimate is: 0.72');
WRITELN( OutFile );

{ P(BAR|LE) = P(BAR&LE)/P(LE) }
BARLE := (P_10101 + P_10111 + P_11101 + P_11111 +
          P_10110 + P_11110 + P_10100 + P_11100)/LEP;
WRITELN( OutFile, ' P(BAR|LE) =', BARLE:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'JLK estimate is: 0.83');
WRITELN( OutFile );

{ P(BAR|HSW) = P(BAR&HSW)/P(HSW) }
BARHSW := (P_10011 + P_10111 + P_11011 + P_11111 +
           P_10010 + P_10110 + P_11010 + P_11110)/HSWP;
WRITELN( OutFile, ' P(BAR|HSW) =', BARHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'JLK estimate is: 0.45');
WRITELN( OutFile );

{ P(BAR|HSS) = P(BAR&HSS)/P(HSS) }
BARHSS := (P_10001 + P_10011 + P_10101 + P_11001 +
           P_10111 + P_11011 + P_11101 + P_11111)/HSSP;
WRITELN( OutFile, ' P(BAR|HSS) =', BARHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'JLK estimate is: 0.99');
WRITELN( OutFile );

{ P(LO|BAR) = P(LO&BAR)/P(BAR) }
LOBAR := (P_11001 + P_11011 + P_11101 + P_11111 +
          P_11010 + P_11110 + P_11100 + P_11000)/BARP;
WRITELN( OutFile, ' P(LO|BAR) =', LOBAR:10:6);
FORCONSISTANCY := 0.58 + (dM_X_R - dP_X_R)/BARP;
WRITELN( OutFile, 'For Consistancy, P(LO|BAR) =', FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.58');
{  WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_R:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_R:10:6);   }
WRITELN( OutFile );

{ P(LO|LE) = P(LO&LE)/P(LE) }
LOLE := (P_01101 + P_01111 + P_01110 + P_01100 +
         P_11101 + P_11111 + P_11110 + P_11100)/LEP;
WRITELN( OutFile, ' P(LO|LE) =', LOLE:10:6);
FORCONSISTANCY := 0.60 + (dM_X_Y - dP_X_Y)/LEP;
WRITELN( OutFile, 'For Consistancy, P(LO|LE) =', FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{  WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_Y:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_Y:10:6);   }
WRITELN( OutFile );

{ P(LO|HSW) = P(LO&HSW)/P(HSW) }
LOHSW := (P_01011 + P_01111 + P_01010 + P_01110 +
          P_11011 + P_11111 + P_11010 + P_11110)/HSWP;
WRITELN( OutFile, ' P(LO|HSW) =', LOHSW:10:6);
FORCONSISTANCY := 0.40 + (dM_X_Z - dP_X_Z)/HSWP;
WRITELN( OutFile, 'For Consistancy, P(LO|HSW) =', FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.40');
```

```
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_Z:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_Z:10:6);   }
   WRITELN( OutFile );

   { P(LO|HSS) = P(LO&HSS)/P(HSS) }
   LOHSS := (P_01001 + P_01011 + P_01101 + P_01111 +
             P_11001 + P_11011 + P_11101 + P_11111)/HSSP;
   WRITELN( OutFile, ' P(LO|HSS) =', LOHSS:10:6);
   FORCONSISTANCY := 0.40 + (dM_X_J - dP_X_J)/HSSP;
   WRITELN( OutFile, 'For Consistancy, P(LO|HSS) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.40');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_J:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_J:10:6);   }
   WRITELN( OutFile );

   { P(LE|BAR) = P(LE&BAR)/P(BAR) }
   LEBAR := (P_10101 + P_10111 + P_11101 + P_11111 +
             P_10110 + P_11110 + P_10100 + P_11100)/BARP;
   WRITELN( OutFile, ' P(LE|BAR) =', LEBAR:10:6);
   FORCONSISTANCY := 0.33 + (dM_Y_R - dP_Y_R)/BARP;
   WRITELN( OutFile, 'For Consistancy, P(LE|BAR) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.33');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_R:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_R:10:6);   }
   WRITELN( OutFile );

   { P(LE|LO) = P(LE&LO)/P(LO) }
   LELO := (P_01100 + P_01101 + P_01110 + P_01111 +
            P_11100 + P_11101 + P_11110 + P_11111)/LOP;
   WRITELN( OutFile, ' P(LE|LO) =', LELO:10:6);
   FORCONSISTANCY := 0.40 + (dM_Y_X - dP_Y_X)/LOP;
   WRITELN( OutFile, 'For Consistancy, P(LE|LO) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.40');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_X:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_X:10:6);   }
   WRITELN( OutFile );

   { P(LE|HSW) = P(LE&HSW)/P(HSW) }
   LEHSW := (P_00111 + P_01111 + P_00110 + P_01110 +
             P_10111 + P_11111 + P_10110 + P_11110)/HSWP;
   WRITELN( OutFile, ' P(LE|HSW) =', LEHSW:10:6);
   FORCONSISTANCY := 0.20 + (dM_Y_Z - dP_Y_Z)/HSWP;
   WRITELN( OutFile, 'For Consistancy, P(LE|HSW) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.20');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_Z:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_Z:10:6);   }
   WRITELN( OutFile );

   { P(LE|HSS) = P(LE&HSS)/P(HSS) }
   LEHSS := (P_00101 + P_00111 + P_01101 + P_01111 +
             P_10101 + P_10111 + P_11101 + P_11111)/HSSP;
   WRITELN( OutFile, ' P(LE|HSS) =', LEHSS:10:6);
   FORCONSISTANCY := 0.40 + (dM_Y_J - dP_Y_J)/HSSP;
   WRITELN( OutFile, 'For Consistancy, P(LE|HSS) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.40');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_J:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_J:10:6);   }
   WRITELN( OutFile );

   { P(HSW|BAR) = P(HSW&BAR)/P(BAR) }
```

```
   HSWBAR := (P_10011 + P_10111 + P_11011 + P_11111 +
              P_10010 + P_10110 + P_11010 + P_11110)/BARP;
   WRITELN( OutFile, ' P(HSW|BAR) =', HSWBAR:10:6);
   FORCONSISTANCY := 0.55 + (dM_Z_R - dP_Z_R)/BARP;
   WRITELN( OutFile, 'For Consistancy, P(HSW|BAR) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.55');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_R:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_R:10:6);  }
   WRITELN( OutFile );

   { P(HSW|LO) = P(HSW&LO)/P(LO) }
   HSWLO := (P_01011 + P_01111 + P_01010 + P_01110 +
             P_11011 + P_11111 + P_11010 + P_11110)/LOP;
   WRITELN( OutFile, ' P(HSW|LO) =', HSWLO:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_X - dP_Z_X)/LOP;
   WRITELN( OutFile, 'For Consistancy, P(HSW|LO) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_X:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_X:10:6);  }
   WRITELN( OutFile );

   { P(HSW|LE) = P(HSW&LE)/P(LE) }
   HSWLE := (P_00111 + P_01111 + P_00110 + P_01110 +
             P_10111 + P_11111 + P_10110 + P_11110)/LEP;
   WRITELN( OutFile, ' P(HSW|LE) =', HSWLE:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_Y - dP_Z_Y)/LEP;
   WRITELN( OutFile, 'For Consistancy, P(HSW|LE) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_Y:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_Y:10:6);  }
   WRITELN( OutFile );

   { P(HSW|HSS) = P(HSW&HSS)/P(HSS) }
   HSWHSS := (P_00011 + P_00111 + P_01011 + P_01111 +
              P_10011 + P_10111 + P_11011 + P_11111)/HSSP;
   WRITELN( OutFile, ' P(HSW|HSS) =', HSWHSS:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_J - dP_Z_J)/HSSP;
   WRITELN( OutFile, 'For Consistancy, P(HSW|HSS) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_J:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_J:10:6);  }
   WRITELN( OutFile );

   { P(HSS|BAR) = P(HSS&BAR)/P(BAR) }
   HSSBAR := (P_10001 + P_10011 + P_10101 + P_11001 +
              P_10111 + P_11011 + P_11101 + P_11111)/BARP;
   WRITELN( OutFile, ' P(HSS|BAR) =', HSSBAR:10:6);
   FORCONSISTANCY := 0.43 + (dM_J_R - dP_J_R)/BARP;
   WRITELN( OutFile, 'For Consistancy, P(HSS|BAR) =', FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.43');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_R:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_R:10:6);  }
   WRITELN( OutFile );

   { P(HSS|LO) = P(HSS&LO)/P(LO) }
   HSSLO := (P_01001 + P_01011 + P_01101 + P_01111 +
             P_11001 + P_11011 + P_11101 + P_11111)/LOP;
   WRITELN( OutFile, ' P(HSS|LO) =', HSSLO:10:6);
   FORCONSISTANCY := 0.20 + (dM_J_X - dP_J_X)/LOP;
   WRITELN( OutFile, 'For Consistancy, P(HSS|LO) =', FORCONSISTANCY:10:6);
```

```
    WRITELN( OutFile, 'JLK estimate is: 0.20');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_X:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_X:10:6);  }
    WRITELN( OutFile );

    { P(HSS|LE) = P(HSS&LE)/P(LE) }
    HSSLE := (P_00101 + P_00111 + P_01101 + P_01111 +
              P_10101 + P_10111 + P_11101 + P_11111)/LEP;
    WRITELN( OutFile, ' P(HSS|LE) =', HSSLE:10:6);
    FORCONSISTANCY := 0.60 + (dM_J_Y - dP_J_Y)/LEP;
    WRITELN( OutFile, 'For Consistancy, P(HSS|LE) =', FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.60');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_Y:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_Y:10:6);  }
    WRITELN( OutFile );

    { P(HSS|HSW) = P(HSS&HSW)/P(HSW) }
    HSSHSW := (P_00011 + P_00111 + P_01011 + P_01111 +
               P_10011 + P_10111 + P_11011 + P_11111)/HSWP;
    WRITELN( OutFile, ' P(HSS|HSW) =', HSSHSW:10:6);
    FORCONSISTANCY := 0.20 + (dM_J_Z - dP_J_Z)/HSWP;
    WRITELN( OutFile, 'For Consistancy, P(HSS|HSW) =', FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.20 *Question not asked*');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_Z:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_Z:10:6);  }
    WRITELN( OutFile );

    {
     Close Up - Output File No Longer Necessary
    }
    CLOSE( OutFile );

END;  { of PROCEDURE Calculate Probabilities 1 }

{--------------------------------------------------------------------}
{
   This procedure does the respective calculations for the 2nd-Order
      probabilities.
}

PROCEDURE Calculate_Probabilities_2;

VAR
   OutFile : TEXT;        { Data Output File }

   { 2nd-Order Posteriors and Conditionals }
   BARLOLE,               { BAR | LO & LE }
   BARLOHSW,              { BAR | LO & HSW }
   BARLOHSS,              { BAR | LO & HSS }
   BARLEHSW,              { BAR | LE & HSW }
   BARLEHSS,              { BAR | LE & HSS }
   BARHSWHSS,             { BAR | HSW & HSS }
   LOBARLE,               { LO | BAR & LE }
   LOBARHSW,              { LO | BAR & HSW }
   LOBARHSS,              { LO | BAR & HSS }
   LOLEHSW,               { LO | LE & HSW }
   LOLEHSS,               { LO | LE & HSS }
   LOHSWHSS,              { LO | HSW & HSS }
   LEBARLO,               { LE | BAR & LO }
   LEBARHSW,              { LE | BAR & HSW }
```

```
   LEBARHSS,              { LE | BAR & HSS }
   LELOHSW,               { LE | LO & HSW }
   LELOHSS,               { LE | HSW & HSS }
   LEHSWHSS,              { LE | HSW & HSS }
   HSWBARLO,              { HSW | BAR & LO }
   HSWBARLE,              { HSW | BAR & LE }
   HSWBARHSS,             { HSW | BAR & HSS }
   HSWLOLE,               { HSW | LO & LE }
   HSWLOHSS,              { HSW | LO & HSS }
   HSWLEHSS,              { HSW | LE & HSS }
   HSSBARLO,              { HSS | BAR & LO }
   HSSBARLE,              { HSS | BAR & LE }
   HSSBARHSW,             { HSS | BAR & HSW }
   HSSLOLE,               { HSS | LO & LE }
   HSSLOHSW,              { HSS | LO & HSW }
   HSSLEHSW,              { HSS | LE & HSW }

   FORCONSISTANCY : REAL;  { Temporary variable }

BEGIN
   {
    Open output file
   }
   ASSIGN( OutFile, 'C:\LINDO\LP_Rev.OUT' );
   APPEND( OutFile );

   {
    Calculate the 2nd-Order Posteriors and Conditionals from their
       component bits
   }
   WRITELN( OutFile );
   WRITELN( OutFile, '>>>>>  2nd-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<');
   WRITELN( OutFile );

   { P(BAR|LO&LE) = P(BAR&LO&LE)/P(LE&LO) which is the same as
     P(BAR|LE&LO) = P(BAR&LE&LO)/P(LO&LE) }
   BARLOLE := (P_11100 + P_11110 + P_11101 + P_11111)/
              (P_01100 + P_01110 + P_01101 + P_01111 +
               P_11100 + P_11110 + P_11101 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&LE) =', BARLOLE:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(BAR|LO&HSW) = P(BAR&LO&HSW)/P(HSW&LO) which is the same as
     P(BAR|HSW&LO) = P(BAR&HSW&LO)/P(LO&HSW) }
   BARLOHSW := (P_11010 + P_11110 + P_11011 + P_11111)/
               (P_01010 + P_01110 + P_01011 + P_01111 +
                P_11010 + P_11110 + P_11011 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&HSW) =', BARLOHSW:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(BAR|LO&HSS) = P(BAR&LO&HSS)/P(HSS&LO) which is the same as
     P(BAR|HSS&LO) = P(BAR&HSS&LO)/P(LO&HSS) }
   BARLOHSS := (P_11001 + P_11101 + P_11011 + P_11111)/
               (P_01001 + P_01101 + P_01011 + P_01111 +
                P_11001 + P_11101 + P_11011 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&HSS) =', BARLOHSS:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );
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{ P(BAR|LE&HSW) = P(BAR&LE&HSW)/P(HSW&LE) which is the same as
  P(BAR|HSW&LE) = P(BAR&HSW&LE)/P(LE&HSW) }
BARLEHSW := (P_10110 + P_11110 + P_10111 + P_11111)/
            (P_00110 + P_01110 + P_00111 + P_01111 +
             P_10110 + P_11110 + P_10111 + P_11111);
WRITELN( OutFile, ' P(BAR|LE&HSW) =', BARLEHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(BAR|LE&HSS) = P(BAR&LE&HSS)/P(HSS&LE) which is the same as
  P(BAR|HSS&LE) = P(BAR&HSS&LE)/P(LE&HSS) }
BARLEHSS := (P_10101 + P_11101 + P_10111 + P_11111)/
            (P_00101 + P_01101 + P_00111 + P_01111 +
             P_10101 + P_11101 + P_10111 + P_11111);
WRITELN( OutFile, ' P(BAR|LE&HSS) =', BARLEHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(BAR|HSW&HSS) = P(BAR&HSW&HSS)/P(HSS&HSW) which is the same as
  P(BAR|HSS&HSW) = P(BAR&HSS&HSW)/P(HSW&HSS) }
BARHSWHSS := (P_10011 + P_11011 + P_10111 + P_11111)/
             (P_00011 + P_01011 + P_00111 + P_01111 +
              P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, ' P(BAR|HSW&HSS) =', BARHSWHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(LO|BAR&LE) = P(LO&BAR&LE)/P(LE&BAR) which is the same as
  P(LO|LE&BAR) = P(LO&LE&BAR)/P(BAR&LE) }
LOBARLE := (P_11100 + P_11110 + P_11101 + P_11111)/
           (P_10100 + P_10110 + P_10111 + P_10101 +
            P_11100 + P_11110 + P_11101 + P_11111);
WRITELN( OutFile, ' P(LO|BAR&LE) =', LOBARLE:10:6);
FORCONSISTANCY := 0.60 + (dM_X_RY - dP_X_RY)/
                  (P_10101 + P_10111 + P_11101 + P_11111 +
                   P_10110 + P_11110 + P_10100 + P_11100);
WRITELN( OutFile, 'For Consistancy, P(LO|BAR&LE)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_RY:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_RY:10:6);   }
WRITELN( OutFile );

{ P(LO|BAR&HSW) = P(LO&BAR&HSW)/P(HSW&BAR) which is the same as
  P(LO|HSW&BAR) = P(LO&HSW&BAR)/P(BAR&HSW) }
LOBARHSW := (P_11010 + P_11110 + P_11011 + P_11111)/
            (P_10010 + P_11010 + P_10110 + P_10011 +
             P_10111 + P_11110 + P_11011 + P_11111);
WRITELN( OutFile, ' P(LO|BAR&HSW) =', LOBARHSW:10:6);
FORCONSISTANCY := 0.60 + (dM_X_RZ - dP_X_RZ)/
                  (P_10010 + P_11010 + P_10110 + P_10011 +
                   P_10111 + P_11110 + P_11011 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LO|BAR&HSW)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_RZ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_RZ:10:6);   }
WRITELN( OutFile );

{ P(LO|BAR&HSS) = P(LO&BAR&HSS)/P(HSS&BAR) which is the same as
  P(LO|HSS&BAR) = P(LO&HSS&BAR)/P(BAR&HSS) }
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LOBARHSS := (P_11001 + P_11101 + P_11011 + P_11111)/
            (P_10001 + P_11001 + P_10101 + P_10011 +
             P_10111 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, ' P(LO|BAR&HSS) =', LOBARHSS:10:6);
FORCONSISTANCY := 0.60 + (dM_X_RJ - dP_X_RJ)/
                  (P_10001 + P_11001 + P_10101 + P_10011 +
                   P_10111 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LO|BAR&HSS)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_RJ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_RJ:10:6);  }
WRITELN( OutFile );

{ P(LO|LE&HSW) = P(LO&LE&HSW)/P(HSW&LE) which is the same as
  P(LO|HSW&LE) = P(LO&HSW&LE)/P(LE&HSW) }
LOLEHSW := (P_01110 + P_11110 + P_01111 + P_11111)/
           (P_00110 + P_01110 + P_00111 + P_01111 +
            P_10110 + P_11110 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LO|LE&HSW) =', LOLEHSW:10:6);
FORCONSISTANCY := 0.60 + (dM_X_YZ - dP_X_YZ)/
                  (P_00110 + P_01110 + P_00111 + P_01111 +
                   P_10110 + P_11110 + P_10111 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LO|LE&HSW)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_YZ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_YZ:10:6);  }
WRITELN( OutFile );

{ P(LO|LE&HSS) = P(LO&LE&HSS)/P(HSS&LE) which is the same as
  P(LO|HSS&LE) = P(LO&HSS&LE)/P(LE&HSS) }
LOLEHSS := (P_01101 + P_11101 + P_01111 + P_11111)/
           (P_00101 + P_01101 + P_00111 + P_01111 +
            P_10101 + P_11101 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LO|LE&HSS) =', LOLEHSS:10:6);
FORCONSISTANCY := 0.60 + (dM_X_YJ - dP_X_YJ)/
                  (P_00101 + P_01101 + P_00111 + P_01111 +
                   P_10101 + P_11101 + P_10111 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LO|LE&HSS)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_YJ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_YJ:10:6);  }
WRITELN( OutFile );

{ P(LO|HSW&HSS) = P(LO&HSW&HSS)/P(HSS&HSW) which is the same as
  P(LO|HSS&HSW) = P(LO&HSS&HSW)/P(HSW&HSS) }
LOHSWHSS := (P_01011 + P_11011 + P_01111 + P_11111)/
            (P_00011 + P_01011 + P_00111 + P_01111 +
             P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LO|HSW&HSS) =', LOHSWHSS:10:6);
FORCONSISTANCY := 0.40 + (dM_X_ZJ - dP_X_ZJ)/
                  (P_00011 + P_01011 + P_00111 + P_01111 +
                   P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LO|HSW&HSS)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.40 *Question not asked*');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_X_ZJ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_X_ZJ:10:6);  }
WRITELN( OutFile );

{ P(LE|BAR&LO) = P(LE&BAR&LO)/P(LO&BAR) which is the same as
  P(LE|LO&BAR) = P(LE&LO&BAR)/P(BAR&LO) }
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    LEBARLO := (P_11100 + P_11110 + P_11101 + P_11111)/
               (P_11001 + P_11011 + P_11101 + P_11111 +
                P_11010 + P_11110 + P_11100 + P_11000);
    WRITELN( OutFile, ' P(LE|BAR&LO) =', LEBARLO:10:6);
    FORCONSISTANCY := 0.60 + (dM_Y_RX - dP_Y_RX)/
                      (P_11001 + P_11011 + P_11101 + P_11111 +
                       P_11010 + P_11110 + P_11100 + P_11000);
    WRITELN( OutFile, 'For Consistancy,P(LE|BAR&LO)=',FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.60');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_RX:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_RX:10:6);   }
    WRITELN( OutFile );

    { P(LE|BAR&HSW) = P(LE&BAR&HSW)/P(HSW&BAR) which is the same as
      P(LE|HSW&BAR) = P(LE&HSW&BAR)/P(BAR&HSW) }
    LEBARHSW := (P_10110 + P_11110 + P_10111 + P_11111)/
                (P_10011 + P_10111 + P_11011 + P_11111 +
                 P_10010 + P_10110 + P_11010 + P_11110);
    WRITELN( OutFile, ' P(LE|BAR&HSW) =', LEBARHSW:10:6);
    FORCONSISTANCY := 0.33 + (dM_Y_RZ - dP_Y_RZ)/
                      (P_10011 + P_10111 + P_11011 + P_11111 +
                       P_10010 + P_10110 + P_11010 + P_11110);
    WRITELN( OutFile, 'For Consistancy,P(LE|BAR&HSW)=',FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.33');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_RZ:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_RZ:10:6);   }
    WRITELN( OutFile );

    { P(LE|BAR&HSS) = P(LE&BAR&HSS)/P(HSS&BAR) which is the same as
      P(LE|HSS&BAR) = P(LE&HSS&BAR)/P(BAR&HSS) }
    LEBARHSS := (P_10101 + P_11101 + P_10111 + P_11111)/
                (P_10001 + P_10011 + P_10101 + P_11001 +
                 P_10111 + P_11011 + P_11101 + P_11111);
    WRITELN( OutFile, ' P(LE|BAR&HSS) =', LEBARHSS:10:6);
    FORCONSISTANCY := 0.60 + (dM_Y_RJ - dP_Y_RJ)/
                      (P_10001 + P_10011 + P_10101 + P_11001 +
                       P_10111 + P_11011 + P_11101 + P_11111);
    WRITELN( OutFile, 'For Consistancy,P(LE|BAR&HSS)=',FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.60');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_RJ:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_RJ:10:6);   }
    WRITELN( OutFile );

    { P(LE|LO&HSW) = P(LE&LO&HSW)/P(HSW&LO) which is the same as
      P(LE|HSW&LO) = P(LE&HSW&LO)/P(LO&HSW) }
    LELOHSW := (P_01110 + P_11110 + P_01111 + P_11111)/
               (P_01010 + P_01110 + P_01011 + P_01111 +
                P_11010 + P_11110 + P_11011 + P_11111);
    WRITELN( OutFile, ' P(LE|LO&HSW) =', LELOHSW:10:6);
    FORCONSISTANCY := 0.40 + (dM_Y_XZ - dP_Y_XZ)/
                      (P_01010 + P_01110 + P_01011 + P_01111 +
                       P_11010 + P_11110 + P_11011 + P_11111);
    WRITELN( OutFile, 'For Consistancy,P(LE|LO&HSW)=',FORCONSISTANCY:10:6);
    WRITELN( OutFile, 'JLK estimate is: 0.40');
{    WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_XZ:10:6);
    WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_XZ:10:6);   }
    WRITELN( OutFile );

    { P(LE|LO&HSS) = P(LE&LO&HSS)/P(HSS&LO) which is the same as
      P(LE|HSS&LO) = P(LE&HSS&LO)/P(LO&HSS) }
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LELOHSS := (P_01101 + P_11101 + P_01111 + P_11111)/
           (P_01001 + P_01101 + P_01011 + P_01111 +
            P_11001 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, ' P(LE|LO&HSS) =', LELOHSS:10:6);
FORCONSISTANCY := 0.60 + (dM_Y_XJ - dP_Y_XJ)/
                  (P_01001 + P_01101 + P_01011 + P_01111 +
                   P_11001 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LE|LO&HSS)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.60');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_Y_XJ:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_Y_XJ:10:6);  }
WRITELN( OutFile );

{ P(LE|HSW&HSS) = P(LE&HSW&HSS)/P(HSS&HSW) which is the same as
  P(LE|HSS&HSW) = P(LE&HSS&HSW)/P(HSW&HSS) }
LEHSWHSS := (P_00111 + P_10111 + P_01111 + P_11111)/
            (P_00011 + P_01011 + P_00111 + P_01111 +
             P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LE|HSW&HSS) =', LEHSWHSS:10:6);
FORCONSISTANCY := 0.40 + (dM_Y_ZJ - dP_Y_ZJ)/
                  (P_00011 + P_01011 + P_00111 + P_01111 +
                   P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, 'For Consistancy,P(LE|HSW&HSS)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.40 *Question not asked*');
WRITELN( OutFile );

{ P(HSW|BAR&LO) = P(HSW&BAR&LO)/P(LO&BAR) which is the same as
  P(HSW|LO&BAR) = P(HSW&LO&BAR)/P(BAR&LO) }
HSWBARLO := (P_11010 + P_11110 + P_11011 + P_11111)/
            (P_11001 + P_11011 + P_11101 + P_11111 +
             P_11010 + P_11110 + P_11100 + P_11000);
WRITELN( OutFile, ' P(HSW|BAR&LO) =', HSWBARLO:10:6);
FORCONSISTANCY := 0.55 + (dM_Z_RX - dP_Z_RX)/
                  (P_11001 + P_11011 + P_11101 + P_11111 +
                   P_11010 + P_11110 + P_11100 + P_11000);
WRITELN( OutFile, 'For Consistancy,P(HSW|BAR&LO)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.55');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_RX:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_RX:10:6);  }
WRITELN( OutFile );

{ P(HSW|BAR&LE) = P(HSW&BAR&LE)/P(LE&BAR) which is the same as
  P(HSW|LE&BAR) = P(HSW&LE&BAR)/P(BAR&LE) }
HSWBARLE := (P_10110 + P_11110 + P_10111 + P_11111)/
            (P_10101 + P_10111 + P_11101 + P_11111 +
             P_10110 + P_11110 + P_10100 + P_11100);
WRITELN( OutFile, ' P(HSW|BAR&LE) =', HSWBARLE:10:6);
FORCONSISTANCY := 0.55 + (dM_Z_RY - dP_Z_RY)/
                  (P_10101 + P_10111 + P_11101 + P_11111 +
                   P_10110 + P_11110 + P_10100 + P_11100);
WRITELN( OutFile, 'For Consistancy,P(HSW|BAR&LE)=',FORCONSISTANCY:10:6);
WRITELN( OutFile, 'JLK estimate is: 0.55');
{ WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_RY:10:6);
WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_RY:10:6);  }
WRITELN( OutFile );

{ P(HSW|BAR&HSS) = P(HSW&BAR&HSS)/P(HSS&BAR) which is the same as
  P(HSW|HSS&BAR) = P(HSW&HSS&BAR)/P(BAR&HSS) }
HSWBARHSS := (P_10011 + P_11011 + P_10111 + P_11111)/
             (P_10001 + P_10011 + P_10101 + P_11001 +
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                  P_10111 + P_11011 + P_11101 + P_11111);
   WRITELN( OutFile, ' P(HSW|BAR&HSS) =', HSWBARHSS:10:6);
   FORCONSISTANCY := 0.55 + (dM_Z_RJ - dP_Z_RJ)/
                      (P_10001 + P_10011 + P_10101 + P_11001 +
                       P_10111 + P_11011 + P_11101 + P_11111);
   WRITELN( OutFile,'For Consistancy,P(HSW|BAR&HSS)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.55 *Question not asked*');
   WRITELN( OutFile );

   { P(HSW|LO&LE) = P(HSW&LO&LE)/P(LE&LO) which is the same as
     P(HSW|LE&LO) = P(HSW&LE&LO)/P(LO&LE) }
   HSWLOLE := (P_01110 + P_11110 + P_01111 + P_11111)/
              (P_01100 + P_01110 + P_01101 + P_01111 +
               P_11100 + P_11110 + P_11101 + P_11111);
   WRITELN( OutFile, ' P(HSW|LO&LE) =', HSWLOLE:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_XY - dP_Z_XY)/
                      (P_01100 + P_01110 + P_01101 + P_01111 +
                       P_11100 + P_11110 + P_11101 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSW|LO&LE)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_XY:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_XY:10:6);  }
   WRITELN( OutFile );

   { P(HSW|LO&HSS) = P(HSW&LO&HSS)/P(HSS&LO) which is the same as
     P(HSW|HSS&LO) = P(HSW&HSS&LO)/P(LO&HSS) }
   HSWLOHSS := (P_01011 + P_11011 + P_01111 + P_11111)/
               (P_01001 + P_01101 + P_01011 + P_01111 +
                P_11001 + P_11101 + P_11011 + P_11111);
   WRITELN( OutFile, ' P(HSW|LO&HSS) =', HSWLOHSS:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_XJ - dP_Z_XJ)/
                      (P_01001 + P_01101 + P_01011 + P_01111 +
                       P_11001 + P_11101 + P_11011 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSW|LO&HSS)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_XJ:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_XJ:10:6);  }
   WRITELN( OutFile );

   { P(HSW|LE&HSS) = P(HSW&LE&HSS)/P(HSS&LE) which is the same as
     P(HSW|HSS&LE) = P(HSW&HSS&LE)/P(LE&HSS) }
   HSWLEHSS := (P_00111 + P_10111 + P_01111 + P_11111)/
               (P_00101 + P_01101 + P_00111 + P_01111 +
                P_10101 + P_11101 + P_10111 + P_11111);
   WRITELN( OutFile, ' P(HSW|LE&HSS) =', HSWLEHSS:10:6);
   FORCONSISTANCY := 0.48 + (dM_Z_YJ - dP_Z_YJ)/
                      (P_00101 + P_01101 + P_00111 + P_01111 +
                       P_10101 + P_11101 + P_10111 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSW|LE&HSS)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.48 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_Z_YJ:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_Z_JJ:10:6);  }
   WRITELN( OutFile );

   { P(HSS|BAR&LO) = P(HSS&BAR&LO)/P(LO&BAR) which is the same as
     P(HSS|LO&BAR) = P(HSS&LO&BAR)/P(BAR&LO) }
   HSSBARLO := (P_11001 + P_11101 + P_11011 + P_11111)/
               (P_11001 + P_11011 + P_11101 + P_11111 +
                P_11010 + P_11110 + P_11100 + P_11000);
   WRITELN( OutFile, ' P(HSS|BAR&LO) =', HSSBARLO:10:6);
```

```
   FORCONSISTANCY := 0.43 + (dM_J_RX - dP_J_RX)/
                     (P_11001 + P_11011 + P_11101 + P_11111 +
                      P_11010 + P_11110 + P_11100 + P_11000);
   WRITELN( OutFile, 'For Consistancy,P(HSS|BAR&LO)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.43');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_RX:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_RX:10:6);  }
   WRITELN( OutFile );

   { P(HSS|BAR&LE) = P(HSS&BAR&LE)/P(LE&BAR) which is the same as
     P(HSS|LE&BAR) = P(HSS&LE&BAR)/P(BAR&LE) }
   HSSBARLE := (P_10101 + P_11101 + P_10111 + P_11111)/
               (P_10101 + P_10111 + P_11101 + P_11111 +
                P_10110 + P_11110 + P_10100 + P_11100);
   WRITELN( OutFile, ' P(HSS|BAR&LE) =', HSSBARLE:10:6);
   FORCONSISTANCY := 0.60 + (dM_J_RY - dP_J_RY)/
                     (P_10101 + P_10111 + P_11101 + P_11111 +
                      P_10110 + P_11110 + P_10100 + P_11100);
   WRITELN( OutFile, 'For Consistancy,P(HSS|BAR&LE)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.60');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_RY:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_RY:10:6);  }
   WRITELN( OutFile );

   { P(HSS|BAR&HSW) = P(HSS&BAR&HSW)/P(HSW&BAR) which is the same as
     P(HSS|HSW&BAR) = P(HSS&HSW&BAR)/P(BAR&HSW) }
   HSSBARHSW := (P_10011 + P_11011 + P_10111 + P_11111)/
                (P_10011 + P_10111 + P_11011 + P_11111 +
                 P_10010 + P_10110 + P_11010 + P_11110);
   WRITELN( OutFile, ' P(HSS|BAR&HSW) =', HSSBARHSW:10:6);
   FORCONSISTANCY := 0.43 + (dM_J_RZ - dP_J_RZ)/
                     (P_10011 + P_10111 + P_11011 + P_11111 +
                      P_10010 + P_10110 + P_11010 + P_11110);
   WRITELN( OutFile,'For Consistancy,P(HSS|BAR&HSS)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.43 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_RZ:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_RZ:10:6);  }
   WRITELN( OutFile );

   { P(HSS|LO&LE) = P(HSS&LO&LE)/P(LE&LO) which is the same as
     P(HSS|LE&LO) = P(HSS&LE&LO)/P(LO&LE) }
   HSSLOLE := (P_01101 + P_11101 + P_01111 + P_11111)/
              (P_01100 + P_01110 + P_01101 + P_01111 +
               P_11100 + P_11110 + P_11101 + P_11111);
   WRITELN( OutFile, ' P(HSS|LO&LE) =', HSSLOLE:10:6);
   FORCONSISTANCY := 0.60 + (dM_J_XY - dP_J_XY)/
                     (P_01100 + P_01110 + P_01101 + P_01111 +
                      P_11100 + P_11110 + P_11101 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSS|LO&LE)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.60');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_XY:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_XY:10:6);  }
   WRITELN( OutFile );

   { P(HSS|LO&HSW) = P(HSS&LO&HSW)/P(HSW&LO) which is the same as
     P(HSS|HSW&LO) = P(HSS&HSW&LO)/P(LO&HSW) }
   HSSLOHSW := (P_01011 + P_11011 + P_01111 + P_11111)/
               (P_01010 + P_01110 + P_01011 + P_01111 +
                P_11010 + P_11110 + P_11011 + P_11111);
   WRITELN( OutFile, ' P(HSS|LO&HSW) =', HSSLOHSW:10:6);
```

```
   FORCONSISTANCY := 0.20 + (dM_J_XZ - dP_J_XZ)/
                     (P_01010 + P_01110 + P_01011 + P_01111 +
                      P_11010 + P_11110 + P_11011 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSS|LO&HSW)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.20 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_XZ:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_XZ:10:6);   }
   WRITELN( OutFile );

   { P(HSS|LE&HSW) = P(HSS&LE&HSW)/P(HSW&LE) which is the same as
     P(HSS|HSW&LE) = P(HSS&HSW&LE)/P(LE&HSW) }
   HSSLEHSW := (P_00111 + P_10111 + P_01111 + P_11111)/
               (P_00110 + P_01110 + P_00111 + P_01111 +
                P_10110 + P_11110 + P_10111 + P_11111);
   WRITELN( OutFile, ' P(HSS|LE&HSW) =', HSSLEHSW:10:6);
   FORCONSISTANCY := 0.60 + (dM_J_YZ - dP_J_YZ)/
                     (P_00110 + P_01110 + P_00111 + P_01111 +
                      P_10110 + P_11110 + P_10111 + P_11111);
   WRITELN( OutFile, 'For Consistancy,P(HSS|LE&HSW)=',FORCONSISTANCY:10:6);
   WRITELN( OutFile, 'JLK estimate is: 0.60 *Question not asked*');
{   WRITELN( OutFile, 'MINUS Deviation is: ', dM_J_YZ:10:6);
   WRITELN( OutFile, ' PLUS Deviation is: ', dP_J_YZ:10:6);   }
   WRITELN( OutFile );

   {
    Close Up - Output File No Longer Necessary
   }
   CLOSE( OutFile );

END;  { of PROCEDURE Calculate Probabilities 2 }

{-------------------------------------------------------------------------}
{
   This procedure does the respective calculations of the 3rd and 4th
      Order Probabilities
}

PROCEDURE Calculate_Probabilities_3and4;

VAR
   OutFile : TEXT;        { Data Output File }

   { 3rd-Order Posteriors and Conditionals }
   BARLOLEHSW,            { BAR | LO & LE & HSW }
   BARLOLEHSS,            { BAR | LO & LE & HSS }
   BARLOHSWHSS,           { BAR | LO & HSW & HSS }
   BARLEHSWHSS,           { BAR | LE & HSW & HSS }
   LOBARLEHSW,            { LO | BAR & LE & HSW }
   LOBARLEHSS,            { LO | BAR & LE & HSS }
   LOBARHSWHSS,           { LO | BAR & HSW & HSS }
   LOLEHSWHSS,            { LO | LE & HSW & HSS }
   LEBARLOHSW,            { LE | BAR & LO & HSW }
   LEBARLOHSS,            { LE | BAR & LO & HSS }
   LEBARHSWHSS,           { LE | BAR & HSW & HSS }
   LELOHSWHSS,            { LE | LO & HSW & HSS }
   HSWBARLOLE,            { HSW | BAR & LO & LE }
   HSWBARLOHSS,           { HSW | BAR & LO & HSS }
   HSWBARLEHSS,           { HSW | BAR & LE & HSS }
   HSWLOLEHSS,            { HSW | LO & LE & HSS }
   HSSBARLOLE,            { HSS | BAR & LO & LE }
```

```
    HSSBARLOHSW,           { HSS | BAR & LO & HSW }
    HSSBARLEHSW,           { HSS | BAR & LE & HSW }
    HSSLOLEHSW,            { HSS | LO & LE & HSW }

    { 4th-Order Posterior }
    BARLOLEHSWHSS          { BAR | LO & LE & HSW & HSS }

    : REAL;

BEGIN
   {
    Open output files and intialize variables
   }
   ASSIGN( OutFile, 'C:\LINDO\LP_Rev.OUT' );
   APPEND( OutFile );

   {
    Calculate the 3rd-Order Posteriors and Conditionals from their
       component bits
    Note that there are no deviational values for these 3rd-order
       probabilities and therefore no consistancy checks.
   }
   WRITELN( OutFile );
   WRITELN( OutFile, '>>>>>  3rd-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<');
   WRITELN( OutFile );

   { P(BAR|LO&LE&HSW) = P(BAR&LO&LE&HSW)/P(LO&LE&HSW) }
   BARLOLEHSW := (P_11110 + P_11111)/
                 (P_01110 + P_11110 + P_01111 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&LE&HSW) =', BARLOLEHSW:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(BAR|LO&HSW&HSS) = P(BAR&LO&HSW&HSS)/P(LO&HSW&HSS) }
   BARLOHSWHSS := (P_11011 + P_11111)/
                  (P_01011 + P_11011 + P_01111 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&HSW&HSS) =', BARLOHSWHSS:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(BAR|LO&LE&HSS) = P(BAR&LO&LE&HSS)/P(LO&LE&HSS) }
   BARLOLEHSS := (P_11101 + P_11111)/
                 (P_01101 + P_11101 + P_01111 + P_11111);
   WRITELN( OutFile, ' P(BAR|LO&LE&HSS) =', BARLOLEHSS:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(BAR|LE&HSW&HSS) = P(BAR&LE&HSW&HSS)/P(LE&HSW&HSS) }
   BARLEHSWHSS := (P_10111 + P_11111)/
                  (P_00111 + P_10111 + P_01111 + P_11111);
   WRITELN( OutFile, ' P(BAR|LE&HSW&HSS) =', BARLEHSWHSS:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile );

   { P(LO|BAR&LE&HSW) = P(LO&BAR&LE&HSW)/P(BAR&LE&HSW) }
   LOBARLEHSW := (P_11110 + P_11111)/
                 (P_10110 + P_11110 + P_10111 + P_11111);
   WRITELN( OutFile, ' P(LO|BAR&LE&HSW) =', LOBARLEHSW:10:6);
   WRITELN( OutFile, 'No Consistancy check [no goal]');
   WRITELN( OutFile, 'Experts estimate is: 0.60');
```

```
WRITELN( OutFile );

{ P(LO|BAR&LE&HSS) = P(LO&BAR&LE&HSS)/P(BAR&LE&HSS) }
LOBARLEHSS := (P_11101 + P_11111)/
              (P_10101 + P_11101 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LO|BAR&LE&HSS) =', LOBARLEHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'Experts estimate is: 0.60');
WRITELN( OutFile );

{ P(LO|BAR&HSW&HSS) = P(LO&BAR&HSW&HSS)/P(BAR&HSW&HSS) }
LOBARHSWHSS := (P_11011 + P_11111)/
               (P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LO|BAR&HSW&HSS) =', LOBARHSWHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(LO|LE&HSW&HSS) = P(LO&LE&HSW&HSS)/P(LE&HSW&HSS) }
LOLEHSWHSS := (P_01111 + P_11111)/
              (P_00111 + P_10111 + P_01111 + P_11111);
WRITELN( OutFile, ' P(LO|LE&HSW&HSS) =', LOLEHSWHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(LE|BAR&LO&HSW) = P(LE&BAR&LO&HSW)/P(BAR&LO&HSW) }
LEBARLOHSW := (P_11110 + P_11111)/
              (P_11010 + P_11110 + P_11011 + P_11111);
WRITELN( OutFile, ' P(LE|BAR&LO&HSW) =', LEBARLOHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'Experts estimate is: 0.60');
WRITELN( OutFile );

{ P(LE|BAR&LO&HSS) = P(LE&BAR&LO&HSS)/P(BAR&LO&HSS) }
LEBARLOHSS := (P_11101 + P_11111)/
              (P_11001 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, ' P(LE|BAR&LO&HSS) =', LEBARLOHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'Experts estimate is: 0.60');
WRITELN( OutFile );

{ P(LE|BAR&HSW&HSS) = P(LE&BAR&HSW&HSS)/P(BAR&HSW&HSS) }
LEBARHSWHSS := (P_10111 + P_11111)/
               (P_10011 + P_11011 + P_10111 + P_11111);
WRITELN( OutFile, ' P(LE|BAR&HSW&HSS) =', LEBARHSWHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(LE|LO&HSW&HSS) = P(LE&LO&HSW&HSS)/P(LO&HSW&HSS) }
LELOHSWHSS := (P_01111 + P_11111)/
              (P_01011 + P_11011 + P_01111 + P_11111);
WRITELN( OutFile, ' P(LE|LO&HSW&HSS) =', LELOHSWHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSW|BAR&LO&LE) = P(HSW&BAR&LO&LE)/P(BAR&LO&LE) }
HSWBARLOLE := (P_11110 + P_11111)/
              (P_11100 + P_11110 + P_11101 + P_11111);
WRITELN( OutFile, ' P(HSW|BAR&LO&LE) =', HSWBARLOLE:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'Experts estimate is: 0.40');
```

```
WRITELN( OutFile );

{ P(HSW|BAR&LO&HSS) = P(HSW&BAR&LO&HSS)/P(BAR&LO&HSS) }
HSWBARLOHSS := (P_11011 + P_11111)/
               (P_11001 + P_11101 + P_11011 + P_11111);
WRITELN( OutFile, ' P(HSW|BAR&LO&HSS) =', HSWBARLOHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSW|BAR&LE&HSS) = P(HSW&BAR&LE&HSS)/P(BAR&LE&HSS) }
HSWBARLEHSS := (P_10111 + P_11111)/
               (P_10101 + P_11101 + P_10111 + P_11111);
WRITELN( OutFile, ' P(HSW|BAR&LE&HSS) =', HSWBARLEHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSW|LO&LE&HSS) = P(HSW&LO&LE&HSS)/P(LO&LE&HSS) }
HSWLOLEHSS := (P_01111 + P_11111)/
              (P_01101 + P_11101 + P_01111 + P_11111);
WRITELN( OutFile, ' P(HSW|LO&LE&HSS) =', HSWLOLEHSS:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSS|BAR&LO&LE) = P(HSS&BAR&LO&LE)/P(BAR&LO&LE) }
HSSBARLOLE := (P_11101 + P_11111)/
              (P_11100 + P_11110 + P_11101 + P_11111);
WRITELN( OutFile, ' P(HSS|BAR&LO&LE) =', HSSBARLOLE:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile, 'Experts estimate is: 0.40');
WRITELN( OutFile );

{ P(HSS|BAR&LO&HSW) = P(HSS&BAR&LO&HSW)/P(BAR&LO&HSW) }
HSSBARLOHSW := (P_11011 + P_11111)/
               (P_11010 + P_11110 + P_11011 + P_11111);
WRITELN( OutFile, ' P(HSS|BAR&LO&HSW) =', HSSBARLOHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSS|BAR&LE&HSW) = P(HSS&BAR&LE&HSW)/P(BAR&LE&HSW) }
HSSBARLEHSW := (P_10111 + P_11111)/
               (P_10110 + P_11110 + P_10111 + P_11111);
WRITELN( OutFile, ' P(HSS|BAR&LE&HSW) =', HSSBARLEHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{ P(HSS|LO&LE&HSW) = P(HSS&LO&LE&HSW)/P(LO&LE&HSW) }
HSSLOLEHSW := (P_01111 + P_11111)/
              (P_01110 + P_11110 + P_01111 + P_11111);
WRITELN( OutFile, ' P(HSS|LO&LE&HSW) =', HSSLOLEHSW:10:6);
WRITELN( OutFile, 'No Consistancy check [no goal]');
WRITELN( OutFile );

{
 Calculate the 4th-Order Posterior from its component bits
}
WRITELN( OutFile );
WRITELN( OutFile, '>>>>>  4th-ORDER POSTERIOR  <<<<<<<<<<<<<<<<<<<<<<<');
WRITELN( OutFile );

{ P(BAR|LO&LE&HSW&HSS) = P(BAR&LO&LE&HSW&HSS)/P(LO&LE&HSW&HSS) }
```

```
    BARLOLEHSWHSS := (P_11111)/(P_01111 + P_11111);
    WRITELN( OutFile, ' P(BAR|LO&LE&HSW&HSS) =', BARLOLEHSWHSS:10:6);
    WRITELN( OutFile, 'No Consistancy check [no goal]');
    WRITELN( OutFile );

    {
     Close Up - Output File No Longer Necessary
    }
    CLOSE( OutFile );

END;  { of PROCEDURE Calculate Probabilities 3and4 }

{*************************** MAIN PROCEDURE ****************************}

BEGIN

   Get_Data;

   Calculate_Probabilities_1;

   Calculate_Probabilities_2;

   Calculate_Probabilities_3and4

END.  { of PROGRAM }

{****************************>>>>>><<<<<<*******************************}
```

A13.2 EXAMPLE OF CONVERTED OPUTPUT FILE

```
******************************************
      LP CALCULATED PROABABILITIES
      USING 2nd-ORDER CONDITIONALS
******************************************
           JLK Revised Dataset
******************************************


>>>>>  PRIOR/MARGINALS  <<<<<<<<<<<<<<<<<<<<<<<<<

 P(BAR) =  0.365289
JLK estimate is: 0.39
MINUS Deviation is:  0.000000
 PLUS Deviation is:  0.024708

 P(LO) =  0.355288
JLK estimate is: 0.38
MINUS Deviation is:  0.000000
 PLUS Deviation is:  0.024708

 P(LE) =  0.195288
JLK estimate is: 0.22
MINUS Deviation is:  0.000000
 PLUS Deviation is:  0.024708

 P(HSW) =  0.504703
JLK estimate is: 0.48
MINUS Deviation is:  0.024708
 PLUS Deviation is:  0.000000

 P(HSS) =  0.184703
JLK estimate is: 0.16
MINUS Deviation is:  0.024708
 PLUS Deviation is:  0.000000


>>>>>  1st-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<

 P(BAR|LO) =  0.526784
No Consistancy check [no goal]
JLK estimate is: 0.72

 P(BAR|LE) =  0.655104
No Consistancy check [no goal]
JLK estimate is: 0.83

 P(BAR|HSW) =  0.370832
No Consistancy check [no goal]
JLK estimate is: 0.45

 P(BAR|HSS) =  0.716648
No Consistancy check [no goal]
JLK estimate is: 0.99

 P(LO|BAR) =  0.512361
For Consistancy, P(LO|BAR) =  0.512360
JLK estimate is: 0.58
```

```
 P(LO|LE) =  0.601199
For Consistancy, P(LO|LE) =  0.601198
JLK estimate is: 0.60

 P(LO|HSW) =  0.351046
For Consistancy, P(LO|HSW) =  0.351044
JLK estimate is: 0.40

 P(LO|HSS) =  0.443626
For Consistancy, P(LO|HSS) =  0.443632
JLK estimate is: 0.40

 P(LE|BAR) =  0.350227
For Consistancy, P(LE|BAR) =  0.350228
JLK estimate is: 0.33

 P(LE|LO) =  0.330456
For Consistancy, P(LE|LO) =  0.330456
JLK estimate is: 0.40

 P(LE|HSW) =  0.185729
For Consistancy, P(LE|HSW) =  0.185732
JLK estimate is: 0.20

 P(LE|HSS) =  0.500620
For Consistancy, P(LE|HSS) =  0.500621
JLK estimate is: 0.40

 P(HSW|BAR) =  0.512361
For Consistancy, P(HSW|BAR) =  0.511466
JLK estimate is: 0.55

 P(HSW|LO) =  0.498677
For Consistancy, P(HSW|LO) =  0.498675
JLK estimate is: 0.48

 P(HSW|LE) =  0.479999
For Consistancy, P(HSW|LE) =  0.480000
JLK estimate is: 0.48

 P(HSW|HSS) =  0.443626
For Consistancy, P(HSW|HSS) =  0.443628
JLK estimate is: 0.48 *Question not asked*

 P(HSS|BAR) =  0.362362
For Consistancy, P(HSS|BAR) =  0.362360
JLK estimate is: 0.43

 P(HSS|LO) =  0.230627
For Consistancy, P(HSS|LO) =  0.230631
JLK estimate is: 0.20

 P(HSS|LE) =  0.473485
For Consistancy, P(HSS|LE) =  0.473479
JLK estimate is: 0.60

 P(HSS|HSW) =  0.162351
For Consistancy, P(HSS|HSW) =  0.162354
JLK estimate is: 0.20 *Question not asked*
```

```
>>>>>  2nd-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<

 P(BAR|LO&LE) =  0.777117
No Consistancy check [no goal]

 P(BAR|LO&HSW) =  0.494367
No Consistancy check [no goal]

 P(BAR|LO&HSS) =  0.680640
No Consistancy check [no goal]

 P(BAR|LE&HSW) =  0.720839
No Consistancy check [no goal]

 P(BAR|LE&HSS) =  0.716999
No Consistancy check [no goal]

 P(BAR|HSW&HSS) =  0.680640
No Consistancy check [no goal]

 P(LO|BAR&LE) =  0.713172
For Consistancy, P(LO|BAR&LE) =  0.713168
JLK estimate is: 0.60

 P(LO|BAR&HSW) =  0.467990
For Consistancy, P(LO|BAR&HSW) =  0.467985
JLK estimate is: 0.60

 P(LO|BAR&HSS) =  0.421336
For Consistancy, P(LO|BAR&HSS) =  0.421338
JLK estimate is: 0.60

 P(LO|LE&HSW) =  0.720839
For Consistancy, P(LO|LE&HSW) =  0.720826
JLK estimate is: 0.60

 P(LO|LE&HSS) =  0.603151
For Consistancy, P(LO|LE&HSS) =  0.603147
JLK estimate is: 0.60

 P(LO|HSW&HSS) =  0.680640
For Consistancy, P(LO|HSW&HSS) =  0.680636
JLK estimate is: 0.40 *Question not asked*

 P(LE|BAR&LO) =  0.487492
For Consistancy, P(LE|BAR&LO) =  0.487487
JLK estimate is: 0.60

 P(LE|BAR&HSW) =  0.361028
For Consistancy, P(LE|BAR&HSW) =  0.361027
JLK estimate is: 0.33

 P(LE|BAR&HSS) =  0.500865
For Consistancy, P(LE|BAR&HSS) =  0.500859
JLK estimate is: 0.60

 P(LE|LO&HSW) =  0.381376
For Consistancy, P(LE|LO&HSW) =  0.381374
```

```
JLK estimate is: 0.40

 P(LE|LO&HSS) =  0.680640
For Consistancy, P(LE|LO&HSS) =  0.680633
JLK estimate is: 0.60

 P(LE|HSW&HSS) =  0.680640
For Consistancy, P(LE|HSW&HSS) =  0.680636
JLK estimate is: 0.40 *Question not asked*

 P(HSW|BAR&LO) =  0.467990
For Consistancy, P(HSW|BAR&LO) =  0.467990
JLK estimate is: 0.55

 P(HSW|BAR&LE) =  0.528163
For Consistancy, P(HSW|BAR&LE) =  0.528161
JLK estimate is: 0.55

 P(HSW|BAR&HSS) =  0.421336
For Consistancy, P(HSW|BAR&HSS) =  0.421343
JLK estimate is: 0.55 *Question not asked*

 P(HSW|LO&LE) =  0.575519
For Consistancy, P(HSW|LO&LE) =  0.575514
JLK estimate is: 0.48

 P(HSW|LO&HSS) =  0.680640
For Consistancy, P(HSW|LO&HSS) =  0.680637
JLK estimate is: 0.48 *Question not asked*

 P(HSW|LE&HSS) =  0.603151
For Consistancy, P(HSW|LE&HSS) =  0.603159
JLK estimate is: 0.48 *Question not asked*

 P(HSS|BAR&LO) =  0.297986
For Consistancy, P(HSS|BAR&LO) =  0.297985
JLK estimate is: 0.43

 P(HSS|BAR&LE) =  0.518220
For Consistancy, P(HSS|BAR&LE) =  0.518216
JLK estimate is: 0.60

 P(HSS|BAR&HSW) =  0.297986
For Consistancy, P(HSS|BAR&HSS) =  0.297985
JLK estimate is: 0.43 *Question not asked*

 P(HSS|LO&LE) =  0.475023
For Consistancy, P(HSS|LO&LE) =  0.475016
JLK estimate is: 0.60

 P(HSS|LO&HSW) =  0.314781
For Consistancy, P(HSS|LO&HSW) =  0.314785
JLK estimate is: 0.20 *Question not asked*

 P(HSS|LE&HSW) =  0.594967
For Consistancy, P(HSS|LE&HSW) =  0.594965
JLK estimate is: 0.60 *Question not asked*


>>>>>  3rd-ORDER POSTERIORS/CONDITIONALS  <<<<<<<<
```

```
P(BAR|LO&LE&HSW) =  0.806364
No Consistancy check [no goal]

P(BAR|LO&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(BAR|LO&LE&HSS) =  0.765398
No Consistancy check [no goal]

P(BAR|LE&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(LO|BAR&LE&HSW) =  0.806364
No Consistancy check [no goal]
Experts estimate is: 0.60

P(LO|BAR&LE&HSS) =  0.643866
No Consistancy check [no goal]
Experts estimate is: 0.60

P(LO|BAR&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(L0|LE&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(LE|BAR&LO&HSW) =  0.622064
No Consistancy check [no goal]
Experts estimate is: 0.60

P(LE|BAR&LO&HSS) =  0.765398
No Consistancy check [no goal]
Experts estimate is: 0.60

P(LE|BAR&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(LE|LO&HSW&HSS) =  0.765398
No Consistancy check [no goal]

P(HSW|BAR&LO&LE) =  0.597179
No Consistancy check [no goal]
Experts estimate is: 0.40

P(HSW|BAR&LO&HSS) =  0.765398
No Consistancy check [no goal]

P(HSW|BAR&LE&HSS) =  0.643866
No Consistancy check [no goal]

P(HSW|LO&LE&HSS) =  0.765398
No Consistancy check [no goal]

P(HSS|BAR&LO&LE) =  0.467859
No Consistancy check [no goal]
Experts estimate is: 0.40

P(HSS|BAR&LO&HSW) =  0.487356
No Consistancy check [no goal]
```

```
 P(HSS|BAR&LE&HSW) =  0.631745
No Consistancy check [no goal]

 P(HSS|LO&LE&HSW) =  0.631745
No Consistancy check [no goal]


>>>>>  4th-ORDER POSTERIOR  <<<<<<<<<<<<<<<<<<<<<<

 P(BAR|LO&LE&HSW&HSS) =  0.846745
No Consistancy check [no goal]
```

Appendix 14

LGP RESULTS

The tables below summarize the final probabilities for the three and two experiments proposed for a) the expert assessed data, using as goals to drive the LGP the expert assessed probabilities and, b) the empirical data, using as goals to drive the LGP the empirical probabilities. Refer to Appendix 8 for a list of the probability abbreviations used in the tables.

A14.1 EXPERT ASSESSED DATA

PRIOR PROBABILITY	EXPERT ASSESSMENT	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR	0.33	0.29	0.30	0.33
LO	0.15	0.19	0.14	0.17
LE	0.10	0.14	0.13	0.12
HSW	0.40	0.44	0.43	0.40
HSS	0.15	0.19	0.18	0.17

Table A14.1: LGP estimated prior probabilities (using as goals the expert assessed probabilities) for the three experiments proposed in Chapter 6; *Exp-I* - all the data from the priors to the 2nd-order conditionals; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only.

1st-ORDER PROBABILITY	EXPERT ASSESSMENT	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR | LO	0.88	0.68	0.68	0.64
BAR | LE	1.32	0.59	0.72	0.50
BAR | HSW	0.50	0.49	0.49	0.55
BAR | HSS	1.32	0.74	0.86	0.64
LO | BAR	0.40	0.44	0.33	0.34
LO| LE	0.40	0.55	0.45	0.50
LO| HSW	0.20	0.24	0.20	0.15
LO | HSS	0.20	0.25	0.14	0.64
LE | BAR	0.40	0.28	0.31	0.18
LE | LO	0.40	0.40	0.40	0.36
LE | HSW	0.05	0.13	0.06	0.15
LE | HSS	0.05	0.25	0.21	0.36
HSW | BAR	0.60	0.73	0.69	0.66
HSW | LO	0.40	0.55	0.60	0.36
HSW | LE	0.40	0.43	0.20	0.50
HSW | HSS	*Q not asked*	0.75	0.79	0.36
HSS | BAR	0.60	0.47	0.51	0.34
HSS | LO	0.05	0.25	0.17	0.64
HSS | LE	0.20	0.34	0.29	0.50
HSS | HSW	*Q not asked*	0.32	0.33	0.15

Table A14.2: LGP estimated 1st-order probabilities (using as goals the expert assessed probabilities) for the three experiments proposed in Chapter 6; *Exp-I* - all the data from the priors to the 2nd-order conditionals; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. *Q not asked* indicates that the question associated with the probability did not form part of the original questionnaire, and that a goal value was not specified. The shaded values were not used as goals when applying the LGP; they are included merely for comparison.

2nd-ORDER PROBABILITY	EXPERT ASSESSMENT	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR | LO&LE	**	0.64	0.78	0.50
BAR | LO&HSW	**	0.77	0.62	0.50
BAR | LO&HSS	**	1.00	0.50	0.72
BAR | LE&HSW	**	0.10	0.50	0.50
BAR | LE&HSS	**	1.00	0.66	0.50
BAR | HSW&HSS	**	0.66	0.91	0.50
LO | BAR & LE	0.60	0.59	0.49	0.50
LO | BAR & HSW	0.20	0.37	0.25	0.14
LO | BAR & HSS	0.60	0.33	0.08	0.74
LO | LE & HSW	0.40	0.40	0.50	0.50
LO | LE & HSS	0.40	0.88	0.34	0.50
LO | HSW & HSS	*Q not asked*	0.04	0.09	0.50
LE | BAR & LO	0.60	0.37	0.46	0.28
LE | BAR & HSW	0.20	0.03	0.06	0.14
LE | BAR & HSS	0.60	0.33	0.16	0.28
LE | LO & HSW	0.40	0.23	0.15	0.50
LE | LO & HSS	0.60	0.88	0.50	0.28
LE | HSW & HSS	*Q not asked*	0.04	0.09	0.50
HSW | BAR & LO	0.40	0.62	0.54	0.28
HSW | BAR & LE	0.40	0.07	0.14	0.50
HSW | BAR & HSS	*Q not asked*	0.66	0.84	0.28
HSW | LO & LE	0.40	0.31	0.22	0.50
HSW | LO & HSS	*Q not asked*	0.11	0.50	0.28
HSW | LE & HSS	*Q not asked*	0.12	0.34	0.50
HSS | BAR & LO	0.40	0.36	0.13	0.72
HSS | BAR & LE	0.40	0.58	0.26	0.50
HSS | BAR & HSW	*Q not asked*	0.43	0.61	0.14
HSS | LO & LE	0.05	0.54	0.22	0.50
HSS | LO & HSW	*Q not asked*	0.05	0.15	0.50
HSS | LE & HSW	*Q not asked*	0.10	0.50	0.50

Table A14.3: LGP estimated 2nd-order probabilities (using as goals the expert assessed probabilities) for the three experiments proposed in Chapter 6; *Exp-I* - all the data from the priors to the 2nd-order conditionals; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified, while *Q not asked* indicates that the question associated with the probability did not form part of the original questionnaire, and that a goal value was not specified.

3rd-ORDER PROBABILITY	EXPERT ASSESSMENT	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR|LO&LE&HSW	**	Undefined	0.50	0.50
BAR|LO&LE&HSS	**	1.00	0.50	0.50
BAR|LO&HSW&HSS	*Q not asked*	1.00	0.50	0.50
BAR|LE&HSW&HSS	*Q not asked*	1.00	0.50	0.50
LO|BAR&LE&HSW	0.60	Undefined	0.50	0.50
LO|BAR&LE&HSS	0.60	0.88	0.26	0.50
LO|BAR&HSW&HSS	*Q not asked*	0.06	0.05	0.50
LO|LE&HSW&HSS	*Q not asked*	Undefined	0.50	0.50
LE|BAR&LO&HSW	0.60	Undefined	0.12	0.50
LE|BAR&LO&HSS	0.60	0.88	0.50	0.19
LE|BAR&HSW&HSS	*Q not asked*	0.06	0.05	0.50
LE|LO&HSW&HSS	*Q not asked*	Undefined	0.50	0.50
HSW|BAR&LO&LE	0.40	Undefined	0.14	0.50
HSW|BAR&LO&HSS	*Q not asked*	0.11	0.50	0.19
HSW|BAR&LE&HSS	*Q not asked*	0.12	0.26	0.50
HSW|LO&LE&HSS	*Q not asked*	Undefined	0.50	0.50
HSS|BAR&LO&LE	0.40	0.85	0.14	0.50
HSS|BAR&LO&HSW	*Q not asked*	0.07	0.12	0.50
HSS|BAR&LE&HSW	*Q not asked*	1.00	0.50	0.50
HSS|LO&LE&HSW	*Q not asked*	Undefined	0.50	0.50

Table A14.4: LGP estimated 3rd-order probabilities (using as goals the expert assessed probabilities) for the three experiments proposed in Chapter 6; *Exp-I* - all the data from the priors to the 2nd-order conditionals; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified, while *Q not asked* indicates that the question associated with the probability did not form part of the original questionnaire, and that a goal value was not specified. The shaded values were not included as goals when applying the LGP; they are included merely for comparison.

4th-ORDER PROBABILITY	EXPERT ASSESSMENT	LGP ASSESSMENT		
		Exp-I	Exp-II	Exp-III
BAR|LO&LE& HSW&HSS	**	Undefined	0.50	0.50

Table A14.5: LGP estimated 4th-order posterior probability (using as goals the expert assessed probabilities) for the three experiments proposed in Chapter 6; *Exp-I* - all the data from the priors to the 2nd-order conditionals; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified.

A14.2 EMPIRICAL DATA

PRIOR PROBABILITY	REAL DATA ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR	0.44	0.43	0.44
LO	0.60	0.58	0.60
LE	0.33	0.33	0.33
HSW	0.55	0.55	0.53
HSS	0.17	0.19	0.19

Table A14.6: LGP estimated prior probabilities (using as goals the empirical probabilities) for the two experiments proposed in Chapter 6; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only.

1st-ORDER PROBABILITY	REAL DATA ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR | LO	0.55	0.59	0.58
BAR | LE	0.33	0.27	0.29
BAR | HSW	0.40	0.40	0.52
BAR | HSS	0.65	0.54	0.50
LO | BAR	0.75	0.79	0.78
LO| LE	**	0.73	0.71
LO| HSW	**	0.68	0.82
LO | HSS	**	0.54	0.50
LE | BAR	0.25	0.21	0.22
LE | LO	**	0.41	0.39
LE | HSW	**	0.44	0.44
LE | HSS	**	0.46	0.50
HSW | BAR	0.50	0.51	0.63
HSW | LO	**	0.64	0.73
HSW | LE	**	0.74	0.71
HSW | HSS	**	0.46	0.50
HSS | BAR	0.25	0.24	0.22
HSS | LO	**	0.17	0.16
HSS | LE	**	0.26	0.29
HSS | HSW	**	0.16	0.18

Table A14.7: LGP estimated 1st-order probabilities (using as goals the empirical probabilities) for the two experiments proposed in Chapter 6; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified.

2nd-ORDER PROBABILITY	REAL DATA ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR | LO&LE	**	0.18	0.20
BAR | LO&HSW	**	0.47	0.52
BAR | LO&HSS	**	0.58	0.50
BAR | LE&HSW	**	0.18	0.20
BAR | LE&HSS	**	0.50	0.50
BAR | HSW&HSS	**	0.50	0.50
LO | BAR & LE	**	0.49	0.50
LO | BAR & HSW	**	0.80	0.83
LO | BAR & HSS	**	0.58	0.50
LO | LE & HSW	**	0.82	0.80
LO | LE & HSS	**	0.50	0.50
LO | HSW & HSS	**	0.50	0.50
LE | BAR & LO	**	0.13	0.14
LE | BAR & HSW	**	0.20	0.17
LE | BAR & HSS	**	0.42	0.50
LE | LO & HSW	**	0.53	0.43
LE | LO & HSS	**	0.42	0.50
LE | HSW & HSS	**	0.50	0.50
HSW | BAR & LO	**	0.52	0.66
HSW | BAR & LE	**	0.51	0.50
HSW | BAR & HSS	**	0.42	0.50
HSW | LO & LE	**	0.82	0.80
HSW | LO & HSS	**	0.42	0.50
HSW | LE & HSS	**	0.50	0.50
HSS | BAR & LO	**	0.18	0.14
HSS | BAR & LE	**	0.49	0.50
HSS | BAR & HSW	**	0.20	0.17
HSS | LO & LE	**	0.18	0.20
HSS | LO & HSW	**	0.12	0.11
HSS | LE & HSW	**	0.18	0.20

Table A14.8: LGP estimated 2nd-order probabilities (using as goals the empirical probabilities) for the two experiments proposed in Chapter 6; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified.

3rd-ORDER PROBABILITY	REAL DATA ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR|LO&LE&HSW	**	0.11	0.13
BAR|LO&LE&HSS	**	0.50	0.50
BAR|LO&HSW&HSS	**	0.50	0.50
BAR|LE&HSW&HSS	**	0.50	0.50
LO|BAR&LE&HSW	**	0.49	0.50
LO|BAR&LE&HSS	**	0.50	0.50
LO|BAR&HSW&HSS	**	0.50	0.50
LO|LE&HSW&HSS	**	0.50	0.50
LE|BAR&LO&HSW	**	0.12	0.10
LE|BAR&LO&HSS	**	0.36	0.50
LE|BAR&HSW&HSS	**	0.50	0.50
LE|LO&HSW&HSS	**	0.50	0.50
HSW|BAR&LO&LE	**	0.50	0.50
HSW|BAR&LO&HSS	**	0.36	0.50
HSW|BAR&LE&HSS	**	0.50	0.50
HSW|LO&LE&HSS	**	0.50	0.50
HSS|BAR&LO&LE	**	0.50	0.50
HSS|BAR&LO&HSW	**	0.12	0.10
HSS|BAR&LE&HSW	**	0.49	0.50
HSS|LO&LE&HSW	**	0.11	0.13

Table A14.9: LGP estimated 3rd-order probabilities (using as goals the empirical probabilities) for the two experiments proposed in Chapter 6; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified.

4th-ORDER PROBABILITY	REAL DATA ASSESSMENT	LGP ASSESSMENT	
		Exp-II	Exp-III
BAR|LO&LE& HSW&HSS	**	0.50	0.50

Table A14.10: LGP estimated 4th-order posterior probability (using as goals the empirical probabilities) for the two experiments proposed in Chapter 6; *Exp-II* - priors and 1st-order conditionals only; *Exp-III* - priors only. ** indicates that no goal value was specified.

Appendix 15

REVISING THE PROBABILITIES

15.1 ARGUMENTS FOR THE REVISION OF THE PROBABILITY DATASETS

The expert assessed (subjective) probabilities elicited by questionnaire are not consistent with the axioms of probability, while there appears to be no problems with the empirical probabilities (see Chapter 6, section 6.7). We have applied Linear Goal Programming techniques to estimate a consistent set of probabilities, using as goal the probabilities as defined by the experts (see Chapter 6, section 6.9). Because these "new" probabilities are based on the original expert assessments, they carried with them an inherently deeper problem that has somehow escaped attention by all so far - the probabilities fail to adhere to the "*additive* information" assumption (see Chapter 6, section 6.12). So, we need a new set of data.

Note that all that is required is a re-assessment of the priors, and 1st- and 2nd-order probabilities. Although we have 3rd-order probabilities from the questionnaire assessment, these are considered tenuous at the very least, and unusable at best. These probabilities are not used in any assessment.

Revising the Prior Probabilities:

First off, we need to start with a new set of priors in order to have a starting point to be able to set about revising the remainder of the probabilities/likelihoods with the "*additive* information" assumption. These were constructed from the two probability datasets; the revised priors are derived from a simple average of the original empirical and expert assessments (Table A15.1).

Revising the 1st-Order Likelihoods: (Table A15.2):

Where both empirical and expert assessed probabilities exists, we stick to the original "formula" of taking averages. In this, only the 1st-order probabilities, there already a scarcity of empirical data, so the only likelihoods we can take averages for are *P*(LO|BAR), *P*(LE|BAR), *P*(HSW|BAR) and *P*(HSS|BAR). If you don't know the abbreviations by now........they are presented in Appendix 8.

For the majority of the remaining likelihoods, only expert assessed data exists. It should be noted that this re-assessment, and re-assigning of probabilities where necessary, takes place very much under the auspices of the original expert assessment. It is believed that the experts would have weighted the variables off against each other in some form of hierachical arrangement of importance, and that this is reflected in the probabilities. We try to adhere to this inherent weighting.
Some probabilities are just blatantly incorrect however. For example, the probability of observing Low Egg Production given that there is a High percentage of "Starvation Stations", P(LE|HSS), is given by the experts as 0.05. If there is poor food availability for the spawning fish, my guess is that there is a good probability (much greater than 0.05) that low egg production will be observed - this probability is increased to 0.40.

There are also a few variable combinations that the experts would not have seen in the questionnaire, because these variables (N-S wind anomaly and percentage "Starvation Stations") were never intended to be used together in the same system. With LGP however, it's just as easy to incorporate the extra variable, so we do. These unasked questions, for which no probability exists, have to assessed "from scratch".

Revising the 2st-Order Likelihoods: (Table A15.3):

Once we have the 1st-order probabilities, we can now begin to assess the 2nd-order probabilities. Here's where the majority of the sins were committed by the experts - predominantly of the "additive information" kind. For example, P(HSS|LO) = 0.05 and P(HSS|LE) = 0.20 were two probabilities assessed by the experts. When it came to revising these probabilities in the light of new information, things went off track. When revised, P(HSS|LO&LE) was assessed at 0.05. If we adhere to the "additive information" assumption, the smallest this probability can be is 0.20 (and that is only if the presence of

Low Oil yield adds no information, unlikely as that may seem). There are a number of other similar examples.

Essentially then, when revising a probability in the light of new evidence, one should always ensure that the probability does not "regress", but progress if the new information adds confidence to the original probability.

15.2 TABLES OF REVISED EXPERT DATASET WITH LGP ASSESSMENT

The tables below summarize the final probabilities obtained by the various methods of combining and averaging and the authors personal revision (described in Chapter 6, section 6.12). The *Revised Data* column contains the probabilities used as goals in the LGP experiments, and the *LGP Assessment* column shows the probabilities resulting from the LGP assessment. See Appendix 8 for a list of the probability abbreviations used in the tables.

PRIOR PROBABILITY	EXPERT DATA	EMPIRICAL DATA	REVISED DATA	LGP ASSESSMENT
BAR	0.33	0.44	**0.39**	0.37
LO	0.15	0.60	**0.38**	0.36
LE	0.10	0.33	**0.22**	0.20
HSW	0.40	0.55	**0.48**	0.50
HSS	0.15	0.17	**0.16**	0.18

Table A15.1: Comparing the prior probabilities from the revised probability dataset with the original expert and empirical assessed probabilities, and with the prior probabilities estimated by the LGP (using the revised probabilities as goals).

1st-ORDER PROBABILITY	EXPERT DATA	EMPIRICAL DATA	REVISED DATA	LGP ASSESSMENT
BAR | LO	0.88	0.55	0.72	0.53
BAR | LE	1.32	0.33	0.83	0.66
BAR | HSW	0.50	0.40	0.45	0.37
BAR | HSS	1.32	0.65	0.99	0.72
LO | BAR	0.40	0.75	**0.58**	0.51
LO| LE	0.40	**	**0.60**	0.60
LO| HSW	0.20	**	**0.40**	0.35
LO | HSS	0.20	**	**0.40**	0.44
LE | BAR	0.40	0.25	**0.33**	0.35
LE | LO	0.40	**	**0.40**	0.33
LE | HSW	0.05	**	**0.20**	0.19
LE | HSS	0.05	**	**0.40**	0.50
HSW | BAR	0.60	0.50	**0.55**	0.51
HSW | LO	0.40	**	**0.48**	0.50
HSW | LE	0.40	**	**0.48**	0.48
HSW | HSS	*Q not asked*	**	**0.48**	0.44
HSS | BAR	0.60	0.25	**0.43**	0.36
HSS | LO	0.05	**	**0.20**	0.23
HSS | LE	0.20	**	**0.60**	0.47
HSS | HSW	*Q not asked*	**	**0.20**	0.16

Table A15.2: Comparing 1st-order probabilities and likelihoods from the revised probability dataset with the original expert and empirical assessed probabilities, and with the 1st-order probabilities estimated by the LGP (using the revised probabilities as goals). The probabilities in the shaded boxes were not used as goals, they are shown for comparison purposes only; "*Q not asked*" indicates that the probability did not form part of the original questionnaire; ** indicates the datum is not available.

2nd-ORDER PROBABILITY	EXPERT DATA	EMPIRICAL DATA	REVISED DATA	LGP ASSESSMENT
BAR | LO&LE	**	**	**	0.77
BAR | LO&HSW	**	**	**	0.50
BAR | LO&HSS	**	**	**	0.68
BAR | LE&HSW	**	**	**	0.72
BAR | LE&HSS	**	**	**	0.72
BAR | HSW&HSS	**	**	**	0.68
LO | BAR & LE	0.60	**	**0.60**	0.71
LO | BAR & HSW	0.20	**	**0.60**	0.47
LO | BAR & HSS	0.60	**	**0.60**	0.42
LO | LE & HSW	0.40	**	**0.60**	0.72
LO | LE & HSS	0.40	**	**0.60**	0.60
LO | HSW & HSS	*Q not asked*	**	**0.40**	0.68
LE | BAR & LO	0.60	**	**0.60**	0.49
LE | BAR & HSW	0.20	**	**0.33**	0.36
LE | BAR & HSS	0.60	**	**0.60**	0.50
LE | LO & HSW	0.40	**	**0.40**	0.38
LE | LO & HSS	0.60	**	**0.60**	0.68
LE | HSW & HSS	*Q not asked*	**	**0.40**	0.68
HSW | BAR & LO	0.40	**	**0.55**	0.47
HSW | BAR & LE	0.40	**	**0.55**	0.53
HSW | BAR & HSS	*Q not asked*	**	**0.55**	0.42
HSW | LO & LE	0.40	**	**0.48**	0.58
HSW | LO & HSS	*Q not asked*	**	**0.48**	0.68
HSW | LE & HSS	*Q not asked*	**	**0.48**	0.60
HSS | BAR & LO	0.40	**	**0.43**	0.30
HSS | BAR & LE	0.40	**	**0.60**	0.52
HSS | BAR & HSW	*Q not asked*	**	**0.43**	0.30
HSS | LO & LE	0.05	**	**0.60**	0.48
HSS | LO & HSW	*Q not asked*	**	**0.20**	0.31
HSS | LE & HSW	*Q not asked*	**	**0.60**	0.59

Table A15.3: Comparing 2nd-order probabilities and likelihoods from the revised probability dataset with the original expert and empirical assessed probabilities, and with the 2nd-order probabilities estimated by the LGP (using the revised probabilities as goals). "*Q not asked*" indicates that the probability did not form part of the original questionnaire; ** indicates the datum is not available.

3rd-ORDER PROBABILITY	EXPERT DATA	EMPIRICAL DATA	REVISED DATA	LGP ASSESSMENT
BAR|LO&LE&HSW	**	**	**	0.81
BAR|LO&LE&HSS	**	**	**	0.77
BAR|LO&HSW&HSS	*Q not asked*	**	**	0.77
BAR|LE&HSW&HSS	*Q not asked*	**	**	0.77
LO|BAR&LE&HSW	0.60	**	**	0.81
LO|BAR&LE&HSS	0.60	**	**	0.64
LO|BAR&HSW&HSS	*Q not asked*	**	**	0.77
LO|LE&HSW&HSS	*Q not asked*	**	**	0.77
LE|BAR&LO&HSW	0.60	**	**	0.62
LE|BAR&LO&HSS	0.60	**	**	0.77
LE|BAR&HSW&HSS	*Q not asked*	**	**	0.77
LE|LO&HSW&HSS	*Q not asked*	**	**	0.77
HSW|BAR&LO&LE	0.40	**	**	0.60
HSW|BAR&LO&HSS	*Q not asked*	**	**	0.77
HSW|BAR&LE&HSS	*Q not asked*	**	**	0.64
HSW|LO&LE&HSS	*Q not asked*	**	**	0.77
HSS|BAR&LO&LE	0.40	**	**	0.47
HSS|BAR&LO&HSW	*Q not asked*	**	**	0.49
HSS|BAR&LE&HSW	*Q not asked*	**	**	0.63
HSS|LO&LE&HSW	*Q not asked*	**	**	0.63

Table A15.4: Comparing 3rd-order probabilities and likelihoods from the revised probability dataset with the original expert and empirical assessed probabilities, and with the 3rd-order probabilities estimated by the LGP (using the revised probabilities as goals). "*Q not asked*" indicates that the probability did not form part of the original questionnaire; ** indicates the datum is not available.

4th-ORDER PROBABILITY	EXPERT DATA	EMPIRICAL DATA	REVISED DATA	LGP ASSESSMENT
BAR|LO&LE& HSW&HSS	**	**	**	0.85

Table A15.5: Comparing the 4th-order posterior probability from the revised probability dataset with the original expert and empirical assessed probabilities, and with the 2nd-order probabilities estimated by the LGP (using the revised probabilities as goals). ** indicates the datum is not available.

The Final Word............