The use and disaggregation of survey data to study the cross-sectional and spatial distribution of multimorbidity and its association with socioeconomic disadvantage in South Africa

Amy Weimann

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Supervisors: Dr. Tolu Oni & Professor Sue Parnell

This work has not been previously submitted in whole, or in part, for the award of any degree. It is my own work. Each significant contribution to, and quotation in, this dissertation from the work, or works, of other people has been attributed, and has been cited and referenced.

Declaration II

This dissertation is part of a wider research project that I conducted under the permission of my supervisors. Prior to submission of this dissertation to the University of Cape Town for examination, a manuscript was submitted to the Social Science & Medicine Journal entitled, “A cross-sectional and spatial analysis of the prevalence of multimorbidity and its association with socioeconomic disadvantage in South Africa: A comparison between 2008 and 2012”, which contains text, results, figures and tables used in this dissertation. The manuscript has been accepted for publication. One of the co-authors of the manuscript provided supervision for this dissertation.

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Abstract

This study identified the need to provide a proof of concept of the use and disaggregation of existing health data in order to study the cross-sectional and spatial distribution of HIV, tuberculosis and non-communicable disease multimorbidity and the association with socioeconomic disadvantage at a South African, Western Cape Province and urban/intra-urban scale for 2008 and 2012. This study was framed within a health geography context and draws attention to the reality of health variations which are influenced by place-based effects, including the surrounding social, cultural and economic structural factors and mechanisms that, together, constitute the social determinants of health. However, in order to identify and understand these variations in health, access to health data that is able to be disaggregated by key characteristic and spatial scales, is essential. Therefore, this study utilised existing health data from the National Income Dynamics Study, a longitudinal study with a sample of approximately 28 000 people, to perform secondary data analysis using a positivist approach to research. This study found that the coupling of geospatial and health data is able to produce new health information and the graphical representation of data provides unique insights in health variations. Secondly, the burden of disease is not consistent between spatial scales which suggests variations in epidemiological profiles between sub-national geographies, thereby supporting the argument for the need of data disaggregation. Finally, the cross-sectional analysis of this study found multimorbidity to be associated with age, socioeconomic deprivation, obesity and urban areas, while the spatial analysis showed clusters (hot spots) of higher multimorbidity prevalence in parts of KwaZulu-Natal and the Eastern Cape, which compared with the socioeconomic disadvantage spatial pattern. Therefore, this study provides an example of the research needed to provide information to support policy improvement and enable the urban planning and public health professions to work together.

List of Acronyms and Abbreviations

AIDS	Acquired Immune Deficiency Syndrome
ARV	Antiretroviral
BMI	Body Mass Index
CI	Confidence Intervals
CSDH	Commission on the Social Determinants of Health
DAG	Directed Acyclic Graph
DHS	Demographic and Health Survey
GPS	Global Positioning System
HIV	Human Immunodeficiency Virus
IQR	Interquartile Range
MDPI	Multidimensional Poverty Index
NCD	Non-communicable disease
NIDS	National Income Dynamics Study
OR	Odds Ratio
PSU	Primary Sampling Units
SA	Spatial Autocorrelation
SALDRU	Southern Africa Labour and Development Research Unit
SANHANES-1	South African National Health and Nutrition Examination Survey
SDGs	Sustainable Development Goals
Stats SA	Statistics South Africa
TB	Tuberculosis
UNAIDS	Joint United Nations Programme on HIV/AIDS
USA	United States of America
USAID	United States Agency for International Development

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PART ONE:
INTRODUCTION, CONTEXT AND RESEARCH METHODOLOGY

CHAPTER ONE: INTRODUCTION

1.1. URBAN HEALTH CHALLENGES AND AN OPPORTUNITY FOR INTERDISCIPLINARY ACTION

Today, more than half of the world's population inhabits urban areas (UN-HABITAT, 2010). The African population currently has the highest growth rate of any continent and is projected to increase twofold between 2015 and 2015, contributing to more than 50% of the global population growth for the same period (United Nations, 2015a). Moreover, the United Nations Department of Economics and Social Affairs estimates that approximately 40% of the African population currently inhabits urban areas and that half of the population will be urbanised by 2030 (Parnell & Pieterse, 2014).

The rapid and unplanned urbanisation that has occurred in developing counties has placed a strain on economic resources and a burden on basic services, housing, health services and infrastructure (Chirisa, 2008). Unplanned urbanisation coupled with inadequate housing and tenure opportunities in many developing countries has resulted in the growth of urban informal settlements or slums, many of which contain overcrowded dwellings and poor basic services (Vlahov et al., 2007). Intra and inter-urban inequalities have intensified with urbanisation and have resulted in disparities in social determinants of health between areas, such as access to health services and medical care (Vearey et al., 2010). The shortage of basic and healthcare services together with deprivation of other social determinants of health in many poorer areas have together created an enabling environment for the development and spread of disease and illness. In addition, urbanisation brings about some diseases that have stereotypically been associated with a more sedentary or 'Westernised' lifestyle, which include hypertension, asthma, obesity and diabetes (Godfrey & Julien, 2005). In developing countries, these western lifestyle diseases are usually more prevalent among people living in urban areas compared to their rural counterparts (Godfrey & Julien, 2005). Now, an overwhelming challenge of the 21st Century lies in the interspace between the aspiration to develop, improve and sustain wellbeing and health, and the reality that urban and intra-urban areas are constantly changing due to a continuous growth in population over time (Salem & Fournet, 2003; Vlahov et al., 2007).

South Africa is one of the most developed and urbanised sub-Saharan African countries, with approximately two thirds of its national population inhabiting urban areas (McGranahan & Martine, 2012). It is characterised by a quadruple burden of disease, which includes infectious diseases such as the human immunodeficiency virus (HIV) and tuberculosis (TB); non-communicable diseases (NCDs);

perinatal and maternal; and injury-related disorders (Bradshaw et al., 2003). The national population is increasingly ageing and the widespread use of antiretroviral (ARV) therapy is resulting in an ageing population of HIV-infected persons and an accompanying rise in coexisting health conditions, also known as multimorbidity (Tseng, Seet & Phillips, 2014).

The data from the 1998 South African Demographic and Health Survey (DHS), as reported in the Poverty and Chronic Diseases Report, suggest that areas associated with low socioeconomic status experience a significant burden of premature mortality that can be linked to various diseases in the country (Bradshaw & Steyn, 2001). Research has revealed that the presence of socioeconomic factors such as crowded living conditions, poor nutrition, limited financial resources, and poor housing and sanitation, are likely to increase the risk of TB infection and exacerbate the transmission of the disease in communities, particularly where there is a high HIV prevalence (Harling, Ehrlich & Myer, 2008; Lönnroth et al., 2010; Rasanathan et al., 2011; Van Leth et al., 2011). In addition, lower socioeconomic groups have been associated with a higher prevalence of NCD risk factors, including alcohol consumption, increased salt consumption, and obesity which affects 40% of South African adult females (Bradshaw & Steyn, 2001).

Despite these health challenges, South Africa has made notable progress within the public health field by becoming a world leader in ARV therapy programmes and is also making strides in the development of diagnostics and the implementation of treatments for TB (Mayosi et al., 2012). Nevertheless, social, economic, infrastructural and health inequalities are still prominent in the South African urban environments and together amalgamate to place pressure on both the public health and urban planning fields. These two fields will need to respond through cooperative efforts in order to improve and sustain health and wellbeing while addressing the infrastructural, service-related and other structural demands that accompany urbanisation and development.

1.1.1. The need to reconnect the public health and urban planning fields

Urban planners are responsible for the development of urban planning processes that optimize the effective use of land, buildings and resources so as to cater for and address growing urban populations (Barton & Tsourou, 2000). Consequently, urban planners have the ability to influence not only spatial and infrastructural factors within the physical environment, but also indirectly influence social and lifestyle factors, making them instrumental in addressing the 21st Century challenge of supporting urban population growth with sustainable planning that will promote and sustain health and wellbeing through the development of liveable communities (Barton & Tsourou, 2000; Giles-corti et al., 2014).

During the 19th Century, the fields of urban planning and public health originally had a common objective of deterring the spread of many infectious diseases that were widely prevalent due to poor sanitation and overcrowded conditions (Barton, 2009). However, through the 20th Century this objective was deprioritised, possibly due to rapid urban population growth and a renewed focus on 'urban sustainability' that prioritised environmental issues, and now there appears to be little coordination in the efforts made to sustain urban health and wellbeing (Northridge, Sclar & Biswas, 2003; Corburn, 2004, 2009; Smit & Parnell, 2012). In an era where infectious diseases are still prevalent in the urban setting and lifestyle-related health issues are on the rise such as obesity, hypertension and diabetes, the focus needs to be pulled back to *urban health planning* which places health and wellbeing at the centre of urban planning and acknowledges the significant influence that urban planning processes and practices can have over the wellbeing and health of citizens (Barton & Tsourou, 2000; Smit et al., 2011). The call for the reconnection of the fields of urban planning and public health has been echoed by numerous researchers (Northridge, Sclar & Biswas, 2003; Corburn, 2004; Barton, 2009; Smit et al., 2011; Koohsari, Badland & Giles-Corti, 2013).

This reconnection is particularly important for the situation in sub-Saharan Africa where many cities are not only experiencing spatial and infrastructural changes due to urban development, but also a burden of infectious and non-communicable diseases which are influenced by the urban environment and are causing a noticeable deterioration in health outcomes, particularly for the urban poor (Ambert, Jassey & Thomas, 2007; Kjellstrom & Mercado, 2008; Herrick, 2014; Tanner & Harpham, 2014). A concerning question raised is whether living in urban environments is still advantageous compared to life in the rural setting, or whether an urban penalty is emerging as a result of the aforementioned urban health challenges that impact quality of life and wellbeing (Herrick, 2014). Therefore, there needs to be realignment of objectives where both the public health and urban planning agendas are considered within each field and where urban health is reprioritised. However, a challenge for this reconnection evolves around the issue of space and scale and the political processes that are subsequently involved (Koohsari, Badland & Giles-Corti, 2013). More specifically, in order to reconnect these two fields, the concept of space and its relation to health should be explored and investigated, while careful considerations need to be made for the geographical scale of focus for the merging of urban planning and public health agendas and objectives.

1.2. THINKING ABOUT HEALTH, SPATIALLY

Geography has been one of the main research fields that have re-directed attention towards the role that 'space' and 'place' have to play in disease risk and health variation, alongside epidemiology and sociology (Cummins et al., 2007). These fields have argued that the concept of 'place' should not be treated as a mere contextual container but should also be seen as a structure that is made up of various social and physical interactions and resources, which can influence general health and wellbeing (Cummins et al., 2007). The link between place and health variation is a key conversation within the field of geography and this realisation is likely to have contributed to the development of the health geography sub-discipline, which has incorporated a number of novel concepts, particularly looking at 'place-based' effects on health. This lies in comparison to the more conventional medical geography sub-disciple, in which researchers have traditionally considered place to be an inactive, geometric variable (Kearns, 1993).

Exploring these sub-disciplines more closely, medical geography has been an important tool in bio-medicine but exists within the field of geography and primarily focuses on exploring the geographic variations of diseases as well as the geography of health care services (Litva & Eyles, 1995). However, it has been argued that the typical research trends prior to the 1990s saw many medical geographers overlook the importance of place and space concepts in understanding health inequalities, and habitually associate inequalities in health primarily with individual-level factors and processes (Curtis & Jones, 1998). Key authors such as Jones and Moon (1993), Curtis and Jones (1998) and Kearns and Moon (2002) have drawn attention to the possibility that the concepts of space and place could actually be important factors in themselves and in fact contribute towards shaping individual-level factors and processes, thereby resulting in place-based inequalities. These perspectives on the concept of space are being increasingly applied in medical geographical research and have contributed to the emergence of the new health geography field, which largely favours research that is concerned with overall health and wellbeing and seeks to incorporate broad social models in understanding health inequalities (Kearns & Moon, 2002).

Within this context, the concept of space can be defined as "a dimension in which phenomena are distributed" (Curtis & Jones, 1998: 646). In the emerging health geography sub-discipline, space is beginning to be viewed and recognised as more than just a passive container for spatial analysis. It is now frequently recognised as being implicated in wellbeing, as well as health and social outcomes, and has even been acknowledged in general health research which used to habitually overemphasise the social aspects contributing towards health differences and underestimate the role that space and place had to play (Jones & Moon, 1993). More specifically, space is accepted as being both a contributing cause and a consequence of various social, socioeconomic and health processes and therefore influences and is influenced by existing social processes (Kearns & Joseph, 1993; Curtis & Jones, 1998; Kearns & Moon, 2002). An example of this is how space has implications for social integration and exclusion, as the societies that are more spatially dispersed are likely to experience some degree of social exclusion while those societies that have clustered residential areas are sometimes likely to be more socially inclusive (Curtis & Jones, 1998). The degree of social exclusion or inclusion may contribute to health variations across spaces.

Similar to the concept of space, Eyles (1985) originally drew attention to the interaction between 'place' and one's position in society. In this research context, 'place' refers to specific locations which may sometimes be spatially organised, for example districts in a country, and therefore the concept of place is often influenced by various social, economic and political processes (Curtis & Jones, 1998). Eyles (1985) presented the notion that people's socioeconomic position in society will contribute to and influence the way they experience 'place' and, in turn, an individual's location or 'place' will produce different socioeconomic opportunities or hardships that may possibly shape their wellbeing and ultimately impact their health. This idea has not only been applied within health geography, but has also contributed to a refocusing of some medical geographical research to go beyond considering 'place' as a mere raw object and to start considering the role of the 'experienced place' within health research (Kearns, 1993).

1.3. HEALTH GEOGRAPHY AND THE RECONNECTION OF THE HEALTH AND URBAN PLANNING FIELDS

Health geography research is relevant to both the public health and urban planning fields. Space and place are important concepts for the field of public health, where health service management and public health professionals seek to identify health disparities as well as understand the needs and demands of communities for health care services and interventions (Jones & Moon, 1993). Recently, there has been a growing call for researchers to investigate health geography theories and to provide substantiated evidence that may be proposed to the public health field (Cummins et al., 2007; Tanner & Harpham, 2014).

In addition, place-based effects are important to the field of urban planning, as the design, location and structure of places and spaces not only contribute to a sense of identity for individuals, but also to the development of social and physical factors that influence lifestyles, behaviour, safety, and general wellbeing and health (Eyles & Williams, 2008; Marmot et al., 2008). According to Marmot et al. (2008), urban governance and planning will need to prioritise health and wellbeing by developing communities and places that provide access to basic services, enhance psychological and physical wellbeing, prioritise environmental sustainability and promote social cohesion in order to address issues of health inequality. Furthermore, identifying health inequalities between communities, groups of people and places will be important for this field.

The need to consider the role that space and place play in health inequality is thus essential to the reconnection of urban planning and public health professions. Unfortunately, a large challenge for addressing inequalities in health across space and place, and thus for the reconnection of the urban planning and public health fields, is the lack of available disaggregated data that can provide information on status and inequalities of health.

1.4. THE NEED FOR DISAGGREGATED HEALTH DATA

Goal number 10 of the Sustainable Development Goals (SDGs) is to reduce the inequality that currently exists between and within countries (The United Nations General Assembly, 2015). This includes inequalities in health and wellbeing. However, in order to first recognise and understand inequalities at the national and sub-national level, appropriate data and information are needed. This has been a recurrent call in the 2030 SDG agenda.

This call stems from a realisation that national level averages tend to mask underlying sub-national inequalities. In light of the SDG ambition that no person or people group should be 'left behind' during progress and development, there has been an appeal specifically for data to be disaggregated to reflect key demographic, socioeconomic and social characteristics at sub-national levels (United Nations, 2015b). The disaggregation of data will be critical for supporting policy improvement efforts, for identifying vulnerable and impoverished communities and groups of people, and for monitoring progress of all groups of people towards achieving the SDGs (Dornan, 2015).

This conversation is highly relevant to the health geography field as well as to the fields of urban planning and public health as information and data will be needed to inform policies and interventions aimed at addressing inequalities in health.

1.5. RESEARCH RATIONALE, AIM, OBJECTIVES & HYPOTHESES

1.5.1. South Africa: a key area for health research

South Africa provides an interesting setting for health geography research as the space, place, socioeconomic and health characteristics of the country create a remarkable backdrop: the notorious Apartheid era saw many groups of people segregated and placed into new locations or places based on race; many disparities exist between developed urban cities and the tradition tribal homelands that still exist in more rural locations; there is a high rate of unemployment in the country; provinces and districts have different levels of basic service provision; and South Africa is believed to be undergoing an epidemiological transition in which a rise in NCDs is met with widespread and ever-prevalent infectious diseases, as well as perinatal and maternal, and injury-related disorders in an ageing population together with violence and noticeable social and economic inequalities (Bradshaw et al., 2003; Adato, Carter & May, 2006; Mayosi et al., 2009). In addition, South Africa's population is slowly ageing and as chronic infectious and non-communicable diseases become more prevalent among adults, so does the risk for the development of multiple chronic health conditions in an individual, also known as multimorbidity (Mayosi et al., 2009).

Multimorbidity brings about a decline in quality of life for patients as well as increased expenses and complications for treatment plans and medical care which have implications for healthcare services and public health (Marengoni et al., 2011). Multimorbidity is usually associated with age, particularly with adults older than 65 years and is increasingly common in patients, due to a number of factors including ageing populations and a rise in chronic health conditions (Van den Akker et al., 1998; Uijen & van de Lisdonk, 2008). However, recently multimorbidity has also been found emerging in people younger than 65 years (Salisbury et al., 2011; Agborsangaya et al., 2012), particularly when people are socioeconomically deprived (Uijen & van de Lisdonk, 2008; Barnett et al., 2012; Alaba & Chola, 2013). In South Africa, the prevalence of multimorbidity is largely unknown and there is a paucity of research on the social determinants of multimorbidity (Alaba & Chola, 2013). Alaba and Chola (2013) estimated the prevalence of multimorbidity to be higher among females and in approximately 4% of the South African adult population; however it was suggested that the prevalence of multimorbidity was likely underestimated.

NCDs contribute to the quadruple burden of disease in South Africa where hypertension and diabetes have been recognised as two of the most prevalent NCDs, alongside cancers, respiratory diseases and neuropsychiatric disorders (Mayosi et al., 2009). NCDs have been associated with socioeconomic deprivation in both urban and rural settings in South Africa and said to be increasingly affecting the urban poor (Mayosi et al., 2009). Data on hypertension prevalence for the country are available from the 1998 South African Demographic and Health Survey and reveal a prevalence of 21% for both males and females using the 140/90 mm Hg threshold (Steyn, 2006). Cois and Ehrlich (2014) suggest this may have increased by approximately 22% and 28% in males and females, respectively, between 1998 and 2008. Although hypertension has been associated with factors such as alcohol consumption, smoking, high body mass index (BMI) and inadequate exercise, research has suggested that the degree of association between socioeconomic status and hypertension may vary between males and females (Cois & Ehrlich, 2014). In addition, although hypertension is shown to have prevalence disparities between urban and rural areas in many other sub-Saharan African countries, this is reportedly not the case in South Africa (Steyn, 2006). Hypertension is often found to be implicated in multimorbidity cases as it frequently coexists with other chronic diseases of lifestyle, including diabetes and obesity (Steyn, 2006).

Regarding diabetes, 6.5% of South African adults between 20 and 79 years of age were estimated to have diabetes in 2011 (Whiting et al., 2011). Although South Africa has very few prevalence statistics for diabetes, studies have shown an association with age and have revealed prevalence disparities between ethnic groups, with members from the Asian/Indian population more likely to develop type 2 diabetes due to a greater risk of developing insulin resistance compared to other ethnic groups (Bradshaw et al., 2003; Bajaj & Banerji, 2004). It is a common perception that diabetes is associated with urbanisation due to exposure to more sedentary lifestyles (Green, Hirsch & Pramming, 2003). Unfortunately, the heavy burden of infectious diseases in South Africa has subsequently resulted in the side-lining of many non-communicable disease intervention and treatment plans (Mayosi et al., 2009).

Infectious diseases remain a large health burden in urban areas in South Africa. According to the South African National HIV Prevalence, Incidence and Behaviour Survey (Shisana, Rehle, et al., 2014), HIV was prevalent in approximately 10.6% of the national population in 2008 and increased to 12.2% in 2012. In 2012, the prevalence of HIV was generally highest in females across age groups, highest in the province of KwaZulu-Natal (16.9%) and lowest in the Western Cape (5.0%) (Shisana, Rehle, et al., 2014). Disparities in HIV were most visible between urban informal areas (19.9%) and urban formal areas (10.1%), compared to rural informal (13.4%) and rural formal geotypes (10.4%) and results showed an association between high HIV prevalence and low socioeconomic status (Shisana, Rehle, et al., 2014).

In addition, HIV is the strongest known driver of the TB epidemic in South Africa, which was one of six countries with the highest number of new TB cases in 2013 (410 000 - 520 000 incident cases) (Creswell et al., 2011; World Health Organization, 2014). South Africa contributes a large number of new or relapsed cases to the global TB case number and had one of the lower treatment success rates of countries in 2012 (77%), however this number has increased continually since 1995 (58%) (World Health Organization, 2014). TB has historically been known as “a disease of the poor” (Creswell et al., 2011: 1270), particularly in Europe in the 19th Century and many modern studies have acknowledged an association between TB and low socioeconomic status (Vendramini et al., 2006; Harling, Ehrlich & Myer, 2008). Local studies have shown TB to be associated with overcrowding, unemployment, alcohol consumption, housing quality and social capital (Munch et al., 2003; Cramm et al., 2011).

It is evident that South Africa provides an interesting setting for health research. It is likely that the quadruple burden of disease and place-bound and socioeconomic disparities in health will feature as important areas for concern in South African health geography. However, it is expected that the quality of research will be limited to the external and internal validity of data and information. A challenge that some South African health geography researchers can face relates to the shortage of regularly updated urban health data that are available and representative at a lower geospatial level across the country; that provide quality information on health status variations associated with socioeconomic status, and that can support investigations into place-based effects (Bradshaw D, 2008). Therefore, it is important to note that the degree of data availability and data quality will determine the extent to which the data are spatially disaggregated and accurately portray the health risks and socioeconomic factors at play, as well as the extent to which place and space processes can be taken into account. Ultimately, the quality and abundance of existing health information may influence the reconnection between the fields of public health and urban planning.

1.5.2. Research aims, objectives & hypotheses

1.5.2.1. Research aim

This dissertation aims to provide a proof of concept of the use of existing survey data to study the cross-sectional and spatial distribution of HIV, TB and NCD multimorbidity and the association with socioeconomic disadvantage at a national, Western Cape Province and urban/intra-urban level for 2008 and 2012.

1.5.2.2. Research objectives

The study aim will be addressed through the following objectives:

1. To determine if geospatial data can be coupled with health data to generate new health knowledge for the South African, Western Cape and urban/intra-urban scales.
2. To utilize the National Income Dynamics Study (NIDS) to estimate the prevalence of HIV, TB and NCD multimorbidity, focusing on hypertension, the most prevalent NCD in this setting.
3. To determine the changes in reported HIV, TB and NCD multimorbidity over time.
4. To compare the cross-sectional and spatial association between socioeconomic disadvantage and respondents with multimorbidity who completed waves 1 (2008) and 3 (2012) of the NIDS survey.

1.5.2.3. Research hypotheses

The hypotheses of this study are that:

1. It will be possible to link geospatial data with health data to generate new health knowledge for the South African, Western Cape and urban/intra-urban spatial levels.
2. The coupling of cross-sectional and spatial analysis methods will provide unique comprehensive insight into health patterns.
3. There will be an increase in the prevalence of HIV, TB and NCD multimorbidity between waves 1 (2008) and 3 (2012) of the NIDS survey.
4. Socioeconomic disadvantage will be associated with the presence of hypertension and multimorbidity.
5. There will be heterogeneity in the spatial distribution of HIV, TB and NCD multimorbidity; with multimorbidity geographically associated with higher socioeconomic disadvantage.

1.6. THESIS STRUCTURE

This thesis is compartmentalised into three parts. *Part One* seeks to situate the thesis within the context of health geography by drawing attention to the reality of health and wellbeing inequality and the opportunities for addressing inequality through interdisciplinary action, which will be informed and supported by the analysis and disaggregation of national health data. Thus far, *Part One* has also drawn attention to the changing status of health in South Africa and its usefulness as a backdrop for health geography research. In the following chapters, *Part One* will provide an overview of the health geography discipline and the methodology used in this study.

In *Part Two*, the results of the research will be presented in the first three chapters, with each chapter representing a different spatial scale of analysis: The South African scale, The Western Cape Province and the urban and intra-urban setting of South Africa. *Part Two* will include a fourth chapter which will discuss the implications of the findings for South African health and will draw attention to the different epidemiological profiles emerging at different spatial scales, which supports the argument for the need of disaggregated data at sub-national scales and by key demographic, socioeconomic and social characteristics.

Finally, *Part Three* will highlight conclusions, strengths and limitations of the study. A recurring theme in this thesis, which will be emphasised in *Part Three*, relates to the ability to disaggregate health data to reveal new health information for South African national and sub-national scales.

CHAPTER TWO: THEORY AND METHODOLOGICAL APPROACHES TO HEALTH GEOGRAPHY

2.1. INTRODUCTION

The previous chapter highlighted the relevance of the field of health geography in identifying variations in health and the resultant value it will have for supporting the reconnection of the urban planning and public health fields. The importance of the space and place concepts were also discussed as well as the need for the disaggregation of health data. South Africa was identified as a useful and important setting for health geography research particularly as it is reportedly experiencing a quadruple burden of disease, undergoing epidemiological transition.

This chapter will provide a theoretic backdrop for health geography research as well as some of the methodological approaches available. It is suggested that the field of health geography has remained largely atheoretical, as health geographers have tended to borrow theories and perspectives from a range of other fields and disciplines (Kearns & Moon, 2002; Kearns & Collins, 2010). However, the epidemiological transition model as borrowed from the Epidemiology and Public Health fields, as well as the well-known structure and agency debate from the social sciences will be discussed. These theories are relevant for determining the best approach to investigation within the field of health geography.

2.2. THEORIES RELEVANT TO HEALTH GEOGRAPHY RESEARCH

2.2.1. The theory of epidemiological transition

Omran's (1971) theory of epidemiological transition provides a useful context to understanding health. Theoretically, it is expected that the general state of health, indicated through the monitoring of mortality rates, will gradually change and respond to urban development over time and this change will be determined by and have consequences for the social, economic and demographic systems. Generally, epidemiological transition has already occurred in today's developed countries and is still in progress in developing countries. The typical model suggests that countries experience a gradual, yet long-term transition in health that usually occurs over three stages as specified by Omran (1971).

The first stage is *The Age of Pestilence and Famine* which generally comprises high birth rates as well as high mortality rates that fluctuate sharply due to famines, epidemics and wars (Omran, 1971). Life expectancy for this stage is generally low, usually between 20 - 40 years. Population growth is not well sustained during this stage. Infectious diseases are common, alongside frequent maternity complications and malnutrition (Omran, 1971). It has been suggested that 11% of the global population and parts of sub-Saharan Africa are still in this phase (Gaziano, 2005).

The second stage is known as *The Age of Receding Pandemics*. Mortality rates decline as epidemics and pandemics become less prevalent, while life expectancy gradually improves to between 30 – 50 years (Omran, 1971). Arguably, for many now-developed countries, it may be suggested that this phase also saw the acceptance of the *germ theory* during the 19th and early 20th Centuries, in which health professionals recognised the role that bacteria and virus have to play in infectious diseases, as described by Brown and Duncan (2002). Therefore, there was a realisation that many infectious diseases can be prevented through improvements to sanitation and the development of the health care system. Omran (1971) acknowledges this by suggesting that the public health and medical developments made during the 20th Century were contributing factors for transition for many European countries. Wilkinson (1994) suggests that the main contributor to the decline in infectious diseases was the improvement of living conditions, including improvements to sanitation. As a result, mortality rates typically decline during this stage and the overall population continues to grow.

The third stage is *The Age of Degenerative and Man-Made Diseases* in which life expectancy exceeds 50 years and infectious diseases are slowly displaced with non-communicable degenerative diseases that are associated with ageing and the adoption of a more unhealthy 'westernised' lifestyle (Omran, 1971). Generally, mortality rates have reduced substantially with time and are low and stable, and the population begins to show signs of overall ageing. Many East Asian countries, as well as some in the Pacific region, are said to be transitioning between the second and third stages.

It is important to note that each country experiences a different rate of epidemiological transition. For example, Japan experienced an accelerated epidemiological transition while some African countries show signs of a slow transition (1971). South Africa, being the most urbanised sub-Saharan African country, is possibly further along the transition than other sub-Saharan African countries. However, as indicated by its high HIV prevalence and TB incidence rates, it is clear that it has not yet achieved complete transition into *The Age of Degenerative and Man-Made Diseases.*

A critique of the epidemiological transition model is that it depicts a simplistic, unidimensional and almost "straight forward" progression through three different stages. It is argued that the transition from infectious diseases and degenerative diseases is a complex process that may in fact witness a re-emergence of infectious diseases in the third stage (Mascie-Taylor & Karim, 2003). In addition, some developing countries that have high prevalence rates of infectious diseases are now also observing an increase in coexisting non-communicable, chronic diseases, such as obesity and hypertension. This is referred to as the protracted-polarised model of epidemiological transition (Frenk et al., 1989; Mascie-Taylor & Karim, 2003). Nevertheless, the epidemiological transition model has provided a fundamental contribution towards understanding the temporal pattern of health for countries.

2.2.2. Structure and agency debate

Another theory relative to the geography of health is the social theory of agency and structure, as articulated by Giddens (1984). Human agency may be viewed as the capability of individuals to act or behave intentionally according to their will, while structure may be described as the structural components that govern society and that mould or delineate human behaviour (Giddens, 1984; Cockerham, 2005). The crux of this social theory debate lies in the uncertainty of how much control individuals have (and should have) in governing their own decisions.

Within the context of health, Herrick (2014) draws attention to the agency that citizens have to improve their health, especially among those who are considered poor. An example of this is the use of physical activity to improve health, as a large focus of the health sector and the World Health Organisation is on promoting an active lifestyle to improve wellbeing (Smit, 2013). As stated by Herrick (2009: 2451), "physical activity seems to have become a panacea for an increasingly wide array of social ills". Citizens can actively decide if, and how, they should increase their physical activity and thus have the ability to demonstrate agency when they attempt to improve their lifestyle (Smit, 2013). However, the capability of citizens to exercise agency may be influenced by various societal and environmental structures, such as the availability and expense of sports or recreational facilities or the extent to which an active lifestyle culture is promoted. Therefore, it is argued that the ability to achieve health lies at the interspace between the active agency of citizens and the quality of governance, or more specifically, the governing structures that are required to shape and influence the development of health (Smit & Parnell, 2012; Herrick, 2014). However, it is widely supported that the influence that societal structures have over individual agency is stronger than the influence that individuals have over the structures of society.

Within the context of health geography, it is common for health geographers, as well as researchers in similar fields that are linked to the 'medical', to forget about the structure and agency framework and instead view an individual as an ordinary observation and not as a body or person (Kearns & Moon, 2002). Therefore, an apparent key theoretical gap in the field of health geography relates to literature on the human body. Kearns and Moon (2002) argue that the concepts of structure and agency have the potential to bridge the mosaic of theories and perspectives in the field of health geography, as well as integrate the place-based effects with human capabilities and agency.

Therefore, this study will incorporate a structure and agency perspective by acknowledging that there are many place-related political, environmental, economic, cultural and social structures at play that influence an individual's health; however individuals do have some autonomy – to an extent – in the decisions related to their health and wellbeing.

2.3. HEALTH GEOGRAPHY APPROACHES TO RESEARCH

Within the geography of health, there are five broad philosophical approaches to investigation and interpretation. The first, and probably the most popular in health geography, is the positivist approach.

2.3.1. The positivist approach

The positivist theoretical approach, which attempts to use maps to model the distribution and spatial variation of disease and illness and then endeavour to explain these spatial patterns through the investigation of statistical associations between variables, has steered a sizeable portion of health geography research (Gatrell & Elliott, 2002; Kearns & Moon, 2002). This approach has a realist ontology and seeks to model the 'way things are' through objectively investigating the subject at hand using predominately quantitative methodologies. Therefore, the epistemology of this approach is said to be both dualist and objectivist, as it is assumed that the researcher makes observations and inquiries "through a one-way mirror" (Guba & Lincoln, 1994: 110) and thus the researcher is an independent entity that does not influence or is uninfluenced by the studied object or phenomenon. The typical positivist methodology is experimental and manipulative in nature as the researcher will use empirical research to test and address proposed questions and hypotheses (Guba & Lincoln, 1994). Generally, positivist investigations statistically analyse large sample datasets to extract generalisable information that is representative of a wider population.

One critique against this approach stems from the new health geography field, as place-based effects are often deprioritised in the positivist approach and instead location and space concepts are viewed as central elements. This is supported by Corburn (2013) who argues that any research seeking to explore concepts relating to 'healthy city planning' will be anti-positivist, as it disagrees with the 'placelessness' and objectivist nature of positivism. A possible reason for this critique is that the positivist philosophy relies on scientific and quantitative analysis, while place-based effects are easier to explore through qualitative research which is often strongly informed by social theory (Gatrell & Elliott, 2002). A second critique is that this approach may be prone to reductionism, in which the individual is viewed merely as an anonymous person to which certain key characteristics are attached in order to better understand selected diseases through statistical analysis (Gatrell & Elliott, 2002).

Nevertheless, there is still a use for positivist research as it shares links with the epidemiological traditions of mapping and modelling, and can thus contribute towards health surveillance and understanding the complex interaction between health and the environment (Elliott & Wartenberg, 2004). Although dependant on data availability, positivist research has the opportunity to disaggregate data to smaller spatial scales and explore local area variations in health and living conditions, particularly in urban areas. It is important to consider the heterogeneity that exists within urban areas, as some urban citizens experience poor health and living conditions and are sometimes worse off than their rural counterparts (Salem, 1993; Niakara et al., 2007; Herrick, 2014). The localised of heterogeneity in space may assist planners with the placement of services, and public health professionals with the targeting of interventions (Salem, 1993; Borrell et al., 2013). Therefore, it is argued that positivist research that is informed by social theory and that seeks to use modelling methods to take place-based effects into account is still applicable and relevant to the emerging health geography field (Kearns & Moon, 2002). Furthermore, the findings of positivist investigations may be of use to governments and municipalities, as space and distance elements have political importance for the planning of medical and health care services.

2.3.2. The social interactionist approach

The social interactionist approach to health geography investigation aims to engage with individuals to understand what the disease or illness means to them and how they go about managing their lives while being ill (Gatrell & Elliott, 2002). Health sociologists have suggested that individuals who acknowledge that they are unable to continue with their normal lives as a result of illness are likely to change routines and behaviours in attempt to adapt, and thereby embrace a new normality (Bowling, 2014). Social interactionist research, which is often conducted on small samples, therefore seeks to provide information from the individuals' points of view and attempts to rationalise the individuals' perspectives (Gatrell & Elliott, 2002). This qualitative approach directly contrasts the more quantitative positivist philosophy and may be best suited to account for human agency.

2.3.3. The structuralist approach

The structuralist approach suggests that health largely stems from, and is thus fundamentally influenced by, political and economic structures (Gatrell & Elliott, 2002). A difference between this approach and the positivist approach is that there is no analysis of individual behaviours or characteristics, such as investigating what type of people or what risk factors are most associated with illness. In addition, this approach directly contrasts the social interactionist approach as it completely discounts the role of human agency and does not consider free will to influence health. Instead, this philosophy believes that research should be focused on understanding the influence that the social fabric of society has on health variations. Therefore, within the structure and agency debate, this approach exemplifies structuralism.

2.3.4. The structurationist approach

At the interspace between the social interactionist approach and the structuralist approach lies the structurationist approach, which may be said to best portray the symmetry of human agency and structure. This approach adopts the principle that the social practices of systems exist across time and space and comprise various structures that shape and impact human agency and that these structures, in turn, are influenced by human agency (Giddens, 1984; Gatrell & Elliott, 2002). Within the health context, an example may be that the social stigma of HIV may prevent people from being tested for HIV at local clinics which have set open hours. In turn, the health care system may acknowledge this behavioural trend and implement health care practices that improve confidentiality of test results while increasing the number of free testing centres in an area, decreasing the time it takes to take the test, promoting awareness and adopting a human rights approach to HIV/AIDS which seeks to empower those with the disease. In turn, this may result in a greater number of people taking HIV tests. This approach criticises the structuralist and the social interactionist approaches for not taking such behavioural and economic, political and social interactions into account.

2.3.5. Post-structuralist approach

Recently, some health researchers and social scientists, including health geographers, have started to look at other theories to inform health research. This has led to the post-structuralist approach to health. This approach has focused attention on healthy lifestyles, as well as acknowledging health risks. A key post-structuralist philosophy that has emerged is the New Public Health philosophy, which motivates for sustainable environments that prioritise the health of citizens and strongly encourages the adoption of healthy lifestyles and behaviours (Gatrell & Elliott, 2002). It is suggested to have stemmed from the epidemiological transition that developed countries have experienced, as these countries have largely succeeded in dealing with infectious disease epidemics. For developed countries, the attention of the public health system is now shifting towards chronic health conditions and illnesses, which are largely influenced by lifestyle (Gatrell & Elliott, 2002).

However, health is not only determined by individual lifestyle, such as exercise, diet, smoking, and alcohol consumption, but is also determined by environmental factors such as pollution, climate change and exposure to harmful chemicals. Michael Foucault's work particularly on surveillance is key to this philosophy as it has been observed that the concept definition of "health" within post-structuralism, and the interventions needed to promote healthy lifestyles, are determined by epidemiologists and public health experts, who produce adept knowledge and information on health through measuring and monitoring, rather than being defined and determined through general consensus (Petersen & Lupton, 1996). The new public health approach essentially encourages members of the public to actively improve their own health through changes to lifestyle, public participation and volunteer work, thereby shifting a large portion of the responsibility from the government onto individuals (Petersen & Lupton, 1996). It has been suggested that this shift of attention towards individual health has increased the use of social surveys, in which information from individuals may be aggregated to inform public health experts of the general state in health of the wider population. Using this information, experts are able to put forward plans for interventions to subtly manage population health (Gatrell & Elliott, 2002).

Another project that falls under the post-structuralist philosophy is the World Health Organization's Healthy Cities Movement. This project aims to see the collaboration of organisations, professional associations, community leaders, as well as members of the public within a particular city support and encourage, and work towards reducing health risks and achieving sustainable healthy environments and healthy lifestyles within the local urban setting (Gatrell & Elliott, 2002). Once this has been achieved, the city will be modelled as a practical example to other cities in hopes of inspiring a chain reaction around the world. However, it has been suggested that the core idea of health being achieved through intersectoral cooperation and public participation can only be accepted in cities where "most health is gained and lost outside medical services" (Ashton, 1988: 232).

2.3.6. Selecting an approach to investigation

In section 1.1, South Africa was described as the most urbanised Southern African country and is known to contribute the second highest gross national product (GNP) for the African continent behind Botswana (Tyler & Gopal, 2010). The described literature has suggested that South Africa is in the process of transitioning from an epidemiology largely influenced by infectious diseases to one that addresses the rise in chronic health conditions and NCDs. The urban and economic development, as well as the current phase of epidemiological transition, suggests that South Africa may not be too far behind some developed countries in terms of development and health. It is therefore important that South Africa does not get left behind in the post-modern New Public Health Movement. However, given the paucity of regularly updated health data in South Africa, it is suggested that a surveillance-type approach is used to diagnose the current status of population health and to determine the role that lifestyle risk factors, living conditions and demographics have over health, prior to policy implementation and interventions. In addition, it is important to monitor infectious disease epidemics, specifically HIV and TB, and the progress made in reducing these over time.

Therefore, this study is motivated by and emerges from a post-structuralist philosophy as it seeks to measure and survey population health in order to assess the impact of lifestyle and socioeconomic risk factors on health, as these fall outside health care services. However, it will employ a positivist methodology to provide baseline 'surveillance' health information of the population that assesses the spatial distribution of infectious and non-communicable disease prevalence and uses statistical analysis in an attempt to explain these spatial patterns. The reason for this is that, in order to understand the burden of disease, a baseline statistical analysis of health data is needed, as per epidemiological traditions. Therefore, it is hoped that such an investigation will contribute to efforts in addressing the paucity of regularly updated health information for South Africa. It also should be stated that, although the positivist approach to methodology has limitations and is not able to fully account for place-based effects, the analysis of survey data - which may be viewed as a social-positivism approach to investigation (Gatrell & Elliott, 2002) - may assist in understanding some of the social and behavioural elements at play within the context of health. A social-positivist approach may provide insight into why certain individuals in certain areas are experiencing reduced health and wellbeing, while others remain healthy. In addition, a positivist approach is useful in providing an empirical foundation for future qualitative research that specifically seeks to better understand place-based effects and the general burden of disease.

2.4. MEASURING HEALTH AND WELLBEING IN HEALTH GEOGRAPHY

2.4.1. The measurement of health and wellbeing

Within the fields of health geography, Kearns and Moon (2002) have identified three main areas of work that have contributed towards showing that 'place' matters, namely those that focus on analysing health within specific spatial locations; those that take 'landscapes' into account by considering the cultural and politico-economic processes at play with regard to health and health care, and finally those that have employed a more sensitive approach to place and space concepts by using quantitative methods such as multilevel modelling to understand the interactions between health and place and to investigate other complex processes. Although all three areas of work are important, this study will focus on exploring the use of quantitative data and multilevel modelling in understanding health variations.

Multilevel modelling methods are useful to health geography research, as they are able to integrate various temporal and contextual processes within analysis, recognise the way in which individuals are nested in places, and are therefore able to effectively represent place effects on health (Kearns & Moon, 2002). In addition, multilevel modelling also allows for analysis of space, place and time links, which are also important in health geography. The acknowledgment of time and place concepts allows researchers to study trends, changes and movements of phenomena within and between space and place dimensions and these variations could provide insight into other possible processes at play (Curtis & Jones, 1998). However, there are some disadvantages to multilevel methods, primarily the fact that they cannot truly represent the complexity of theoretical or genuine space, place and health concepts and that they are quite often limited to data availability, data collection techniques and the pre-set spatial and sampling frames (Kearns & Moon, 2002).

The limitations of quantitative methodologies as a whole, include the way that many still incorporate a conventional representation of place and this may lead to results that overemphasise the role of individual level factors in health variation and inequality, and underestimate place-based effects (Cummins et al., 2007). Therefore, qualitative research has frequently been favoured in exploring 'place-based' effects on health and is becoming more popular in health geography. However, recently quantitative research has also started to explore how various social and physical factors in the surrounding environment may be linked to health status and is able to provide generalised information for large populations to inform the development of public health policies and interventions (Cummins et al., 2007). Moreover, although Cummins et al. (2007) suggest that some quantitative research may insufficiently portray the interrelation between individuals and the social and physical environments of neighbourhoods or communities, other literature suggests that the use of multilevel modelling methods in health geography has the potential to produce valuable insight into some of the contextual intricacies present within the theoretical concept of health and health variations (Kearns & Moon, 2002).

2.4.2. Considering the role of place in measuring health variations

The Commission on the Social Determinants of Health (CSDH, 2008), as released by the World Health Organization, made a significant contribution to global health by raising awareness, drawing attention to the need for interdisciplinary action, and providing recommendations for addressing issues of health inequality and wellbeing for all people (Brown & Moon, 2012). The report has important implications for the field of geography and further acknowledges that 'place' does influence health and wellbeing, such as the place of birth and the place where one is raised, as the structure, characteristics and degree of liveability of these places can often influence quality of life and potentially impact on life expectancy (Marmot et al., 2008). The report also acknowledges that health is not solely determined by income poverty, but instead follows a socioeconomic gradient, where ill-health often affects people who are "worst off" (Marmot et al., 2008). Therefore, it is likely that the conditions of living as well as surrounding social, cultural and economic structural factors, together constitute the social determinants of health and thus ultimately influence the degree of health inequality experienced (Marmot et al., 2008).

Traditionally, health inequality concerns have predominately come from health geographers (Brown & Moon, 2012). A popular method of conceptualising and understanding health inequalities is to explore the social determinants of health within populations. This is acknowledged by Marmot (2008) who emphasises the importance of measuring and understanding health inequality prior to developing plans of action.

2.4.3. The social determinants of health and associated research methods

The traditional understanding of health originally focused on the absence of disease, illness or infirmity, however the World Health Organization has attempted to provide a more holistic understanding of the concept of health in the 1940s by defining it as “a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity” (World Health Organization, 1946). This is elaborated on by Greenberg (1985) who emphasises the complexity of health and claims that it is a multifaceted concept comprising physical, mental, emotional, spiritual, and social components. ‘Wellness’ is therefore viewed as the integration of these five components and can thus be interpreted as the overall health of these components. However, Northridge, Sclar and Biswas (2003) take this further by exploring the concept of health in connection to the built environment of cities, thereby supporting the call for the reconnection between public health and urban planning, and attempt to illustrate this complex relationship.

The illustration provided by Northridge, Sclar and Biswas (2003), as shown in Figure 2.1, illiterates the complexity of the concepts of health and wellness and provides support to the argument that the general health and wellness of individuals and populations should not merely be assessed on medical factors alone, but should also be viewed as a reflection of the state of the built environment and social context of urban areas that citizens experience, thereby taking place-based effects into account.

According to Northridge, Sclar and Biswas (2003), the fundamental mechanisms that underlie health and wellbeing relate to issues of the natural environment, macrosocial factors (for example, historic conditions and political orders), and inequalities (including inequalities relating to wealth, education and occupation), as displayed in Figure 2.1. These fundamental mechanisms influence (and are influenced by) intermediate factors relating to the built environment and social context, which influence (and are influenced by) proximate factors such as stressors, health behaviours and social integration and social support (Northridge, Sclar & Biswas, 2003; Marmot et al., 2008). These factors are further linked to experienced changes in health and wellbeing. In addition, due to the way in which these factors are all interconnect and interdependent, and the way in which the health and wellbeing of populations is influenced by changes to these structural factors, the health and wellbeing of individuals and populations is therefore intricately connected to processes of urbanisation (Maas et al., 2006; Marmot et al., 2008; ICSU, 2011). This is supported by Omran’s (1971) theory of epidemiological transition, which provides a useful context to understanding health in populations and how it changes over time. In addition, the suggested fundamental, intermediate, proximate, and health and wellbeing factors, provide some examples of structures that can influence an individual's health. Thus, the work of Northridge, Sclar and Biswas is relevant to the structure and agency debate.

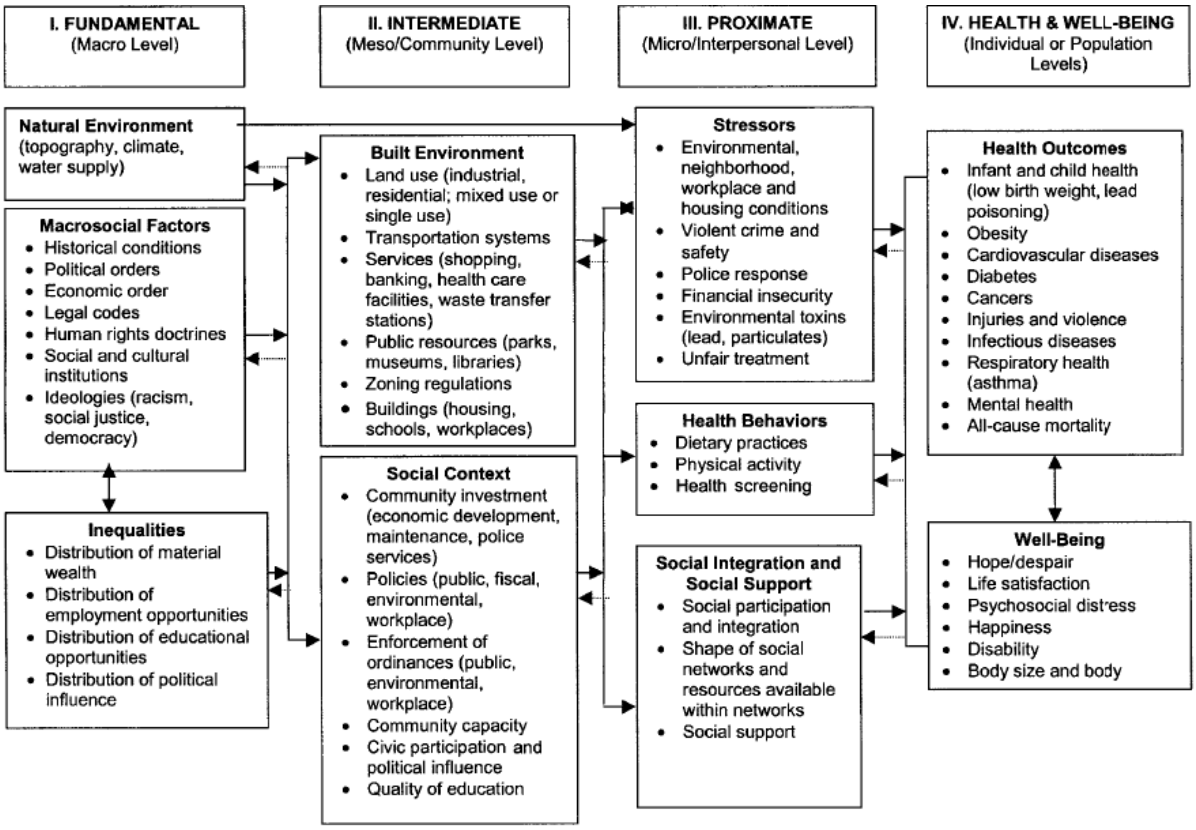


Figure 2.1. Illustrating the complex interaction between the built environment, social context and the concepts of health and wellbeing.

Source: Northridge, Sclar and Biswas (2003)

Adding to the complexity of the concepts of health and wellness is the way in which they are not only shaped by external factors relating to the built environment and social context of places, but also to personal factors and the capability of individuals to adapt to their environments. Amartya Sen's Capability approach (1985, as cited in Clark, 2006) to understanding quality of life is useful to this theoretical discussion and further adds that it is not only the functionings of citizens, such as the state of living conditions, varying levels of education, and the availability of good quality healthcare that directly impact on experienced levels of wellness, but it is also the capabilities of individuals and their ability to choose to improve their functionings that will determine their experienced quality of life. This provides support for human agency in the way that people are viewed as agents of change. Therefore, as people's functionings and capabilities vary due to a range of factors relating to the social, economic, political, natural, and built environments, disparities in the level of health and wellness are likely to be experienced by individuals and populations both within and between places (Marmot et al., 2008). These disparities are able to be measured.

The use of an integrated social determinants approach to understanding health disparities within and between places is a common method used in both health and medical geography, with many researchers investigating the correlation between health and the situational factors relating to people's living and working spaces. According to Koh et al. (2010), the integrated social determinants approach seeks to overlay various lenses to produce a holistic view and understanding of health disparities. Four popular lenses include the investigation of different diseases such as HIV, TB or diabetes mellitus, overlaid with socio-demographic fields such as gender, age, or socioeconomic status; risk factors such as smoking or alcohol consumption; and geography such as urban or rural areas, or developing or developed countries (Koh et al., 2010). The use of a socioeconomic index in assessing the association between socioeconomic status or disadvantage and health inequalities has been a particularly popular research method as it can provide clues about the actual mechanisms involved in determining health, as formerly depicted in Figure 2.1 (Oakes & Rossi, 2003).

A spatial analysis approach to studying the prevalence and distribution of certain diseases and their link to socioeconomic status has proven useful in understanding disparities in health and in highlighting hot spot areas for possible interventions (Bellec et al., 2006; Tiwari et al., 2006; Liu et al., 2012). Mapping the results of an index can provide urban planners, policy makers and public health professionals with key information and insight into the spatial patterns of diseases and health inequalities (Weaver et al., 2014). Spatial analysis that focuses on analysing spatial patterns of diseases and the associations with socioeconomic determinants has been used by researchers such as Harling and Castro (2014) to map hot spots of TB incidence rates in Brazil; by Liu et al (2013) to analyse the prevalence of hypertension across neighbourhoods in Philadelphia in The United States of America (USA); and by Harling, Ehrlich and Myer (Harling, Ehrlich & Myer, 2008) to investigate the spatial distribution of TB in South Africa.

2.4.4. Underlying socioeconomic measurement issues

Socioeconomic status is suggested to be the most accurate indication of health, and this association has been confirmed by numerous research studies (Winkleby et al., 1992; Roberge, Berthelot & Wolfson, 1995; Oakes & Rossi, 2003; Vendramini et al., 2006). However, the effectiveness of this methodology is linked to data availability, as well as the criterion validity of the selected socioeconomic variables for use. This opens up the debate within literature concerning the methodologies used in constructing measures of true socioeconomic disadvantage.

The most popular critique is that there appears to be a lack of consensus on the definition of socioeconomic deprivation or disadvantage (Krieger, 1994; Oakes & Rossi, 2003; Braveman et al., 2005; Fontaine, 2005). It has been suggested that many socioeconomic indices fail to grasp the full complexity of the urban system and the multifaceted concept of health and wellness (Braveman et al., 2005). Therefore, although many researchers agree that variables such as education, employment, household income and overcrowding are useful to understanding health disparities (Roberge, Berthelot & Wolfson, 1995; Zimmer & Amornsirisomboon, 2001; Singh & Siahpush, 2002; Lalloué et al., 2013), the complexity of the concept of health has led to an unclear picture of what constitutes true socioeconomic disadvantage within the context of health. This is reflected in literature which critiques the many currently available indices that have been used to measure socioeconomic status, such as Duncan's (1961) Socioeconomic Index, the 2014 Multidimensional Poverty Index (Alkire et al., 2011), Hollingshead's (1975) Four Factor Index of Social Status, and the Townsend Index of Deprivation (Townsend, Phillimore & Beattie, 1988). Therefore, it has been argued that researchers need to use existing literature and well-informed value judgements to determine the most relevant measure of socioeconomic status or human deprivation for use, based on their project objectives and the relevance of the measure to their sample population and study area (Oakes & Rossi, 2003; Fontaine, 2005).

2.4.5. The data dilemma: the need for health knowledge and use of secondary data

Health research inevitably relies on the availability of personal health information and data of people. We live in a technological era where health data is able to be captured, stored and accessed electronically which has improved health research as well as health services in many countries, as it has empowered researchers to undertake large and complex studies that seek to answer important health questions (Harrison, 2008; Häyrinen, Saranto & Nykänen, 2008). Secondary analysis of existing information has many benefits within health research and allows researchers to revisit or explore existing datasets to answer questions that may not have been considered when the data was being collected (Rew et al., 2000). Secondary data sets are those most often collected from surveys, qualitative studies, national censuses, as well as existing health databases (Rew et al., 2000).

In research, additional advantages to the use of existing datasets include: researchers being able to save time and money as they do not have to collect the primary data themselves; being able to avoid certain data collection challenges, especially those surrounding sensitive topics such as personal health; and being able to use datasets that contain a large and diverse sample or a greater selection of variables that may not have been feasible for smaller research projects (Rew et al., 2000). The use of secondary data, and particularly disaggregated health information can provide invaluable insight into health trends and patterns; contribute information to understanding diseases and their risk factors; allow for the opportunity to identify individual and interacting health predictors, as well as inform public health policies and interventions (Macintyre, Ellaway & Cummins, 2002). The data recorded by hospitals, clinics and pharmacies is particularly valuable as these data, when aggregated, provide live and immediate information relating to the health status of local citizens, making it especially useful for early detection of emerging health epidemics (Safran et al., 2007). However this information is often difficult to obtain due to many legal and political issues relating to confidentiality and privacy (Harrison, 2008).

A common limitation in using existing datasets is data accessibility, which is sometimes due to constraints around confidentiality (Rew et al., 2000). In addition, secondary datasets ultimately reflect the subjective decisions of the original investigator, making it impossible for secondary researchers to account for any methodological or measurement errors, and essentially provide answers to the original investigator's questions and thus are bound by the investigator's temporal and spatial interests (Jacobson, Hamilton & Galloway, 1993; Rew et al., 2000). Therefore, although secondary data can provide many benefits to researchers, the secondary researcher needs to be cautious of the limitations of the secondary dataset.

2.4.5.1. The importance of disaggregating health survey data

Health surveys, particularly at national and sub-national levels, are often a convenient source of data for health research as they are more accessible to researchers and often do not pose the same ethical dilemmas as electronic health records do. Data gathered from health surveys are not only able to provide useful information on the possible health status of the study area, but occasionally include demographic and socioeconomic data, making them useful for investigating social determinants of health, and thus can assist in identifying inequalities in health and in understanding the pattern of disease and illness distribution. Occasionally, health surveys contain spatial information. Survey data that are able to be disaggregated to sub-national level generate the most valuable information as they can be used to identify areas of risk; are able to take 'place' effects into account and assist in understanding area-specific health issues; provide information for local-area programme planning and evaluations that are tailored for the specific needs of the community, and can be used to assess whether the needs of communities are being met (Wang, 2003; AbouZahr & Boerma, 2005). In addition, these data provide essential information for the development of policies and strategies for key sub-national areas.

The topic of data disaggregation is highly relevant to the current debates occurring in the 2030 SDG agenda, as highlighted in section 1.4. In order for inequality to be addressed, data disaggregation to sub-national levels is essential (Saad, 2015). Data disaggregation does not only refer to spatial boundaries but also to other key stratifiers such as socioeconomic status and gender, so that inequalities may be identified through dissection (Dornan, 2015). Therefore, the disaggregation of data is critical to supporting policy improvement efforts and for monitoring progress of all groups of people towards achieving the SDGs (Dornan, 2015).

2.5. CONCLUSION

In summary, the extent to which researchers can assess current health patterns and epidemiological profiles and assess their associations to social and spatial factors, as well as the extent to which 'place' effects can be considered, is limited to data availability and data quality. This study aims to enter into the health geography conversation by providing a baseline evaluation of health in South Africa, while considering place-based effects and social determinants of health through the disaggregation of data. This will be accomplished through the quantitative analysis of an existing dataset using a positivist research approach, with the intention of measuring health and socioeconomic factors at a range of spatial scales, including the urban and intra-urban scales. It is hoped that the findings of this study will be informative and relevant to both the urban planning and public health fields, and will stimulate further conversations on health and wellbeing.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1. INTRODUCTION

Chapters 1 and 2 have highlighted the complexity of the concept of health and that variations and inequalities in health can be as a result of place-based effects. More specifically, the conditions of living as well as surrounding environmental, social, cultural and economic structural factors and mechanisms together constitute the social determinants of health and thus ultimately influence the degree of health inequality experienced. However, in order to understand and measure health inequality for a place of interest, health data needs to be available for use.

For South Africa, the paucity of readily available national health data that is able to be disaggregated to smaller scales to reveal cross-sectional variations in health is a concern, as it suggests that the status of health at disaggregated scales is not yet fully realised. Therefore, this quantitative study will incorporate methodologies from the field of health geography, using a positivist approach, and also from the epidemiological field, in order to conduct secondary data analysis on the status of health in South Africa at different spatial scales using data from the National Income Dynamics Study (NIDS).

This chapter will essentially provide a detailed framework of the methodology to be used in this study, which will include describing the sources of data, the analytical approaches to investigation including the selection of variables for study, the statistical approaches adopted and the spatial analysis methodology. Ethical considerations for this research will also be discussed

3.2. STUDY DESIGN, POPULATION AND SCOPE

3.2.1. The National Income Dynamics Study design

Household panel studies are widely available and are a popular source of data for social science researchers (Rose, 1995). These studies are particularly useful for health research as they are able to investigate participants' experiences of health and monitor general health changes within a nationally representative sample over time. More specifically, these studies can be used to assess changes in incidence and prevalence of disease, and associations between health and other variables such as socioeconomic status, and thus can provide valuable insight into national health patterns (Rose, 1995).

Some specific examples of international studies making use of panel study data include the investigation of: direct causal paths between health and socioeconomic status in the elderly population in the United States of America (USA) using the Asset and Health Dynamics of the Oldest Old Panel (Adams et al., 2003); socioeconomic status indicators and their relationship with health in the USA using the Panel Study of Income Dynamics (Duncan et al., 2002); and associations between socioeconomic status, gender and health and wellbeing behaviours in young British adolescents using the British Household Panel Study (Bergman & Scott, 2001)

This study utilised data from wave 1 (Southern Africa Labour and Development Research Unit, 2014a) and wave 3 (Southern Africa Labour and Development Research Unit, 2014b) of the NIDS, representing the years of 2008 and 2012, respectively. The NIDS is a panel study that provides nationally representative socioeconomic, behavioural and anthropometric data for South Africa and is conducted by the Southern Africa Labour and Development Research unit (SALDRU), based at the University of Cape Town. This longitudinal study began in 2008 with a nationally representative sample of over 28,000 individuals, including adults and children from 7,300 households across the country (Leibbrandt, Woolard & De Villiers, 2009). The same households and individuals are sampled every two years and therefore the study collects data on the livelihoods, health and education, vulnerability and social capital of individuals and households over time. In total, there have been three waves of data collection in 2008, 2010 and 2012.

The NIDS is the first longitudinal panel study to be conducted in South Africa using a nationally representative household sample (Leibbrandt, Woolard & De Villiers, 2009), and thus its use is growing within South African research. Although other data sources are available such as the South African National Census of 2011 or the South African National Health and Nutrition Examination Survey (SANHANES-1), the NIDS data is advantageous as it is stored at the University of Cape Town, contains geospatial information, comprises interesting health information including data on self-reported TB and self-reported HIV, and contains a wide range of demographic and socioeconomic variables that were considered to be useful for this study.

To date, the NIDS has been used for research under the themes of income inequality, education, health, demographics and poverty. Examples of specific studies that have used the NIDS include research on income mobility (Finn, Leibbrandt & Levinsohn, 2012), labour migration (Posel, 2010), inequalities in children attaining education (Timæus, Simelane & Letsoalo, 2013), differences in marriage rates between South African racial groups (Posel, Rudwick & Casale, 2011), social determinants of health regarding health inequality (Ataguba, 2013), social capital and depression (Tomita & Burns, 2013) and childbearing among young people (Kara & Maharaj, 2015). It is also a particularly common data source for investigating the associations between socioeconomic status or poverty and health variables (Ardington & Case, 2010; Alaba & Chola, 2013; Cois & Ehrlich, 2014; McLaren, Ardington & Leibbrandt, 2014; Ataguba, Day & McIntyre, 2015; Rogan, 2015). However, the NIDS has not yet been used to investigate the spatial distribution of disease or the patterns of disease at disaggregated spatial scales.

3.2.2. Study population

The targeted population under analysis in this study is the adult sub-sample from the NIDS which contains 18 526 respondents aged 15 years and older in wave 1 (2008), including respondents from the Child questionnaire who were 15 years and older at the time of the survey, adults from the Proxy questionnaire and adults who refused to participate in wave 1 but were still part of the panel study and would be interviewed in future waves. The 18 526 adults in the sub-sample represent a total South African adult population of approximately 34 million, and were re-interviewed in wave 2 (2010) and wave 3 (2012) of the NIDS. The temporal scope of this study is confined to the wave 1 and wave 3 of the NIDS, namely 2008 and 2012 respectively.

3.2.3. Geographic scope of study

Due to the paucity of regularly updated health data for South Africa, data from national surveys are valuable and can provide further insight into the changing state of health in the country, especially if data may be disaggregated to smaller spatial scales, such as districts. This is supported by Day and Gray (2006), who acknowledge the lack of disaggregated health data from the national Department of Health and the resulting challenge this creates for implementing public health care and for determining health inequalities and related socioeconomic disparities that are often concealed in data analysis at the national level. Therefore, they argue the need for the disaggregation of data at sub-national and sub-provincial levels to allow for the identification of subtle patterns to inform efforts to improve health at lower administrative levels in the country (Day & Gray, 2006).

Although the NIDS data are best represented at the national level, this study attempted to make the most of the available health, anthropometric and socioeconomic information from the NIDS by, first assessing a baseline health status at the national level, and then disaggregating the dataset to assess the health status at the Western Cape Province, urban, and intra-urban geographic levels. The health patterns emerging from the Western Cape Province and the urban geographic level were contrasted and compared to those at the national level.

Therefore, the primary study area was the South African national level with secondary study areas of the Western Cape Province and the urban and intra-urban setting. The spatial scope was largely determined by the extent to which the NIDS data can be disaggregated to reveal useful health patterns at sub-national levels. It is important to emphasise that although the disaggregated data is not representative of sub-national populations, it still provides valuable insight into possible sub-national health patterns. The 2011 Census district and provincial boundaries were used as comparative spatial units for the spatial analysis of the distribution of disease and socioeconomic disadvantage at the national level, and ArcGIS shapefiles were obtained from the Municipal Demarcation Board of South Africa (Demarcation Board of South Africa, 2011).

3.3. DESCRIPTION OF DATA SOURCES

3.3.1. The National Income Dynamics Study sampling frame

The National Income Dynamics Study used a stratified, two-stage cluster sampling design to form the base wave, namely wave 1 in 2008 (Leibbrandt, Woolard & De Villiers, 2009). Non-overlapping samples of dwelling units were taken from 400 Primary Sampling Units (PSU) from Statistics South Africa's (Stats SA) 2004 Master Sample, which contains 3 000 PSUs. The Stats SA Master Sample has been used in other national surveys including the Stats SA Labour Force and General Household Survey. Private households as well as residents in convents, monasteries and workers' hostels were the target population for the sample and were selected from each of the nine provinces of South Africa. Residents in collective living quarters such as prisons, hospitals, old age homes and military barracks were not included in the sample frame.

Racial classification terms were also considered in the development of the sampling frame. The term 'race' is not defined in any South African national legislation, however it is often substituted with the term 'population group' which may be defined by Stone and Erasmus (2012: 137) as:

> *"A group with common characteristics (in terms of descent and history), particularly in relation to how they were (or would have been) classified before the 1994 elections. The following categories are provided in the census: Black African, Coloured, Indian or Asian, White, other."*

In the NIDS, the racial classifications used are Black African, Coloured, Asian/Indian and White. It is important to note that these racial classification terms were not assigned to respondents in the 2011 Census or the NIDS, but merely reflected their chosen identity (Statistics South Africa, 2012a).

According to Leibbrandt, Woolard and De Villiers (2009), the interviews were conducted by trained fieldworkers and the target number of successfully interviewed households was 8 000. Unfortunately, this target was not met in phase 1 and thus 1 856 households were revisited in phase 2 in an attempt to overturn their previous participation refusals. In order to improve the representation of White and Asian racial groups in the NIDS sample, additional dwelling units were visited in PSUs that had a predominant number of White and Asian/Indian households. This almost doubled the number of participating White households in the survey. In total, the baseline field work for NIDS had 7 305 participating households with a total of 28 255 individuals. In situations where adults were unable or unavailable to answer questions, proxy questionnaires were used. A total of 1 754 proxy questionnaires were completed (Leibbrandt, Woolard & De Villiers, 2009).

Household response rates were calculated by dividing the number of participating households by the total number of households visited (Leibbrandt, Woolard & De Villiers, 2009). In total, 10 642 households were visited, however only 7 305 households agreed to be interviewed, producing a response rate of 69%. Overall, the response rates by racial groups after phase 2 revealed that only 36% of White households visited actually participated in the survey, while Asian/Indian, Coloured and Black African households had response rates of 66%, 73% and 76%, respectively. Response rates of individuals within households was 93%. In total there are three reasons why household or individual data may be missing from the dataset, namely household non-response, individual non-response and item-nonresponse (Leibbrandt, Woolard & De Villiers, 2009).

3.3.2. The National Income Dynamics Study weighting method

In situations where the survey sample disproportionally represents the target population, sampling weights are applied to the data in order to adjust and correct these proportions (Pfeffermann, 1993). Sampling weights, in the form of design and post-stratification weights, were calculated and provided for the NIDS by SALDRU at the University of Cape Town (Wittenberg, 2009). The design weights were calculated by taking into account the probability of both the PSU and dwelling unit being included in the sample. This calculation corrects for household non-response. To make the sample representative of the national population across provinces and for demographic characteristics such as age, sex and race, these design weights were calibrated to the 2013 Mid-Year Population Estimates for 2008 (wave 1) and 2012 (wave 3) (Leibbrandt, Woolard & De Villiers, 2009; Wittenberg, 2009; De Villiers et al., 2013). These became the post stratification weights. In the dataset, both the design weights and the post stratification weights were provided. The post stratification weights were used in this research project. In Stata, the weights were applied to the data and the NIDS sample design was stratified by district and clustered by PSU, as recommended by NIDS (Southern African Labour and Development Research Unit, 2013).

Sample weights are habitually used and applied to survey data in research to improve study robustness (Pfeffermann, 1993). The application of sample weights allows the results to be generalisable to the whole target population and not just the sample, and are particularly important in research that seeks to use survey data to investigate the prevalence of diseases in a population. Many researchers that have used the NIDS have applied the sampling weights into their data (Timæus, Simelane & Letsoalo, 2013; Tomita & Burns, 2013; Cois & Ehrlich, 2014; McLaren, Ardington & Leibbrandt, 2014). Examples of other South African surveys that provide sample weights include the Quarterly Labour Force Survey (StatsSA), the General Household Survey and the SANHANES-1. The inclusion of post-stratification weights in this study therefore suggests a good degree of robustness that is comparative to other published studies that have made use of survey data.

3.3.3. Other data sources

Other data sources used in this study include the 2011 Census district and provincial spatial boundaries, which were used as the units of analysis during the spatial analysis. As mentioned, ArcGIS shapefiles were obtained from the Demarcation Board of South Africa (2011). In order to assess the racial composition of the 2008 NIDS adult sub-sample for South Africa and the Western Cape, the NIDS racial compositions were compared to the those of the 2007 Community Survey (Statistics South Africa, 2012b).

3.4. ANALYTICAL APPROACH

3.4.1. Selecting and defining the primary and secondary variables for analysis

3.4.1.1. The primary outcome variable: multimorbidity

The primary outcome variable in this study was multimorbidity (refer back to Chapter 1 section 1.5.1 for a discussion on multimorbidity). As previously mentioned, multimorbidity is defined as the co-occurrence of two or more chronic diseases or health conditions in an individual (Van den Akker et al., 1998). This study specifically measures multimorbidity as the simultaneous occurrence of two or more of the following diseases: HIV, TB and the NCDs of hypertension and diabetes mellitus. Therefore, a primary (dichotomous) multimorbidity variable was created and labelled as HIV/TB/NCD multimorbidity. During analysis, the HIV/TB/NCD multimorbidity variable was further explored by separating the multimorbidities into the following components, using the selected diseases of hypertension, diabetes mellitus, TB and HIV: respondents with only two coexisting diseases (double morbidity); respondents with three coexisting diseases (triple morbidity); and respondents with all four diseases coexisting (quadruple morbidity).

3.4.1.2. The secondary outcome variables: hypertension, diabetes, TB, HIV

In this study, the secondary outcome variables were the selected diseases for analysis, namely hypertension, diabetes mellitus, TB and HIV. These were all dichotomous variables; either the respondent had the disease, or they did not. Hypertension was identified as a key secondary outcome variable, having been identified as the most prevalent of the selected chronic diseases and found to contribute most to multimorbidity. Therefore, while the other secondary outcome variables were excluded from the multivariable analysis as this fell outside the scope of the project, hypertension was included in the multivariable analysis for further study. However, all the secondary outcome variables, including hypertension, were omitted from the spatial hot spot analyses (to be discussed in section 3.6), as this too fell outside the scope of the project which primarily focuses on HIV/TB/NCD multimorbidity.

3.4.1.2.1. Measuring hypertension in the NIDS

The NIDS study primarily relies on self-reporting of health conditions, however blood pressure, height and weight measurements are taken as part of the NIDS survey. In this study, the prevalence of hypertension was calculated through a two-stage process. Firstly, respondents were classified as hypertensive if they acknowledged having ever been diagnosed with high blood pressure by a doctor, nurse or health care professional (self-reported measure). Secondly, if respondents had an average systolic blood pressure reading $\geq$ 140 mmHg and/or an average diastolic pressure reading $\geq$ 90 mmHg during the NIDS assessment, the respondents were classified as hypertensive regardless of whether they self-reported having hypertension. This is in line with the internationally acceptable hypertension threshold of 140/90 mmHg (World Health Organization, 2003; Steyn, 2006). In this study, measurement readings were only included if the diastolic blood pressure was $\geq$ 30 mmHg and if the systolic blood pressure reading was between 80 and 240 mmHg, as suggested by Cois and Ehrlich (2014).

3.4.2. The descriptive variables

The descriptive variables used in this study include age (originally treated as a continuous variable but later categorised), socioeconomic status with a focus on the category of socioeconomic disadvantage (using a multidimensional poverty index), gender, racial groups, the urban and rural geographical types, and the sub-urban geographical types of *urban formal* and *urban informal,* as classified by NIDS. Risk factor variables were explored and four were selected for inclusion in this study, namely alcohol drinking status, smoking status and exercise (all of which were self-reported), and obesity (as defined by the body mass index). Refer to Appendix 1 for the definitions and classifications of each of these descriptive variables.

The NIDS contains variables relating to food consumption, such as the frequency that households purchase salt, soft drinks and juice, fruits and vegetables, and ready-made meals. However, due to the large number of missing data as a result of item-nonresponses, these variables were not included in this study.

3.4.2.1. Calculating the body mass index (BMI)

The risk factor variable of obesity was created by calculating a BMI score for each adult respondent using their average weight and height measurements from the NIDS anthropometric assessment, only retaining plausible measurements (height > 100 cm and < 200 cm; weight > 20 Kg and < 200 Kg) (Cois & Ehrlich, 2014). The BMI score (kg/m^2) was calculated by dividing the respondent's squared-height (m^2) by their weight in kilograms (kg) and respondents were classified as underweight, normal weight, overweight and obese according to the World Health Organization guidelines, as shown in Table 3.1 (World Health Organization, 1995). The BMI scores were also used in the construction of the Multidimensional Poverty Index (MDPI) (to be discussed further in section 3.4.2.2.).

Table 3.1. Weight classification cut-off points

Weight Classification	BMI Score (kg/m^2)
Underweight	< 18.50
Normal	18.50 – 24.99
Overweight	25.00 – 29.99
Obese	$\geq$ 30.00

Source: adapted from World Health Organization (1995)

3.4.2.2. Constructing the multidimensional poverty index

Although socioeconomic status is suggested to be the most accurate indication of health, a consensus has yet to be reached in South Africa on the standard measure of deprivation or socioeconomic disadvantage (refer to section 2.4.4). During the process of selecting a measure for socioeconomic status, three other national level indices were considered for use in this study, all of which have previously been used to measure human wellbeing, deprivation or socioeconomic status in health research. These included The Deprivation Index, a composite measure designed by the Health Systems Trust in South Africa; The Demographic and Health Surveys (DHS) Wealthy Index, funded by the United States Agency for International Development (USAID) and originally based on the DHS; and The Human Development Index, which was developed by the United Nations and attempts to illustrate that the development of a country should be measured through the assessment of its people and their capabilities, and that these criteria should ultimately determine human development, and not through economic growth alone (United Nations Development Programme, 2015).

A key criteria for selecting an index for use in this study was that the index needed to allow for a measure of socioeconomic disadvantage which could be isolated for further use, as this is a key variable for this study. In addition, the index needed to provide a measure of socioeconomic status that is relative to the concept of health and that contains indicators that can be measured sufficiently through the NIDS dataset. An index that relied on measures of income or wealth, like The Human Development Index, were considered undesirable for the NIDS for a number of reasons. Firstly, some households may be reluctant to reveal their total income and thus there can be a higher nonresponse rate for this variable (Riphahn & Serfling, 2005). Secondly, many households do not actually know what the total household income equates to, and thirdly, there may be more than one earner in some households and not all the income is shared equally with the household members.

The Acute Multidimensional Poverty Index for Developing Countries, as developed by the Oxford Poverty and Human Development Initiative for the United Nations Development Programme (Alkire & Santos, 2010), was thus selected as a measure of socioeconomic status for this study. The MDPI has been used to measure poverty across more than 109 different countries, including South Africa. The strength of this international poverty measure lies in the way that it looks beyond income poverty and, instead, seeks to measure the many educational, health and material deprivations that individuals are faced with simultaneously, thereby appreciating the multifaceted nature of poverty and deprivation (Alkire et al., 2011).

The structure of the MDPI is similar to the Human Development Index in the way that the index encompasses three dimensions, namely health, education and basic standards of living. The index contains 10 indicators that are distributed under these themes: both the education and health dimensions contain two indicators each, while the standards of living dimension contains six indicators (Figure 3.1). Each indicator within a dimension, and each of the three dimensions, are equally weighted.

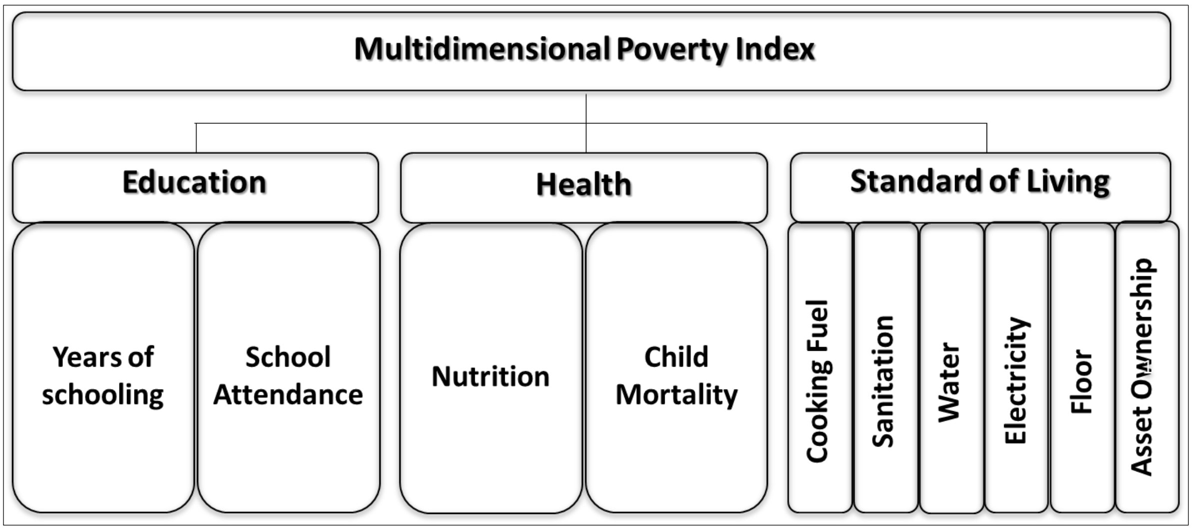


Figure 3.1. Structure of the Multidimensional Poverty Index comprising three themes (Education, Health and Standard of Living) with their respective indicators.

Source: adapted from Alkire et al (2011)

A final score was calculated for each individual and the socioeconomic status scores were categorised by the suggested deprivation categories of Alkire, Conconi and Seth (2014), and adapted to include the primary categories of "socioeconomically disadvantaged" and "not socioeconomically disadvantaged" (Table 3.2). Individuals were ultimately classified as socioeconomically disadvantaged if their final weighted deprivation score was more than a third of the total possible score for the weighted indicator, thereby producing a binary socioeconomic disadvantage variable.

Table 3.2. The MDPI deprivation categories further adapted to include the primary socioeconomic status categories of *not socioeconomically disadvantaged* and *socioeconomically disadvantaged*

SOCIOECONOMIC STATUS CATEGORIES		MDPI SCORE
Primary	***Secondary***	***% Deprived***
Not Socioeconomically Disadvantaged	Not Deprived	< 20%
	Vulnerable	20 – 33.33%
Socioeconomically Disadvantaged	Deprived	34 – 49.99%
	Severe Poverty	≥ 50%

Source: adapted from Alkire, Conconi and Seth (2014)

The recent adaptation of the MDPI for developing countries has made it relevant to South Africa and provides a strong motive for its use in this study. In addition, according to the *MDPI 2014 Brief methodological note and results* report by Alkire, Conconi and Seth (2014), the NIDS is an acceptable data source for determining an MDPI score for South Africa. Although the NIDS wave 1 dataset does not contain the ‘flooring type’ variable, which was an original variable of the MDPI framework, this was substituted with the NIDS ‘dwelling type’ variable so that it may stand as a proxy measure for housing quality. Due to the way the international MDPI was developed using the Alkire Foster Method, which allows for the index structure to adapt and change to suit the society or circumstances (Alkire et al., 2011), this substitution was considered acceptable. Moreover, this study is not looking to produce a standalone MDPI score for South Africa. The MDPI is merely being used to create an adapted measure for socioeconomic disadvantage.

In this study, 2008 NIDS data (wave 1) was used to calculate the MDPI so that a baseline socioeconomic score could be assigned to each individual. These scores were aggregated to provide information for the cross-sectional and spatial analyses of multimorbidity. Therefore, the MDPI scores were used to assess the association between baseline socioeconomic disadvantage and disease multimorbidity changes between 2008 and 2012.

3.4.2.3. Multidimensional poverty index troubleshooting

Alkire et al. (2011) acknowledge that the MDPI structure can be constrained by data availability. In this study, there were instances where respondents did not provide answers to the questions that were needed for the construction of the MDPI. This created a challenge as the overall MDPI score would be effected. Due to the nature in which item non-response occurred haphazardly and was not consistent across respondents and variables, it was decided that it would be unreasonable to exclude all respondents who had missing information. Instead, after analysing the descriptive statistics for each variable to be used in the MDPI, it was decided that respondents would only be assigned an MDPI score if they provided answers to at least 7 of the 10 questions to be used in the MDPI, which would allow 91.70% of the total NIDS sample to be included in the MDPI. This threshold allowed for a reasonable proportion of the sample to be included, while still accounting for item non-response. If the threshold was to be set at answering at answering at least 8 of the 10 questions, only 61.53% of respondents would be included in the MDPI, which was thought to be insufficient.

3.5. STATISTICAL APPROACH

3.5.1. The conceptual framework

This study is part of a wider project funded by the World Health Organization TDR (Grant ID: 184732). Therefore, the conceptual framework of this study is based on the wider project which seeks to understand the cross-sectional and spatial distribution of the prevalence of HIV/TB/NCD multimorbidity and its association with socioeconomic disadvantage at a South African national level only. This study takes this further by exploring these associations through a health geography lens and disaggregating the NIDS data to analyse health patterns at a sub-national level in order to explore spatial differences and acknowledge the possibility of place-based effects. This study, which seeks to use and disaggregate existing health survey data, is thus highly relevant to the current debates occurring in the 2030 SDG agenda, as previously discussed in section 1.4 and section 2.4.5.1.

3.5.2. Software

All descriptive and statistical data analysis were performed using Stata software (StataCorp, 2013). Spatial analysis was performed and maps were generated using a Geographic Information System (ESRI, 2011). ArcGIS desktop software has been used by published authors such Rossen, Khan and Warner (2014), Ghanbarnezhad et al. (2014) and DeGroote et al. (2008) to perform statistical spatial analysis, specifically Global Moran's I and local indicators of spatial associations (hot spot analysis), as well as Liu et al. (2013) to map the prevalence of hypertension by neighbourhoods in the USA, and Brunello et al. (2011) to map socioeconomic status by Census tracts in Brazil. The online Directed Acyclic Graph (DAG) tool (www.dagitty.net/) was used to create causal diagrams to identify possible confounding variables for multimorbidity as well as for hypertension in preparation for statistical analysis.

3.5.3. Data extraction and preparation

Access to the NIDS datasets was granted by DataFirst, a South African research data service (https://www.datafirst.uct.ac.za/), through an accreditation process and the data was retrieved and analysed within the DataFirst Secure Data Lab at the University of Cape Town.

In order to maintain representation of the national population, each NIDS wave was regarded as an independent cross-section. Therefore, data were extracted, merged and analysed within each wave.

All respondents who were classified as temporary sample members in wave 3 were excluded from this study as these members are not part of the original continuing sample and thus were not present in the wave 1 sample (De Villiers et al., 2013).

3.5.4. Statistical analysis

The descriptive statistics methodology described below, was performed successively at the national, Western Cape Province, and urban and intra-urban scales (refer to Appendix 1 for definition of *Urban* and *intra-urban*).

3.5.4.1. Descriptive statistics and exploratory bivariate analysis

The sample was analysed through descriptive statistics, which were presented using proportions and frequencies for categorical data, and median, interquartile range and full range for continuous data. Tabulations and chi-squared tests were used in the exploratory bivariate analysis for categorical variables, while logistic regression was used for assessing the association between continuous data (age) and the dichotomous outcome variables. Numerous simple cross-tabulations were carried out in order to explore the data and possible associations. Age group categories were assigned to the age variable so that the distribution of health and risk factors may be explored by age group. Therefore, the outcome variables of hypertension, diabetes, HIV, TB and multimorbidity were stratified by age group, gender, racial group, and rural and urban, and urban informal and formal geographies. The binary variable of multimorbidity was also stratified by health condition, namely hypertension, diabetes, HIV and TB. Confidence intervals were set at 95% and values were considered statistically significant if p=<0.05. All variables that showed a statistically significant association with the outcome variables or that were potential confounding variables were included in the multivariable analysis.

3.5.4.2. Multivariable analysis

Multivariable analysis of the NIDS data was performed using logistic regression models, but was limited to the national level as the models showed signs of instability at sub-national levels due to the high levels of non-response across variables and respondents.

Multimorbidity was the primary outcome variable, however hypertension was identified as the most prevalent health condition in multimorbidity cases and thus was also explored in the multivariable analysis. The logistic regression models included all significantly associated risk factors, descriptive variables including urban/rural geographical types, gender, race and age, socioeconomic categories, and obesity, as well as the dichotomous outcome variables of either multimorbidity or hypertension. DAGs were used to identify potential confounders among the selected variables for hypertension (Figure 3.2.) and multimorbidity (Figure 3.3.). Race and the rural/urban geographical types (see Appendix 1) were identified as potential confounders for both multimorbidity and hypertension, and were controlled for in both multivariable models.

Age ($p<0.001$) and gender ($p<0.001$) had statistically significant associations with both hypertension and multimorbidity as revealed by exploratory chi-square tests, and both variables were also controlled for in the final model. The primary exposure variable for both hypertension and multimorbidity is socioeconomic status. Collinearity was tested for but none was found between any variables. Interactions were tested for between obesity and age in both models; however the interaction terms did not contribute significantly to the models and were not included.

Exploratory logistic regression was applied in three main steps. The first was to perform univariate analysis by constructing unadjusted models for variables in association with the multimorbidity or hypertension outcome variables. Step two was performed using forward logistic modelling with all variables that were significantly associated with the outcome variable, as identified through the exploratory bivariate analysis. This step involved the addition of the primary independent variable to the model (e.g. socioeconomic status) and the gradual addition of the structural variables (i.e. age, gender, race and urban/rural) and the risk factors (i.e. obesity and exercise). The forward modelling approach was used to identify any potential interactions between variables in the construction of the model. This led to the development of the full model. Step three was the creation of the final which removed any non-confounding variables that were not significantly contributing to the full model. The results of the final model were validated by comparing them with those from earlier cross-tabulation.

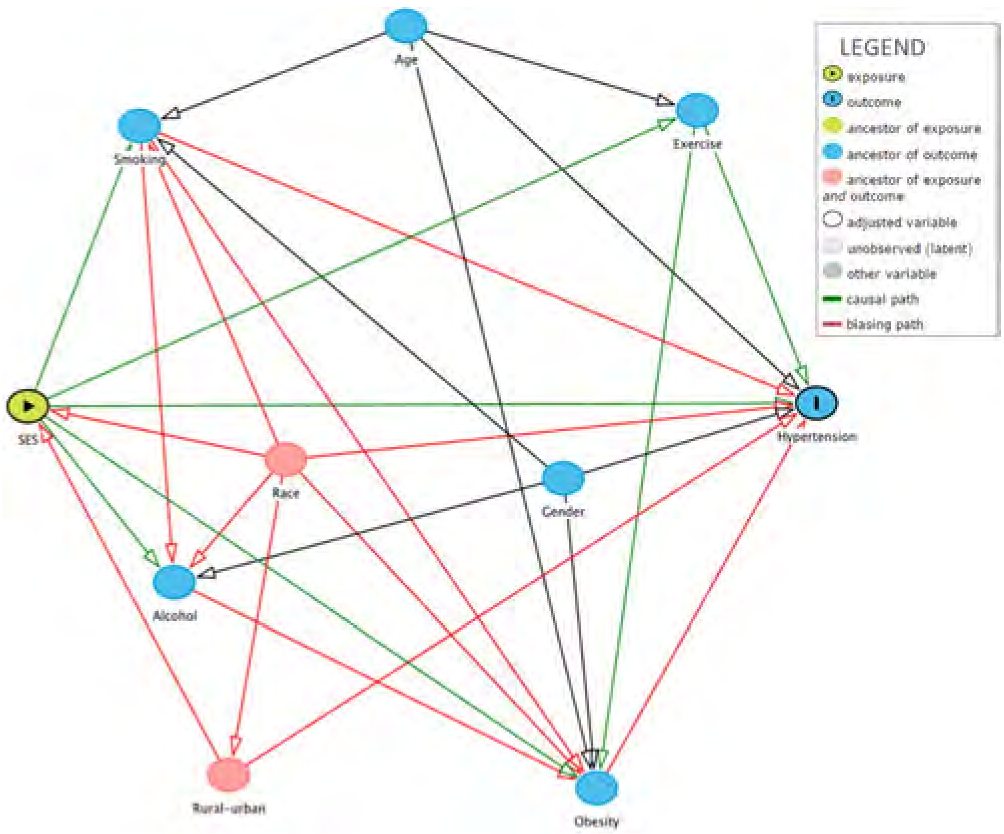


Figure 3.2. Directed Acyclic Graph of hypothesised causal paths between socioeconomic status, hypertension and other selected variables. Arrows indicate hypothesised causal pathways. Race and rural-urban variables (pink circles) were identified as potential confounding variables. Source: Author

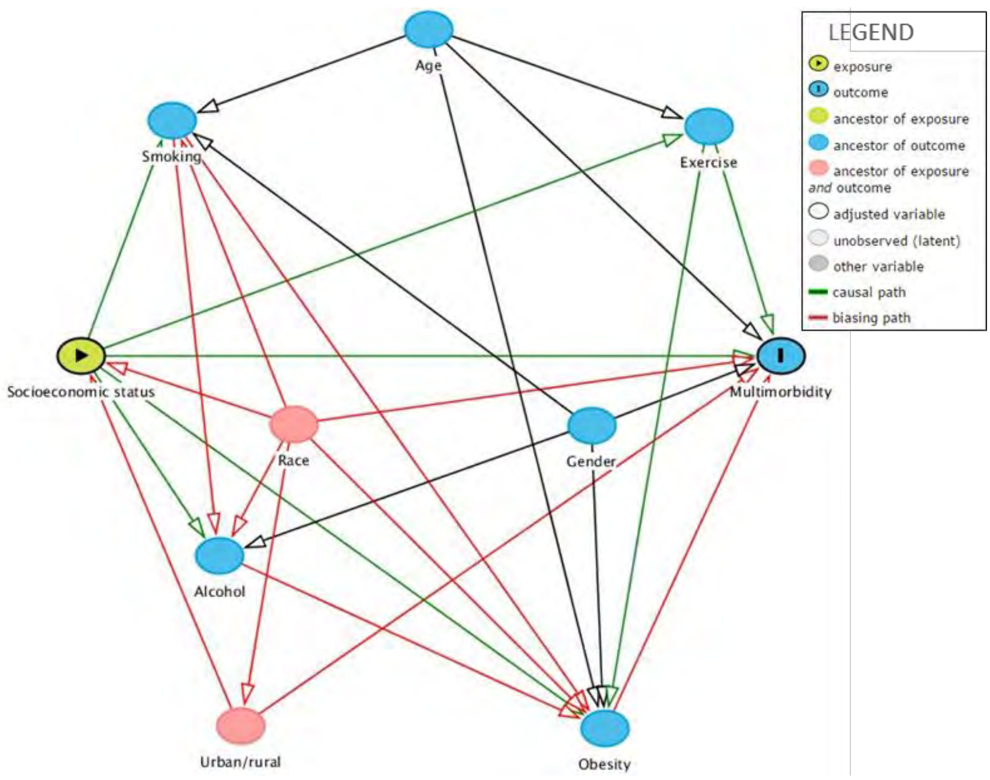


Figure 3.3. Directed Acyclic Graph of hypothesised causal paths between socioeconomic status, multimorbidity and other selected variables. Arrows indicate hypothesised causal pathways. Race and rural-urban variables (pink circles) were identified as potential confounding variables. Source: Author

3.5.4.3. Data disaggregation troubleshooting

In the project proposal, this study originally aimed to establish urban health information at a national and provincial level, with the focus on the Western Cape, and to infer health patterns from the available data for the city level, with a focus on the Cape Town urban area. After extensively assessing the data it was realised that it would not be wise to disaggregate the data for the urban area below a Western Cape level, even to make inferences, as the data would be incomplete and too unreliable to statistical analyse. Although this limitation was anticipated, it was hoped that comparable patterns would be available at a city level, even if the data was not representative of the population, but this was not the case. Therefore, after assessing the data, it was decided to shift the scope of the project to the national level, the Western Cape Province and the general urban and intra-urban setting.

3.6. SPATIAL ANALYSIS

The techniques used by Liu et al. (2013), Ghanbarnezhad et al. (2014) and Rossen, Khan and Warner (2014) were adapted and applied to this study. More specifically Liu et al. (2013) mapped the age-adjusted prevalence of hypertension across neighbourhoods in Philadelphia USA in order to determine the spatial location of higher hypertension prevalence. Ghanbarnezhad et al. (2014) used Global Moran's I to assess the degree of global clustering of TB and HIV in South Iran using administrative regions as spatial units. However, as demonstrated by Rossen, Khan and Warner (2014), the Getis-Ord Gi* statistics, when complimented with the use of Global Moran's I, is a useful and highly appropriate technique for map hot spots of higher disease prevalence. These techniques will be discussed further in section 3.6.3.

3.6.1. The spatial scope

The nine national provinces and the 2011 South Africa Census districts, which exist as the second administrative level of South Africa below the provinces, were used as the spatial units of analysis (Figure 3.4.). There are 52 districts in South Africa, which are perfectly delineated to fit together and within province boundaries.

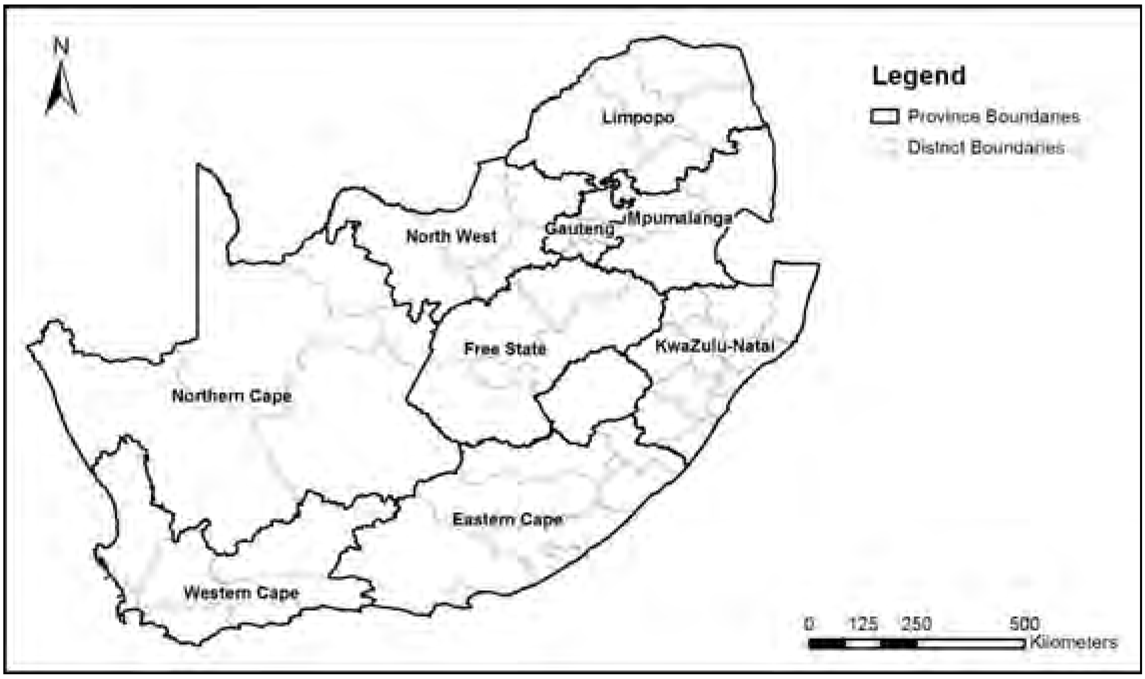


Figure 3.4. The 2011 Census districts of South Africa (outlined in grey) situated within the nine provinces of South Africa (outlined in black)
Source: Author

Due to the challenge of data availability and the lack of representativeness below the national level, the age-adjusted prevalence of multimorbidity and the selected health conditions of hypertension, diabetes, TB and HIV were recalculated as a rate of the unweighted NIDS sample within the relevant 2011 Census districts. The weights were not able to be used as these were only applicable for the national population as a whole. Therefore, it is important to note that the results of the district level spatial analysis of the prevalence of multimorbidity and the selected health conditions are only representative of the NIDS adult sub-*sample* at the district level and not the true district *population*. This prevalence was mapped using a Geographic Information System (ESRI ArcGIS vs 10.3 desktop). Although Global Positioning System (GPS) coordinates were available for the NIDS data, the anonymity of the respondents was assured as these coordinates were aggregated together to a district level.

3.6.2. Spatial analysis of chronic health conditions and the association with socioeconomic disadvantage

The age-adjusted sample prevalence of hypertension, diabetes, TB and HIV were mapped by 2011 Census districts to assist in the national level analysis. To explore the spatial distribution of disease prevalence across the 52 districts of South Africa at a selected point in time (2008 or 2012), the prevalence rates for each chronic health condition were categorised into five quantiles, based on the distribution of data for each health condition. In addition, the proportion of the adult sub-sample in each district that was classified as being socioeconomically disadvantaged, was mapped. Socioeconomic disadvantage was mapped by calculating the percentage of the NIDS adult sub-sample within each district that were classified as being either socioeconomically deprived or in severe poverty, according to the MDPI guidelines as adapted from Alkire, Conconi and Seth (2014) (refer to Table 3.2). These proportions were also categorised into five quantiles to assist in exploratory comparative analysis between districts. A comparison of the visible spatial pattern was made between each of the chronic health conditions and the mapped prevalence of socioeconomic disadvantage.

Due to restrictions around the use of the NIDS data, the spatial analysis was limited to the national level using the district and provincial boundaries as spatial units. Therefore, the results of this spatial analysis reflect the distribution of health conditions for South Africa and for the Western Cape Province using the provincial boundary. Spatial analyses was not able to be performed using urban areas or GPS coordinates as spatial units.

3.6.3. Spatial statistics

In order to assess the spatial pattern of multimorbidity in South Africa, the spatial statistical techniques of Rossen et al (2014) were applied. These include the Global Moran's I (also used by Ghanbarnezhad et al. (2014)) and the Getis-Ord Gi* statistic.

3.6.3.1. Global Moran's I

The Global Moran's I was used to measure global spatial autocorrelation to determine if there was spatial clustering of multimorbidity across districts in South Africa. This was performed using ArcGIS 10.1 software. Spatial autocorrelation may be used to determine spatial patterns as it assesses the relationship between observations within a selected variable across spatial units. As defined by Hubert, Golledge and Costanzo (1981: 224):

> "Given a set of *S* containing *n* geographical units, spatial autocorrelation (SA) refers to the relationship between some variable observed in each of the *n* localities and a measure of geographical proximity defined for all *n(n - 1)* pairs chosen from *S*".

Moran's I is the most popular method of measuring spatial autocorrelation (Getis, 2008) and is assessed under the null hypothesis that the spatial distribution of the variable of concern is random.

According to Guo et al. (2013), the term 'global' when referring to global statistics indicates a measure of spatial association for the entire study area. Moran's I assesses the degree of clustering in the study area. Therefore, in this study, Moran's I was used to assess whether the spatial distribution of multimorbidity across districts (the geographical unit) was random or whether there was an indication of clustering or dispersion. The Global Moran's I statistic is computed as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \left(x_i - \bar{x}\right) \left(x_j - \bar{x}\right)}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}\right) \sum_{i=1}^{n} \left(x_i - \bar{x}\right)^2}$$

where *n* represents the total number of 2011 Census district in South Africa indexed by *i* and *j*, $\left(x_i - \bar{x}\right)$ is the deviation of age-adjusted mortality rates for district *i* from the overall mean, and ω_{ij} is the element within the spatial weight matrix that measures the nearness or connectivity between districts *i* and *j* (Cliff & Ord, 1981). The values of Moran's I generally vary between -1 and +1, which indicate perfect dispersion and perfect clustering, respectively (Legendre & Fortin, 1989). The null hypothesis may be rejected if Moran's I produces a high index value and a z-score greater than 1.96, as this indicates statistically significant clustering ($p<0.05$). On the contrary, a low index value for Moran's I and a z-score less than -1.96 suggests dispersion, or no clustering.

Global statistics do not reveal information about local spatial patterns and can even hide heterogeneous spatial patterns at local spatial scales (Anselin, 1995). Therefore, G statistics are often used in conjunction with global statistics to explore local spatial patterns and identify clusters of high or low attribute values (Getis & Ord, 1992). This links to the discussion in section 1.4 and section 2.4.5.1 on the importance of data disaggregation, in which it was discussed that high level national data can mask inequalities that are occurring at lower levels. This is also supported by Salem (1993) and Niakara et al. (2007) who draw attention to the heterogeneity that is often masked at higher spatial scales - even at a city level. Data analysis that is able to reveal sub-national data patterns is essential for supporting policy improvement efforts and for monitoring progress made to address inequalities. Therefore, the use of a more localised spatial statistic is important.

3.6.3.2. Getis-Ord Gi* Statistic

The Getis-Ord Gi* statistic through the Hot Spot Analysis spatial statistics tool in ArcGIS 10.1 was used to detect any statistically significant spatial clusters or pockets of high values and low values within the data that would produce hot spots and cold spots, respectively. Getis-Ord Gi* is an area-based statistic and is assessed under the null hypothesis that there is no spatial clustering of attribute values in the local area (Guo et al., 2013). As described by Rossen, Khan and Warner (2014), the Getis-Ord Gi* statistic is computed in ArcGIS as:

$$G_i^* = \frac{\sum_{j=1}^{n} \omega_{ij} x_j - \bar{X} \sum_{j=1}^{n} \omega_{ij}}{S \sqrt{\left(n \sum_{j=1}^{n} \omega_{ij}^2 - \left(\sum_{j=1}^{n} \omega_{ij}\right)^2\right) / (n-1)}}$$

where *n* represents the total number of 2011 Census districts in South Africa indexed by *i* and *j*, x_j is the age-adjusted mortality rates for each district *j*, ω_{ij} is the element within the spatial weight matrix that measures the nearness or connectivity between districts *i* and *j*, and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

and

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$$

For each district, the Getis-Ord Gi* statistic provides both a z-score and a p-value that determine whether the district may be considered a hot spot or a cold spot. The z-scores are used to assess the intensity of the clustering, as the greater the z-score is from zero, the greater the degree of clustering. The closer the z-score is to zero, the less spatial clustering there is in the data. This process allows for the spatial clustering of high and low prevalence rates to be identified. A district with a z-score greater than 1.96 was identified as a statistically significant hot spot ($p<0.05$), while z-scores less than -1.96 indicated a statistically significant cold spot ($p<0.05$). Therefore, in this study, a hot spot is defined as a clustering of districts with high prevalence rates while a cold spot represents the clustering of districts with low prevalence rates. It is important to note that the location of hot and cold spots do not necessarily highlight the location of the *highest* and *lowest* prevalence rates, but instead highlight districts that have similar attribute values to their neighbour districts that are either higher or lower than the general mean value of the attribute (Getis & Ord, 1992).

Another South African study, conducted by Mudau et al. (2014), has used the Getis-Ord Gi* statistic in combination with the Global Moran's I to determine the pattern and clustering of multi-drug-resistant TB across South African districts, using ArcGIS version 10.1. According to Mudau et al. (2014), this type of analysis has been conducted at smaller geographical scales in South Africa, but never at a national scale prior to their research. An example of a study that has used made us of the Global

Moran's I and Getis-Ord Gi* statistics for spatial analysis at a smaller scale in South Africa is Daniels (2014), who assessed levels of basic services in the City of Cape.

3.6.3.3. Spatial outliers and conceptualisation of spatial relationships

The 52 South African districts are not all homogenous in size. This study tested for spatial outliers among the 2011 Census districts by standardising all districts according to their area size. Any districts that had an area size of three or more standard deviations above the mean were identified as spatial outliers. Three of the 52 districts were found to be outliers, all of which were located in the Northern Cape Province, namely Namakwa District Municipality, Pixley ka Seme District Municipality and Siyanda District Municipality (Figure 3.5).

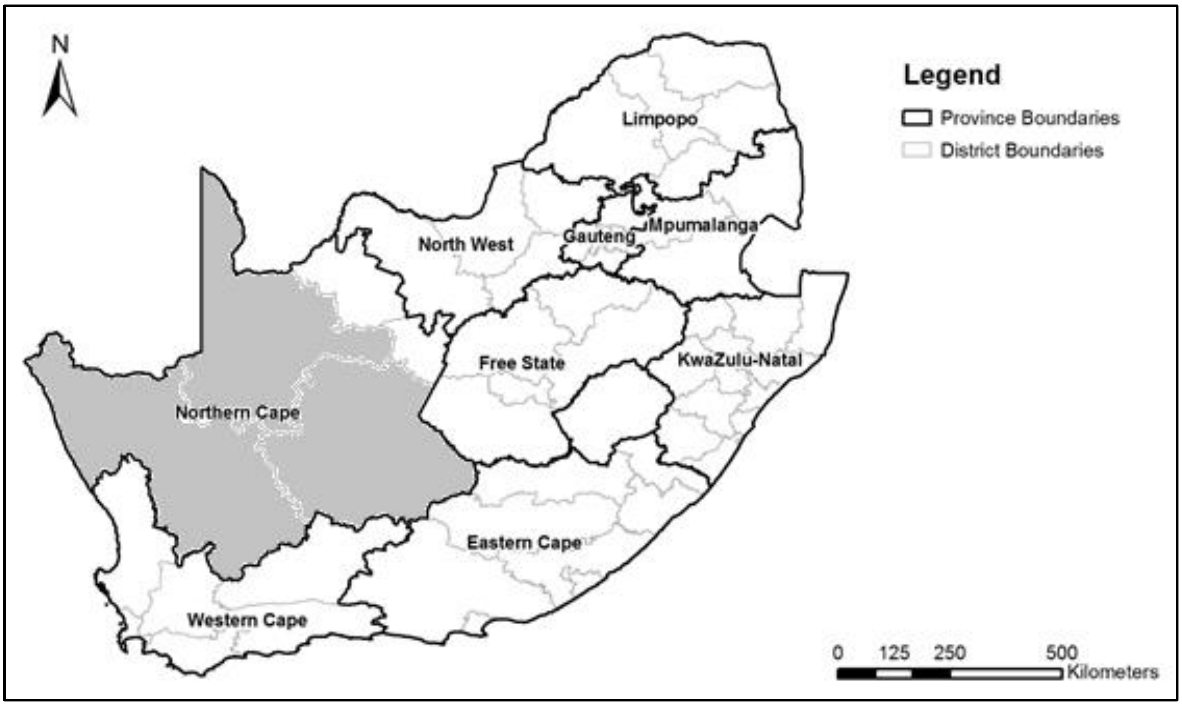


Figure 3.5. The three 2011 Census districts of South Africa that were found to be spatial outliers (highlighted in grey)
Source: Author

Therefore, due to the heterogeneity of district sizes and to account for the presence of spatial outliers, a spatial weights matrix was generated by means of Delaunay Triangulation for the conceptualisation of spatial relationships. Delaunay Triangulation constructs natural neighbours for each district and is useful in situations where there is variation in district sizes, as recommended by Rossen, Khan and Warner (2014). An example of Delaunay Triangulation is shown in Figure 3.6.

Figure 3.6. An example of the Delaunay Triangulation method in identifying district neighbours. The selected district is shaded dark grey while neighbouring districts are shaded in light grey.
Source: Rossen, Khan and Warner (2014).

3.7. ETHICAL CONSIDERATION

This dissertation project is part of a wider project funded by the World Health Organization TDR. Ethics approval was received from the University of Cape Town Faculty of Health Sciences Human Ethics committee (HREC Ref no: 524/2014) for the wider project.

3.7.1. Autonomy and confidentiality

The NIDS survey is conducted to the highest ethical standard where all NIDS participants were given informed consent forms to sign and had the option of refusing to participate in the study (Leibbrandt, Woolard & De Villiers, 2009). All respondents have given consent for their data to be used for research. The NIDS data for all three waves are only shared with researchers who have gone through an accreditation process with the Secure Data Service. Once accreditation has been approved, researchers can access the data at the Secure Data Centre at DataFirst. Although the data does contain household-level geospatial coordinates, any attempt to identify individuals through analysis of the data is prohibited and punishable. In addition, no data can be copied and no information can be removed from the Secure Data Service without thorough inspection by both the Secure Data Service and the NIDS data owners. Researchers are not permitted to take in any electronic or data transfer devices into the Secure Data Laboratory, which is under camera surveillance.

3.7.2. Beneficence

This dissertation aims to generate new knowledge on the prevalence and determinants of, and temporal changes in, HIV/TB/NCD multimorbidity at the South African national, Western Cape and urban spatial levels. The multimorbidity data and socioeconomic score outputs will add to the next NIDS dataset to build on research and inform health policymaking. In addition, this project aims to merge the two fields of classical epidemiology and health geography, thus demonstrating the usefulness of trans-disciplinary and trans-faculty work.

3.7.3. Nonmaleficence

This dissertation involves secondary data analysis and therefore I did not have any direct contact with the respondents of the NIDS survey. Due to the strict controls around using the NIDS dataset, no attempt was or will be made to identify any respondents or the location of dwelling units below the district level.

PART TWO:
PRESENTATION OF RESULTS AND DISCUSSION

INTRODUCTION

In *Part One*, the thesis was situated within the context of the health geography discipline and highlighted the reality and challenges of health and wellbeing inequality, some of the causes of health inequality, the need for disaggregated data, as well as the opportunities researchers, urban planners and public health officials have in addressing these inequalities. *Part One* has also drawn attention to the changing status of health in South Africa and its usefulness as a backdrop for health geography research. Finally, *Part One* provided an overview of the methodology framework that was used in this study.

Part Two seeks to present and discuss the results of this study, which will be structured into four chapters. The first three chapter will present the results of the study, with each chapter representing a spatial scale of analysis; namely the South African level, the Western Cape Province level, and the urban/intra-urban level. Each of these chapters will also include a brief discussion section so that the results may be deliberated and compared to the findings of other studies and, in the case of the disaggregated data, to the national level results. This study primarily aims to explore the health status at the South African level before subsequently disaggregating the data to smaller spatial scales. Therefore, the results and discussion sections of the South African level chapter will be more detailed compared to the chapters of the other spatial scales, and will include more in-depth analysis using logistic regression and spatial hot spot analysis. The aim of disaggregating the NIDS data to the Western Cape and urban/intra-urban level is only to explore changes in health patterns at different spatial scales in order to assess possible place-based effects. Therefore, only basic analysis was performed at the Western Cape Province and urban/intra-urban levels. Finally, the fourth chapter will be a discussion on the implications of the findings for South African health and the opportunities available to improve health and wellbeing.

CHAPTER FOUR: THE SOUTH AFRICAN SETTING

4.1. INTRODUCTION

This section provides an assessment of the status of health in South Africa at the national level using the first and third wave of the NIDS, representing 2008 and 2012, respectively. These results show both similarities and differences with findings from other data sources that make use of the same health variables, namely hypertension, diabetes, HIV and TB. The following data sources offer information on the status of health in South Africa and provide insight into what one can expect from the NIDS results. A comparison between the findings of these sources and the NIDS results will be made in the discussion section of this chapter (section 4.7).

Regarding the NCDs of hypertension and diabetes, the 1998 Demographic and Health Survey is suggested to offer the most comprehensive hypertension estimates and provides a national hypertension age-adjusted prevalence of 21% for South African adults 15 years and older, using the 140/90 mmHg threshold (Steyn et al., 2001). Using a more recent data source, the South African National Health and Nutrition Examination Survey (SANHANES-1) estimated hypertension prevalence for South African adults (15 years and older) in 2012 to be 31.8%, measured using the 140/90 mmHg threshold and including respondents who were currently on blood pressure medication (Shisana, Labadarios, et al., 2014). In 2011, the International Diabetes Federation Diabetes Atlas estimated diabetes to be prevalent in 6.5% of South African adults aged 20-79 years (Whiting et al., 2011), while the SANHANES-1 survey diagnosed diabetes in 9.5% of the 25 532 respondent sample in 2012 (Shisana, Labadarios, et al., 2014).

Regarding chronic infectious diseases, the Nelson Mandela/Human Sciences Research Council study of HIV/AIDS (Shisana & Simbayi, 2002) estimated the 2002 HIV prevalence to be 11.4% for the total South African population and 15.6% for adults (15-49 years). In 2008, HIV was estimated to be prevalent in 17.9% of the national adult population (aged 15-49 years) by UNAIDS, as described by the National Antenatal Sentinel HIV and Syphilis Prevalence Survey (South African National Department of Health, 2010). In 2012, the South African National HIV Prevalence, Incidence and Behaviour Survey estimated the HIV prevalence to be 12.2% for the national population and 16.9% and 18.8% for the South African adult population (aged 15 – 49 years) for 2008 and 2012, respectively (Shisana, Rhele, et al., 2014). These sources together suggest that HIV is increasing in prevalence within the South

African adult population with time and it will be interesting to compare these findings with the estimated HIV prevalence results of the NIDS.

HIV is also known to coexist with TB, and to such a degree that an estimated 50% of TB patients in South Africa typically have HIV (Shisana, Labadarios, et al., 2014). Whilst the prevalence of HIV has been well described in South Africa, the TB burden is normally reported as case notification rates, not prevalence. TB incidence was estimated to be 993 per 100 000 by the World Health Organization for 2011 (World Health Organization, 2012).

The results to follow in this chapter will show that the estimated hypertension prevalence rates in the NIDS are supported by the above mentioned data sources and will highlight that hypertension is a serious health burden in South Africa and shows signs of increasing in prevalence with time. However, the results for the self-reported chronic health conditions, namely diabetes, TB and HIV are less supported by the comparable data sources and instead show evidence of being underreported in the NIDS for the South African adult population. This will be further discussed later in this chapter.

This particular chapter on the context of health in South Africa will first present the composition of the NIDS adult sample for 2008 and 2012, and will go on to present the estimated prevalence and spatial distribution of the chronic infectious and non-communicable diseases in South Africa for 2008 and 2012, as well as the composition and spatial distribution of HIV/TB/NCD multimorbidity in South Africa. Finally, multivariable analysis will be used to explore hypertension and multimorbidity further and spatial analysis will be used to assess the association between socioeconomic disadvantage and multimorbidity. A short discussion on these findings at the South African scale in relation to external data sources will conclude this chapter.

4.2. BASELINE CHARACTERISTICS AND DESCRIPTIVE ANALYSIS OF NIDS ADULT SUB-SAMPLE

The unweighted baseline characteristics for the 2008 NIDS adult sub-sample are available in Table 4.1, with the adult sub-sample limited to respondents aged 15 years and older. The total number of adult respondents was 18 526, with a median age of 34 years (Interquartile Range (IQR): 22-50), and the oldest respondent being 105 years old. The highest proportion of adults were in the 15-24 age group (30.65%) while the proportion of adult respondents within each age group decreased with increasing age. The 2008 adult sample comprised 56.31% females (n = 10 432), while the racial composition of the sample (Black African: 76.58%; Coloured: 15.36%; Indian/Asian: 1.72%; White: 6.34%) was similar to that of the national population in 2007 (Black African: 78.9%; Coloured: 9.0%; Indian/Asian: 2.6%; White: 9.5%) (Statistics South Africa, 2012b). Furthermore, 50.13% (n = 9 288) of the adult respondents were from urban areas while a total of 2 626 (14.52%) respondents were classified as socioeconomically disadvantaged with 2 151 respondents (11.90%) deprived and 475 respondents (2.63%) in severe poverty. Regarding self-reported risk factors, 34.55% of respondents self-report to drink alcohol, while 25.58% claim to regularly smoke and 70.08% never exercise. Over a quarter (27.86%) of respondents who provided height and weight measurements were found to be obese.

In 2012 (Table 4.2), the NIDS adult sub-sample was 20 015 respondents of which 55.72% (n = 11 152) were female. The population group composition remained similar to that of 2008 (Black African: 77.05%; Coloured: 15.24%; Indian/Asian: 1.72%; White: 6.00%) and 51.72% of respondents were from urban areas. Socioeconomic disadvantage was not included in the sample description for 2012 as the 2008 socioeconomic status was used as a baseline measure and was not recalculated for 2012. Regarding risk factors, 2012 has a similar trend to 2008, with 32.21% (n = 4 636) of respondents classified as alcohol drinkers, while 20.45% (n = 2 942) smoke, 71.06% (n = 10 233) never exercise and 29.19% (n = 3 348) were obese.

Table 4.1. Unweighted Descriptive Statistics for the South African adult sub-sample in 2008 (wave 1) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		30.65%	5 678	
	25-34		19.75%	3 659	
	35-44		16.63%	3 080	
	45-54		13.81%	2 559	
	55-64		9.57%	1 773	
	65+		9.59%	1 777	
TOTAL		18 526	34	22-50	15-105
Gender		18 525			
	Male		43.69%	8 093	
	Female		56.31%	10 432	
Race		18 526			
	Black African		76.58%	14 188	
	Coloured		15.36%	2 845	
	Asian/Indian		1.72%	319	
	White		6.34%	1 174	
Rural/Urban		18 526			
	Rural		49.87%	9 238	
	Urban		50.13%	9 288	
Socioeconomic status		18 082			
	Not Deprived		66.77%	12 073	
	Vulnerable		18.71%	3 383	
	Deprived		11.90%	2 151	
	Severe Poverty		2.63%	475	
Alcohol drinking status		15 484			
	Never		65.45%	10 134	
	Drinker		34.55%	5 350	
Smoking status		15 463			
	Never		74.42%	11 507	
	Smoker		25.58%	3 956	
Exercise		15 437			
	Never		70.08%	10 818	
	Exercise		29.92%	4 619	
Obesity		11 200			
	Obese		27.86%	3 120	
	Not Obese		72.14%	8 080	

Source: Author

Table 4.2. Unweighted Descriptive Statistics for the South African adult sub-sample in 2012 (wave 3) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		31.23%	6 251	
	25-34		21.02%	4 207	
	35-44		15.35%	3 073	
	45-54		13.33%	2 667	
	55-64		9.67%	1 936	
	65+		9.40%	1 881	
TOTAL		20 015	33	22-50	15- 105
Gender		20 015			
	Male		44.28%	8 863	
	Female		55.72%	11 152	
Race		20 015			
	Black African		77.05%	15 421	
	Coloured		15.24%	3 050	
	Asian/Indian		1.72%	344	
	White		6.00%	1 200	
Rural/Urban		18 815			
	Rural		48.28%	9,083	
	Urban		51.72%	9 732	
Alcohol drinking status		14 392			
	Never		67.79%	9 756	
	Drinker		32.21%	4 636	
Smoking status		14 388			
	Never		79.55%	11 446	
	Smoker		20.45%	2 942	
Exercise		14 400			
	Never		71.06%	10 233	
	Exercise		28.94%	4 167	
Obesity		11 468			
	Obese		29.19%	3 348	
	Not Obese		70.81%	8 120	

Source: Author

4.3. CHRONIC INFECTIOUS AND NON-COMMUNICABLE DISEASES IN SOUTH AFRICA 2008 AND 2012

The following section explores the status of health in South Africa using selected chronic infectious and non-communicable diseases from the NIDS dataset, namely hypertension, diabetes mellitus, TB and HIV, and investigates how the prevalence of these diseases has changed alongside HIV/TB/NCD multimorbidity between 2008 (wave 1) and 2012 (wave 3).

4.3.1. The prevalence of hypertension, diabetes, TB, HIV and associated multimorbidity in 2008 and 2012

Using the results from the NIDS, age-adjusted prevalence was estimated for hypertension, diabetes, TB, HIV and multimorbidity for the South African adult population for 2008 (wave 1) and 2012 (wave 3), as displayed in Table 4.3. In 2008, hypertension was prevalent in 22.73% of the adult population which increased to 32.14% in 2012. Diabetes, TB and HIV were all self-reported health conditions in the NIDS and had noticeably lower prevalence than hypertension. In 2008, diabetes was self-reported in 2.81% of adults, which decreased to 2.71% in 2012. Self-reported TB prevalence also declined from 1.59% in 2008 to 0.59% in 2012, while HIV showed a slight increase from 1.11% in 2008 to 2.13% in

2012. Multimorbidity, which is the presence of any combination of these health conditions, also had an increase in prevalence from 2.73% in 2008 to 2.84% in 2012.

Table 4.3. Age-adjusted prevalence estimates and 95% confidence intervals (CI) for the South African adult population for 2008 (wave 1) and 2012 (wave 3) using the NIDS

	2008 - Wave 1 (age-adjusted)		2012 - Wave 3 (age-adjusted)	
	Estimated Prevalence (%)	95% CI	Estimated Prevalence (%)	95% CI
Hypertension	22.73%	(22.13-23.34)	32.14%	(31.49-32.79)
Diabetes	2.81%	(2.58-3.06)	2.71%	(2.49-2.94)
Tuberculosis	1.59%	(1.42-1.78)	0.59%	(0.49-0.71)
HIV	1.11%	(0.97-1.27)	2.13%	(1.93-2.34)
Multimorbidity	2.73%	(2.50-2.98)	2.84%	(2.61-3.08)

Source: Author

In order to explore health variations across ages, prevalence rates were estimated by adult age group and presented in Figure 4.1. In both 2008 and 2012, hypertension is the most prevalent health condition across all adult age groups and is strongly associated with age ($p<0.001$). Looking at the results from 2008 (wave 1), hypertension was prevalent in 5.46% of adults in the 15-24 age group and in 62.05% of adults 65 years and older. A slight increase in prevalence by age group may be seen after the 25 – 34 age group. Self-reported diabetes was most prevalent in the 55-64 age group (10.69%) and was also associated with age ($p<0.01$). Both self-reported TB and self-reported HIV were scarce in the 15-24 age group, with an estimated prevalence of 0.43% and 0.27% respectively. Although both health conditions showed low prevalence rates across age groups, both TB and HIV peaked in the middle age groups, with TB peaking in the 45-54 age group (2.50%) before declining to a rate of 2.21% for the 65+ age group, and HIV peaking for the 35-44 age group (2.48%) before declining to 0.00% in the 65+ age group. Although multimorbidity was also associated with age ($p<0.001$) and found to be most prevalent in the older age groups, it also features in the younger and middle age groups. The prevalence of multimorbidity increased with age from 0.11% in the 15-24 age group to a rate of 9.73% in the 55-64 age group before slightly declining to 8.83% in the 65+ age group. The decline in multimorbidity prevalence between the 55-64 and 65+ age groups may possibly be linked to the slight decline in prevalence of diabetes, as well as the decrease in TB prevalence across these age groups in wave 1 from 2.43% (55-64 years) to 2.21% (65+ years) and the decline of HIV from 0.49% (55-64 years) to 0.00% (65+ years). Multimorbidity follows a similar prevalence pattern across age groups to diabetes and an increase in prevalence for both multimorbidity and diabetes is seen after the 35-44 age group until the 55-64 age group.

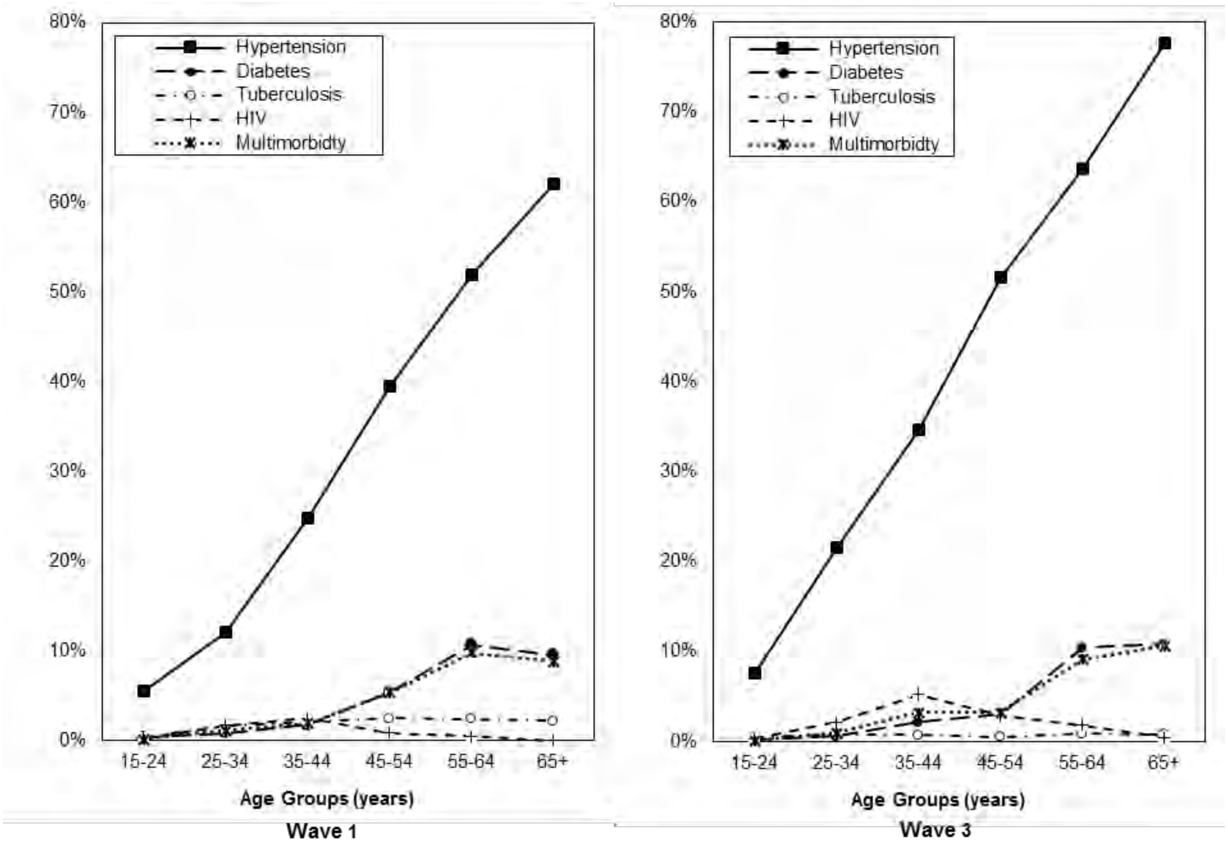


Figure 4.1. Hypertension, diabetes, TB, HIV, multimorbidity prevalence by age group for the South African adult population for 2008 (wave 1) and 2012 (wave 3) using the NIDS

Source: Author

In 2012 (wave 3), hypertension maintains its strong association with age ($p<0.001$), as hypertension prevalence was considerably higher for older adults (65+ (77.71%); 55-64 (63.71%); and 45-54 (51.52%) age groups) compared to their younger counterparts (15-24 (7.62%); 25-34 (21.46%); and 35-44 (34.67%) age groups). Again, diabetes prevalence is shown to be highest for the 55-64 (10.36%) and 65+ age groups (10.83%). Self-reported TB showed low prevalence across all age groups and, once again self-reported HIV was most prevalent in adults in the 35-44 age group (5.21%). Overall, self-reported HIV had a slightly higher prevalence rate across age groups in 2012 compared to 2008, except for the 15-24 (0.25%) age groups. In 2012, multimorbidity continued to imitate the diabetes prevalence pattern across age groups. The noticeably lower multimorbidity prevalence rate for the 45-54 age group in 2012 compared to 2008 may be attributed to the decline in diabetes prevalence between wave 1 (5.29%) and wave 3 (3.05%) in the 45-54 age group, as well as the decline in TB prevalence between wave 1 (2.50%) and wave 3 (0.46%) for the age group. Similar to wave 1, multimorbidity was highest among the older age groups, namely the 55-64 age group (9.09%) and the 65+ age group (10.61%). However, unlike in wave 1, multimorbidity peaks in the 65+ age group in wave 3.

4.3.2. The spatial distribution of chronic infectious and non-communicable diseases in South Africa 2008 and 2012

Spatial representations of age-adjusted prevalence for hypertension, diabetes, TB and HIV were used to contribute towards building a baseline health assessment for South Africa and provided a foundation for further statistical analysis which will follow in section 4.4.

4.3.2.1. Hypertension

Figure 4.2 displays the age-adjusted prevalence of hypertension for the NIDS adult sub-sample by district for 2008 (wave 1) and 2012 (wave 3). In 2008, higher hypertension prevalence rates were located mainly in the North West Province, the Northern Cape, the Eastern Cape and parts of the Western Cape Province. One of the eleven districts in KwaZulu-Natal had a hypertension prevalence rate $\geq$ 30.85% (i.e. $\geq$ the highest quantile) while five districts had a hypertension prevalence between 21.16% and 24.54% (i.e. the second quantile). Lower prevalence rates are predominantly located in the northern districts of the country, particularly in the Limpopo and Mpumalanga provinces.

In 2012, four of the six districts in the Western Cape have a prevalence $\geq$ 37.41% (i.e $\geq$ the highest quantile). In addition, a band of districts with prevalence rates greater than the second highest quantile ($\geq$ 33.52%) is visible across the Western Cape and the Eastern Cape; these districts had higher prevalence rates relative to other parts of the country for 2012. No district in KwaZulu-Natal has a prevalence rate $\geq$ the highest quantile in wave 3. Hypertension prevalence for districts in the northern parts (i.e. Limpopo, Mpumalanga, and parts of Gauteng and the North West Province) are low relative to other parts of the country.

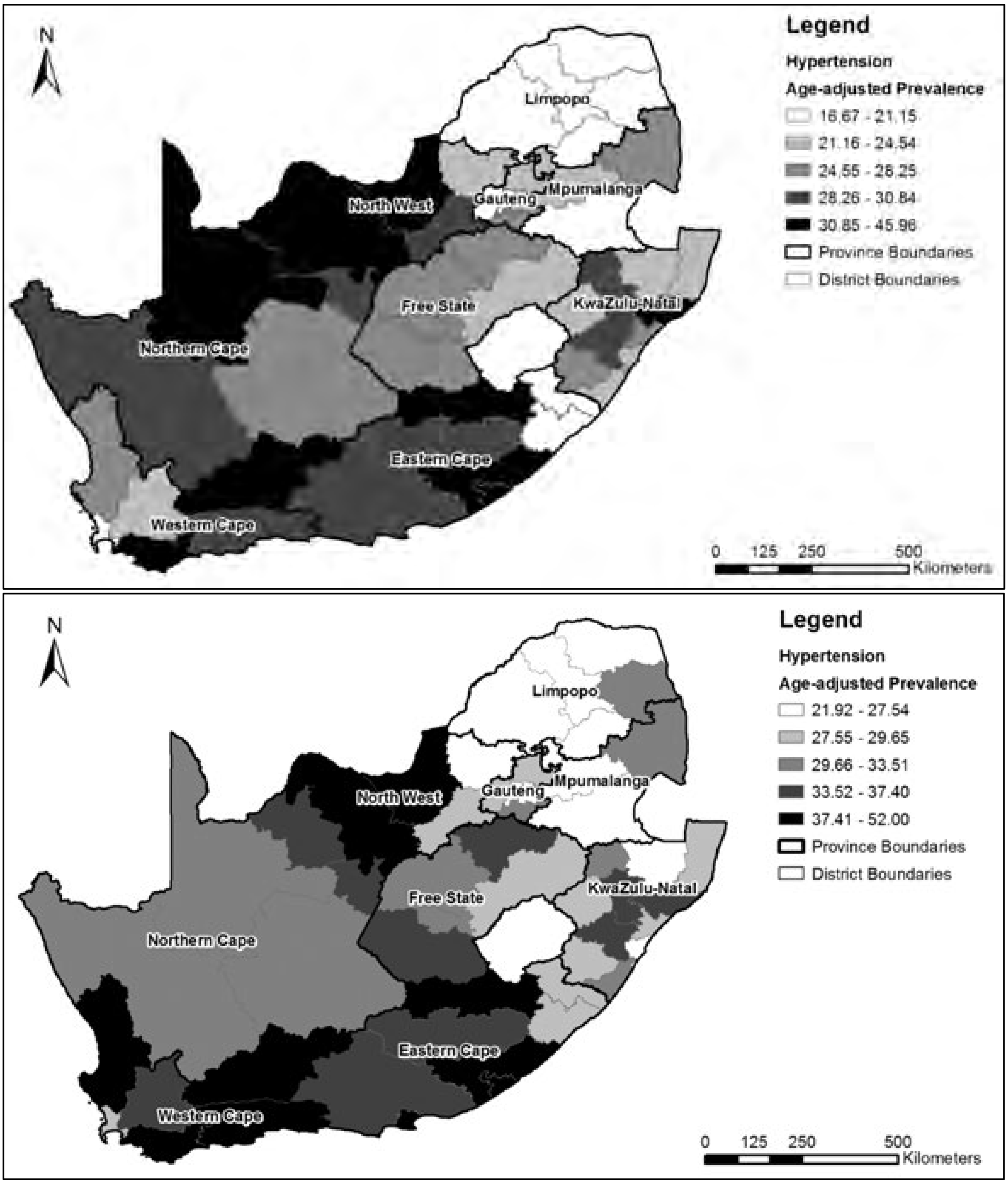


Figure 4.2. Age-adjusted prevalence of hypertension in the South African adult sub-sample by district for 2008 (top) and 2012 (bottom)

Source: Author

4.3.2.2. Diabetes

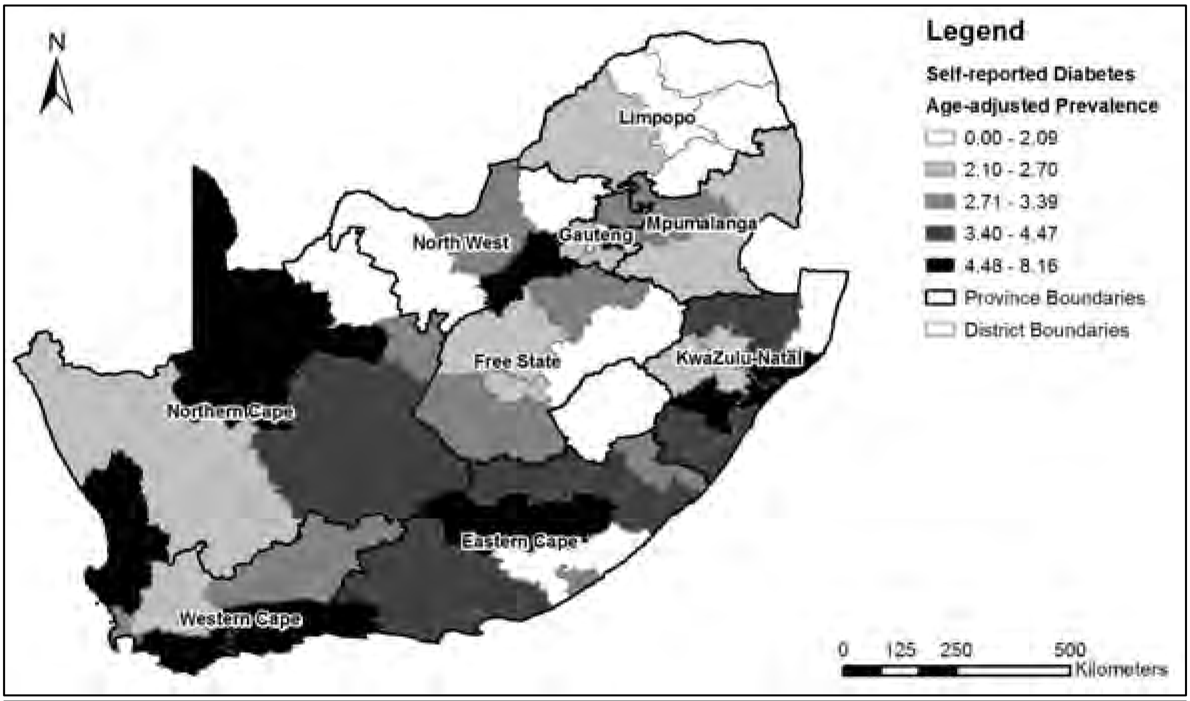
In 2008, the age-adjusted prevalence for diabetes in the NIDS adult sub-sample show lower overall prevalence rates of diabetes in the Limpopo Province, with four of the five districts having prevalence rates less than the lowest quantile (≤ 2.09%), as shown in Figure 4.3. The Western Cape has three districts with prevalence rates ≥ 4.48% (i.e. the highest quantile). Of the eleven districts in the KwaZulu-Natal Province, five have prevalence rates between 3.40% - 4.47% (i.e. the second highest quantile) while three have rates ≥ 4.48 (i.e. ≥ the highest quantile). In the Eastern Cape, one district has a prevalence rate ≥ the highest quantile (4.48%) and four have a rate between 3.40% and 4.47% (i.e. the second highest quantile).

In 2012, the northern parts of the country have districts with lower prevalence rates, particularly in the North West, Limpopo and Gauteng provinces, relative to other parts of the country. The Eastern Cape has three districts with prevalence rates ≥ 3.74% (i.e. ≥ the highest quantile). Six of the eleven districts in KwaZulu-Natal have diabetes rates between 3.22% and 3.73% (i.e. the second highest quantile) and an addition two have rates ≥ 3.74% (i.e. ≥ the highest quantile). The Western Cape has three districts that have prevalence rates ≥ 3.74% (i.e. ≥ the highest quantile).

4.3.2.3. Tuberculosis (TB)

The prevalence rates of TB across districts for 2008 (wave 1) and 2012 (wave 3) are shown in Figure 4.4. In 2008, districts in the northern parts of the country appear to have lower TB prevalence than districts in the central and eastern parts of the country. Four of the five districts in Limpopo have prevalence rates less than the lowest quantile for wave 1 (≤ 1.02%), while districts in Mpumalanga, Gauteng and the North West Province also have low prevalence rates ≤ 1.02%. However, the North West Province also has districts with high prevalence rates. Wave 1 also shows three of the eleven districts in KwaZulu-Natal with prevalence rates greater than the highest quantile (≥ 3.36), while three of the eight districts in the Eastern Cape have prevalence rates greater than the highest quantile.

The prevalence rates for TB have generally declined between 2008 (wave 1) and 2012 (wave 3), as shown previously in Table 4.3. Comparing the relative distribution of TB across districts, wave 3 presents a fairly heterogeneous spatial pattern. The Eastern Cape Province has areas in the south with prevalence rates ≥ 1.31% (i.e. the highest quantile), which starkly contrasts the central districts in the province that have 0.00% TB prevalence. The Northern Cape, Free State and KwaZulu-Natal provinces also have districts with some relatively higher prevalence rates ≥ 0.91% (i.e. the second highest quantile). However, caution must be taken when assessing diseases with low prevalence rates, as spatial differences are likely to be exaggerated.



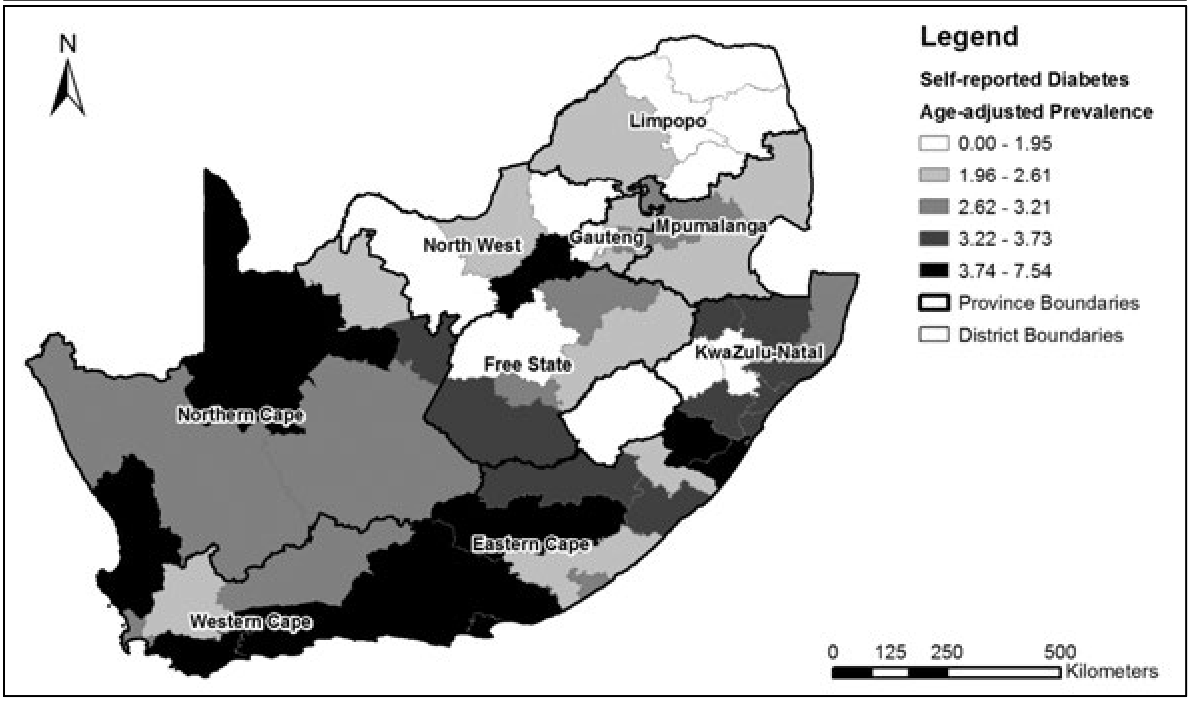
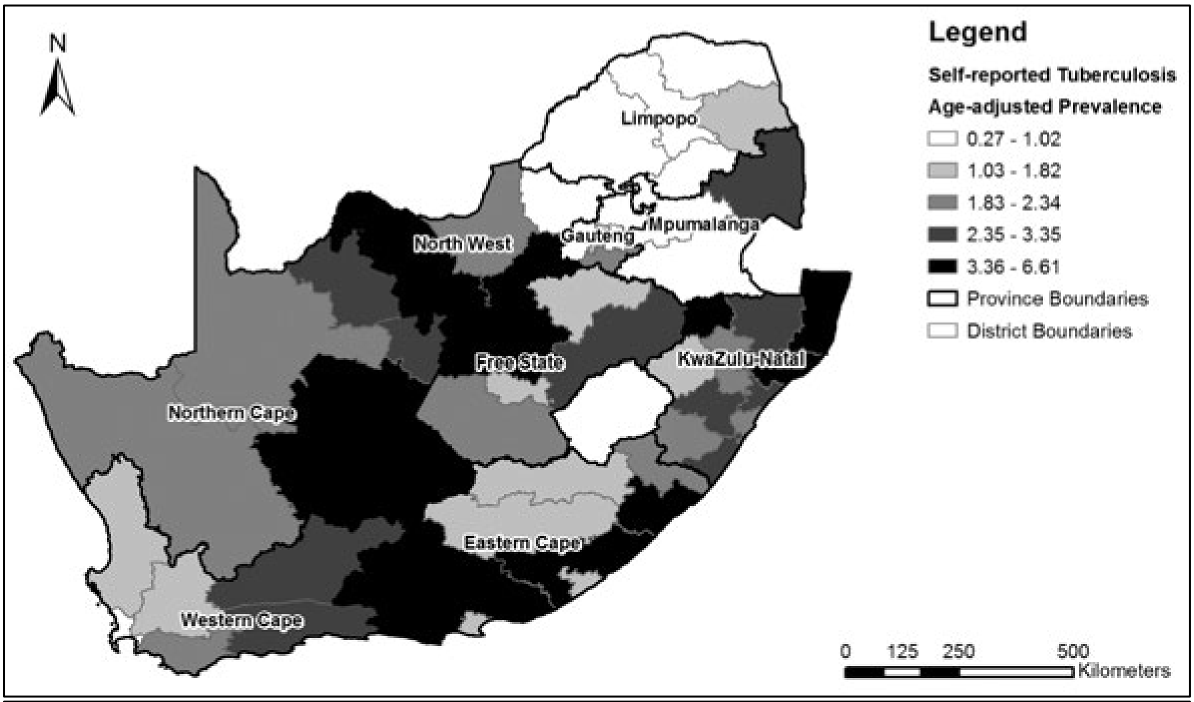


Figure 4.3. Age-adjusted prevalence of diabetes in the South African adult sub-sample by district for 2008 (top) and 2012 (bottom)

Source: Author



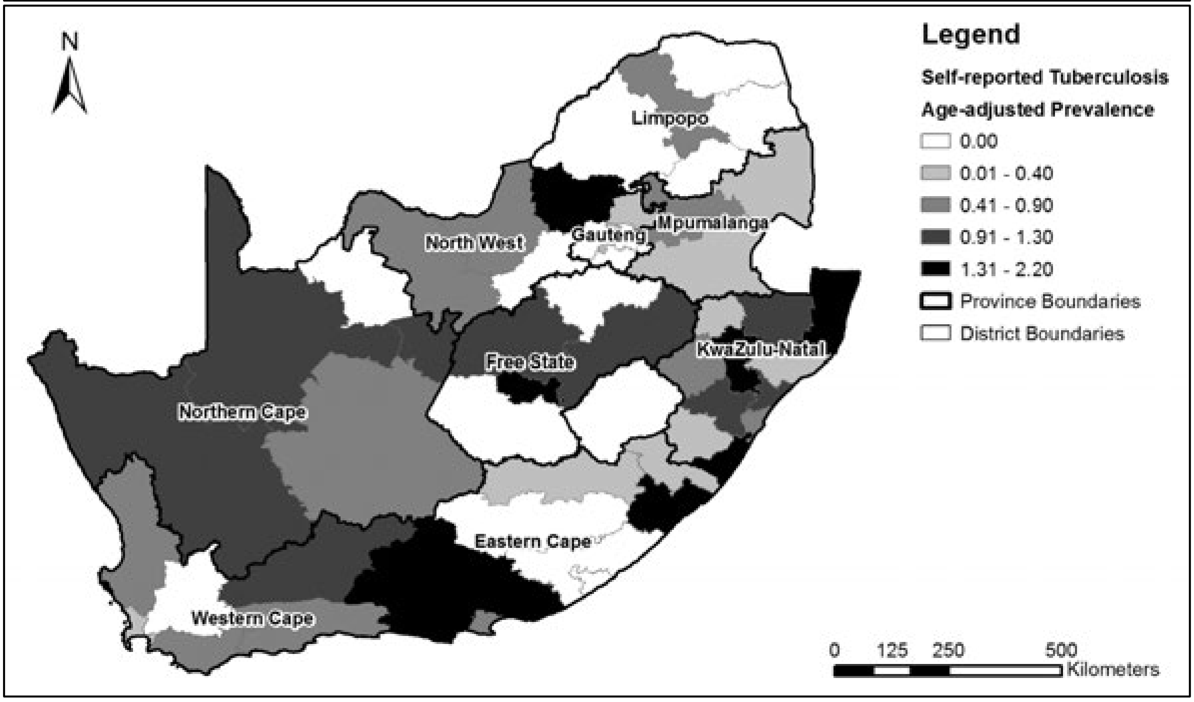


Figure 4.4. Age-adjusted prevalence of tuberculosis in the South African adult sub-sample by district for 2008 (top) and 2012 (bottom)

Source: Author

4.3.2.4. Human Immunodeficiency Virus (HIV)

When assessing the spatial distribution of HIV across the South African districts, a reduced prevalence in HIV is noticeable in the western parts of the country in both waves, specifically in the Northern Cape and Western Cape provinces, as well as in some northern districts in wave 1 (Figure 4.5). This has not been consistent with the spatial pattern of the other chronic health conditions.

In 2008, higher prevalence rates of HIV are visible in the central and eastern parts of the country, with two districts in the North West province, one district in the Free State and Northern Cape provinces, and four districts in KwaZulu-Natal having prevalence rates ≥ 1.65% (i.e. ≥ the highest quantile). The Northern Cape, Western Cape and Limpopo provinces all have more than one district with prevalence rates ≤ 0.29% (i.e. ≤ the lowest quantile).

In 2012, four of the six districts in the Western Cape have prevalence rates ≤ 0.78% (i.e. the lowest quantile), while two districts in the Northern Cape, Eastern Cape and Limpopo also have prevalence rates ≤ 0.78%. The KwaZulu-Natal Province has five districts with prevalence rates ≥ 2.71% (i.e. ≥ the highest quantile) and another five districts with rates between 2.24% and 6.28% (i.e. the second highest quantile). In the Eastern Cape, one district has a prevalence rate ≥ 2.71%, but it is neighboured by three districts with low prevalence rates ≤ 0.78% (i.e. ≤ the lowest quantile). Although the Limpopo Province has two districts with prevalence rates ≤ the lowest quantile, two districts have rates between 0.79% and 1.51% (i.e. the second lowest quantile) and one has a rate between 1.52% and 2.23% (i.e. the middle quantile).

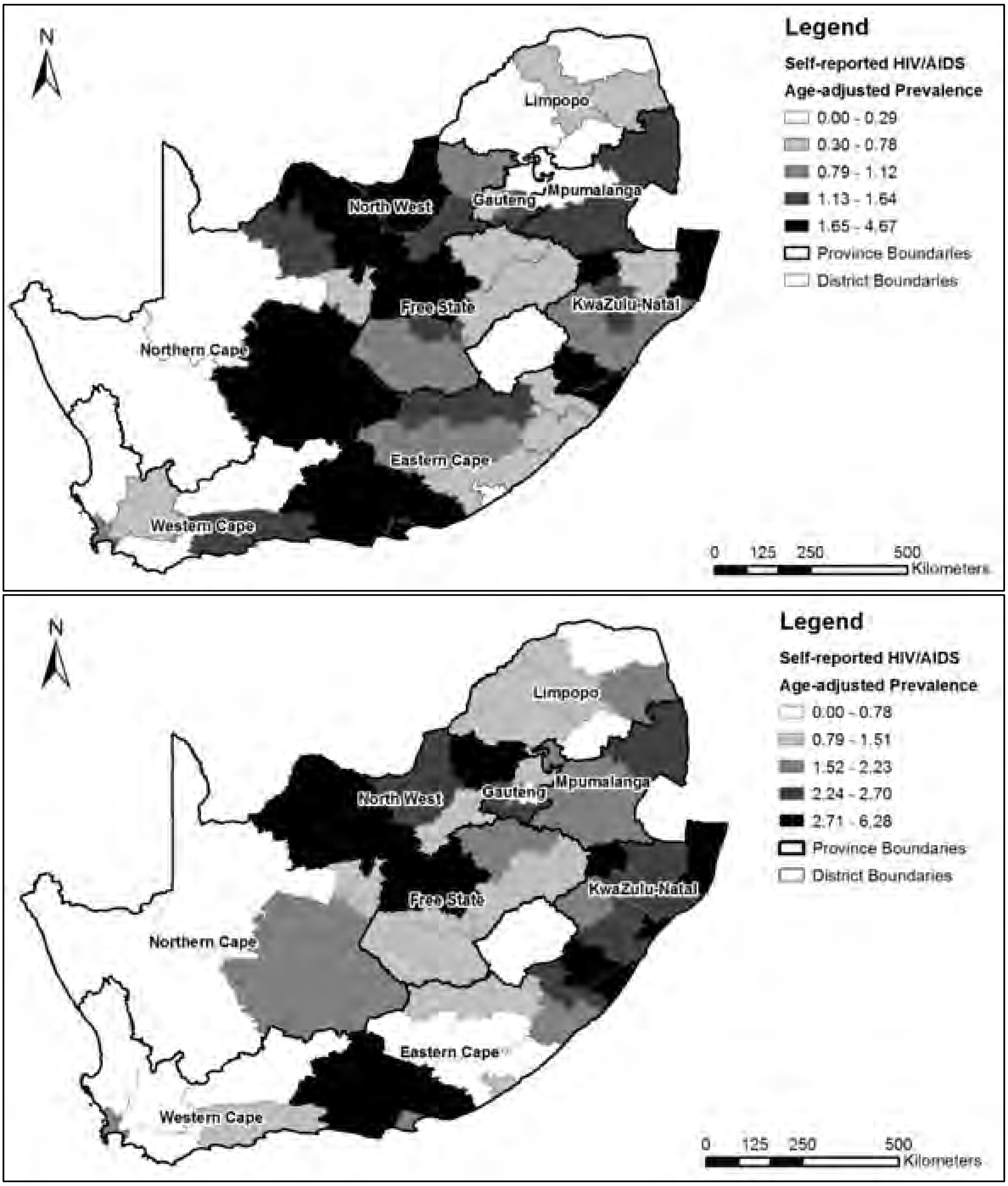


Figure 4.5. Age-adjusted prevalence of HIV/AIDS in the South African adult sub-sample by district for 2008 (top) and 2012 (bottom)

Source: Author

4.4. MULTIMORBIDITY IN SOUTH AFRICA IN 2008 AND 2012

4.4.1. A deeper look into multimorbidities in South Africa between 2008 and 2012

Detailed schematics of multimorbidity are provided in Figure 4.6 and Figure 4.7 in order to better understand the composition of multimorbidity in South Africa for 2008 and 2012, respectively. As mentioned, multimorbidity was estimated to be prevalent in 2.73% (2008) and 2.84% (2012) of the South African population. However, it was prevalent in 10.61% of adults in the 65+ age group in 2012. In the schematics, single disease morbidity refers to the presence of one disease, while double, triple and quadruple disease morbidities refer to two, three and four coexisting diseases, respectively.

In 2008 (wave 1), single morbidities were prevalent in 89.22% of all disease morbidities. Double (10.58%) and triple (0.19%) disease morbidities were less prevalent compared to single morbidities. Hypertension was the most prevalent single disease (88.61%), followed by TB (4.67%), diabetes (3.71%) and HIV (3.00%). The three most prevalent combinations of health conditions for double morbidities were diabetes/hypertension (DIA HYP; 70.80%), TB/hypertension (TB HYP; 13.27%), and HIV/hypertension (HIV HYP: 10.83%). The only triple disease morbidities were TB/diabetes/hypertension (TB DIA HYP: 63.98%) and hypertension/HIV/TB (HYP HIV TB: 36.02%). Quadruple morbidity was not present.

In 2012 (wave 3), single morbidities increased to 91.78% of all disease morbidities, while double morbidities declined to 7.67% and triple morbidities increased to 0.53% (Figure 4.7). Quadruple morbidity was present, contributing just 0.02% (N = 2 509) to all morbidities in 2012. Hypertension contributed 92.49% to single disease morbidities, the DIA HYP multimorbidity increased from 70.80% (2008) to 71.22% (2012), and the TB HYP multimorbidity declined in prevalence from 13.27% (2008) to 5.19% (2012), which may be attributed to the overall decrease in TB prevalence in the adult population in 2012. The HIV HYP multimorbidity increased from 10.83% in 2008 to 23.08% in 2012, which may be attributed to the increase in the overall prevalence of both hypertension and HIV between 2008 and 2012 (Table 4.3). The triple morbidity of TB DIA HYP declined between 2008 (63.98%) and 2012 (22.02%), possibly due to the decline in overall prevalence rates of TB as well as diabetes over time (Table 4.3), while the HYP HIV TB declined from 36.02% (2008) to 7.89% (2012) possibly due to the decrease in TB prevalence in 2012 (Table 4.3). The DIA HYP HIV multimorbidity, which did not feature in 2008, contributed 70.08% to triple disease multimorbidities in 2012, which may be attributed to an increase in prevalence of both HIV and hypertension over time (Table 4.3).

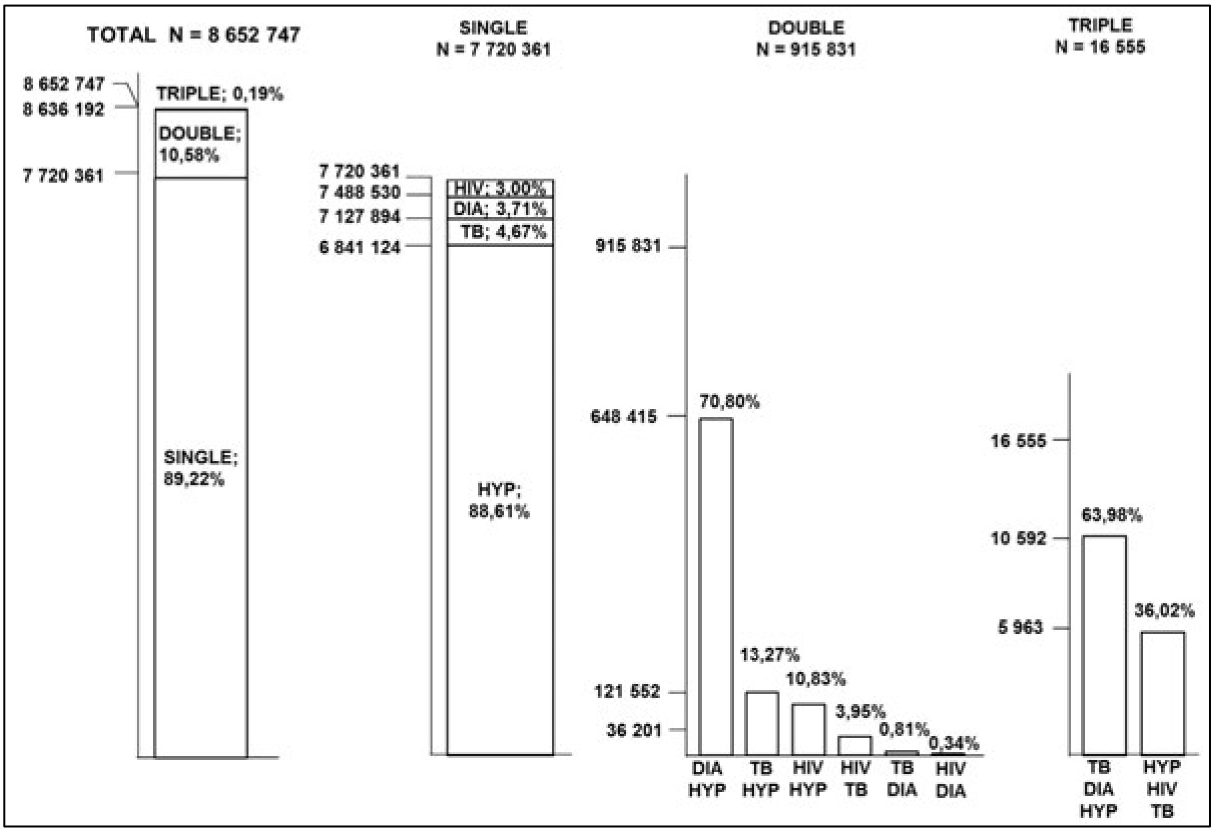


Figure 4.6. Schematic detailing the 2008 (wave 1) South African adult population with existing single, double and triple disease morbidities.

Source: Author

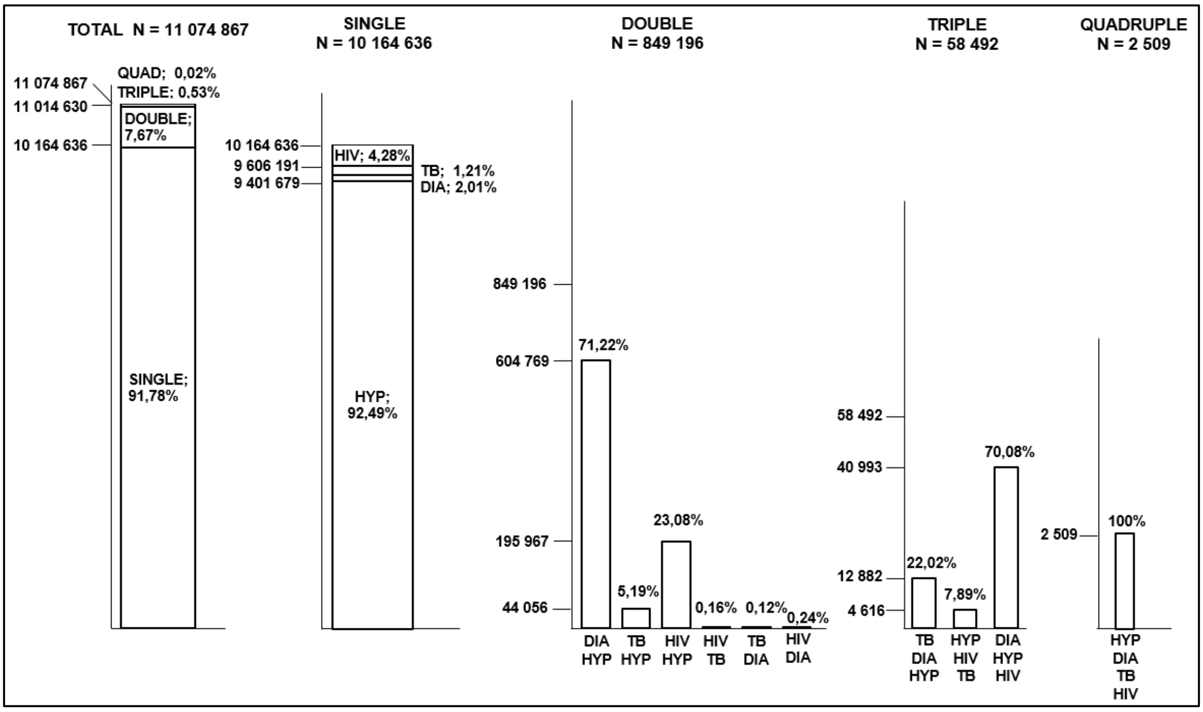


Figure 4.7. Schematic detailing the 2012 (wave 3) South African adult population with existing single, double and triple disease morbidities.

Source: Author

4.4.2. The spatial distribution of multimorbidity prevalence in South Africa 2008 and 2012

In order to explore the spatial context, age-adjusted multimorbidity was mapped by the 52 South African districts for 2008 and 2012 (Figure 4.8).

In 2008, multimorbidity prevalence was lower in all five districts in the Limpopo Province (≤ 2.19%; i.e. ≤ the lowest quantile). Two of the five districts in Gauteng, as well as one district in the North West Province also had multimorbidity prevalence rates ≤ 2.19%. Districts with prevalence rates ≥ 4.72% (i.e. the highest quantile) were located in the Northern Cape (1 district), North West Province (1 district), the Free State (1 district), the Western Cape (1 district), the Eastern Cape (1 district), and in KwaZulu-Natal (5 districts). KwaZulu-Natal also had three other districts with prevalence rates between 3.94% and 4.71% (i.e. the second highest quantile). The Western Cape had two districts with prevalence rates between 3.94% and 4.71%.

Multimorbidity prevalence was lower for all districts in the Limpopo Province in 2012, with all five districts having a prevalence rate ≤ the lowest quantile (< 2.34%). Five of the 11 KwaZulu-Natal districts, two of the six Northern Cape districts, and two of the eight Eastern Cape districts have prevalence rates ≥ the highest quantile. In addition, two districts in both the Northern Cape and the Eastern Cape have rates between 3.74% and 4.27% (i.e. the second highest quantile). However, two districts in the Eastern Cape have rates ≤ 2.34% (i.e. ≤ the lowest quantile). The Western Cape has one district with a prevalence rate ≥ the highest quantile (≥ 4.28%), although one district has a rate ≤ the lowest quantile (2.34%).

Despite hypertension being the main contributor to multimorbidity, the spatial patterns of multimorbidity and hypertension are not visibly alike, with the exception of lower prevalence rates in the Limpopo Province districts. However, lower prevalence rates in Limpopo are also consistent with diabetes and TB.

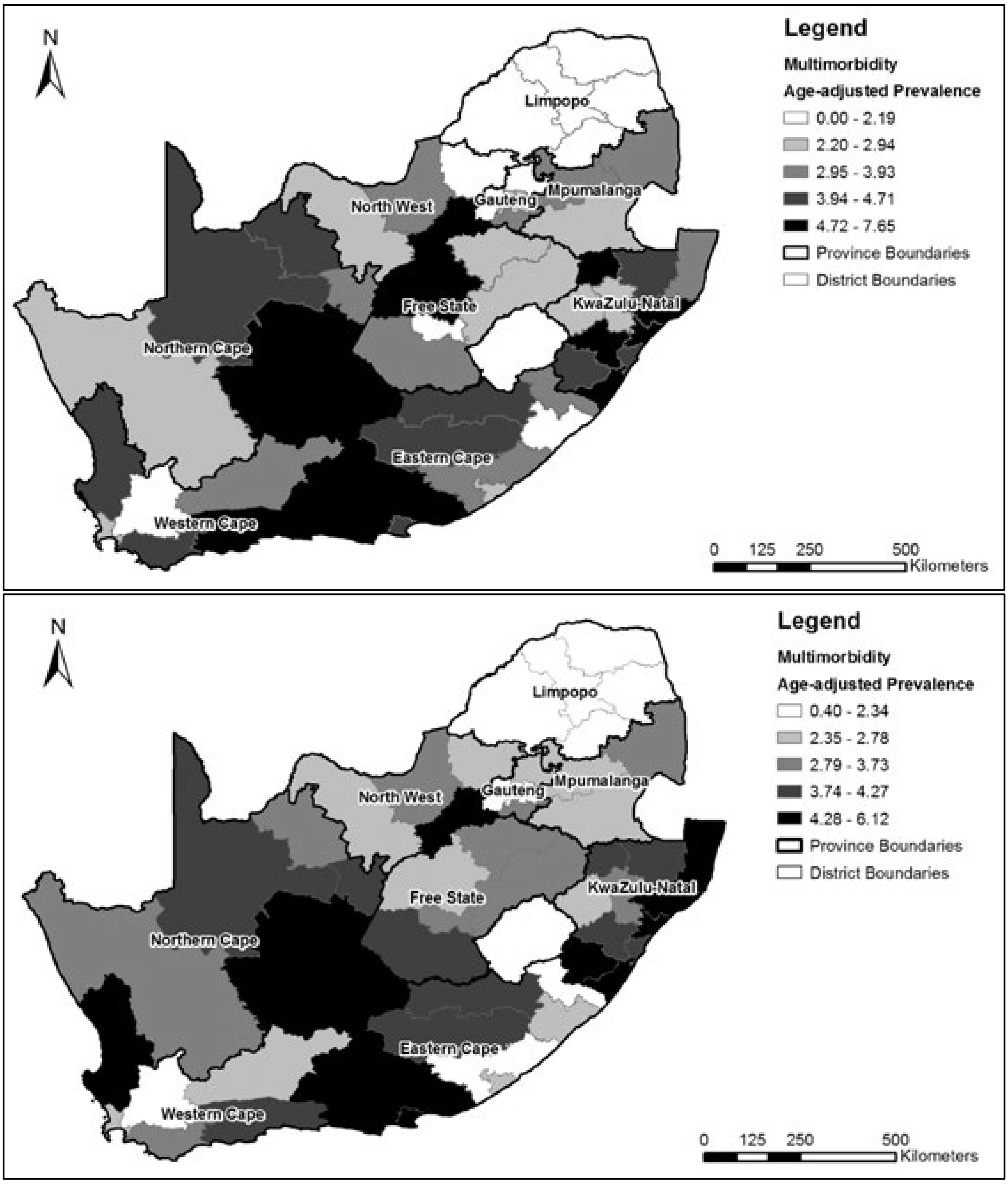


Figure 4.8. Age-adjusted prevalence of multimorbidity in the South African adult sub-sample by district for 2008 (top) and 2012 (bottom)

Source: Author

4.5. MULTIVARIABLE ANALYSES OF HYPERTENSION AND MULTIMORBIDITY

The aim of this study is not only to assess the prevalence of chronic infectious and non-communicable diseases and multimorbidity in South Africa; it also aims to assess the association between multimorbidity, socioeconomic disadvantage and selected risk factors. This was assessed using logistic regression models. Having identified hypertension as the largest contributing chronic disease to multimorbidity, a multivariable analysis of hypertension was also included.

4.5.1. Logistic regression analyses of factors affecting hypertension

Results of the multivariable logistic regression of hypertension and associated explanatory variables (see Table 4.4 for Odds Ratio (OR) and 95% confidence intervals (CI)), as shown by the unadjusted OR (Model I), reveal a significant ($p<0.01$) association between socioeconomic status categories and hypertension. Respondents who have some degree of *socioeconomic disadvantage*, being categorised as either 'Deprived' (1.84; 95% CI, 1.52-2.22) or in 'Severe Poverty' (2.10; 95% CI, 1.53-2.89) had higher odds of having hypertension relative to the '*not socioeconomically disadvantaged*' categories of 'Vulnerable' and 'Not Deprived'. However, respondents who are socioeconomically 'Vulnerable' are still 1.52 time more likely (95% CI 1.24-1.87) to have hypertension than respondents who are 'Not Deprived'. Overall, respondents in 'Severe Poverty' have the highest odds of having hypertension.

Model II shows that once age and gender are controlled for, the socioeconomic categories relating to socioeconomic disadvantage (i.e. 'Deprived' and 'Severe Poverty') were no longer significant predictors of hypertension. However, being socioeconomically 'Vulnerable' was still significantly associated ($p<0.05$), with 'Vulnerable' respondents being 1.32 times more likely (95% CI 1.10-1.58) to have hypertension than those 'Not Deprived'. Age is shown to be a significant predictor of hypertension ($p<0.01$), with the odds of having hypertension increasing with age so that respondents in the 65+ age group are 26.61 times more likely (95% CI 19.68-35.97) of having hypertension than those in the 15-24 age group. Females are 1.48 times more likely (95% CI 1.29-1.69) to have hypertension relative to males.

Model III controlled for the variables of race and rural/urban geography. The addition of these variables did not significantly influence the association between hypertension and the variables of socioeconomic status, age and gender.

Model IV included the risk factors of obesity and exercise. The inclusion of these variables did not significantly alter the association between hypertension and being socioeconomic 'Vulnerable', or hypertension and age; however the association between gender and hypertension was influenced. In exploratory analysis, the inclusion of obesity in the model resulted in gender no longer being a significant predictor of hypertension. In Model IV, respondents in the Coloured racial group were now 1.37 times more likely than Black Africans to have hypertension ($p<0.001$), while being White was a protective characteristic (0.74; 95% CI 0.50-1.10). The rural/urban variable was now a significant ($p<0.05$) predictor of hypertension, with respondents living in urban areas being 1.27 times more likely (95% CI 1.05-1.54) to have hypertension than respondents in rural areas. Finally, obesity (1.93; 95% CI 1.58-2.36) was a strong predictor of hypertension ($p<0.001$). Although exercise was significantly associated with hypertension ($p<0.01$) in the unadjusted model (Model I), it was no longer significantly associated with hypertension once obesity was included in the model and thus the final model excluded exercise.

Model V shows the final model for hypertension. In the final model, respondents who are socioeconomically 'Vulnerable' (1.28; 95% CI 1.05-1.55), older, Coloured (1.37; 95% CI, 1.11-1.70), living in urban areas (1.27; 95% CI 1.04-1.54) or who are obese (1.93; 95% 1.58-2.36) have the highest odds of having hypertension. Tests for potential interactions were carried out between obesity and age by creating interaction terms. These interaction terms did not contribute significantly to the final model. The age group variable ($p<0.001$) was the strongest predictor for hypertension while obesity also contributed significantly to the model ($p<0.001$). Exercise was removed as it was not a significant predictor of hypertension. Although gender was not significantly contributing to the model, it was included so as to control for gender differences.

4.5.2. Logistic regression analyses of factors affecting multimorbidity

The results of the logistic regression of multimorbidity and associated variables (see Table 4.5 for Unadjusted OR (Model I) and 95% confidence intervals) revealed that the odds of respondents having multimorbidity were significant and highest for respondents who were socioeconomically 'Deprived'. These respondents were 1.91 times more likely (95% CI 1.34-2.72) to have multimorbidity compared to respondents who were 'Not Deprived'.

Model II (Table 4.5) shows that once age and gender were controlled for, socioeconomic status categories were no longer significantly contributing to the model. The model also shows the significant influence that age has on multimorbidity. The odds of having multimorbidity increased with age until the 55-64 age group where respondents were 9.6 times more likely (95% CI 5.30-17.37) of having multimorbidity than respondents in the 25-34 age group (the 15-24 age group was omitted in this analyses due to an insufficient number of observations). However, the odds were slightly lower for the 65+ age group (7.87; 95% CI 4.03-15.37). Females are 1.37 times more likely than males to have multimorbidities (95% CI 1.07-1.76).

Model III shows that once the structural variables of race and urban/rural geography are controlled for, the odds of having multimorbidity become significant and were highest for respondents who are socioeconomically 'Deprived'. These respondents were 1.49 times more likely (95% CI 1.04-2.12) to have multimorbidity compared to those 'Not Deprived'. Age remains a very strong predictor of multimorbidity with the 55-64 age group still having the highest odds (10.84; 95% Cl 5.95-19.77). Racial comparisons reveal that the Asian/Indian population group are 2.35 times more likely (95% CI 1.45-3.81) to have multimorbidity relative to Black Africans, while Whites have significantly lower odds of having multimorbidity (0.38; 95% CI 0.20-0.72). Those respondents living in urban areas are 1.77 times more likely (95% CI 1.31-2.39) to have multimorbidities than their rural counterparts.

In the final model (Model IV), which included the risk factor variable of obesity, respondents who were socioeconomically 'Deprived' still had significantly higher odds of having multimorbidity (1.50; 95% CI 1.00-2.25). Age continued to be the strongest predictor of multimorbidity, although the 35-44 age group did not significantly contribute to the model. Gender was no longer significantly contributing to the model once obesity was included, which suggests gender differences in obesity. The odds of having multimorbidity are still significant and highest for Asians/Indians (2.38; 95% CI 1.15-4.94), those living in urban areas (1.87; 95% CI 1.32-2.66) and respondents who are obese (1.66; 95% CI, 1.08-2.54), once all variables were included in the model. Alcohol, exercise, and smoking variables were omitted from the model as they were not found to be statistically associated with multimorbidity in the exploratory unadjusted model (Model I). Collinearity was tested for but none was found between any variables. Interactions were tested for between obesity and age, and obesity and gender, but the interaction terms did not significantly contribute to the models.

Table 4.4. Logistic regression analyses of factors affecting hypertension using the NIDS wave 1 (2008)

Hypertension		Model I		Model II		Model III		Model IV		Model V	
		OR	(95% CI)	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
Socioeconomic status	Not deprived	(base)		(base)		(base)		(base)		(base)	
	Vulnerable	1.52**	(1.24, 1.87)	1.32**	(1.10, 1.58)	1.29**	(1.07, 1.56)	1.28**	(1.06, 1.55)	1.28*	(1.05, 1.55)
	Deprived	1.84**	(1.52, 2.22)	1.07	(0.87, 1.31)	1.07	(0.86, 1.32)	1.13	(0.89, 1.43)	1.12	(0.89, 1.42)
	Severe Poverty	2.10**	(1.53, 2.89)	1.05	(0.77, 1.43)	1.05	(0.78, 1.43)	1.08	(0.79, 1.49)	1.07	(0.78, 1.47)
Age											
	15-24	(base)		(base)		(base)		(base)		(base)	
	25-34	2.38**	(1.90, 2.98)	2.40**	(1.92, 3.01)	2.38**	(1.90, 2.99)	1.97**	(1.40, 2.76)	1.97**	(1.40, 2.76)
	35-44	5.71**	(4.56, 7.15)	5.79**	(4.62, 7.27)	5.81**	(4.62, 7.31)	4.73**	(3.40, 6.59)	4.74**	(3.40, 6.59)
	45-54	11.29**	8.74, 14.58)	11.54**	(8.89, 14.98)	11.79**	(9.16, 15.18)	8.93**	(6.28, 12.71)	8.94**	(6.26, 12.78)
	55-64	18.73**	4.05, 24.95)	18.81**	(14.11, 25.07)	19.81**	(14.99, 26.16)	15.88**	(11.01, 22.89)	15.85**	(10.97, 22.90)
	65+	28.32**	1.18, 37.87)	26.61**	(19.68, 35.97)	28.60**	(21.27, 38.46)	25.83**	(17.53, 38.05)	25.60**	(17.31, 37.85)
Gender											
	Males	(base)		(base)		(base)		(base)		(base)	
	Females	1.61**	(1.41, 1.83)	1.48**	(1.29, 1.69)	1.48**	(1.29, 1.70)	1.13	(0.95, 1.33)	1.12	(0.96, 1.30)
Race											
	Black African	(base)				(base)		(base)		(base)	
	Coloured	1.23	(1.00, 1.52)			1.11	(0.86, 1.43)	1.37**	(1.1, 1.71)	1.37**	(1.11, 1.70)
	Asian/Indian	1.08	(0.66, 1.76)			0.91	(0.57, 1.47)	1.06	(0.57, 1.95)	1.06	(0.57, 1.97)
	White	1.30*	(1.02, 1.65)			0.71*	(0.50, 0.99)	0.74	(0.50, 1.10)	0.76	(0.51, 1.11)
Rural/Urban											
	Rural	(base)				(base)		(base)		(base)	
	Urban	0.99	(0.86, 1.13)			1.131	(0.93, 1.37)	1.27*	(1.05, 1.54)	1.27*	(1.04, 1.54)
Obesity											
	Not obese	(base)						(base)		(base)	
	Obese	2.67**	(2.23, 3.19)					1.93**	(1.58, 2.36)	1.93**	(1.58, 2.36)
Exercise											
	Exercises	(base)						(base)			
	Does not exercise	1.49**	(1.29, 1.73)					0.97	(0.80, 1.16)		
Smoking											
	Does not smoke	(base)									
	Smokes/smoked regularly	1.11	(0.98, 1.25)								
Alcohol											
	Does not drink	(base)									
	Drinks alcohol	1.05	(0.93, 1.19)								

*p<0.05, **P<0.01

Source: Author

Table 4.5. Logistic regression analyses of factors affecting multimorbidity using the NIDS wave 1 (2008)

Multimorbidity		Model I		Model II		Model III		Model IV	
		OR	(95% CI)	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
Socioeconomic status	Not deprived	(base)		(base)		(base)		(base)	
	Vulnerable	1.19	(0.85, 1.67)	0.94	(0.70, 1.27)	0.97	(0.69, 1.34)	0.964	(0.65, 1.43)
	Deprived	1.91**	(1.34, 2.72)	1.27	(0.90, 1.80)	1.49*	(1.04, 2.12)	1.50*	(1.00, 2.25)
	Severe Poverty	1.13	(0.64, 2.00)	0.71	(0.41, 1.23)	0.87	(0.49, 1.54)	0.85	(0.45, 1.62)
Age									
	15-24								
	25-34	(base)		(base)		(base)		(base)	
	35-44	1.80*	(1.11, 2.92)	1.78*	(1.10, 2.88)	1.81*	(1.11, 2.95)	1.64	(0.96, 2.81)
	45-54	5.15**	(2.58, 10.29)	5.07**	(2.56, 10.05)	5.35**	(2.70, 10.62)	4.07**	(1.95, 8.49)
	55-64	9.89**	(5.36, 18.25)	9.59**	(5.30, 17.37)	10.84**	(5.95, 19.77)	8.63**	(4.47, 16.64)
	65+	8.89**	(4.41, 17.89)	7.87**	(4.03, 15.37)	9.44**	(4.78, 18.62)	7.62**	(3.57, 16.20)
Gender									
	Males	(base)		(base)		(base)		(base)	
	Females	1.59**	(1.23, 2.05)	1.37*	(1.07, 1.76)	1.39*	(1.08, 1.79)	1.17	(0.86, 1.60)
Race									
	Black African	(base)				(base)		(base)	
	Coloured	1.02	(0.75, 1.41)			0.82	(0.57, 1.16)	0.83	(0.54, 1.27)
	Asian/Indian	2.74**	(1.47, 5.14)			2.35**	(1.45, 3.81)	2.38*	(1.15, 4.94)
	White	0.69	(0.39, 1.22)			0.38**	(0.20, 0.72)	0.45*	(0.21, 0.95)
Rural/Urban									
	Rural	(base)				(base)		(base)	
	Urban	1.13	(0.85, 1.50)			1.77**	(1.31, 2.39)	1.87**	(1.32, 2.66)
Obesity									
	Not obese	(base)						(base)	
	Obese	2.18**	(1.45, 3.27)					1.66*	(1.08, 2.54)
Exercise									
	Exercises	(base)							
	Does not exercise	1.107	(0.74, 1.64)						
Smoking									
	Does not smoke	(base)							
	Smokes/smoked regularly	0.92	(0.69, 1.22)						
Alcohol									
	Does not drink	(base)							
	Drinks alcohol	0.66	(0.47, 0.94)						

*p<0.05, **P<0.01

Source: Author

4.6. SPATIAL ANAYSIS

The results of the logistic regression analysis suggest that multimorbidity was significantly associated with socioeconomic deprivation, one of the categories of socioeconomic disadvantage. However, hypertension was not associated with the socioeconomic disadvantage categories (i.e. 'Deprived', 'Severe Poverty). In order to further test the hypothesis that multimorbidity is associated with socioeconomic disadvantage, spatial statistics through ArcGIS (v10.1) will be used to explore and compare the spatial distribution of both variables across the 52 districts of South Africa.

4.6.1. The spatiotemporal association between socioeconomic disadvantage and respondents with multimorbidity

4.6.1.1. Spatial analysis of the distribution of multimorbidity in South Africa 2008 and 2012

To explore the spatial comparison between multimorbidity and socioeconomic disadvantage, the spatial pattern of multimorbidity was analysed using the Global Moran's I and Getis-Ord Gi* statistic, while socioeconomic disadvantage was mapped by the 2011 Census districts.

4.6.1.1.1. Global Moran's I

In order to determine if there is spatial clustering in the prevalence of multimorbidity across South African districts, Global Moran's I was calculated. The values of Moran's I generally vary between -1 and +1, which indicate perfect dispersion and perfect clustering, respectively (Legendre & Fortin, 1989). The results of the Global Moran's Index, as presented in Figure 4.9 (2008) and Figure 4.10 (2012), were 0.25 for 2008 and 0.26 for 2012. Although the results are not very high, the positive values do indicate that multimorbidity is clustering across districts. The z-scores of 3.34 (2008) and 3.41 (2012) are both greater than 1.96 and thus indicate that the null hypothesis, that there is no clustering of multimorbidity across districts, can be rejected. This shows that there is a $\leq$ 1% likelihood that these results are due to random chance.

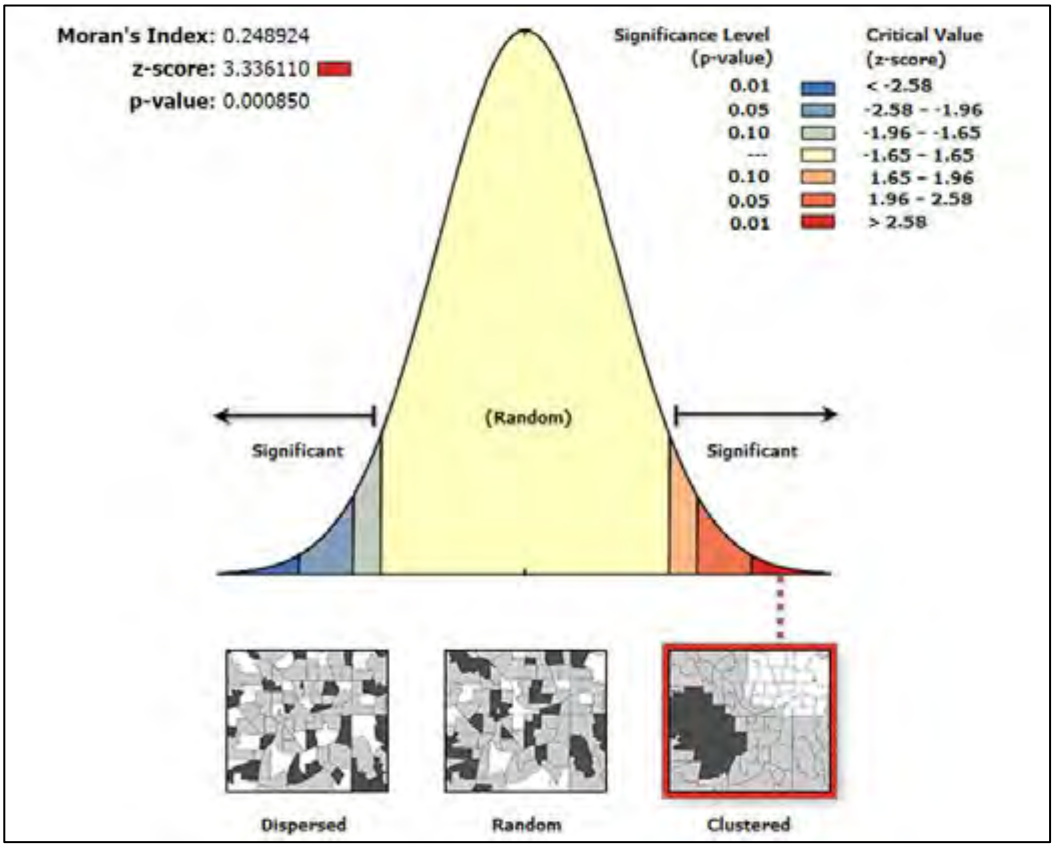


Figure 4.9. The Global Moran's Index classifications for multimorbidity in 2008 (wave1)
Source: Author's calculations, generated by ArcGIS (ESRI, 2011)

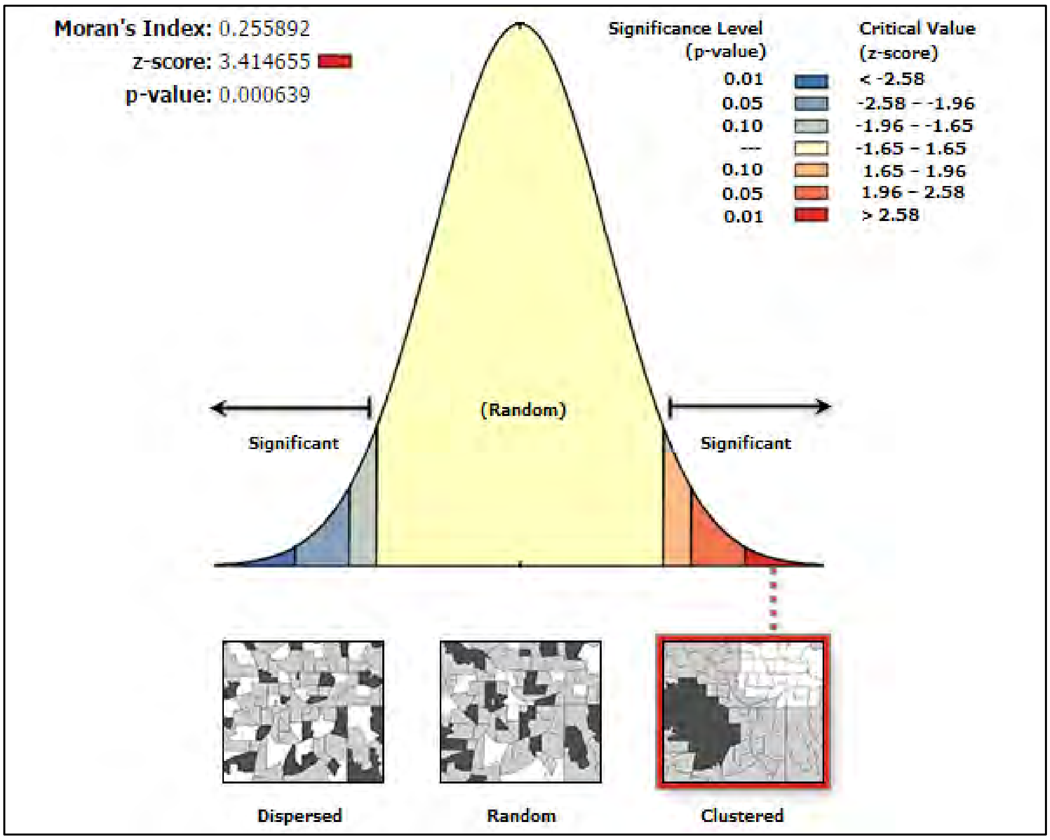


Figure 4.10. The Global Moran's Index classifications for multimorbidity in 2012 (wave3)
Source: Author's calculations, generated by ArcGIS (ESRI, 2011)

*4.6.1.1.2. Getis-Ord Gi*statistic*

The Getis-Ord Gi* statistic, which identifies statistically significant spatial clusters of districts with high prevalence rates (hot spots) and low prevalence rates (cold spots), was used to better understand the spatial pattern of multimorbidity and to compare it to that of socioeconomic disadvantage in South Africa. In both waves, as shown in Figure 4.11, the results of the Getis-Ord Gi* statistic were able to confirm the presence of a cold spot in the northern part of the country, specifically the Limpopo Province and parts of Gauteng and Mpumalanga, which indicate a statistically significant clustering of lower prevalence among neighbouring districts that are non-random. In addition, statistically significant hot spots of multimorbidity are visible in parts of KwaZulu-Natal and the Eastern Cape, suggesting clusters of higher prevalence rates of multimorbidity among neighbouring districts. The multimorbidity cluster patterns are similar between waves, however wave 3 reveals a hot spot of 90% confidence over districts in both the Eastern Cape and the Northern Cape.

4.6.1.2. The spatial distribution of socioeconomic disadvantage

As shown in Figure 4.12, the spatial distribution of socioeconomic disadvantage, measured as the proportion of respondents in each district that were categorised as being socioeconomically disadvantaged, shows that nine of the 52 districts in South Africa had a socioeconomic disadvantage rate ≥26.86% (i.e. ≥ the highest quantile). These districts were predominately located in the eastern (KwaZulu-Natal Province) and south-eastern (Eastern Cape Province) parts of the country. A total of 11 districts had a socioeconomic disadvantage rate ≤4.14% (i.e. ≤ the lowest quantile). These districts were mainly found in the south-western (Western Cape) and central (Gauteng and Free State) parts of the country.

The spatial pattern for socioeconomic disadvantage does show similarities to that of multimorbidity using the hot spot analysis (Figure 4.11), as there are higher rates of both socioeconomic disadvantage and multimorbidity in parts of KwaZulu-Natal and the Eastern Cape Provinces. As a reminder, KwaZulu-Natal had five districts with prevalence rates ≥ the highest quantile in both waves, while the province also had three other districts with prevalence rates in the second highest quantile in wave 1. However, the multimorbidity cold spot found in the Limpopo Province does not appear to correspond with the socioeconomic disadvantage spatial pattern, as two of the five Limpopo Province districts have prevalence rates ≥ 26.86% (i.e. ≥ the highest quantile) and two other districts with prevalence rates in the second quantile (13.24% - 26.85%).

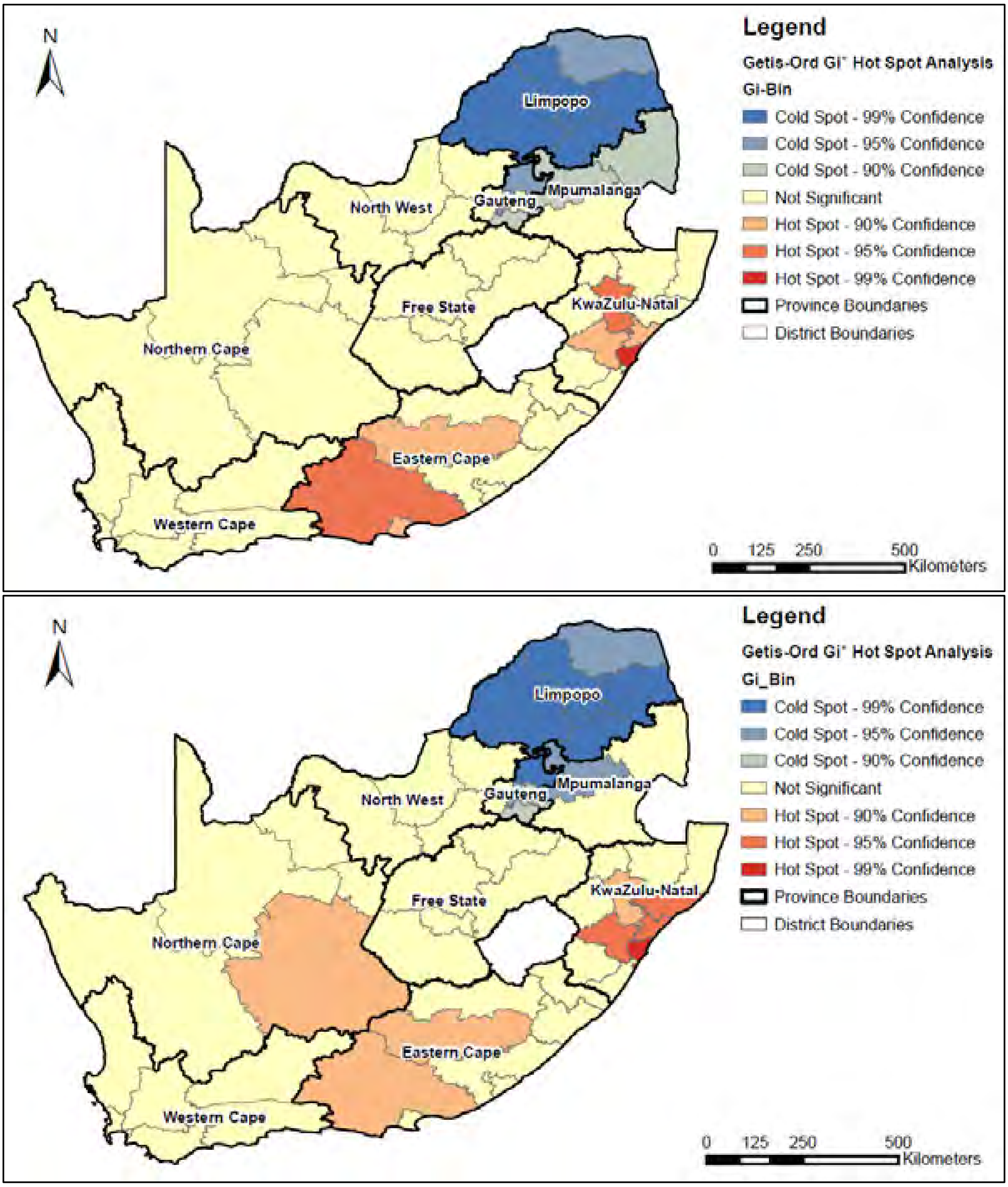


Figure 4.11. Getis-Ord Gi* hot spot analysis of the age-adjusted prevalence of multimorbidity in the National Income Dynamics Study South African adult sub-sample by district for 2008 wave 1 (top) and 2012 wave 3 (bottom)

Source: Author

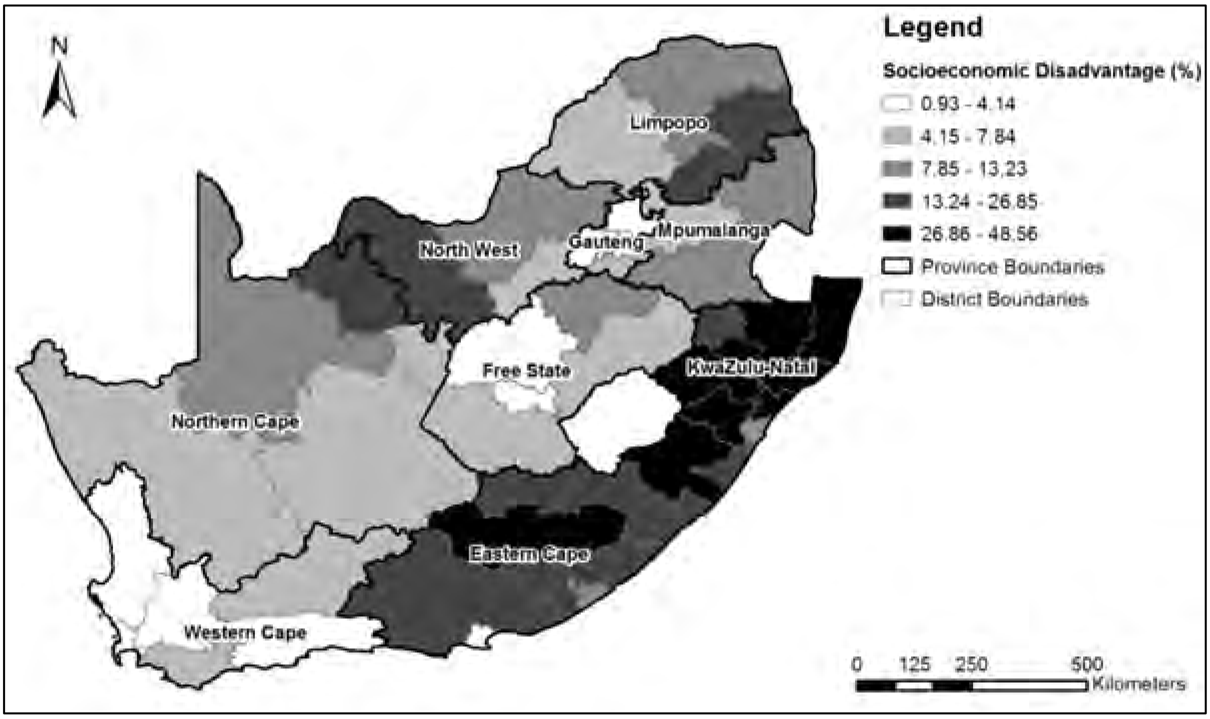


Figure 4.12. The proportion of the 2008 (wave 1) NIDS South African adult sub-sample classified as being socioeconomically disadvantaged (i.e. either deprived or in severe poverty) within each district
Source: Author

4.7. DISCUSSION OF RESULTS AT THE SOUTH AFRICAN LEVEL

This section aims to discuss the results of the NIDS at the South African scale and will compare these with the findings of external South African data sources, which were presented in the introduction of this chapter (section 4.1). This chapter will ultimately provide a foundation for further analysis at disaggregated spatial scales, namely the Western Cape Province level and the urban/intra-urban levels of South Africa, which will be explored in the following chapters.

4.7.1. Non-communicable diseases in South African – hypertension and diabetes mellitus

Firstly, these results have demonstrated that hypertension is a serious health burden for South African adults and that it continues to grow in prevalence with time. The results for 2008 (wave 1) were consistent with those of the 1998 Demographic and Health Survey (Steyn et al., 2001) and revealed an 8.24% increase in hypertension prevalence from 1998 to 2008. Of note, there was a considerable increase of 41.36% in the prevalence of hypertension between 2008 (wave 1) and 2012 (wave 3). A possible reason for this considerable increase is that the NIDS seeks to interview the same sample of respondents for each wave. Due to the chronic condition of hypertension, it is expected that the prevalence of hypertension will increase within the same group of people with time, given that it is strongly associated with age, as confirmed in this study and numerous other studies (Bunker et al., 1992; Kandala, 2014; Liu et al., 2013; Steyn, 2006).

Alongside the variable of age, the multivariable analysis (section 4.5) revealed that hypertension was also strongly associated with obesity. This is a common finding for international, as well as South African studies (Steyn et al., 1996; van Rooyen et al., 2000; Vorster et al., 2000). The association between obesity and hypertension is an important finding and provides support for the notion that a more "Westernised" and sedentary lifestyle may predispose an individual to NCDs, such as hypertension (Godfrey & Julien, 2005). Although the self-reported risk factors of alcohol consumption and smoking were not significantly associated with hypertension, exercise was significantly associated in the unadjusted model ($p<0.01$) and no longer contributed to the logistic regression model once obesity was controlled, suggesting a possible link between exercise and obesity. Another interesting finding was that obesity was linked to gender, as shown by the logistic regression model (Table 4.4). In addition, the odds of having hypertension were significant and highest for respondents who were *vulnerable* to socioeconomic disadvantage and for those living in urban areas. This is an interesting finding and will be further explored in the urban and intra-urban analyses of the NIDS in Chapter 6.

Of the selected health conditions, this study mainly explored hypertension due to its large contribution to multimorbidity in South Africa, as found in section 4.4. However, there were still some interesting findings for diabetes. As previously mentioned, the International Diabetes Foundation had estimated a diabetes prevalence of 6.5% for South African adults (20-79 years) for 2011 (Whiting et al., 2011). Given that this study only estimated a prevalence of 2.81% in 2008 and 2.71% in 2012, it is likely that diabetes has been underreported in the NIDS. This is not an unusual finding and is supported by results from the 2012 SANHANES-1 survey, which diagnosed diabetes in 9.5% of adult participants aged 15 years and older in 2012, yet only 5% of the sample had self-reported having diabetes (Shisana, Labadarios, et al., 2014). This is a large concern, as national level statistics for diabetes predominately rely on self-reported data (Shisana, Labadarios, et al., 2014). In addition, the decline in diabetes prevalence in the NIDS between 2008 and 2012 is interesting, as it is a chronic disease. The NIDS survey specifically asked respondents if they have ever been told by a healthcare professional that they have diabetes. Therefore, this finding suggests that a small portion of respondents who claimed to have diabetes in 2008 either dropped out of the survey after the first wave, failed to report their condition in the third wave, had incorrectly reported their condition in the first wave, or were deceased in 2012 (wave 3).

Despite the evidence of underreporting, the prevalence of diabetes was found to be closely associated with that of multimorbidity across age groups (refer to Figure 4.1). This finding will be discussed further in section 4.7.4.1 and will be explored at the Western Cape Province and urban/intra urban spatial scales (Chapters 5 and 6). In addition, this study found diabetes to be associated with age and was shown to increase in prevalence from the middle age groups (i.e. 34-45 age group in wave 1; 45-54 group in wave 3). The SANHANES-1 diabetes data for 2012 also presented an association with age, where diabetes greatly increased in prevalence from the 45-54 age group, thus supporting the pattern of disease found for the middle age groups in the NIDS.

These results, supported by those from the SANHANES-1, suggest that the true burden of diabetes in South Africa, particularly for middle age-groups, might not be fully realised at the public health level and by individual South Africans themselves. It may be a reality that many South Africans are simply unaware of their diabetes status, which suggests that they may also be unaware of the opportunities they have to adapt their lifestyles to alleviate the ailments of the disease. Nevertheless, these findings emphasise the importance of raising awareness for diabetes testing, specifically for adults in the middle age groups.

In summary, these findings for both hypertension and self-reported diabetes highlight the need to bring NCDs back into the spotlight alongside infectious diseases, so that effective intervention and treatment plans may be put in place to improve health and wellbeing for South African adults.

4.7.2. Chronic infectious diseases in South Africa – TB and HIV

Comparing the NIDS self-reported HIV prevalence to that of other national data sources, as detailed in section 4.1, it is clear that the self-reported HIV prevalence in the NIDS is grossly underreported. Fortunately, the prevalence of HIV has been well described in South Africa and this has made it possible to detect underreporting in the NIDS. However, the TB burden is normally reported as case notification rates, not prevalence, and thus it is difficult to assess the accuracy of the self-reported TB prevalence within the NIDS. Nevertheless, the social stigma around having HIV/AIDS or TB in South Africa, as found in a number of studies (Daftary, Padayatchi & Padilla, 2007; Møller & Erstad, 2007; Murray et al., 2012), is enough to suggest that self-reported HIV and TB are likely to be underreported by participants in self-report surveys, like the NIDS.

Although there is evidence of underreporting and thus caution needs to be exercised when making inferences using these results, an interesting finding was that HIV prevalence peaked in the 35-44 age group and subsequently declined with age. This finding is supported by the results of the 2012 SANHANES-1 which showed HIV prevalence to peak in the 30-34 age group for females and in the 35-39 age group for males, as well as by the findings of Mash et al. (2012), in which a cross-sectional survey found HIV to peak in the 30-34 age group in South African. Together with the findings of diabetes, this highlights the increased burden of disease for the middle age groups.

4.7.3. The spatial analysis of non-communicable and chronic infectious diseases

At times, the spatial scale of analysis for the maps presenting the prevalence of disease across districts and provinces produced some indistinct spatial patterns. This is most likely a consequence of using a high spatial scale of analysis. Ideally, this study would have mapped these diseases at a finer spatial level, for example using the 226 South African local municipalities; however, this was not possible due to restrictions around the use of the NIDS data. This subsequently prevented any consideration for place-based effects below the national district level. Nevertheless, the analysis did produce some useful findings from which inferences could be made. The spatial analysis of hypertension, diabetes and TB revealed generally lower prevalence rates in the northern parts of the country, particularly in districts in the Limpopo Province for both 2008 and 2012, while the spatial pattern of HIV showed lower prevalence rates in the western parts of South Africa and particularly in the Western Cape Province.

The spatial pattern of hypertension prevalence in the NIDS is supported by the findings of Kandala et al. (2013), who performed a provincial level analysis using the 1998 South African Demographic and Health Survey and found that the Limpopo and Mpumalanga provinces generally were associated with a low prevalence of hypertension while north-western provinces had higher hypertension prevalence. However, in a more recent study by Kandala et al. (2014) in which the 1998 South African Demographic and Health Survey data was once again used to map prevalence of selected diseases at health district level, the findings confirmed low prevalence rates for districts in the Limpopo and Mpumalanga areas and revealed a high prevalence of hypertension in districts of the south-western parts of South Africa, particularly the Western Cape districts, further supporting the findings of this study.

The apparent underreporting of diabetes, TB and HIV in the NIDS suggests that a comparison of the geographic distribution of these diseases with findings from other studies may be futile. Furthermore, there appears to be a paucity of studies that map the prevalence of these diseases by districts and provinces. However, the SANHANES-1 did compare the prevalence of diabetes between provinces in South Africa and found that it was least prevalent in the Limpopo Province (14.4%), thereby supporting the spatial findings in this study. A study conducted by Kleinschmidt et al. (2007), which investigated HIV prevalence within 2001 Census Enumerator Areas, found that HIV prevalence does differ considerably within provincial areas, which may support the finding of a heterogeneous spatial pattern of HIV in the NIDS. Although the findings did not support the locations of high HIV prevalence as presented in the NIDS, the study was able to provide support for lower HIV prevalence in areas within the Western Cape Province (Kleinschmidt et al., 2007).

The paucity of research on the spatial distribution of diabetes, TB and HIV across districts and provinces in South Africa raises a concern that the prevalence, location and place-based effects of these diseases across national provinces and districts may not be fully realised. Therefore, the findings of this study contribute to addressing this gap in knowledge.

4.7.4. Multimorbidity and the association with socioeconomic disadvantage

4.7.4.1. Multimorbidity

The analysis of health data in the NIDS has revealed an increase in multimorbidity prevalence between 2008 and 2012, and that most people with multimorbidity have two coexisting health conditions. Together, diabetes and hypertension were the most predominant form of multimorbidity, which is supported by other studies (Folb et al., 2015; Oni et al., 2015). In this study, other common combinations of double morbidities included TB/hypertension and HIV/hypertension, which emphasise the role that hypertension plays in multimorbidity. While it is clear that hypertension was a common contributor to multimorbidity, it is important to highlight that the prevalence of multimorbidity in this study was limited by the prevalence of the other health conditions, namely diabetes. A possible explanation is that the coexistence of diabetes together with hypertension makes up the majority of all multimorbidities and therefore the prevalence of multimorbidity in the NIDS is likely to follow the rate of the less prevalent of these two diseases, namely diabetes.

Regarding coexisting diseases, it is surprising that TB and HIV were not more prevalent together, as the association between these two diseases is well documented (Jeena et al., 2002; Tollman et al., 2008; Roeger, Feng & Castillo-Chavez, 2009). In fact, much of the stigma around TB is said to stem from the association that TB has with AIDS (Møller & Erstad, 2007). Nevertheless, a likely reason for this may be that both HIV and TB were substantially underreporting in the NIDS.

The results for multimorbidity prevalence cannot easily be compared to findings from other studies, as the multimorbidity variable is often defined differently within each study, with the use of different combinations of diseases and measures. For example, a recent South African study estimated the national prevalence of multimorbidity to be 4%, however the study incorporated TB, high blood pressure, diabetes, asthma and cancer as the selected health conditions for analysis (Alaba & Chola, 2013). Nevertheless, the coexistence of hypertension and diabetes has been well documented, even in South Africa, and is said to be increasingly common (Steyn et al., 2004; Mashitisho, 2013; Mohan, Seedat & Pradeepa, 2013)

4.7.4.2. The association between multimorbidity and socioeconomic disadvantage

One of the main objectives of this study was to explore the association between multimorbidity and socioeconomic disadvantage and this was done, in part, through the analysis of a logistic regression model. As hypertension was found to be the main contributor to multimorbidity, a logistic regression model was also created for hypertension to assess the association between hypertension and associated variables.

The results of the multivariable analysis showed that, the odds of having hypertension were significant and higher for respondents who were *vulnerable* to socioeconomic disadvantage, as previously mentioned in section 4.7.1. However, in the case of multimorbidity, it is those respondents who are *socioeconomically deprived* who have higher odds of having multimorbidity. Therefore, despite hypertension contributing considerably to multimorbidity cases, the socioeconomic group with the highest odds of having hypertension was different to the socioeconomic group with the highest odds of having multimorbidity.

The multivariable analysis also revealed that obesity was significantly associated with multimorbidity ($p<0.05$). In addition, although gender was originally found to be associated with multimorbidity, the logistic regression forward model revealed that the association between gender and multimorbidity was driven by obesity.

The spatial analysis of socioeconomic disadvantage did show similarities to that of multimorbidity, particularly in the Eastern Cape and KwaZulu-Natal provinces, through hot spot analysis. However, it is likely that the district level may have been too expansive to truly represent the spatial differences in socioeconomic status and multimorbidity. These spatial differences are likely to be more discernible at a smaller spatial scale. However, due to limitations around the use of secure data of NIDS, no analysis was able to be performed below the national district level. This highlights the need for data disaggregation on health to smaller spatial scales, which links to the discussion in section 1.4 and section 2.4.5.1 and will be discussed further in section 8.1.2.

4.8. CONCLUSION

The analysis of the NIDS data at the South African level has contributed to knowledge on the status of health in South Africa for 2008 and 2012, and has particularly contributed towards addressing the paucity of information on the social determinants of multimorbidity, and spatial information on the distribution of diabetes, HIV and TB across districts and provinces in South Africa. The findings of the national level analyses support the following hypotheses (refer to section 1.5.2.3): that it is possible to link geospatial information with health data to generate new health knowledge for South Africa, and that the coupling of cross-sectional and spatial analysis methods provides comprehensive insight into health patterns that would be deficient if only one method were used. Finally, the results of the national level analysis revealed an increase in the prevalence of multimorbidity between 2008 and 2012, as well as heterogeneity in the spatial distribution of multimorbidity, which was found to be similar to the spatial pattern of socioeconomic disadvantage, further supporting the hypotheses made in section 1.5.2.3.

CHAPTER FIVE: THE WESTERN CAPE PROVINCE

5.1. INTRODUCTION

This section explores the health status of the Western Cape Province by disaggregating the NIDS data in hope of revealing useful health patterns at a smaller spatial scale. Basic analyses of the health variables of hypertension, diabetes, TB, HIV and multimorbidity were conducted for the Western Cape Province and were compared to the results from the South African level, which was the primary scope of analysis.

The following results for hypertension prevalence will be compared to the findings of the SANHANES-1, which estimated that 36.7% of the adult sample respondents (15 years and older) in the Western Cape in 2012 had an average systolic blood pressure reading $\geq$ 140 mmHg and/or an average diastolic pressure reading $\geq$ 90 mmHg or were on blood pressure medication (Shisana, Labadarios, et al., 2014). The SANHANES-1 also revealed a self-reported diabetes/high blood sugar prevalence of 6.7% for the Western Cape in 2012, which will be used to assess the estimated diabetes prevalence in the NIDS (Shisana, Labadarios, et al., 2014). The Joint United Nations Programme on HIV/AIDS (UNAIDS) estimated the prevalence of HIV in the Western Cape Province to be 6.2% in 2010 (South African National Department of Health, 2010). As previously mentioned at the South African scale, TB burden is normally reported as case notification rates, not prevalence, and thus it is difficult to assess the accuracy of the self-reported TB prevalence within the NIDS.

The comparison of health patterns between the Western Cape and the national level will show that while data disaggregation is possible and able to provide useful health inferences at lower levels, the pattern of health at the Western Cape level is not the same as the national level. The Western Cape has lower prevalence rates for the chronic infectious conditions (i.e. TB and HIV) compared to the national level, but shows greater prevalence growth rates for the two NCDs (i.e. hypertension and diabetes) between 2008 and 2012, compared to the national level. This is an interesting finding. The following results will also support the national level finding that hypertension has been fairly accurately reported in the NIDS and that the self-reported chronic health conditions of diabetes and HIV are likely to have been underreported.

This chapter, on the context of health in the Western Cape using disaggregated data, will first present the composition of the NIDS adult sample for the Western Cape for 2008 and 2012, and will then present the findings on hypertension, diabetes, TB, HIV and multimorbidity prevalence in the Western Cape from 2008 to 2012. This chapter will also explore the composition of multimorbidities in the Western Cape, as well as the association between multimorbidity and socioeconomic status. The chapter will conclude with a brief discussion of these findings in relation to the findings from other data sources.

5.2. BASELINE CHARACTERISTICS AND DESCRIPTIVE ANALYSIS OF THE NIDS ADULT SUB-SAMPLE FOR THE WESTERN CAPE PROVINCE

The unweighted baseline characteristics of the adult sub-sample for the Western Cape Province for 2008 (wave 1) are displayed in Table 5.1. The total number of adult respondents is 2 630 with a median age of 38 years (IQR: 25-52). The highest proportion of adults were in the 15-24 age group (23.08%), with the proportion of adults in each age group decreasing with increasing age. The 2008 sub-sample comprised 54.79% (n = 1 441) females, while the racial composition was 18.44% Black African, 61.60% Coloured, 0.23% Asian/Indian and 19.73% White. This is different to the 2007 Community Survey results for the province which estimate 30.1% Black African, 50.2% Coloured, 1.3% Asian/Indian and 18.4% White (Statistics South Africa, 2012b). Furthermore, 83.54% (n = 2 197) of the sub-sample were from urban areas, while 3.59% (n = 91) of the sample was socioeconomically disadvantaged, being either socioeconomically ‘Deprived’ (3.27%; n = 86) or in ‘Severe Poverty’ (0.19%; n = 5). Regarding risk factors, 60.30% (n = 1 165) of adults drink alcohol, 53.81% (n = 1 037) smoke, 55.29% (n = 1 066) never exercise and 31.43% (n = 413) are obese.

The 2012 (wave 3) unweighted baseline characteristics for the Western Cape adult sub-sample are available in Table 5.2. The only characteristics that have noticeably changed from wave 1 are the risk factor proportions. In wave 3, 43.34% (n = 791) of Western Cape adults claim to drink alcohol, 43.48% (n = 793) claim to smoke and 49.48% (n = 903) report never exercising. When comparing these results to those of wave 1, these results suggest a decline in health risk behaviour.

Table 5.1. Unweighted Descriptive Statistics for the Western Cape adult sub-sample in 2008 (wave 1) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		23.08%	607	
	25-34		20.57%	541	
	35-44		19.43%	511	
	45-54		15.93%	419	
	55-64		11.63%	306	
	65+		9.35%	246	
TOTAL		2 630	38	25-52	15-94
Gender		2 630			
	Male		45.21%	1 189	
	Female		54.79%	1 441	
Race		2 630			
	Black African		18.44%	485	
	Coloured		61.60%	1 620	
	Asian/Indian		0.23%	6	
	White		19.73%	519	
Rural/Urban		2 630			
	Rural		16.46%	433	
	Urban		83.54%	2 197	
Socioeconomic status		2 532			
	Not Deprived		85.86%	2 258	
	Vulnerable		6.96%	183	
	Deprived		3.27%	86	
	Severe Poverty		0.19%	5	
Alcohol drinking status		1 932			
	Never		39.70%	767	
	Drinker		60.30%	1 165	
Smoking status		1 927			
	Never		46.19%	890	
	Smoker		53.81%	1 037	
Exercise		1 928			
	Never		55.29%	1 066	
	Exercise		44.71%	862	
Obesity		1 314			
	Obese		31.43%	413	
	Not obese		68.57%	901	

Source: Author

Table 5.2. Unweighted Descriptive Statistics for the Western Cape adult sub-sample in 2012 (wave 3) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		23.55%	620	
	25-34		19.37%	510	
	35-44		17.96%	573	
	45-54		16.26%	428	
	55-64		11.74%	309	
	65+		11.13%	293	
TOTAL		2 633	38	25-53	15-98
Gender		2 633			
	Male		45.35%	1 194	
	Female		54.65%	1 439	
Race		2 633			
	Black African		19.41%	511	
	Coloured		62.93%	1 657	
	Asian/Indian		0.15%	4	
	White		17.51%	461	
Rural/Urban		2 627			
	Rural		15.65%	411	
	Urban		84.35%	2 216	
Alcohol drinking status		1 825			
	Never		56.66%	1 034	
	Drinker		43.34%	791	
Smoking status		1 824			
	Never		56.52%	1 031	
	Smoker		43.48%	793	
Exercise		1 825			
	Never		49.48%	903	
	Exercise		50.52%	922	
Obesity		1 510			
	Obese		33.58%	507	
	Not obese		66.42%	1 003	

Source: Author

5.3. THE CHANGING STATUS OF HEALTH IN THE WESTERN CAPE PROVINCE THROUGH NIDS

This section explores the prevalence of selected diseases for the Western Cape Province and how the prevalence of these diseases have changed between 2008 (wave 1) and 2012 (wave 3) of the NIDS.

5.3.1. The prevalence of hypertension, diabetes, TB, HIV and multimorbidity in 2008 and 2012

Table 5.3 displays the estimated prevalence and 95% confidence intervals (CI) for the selected health conditions, namely hypertension, diabetes, TB and HIV, as well as associated multimorbidity for 2008 (wave 1) and 2012 (wave 3). Hypertension is shown to increase in prevalence from 22.29% in wave 1 to 37.39% in wave 3, which is similar to the national trend. However, although self-reported diabetes decreased nationally between 2008 and 2012, it increased in prevalence in the Western Cape from 2.60% (2008) to 2.99% (2012). Self-reported TB declined from 1.21% to 0.25% and self-reported HIV increased from 0.67% to 0.88% from 2008 to 2012, respectively, which is similar to the trend for South Africa. However, HIV rates are slightly lower in the Western Cape compared to South Africa (1.11% [2008]; 2.13% [2012]). In the Western Cape, the estimated prevalence for multimorbidity increased between 2008 and 2012 from 2.43% to 2.64%, which is similar to the trend for South Africa (2.73% [2008]; 2.84% [2012]).

Table 5.3. Age-adjusted prevalence estimates and 95% confidence intervals for the Western Cape adult population for 2008 (wave 1) and 2012 (wave 3) using the NIDS

	2008 - Wave 1 (age-adjusted)		2012 - Wave 3 (age-adjusted)	
	Estimated Prevalence (%)	95% CI	Estimated Prevalence (%)	95% CI
Hypertension	22.29%	(20.70-23.92)	37.39%	(35.52-39.25)
Diabetes	2.60%	(2.01-3.27)	2.99%	(2.38-3.73)
Tuberculosis	1.21%	(8.34-1.71)	0.25%	(0.11-0.55)
HIV	0.67%	(0.41-0.12)	0.88%	(0.55-0.13)
Multimorbidity	2.43%	(1.88-3.10)	2.64%	(2.08-3.35)

Source: Author

The estimated prevalence rates for each health condition, including multimorbidity, were distributed across age groups for 2008 (wave 1) and 2012 (wave 3), as displayed in Figure 5.1. In the Western Cape Province, the prevalence of hypertension, diabetes, TB and HIV are similar to national levels across age groups. Prevalence rates for the Western Cape Province across age groups show that hypertension is associated with age ($p<0.01$), with the prevalence of hypertension strongly increasing with age in both waves. In wave 1, hypertension steadily increases in prevalence with age, yet in wave 3 there is a noticeable increase in prevalence for the 35-44 age group. Diabetes shows a particularly gradual increase with age for both waves in the Western Cape from the 15-24 age group to the 65+ age group.

However, wave 3 shows a greater increase in prevalence from the 45-54 age group (3.06%) to the 55-64 age group (10.48%), compared to wave 1 (45-54 age group (4.81%); 55-64 age group (7.59%)). Again, the prevalence of diabetes across age groups for both waves show similarities to those of multimorbidity, yet the prevalence of multimorbidity appears to form a more prominent plateau between the 55-64 and 65+ age groups in wave 1 (55-64 age group (8.35%); 65+ age group (8.17%)) and wave 3(55-64 age group (10.63%); 65+ age group (10.95%)) compared to diabetes.

TB appears to be more frequently reported in wave 1 than in wave 3. In wave 1, TB prevalence is highest for the 55-64 age group (2.95%); however the prevalence rates for age groups in wave 3 remain below 1.00%. The prevalence for HIV remains low across age groups in wave 1 and wave 3, with the highest prevalence occurring in the 25-34 age group for wave 1 (1.34%) and wave 3 (2.03%). This contrasts to the national pattern which shows the highest prevalence rate for HIV occurring in the 35-44 age group. HIV appears to be considerably under-reported in the Western Cape.

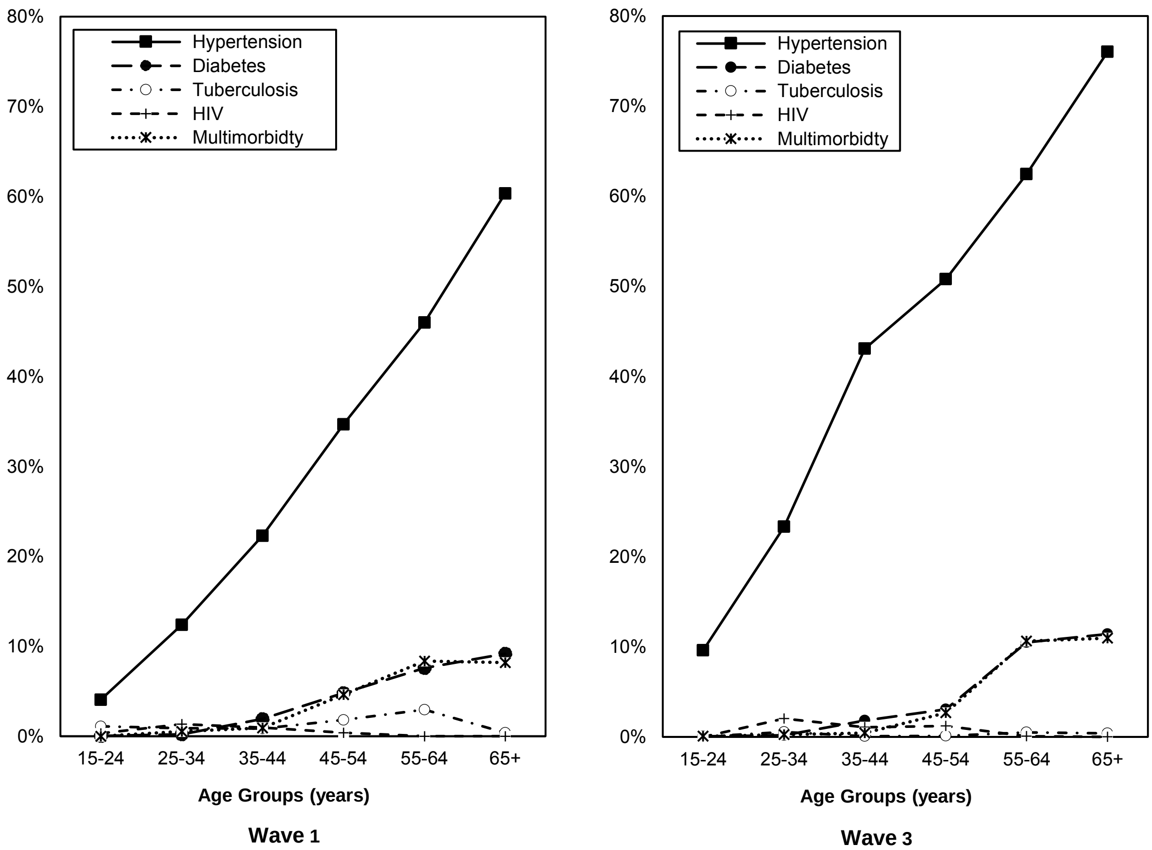


Figure 5.1. Hypertension, diabetes, TB, HIV, multimorbidity prevalence by age group for the Western Cape adult population for 2008 (wave 1) and 2012 (wave 3) using the NIDS
Source: Author

5.3.2. A deeper look into multimorbidities in the Western Cape for 2008 and 2012

A detailed schematic of the composition of multimorbidity in the Western Cape Province is provided in Figure 5.2. As mentioned, multimorbidity was prevalent in 2.43% and 2.64% of the Western Cape population in 2008 and 2012, respectively. In the schematic, single disease morbidity refers to the presence of one disease, while double and triple disease morbidities refer to two and three coexisting diseases, respectively.

As shown in Figure 5.2, 90.17% of disease morbidity in the Western Cape for 2008 comprised single diseases and the remaining 9.83% comprised double disease morbidities. Hypertension was the largest contributor towards single disease morbidity (91.51% of single disease morbidity), followed by TB (3.35%), diabetes (2.84%) and HIV (2.29%). The most prevalent coexisting disease combinations (double disease morbidities) for 2008 were diabetes/hypertension (DIA HYP: 80.47%), followed by TB/hypertension (TB HYP: 13.18%), HIV/TB (5.70%) and HIV/hypertension (HIV HYP: 0.65%).

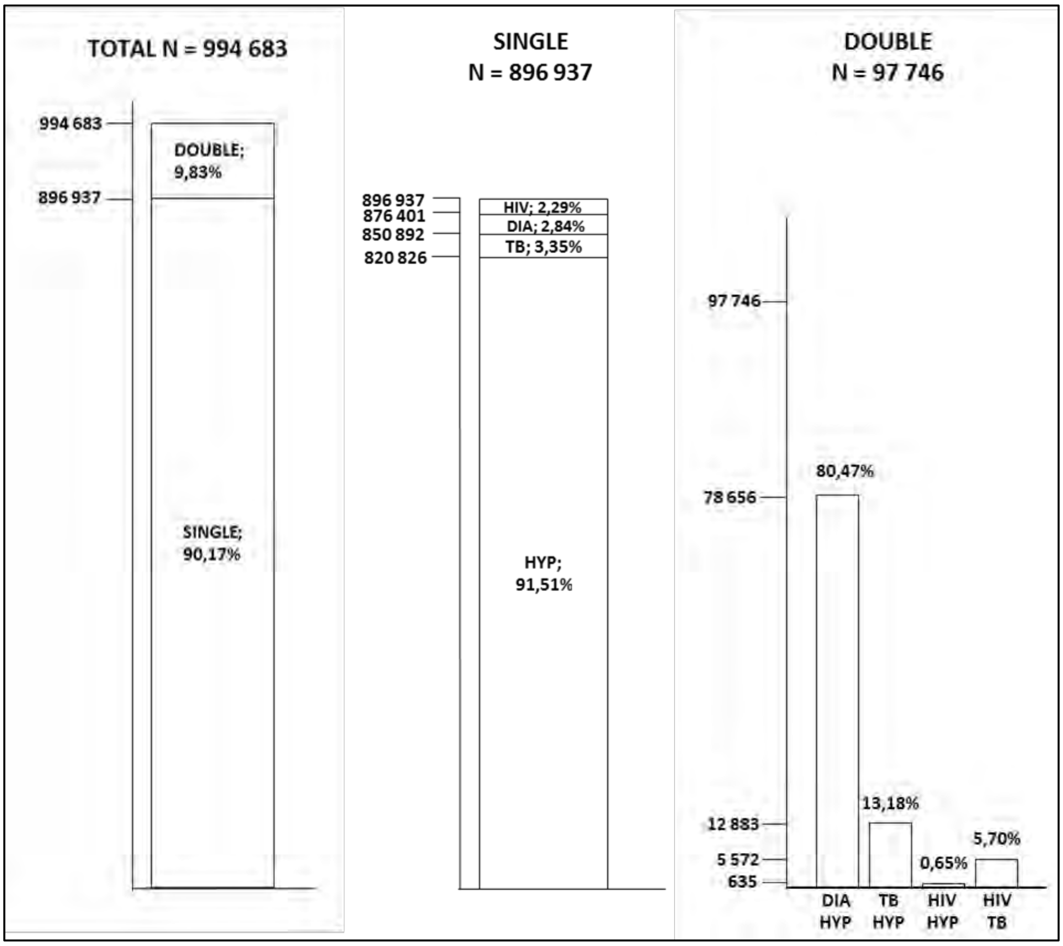


Figure 5.2. Schematic detailing the 2008 (wave 1) Western Cape adult population with existing single, double and triple disease morbidities

Source: Author

In 2012, single disease morbidity (93.22%) continued to contribute the most to morbidity, while double disease morbidity contributed 6.69% (Figure 5.3). Triple disease morbidity was not present in 2008 and only contributed 0.09% to all morbidities in 2012. The proportion that hypertension contributed to single disease morbidity increased from 91.51% in wave 1 to 95.93% in wave 3. TB, diabetes and HIV only contributed 0.5%, 1.19%, and 2.33%, respectively. Regarding double morbidities, diabetes/hypertension was the most common coexisting combination (DIA HYP: 97.31%), followed by HIV/hypertension (HIV HYP: 1.39%) and TB/hypertension (TB HYP: 1.30%). The only existing triple disease combination was TB/diabetes/hypertension.

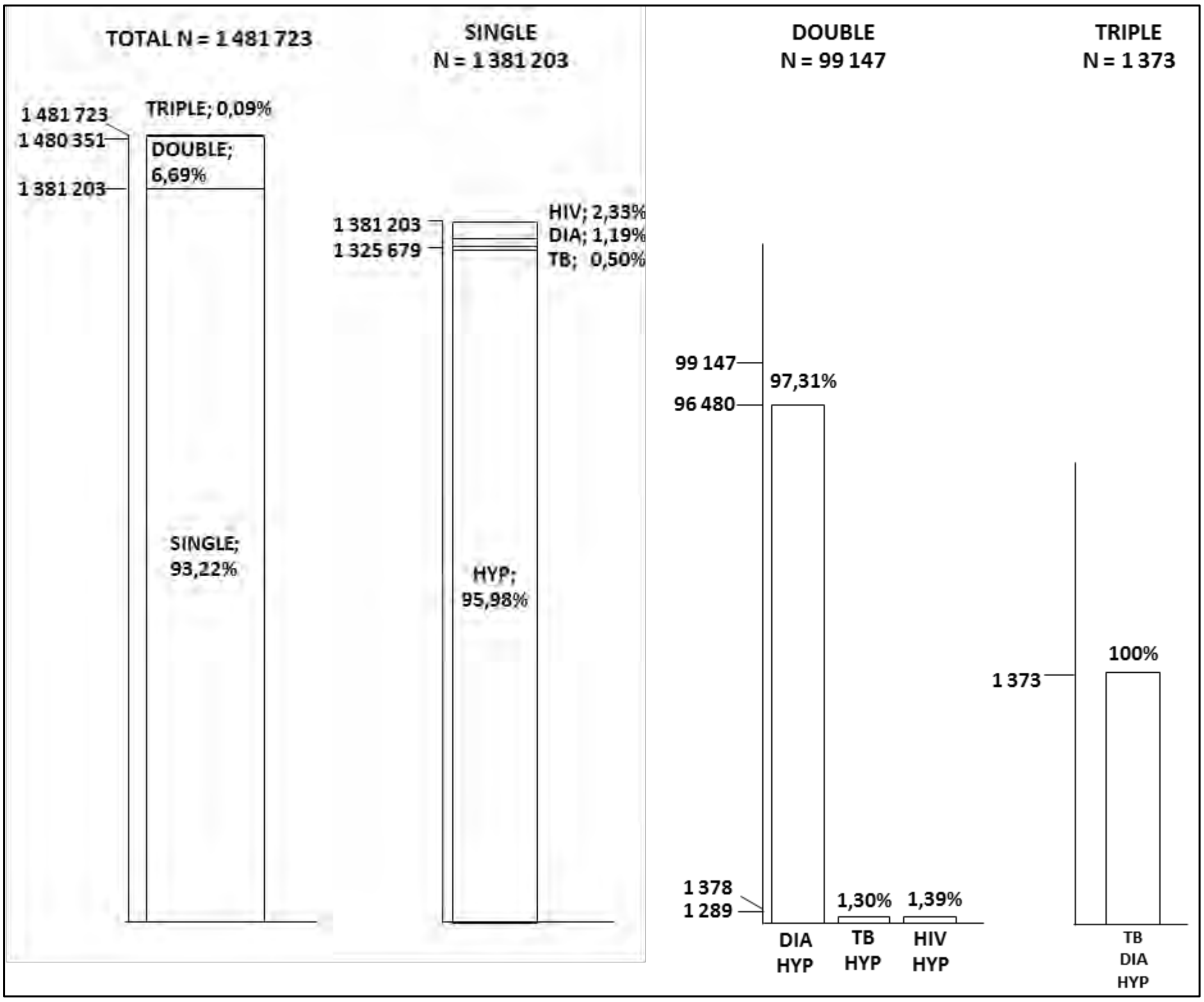


Figure 5.3. Schematic detailing the 2012 (wave 3) Western Cape adult population with existing single, double and triple disease morbidities

Source: Author

5.4. THE ASSOCIATION BETWEEN MULTIMORBIDITY AND SOCIOECONOMIC DISADVANTAGE

Although multivariable analysis cannot be used at sub-national levels due to data limitations, including high levels of item non-response and individual non-response, exploratory bivariate analysis was conducted to investigate the possible association between baseline multimorbidity and socioeconomic disadvantage at the Western Cape spatial level. The exploratory chi-squared bivariate analysis revealed a statistically significant association between socioeconomic status and multimorbidity ($p = 0.013$). The association between socioeconomic status and multimorbidity is presented in Table 5.4. Only 2.35% of respondents who were classified as 'Not Deprived' had at least one multimorbidity, while 2.65% of respondents who were socioeconomically 'Vulnerable' had at least one multimorbidity. Of note, multimorbidity was prevalent in 14.50% of respondents who were classified as socioeconomically 'Deprived'. This corresponds to the results found in the multivariable analysis at the national level, as multimorbidity was found to be significantly associated with being socioeconomically 'Deprived'. Respondents in the category of 'Severe Poverty' had no multimorbidities. Even though the data was weighted for analysis, this is likely to do with the fact that the category of 'Severe Poverty' only comprised five respondents from the sub-sample.

Table 5.4. The association between socioeconomic status categories and the absence or presence of HIV/TB/NCD multimorbidity in the Western Cape in 2008

Socioeconomic status	Multimorbidity Absent	Multimorbidity Present	TOTAL
Not Deprived	97.65%	2.35%	100%
Vulnerable	97.16%	2.65%	100%
Deprived	85.50%	14.50%	100%
Severe Poverty	100.00%	0.00%	100%

Source: Author

5.5. DISCUSSION OF RESULTS IN THE WESTERN CAPE

While the Western Cape health status was not able to be investigated in greater spatial or statistical detail, the disaggregation of the NIDS data to the Western Cape level has provided new health information at a provincial level that is comparable to the national level results. This chapter will discuss these results in relation to existing data sources (as described in section 5.1) and in comparison with the findings at the national level.

Firstly, the estimated hypertension prevalence for the Western Cape in 2012 (37.39%) is similar to that reported by the SANHANES-1 (36.7%) for the same year, as described in section 5.1, and this provides support for the notion that hypertension prevalence has been fairly accurately reported in the NIDS (Shisana, Rehle, et al., 2014). Secondly, the hypertension prevalence for the Western Cape in 2012 (37.39%) is higher than that of South Africa (32.14%) and shows a greater rate of increase between 2008 and 2012 than at the national scale, which was an interesting finding.

Regarding diabetes, the 2012 self-reported prevalence of diabetes for the Western Cape (2.99%) is notably less than that estimated by SANHANES-1 for the same year (6.7%) (Shisana, Labadarios, et al., 2014). This suggests a possible underreporting in the NIDS, which was found at the national level. However, unlike the national level pattern which showed diabetes to decline in prevalence between 2008 and 2012, diabetes prevalence increased in the Western Cape over time. The fact that both hypertension and diabetes showed an increase in prevalence in the Western Cape is concerning, as the combination of hypertension/diabetes contributed 97.31% to all double disease morbidities in the Western Cape. Therefore, this suggests that the increase in multimorbidity in the Western Cape, as found between 2008 and 2012, might continue through future waves of the NIDS.

As already mentioned in the findings at the national scale, HIV prevalence peaked in the 35-44 age group and subsequently declined in prevalence with age. The Western Cape HIV prevalence presented similar findings, where HIV peaked in the 25-34 age group, suggesting that HIV is more prevalent in middle age groups. The fact that this finding is reflected at this disaggregate scale suggests that a decline in life expectancy is likely to accompany HIV, as supported by Kahn et al. (2007). However, caution is needed when interpreting these findings as both self-reported TB and self-reported HIV show signs of being underreported, with both diseases having very low prevalence rates in the Western Cape, especially when contrasted against the national level findings. The self-reported NIDS prevalence of HIV in the Western Cape for both 2008 and 2012 are substantially lower than the 6.2% that was estimated by UNAIDS in 2010.

Lastly, the relationship between socioeconomic status categories and multimorbidity at the Western Cape level provides further support for the association found between the socioeconomic status category of 'Deprived' and multimorbidity at the national level.

5.6. CONCLUSION

In conclusion, the findings on the prevalence of disease suggest that the Western Cape is likely to experience a greater growth in NCD prevalence over time compared to the national level. Although the Western Cape has lower prevalence rates for chronic infectious conditions compared to the national level, it is likely that these conditions have been underreported in the NIDS. Therefore, further research and investigation will be needed to produce more accurate representations of TB and HIV at the Western Cape level. These findings have demonstrated that the disaggregation of data provides useful insight into health patterns at a sub-national scale and also an opportunity for further research that seeks to explores place-based effects on health between scales.

CHAPTER SIX: THE URBAN AND INTRA-URBAN SETTING IN SOUTH AFRICA

6.1. INTRODUCTION

The multivariable logistic regression analysis of the NIDS data highlighted a significant association between hypertension and the urban setting in South Africa, as well as between multimorbidity and the urban setting. Trends in the literature suggest that one can expect NCDs, such as hypertension and diabetes, to have a higher prevalence in the urban setting, particularly in developing countries, due to the associated increase in trans- and saturated fat, sugar and salt consumption that accompanies urbanisation (Malan et al., 1992; Singh et al., 1998; Popkin & Gordon-Larsen, 2004; Godfrey & Julien, 2005).

However, it is also suggested that there are intra-urban differences in NCD prevalence between urban formal and urban informal areas (Shisana, Labadarios, et al., 2014). Some studies have found hypertension and diabetes to be most prevalent in the urban formal areas, possibly due to the higher fat and sugar intake in these areas compared to urban informal areas (Shisana, Labadarios, et al., 2014). However, studies have also shown that the risk of hypertension is increasing amongst the poor and in areas that have a disadvantaged socioeconomic and physical environment, like the urban informal setting, which is reportedly facing high levels of chronic infectious diseases such as HIV and TB (van Rooyen et al., 2000; Popkin & Gordon-Larsen, 2004; David et al., 2007; Mayosi et al., 2009; Liu et al., 2013). Therefore, this provides some support for the interesting finding at the South African level that the NIDS respondents who were classified as '*vulnerable to socioeconomic* disadvantage' had higher odds of having hypertension - not those who were classified as '*not deprived'*. This finding may point to the apparent epidemiological shift occurring for hypertension, whereby the 'vulnerable' and 'poor' are starting to become disproportionately affected by hypertension, as suggested by the mentioned literature. However, this will need further external investigation.

Regarding infectious diseases, while South Africa does have some health data available for urban and rural areas, a major concern for South Africa and many other countries is that disaggregated HIV and TB data is not readily available for intra-urban areas (David et al., 2007). The SANHANES-1 has provided some relief by providing disaggregated health information on HIV for intra-urban locations in South

Africa, and thus will be used to validate the findings of this study. Nevertheless, this is a data gap that needs to be acknowledged and addressed.

HIV is expected to be found more prevalent in urban informal areas in the NIDS, as suggested by the findings of SANHANES-1. In 2012, SANHANES-1 estimated an HIV prevalence of 19.9% for urban informal areas in South Africa, which is remarkably higher than the prevalence estimated for urban formal areas of 10.1% (Shisana, Rhele, et al., 2014). TB is expected to be more common in urban areas in general, according to the 2014 Global Tuberculosis Report (World Health Organization, 2014), but has also been linked to socioeconomic status factors, namely low education, unemployment and household deprivation (Harling, Ehrlich & Myer, 2008).

The literature demonstrates that the analysis of health purely at the urban level may mask underlying patterns occurring at sub-urban levels, as suggested by Salem (1993) and Niakara et al. (2007). Therefore, in order to consider possible place-based effects, this chapter will not only disaggregate the NIDS data to the urban level, but also to the intra-urban level (i.e. urban formal and urban informal) of South Africa. It is expected that the disaggregation of the NIDS data to the urban and intra-urban levels will provide new health information that may be useful for future research. The chapter will first assess the composition of the adult NIDS sample at the urban level before presenting findings on the prevalence of hypertension, diabetes, TB, HIV and multimorbidity at the urban and intra-urban levels from 2008 to 2012. As this chapter is merely seeking to test the hypothesis that there are underlying health patterns at a sub-national and sub-urban scale, this section will only focus on presenting and comparing prevalence rates of hypertension, diabetes, TB, HIV and multimorbidity.

6.2. BASELINE CHARACTERISTICS AND DESCRIPTIVE ANALYSIS OF NIDS ADULT SUB-SAMPLE FOR THE URBAN SETTING

The unweighted baseline characteristics of the South African urban adult sub-sample for the wave 1 of the NIDS is shown in Table 6.1. There were 9 288 adults in the urban setting in wave 1, with a median age of 35 years (IQR: 23-49 years). The highest proportion of adults were in the 15-24 age group (28.20%). Only 7.81% (n = 725) of adults were 65 years or older. The sample comprised more females (54.35%) than males (45.65%), while the racial composition showed that 61.74% of adults were Black African, 24.89% were Coloured, 2.28% were Asian/Indian and 11.09% were White. Of the 9 288 urban adult respondents, only 9 042 specified whether they lived in an urban formal or urban informal setting. Of these 9 042 respondents, 87.44% (n = 7 906) lived in urban formal areas and 12.56% (n = 1 136) lived in urban informal areas. Regarding risk factors, 45.24% (n = 3 376) of urban respondents drink alcohol, 33.18% (n = 2 469) smoke, 62.59% (n = 4 652) claim to never exercise and 30.88% (n = 1 626) are obese.

The socioeconomic status variable showed that only 0.35% (n = 32) of respondents in urban areas were in 'Severe Poverty', 3.87% (n = 349) were socioeconomically 'Deprived', 9.55% (n = 862) were socioeconomically 'Vulnerable' and 86.22% (n = 7 780) were 'Not Deprived'. This contrasts against the rural setting (data not shown), in which 4.89% (n = 443) of the 9 059 rural respondents were in 'Severe Poverty', 19.89% (n = 1 802) were socioeconomically 'Deprived', 27.83% (n = 2 521) were socioeconomically 'Vulnerable', and 47.39% (n = 4 293) were 'Not Deprived'.

For wave 3, the unweighted baseline characteristics for the urban adult sub-sample are shown in Table 6.2. Once again, the only characteristics that have noticeably changed from wave 1 (2008) are the risk factor proportions. In wave 3, 39.08% (n = 2 790) of urban respondents drink alcohol, 26.30% (n = 1 878) smoke, 67.56% (n = 4 829) claim to never exercise and 31.41% (n = 1 846) are obese.

Table 6.1. Unweighted Descriptive Statistics for the urban adult sub-sample in 2008 (wave 1) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		28.20%	2 619	
	25-34		20.75%	1 927	
	35-44		18.84%	1 750	
	45-54		15.03%	1 396	
	55-64		9.38%	871	
	65+		7.81%	725	
TOTAL		9 288	35	23-49	15-101
Gender		9 288			
	Male		45.65%	4 240	
	Female		54.35%	5 048	
Race		9 288			
	Black African		61.74%	5 734	
	Coloured		24.89%	2 312	
	Asian/Indian		2.28%	212	
	White		11.09%	1 030	
Urban		9 042			
	Urban Formal		87.44%	7 906	
	Urban Informal		12.56%	1 136	
Socioeconomic status		9 023			
	Not Deprived		86.22%	7 780	
	Vulnerable		9.55%	862	
	Deprived		3.87%	349	
	Severe Poverty		0.35%	32	
Alcohol drinking status		7 462			
	Never		54.76%	4 086	
	Drinker		45.24%	3 376	
Smoking status		7 442			
	Never		66.82%	4 973	
	Smoker		33.18%	2 469	
Exercise		7 432			
	Never		62.59%	4 652	
	Exercise		37.41%	2 780	
Obesity		5 266			
	Obese		30.88%	1 626	
	Not obese		69.12%	3 640	

Source: Author

Table 6.2. Unweighted Descriptive Statistics for the urban adult sub-sample in 2012 (wave 3) of the National Income Dynamics Study

Variable		N	Median/percentage	IQR/frequency	Range
Age					
	15-24		28.35%	2 759	
	25-34		21.97%	2 138	
	35-44		17.27%	1 681	
	45-54		14.36%	1 398	
	55-64		9.71%	945	
	65+		8.33%	811	
TOTAL		9 732	34	15-49	15-105
Gender		9 732			
	Male		45.37%	4 415	
	Female		54.63%	5 317	
Race		9 732			
	Black African		63.73%	6 202	
	Coloured		24.48%	2 382	
	Asian/Indian		2.31%	225	
	White		9.48%	923	
Urban		9 309			
	Urban Formal		87.27%	8 124	
	Urban Informal		12.73%	1 185	
Alcohol drinking status		7 140			
	Never		60.92%	4 350	
	Drinker		39.08%	2 790	
Smoking status		7 140			
	Never		73.70%	5 262	
	Smoker		26.30%	1 878	
Exercise		7 148			
	Never		67.56%	4 829	
	Exercise		32.44%	2 319	
Obesity		5 878			
	Obese		31.41%	1 846	
	Not obese		68.59%	4 032	

Source: Author

6.3. THE CHANGING STATUS OF HEALTH IN THE URBAN AND INTRA-URBAN SETTING THROUGH NIDS

This section explores changes in health between 2008 and 2012 for the urban and intra-urban setting. An urban area can be described as one that contains formal cities and towns, characterised by high levels of economic activity, higher population densities, high levels of infrastructure and constant development (see Appendix 1). The intra-urban setting includes the urban formal setting, defined as an area within a declared residential urban space that predominately contains structured and organised formal dwellings, and the urban informal setting, described as areas that are predominately made up of informal settlements but are located in declared urban areas that have not been declared as residential areas (Statistics South Africa, 2003, 2012a). Although the results may not be representative of the urban and intra-urban populations, important differences in health patterns can be identified.

6.3.1. The prevalence of hypertension, diabetes, TB, HIV and multimorbidity for 2008 and 2012

6.3.1.1. The South African urban setting

Age-adjusted prevalence was estimated for hypertension, self-reported diabetes, self-reported TB, self-reported HIV and multimorbidity for the South African urban adult population for 2008 (wave 1) and 2012 (wave 3), as displayed in Table 6.3. Hypertension increased in prevalence between 2008 and 2012 from 22.67% to 33.44%, which mirrors the national trend for hypertension. Self-reported diabetes decreased slightly between 2008 and 2012 from 3.17% to 3.15%. Self-reported TB prevalence also declined from 1.28% in 2008 to 0.54% in 2012. Self-reported HIV increased from 1.14% in 2008 to 1.91% in 2012. Multimorbidity increased slightly from 2.91% to 2.96% from wave 1 to wave 3. These results are similar to those of the national adult sample.

Table 6.3. Age-adjusted prevalence estimates and 95% confidence intervals for the South African urban adult population for 2008 (wave 1) and 2012 (wave 3)

	Wave 1 (age-adjusted)		Wave 3 (age-adjusted)	
	Estimated Prevalence (%)	95% CI	Estimated Prevalence (%)	95% CI
Hypertension	22.67%	(21.83-23.54)	33.44%	(32.50-34.38)
Diabetes	3.17%	(2.82-3.54)	3.15%	(2.82-3.52)
Tuberculosis	1.28%	(1.06-1.53)	0.54%	(0.41-0.71)
HIV	1.14%	(0.94-1.38)	1.91%	(1.65-2.20)
Multimorbidity	2.91%	(2.57-3.27)	2.96%	(2.63-3.32)

Source: Author

The prevalence estimates for hypertension, diabetes, TB, HIV and multimorbidity in the urban adult population are presented by age group in Figure 6.1. The pattern of health for the urban setting is similar to the South African health pattern. In 2008, hypertension prevalence increased with age, particularly after the 24-34 age group. Hypertension was prevalent in 5.40% of adults in the 15-24 age group and reached a prevalence of 65.31% in the 65+ age group in the urban setting. Between 2008 and 2012, the prevalence of hypertension had increased in each age group. In 2012, hypertension was prevalent in 7.41% of adults in the 15-24 age group and in 77.47% of adults in the 65+ age group.

Self-reported diabetes prevalence across age groups in the urban setting showed a similar trend to that of the national setting. In wave 1, diabetes increased with age from 0.48% (15-24 age group) to 11.79% (55-64 age group), before slightly declining to 10.63% (65+ age group). In wave 3, diabetes was most prevalent in the 65+ age group (11.96%); however prevalence was lower for the 15-24 (0.34%), 25-34 (0.44%), 45-54 (3.00%) and the 55-64 (10.77%) age groups compared to wave 1 (15-24 age group: 0.48%; 24-35 age group: 1.12%; 45-54 age group: 5.71%; 55-64 age group: 11.79%).

Similar to the national prevalence trend, self-reported TB prevalence was low across all age groups in both waves and was lower in wave 3 compared to wave 1 for all age groups excluding the 15-24 age group (wave 1: 0.46%; wave 3: 0.50%). In wave 1, TB was most prevalent in the 55-64 age group (2.04%); however the highest estimated prevalence for wave 3 was only 0.76% (65+ age group). This suggests a possible underreporting of TB, particularly in wave 3.

In both waves, self-reported HIV prevalence was higher in the middle age groups and highest in the 35-44 age group. In wave 1, HIV increased in prevalence from 0.15% (15-24 age group) to 2.76% (35-44 age group) before declining to 0.00% (65+ age group). In wave 3, HIV increased from 0.22% (15-24 age group) to 4.46% (35-44 age group) before declining to 0.00% in the 65+ age group. The fact that both waves had a prevalence of 0.00% for the 65+ age group suggests a reduced life expectancy for respondents who have HIV.

Multimorbidity showed a similar trend to diabetes across age groups for both waves. Across age groups in wave 1, multimorbidity increased with age from 0.05% (15-24 age group) to 10.79% (55-64 age group) and declined to 9.12% (65+ age group). However, in wave 3, multimorbidity prevalence increased from 0.01% (15-24 age group) to 3.08% (35-44 age group) before slightly declining to 2.83% (45-54 age group), and increasing again to 11.42% (65+ age group). The slight drop in prevalence for the 45-54 age group in wave 3 may be due to the drop in HIV and TB prevalence in the same age group.

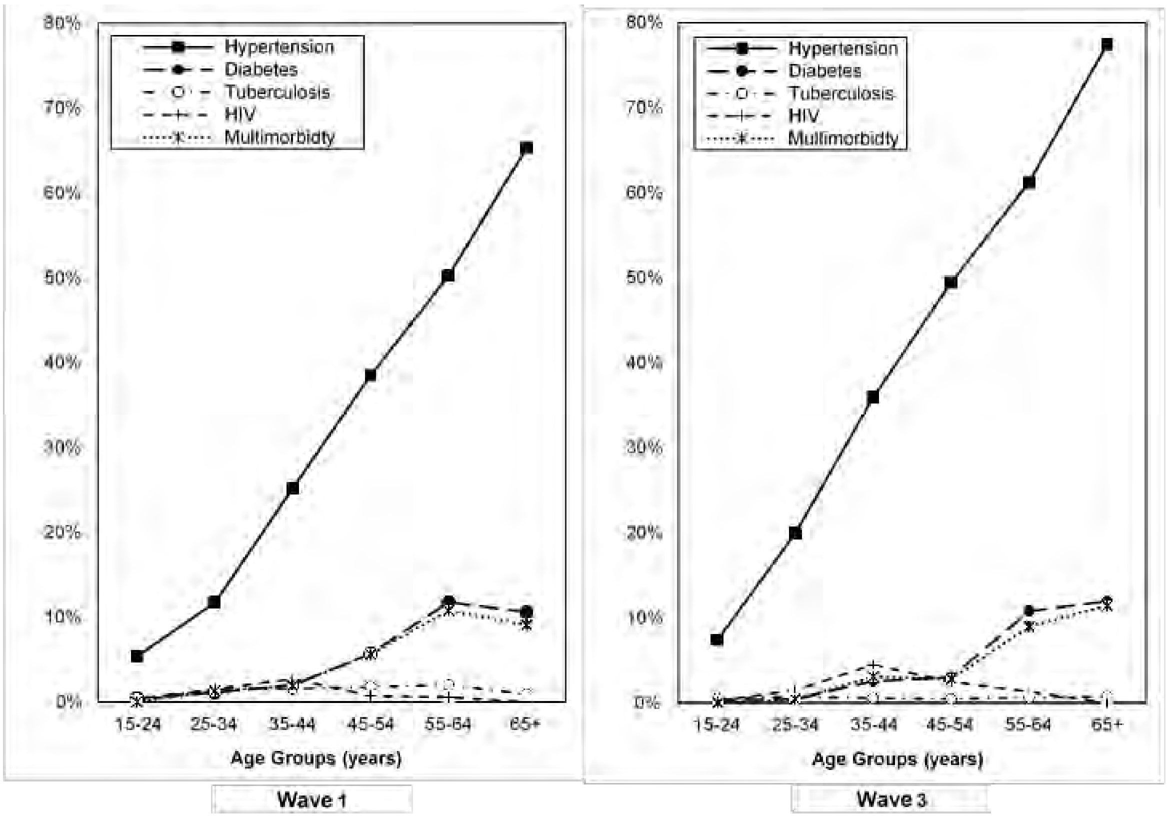


Figure 6.1. Hypertension, diabetes, TB, HIV, multimorbidity prevalence by age group for the South African urban adult population for 2008 (wave 1) and 2012 (wave 3) using the NIDS

Source: Author

Summary of findings for the urban setting

Hypertension and self-reported HIV increased in prevalence in the urban setting between 2008 and 2012, while self-reported diabetes and TB declined in prevalence between 2008 and 2012. These urban health patterns mirror the national level health trends. In order to further investigate the results of the urban setting and to consider possible place-based effects, the data was further disaggregated to the intra-urban setting to explore basic health patterns at a smaller spatial level.

6.3.1.2. The South African urban formal and urban informal setting

This section seeks to explore the differences in health between two sub-urban settings, namely the urban formal and the urban informal setting. Therefore, the focus will be on comparing the general health trends between the urban formal and the urban informal for each wave.

The prevalence estimates for the South African adult sample for urban formal and urban informal areas are shown in Table 6.4, for 2008 (wave 1) and 2012 (wave 3) of the NIDS data. In the urban formal areas, hypertension, self-reported diabetes and self-reported HIV increased in prevalence over time, while self-reported TB declined in prevalence with time. The increase in multimorbidity prevalence from 2.65% (2008) to 3.24% (2012), may be attributed to the increase in both hypertension and diabetes, which are the two leading contributors to multimorbidity.

In the urban informal areas, hypertension has increased from 2008 to 2012, however Diabetes, TB and HIV prevalence have decreased between 2008 and 2012. Therefore, the decline in multimorbidity from 3.61% (2008) to 1.90% (2012) may be attributed to the decline of these three diseases, particularly diabetes.

Comparing the prevalence estimates between the urban formal and urban informal setting, diabetes has a higher prevalence in the urban formal setting for both wave 1 (3.40%) and wave 3 (3.54%), which increased over time, compared to the urban informal setting (wave 1: 1.50%; wave 3: 1.13%). Although TB and HIV have both declined in prevalence between 2008 and 2012 in the urban informal setting, they still have higher rates of prevalence in the urban informal setting for both waves compared to the urban formal setting. Hypertension is slightly more prevalent in the urban informal setting for 2008 (22.77%) compared to the urban formal setting (22.39%), however it is more prevalent in the urban formal setting in 2012 (33.97%) compared to the urban informal setting (30.77%). This suggests that hypertension prevalence may increase more in the urban formal setting over time.

Table 6.4. Age-adjusted prevalence estimates and 95% confidence intervals for the South African urban formal (top) and urban informal (bottom) adult population for 2008 (wave 1) and 2012 (wave 3)

URBAN FORMAL

	2008 - Wave 1 (age-adjusted)		2012 - Wave 3 (age-adjusted)	
	Estimated Prevalence (%)	95% CI	Estimated Prevalence (%)	95% CI
Hypertension	22.39%	(21.47-23.21)	33.97%	(32.94-35.02)
Diabetes	3.40%	(3.01-3.83)	3.54%	(3.15-3.97)
Tuberculosis	1.07%	(0.86-1.33)	0.42%	(0.29-0.58)
HIV	0.69%	(0.52-0.90)	1.94%	(1.66-2.27)
Multimorbidity	2.65%	(2.31-3.03)	3.24%	(2.86-3.65)

URBAN INFORMAL

	2008 - Wave 1 (age-adjusted)		2012 - Wave 3 (age-adjusted)	
	Estimated Prevalence (%)	95% CI	Estimated Prevalence (%)	95% CI
Hypertension	22.77%	(20.39-25.35)	30.77%	(28.18-33.52)
Diabetes	1.50%	(0.87-2.39)	1.13%	(0.59-1.87)
Tuberculosis	2.31%	(1.50-3.33)	0.92%	(0.46-1.65)
HIV	3.39%	(2.45-4.66)	2.24%	(1.51-3.30)
Multimorbidity	3.61%	(2.60-4.86)	1.90%	(1.23-2.90)

Source: Author

Figure 6.2 compares the health patterns of hypertension, diabetes, TB, HIV and multimorbidity across age groups between the South African urban formal and urban informal areas for each wave. In the urban formal setting, hypertension prevalence increased with age from 4.80% in the 15-24 age group to 65.77% in the 65+ age group in wave 1, and from 7.27% (15-24 age group) to 77.45% (65+ age group) in wave 3. Of note, in the urban informal setting for both waves, hypertension increased in prevalence with age from the 15-24 age group (wave 1: 6.96%; wave 3: 8.21%) to the 55-64 age group (wave 1: 66.25%; wave 3: 87.52%) and then dropped in prevalence in the 65+ age group (wave 1: 58.83%; wave 3: 82.95%).

The pattern of diabetes prevalence across age groups in the urban formal setting mirrors the trend of the national and urban setting for both waves. In the urban formal setting, wave 1 diabetes prevalence increased with age from the 15-24 age group (0.46%) and peaked in the 55-64 age group (12.11%), before slightly dropping in the 65+ age group (10.52%). In wave 3, the prevalence of diabetes increased with age from the 15-24 age group (0.37%) to the 65+ age group (12.44%). In the urban informal setting for wave 1, diabetes increased continually across age groups from 0.48% (15-24 age group) to 8.91% (65+ age group). In the urban informal setting in wave 3, diabetes increased from 0.21% (15-24 age group) to 1.35% (35+44 age group) but showed a drop in the 45-54 age group (0.47%) that was inconsistent with the national, urban and urban formal trends.

Regarding TB, prevalence remained low across age groups for both waves of the urban formal setting, similar to the national and urban trend. In the urban formal setting for wave 1, the prevalence of TB was highest in the middle age groups (25-34 (1.09%); 35-44 (1.42%); and 45-54 (1.42%) age groups). Comparing the prevalence of TB in the urban formal setting between waves, the prevalence was highest in all age groups in wave 1 when compared to wave 3, in which the highest prevalence rate was only 0.84% (24-34 age group). Comparing the urban formal setting to the urban informal setting in wave 1, TB prevalence was higher in the middle age groups in the urban formal setting (25-34 (2.69%); 35-44 (3.22%); 45-54 (5.09%); and 55-64 (5.84%) age groups) compared to the urban formal setting. However, this was not the case in wave 3.

HIV prevalence estimates for the urban formal setting were also consistent with that of the national and urban settings for both waves. Both waves showed an increase in prevalence with age before peaking at the 35-44 age group (wave 1: 4.46%; wave 3: 1.79%). Both waves had a prevalence of 0.00% in the 65+ age group. In the urban informal setting, HIV had higher prevalence rates for the middle age groups compared to the urban formal setting, particularly for the 25-34 (5.59%), 34-44 (8.36%)

and 45-54 (1.59%) age groups in wave 1, and the 25-34 (3.75%) and 45-54 (3.17%) age groups in wave 3. Yet, both waves had a prevalence of 0.00% in the 65+ age group.

Multimorbidity followed a similar trend to diabetes in the urban formal setting for both waves, which is consistent with national and urban trends; however this was not the case for the urban informal setting. In the urban informal setting, multimorbidity prevalence was highest in the 55-64 age group for wave 1 (12.94%), yet the prevalence dropped in the 65+ age group (8.91%) more so than in the national, urban and urban formal settings. This drop in prevalence for the 65+ age group might suggest a lower level of life expectancy for people who live in informal urban areas and have multimorbidity. Comparing the urban informal and the urban formal settings, multimorbidity prevalence was higher across all age groups in the urban informal setting in wave 1, except for the 15-24 age group (urban formal: 0.06%; urban informal: 0.00%). However, in wave 3, the prevalence of multimorbidity was only higher in the urban informal setting for the 25-34 (1.03%) and the 35-44 (3.44%) age groups compared to the urban formal setting (25-34 (0.68%) and 35-44 (1.40%) age groups).

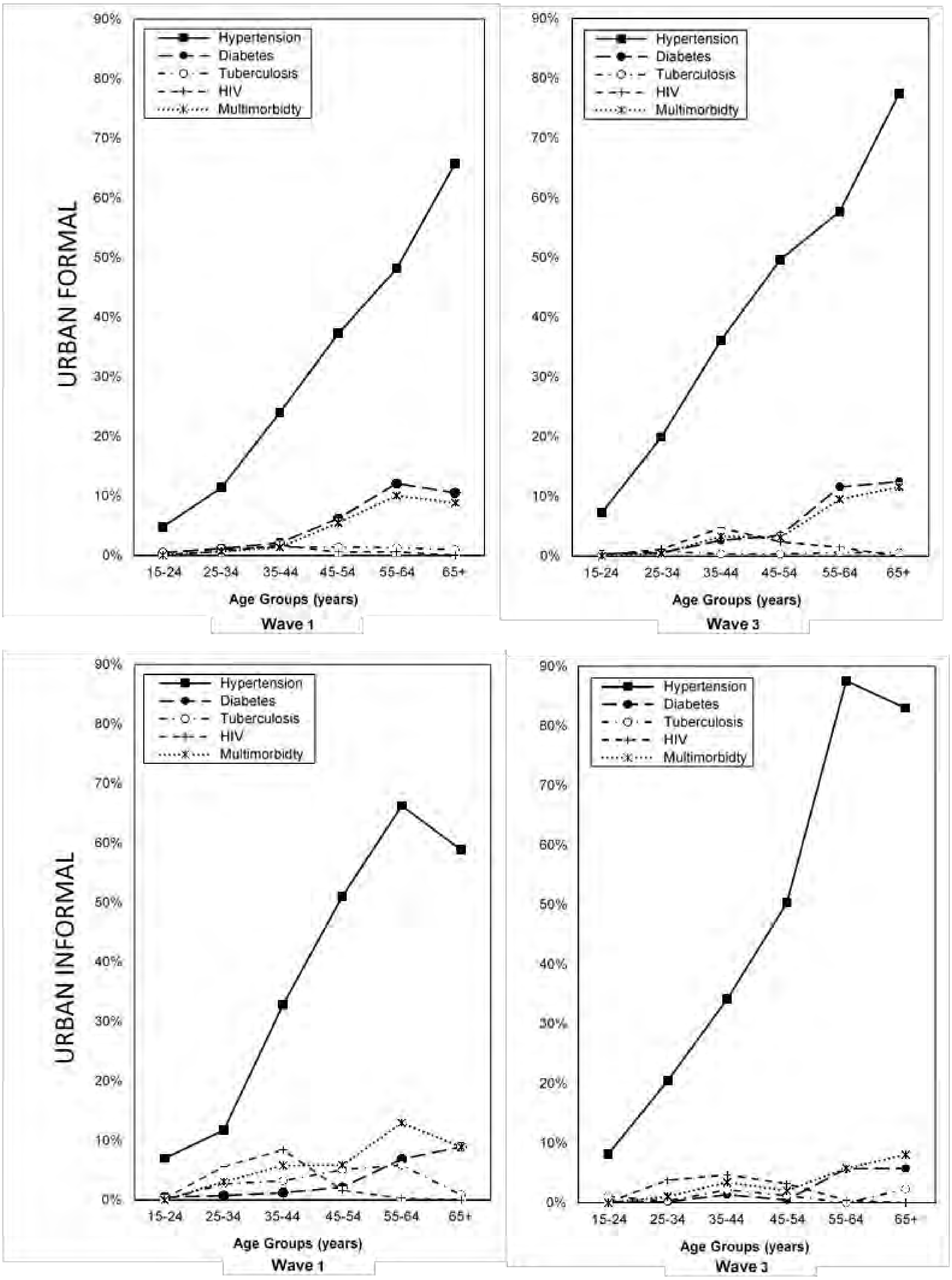


Figure 6.2. Hypertension, diabetes, TB, HIV, multimorbidity prevalence by age group for the South African urban formal (top) and urban informal (bottom) adult population for wave 1 and wave 3

Source: Author

6.4. DISCUSSION OF FINDINGS AT THE URBAN AND INTRA-URBAN LEVELS

As indicated by the literature in the introduction of this chapter, the link between hypertension and the urban environment is well documented, as it is suggested to be associated with a more Westernised, sedentary lifestyle. However, this is not strongly reflected in the NIDS at the urban level. The prevalence of hypertension in the urban setting is only slightly higher than the national prevalence in 2012. However, diabetes has a slightly higher prevalence in the urban setting compared to the national level for both waves. The prevalence of HIV and TB at the urban level for both 2008 and 2012 also show similarities to the national prevalence rates, as well as similar evidence of underreporting.

Considering possible place-based effects at the sub-urban level, the intra-urban results showed slight differences in health between the urban formal and urban informal setting. An interesting finding is that hypertension prevalence increased more in the urban formal setting over time compared to the urban informal setting and was more prevalent in the urban formal setting in 2012. The intra-urban results also showed self-reported diabetes to be more prevalent in the urban formal setting in the NIDS. These findings are supported by the SANHANES-1 data which found that the prevalence of both hypertension and self-reported diabetes were highest for respondents living in urban formal settings, in which the fat and sugar intake was also found to be highest, compared to the urban informal, rural formal and rural informal settings (Shisana, Labadarios, et al., 2014). However, further research using a larger temporal scope would be needed to assess the possibility of different rates of change for hypertension prevalence between the two geographical settings over time. Nevertheless, these findings have demonstrated that hypertension remains a large health burden for both the urban formal and urban informal setting.

The prevalence rates for both TB and HIV may be too low to make any meaningful conclusions; however, both HIV and TB are more prevalent in the urban informal areas. In addition, HIV is noticeably higher for the 34-44 age group in both the urban formal and urban informal settings. This supports the findings at the national and urban scales, as previously discussed in section 4.7.2 and in section 5.5.

6.5. CONCLUSION

The disaggregated data at the intra-urban scale has provided useful information for hypertension, has revealed the heterogeneity in health patterns within urban areas, and thus has highlighted the importance of exploring sub-level health patterns. Finally, the finding that multimorbidity closely followed the diabetes prevalence pattern across age groups has now been demonstrated at the national, Western Cape, urban and intra-urban geographic levels.

CHAPTER SEVEN: DISCUSSION OF RESULTS

7.1. INTRODUCTION

The purpose of this chapter is to discuss the overall findings of this study in light of the theories discussed in section 2.2., namely the epidemiological transition theory (Omran, 1971) and the debate on structure and agency (Giddens, 1984). When applied to the interpretation of findings, these theories are able to provide further insight into the status of health in South Africa at the national and sub-national scales, as well as an understanding of how this health status may be influenced.

7.2. THE IMPLICATIONS FOR SOUTH AFRICAN HEALTH USING EPIDEMIOLOGICAL TRANSITION THEORY

Although the primary aim of this study was to provide a proof of concept on the use and disaggregation of existing health survey data and to explore a spatial distribution of health in South Africa for 2008 and 2012, it would be inapt to disregard the signs of epidemiological transition that are emerging from the findings.

As discussed in detail in section 2.2.1, South Africa's epidemiological transition is suggested to be one that has not yet achieved complete transition into *The Age of Degenerative and Man-Made Diseases,* although it is likely to be further along the transition than other sub-Saharan African countries.

The results of the NIDS revealed a high burden of hypertension, an NCD that is increasing in prevalence with time at all spatial scales and is strongly associated with age and obesity, and with diabetes in multimorbidity cases. The infectious diseases of TB and HIV were found to be low in prevalence relative to the reported hypertension and diabetes prevalence. If these findings were to be evaluated only in light of the epidemiological transition theory, it may be suggested that South Africa is transitioning more into an *Age of Degenerative and Man-Made Diseases.* However, through careful examination of the findings, it is with reasonable confidence that one can conclude that self-reported HIV and TB within the NIDS has been underreported by respondents, thereby resulting in the underestimation of these infectious diseases in South Africa. This highlights the importance of cross-checking findings with other studies and suggests that any analysis on the current status of chronic infectious diseases in South Africa using the NIDS data will remain questionable. Nevertheless, inferences may still be made using the findings of the NIDS.

Firstly, the NIDS results show that both infectious and non-communicable diseases are present in South Africa. Although the prevalence of infectious diseases are underestimated, this suggests that South Africa is at least in *The Age of Receding Pandemics* and beginning to move into *The Age of Degenerative and Man-Made Diseases.* This is supported by Omran (1971), who suggests that developing countries are currently experiencing a transition from an epidemiology dominated by infectious diseases into one that is experiencing a gradual emergence of NCDs.

Secondly, this study has shown that the disaggregation of health data to the sub-national level reveals interesting variations in epidemiological profiles between geographies, namely between the urban informal and urban formal areas. Hypertension was not associated with socioeconomic disadvantage and was more prevalent in urban areas. Through the analysis at the intra-urban scale, it was discovered that both hypertension and diabetes have a greater prevalence in the urban formal areas compared to the urban informal areas, with the exception of the hypertension prevalence in 2008. In addition, urban informal areas have a higher prevalence of infectious diseases (both HIV and TB) compared to urban formal areas. This indicates the possibility that the urban formal and urban informal areas of South Africa are at different stages of epidemiological transition.

Applying Omran's theory, which suggests that epidemiological transition is affected by a number of complex determinants, including socioeconomic processes, the level of hostility of the environment towards disease and illness, and medical and public health opportunities; variations in the epidemiological profiles of intra-urban geographies would make sense if the urban formal and urban informal areas differ in a number of these determinants. This notion is also supported by Northridge, Sclar and Biswas (2003), who suggest that the general health and wellness of individuals and populations is a reflection of the state of the built environment and social context of urban areas, as experienced by citizens (illustrated in Figure 2.1, Section 2.4.3). The urban informal and urban formal areas of South Africa have been found to differ substantially in a number of aspects, including household income, socioeconomic status, as well as in general levels of health and service provision (Del Mistro & Hensher, 2009; Daniels et al., 2013; Wabiri & Taffa, 2013; Wabiri et al., 2013). Therefore, it is likely that these settings will experience different levels of health and a different rate of epidemiological transition. Therefore, it is argued that Omran's epidemiological transition theory should be applicable to sub-national levels so that variations in epidemiological profiles can be identified.

Based on this premise, and in light of the findings that both NCDs (i.e. hypertension and diabetes) were more prevalent in urban formal areas in 2012, while TB and HIV were most prevalent in urban informal areas, a third inference can be made: urban formal areas in the NIDS are slightly more progressed towards experiencing an *Age of Degenerative and Man-Made Diseases*, in which infectious diseases are slowly becoming replaced by NCDs. This inference is supported by the literature discussed in Chapter 2, suggesting that urbanised areas may typically experience a higher prevalence of NCDs, which are stereotypically linked to the adoption of a more sedentary, 'Westernised' lifestyle (Godfrey & Julien, 2005). Although additional research is needed to explore this further, particularly through the use of representative data at the intra-urban scale, this finding may be of interest to government and public health officials, as well as urban planners, as it implies that different interventions may be needed to address health and wellbeing in the urban formal and urban informal areas.

A fourth inference that can be made from the NIDS findings relates to the apparent epidemiological shift that may be occurring for hypertension. As previously discussed earlier in Chapter 6 (section 6.1), the findings of the NIDS suggest that the 'vulnerable' and 'poor' are starting to become disproportionately affected by hypertension – a finding that is supported by a number of studies (van Rooyen et al., 2000; Mayosi et al., 2009; Liu et al., 2013). If this is true, an increase in NCDs is likely to increase inequalities, as the urban informal areas often lack the protocols and regulations, as well as the health services needed to address NCDs (Beaglehole et al., 2011). In addition, poverty and non-compliance to treatment regimens could increase due to the cost of chronic treatment for NCDs (Buabeng, Matowe & Plange-Rhule, 2004; Beaglehole et al., 2011).

The limitations of the self-reported NIDS data for diabetes, TB and HIV make it difficult to provide a conclusive description of the epidemiological transition of South Africa at the national and sub-national levels. However, these inferences do provide a foundation for future research into the epidemiological transition theory of South Africa at the national and sub-national levels.

7.3. OPPORTUNITIES FOR IMPROVING HEALTH AND WELLBEING IN SOUTH AFRICA – A DISCUSSION ON STRUCTURE AND AGENCY

As discussed within the section 2.2.2, various political, environmental, economic, cultural and social structures can influence health patterns, while people's agency in the form of actions and behaviours can also influence health and wellbeing. Within the NIDS data, several factors that have the potential to structurally influence health were included in the analysis, such as gender, race, geographical type (i.e. urban, intra-urban types) and socioeconomic status. Variables that may be linked to one's agency, or more specifically to one's lifestyle and behavioural choices, were also included. These comprised the self-reported risk factors of smoking, alcohol consumption and exercise.

In the exploratory bivariate analysis, all variables that could possibly play a structural role in health were found to be significantly associated with both hypertension and multimorbidity, and were thus included in the multivariable analyses, namely age, gender, socioeconomic status, race, and geographical setting. In contrast, the bivariate analysis of the selected behavioural and lifestyle risk factors, namely smoking, alcohol consumption and exercise, did not show any statistical association with multimorbidity or hypertension, with the exception of exercise which was only statistically associated with hypertension (refer to Table 4.4). This was an interesting yet unexpected finding, as the associations between NCDs and lifestyle and behavioural risk factors such as alcohol consumption, smoking, and exercise have been well described in the literature. Furthermore, research has shown that much of the NCD burden in South Africa has been attributed to the high prevalence of risk factors in the population such as smoking, alcohol consumption, poor diet and a lack of exercise (Bradshaw & Steyn, 2001; Mayosi et al., 2009; Cois & Ehrlich, 2014). At face value, this finding is also concerning for South Africa, as it is more difficult to modify the influence that structural factors have over health than to influence or alter behavioural and lifestyle choices (Mayosi et al., 2009).

Exclusively looking at the NIDS results, it may appear that health is more associated with, or better predicted by, factors that play a structural role; however, a possible reason why there were no associations found between the selected risk factors and health conditions might be that some respondents underreported their risk factors in the NIDS. Within the NIDS adult questionnaire, the questions on exercise, smoking and alcohol consumption were asked directly after the health section in the survey. This may have unintentionally made the respondent more health conscious and predisposed the respondent to a biased response. Although self-reporting is necessary to gain information about lifestyle and behavioural choices, the self-reporting of risk factors in household surveys has been linked to self-report bias in numerous studies, in which respondents provided misleading information or inadvertently provided incorrect answers (Gillham & Endacott, 2010; Bauhoff, 2011; Gray et al., 2013). Self-report bias may be caused by a number of individual or social factors, including interview conditions or due to social desirability bias, in which respondents tend to overreport socially desirable behaviours or attitudes and underreport socially undesirable ones (Bound, Brown & Mathiowetz, 2001; Gray et al., 2013).

However, one risk factor variable that was not vulnerable to self-report bias in the NIDS was obesity, as it was calculated from the respondents' anthropometric measurements taken during the NIDS interview. Although obesity is a health risk factor, it was not categorised alongside alcohol consumption, exercise or smoking, as obesity is not a behaviour but rather an outcome of lifestyle or behavioural choices, or a result of an obesogenic environment, or a result of underlying health issues (Swinburn et al., 2011). In the NIDS, obesity was a strong predictor of both multimorbidity and hypertension and this finding is supported by a number of international and national studies (Mollentze et al., 1995; Richards, Thakur & Reisin, 1996; van Rooyen et al., 2000; Agborsangaya et al., 2012).

Unfortunately, obesity is a challenging health condition to address and public health measures have not yet been successful at reversing the obesity epidemic in any population (Swinburn et al., 2011). Therefore, this highlights the need and opportunity for interdisciplinary action, in which both the fields of public health and urban planning must come together to solve health challenges in South Africa.

7.4. CONCLUSION

This chapter has applied the epidemiological transition theory, as well as concepts from the structure and agency literature, to the discussion on the implications of the NIDS data for South African health. Although the NIDS data has limitations, including findings that suggest an underreporting or underestimation of self-reported health conditions, these results have allowed for inferences to be made on the status of health and epidemiological transition at the national and sub-urban levels. While, these inferences are not conclusive and require further research, they have provided a platform for further discussion on the future of health in South Africa.

PART THREE:
CONCLUSIONS AND RECOMMENDATIONS

CHAPTER EIGHT: CONCLUSIONS AND RECOMMENDATIONS

8.1. CONCLUSIONS

The NIDS findings suggest that age and obesity are strong predictors of both hypertension and multimorbidity. In addition, this study found that multimorbidity and hypertension are associated with structural characteristics such as race, socioeconomic status and geographic location (i.e. urban formal and urban informal). As previously discussed, any effect that structural characteristics have over health will not be easy to mitigate (section 2.2.2). Although literature strongly suggests otherwise, the health risk factors of smoking, alcohol consumption and exercise were not found to be associated with multimorbidity or hypertension in the multivariable analyses. Moreover, this study found that different patterns of health exist at different spatial scales, and particularly between the urban formal and urban informal setting.

8.1.1. The need to reconnect the public health and urban planning fields

Although the public health field is usually responsible for addressing health and wellbeing issues in South Africa, part of the responsibility needs to shift to the urban planning sector. As previously discuss in Chapter 1 (section 1.1.1), urban planners are accountable for the development of the environment in which people live, as well as the provision of services and amenities. Therefore, urban planners have the authority to improve access to basic services, health care and medical services, as well as recreational and sporting facilities. Moreover, they are able to provide services and amenities to those population groups that are most vulnerable to ill-health, such as people living in urban informal areas, thereby contributing towards health equality. The field of public health will need to compliment this by disseminating health knowledge, educating the public on the hypertension and multimorbidity risk factors, conducting further research, and implementing health interventions and public health policies. In addition, the public health field will need to encourage treatment compliance for multiple chronic conditions and raise awareness of the importance of adopting healthy lifestyles and the affordability and availability of disease screening.

8.1.2. Strengths and limitations

This study has demonstrated that geospatial information is able to be coupled with health data to reveal new health information at different spatial scales for 2008 and 2012. More specifically, the pairing of disaggregated health data with geospatial information was able to provide insight into the spatial distribution of selected chronic health conditions across South Africa, thereby revealing 'hot spots' of disease. Through this, the study contributed towards addressing the paucity of research on the spatial distribution of diabetes, TB and HIV across districts and provinces in South Africa. These findings on the spatial clustering of disease may be useful to public health officers and urban planners for directing interventions.

However, a large limitation in this study was the scale to which geospatial information and health data were able to be disaggregated and coupled, which was at the national district level. If it were possible to perform spatial analysis below a district level, kernel density calculations and neighbourhood level hot spot analysis would have been used to interrogating the results of the Getis-Ord Gi* hot spot analysis. As mentioned in Chapter 2 (section 2.4.5.), the use of secondary health data is often limited by the original investigator's temporal and spatial interests or due to constraints around confidentiality, and this was found to be the case with the NIDS data. However, although the spatial analysis was limited, cross-sectional analysis of the data was possible for the urban and intra-urban scales.

The disaggregation of the NIDS data provided information on the current status of health and epidemiological transition at the South African, Western Cape, urban and intra-urban scales which contributed towards addressing the paucity of health data for the urban formal and urban informal settings. This was an important exercise, as it has been suggested that the paucity of information on disease prevalence in urban informal areas is the greatest obstacle in addressing inequalities in health at the intra-urban level (David et al., 2007).

The disaggregation of the NIDS health data to the urban and intra-urban level also revealed different health patterns for the urban formal and urban informal spaces. Although it is important to acknowledge that space is both a contributing cause and a consequence of various social, socioeconomic and health processes, this finding supports the notion that space is implicated in health and wellbeing outcomes, as proposed in Chapter 2 (Jones & Moon, 1993; Kearns & Joseph, 1993; Curtis & Jones, 1998; Kearns & Moon, 2002). Unfortunately the spatial limitations of the data prevented an investigation into the spatial distribution of disease within urban, and between intra-urban, spaces.

Finally, the coupling of geospatial information with health data has allowed a positivist approach to be used for health geography research. Although positivism is arguably a more conventional approach to health geography, it has stemmed from a post-structuralist school of thought within this study and has allowed a baseline investigation of the health status of South Africa to be conducted on which further studies may be mounted.

8.1.2.1. The evaluation of the NIDS as a data source

To date, this is the first time that the NIDS has been used for positivist health geography research involving spatial and statistical analysis of health information. The NIDS data was able to provide useful baseline information on health and socioeconomic status for the South African adult population at a national level, as well as at the disaggregated Western Cape, urban and intra-urban levels. Being a panel study, this data source has allowed for an investigation into adult health for two segments in time, namely 2008 and 2012, thereby setting up the opportunity for future monitoring and evaluation processes, while the spatial co-ordinates have allowed for analysis of the spatial distribution of health and socioeconomic status at a national district level.

There are some disadvantages to the use of secondary data. This study was limited to the data available in the NIDS, and thus the variables selected for this study were limited to the quality of the variable data, responsiveness of respondents, as well as the relevance and specificity of the questions in the NIDS survey. In addition, the estimated prevalence of all four diseases as well as the risk factors of alcohol, smoking and exercise relied partially, if not completely, on self-reported data. As previously mentioned in section 7.3, health surveys are likely to be influenced by self-report bias. Moreover, hypertension is likely to have been underestimated if respondents self-reported a hypertension diagnosis in situations where a healthcare professional identified them as only being pre-hypertensive. However, hypertension prevalence could have been overestimated due to the white coat effect, in which elevated blood pressure may be attributed to visiting a healthcare professional or entering a medical setting (Verdecchia et al., 1995). As revealed in the results, this study has demonstrated that diabetes, TB and HIV were most likely underreported in the NIDS. Language barriers surrounding the diagnosis of diabetes could have resulted in the possible underestimation of prevalence, while stigmas around having HIV and TB may have led to underreporting, as proposed in section 4.7.2. One needs to acknowledge the possibility of potential reverse causation bias in studies that use cross-sectional methods, as people who were aware of their health status would have had the opportunity to change their lifestyle and adopt more healthy habits, such as exercising and losing weight (Liu et al., 2013).

Unfortunately the underreporting or underestimating of diseases, particularly at the national level, affects the ability of the country to use surveillance methods for disease. According to Mtema (2013), one of the greatest challenges within the public health sector, particularly in developing countries, is accurately monitoring the status and spatial distribution of infectious disease, especially when underreporting is so common. This is particularly the case for HIV and is made worse by the fact that underreporting does not only occur in health surveys, but also on death notification forms. It was previously found that 61% of deaths caused by AIDS in 1996 and 2000 to 2001 had an AIDS-related condition referenced as the cause of death, instead of HIV/AIDS (Groenewald et al., 2005).

In conclusion, this study makes use of a large study sample representative of the country, which includes respondents from all nine provinces and all 52 districts, and uses a combination of both epidemiological and spatial tools to generate new health information for South Africa. Furthermore, this study provides evidence of the burden of hypertension and multimorbidity in South Africa, and has contributed to the conversation around self-reported health data, particularly concerning diabetes, HIV and TB. In addition, this study has drawn attention to the importance of interdisciplinary action for the public health and urban planning fields and for the need for disaggregated data in supporting policy improvement efforts, for identifying vulnerable and impoverished communities and groups of people, and for monitoring progress of all groups of people towards achieving the SDGs. Finally, the results of this study may be used to inform and promote healthy public policies that support the prevention and control of prevalent diseases and risk factors in the population.

8.1.3. Recommendations for future research

With regards to future research, the finding that multimorbidity is associated with socioeconomic disadvantage (which was measured under the three themes of health, education and living conditions) has implications for government, urban planners and policy makers. However, action at the district level may be futile and further research will be needed to investigate the association between socioeconomic disadvantage and multimorbidity below the district level. This highlights the importance and need for more disaggregated data for smaller spatial scales. In addition, future qualitative research that investigates the possible determinants of multimorbidity, particularly in respondents with hypertension, will greatly contribute to further understanding the burden and drivers of disease in South Africa. Lastly, further research that seeks to explore heterogeneity in urban health in South Africa will be useful for understanding place-based effects on health.

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APPENDIX 1 (FOR SECTION 3.4.2.):
DEFINITIONS AND CLASSIFICATIONS OF DESCRIPTIVE VARIABLES

1) Age

Age refers to the age of a respondent in completed years at the time of the survey. This study focuses on respondents aged 15 years and older. Originally the age variable was a continuous variable in the dataset, however respondents were later categorised into age groups to assist analysis. Therefore, the classification of the age variable are age groups: 15-24 years, 25-34 years, 35-44 years, 45-54 years, 55-64 years and 65 years and older (65+ years).

2) Socioeconomic Status (a measure for socioeconomic disadvantage)

In this study, the Acute Multidimensional Poverty Index, as developed by the Oxford Poverty and Human Development Initiative for the United Nations Development Programme (Alkire & Santos, 2010), was applied to the NIDS data in order to measure the socioeconomic standing of respondents relative to each other and according to the socioeconomic categories as presented below. This study focused on exploring the association between *socioeconomic disadvantage* and health variables, specifically multimorbidity. For a detailed explanation of the methodology used to construct the multidimensional poverty index to calculate socioeconomic status, refer to section 3.4.2.2.

SOCIOECONOMIC STATUS CATEGORIES		MDPI SCORE
Primary	*Secondary*	*% Deprived*
Not Socioeconomically Disadvantaged	Not Deprived	< 20%
	Vulnerable	20 – 33.33%
Socioeconomically Disadvantaged	Deprived	34 – 49.99%
	Severe Poverty	≥ 50%

Source: adapted from Alkire, Conconi & Seth (2014)

3) Gender

In the NIDS questionnaire, respondents were asked to classify themselves as either male or female. No other categories were available.

4) Racial group

As mentioned in section 3.3.1., the term ‘race’ is not defined in any South African national legislation, however it is often substituted with the term ‘population group’ which may be defined by Stone and Erasmus (2012: 137) as:

> *“A group with common characteristics (in terms of descent and history), particularly in relation to how they were (or would have been) classified before the 1994 elections. The following categories are provided in the census: Black African, Coloured, Indian or Asian, White, other.”*

The NIDS uses the racial classifications of Black African, Coloured, Asian/Indian and White.

5) Intra-urban geographic type

The NIDS dataset included a ‘geographical type’ variable (also known as settlement type) that identified the respondent as being from an urban formal, urban informal, tribal or rural formal enumerator area. Following definitions are from the 2001 and 2011 Census metadata (Statistics South Africa, 2003, 2012a)

Urban formal areas are defined as formal, structured and organised urban settlements that have been developed on proclaimed residential land. Services such as sanitation, water and electricity are usually provided by a local or district council.

Urban informal areas constitute informal settlements located in towns, on the outskirts of towns or along railways and roads.

Tribal areas are any areas that are legally claimed to be under tribal authority and usually contain settlements.

Rural formal areas mainly comprise farms and small holdings.

6) Urban/rural geographical type

According to the Statistics South Africa (2007), an urban area is defined as one that contains formal cities and towns and experiences constant development and building and is characterised by high levels of economic activity, higher population densities and high levels of infrastructure.

In order to create a broad urban classification term, all respondents listed as being either from an *urban informal* or *urban formal* area were categorised under ***Urban,*** as these respondents would most likely experience an urban environment which has been established to have health effects (section 1.1.).

Statistics South Africa (2012a) defined a rural area as one that comprises farms and traditional areas and is characterised by low economic activity, low population density and limited infrastructure. Therefore, respondents listed as being either from a *tribal* or *rural formal* enumerator area were categorised under ***Rural.***

7) Alcohol drinking status

In this study, this variable was classified into two categories of alcohol drinking status: respondents who **drink alcohol;** respondents who **never drink alcohol.**

8) Smoking status

This variable was classified into two categories of smoking status: respondents who **smoke** (this includes respondents who used to smoke regularly)**;** respondents who **have never smoked.**

9) Exercise

In this study, this variable was classified into two categories: respondents who **exercise;** respondents who **never exercise.**