



**Title: Factors associated with Malnutrition among children under five years of age in Zimbabwe 2010/2011**

**By**

**Charity Vhurumuku**

**Student Number 747731**

**University of the Witwatersrand, School of Public Health**

**A Research Project**

**Submitted in partial fulfilment of the requirements for the  
Master of Science Degree in Epidemiology and Biostatistics**

**Supervised by:**

**Dr. Thomas Achia**


**Professor Benn Sartorius**

**Final Submission: November 2014**



## Declaration

I, Charity Vhurumuku, declare that this research report is a result of my own independent work. Other sources are acknowledged by explicit references. It is submitted in partial fulfilment of the requirements for the degree of Master of Science in Epidemiology and Biostatistics, in the University of the Witwatersrand, Johannesburg. This work has not been submitted in substance for any other degree or award at this or any other university or place of learning.

Signed: 

Date: 12 November 2014

## **Dedication**

### **To my parents, as I say;**

Dad, the example you set as a young boy gave me the strength to go on. You always say, "Time is what we all share in, what we want the most but, what we get out of it is up to us" Your hardworking nature reminds me that life is all about what we do with our time. Dad, you are my hero. Mom, every word you said gave me encouragement. You always set your mind to what you do and you do it with all your strength; that to me has been a good example of how I can achieve. You are a strong, hardworking and intelligent woman; my role model, the queen of my heart.

## **Abstract**

**Background:** There is evidence suggesting a considerably high prevalence of malnutrition in Zimbabwe. However, there is little evidence available to suggest the factors that may be associated with malnutrition in the local context.

**Objectives:** This study investigates the distribution of malnutrition and the factors associated with each of three types of malnutrition (stunting, wasting and underweight) among Zimbabwean children aged 0-59 months for the period 2010/2011

**Methods:** The study makes use of the Zimbabwean Demographic and Health Survey (ZDHS) data from the 2010/11 survey. SaTScan software was used to identify clustering of malnutrition outcomes at the time of data collection. Binary Logistic regression for survey data was used to determine factors associated with each type of malnutrition, while unconstrained Generalised Ordered Logistic (GOLOGIT) regression for survey data was used to determine the factors associated with a four-level ordinal malnutrition variable, generated by summing up all the types of malnutrition a child had at the time of data collection. Bayesian hierarchical spatial models were built in INLA to incorporate spatial autocorrelation in the modelling of malnutrition.

**Results:** Factors associated with at least two types of malnutrition in this study were mother's body mass index (BMI), mother's breastfeeding status, child's sex, age group, birth weight category and twin status as well as household's wealth index. There was a consistent observation that female children were at a less risk for malnutrition than males and also that higher birth weight was protective of malnutrition. There was no clustering of malnutrition outcomes. The spatial random components that were added to the Bayesian hierarchical models did not improve any of the models.

**Conclusion:** The findings from this study are consistent with findings from other researches and identify the factors associated with each of the common types of malnutrition. In addition the study reveals that there was no particular spatial distribution of malnutrition outcomes at the time of data collection. The study suggests further investigation of the effects of dietary diversity and mothers' decision making power on malnutrition. Zimbabwean policy makers can make use of the findings from this study to provide evidence on which to base nutritional programmes in the country.

## **Acknowledgements**

I appreciate the help I received from anyone who may have contributed to the success of this research project but most importantly, I want to acknowledge the support I received from:

All the staff members at the Wits School of Public Health. Even the security and cleaners who made sure the place was always safe and clean.

Grace chaora and the entire Measure DHS and ZIMSTAT teams, for availing the data used for this study and for answering my calls for clarification.

Benn Sartorius; my co-supervisor whose advice during the development of the protocol is invaluable.

Thomas Achia; my primary supervisor cum mentor, I wouldn't have been able to do this without your help, thank you. For your patience, time and intelligence, I am forever grateful.

My brother; Prof E. Vhurumuku, wife and kids, you gave me a roof and everything I needed for a comfortable stay in the city of Johannesburg. Maiguru, I am indebted to you.

Teu; for the the chats and for reading the first draft, thank you.

Courage; your support, encouragement, patience and endurance during this most trying period of our relationship is commendable, thank you. You definitely showed your friends and those who had lost faith in waiting that it is still possible!!!

Trust and Kuda; you were deprived of your small needs so that my needs could be met, Thank you brothers for understanding.

My parents; no words can express my gratitude, you provided for all my needs, from the fees to everything, all my needs were taken care of. Thank you for reading my drafts.

Most importantly, I cannot claim to have done this by my own strength or intelligence. I am grateful for God's everlasting mercy. My coming for this master's degree remains a miracle to those who believe in a higher Power. The Lord believed in me, chose me and sent me to do His work. He never starts something He won't finish. This is the work of your hands Lord; I give it back to you. Thank you Lord for this miracle!! AMEN.

**Table of Contents**

Declaration.....	i
Dedication.....	ii
Abstract.....	iii
Acknowledgements.....	iv
Table of Contents.....	v
List of Figures.....	vii
List of Tables.....	viii
Acronyms and Abbreviations.....	ix
Nomenclature.....	x
Chapter One: Introduction.....	1
1.1 Introduction.....	1
1.1.1 Background.....	1
1.1.2 Statement of the problem.....	3
1.1.3 Justification of the study.....	3
1.2 Literature Review.....	4
1.3 Study objectives.....	13
1.3.1 Study aim.....	13
1.3.2 Specific objectives.....	13
Chapter 2: Methodology.....	14
2.1 Study Design, Setting and Population.....	14
2.2 Primary Study.....	15
2.3 Secondary Study Variables.....	17
2.3.1 Outcome variables.....	17
2.3.2 Risk factor variables.....	17
2.4 Data management and processing methods.....	18
2.4.1 Data cleaning.....	18
2.4.2 Imputation of missing values.....	18
2.4.3 Principal Component Analysis.....	19
2.4.4 Research design based analysis - Sample weights and survey setting the data.....	21
2.5 Data analysis.....	22
2.5.1 Descriptive analysis.....	22
2.5.2 Inferential analysis.....	24
2.6 Ethical Considerations.....	28
Chapter 3: Results.....	29
3.1 Outcome Variable.....	29

3.2 Socio-Demographic characteristics of study participants .....	31
3.3 Bivariate associations .....	35
3.3.1 Stunting.....	35
3.3.2 Wasting.....	35
3.3.3 Underweight .....	35
3.4 Spatial distribution of malnutrition .....	36
3.4.1 Stunting.....	36
3.4.2 Wasting.....	38
3.4.3 Underweight .....	40
3.5 Factors associated with malnutrition.....	42
3.5.1. Binary Logistic Regression .....	42
3.5.2 Unconstrained Generalised Ordered Logistic Regression.....	50
3.6 Spatial effects on malnutrition .....	54
Chapter 4: Discussion .....	59
4.1 Introduction .....	59
4.2 Factors associated with malnutrition.....	59
4.2.1 Stunting.....	59
4.2.2 Wasting.....	62
4.2.3 Underweight .....	63
4.2.4 Religion and malnutrition.....	64
4.2.5 Age and malnutrition .....	64
4.2.6 Birth order and malnutrition .....	65
4.2.7 Spatial effects on malnutrition.....	65
4.3 Limitations of the study.....	66
4.4 Summary .....	67
Chapter 5: Recommendations and conclusions .....	68
5.1 Recommendations .....	68
5.2 Conclusion.....	70
References.....	71
Appendices.....	76
Appendix 1: Plagiarism Form .....	76
Appendix 2- Data cleaning flow chart .....	77
Appendix 3: Imputation of missing values .....	78
Appendix 4: Ethics Clearance Certificate .....	79

**List of Figures**

Figure 1: Theoretical Framework .....	13
Figure 2: Map of Zimbabwe showing the country's districts .....	14
Figure 3: The three types of malnutrition by sex and age group .....	30
Figure 4: The four level ordinal malnutrition variable by sex .....	30
Figure 5: Distribution of Stunting by District.....	36
Figure 6: Moran's autocorrelation scatter plot for stunting.....	36
Figure 7: Stunting Significance Cluster map .....	37
Figure 8: Types of stunting clusters.....	37
Figure 9: SaTScan Clusters for Stunting .....	38
Figure 10: Distribution of Wasting by district .....	38
Figure 11: Moran's autocorrelation scatter plot for wasting .....	39
Figure 12: Wasting Significance Cluster map .....	39
Figure 13: Types of wasting clusters .....	39
Figure 14: SatScan Clusters for Wasting .....	40
Figure 15: Distribution of underweight by district .....	40
Figure 16: Moran's autocorrelation Scatter plot for underweight.....	41
Figure 17: Underweight significance map .....	41
Figure 18: Types of Underweight clusters.....	41
Figure 19: SatScan Clusters for underweight .....	42
Figure 20: Spatial effects on Stunting.....	56
Figure 21: Spatial effects on Wasting.....	57
Figure 22: Spatial effects on underweight .....	58

**List of Tables**

Table 1: Description of the outcome variables .....29

Table 2: Socio-Demographic characteristics of study participants and bivariate associations 31

Table 3: Unadjusted and Adjusted Odds Ratios from binary logistic regression .....46

Table 4: Unadjusted and Adjusted Odds Ratios from GOLOGIT Regression .....53

Table 5: DIC, number of effective parameters and precision measures for the three types of malnutrition.....55

## Acronyms and Abbreviations

<b>BMI</b>	Body Mass Index
<b>CDC</b>	Centres for Disease Control and Prevention
<b>DHS</b>	Demographic and Health Survey
<b>DIC</b>	Deviance Information Criterion
<b>EA</b>	Enumeration Area
<b>HIV</b>	Human Immunodeficiency Virus
<b>MCMC</b>	Markov Chain Monte Carlo
<b>MDG</b>	Millennium Development Goal
<b>PCA</b>	Principal Component Analysis
<b>UNICEF</b>	United Nations Children's Fund
<b>WHO</b>	World Health Organisation
<b>WinBUGS</b>	Bayesian inference Using Gibbs Sampler for Windows version
<b>ZDHS</b>	Zimbabwe Demographic and Health Survey

## **Nomenclature**

**Malnutrition:** An imbalance between nutrient demand and nutrient supply which results from lack of either macro nutrients or micro nutrients or a lack of both (1). Malnutrition leads to a cumulative nutrient deficiency which in turn diminishes bodily performance and function; it includes both under and over nutrition (1-3). For the purposes of this study, malnutrition will be used to refer to under nutrition.

**Nutritional z scores:** Standard deviation units which describe how much a child's weight differs from the mean weight of a child at the same height in a reference data set (2, 4).

**Anthropometry:** The measurement of proportions of the human body (1). Basic information and measurements constituting anthropometry in children include age, sex, height, length, weight and oedema (1, 2).

**Wasting:** weight for height z-score which is less than -2 (5).

**Stunting:** height for age z-score which is less than -2 (1, 2, 5-7).

**Underweight:** weight for age z-score which is less than -2 (5, 7)

## **Chapter One: Introduction**

This chapter presents an overview of the extent of the malnutrition problem globally, in Sub-Saharan Africa and in Zimbabwe. It provides information on how malnutrition is diagnosed and classified. A review of the relevant published literature about the malnutrition problem is presented. The literature review does not cover all articles that have been written on malnutrition but only those that were relevant to this study. The problem that this study investigates is presented as well as a justification of the study. The chapter ends with the aims and objectives of this study.

### **1.1 Introduction**

#### **1.1.1 Background**

Nutrition includes processes leading to and involved with the utilisation of nutrients for growth, development, maintenance and activity (8). Malnutrition is poor nutrition that results in over or under nutrition (1). In general, when referring to malnutrition in developing countries, malnutrition is used to refer to under nutrition unless otherwise stated (1, 2). Under nutrition results from the inadequate intake of nutrients or from disease factors that affect uptake of nutrients in the form of digestion, absorption, transportation and the utilisation of nutrients (8). These are the direct physiological factors leading to malnutrition. In addition to these physiological factors, there are other economic, social, political and cultural factors that contribute to the nutritional problems (8).

Young children face the greatest risk of the adverse consequences of malnutrition because they respond faster to any reduced amounts of food compared to adults (2, 6, 8, 9). As a result, malnutrition in children is a health outcome that has been increasingly used as an indicator of a population's nutritional status and quality of life (1, 10, 11).

Malnutrition prevents children from reaching their full potential. Prolonged malnutrition among children contributes to delayed growth, behavioural problems, deficient social skills and increased susceptibility to disease during infancy and in later life (9, 12, 13). Immune functions that normally protect and restore bodily functions during illnesses or injury are compromised in malnourished people, especially children; whose immune systems are immature (12).

Existing evidence suggests that under nutrition is more pronounced in developing nations than in developed ones. Malnutrition remains a big challenge for developing countries and threatens the possibility of many of these countries meeting the Millennium Development Goals (MDGs) (6, 14). Worldwide, 36 countries account for 90% of all malnourished children and of these, 21 are in Africa (14). Although fewer countries are in Asia, they account for 61% of stunted children because of their large populations (14); but this does not mean that malnutrition is a less burden for Africa than it is for Asia.

In Sub-Saharan Africa, malnutrition is generally highest for the poorest segments of the populations (14) and as such, prevalence of malnutrition varies substantially by geographical area. These geographic differences in prevalence have a great impact on malnutrition interventions because they imply differences in access to formal health care services (15).

In 2011 it was estimated that 30.8% of children in Southern Africa were stunted compared to 39.6% in the whole of sub Saharan Africa, 35.6% in the whole of Africa and 25.7% in the whole world (16). In Zimbabwe, stunting rates have been on the increase in recent years. In 1999, 27% of Zimbabwean children 0-59 months old were stunted while 6% were wasted and 13% were underweight (17). The percentage of Zimbabwean children under 3 years who were stunted increased slightly from 21% in 1994 to 27% in 1999, a statistically significant increase (17). At the time of the 2010-11 ZDHS, 32% of children were stunted, 3% were wasted, 10% were underweight, and 6% were overweight (18).

A third of childhood deaths and more than 10% of the global disease burden can be attributed to malnutrition (14). The World Health Organisation (WHO) (19) proposes that decreasing child mortality depends heavily on reducing malnutrition, which is responsible, directly or indirectly, for 35% of deaths among children under five.

The effects of malnutrition are vast and far-reaching. It is evident that malnutrition in early life is associated with nutrition related non-communicable chronic diseases in later life, like obesity, diabetes, blood pressure and mental illnesses thus malnutrition is associated with lower human capital (8, 13). Moreover, severe malnutrition during infancy may contribute to lasting intellectual deficits while chronic malnutrition combined with poor environmental stimulation is associated with impaired cognitive development (9). Women who suffered malnutrition as children are more likely to give birth to low birth weight babies (13, 20).

Consequently, if the environment in which these women and children are born is not changed drastically, breaking the malnutrition cycle remains difficult (20). Evidently, the prevention of malnutrition leads to health, educational and economic benefits (13).

### **1.1.2 Statement of the problem**

Malnutrition is an adverse outcome which causes irreparable damage to a lot of children in developing countries. The prevalence and determinants of malnutrition differ with time and geographical location. Studies that look at spatial and temporal trends are important as they provide current evidence. Though there is evidence suggesting that malnutrition prevalence in Zimbabwe is substantially high, little has been done to study its recent local determinants and spatial distribution.

### **1.1.3 Justification of the study**

There is lack of recent literature regarding the determinants and spatial distribution of malnutrition among Zimbabwean children. This study contributes to the literature by providing a description of the factors associated with malnutrition including spatial factors.

Before embarking on any programme targeted at combating malnutrition in any place, it is important to develop a sound understanding of the context specific causes of malnutrition not just its prevalence (6, 21). Programmes targeted at combating malnutrition have been implemented in the country based on previous studies whose results are out-dated given the nature of malnutrition; that the nutritional status of children tends to react to changes in the way in which society is organised and changes in the economic status of a country (4, 22). This study will provide policy makers with evidence regarding the determinants of malnutrition on which policies and programmes can be based.

This study adds to the body of existing knowledge by using spatial analytical methods, which are becoming increasingly more popular in epidemiological studies, to model and map malnutrition. These approaches allow for a comparative analysis of the distribution of the prevalence of a phenomenon (23). By employing spatial analysis techniques, this study reveals facts about the distribution of malnutrition in the country at the time of the study. This is essential in targeting areas for intensive interventions on malnutrition.

## 1.2 Literature Review

Malnutrition is classified as acute if it affects a child for less than three months or chronic if it affects a child for three months or more (2). It can further be classified as mild, moderate or severe (2). Nutritional status can be assessed using clinical signs of malnutrition, biochemical indicators or anthropometry. Overall, anthropometry has an important advantage over other nutritional indicators because it is sensitive over the full spectrum of malnutrition. In addition, anthropometry is non-invasive, inexpensive and easy to obtain whereas biochemical and clinical indicators in addition to being invasive and expensive are only useful at the extremes (9). To classify a child's nutritional status, anthropometric measurements from an individual are compared to a reference population's median or mean measurement (1).

The choice of reference population to assess nutritional status has a significant impact on the proportion of children identified as being malnourished. In turn, this has important implications for establishing relationships between nutritional status and functional outcomes (9). In the year 2006, the World Health Organisation recommended the use of the WHO Multicentre Growth Reference Study as the reference population data for comparison with anthropometric measurements from children under the age of two years and the CDC National Centre for Health Statistics Reference study for children two to five years of age (though the reference population applies for children two to twenty years of age) (2, 3).

Evidence has shown that the growth patterns of well-fed, healthy preschool children from diverse ethnic backgrounds are similar (1). Also, geographic location and ethnic group differences do not have as much influence on nutritional status as socio-economic factors that affect nutrient intake and uptake (24). This implies that data from a reference population are applicable for children from all races and ethnicities; justifying the use of reference populations to classify children's nutritional status.

Anthropometric measurements from an individual can be expressed in relationship to the reference population in three different statistical terms, as a standard deviation from the mean of the reference population, as a percentage of the median of the reference population or as a percentile of the median of the reference population (1, 2, 9). For survey results and generally, the WHO recommends that standard deviations be used because they are more sensitive to variations between males and females as well as variations in different age groups unlike percentiles (1, 2).

Standard deviations from the reference population are often referred to as z-scores which describe how much a child's weight deviates from the mean weight of a child at the same height in the reference data (2, 4). Z-scores are calculated using the formula:

$$Z_i = \frac{Y_i - \mu}{\sigma}$$

where  $Z_i$  denotes the Z-score for the  $i$ -th individual in the sample of size  $n$ ,  $Y_i$  denotes the measured weight for this individual,  $\mu$  denotes mean of the reference population and  $\sigma$  denotes the standard deviation for reference population.

Once the z-scores have been calculated, it is then necessary to decide how they will be analysed; either as a continuous variable or as a categorical variable. When analysing the variable in the categorical form, it is necessary to define what is normal or abnormal (9). Historically people have used a cut-off point to determine normality but the use of cut-off points is arbitrary because in reality there does not exist two distinct populations; one malnourished and the other well-nourished but rather a continuous gradation of nutritional status (9). Accordingly, the risk of undesirable health outcomes such as mortality does not change dramatically by simply crossing the cut-off line but risks are continuous within the "normal" range (9).

The z-score cut-off based classification of malnutrition is as follows:

<b>Class</b>	<b>Cut off z-score</b>
Mild/ susceptible	$-2 < \text{z-score} < -1$
Moderate malnutrition	$-3 < \text{z-score} < -2$
Severe malnutrition	$\text{z-score} < -3$ (1).

There are three types of malnutrition which are all classified in the same way using z-scores, percentages or percentiles. These are *stunting*, *wasting* and *underweight* (1, 4).

**Wasting** is recent weight loss which depicts a deficit in weight relative to height due to a deficiency in tissue and fat mass (20). This condition is sensitive to prevailing conditions like disease or distribution of food and can be exacerbated by changes in infant feeding practices like weaning (5).

Wasting which depicts acute growth disturbance and is the first bodily response to a nutritional or disease insult followed by retardation in linear growth known as stunting (5, 20). In a population where malnutrition is prolonged, children who survive will become chronically wasted, therefore in such cases; the prevalence of chronic wasting is a superior measure of malnutrition as it reflects the children who are at a heightened risk of dying (9, 20).

**Stunting** is short stature which depicts retarded linear growth (20). It is a characteristic of chronic malnutrition which reveals long-term growth failure in children and is associated with suboptimal brain development (1, 2, 5-8). Stunting reflects deficiencies in the first one thousand days of life including during pregnancy (8). This type of malnutrition is likely to cause long-lasting harmful consequences on cognitive ability, school performance and future earnings (1, 2, 5-8). This in turn affects the development potential of nations (8). Stunting is a risk factor for poor health and impaired functioning in children (2). It can be exacerbated in a disaster and may manifest before three months if nutrient deficiency is severe; in such cases it may be irreversible (2, 10). The international community now places more emphasis on stunting (inadequate length/height for age) as the indicator of choice for measuring progress towards reducing malnutrition because evidence suggests that this measure of malnutrition reveals chronicity and impaired brain development (8).

**Underweight** is low weight for age which could be low because of stunting, wasting or a combination of both wasting and stunting (9, 10). While stunting and wasting discriminate between different biological processes, underweight, only reflects body mass relative to chronological age and therefore cannot discriminate between short and long-term forms of malnutrition given that children classified on its basis are a mixed group in terms of their nutritional status (9).

Malnutrition has been shown to be associated with different factors in different areas, even within one country (25). Since objects in close proximity are often more alike than those far apart, (26, 27) common exposures, measured or unmeasured may influence rates of malnutrition in a similar fashion for households in the same geographical area (12). When this happens, spatial correlation exists in the malnutrition outcomes (12, 26, 27). Geographical location is associated with food security and accessibility, as such can be considered an important modifier of the known predictors of malnutrition (12).

In many cases, most national variability for malnutrition can be explained by national factors and geographic region (22).

Some of the factors that were considered to be associated with malnutrition regardless of type at the individual level in different regions of the world include; maternal HIV status, maternal education level, mother's occupation, low birth weight, household socio-economic status, geographical location, household size, dietary diversity or feeding practices, duration of breastfeeding, previous illness as well as age and gender of the child (25, 28-33).

### **1.2.1 Factors associated with Stunting**

Several studies that used different study designs and data analysis procedures consistently revealed *increasing child age, decreasing socio-economic status, and lower birth weight* to be some of the risk factors for malnutrition. Studies which included birth intervals revealed that smaller birth interval is another risk factor for stunting (34). Some studies suggest that *current breastfeeding, higher maternal education and higher maternal BMI* are some of the factors that protect children from stunting (34-36).

There is inconsistent evidence regarding the relationship between stunting and birth order. Singh et al (37) found that there is no sufficient evidence to suggest a relationship between birth order and stunting while Zottarelli et al. and Fenske et al (35, 36) both found a significant association between the two. Also, evidence regarding the relationship between stunting and child's sex is inconclusive. Zottarelli et al. did not find a significant association between gender and malnutrition while several others found a significant association between sex and stunting (34, 38, 39).

### **1.2.2 Factors associated with wasting**

Factors such as *lower maternal BMI, season, illness in the two weeks prior to data collection, father with low paying job, lower socio-economic status and birth weight less than 2500g* were identified as risk factors for wasting in different researches that used different study designs and analysis methods (34, 39-41). There is conflicting evidence however regarding the association between age and wasting. One study suggests that increasing age is associated with lower odds of wasting (39), another study suggests that increasing age is associated with increased odds of wasting (41) while another study found no association between age of the child and wasting (40).

### **1.2.3 Factors associated with underweight**

Among the factors that were found to be associated with underweight in studies that used different designs and analysis methods; the risk factors for underweight include: *number of children in the household, child's age higher than one year, higher birth order, lower socio-economic status, shorter birth interval, underweight mother, teen mother, predominant breastfeeding less than four months and less educated father* (37, 40, 42). On the other hand, *3+ Vitamin A supplementations, participation in nutritional programmes, use of family planning methods* as well as *higher maternal educational status* were found to be protective of underweight (37, 40).

### **1.2.4 Effect of mother's HIV status on child nutrition**

The effect of a mother's HIV status on child nutritional status varies across communities within countries, with the effect being lower in areas with higher malnutrition levels (43). Across countries in Sub-Saharan Africa, children whose mothers are HIV positive are more likely to be stunted, wasted or underweight in comparison to children whose mothers are not HIV infected (31). The effect of maternal HIV can be viewed from two points of view. Firstly, an HIV infected mother is more likely to give birth to a low birth weight baby (44), leading to perpetual smallness since low birth weight is a risk factor for malnutrition. Secondly the baby born to an HIV infected mother may be HIV infected as well leading to poor health outcomes including malnutrition (45).

### **1.2.5 Women's Status and child malnutrition**

Recently studies have been interested in establishing the relationship that may exist between women's status in the community and child health outcomes. To measure women's status, their decision making power in relationships is one variable that has been used (4, 32). In a research on the relationship between women's status and child nutrition, Smith et al. 2003 (46), claim that women with low status relative to men have tighter time constraints, less access to information and health services, poor mental health, lower self-image and weaker control over health resources. According to them, these factors affect women's own nutritional status, the quality of care they get for themselves and in turn the quality of care they give to their children. This in turn affects their children's birth weights and general upkeep. Consequently, women with higher decision making power have better nutritional status themselves, are better cared for and provide better care to their children, implying a positive association between decision making status and child nutritional status (46).

According to Desai and Johnson (32), women's decision making power may be associated with improved child health outcomes in one of two ways; firstly, improved day to day healthy behaviours and better allocation of resources for child centred expenditures and secondly, improved access to emergency health care.

### **1.2.6 Maternal Nutrition, Low birth weight and malnutrition**

Children with malnutrition are more likely to have been born with a low birth weight among other factors (47, 48). While low birth weight is a risk factor for malnutrition and other health conditions in later life, it is a manifestation of several maternal factors including short stature and poor gestational weight gain among other things (8). An undernourished mother is more likely to give birth to a low birth weight baby who is at risk of being stunted, perpetuating a vicious cycle of malnutrition and poverty (8, 46). Malnourished women (as reflected by low BMI <18.5) may have less ability to breastfeed, lower energy levels and reduced cognitive abilities all of which may affect a child's health and proper growth (46).

### **1.2.7 Economic status and malnutrition**

Malnutrition can trap children, families, communities and nations in an intergenerational cycle of poor nutrition, illness and poverty (8). Children who have some form of malnutrition are more likely to come from households where the father is absent or the mother is unmarried or the mother has less than secondary education, factors which affect socio-economic status (6, 47). Socio-economic factors that disturb nutrient intake and uptake are more important in explaining nutritional outcomes of children than geographic and ethnic group differences (1, 24).

### **1.2.8 Dietary diversity and malnutrition**

Several studies have been conducted to establish the relationship between dietary diversity and child malnutrition. In those studies, a consistent positive relationship has been shown to exist between dietary diversity and child nutritional status; as diversity increases, nutritional status improves (33, 49). Conversely, lower diversity is associated with poor nutritional outcomes in children; especially among poor communities because their diets are primarily comprised of starchy food and include little or no proteins and vitamins (33).

Dietary diversity has a direct impact on nutrient intake. When there is an insufficient quantity of food absorbed as well as poor quality of nutrients consumed, children become more susceptible to disease, decreasing nutrient intake (50).

Improving dietary intake to suggested levels would have a greater effect on malnutrition than eliminating diarrhoea and feverish illnesses; however, doing both concurrently would be necessary to achieve growth identical to an international reference population (9).

### **1.2.9 Disease and malnutrition**

The relationship between child nutritional status and disease is characterised by a vicious cycle, reflecting a bidirectional association. In young children, the frequently contaminated environments and poor childcare practices cause high rates of infectious diseases (9). Diseases like diarrhoea are highly likely to induce malnutrition in a healthy child because when a child has diarrhoea, their appetite decreases, absorption of nutrients is inhibited and disease competes for the child's food thereby increasing the chances of malnutrition (2). On the other hand, children who have some form of malnutrition are more likely to suffer from diseases like diarrhoea (2). In the meta-analysis by Fishman et.al (9), underweight status among preschool-age children was significantly associated with subsequent risk of diarrhoea and pneumonia episodes, but the association with malaria was not statistically significant.

### **1.2.10 Age and malnutrition**

Nutritional status of children is most important in the first two years of life, beyond which any efforts to correct malnutrition are fruitless (8). During this period, children have a high rate of growth and demand for calories, proteins, essential fats, vitamins and minerals (9). On the contrary, during this period, the diets of many children in developing countries are inadequate (8).

In the year 1999 in Zimbabwe, there was a sharp increasing trend of the proportion of stunting from 0 to 20 months of age, while there was a decreasing trend in the proportion of wasting in the first six months of life. At the same time, the proportion of underweight showed an increasing trend between 3 and 13 months of age (17). This implies that the first 20 months of life are the most important in Zimbabwe.

Zotarelli et al (36) found that Egyptian children 12-23 months old are the most likely to be stunted and that the likelihood of stunting at age group 36-47 months old was not significantly different from that of children 0-11 months old. Meanwhile, Fuchs et al (41) found out that age higher than 12 months is associated with increased odds of wasting and Vitolo et al (39) found that children 0-36 months were 77% times more likely to be wasted than children over 36 months old.

### **1.2.11 Gender and malnutrition**

The prevalence of stunting differs significantly between males and females; with prevalence among males being higher than that among females (25). Furthermore, the mean height-for-age z-score for females is significantly higher than that for males meaning that females are less likely to be stunted than males (25). In a meta-analysis of data that came from 310 nationally representative nutritional surveys that collected data on child anthropometry in 112 countries and used underweight as the dependent variable, no significant underweight prevalence differences were observed between female and male children, indicating that there was no significant association between sex and underweight (9).

### **1.2.12 Spatial effects on malnutrition**

Classical analyses assume that outcomes in individuals under study are independent of each other but a closer look at the observations may reveal that they are not independent but are in fact spatially autocorrelated (23). Spatial analyses allow researchers to take care of unmeasured variables missing from the model thereby increasing the percentage of variance explained for the dependent variable (51). A study that examined spatial factors on stunting revealed that model covariates only provided partial explanation for regional differences and that controlling for spatial autocorrelation helped explain some of the observed variability in the nutritional outcomes of children (35).

Spatial autocorrelation occurs when outcome values measured at locations closer to each other are more likely to be similar compared to those in distant locations. This phenomenon is referred to as Tobler's first law of geography (26, 27). Spatial autocorrelation measures the correlation of a variable with itself through space (27). It can either be positive or negative. Positive spatial autocorrelation occurs when similar values occur near one another while negative spatial autocorrelation occurs when dissimilar values occur near one another (27).

For non-communicable health outcomes like malnutrition, occurrence of disease may be affected by proximity to environmental risk factors which cannot be measured directly (23). Also, unknown risk factors often vary in space which in turn induces spatial autocorrelation between the observed outcomes in each area and its neighbours (23). Spatial autocorrelation can be considered a confounding factor because when it exists it reveals spatial associations among geographic entities (26). Although spatial autocorrelation does not imply causality, it provides evidence for causality that can be examined in the light of theory (26).

### **1.2.13 Theoretical Framework**

To explain malnutrition, the United Nations Children's Fund (UNICEF) developed a theoretical framework in the year 1990 (21). The framework proposes that there are three levels of causality for malnutrition in children. The three levels of causality are: basic, underlying and immediate causes/determinants (24). This framework has been used and adapted by many researchers in different settings to help model the risk factors associated with malnutrition.

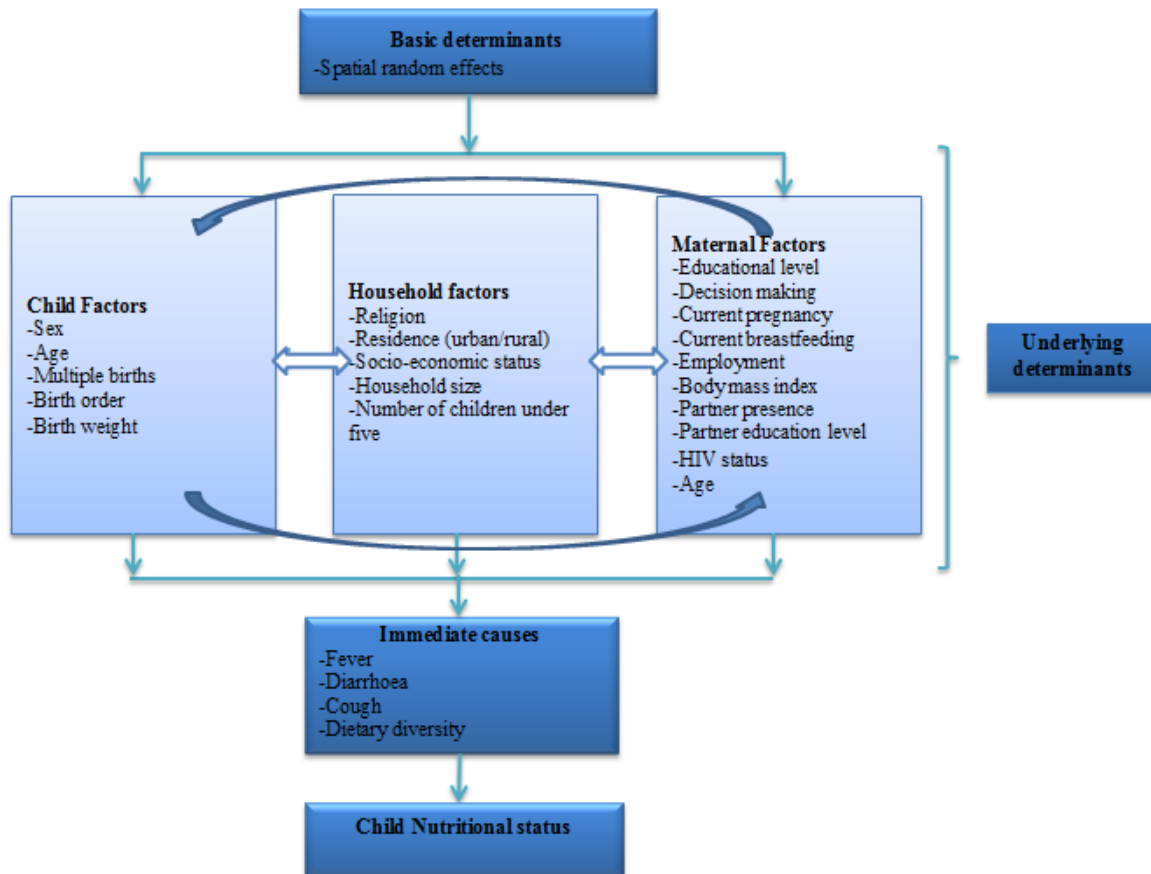
Basic determinants manifest at the community level and concern the potential resources available to a country or community (4, 14, 21). Availability of potential resources is limited by the natural environment where the child lives, access to technology as well as quality of human resources (4). Prevailing economic, cultural and social factors affect the utilisation of potential resources and how they are translated into resources for food security, care and services (4). Basic causes include political, legal and cultural factors that could counteract the best efforts of households to attain good nutrition for all its members (24).

The underlying determinants of malnutrition are influenced by the basic causes. There are three underlying determinants of malnutrition which are: food security, care for mothers and children, health services and the environment (4, 6, 11). These underlying factors operate at the household level and are affected by poverty (4, 14).

The immediate determinants of malnutrition manifest at the individual level and are mainly determined by dietary intake and health status of a child (4, 24). The framework suggests that there is a bidirectional relationship between nutrient intake and disease (4, 11).

This framework does not imply that all factors are inadequate in all contexts in a similar fashion but rather provides the full range of possibilities for causality (21). This context-specificity applies at household, community, district and national levels implying highly decentralized approaches which emphasise capacity-building and community participation in interventions (21).

The conceptual framework based on which we identified and classified the variables available for study is presented in Figure 1.



Source: Adapted from UNICEF (1990)

**Figure 1: Theoretical Framework**

### 1.3 Study objectives

#### 1.3.1 Study aim

The main aim of this study was to establish the factors associated with child malnutrition, as well as to reveal the spatial distribution of child malnutrition in Zimbabwe for the study period 2010/11

#### 1.3.2 Specific objectives

1. To determine the spatial distribution of malnutrition among children under five years of age in Zimbabwe for the years 2010/2011
2. To determine the factors associated with malnutrition among children under five years of age in Zimbabwe for the years 2010/2011

## Chapter 2: Methodology

This chapter presents the materials and statistical methods that were used in the implementation of this study. In addition, the characteristics of the primary study that could have affected this secondary study are outlined in this chapter.

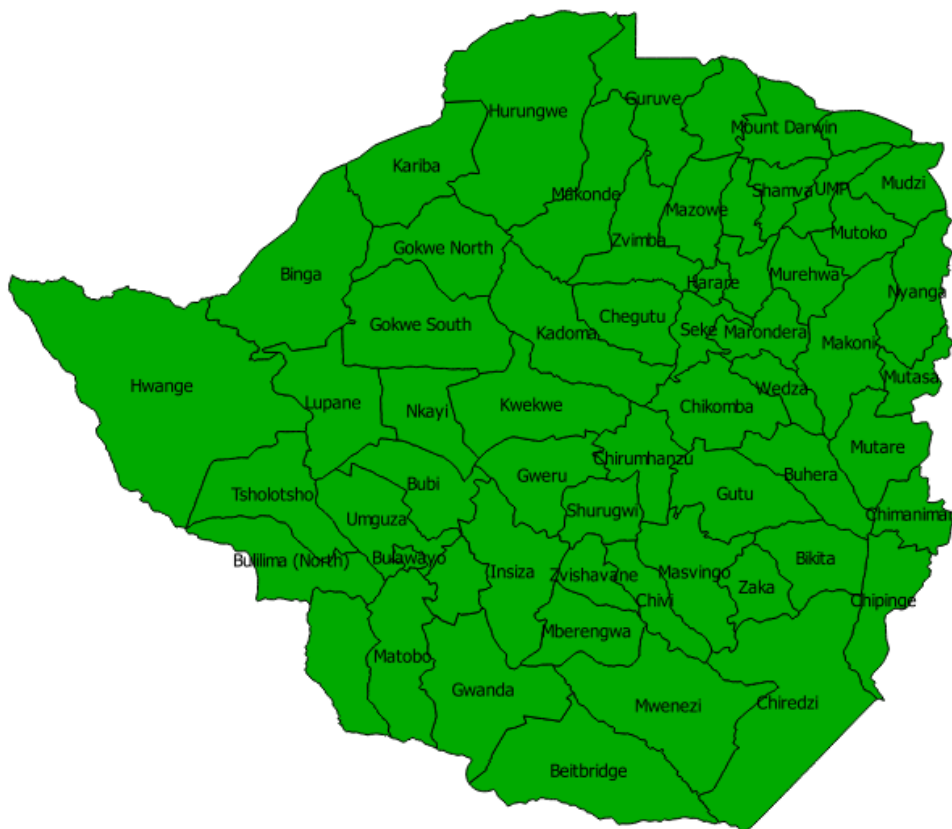
### 2.1 Study Design, Setting and Population

#### 2.1.1 Study Design

A secondary analysis of the Zimbabwe Demographic and Health Survey (ZDHS) 2010/2011 was conducted in this study. The ZDHS 2010/2011 is a single cross-sectional nationally representative survey conducted over six months from September 2010 to March 2011.

#### 2.1.2 Study setting

The data for this study were collected in Zimbabwe, a Sub-Saharan African country which is divided into ten provinces and each province is divided into several districts. The districts are further divided into administrative wards. Figure 2 shows the country's districts.



Source: DIVA-GIS (52)

**Figure 2: Map of Zimbabwe showing the country's districts**

### **2.1.3 Study population**

For this secondary analysis, the study population comprised all children in sampled households, alive at the time of primary study data collection and whose anthropometric data were not missing.

## **2.2 Primary Study**

The study population for the primary study comprised all men and women residing in the sampled households during the data collection period. This is a large number of people, as a result a representative sample was selected for study and inference (18). Caregivers of children under the age of five (usually mothers) gave responses regarding the children in the selected households (18).

The 2002 population census was used to provide the sampling frame for ZDHS 2010/2011. This census divided the administrative wards into Enumeration Areas (EAs) which formed the sampling frame for the ZDHS 2010/11 in which a stratified two stage cluster sampling design was used (18). EAs (Clusters) were the sampling units for the first stage and households were the sampling units for the second stage of sampling. In total 406 EAs were selected with 169 from urban areas and 237 from rural areas. A complete listing of households was conducted for all the 406 EAs and a representative sample of 10828 households (excluding institutional households) was selected for the 2010-2011 ZDHS (18)

All women aged 15-49 and men aged 15-54, permanent residents of the selected households or who spent the night before the survey in the household were eligible for interview. Among the eligible men and women who consented, blood was collected for laboratory testing of HIV in the households selected for HIV testing. In all households, height and weight measurements were recorded for children 6-59 months old, men 15-54 years old and women 15-49 years old (18).

### **2.2.1 Response rates**

The survey yielded an overall 96% household response rate; 93% women response rate and 86% male response rate (18).

## **2.2.2 Measurement and data sources**

### **2.2.2.1 Data collection**

Socio-demographic data were collected using the interviewer administered questionnaire method. Questionnaires that were used in the survey were adapted from the MEASURE DHS project to reflect population and health issues relevant to Zimbabwe. The questionnaires were translated into the two major languages in the country, Shona and Ndebele. Interviewers used personal digital assistants to record responses during the study. Socio-demographic information about children was gathered using the women's questionnaire (18).

The protocol for blood specimen collection and analysis was based on the anonymous linked protocol, developed for MEASURE DHS (18). This protocol allows for linking of HIV test results with the socio-demographic data collected in the individual interviews after removal of all information that could potentially identify an individual. Because of removal of identifying information, people did not receive HIV test results but were informed about local places where they could get free HIV test and results if they wanted to know their HIV status (18).

### **2.2.2.2 Anthropometry**

Children's standing height or recumbent length and weight were measured regardless of whether their mother was interviewed in the survey or not. Lightweight SECA<sup>1</sup> mother-infant scales were used to measure weight (18).

Height measurements were carried out using a Shorr Productions measuring board<sup>2</sup>. Recumbent length was measured for children under 24 months of age while standing height was measured for older children (18).

Height-for-age, weight-for-height, and weight-for-age were calculated using the anthropometric measurements that were taken in the study. Z-scores for individual children were calculated using new growth standards published by the WHO in 2006 (18).

---

<sup>1</sup> SECA is a brand name for the scales which were designed and manufactured under the guidance of UNICEF

<sup>2</sup> The Shorr productions measuring board is a convertible board that can be used to measure both recumbent length and standing height.

## 2.3 Secondary Study Variables

### 2.3.1 Outcome variables

#### 2.3.1.1 Binary outcome variable

In this study, each of the three types of malnutrition; stunting, wasting and underweight were considered separately. The variable for each type of malnutrition was dichotomised according to the classification below:

- Wasting: weight for height z-score which is less than -2
- Stunting: height for age z-score which is less than -2
- Underweight: weight for age z-score which is less than -2

#### 2.3.1.2 Ordinal outcome variable

We generated a four-level ordinal malnutrition variable by adding up the types of malnutrition that a child suffered from at the time of data collection. This was based on the assumption that there is an underlying malnutrition or growth variable that we cannot observe and that as people cross thresholds in this underlying variable, their values on an observed ordinal variable malnutrition changes (53). The ordinal variable reflects children with no malnutrition at all, one type, two types or all three types of malnutrition. We used this variable as the outcome variable to run an unconstrained generalised ordinal logistic GOLOGIT regression model in STATA 12 (53).

### 2.3.2 Risk factor variables

We considered the following factors in this study

**Maternal Factors:** Age, education level, currently pregnant, currently breastfeeding, currently working, marital status, partner presence, partner education level, HIV status, decision making tertile and BMI.

**Child factors:** Sex, age, fever, diarrhoea, cough, birth weight, birth order, multiple birth status, dietary diversity tertile, having received vitamin A in the six months prior to data collection and dietary diversity.

**Household factors:** Religion, wealth index quintile, household size, province, type of place of residence (rural/urban) and number under five children in the household.

## **2.4 Data management and processing methods**

### **2.4.1 Data cleaning**

Two sets of STATA format data were extracted from the Measure DHS database. One of the datasets contained responses on socio-demographic characteristics of children and their mothers. The other dataset contained HIV test results. The third dataset contained codes identifying the different clusters in the two datasets. These identifying data were received from the Zimbabwe Statistical (ZIMSTAT) office in an excel spread sheet.

Data management involved checking for extreme and inconsistent values, dropping respondents who did not fit the inclusion criteria. We also did imputation of missing values, recoding and categorisation of continuous data. Principal Component Analysis (PCA) was done to generate some independent variables. Data management was concluded by the merging of the three datasets.

Appendix 2 shows how we arrived at the final 4299 study population for this study. Imputations were only done for independent variables and after dropping respondents who did not fit the inclusion criteria. PCA was done after all imputations had been completed. Data sets were merged in a Microsoft Access database after all PCA. Data recoding and categorisation was done using STATA statistical software package. Imputation of missing values as well as PCA was done using IBM SPSS Statistical package (54).

### **2.4.2 Imputation of missing values**

The iterative Markov Chain Monte Carlo (MCMC) method was used to impute missing values only for those independent variables that had missing values for some observations based on the assumption that the data were missing at random. A maximum of five imputations and ten iterations per imputation were specified for the MCMC method. For each of the five imputations, when the tenth iteration was reached, the imputed values at the maximum iteration were saved to the imputed dataset and used as predictors of missing values in the next imputation until the fifth imputation was reached. Data from the fifth imputation were saved in STATA format and exported to STATA for further management and analyses. Appendix 3 shows the variables for which imputations were done and the variables which were used as the predictors for the imputed values.

For each variable with missing values, a univariate model was fitted using the variable with missing values as the response variable and other selected variables with complete sets of data as the predictors of the missing values. Linear regression was used to fit the univariate models for the continuous variables while logistic regression was used for the categorical variables. Imputation of missing values was done for all continuous independent variables with missing values and only for those categorical independent variables that would yield plausible imputed values. For variables whose imputed values depended on marital status, data were only imputed for children whose mothers were in a marital relationship at the time of data collection.

### **2.4.3 Principal Component Analysis**

Principal Component Analysis (PCA) is a data reduction technique which is done to restructure data and come up with a reduced number of variables that reflect much of the information contained in the original dataset (55). To be able to use this data reduction technique, one observes and considers the variability within and covariation across the variables to be reduced. The reduction of data may lead to one of two things; firstly that a linear combination of the variables accounts for a large percentage of the total variability in the data or secondly, that several of the variables reflect another latent variable. A latent variable is one which cannot be measured or observed directly but indirectly through several variables (55).

In this study we observed that the original data set contained two sets of correlated variables for which we studied the variability within and the covariation across each set of correlated variables using a correlation matrix. We found that the two sets of correlated variables each reflected a latent variable for which we used the Bartlett's test for sphericity and the Kaiser-Meyer Olkin Measure of Sampling Adequacy (MSA) to see if PCA was applicable to each (55). Based on the results from both tests (Bartlett's test p-value  $<0.05$  and MSA  $>0.5$ ), we decided to apply PCA.

During the PCA process, we retained components with eigen values greater than one in the dataset and saved their regression scores as variables. We used the varimax rotation option to obtain a rotated component matrix and we drew a scree plot in each case. To decide which components we would keep, we observed the variable loadings from both the component matrix and the rotated component matrix and we also observed the scree plots.

The components that we retained had high loadings for most of the variables in the two component matrices were the same components that were suggested by the scree plots. We used the regression scores from each retained component to rank cases and categorise them into tertiles. As a result we came up with two indicators, one reflecting mother's decision making power and the other reflecting dietary diversity for the child.

#### **2.4.3.1 Women's decision making index**

We only generated mother's decision making index for children whose mothers were in a marital relationship at the time of data collection. The index was based on the women's responses to the questions regarding the person who usually decides on; how to spend respondent's earnings, respondent's health care, large household purchases, visits to relatives and how to spend husband's money. The index that we generated was a trichotomous variable with levels; independent, consults and subservient (56).

#### **2.4.3.2 Dietary diversity**

Dietary diversity is a concept that is becoming more and more popular in researches of child nutritional status and nutrient adequacy (57). The term dietary diversity is used to imply either the number of foods or the number of food groups consumed over a given period (57). We used dietary diversity as a proxy for adequate micronutrient density of foods in accordance with the theoretical framework (58). In this study we generated two variables to represent dietary diversity for the study sample.

##### ***2.4.3.2.1 WHO dietary diversity***

The World Health Organisation defines minimum dietary diversity as the proportion of children 6-23 months old who receive foods from four or more food groups (58). This definition is based on the assumption that if a child ate from at least four food groups on the previous day, then most likely they ate at least one animal source food, at least one fruit or vegetable in addition to a staple food (58). The four food groups come from a universe of seven food groups: (i) grains roots and tubers (ii) legumes and nuts (iii) dairy products [milk yoghurt cheese] (iv) flesh foods [meat, fish, poultry, liver/ organ meats] (v) eggs (vi) vitamin A rich fruits and vegetables (vii) other fruits and vegetables.

To generate the seven food groups, we added a score if any food in the group was eaten (58). We then added up the scores to come up with the dietary diversity variable. We categorised the children who ate from four or more food groups as having a good dietary diversity and children who ate less than four food groups as having a poor dietary diversity.

#### **2.4.3.2.2 Dietary diversity by PCA**

Arimond and Ruel 2004 (57) notes that different researchers have used different operational definitions of dietary diversity with consistent results that show an association between the indicator for diversity and child nutritional status. Therefore, we made use of the child feeding variables in our dataset to apply PCA and came up with another measure of dietary diversity. From the PCA, we came up with dietary diversity scores which we used to rank the cases. We ended up with a trichotomous variable reflecting dietary diversity. The three categories for this variable are good, moderate and poor.

#### **2.4.4 Research design based analysis - Sample weights and survey setting the data**

Standard data analyses assume independence of outcome measures among individuals (59). When this assumption is violated, researchers need to use other methods to analyze their data (23). Data for this study were collected based on a two-stage cluster sampling design where the EAs (clusters) were the primary sampling units and households were then randomly selected from each of the selected EAs (clusters) (18). The data are therefore characterised by sampling weights, clustering and stratification. Sampling weights are factors that are applied to each case to adjust for the differences in probability of selection among the cases in a sample (60, 61). Clustering is when individuals are not sampled individually but rather as groups known as clusters (61). Stratification is when different groups of clusters are sampled separately and independently across strata (61). Data used for this study violate the assumption of independence of observations which implies correlation of malnutrition outcomes in children from the same geographical area. To correct for this, data were survey set in analysis so as to account for the clustering that comes by design.

Survey setting the data is declaring that the data came from a survey and involves specifying the variables that contain information about the survey design as well as the method for variance estimation (61). Survey setting the data entails taking care of sampling weights, clustering or stratification or taking care of all three.

Using sampling weights is important in getting the point estimates right while using all three; weights, clustering and stratification of the survey design helps produce more accurate estimates of standard errors (61). Survey setting the data prevents overestimating statistical significance and drawing wrong conclusions about the populations.

For descriptive analyses we only considered sampling weights because it is the only phenomenon among the three which makes a difference in calculating point estimates for the population (60). The differences in probability of selection among the respondents for this study did not just happen by chance but were actually a result of the study design. (62). The individual sampling weight that we used in this study was calculated by multiplying the household weight<sup>3</sup> by the inverse of the individual response rate of the woman's response rate group (62).

For inferential analyses we only considered clustering and stratification; based on the assumption that the error terms within a cluster were correlated with each other since they have unobserved group level factors in common (60). We also considered that other researchers note that, the use of sampling weights is inappropriate for estimating relationships like regression and correlation coefficients (62).

## **2.5 Data analysis**

### **2.5.1 Descriptive analysis**

#### **Socio-Demographic descriptive analysis**

We used tables and graphs to present the socio-demographic descriptive characteristics of the study participants. We used the Pearson's chi-square test to find out if any associations existed between any of the exposure variables and each of the three types of malnutrition. Table 1 presents the summary of the descriptive statistics. We also used graphs to show the distribution of the outcomes among the age groups and between the sexes. Figures 3 and 4 graphically present the findings from this study.

#### **Spatial Descriptive analysis**

In this study we considered the fact that data were collected in a two-stage cluster sampling design. We therefore hypothesised that there could be spatial autocorrelation in the outcome

---

<sup>3</sup>Household weight = inverse of household selection probability x household response rate (of its household response rate group)

variables. With this in mind, we did exploratory (descriptive) spatial analysis on the data in order to observe if any spatial patterns existed in the data.

For easier interpretation by policy makers, we did our exploratory spatial analyses at district level. To enable these aerial spatial analyses we made use of district data that were availed by the ZIMSTAT office to aggregate the data from individual level to district level. Analyses of aggregated spatial data allows for the identification of any areas which have higher than expected counts of disease (23).

Firstly we used Moran's Global autocorrelation coefficient (Moran's I) and its associated scatter plot hosted in the free access GeoDA software (63) to determine if there was any significant global spatial autocorrelation/pattern for each of the three types of malnutrition. Spatial patterns can be clustered, dispersed or random (64). We went on to check for any local spatial patterns for each of the three outcomes because it is desirable to study spatial patterns at a local scale (65). Where patterns were identified, we checked for their statistical significance as well as the type of clusters that existed using Univariate Local Moran's I statistical methods hosted in GeoDA. Researchers have recommended the use of two methods to determine spatial patterns (66). For comparison purposes, we used the Kulldoff's spatial scan statistic in SaTScan (67) to see if we would observe similar clusters as those we observed using Moran's statistics.

The initial step in Moran's statistical analyses is to specify who is whose neighbour in the dataset by specifying spatial weights (68). We used first order Queen's contiguity weights for this analysis. (68) Thereafter, the Moran's I spatial autocorrelation statistic was computed. This statistic is visualized as the slope in the scatter plot with the spatially lagged variable (a sum of spatial weights multiplied with values for observations at neighbouring locations which is created spontaneously in GeoDA) on the vertical axis and the original variable on the horizontal axis (68). From this scatter plot, the Moran's autocorrelation coefficient (Moran's I) is calculated. To determine significance of Moran's I statistic against a null hypothesis of no spatial autocorrelation, GeoDa uses a permutation procedure whereby the mean, standard deviations and p-values for the Local Moran's I that are observed are not exactly reproducible for each set of permutations (68). We tried different number of permutations until we reached a decision to use 19999 permutations as these resulted in the most stable estimators of the mean Moran's I, standard deviations and p-values for each set of permutations.

The Kulldoff spatial scan statistic is a likelihood ratio test which provides a p-value to determine if the observed spatial pattern differs from the null of complete randomness. The statistic tests the null hypothesis that the risk of malnutrition is the same in all districts in the study area (67). To do the likelihood ratio test, the number of observed cases is compared against the number of expected cases which are obtained by Monte Carlo random data simulation methods. Comparing the observed cases versus the simulated random expected cases enables the observation of clusters that are least likely to have occurred by chance (69).

We used 19999 Monte Carlo replications (like the 19999 permutations used in Moran's analyses) for the simulation of random data and a circular window shape with a maximum spatial cluster size of 10% population at risk for this analysis as these led to the identification of smaller more defined areas compared to the default 99 replications and maximum spatial cluster size of 50% (66).

### **2.5.2 Inferential analysis**

#### **Binary Logistic regression**

After testing for bivariate associations between each of the independent variables with each of the three types of malnutrition using Pearson's chi-square test, we used all the independent variables that we were considering to do univariate logistic regression in order to allow for a comparison between unadjusted and adjusted odds ratios.

Based on chi-square test p-values, we considered all variables that showed a significant association with any type of malnutrition at 10% significance level eligible for multivariable regression for that particular type of malnutrition. During the model building stage, we did not survey set the data so as to allow variable selection based on results from the Likelihood Ratio (LR) test which is impossible with survey set data (61). The LR test is considered superior for variable selection into multivariable logistic regression compared to the Wald test and the Lagrange score test (70).

According to the adapted framework we grouped the eligible variables into three levels/groups: maternal factors, individual child factors and household factors to make the modelling process easier. For each type of malnutrition, we built a group level multivariable logistic model for each group of variables.

We put variables that were significant at group level into one model that combined all three groups of variables. Based on LR test results, we included all those variables that were shown to improve model fit in the final model. Before accepting the final model, we tested again all the initially eligible variables that were not significant at group stage modelling to see if they would improve model fit based on LR test results. Most of them did not improve model fit once they did not qualify at group stage.

We did model diagnostics before survey setting the data because after survey setting the data in STATA it is not possible to test a number of assumptions for logistic regression (61). We examined if removing influential observations as well as observations with high leverage would have an impact on model fit or parameter estimates. We decided to include all the observations in the analysis since deleting observations based on normal cut off points for influence or leverage would have led to deletion of too many observations. We tested the final models for model specification and model fit both before and after survey setting the data.

We built two multivariable models for each of wasting and underweight; one for all children and another one for children whose mothers who were in a marital relationship at the time of data collection. We did this because the children whose mothers were not in marital relationships at the time of data collection had missing values for some partner level variables which showed significant bivariate associations with these two types of malnutrition. At the inception of the study we were concerned with all children whose data were available regardless of whether their mothers were married or not and so presenting results with partner level data would exclude those children whose mothers were not in marital relationships at the time of data collection. We do not present regression results for the models which controlled for partner level factors but only comment on them. We present results for those models which ignored partner level variables for these two types of malnutrition.

### **Generalised Ordered Logistic Regression**

Using the four-level outcome variable for malnutrition, we built an ordinal logistic regression model in STATA 12. At the model building stage we did not survey set the data. We used the LR test to select variables for the model like we did for binary logistic regression. After coming up with a final model, we tested to see if the model upheld the parallel lines assumption requisite for ordinal logistic regression using the Brant test (71).

We found out that six indicator variables were violating this assumption and we then opted to do an unconstrained Generalised Ordered Logistic (GOLOGIT) regression model to see the factors associated with the ordinal variable for malnutrition (53).

We used the user written command GOLOGIT2 in STATA 12 to run the unconstrained GOLOGIT regression model (72). This command enabled us to take care of the survey study design by making use of the survey option. We used the survey option to reduce the chances of overestimating statistical significance. We did not use the pl (parallel lines) or npl (non-parallel lines) options with the GOLOGIT command but used the auto fit option with significance level set at 0.02 to reduce the chances of concluding that some of the factors violated the parallel lines assumption due to the high sample size we had (53, 73). The GOLOGIT model that we ended up with did not violate the parallel lines assumption, (F-test 1.18, p-value 0.2441).

For the reason that the model was unconstrained, it had three equations reflecting three levels of comparison. The first level of comparison compared children with one, two or three types of malnutrition as one group against the group of children with no malnutrition. The second level compared children with two types or three types of malnutrition as one group against the group of children with no malnutrition or only one type of malnutrition as the other comparison group. The third level compared children with all three types of malnutrition as one comparison group against the group of children with no malnutrition, one type of malnutrition or two types of malnutrition.

### **Inferential Spatial Analysis**

We used the Bayesian approach to do all analytical spatial analyses. The Bayesian approach assumes that the parameters (odds ratios) that we estimate are not fixed but follow a certain distribution and that each study will only be able to show a summary measure of the parameter from its distribution (74-76). While a confidence interval is reported with parameter estimates in the Frequentist approach, a credible interval is reported with each parameter in the Bayesian approach (77). Bayesian inference depends a lot on the likelihood of the observed data and the prior distribution.

The prior distribution is based on the researcher's prior assumptions regarding the behaviour of the parameter under study (75). The likelihood in the Bayesian context refers to a function describing the dependence of the parameter under study on sample values (75). This implies that the information contained in the data is entirely expressed by the likelihood function (23, 75). The likelihood function assumes that the sample values of the outcome given the parameters are conditionally independent. When this assumption is violated, other different approaches are required (75).

The prior distribution and the likelihood provide important information about any problem. The likelihood brings in information about the parameter via the data while the prior brings in information about the parameter via a priori assumption about the distribution of the parameter (74, 75). The product of the likelihood and the prior distribution is called the posterior distribution; which describes the behaviour of the parameters given the data and the prior assumptions about the parameters (74, 75). As data become more abundant, the likelihood speaks to the posterior distribution more than the prior and also the posterior distribution tends to be more concentrated around a single value of the parameter (74, 75).

In this study we considered the fact that due to possible spatial autocorrelation; the malnutrition outcome values were not conditionally independent, thus violating the likelihood assumption of independence. We therefore considered conditional independence of the data given parameters at a higher level of hierarchy beyond the likelihood (75), leading to the specification of hierarchical spatial models. This assumption that conditional independence exists at a higher level allows the correlation to appear in prior distributions rather than in the likelihood itself (75). We made use of non-informative priors which we assumed would have no strong preferences over the likelihood of the data in determining the odds ratios for the factors associated with malnutrition (74-76).

The most common approach in Bayesian statistics is, once the likelihood and the prior distribution have been specified, MCMC iterations are run to allow for sampling of the parameter from the posterior distribution (78). Recently researchers have however shown that it is not really necessary to run MCMC iterations for posterior sampling. They propose that parameters can indeed be very precisely estimated by deterministic schemes like Integrated Nested Laplace Approximation (INLA) whose computation is nearly instant, taking minutes and seconds compared to the MCMC techniques which may take days and hours. (79)

In our study, we used both approaches to posterior sampling, namely the MCMC iterations and INLA. For the MCMC approach, we used the Gibbs Sampler algorithm hosted in WinBUGS (Bayesian inference Using Gibbs Sampling) software (80) while for the deterministic scheme we used R's interface to INLA (81). We used INLA to do our final spatial analyses and mapping while we used WinBUGS with fewer iterations to confirm INLA results.

In accounting for possible spatial autocorrelation in our data, we assumed that the unexplained variation in the outcome comprised of a spatially structured random component, a spatially unstructured random component or both (23). We therefore built four Bayesian models on the data for each of the three malnutrition types. The first model was a simple model with fixed effect and no spatial components in it, the second model had the fixed effects plus a spatially unstructured component, the third had a spatially structured component in addition to the fixed effects and the fourth was a convolution model with both the spatially structured and the spatially unstructured components as well as the fixed effects.

For each model we observed the convergence of the time series as well as the auto correlation structure using a burn-in period of 1000 as well as a thinning of 10 in WinBUGS to ensure that the model was a good fit to the data (76). We used the Deviance Information Criterion (DIC) and effective number of parameters to decide the model that best fit the data.

## **2.6 Ethical Considerations**

This study was conducted in full conformance to the principles outlined in the declaration of Helsinki. Participation in the primary study was voluntary and written consent was provided by the participants. The protocol for anaemia testing and blood collection for HIV testing was reviewed and approved by the Medical Research Council of Zimbabwe, the Institutional Review Board of ICF Macro and the United States' CDC. For this secondary study, permission to proceed was granted by the University of the Witwatersrand Human Research Ethics committee (Clearance Certificate Number M130960). The data used in this study were de-identified before access to the data was granted by Measure DHS.

### Chapter 3: Results

This chapter presents the results from the analyses that were done in this study. First, descriptive results are given then results from binary logistic regression followed by results from GOLOGIT regression and lastly results from Bayesian spatial analyses. Tables and figures are used to summarize the results as appropriate and a brief interpretation of the tables and figures is given in each case.

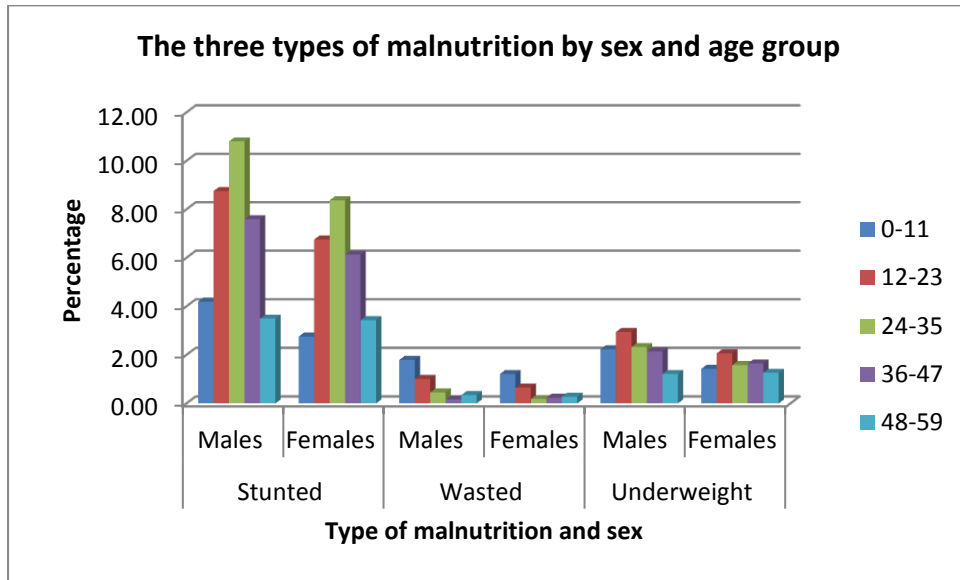
#### 3.1 Outcome Variable

Of the 4299 children under study, 1367 (31.10%) were stunted, 150 (3.14%) were wasted and 434 (9.39%) were underweight. Of the 1489 children who displayed some form of malnutrition, 1001 (68.79%) were stunted only and 38 (2.32%) had all forms of malnutrition. A substantial number, 91 (60.67%) of the wasted children and the majority 407 (93.78%) of the underweight children had another form of malnutrition. None of the children had a combination of stunting and wasting. Table 1 presents a summary of the outcome variables.

**Table 1: Description of the outcome variables**

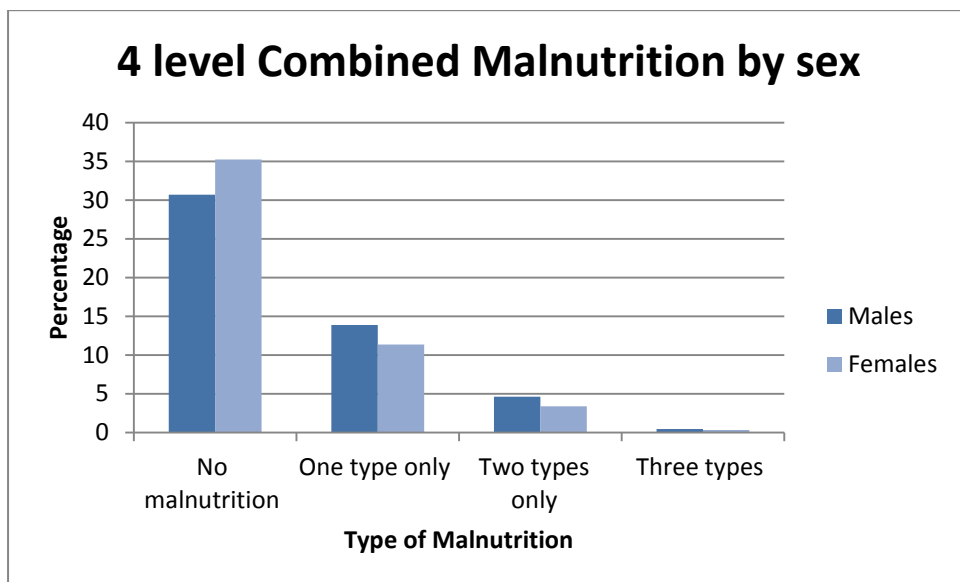
Variable	n	%
<b>Stunted</b>		
Yes	1367	31.1
No	2932	68.9
<b>Wasted</b>		
Yes	150	3.14
No	4149	96.86
<b>Underweight</b>		
Yes	434	9.39
No	3865	90.61
<b>Eight level combined malnutrition</b>		
No malnutrition	2810	65.96
Stunted only	1001	23.42
Wasted only	59	1.23
Underweight only	27	0.59
Stunted & underweight	314	6.89
Wasted & underweight	50	1.11
All three	38	0.79
<b>Four level Combined malnutrition</b>		
No	2810	65.96
One type only	1087	25.25
Two types only	364	8.01
All three types	38	0.79

Figures 3 and 4 summarise the distribution of the outcome variables. Figure 3 presents the distribution of each of the three types of malnutrition by sex and age group. Figure 4 presents the distribution of the ordinal malnutrition variable by sex.



**Figure 3: The three types of malnutrition by sex and age group**

For all age groups, the percentage of females who are malnourished was lower than that for males, regardless of type of malnutrition.



**Figure 4: The four level ordinal malnutrition variable by sex**

A negligible number of children had all three types of malnutrition. Again, percentage of males who are malnourished is higher than that of females while the percentage of females without any form of malnutrition is higher than that for males.

### 3.2 Socio-Demographic characteristics of study participants

The distribution of the study participants was almost equal for both sexes; 2156 (50.31%) were males. A considerable number of the children in this study were under the age of one, 1150 (26.98%). 88 (1.93%) of the children were one of a pair of twins and of all the study participants, only 64 (1.47%) children never breastfed. Quite a huge number; 1861 (41.87%) of the children under study came from households with six or more members and also 2172 (49.50%) of the children came from households where there were two or more children under the age of five. Majority of the children under study; 3185 (73.40%) were from rural areas and a significant number of them 1116 (23.95%) were from households in the poorest wealth quintile. Table 2 presents a summary of the socio-demographic characteristics of the study participants as well as results from Pearson's chi-square tests.

**Table 2: Socio-Demographic characteristics of study participants and bivariate associations**

Variable	n	%	Row %		
			Stunting	Wasting	Underweight
<b>Maternal Factors</b>					
<b>Mother's age (p-value)</b>			<b>0.1888</b>	<b>0.006</b>	<b>0.0049</b>
15-19	313	7.40	2.21	0.45	0.81
20-24	1234	29.11	9.02	1.08	2.52
25-29	1290	29.45	9.00	0.57	2.16
30-34	766	17.78	5.81	0.42	1.72
35-39	492	11.49	3.20	0.46	1.42
40-49	204	4.77	1.87	0.15	0.76
<b>Mother's BMI (p-value)</b>			<b>0.0003</b>	<b>(&lt;0.0001)</b>	<b>(&lt;0.0001)</b>
Normal	2815	64.72	20.85	2.15	6.20
Underweight	293	6.41	2.60	0.52	1.45
Overweight	876	21.09	5.55	0.40	1.26
Obese	315	7.77	2.04	0.07	0.48
<b>Mother's HIV status (p-value)</b>			<b>0.0010</b>	<b>0.3939</b>	<b>0.0519</b>
Positive	614	14.57	5.40	0.56	1.70
Negative	3267	85.43	25.49	2.66	7.63
<b>Tobacco Use (p-value)</b>			<b>0.0898</b>	<b>0.4171</b>	<b>0.2298</b>
Yes	25	0.44	0.21	0.03	0.07
No	4274	99.56	30.89	3.11	9.32
<b>Currently Pregnant (p-value)</b>			<b>0.0221</b>	<b>0.247</b>	<b>0.2305</b>
Yes	286	7.03	2.64	0.13	0.81
No	4013	92.97	28.47	3.00	8.58
<b>Currently Breastfeeding (p-value)</b>			<b>(&lt;0.0001)</b>	<b>0.0117</b>	<b>0.0001</b>
Yes	2245	52.88	12.48	2.02	4.01
No	2054	47.12	18.63	1.12	5.38

<b>Currently Working (p-value)</b>			<b>0.8121</b>	<b>0.6807</b>	<b>0.1229</b>
Yes	1383	34.31	10.47	1.02	3.59
No	2916	65.69	20.34	2.12	5.80
<b>Mother's Occupation (p-value)</b>			<b>0.1187</b>	<b>0.9927</b>	<b>0.3031</b>
Not Working	2662	60.05	18.72	1.88	5.35
Special Skills	717	17.72	4.82	0.55	1.58
Agricultural	467	12.10	4.15	0.40	1.46
Manual	427	10.13	3.37	0.30	0.99
<b>Marital Status (p-value)</b>			<b>0.0001</b>	<b>0.2882</b>	<b>0.0291</b>
Never in union	196	3.37	1.30	0.15	0.43
Married	3557	84.26	25.07	2.53	7.44
Cohabiting	154	3.53	1.06	0.12	0.36
Widowed	101	2.01	0.97	0.02	0.23
Divorced	102	2.52	1.01	0.14	0.21
Separated	189	4.32	1.70	0.19	0.71
<b>Living with partner (p-value)</b>			<b>0.3054</b>	<b>0.0292</b>	<b>0.2338</b>
Yes	2839	77.07	23.28	2.03	7.10
No	872	22.93	6.48	0.99	1.79
<b>Partner Age (p-value)</b>			<b>0.5788</b>	<b>0.2331</b>	<b>0.0022</b>
<30	1233	33.73	10.42	1.25	3.31
30-45	2095	56.02	16.24	1.46	4.20
>45	383	10.26	3.10	0.31	1.38
<b>Partner Education level (p-value)</b>			<b>0.0637</b>	<b>0.5148</b>	<b>(&lt;0.0001)</b>
No education	88	1.79	0.74	0.07	0.48
Primary	897	21.42	6.40	0.77	2.43
Secondary	2832	71.24	21.32	2.07	5.85
Higher	206	5.55	1.29	0.11	0.13
<b>Partner Occupation (p-value)</b>			<b>0.0108</b>	<b>0.7173</b>	<b>0.1141</b>
Not Working	668	15.78	4.87	0.39	1.29
Special Skills	845	21.29	5.27	0.76	1.46
Agricultural	827	23.06	7.59	0.66	2.23
Manual	1608	39.88	12.02	1.20	3.91
<b>Decision making (p-value)</b>			<b>0.739</b>	<b>0.0183</b>	<b>0.6054</b>
Subservient	2392	64.41	19.43	1.70	5.60
Consults	304	7.98	7.98	0.50	0.85
Independent	1051	27.61	8.04	0.81	2.44
<b>Child Factors</b>					
<b>Sex (p-value)</b>			<b>(&lt;0.0001)</b>	<b>0.0369</b>	<b>0.0025</b>
Male	2156	50.31	17.30	1.86	5.38
Female	2143	49.69	13.80	1.27	4.01
<b>Child's age</b>			<b>(&lt;0.0001)</b>	<b>(&lt;0.0001)</b>	<b>0.0038</b>
0-11	1150	26.98	3.46	1.50	1.82
12-23	920	20.88	7.74	0.83	2.49
24-35	822	19.22	9.58	0.31	1.95
36-47	745	17.90	6.86	0.19	1.89
48-59	662	15.02	3.46	0.30	1.23

<b>Birth weight in kg (p-value)</b>			<b>(&lt;0.0001)</b>	<b>0.0001</b>	<b>(&lt;0.0001)</b>
<= 2.90	1460	34.10	12.91	1.70	4.97
2.91 – 3.40	1479	34.06	10.20	0.86	2.42
>=3.41	1360	31.83	8.00	0.58	2.00
<b>Birth Order (p-value)</b>			<b>0.8522</b>	<b>0.1610</b>	<b>0.0434</b>
1	1305	30.45	9.39	0.80	2.31
2	1178	27.53	8.43	1.09	2.65
>=3	1816	42.02	13.28	1.25	4.43
<b>Twin (p-value)</b>			<b>0.0759</b>	<b>0.0084</b>	<b>0.0001</b>
Yes	88	1.93	0.84	0.16	0.51
No	4211	98.07	30.26	2.98	8.88
<b>Breastfeeding Status (p-value)</b>			<b>(&lt;0.0001)</b>	<b>(&lt;0.0001)</b>	<b>0.0008</b>
Ever Breastfed	2568	59.23	22.76	1.27	6.30
Never breastfed	64	1.47	0.69	0.08	0.23
Still Breastfeeding	1667	39.30	7.66	1.78	2.86
<b>When put to breast (p-value)</b>			<b>0.2245</b>	<b>0.7484</b>	<b>0.664</b>
Within 1 Hr	2935	68.66	21.45	2.08	6.42
Within hours	1114	27.11	8.09	0.89	2.45
Within Days	172	4.23	1.56	0.17	0.48
<b>Vitamin A 6 months (p-value)</b>			<b>0.0024</b>	<b>0.0004</b>	<b>0.7154</b>
Yes	2572	60.15	19.85	1.37	5.57
No	1727	39.85	11.25	1.77	3.82
<b>Fever in 2 weeks (p-value)</b>			<b>0.6628</b>	<b>0.3872</b>	<b>0.7907</b>
Yes	452	10.37	3.34	0.41	1.02
No	3847	89.63	27.77	2.73	8.37
<b>Cough in 2 weeks (p-value)</b>			<b>0.005</b>	<b>0.6744</b>	<b>0.718</b>
Yes	972	23.20	6.35	0.78	2.25
No	3327	76.80	27.76	2.35	7.14
<b>Diarrhoea in 2 weeks (p-value)</b>			<b>0.0051</b>	<b>0.6227</b>	<b>(&lt;0.0001)</b>
Yes	613	14.51	5.28	0.50	2.21
No	3686	85.49	25.82	2.63	7.18
<b>WHO diet diversity (p-value)</b>			<b>0.2351</b>	<b>0.7612</b>	<b>0.1091</b>
Poor	3222	74.28	22.69	2.38	6.57
Good	1077	25.72	8.41	0.76	2.82
<b>Diet diversity by PCA (p-value)</b>			<b>0.1282</b>	<b>0.6948</b>	<b>0.3972</b>
Low	1484	33.63	10.08	1.12	2.99
Moderate	1382	32.09	9.54	1.06	2.85
High	1433	34.28	11.49	0.96	3.55
<b>Household factors</b>					
<b>Province (p-value)</b>			<b>0.3764</b>	<b>0.05</b>	<b>0.0109</b>
Bulawayo	243	3.65	1.01	0.09	0.32
Manicaland	517	14.76	4.75	0.27	1.07
Mashonaland Central	493	11.36	3.69	0.47	1.36
Mashonaland East	460	10.42	3.72	0.42	0.94
Mashonaland West	507	12.58	3.67	0.31	1.25
Matebeleland North	369	4.85	1.66	0.31	0.76
Matebeleland South	401	5.13	1.65	0.24	0.61

Midlands	496	13.31	4.06	0.37	1.36
Masvingo	434	11.42	3.37	0.28	0.67
Harare	374	12.53	3.52	0.36	1.05
<b>Type of residence (p-value)</b>			<b>0.0061</b>	<b>0.1202</b>	<b>0.1895</b>
Urban	1114	26.60	7.32	0.63	2.18
Rural	3185	73.40	23.79	2.51	7.21
<b>Sex of household head (p-value)</b>			<b>0.2817</b>	<b>0.4558</b>	<b>0.6959</b>
Male	2471	58.85	17.86	1.74	5.62
Female	1828	41.15	13.24	1.39	3.77
<b>Household Size (p-value)</b>			<b>0.9947</b>	<b>0.0777</b>	<b>0.0896</b>
<= 5	2438	58.13	18.08	1.56	5.05
>= 6	1861	41.87	13.03	1.58	4.35
<b>Number of U5 Children (p-value)</b>			<b>0.3814</b>	<b>0.0169</b>	<b>0.3269</b>
1	2127	50.50	15.34	1.23	4.47
>=2	2172	49.50	15.76	1.90	4.92
<b>Religion (p-value)</b>			<b>0.0163</b>	<b>0.1067</b>	<b>0.227</b>
Apostolic	1911	45.59	14.89	1.69	4.60
Other Christian	1973	45.28	13.00	1.13	3.84
No/Other Religion	415	9.13	3.21	0.32	0.95
<b>Wealth Index (p-value)</b>			<b>0.0003</b>	<b>0.0909</b>	<b>0.0059</b>
Poorest	1116	23.95	8.45	0.86	2.82
Poorer	918	21.86	6.70	0.73	2.27
Middle	804	19.90	6.79	0.58	1.60
Richer	863	20.30	5.79	0.79	1.86
Richest	598	14.00	3.37	0.18	0.85
<b>Source of drinking water (p-value)</b>			<b>0.0014</b>	<b>0.0931</b>	<b>0.0722</b>
Piped	1122	24.98	6.67	0.53	1.90
Other Safe	2071	49.33	15.53	1.74	4.74
Unsafe	1106	25.70	8.90	0.87	2.75
<b>Time to get to water source (p-value)</b>			<b>0.1883</b>	<b>0.2306</b>	<b>0.0608</b>
Within Household	1435	33.91	9.79	0.80	2.60
Short	970	24.45	7.98	0.80	2.54
Average	1280	28.38	8.93	1.09	2.72
Long	614	13.26	4.41	0.44	1.52
<b>Type of toilet facility (p-value)</b>			<b>0.0069</b>	<b>0.2438</b>	<b>0.0386</b>
Flush	1079	25.26	6.72	0.58	1.91
Safe	1659	40.65	13.34	1.33	3.77
Other	1561	34.08	11.03	1.23	3.71
<b>Toilet facility shared (p-value)</b>			<b>0.5597</b>	<b>0.7249</b>	<b>0.5678</b>
Yes	1745	41.77	13.23	1.26	4.07
No	2554	58.23	17.87	1.88	5.33
<b>Type of cooking fuel (p-value)</b>			<b>0.0051</b>	<b>0.0304</b>	<b>0.0174</b>
Electricity/Gas	915	20.68	5.55	0.41	1.46
Other	3384	79.32	25.55	2.72	7.39

### **3.3 Bivariate associations**

#### **3.3.1 Stunting**

Among the maternal factors investigated, BMI, whether mother was breastfeeding or pregnant, marital status and HIV status showed a statistically significant association with stunting at the 5% level while the partner level variables; partner occupation and educational level showed a significant association at the 10% level. The child factors; sex, age, breastfeeding status, birth weight, having suffered from diarrhoea or cough in the last two weeks as well as having received vitamin A in the last six months were significantly associated with stunting at the 5% significance level while being a twin was significant at the 10% level. Wealth index, type of residence, religion, source of drinking water, type of toilet facility and type of cooking fuel are the household factors that showed an association with stunting at 5% significance level.

#### **3.3.2 Wasting**

Among the maternal variables under investigation, the variables; age, BMI, whether mother was living with a partner or breastfeeding and her decision making power were significantly associated with wasting at the 5% level while the child factors; sex, age, twin status, breastfeeding status, birth weight and whether child received vitamin A in the last six months showed a significant association at the 5% significance level. Amongst the household factors under investigation, number of children under five in the household, religion, wealth index score, source of drinking water and type of cooking fuel showed significant associations with wasting at the 5% level while household size and province showed associations at the 10% significance level.

#### **3.3.3 Underweight**

Maternal age, BMI, HIV status, partner's age, and partner's educational level are the maternal factors that showed a statistically significant association with underweight at the 5% level while the child factors sex, age, birth order, breastfeeding status, twin status and having suffered from diarrhoea two weeks prior to data collection showed a significant association at the same significance level. Wealth index, province, type of toilet facility and type of cooking fuel are the household level variables that showed an association with underweight at the 5% significance level while source of drinking water, time to get to water source and household size were significant at the 10% level.

### 3.4 Spatial distribution of malnutrition

#### 3.4.1 Stunting

The crude choropleth map revealing the distribution of stunting in the country by district reveals that approximately half of the districts had a stunting prevalence that is above the national average. There was no apparent pattern in the prevalence of stunting where one can point that stunting was higher in this particular province.

All the provinces, excluding the metropolitan provinces (Harare and Bulawayo) had at least one district falling in the fourth quantile. Figure 5 presents the distribution of stunting by district.

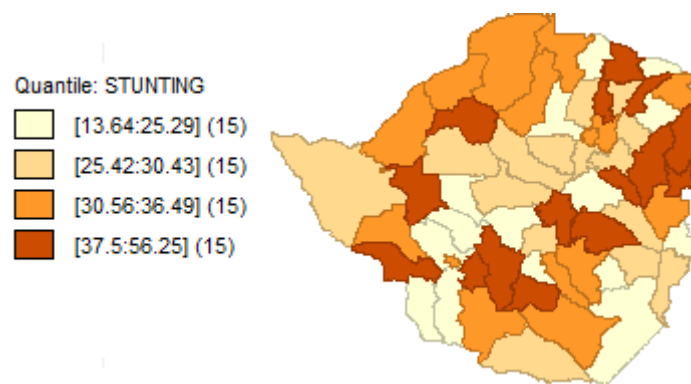


Figure 5: Distribution of Stunting by District

Global Moran's autocorrelation coefficient ( $I=-0.083$  p-value 0.198) and its associated scatter plot reveal that there is no spatial autocorrelation at the global level as shown in Figure 6

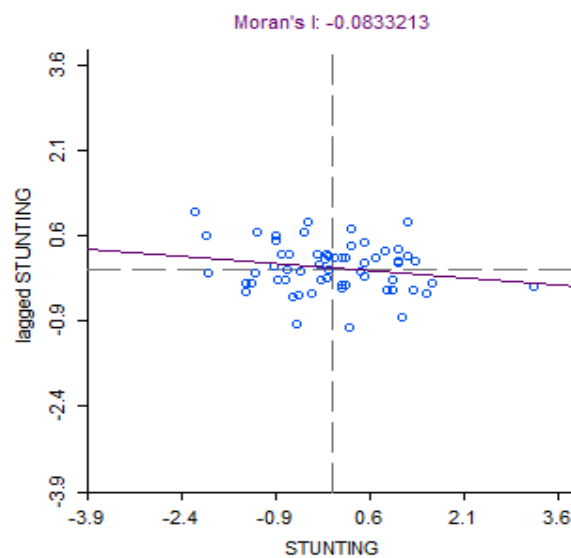
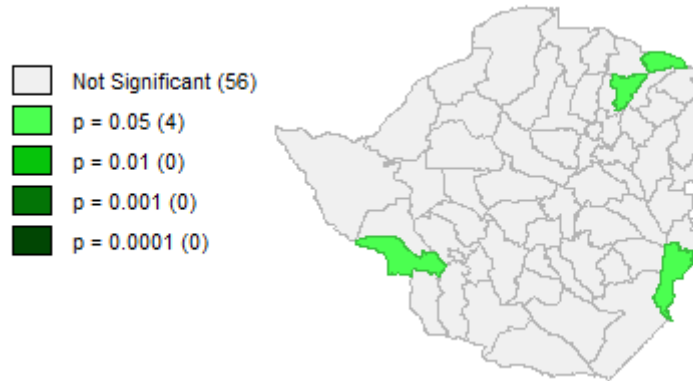


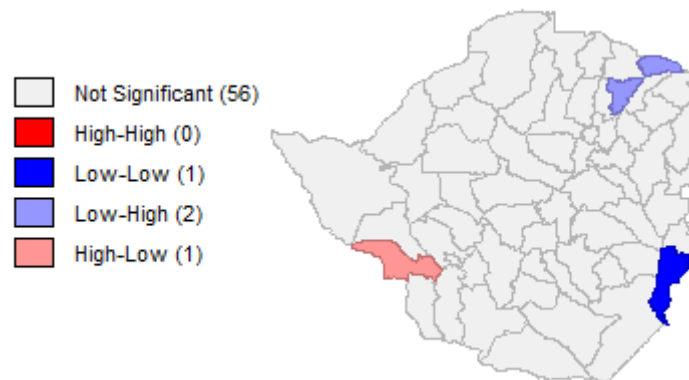
Figure 6: Moran's autocorrelation scatter plot for stunting

A look at Moran's local autocorrelation coefficient reveals that only four statistically significant clusters of stunting existed at the time of data collection and these were all significant at 5% significance level as shown in Figure 7.



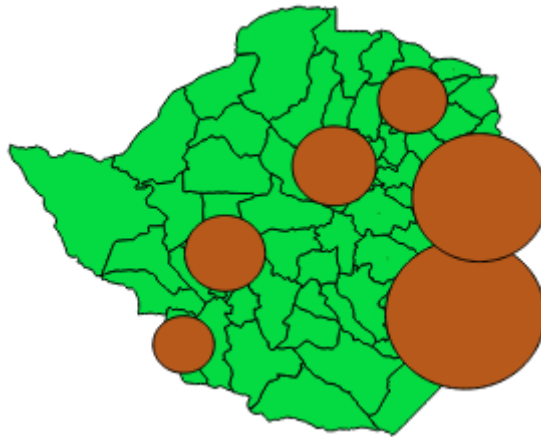
**Figure 7: Stunting Significance Cluster map**

Two of the clusters that were identified were low prevalence districts surrounded by high prevalence districts while the other one was a low prevalence district surrounded by other low prevalence districts and the last cluster was a high prevalence district surrounded by low prevalence districts as shown in Figure 8.



**Figure 8: Types of stunting clusters**

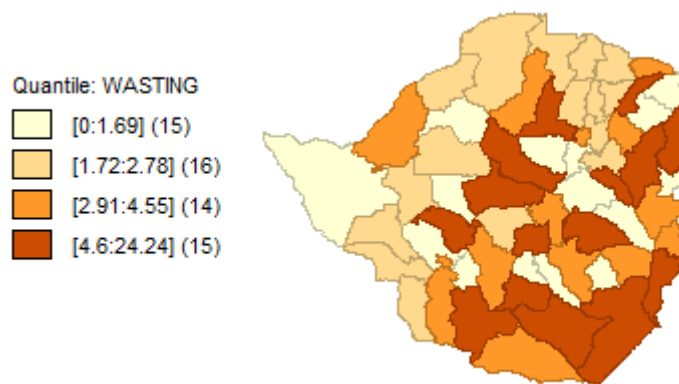
SatScan analyses did not reveal any significant clusters. The clusters that were identified, though insignificant were in positions quite different from those identified by Moran's I analyses as shown in Figure 9.



**Figure 9: SaTScan Clusters for Stunting**

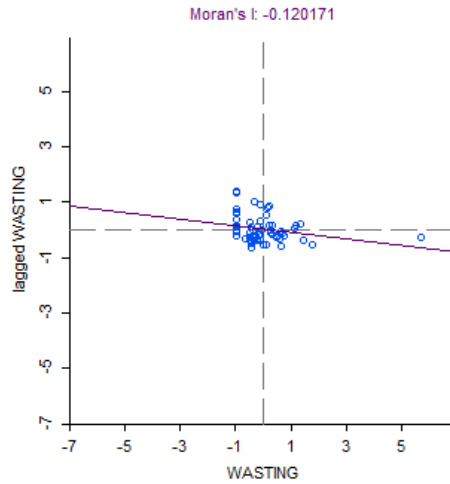
### 3.4.2 Wasting

The crude choropleth map for the distribution of stunting in the country by district reveals that the greater number of the western districts had wasting prevalences below the national average while the southern part had the highest number of districts in the fourth quantile. Though some fourth quantile districts are surrounded by other fourth quantile districts, it is interesting to note that in some cases first quantile districts separate fourth quantile districts from other fourth quantile or third quantile district as shown by Figure 10.



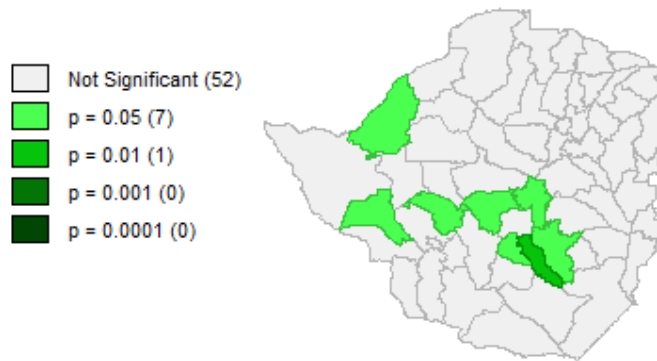
**Figure 10: Distribution of Wasting by district**

Global Moran's autocorrelation coefficient ( $I = -0.12$ ;  $p$ -value 0.046) and its associated scatter plot reveal that there is marginal evidence suggesting spatial autocorrelation of wasting at the global level. The scatterplot suggests that prevalence of wasting is characterized by dispersion or outliers whereby high prevalence districts are surrounded by low prevalence districts or low prevalence districts are surrounded by high prevalence districts as shown in Figure 11.



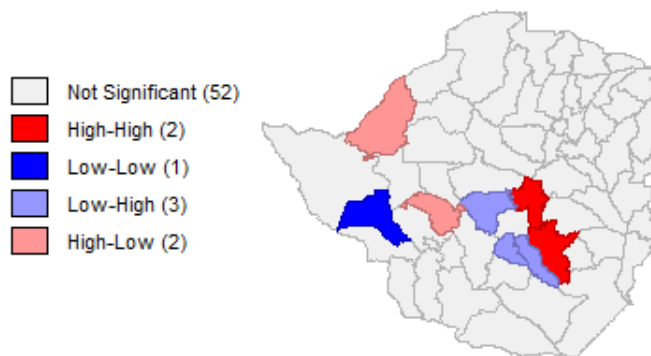
**Figure 11: Moran's autocorrelation scatter plot for wasting**

A look at Moran's local autocorrelation coefficient and scatter plot reveals that eight of the districts were significant clusters, seven of them significant at 5% significance level and one of them significant at 1% significance level as shown in Figure 12.



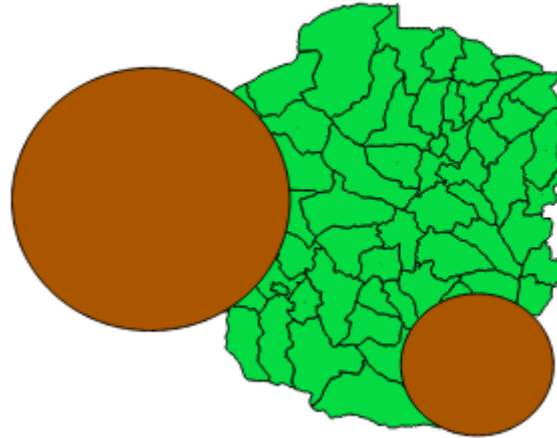
**Figure 12: Wasting Significance Cluster map**

Two of the eight clusters that were identified were high prevalence districts surrounded by other high prevalence districts while another two were high prevalence districts surrounded by low prevalence districts. The other three clusters were low prevalence districts by high prevalence districts. Only one of the clusters was a low prevalence district surrounded by low prevalence districts as well. Figure 13 presents these findings graphically.



**Figure 13: Types of wasting clusters**

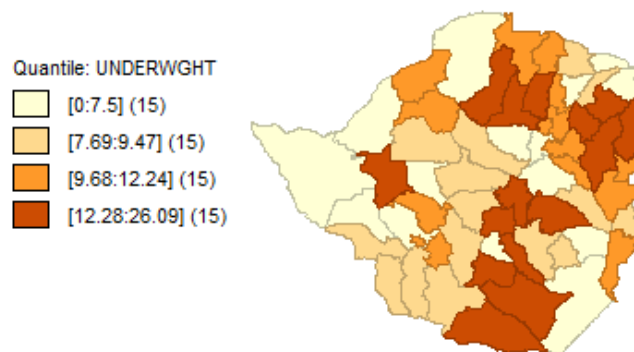
Though SatScan analyses did not identify any significant clusters, the insignificant clusters that were identified were totally different from what Moran's analyses revealed as shown in Figure 14.



**Figure 14: SatScan Clusters for Wasting**

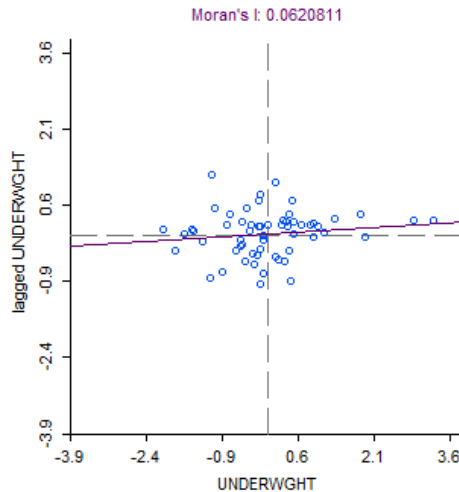
### 3.4.3 Underweight

The crude choropleth map for the distribution of stunting in the country by district reveals that there is at least an apparent pattern in the appearance of the prevalence of underweight whereby districts with high prevalence are surrounded by districts with high prevalence as well. However, in the southern part of the country, fourth quantile districts are surrounded by second and first quantile districts implying the need for confirmation of this appearance through further analyses as shown in Figure 15.



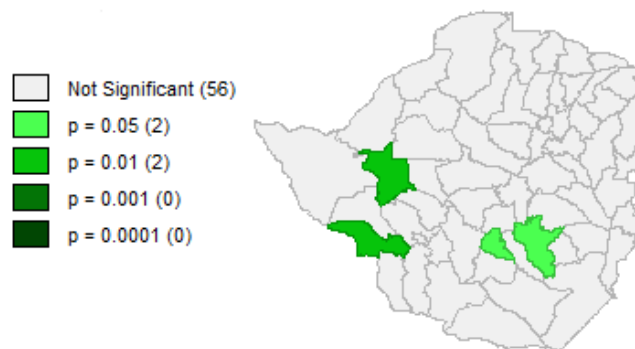
**Figure 15: Distribution of underweight by district**

Moran's global autocorrelation coefficient ( $I = 0.06$ ;  $p$ -value 0.1498) and its associated scatter plot reveal that there is no sufficient evidence to suggest any spatial autocorrelation of underweight in the study population as shown by Figure 16.



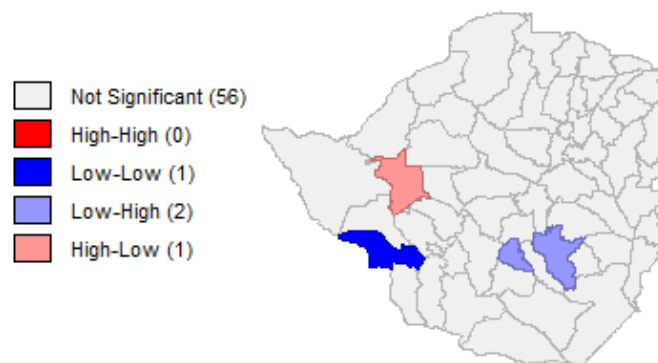
**Figure 16: Moran's autocorrelation Scatter plot for underweight**

Analysis of spatial autocorrelation at the local level reveals that there are four significant clusters, two significant at the 5% level and the other two significant at the 1% level as shown in Figure 17.



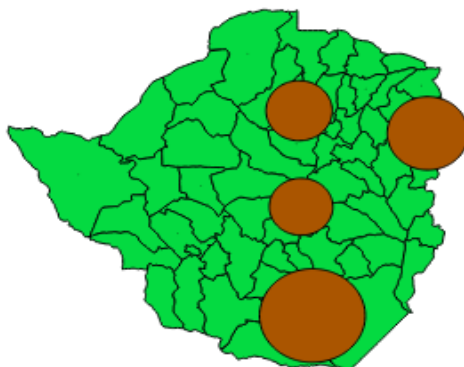
**Figure 17: Underweight significance map**

One of the clusters that were identified was a low prevalence district surrounded by other low prevalence districts while two of the other significant clusters were low prevalence districts surrounded by high prevalence districts and one was a high prevalence district surrounded by low prevalence districts as shown in Figure 18.



**Figure 18: Types of Underweight clusters**

Although SatScan did not reveal any significant clusters as in other cases, the insignificant clusters that were revealed were in different positions from those that were revealed by Moran's analyses as shown in Figure 19.



**Figure 19: SatScan Clusters for underweight**

It is interesting to note that the two methods that we used to do exploratory analyses gave different results and as such it is important to then consider findings from inferential analyses.

### **3.5 Factors associated with malnutrition**

#### **3.5.1. Binary Logistic Regression**

Table 3 presents the results from binary logistic regression.

##### **3.5.1.1 Stunting**

We found mother's HIV status and breast feeding status to be the only maternal factors associated with stunting at the 5% significance level in the multivariable regression while sex, age, birth weight, twin status, having a cough two weeks prior to data collection and WHO dietary diversity were the child level factors found to be associated with stunting. Meanwhile, religion and wealth index were the only household factors significantly associated with stunting at the 5% level.

Controlling for all the other factors in the model, children whose mothers were HIV positive at the time of data collection had 39% increased odds of being stunted compared to children whose mothers were HIV negative. Females were 33% times less likely to be stunted compared to males holding all the other factors in the model constant.

Children between 24 and 35 months of age were six times more likely to be stunted compared to children 0-11 months old, holding all other factors in the model constant, otherwise with increasing age, the odds of being stunted were decreasing in the study population.

Likelihood of being stunted decreased with increasing birth weight. Compared to children less than 2.9kg at birth, children with a birth weight between 2.91 and 3.40kg were 38% times less likely to be stunted while children 3.41 kg or more at birth were 51% times less likely to be stunted, holding all other factors in the model constant. Twins were two times more likely to be stunted compared to singletons, holding all the other factors in the model constant. Contrary to reason, children who suffered a cough two weeks prior to data collection were 0.18 times less likely to be stunted compared to children who did not suffer a cough in the same time period; controlling for all the other factors in the model.

### **3.5.1.2 Wasting**

For all children, maternal BMI, child's sex, age, birth weight, and having received vitamin A in the six months prior to data collection are the factors that showed a significant association with wasting after multivariable modelling. In addition to these factors, mother's decision making index showed a significant association with wasting for children whose mothers reported being in a marital relationship at the time of data collection. None of the household factors showed a significant association with wasting at the 5% level in multivariable regression.

Children whose mothers were underweight were 2.3 times more likely to be wasted compared to children whose mothers' BMI was normal; holding all the other factors in the model constant but there was no statistically significant difference in the odds of being wasted for children whose mothers were overweight or obese when compared to children whose mothers had a normal BMI. Female children were 0.4 times less likely to be wasted compared to male children, controlling for other factors in the model. Compared to children 0-11 months old, odds of being wasted for children 12-23 months old were not significantly different while older children 24-35, 36-47 and 48-59 months old were 0.66, 0.80 and 0.74 times less likely to be stunted respectively; holding all other factors in the model constant. The heavier a child was at birth, the less likely the child was to be wasted at the time of data collection. Controlling for all other factors in the model, children between 2.91 and 3.40 kg at birth were 0.5 times less likely to be wasted while children 3.4 kg or greater at birth were 0.69 times less likely to be stunted compared to children less than 2.90 kg at birth.

Having received vitamin A six months prior to data collection was protective of wasting for the children in this study, where children who received vitamin A supplements were 35% times less likely to be wasted compared to children who did not receive supplements controlling for all other factors in the model.

### **3.5.1.3 Underweight**

In multivariable regression, the maternal factors significantly associated with underweight were mother's BMI and whether the mother was breastfeeding or not while the significant child factors were child's sex, age group, birth weight, birth order, twin status, and having suffered from diarrhoea in the two weeks prior to data collection. Wealth index was the only household factor significantly associated with underweight at the 5% level.

Children whose mothers were underweight were more than twice as likely to be underweight compared to children whose mothers had a normal BMI while there was no significant difference in the odds of being underweight between children whose mothers were overweight or obese compared to children whose mothers had a normal BMI; controlling for other factors in the model. Children whose mothers were breast feeding at data collection time were 37% times less likely to be underweight compared to children whose mothers were not breast feeding, holding all other factors in the model constant.

Female children were 34% times less likely to be underweight compared to male children; controlling for other factors in the model. The higher a child's birth weight was, the less likely the child was to be underweight where compared to children 2.90kg or less at birth, children 2.91-3.40 kg at birth were 52% times less likely to be underweight while children 3.40kg or more at birth were 65% times less likely to be underweight; controlling for all the other factors in the model. A child of the third or higher birth order was 44% times more likely to be underweight compared to the first child while a child of the second birth order was not significantly different from the first child, controlling for all other factors in the model. A child who was one of a pair of twins was almost three times more likely to be underweight compared to a singleton, holding all other factors in the model constant while having suffered from diarrhoea in the two weeks prior to data collection decreased the chances of being underweight by 64% times.

Compared to children from households in the poorest wealth quintile, there were statistically significant differences only with children from households in the middle and richest wealth quintiles, no difference was seen when comparing children from poorer or richer households with children from the poorest wealth quintile. Children in the middle wealth quintile were 37% times less likely while children in the richest category were 48% times less likely to be underweight compared to children from the poorest wealth quintile, holding all other factors in the model constant.

**Table 3: Unadjusted and Adjusted Odds Ratios from binary logistic regression**

Variable	Categories	Stunting				Wasting				Underweight			
		Unadj OR	CI	Adj OR	CI	Unadj OR	CI	Adj OR	CI	Unadj OR	CI	Adj OR	CI
Maternal Factors													
Mother's age	15-19	1.02	0.78-1.34			2.48**	1.35-4.55			1.30	0.85-1.99		
	20-24	1.04	0.86-1.23			1.64	0.99-2.74			1.11	0.85-1.47		
	25-29			1 ref				1 ref				1 ref	
	30-34	1.15	0.93-1.41			1.26	0.73-2.16			1.34	0.97-1.86		
	35-39	0.91	0.72-1.16			1.63	0.86-3.10			1.65**	1.21-2.25		
	40-49	1.41	1.02-1.94			1.66	0.73-3.77			1.83*	1.14-2.93		
Mother's BMI	Normal			1 ref				1 ref				1 ref	
	Underweight	1.28	0.97-1.70			2.29**	1.39-3.78	2.30**	1.37-3.86	2.68***	1.96-3.67	2.69***	1.97-3.67
	Overweight	0.74**	0.62-0.89			0.58*	0.35-0.92	0.64	0.39-1.06	0.68*	0.49-0.93	0.73*	0.54-0.98
	Obese	0.71*	0.54-0.93			0.43	0.17-1.08	0.55	0.22-1.40	0.65	0.40-1.05	0.67	0.42-1.09
Mother's HIV status	Negative			1 ref				1 ref				1 ref	
	Positive	1.39**	1.15-1.67	1.39**	1.15-1.69	1.22	0.76-1.95			1.39*	1.05-1.83		
Tobacco Use	No			1 ref				1 ref				1 ref	
	Yes	2.02	0.85-4.75			2.48	0.55-11.11			2.27	0.86-5.98		
Currently Pregnant	No			1 ref				1 ref				1 ref	
	Yes	1.35*	1.05-1.73			0.49	0.20-1.19			1.19	0.81-1.74		
Currently Breastfeeding	No			1 ref				1 ref				1 ref	
	Yes	0.51***	0.44-0.58	0.84	0.69-1.03	1.51*	1.05-2.16			0.67**	0.53-0.84	0.63***	0.51-0.77
Currently Working	No			1 ref				1 ref				1 ref	
	Yes	1.00	0.87-1.16			0.84	0.58-1.21			1.02	0.82-1.28		
Mother's Occupation	Not Working			1 ref				1 ref				1 ref	
	Special Skills	0.83	0.69-1.02			0.86	0.54-1.38			0.85	0.63-1.15		
	Agricultural	1.10	0.87-1.40			0.91	0.51-1.61			1.15	0.81-1.62		
	Manual	1.06	0.85-1.33			0.93	0.53-1.61			0.98	0.67-1.44		
Marital Status	Never in union	1.47*	1.06-2.03			1.45	0.74-2.84			1.29	0.81-2.05		
	Married			1 ref				1 ref				1 ref	
	Cohabiting	0.99	0.68-1.44			1.22	0.55-2.74			1.04	0.57-1.90		
	Widowed	2.02**	1.33-3.06			0.30	0.04-2.24			1.56	0.83-2.92		

	Divorced	1.38	0.93-2.05			2.23*	1.02-4.88			1.05	0.53-2.07		
	Separated	1.49*	1.10-2.02			1.69	0.88-3.23			2.12***	1.42-3.18		
Living with partner	Yes	1 ref				1 ref				1 ref			
	No	0.96	0.81-1.14			1.30	0.86-1.97			0.84	0.63-1.11		
Partner Age	<30	1 ref				1 ref				1 ref			
	30-45	0.94	0.81-1.11			0.77	0.51-1.14			0.83	0.64-1.09		
	>45	0.96	0.74-1.24			1.15	0.63-2.12			1.29	0.91-1.85		
Partner Education level	No education	1.63	1.00-2.65			2.29	0.92-5.72			3.63***	2.15-6.15		
	Primary	1.02	0.86-1.23			1.55	0.95-2.56			1.53**	1.18-1.97		
	Secondary	1 ref				1 ref				1 ref			
	Higher	0.70	0.49-1.00			0.91	0.36-2.29			0.35*	0.15-0.80		
Partner Occupation	Not Working	1.00	0.81-1.23			1.03	0.61-1.72			0.98	0.70-1.36		
	Special Skills	0.74**	0.61-0.90			1.06	0.66-1.71			0.73	0.52-1.02		
	Agricultural	1.09	0.90-1.32			1.13	0.72-1.78			1.02	0.76-1.37		
	Manual	1 ref				1 ref				1 ref			
Mother's decision score	Subservient	1 ref				1 ref				1 ref			
	Consults	0.99	0.76-1.30			2.37**	1.40-4.02			1.48	1.00-2.19		
	Independent	1.01	0.87-1.18			1.06	0.69-1.64			1.12	0.87-1.43		
Child factors													
Sex	Male	1 ref				1 ref				1 ref			
	Female	0.73***	0.65-0.83	0.67***	0.57-0.77	0.69*	0.49-0.96	0.61**	0.43-0.85	0.74**	0.60-0.91	0.65***	0.52-0.80
Child's age	0-11	1 ref				1 ref				1 ref			
	12-23	3.87***	3.09-4.84	4.25***	3.32-5.45	0.77	0.51-1.16	0.82	0.53-1.27	1.80***	1.31-2.47		
	24-35	6.48***	5.20-8.08	6.67***	5.07-8.78	0.33***	0.19-0.55	0.36***	0.21-0.63	1.62**	1.17-2.25		
	36-47	3.66***	2.88-4.65	3.62***	2.74-4.79	0.18***	0.09-0.37	0.20***	0.09-0.44	1.50*	1.09-2.07		
	48-59	1.98***	1.55-2.54	2.04***	1.51-2.75	0.41**	0.23-0.71	0.46**	0.26-0.80	1.35	0.94-1.95		
	Birth weight categories												
Birth weight categories	<= 2.90	1 ref				1 ref				1 ref			
	2.91-3.40	0.67***	0.57-0.78	0.62***	0.51-0.74	0.52**	0.35-0.76	0.49**	0.33-0.72	0.49***	0.38-0.63	0.48***	0.38-0.61
	>= 3.41	0.53***	0.45-0.63	0.49***	0.41-0.60	0.31***	0.20-0.49	0.30***	0.19-0.48	0.35***	0.26-0.46	0.35***	0.26-0.45
Birth Order	1	1 ref				1 ref				1 ref			
	2	0.98	0.83-1.16			1.32	0.87-2.00			1.18	0.89-1.55	1.21	0.91-1.61

	>=3	1.07	0.91-1.26			1.15	0.77-1.72		1.46**	1.14-1.88	1.43***	1.10-1.86
Twin	No			1 ref				1 ref			1 ref	
	Yes	1.52	0.88-2.64	2.02*	1.12-3.66	2.93**	1.32-6.48		3.52***	1.92-6.48	2.99**	1.79-4.97
Breastfeeding Status	Ever Breastfed			1 ref				1 ref			1 ref	
	Never BF	1.26	0.75-2.10			4.11**	1.66-10.21		1.64	0.84-3.19		
	Still BF	0.42***	0.36-0.49			1.95***	1.36-2.80		0.66***	0.53-0.83		
When put to breast	Within 1 Hr			1 ref				1 ref			1 ref	
	Within hours	0.96	0.82-1.13			1.18	0.80-1.73		0.95	0.75-1.20		
	Within Days	1.26	0.93-1.72			1.42	0.68-2.97		1.21	0.72-2.02		
Vitamin A 6 months	No			1 ref				1 ref			1 ref	
	Yes	1.23**	1.08-1.40			0.54***	0.38-0.75	0.64*	0.45-0.92	0.94	0.78-1.14	
Fever in 2 weeks	No			1 ref				1 ref			1 ref	
	Yes	1.09	0.88-1.36			1.27	0.77-2.12		1.05	0.75-1.48		
Cough in 2 weeks	No			1 ref				1 ref			1 ref	
	Yes	0.86*	0.74-1.00	0.82*	0.69-0.97	0.87	0.58-1.32		1.04	0.82-1.32		
Diarrhoea in 2 weeks	No			1 ref				1 ref			1 ref	
	Yes	1.25*	1.05-1.49			1.06	0.67-1.68		1.64***	1.27-2.13	1.64***	1.26-2.13
WHO diet diversity	Poor			1 ref				1 ref			1 ref	
	Good	1.05	0.91-1.22	0.8*	0.67-0.95	0.73	0.47-1.13		1.04	0.81-1.32		
Diet diversity by PCA	Good			1 ref				1 ref			1 ref	
	Moderate	0.97	0.81-1.16			1.23	0.84-1.81		1.01	0.78-1.30		
	Poor	1.11	0.94-1.31			0.77	0.51-1.16		1.04	0.80-1.36		
Household factors												
Province	Manicaland	1.23	0.90-1.67			0.78	0.29-2.08		0.80	0.46-1.37		
	Mash Central	1.18	0.84-1.65			1.58	0.65-3.88		1.26	0.78-2.04		
	Mash East	1.45*	1.03-2.04			1.80	0.74-4.36		1.09	0.66-1.79		
	Mash West	1.03	0.74-1.44			1.04	0.40-2.73		1.12	0.71-1.78		
	Mat North	1.45*	1.02-2.06			2.99*	1.20-7.49		1.99	1.26-3.15		
	Mat South	1.25	0.89-1.75			1.96	0.78-4.95		1.40	0.88-2.22		
	Midlands	1.13	0.81-1.57			1.06	0.44-2.60		1.23	0.75-2.00		
	Masvingo	1.12	0.79-1.61			0.93	0.33-2.59		0.64	0.37-1.11		

	Harare	0.99	0.70-1.40			1.18	0.45-3.07			0.80	0.46-1.41		
	Bulawayo		1 ref				1 ref				1 ref		
Type of Residence	Rural		1 ref				1 ref				1 ref		
	Urban	0.77**	0.66-0.90			0.61*	0.39-0.93			0.75*	0.59-0.95		
Sex of household head	Male		1 ref				1 ref				1 ref		
	Female	1.03	0.89-1.18			1.20	0.87-1.66			0.99	0.80-1.21		
Household Size	<= 5		1 ref				1 ref				1 ref		
	>= 6	1.00	0.88-1.14			1.30	0.92-1.84			1.24*	1.00-1.52		
Number of U5 Children	1		1 ref				1 ref				1 ref		
	>=2	1.10	0.96-1.26			1.57*	1.10-2.24			1.17	0.94-1.45		
Religion	Apostolic		1 ref				1 ref				1 ref		
	Other Christian	0.82**	0.71-0.95	0.83*	0.70-0.99	0.79	0.54-1.14			0.83	0.67-1.03		
	No/Other Religion	1.07	0.83-1.36	1.04	0.79-1.35	1.02	0.59-1.78			1.07	0.75-1.53		
Wealth Index	Poorest		1 ref				1 ref				1 ref		
	Poorer	0.79*	0.66-0.94	0.78*	0.64-0.95	0.79	0.47-1.33			0.78	0.60-1.03	0.81	0.61-1.08
	Middle	0.94	0.78-1.14	0.87	0.71-1.08	0.70	0.41-1.19			0.59**	0.43-0.82	0.63**	0.46-0.87
	Richer	0.75**	0.61-0.91	0.68**	0.54-0.85	0.84	0.50-1.40			0.73*	0.53-0.99	0.80	0.59-1.08
	Richest	0.53***	0.41-0.68	0.57***	0.43-0.77	0.33**	0.16-0.69			0.41***	0.28-0.61	0.50**	0.34-0.76
Source of drinking water	Piped		1 ref				1 ref				1 ref		
	Other Safe	1.29**	1.09-1.54			1.64*	1.06-2.54			1.32*	1.01-1.72		
	Unsafe	1.42***	1.18-1.72			1.69*	1.01-2.85			1.38*	1.03-1.85		
Time to get to water source	Within HH		1 ref				1 ref				1 ref		
	Short	1.20*	1.01-1.43			1.27	0.78-2.06			1.34*	1.02-1.77		
	Average	1.19	1.00-1.45			1.52	1.00-2.31			1.26	0.95-1.66		
	Long	1.19	0.96-1.47			1.59	0.90-2.81			1.48*	1.09-2.00		
Type of toilet facility	Other	0.76**	0.63-0.90			0.53*	0.33-0.87			0.60***	0.46-0.79		
	Flush	1.04	0.88-1.22			0.86	0.58-1.28			0.75*	0.58-0.95		
	Safe		1 ref				1 ref				1 ref		
Toilet facility shared	No		1 ref				1 ref				1 ref		
	Yes	1.04	0.91-1.20			0.87	0.61-1.22			1.01	0.82-1.25		
Type of cooking fuel	Electricity/Gas	0.73***	0.61-0.87			0.61*	0.38-0.98			0.72*	0.54-0.95		
	Other		1 ref				1 ref				1 ref		

Level of significance: \*&lt;0.05

\*\*&lt;0.01

\*\*\*&lt;0.001

### **3.5.2 Unconstrained Generalised Ordered Logistic Regression**

Mother's HIV status, breastfeeding status and BMI were the maternal factors significantly associated with the four level ordered malnutrition outcome in multivariable regression at 5% significance level while the significant child factors were; sex, age group, birth weight, twin status as well as having suffered a cough or diarrhoea in the two weeks prior to data collection. Religion and wealth index were the significant household factors in the GOLOGIT model.

The effects of HIV status, breastfeeding status, child's sex, birth weight, twin status having suffered a cough as well as religion were uniform for all the three levels of comparison while the effects of child's age, mother's underweight BMI, having suffered from diarrhoea in the two weeks prior to data collection as well as wealth index varied with level of comparison.

#### **3.5.2.1 Maternal factors**

Compared to children whose mothers were not breastfeeding, children whose mothers were breastfeeding at the time of data collection were 19% times less likely to be malnourished, irrespective of comparison level and holding all other factors in the model constant. Regardless of comparison level, children whose mothers were HIV positive were 36% times more likely to be malnourished compared to children whose mothers were HIV negative, controlling for all other factors in the model.

Regardless of comparison level, the effect of a mother's BMI on child malnutrition was similar only when comparing children of overweight or obese mothers against children of mothers of normal BMI where children whose mothers were obese or overweight were 22% times less likely to be malnourished compared to children of mothers with normal BMI, controlling for all other factors in the model. The effect of mother's underweight BMI was however different across the three levels of comparison for children whose mothers were underweight where chances of having more types of malnutrition increased across the three levels of comparison when compared to children of normal BMI women. Comparing children with one, two or all three types of malnutrition to children with no malnutrition, odds of malnutrition for children of underweight women were not significantly different from the odds of children of normal BMI women, holding all other factors in the model constant.

Significant differences were only noted for the second and third comparison levels where compared to children of normal BMI women, children of underweight women were 2.46 times and 6.50 times more likely to be malnourished respectively; holding other factors in the model constant.

### **3.5.2.2 Child factors**

Regardless of comparison level, female children were 36% times less likely to be malnourished compared to male children, holding all the other factors in the model constant. Compared to children who did not suffer a cough in the two weeks prior to data collection, children who suffered a cough during the same time period were 21% times less likely to be malnourished, regardless of comparison level and holding all the other factors in the model constant. Irrespective of comparison level, children who were one of a pair of twins were 2.53 times more likely to be malnourished compared to singletons, controlling for all the other factors in the model.

With increasing birth weight, the chances of being malnourished decreased. Compared to children weighing 2.90 kg at birth, children weighing 2.91-3.40 kg at birth had a 43% times reduced chance of being malnourished while children weighing 3.41kg or more at birth were 56% times less likely to be malnourished; controlling for all the factors in the model.

Controlling for other factors in the model, the effect of a child's age group on malnutrition differed with comparison level for all other age groups except for the age group 48-59 months where regardless of comparison level, children 48-59 months old were 44% times more likely than children 0-11 months old to be malnourished. Meanwhile, holding other factors in the model constant, compared to children 0-11 months old, children 12-23 months old were almost three times more likely and twice as likely to be malnourished for the first and second comparison levels respectively. For the third comparison level there was no significant difference in odds of being malnourished for children 12-23 months compared to children 0-11 months old. Children 24-35 months old were 4.24 times more likely and 1.56 times more likely to be malnourished compared to children 0-11 months old for the first and second levels of comparison respectively, no significant differences were noted for the third level of comparison. Compared to children 0-11 months old, children 36-47 months old were 2.26 times more likely and 1.49 times more likely to be malnourished for the first and second levels of comparison respectively, holding all other factors constant, again no significant differences were noted for the third level of comparison.

For the first level of comparison, children who suffered from diarrhoea were not significantly different from children who did not suffer from diarrhoea in the two weeks prior to data collection. For the second comparison level, children who suffered from diarrhoea in the two weeks prior to data collection were 71% times more likely to have two or three types of malnutrition compared to children who did not suffer from diarrhoea during the same time period while children who suffered diarrhoea were almost three times more likely to have all three types of malnutrition compared to having two or less types of malnutrition; holding all other factors in the model constant.

### **3.5.2.3 Household factors**

The effect of religion on the four-level outcome variable was uniform regardless of comparison level. There was a significant difference when comparing between children from other Christian households against children from apostolic sect households where children from other Christian homes were 18% times less likely to be malnourished; holding other factors constant. There was no significant difference in odds of malnutrition when comparing children from households practicing other or no religion with children from apostolic sect households.

Compared to the poorest wealth quintile, the effect of middle wealth quintile differed with differing comparison level while the effect of other wealth quintiles was uniform throughout all the three comparison levels. For the third comparison level, children from the middle wealth quintile and children from the poorest wealth quintile did not differ significantly in odds for malnutrition. Significant differences were only noted for the first and second comparison levels where compared to children from the poorest wealth quintile, children from the middle wealth quintile were 19% times less likely and 44% times less likely to be malnourished respectively. Compared to children from the poorest wealth quintile, children from the poorer, richer and richest households were respectively 22%, 29% and 48% times less likely to be malnourished for all the comparison levels; holding all other factors in the model constant.

The results from the GOLOGIT model are presented in Table 4.

**Table 4: Unadjusted and Adjusted Odds Ratios from GOLOGIT Regression**

Variable	Categories	No Malnutrition vs 1type +2types +3types OR	vs CI	No malnutrition +1type vs 2types +3types OR	CI	No malnutrition +1type +2types vs 3types OR	CI
<b>Maternal Factors</b>							
Mother's BMI	Normal	1 ref		1 ref		1 ref	
	Underweight	1.32	0.97-1.78	2.46***	1.75-3.46	6.49**	2.86-14.78
	Overweight	0.78*	0.65-0.95	0.78*	0.65-0.95	0.78*	0.65-0.95
	Obese	0.77	0.56-1.07	0.77	0.56-1.07	0.77	0.56-1.07
Mother's HIV status	Negative	1 ref		1 ref		1 ref	
	Positive	1.36**	1.13-1.63	1.36**	1.13-1.63	1.36**	1.13-1.63
Currently Breastfeeding	No	1 ref		1 ref		1 ref	
	Yes	0.81*	0.67-0.98	0.81*	0.67-0.98	0.81*	0.67-0.98
<b>Child factors</b>							
Sex	Male	1 ref		1 ref		1 ref	
	Female	0.64***	0.55-0.74	0.64***	0.55-0.74	0.64***	0.55-0.74
Child's age	0-11	1 ref		1 ref		1 ref	
	12-23	2.92***	2.34-3.64	1.82***	1.33-2.50	2.17	0.94-5.00
	24-35	4.24***	3.30-5.46	1.56**	1.12-2.17	1.28	0.49-3.35
	36-47	2.26***	1.75-2.91	1.49*	1.05-2.10	0.66	0.18-2.43
	48-59	1.44*	1.09-1.90	1.44*	1.09-1.90	1.44*	1.09-1.90
Birth weight categories	<= 2.90	1 ref		1 ref		1 ref	
	2.91-3.40	0.57***	0.48-0.69	0.57***	0.48-0.69	0.57***	0.48-0.69
	>= 3.41	0.44***	0.36-0.53	0.44***	0.36-0.53	0.44***	0.36-0.53
Twin	No	1 ref		1 ref		1 ref	
	Yes	2.54**	1.35-4.76	2.54**	1.35-4.76	2.54**	1.35-4.76
Cough in 2 weeks	No	1 ref		1 ref		1 ref	
	Yes	0.79**	0.67-0.93	0.79**	0.67-0.93	0.79**	0.67-0.93
Diarrhoea in 2 weeks	No	1 ref		1 ref		1 ref	
	Yes	1.13	0.93-1.38	1.71***	1.29-2.27	2.93**	1.40-6.14
<b>Household factors</b>							
Religion	Apostolic	1 ref		1 ref		1 ref	
	Other Christian	0.83*	0.70-0.98	0.83*	0.70-0.98	0.83*	0.70-0.98
	No/Other Religion	1.02	0.79-1.32	1.02	0.79-1.32	1.02	0.79-1.32
Wealth Index	Poorest	1 ref		1 ref		1 ref	
	Poorer	0.78*	0.64-0.94	0.78*	0.64-0.94	0.78*	0.64-0.94
	Middle	0.81*	0.66-1.00	0.56***	0.42-0.76	1.03	0.44-2.41
	Richer	0.71**	0.57-0.89	0.71**	0.57-0.89	0.71**	0.57-0.89
	Richest	0.52***	0.40-0.68	0.52***	0.40-0.68	0.52***	0.40-0.68

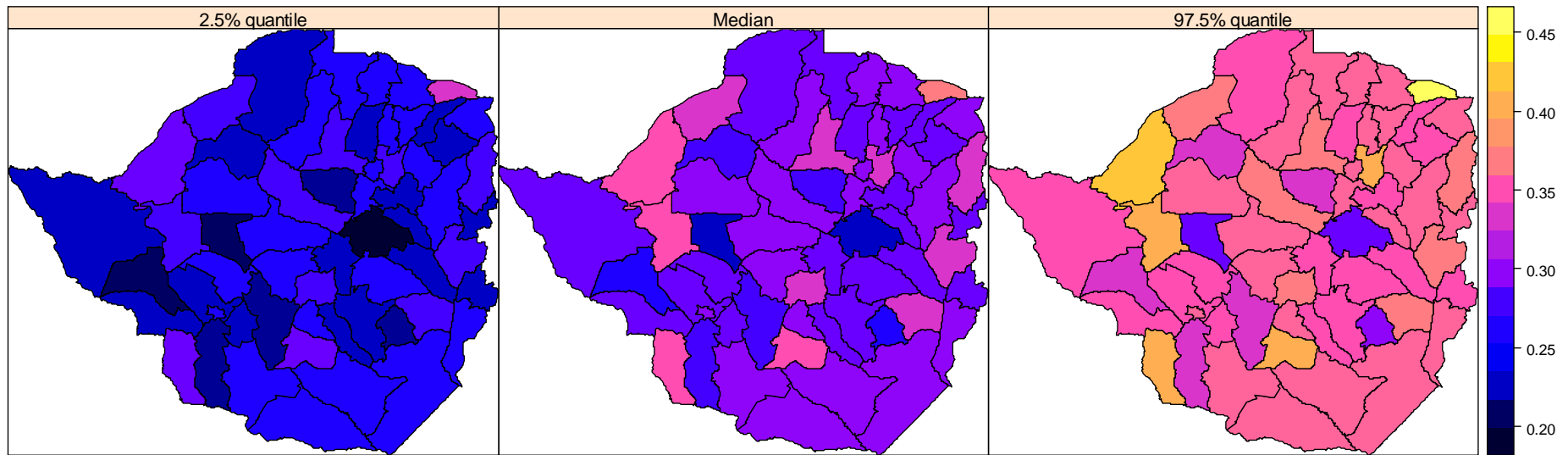
### **3.6 Spatial effects on malnutrition**

None of the random components that were included in the models had a significant effect on any of the three types of malnutrition. The odds ratios that we obtained from using Bayesian methods of analysis were not different from those obtained from the frequentist approach. We therefore avoid duplication and here present only results for the DIC, number of effective parameters as well as the precisions we obtained from each of the four models for each of the three types of malnutrition. We also present maps from the simplest model (model without any spatial random components) to provide an idea of what the results looked like.

**Table 5: DIC, number of effective parameters and precision measures for the three types of malnutrition**

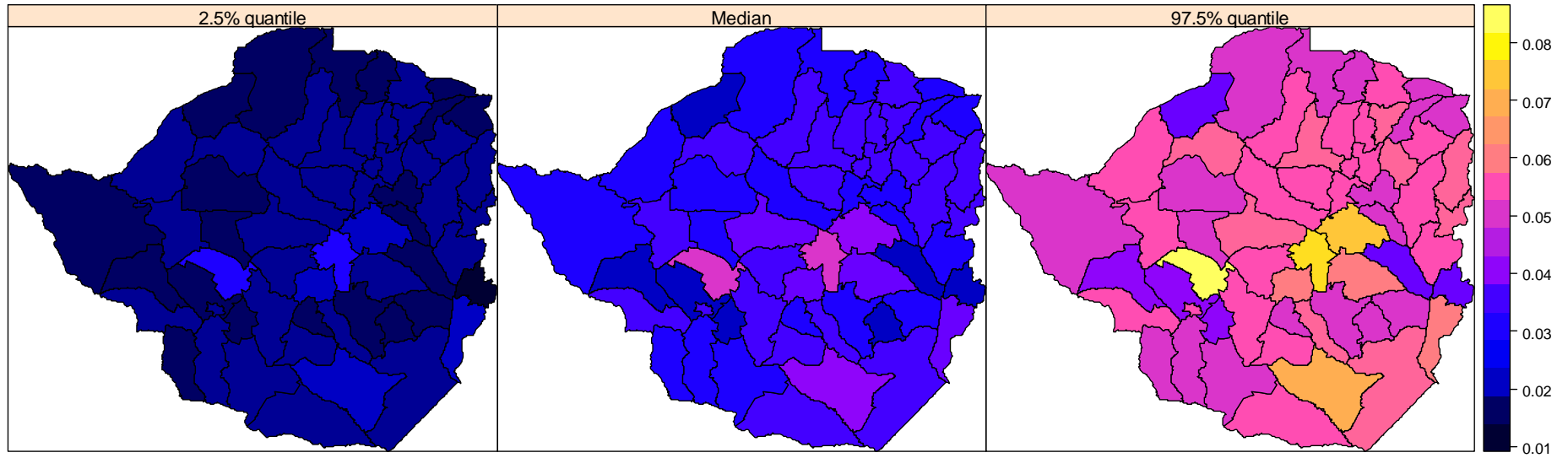
	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>	<b>Model 4</b>
<b>Stunting</b>				
Unstructured Random Effects		18418.59(1217.61-66492.92)		18416.72(1217.65-66490.48)
Structured Random Effects			18594.78(126.22-66948.63)	18601.85(1266.94-66953.73)
No of effective parameters	15.96	16.02	15.98	16.06
DIC	4382.85	4382.82	4382.85	4382.81
<b>Wasting</b>				
Unstructured Random Effects		18572.97(1264.77-66900.22)		18702.81(1287.78-67366.61)
Structured Random Effects			18342.64(1264.58-66891.08)	18637.43(1272.06-67144.03)
No of effective parameters	10.82	10.83	10.82	10.83
DIC	1199.49	1199.48	1199.48	1199.48
<b>Underweight</b>				
Unstructured Random Effects		18634.39(1257.93-67044.11)		18633.34(1275.81-67037.39)
Structured Random Effects			18578.28(1263.53-66928.66)	18585.94(1263.45-66919.46)
No of effective parameters	13.90	13.93	13.91	13.96
DIC	2606.67	2606.68	2606.67	2606.67

There is not much of a difference in the Deviance Information Criterion for all four models of each type of malnutrition meaning that reporting the simplest model is the best option. The simplest model in this case is the model without any spatial random components. The precision measures that were obtained for each type of malnutrition were too large implying that the random components did not add any value to the percentage of variation that was explained by the fixed effects.



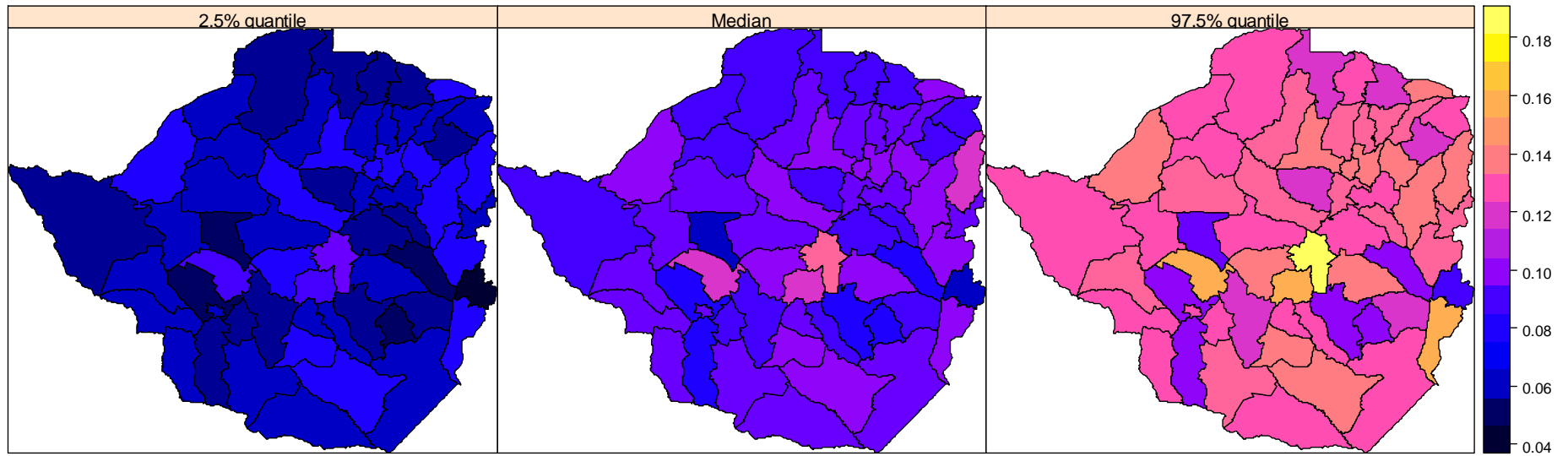
**Figure 20: Spatial effects on Stunting**

There is no evidence to suggest that any of the spatial random components that were added to the stunting model improved model fit as shown in the figure above, which represents the simplest stunting model (without any spatial random components).



**Figure 21: Spatial effects on Wasting**

There is no evidence to suggest that any of the spatial random components that were added to the wasting model improved model fit as shown in the figure above, which represents the simplest wasting model (without any spatial random components).



**Figure 22: Spatial effects on underweight**

There is no evidence to suggest that any of the spatial random components that were added to the underweight model improved model fit as shown in the figure above, which represents the simplest underweight model (without any spatial random components).

## **Chapter 4: Discussion**

### **4.1 Introduction**

This chapter discusses the findings of this study in light of the literature. Similarities and differences between this study and existing evidence are noted. Where applicable, suggested explanations of why the differences could exist are given. Any seemingly relevant suggestions are made for future research. Expectations at the beginning of the research as well as strengths and limitations of the research are noted. It is therefore important to take note of the limitations of this study when interpreting the findings.

The overall aim of this study was to establish the factors associated with malnutrition among children under the age of five in Zimbabwe including spatial effects on malnutrition. We managed to establish the effects of fixed factors on malnutrition and there was no evidence to suggest spatial random effects on any of the three malnutrition outcomes

### **4.2 Factors associated with malnutrition**

#### **4.2.1 Stunting**

This study found factors associated with stunting to be: mother's HIV status, mother's current breast feeding status, sex of the child, age of the child, child's birth weight, twin status, having suffered a cough in the two weeks prior to data collection, dietary diversity, household religion and wealth index.

The study reveals that children whose mothers are HIV positive are more likely to be stunted. This result concurs with others in the literature, like what was found in two studies by Magadi (31, 82) that used DHS data as well. It is possible that some of the mothers who tested HIV positive at the time of data collection were not positive when they gave birth to the child in question. In such cases where the mother only contracted HIV after the birth of the child, the association between HIV status and malnutrition could be explained by something else which is beyond the scope of this study.

Like other studies, we found an association between breastfeeding and malnutrition. Magadi (31) found that breastfeeding was beneficial for children who were breastfed for at least six months while Ruel (83) found that continued breastfeeding was beneficial for children receiving low quality diets.

We used the variable mother's breastfeeding status as an indicator of the breastfeeding status of a child so as to enable us to take care of the effects of breastfeeding on a child's nutritional status.

The finding that breastfeeding children are more likely to be stunted is consistent with findings from other research which shows that breastfeeding is protective of malnutrition in the first year of life especially when using the WHO reference population to determine child nutritional status (5). We however did not observe the effects of prolonged breastfeeding in this study because the duration of breastfeeding variable had lots of missing values which resulted in inconsistent data upon imputation. It is possible that prolonged breastfeeding was the factor leading to malnutrition among older children (84). Research has shown that several factors including the appetite and appearance of a child affect the timing when women wean their children (85). It is possible that in the years 2007-2009, women delayed weaning their children due to the effects of the economic crisis in the country, leading to prolonged breastfeeding thus predisposing the children to malnutrition especially stunting.

The study, like others in the literature found that female children are less likely than male children to be stunted. Wamani (25) found that boys are more likely to be stunted than girls while Ricci and Becker (34) found that being female was protective of malnutrition.

Like other studies we also found that higher birth weight is associated with decreased odds of stunting, wasting and underweight. Ricci and Becker (34) found low birth weight to be a risk factor for stunting. Saloojee et al (47) found that among the cases of severe malnutrition in their study, majority of them were low birth weight babies and there was a significant association between birth weight and stunting.

With this study we also found increasing age to be associated with increasing likelihood of being stunted. While other researchers have investigated the effects of age in the continuous (32, 40) or binary form (34), we categorised the age variable the same way Zottarelli et al. (36) did. We also found a non-linear relationship between stunting and age. However, unlike Zottarelli et al. who found that stunting reached a peak at the 12-23 months age group, levelling off thereafter we found our peak at the 24-35 month age group (36). Though the Zimbabwean statistics for the year 1999 (17) were not tested in multivariable models, it is possible that at that same time, the same age group (12-23 months) found by Zottarelli et al. was the peak for Zimbabwe. Like Zottarelli et al. we also found that the odds ratios of stunting at age groups 36-59 months are lower than those for age groups 12-35 months.

This study reveals that children born from multiple pregnancies are more likely to be stunted compared to singletons. A study that applied multi-level modelling revealed that height-for-age z-scores for twins were lower than those for singletons (31). A study that looked at severe malnutrition regardless of type also revealed that twins were more likely to suffer malnutrition compared to singletons (47). Our study reveals that during the study time in Zimbabwe, twins were two times more likely to be stunted when compared with singletons. We propose that the propensity to be stunted among twins is fuelled by the fact that intra-uterine growth is worse for twins compared to singletons therefore they are born with low birth weight and hence are more likely to be stunted (86).

Having suffered a cough two weeks prior to data collection in this study is associated with 18% times less likelihood of stunting. This is contrary to what other researchers have found. Mehta et al and Saloojee et.al found that disease is associated with increased chances of stunting (2, 47). With our cross sectional data, we cannot determine temporality and therefore we cannot say with certainty that the cough was protective of malnutrition. It is possible that this association was observed because of recall bias, where mothers whose children who were not malnourished could have better child care practices and therefore remembered the disease episodes suffered by their children more than mothers whose children were malnourished.

Studies that investigated the effect of dietary diversity on nutritional status have revealed that children who have less diversity are more likely to be stunted (33, 49), which is what we also found in this study. It is however important to note that the data that we used to generate the dietary diversity variables were a result of recall by care- givers and multiple imputations. We may have observed this association because of the fact that the data were imputed not necessarily because of the true effects of dietary diversity on nutritional status.

We found that children from households with higher wealth index were less likely to be stunted which is consistent with what other researchers have found, that children from households with lower possession score were more likely to be stunted (28).

We did not find any significant association between stunting and birth order or maternal BMI like what other researchers have found.

#### 4.2.2 Wasting

The only significant risk factor for wasting that we found in this study is lower maternal BMI. This finding is consistent with what other studies have found. The protective factors that we found in this study are: age higher than 23 months, birth weight higher than 2.90 kg and having received vitamin A in the six months prior to data collection.

We found out that age higher than 23 months is associated with decreased odds of wasting and that there is no significant difference in wasting between children 12-23 and the baseline; 0-11 months old. Fuchs et al. found out that age higher than 12 months is associated with increased odds of wasting (41), while Vitolo et al. found that children 0-36 months were 77% times more likely to be wasted than children over 36 months old (39). Other researchers who studied wasting are silent about the association between age and wasting. Because of the agreement between what we observed and what was observed by Vitolo (39), we propose that increasing age is therefore associated with decreased odds of wasting and that the difference in study design could explain the difference between our findings and Fuchs et al.'s findings.

In addition to what other researchers have found about the factors associated with wasting, we found out that having received vitamin A supplementation in the six months prior to data collection was protective of wasting. The other study that looked at vitamin A supplementation was not specific on the timing but the number of supplementations. This study found an association with underweight not wasting (40). However, it is not only the lack of vitamin A that can lead to malnutrition as evidence has shown that malnutrition results from poor uptake or intake of nutrients not only one nutrient. We suggest that though it is possible that these are the true effects of vitamin A supplementation, something else beyond vitamin A supplementation could be the reason why we observed this association. It is therefore our recommendation that further studies be conducted to confirm the existence of this association.

For children whose mothers were in a marital relationship at the time of this study, the decision making index for women was a significant factor. This finding is consistent with what has been found by other researchers regarding the relationship between decision making and malnutrition. Though the variable we used in this study was a result of principal component analysis, we think that this is the truth about the relationship between decision making and malnutrition in Zimbabwe. It may be interesting however to try and find out the relationship between status of women in Zimbabwe (including those that are not in marital

relationships) using different variables as suggested by Smith et al. 2003 (46). We think that this may enrich the knowledge we have on this relationship.

### **4.2.3 Underweight**

In this study the risk factors for underweight were: lower than normal maternal BMI, third or higher birth order, being a twin, and having suffered from diarrhoea in the two weeks prior to data collection. The protective factors were: female sex, birth weight higher than 2.90 kg and middle or richest household wealth index. Majority of the factors that we found to be associated with underweight in this study have been found by other researchers but our study adds that children who are a pair of twins are more likely to be underweight compared to singletons, that having suffered from diarrhoea in the two weeks prior to data collection increases the chances of underweight and also that female children are less likely to be underweight compared to males.

For children whose mothers were married, we found a significant association between father's educational status and underweight which was also found by Saloojee and Makoka (6, 47). We did not find an association between mothers' occupation or educational level with underweight like what was found by other researchers. We also did not find a significant association between underweight and child's age as was found by Singh et al (37).

The association between socio-economic status and underweight that was found by Nahar et al and Singh et al (37, 42) was not revealed by this study. Rayhan and Khan (40) also did not find this association in their study though they investigated its existence. We can only say that the information we have on the effects of socio-economic status is inconclusive because all the available researches we have made use of have used different ways of looking at the variable. It is possible that if those who used the variable as a continuous variable had categorised it they could have observed a different result, same as if those who investigated its effects as a categorical variable had used it as a continuous variable. Our recommendation is to try and use both ways of looking at the effects of a variable to ensure that the findings are consistent and conclusive.

It is interesting to note that though like Rayhan and Khan (40) we did not observe an association between age and underweight, they investigated and found an association between previous birth interval which we did not investigate. Meanwhile, Singh et al (37) who investigated the effects of both previous birth interval and age found an association with

age and not with previous birth interval. We suggest that future research investigates to find out the true effects of age and previous birth interval on underweight. We think that it is possible that the association between age and underweight covers the association between underweight and previous birth interval in the study by Singh et al (37).

#### **4.2.4 Religion and malnutrition**

We found out that children who were not from Apostolic-Sect households were less likely to be stunted than children from Apostolic-Sect households. Experience from working with people from apostolic sects in Zimbabwe has shown that people in apostolic sects do not always adhere to formal health care interventions like immunisation, nutrient supplementation and growth monitoring among others. It is important to note that some of these practices in the apostolic sects could predispose children to chronic malnutrition. However, it is possible that some other factors beyond the scope of this study could explain why this relationship. We recommend further qualitative research to unpack the factors that could explain why we observed this association in this study.

#### **4.2.5 Age and malnutrition**

Increasing age has consistently been found to be associated with increasing odds of stunting. Studies that used age as a categorical variable reveal that the odds of stunting increase up to a point where odds of being stunted for age groups higher than 35 months, though higher than the baseline are lower than the odds for age groups lower than 35 months (36, 39). It is also interesting to note that the relationship between age and malnutrition changes with the type of malnutrition. In this study as in other studies, we found that the odds of stunting increase with increasing age up to a point while the odds of wasting decrease with age. Though there is conflicting evidence, we found out in this study that there is no association between age and underweight.

We suggest that in Zimbabwe, it is possible that the main reason why we observed a peak in stunting at age 24-35 months is because children 0-23 months are more likely to be wasted. Since evidence has shown that wasting is the first bodily response to decreased intake or uptake of nutrients (5, 20), it is possible that children who were stunted at the time of data collection were wasted at lower ages. We cannot say this with confidence though, since our data do not have temporality characteristics. It is also possible that at the time of data collection if there was a prolonged season of hunger, children could have ended up stunted not necessarily because malnutrition occurred for three months or longer but because of the

prolonged hunger (2). A longitudinal study in Zimbabwe would help shed more light on the relationships among the different types of malnutrition and age group.

#### **4.2.6 Birth order and malnutrition**

In this study, birth order was associated with underweight and not with stunting or wasting while in another study an association was found between stunting and birth order. It may be interesting to further investigate the effects of this factor on malnutrition as it is possible that this factor is actually associated with both or all three types of malnutrition though in this study we only managed to observe the association with only one type.

#### **4.2.7 Spatial effects on malnutrition**

We expected to find that outcome values measured at locations closer to each other would be more likely to be similar compared to those in distant locations but we did not observe any such thing. Kandala et al. 2011 and Fenske et al. 2013 (12, 35) found significant associations between some spatial random components and malnutrition in other regions of the world. It may be interesting for further studies to investigate the spatio-temporal effects and distribution of malnutrition in Zimbabwe so as to find out if ever spatial effects have affected malnutrition in Zimbabwe.

This study reveals the spatial distribution of malnutrition in Zimbabwe but, it is interesting to note that unlike what other researchers found; that similar clusters can be identified using two different methods (66), we did not observe the same clusters based on Moran's analyses and SaTScan analyses. This could be due to the fact that there was no significant clustering in the outcomes anyway.

The study shows that for the greater majority of the country, spatial distribution of malnutrition is not significantly different from complete randomness. In the few cases where spatial distribution matters, the malnutrition outcomes are dispersed. This finding is important as it reveals that in Zimbabwe at the time of data collection, all the districts were almost equally affected by malnutrition. The only cluster that was revealed by this study which can provide information regarding target areas for interventions is the wasting cluster revealing high prevalence districts that are surrounded by other high prevalence districts. The other clusters that we found are not of much concern when targeting areas for nutritional interventions as they just show that malnutrition outcomes in Zimbabwe were dispersed.

### 4.3 Limitations of the study

When looking at malnutrition, one can choose to make use of the standard deviations in their continuous form or use a cut-off point to determine normality (9). While in this study we used a cut-off point to determine normality, we may have ignored the fact that nutritional status exists on a continuum and that crossing the cut-off line is not the only important factor that determines the outcomes for malnourished children. We used logistic regression where linear regression could have also been applied as well.

This study made use of readily available data that are quantitative in nature. While this made available a lot of respondents for study, it limited the study in several ways. With these data, it is difficult to establish the reasons why some relationships (like the relationship between religion and stunting) exist because the quantitative data can only be used to establish the existence of such relationships not why they exist. In addition, since data were readily available, it was not possible to investigate the effects of some factors on malnutrition because the data that were collected did not contain the variables that could have been used to investigate these factors like; duration of breastfeeding, previous birth interval, season and vaccination status.

This study was cross sectional in nature. With this study type it is difficult to verify issues that are affected by temporality like the relationship between disease and malnutrition or factors to do with chronicity of malnutrition. While evidence suggests a bidirectional relationship between disease and malnutrition, it is difficult with our cross sectional data to say whether disease preceded malnutrition or malnutrition preceded disease.

Also ascertaining the chronicity of malnutrition may have been important since there is evidence suggesting that stunting can develop in less than three months if disease or food shortages are serious (2, 10). We could not do this because of the nature of our study.

We made use of self-reported data which predisposes our findings to reporting bias especially social desirability bias where some respondents may have reported an answer they deemed socially acceptable than would be their true answer so as to project a good image of themselves and avoid being judged (82). Social desirability score has been shown to be negatively correlated with most nutritional variables, even worse for women (who gave responses for this study) than for men (83). If this limitation is true then the dietary diversity

variables that we extracted from the infant feeding variables could lead to erroneous conclusions.

We used multiple imputations to avoid affecting the power of our study through losing a lot of respondents via list-wise deletion (84). Though this is a good way of taking care of missing data, it may also have led to biased conclusions because imputations do not exactly reveal the reality of the situation (85).

This study employed aerial spatial analysis techniques which are good enough to communicate findings with policy makers. This technique however may have been improved by taking care of edge effects (how the length of the borders between aerial units affects the spatial distribution of the outcome in the study area.) (23).

#### **4.4 Summary**

This study reveals the factors associated with malnutrition at the time of data collection. Among them, higher birth weight of a child was consistently associated with decreased odds of malnutrition. For all types of malnutrition, birth weight had associations significant at <1% showing the importance of birth weight in child nutritional status and in turn child survival. It may be interesting to observe a group of children from birth to five years old and see how nutritional status changes over time. The absence of clustering of nutritional outcomes at the time of data collection implies a need to further look at malnutrition in Zimbabwe. Further studies can reveal the important information of how malnutrition has evolved in Zimbabwe.

## **Chapter 5: Recommendations and conclusions**

This chapter presents recommendations based on what this study found. The recommendations include areas of focus for further research. The chapter closes with a conclusion that is also based on what this study found as well as what has been found by others.

### **5.1 Recommendations**

When looking at malnutrition at the individual level, it is important to note that biological factors like birth weight and age that are always associated with all types of malnutrition. Birth weight is a direct manifestation of women's status and socio-economic status (46). As such we recommend that interventions that target malnutrition in children should not only target the malnutrition in a child while ignoring these underlying factors. Interventions that target only the outcome will not achieve the necessary desired outcome of significantly reduced malnutrition rates among children under the age of two (8). Nutrition based interventions would do better by taking into consideration what researchers have said; that, if the environment in which women and children are born and live is not changed drastically, breaking the malnutrition cycle remains a dream (20). While health systems target and treat malnutrition in children, the environment will perpetuate malnutrition if the environment is not changed.

We reiterate the importance of dealing with the status of women in order to address malnutrition in children because malnourished women are more likely to have malnourished children as was revealed by this study. This finding is supported by the writing of Smith et al. 2003 who say that the care that women get indicates the care women give to their children (46). If the care that women receive affects the number of children who die because of malnutrition, then it is essential to ensure that the status of women is improved. We join UNICEF (8) in recommending improved women's nutrition particularly before, during and after pregnancy especially in Zimbabwe where women's nutritional status has been shown to be related to children's nutritional status.

In light of the observation made in this study that children from Apostolic-Sect households are more likely to be malnourished, it is important to note what researchers, Muller and Krawinkel say; that interventions targeted at treating and combating malnutrition have been quite successful but in most cases the people who are at increased risk have little or no access

to formal health care services and in some cases are never seen in such settings (15). We propose that the increased odds for malnutrition among children from apostolic sects are a result of limited access to formal health care. We recommend that interventions targeting malnutrition in Zimbabwe take care of the fact that certain populations that may be at risk may never visit formal health care settings therefore exploring other intervention avenues may prove more effective than just relying on treatment based interventions.

Making use of the UNICEF theoretical framework was important as it helped in identifying variables for study but at an individual level it is not conclusive. From the different papers that used this framework to guide the modelling processes, it is evident that when the framework is used with aggregated data, it provides more information than when it is used with individual level data. Black et al 2008 (14) used the framework at country level and did not need to add any biological factors in their models while Makoka (6) who used it at individual level had to add biological factors in his model. We recommend the use of this framework whenever possible but to recognise level of usefulness of the model for each study.

It is interesting to note that the prevalence of wasting was very low in comparison with that of stunting in this study. If wasting is the first bodily response to poor nutrient uptake and intake then the findings from this study reveal a situation that leaves a lot to be desired. One would expect more children to be wasted if they will end up stunted. A longitudinal study on the nutritional status of Zimbabwean children would be handy in answering questions like “Is it possible that stunting in Zimbabwe by-passes wasting and manifests before three months as suggested in the literature?” or “Is it that the WHO recommended reference population is not appropriate for the Zimbabwean children, in determining the prevalence of stunting?”

With the findings of this study which show that the spatial distribution of malnutrition is not significantly different from complete randomness we can conclude that at the time of data collection, the basic and underlying determinants of malnutrition (as proposed by the UNICEF theoretical framework) that were not measured in this study and could have been represented by spatial effects did not have an influence on malnutrition as much as the measured factors which we found to be related with malnutrition in this study.

Consequently, it is our recommendation that when studying malnutrition at the individual level, it is important to consider biological factors (like birth weight, age, gender and twin status) as these have consistently shown significant associations with the three different types of malnutrition.

Since this study did not reveal any spatial effects on malnutrition, we recommend further studies that investigate the spatio-temporal effects on malnutrition to see if ever spatial effects were significantly associated with malnutrition in Zimbabwe. It may also be interesting to study the distribution of malnutrition in Zimbabwe so as to find out if there have been any changes in the distribution, especially taking into consideration the effects of the Land Reform Programme that was conducted in the country in recent years.

## **5.2 Conclusion**

This study reveals that at the time of data collection there was no significant spatial residual effects on malnutrition, and that the most important things that explain malnutrition in children at the time of data collection are the socio-economic and biological factors that were measured in the ZDHS 2010/11. Important to note is the effect of birth weight on malnutrition which remains highly significant for all the three types of malnutrition unlike all other factors which are significant for one or two types. Factors that affect birth weight should be placed on the agenda for malnutrition to be fully addressed.

This study has revealed the factors associated with malnutrition as well as the spatial distribution of malnutrition. In addition to the evidence provided by this study, there is plenty of proven and documented technical intervention approaches that can be used to conduct nutrition oriented programmes in Zimbabwe. It is however, upon the policy makers to harness the existing community skills and resources in concert with the available technical information to create an environment and a support structure that is conducive to improved nutrition as was advocated for by UNICEF in 1990 at the inception of the theoretical framework used for this study. They say nutrition oriented programmes fail not because of unavailability of technical know-how but because of failure to combine local skills and technical information (24).

## References

1. Centers for Disease Control and Prevention, World Food Programme. A Manual: Measuring and Interpreting Malnutrition and Mortality. Rome: World Food Programme. 2005.
2. Mehta NM, Corkins MR, Lyman B, Malone A, Goday PS, Carney LN, et al. Defining Pediatric Malnutrition A Paradigm Shift Toward Etiology-Related Definitions. *Journal of Parenteral and Enteral Nutrition*. 2013;37(4):460-81.
3. Van de Poel E, Hosseinpoor AR, Speybroeck N, Van Ourti T, Vega J. Socioeconomic inequality in malnutrition in developing countries. *Bulletin of the World Health Organization*. 2008;86(4):282-91.
4. Smith LC, Haddad LJ. Explaining child malnutrition in developing countries: A cross-country analysis: Intl Food Policy Res Inst; 2000.
5. Vesel L, Bahl R, Martines J, Penny M, Bhandari N, Kirkwood BR. Use of new World Health Organization child growth standards to assess how infant malnutrition relates to breastfeeding and mortality. *Bulletin of the World Health Organization*. 2010;88(1):39-48.
6. Makoka D. The impact of maternal education on child nutrition: Evidence from Malawi, Tanzania and Zimbabwe. Calverton, Maryland USA: Measure DHS ICF International 2013.
7. WHO Multicentre Growth Reference Study Group. WHO Child Growth Standards based on length/height, weight and age. *Acta Paediatrica* (Oslo, Norway: 1992) Supplement. 2006;450:76.
8. UNICEF. Improving child nutrition: The achievable imperative for global progress: United Nations Children's Fund; 2013.
9. Fishman SM, Caulfield LE, De Onis M, Blossner M, Hyder AA, Mullany L, et al. Childhood and maternal underweight. Comparative quantification of health risks: global and regional burden of disease attributable to selected major risk factors. 2004;1:39-161.
10. World Health Organisation, United Kingdom Health Protection Agency, Save the Children, and partners. Disaster risk management for health 2011.
11. Garcia V. Children Malnutrition and horizontal Inequalities in Sub-Saharan Africa: A Focus on Contrasting Domestic Trajectories. 2012.
12. Kandala N-B, Madungu TP, Emina JB, Nzita KP, Cappuccio FP. Malnutrition among children under the age of five in the Democratic Republic of Congo (DRC): does geographic location matter? *BMC Public Health*. 2011;11(1):261.
13. Victora C, Adair L, Fall C. Maternal and child undernutrition: consequences for adult health and human capital (vol 371, pg 340, 2008). *Lancet*. 2008;371(9609):302-.
14. Black RE, Allen LH, Bhutta ZA, Caulfield LE, De Onis M, Ezzati M, et al. Maternal and child undernutrition: global and regional exposures and health consequences. *The lancet*. 2008;371(9608):243-60.
15. Müller O, Krawinkel M. Malnutrition and health in developing countries. *Canadian Medical Association Journal*. 2005;173(3):279-86.
16. UNICEF, WHO, WorldBank. UNICEF-WHO-WB estimated prevalence (%) of stunted preschool children 1990-2025 with 95% confidence intervals by UN regions and sub-regions [cited 24/04/2013]. Available from: <http://www.who.int/nutgrowthdb/estimates/en/index.html>

17. ORC Macro International. Nutrition of young children and mothers in Zimbabwe. Findings from the 1999 Zimbabwe DHS Survey. Calvaton, Marlyland USA: Measure DHS, ORC Macro International, 2001.
18. Zimbabwe National Statistics Agency, ICF International. Zimbabwe Demographic and Health Survey 2010-11. Calverton, Maryland: ZIMSTAT and ICF International Inc.; 2012.
19. World Health Organization, UNICEF. WHO child growth standards and the identification of severe acute malnutrition in infants and children: joint statement by the World Health Organization and the United Nations Children's Fund. 2009.
20. Fernandez ID, Himes JH, Onis Md. Prevalence of nutritional wasting in populations: building explanatory models using secondary data. *Bulletin of the World Health Organization*. 2002;80(4):282-91.
21. Pelletier D. Toward a common understanding of malnutrition: assessing the contributions of the UNICEF framework. *World Bank/UNICEF Nutrition Assessment*. 2002.
22. Frongillo EA, de Onis M, Hanson KM. Socioeconomic and demographic factors are associated with worldwide patterns of stunting and wasting of children. *The Journal of nutrition*. 1997;127(12):2302-9.
23. Pfeiffer D, Robinson T, Stevenson M, Stevens KB, Rogers DJ, Clements AC. *Spatial analysis in epidemiology*: Oxford University Press New York; 2008.
24. UNICEF. *Strategy for improved nutrition of children and women in developing countries*: Unicef; 1990.
25. Wamani H, Åström AN, Peterson S, Tumwine JK, Tylleskär T. Boys are more stunted than girls in sub-Saharan Africa: a meta-analysis of 16 demographic and health surveys. *BMC pediatrics*. 2007;7(1):17.
26. Miller HJ. Tobler's first law and spatial analysis. *Annals of the Association of American Geographers*. 2004;94(2):284-9.
27. Griffith DA. *Spatial autocorrelation. A Primer* Washington DC: Association of American Geographers. 1987.
28. Mohsena M, Mascie-Taylor C, Goto R. Association between socio-economic status and childhood undernutrition in Bangladesh; a comparison of possession score and poverty index. *Public health nutrition*. 2010;13(10):1498-504.
29. Haughton D, Haughton J. *Explaining Child Nutrition in Vietnam\**. *Economic Development and Cultural Change*. 1997;45(3):541-56.
30. UNICEF. *The state of the world's children 2008: Child survival*: Unicef; 2007.
31. Magadi MA. Cross-national analysis of the risk factors of child malnutrition among children made vulnerable by HIV/AIDS in sub-Saharan Africa: evidence from the DHS. *Tropical Medicine & International Health*. 2011;16(5):570-8.
32. Desai S, Johnson K. *Women's Decisionmaking and Child Health: Familial and social hierarchies. A focus on gender: Collected papers on gender using DHS data*. 2005:55-68.
33. Ruel MT, Menon P. Child feeding practices are associated with child nutritional status in Latin America: innovative uses of the demographic and health surveys. *The Journal of nutrition*. 2002;132(6):1180-7.
34. Ricci JA, Becker S. Risk factors for wasting and stunting among children in Metro Cebu, Philippines. *The American journal of clinical nutrition*. 1996;63(6):966-75.
35. Fenske N, Burns J, Hothorn T, Rehfuess EA. Understanding child stunting in India: a comprehensive analysis of socio-economic, nutritional and environmental determinants using additive quantile regression. *PloS one*. 2013;8(11):e78692.

36. Zottarelli L, Sunil T, Rajaram S. Influence of parental and socioeconomic factors on stunting in children under 5 years in Egypt. *Eastern Mediterranean Health journal*. 2006;13(6):1330-42.
37. Singh GP, Nair M, Grubestic RB, Connell FA. Factors associated with underweight and stunting among children in rural Terai of eastern Nepal. *Asia-Pacific Journal of Public Health*. 2009;21(2):144-52.
38. Agho KE, Inder KJ, Bowe SJ, Jacobs J, Dibley MJ. Prevalence and risk factors for stunting and severe stunting among under-fives in North Maluku province of Indonesia. *BMC pediatrics*. 2009;9(1):64.
39. Vitolo MR, Gama CM, Bortolini GA, Campagnolo PD, Drachler MdL. Some risk factors associated with overweight, stunting and wasting among children under 5 years old. *Jornal de pediatria*. 2008;84(3):251-7.
40. Rayhan MI, Khan MSH. Factors causing malnutrition among under five children in Bangladesh. *Pak J Nutr*. 2006;5(6):558-62.
41. Fuchs C, Sultana T, Ahmed T, Iqbal Hossain M. Factors Associated with Acute Malnutrition among Children Admitted to a Diarrhoea Treatment Facility in Bangladesh. *International journal of pediatrics*. 2014;2014.
42. Nahar B, Ahmed T, Brown KH, Hossain MI. Risk factors associated with severe underweight among young children reporting to a diarrhoea treatment facility in Bangladesh. *Journal of health, population, and nutrition*. 2010;28(5):476.
43. NGO/Civil Society Constituency. World nutrition is under threat. UN Standing Committee on Nutrition; Hanoi, Viet Nam: United Nations System; 2008.
44. Markson LE, Turner BJ, Houchens R, Silverman NS, Cosler L, Takyi BK. Association of maternal HIV infection with low birth weight. *JAIDS Journal of Acquired Immune Deficiency Syndromes*. 1996;13(3):227-34.
45. National Institute of Child Health and Human Development. Preventing HIV Transmission from Mother to Child [cited 25/07/2014]. Available from: <https://www.nichd.nih.gov/about/overview/50th/discoveries/Pages/hiv-transmission.aspx>.
46. Smith LC, Ramakrishnan U, Ndiaye A, Haddad L, Martorell R. The importance of women's status for child nutrition in developing countries: Intl Food Policy Res Inst; 2003.
47. Saloojee H, De Maayer T, Garenne ML, Kahn K. What's new? Investigating risk factors for severe childhood malnutrition in a high HIV prevalence South African setting. *Scandinavian Journal of Public Health*. 2007;35(69 suppl):96-106.
48. Rice AL, Sacco L, Hyder A, Black RE. Malnutrition as an underlying cause of childhood deaths associated with infectious diseases in developing countries. *Bulletin of the World Health Organization*. 2000;78(10):1207-21.
49. Nti CA. Dietary Diversity is associated with nutrient intakes and nutritional status of children in Ghana. *Asian Journal of Medical Sciences*. 2011;2(2):105-9.
50. Arimond M, Ruel MT. Dietary diversity is associated with child nutritional status: evidence from 11 demographic and health surveys. *The Journal of Nutrition*. 2004;134(10):2579-85.
51. Cressie NA. *Statistics for Spatial Data*. Wiley Series in Probability and Mathematical Statistics: Applied Probability and Statistics. John Wiley & Sons; 1991.
52. Diva-GIS, cartographer Zimbabwe Shape File 2009.
53. Williams R. *Generalized Ordered Logit/Partial Proportional Odds Models*. 2013.
54. SPSS I. *IBM SPSS Statistics Version 21*. Boston, Mass: International Business Machines Corp. 2012.

55. Beaumont R. An introduction to Principal Component Analysis & Factor Analysis Using SPSS 19 and R (psych package). 2012.
56. Achia TN, Obayo E. Trends and correlates of HIV testing amongst women: lessons learnt from Kenya. *African Journal of Primary Health Care & Family Medicine*. 2013;5(1):10 pages.
57. Arimond M, Ruel M. Dietary diversity dietary quality and child nutritional status: evidence from eleven Demographic and Health Surveys. 2004.
58. WHO, UNICEF. Indicators for assessing infant and young child feeding practices. Part 3: country profiles. World Health Organization. 2010.
59. Sartorius BK, Kahn K, Vounatsou P, Collinson MA, Tollman SM. Young and vulnerable: Spatial-temporal trends and risk factors for infant mortality in rural South Africa (Agincourt), 1992-2007. *BMC Public Health*. 2010;10(1):645.
60. Solon G, Haider SJ, Wooldridge J. What are we weighting for Cambridge: National Bureau of Economic Research; 2013.
61. StataCorp. Stata Survey Data Reference Manual Release 12. Texas, United States of America: Stata Press 2011. 202 p.
62. Rutstein SO, Rojas G. Guide to DHS statistics, Demographic and Health Surveys Methodology. Calverton, Maryland: ORC Macro; 2006 160 p.
63. Anselin L. GeoDa (software). Spatial Analysis Laboratory, University of Illinois; 2005.
64. ArcGIS Resource Centre. How Spatial Autocorrelation (Global Moran's I) works 2012 [cited 07/08/2014]. Available from: <http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#//005p0000000t000000>.
65. Getis A, Ord JK. The analysis of spatial association by use of distance statistics. *Geographical analysis*. 1992;24(3):189-206.
66. Sugumaran R, Larson SR, DeGroot JP. Spatio-temporal cluster analysis of county-based human West Nile virus incidence in the continental United States. *International journal of health geographics*. 2009;8(1):43.
67. Kulldorff M. A spatial scan statistic. *Communications in Statistics-Theory and methods*. 1997;26(6):1481-96.
68. Anselin L. An introduction to spatial autocorrelation analysis with GeoDa. Spatial Analysis Laboratory, University of Illinois, Champagne-Urbana, Illinois. 2003.
69. Kulldorff M, Nagarwalla N. Spatial disease clusters: detection and inference. *Statistics in medicine*. 1995;14(8):799-810.
70. UCLA Statistical Consulting Group. How can I perform the likelihood ratio, Wald, and Lagrange multiplier (score) test in Stata? [cited 13/04/2014]. Available from: [http://www.ats.ucla.edu/stat/stata/faq/nested\\_tests.htm](http://www.ats.ucla.edu/stat/stata/faq/nested_tests.htm).
71. UCLA Statistical Consulting Group. Ordered Logistic Regression [cited 01/04/2014]. Available from: <http://www.ats.ucla.edu/stat/stata/dae/ologit.htm>.
72. Williams R. Gologit2: A Program for Generalized Logistic Regression/ Partial Proportional Odds Models for Ordinal Variables. 2005.
73. Williams R. Generalized Logistic Regression/ Partial Proportional Odds Models for Ordinal Variables. *The Stata Journal*. 2006;6(1):58-82.
74. Diggle P, Ribeiro PJ. *Model-based geostatistics*: Springer; 2007.
75. Lawson AB. *Bayesian disease mapping: hierarchical modeling in spatial epidemiology*: CRC Press; 2013.
76. Ntzoufras I. *Bayesian modeling using WinBUGS*: John Wiley & Sons; 2011.
77. Eberly LE, Casella G. Estimating Bayesian credible intervals. *Journal of statistical planning and inference*. 2003;112(1):115-32.

78. Rue H, Martino S. Approximate Bayesian inference for hierarchical Gaussian Markov random field models. *Journal of statistical planning and inference*. 2007;137(10):3177-92.
79. Martino S, Rue H. Implementing approximate Bayesian inference using Integrated Nested Laplace Approximation: A manual for the inla program. Department of Mathematical Sciences, NTNU, Norway. 2009.
80. Spiegelhalter D, Thomas A, Best N. Bayesian inference using Gibbs sampling for Window version (WinBUGS), software for Bayesian analysis using MCMC method and Gibbs sampler. Available from <http://www.mrc-bsu.cam.ac.uk/bugs>, the website of the BUGS project by the Biostatistics Unit of the Medical Research Council, in the University of Cambridge. 2000.
81. Martino S, Rue H. R Package: INLA. Norway: Department of Mathematical Sciences, NTNU Available from <http://www.r-inla.org>. 2009.
82. Magadi MA. Household and community HIV/AIDS status and child malnutrition in sub-Saharan Africa: evidence from the demographic and health surveys. *Social Science & Medicine*. 2011;73(3):436-46.
83. Ruel MT. Operationalizing dietary diversity: a review of measurement issues and research priorities. *The Journal of nutrition*. 2003;133(11):3911S-26S.
84. Brakohiapa L, Bille A, Quansah E, Kishi K, Yartey J, Harrison E, et al. Does prolonged breastfeeding adversely affect a child's nutritional status? *The Lancet*. 1988;332(8608):416-8.
85. Simondon KB, Costes R, Delaunay V, Diallo A, Simondon F. Children's height, health and appetite influence mothers' weaning decisions in rural Senegal. *International journal of epidemiology*. 2001;30(3):476-81.
86. Vandenbosche RC, Kirchner JT. Intrauterine growth retardation. *American family physician*. 1998;58:1384-90.

## Appendices

### Appendix 1: Plagiarism Declaration

**Faculty of Health Sciences, Postgraduate Office**

Phillip V Tobias Building, 2<sup>nd</sup> Floor

Cnr York & Princess of Wales Terrace, Parktown 2193

Tel: (011) 717 2745 | Fax: (011) 717 2119

Email: Mathoto.senamela@wits.ac.za




### PLAGIARISM DECLARATION TO BE SIGNED BY ALL HIGHER DEGREE STUDENTS

#### SENATE PLAGIARISM POLICY: APPENDIX ONE

I **Charity Vhurumuku** (Student number: **747731**) am a student registered for the degree of Master of Science in Epidemiology and Biostatistics in the academic year 2014.

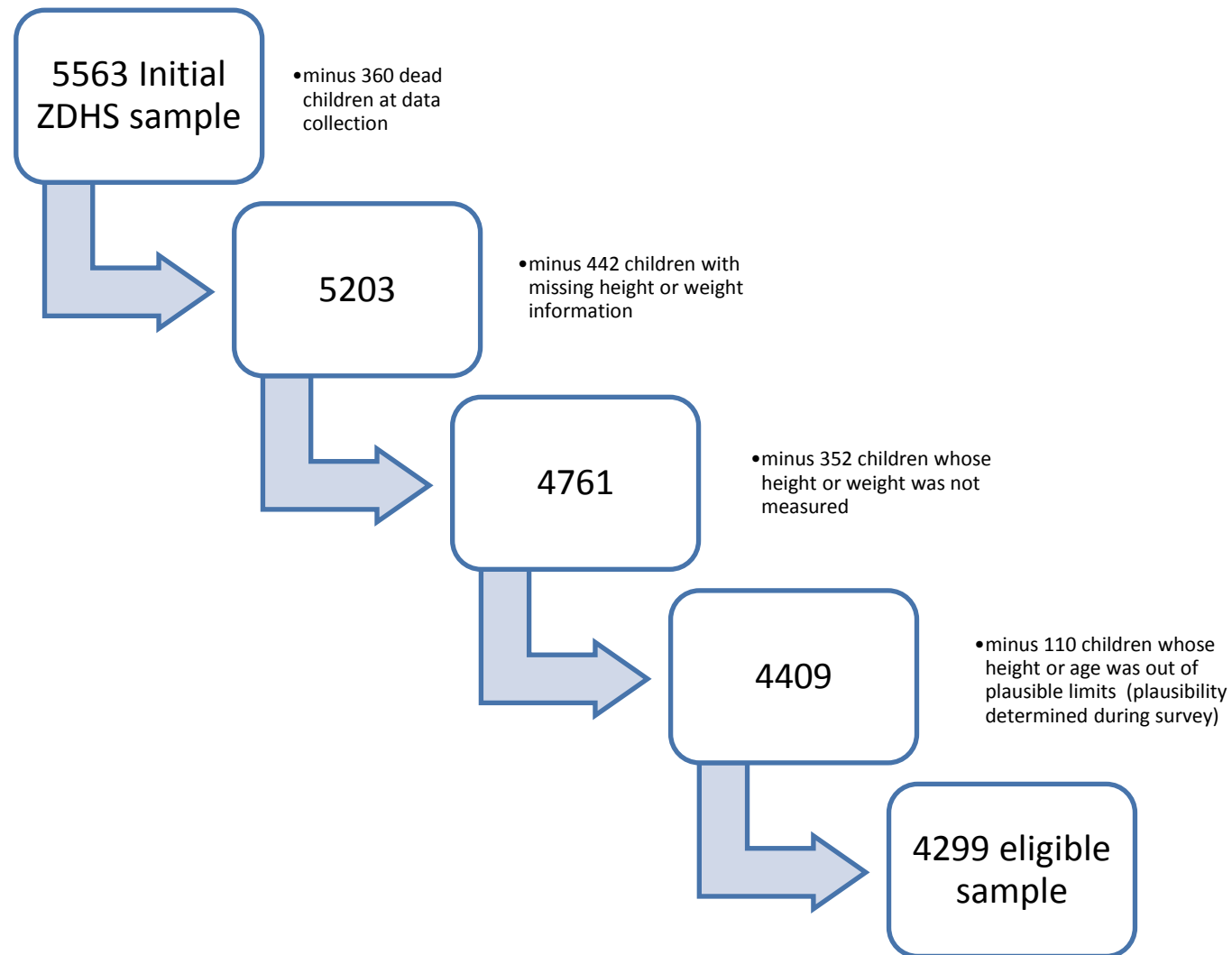
I hereby declare the following:

- I am aware that plagiarism (the use of someone else's work without their permission and/or without acknowledging the original source) is wrong.
- I confirm that the work submitted for assessment for the above degree is my own unaided work except where I have explicitly indicated otherwise.
- I have followed the required conventions in referencing the thoughts and ideas of others.
- I understand that the University of the Witwatersrand may take disciplinary action against me if there is a belief that this is not my own unaided work or that I have failed to acknowledge the source of the ideas or words in my writing.
- I have included as an appendix a report from "Turnitin" (or other approved plagiarism detection) software indicating the level of plagiarism in my research document.

Signature: 

Date: 12 November 2014

**Appendix 2- Data cleaning flow chart**



**Appendix 3: Imputation of missing values**

<b>Level of Variables according to Conceptual Framework</b>	<b>Imputed Variables</b>	<b>Predictors</b>
Maternal level	-Weight -Height	Age
	-Husband/partners education level -Husband/partner's occupation -Husband/partner's age	-Wealth index -Woman's age -province -Religion -Highest educational level
	Person who usually decides on -how to spend respondent's earnings -respondent's health care -large household purchases -visits to relatives -how to spend husband's money	-Woman's age -Woman's highest educational level -Religion -wealth index -province -husband/partner's age
Child level	-birth weight -diarrhoea in the last two weeks -cough in the last two weeks -fever in the last two weeks -vitamin A supplementation in the last six months	-sex -age -height -weight
	-child feeding variables	-wealth index -currently breastfeeding -sex of child -age of child in months
Household level	-source of drinking water -time to get to water source -type of toilet facility -religion -type of cooking fuel -whether toilet is shared with another household	-wealth index -type of place of residence -province

\*\*to do the imputations we set the seed 747731 for reproducibility of results

**Appendix 4: Ethics Clearance Certificate**



R14/49 Ms Charity Vhurumuku

**HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)**  
**CLEARANCE CERTIFICATE NO. M130960**

**NAME:** Ms Charity Vhurumuku  
**(Principal Investigator)**

**DEPARTMENT:** Public Health  
University of Witwatersrand  
Epidemiology and Biostatistics

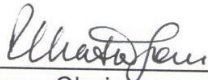
**PROJECT TITLE:** Factors Associated with Malnutrition among  
Children under Five Years of Age in Zimbabwe  
2010/2011

**DATE CONSIDERED:** 27/09/2013

**DECISION:** Approved unconditionally

**CONDITIONS:**

**SUPERVISOR:** Benn Sartorius

**APPROVED BY:**   
\_\_\_\_\_  
Professor PE Cleaton-Jones, Chairperson, HREC (Medical)

**DATE OF APPROVAL:** 30/09/2013

**This clearance certificate is valid for 5 years from date of approval. Extension may be applied for.**

**DECLARATION OF INVESTIGATORS**

To be completed in duplicate and **ONE COPY** returned to the Secretary in Room 10004, 10th floor, Senate House, University.  
I/we fully understand the conditions under which I am/we are authorized to carry out the above-mentioned research and I/we undertake to ensure compliance with these conditions. Should any departure be contemplated, from the research protocol as approved, I/we undertake to resubmit the application to the Committee. **I agree to submit a yearly progress report.**

\_\_\_\_\_  
Principal Investigator Signature

\_\_\_\_\_  
Date

**PLEASE QUOTE THE PROTOCOL NUMBER IN ALL ENQUIRIES**