# Spatial Analysis of Child Mortality in South Africa in Relation to Poverty and Inequality: Evidences from the 2011 census

**by**

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## ABSTRACT

Subnational estimates of child mortality are difficult to produce and are rare in Sub-Saharan Africa. It is the overall aim of this research to derive estimates of child mortality rates for the municipalities and provinces of South Africa using the 2011 census data, and to assess the results in relation to the level of poverty and inequality. The estimation of child mortality rates is achieved through the use of direct synthetic cohort methods with Bayesian spatial smoothing. The Bayesian spatial smoothing process is used to generate municipal level estimates of child mortality rates. The model utilises information from neighbouring municipalities by controlling the effects of women's education and HIV/AIDS. It is found that there are clear and significant spatial differentials in child mortality in the country, where at province level the under-five mortality rate ranges from 26 deaths per 1000 live births in the Western Cape (WC) to 71 deaths per 1000 live births in KwaZulu-Natal (KZN). At municipal level, it ranges from as low as 24 deaths per 1000 live births in the City of Cape Town (in WC) to as high as 109 deaths per 1000 live births in uPhongolo (in KZN). Furthermore, the estimates obtained are reasonable, and those at national and province level are in agreement with results from many other researches. In evaluating the spatial differentials in child mortality with the levels of poverty and inequality, it is shown that child mortality is higher in poorer areas and vice-versa, although there are some cases where an inverse relationship is observed. For instance, several municipalities in Limpopo province scored relatively lower child mortality rates though the level of poverty is very high. It is also shown that the distribution of income similarly matters to some extent as greater child mortality is observed in more unequal areas – although the degree of association is not as strong as that of poverty. These results are confirmed by multilevel logistic regression model of child mortality. The findings of this study may help the government to implement policies more effectively and make more focused decisions in the fight for the reduction of child mortality in the country.

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# 1. INTRODUCTION

## 1.1 Background

Disparities in health and mortality have been the concern of development agencies, governments and the international public health community for many years. Various declarations were signed by leaders of nations and representatives of key international organisations so that the gap would be reduced to a noteworthy level (WHO 1978). Especially reducing child mortality to improve the health of children is one of the eight Millennium Development Goals (MDGs) and the topic of many researchers. Child mortality is considered to be one of the key measures of a country's health system, and rates of child mortality of an area have long been believed to be important indicators of health status and socioeconomic development (Kabir, Islam, Ahmed *et al.* 2001; IGME 2013a). This is due to its sensitivity to various changes that affect the health of the entire population, such as disease epidemics and economic development, and to other changes that affect general living conditions, such as social well-being and the quality of the environment (Reidpath and Allotey 2003).

According to a United Nations (UN) report, child mortality in South Africa has declined from 61 deaths per 1000 live births in 1990 to 45 deaths per 1000 live births in 2012 (IGME 2013a). The performance of the country in this regard is, however, found to be low compared to many other countries' performance. For instance, the world has made substantial progress in reducing the under-five mortality rate by 47 per cent in the period 1990-2012 while South Africa has attained a reduction of only about 26 per cent, which makes the country very unlikely to achieve the MDG goal number four – targets to have an infant and under-five mortality rates of 18 and 20 per 1000 births respectively by 2015 (StatsSA 2013). Although HIV/AIDS is usually quoted as the main reason for this poor performance, the role of poverty and inequality should not be ignored. It has been reported that the health of infants and children in South Africa is largely influenced by social and economic conditions under which they live and approximately 66 per cent of children in the country live in poverty, with a monthly household income of less than R1200 per month (Whiting 2013).

Furthermore, child mortality rates in the country have been found to be much higher in certain geographical areas and certain disadvantaged social groups. Many studies in different countries show that the geographic distribution of health problems and their relationship to potential risk factors can be invaluable for cost-effective intervention planning (Freedman, Waldman, Pinho *et al.* 2005; McKinnon 2010). Addressing inequalities in health status and access to health care services within countries is as important as addressing these issues among countries, and hence, in order to effectively address the problem and work towards further reductions in child mortality in the country it is essential that the efforts be focused more on lower administrative levels as, at municipality level for example, opposed to concentrating only on the level of mortality at national level (Freedman, Waldman, Pinho *et al.* 2005).

## 1.2 Importance of the study

Accurate and timely estimates of child mortality at lower geographical units are very important for a country in order to evaluate the effectiveness of intervention programmes as well as for policy planning. In addition, studying this in relation to poverty and inequality will help to make more focused and potentially effective decisions. Many of the researches conducted so far on child mortality in South Africa lack comprehensiveness in that either they focus only on country or province level, or certain specific geographical areas. To the best of our knowledge, there is not any research which attempts to estimate child mortality of the country at municipal level. Besides, very few of these researches tried to analyse the relationship of child survival with poverty and inequality. Thus this research is unique because it will provide new and comprehensive estimates of child mortality for the country at lower administrative units, specifically for the municipalities of South Africa, and it helps to see how these estimates are related with poverty and inequality.

## 1.3 Objectives of the research

The primary objective of this research is to estimate infant and child mortality rates for the municipalities and provinces of South Africa using the 2011 South African census and to study the spatial differentials in relation to poverty and inequality. The hypothesis is that there are significant spatial variations of child mortality, which is associated with socioeconomic differentials in the country, and hence deriving estimates at lower administrative levels helps to achieve faster and greater reduction of child mortality in the country.

The study aims to achieve three specific objectives. First, it attempts to estimate child mortality rates at municipal, provincial and national levels using the 2011 census data. The direct synthetic cohort method is employed to estimate the rates at national and province level while Bayesian spatial smoothing techniques are used to derive the estimates at municipal level. Second, it assesses the estimates of child mortality in relation to poverty and inequality at different levels after computing measures of poverty and inequality from the census data. Third, it aims to identify important risk factors for child mortality in South Africa and study their impact on child survival using data on children born twelve months before the census date. A three-level logistic regression model is used where child, municipality and province are the first, second, and third levels.

## 1.4 Dissertation organisation

This thesis is divided into five chapters. Chapter 1, the introduction, gives the background of the study, the importance of the study, and the main objectives of the research. The literature on child mortality in South Africa, methods of estimating child mortality and its correlates are presented in Chapter 2. This is where the findings of other studies which are relevant for the research are presented and childhood mortality and its correlates in South Africa are also discussed. Chapter 3 discusses the quality of the 2011 South African census, the methods of child mortality estimations and smoothing used in the research as well as basic techniques of measuring poverty, living standard and inequality. It also discusses the multilevel logistic regression model including the identification of the dependent and independent variables, the methods of estimating the parameters of the model and model adequacy checking. The results of all the analysis with some descriptions are presented in Chapter 4. Finally, Chapter 5 gives a discussion of the results and major conclusions which can be inferred from the results, limitations of the research and scope for future research.

# 2. LITERATURE REVIEW

This chapter reviews the literature on child mortality. It comprises 5 sections. The first section looks at the general overview of child mortality while the second one concentrates on its trends and spatial differentials in South Africa. In the third section, the Mosley and Chen analytical framework and demographic, socioeconomic and environmental factors affecting child mortality are revised followed by definitions and measurement of poverty. Sources and methods of estimating child mortality as well as smoothing techniques are discussed in the last section.

## 2.1 Overview of child mortality

Disparities in health and mortality have been the concern of government and non-government organisations for many years. Various declarations were signed by leaders of nations and representatives of key international organisations to address the issue at different times so that the gap could be reduced at a noteworthy level. The famous declaration in Alma-Ata in 1978 with the goal of "health for all by 2000" (WHO 1978) followed by the Millennium Development Goals (MDGs) in 2000 are the two declarations quoted most frequently in the past three and half decades. Both of these declarations state that health and mortality disparities are politically, socially and economically unacceptable. The MDGs are the current priorities of the United Nations (UN) and require the commitment of member countries to the realisation of eight major goals and eighteen targets by the year 2015. Of particular interest to this study is goal number four that focuses on reducing child mortality by two-thirds between 1990 and 2015. Child mortality is usually monitored using two indicators: Infant mortality – death between birth and first year of life – and Under-five mortality (U5M) – death between birth and the fifth year of life. Child mortality in this research may refer to deaths of infants and under-five children interchangeably though efforts are made to state them explicitly.

The main reason for the greater attention given to infant and child mortality by governments and various organisations is that they are considered to be key measures of a country's health that are crucial to monitor. The rates of infant and child mortality of an area have long believed to be important indicators of health and development. Biologically, children have much weaker immune systems than adults and are therefore far more vulnerable to environmental or social complications (Caldwell 1996). In addition, they are unable to care for themselves and are hence completely dependent on others. As a result, children are generally the group first and most strongly affected by standards of living. Likewise, advances in health or social conditions are often first observed in improvements in child mortality (Omran 1971).

Studies on child mortality have accumulated a huge list of possible determinants, including individual- and community-level factors such as maternal age, race, income, sanitation, water source, electricity, urban/rural residence, region of residence, household composition, occupation, female education, and access to health care (Caldwell 1979; Hobcraft, McDonald and Rutstein 1985; Victora, Wagstaff, Schellenberg *et al.* 2003; Wang 2003; Omariba, Beaujot and Rajulton 2007; Kembo and Ginneken 2009). Some of these factors are also studied in this research and hence, they are discussed in detail in section 2.3.

Child mortality rates vary considerably among different countries and regions of the world. According to estimates developed by UN Inter-agency Group for Child Mortality Estimation (IGCME), under-five mortality rates (U5MR) in 2012 were highest in Sierra Leone, with an estimated 182 deaths per 1000 live births and lowest in Iceland and Luxembourg, where there are fewer than 2.5 deaths per 1000 live births (IGME 2013a). The level of mortality has been found to be highly correlated with the relative development status of a country, with 25 times higher rates in the least developed countries compared to the most developed countries (153 deaths per 1000 children vs. 6 deaths per 1000 children) (WB 2013). This has to do with many other factors, but the role of poverty in provoking mortality is undeniable. For instance, if we consider availability of skill attendant at birth as one factor, UNICEF has reported that the world's poorest children are 2.7 times less likely than the richest ones to have skill attendant at birth (UNICEF 2014). Despite differentials, child mortality rates in the last several decades have declined substantially worldwide with estimates falling globally from 191 deaths per 1000 live births in 1960 to 76 deaths per 1000 live births in 2005 and 48 deaths per 1000 live births in 2012 (IGME 2013a). While every nation has experienced some level of decline, there is a great amount of disparity in the overall amount of decline. For instance, countries such as Turkey, Estonia, and Saudi Arabia have had a greater than 80 per cent decline in rates of child mortality while in countries like Botswana, Zimbabwe, Lesotho and Swaziland where child mortality had been reversed that they have yet to achieve a decline of 10-20 per cent in order to reach the rates evident in 1990. On the other hand, the decline in child mortality has increased since 2005 compared to the decline before 2005. For instance, between 2005 and 2012, there were only six countries with a decline of less than 5% (UNICEF, 2013).

The MDGs have mainly emphasised global level results for monitoring progress rather than the reduction in disparities. However, within-country variation in child mortality has also been well documented, with rates often varying substantially across different regions and social groups (Mosley and Chen 1984; Moser, Leon and Gwatkin 2005). It is said that although global results are vital for assisting policy makers to better prepare for the emerging health needs of populations, they constitute an inappropriate guide for refocusing health priorities (Heuveline, Guillot and Gwatkin 2002). This research, therefore, undertakes childhood mortality analysis in relation to poverty and inequality in South Africa at national, provincial and municipality levels to highlight concentration at lower levels of geography that in turn underscores the ineffectiveness of global indicators for monitoring progress in health achievement.

## 2.2 Review of trends and differentials of child mortality in South Africa

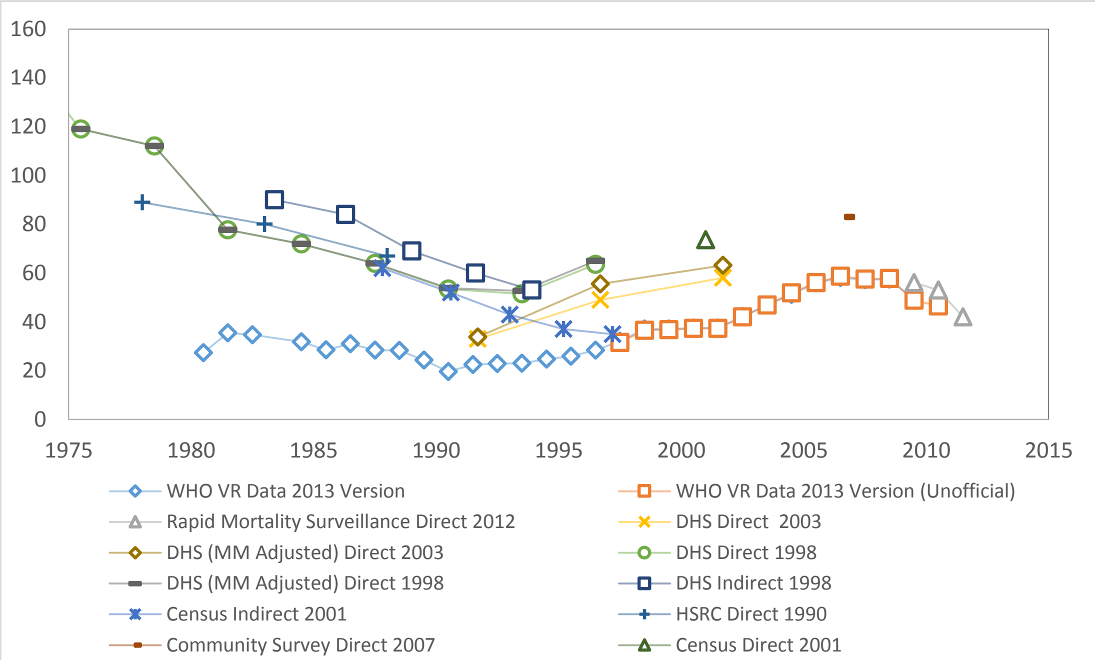
### 2.2.1 Trends in child mortality

Although South Africa has progressed well over the past decade, its child mortality rates are still higher than other countries with similar economic status such as Brazil, China, and Mexico as well as a number of other less developed countries including Namibia, Indonesia, Bangladesh, Philippines and many of the North African countries. South Africa's child mortality rates are, in fact, not far from the rates for Botswana, Rwanda, Tanzania and India – countries whose development indices are far below those of South Africa (WB 2013; UNICEF 2014). Based on historical estimates of child mortality developed by IGME (2013a), South Africa's U5MR in the period 1990-2012 fell from 61 to 45 deaths per 1000 live births. However, the decline has not been consistent as in many other countries or the worldwide pattern. A number of researches have documented that because of the HIV endemic there had been a reversal of child mortality beginning from mid-1990 and lasting to 2005, after which it has started to decline at a higher rate due to the introduction of PMTCT (prevention of mother-to-child transmission) programme (Dorrington, Johnson, Bradshaw *et al.* 2006; Nannan, Dorrington, Laubscher *et al.* 2012; Kerbera, Lawnb, Johnson *et al.* 2013). For instance, based on Stats SA estimates, under-five mortality between 1998 and 2007 had increased from 59 to 67 deaths per 1000 births before it declined to reach a level of 53 deaths per 1000 births in 2010 (StatsSA 2013).

The major problem one might come across in reviewing South Africa's estimates of child mortality as computed by different researchers over time is the diverseness of the estimates. Different researchers have come up with different estimates, even using the same data and similar methods of estimation. Researches, which have attempted to review different studies on child mortality estimation in South Africa (Darikwa 2009; Nannan, Dorrington, Laubscher *et al.* 2012) indicate that the main reason for this problem, is the inadequate and poor quality of data available, especially for the estimates of child mortality before 1996 when there were less nationally representative data. Nevertheless, the problem of data quality still persists, though there are considerable improvements. For example, the total number of children surviving, which is a very important variable for indirect estimation of child mortality, was discarded from the 2011 census data release because of its poor quality (StatsSA 2014b). In addition, it has been reported that in the 2001 census the total number of children born to a woman is under-reported, giving implausible indirect estimates of under-five mortality rates (Dorrington, Moultrie and Timaeus 2004). These two cases from the two most recent censuses suffice to show that data quality is still a major problem in estimating child mortality in the country.

One appreciable source of estimates of child mortality for a country is the database compiled by the Inter-agency Group for Child Mortality Estimation (IGME) which was formed at the initiation of UNICEF, The World Health Organization (WHO), The World Bank and The United Nations Population Division to harmonise the works by the respective organisations in formulating child mortality indicators. They compile countries' data which they deem to be as representative as possible of the prevailing child mortality levels at a given time and use these to derive mortality trends. They use data from different sources including vital registrations, demographic and health surveys, censuses and other surveys. These estimates for South Africa from this database are shown below on Figure 2.1 (IGME 2013b). As noted above, there are significant variations on the estimates, almost every source and method producing different results, which partly depicts the unreliability and poor quality of the data in the country. However, despite the variation, they help to understand the general trend of under-five mortality in the country that the mortality decline had been reversed around 1995 and started declining again from 2005.

**Figure 2-1 Estimates of trends of under-five mortality in South Africa**




Source: UN IGME, 2013a

Other estimates of trends of child mortality for South Africa can be found from Rapid Mortality Surveillance (RMS) and Institute of Health Metrics and Evaluation (IHME). The recent study by IHME reports that the annualized rate of change of under-five mortality in South Africa was 1.4 and -6.1 in the time period 1990-2000 and 2000-2013 respectively (Wang, Liddell, Coates *et al.* 2014). On the other hand, the 2012 RMS report gives an annualized rate of change of 7.8 from 2009-2012 indicating that the rate of decline is much higher in recent years (Dorrington, Bradshaw and Laubscher 2014) .

### 2.2.2 Spatial differentials in child mortality

Child mortality in South Africa is characterised by large spatial differentials which are strongly associated with the level of socio-economic disparities. Geographically, the country is divided into nine different provinces: Western Cape (WC), Eastern Cape (EC), Northern Cape (NC), Free State (FS), Gauteng (GT), North-West (NW), KwaZulu-Natal (KZN), Mpumalanga (MP) and Limpopo (LP); and 234 municipalities, each reflecting broad differences in geography, environment, population, and development. In the poorer provinces like LP and MP, there are relatively low levels of infrastructure development (housing, water, sanitation, electricity, etc.), education and income, higher unemployment rates, and poor health care services (UNICEF 2013; HSRC 2014a). In contrast, in richer provinces like WC and GT there are better infrastructure development, higher income and education levels. Child mortality rates in the poorer provinces are usually estimated to be very high compared to the richer provinces.

In reviewing the studies on spatial differential of child mortality in the country, differentials at province level are better studied by several researchers than differentials at municipal level or other lower geographical units. The work by Dorrington, Timaeus, Moultrie *et al.* ( 2004) reports provincial estimated trends of U5M rates from 1986 to 1996 using the 1996 census. Over the period considered, the lowest and highest mortalities were recorded in WC and EC respectively. The estimate for boys per 100 live births varied from 44 in WC to 114 in EC in 1986, while in 1996 it varied from 47 in WC to 102 in EC. Similarly, the estimates for girls, respectively for WC and EC, were 30 and 107 in 1986 and 32 and 87 in 1996. In their review of available empirical data on levels and causes of child mortality in South Africa in the period 1997-2007 Nannan, Dorrington, Laubscher *et al.* (2012) also show the trends of provincial estimates of infant mortality rates over the time period. It is indicated that in each of the provinces infant mortality was mostly increasing and in some provinces, such as FS, NW, MP and GT, the rate was much higher (above 50 deaths per 1000 live births).

One comprehensive source of national and provincial estimates of child mortality is the HIV and demographic model developed by the Actuarial Society of South Africa (ASSA). The table below (Table 2.1) presents the trends in U5M rates for the country and each province based on the 2008 version of the model (ASSA 2010). It can be observed that under-five mortality rate in EC, FS, KZN and MP had been consistently higher as compared to the rates in the other provinces. One can also note from the table that child mortality was increasing in 2000 before it has started to decline in 2005 in all the provinces due to the HIV endemic as indicated previously for the national estimates.

**Table 2-1 Trends of provincial estimates of U5MR (per 1000 births)**

| | 1990 | 1995 | 2000 | 2005 | 2010 | 2015 |
|---|---|---|---|---|---|---|
| EC | 95.9 | 84.7 | 92.2 | 89.7 | 67.7 | 59.6 |
| FS | 76.1 | 74.0 | 86.1 | 83.9 | 60.2 | 53.5 |
| GT | 33.7 | 41.3 | 54.4 | 51.6 | 38.0 | 33.7 |
| KZN | 79.6 | 78.4 | 95.6 | 91.9 | 64.5 | 57.8 |
| LP | 51.2 | 50.0 | 55.5 | 56.7 | 40.6 | 36.6 |
| MP | 73.2 | 68.3 | 81.9 | 83.5 | 57.7 | 49.6 |
| NC | 49.9 | 45.1 | 51.2 | 44.2 | 38.2 | 32.2 |
| NW | 53.9 | 55.5 | 68.9 | 67.8 | 45.9 | 40.9 |
| WC | 42.7 | 36.2 | 41.1 | 34.1 | 27.4 | 23.1 |
| SA | 66.3 | 62.5 | 72.0 | 69.5 | 49.9 | 44.8 |

Source: ASSA model 2008

Unlike the number of studies at national and provincial levels, the researches on measuring child mortality at lower geographical levels are very limited. One comparable attempt with this research is by Bangha and Simelane (2008), who have used the 2001 census data to map the spatial distribution of under-five mortality at magisterial district (MD) level. They have found a significant extent of differentials in CM among MDs. For instance, based on their computation, U5M rate per 1000 births among MDs ranges from 5.6 to as high as 108.5. However, it seems that they have somehow under-estimated the CM level in general. For example, it is very unlikely that provincial U5M rate in 2001 ranges from as small as 19 deaths per 1000 births in WC to only 66 deaths per 1000 births in EC as they have reported. In another study, marked geographical differentials of infant mortality is observed among provinces, districts and sub-districts (Sartorius, Sartorius, Chirwa *et al.* 2011). Especially, the Bayesian Poisson model containing only a constant and the conditional autoregressive parameters is fitted to estimate standardised mortality ratio (SMR) of infant deaths in the sub-districts of South Africa using the 2007 community survey data.

## 2.3 The Mosley and Chen analytical framework and factors associated with infant and child mortality

Mortality of children has been explained by different theories such as the social and economic explanation, the public health explanation, and the Mosley and Chen analytical framework (Mosley and Chen 1984). The Mosley and Chen framework is the most accepted framework for the study of child morbidity and mortality in the developing world, where the levels of infant and under-five mortality are high. The basis for this framework is that social and economic factors have to operate through the set of proximate determinants in order for them to have an impact on child mortality (Mosley and Chen 1984). The framework combines the methodologies of social and medical science and provides a better understanding and a clearer distinction between the causes of diseases and the causes of deaths.

The approach to the study of child survival is based on the following 5 premises by Mosley and Chen (1984). First, in order for a society to progress, in an optimal setting over 97 per cent of children born in the country or society must survive the first 5 years of life. This is most unlikely, particularly in the developing world, where health hazards and infectious diseases are still prevalent. The second premise is that improvement in child survival probabilities in any society is due to the operation of social, economic, biological, and environmental factors. In the third premise, Mosley and Chen further emphasise that the socioeconomic factors must operate through the set of proximate determinants to directly influence the risk of diseases and the outcome of diseases. The fourth premise is that the specific diseases and nutrient deficiencies observed in the surviving population should be regarded as indicators of the operations of the proximate determinants. The fifth and final premise is that several disease processes may eventually lead to child mortality.

Mosley and Chen then identified a set of proximate determinants that directly have an impact on the morbidity and mortality of children. The factors are then grouped into 5 categories: Maternal factors (age, parity and birth interval), environmental contamination (air, food/water/fingers, skin/soil/inanimate objects, insect vectors), nutrient deficiency (calories, protein, micronutrient, vitamins and minerals), injury (accidental, intentional); the last category is personal illness control (personal preventive measures, medical treatment). It is within this framework that many studies on child mortality and its correlates have been carried out. This study also follows this framework but based on the following classifications. Note that in the specific case of South Africa, one need to consider also the impact of HIV.

### 2.3.1 New-born demographic factors

Infant and child mortality differential by sex of the child is a well-recognised fact (Hill and Upchurch 1995; Mustafa and Odimegwu 2008; Kembo and Ginneken 2009; Boco 2010). The probability of male children dying is higher than that of female children. This is particularly common in societies in which there is less gender discrimination, like

South Africa (Kaufman 1997), unlike the situation in India and some other Asian countries where females are disadvantaged (Singh, Hazra and Ram 2007). Using 35 countries' DHS data, Hill and Upchurch (1995) indicated that higher mortality rates for male children as compared to their female counterparts is a common phenomenon in most populations. Their results show that in most of the countries studied, girls have a significant survival advantage over boys for both infants and under-five children. However, the differential in mortality between boys and girls is more apparent during the first month of life than afterwards (Hobcraft, McDonald and Rutstein 1985). A small difference of infant and child mortality between boys and girls is observed in South Africa and Zimbabwe from studies by Kaufman (1997) and Kembo and Ginneken (2009) respectively. After controlling various maternal, socioeconomic and environmental determinants, the risk of infant and mortality of boys is slightly higher than that of girls.

The age of the child is also another demographic factor associated with the mortality of children. It has been studied by many scholars on the subject that mortality falls with the age of the child.

### 2.3.2 Maternal factors

Among the proximate determinants of child mortality related to the characteristics of the mother, researchers have focused on demographic factors such as age of mother at child's birth, parity, and preceding birth interval, and socio-economic factors including level of education, and employment status (Hobcraft, McDonald and Rutstein 1985; Kabir, Islam, Ahmed *et al.* 2001; Omariba, Beaujot and Rajulton 2007; Kembo and Ginneken 2009; Boco 2010).

For instance, the study by Kabir, Islam, Ahmed *et al.* (2001), using the 1993/4 Bangladesh DHS data, with a primary objective of determining important factors affecting infant and child mortality discovered that the risk of child survival at infancy and post infancy is much higher among women who are older than 16 years relative to younger women, and that the effect is more pronounced on infant mortality than child mortality. Similar results are found by Kembo and Ginneken (2009) in Zimbabwe in their study of factors associated with infants and child mortality in the country. After controlling for some socioeconomic, environmental and maternal determinants, a 13.2 and 41.6 per cent higher child and infant mortality risks are found for children born from women aged 30-39 years in comparison with children of women aged less than 20 years. The risk of infant mortality, however, is 8.1 per cent lower for children of women aged 30-39 years relative to children of women aged 40-49 years while the risk of child mortality is higher by 73.8 per cent. Another study by Hobcraft, McDonald and Rutstein (1985), where 39 world fertility surveys were used found that mortality is higher among children of younger women (teenage mothers), particularly mortality before age two. The study found no evidence of higher risk of mortality among children of older women as has been found in other studies. In contrast, in a study on the determinants of infant and child mortality in Kenya, using the 1998 DHS, Omariba, Beaujot and Rajulton (2007) indicate that the risk of dying at infancy is higher for children born to older women (35+ years). These children have an about 33 per cent higher risk of dying relative to infants born to women aged 20-24 years. The relative risk of child mortality is 35 per cent higher among children born to teenage mothers compared with children of mothers aged 20-24 years. All findings point to a higher risk of dying for infants and older children of teenage mothers when compared with children born to older mothers. According to Kabir, Islam, Ahmed *et al.* (2001), teenage mothers are faced with high risk of their children dying probably due to biological complications as they are more likely to give birth to underweight children. As Mosley and Chen (1984) have indicated, mothers have to have proper skills, and be able to take proper care of themselves and their children, which is not likely to be the case with younger women.

Short birth interval is also considered as a determinant of child mortality because it obviously makes mothers stop breastfeeding at earlier time which has a significant contribution to a higher risk of mortality (Hobcraft, McDonald and Rutstein 1985). In addition, the short interval may have an effect on the next child since women who give birth within short preceding birth intervals may not have sufficient time to restore their nutritional reserves (Mondal, Hossain and Ali 2009). This implies that when there is maternal depletion caused by pregnancies and lactation, the survival chances of children are reduced and that a child born after a short interval is likely to be born with low birth weight, which is one of the factors associated with poor survival of a child, especially at early ages. According to Hobcraft, McDonald and Rutstein (1985), births that occur within 24 months of the index births are associated with higher risk of dying than births that happen beyond two years

Rustein (2005, 2008) has studied the impact of preceding birth interval on neonatal, infant and under-five mortality using 17 developing countries' DHS data and found a negative relationship between the risk of dying at neonatal, infant and child ages and the length of the preceding birth interval. In the countries studied neonatal and infant mortality respectively are about 55 and 58 per cent higher when the birth interval is between 18 and 23 months relative to when the interval is 36-47 months.

The combined effect of birth order and birth interval was also studied by some researchers including Mustafa and Odimegwu (2008) and Kembo and Ginneken (2009). The identified correlation is that higher birth order children with short preceding birth intervals tend to have a lower chance of survival than children of lower birth order. However, infants are more affected by higher birth order with short preceding birth interval than children older than one year.

### 2.3.3 Socioeconomic factors

The relationship between child mortality and socioeconomic factors has been studied by many researchers (Cleland 1990; Hobcraft 1993; Sastry 1996; Wagstaff 2000; Bawah and Zuberi 2005; Mustafa and Odimegwu 2008). The socioeconomic factors considered in this research as adopted from the Mosley and Chen (1984) framework are mother's level of education, place of residence, employment status of the mother, income poverty of the mother.

Mother's education is considered to be the most socioeconomic variable affecting child survival. It may affect child survival by influencing her choices and improving her skill on contraception and other health care practices. The relationship has gained the attention of many researchers. An increased chance of survival can even be associated with a small increase on amount of education of mothers ((Hobcraft 1993). Cleland (1990) indicates that the improvement of child survival due to mother's education is because of the modest effect of education on health knowledge and beliefs. As births to teenage mothers are associated with a high risk of mortality at the early ages of the child, mother's education has an advantage by delaying the age at first birth. It may also be related to factors that form and change the economic choices and health-related practices of individuals. Some studies, however, have shown that the degree of association in Sub-Saharan Africa is weaker than in other regions. Hobcraft (1993) suggests that the reason for this is the weak health infrastructure in the sub-continent.

Studies have found that the risk of death of children is lower in the urban areas compared with the rural areas (Kabir, Islam, Ahmed *et al.* 2001; Kembo and Ginneken 2009). This is the general expectation considering that the level of development is more advanced for urban than for rural areas. However, there are some studies that have found contradictory results, where children in rural areas have the lower risk of dying than their urban counterparts (Manda 1998). However, such findings are quite unusual considering that urban areas are associated with better socioeconomic and environmental factors that contribute to the reduction of child mortality.

The employment status of the mother can affect child survival in both directions. It may prevent her from giving care for the child including breastfeeding and hence, the child's survival be negatively affected (Hobcraft, McDonald and Rutstein 1985). For instance, in India greater child loss is experienced among working mothers than non-working mothers (Kishor and Parasuraman 1998). On the other hand, a working mother helps her family by increasing the household income, which may increase the likelihood of survival of the child.

Poverty can also be considered as one socioeconomic factor having a detrimental impact on the survival of children. It plays a major role starting from pregnancy-related complications to later childhood health problems, and its greater risk among poor children relates to their greater exposure to multiple risk factors. Many studies have documented that poverty affects infant and child health and mortality in developed and developing countries (Barker 1992; Aber, Bennett, Conley *et al.* 1997; Spencer 2004; 2008; Olson, Diekema, Elliott *et al.* 2010). The rapidly growing children seem to be particularly more vulnerable to the adverse effects of poverty than adults (Penn 2005). The researches show that children from poor families are more likely to be exposed to the risks of health problems and mortality. Malnutrition, inadequate water and sanitation, environmental pollution, poor housing and insufficient health care are most of the problems which increase the likelihood of death of children in poor families. Poverty also plays a major role in pregnancy outcomes, such as preterm birth and low birth weight, stunting and underweight in early childhood – all of which greatly affect the survival status of the children (Spencer 2008; Santos, Matijasevich, Domingues *et al.* 2009).

Substantial socio-economic disparities lie behind the challenges faced by children in South Africa where there is huge gap between rich and poor and child poverty is far higher than that of the general population (UNICEF 2013). The National Planning Commission estimated that 39% of people in South Africa live below the R432 per person per month poverty line (National Planning Commission 2011) while approximately 66% of children in the country live in poverty, with a monthly household income of less than R1200 per month (Whiting 2013). Moreover, according to the report by UNICEF, the percentages of children living in poverty using R575 per month as poverty line were 73, 64 and 60 respectively in 2003, 2008 and 2010 (UNICEF 2013). This report also revealed provincial poverty levels as: LP (80.1%), EC (77.5%), KZN (73.1%), MP (71.5%), FS (69.4%), NW (68%), NC (67.3%), WC (38.7%), and GT (38%), showing how big is the poverty differentials among provinces. In a recent report by Human Science Research Council (HSRC 2014a), it is also indicated that currently the poorest provinces are LP, EC and KZN, and hence they attract particular emphasis.

The overall trend of income distribution and poverty for the period 1993-2004, as studied by Leibbrandt, Woolard, Finn *et al.* (2010), indicates that using R3000 per capita income per year as poverty line, the proportion of poor people in the country had decreased from 40.6 per cent in 1993 to 33.2 per cent in 2004. In a latest report released by Statistics South Africa (StatsSA 2014a) the percentage of the population that is poor has decreased from 57.2 per cent in 2006 to first 56.8 per cent in 2009, and then to 45.5 per cent in 2011, using inflation-adjusted poverty lines of R431, R577 and R620 (monthly per capita income) respectively for 2006, 2009 and 2011. This report shows that the level of poverty in the country is still very high, although it is declining to some extent. Even though South Africa has the largest economy on the continent, 45.5 per cent of its people live on less than 2 dollars each day. The impact of this on children's health is undeniable, based on the evidences discussed in the first paragraph of this section.

Poverty may also impact child mortality through HIV/AIDS which is the most frequently quoted reason for the death of children in the country. This is because an increase in poverty exacerbates the spread of HIV, hence triggering more deaths of children. On the other hand, besides its being the primary cause of death, an increase in HIV/AIDS also causes the deaths of more children by aggravates poverty. One may see Ganyaza-Twalo and Seager (2005) for a detailed literature review of the two-way link between poverty and HIV/AIDS.

### 2.3.4 Environmental factors

The environment in which the child lives has long been considered to have an impact on its survival status. Commonly, factors related to the environment are: dwelling type, source of drinking water, type of toilet facilities, access to electricity, material floor made of, etc. Environmental contamination is one of the proximate determinants of child mortality outlined by Mosley and Chen (1984). Various studies have included household environmental variables as determinants of infant and child mortality, and have found strong association (Kabir, Islam, Ahmed *et al.* 2001; Bartlett 2005; Kembo and Ginneken 2009; Kazembe, Clarke and Kandala 2012). However, such researches found out that environmental factors may not have an independent effect on childhood mortality but are influenced by some socioeconomic factors.

In most researches, environmental factors are captured by different indicator variables which are then aggregated as an index containing the combined information using multivariate statistical technique. This latent variable generated is supposed to capture the most relevant information concerning the environment within which the child lives. For the purpose of this research, one such index is computed as a measure of living standard of households from sets of physical characteristics of household (see Section 3.4.2).

Another important environmental factor which might have impact on the survival of children is the level of inequality of in the community. Studies shows that besides the level of poverty, child mortality is also associated with the distribution of income in both developed and developing countries (Flegg 1982; Waldmann 1992; Judge 1995; Wilkinson 1995; Wagstaff 2000; Rodgers 2002; Olson, Diekema, Elliott *et al.* 2010). A significant association of infant mortality and income distribution in 59 developing countries is found in the study by Flegg (1982). Similarly, based on the analysis of data from 70 countries Waldmann (1992) found that, the rise of infant mortality is associated with 5 per cent increase of income of the richest 5 per cent of the population, keeping the incomes of the poorest 20% constant.

South Africa is known to have a very high level of income inequality characterised by huge racial differentials and evidences show that inequality is still on increasing trend even in the post-apartheid period (Van der Berg and Louw 2004; Leibbrandt, Woolard, Finn *et al.* 2010; StatsSA 2014a). Based on the computation by Leibbrandt, Woolard, Finn *et al.* (2010) the Gini index[1] for the country has increased consistently from 0.66 in 1993, to 0.68 in 2000 and 0.70 in 2008. On the other hand, Statistics South Africa has estimated the Gini index for 2006, 2009 and 2011 to be 0.72, 0.70 and 0.69 respectively – indicating a small decline but still showing a very high degree of inequality. This persistent increase is also for all population groups. The impact of this rising inequality in mortality in general, however, has not been studied so far. As part of this study, an attempt will be made to assess the relationship between child mortality and income inequality as measured by Gini index at national, provincial and municipal levels.

### 2.3.5 HIV and child mortality

HIV is one of the major factors for the reversal of child mortality decline in Sub-Saharan Africa and its impact has been studied by various researchers (Ng'weshemi, Urassa, Usingo *et al.* 2003; Zaba, Marston and Floyd 2003; Dorrington, Johnson, Bradshaw *et al.* 2006; Wang, Liddell, Coates *et al.* 2014). In addition to the direct effect, HIV can also affect child mortality indirectly through maternal HIV infection. If the mother dies of HIV, even if the child is not infected, the fact that the child will be an orphan increases the risk of dying by severely affecting child's health (Ng'weshemi, Urassa, Usingo *et al.* 2003). The main problem in studying the impact of HIV on mortality, as indicated by Zaba, Marston and Floyd (2003), is that determining by how much the epidemic is affecting mortality of children, i.e. disentangling the exact share of HIV from other background causes of death. Despite this, some studies have attempted to quantify children deaths due to HIV/AIDS. For example, analysis for the 2013 Global Burden of Disease study indicates that HIV/AIDS has resulted in a 32 400 under-five deaths worldwide from 1990 to 2013 (Wang, Liddell, Coates *et al.* 2014). The 2012 Rapid Mortality Surveillance report shows that the number of reported deaths of children in South Africa due to HIV and related cause are much lower than expected (Dorrington, Bradshaw and Laubscher 2014).

1 Gini index/coefficient is a widely used measure of income inequality that condenses the entire income distribution into a single number between 0 to 1; the higher the number the greater the inequality. See Section 3.6.3 for more description.

## 2.4 Definition and measurement of poverty and inequality

The definition of poverty may be expressed in terms of a 'poverty line' by reference to the amount of money (income) required to circumvent poverty or using a set of poverty indicators (in terms of consumption). These are respectively sometimes referred to as indirect and direct definitions of poverty (Ringen 1988). In the direct case, the set of poverty indicators identified are usually combined to create an index, called wealth or living standard index (Deaton 1997). There are, however, strengths and weaknesses with both approaches to defining poverty.

Despite the controversies on the definition, absolute and relative poverty lines are two typical poverty thresholds in measuring poverty (Ravallion 1998). Absolute poverty lines define income thresholds below which people are unable to purchase a bundle of goods and services thought to be an essential part of the basic necessities of life in the society in which they live (Deaton 1997). Relative poverty lines, on the other hand, are ideally defined with reference to a measure of typical consumption levels or against household income. For example, in South Africa a per capita monthly income of R515 is usually used as absolute poverty line (Leibbrandt, Woolard, Finn *et al.* 2010; Finn, Leibbrandt and Levinsohn 2012) while the relative poverty line is often set at the level that includes people living below 40% of national income, with those living below 20% as being very poor (SPII 2007). The final Copenhagen Declaration of the World Summit for Social Development in 1995 banned the concept of relative poverty and suggested a new and comprehensive definition of absolute poverty (UN 1995:41) as

> "----- a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information. It depends not only on income but also on access to social services."

Once the poverty line is set, it is possible to work out different measures of poverty of a country or a region including poverty headcount ratio and poverty gap. 'Poverty headcount ratio' (PHCR) is the proportion of population that lives below the poverty line, while 'poverty gap' is the average shortfall from the poverty line expressed as a proportion of the poverty line; that is the average amount of money required by the population to be non-poor.

Defining inequality among societies is relatively hard compared to the definition of poverty (Field 2001). It requires the identification of a welfare measure to be used for computation of inequality and an appropriate procedure or method of computing a single statistics for comparing societies. In this research, as it is the case in most researches, income is used as a welfare variable and Gini index is taken as a method of determining the level of inequality (see Section 3.6.3). Detail discussion on meaning and measurement of inequality can be referred in Field (2001) or (Deaton 1997)

## 2.5 Methods of estimating child mortality

### 2.5.1 Data sources for estimating child mortality

The three common sources of data for child mortality estimation are vital statistics, sample surveys and censuses. Among these, the incompleteness of a vital registration system in developing countries makes such sources of data unsuitable. In most cases, large-scale nationally representative surveys like the Demographic and Health Surveys (DHSs), which include detailed birth histories of women, are the main options in countries where the vital registration system is very weak. For instance, a number of studies have used the 1998 and 2003 South African DHSs in order to estimate child mortality in the country. The main limitation of such surveys, however, is that they are not representative at lower geographical areas such as districts and municipalities. Therefore, census is the preeminent alternative to compute mortality rates at lower geographical areas in the absence of complete vital registration system. There are two reasons for this: first census covers every administrative area (it includes all municipalities at least) and second, it has a far greater sample size than sample surveys for better statistical analysis (the 10 per cent census data has much more observations than the whole data from DHS or any other big survey).

### 2.5.2 Direct and indirect methods of estimating child mortality

By using census data, child mortality can be estimated following different approaches depending on the type of questions asked in the census. The most commonly used method in developing countries is the Brass 'children ever born/children surviving' technique which requires information on total number of children born and total number of surviving children by age of mothers in a 5-year age group (Moultrie, Dorrington, Hill *et al.* 2013). The procedure of determining the mortality rates in this approach involves determining the proportion of children who have died in each age group and multiplying the proportion by appropriate correction factors derived, based on the fertility patterns of the population.

The other approach is direct computation of mortality rates from household deaths occurred some period of time, usually 12 months, before the census night as reported by households. This method of estimating child mortality rates requires data on the date of birth of every child, their survival status and the date of death or age at death for those children who have died (Moultrie, Dorrington, Hill *et al.* 2013). The synthetic cohort life table approach, which is used in this research, determines the probability of dying between birth and certain age from the mortality experiences of a real cohort. The infant and under-five mortality rates are estimated by generating a complete life table up to age 5.

Given the number of deaths of children aged x in that year, $D_x$, and the corresponding mid-year population, $P_x$, it is possible to compute the central death rate ${}_1M_x = D_x / P_x$ and convert these rates to probability of dying between ages $x$ *and* $x+1$ denoted by ${}_1q_x$ for $x = 0, 1, 2, 3, 4$ using different approaches. Infant and under-five mortality rates can then be computed easily from the life table constructed. However, the infant mortality rate, an approximate value of the probability of dying between birth and age one $({}_1q_0)$ is commonly approximated by the ratio of total number of deaths under age one to the total number of births occurred in the same periods. This is because census counts are particularly inaccurate at the younger ages (Siegel and Swanson 2004).

In the case of South Africa, all the three most recent censuses conducted in 1996, 2001 and 2011 have incorporated summary birth history questions from which child mortality rates would be estimated indirectly using the Brass method. In addition, the 2001 and 2011 censuses have included questions about deaths happened in households 12 months prior to respective census dates for direct estimation of child mortality. However, the number of children born to women of reproductive age in the 2001 census is found to be under-reported significantly resulted in inflated estimates of under-five mortality rates (Dorrington, Moultrie and Timaeus 2004) Furthermore, the number of surviving children to a woman reported in the 2011 census was not released with the 10 per cent unit level record as it was deemed to be problematic (StatsSA

2014b). Therefore, this study uses the household death data of the 2011 census for direct estimation of child mortality rates at different geographical levels. This has the added advantage of obtaining more recent estimates of child mortality than estimates we would have obtained from Brass indirect estimation method using summary of birth histories data.

### 2.5.3 Spatial smoothing techniques

One of the main concerns in estimating mortality at smaller geographical areas is that the number of events/deaths would be too small so that the estimates might be unstable or unreliable (Waller and Gotway 2004; Lunn, Jackson, Best *et al.* 2013). Especially in less populated areas a few child deaths can result in a big change on the mortality estimates as these rates have higher variances. One way of improving the quality of estimates in such cases is employing spatial smoothing techniques. In this regard, a variety of spatial smoothing methods have been suggested which make use of data values of neighbouring areas. A simple approach of smoothing a given rate in an area is to determine a local mean or median from each observation in that area and its neighbours (Waller and Gotway 2004). The method of adopting this approach is called locally weighted averages spatial smoothing (LWASS). A spatial weights object is used to specify the neighbourhood relationships among observations. Neighbourhood relationships may be defined based on distance, areas that fall within a certain distance from the centre of the area; or adjacency, areas which are physically connected with the area of interest. Another method of spatial smoothing is through nonparametric regression (NPR). It helps to estimate rates by fitting a nonparametric regression model instead of simply computing an average. The most commonly used method of such type is called locally weighted polynomial regression (LWPR), which uses the values of the independent variables from neighbourhood areas (Cleveland and Devlin 1988).

The last method of spatial smoothing is Bayesian spatial smoothing (BSS), which relies on the concept of Bayesian statistics, an emerging discipline in modern statistics. The basic principle of Bayesian statistics is that rather than relying entirely on the observed data, stronger and more stable measures can be obtained by combining the data with some additional information known in advance, called priori information. In other words, given both the data (expressed as likelihood function) and some prior information for the parameters of interest, the method attempts to generate a conditional distribution, known as posterior distribution, which can be used to make the inferences.

To specifically illustrate the link among the concepts of prior, likelihood and posterior functions as described by Waller and Gotway (2004), let the vector of data be $\mathrm{Y} = (y_1, y_2, \cdots, y_n)$ and a corresponding model parameters $\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_k)$. If we allow $f(.)$ to denote a general probability density function, we have

$$\begin{aligned} prior &= f(\pi) \\ likelihood &= f(\mathrm{Y} \mid \pi) \\ posterior &= f(\pi \mid Y) = \frac{f(\mathrm{Y} \mid \pi) f(\pi)}{C} \end{aligned} \tag{2.1}$$

where

$\mathrm{C} = \int f(\mathrm{Y} \mid \pi) f(\pi) d_\pi$ denotes a normalising constant to ensure that the posterior density integrates to 1. One may refer to the texts by Carlin and Louis (2000), Gelman, Carlin, Stern *et al.* (2004) or Gill (2002) to have a thorough understanding of Bayesian inference and its applications. The theoretical detail of Bayesian statistics is beyond the scope of this research and it suffices to note that incorporating the prior information provides a much more complete picture of uncertainty in the estimation of unknown parameters than relying only on the likelihood function.

In applying Bayesian techniques to spatial smoothing, priors are derived from data in other areas based on the assumption of spatial autocorrelations. The resulting posterior distribution obtained is characterised by a compromise between the estimates in each area and the estimates in neighbouring areas.

Assume that the number of children died $y_i$ represent a random variable, each following a binomial distribution with parameters $\pi_i$, risk of dying (probability) and $n_i$, total number of children in the area. Given this, we have

$$y_i \mid \pi_i \overset{ind}{\sim} Binomial(n_i, \pi_i) \tag{2.2}$$

Under this model, we are assuming that $y_i$ are conditionally independent given $\pi_i$. This does not mean that the $\mathrm{Y_i}$ are mutually independent; rather, it implies that any spatial correlation observed in the Yi is a function of a spatial trend in either the population sizes $n_i$ or the risks, $\pi_i$. Since the Yi are conditionally independent given the $\pi_i$ parameters, the likelihood takes a particularly simple form as the product of the conditional distribution given in equation (2.4) across all areas $i = 1, 2, \ldots, k$

A Bayesian analysis treats the $\pi_i$ as random variables and a prior distribution must be defined for each $\pi_i$. The prior mean and variance of $\pi_i$ respectively can be denoted by $E_\pi(\pi_i) = m_{\pi_i}$ and $Var_\pi(\pi_i) = \upsilon_{\pi_i}$ (Marshall 1991), while from equation (2.2) the conditional mean and variance of each observed rate of mortality of each area, $r_i$ are

$$\begin{aligned} E(r_i \mid \pi_i) &= E[(y_i / n_i) \mid \pi_i] = \pi_i \\ Var(r_i \mid \pi_i) &= Var[(yi / n_i) \mid \pi_i] = \pi_i / n_i \end{aligned} \tag{2.3}$$

The unconditional mean and variance of the rate observed in area i, $r_i$ can be determined as follows where $E_r$ and $E_\pi$ $/Var_r$ and $Var_\pi /$ denote expectation /variance/ with respect to the marginal distribution of r and π respectively.

$$\begin{aligned} E_r(r_i) &= E_\pi E(r_i \mid \pi_i) = E_\pi(\pi_i) = m_{\pi_i} \\ Var_r(r_i) &= Var_\pi(\pi_i) + E_\pi(\pi_i / n_i) = \upsilon_{\pi_i} + m_{\pi_i} / n_i \end{aligned} \tag{2.4}$$

The best linear Bayes estimator of $\pi_i$ can then be derived by minimising the expected total squared-error loss (see Marshal 1991)

$$\hat{\pi}_i = m_{\pi_i} + C_i(r_i - m_{\pi_i}) = C_i r_i + (1 - C_i) m_{\pi_i} \tag{2.5}$$

where

$C_i = \upsilon_{\pi_i} / (\upsilon_{\pi_i} + m_{\pi_i} / n_i)$, called the shrinkage factor, is the ratio of the prior variance to the data variance. It measures by how much the crude rate $r_i = y_i / n_i$ "shrinks" towards the prior mean. One can easily note that the estimator given above is a weighted average of the crude estimate and the prior mean. However, in order to compute the estimates, the values of $m_{\pi_i}$ and $\upsilon_{\pi_i}$ must be determined. In this regard, there are two approaches: empirical and full Bayesian spatial smoothing approaches (EBSS and FBSS). In EBSS these unknown parameters are estimated from the data itself; for example, by assigning the same prior mean and variance for all areas (Marshall 1991). In FBSS, however, the parameters of the prior distribution are considered to be random variables by themselves with their own distributions, resulting in a hierarchical model where the first level of the model is defined by the observed data itself and the second level of the model, the prior distribution, defines spatial dependency between nearby areas through its hyper-parameters (Bernardinelli and Montomoli 1992). In the third level of the model, hyper-prior distributions for the hyper-parameters are defined. The hyper-prior distributions provide information on prior belief about how similar neighbouring areas should be. As Bernardinelli and Montomoli (1992) indicated, the inclusion of this additional uncertainty about the prior distribution allows for the calculation of credibility intervals which can be used to assess confidence in the estimates.

Despite the advantages of using Bayesian inference, the process of constructing posterior distribution has been a big challenge due to the complex nature of the function to integrate. However, with the advent of a sampling method known as the Markov Chain Monte Carlo (MCMC) which was developed in 1990s together with the great development of computing technology, it is possible to simulate a posterior distribution (Gill 2002; Ntzoufras 2009). The Markov chain is a series of random states wherein each future state is only dependent on the current state and is independent of any past states, known as the Markov property. The Monte Carlo specification, on the other hand, helps to create a set of simulated values that share the same distributional property as the posterior distribution and describe it by using empirical summaries of these simulated values.

In using MCMC to simulate a posterior distribution, a Markov chain consists of a set of states in which each state contains a value for the parameter of interest. The chain begins in a starting state (defined by an initial probability distribution) and then moves successively to additional states. After a number of steps, the Markov chain should eventually stabilise so that the value of the parameter in each successive state is determined only by the current state and a probability distribution defined by the combined effect of the data and prior distribution. Once the posterior distribution has been effectively simulated, it is then possible to sample values from the Markov chain which accurately represent the values from the posterior distribution (Besag, York and Mollie 1991).

There are several MCMC methods that can be used to simulate samples of the posterior distribution of which, Gibbs sampling is the most common that has been used for over two decades. Gibbs sampling consists of assigning starting values for all parameters. In the first iteration, the first parameter is assigned an "updated" value obtained by randomly sampling the conditional probability distribution given the values of all other parameters and the observed data/prior distribution (Besag, York and Mollie 1991; Gill 2002; Ntzoufras 2009). Next, the second parameter is also assigned a new value sampled from the probability distribution given the new value of the first parameter, the starting values of the other parameters, and the data. This process continues until all parameters have been assigned new values resulting in the completion of one Markov chain. Then, in the next iteration, the first parameter is given a new value dependent, again, on the probability distribution, the data, and the new values assigned to all the other parameters in the first iteration. This process continues until eventually the chain converges so that the values of all parameters are determined by the combined effect of the observed data and the probability distribution, the prior distribution.

The use of EBSS or FBSS is very common, especially among public health researchers usually to smooth disease or mortality rates. There are, however, relatively fewer works by demographers partly because demographers are generally more interested on national level estimates of demographic rates than at lower geographic areas. To name some of the works, Potter, Schmertmann, Assunção *et al.* (2010) have successfully mapped fertility rates in Brazil at municipal level using the Bayesian approach. In the same country, McKinnon (2010) in her study of child mortality, has applied FBSS technique to smooth municipal level estimates of under-five mortality originally computed by applying Brass's 'children ever born/children surviving' method. She has also attempted to improve the estimates by incorporating the average years of education of women living in the municipalities as a predicator of child mortality in addition to the estimates generated by considering only spatial autocorrelation.

# 3. DATA AND METHODS

## 3.1 Data source and data quality assessment

The study uses data from the 10 per cent unit record of the 2011 *de facto* population and housing census of South Africa which was the third census to be conducted in the country after the instauration of democracy. The main objective of the census was to provide statistics on population, demographic, social, economic and housing characteristics (StatsSA 2014b). Based on the location of persons on the census night (9/10 October 2011), three types of questionnaires were used for three specific target groups: the population in a household set-up, the population in collective living quarters such as old age homes, prisons, hospitals, and the population in transit (departing/leaving the country). The population in a household set-up forms the basis for planning and service delivery. The household questionnaire was therefore designed to collect comprehensive information from this group. The 10 per cent sample data consists of data on Demographics, Migration, General health functioning, Parental survival and income, Education, Employment, Fertility, Household characteristics and Mortality variables.

### 3.1.1 Reported household death data

The mortality data at household level is obtained using responses to section *I* of the household questionnaire of the census. Respondents were asked if there had been a death(s) in the household in the past 12 months between 10 October 2010 and 9 October 2011. If they respond 'yes' then they were to provide information on the month and year of death, the sex and age of the deceased at the time of death and the cause of death. Based on an assessment report on household deaths released by Stats SA together with the 10 per cent sample data, there were a significant under-reporting of deaths due to one or more of the following reasons: respondent fatigue, sensitivity of the mortality questions, poor training strategy and lack of supervision during data collection (StatsSA 2014b). Hence, the variables of interest: age at death, month of death, year of death and the sex of the dead child, had in some instances missing and implausible non-missing responses. These were edited by Statistics South Africa and it is not possible to look at the significance of the impact of the editing procedures on the quality of the data as the final data released do not show the records which were imputed or deleted.

Considering the 10 per cent sample census data released by Stats SA, there are 5 119 (un-weighted) reported deaths of children under the age of 5 years, which represent 58 208 household deaths in the South African population after applying the given household weights to scale up the sample to the population as a whole. It is reported that 2.6 per cent of the deaths have ages labelled as inconsistent and hence they are imputed for the purpose of this research. The procedure followed for imputation is to apportion the total inconsistent ages according to the age distribution and randomly assigning over the death records within each age. The overall distribution of the deaths by age at death (grouped as 0, 1-4, 5-9 …. 95+) and sex is shown below on Figure 3.1. It seems that the data is of good quality with regard to reflecting the general pattern of mortality in South African population. The shares of the deaths of children under age 1 and age 5 are found to be 8.8 % and 11.9% respectively.

**Figure 3-1 Age distribution of the number of household deaths**


Source: Stats SA census 2011

### 3.1.2 Data on survival of last child born

Women aged 12 to 50 years who had at least one live birth, excluding stillbirths, were asked about the survival of their previous birth. If there were multiple births, only the information on the last birth was recorded. They gave responses to the following:

i. the date of birth of the last child born by day, month and year of birth;
ii. the sex of the last child born; and

iii. the survival status of the last child born, whether child is still alive or dead. If the survival status is death, then the day, month and year of death are reported

If the woman failed to remember the day and the month, she was encouraged to specify the year in which the last child was born or the year of death.

It is common in surveys or censuses of this nature to have unreported birth dates, survival status and gender for last live birth. The overall quality of the reported data can be assessed based on the information provided in Table 3.1 which shows the summary of proportion of unreported, reported as 'unknown' or implausible values. The wrongly reported cases, such as women who have stated an implausible year in which the last child was born with the current age of the mother are labelled as 'inconsistent' values by Statistics South Africa. It can be seen from the table that the day, month and year of death variables are badly reported and hence will not be used for our analysis. On the other hand, the missing, unknown or inconsistent year, month and day of birth variables are imputed for the purpose of this research. The year of birth is imputed by first apportioning the number of invalid cases into valid years based on the respective proportions from the valid years reported, and randomly distributing over each of the cases using pseudo-random numbers. The imputations of month and day variables, however, are done by assigning valid months and days uniformly. Improper values for sex and child's survival status are totally deleted from the analysis.

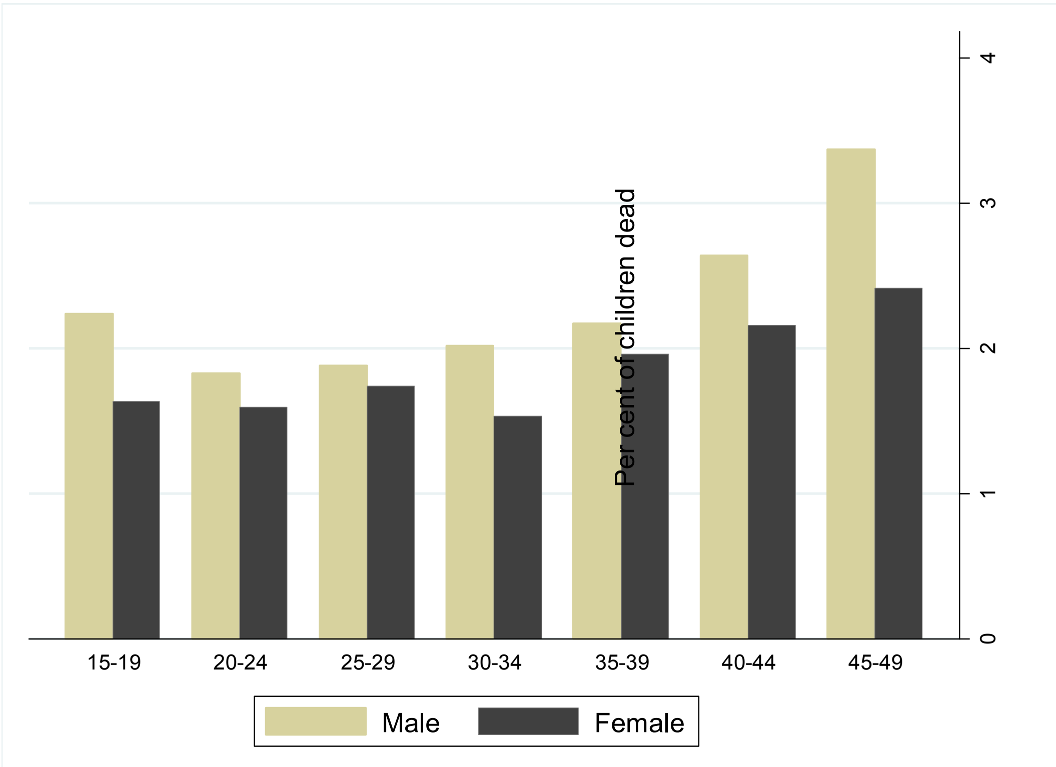
**Table 3-1 Percentages of missing, unknown and inconsistent values of data on last birth of women**

| Variable | Missing | Unknown | Inconsistent | Total invalid |
|---|---|---|---|---|
| Day of Birth | 3.4% | 0.6% | 0.2% | 4.2% |
| Month of Birth | 0.7% | 0.2% | 3.1% | 4.0% |
| Year of Birth | 0.0% | 0.2% | 3.4% | 3.6% |
| Sex of Child | 0.0% | 0.1% | 1.3% | 1.4% |
| Survival Status | 0.0% | 0.9% | 0.1% | 1.0% |
| Day of Death | 18.8% | 1.7% | 0.4% | 20.9% |
| Month of Death | 19.4% | 0.7% | 0.4% | 20.5% |
| Year of Death | 16.7% | 1.0% | 0.4% | 18.1% |

Source: Stats SA census 2011

The sex-ratio at birth is found to be 102.5 male births to 100 female births, which is a reasonable estimate for South Africa. Figure 3.2 shows the proportion 'dead by age of mother' and 'sex of the children born 12 months before the census'. It can be seen that the proportion of dead for male births is always higher than that of female births for all the age groups of mothers. Nationally, the percentages of children died for male and female children born 12 months before the census are computed to be 2.6% and 1.8% respectively. While the higher male death figure is as expected as in many literatures, the magnitude of the difference for the last age group of mothers seems to be exaggerated to some extent.

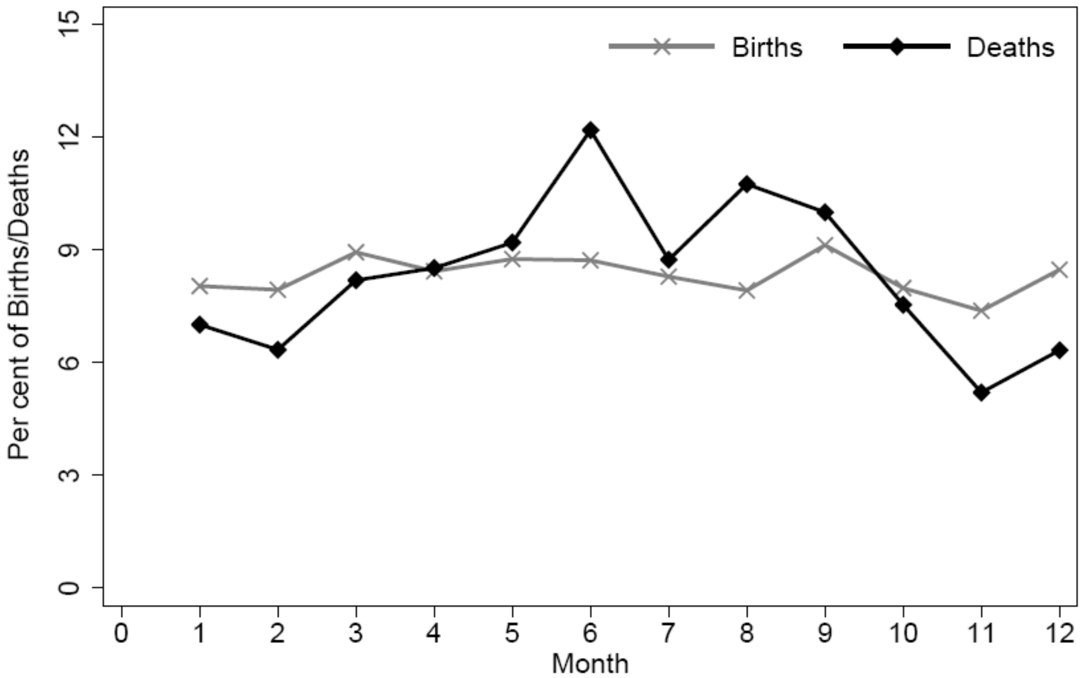
**Figure 3-2 Proportion of children dead by age of mothers and sex of the child**




Source: Stats SA Census 2011

Births and deaths that occurred 12 months before the census date can be derived from the census questions on child last born by women, and serve as the most important input for this research. In using these data, it is first assumed that under-reporting of births in the past 12 months is the same as under-reporting of deaths in the past 12 months so that the effect on mortality estimates is negligible. Second, as a way of assessing the quality of these data Figure 3.3 displays the distribution of births and deaths that occurred 12 months before the census date over the months of the year. It can easily be seen that the birth's data are more or less uniformly distributed over the months while the death data are significantly far from uniformity –higher and lowest number of deaths are reported in 6 and 11 months before the census respectively. This might be due to the problem of age heaping in reporting date of deaths or a census data editing problem by Stats SA.

**Figure 3-3 Monthly percentage distribution of births and deaths that occurred 12 months before census**




Source: Stats SA Census 2011

## 3.2 Methods of estimating child mortality

The two main demographic approaches of estimating child mortality (direct and indirect) could be applied to the 2011 South African census data. However, as the number of children surviving to mothers of reproductive age was not released with the 10 per cent sample data the Brass 'children ever born/children surviving method' of estimating child mortality will not be used in this research. Hence, direct synthetic cohort method is the only feasible approach from the given data. Reported deaths by households are used to compute infant and under-five mortality rates. This is achieved by calculating a complete life table for children aged 0 to 4. First, infant mortality rate, an approximate estimate of ${}_1q_0$, is calculated by the ratio of the number of deaths of children under age 1 and the number of births occurred 1 year before the census date.

The number of births occurred 12 months before the census can easily be computed from the census question on day, month and year of the last birth administered to women of age 12-50 years at the census date. Then, the central mortality rate, ${}_1M_x$ for children between ages $x$ and $x+1$ for $x=1,2,3,4$ are determined by dividing the number of deaths of children aged $x$ by their expected number of children or mid-year population[2]. The mid-year population at age x are computed by first projecting back the number of survivors at the census date by exactly one year before the census using survival factors from ASSA 2008 demographic and AIDS model (ASSA 2010) to get the population size one year before the census date and then taking the average (geometric mean) of these projected numbers and the actual census counts. This implies that the number of children between age $x$ and $x+1$ about six months before the census, ${}_1N_x$ is given by

$$ {}_1N_x = \left(P_x^t \times P_x^{t-1}\right)^{\frac{1}{2}} = \left(P_x^t \times \frac{P_{x+1}^t}{{}_1S_x}\right)^{1/2} \tag{3.1} $$

where

$P$ and $S$ respectively denote the census population counts and the ASSA model survival factors. The probability of dying between birth and before reaching their fifth birthdays, ${}_5q_0$ is then calculated as ${}_5q_0 = {}_1q_0 + (1 - {}_1q_0)\,{}_4q_1$ where ${}_4q_1$, the probability of dying between age 1 but before reaching the fifth birthday is calculated from the central mortality rates using

$$ {}_4q_1 = 1 - \exp\left(-\int_1^4 \mu(x)d_x\right) \approx 1 - \exp\left(-\sum_{x=1}^{4} {}_1M_x\right) \tag{3.2} $$

where

$\mu(x)$ is the actual force of mortality approximated by the central mortality rate, ${}_1M_x$. Note that in the calculation of ${}_1M_x$, it is assumed that those who die between ages $x$ and $x+1$ do so halfway between the census date and one year before the census date.

[2] Mid-year refers to half-way between the census date and 12 months before the census.

In addition to the national estimate, infant and under-five mortality rates for each of the nine provinces of South Africa are computed following the same procedure except that instead of the national level survival factors, provincial survival factors are used from the ASSA model in order to get the respective estimates of the number of children exposed to the risk of death between age $x$ and $x+1$ for $x=1,2,3,4$ and in each province.

However, for municipal-level estimates a different approach is implemented as it is not feasible to follow the same procedure as the national or provincial level estimates. First, it is assumed that the ratio of under-five to infant mortality rate in each municipality is the same as the ratio at the respective province and hence the under-five mortality rates are computed by multiplying the infant-mortality rates by these factors (ratios). Second, the infant mortality rates are estimated by fitting a spatial Bayesian smoothing model using the number of infant deaths and births that occurred 12 months before the census in each municipality as inputs (as discussed in the next section). The original or crude mortality rates are used as initial values for the parameter of interest in the smoothing model during MCMC simulation. The smoothing is important because otherwise the estimates become unstable as there are fewer deaths in many municipalities and hence, a few more or less child deaths can greatly impact the estimates especially in less-populated municipalities. The method also helps to obtain mortality rates estimates for those municipalities which have zero observed deaths in the data.

The smoothed municipal-level infant and under-five mortality estimates are aggregated up to give a smoothed estimates of the respective rates at national and province levels. It is expected that the difference between the smoothed and unsmoothed estimates at national and province levels is very small. The real advantage of the smoothing is for the municipal-level estimates.

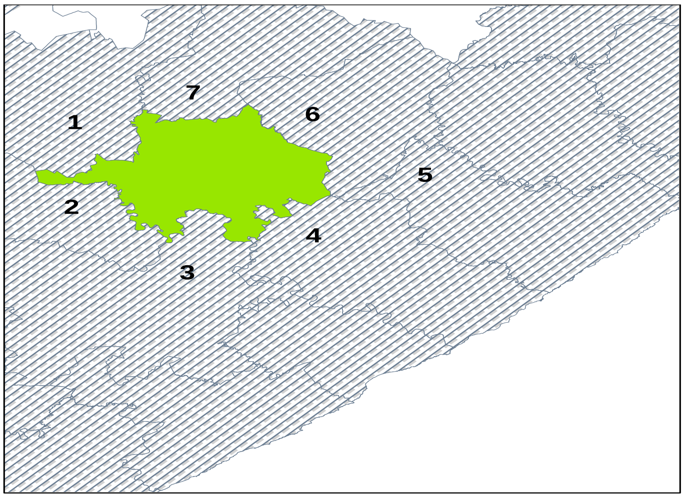
## 3.3 Bayesian Spatial Smoothing

### 3.3.1 Model specification

A full Bayesian spatial smoothing method is applied to the municipal-level infant mortality rates to improve the quality of the estimates. As discussed in Chapter 2, the parameters of the prior distribution in full Bayesian smoothing are considered to be random variables with their own distributions, resulting in a hierarchical model. The first level of the model is defined by the observed data itself while in the second level the prior distribution defines spatial dependence between nearby areas through its hyper-parameters.

In this study an adjacency matrix is used to identify neighbouring areas. Neighbours are defined as municipalities that are physically connected to one another. For example, the selected municipality shown on Figure 3.4 has seven neighbouring municipalities contributing information for its estimate of child mortality. There are a total of 234 municipalities and 1244 distinct adjacent pairs of municipalities (neighbours) in South Africa which give an average of 5.3 neighbours per municipality with the smallest number of neighbours being 1 and the largest number of neighbours being 11.

**Figure 3-4 An example showing the neighbours for a municipality**




To use prior distributions obtained from neighbouring areas, a hierarchical Bayesian model is employed in which the first level of the model consists of the level of child mortality in an area in which the number of child deaths reported in each municipality, $Y_i$, is modelled using a binomial distribution as given below.

$$Y_i \sim Binomial(p_i, n_i) \quad (3.3)$$

where

$p_i$ is the probability that a child is dying before reaching the first birthday in municipality $i$ and $n_i$ is the total number of children in the municipality. The resulting fitted values of $p_i$ will be used as a smoothed estimate of infant mortality in municipality *i*. This parameter of interest is modelled using a generalised linear model:

$$\log it(p_i) = \alpha + S_i \tag{3.4}$$

where α is an unstructured random effect representing the global mean of the log-relative risks for all areas and $S_i$ is a spatially structured random effect representing the municipal-specific effects or the deviation from the global mean (Lunn, Jackson, Best *et al.* 2013).

In order to further improve the estimates; it is a good practice to include some important determinants of child mortality in the model specified above. In this regard, two variables are included: level of females' education and the level of HIV in the municipalities. Females' education is known to be a strong predicator of child mortality in many researches. On the other hand, HIV has significantly affected the mortality of children in South Africa. Therefore, the average years of schooling of women aged 15-49 in each municipality and the provincial HIV prevalence rate among adults in the 15-49 age group are included in the model specified above. HIV prevalence rates are taken from the 2012 South African national HIV prevalence, incidence and behaviour survey conducted by the Human Science Research Council (HSRC 2014b). The revised generalised linear model for the probability of death controlling for these variables becomes:

$$\log it(p_i) = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + S_i \tag{3.6}$$

where

$X_{1i}$ and $X_{2i}$ are respectively the education and HIV variables as defined above. The inclusion of these two variables in the model helps to effectively use the spatial neighbourhood, females' education and HIV prevalence rate to predict the probability of death for each municipality.

The second level of the hierarchical Bayesian model is the prior distributions for the random effects. An improper uniform prior distribution is assigned for the unstructured random effect, α (Lunn, Jackson, Best *et al.* 2013).

$$\alpha \sim dflat() \tag{3.7}$$

Since there is very little information available on how much education or HIV impact child mortality occurs in each municipality, very weak prior distributions for $\beta_1$ and $\beta_2$ are given by assigning a small value for the precision. In doing so, the data will be guaranteed to be the main determinant of the estimates.

$$\beta_{1i}, \beta_{2i} \sim N(0, 0.001) \tag{3.8}$$

The spatially structured random effect is assigned a conditional autoregressive (CAR) distribution with parameter $\tau$

$$S_i \sim CAR(\tau) \tag{3.9}$$

The CAR model specifies how each $S_i$ is related to the $S_j$ at all other locations via a set of univariate conditional distributions. One of the most commonly used formulations (see Lunn, Jackson, Best *et al.*) which is applied in this research is

$$S_i \mid S_{\setminus i} \sim Normal\left(\sum_{j \neq i} \frac{w_{ij} S_j}{w_{i+}}, \frac{\tau^2}{w_{i+}}\right) \tag{3.10}$$

where

$w_{ij}$ are weights used to express spatial dependence between municipality i and municipality j, with $w_{ij} = w_{ji}$, $w_{ii} = 0$ and $w_{i+} = \sum_j w_{ij}$ . Usually $w_{ij}$ is defined as $w_{ij} = 1$ if municipality $i\ and\ j$ are neighbours and $w_{ij} = 0$ otherwise. Thus, the conditional mean of $S_i$ is a weighted average of the other $S_i s$ . This model is available in WinBUGS (Bayesian Inference Using Gibbs Sampling), a software dedicated for Bayesian modelling, as

$$S[1:n] \sim car.normal(adj[\,], weights[\,], num[\,], inv.tau.sqared) \tag{3.11}$$

The CAR model also includes the hyper-parameter τ, the precision of the variance, which denotes how similar or variable neighbouring areas should be. Due to uncertainty in the degree of similarity in neighbouring areas, in the third level of the hierarchical model, τ is assigned its own distribution, a hyper-prior distribution, with a very weak gamma distribution.

$$\tau \sim \gamma(0.5, 0.0005) \quad (3.12)$$

To determine the standard deviation of S, $\tau$ is normally converted into the form $\varsigma.S = \sqrt{1/\tau}$, where $\varsigma$ is scalar.

### 3.3.2 Model fitting

The parameters of the specified Bayesian models are estimated by the use of WinBUGS software which performs Bayesian inference based on the MCMC sampling scheme. The two models are fitted and compared with DIC (deviance information criterion). The first one is with only spatial structure, and the second model incorporating females' education and HIV prevalence rates. For each model 100 000 iterations are run with the initial 10 000 discarded from the use for parameter estimation. After convergence, the model with the lowest DIC is selected. Convergence is evaluated by inspecting trace and autocorrelation plots of samples for each chain, as well as other numerical summaries as shown below.

### 3.3.3 Model diagnostics in Bayesian modelling

To ensure that the simulated posterior distribution is an accurate representation of the true posterior distribution, some diagnostic tests are necessary. Among these, the diagnostics performed here are: Gelman-Rubin statistic and examinations of autocorrelations and Monte Carlo errors. The Gelman-Rubin statistic is used for assessing convergence of MCMC simulation. For a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel chains. The model is judged to have converged if the ratio of between variability to within variability is close to 1.

Examination of the autocorrelation function between successive iterations of chains for the parameters is the other important tool used in Bayesian model diagnostics. This is done for each of the parameters: the proportion of children who have died (pi), the spatially structured random effects ($S_i$), the education effect ($\beta_1$), the HIV effect ($\beta_2$) and the standard deviation of $S_i$. The autocorrelation values for all these parameters should be close to 0 for the model to be good.

As assessment of model accuracy, the Monte Carlo error for each parameter of interest is investigated. As a rule of thumb, to have accurate posterior estimates the simulation should run until the MC error for each parameter of interest is less than about 5% of the sample standard deviation. This ensures whether convergence and accuracy of posterior estimates are attained and the model is appropriate to estimate posterior statistics.

### 3.4 Comparison of Mortality Estimates

For ease of comparison, the smoothed under-five mortality estimates for the municipalities of South Africa are compared with the estimate of the municipality which has got the smallest estimate. This helps to assess the level of disparity among the municipalities in terms of child mortality – by how much the risk of death among children differ between the best and the worst municipalities, for example. Let $M_i$ be the final estimates of under-five mortality in municipality $i$ and let $M^s$ be the same estimate for standard municipality (municipality with the smallest estimate), then the index for comparing the rates can be computed as

$$SM_i = \frac{M_i}{M^s} \tag{3.13}$$

### 3.5 Mapping mortality estimates

Again for visualisation and further ease of comparison, the estimated under-five mortality rates of the municipalities and provinces are mapped with a GIS software. The shape files corresponding to the 2011 census which are used for creating the maps were obtained from Municipal Demarcation Board of South Africa (MDBSA 2014). They are defined as the GCS WGS 1984 geographic coordinate system and adopted the Africa Albers Equal Conic Area System for projecting the final maps. These options are available in the ArcGIS software.

### 3.6 Methods for measuring poverty and inequality

As examination of the relationship between child mortality and socioeconomic differentials is one of the objectives in this research, two methods of measuring poverty: based on income and living standard and one measure of inequality are considered. The measures are determined at national, provincial and municipality levels. The first approach of measuring poverty is based on monthly per capita income and comparing it with the national poverty line of the country. As the measure based on this approach is not the best method to reflect the actual living standard of the population, another measure of poverty is computed by constructing an index from different variables which are supposed to be related with the living standard of people in a better way. The data used for the computation of poverty and inequality are exclusive from the 10 per cent household data of the 2011 census.

### 3.6.1 Head count poverty index – Income poverty

The poverty headcount ratio (PHCR) or index is defined as the percentage of the population whose living standards, typically measured by income/consumption, lie below a given threshold referred to as 'poverty line' (Deaton 1997). In this research, the absolute monthly per capita income is computed by dividing the total monthly household income by the household size while the poverty line of R515 is considered as the threshold. The PHCR can then be calculated as

$$PHCR = \frac{N_Z}{N} * 100 = \frac{100}{N} \sum_{i=1}^{N} I(X_i \leq Z) \tag{3.14}$$

where

$I(.)$ is an indicator function that is 1 if its argument is true and 0 otherwise, $X$ is the per capita income of people living in the area (country, province or municipality), $Z$ is the poverty line considered, and N is the total population in the area under consideration. The sum of the indicators gives the number of people in poverty ($N_Z$).

### 3.6.2 Living Standard Index (LSI)

This is an alternative measure of wellbeing of people in a society that takes into account different factors instead of only looking at income. A living standard index (LSI) is constructed based on different indicators of wellbeing from the 2011 census household data, specifically on those variables which measure how good the environment is for the child to live in. Factor analysis (FA) is chosen to be the best statistical method for constructing the index as its purpose is to group set of variables based on their correlations and condense the information into fewer factor variables called latent variables (Hair, Black, Babin *et al.* 2010). It mainly involves extracting the factor(s) by partitioning the total variance in each of the variables into variances which are shared and unique variance. The detail theory and application of FA can be found in any standard multivariate text like Hair, Black, Babin *et al.* (2010).

Sixteen variables were identified for the purpose of constructing the index from the census data. The variables are selected in such a way that each of them somehow has some contribution to the wellbeing of the household. Instead of using the variables as they are collected from the census, attempts are made to dichotomise most of them as 'worse off' and 'better off' or 'poor' and 'not poor' (0 and 1) for ease of understanding and interpretation as well as to make the units consistent across all the variables so that FA can be done without any problem. However, type of construction material for the roof and the wall are categorised into three levels. As a measure of internal consistency of the scale, *Cronbach Alpha* – a known measure of reliability – is computed giving a scale reliability coefficient of 0.8597, which is good. The descriptions of the variables used for constructing the index including some summary statistics of the variables are shown in Table 3.2.

**Table 3-2 Summary of variables used for LSI construction**

| Variable | Category (code) | Mean | SD | Factor loading | Coeff-icient |
|---|---|---|---|---|---|
| Dwelling Type | House (1), Other (0) | 0.66 | 0.48 | 0.384 | 0.066 |
| Room per person | Greater or equal to 1 (1), less than 1 (0) | 0.69 | 0.46 | 0.257 | 0.030 |
| Roof made of | Tiles(3), Concrete/Block(2) Other(1) | 1.98 | 0.66 | 0.431 | 0.058 |
| Wall made of | Brick(3), Concrete/Block(2) Other(1) | 1.93 | 0.60 | 0.388 | 0.067 |
| Energy used for lighting | Electricity (1), Other(0) | 0.85 | 0.36 | 0.631 | 0.128 |
| Energy used for cooking | Electricity/Gas(1), Other(0) | 0.77 | 0.42 | 0.674 | 0.123 |
| Piped water on premises | Available (1), Not available(0) | 0.73 | 0.44 | 0.667 | 0.106 |
| Flush Toilet | Available (1), Not available(0) | 0.60 | 0.49 | 0.717 | 0.179 |
| Television | Available (1), Not available(0) | 0.76 | 0.43 | 0.595 | 0.096 |
| Satellite Dish | Available (1), Not available(0) | 0.26 | 0.44 | 0.554 | 0.092 |
| Refrigerator | Available (1), Not available(0) | 0.70 | 0.46 | 0.641 | 0.118 |
| Washing Machine | Available (1), Not available(0) | 0.32 | 0.47 | 0.645 | 0.120 |
| Vacuum Cleaner | Available (1), Not available(0) | 0.17 | 0.38 | 0.536 | 0.097 |
| Computer | Available (1), Not available(0) | 0.22 | 0.41 | 0.555 | 0.105 |
| Internet access | Available (1), Not available(0) | 0.36 | 0.48 | 0.436 | 0.057 |
| Rubbish collected by local authority | Yes (1), No(0) | 0.62 | 0.49 | 0.625 | 0.104 |

Source: Stats SA census 2011

The first factor is found to be enough to explain about 80% of the variance in the dataset and hence it's used to construct the index. The factor loadings and the coefficients of each variable used to generate the index are also given on Table 3.2. The factor loadings are the correlations between each of the original variables and the latent variable generated (factor). The square of the factor loadings indicates the percentage of the total variance in the original variables explained by the factor. The coefficients, on the other hand, are the factor weights used in conjunction with the original values to calculate each observation's score. In other words, the index is simply a linear combination of the coefficients given and the values of the variables for each household. For ease of understanding, the constructed index is categorised into 5 quintiles which can be used as ranking the level of living standard to households. A household lying in the first quintile is categorised as to have the poorest living standard while a household lying in the fifth quintile is categorised to have the best living standard. Furthermore, households in the first two quintiles are categorised as poor and living standard poverty headcount ratio (LS PHCR) is computed for each area.

### 3.6.3 Gini Index – Income Inequality

The Gini coefficient or index (GI) is the most widely used index to measure the level of income inequality in a society. It is expected to be positively correlated with child mortality as greater inequality in income within communities reflects unequal access to healthcare, nutrition and other services which is likely to reduce the health of the poor (Waldmann 1992; Rodgers 2002). The GI is a number between 0 and 1, where 0 corresponds with perfect equality and 1 corresponds with perfect inequality (where one person has all the income and everyone else has zero income). It is computed from a Lorenz curve (LC) which is literally a plot of the cumulative percentage of population versus the cumulative percentage of wealth/income. From the LC, GI is then calculated as the area between the line of perfect equality and the observed LC, as a percentage of the area between the line of perfect equality and the line of perfect inequality.

In this research, GI is computed for each province and municipality of the country from the distribution of their population and income class as reported in the 2011 census. This helps us to compare provinces and municipalities according the level of income inequality in relation to the level of child mortality.

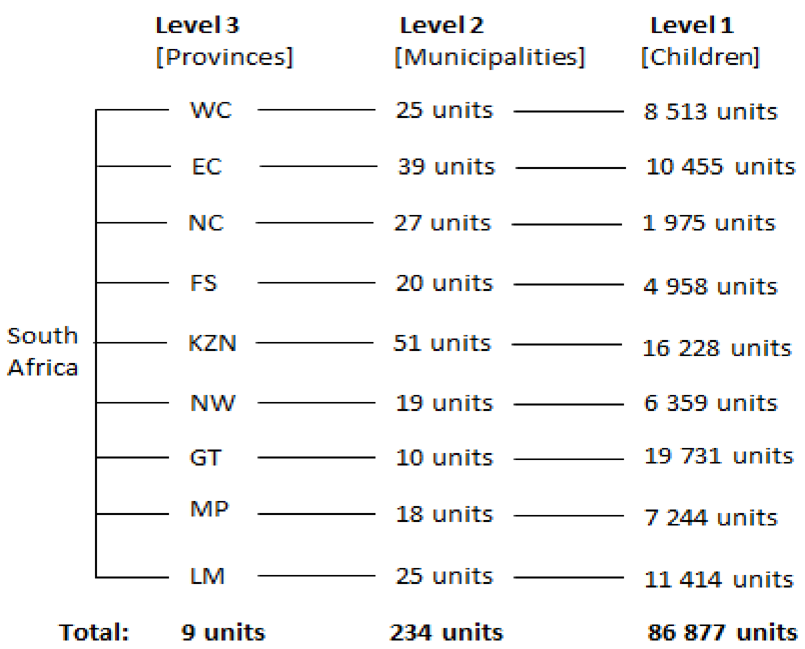
## 3.7 Multilevel modelling of child mortality

As the last part of the research, besides examining child mortality in relation to poverty and inequality at different geographical levels through various descriptive statistics, factors affecting child mortality are investigated by fitting multilevel logistic regression model. This is important especially to quantify the impact of socioeconomic factors including poverty and inequality on mortality of children. The investigation goes beyond simple correlation analysis between child mortality, and poverty and inequality. It also helps to address the issue of ecological fallacy where conclusion reached at aggregate level is inadequate to hold at individual level. Unfortunately, since the quality of the data on date of death of the deceased children is very poor, survival analysis is not attempted. Multilevel analysis is a suitable approach to take into account community level contexts at different levels, like at municipal and province levels, as well as individual subjects.

### 3.7.1 Data and variables

Using the 2011 census data, children born within 12 months before the census date are considered for this part of the research. After removing missing, unknown and inconsistent cases, there are 86 877 (un-weighted) children with valid survival status and ready for analysis. These children can be viewed as they are nested in a structure under 234 municipalities and 9 provinces as shown on Figure 3.5.

**Figure 3-5 Structure of number of children in the data used for regression**



The dependent variable considered has a binary outcome indicating the survival status of the child with value 0 if the child is still alive at the census date and 1 if the child has died. Based on the literature review we had in the previous chapter, various independent variables which might affect child mortality at individual, municipal and province level are identified. The list of the variables used in the regression together with some descriptive statistics is given on Table 3.3. Missing values in the independent variables are also discarded from the analysis as they constitute only less than 1.3 per cent of the total observations.

**Table 3-3 Summary statistics of the variables in the regression model**

| | Label | Variable | Mean | Std. Dev. | Odds of death |
|---|---|---|---|---|---|
| | Y | Child died | 0.0187 | 0.1353 | 0.0190 |
| Independent Variables | | **Child level** | | | |
| | X1 | Female child | 0.5066 | 0.5000 | 1.2065 |
| | X2 | Age < 1 month (Neonatal) | 0.1142 | 0.3181 | 0.8180 |
| | | Mother's age at birth, 20-34 (Ref) | | | |
| | X3 | <20 years | 0.1947 | 0.3960 | 1.0488 |
| | X4 | >34 years | 0.1514 | 0.3584 | 1.1127 |
| | | Birth order, First birth (Ref) | | | |
| | X5 | 2 | 0.2955 | 0.4562 | 0.9615 |
| | X6 | 3 | 0.1604 | 0.3670 | 1.1718 |
| | X7 | 4+ | 0.1381 | 0.3450 | 1.5490 |
| | | Mother's education, No/primary education (Ref) | | | |
| | X8 | Secondary education | 0.7693 | 0.4213 | 0.7037 |
| | X9 | Higher education | 0.0954 | 0.2937 | 0.3775 |
| | X10 | Mother never married | 0.5288 | 0.4992 | 1.1767 |
| | X11 | Mother works | 0.2005 | 0.4004 | 0.9166 |
| | X12 | Mother is Black African | 0.8596 | 0.3474 | 2.0488 |
| | | Living Standard Quintiles, Q1 (Ref) | | | |
| | X13 | Q2 | 0.2319 | 0.4221 | 0.8294 |
| | X14 | Q3 | 0.2036 | 0.4027 | 0.7888 |
| | X15 | Q4 | 0.1898 | 0.3922 | 0.6052 |
| | X16 | Q5 | 0.1311 | 0.3375 | 0.3585 |
| | | **Municipal level** | | | |
| | X17 | Higher proportion of poor | 0.4889 | 0.4998 | 1.3627 |
| | X18 | More educated mothers | 0.7873 | 0.4092 | 0.6787 |
| | X19 | Greater income inequality | 0.1497 | 0.3567 | 1.2473 |
| | | **Province level** | | | |
| | X20 | Heavier HIV prevalence | 0.6290 | 0.4831 | 1.3275 |

All the independent variables are defined as categorical and hence, the odds of death given in the last column of the tables measures the odds of the category compared to the reference group. Note that the independent variables are listed according to their level such that the variables on proportion of poor, mean mothers' years of education and income inequality as measured by Gini index, are identified at municipal level while HIV prevalence rate is at province level. All these four variables are defined with two categories: lower and higher magnitude of the respective measures. The lower and higher values dictate that the respective quantity in the area is less than and greater than the national estimate. For instance, about 49 per cent of the children live in municipalities where the level of income poverty is higher than the national poverty head count ratio of 41 per cent. Note also that among the child level variables, age of the child is an indicator variable showing whether the child has age of less than one month (neonatal) or not.

### 3.7.2 The model

As noted above, a three-level random intercept logistic regression model is considered where the first level is children born 12 months before the census while the municipalities and provinces in which the children live are the second and third levels respectively. Let $\pi_{ijk}$ be the probability that child $i$ living in municipality $j$ and province $k$ dies before reaching age one. Then, the three-level random intercept logistic regression model in question with the predicator variables described above can, therefore, be expressed as

$$\begin{aligned}\ln[\pi_{ijk}/(1-\pi_{ijk})] = {} & \beta_{0jk} + \beta_1 X_{1ijk} + \beta_2 X_{2ijk} + \beta_3 X_{3ijk} + \beta_4 X_{4ijk} + \beta_5 X_{5ijk} + \\ & \beta_6 X_{6ijk} + \beta_7 X_{7ijk} + \beta_8 X_{8ijk} + \beta_9 X_{9ijk} + \beta_{10} X_{10ijk} + \beta_{11} X_{11ijk} + \\ & \beta_{12} X_{12ijk} + \beta_{13} X_{13ijk} + \beta_{14} X_{14ijk} + \beta_{15} X_{15ijk} + \beta_{16} X_{16ijk}, \qquad \text{(level 1 model)}\end{aligned}$$

$$\beta_{0jk} = \beta_{00k} + \beta_{17} X_{17jk} + \beta_{18} X_{18jk} + \beta_{19} X_{19jk} + u_{0jk}, \quad \text{(level 2 model)}$$

$$\beta_{00k} = \beta_{000} + \beta_{20} X_{20k} + v_{00k}, \quad \text{(level 3 model)}$$

where

$v_{00k} \sim N(0, \sigma^2_{v0})$, $u_{0jk} \sim N(0, \sigma^2_{u0})$, and the notations of the independent variables are as given on the 'Notation' column in Table 3.4 above. The coefficients $\beta_1, \beta_2, \ldots, \beta_{20}$, called fixed effects, measure the impact of the corresponding predicator variable on the log of odds of death while $\beta_{0jk}$, the random effect, measures the combination of municipal and provincial level effects as defined in the second and third level of the model. Unlike ordinary logistic regression, there are two types of residual terms, $u_{0jk}$ and $v_{00k}$, defined at level 2 and level 3 respectively and assumed to be normally distributed with mean zero and constant variance.

### 3.7.3 Parameters estimation and model diagnostics

There are two commonly used estimation methods for multilevel logistic regression models: quasi-likelihood (QL) approach and Bayesian approach with Markov Chain Monte Carlo (MCMC) methods (Goldstein 2011). In QL approach, the non-linear logistic regression equation is estimated first using a Taylor series expansion which approximates a nonlinear function by an infinite series of terms (Breslow and Clayton 1993). If the Taylor series is expanded about the fixed and the random parameters, then the estimation is known as penalised quasi-likelihood (PQL) (Breslow and Clayton). Once the quasi-likelihood has been formed, unbiased estimates of the random parameters can be found by applying either iterative generalised least squares (IGLS) or restricted generalised least square (RGLS) which are estimation procedures in the case of continuous response variables (Goldstein 2011). On the other hand, the Bayesian approach using MCMC estimation methods can be used by first specifying starting values prior distributions for each of the model parameters and then sequentially sampling subsets of parameters from their conditional posterior distributions using Markov chain. A discussion and technical details of MCMC estimation methods for multilevel models can be found from in Browne (2003) and Goldstein (2011)

The MCMC procedure followed by MLwiN – software dedicated for multilevel modelling and used by this research – by default assigns flat prior distributions to the parameters of the model. That is, for fixed terms $p(\beta) \propto 1$ and for random terms, $p(1/\sigma^2) \sim Gamma(\varepsilon, \varepsilon)$ where $\varepsilon$ is a very small number. After assigning initial values, usually estimates from QL methods, the MCMC procedure in MLwiN then performs the simulations in two phases. In the initial burn-in period it runs until the chain converges to its stationary distribution; and in the next stage (monitoring period) it runs so that the means and standard errors of the parameters are estimated. The 2.5th and 97.5th quantiles of the chains provide Bayesian 95% credible intervals in order to make inferences concerning the estimated parameters, serving the same purpose as 95 per cent confidence intervals. For fitting the aforementioned model, the number of iterations run is 1000 in the burn-in period and 10 000 for the monitoring period.

After running the model, residuals at municipal and province level (estimates of $u_{0jk}$ and $v_{00k}$) are calculated so that the underlying assumptions, such as normality and constant variance of residuals, be investigated with the help diagnostic plots. Furthermore, as part of model diagnostics, the trace of the chains, autocorrelations (AC) and partial autocorrelations (PAC) functions at iteration $t$ and $t-k$ having accounted for iterations $t-1,\ldots,t-(k-1)$, and Monte Carlo standard errors (MCSE) are investigated for each of the posterior distributions of the parameter in the model. For the model to be good it is expected that the traces be not skewed, the AC and PAC functions be less correlated and the MCSE be close to zero. Increasing the number of iterations produces better results in all these dimensions. A comprehensive detail of parameter estimation and model diagnostics using MCMC simulations methods can be found from MLwiN manual (Rasbash, Charlton, Browne *et al.* 2012).

## 3.8 Software

The majority of data management and analyses are carried out with Stata 13 (StataCorp 2013) and the spatial Bayesian smoothing part is done with WinBUGS (Bayesian Inference Using Gibbs Sampling) version 14.4.3 after generating the adjacency matrix with GeoDa (Anselin 2013) from the shape files obtained from Municipalities Demarcation Board of South Africa (MDBSA 2014). In addition, the provincial and municipal-level estimates of under-five mortality rates are mapped with the help of ArcGIS/ArcMap (Esri 2012). For the multilevel modelling part, the use of MLwiN (Rasbash, Charlton, Browne *et al.* 2012) is a better choice because of its computing efficiency for large datasets and better estimation methods than the multilevel modules of Stata. It is used in conjunction with *runmulwin* – a Stata module designed to run MLwiN multilevel modelling software from within Stata (Leckie and Charlton 2013).

# 4. RESULTS OF ANALYSIS

This chapter summarises the main results of the analysis in this research. Estimates of child mortality from the 2011 household death data at national, provincial and municipal level will be first presented together with the Bayesian spatial smoothed estimates. The later estimates will then be assessed in relation to poverty and inequality at the respective geographical levels. Finally, the results of the multilevel logistic regression model which investigates the relationship between child mortality and its determinants will be presented.

## 4.1 Estimates of child mortality from household deaths data

The 2011 South African census asked questions on deaths occurred in households twelve months before the census. These data are used to determine estimates of child mortality at national, provincial and municipality levels. There are a total of un-weighted 5 119 under-five deaths enumerated by the census of which 3 710 were infant deaths. The corresponding weighted numbers are 58 208 and 42 186 respectively. Using the weighted total infant deaths and the number of births that occurred in the country one year before the census, which is calculated as 1 136 387, infant mortality rate or probability of dying before age one (${}_1q_0$) is estimated to be 37 per 1000 live births. On the other hand, the probability of dying between age one and 5 (${}_4q_1$) is computed based on the method discussed in Section 3.3 and as shown in Table 4.1 as 13 deaths per 1000 live births. Combining the estimates of ${}_1q_0$ and ${}_4q_1$, the national estimate of under-five mortality rate or the probability of dying before reaching age 5 is 49 deaths per 1000 births. Note that all these estimates of mortality are applicable to about six months before the census, i.e. April 2011. It can be easily observed that the majority of the under-five deaths, about 75 per cent, are accounted by deaths under age one. Only 25 per cent of the deaths occur between age one and 5.

**Table 4-1  National level child mortality estimates**

| Age | No of Deaths | Average Population/Births | Central Death Rate | Mortality Rates |
|---|---|---|---|---|
| 0 | 42 186 | 1 136 387 | NA | |
| 1 | 7 169 | 1 147 273 | 0.0062 | ${}_1q_0$ = 37.12 |
| 2 | 3 329 | 1 147 342 | 0.0029 | ${}_4q_1$ = 12.76 |
| 3 | 2 228 | 1 121 930 | 0.0020 | ${}_5q_0$ = 49.41 |
| 4 | 1 851 | 1 082 251 | 0.0017 | |

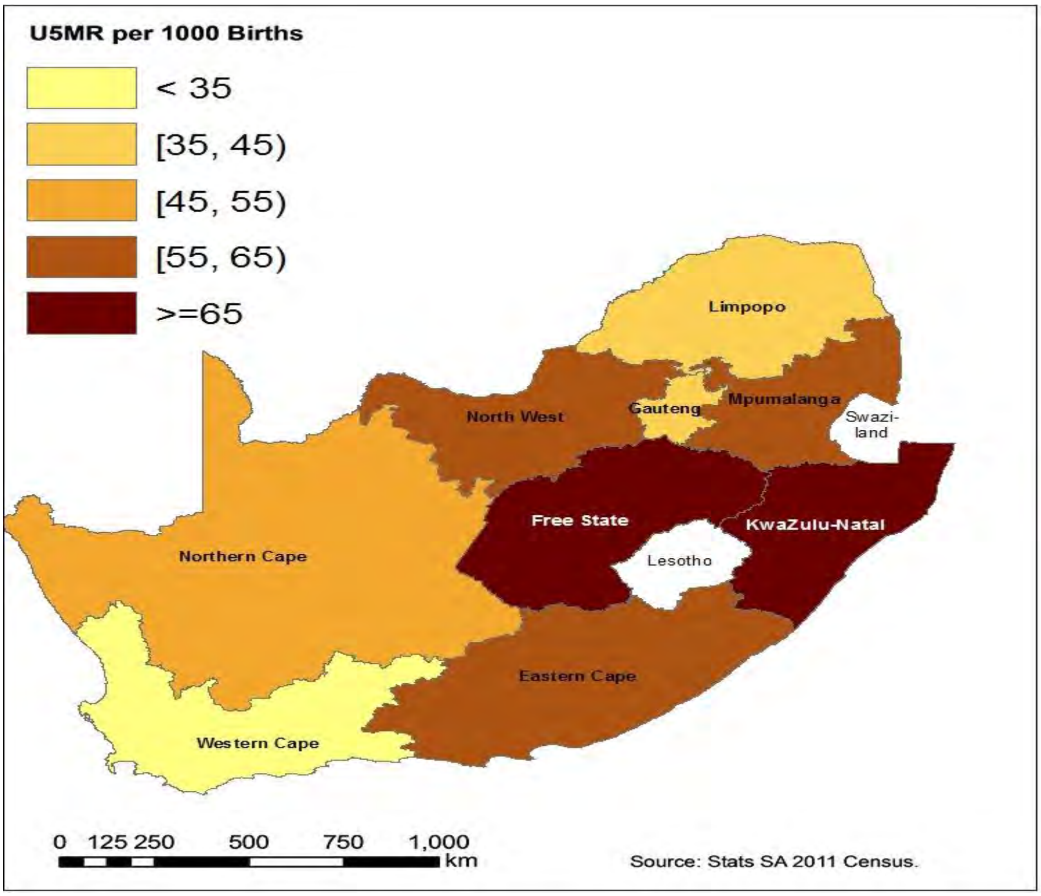
Applying the same procedure but by disaggregating the census data by province and taking provincial survival factors from ASSA model, infant and under-five mortality rates are estimated. These estimates are provided in Table 4.2 together with the smoothed estimates computed by aggregating the municipal level Bayesian smoothed estimates, which is the topic of the next section. Although there are small differences between the direct and smoothed estimates of infant and under-five mortality rates at province level, the smoothed estimates are taken to be the final estimates of child mortality in this research. As it can be seen from the table, Western Cape (WC) is the province with the lowest level of infant and under-five mortality rates, values close to 20, and 26 deaths per 1000 births respectively. It is followed by Gauteng (GT) with infant and under-five mortality rates close to 27, and 37 respectively. On the contrary, KwaZulu-Natal (KZN) and Free State (FS) have registered the highest mortality rates – about 2.7 times heavier than that of WC. They have attained an infant mortality rates of 51, and 48 deaths per 1000 births respectively while their under-five mortality rate are correspondingly 71, and 68. The mortality rates of all the remaining provinces except Limpopo (LP) are at least twice as the mortality rate of the WC. This somehow illustrates the significance of child mortality inequality among the provinces.

The spatial distribution of under-five mortality among the nine provinces is shown on the map in Figure 4.1. The map is created by categorising the provinces into 5 classes based on the severity of their under-five mortality rates. WC lies in the first quintile followed by GT and LP while Northern Cape (NC) seized the third quintile. KZN and FS are in the last class preceded by North West (NW), EC and MP.

**Table 4-2 Provincial level direct and smoothed estimates of child mortality**

| Province | Direct Estimates | | | | Smoothed Estimates | | |
|---|---|---|---|---|---|---|---|
| | 1q0 | 5q0 | 1q4 | 5q0/1q0 | 1q0 | 5q0 | 1q4 |
| Western Cape | 18.86 | 24.75 | 6.00 | 1.31 | 19.86 | 26.06 | 6.33 |
| Eastern Cape | 41.69 | 55.96 | 14.89 | 1.34 | 42.49 | 57.04 | 15.19 |
| Northern Cape | 40.27 | 52.55 | 12.79 | 1.30 | 38.50 | 50.24 | 12.20 |
| Free State | 47.82 | 68.47 | 21.69 | 1.43 | 47.61 | 68.17 | 21.59 |
| KwaZulu-Natal | 49.81 | 68.78 | 19.96 | 1.38 | 51.14 | 70.61 | 20.52 |
| North West | 44.98 | 61.79 | 17.60 | 1.37 | 45.15 | 62.03 | 17.67 |
| Gauteng | 25.95 | 36.07 | 10.40 | 1.39 | 26.75 | 37.19 | 10.73 |
| Mpumalanga | 41.29 | 58.13 | 17.57 | 1.41 | 42.51 | 59.85 | 18.11 |
| Limpopo | 28.37 | 39.27 | 11.22 | 1.38 | 28.87 | 39.98 | 11.43 |
| **ZA** | **37.12** | **49.41** | **14.09** | **1.34** | **36.03** | **49.95** | **14.45** |

**Figure 4-1 Provincial smoothed estimates of under-five Mortality rate**




Computing direct estimates of under-five mortality at municipal levels using the same procedure as applied for the national or provincial level estimates, however, is found to be problematic as the number of deaths at municipal-level are very rare in many municipalities to generate stable estimates. Therefore, two additional tasks were necessary. First, stable estimates of infant mortality rate for each municipality are computed using Bayesian spatial smoothing technique. Second, it is assumed that the ratio of under-five mortality rate to infant mortality rate in each municipality within a province is the same as the ratio of the two quantities at the respective province. These ratios for each province are as shown in Table 4.2, which ranges from 1.3 in NC to 1.43 in FS. Therefore, the municipal-level smoothed infant mortality rates are multiplied by their corresponding factors in order to get the respective estimates of under-five mortality rates.

## 4.2 Spatially smoothed municipal-level Bayesian estimates of child mortality

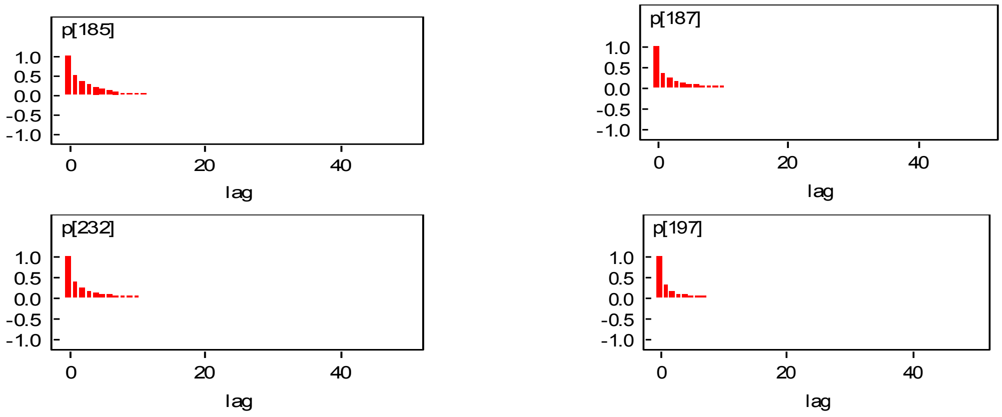
### 4.2.1 Results of model diagnostics

In order to address issues related to sample size and unstable (or missing) estimates of child mortality, Bayesian estimates are constructed smoothing on data in neighbouring areas. As it is discussed in Chapter Three, the main inputs for the smoothing model are the number of infant deaths and births occurred 12 months before the census. For this purpose, two different Bayesian models are compared. The first model (Model-1) is only with spatial smoothing (Model-1) – pure conditional autoregressive (CAR) model while the second one (Model-2) incorporates municipal level mean years of women education and provincial HIV prevalence rate for adults aged 15-49. After running each of the models initially for 10 000 iterations and another 100 000 iterations for monitoring stage, the respective models has returned DIC values of 1187.1, and 1164.7 respectively. Hence, the improved model by the inclusion of women education and HIV prevalence rate is the best model to estimate municipal-level child mortality rates.

Basic model diagnostics using Model-2 are also done on two of the most important parameters; namely, the proportion of children who have died ($p_i$) and the spatially structured random effect ($S_i$). The autocorrelation functions and the Brooks-Gelman-Robins (BGR) statistic plots presented on from Figure 4.2 to Figure 4.5 for four municipalities with smaller number of children and another four municipalities with larger number of children helps to show the very weak nature of autocorrelations of successive iterations of the chains and convergences of the posterior distributions of the parameters of interest.

**Figure 4-2 Autocorrelation values for the proportions of children who have died ( $p_i$ ) for selected municipalities**

a) For municipalities with smaller number of children




b) For municipalities with higher number of children

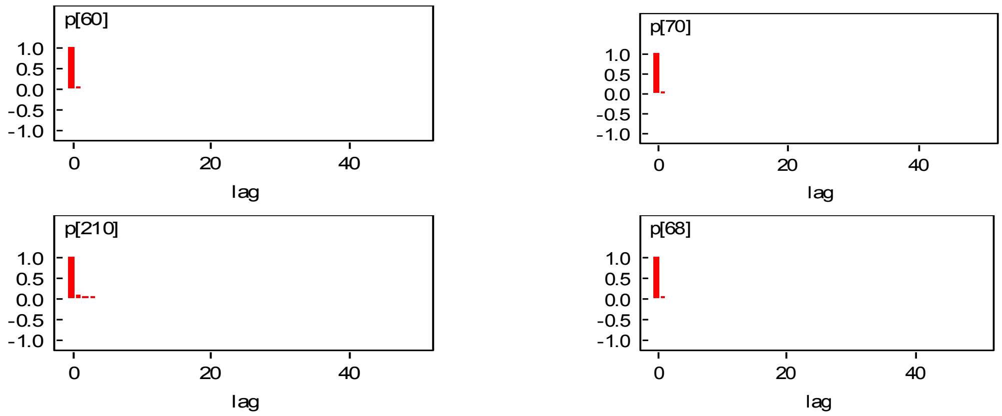
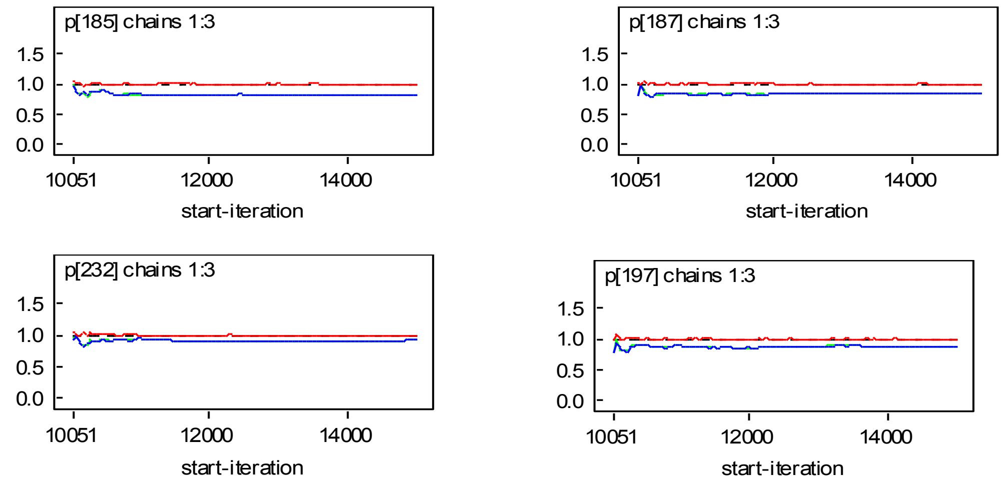



**Figure 4-3 BGR statistics for the proportions of children who have died ( $p_i$ ) and spatially structured random effect ( $S_i$ )**

a) For municipalities with smaller number of children



b) For municipalities with larger number of children

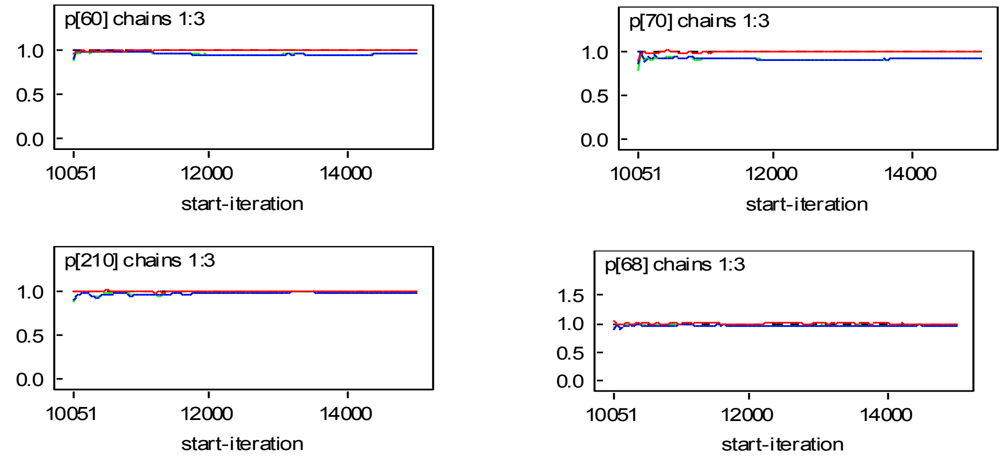
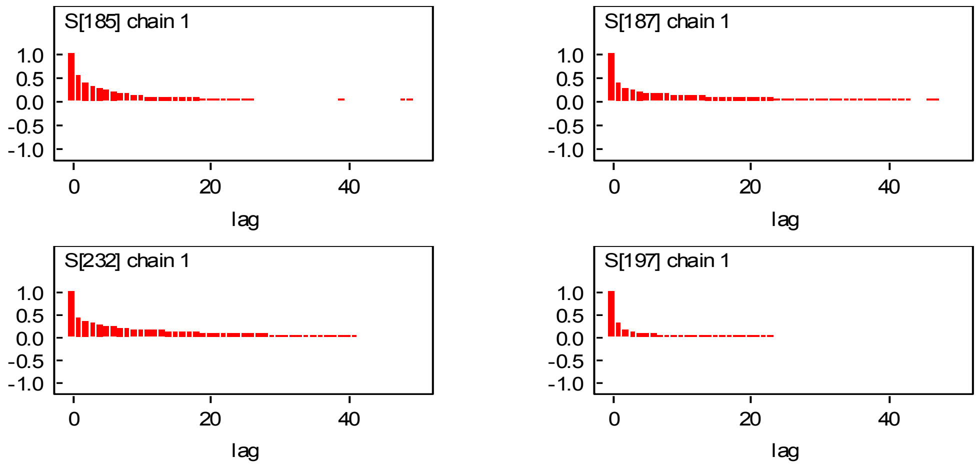



**Figure 4-4 Autocorrelation values for the spatially structured random effect ($S_i$) for selected municipalities**

a) For municipalities with smaller number of children




b) For municipalities with larger number of children

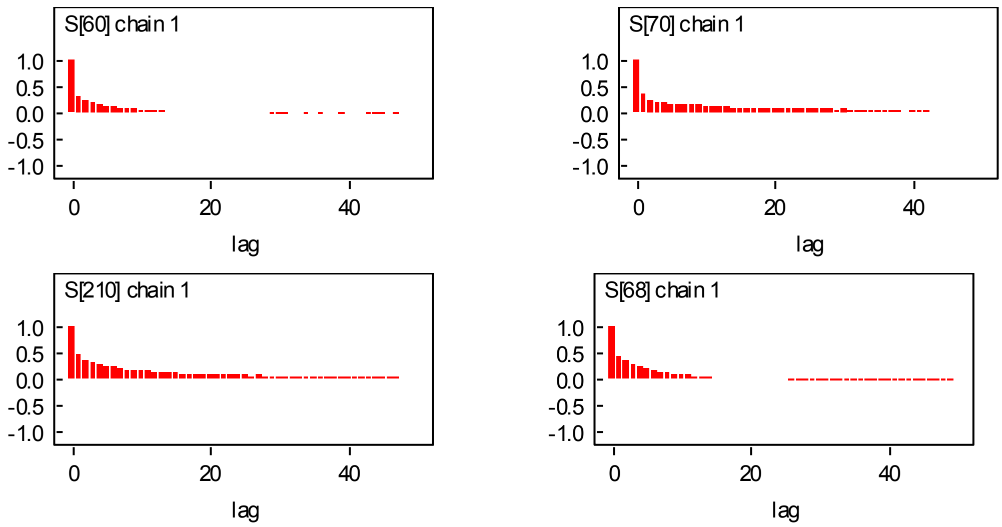
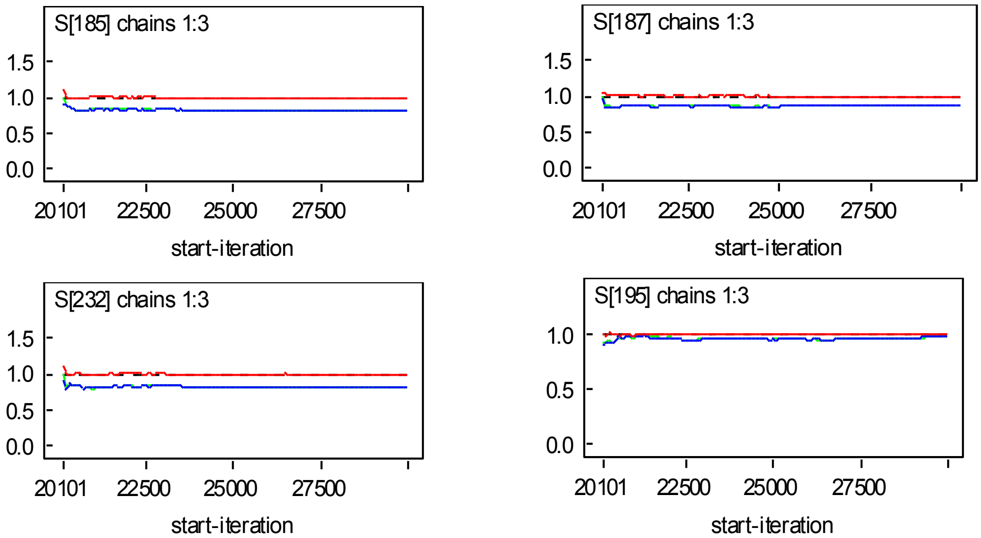
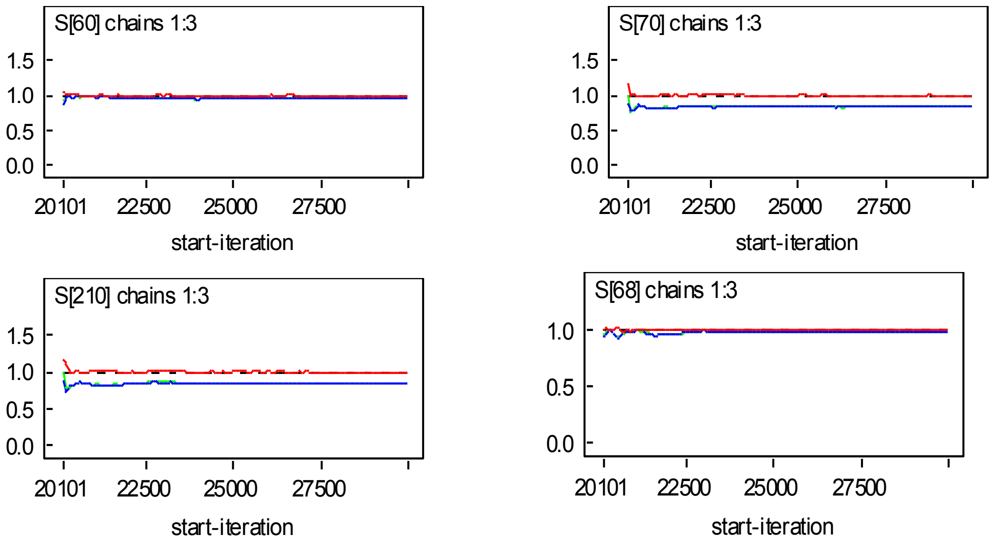


**Figure 4-5 BGR statistics for the spatially structured random effect ($S_i$) for selected municipalities**

a) For municipalities with smaller number of children




b) For municipalities with larger number of children




The model is then used to generate estimates of infant and under-five mortality rates to each municipality. The inclusion of the two variables in the CAR model has improved the estimates to some extent. This can, to some extent, be demonstrated by looking at the relationship between the under-five mortality estimates and the two included variables as indicated in the two scatter plots shown in Figure 4.6 and 4.7 below. A decrease in child mortality is associated with an increase in women's mean years of education and a decrease in adult HIV prevalence rate. Specifically, there are significant correlations between U5MR and women's education and HIV prevalence resulting in a correlation coefficients of -0.50 and 0.76 respectively. However, it is important to note that there is a high level of variability in estimates of child mortality at all levels of education and at areas where the HIV prevalence is higher.

**Figure 4-6 Under-five mortality rate and mean years of mothers' education**

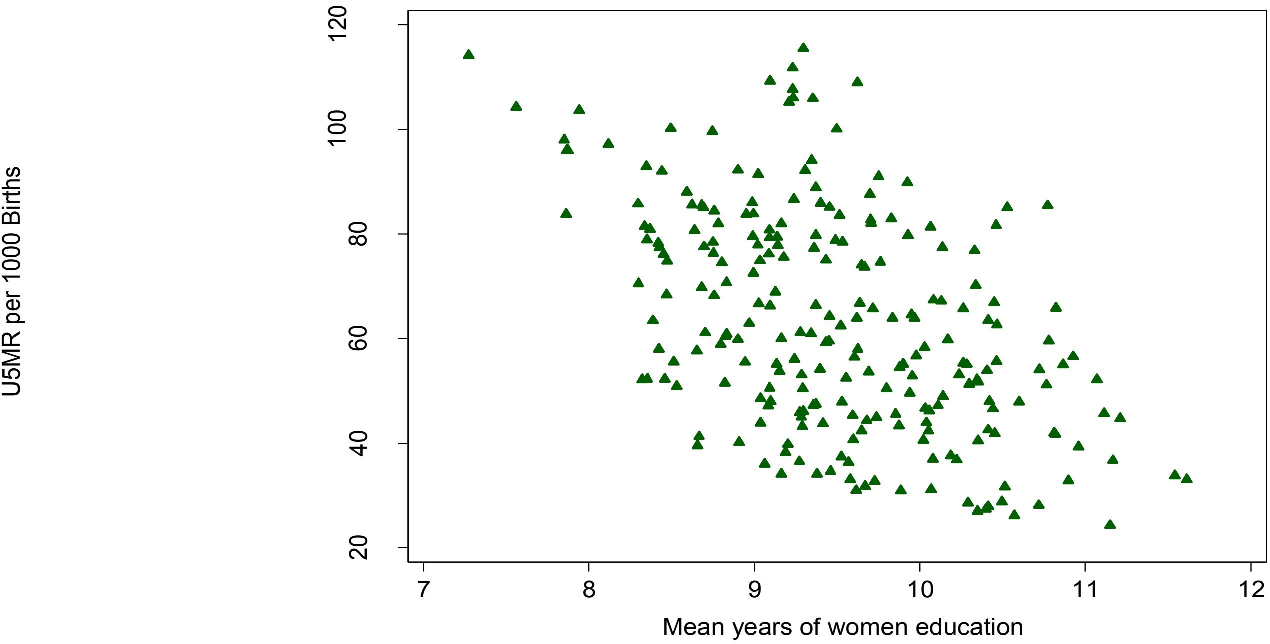
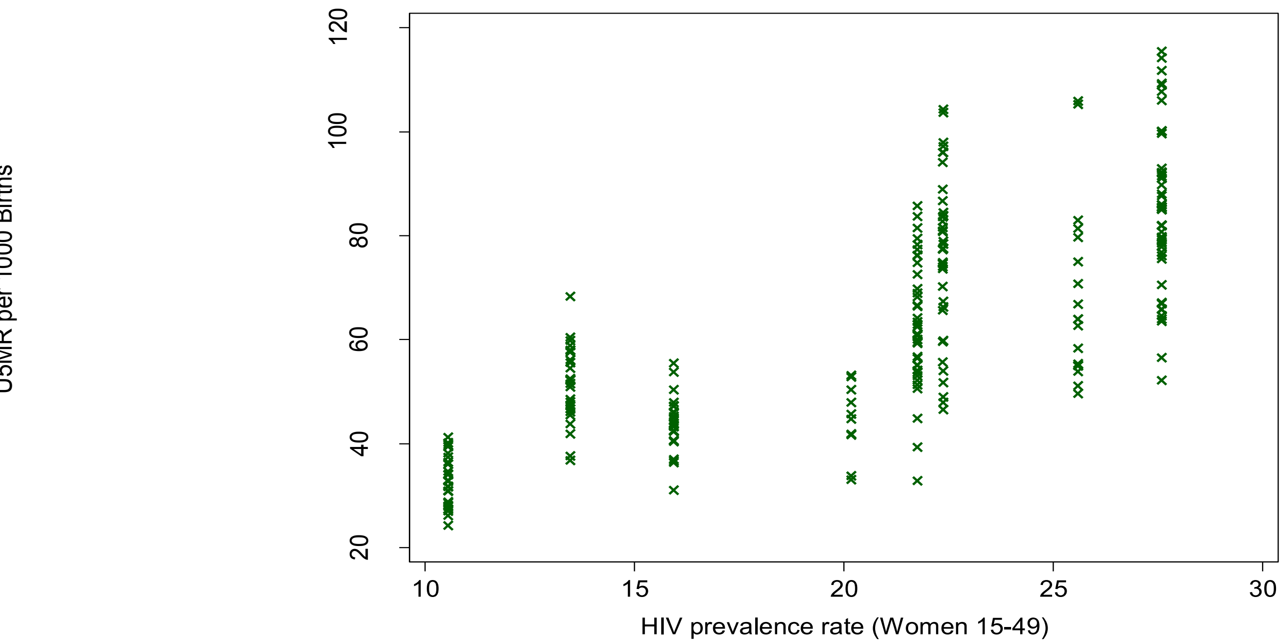



**Figure 4-7 Under-five mortality rate vs HIV prevalence rate**

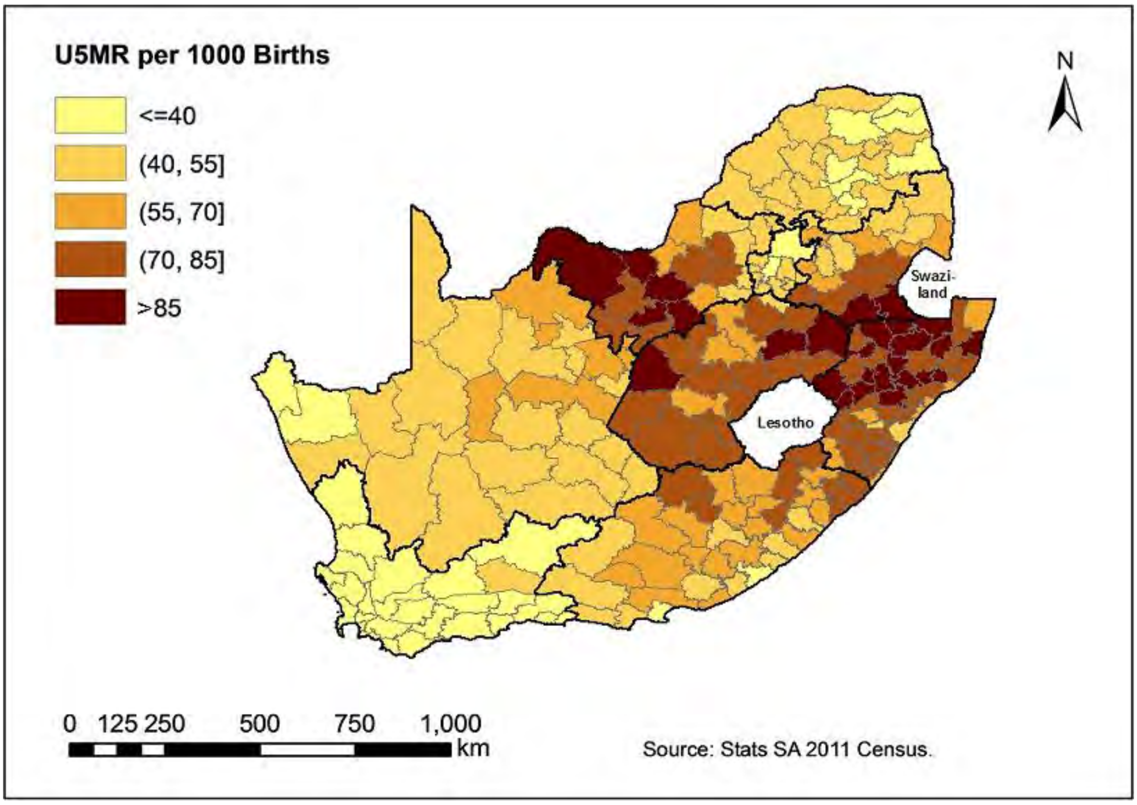


### 4.2.2 Estimates of municipal level infant and child mortality rates

The final municipal level estimates of infant and under-five mortality rates are provided together with other relevant statistics in Table 4.4. The municipalities in the table are ranked based on their level of U5MR. In addition, the estimates of child mortalities are associated with geo-referenced data of the municipalities and mapped as shown on Figure 4.8. The map presents the estimates of U5MRs per 1000 live births with the following breakdown: 16 per cent of municipalities have under-five mortality rates of less than 40, 29 per cent have values between 40 and 54, 19 per cent have values between 55 and 69, 24 per cent have values between 65 and 84, and 12 per cent have values of 85 and above. The map helps one to see the spatial patterns of child mortality in the country in that mortality is heavier in north-east, central and north-west part and lighter in south-east and northern parts of the country. Among all the municipalities, City of Cape Town (CCPT) has got the minimum under-five mortality of 24.0 deaths per 1000 live births while uPhongolo of the KwaZulu-Natal province has recorded the maximum rate of 109.1 which is about 4.6 times higher than the mortality rate of CCPT. This implies that the probability that a child who is born in uPhongolo is 4.6 times more likely to die before reaching its fifth birthday than a child who is born in CCPT.

For such ease of comparisons, the under-five mortality rate estimates of all municipalities are divided by the minimum under-five mortality rate (CCPT) in order to get a kind of standardised mortality index (SM). These index and the corresponding under-five mortality ranks for each of the municipalities are also given in Table 4.4. From this table one can appreciate the degree of differential of child mortality among municipalities in South Africa. In the time period where the mortality estimate applies, the under-five mortality rate of 60 per cent of the municipalities is more than twice the mortality rate of the city of Cape Town. Furthermore, in 30 per cent of the municipalities, child mortality is three times higher while in 7 per cent of the municipalities the mortality is four times higher than the mortality in CCPT. Further interpretation of child mortality estimates in relation to poverty and inequality will be given later.

**Figure 4-8 Spatially smoothed municipal-level estimates of U5MRs**




Generally, there are far less variation in municipalities that are geographically close, but there is clear and consistent evidence of elevated mortality levels in municipalities in provinces like KwaZulu-Natal and North West and lowest levels in municipalities of the Western Cape, Gauteng and Limpopo. Summary statistics of municipal-level under-five mortality estimates in each province are given on Table 4.3. The information in the table together with the map helps to appreciate not only the magnitude of child mortality in the municipalities within provinces but also the degree of variation in mortality in each of the provinces. One can understand from the given table that Western Cape has the lowest average child mortality rate and the fourth lowest dispersion in child mortality considering coefficient of variation (CV) as a standard measure of variation. On the other hand, while most of the municipalities in Kwazulu-Natal province have registered the highest mortality rates, the variation in mortality among them is not found to be the highest. The greatest disparity in child mortality among municipalities is observed in North-West and Mpumalanga provinces with a CV of 25 and 24 per cent respectively. The municipalities in Limpopo province, on the other hand, have the lowest variation in child mortality, scoring a CV of about 12 per cent indicating that they are the most alike relative to municipalities in other provinces. Nationwide, the 234 municipalities vary in child mortality by 33 per cent while the mean and median values are 61 and 62 respectively. The box plots shown in Figure 4.5 present the combined information of extent and disparity of the mortalities among municipalities in each province.

**Table 4-3 Summary Statistics of U5MR Municipal-level estimates**

| Province | n | Mean | Median | Min | Max | SD | CV |
|---|---|---|---|---|---|---|---|
| Western Cape | 39 | 32.28 | 32.18 | 23.97 | 40.41 | 4.72 | 14.61 |
| Eastern Cape | 20 | 60.99 | 59.31 | 32.28 | 82.18 | 11.26 | 18.46 |
| Northern Cape | 10 | 50.10 | 50.82 | 36.13 | 66.07 | 6.89 | 13.74 |
| Free State | 51 | 74.67 | 74.46 | 54.14 | 91.57 | 9.45 | 12.66 |
| KwaZulu-Natal | 25 | 81.09 | 81.54 | 50.80 | 109.08 | 13.60 | 16.77 |
| North West | 18 | 72.28 | 75.43 | 45.51 | 99.06 | 18.28 | 25.29 |
| Gauteng | 27 | 43.51 | 44.18 | 32.48 | 51.71 | 6.79 | 15.61 |
| Mpumalanga | 19 | 66.27 | 61.93 | 48.39 | 100.51 | 15.70 | 23.69 |
| Limpopo | 25 | 42.76 | 42.90 | 30.60 | 53.97 | 5.12 | 11.97 |
| ZA | 234 | 60.84 | 61.55 | 23.97 | 109.08 | 19.79 | 32.52 |

**Figure 4-9 Distribution of municipal level estimates of U5MR among the provinces**

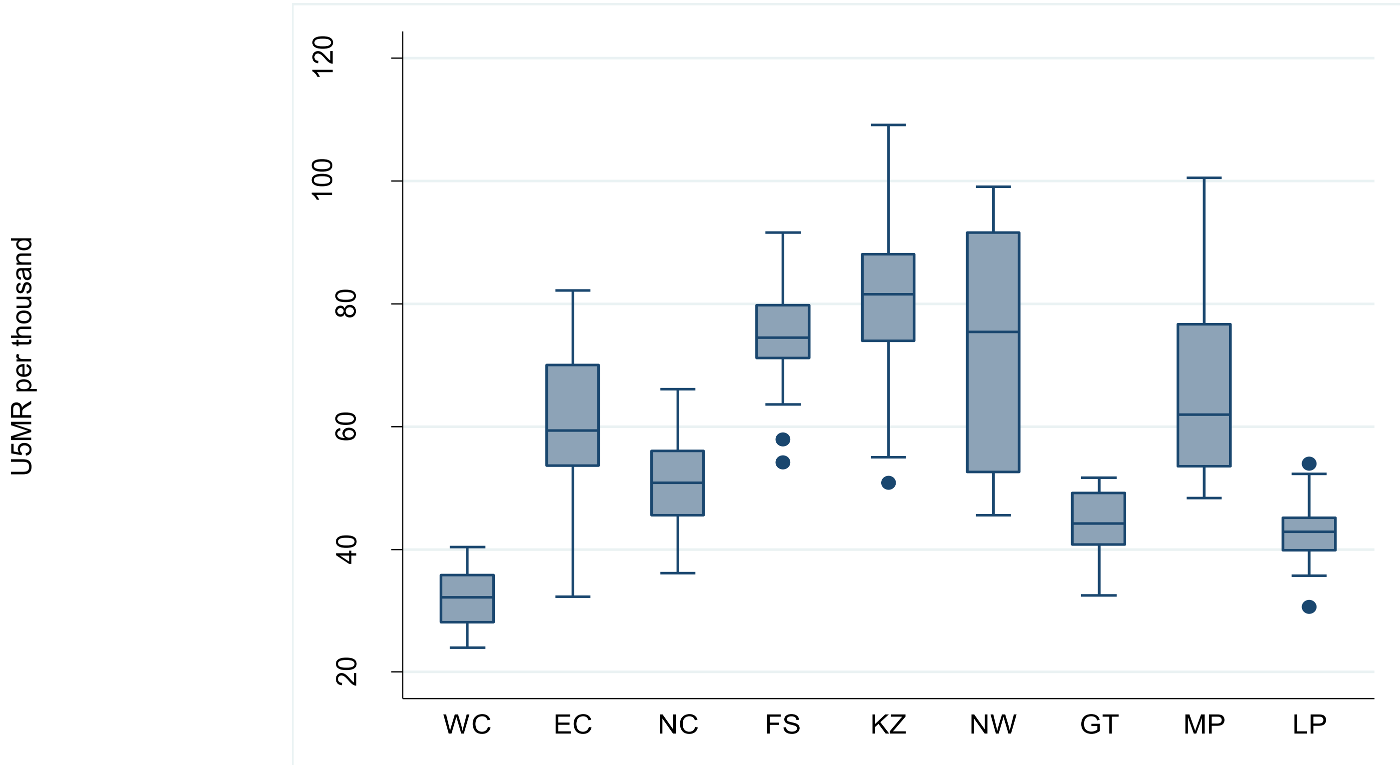


**Table 4-4 Municipal level estimates of infant and under-five mortality rates with the level of poverty and inequality♠**

| | | | | | | | | Ranks | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Province | Municipality | IMR | U5MR | PHCR | GI | LS PHCR | SMR | U5M | PV | II | LSP |
| WC | City of Cape Town | 18.3 | 24.0 | 29.6 | 0.673 | 16.9 | *1.00* | *1* | *33* | *86* | *14* |
| WC | Mossel Bay | 19.7 | 25.8 | 34.4 | 0.655 | 14.3 | *1.08* | *2* | *48* | *55* | *3* |
| WC | Knysna | 20.4 | 26.6 | 34.9 | 0.704 | 27.2 | *1.11* | *3* | *52* | *170* | *60* |
| WC | Overstrand | 20.6 | 27.0 | 32.0 | 0.648 | 20.9 | *1.13* | *4* | *40* | *47* | *25* |
| WC | Bitou | 21.0 | 27.5 | 37.2 | 0.706 | 24.5 | *1.15* | *5* | *72* | *176* | *46* |
| WC | Stellenbosch | 21.2 | 27.7 | 33.7 | 0.681 | 20.6 | *1.16* | *6* | *44* | *104* | *24* |
| WC | George | 21.6 | 28.2 | 31.4 | 0.652 | 19.2 | *1.18* | *7* | *38* | *52* | *20* |
| WC | Drakenstein | 21.7 | 28.4 | 28.4 | 0.667 | 15.1 | *1.18* | *8* | *23* | *75* | *7* |
| WC | Breede Valley | 23.3 | 30.4 | 28.7 | 0.651 | 24.1 | *1.27* | *9* | *27* | *50* | *43* |
| WC | Theewaterskloof | 23.3 | 30.5 | 27.9 | 0.647 | 21.7 | *1.27* | *10* | *21* | *42* | *28* |
| LP | Thulamela | 22.2 | 30.6 | 60.1 | 0.688 | 77.3 | *1.28* | *11* | *195* | *123* | *184* |
| WC | Saldanha Bay | 23.9 | 31.2 | 27.8 | 0.636 | 13.3 | *1.30* | *12* | *19* | *26* | *1* |
| GT | City of Tshwane | 23.5 | 31.3 | 28.4 | 0.663 | 22.0 | *1.31* | *13* | *24* | *68* | *31* |
| GT | City of Johannesburg | 24.0 | 32.2 | 29.7 | 0.694 | 17.2 | *1.34* | *14* | *34* | *146* | *15* |
| EC | Nelson Mandela Bay | 24.2 | 32.3 | 40.7 | 0.694 | 15.9 | *1.35* | *15* | *104* | *144* | *11* |
| WC | Cape Agulhas | 24.8 | 32.5 | 21.0 | 0.623 | 14.8 | *1.35* | *16* | *1* | *13* | *4* |
| WC | Oudtshoorn | 23.9 | 32.5 | 36.1 | 0.688 | 23.5 | *1.36* | *17* | *66* | *122* | *38* |
| WC | Swartland | 24.6 | 33.2 | 25.5 | 0.660 | 16.2 | *1.39* | *18* | *12* | *63* | *13* |
| WC | Langeberg | 25.6 | 33.5 | 28.8 | 0.677 | 18.5 | *1.40* | *19* | *28* | *94* | *16* |
| WC | Hessequa | 25.7 | 33.6 | 23.0 | 0.613 | 13.5 | *1.40* | *20* | *5* | *9* | *2* |
| WC | Bergrivier | 26.0 | 34.0 | 21.6 | 0.592 | 19.2 | *1.42* | *21* | *2* | *4* | *19* |
| WC | Swellendam | 27.1 | 35.4 | 24.2 | 0.627 | 22.1 | *1.47* | *22* | *9* | *16* | *32* |
| LP | Mutale | 25.9 | 35.7 | 61.9 | 0.707 | 87.5 | *1.49* | *23* | *206* | *182* | *208* |
| WC | Laingsburg | 27.4 | 35.8 | 23.0 | 0.636 | 30.7 | *1.49* | *24* | *4* | *28* | *81* |
| LP | Polokwane | 26.2 | 36.0 | 40.4 | 0.711 | 49.7 | *1.50* | *25* | *103* | *191* | *129* |
| NC | Richtersveld | 27.8 | 36.1 | 22.9 | 0.614 | 15.5 | *1.51* | *26* | *3* | *10* | *8* |
| LP | Makhado | 26.3 | 36.3 | 55.3 | 0.697 | 76.2 | *1.51* | *27* | *173* | *152* | *178* |
| WC | Beaufort West | 28.1 | 36.7 | 37.8 | 0.691 | 15.9 | *1.53* | *28* | *78* | *131* | *10* |
| NC | Nama Khoi | 28.4 | 36.9 | 29.2 | 0.684 | 16.0 | *1.54* | *29* | *32* | *112* | *12* |
| WC | Witzenberg | 28.7 | 37.5 | 23.4 | 0.639 | 25.7 | *1.56* | *30* | *7* | *32* | *50* |
| EC | Buffalo City | 28.9 | 38.6 | 42.7 | 0.705 | 38.4 | *1.61* | *31* | *115* | *171* | *110* |
| WC | Kannaland | 29.6 | 38.7 | 36.5 | 0.719 | 27.0 | *1.61* | *32* | *69* | *203* | *57* |
| WC | Matzikama | 29.9 | 39.0 | 25.3 | 0.658 | 30.4 | *1.63* | *33* | *11* | *60* | *77* |
| WC | Cederberg | 30.1 | 39.4 | 24.7 | 0.636 | 28.5 | *1.64* | *34* | *10* | *24* | *68* |
| LP | Lepele-Nkumpi | 28.8 | 39.6 | 55.3 | 0.704 | 66.2 | *1.65* | *35* | *173* | *167* | *153* |
| LP | Makhuduthamaga | 28.9 | 39.7 | 64.7 | 0.718 | 81.0 | *1.66* | *36* | *218* | *202* | *189* |
| LP | Ba-Phalaborwa | 28.9 | 39.8 | 43.0 | 0.698 | 50.4 | *1.66* | *37* | *116* | *158* | *131* |
| WC | Prince Albert | 31.0 | 40.4 | 35.8 | 0.691 | 26.2 | *1.69* | *38* | *63* | *132* | *52* |
| GT | Randfontein | 29.5 | 40.8 | 28.1 | 0.628 | 22.7 | *1.70* | *39* | *22* | *17* | *35* |
| NC | Sol Plaatjie | 31.6 | 41.0 | 35.5 | 0.695 | 21.7 | *1.71* | *40* | *58* | *148* | *27* |
| GT | Mogale City | 29.7 | 41.1 | 31.1 | 0.667 | 25.3 | *1.71* | *41* | *36* | *75* | *48* |
| LP | Fetakgomo | 30.1 | 41.5 | 56.3 | 0.710 | 72.4 | *1.73* | *42* | *181* | *188* | *166* |
| LP | Greater Tzaneen | 30.2 | 41.5 | 52.2 | 0.719 | 76.9 | *1.73* | *43* | *152* | *204* | *182* |
| LP | Aganang | 30.3 | 41.6 | 56.2 | 0.639 | 75.1 | *1.74* | *44* | *180* | *33* | *172* |
| LP | Greater Giyani | 30.8 | 42.3 | 65.3 | 0.704 | 82.2 | *1.77* | *45* | *219* | *168* | *191* |
| LP | Molemole | 30.8 | 42.4 | 52.7 | 0.697 | 67.7 | *1.77* | *46* | *158* | *154* | *157* |
| NC | Emthanjeni | 33.0 | 42.8 | 35.7 | 0.660 | 21.5 | *1.79* | *47* | *59* | *64* | *26* |
| LP | Musina | 31.2 | 42.9 | 35.8 | 0.679 | 45.7 | *1.79* | *48* | *63* | *100* | *125* |
| LP | Greater Tubatse | 31.2 | 43.0 | 53.2 | 0.708 | 76.0 | *1.79* | *49* | *160* | *184* | *175* |
| LP | Bela-Bela | 31.5 | 43.4 | 33.7 | 0.666 | 29.5 | *1.81* | *50* | *45* | *73* | *71* |
| GT | Ekurhuleni | 31.6 | 43.7 | 33.6 | 0.664 | 23.5 | *1.82* | *51* | *43* | *70* | *40* |

| Province | Municipality | IMR | U5MR | PHCR | GI | LS PHCR | SMR | Ranks U5M | PV | II | LSP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| EC | Kouga | 32.9 | 43.9 | 36.8 | 0.697 | 28.0 | *1.83* | *52* | *70* | *154* | *65* |
| LP | Greater Letaba | 32.0 | 44.0 | 59.7 | 0.685 | 84.3 | *1.84* | *53* | *192* | *116* | *196* |
| LP | Elias Motsoaledi | 32.2 | 44.3 | 56.5 | 0.691 | 70.4 | *1.85* | *54* | *183* | *129* | *163* |
| NC | Mier | 34.3 | 44.5 | 36.8 | 0.693 | 36.0 | *1.86* | *55* | *71* | *137* | *97* |
| GT | Emfuleni | 32.3 | 44.6 | 40.0 | 0.679 | 15.0 | *1.86* | *56* | *98* | *102* | *6* |
| LP | Maruleng | 32.6 | 44.8 | 61.3 | 0.731 | 84.2 | *1.87* | *57* | *204* | *223* | *195* |
| NC | Renosterberg | 34.7 | 45.1 | 38.2 | 0.655 | 27.2 | *1.88* | *58* | *81* | *56* | *59* |
| LP | Lephalale | 32.8 | 45.1 | 35.0 | 0.688 | 52.6 | *1.88* | *59* | *53* | *120* | *134* |
| NW | Rustenburg | 33.3 | 45.5 | 28.9 | 0.597 | 40.1 | *1.90* | *60* | *31* | *6* | *114* |
| NC | //Khara Hais | 35.1 | 45.6 | 35.0 | 0.685 | 25.2 | *1.90* | *61* | *54* | *114* | *47* |
| NC | Kamiesberg | 35.5 | 46.1 | 39.5 | 0.703 | 30.0 | *1.92* | *62* | *91* | *165* | *73* |
| LP | Mogalakwena | 33.5 | 46.1 | 53.9 | 0.698 | 60.0 | *1.92* | *63* | *165* | *155* | *146* |
| LP | Ephraim Mogale | 33.6 | 46.2 | 55.2 | 0.705 | 78.1 | *1.93* | *64* | *170* | *173* | *187* |
| NC | Khâi-Ma | 35.7 | 46.4 | 26.4 | 0.582 | 36.0 | *1.93* | *65* | *15* | *2* | *95* |
| GT | Midvaal | 33.9 | 46.8 | 28.6 | 0.651 | 27.0 | *1.95* | *66* | *26* | *51* | *56* |
| LP | Thabazimbi | 34.0 | 46.8 | 25.6 | 0.597 | 39.9 | *1.95* | *67* | *13* | *5* | *113* |
| NW | Moretele | 34.3 | 46.8 | 51.4 | 0.607 | 66.7 | *1.95* | *68* | *149* | *8* | *154* |
| NC | Umsobomvu | 36.1 | 46.9 | 44.3 | 0.707 | 29.1 | *1.96* | *69* | *121* | *182* | *70* |
| NC | Siyathemba | 36.5 | 47.4 | 35.8 | 0.672 | 28.1 | *1.98* | *70* | *61* | *85* | *66* |
| NW | Local Mun. of Madibeng | 35.0 | 47.8 | 34.3 | 0.648 | 61.2 | *1.99* | *71* | *47* | *45* | *148* |
| MP | Bushbuckridge | 34.6 | 48.4 | 63.9 | 0.690 | 78.0 | *2.02* | *72* | *214* | *127* | *185* |
| GT | Westonaria | 35.6 | 49.2 | 39.8 | 0.601 | 46.2 | *2.05* | *73* | *95* | *7* | *126* |
| LP | Mookgopong | 35.8 | 49.2 | 32.2 | 0.630 | 35.3 | *2.05* | *74* | *41* | *19* | *91* |
| EC | Kou-Kamma | 37.0 | 49.3 | 31.5 | 0.666 | 27.9 | *2.06* | *75* | *39* | *71* | *64* |
| NC | Hantam | 38.3 | 49.6 | 28.5 | 0.720 | 26.9 | *2.07* | *76* | *25* | *206* | *55* |
| MP | Emalahleni | 35.7 | 49.8 | 27.8 | 0.638 | 33.6 | *2.08* | *77* | *20* | *31* | *89* |
| EC | Makana | 37.5 | 50.0 | 37.5 | 0.698 | 23.5 | *2.09* | *78* | *76* | *157* | *40* |
| NC | Thembelihle | 38.7 | 50.2 | 38.6 | 0.733 | 39.1 | *2.09* | *79* | *84* | *224* | *112* |
| NW | Moses Kotane | 37.0 | 50.4 | 43.9 | 0.632 | 55.5 | *2.10* | *80* | *118* | *21* | *142* |
| KZ | eThekwini | 37.1 | 50.8 | 37.4 | 0.681 | 30.4 | *2.12* | *81* | *74* | *105* | *76* |
| NC | Karoo Hoogland | 39.2 | 50.8 | 27.3 | 0.723 | 48.0 | *2.12* | *82* | *18* | *213* | *127* |
| EC | Lukanji | 38.1 | 50.8 | 47.2 | 0.696 | 36.0 | *2.12* | *83* | *129* | *150* | *94* |
| NC | Ubuntu | 39.3 | 50.9 | 38.4 | 0.760 | 35.6 | *2.12* | *84* | *83* | *232* | *92* |
| NC | Kareeberg | 39.3 | 50.9 | 37.2 | 0.678 | 37.3 | *2.13* | *85* | *73* | *98* | *103* |
| NC | Kgatelopele | 39.4 | 51.1 | 26.1 | 0.685 | 15.6 | *2.13* | *86* | *14* | *115* | *9* |
| GT | Merafong City | 37.3 | 51.5 | 31.3 | 0.583 | 31.8 | *2.15* | *87* | *37* | *3* | *85* |
| EC | Baviaans | 38.7 | 51.7 | 35.8 | 0.679 | 20.4 | *2.16* | *88* | *64* | *101* | *23* |
| GT | Lesedi | 37.5 | 51.7 | 34.9 | 0.671 | 20.2 | *2.16* | *89* | *51* | *81* | *22* |
| EC | Mnquma | 39.2 | 52.2 | 53.8 | 0.642 | 84.7 | *2.18* | *90* | *164* | *35* | *198* |
| LP | Modimolle | 38.1 | 52.3 | 36.2 | 0.661 | 31.5 | *2.18* | *91* | *67* | *66* | *84* |
| MP | Mbombela | 37.6 | 52.5 | 40.3 | 0.711 | 48.9 | *2.19* | *92* | *101* | *192* | *128* |
| NW | Tlokwe City Council | 38.6 | 52.6 | 35.7 | 0.672 | 22.3 | *2.19* | *93* | *60* | *83* | *33* |
| EC | Camdeboo | 39.5 | 52.7 | 39.4 | 0.699 | 19.5 | *2.20* | *94* | *90* | *159* | *21* |
| NC | Ga-Segonyana | 40.9 | 53.0 | 47.3 | 0.706 | 62.1 | *2.21* | *95* | *130* | *178* | *150* |
| MP | Steve Tshwete | 38.3 | 53.5 | 26.7 | 0.629 | 22.0 | *2.23* | *96* | *17* | *18* | *29* |
| MP | Dr JS Moroka | 38.4 | 53.6 | 54.2 | 0.637 | 61.0 | *2.24* | *97* | *167* | *29* | *147* |
| EC | Great Kei | 40.2 | 53.6 | 51.2 | 0.743 | 70.8 | *2.24* | *98* | *146* | *228* | *164* |
| EC | Ngqushwa | 40.2 | 53.6 | 53.2 | 0.576 | 86.0 | *2.24* | *99* | *159* | *1* | *202* |
| MP | Thaba Chweu | 38.5 | 53.8 | 28.9 | 0.636 | 43.6 | *2.25* | *100* | *30* | *26* | *120* |
| LP | Blouberg | 39.3 | 54.0 | 62.1 | 0.711 | 82.0 | *2.25* | *101* | *207* | *189* | *190* |
| NC | Kai !Garib | 41.7 | 54.0 | 26.4 | 0.641 | 43.6 | *2.25* | *102* | *16* | *34* | *119* |
| FS | Metsimaholo | 38.1 | 54.1 | 35.9 | 0.693 | 23.7 | *2.26* | *103* | *65* | *136* | *41* |
| NC | Tsantsabane | 42.1 | 54.6 | 33.3 | 0.717 | 36.0 | *2.28* | *104* | *42* | *201* | *96* |
| EC | King Sabata Dalindyebo | 41.2 | 54.9 | 56.1 | 0.729 | 72.0 | *2.29* | *105* | *179* | *220* | *165* |

| Province | Municipality | IMR | U5MR | PHCR | GI | LS PHCR | SMR | Ranks U5M | PV | II | LSP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| KZ | The Msunduzi | 40.1 | 55.0 | 39.7 | 0.702 | 38.1 | *2.29* | *106* | *94* | *163* | *109* |
| EC | Nkonkobe | 41.4 | 55.1 | 52.5 | 0.661 | 68.7 | *2.30* | *107* | *156* | *67* | *160* |
| NC | Siyancuma | 43.2 | 56.0 | 41.1 | 0.710 | 37.4 | *2.34* | *108* | *105* | *187* | *106* |
| NC | !Kheis | 43.4 | 56.3 | 42.3 | 0.702 | 53.5 | *2.35* | *109* | *113* | *164* | *137* |
| NC | Gamagara | 43.5 | 56.3 | 23.3 | 0.652 | 26.5 | *2.35* | *110* | *6* | *53* | *53* |
| MP | Thembisile | 40.6 | 56.6 | 51.3 | 0.644 | 53.9 | *2.36* | *111* | *148* | *39* | *138* |
| NC | Dikgatlong | 44.1 | 57.2 | 49.8 | 0.644 | 37.2 | *2.39* | *112* | *139* | *38* | *102* |
| EC | Amahlathi | 43.2 | 57.5 | 52.5 | 0.675 | 76.3 | *2.40* | *113* | *155* | *91* | *180* |
| EC | Nxuba | 43.4 | 57.8 | 48.5 | 0.670 | 37.4 | *2.41* | *114* | *135* | *79* | *104* |
| FS | Mangaung | 40.8 | 57.8 | 34.8 | 0.694 | 26.8 | *2.41* | *115* | *50* | *143* | *54* |
| NW | Mafikeng | 42.6 | 58.1 | 43.6 | 0.712 | 51.2 | *2.42* | *116* | *117* | *193* | *132* |
| NC | Phokwane | 44.8 | 58.1 | 45.7 | 0.721 | 37.1 | *2.42* | *117* | *124* | *208* | *101* |
| EC | Blue Crane Route | 43.7 | 58.3 | 43.9 | 0.734 | 25.6 | *2.43* | *118* | *119* | *225* | *49* |
| NC | Magareng | 45.3 | 58.7 | 49.6 | 0.663 | 23.7 | *2.45* | *119* | *138* | *69* | *42* |
| EC | Sundays River Valley | 44.3 | 59.0 | 40.3 | 0.620 | 45.2 | *2.46* | *120* | *102* | *12* | *123* |
| EC | Sakhisizwe | 44.4 | 59.2 | 55.0 | 0.725 | 74.5 | *2.47* | *121* | *169* | *217* | *171* |
| EC | Ikwezi | 44.5 | 59.3 | 51.2 | 0.657 | 25.9 | *2.47* | *122* | *146* | *58* | *51* |
| EC | Inxuba Yethemba | 44.5 | 59.3 | 38.1 | 0.695 | 15.0 | *2.47* | *123* | *80* | *148* | *5* |
| EC | Maletswai | 45.4 | 60.5 | 39.7 | 0.693 | 29.7 | *2.52* | *124* | *94* | *140* | *72* |
| MP | Govan Mbeki | 43.6 | 60.8 | 35.1 | 0.689 | 23.0 | *2.54* | *125* | *56* | *125* | *37* |
| EC | Intsika Yethu | 45.8 | 61.0 | 57.4 | 0.678 | 93.9 | *2.54* | *126* | *187* | *97* | *224* |
| EC | Mbhashe | 46.2 | 61.5 | 62.5 | 0.683 | 94.9 | *2.57* | *127* | *208* | *109* | *230* |
| KZ | uMngeni | 45.0 | 61.5 | 28.8 | 0.690 | 28.3 | *2.57* | *128* | *29* | *127* | *67* |
| MP | Umjindi | 44.4 | 61.9 | 30.7 | 0.644 | 38.8 | *2.58* | *129* | *35* | *38* | *111* |
| MP | Victor Khanye | 44.4 | 61.9 | 39.6 | 0.678 | 30.9 | *2.58* | *130* | *92* | *95* | *82* |
| KZ | Umdoni | 45.3 | 61.9 | 38.7 | 0.693 | 54.3 | *2.58* | *131* | *85* | *138* | *139* |
| EC | Ndlambe | 46.7 | 62.2 | 41.7 | 0.708 | 33.9 | *2.60* | *132* | *108* | *183* | *90* |
| KZ | Mandeni | 45.7 | 62.5 | 46.1 | 0.643 | 69.8 | *2.61* | *133* | *125* | *36* | *161* |
| FS | Moqhaka | 44.9 | 63.6 | 37.7 | 0.675 | 18.6 | *2.65* | *134* | *77* | *90* | *17* |
| KZ | KwaDukuza | 46.5 | 63.6 | 33.9 | 0.683 | 54.6 | *2.65* | *135* | *46* | *109* | *140* |
| KZ | uMhlathuze | 46.6 | 63.7 | 37.9 | 0.684 | 36.6 | *2.66* | *136* | *79* | *112* | *99* |
| NW | Ramotshere Moiloa | 47.1 | 64.1 | 50.5 | 0.681 | 67.0 | *2.68* | *137* | *142* | *103* | *155* |
| EC | Umzimvubu | 48.3 | 64.2 | 61.1 | 0.703 | 91.6 | *2.68* | *138* | *200* | *166* | *217* |
| EC | Tsolwana | 48.4 | 64.5 | 51.8 | 0.649 | 68.7 | *2.69* | *139* | *151* | *48* | *159* |
| MP | Emakhazeni | 46.4 | 64.6 | 35.0 | 0.645 | 33.1 | *2.70* | *140* | *55* | *40* | *88* |
| KZ | Greater Kokstad | 47.3 | 64.7 | 38.7 | 0.693 | 37.4 | *2.70* | *141* | *86* | *135* | *105* |
| KZ | Hibiscus Coast | 47.5 | 65.0 | 38.2 | 0.693 | 55.7 | *2.71* | *142* | *82* | *140* | *143* |
| NW | City of Matlosana | 47.9 | 65.2 | 41.2 | 0.678 | 18.8 | *2.72* | *143* | *106* | *99* | *18* |
| EC | Nyandeni | 49.6 | 66.0 | 69.3 | 0.674 | 94.8 | *2.75* | *144* | *229* | *88* | *229* |
| NC | Joe Morolong | 51.0 | 66.1 | 61.6 | 0.748 | 86.8 | *2.76* | *145* | *205* | *229* | *204* |
| EC | Mhlontlo | 50.1 | 66.6 | 63.1 | 0.655 | 93.7 | *2.78* | *146* | *210* | *55* | *222* |
| EC | Emalahleni | 50.7 | 67.4 | 57.3 | 0.650 | 85.6 | *2.81* | *147* | *185* | *49* | *201* |
| FS | Matjhabeng | 47.9 | 67.8 | 42.0 | 0.667 | 22.0 | *2.83* | *148* | *109* | *77* | *30* |
| KZ | Umhlabuyalingana | 49.8 | 68.1 | 67.9 | 0.721 | 91.6 | *2.84* | *149* | *225* | *210* | *216* |
| MP | Nkomazi | 49.0 | 68.3 | 55.9 | 0.696 | 67.4 | *2.85* | *150* | *175* | *149* | *156* |
| EC | Senqu | 52.6 | 70.0 | 56.1 | 0.660 | 76.1 | *2.92* | *151* | *178* | *63* | *177* |
| FS | Mafube | 50.1 | 71.0 | 47.7 | 0.688 | 27.9 | *2.96* | *152* | *133* | *124* | *63* |
| FS | Ngwathe | 50.4 | 71.4 | 45.2 | 0.683 | 22.8 | *2.98* | *153* | *123* | *107* | *36* |
| FS | Kopanong | 50.8 | 71.9 | 38.9 | 0.716 | 24.4 | *3.00* | *154* | *88* | *198* | *45* |
| FS | Mantsopa | 50.8 | 72.0 | 42.2 | 0.714 | 32.4 | *3.00* | *155* | *111* | *197* | *87* |
| EC | Gariep | 54.2 | 72.1 | 38.9 | 0.694 | 30.4 | *3.01* | *156* | *87* | *142* | *78* |
| FS | Naledi | 51.0 | 72.2 | 48.8 | 0.710 | 30.9 | *3.01* | *157* | *136* | *185* | *83* |
| MP | Dipaleseng | 51.9 | 72.3 | 39.9 | 0.635 | 32.0 | *3.02* | *158* | *96* | *23* | *86* |
| KZ | Ubuhlebezwe | 55.1 | 72.8 | 59.7 | 0.684 | 86.7 | *3.04* | *159* | *193* | *113* | *203* |

| Province | Municipality | IMR | U5MR | PHCR | GI | LS PHCR | SMR | Ranks | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | U5M | PV | II | LSP |
| EC | Inkwanca | 53.3 | 73.3 | 46.9 | 0.670 | 24.4 | *3.06* | *160* | *128* | *80* | *44* |
| KZ | Ndwedwe | 53.7 | 73.4 | 60.3 | 0.625 | 91.0 | *3.06* | *161* | *196* | *14* | *215* |
| EC | Elundini | 55.3 | 73.5 | 59.2 | 0.710 | 88.8 | *3.07* | *162* | *190* | *187* | *211* |
| KZ | Endumeni | 54.1 | 74.0 | 39.0 | 0.661 | 27.3 | *3.09* | *163* | *89* | *65* | *61* |
| FS | Masilonyana | 52.6 | 74.4 | 47.5 | 0.659 | 30.2 | *3.10* | *164* | *132* | *61* | *74* |
| EC | Engcobo | 56.0 | 74.5 | 63.4 | 0.713 | 94.2 | *3.11* | *165* | *211* | *195* | *227* |
| FS | Dihlabeng | 52.7 | 74.5 | 34.5 | 0.700 | 27.1 | *3.11* | *166* | *49* | *162* | *58* |
| NW | Kgetlengrivier | 54.9 | 74.7 | 42.2 | 0.705 | 45.6 | *3.11* | *167* | *112* | *173* | *124* |
| KZ | Umzumbe | 54.8 | 74.9 | 64.5 | 0.636 | 92.6 | *3.12* | *168* | *217* | *27* | *220* |
| KZ | uMlalazi | 54.9 | 74.9 | 54.7 | 0.696 | 79.3 | *3.13* | *169* | *168* | *151* | *188* |
| EC | Ngquza Hill | 56.6 | 75.3 | 69.5 | 0.734 | 94.5 | *3.14* | *170* | *230* | *226* | *228* |
| NW | Ditsobotla | 55.5 | 75.4 | 47.4 | 0.722 | 54.9 | *3.15* | *171* | *131* | *211* | *141* |
| KZ | Mtubatuba | 55.2 | 75.5 | 56.1 | 0.726 | 73.1 | *3.15* | *172* | *177* | *218* | *168* |
| KZ | Impendle | 55.5 | 75.8 | 59.3 | 0.647 | 87.0 | *3.16* | *173* | *191* | *41* | *206* |
| NW | Ventersdorp | 55.8 | 75.9 | 52.5 | 0.694 | 58.4 | *3.16* | *174* | *155* | *146* | *145* |
| KZ | Richmond | 55.8 | 76.2 | 46.7 | 0.690 | 78.1 | *3.18* | *175* | *127* | *128* | *187* |
| EC | Matatiele | 57.5 | 76.4 | 58.8 | 0.672 | 87.0 | *3.19* | *176* | *188* | *83* | *205* |
| KZ | Ingwe | 56.0 | 76.5 | 61.2 | 0.727 | 93.3 | *3.19* | *177* | *202* | *219* | *221* |
| MP | Albert Luthuli | 55.1 | 76.6 | 55.4 | 0.720 | 65.9 | *3.20* | *178* | *174* | *207* | *152* |
| KZ | Umzimkhulu | 56.1 | 76.7 | 64.4 | 0.673 | 91.6 | *3.20* | *179* | *216* | *87* | *218* |
| FS | Mohokare | 54.8 | 77.5 | 46.5 | 0.720 | 37.6 | *3.23* | *180* | *126* | *205* | *107* |
| KZ | Mkhambathini | 56.8 | 77.6 | 44.2 | 0.632 | 85.0 | *3.24* | *181* | *120* | *20* | *200* |
| FS | Letsemeng | 55.0 | 77.7 | 40.2 | 0.667 | 30.7 | *3.24* | *182* | *100* | *76* | *80* |
| MP | Msukaligwa | 56.1 | 78.1 | 36.3 | 0.686 | 37.7 | *3.26* | *183* | *68* | *118* | *108* |
| EC | Ntabankulu | 58.9 | 78.3 | 69.8 | 0.674 | 95.4 | *3.26* | *184* | *231* | *89* | *233* |
| FS | Maluti a Phofung | 55.4 | 78.4 | 56.1 | 0.683 | 53.5 | *3.27* | *185* | *177* | *106* | *137* |
| KZ | Kwa Sani | 57.6 | 78.7 | 23.5 | 0.657 | 52.0 | *3.28* | *186* | *8* | *59* | *133* |
| KZ | Ezingoleni | 57.6 | 78.7 | 60.0 | 0.648 | 90.8 | *3.28* | *187* | *194* | *44* | *214* |
| KZ | Mfolozi | 57.7 | 78.8 | 57.4 | 0.648 | 75.5 | *3.29* | *188* | *186* | *46* | *174* |
| FS | Setsoto | 56.1 | 79.4 | 50.2 | 0.704 | 40.5 | *3.31* | *189* | *140* | *169* | *115* |
| MP | Lekwa | 57.2 | 79.6 | 35.4 | 0.677 | 22.5 | *3.32* | *190* | *57* | *94* | *34* |
| FS | Nala | 56.7 | 80.2 | 51.3 | 0.684 | 30.2 | *3.35* | *191* | *147* | *110* | *75* |
| EC | Port St Johns | 60.5 | 80.3 | 72.0 | 0.730 | 96.5 | *3.35* | *192* | *233* | *222* | *234* |
| NW | Naledi | 59.2 | 80.4 | 39.9 | 0.693 | 37.0 | *3.35* | *193* | *97* | *140* | *100* |
| NW | Greater Taung | 59.2 | 80.4 | 60.9 | 0.687 | 82.5 | *3.36* | *194* | *199* | *119* | *192* |
| NW | Lekwa-Teemane | 59.6 | 81.0 | 40.2 | 0.706 | 28.6 | *3.38* | *195* | *99* | *180* | *69* |
| KZ | Vulamehlo | 59.7 | 81.5 | 63.1 | 0.620 | 94.0 | *3.40* | *196* | *209* | *11* | *225* |
| KZ | Emnambithi/Ladysmith | 59.7 | 81.5 | 48.4 | 0.700 | 43.8 | *3.40* | *197* | *134* | *161* | *121* |
| KZ | Mpofana | 59.8 | 81.6 | 37.4 | 0.668 | 45.2 | *3.40* | *198* | *75* | *78* | *122* |
| KZ | Newcastle | 60.0 | 81.9 | 51.7 | 0.724 | 30.5 | *3.42* | *199* | *150* | *215* | *79* |
| KZ | uMuziwabantu | 60.1 | 82.0 | 61.2 | 0.678 | 87.3 | *3.42* | *200* | *203* | *97* | *207* |
| KZ | Maphumulo | 60.1 | 82.0 | 66.2 | 0.688 | 94.2 | *3.42* | *201* | *221* | *121* | *226* |
| EC | Mbizana | 61.9 | 82.2 | 71.5 | 0.711 | 95.3 | *3.43* | *202* | *232* | *190* | *232* |
| KZ | Hlabisa | 60.3 | 82.3 | 63.8 | 0.724 | 87.9 | *3.43* | *203* | *213* | *214* | *210* |
| KZ | uMshwathi | 60.4 | 82.4 | 42.1 | 0.647 | 75.3 | *3.44* | *204* | *110* | *43* | *173* |
| FS | Tswelopele | 58.7 | 83.0 | 50.2 | 0.692 | 27.9 | *3.46* | *205* | *141* | *134* | *62* |
| KZ | Ulundi | 61.5 | 83.9 | 60.9 | 0.716 | 70.0 | *3.50* | *206* | *198* | *199* | *162* |
| KZ | Jozini | 61.8 | 84.3 | 66.5 | 0.784 | 84.0 | *3.52* | *207* | *222* | *234* | *194* |
| FS | Nketoana | 60.2 | 85.1 | 41.3 | 0.722 | 36.2 | *3.55* | *208* | *107* | *212* | *98* |
| KZ | Dannhauser | 63.0 | 85.9 | 64.2 | 0.625 | 77.0 | *3.58* | *209* | *215* | *15* | *183* |
| KZ | Imbabazane | 63.8 | 87.0 | 68.1 | 0.638 | 93.8 | *3.63* | *210* | *226* | *30* | *223* |
| KZ | Nkandla | 64.1 | 87.4 | 63.7 | 0.705 | 90.0 | *3.65* | *211* | *212* | *174* | *213* |
| KZ | Umvoti | 64.5 | 87.9 | 49.3 | 0.672 | 76.0 | *3.67* | *212* | *137* | *83* | *176* |
| KZ | Umtshezi | 64.6 | 88.1 | 52.4 | 0.751 | 49.8 | *3.68* | *213* | *153* | *230* | *130* |

| Province | Municipality | IMR | U5MR | PHCR | GI | LS PHCR | SMR | Ranks U5M | PV | II | LSP |
|---|---|---|---|---|---|---|---|---|---|---|---|
| KZ | Ntambanana | 64.6 | 88.1 | 67.0 | 0.692 | 92.5 | *3.68* | *214* | *224* | *133* | *219* |
| KZ | The Big 5 False Bay | 65.1 | 88.7 | 56.5 | 0.775 | 72.5 | *3.70* | *215* | *184* | *233* | *167* |
| FS | Phumelela | 63.6 | 89.8 | 44.9 | 0.666 | 42.4 | *3.75* | *216* | *122* | *72* | *118* |
| NW | Tswaing | 67.5 | 91.6 | 56.3 | 0.706 | 65.1 | *3.82* | *217* | *182* | *178* | *151* |
| NW | Kagisano/Molopo | 68.8 | 91.6 | 59.2 | 0.739 | 82.9 | *3.82* | *218* | *189* | *227* | *193* |
| NW | Mamusa | 68.3 | 92.6 | 53.7 | 0.716 | 41.6 | *3.86* | *219* | *162* | *200* | *117* |
| FS | Tokologo | 64.9 | 93.3 | 42.6 | 0.713 | 56.9 | *3.89* | *220* | *114* | *196* | *144* |
| KZ | Indaka | 69.6 | 94.8 | 72.1 | 0.635 | 76.3 | *3.96* | *221* | *234* | *22* | *179* |
| KZ | Nongoma | 69.9 | 95.2 | 66.7 | 0.706 | 87.6 | *3.97* | *222* | *223* | *179* | *209* |
| KZ | Mthonjaneni | 70.0 | 95.3 | 51.0 | 0.676 | 76.6 | *3.98* | *223* | *143* | *92* | *181* |
| NW | Maquassi Hills | 72.7 | 98.4 | 53.7 | 0.725 | 35.8 | *4.11* | *224* | *161* | *216* | *93* |
| NW | Ratlou | 73.1 | 99.1 | 61.2 | 0.698 | 89.1 | *4.13* | *225* | *201* | *156* | *212* |
| MP | Pixley Ka Seme | 72.0 | 99.9 | 52.6 | 0.751 | 40.8 | *4.17* | *226* | *157* | *231* | *116* |
| MP | Mkhondo | 72.5 | 100.5 | 53.9 | 0.721 | 61.4 | *4.19* | *227* | *166* | *210* | *149* |
| KZ | Nqutu | 73.9 | 100.6 | 68.4 | 0.656 | 84.4 | *4.20* | *228* | *227* | *57* | *197* |
| KZ | Okhahlamba | 75.0 | 102.1 | 66.0 | 0.712 | 85.0 | *4.26* | *229* | *220* | *194* | *199* |
| KZ | Abaqulusi | 75.9 | 103.3 | 53.7 | 0.729 | 52.8 | *4.31* | *230* | *163* | *221* | *135* |
| KZ | Emadlangeni | 76.1 | 103.5 | 51.1 | 0.691 | 67.8 | *4.32* | *231* | *144* | *130* | *158* |
| KZ | eDumbe | 77.8 | 105.8 | 60.6 | 0.686 | 73.6 | *4.41* | *232* | *197* | *117* | *169* |
| KZ | Msinga | 79.4 | 107.9 | 68.7 | 0.699 | 95.1 | *4.50* | *233* | *228* | *160* | *231* |
| KZ | uPhongolo | 80.2 | 109.1 | 55.3 | 0.705 | 74.2 | *4.55* | *234* | *171* | *175* | *170* |

♠ Note the notations in the headings – IMR: Infant mortality rate per thousand; U5MR: under-five mortality rate per thousand; PHCR: per cent income poverty head-count ratio; GI: Gini index; LSPHCR: living standard poverty head-count ratio; SMR: standardised mortality rate; U5M: under-five mortality; IP: income poverty; II: income inequality; LSP: living standard poverty.

## 4.3 Estimates child mortality in relation to poverty and inequality

Having discussed the differentials in mortality among provinces and municipalities, it is quite important to address the matter in relation to poverty and inequality. It helps to appreciate how the disparities of child mortality among the geographical areas discussed above are associated with poverty and inequality. For this purposes, two measures of poverty and one measure of inequality are computed using the methods stated in the previous chapter. Poverty head count ratio (PHCR) based on per capita monthly income (poverty line of R515), and poverty based on living standard (LS) index (households in the first two LS quintiles are considered as poor), are the two measures of poverty while Gini index (GI) is computed as a measure of income inequality.

The proportion of poor people at national level is estimated to be about 40 per cent both in terms of income and LS index while income inequality as measured by Gini index is estimated to be 0.72. In order to understand the relationships at province level,

Table 4.5 explicitly presents the information for each province. There are large differences in poverty among the provinces which range from 30 to 54 per cent in terms of income and from 18 to 69 per cent in terms of LS index while the variation in inequality is very low, Gini index ranging only from 0.68 to 0.72. These economic disparities can be compared with health differentials as measured by under-five mortality rates (26-71 deaths per 1000 births). Western Cape (WC) has not only registered the lowest child mortality rate but also had the smallest measures of poverty and inequality. It is only 18 per cent of the people living in the province that are classified as poor in terms of living standard as compared to 30 per cent based on per capita monthly income. On the other hand, KwaZulu-Natal (KZN), the province with the highest child mortality rate, stands but third and second from the last in terms of poverty and inequality respectively. Limpopo and Eastern Cape (EC) are the first and second poorest provinces based on both measures of poverty while EC seemed to be relatively the most unequal province, followed by KZN. It is apparent that Limpopo is the only province which had lower mortality rate unlike its higher level of poverty in both dimensions considered in this research. Somehow on the contrary, although Free State has better poverty estimates, the third (LS) and fourth (income) lowest, child mortality is found to be much higher.

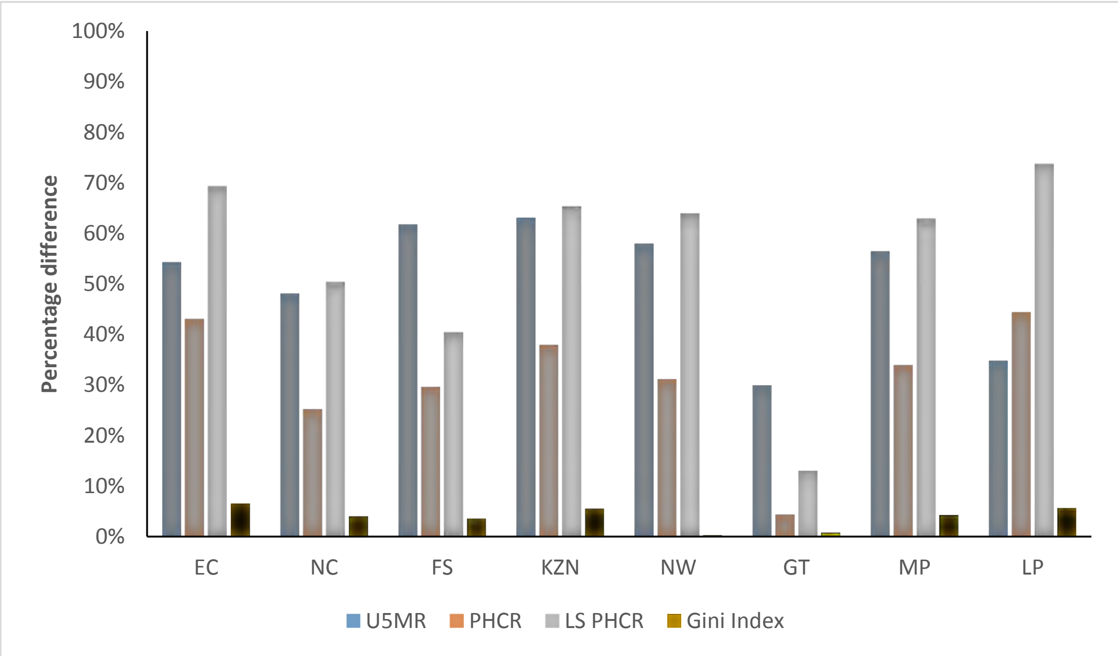
**Table 4-5 Estimates of U5MR, poverty and inequality at province level**

| Province | U5MR | PHCR (Income) | PHCR(LS Index) | Gini Index |
|---|---|---|---|---|
| Western Cape | 26.06 | 30.22 | 18.06 | 0.6771 |
| Eastern Cape | 57.04 | 53.06 | 58.83 | 0.7243 |
| Northern Cape | 50.24 | 40.38 | 36.39 | 0.7054 |
| Free State | 68.17 | 42.92 | 30.33 | 0.7022 |
| KwaZulu-Natal | 70.61 | 48.66 | 52.06 | 0.7164 |
| North West | 62.03 | 43.87 | 50.03 | 0.6790 |
| Gauteng | 37.19 | 31.59 | 20.77 | 0.6824 |
| Mpumalanga | 59.85 | 45.73 | 48.65 | 0.7071 |
| Limpopo | 39.98 | 54.34 | 68.79 | 0.7174 |
| *ZA* | *49.95* | *40.73* | *40.22* | *0.7156* |

Note: U5MR is per thousand while PHCRs are expressed as percentages

It is also attempted to make comparison of estimates from other provinces with Western Cape as it has the lowest estimates in terms of both child mortality and income poverty, living standard poverty and income inequality. Figure 4.10 displays the percentage deviations of each of the four quantities from the corresponding estimates of Western Cape Province. The prime differences are in child mortality and living standard followed by income poverty while the difference income inequality is the smallest in all the provinces.

**Figure 4-10 Comparison of provincial estimates of U5MR, poverty and inequality with WC's estimates**




The estimates of poverty and inequality for the 234 municipalities are also computed and are given together with the smoothed estimates of under-five mortality rates and other related statistics in Table 4.4. It is evident that in most cases both measures of poverty are positively related with child mortality in that municipalities with lighter mortality rates have lower proportion of people living under poverty and in municipalities with heavier child mortality have recorded higher proportion of poor people. In this regard, it must be noted that the poverty measure computed based on the living standard index has shown a stronger association with child mortality – correlation coefficient of 0.573, than the poverty measures computed based on per capita income alone – correlation coefficient of 0.475. In both measures, however, there are many exceptions in that lower poverty does not necessarily guarantee lighter mortality and vice versa. For instance, although Thulamela, a municipality in Limpopo province, is ranked as the 195th and 184th poor municipality in terms of income and living standard respectively, it has recorded the 13th lighter under-five mortality rate. Similarly, Mutale, another municipality in Limpopo, has the 23rd smallest under-five mortality while respectively scoring a rank of 206 and 208 in terms of income and living standard poverty. On the other hand, municipalities like Mpofana (in KZN province) with income poverty rank of 75th and Maquassi Hills (in NW province) with living standard poverty rank of 93 had registered among the highest mortality rates with ranks of 198th and 224th respectively.

The relationship between income inequality and child mortality, however is not as strong as the relationship between child mortality and poverty. In general, all municipalities experienced a very high level of inequality, Gini index ranging from 0.576 in Ngqushwa (in EC province) to 0.784 in Jozini (in KZN province) and 79 per cent of all the 234 municipalities scoring a Gini index greater than 0.65. Nonetheless, there is a weak positive correlation, $r = 0.271$, between income inequality and child mortality implying that on average there are more deaths in municipalities where the people are more unequal in terms of income than in municipalities with less unequal people. However, it is not surprising that there are inverse relationships between income inequality and child mortality in many municipalities including Nqutu and Dannhauser (both in KZN) with much lower inequality and higher mortality, and Knysna and Bitou (both in WC) with much higher inequality but lower mortality.

For a better understanding of the relationship among child mortality, poverty and inequality, municipalities are divided into poverty and inequality quintiles and the corresponding average under-five mortality rates are then computed in each quintile. This information is provided below in Table 4.6. In each of the three cases, an increasing trend of child mortality is observed along the quintiles, confirming that on average an increase in poverty and inequality is associated with an increase in mortality of children. However, the magnitude of the changes in mortality along the quintiles of income inequality (Gini Index) are smaller, which supports the points raised above that child mortality has stronger association with income and living condition than income inequality.

**Table 4-6 Under-five mortality rates under poverty and inequality quintiles**

| | Mean U5MR in Quintiles of | | |
|---|---|---|---|
| **Quintiles** | **PHCR (income)** | **PHCR(LS index)** | **Gini Index** |
| Q1 | 42.77 | 44.00 | 54.99 |
| Q2 | 53.41 | 57.43 | 58.40 |
| Q3 | 65.51 | 63.32 | 59.25 |
| Q4 | 67.87 | 66.10 | 61.08 |
| Q5 | 74.97 | 73.64 | 70.72 |
| **Corr coefficient** | **0.4749** | **0.5727** | **0.2706** |

Table 4.7 presents the poverty and inequality measures for the top and last 15 municipalities according to the child mortality rankings and their corresponding ranks in in poverty and inequality. All the top municipalities are in Western Cape except Thulamela (in Limpopo), City of Tshwane (in Gauteng), Nelson Mandela Bay (in Eastern Cape) and City of Johannesburg (in Gauteng) while the majority of the last municipalities are in KwaZulu-Natal followed by Mpumalanga (Mkhondo and Pixley Ka Seme), North West (Ratlou and Maquassi Hills) and Free State (Tokologo) provinces. This undoubtedly depicts the spatial accumulation of child mortality in the country. The top 15 best municipalities have recorded an average under-five mortality rate of 28.8 per thousand as opposed to 100.6 per thousand by the bottom 15 municipalities. If one is interested to compare these results with the average measures of poverty and inequality (the details are given in Table 4.4), the mean income poverty head-count ratios are 31 and 61 per cent respective for the first 15 and the last 15 municipalities while the mean living standard poverty head-count ratios are 23 and 76. The measure of income inequality (Gini index) has resulted in a mean value of 0.67 and 0.70 respectively for the top 15 and bottom 15 municipalities. All these give additional confirmation on the fact that child mortality is heavier in municipalities where poverty and inequality are worse, and that the association is weaker with inequality than poverty.

**Table 4-7 15 best and worst municipalities in terms of under-five mortality and their associated rankings in poverty and inequality**

| Municipality | Province | U5MR | Ranks | | | Municipality | Province | U5MR | Ranks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | PHCR | LS PHCR | GI | | | | PHCR | LS PHCR | GI |
| City of Cape Town | WC | 23.97 | 33 | 14 | 86 | uPhongolo | KZN | 109.08 | 171 | 170 | 214 |
| Mossel Bay | WC | 25.80 | 48 | 3 | 55 | Msinga | KZN | 107.91 | 228 | 231 | 76 |
| Knysna | WC | 26.62 | 52 | 60 | 170 | eDumbe | KZN | 105.77 | 197 | 169 | 88 |
| Overstrand | WC | 26.97 | 40 | 25 | 47 | Emadlangeni | KZN | 103.53 | 144 | 158 | 59 |
| Bitou | WC | 27.48 | 72 | 46 | 176 | Abaqulusi | KZN | 103.26 | 163 | 135 | 227 |
| Stellenbosch | WC | 27.69 | 44 | 24 | 104 | Okhahlamba | KZN | 102.08 | 220 | 199 | 201 |
| George | WC | 28.19 | 38 | 20 | 52 | Nqutu | KZN | 100.60 | 227 | 197 | 10 |
| Drakenstein | WC | 28.38 | 23 | 7 | 75 | Mkhondo | MP | 100.51 | 166 | 149 | 148 |
| Breede Valley | WC | 30.40 | 27 | 43 | 50 | Pixley Ka Seme | MP | 99.89 | 157 | 116 | 234 |
| Theewaterskloof | WC | 30.48 | 21 | 28 | 42 | Ratlou | NW | 99.06 | 201 | 212 | 102 |
| Thulamela | LP | 30.60 | 195 | 184 | 123 | Maquassi Hills | NW | 98.44 | 161 | 93 | 230 |
| Saldanha Bay | WC | 31.18 | 19 | 1 | 26 | Mthonjaneni | KZN | 95.34 | 143 | 181 | 51 |
| City of Tshwane | GT | 31.29 | 24 | 31 | 68 | Nongoma | KZN | 95.24 | 223 | 209 | 128 |
| City of Johannesburg | GT | 32.18 | 34 | 15 | 146 | Indaka | KZN | 94.81 | 234 | 179 | 32 |
| Nelson Mandela Bay | EC | 32.28 | 104 | 11 | 144 | Tokologo | FS | 93.34 | 189 | 193 | 205 |

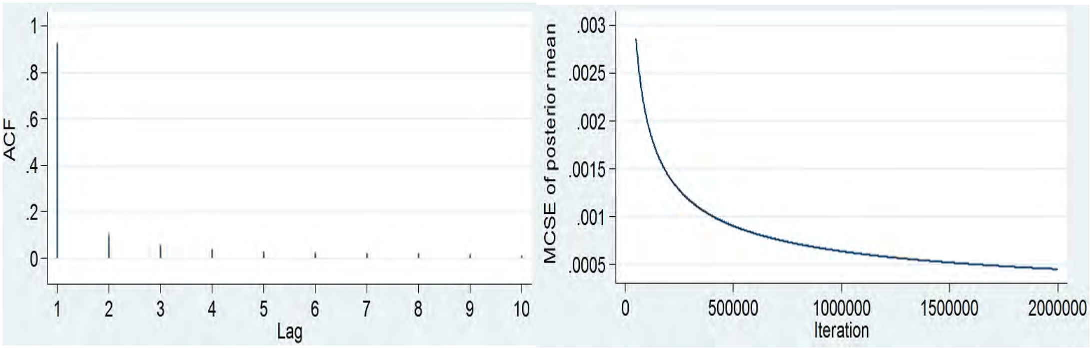
## 4.4 Results from multilevel logistic regression model

### 4.4.1 Model diagnostics

A three-level logistic regression model is fitted on the survival status of children born twelve months before the census. The parameters of the model are estimated using the Bayesian MCMC procedure by running the simulation for 1000 burn-in and 10000 monitoring period. After fitting the model, the reasonableness of the parameter estimates are assessed by looking at some diagnostics plots including the autocorrelation plots of successive iterations of the chains and Monte Carlo standard error plots for checking convergence of the posterior distributions. These is done for each of the fixed and random terms in the model and; as examples, Figure 4.11 presents the two plots for one fixed term (HIV variable) and one random term (municipal-level effect). In addition, the normal probability plots given in Figure 4.12 show that the assumptions of normality of the residual terms at municipality and province level are approximately maintained.

**Figure 4-11 Autocorrelations of iterations at different lags and Monte Carlo standard error of posterior mean**

a) For HIV fixed effect parameter estimate




b) For municipal-level random effect parameter estimate

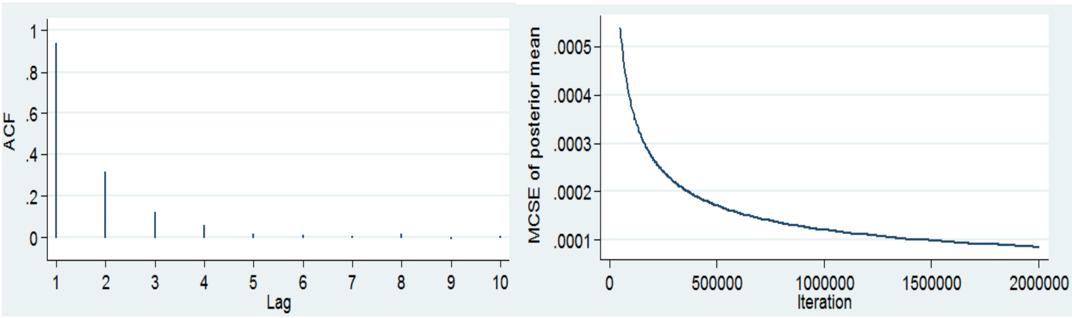
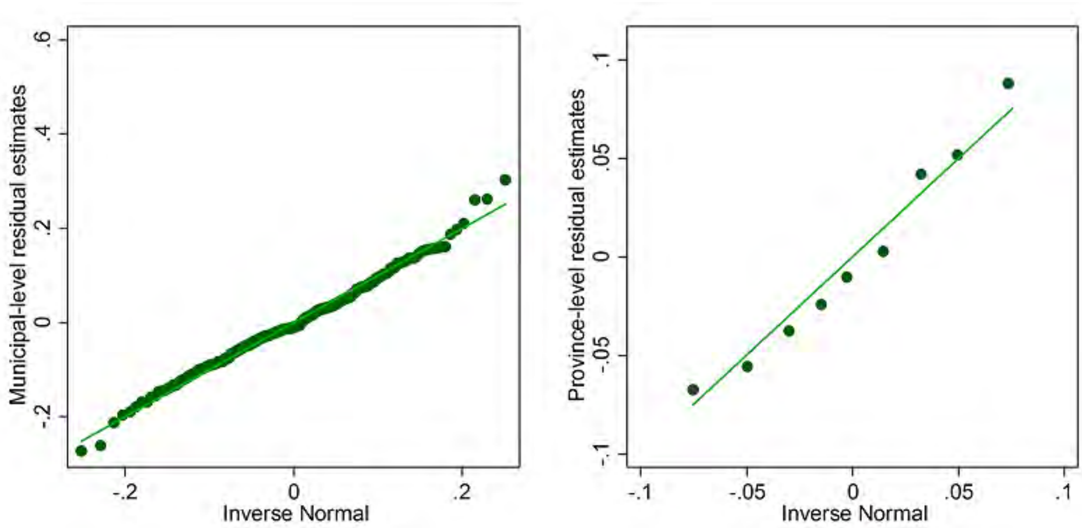



**Figure 4-12 Normal probability plots for municipal-level and province-level residual estimates**




### 4.4.2 Regression model output

The final result of the regression is as shown in Table 4.8. All parameter estimates are measured on the log-odds (logit) scale. In order to make more specific and meaningful inference about the effect of the risk factors on the mortality of children, the odds ratios (ORs) are given corresponding to each coefficient estimate in the same table. Note that among the independent variables, proportion of poor people, income inequality and mean years of mother's education are measured at municipality level whereas HIV prevalence rate is computed at province level. All these four variables are dichotomised as higher and lower values of the respective quantities.

Table 4-8 Output from the multilevel logistic regression model

| ***Variable*** | **Mean** | **Std. Dev.** | **P-value** | **95% Cred. Interval** | **Odds** |
|---|---|---|---|---|---|
| *Fixed effect parameters* | | | | | |
| ***Individual level*** | | | | | |
| *Cons* | (4.3871) | 0.2111 | 0.000 | (-4.811, -3.983) | 0.0124 |
| *Female child* | 0.1937 | 0.0505 | 0.000 | (0.096, 0.293) | 1.2137 |
| *Neonatal* | (0.1954) | 0.0851 | 0.010 | (-0.365, -0.033) | 0.8225 |
| *Mother's age at birth, 20-34 (Ref)* | | | | | |
| *<20 years* | 0.0764 | 0.0752 | 0.155 | (-0.069, 0.223) | 1.0793 |
| *>34 years* | 0.0551 | 0.0750 | 0.230 | (-0.093, 0.2) | 1.0566 |
| *Birth order, First birth (Ref)* | | | | | |
| *2* | (0.0075) | 0.0697 | 0.458 | (-0.142, 0.13) | 0.9925 |
| *3* | 0.1812 | 0.0841 | 0.016 | (0.017, 0.345) | 1.1986 |
| *4+* | 0.3427 | 0.0889 | 0.000 | (0.165, 0.514) | 1.4088 |
| *Mother's education, No/primary education (Ref)* | | | | | |
| *Secondary education* | (0.1743) | 0.0712 | 0.009 | (-0.314, -0.033) | 0.8401 |
| *Higher education* | (0.4929) | 0.1369 | 0.001 | (-0.759, -0.228) | 0.6109 |
| *Mother never married* | 0.1234 | 0.0561 | 0.014 | (0.014, 0.235) | 1.1314 |
| *Mother works* | 0.2272 | 0.0712 | 0.001 | (0.089, 0.366) | 1.2550 |
| *Mother is Black African* | 0.3071 | 0.1107 | 0.002 | (0.101, 0.526) | 1.3595 |
| *LS index quintiles, Q1 (Ref)* | | | | | |
| *Q2* | (0.1289) | 0.0722 | 0.039 | (-0.267, 0.014) | 0.8791 |
| *Q3* | (0.1519) | 0.0801 | 0.026 | (-0.309, 0.003) | 0.8591 |
| *Q4* | (0.3429) | 0.0915 | 0.000 | (-0.526, -0.172) | 0.7097 |
| *Q5* | (0.6988) | 0.1336 | 0.000 | (-0.961, -0.438) | 0.4972 |
| ***Municipal level*** | | | | | |
| *Higher proportion of poor* | 0.0343 | 0.0843 | 0.216 | (-0.129, 0.204) | 1.0349 |
| *More educated mothers* | (0.198) | 0.0802 | 0.007 | (-0.326, -0.003) | 0.8204 |
| *Greater income inequality* | 0.1215 | 0.1405 | 0.103 | (-0.141, 0.417) | 1.1292 |
| ***Province level*** | | | | | |
| *Heavier HIV prevalence* | 0.3374 | 0.1095 | 0.004 | (0.105, 0.541) | 1.4012 |
| *Random effect parameters* | | | | | |
| *Province effect (level 3)* | 0.0154 | 0.0219 | - | (0.001, 0.073) | 1.0155 |
| *Municipality effect (level 2)* | 0.0511 | 0.0224 | - | (0.010, 0.099) | 1.0524 |

All coefficients of the four living standard dummy variables which are used as proxy indicator variables of poverty are negative and their 95% credible intervals excludes zero and hence relative to children who were in the first living standard quintile, those who were in the other quintiles were less likely to die. It can also be noted that, as expected, the better the living standard the less likely the child dies since the magnitude of the coefficients increases with the increase in quintiles – children from households positioned in the second, third, fourth and fifth wealth quintiles have 12, 14, 30 and 50 percent chances of survival compared to children in the first wealth quintile. Likewise, the income poverty has positive and significant coefficient entailing that children living in a household whose members earn a per capita income of less than the South African poverty line are more likely to die than children whose household whose members earn above the poverty line.

The two municipal level indicator variables: proportion of people under poverty and the level of income inequality as measured by Gini index, have positive coefficient although they are not significant at 95 per cent. It means that not only the level of poverty of the household but also the level of poverty and distribution of income of the community/municipality where the child lives affects the survival status of the child. A child is more likely to die in a highly poor and more unequal municipality compared to municipalities where there is lower poverty and inequality after having controlled for the effect of other risk factors. Considering the magnitude of the impact, it seems that the distribution matters more than the size of poverty in the area as the odds of dying of children in more unequal municipalities is 13 per cent higher than in less unequal municipalities while this likelihood difference is only 3.5 per cent between municipalities where poverty is higher and lower. Similarly, children living in municipalities where the average years of education of women is higher have better likelihood of survival irrespective of the education level of their own mother. They are about 16 per cent less likely to die than children living in areas where there is less education of mothers.

Considering the effect of HIV on mortality of children, it is apparent that its coefficient is positive and significant. Children in provinces with high HIV prevalence are 40 per cent more likely to die than children in other provinces after controlling other factors in the model. This indicates that HIV has the greatest impact on mortality as compared to the other community level variables considered.

The sex effect is positive and its 95% credible interval does not include zero, implying a significant positive effect of the sex of the child. More specifically, boys are 21 per cents more likely to die during their first year of life than girls, all else being equal. Similarly, age of the child significantly affects the mortality of the child in that children who survived the first month after birth are less likely to die than those who are less than one month old by about 18 per cent.

In terms of mother characteristics, the results in Table 4.8 show that mothers' age at the birth of the child is not statistically significant as the 95% credible interval contains zero. However, the estimated coefficients for the two dummy variables are positive confirming that children from mothers who are younger than 19 or older than 34 years at the birth of the child are more likely to die than children whose mothers are between 20 and 34 years old. The employment status of mothers is not also significant although it has positive relation with the mortality of children. It seems that the children of employed mothers have less probability of survival. All the other independent variables associated with mothers are significant which includes years of education, birth order, marital status and population group.

In accordance with the literature, the more education a mother gets, the less likely the mortality of her child is. Children whose mothers have completed secondary and higher education are 16 and 39 per cent respectively more likely to survive than those children whose mothers have no education or only have primary education. In addition, mothers having higher birth orders, mother who are never married or single mothers and mothers from African population group have a greater chance of mortality of their children relative to those mothers who have less birth orders, mothers who are not single and mothers from non-African population group. Specifically, the odds of survival of children of mothers having four or more children is 41% higher than first born children while third born children are 20% more likely to survive and second born children have less than one% chance of survival as compared to first born children. Similarly, there are 36 and 15% more survival chance by those children who are from non-Black African and non-single mothers respectively.

The random effects terms included in the model are also significant since the 95 per cent credible interval does not include zero in both cases. Hence, there is a unique effect for each province (level 3) and for each municipality (level 2) in addition to the fixed effects discussed above. The reported mean values in Table 4.8 are the average random effect estimates of all provinces and all municipalities. The addition of the municipality specific effects as well as province specific effects makes the model more accurate than the fixed only model. Specifically, controlling the municipal and province level variations has on average increased the odds of death of children by 5 and 2 per cents respectively.

# 5. DISCUSSIONS AND CONCLUSION

This chapter first discusses the main results of the study and tries to see how they are compared with the findings in other studies so far. It then, describes the major limitations which must be noted in connection with the use of the results in the research and states some of the opportunities for future works. Finally, conclusion follows to pinpoint the key lessons one might take from the study.

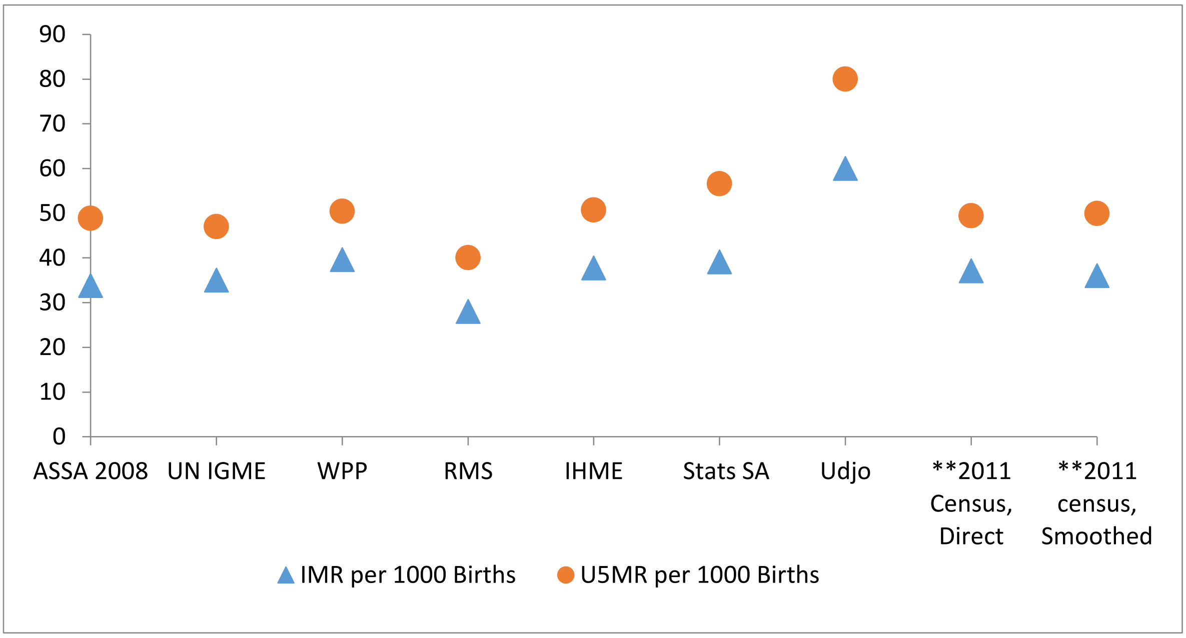
## 5.1 Discussion of results

Although child mortality in South Africa has improved substantially in the last decade, after some period of reversal mainly due to HIV, the level is much higher than the mortality in many other countries with similar economic development level. We believe that, in order to effectively address the problem and work towards further reductions of child mortality in the country it is essential that the efforts be focused more on lower administrative levels as opposed to concentrating only on the level of mortality at national level (Freedman, Waldman, Pinho *et al.* 2005). Hence, for these efforts to move forward, constructing reliable estimates of child mortality for small geographical areas should be considered as one of the first important steps. Consequently, the overall objective of this research was to produce estimates of child mortality rates for the provinces and municipalities of South Africa using the 2011 census data, and assess the differentials in relation to the level of poverty and inequality. In addition, studying the factors associated with child mortality in South Africa considering the hierarchical structure of the data and with special emphasis on poverty and inequality was the second main objective. In this chapter an attempt will be made to discuss the extent at which these objectives have been met. This involves discussing the reasonableness of the estimates of child mortality produced at national, provincial and municipal level and the validity of the results obtained on factors affecting child survival in comparison with other studies.

Estimates of infant and under-five mortality rates at national and province level are generated directly using household death data from the 2011 census. However, in attempting to estimate child mortality for smaller geographical areas it is often difficult to construct accurate estimates because population sizes also tend to be relatively small, resulting in unstable estimates. One common approach that would help us to overcome this issue is to use Bayesian smoothing method. Hierarchical Bayesian model has been used to construct spatially smoothed estimates of child mortality for the municipalities of South Africa. The first level of the model uses the household mortality data from the 2011 South African census while in the next level the probability of a child dying before reaching age one is modelled using a binomial model with a spatially structured random effect. The prior distribution for this random effect is constructed using a conditional autoregressive (CAR) model which incorporates spatial dependence among neighbouring municipalities and allows for its impact to be greater for municipalities with more unstable data. The estimates are further improved by incorporating average years of women's education of each municipality and the provincial HIV prevalence rates of adults aged 15-49. It is assumed that the ratio of under-five mortality rate and infant mortality rate be the same at province level which helps us to get estimates of under-five mortality rates for the municipalities from the infant mortality rates obtained from the Bayesian spatial smoothing model.

Having derived the child mortality rates, the first important question has to be how the estimates are compared with those presented elsewhere. In this regard, the national level estimates can be compared with reports from Stats SA, Rapid Mortality Surveillance (RMS), ASSA model 2008, UN Inter-agency Group for Mortality Estimation (IGME), world population prospectus (WPP) and the Institute for Health Metrics and Evaluation (IHME). Figure 5.1 presents the estimates of infant and under-five mortality rates from these institutions as well as the estimates from this research and estimates from a recently published paper by Udjo (2014). Given the degree of controversy about estimates of child mortality in South Africa and the fact that each of the institutions might have used different approaches and data sources to derive their corresponding values, it is fair to say that the estimates from this research are quite reasonable and consistent with most of these estimates. Relatively, both infant and under-five mortality rates from RMS are lower than the others, for instance they are less by 29 and 25 per cent compared to our estimates, while those from Stats SA seem to be a bit inflated. Despite these, the estimates from Udjo (2014) are found to be highly exaggerated compared to the estimates from this research as well as the estimates from all other sources. It is very hard to have an infant and under-five mortality rates of 60 and 80 per 1000 respectively for South Africa in 2011 unless there is some problem with the data used or the method of estimation applied.

**Figure 5-1 Comparisons of national level infant and under-five mortality rates from various sources***




* Stats SA estimates refer to 2010 while others apply to 2011; ** According to this research computation

In attempting to compare the provincial and municipal levels of estimates of child mortality rates it must be noted that there are very few sources to compare with, especially with regard to municipal level estimates. Table 5.2 helps to compare the provincial estimates in this study with estimates from ASSA 2008 model and the research paper by Udjo (2014). In comparing against the ASSA model estimates, our provincial estimates are reasonable and consistent for six of the nine provinces – with percentage differences ranging only from 0.2 to 12.6 per cent. The estimates for North-West (NW), Northern Cape (NC) and Free State (FS) from ASSA model, however, are underestimated by 38.2, 36.6 and 17.5 per cent respectively compared to our estimates. However, as in the national level the estimates by Udjo (2014) for all the provinces are much higher –percentage differences varying from about 28 to 51.

**Table 5-1 Comparisons of provincial level under-five mortality rates from various sources**

| Province | ASSA | Direct | Smoothed | Udjo |
|---|---|---|---|---|
| Western Cape | 26.53 | 24.75 | 26.06 | 36.1 |
| Eastern Cape | 65.25 | 55.96 | 57.04 | 75.6 |
| Northern Cape | 36.78 | 52.55 | 50.24 | 76.5 |
| Free State | 58.02 | 68.47 | 68.17 | 104.1 |
| KwaZulu-Natal | 62.74 | 68.78 | 70.61 | 102.9 |
| North West | 44.88 | 61.79 | 62.03 | 89.4 |
| Gauteng | 37.13 | 36.07 | 37.19 | 75.1 |
| Mpumalanga | 54.71 | 58.13 | 59.85 | 96.0 |
| Limpopo | 39.92 | 39.27 | 39.98 | 67.0 |
| ZA | 48.81 | 49.41 | 49.95 | 80.0 |

As there are no studies so far which have attempted to generate municipal-level child mortality estimates, it is not possible to compare the estimates computed for the municipalities. The magisterial district level under-five mortality rates derived by Bangha and Simelane (2008) using the 2001 census data may be compared roughly with our estimates though neither the geographical unit nor time reference points are the same. However, one can observe that the estimates for the magisterial districts are somehow underestimated to some extent as for some similar areas their estimates at that time (2001) are much lower than our estimates after ten years (2011). For instance, their provincial under-five mortality rates only ranges from 19 in Western Cape to 66 in Eastern Cape which are very unattainable estimates in 2001. This may be partly due to the fact that the 2001 census data has some problems as noted by Dorrington, Moultrie and Timaeus (2004) in their monograph.

Another way of evaluating the quality of the smoothed municipal level estimates is to compare the robustness of the estimates with the crude estimates and smoothed but not improved by women education and HIV prevalence rate. Table 5.3 describes some summary statistics concerning these estimates. It is evident from the table that the Bayesian method has produced more stable and accurate results compared to the crude estimates as they have smaller variation. On the other hand, incorporating women education and HIV prevalence rate into the hierarchical Bayesian model has very little impact on the overall estimates. However, the real benefit of this adaptation can be felt in individual municipalities whose level of education and HIV prevalence differ from those of nearby municipalities. In such cases, by incorporating these two variables into the construction of estimates of child mortality, these differences are recognised and more reliable estimates can be obtained. The correlations between the two covariates and child mortality rates are much stronger in the case of the Bayesian estimates than the crude rates. It is also very important to note that there are 11 municipalities with missing crude estimates of child mortality, but there are no municipalities with missing Bayesian estimates of child mortality. The general approach was also used by McKinnon (2010) to find under-five mortality rates for the municipalities of Brazil and it can be observed that our results are similar in that the use of Bayesian smoothing together with women education has improved the estimates reasonably.

**Table 5-2 Summary statistics on crude and Bayesian estimates of U5M rates at municipal-level**

| Statistic | Crude estimates | Bayesian-Spatial only | Bayesian-with Education and HIV |
|---|---|---|---|
| No of municipalities | 223 | 234 | 234 |
| Mean | 64.55 | 59.48 | 60.84 |
| Median | 57.41 | 57.44 | 58.18 |
| Standard deviation | 31.57 | 19.49 | 19.79 |
| Coefficient of variation (%) | 48.90 | 32.77 | 32.52 |
| Minimum | 8.72 | 24.64 | 23.97 |
| Maximum | 200.31 | 118.23 | 109.08 |
| Correlation with Education | -0.34 | -0.38 | -0.51 |
| Correlation with HIV | 0.40 | 0.72 | 0.76 |
| Missing municipalities | 11 | 0 | 0 |

The child mortality differentials are believed to be highly associated with the level of poverty and inequality. Poverty in this research is measured both using income and living standard. Income poor people are those who earn an average monthly household per capita income of less than R515 while living standard based poverty is defined from an index constructed using factor analysis on a bunch of variables assumed to affect wealth or living standard of household members. Their living standard is considered to be poor if the index lies either on the first or second quintile while those household whose index lying in the third, fourth or fifth quintiles are considered to be non-poor. The estimates of poverty are quite reasonable compared to Stats SA estimates (StatsSA 2014a). For instance, Stats SA has estimated the percentage of people living under poverty line of R443 to be 32.3 per cent while our estimate is 41 per cent at R515 poverty line.

The proportion of poor people in provinces and municipalities are in general found to be positively correlated, as expected, with the level of child mortality in the respective areas – 95 per cent significant correlation coefficients of 0.49 and 0.58 respectively for income and living standard dimension of poverty. However, there are some exceptions in that higher poverty does not necessarily imply higher child mortality and vice-versa. Many municipalities in Limpopo province including Thulamela and Mutale, for example, have scored lower mortality rates although the levels of poverty remain very high in both dimensions of poverty. This may suggest that socioeconomic differentials are not the sole determinants of child mortality but a combination of many other factors too.

Having used the Gini coefficient as a measure of the level of income distribution with in provinces and municipalities, it is also found that income distribution is associated positively with child mortality. However, the degree of association is weak relative to that of poverty resulting in only a 0.17 significant correlation coefficient at municipal-level – significant at 95 per cent level of confidence.

In order to complement the descriptive results on the association of child mortality, and poverty and inequality, an individual level model is fitted using data on the survival status of children born twelve months before the census and its factor which include several demographic and socioeconomic variables. The hierarchical nature of the data was taken into account in the process by considering provinces, municipalities and children as third, second and first levels respectively – hence, fitting a three-level logistic regression model employing Bayesian MCMC procedure for estimating the parameters of the model. The results obtained from this regression model suggest that child mortality in South Africa is jointly determined by the observed individual demographic and socioeconomic characteristics of the child and mother, and by municipal and province level covariates, as well as unobserved municipal-level and province-level effects

Among the demographic factors incorporated in the model, only age of mother at birth is not significant and the direction of relationships, including for age of mother, are all in agreement with other studies before (Hobcraft, McDonald and Rutstein 1985; Hill and Upchurch 1995; Kembo and Ginneken 2009; Boco 2010). Higher birth order and sex of the child have greater impact on the likelihood of child survival compared to other demographic factors considered.

All the socioeconomic variables considered at level-one of the model are significant at 95 per cent confidence level and are in agreement with the results from other researches(Mosley and Chen 1984; Hobcraft 1993; Sastry 1996; Kabir, Islam, Ahmed *et al.* 2001) as well as our child mortality estimation results presented above. For instance, children of black African mothers have a higher risk of death as compared to other population groups while those who are from better educated mother have much lower risk of death. As expected, the living standard (LS) index, which is used as a measure of poverty, is highly significant too in that the higher the LS index of the household where the child lives the less likely the risk of dying. Note that because of multicollinearity issue the household income poverty indicator variable is not included in the model – LS index and income poverty have a strong correlation coefficient of 0.85. Hence, in relation to poverty the result could be interpreted as, for example, children in the least poor and the second least poor household have more than 50 per cent and 30 per cent chance of survival respectively as compared to those living in the poorest households. Children living in municipalities where the level of income poverty and inequality is higher have greater likelihoods of death, though not statistically significant. Similarly but with greater confidence, the average years of schooling of women at municipal-level affects child survival positively while higher women HIV prevalence rate of provinces is highly related with higher risk of death of children as one expects. The results of the regression model also indicate small but statistically significant residuals which can convey province-level and municipal-level effects on the risk of dying, even after controlling for a range of child-level, municipal-level, and province-level variables.

## 5.2 Limitations of the study

All the analyses in this research are mainly based on the 2011 South African census data. Therefore, the significance and reliability of the results depends on the quality of the census data which includes the quality of enumeration and data processing. It is obvious that any flaw in the census data might seriously impact the results in the research. Moreover, as the research is entirely based on cross-sectional data it is not possible to check the robustness of the methods applied with other sources of data, like previous censuses. This could not be done because the municipalities are not consistent across the censuses of South Africa conducted so far. The ideal approach would be to make use of two or more censuses which would also allow us to see the changes of the results through time in addition to helping us to judge the robustness of the methods applied in this study.

The assumptions made in converting infant mortality rates to under-five mortality rates at municipality-level that the ratios of under-five to infant mortality rates are the same for each province could also be considered as one limitation. Although it is a fair assumption to make, given the fact that the ratios have smaller variations even at province level, it is obvious that there could be some variations in the municipalities which would bring a small change to the estimated under-five mortality rates. Hence, the assumption somehow understates the variation among municipalities.

The other main limitation is the unavailability of municipal level HIV prevalence rates, and hence the assumption that these prevalence rates are the same as the rates at the respective provinces. Ignoring the HIV prevalence variation within provinces might especially impact the results of the regression model to some extent.

### 5.3 Scopes for future research

This section looks at some of interesting topics which are not addressed in this research but could be great opportunities for future research. One such case is estimating trends of child mortality rates for the municipalities of South Africa. This could be done by combining the Brass 'children ever born/children surviving' (CEB/CS) method of estimating child mortality together with Bayesian spatial smoothing technique. The 10 per cent sample of the 2011 census data released did not include the number of children surviving to a woman but it can be done with available data from other censuses or large surveys in future.

The other opportunity could be to reproduce the results of this research using data from two or more censuses or other sources of data so that it would be possible to see the changes in child mortality with the changes in poverty and inequality and other socioeconomic variables. In this regard, it is obvious that the use of longitudinal data would give better results.

## 5.4 Conclusions

The study primarily aimed to derive up-to-date estimates of child mortality for the municipalities and provinces of South Africa using the 2011 census data. This is achieved through the use of direct synthetic cohort and Bayesian spatial smoothing methods. It is revealed particularly that child mortality estimation at municipal level is possible which has never been attempted so far to the best of our knowledge. Clear and significant spatial differentials in child mortality are observed in the country – at province level, under-five mortality rate ranges from 26 deaths per 1000 births in Western Cape to 71 deaths per 1000 births in KwaZulu-Natal province, while at municipality level, it ranges from 24 deaths per 1000 births in the City of Cape Town to as high as 109 deaths per 1000 births in uPhongolo. Furthermore, the estimates obtained are reasonable and, those at national and province level are in agreement with results from many other researches.

The study also aimed to find out how the spatial differentials in child mortality in the country are associated with the level of poverty and inequality. For this purpose, poverty in income and living standard dimensions and the Gini index are computed for each municipality as well as for the provinces and the country using data from the same census. The results show that in fact child mortality is higher in municipalities which are poorer, although there are some cases where inverse relationship is observed like several municipalities in Limpopo province that though the level of poverty is very high, child mortality is much lower in comparison with many other municipalities. It is also shown that the distribution of income similarly matters to some extent as greater child mortality is observed in areas which are more unequal although the degree of association is not as strong as with that of poverty.

The last objective of the research was to investigate child mortality risk factors with special emphasis on the impact of poverty and inequality. The results from the multilevel logistic regression model of child survival suggest that most of the demographic and socioeconomic factors identified as well as the province and municipal level random effects are significant. The most determining factors are found to be HIV, living standard poverty, race, mother's education, birth order and sex of the child. These factors can bring from 50 to 21 per cent change on the odds of death of children. The municipal-level poverty and inequality variables, however, are statistically insignificant though their impacts on mortality are still positive.

Unlike its economic development status and despite policies put in place for reduction of child mortality in the country, South Africa's child mortality rate is still high and it seems that it is very unlikely the country achieves the MDG goal number four unless some additional efforts are made to increase the rate of decline in the rest of the time period. This research has claimed that one approach to bring better outcomes is to address the issues at lower administrative level and has tried to provide the evidences gained from the latest available census data. The results obtained may help the government to implement policies more effectively and make more focused decisions towards better reduction of child mortality in the country.

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