DEBRE BERHAN UNIVERSITY

COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

DEPARTMNET OF STATISTICS

EXPLORATORY SPATIAL ANALYSIS OF UNDERNUTRITION AND ITS DETERMINANTS AMONG UNDERFIVE CHILDREN IN ETHIOPIA: A MULTI_LEVEL ANALYSIS

A THESIS SUMITED TO DEBRE BIRHAN UNIVERSITY IN PARTIAL FULFILMENT FOR THE AWARD OF DEGREE IN MASTER OF BIOSTATISTICS

BY:

KASSA KETSELA (MSc in Maternity Nursing)

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Advisor: AR . MuraliDharan (PhD)

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August, 2022

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DECLARATION

I, Kassa Ketsela- student ID No: PGR/038/10, declare that this research thesis is my own work. It is submitted for the degree of Master of Science in Biostatistics in Debrebirehan University, Ethiopia. It has not been submitted before for any degree or examination at this or any other University.

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ACKNOWLEDGEMENT

Thanks to Almighty GOD-without whose provisions and guidance, my being here and pursuit in this field would have been unthinkable. Most importantly, I cannot claim to have done this and any of those things I ever did by my own strength or intelligence. I am grateful for God's everlasting mercy. The Lord believed in me, chose me and sent me to do His work, which I actually believe this to all human being. 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 Your Everlasting mercy, care and providence!! Amen.

I would like to express my heartfelt gratitude to my advisors (AR. Muralidharan (PhD) and Worku Girma) for your unreserved support and guidance and tuition which was and is of immense importance to my professional development. My thanks also extends to the coordinator of statistics department, Mr Gebremedihin (Assistant professor), and to all staffs of statistics department of whose tutoring have brought me to this level. A similar gratitude is also forwarded to my classmates and friends who contributed a lot to me in diverse ways to my success in the program.

Not only do I owe a debt of gratitude to those whose works are cited in this research/work but also I acknowledge the help and encouragement of colleagues and students. Finally, I would like to thank my family to all things they've made for me from start till now.

Acronyms

ANC…………..Antenatal Care
AIC……………Akaike's Information Criteria
AOR…………...Adjusted Odds Ratio
CGF……………Child Growth Failure
CIAF…………..Composite Index Anthropometric Failure
COHA…………Cost of Hunger in Africa
CSA……………Central Statistical Agency
DIC…………….Deviance Information Criteria
EA……………..Enumeration Area
EMDHS……....Ethiopia Mini_Demographic Health Survey
EPHC………….Ethiopia Population and Housing Census
FAO…………...Food and Agriculture Organization
GBD…………..Global Burden of Disease
GDP…………...Gross Domestic Product
GIS……………Geographic Information System
GLLaMM……..Generalized Linear Latent and Mixed Models
GPS…………... Geographic Positioning System
HAZ…………...Height-for-Age Z-value
IC……………...International Conference o Nutrition
MUAC………...Mid_Upper Arm Circumference
OLS……………Ordinary Least Square
OR……………..Odds Ratio
PCA……………Principal Component Analysis
SAM…………..Severe Acute Malnutrition
SDG…………...Sustainable Development Goals
U5C…………...Underfive Children
WHO………… World Health Organization
WAZ………….Weight-for-Age Z-value
WHZ………….Weight-for-Height Z-value

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Abstract

Background: Undernutrition has been a public health problem in both developed and developing countries. According to the World Health Organization (WHO), children under 5 years of age, 155 million are stunted, 52 million are wasted, 17 million are severely wasted and 41 million are overweight and/or obese. Malnutrition is not just a health issue but also affects the global burden of malnutrition socially, economically, developmentally and medically, affecting individuals, their families and communities with serious and long lasting consequences. Identification of spatial variations and individual and contextual level determinant factors of child undernutrition is essential to deliver targeted, efficient and sustainable solutions to the problems.

Objectives: This study determined exploratory spatial variations and its determinants of undernutrition among underfive children.

Methods ad Result: This study uses Ethiopian Mini_Demographic Health Survey 2019 data set. Spatial and multilevel analysis was used to analyses the data set. Spatial analysis was carried out by using Geographic information system (GIS) (i.e., Arc Map 10.7). Multilevel logistic regression was used to identify determinant factors of undernutrition. The result shows that undernutrition (stunted, wasted, or underweight) affects approximately 38.25% of children in Ethiopia. The proportions of undernourished children in urban and rural areas were 26.5 % and 41.6 %, respectively. The result from Global Moran's I and local indicators of spatial autocorrelation reveal that the distribution of undernutrition is clustered or not random in Ethiopia. The highest prevalence of undernutrition among underfive (U5C) children was identified in the entire Tigray, Northern Amhara, Somalia, and Afar regions. The SaTScan analysis identified a total of 110 significant hotspot areas of children undernutrition with three significant spatial windows of which 100 clusters were primary (most likely clusters) while 10 were secondary clusters. Determinant factors such as regions, diet diversity, the number of household members, and the age of the child in month, the age of the mother at first birth, the partner's education level, the preceding birth interval, and the ANC visit have statistically significant roles in the odds of undernutrition in Ethiopia.

Conclusion and Recommendation: The overall magnitude of childhood stunting, underweight and wasting among underfive children were found to be very high with geographical variations across different region. The study showed heterogeneity in the magnitude of child undernutrition

after adjusting for both individual and community level determinant factors in the multilevel analysis. It is recommended that a geographic and context specific intervention should be launched by Ethiopia government and respective local administrators supported by small area estimation researches done by academia.
Key Terms: Undernutrition, Spatial statistics/pattern, multilevel analysis, EMDHS, R, ArcMap

CHAPTER ONE

1.1 Introduction to Undernutrition

Undernutrition denotes insufficient intake of energy and nutrients to meet an individual's needs to maintain good health. In most literature, undernutrition is used synonymously with malnutrition. In the strictest sense, malnutrition denotes both undernutrition and overnutrition. However, since protein energy malnutrition does not exist in isolation of specific micronutrient deficiencies, neutral terms such as undernutrition are encouraged because they encompass both protein energy undernutrition as well as micronutrient deficiencies (Maleta, 2006) (States & Online, 2013). Child hunger and undernutrition are persistent problems worldwide: one child in three in developing countries is stunted and undernutrition accounts for 35% of annual deaths for under-5 year olds. Children who survive are more vulnerable to infection, don't reach their full height potential and experience impaired cognitive development (Biodim, 2018).

During infancy and early childhood optimal nutrition is vital to ensure that, development and rapid growth demands are met. In the efforts to tackle the nutrition disparities, the first 1000 days of life are an important window period, presenting the opportunity to prevent both stunting and overweight/obesity (Perez-Escamilla et al., 2018). Undernutrition is a lack of proper nutrition, caused by not having enough food, not eating enough food containing substances necessary for growth and health, and other direct and indirect causes. The medical, social, economic, and developmental effects of the global malnutrition burden are lasting and serious for individuals and their families, communities and countries. It is due to a complex and dynamic interaction between the environmental, economic, social, political, and other factors. In the year 2018, 52 million children under-5 were wasted, 17 million were severely wasted and 155 million were stunted, while 41 million were obese or overweight. Approximately 45% of mortality among under-5 children has been related to undernutrition. These usually take place in the low- and middle income countries (Almasi et al., 2019).

Stunting, also known as chronic undernutrition, in under-five children is a form of growth failure which develops over a long period of time in children under five years of age when growing with limited access to food, health and care. In children, it can be measured using the height-for-age nutritional index. Stunting is often associated with cognitive impairments such as delayed motor development, impaired brain function and poor school performance, as it often causes these negative impacts. Wasting in under-five children is thin for their height because of acute food shortages or disease. Also known as 'acute malnutrition', wasting is characterized by a rapid deterioration in nutritional status over a short period of time in children under-five years of age. Wasted children are at higher risk of dying. In children, it can be measured using the weight-for-height nutritional index or mid-upper arm circumference (MUAC) (Aubrun & Nechita, 2012).

Malnutrition, in all its forms, involves undernutrition (wasting, stunting, and underweight), inadequate minerals or vitamins, obesity, overweight and non-communicable diseases related to diet. The poor are more likely to be affected by the different forms of malnutrition. Furthermore, malnutrition increases the costs of healthcare, decreases productivity and slows the economic growth, which can perpetuate a cycle of poverty and illness (Almasi et al., 2019).

Elevated rates of childhood malnutrition have large public health implications. Most importantly, widespread undernutrition is strongly correlated and without a doubt causally linked to higher infant mortality. Even if child deaths are not directly due to undernutrition, it has been shown to be the underlying cause for a large number of child deaths from diarrhoea, pneumonia, malaria or measles occurring in the developing world. Undernourished children are more likely to suffer from poor health compared to well-nourished children and consequently, perform worse in educational terms (Striessnig & Bora, 2020).

Evidence revealed that the problems responsible for child undernutrition are numerous and basic problems like political instability, slow economic growth and lack of education are among them. Underlying causes such as, food insecurity, lack of maternal and child care services provision, and immediate causes, like infections and inadequate dietary intake were the main factors resulting in undernutrition (Kahssay et al., 2020).

The age group that should be concerned with is 0 to 5 years old (infants and toddlers). The underweight condition of children underfive causes them having a higher risk factor in the face of growth disorders than the adult age group. The disruption of growth during this period cannot be fulfilled in the future and will negatively affect the quality of future generations. The nutritional status based on the anthropometry of children could be divided into three indices, namely stunting (length or height not appropriate for age), wasting (unsuitable weight to height) and underweight (lack of weight against age). Public health problem is considered serious if malnutrition prevalence is between 20-29% and very high prevalence if ≥ 30%. Prevalence is the number of incidence of disease within one year compared with the population (Zurnila et al., 2019a).

1.2 Statement of the problem

Malnutrition affects between 2 and 3 billion people worldwide and occurs in all countries regardless of average income. Hunger affects about 795 million people, mostly in low-income countries (Food and Agriculture Organization of the United Nations [FAO], International Fund for agricultural Development). Despite significant progress in reduction of hunger, approximately 2 billion people worldwide suffer from micronutrient deficiencies, which can lead to increased susceptibility to disease, reduced cognitive development, pregnancy complications, and child growth failure. This so-called hidden hunger is most prevalent in developing countries where the diet is dominated by micronutrient-poor cereals (Rocha et al., 2016).

Developing countries are disproportionately affected by a high burden of childhood undernutrition (De Onis et al., 2013). Sub-Saharan African countries such as Ethiopia have a larger share of the global burden of undernutrition (International Food Policy Research Institute, 2014). Hence, WHO member states endorsed a broader agenda to improve nutrition by 2025 including stunting, wasting, low birth weight and overweight in children under five and an eventual elimination of all forms of malnutrition by 2030 (SDG goal 2.2) (Goal et al., 2022). Additionally, findings from the Global Burden of Diseases, Injuries, and Risk Factors Study 2016 (GBD 2016) indicated that an estimated 36.6% of children under five were stunted, 8.6% wasted and 19.5% underweight in sub-Saharan Africa (SSA) in 2015 (Ahmed et al., 2021).

The overall WHO global nutrition target 2025 is to improve maternal, infant and young child nutrition (World Health Organization & United Nations Children’s Fund, 2019). One of the specific nutrition targets is the stunting policy which aims at reduction of childhood stunting by 40% from 2014 to 2025 (Mtambo, 2018a). For stunting, the current rate of reduction is not rapid enough to attain 100 million by 2025(Thrive, 2020). Similarly, for wasting, the current rate of reduction is not rapid enough to reach below 5% by 2025. The third global nutrition target is a relative reduction of 30% of infants born with a weight lower than 2500 gm by the year 2025. This would translate into a 2.7% relative reduction per year between 2012 and 2025 (WHO & UNICEF, 2017).

The Seqota Declaration is Ethiopia's commitment to end child undernutrition by 2030 (Ojewunmi, 2020). It reaffirms the government's commitment to nutrition as a foundation for economic development with a focus on human capital development. The Cost of Hunger in Africa (COHA) study produced for Ethiopia indicates that factors associated with undernutrition lower Ethiopia's GDP by 16.5 percent with huge consequences on economic and inclusive growth (Zurnila et al., 2019b),(World Health Organization & United Nations Children's Fund, 2019), (Mtambo, 2018b), (WHO & UNICEF, 2017). Although Ethiopia has recorded steady and impressive reduction in stunting over the past decade, levels remain high and stark geographical inequalities persist (Ministry of Health of Ethiopia, 2015).

A study done in Nigeria using a Bayesian Quantile Regression Approach to measure the spatial distributions of childhood undernutrition showed that existence of North-South divide in undernutrition and that observed socioeconomic variables could have little influence on the distribution of undernutrition across space in the country and about 36% of the children were stunted, 17% wasted and 27% underweight with overall mean z-score of −1.33, −0.60 and −1.20, respectively. Of all the children surveyed, stunted, wasted and underweight children were more in the rural areas (42%, 17% and 30%, respectively) than in the urban areas (25%, 16%, 20%), respectively. As expected, the proportion of undernourished children is reduced as the mothers' level of educational attainment increases (Gayawan et al., 2019). A comparative analysis results obtained from multi-level statistical models indicated that in Kenya and Nigeria, conflict is associated with lower weight-for-height scores among children, even after accounting for individual-level and climate factors (Grace et al., 2022).

Similarly, a spatial analysis of childhood stunting and its contextual correlates showed big variations and clustering in the childhood malnutrition across districts of India (Bharti et al., 2019). Another study in Bangladish using machine learning methods indicated that the overall stunting prevalence was 36.5% in the study data. The results reveal that children aged two years or older were more stunted (41.8%) than younger children (28.3%). Children of higher birth order were also stunted in higher proportions (42.7%) than the first or second-born children (Mansur et al., 2021). Another study done in India using a regression-decomposition analysis of district-level data from 2015–16 showed that differences in stunting prevalence between low and high burden districts were explained by differences in women's low body mass index (19% of the difference), education (12%), children's adequate diet (9%), assets (7%), open defecation (7%), age at marriage (7%), antenatal care (6%), and household size (5%). The findings emphasize the variability in stunting across India, reinforce the multifactorial determinants of stunting, and highlight that interdistrict differences in stunting are strongly explained by a multitude of economic, health, hygiene, and demographic factors (Menon et al., 2018).

A study on risk factors for severe acute malnutrition among children aged 6-59 months admitted at Lubango Pediatric Hospital in Angola indicated that the significant predictors of severe malnutrition were family order, HIV test results, previous history of admission with diarrhea and malnutrition, duration of breast feeding and number of previous admissions (Francisco et al., 2019). A similar study in Kotri-Pakistan with an objective of determining socio-demographic factors responsible for malnutrition among children less than five years of age using cross-sectional study indicated that poor socioeconomic status, poor antenatal care, poor diet and inadequate breast feeding are responsible factors for severe malnutrition (Qureshi et al., 2019). A Kenyan study using cross-sectional analytical design on sample of 400 showed that strong association between income and stunting (OR=0.47; CI=0.24-0.91) and underweight (OR=0.44; CI=0.22-0.92) and wasting was strongly associated with age of the mother (OR=1.07; CI=1.01-1.33) and mother’s education (OR=0.34; CI=0.14-0.83)(Omondi D. O & Kirabira P, 2016).

In Ethiopia, between 2000 and 2016, the prevalence of stunting fell from 51.5 percent to 38.4 percent, wasting from 10.5 percent to 9.9 percent, and underweight from 47.2 percent to 23.6 percent. Malnutrition rates are falling but remain high overall, and severely high in some regions: for example, wasting rates are 23 percent in Somali and 18 percent in Afar, the stunting rate in Amhara is 46 percent and anaemia affects 83 percent of children in the Somali Region (July, 2020).

A 2016-EDHS based cross-sectional study in Ethiopia aiming to determine the most important maternal factors associated with stunting and quantification of their effects showed that maternal education, number of antenatal care visits, and place of delivery appear to be the most important predictors of child stunting in Ethiopia (Amaha & Woldeamanuel, 2021). Another study based on this dataset using generalized linear latent and mixed models (GLLaMM) to identify factors associated with stunting, underweight, and wasting also indicated that the prevalence of stunting was 38.3%, under-weight 23.3% and wasting 10.1%. Sex of the child, recent experience of diarrhea, household wealth index (poorest) compared to richer, and richest, and administrative regions of Tigray , Amhara and developing regions compared with under-five children from Addis Ababa, Dire Dawa, and Harari had a higher risk of undernutrition (Kasaye et al., 2019).

On the other hand, children born from overweight mothers and educated mother (primary, secondary or higher) had a lower risk of undernutrition (Kasaye et al., 2019). Similar study aimed to investigate the association between socio-economic determinants and undernutrition among children under the age of five in Wolayita zone, Southern Ethiopia using a population based cross-sectional survey also indicated that household asset score, food security and women economic status were significantly associated with stunting among children aged 0-59 months (Maternal, 2019).

An unmatched case-control study in Mekelle City in Tigray Region, North Ethiopia also indicated that stunting is common among children aged 6 to 24 months having no formal education in mother, mother height less than 150cm, low BMI of the mother, low birth weight, low WHO diet diversity score (DDS), number of under-5 children in the household and repeated diarrheal episodes (Berhe et al., 2019). Also with similar study design conducted in Afar region, Ethiopia, revealed that no maternal education, preceding birth interval less than 24 months, no ANC follow-up, no access to latrine, short maternal height, not feeding colostrum, duration of breast feed less than 24 months and non-exclusive breast feeding were determinants of stunting at 95% CI (Kahssay et al., 2020). Yet another study conducted to understand correlates of child stunting in Ethiopia using generalized linear mixed models on 2016 Ethiopian Demographic and Health Survey data showed that the age and sex of the child, preceding birth interval, mother's body mass index, household wealth index, mother's education level, breastfeeding period, type of toilet facility, use of internet and source of drinking water were the major determinants of stunting of under-five children in Ethiopia (Takele et al., 2019).

A Bayesian geostatistic analysis of 2016-EDHS also showed that factors associated with a reduced likelihood of stunting in Ethiopia included non-receipt of breastmilk, mother's BMI (overweight/obese), employment status (employed), and higher household wealth, while the enablers of undernutrition were residence in the "arid" geographic areas, small birth size of the child, and mother's BMI (underweight) (Ahmed et al., 2021). A similar study done on 2016_EDHS dataset using generalized linear mixed models from the cluster specific model family indicated that rural Ethiopian children were more likely than urban Ethiopian children to be stunted (Gobena, 2022).

The need for thorough modelling procedures revealing the relation between person, place (spatial) and time and nutritional status is a top public health priority. However, there are analytic challenges, namely the multi-collinearity due to the multilevel structure, spatial auto-correlation. Geo-mapped data showing the geographical regions, associated risk factors as well as the burden of undernutrition, can be more convincing tools to present to policy makers than text results models alone. Therefore, to design tailored public health interventions, identification of geographical areas with a high prevalence of undernutrition using geographical information system and spatial analysis is very crucial.

All the studies about child undernutrition in Ethiopia reviewed above have used different measures of malnutrition. However, they overlap and none is able to provide a comprehensive estimate of number of undernutrition children in an economy. Some children who are stunted may also be wasted and/or be underweight. Some children who are underweight may also be wasting and/or be stunted and some children who have wasting may also be stunted and/or underweight. Such types of measures are questioned by Svedberg (Svedberg, 2001) and more appropriate measure proposed is Composite Index of Anthropometric Failure (CIAF) (Ejaz et al., 2011). It was first proposed by Swedish development economist, Professor Peter Svedberg (Svedberg, 2001). Svedberg (2000) argued that anthropometric indices like the stunting, wasting and under-weight are necessary for determining their relevant interventions. Svedberg (2000) proposed Composite Index of Anthropometric Failure (CIAF) that incorporates all malnourished children. The needed indicator must incorporate all undernourished children, be they wasted and/or stunted, and/or underweight. The composite index of anthropometric failure (CIAF) is a better indicator of nutritional status than traditional measures of stunting, wasting and underweight because it determines overall anthropometric failure. CIAF is considered as a single measure which provides the overall burden of undernutrition in studied population and represents the higher prevalence when compared with the three conventional measures used separately. We used CIAF measure for Ethiopia which makes the current study different from the previous ones. According to our knowledge, still no study has used this measure for Ethiopia for the previous and 2019 EDHS dataset. Hence, we aim to determine the prevalence of undernutrition using CIAF and the effect of several socio-economic and demographic correlates.

1.3 Research Questions

The research problems include:

1. Does undernutrition occur randomly or does it geographically (spatially) cluster in Ethiopia?
2. Where are the spatially high risk area(s) of undernutrition in Ethiopia?
3. What are the determinants of geographic clustering of undernutrition in Ethiopia?

1.4 Objectives of the study

1.4.1 General objective:

The main objective of this study was to perform exploratory spatial analysis of undernutrition and its determinants among underfive children in Ethiopia.

1.4.2 Specific objectives:

- To identify which residence type has more undernutrition prevalence;
- To explore spatial pattern of undernutrition and identify high risks areas in Ethiopia;
- To investigate the proportion of variation of undernutrition among children across regions (cluster heterogeneity);
- To assess the spatial dependence of undernutrition prevalence on spatial risk factors, and
- To identify the relationship between undernutrition and determinant factors among children in Ethiopia.

1.5 Significance of the study

In public health, identification and quantification of patterns of undernutrition occurrence provide the first steps towards increased understanding towards the prevention and intervention mechanisms. Public health policy-makers rely on data for allocation of resources and interventions. The Ethiopian demographic and health survey data, updated once every five year, embody the strengths of multilevel (hierarchical) data structures. In addition all households data collected are geo-coded which allows the assessment of geographic differentials.

Therefore, the main goal of this study is to examine spatial patterns or clusters of undernutrition distribution using 2019-EMDHS dataset. It seeks to identify undernutrition "hotspot" by producing map of clustering observation and investigate proportion of cluster heterogeneity of undernutrition in Ethiopia. The result of spatial analysis would be helpful in improving our understanding of the distribution of undernutrition and to enhance planning and implementing targeted nutrition intervention programmes. Hence, understanding the spatial distribution of undernutrition in Ethiopia and its determinants are of paramount importance for geographic-specific and evidence-based intervention designing and implementations and also will play a role in meeting the WHO/UNICEF 2030 target of elimination of undernutrition in Ethiopia. It will be also helpful for policymakers and managers at different administrative levels to control and prevent undernutrition more efficiently.

CHAPTER TWO

2. 1 Literature Review

Literature review is the evaluation of the available knowledge in the field of investigation in a unique way to identify research gaps which provide the rationale for the study. It is conducted mainly under three types such as empirical literature, theoretical literature and methodological literature. This study attempts to review empirical literature relating to the different factors for child undernutrition. An empirical literature review is more commonly called a systematic examination of the past empirical studies to answer a particular research question.

The international Conference on Nutrition (ICN, first round, in Italy in December, 1992) affirmed and declared their determination to eliminate hunger and to reduce all forms of malnutrition (Food and Agriculture Organization & World Health Organization, 1992). Hunger and malnutrition are unacceptable in a world that has both the knowledge and the resources to end this human catastrophe. They recognized that access to nutritionally adequate and safe food is a right of each individual and globally there is enough food for all and that inequitable access is the main problem. Bearing in mind the right to an adequate standard of living, including food, contained in the Universal Declaration of Human Rights, they pledged to act in solidarity to ensure that freedom from hunger becomes a reality. They also declared their firm commitment to work together to ensure sustained nutritional well-being for all people in a peaceful, just and environmentally safe world (Food and Agriculture Organization & World Health Organization, 1992).

The delegates emphasized the distressfully high prevalence and increasing numbers of malnourished children under-five years of age in parts of Africa, Asia and Latin America and the Caribbean. Moreover, more than 2000 million people, mostly women and children, are deficient in one or more micronutrients: babies continue to be born mentally retarded as a result of iodine deficiency; children go blind and die of vitamin A deficiency; and enormous numbers of women and children are adversely affected by iron deficiency. Nutrition is one of the foundations of human society and human solidarity. It is always the poor who are at risk of malnutrition (Food and Agriculture Organization & World Health Organization, 1992).

Following the 1992 ICN, many countries prepared National Plans of Action on Nutrition, reflecting their own priorities and strategies for alleviating hunger and malnutrition. Unfortunately, implementation and progress have been patchy and often unsatisfactory due to inadequate commitment and leadership, financial constraints, weak human and institutional capacities, depletion of natural resources exacerbated by climate change, and lack of appropriate accountability mechanisms. The prevalence of those suffering undernourishment has declined, but still remains unacceptably high, with over 800 million people suffering from hunger, mainly in South Asia and sub-Saharan Africa. Addressing malnutrition is strengthened by a common vision and a multi-sector approach that includes coordinated, coherent, equitable and complementary interventions in food and agriculture systems, health, social protection and education among others. Adoption of options will vary among countries, in line with national challenges, plans and priorities. Policy-makers should understand the specific nature of their malnutrition problems to design appropriate, coherent, and targeted interventions that address different needs across population groups, especially of women and children (Sodikin, 2014).

Child malnutrition may be defined as a pathological state resulting from inadequate nutrition, including undernutrition (protein-energy malnutrition) due to insufficient intake of energy and other nutrients; overnutrition (overweight and obesity) due to excessive consumption of energy and other nutrients; deficiency diseases due to insufficient intake of one or more specific nutrients such as vitamins or minerals. It has been also recently defined as a physiological condition that takes many forms including abnormal child development or growth, underweight, overweight and obesity, micronutrient deficiencies, and non-communicable diseases (Rocha et al., 2016). Malnutrition continues as a vicious cycle and child malnutrition is predominant in this vicious cycle (Rathnayake et al., 2021).

Work relating to malnutrition is a high-priority research topic with growing relevance to geographical concepts, but there is no existing overview of geographical approaches to this theme. Malnutrition has conventionally been studied from nutritional, epidemiological, medical, public health, and economic perspectives that pay little attention to environmental concerns and differences in power and access. We consider malnutrition a simultaneously biological, social, and environmental issue and therefore believe that geographers can offer a uniquely broad perspective that improves understanding of how these components are integrated with malnutrition. Geographers are well positioned to help explain why people are malnourished and how to improve nutrition in ways that are culturally appropriate and economically, politically, and environmentally sustainable (Rocha et al., 2016).

2.2 Theoretic and Epidemiologic Literature Review

Nutritional geography is a nutrition-focused subfield of health and medical geography. Nutritional geography was thoroughly described by Grivetti in his review “Nutritional Geography: History and Trends” (Beal et al., n.d.). Grivetti approached nutritional geography from a perspective that integrates cultural, economic, and physical components: Cultural factors influence nutritional status through dietary choices and methods of food preparation and storage; socioeconomic status affects access to food; and environmental characteristics impact the ability to produce or transport food (Grivetti, 2000). Grivetti provided both narrow and broad definitions of nutritional geography. His narrow definition describes research that integrates distinct nutritional and geographic components, such as “deficiency diseases, famine, malnutrition, and other nutrition—or physiological—related topics set within geographic concepts of area, distribution, space, pattern, and time” (Grivetti, 2000). His broad definition includes topics without distinct nutritional and geographic components, such as agricultural geography, food access and distribution, cultural aspects of food patterns, and health consequences of diet choices. In contrast, literature that can be classified under the broad definition of nutritional geography is common but normally not labeled as nutritional geography due to a lack of cohesion and awareness of the field itself (Ritenbaugh, 1982).

Malnutrition is a widespread problem, affecting the global population at some life stage. This public health pandemic targets everyone, but the most vulnerable groups are poverty-stricken people, young children, adolescents, older people, those who are with illness and have a compromised immune system, as well as lactating and pregnant women. Malnutrition includes both undernutrition (wasting, stunting, underweight, and mineral- and vitamin-related malnutrition) and overnutrition (overweight, obesity, and diet-related non-communicable diseases). There is an unprecedented opportunity to address the various forms of malnutrition, especially the 2016–2025 Decade of Action on Nutrition set by the United Nation. This aims to achieve the relevant targets of the Sustainable Development Goals that aim to end hunger and improve nutrition, as well as promote well-being and ensure healthy lives. Thus, at the United Nation's General Assembly in 2016, the United Nations Decade of Action on Nutrition 2016–2025 was announced. This set a time frame for all forms of malnutrition to be addressed and for diet-related and nutrition targets to be met by 2025. This also set the time frame for the Sustainable Development Goals (SDGs) to be achieved before 2030, particularly SDG-2 that aims to improve nutrition, achieve food security and end hunger, as well as SDG-3 that aims to ensure healthy living and promote well-being for all (Dukhi, 2020).

2.2.1 Child Malnutrition

Undernutrition has been cited as a public health problem in both developed and developing countries. Hunger and micronutrient deficiencies are both considered forms of undernutrition. Geographers studying how the food supply (including production, distribution, and access) affects malnutrition were initially concerned with addressing hunger and later began to also address micronutrient deficiencies. An inappropriate diet is also one cause of malnutrition, but various diseases or genetic characteristics that prevent absorption or retention of nutrients also contribute. For example, diarrhea reduces absorption of nutrients and is one of the leading causes of death in low income countries. Genetic characteristics, such as lactose malabsorption, celiac disease, and stomach parasites, are often spatially determined by social and ecological environments and have all been studied from a geographical perspective.

Flukes, worms, and other parasites can cause reduced absorption of nutrients. This topic is particularly geographic, as it is dependent on ecologically and geographically sensitive small organisms. Helminthiases (stomach parasites) are by far the most prevalent soil-transmitted diseases and well suited to study by geographers. The first highly detailed global maps of helminthiases were created in the early 1950s by May (1952) (Schluth et al., 2020). Since then, geographers have contributed to the study of these diseases by applying spatial principles and analysis to more established public health methods, integrating remotely sensed data, and mapping and describing infection hot spots for outbreaks or efficient intervention (Rocha et al., 2016).

2.2.2 Prevalence of Malnutrition

According to the World Health Organization (WHO), children under 5 years of age, 155 million are stunted, 52 million are wasted, 17 million are severely wasted and 41 million are overweight and/or obese. Child and maternal malnutrition together have contributed to 3.5 million annual deaths. Furthermore, children less than 5 years of age have a disease burden of 35%. In 2008, 8.8 million global deaths in children less than 5 years old were due to underweight, of which 93% occurred in Africa and Asia. Approximately one in every seven children faces mortality before their fifth birthday in sub Saharan Africa (SSA) due to malnutrition. A malnutrition cycle exists in populations experiencing chronic undernutrition and in this cycle, the nutritional requirements are not met in pregnant women. Thus, infants born to these mothers are of low birth weight, are unable to reach their full growth potential and may therefore be stunted, susceptible to infections, illness, and mortality early in life. Malnutrition is not just a health issue but also affects the global burden of malnutrition socially, economically, developmentally and medically, affecting individuals, their families and communities with serious and long lasting consequences (Dukhi, 2020).

Progress to tackle all forms of malnutrition remains unacceptably low. There has been some progress in reducing childhood stunting – which is gradually declining – but still 150.8 million children are stunted. In addition, 50.5 and 38.3 million children are wasted and overweight respectively, and 2.01 billion adults are overweight and obese. Countries are struggling with multiple forms of malnutrition. Of the 141 countries analysed, 88% (124 countries) experience more than one form of malnutrition, with 29% (41 countries) having high levels of all three forms. Children can also experience multiple forms of malnutrition: 3.62% of children under five (15.95 million children) are both stunted and wasted, while 1.87% of under-fives globally (8.23 million children) experience both stunting and overweight.

Geospatial and disaggregated data is helping us understand who is malnourished and where and how to target action at subnational levels. By drilling down to the subnational level, the analysis reveals a striking heterogeneity in levels and trends of undernutrition. Even where countries appear to be on track to achieve global targets, the picture is different at the subnational level. In 2018 the journal Nature published the results 56 of a comprehensive geospatial analysis of child growth failure, which covers stunting, wasting and underweight, in 51 African countries from 2000 to 2015. Drawing from more than 200 geo-referenced household surveys representing more than 1.2 million children to estimate child growth failure prevalence on a 5×5km grid, it drills down to unprecedented levels of detail. This provides highly relevant information on key nutrition indicators not only by country, but also by local administrative subdivisions such as provinces, districts and communities. This is significant because national estimates tend to mask disparities at the local level, where most health and nutrition-policy planning and implementation occur (The Global Nutrition Report, 2018).

2.2.3 Measurement of malnutrition in Under 5 Children (U5C)

Undernutrition among children and adolescents 5-19 years is assessed using the nutritional index of body mass index for age (BMI-for-age) and clinical signs (Exchange, 2011). However, the preferred expression for anthropometric indicators in surveys is the standard deviation or Z-score. It is defined as: $Z - score = \frac{Measured\ value - Median\ of\ reference\ population}{Standard\ deviation\ of\ the\ reference\ population}$. The Z-score method of expressing prevalence of malnutrition obtained through survey results is preferred, primarily because the percentage of the median does not take into account the standard deviation associated with the reference distribution of weight for each height category, it takes into account the standard deviation of the distribution and thus standardizes weight deficiencies, regardless of the height of the child and also it is a more statistically valid comparison to the reference population than the percentage of the median.

Since the percentage of the median only uses two factors to calculate malnutrition, as opposed to the three factors used in Z-score calculations, percentage of the median has less likelihood of capturing all the malnourished children. Therefore, when Z-scores are used to define malnutrition, the number of children classified as malnourished is higher than if the percentage of the median is used, and it is a more statistically uniform approach to defining malnutrition (Webb & Bhatia, 2005).

Table 1: Classification of malnutrition for weight-for-height, height-for-age, and weight-for-age based on Z-scores (Fstpt et al., 2012).

Classification	Z-score value
Adequate nutrition status	-2 < Z-score < + 2
Moderately undernourished	-3 < Z-score < - 2
Severely undernourished	Z-score < - 3

2.3 Empirical Literature Review

This section focuses on socio-economic, demographic, health related and environmental factors of child malnutrition. Child nutrition remains one of the most important development concerns of the Ethiopian government. The anthropometrical indicators are generally considered as nutrition status indicators based on the internationally defined (standard) cut-off points. Theoretically, the body of a child responds to malnutrition in two ways that can be measured by anthropometrics survey. First, a reduction in growth over the long-term results in low height-for-age or stunting. Second, a short-term response to inadequate food intakes is assessed by weight relative to height (wasting). The combination of short-term and long-term food shortage and growth disturbances produces low weight-for-age (underweight) (De Onis, 2000).

Many studies have been conducted in health and nutrition in Ethiopia over the last few years. The studies show that Ethiopia is one of the countries with the highest levels of malnutrition in Sub-Saharan Africa. Malnutrition is particularly prevalent among children under five years of age, and pregnant and lactating women. Malnutrition occurs primarily because of inadequate food intake and poor dietary diversity. The root causes of malnutrition in the country include endemic food shortages in many parts of the country, a limited variety of food to choose from, and widespread poverty—which has made it difficult for most families to access the food they need. Other factors contributing to malnutrition include the disease burden, use of unsafe water, poor sanitation, low uptake of primary health services and low levels of maternal education (Ababa, 2011).

2.3.1 Risk factors Associated with Child Malnutrition

Contributing causes to malnutrition include an inappropriate diet, poor health behaviors, a lack of access to adequate health care, and genetic and environmental factors (Rocha et al., 2016). Different types of factors are responsible for child malnutrition. Demographic factors, health factors, social factors, geographic factors and economic factors are well identified among them (Rathnayake et al., 2021)

With the intension of evidence based intervention, a study done in Mekelle city, a town in Ethiopia, found that mother's lack of formal education, mother height less than 150cm, mother with a body mass index less than 18.5 kg/m^2, childbirth weight less than 2.5kg, household with two and above underfive children, a WHO diet diversity score < 4 and repeated diarrheal episodes were risks for stunting (Berhe et al., 2019).

Studies in Sudan, Ethiopia, Bangladesh, and Haiti have indicated that the causes of malnutrition are multi-faceted, with both environmental and dietary factors contributing to malnutrition risk in young children. Diet and disease have been identified as primary immediate determinants; with household food security, access to health facilities, healthy environment, and childcare practices influenced by socio-economic conditions. Mother's antenatal visit and body mass index were also identified as risk factors for malnutrition. In children under 3 years of age some of the main factors included poor nutrition, feeding practices, education and occupation of parent/caregiver, residence, household income, nutrition knowledge of mother (Dukhi, 2020).

2.3.1.1 Socio-economic Characteristics

Socioeconomic status is the social standing or class of an individual or group. It is often measured as a combination of education, income and occupation. Examinations of socioeconomic status often reveal inequities in access to resources, plus issues related to privilege, power and control. Socioeconomic status has been operationalised in a variety of ways, most commonly as education, social class, or income.

A study done whether socioeconomic factors has relation on malnutrition on Data from the Living Standards Measurement Study (LSMS)/General Household Survey (GHS) in

2015/2016 in Nigeria showed that the percentage of children stunted was the highest with 37.8 percent, followed by the percentage of children underweight to be 20.25 and children wasted was 9.63 percent. As one moves up the ladder of the socioeconomic status, a significant fall in the rate of stunting is witnessed. Therefore, increasing the income of the poorest in a society is a sound strategy to curb the high rates of stunting in the socio-economically deprived segments of the country (Adesuyi et al., 2021). Lower income households purchase less healthful foods compared with higher income households.

Another study done in five South Asian countries using demographic and health survey showed that underweight prevalence was 37% in Bangladesh, 38% in India, 19% in Maldives, 29% in Nepal and 28% in Pakistan. Households with higher wealth index or education had lower odds of having underweight children (Hossain et al., 2020). Similarly a cross-sectional study done in Ethiopia revealed that children from the richest households had significantly lower odds (OR_{adj}= 0.64; 95% CI: 0.55, 0.75) of stunting compared with children from the poorest households. Children of women who always had money were significantly associated with 24% (CI: 0.60, 0.96) decrease in the odds of stunting compared with children of women who never had money (Maternal, 2019).

A case study of marginalized district in Punjab, Pakistan, concluded that the high prevalence of malnutrition in the district is correlated with overall socio-economic deprivation (Shahid et al., 2022). A community based cross-sectional study done in Debreberhan (Ethiopia) also indicated that maternal illiteracy, not breastfeeding exclusively, preterm birth, absence of antenatal care, exposure to infectious diseases and diarrhea are contributing factors for under-five undernutrition (Menalu et al., 2021).

A study on Gender Disaggregated Analysis done in Pakistan indicated that the working status of mothers, mothers not having ownership of assets, women not involved in income decisions, and urban place of residence are found major contributors in male child malnutrition. However, factors such as higher birth order and diarrhea contribute to malnutrition in female children (Shahid et al., 2020). A study in Uttar Pradesh India also indicated that mothers with no schooling, about half (46.3%) of their children are underweight, and more than 55 percent of the children are stunted, and approximately 18 percent of children are wasted. The results also indicate that child malnutrition is highly concentrated among the poor. They found that regions with a lower prevalence of child malnutrition still had great socio-economic inequalities (Mishra & Chaurasia, 2021). Also a natural experiment in which the location of research centre within a remote rural village of Gambia created a wide diversity of wealth, education and housing conditions within the same ecological setting and with free health services to all indicated that bad quality housing, without piped water into the home were factors for malnutrition (Husseini et al., 2018).

2.3.1.2. Socio-demographic Characteristics

A cross-sectional analytical study Obunga Slums (Kisumu City, Kenya) wasting was strongly associated with age of the mother (OR=1.07; CI=1.01-1.33) and mother's education (OR=0.34; CI=0.14-0.83) (Omondi D. O & Kirabira P, 2016). A cross-sectional study done by Department of Pediatrics of Bilawal Medical college Hospital Kotri-Pakistan indicated that severe malnutrition was most common among 70.8% of the cases and was significantly linked to the poor socioeconomic status. Inadequate diet was also found as responsible factor for severe malnutrition, because most of the severely malnourished children had history of inadequate diet (Qureshi et al., 2019). Similar cross-sectional studies done in Chandigarh, UT, revealed that out of the total 424 children surveyed, 262 (61.8%) were found to be underweight. Underweight prevalence was maximum among 25-36 months (75%) of age (Kumar et al., 2015). Also a cross-sectional study done in Ghana (GDHS) showed that there was a significantly increasing trend in stunting among males and females (Amugsi et al., 2013) whereas a cross-sectional study done in Ethiopia indicated that the main predictors of underweight were sex of child (AOR = 5.29, 95% CI (2.83-9.92)), type of first complementary food (AOR = 2.47; 95% CI (1.24-4.94)), household food security (AOR = 1.98;95% CI (1.23-3.21)) and age of child (AOR = 7.19; 95% CI (3.81-13.60)) (Tesfaye et al., 2020).

A prospective observational study done in Southern Odisha on 70 Severe Acute Malnutrition (SAM) children one month to 60 months of age with SAM who were admitted to a tertiary teaching hospital showed that majority of them have severe acute malnutrition secondary to diarrhea (36%), fever (34%) and poor weight gain (29%) (Mathew et al., 2021). A case-control study design where cases were compared with age and sex -matched controls with weight for height done in Lubango Pediatric Hospital, Angola indicated that predictors of severe malnutrition were family order, HIV test results, previous history of admission with diarrhea and malnutrition, duration of breast feeding and number of previous admissions (Francisco et al., 2019).

A descriptive cross-sectional study using multistage sampling to select 320 children in three government primary schools in Abuja, Nigeria, showed that age, gender, school name, mothers' education, mothers' income, mothers' marital status and number of children in the family positively influenced the nutritional status of the children (Educatio, n.d.). Similarly, school-based cross-sectional study comprising of 362 adolescent girls aged 10–19 years using simple random sampling technique with proportional allocation to size done in Ethiopia revealed that adolescents aged 14–15years (AOR=3.65; 95%, CI: 1.87, 7.11), adolescents living in rural areas (AOR=1.34; 95% CI: 1.24, 2.33), and adolescents who did not have snack (AOR=11.39; 95% CI: 1.47, 17.8) were positively associated with stunting. Whereas mother's occupation was negatively associated with stunting (AOR=0.12; 95%, CI: 0.17, 0.87). Similarly, educational status of adolescent girls was negatively associated with thinness (AOR=0.13; 95%, CI: 0.05, 0.35) (Arage et al., 2019). Also a study on 2016-EDHS indicated that maternal education, number of antenatal care visits, and place of delivery appear to be the most important predictors of child stunting in Ethiopia (Amaha & Woldeamanuel, 2021).

A multilevel and spatial analysis of childhood malnutrition on examining individual and contextual factors on stunting among children aged under five in Uganda indicated that drought, diurnal temperature and livestock per km^2 on stunting was modified by child, parent and household factors. Likewise, the contextual factors had a modifiable effect on the association between child's sex, mother's education and stunting. The results of the spatial regression models indicate significant spatial error dependence in the residuals. The spatial heterogeneity of rainfall and diurnal temperature as predictors of stunting suggest some areas in Uganda might be more sensitive to variability in these climatic conditions in relation to stunting than others (Amegbor et al., 2020).

A cross-sectional study done among a group of rural school children in Fayoum Governorate, Egypt, revealed that malnutrition is highly prevalent in rural school children in line with the national prevalence and significantly associated with children age, gender, mother's education and regularity of father's work (Hassan et al., 2018). Assessing a sociodemographic risk factors of under-five stunting in Bangladesh using a machine learning method indicated that as individual factors, living in Sylhet division, being an urban resident and having working mothers were associated with higher likelihoods of childhood stunting, whereas belonging to the richest households, higher BMI of mothers and mothers' involvement in decision making about children's healthcare with father were linked to lower likelihoods of stunting (Mansur et al., 2021). Similarly, an institution based cross-sectional study done in Ethiopia using randomly selected 409 pregnant women showed that factors significantly associated with the undernutrition were living in rural areas (AOR = 2.26), low educational status [no formal education (AOR = 2.91), primary education (AOR = 2.69)], history of too many births (AOR = 2.55), anemia (AOR = 2.01), and intestinal parasitic infection (AOR = 2.73) (Kumera et al., 2018).

2.3.1.3 Health and Environmental Factors

A study done on socio-economic determinants of nutritional status of children using secondary data obtained from 2011 Ethiopia DHS indicated that living in urban, having short distance to health services, mothers' use of contraceptive, absence of fever and diarrhea recently, toilet access, radio possession of households were negatively associated with underweight of children living in rural Ethiopia. In other way, mother use of contraceptive, absence of diarrhea recently, household's television possession, and having higher wealth status negatively affect rural child stunting. Older and vaccinated rural children have greater possibility to be stunted. Having electric power in the household, longer period of formal schooling of mothers, and television possessions of households shown to be associated with less child stunting in urban. Moreover, the risks of stunting increased with age of child in urban and rural. Regional variations have also strong impact on child stunting and underweighting in urban and rural parts of Ethiopia. the risks of stunting increased with age of child in urban and rural (Kamiya, 2011).

A study done on determinants of child malnutrition in the rural areas of Kimbibit Woreda Oromia Regional State of Ethiopia with the objective of examining the status of child malnutrition and to identify its socio-economic determinants of child malnutrition in the study area indicated that the prevalence of child malnutrition were higher than the regional and national figures found from EDHS, 2016 National report. The main determinants of stunting were age of child, sex of child, education of mother, family, income, shortage of food, complementary food, incidence (diarrhea, fever, and cough), duration of breast feeding, immunization, ANC, source of drinking water and availability functional toilet. The main determinants of underweight were age of child, income, food shortage, complementary food, diarrhea, breast feeding, immunization status of child and ANC. The main associated factors of wasting were income, food shortage, complementary food and diarrhea.

Another study aimed to identify the extent of malnutrition and associated factors among children aged 12–47 months in remote mountainous communities in Lao PDR found that undernutrition was very high among the 173 children studied 72.8% were stunted, 50.3% underweight and 10.4% wasted. Key factors showing significant positive associations with nutritional status were assets (mobile phone or electric rice mill), collection of non-timber forest products, and household dietary diversity (Boulom et al., 2020). Using the 2000 Ethiopia Demographic and Health Survey data, a study examines the impact of access to basic environmental services, such as water and sanitation on the probability children being stunted and underweight found that biological factors, such as child's age and mother's height, and social economic factors, such as household wealth and mother's education, are important determinants of a child's nutritional status. With respect to the environmental factors, the study found that there were indeed significant externalities associated with access to water and sanitation at the community level. The external impacts of community level of access to these services are an important determinant of the probability of a child to be underweight. The results also showed that the external impact of access to water is larger for children living in rural areas (Sugumaran & Purty, 2017).

A study on Environmental and Socioeconomic Correlates of Child Malnutrition in Iseyin Area of Oyo State of Nigeria indicated that 46% of the children were stunted, 6% underweight and 21% wasted and model estimation identified that age of the child, diarrhoea infection and poor sanitation as key factors that increases the likelihood of malnutrition in the study area (T. Awoyemi et al., 2012). A descriptive epidemiological study on maternal and environmental factors affecting the nutritional status of children in Mumbai Urban slum indicated that parents' higher education, exclusive breast feeding for 6 months, proper weaning, immunization and higher socioeconomic status had beneficial effect on nutritional status of children. Also environmental conditions, birth order and total number of children in family had effect on nutritional status of children(Bhavsar et al., 2012).

A review of food security in Senegal shows that the situation of malnutrition remains a matter of concern, notably in regions such as Kolda, Kédougou and Sédhiou. According to data from the Demographic and Health Survey (DHS), the rate of acute malnutrition among children under five years of age has declined very little overall in Senegal, from 10% in 2010 to 8.9% in 2017. According to the 2017 DHS, this rate ranges from 26% to 31% in these three regions, compared to nearly 17% at the national level (Company, 2018).

An unmatched case control study of malnourished and well-nourished children and their mothers was conducted at Princess Marie Louise Children's Hospital (PML on Ghanaian children indicated that among the interventions, inadequate antenatal visits, faltering growth and not de-worming one's child were associated with malnutrition in the multivariate analysis. However, immunisation and Vitamin A supplementation were not associated with malnutrition (Tette et al., 2015). A findings on climate variability and child nutrition on the weight and wasting status of children ages 0-59 months across 16 countries in sub-Saharan Africa showed that high temperatures and low precipitation are associated with reductions in child weight, and that high temperatures also lead to increased risk of wasting (Syarifudin, 2020).

2.4 Overview of Spatial Statistics and Geospatial Malnutrition

More than a quarter of the world's children under-5 years old are stunted. Of this, 80 percent live in only 14 countries, mostly in South Asia and sub-Saharan Africa. Estimates of UNICEF (2013) in 2011 states that the countries that have the most number of stunted children include India, Nigeria, Pakistan, China, Indonesia, Bangladesh, Ethiopia, Democratic Republic of Congo, Philippines, Tanzania, Egypt, Kenya, Uganda and Sudan (Winter, 2000).

A Global burden of disease study 2000-2017 done in a state of India indicated that the prevalence of stunting ranged 3.8-fold from 16.4% to 62.8% among the 723 districts in 2017, wasting ranged 5.4-fold 5.5% to 30% and underweight ranged 4.6-fold from 11.0% to 51.0% of the districts in India had stunting prevalence 40% or more (Hemalatha et al., 2020). A Bayesian Geostatistical Analysis study done on EDHS_2016 in Ethiopia also showed that the prevalence of stunting among under-five children was 36.3% (95% credible interval (CrI); 22.6%, 51.4%), with wide variations sub-nationally and by age group. The prevalence of childhood stunting ranged from 56.6% (37.4–74.6%) in the Mekelle Special zone of the Tigray region to 25.5% (10.5–48.9%) in the Sheka zone of the Southern Nations, Nationalities and Peoples region (Ahmed et al., 2021).

Study of the Spatial Pattern of Malnutrition (Stunting, Wasting and Overweight) in Countries in the World Using Geographic Information System on World Health Organization data from 2005 to 2016 showed that the prevalence of stunting, wasting and overweight in children under-five was not accidental and has emerged in cluster form based on a regular occurrence in countries around the world. Furthermore, the results of this research indicated that the mean center and standard deviation of stunting and wasting included most of the African and Asian countries especially in the Middle East (Almasi et al., 2019).

Another study with the objective of understanding the geographic burden of stunting in India using regression-decomposition analysis of district-level data from 2015–16 mapped out that stunting prevalence is high (38.4%) and varies considerably across districts (range: 12.4% to 65.1%), with 239 of the 640 districts have stunting levels above 40% and 202 have prevalence of 30–40%. High-stunting districts were heavily clustered in the North and Centre of the country (Menon et al., 2018).

Stunting was the most prevalent form of Child Growth Failure (CGF) across all years, and its change in prevalence across time was visually striking. While large areas of Algeria, Mozambique, Burkina Faso and Ghana showed a reduction in the prevalence of stunting from 2000 to 2015, progress in other countries was more spatially heterogeneous. Progress occurred between 2005 and 2015 in many areas. By 2015, lower levels were found in coastal central Africa, particularly in areas within Ghana, Gabon and Equatorial Guinea. By contrast, Northern Nigeria, Southern Niger, Democratic Republic of the Congo (DRC), Zimbabwe and Northern Mozambique all had areas with a prevalence of stunting near or above 40% in 2000, which was as high as 64.9% (59.3–70.8) in the Lubango municipality within Huila province, Angola. Also some areas in Northern Kenya, Eastern Ethiopia, Northern Nigeria and Madagascar showed temporal variation and increases across the study years. The Afar region in Ethiopia, for example, had a high prevalence in both 2000 (16.7% (14.5–19.4%)) and 2015 (21.7% (18.9–24.7%)) (Rogers et al., 2007).

Viridiana Garcia (a Programme Analyst, Strategic Policy Unit, United Nations Development Programme) conducted a study on children Malnutrition and Horizontal Inequalities in Sub-Saharan Africa that focused on Contrasting Domestic Trajectories of seven African countries (Burkina, Kenya, Malawi, Rwanda, Cameroon, Ghana and Nigeria) analyzed the evolution of three anthropometric indicators: underweight, stunting and wasting, and elaborated a classification of countries based on how inequalities in child malnutrition have changed over the two decades and identified three main types of trajectories; first, the case of countries where improvements in aggregate malnutrition have been offset by large increases in inequality (Cameroon, Rwanda and Nigeria); second, the case of countries where progress in malnutrition has translated into modest reductions in inequality (Kenya); third, the case of countries that have been successful in reducing both aggregate malnutrition and inequality (Burkina Faso, Malawi and Ghana).One strong finding of the analysis is that the countries that have registered the highest improvements in overall malnutrition rates are not the countries that have experienced the highest growth rates, indicating that changes in malnutrition are not proportionate to the pace of economic growth (Garcia, 2012).

A space-time analysis of recurrent malnutrition-related hospitalizations in Kilifi, Kenya for children under-5 years indicated that there was a seasonal pattern of re-admissions, peaking from May to July over the years. Hotspots were found in both the Northern and Southern areas of the Kilifi Health and Demographic Surveillance System (KHDSS), while the areas near Kilifi Town were least affected. They found that disease severity was most likely associated with a malnutrition re-admission to the hospital (Wambui & Musenge, 2019). Under-Five Child Growth and Nutrition Status of Spatial Clustering of Indian Districts study with the objective of assessing the geographical variance of under-five nutritional status and its related covariates employing principal component analysis (PCA) on the demographic and socio-economic determinants of childhood morbidity and hierarchical clustering analysis to identify geographical patterns in nutritional status at the district level showed that strong geographical clustering among 640 districts of India, often crossing state borders (Striessnig & Bora, 2020).

A study that mapped out geographic differences and examined the determinants of childhood stunting in Ethiopia using a Bayesian Geostatistical Analysis on 2016-EDHS dataset indicated that the prevalence of childhood stunting ranged from 56.6% (37.4–74.6%) in the Mekelle Special zone of the Tigray region to 25.5% (10.5–48.9%) in the Sheka zone of the Southern Nations, Nationalities and Peoples region (Ahmed et al., 2021). The conceptual frame below will briefly show the variables that this study focused on for analysis.

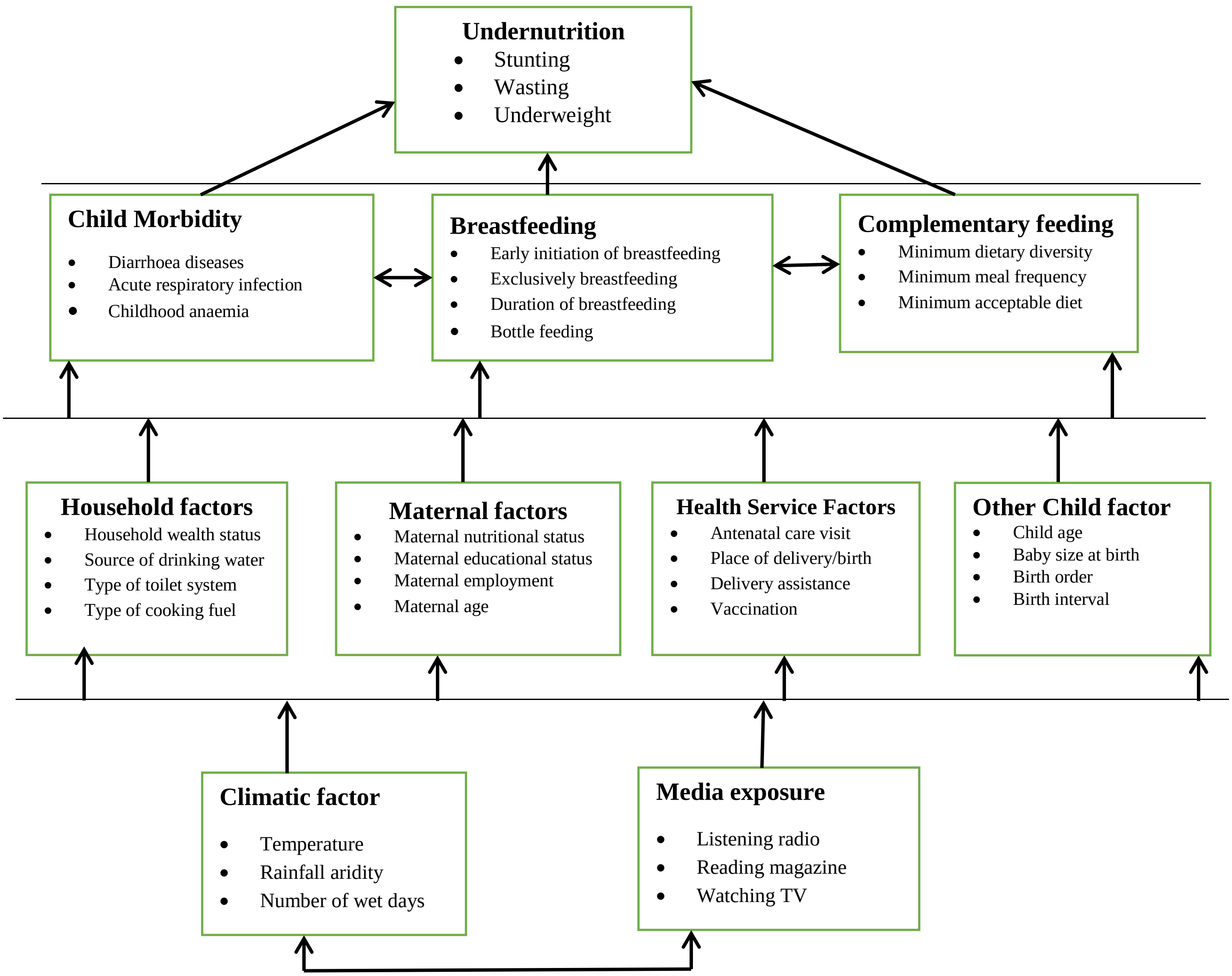

Fig. 1: Conceptual framework for proximal and contextual factors associated with undernutrition among children under five years of age (Adapted from Ahmed et al., 2021)

CHAPTER THREE

3. Source of Data and Methodology

3.1 Introduction

This chapter outlines various methods which were applied in conducting this research. It includes the research design that was utilized, population of the study, study area description and data analysis method.

3.2 Source and type of Data

Four full-scale DHS surveys were conducted in 2000, 2005, 2011, and 2016. The first Ethiopia Mini-DHS (EMDHS) was conducted in 2014. The 2019 EMDHS provides valuable information on trends in key demographic and health indicators over time. The information collected through the 2019 EMDHS is intended to assist policymakers and programme managers in evaluating and designing programmes and strategies for improving the health of the country's population (Demographic & Survey, 2019).

The source of data for this study was 2019 Mini-Ethiopia Demographic and Health Survey (2019-EMDHS) implemented by Central Statistical Agency (CSA). This report presents comprehensive outcomes of the survey at the national level in Ethiopia's nine regional states and two city administrations. The 2019 Ethiopia Mini-Demographic and Health Survey (EMDHS) is the second Mini-Demographic and Health Survey conducted in Ethiopia. Data collection took place from March 21, 2019, to June 28, 2019. The sample for the 2019 EDHS is designed to provide estimates of population and health indicators that include nutritional status of underfive children for the country as a whole: urban and rural areas separately.

The sampling frame used for the 2019 EMDHS is a frame of all census enumeration areas (EAs) created for the 2019 Ethiopia Population and Housing Census (EPHC) and conducted by the Central Statistical Agency (CSA). The census frame is a complete list of the 149,093 EAs created for the 2019 EPHC. The sampling frame contains information about EA location, type of residence (urban or rural), and estimated number of residential households.

The 2019 EMDHS sample was stratified and selected in two stages. Administratively, Ethiopia is divided into nine regions and two administrative cities as of 2019. Each region was stratified into urban and rural areas, yielding 21 sampling strata. Samples of EAs were selected independently in each stratum in two stages. Implicit stratification and proportional allocation were achieved at each of the lower administrative levels by sorting the sampling frame within each sampling stratum before sample selection, according to administrative units in different levels, and by using a probability proportional to size selection at the first stage of sampling. Detailed information was collected on respondents' background characteristics, fertility determinants, marriage, awareness and use of family planning methods, child feeding practices, nutritional status of children, childhood mortality, and height and weight of children age 0-59 months.

The anthropometric data collected in the 2019 EMDHS permit the measurement and evaluation of the nutritional status of infants and young children in Ethiopia. The 2019 EMDHS collected data on the nutritional status of children by measuring the weight and height of children under age 5 in all sampled households, regardless of whether their mothers were interviewed in the survey. Weight was measured with an electronic mother-infant scale (SECA 874 flat) designed for mobile use. Height was measured with a UNICEF measuring board. Children younger than age 24 months were measured lying down on the board (recumbent length), while older children were measured standing up (Demographic & Survey, 2019).

3.3 Study variables

3.3.1 Dependent Variable

The dependent/outcome variable of the study is the undernutrition in Ethiopia. It consists of three components: stunting, wasting, and underweight. These three indicators are standardized scores units used as references. The three anthropometric variables are measured through z-scores for height-for-age (HAZ), weight-for-height (WHZ) and weight-for-age (WAZ) and defined as: $Z_i=\frac{AIi-MAIi}{\sigma}$; where AI refers to the child's anthropometric indicator (e.g. height at certain age), while MAI and σ correspond to the median and the standard deviation in the reference population, respectively (Preedy, 2012).

$$Yij = \begin{cases} Normal, if\ Z-score\ \geq -2.0 \\ Moderately\ undernourished, if\ Z-score\ -3 \leq\ z-score\ < -2.0, and \\ severely\ undernourished\ if\ z-score\ < -3 \end{cases}$$

A single composite index was created from HAZ, WHZ and WAZ. Therefore, the Composite Index of Anthropometric Failure (CIAF) was taken as a new composite index of undernutrition and further nutritional status was reclassified as binary outcome and recoded as ‘0’ = nourished, ‘1’= undernourished.

3.3.2 Independent variables:

The selection of explanatory variables are theoretically driven and supported through prior research on factors affecting children nutritional status. Previous research works have been referenced in the creation of categories for naturally continuous and discrete variables. State of residence will be geo-referenced and used for spatial analysis.

Table 2: Independent variable description, 2019

Variables	Categories (codes)
Region	Tigray (1) Afar (2) Amhara (3) Oromiya (4) Somali (5) Benishangul (6) SNNPR (7) Gambela (8) Harari (9) Addis Ababa (10) Dire Dawa (11)
Place of residence	Urban (1) Rural (2)
Sex of a child	Male (1)

Variables	Categories (codes)
Multiple birth	Single birth (0) 1st of multiple birth 2nd of multiple birth
Educational level of mother	No education (0) Primary (1) Secondary and higher (2)
Age of mother at first birth	<20 (0) 20-34 (1) 35- 49 (2)
Dietary diversity	No(0) Yes (1)
Place of delivery	Home (0)

	Female (2)			Health facility (1)
Age of child in month	0-5 (0) 6-11 (1) 12-23 (2) 24-35 (3) 36-47 (4) 48-59 (5)		Sex of house hold head	Male (1) Female (2)
			Age of house hold head	15-19(0) 20-25(1) 26-30(2) 31-35(3) 35+(4)
			Ante-natal care visit	No (0) Yes (1)
Birth order	1st (0) 2-3 (1) 4-5 (2) 6 and more (3)		Husband/partner's education	No education (0) Primary (1) Secondary and Higher (2)
Wealth Index	Poorest (1) Poorer (2) Middle (3) Richer (4) Richest (5)		House hold size	1-4 (0) (small) 5-9 (1) (medium) 10 and more (2) (large)
No of children under five years in the household	1 (0) 2 (1) 3 or more (2)		Source of drinking water	Improved source (0) Unimproved source (1)
Toilet facility	No (0) Yes (1)		Community Health insurance	No (0) Yes (1)
Birth interval	<24 month(0) 24-35 month(1) 35+ month(2)			

Designed from literature review and EMDHS (Demographic & Survey, 2019)

3.4 Study area and study design

Ethiopia, the second most populous country in Africa (May, 2019), is situated in the Horn of Africa between 3 and 15 degrees North latitude and 33 and 48 degrees East longitude (3°–15°N and 33°–48°E). It has an administrative structure of nine regional states (Tigray, Afar, Amhara, Oromiya, Somali, Benishangul-Gumuz, Southern Nations Nationalities and People [SNNP], Gambela, and Harari) and two city administrations (Addis Ababa and Dire Dawa). These are subdivided into 68 zones, 817 administrative districts which are further divided into 16,253 Kebeles, the smallest administrative units of the country. It has an estimated population of 114.96 million in 2020, which makes it second next to Nigeria (206.14 million) in Africa and 12th in the world's most populous country. Ethiopian Demographic Health Information Survey (EDHS) of 2019 dataset was used to identify factors associated with undernutrition which are community-based cross-sectional surveys conducted across the country.

3.5 Data Extraction and Study Participants

EDHS is collected every five years by the Ethiopian Central Statistical Agency (CSA) along with ICF International and funded by USAID. The data sets for EDHSs was downloaded in any form (e.g.: SPSS and STATA format for this study) with permission from the Measure DHS website **(*http://www.dhsprogram.com*).** The shapefile of the map of Ethiopia was accessed from Open Africa website (***https://africaopendata.org/dataset/ethiopia-shapefiles***).

All underfive children within five years during the surveys in Ethiopia was the source of the population for this study, whereas all underfive children in the selected enumeration areas (EAs) within five years during the survey were the study population. Ultimately, a total representative sample of 5057 underfive children was included in the 2019 survey. Geographic coordinates of each survey cluster were also collected using Global Positioning System (GPS) receivers. To ensure confidentiality, GPS latitude/longitude positions for all surveys were randomly displaced before public release.

3.6 Data Management and Analysis

After downloading EDHS data, sample weights was applied to compensate for the unequal probability of selection between each stratum, data cleaning and recording was carried out in SPSS statistical software version 25. The EDHS datasets is joined to Global Positioning System (GPS) coordinates of EDHS using the joining variable as recommended by DHS measure.

3.7 Inclusion and Exclusion Criteria

All selected variables described above having a complete dataset from 2019_EMDHS were used for analysis. Incomplete dataset and variables of no interest were excluded.

3.8 Ethical Considerations

Publicly available EDHSs data was used for this study. Ethical approval of EDHS was obtained from the ICF (International Classification of Functioning, Disability and Health, known as ICF) Institutional Review Board (IRB), Ethiopia Health and Nutrition Research Institute Review Board, and the Ministry of Science and Technology. For this particular study, a brief description of the protocol was submitted to the MEASURE DHS program to access and analyze the data. During EDHS data collection, informed consent was taken from each participant, and all identifiers are removed and the confidentiality of the information was maintained.

3.9 Methods of Analysis

3.9.1 Spatial Analysis

The famous Newtonian formula, (m_1m_2 /d^2, where m_1 and m_2 are measures of mass at sites 1 and 2 respectively, and d is the distance separating the masses at those sites), was the foundation stone for spatial statistics. Modified by spatial theorists, this physical law has been used to great advantage to study and to predict a wide variety of human spatial interactions, such as transportation movements, the spread of information, potential for economic growth and the distribution of health events like undernutrition (Hatfield, 2018).

The field of spatial statistics is based on the assumption that nearby georeferenced units are associated in some way. The precursors of current spatial statistical researchers include those who sought to describe areal distributions, the nature of spatial interactions, and the complexities of spatial correlation. Spatial statistics can be considered a distinct area of research. Traditional statistical theory bases its models on assumed independent observations. Although common sense tells us that in most real-world situations independence among observations on a single variable is more the exception than the rule, independence is still a suitable benchmark from which to identify statistically significant non-independent phenomena. The field of spatial statistics is based on the non-independence of observations; that is, the research is based on the assumption that nearby units are in some way associated (Tobler, 1961).

Spatial autocorrelation hence may be defined as the relationship among values of a single variable that comes from the geographic arrangement of the areas in which these values occur. It measures the similarity of objects within an area; the degree to which a spatial phenomenon is correlated to itself in space (Getis, 2008), the level of interdependence between the variables, the nature and strength of the interdependence, i.e. spatial autocorrelation is an assessment of the correlation of a variable in reference to spatial location of the variable. Spatial autocorrelation is used to test whether the observed value of a variable at one locality is independent of values of the variable at neighboring localities. It may be classified as either positive or negative: Positive if similar values appear together, or negative if dissimilar values appear in close association. When no statistically significant spatial autocorrelation exists, the pattern of spatial distribution is considered random. Spatial autocorrelation requires measuring a spatial weights matrix that reflects the intensity of the geographic relationship between observations in a neighborhood, e.g., the distances between neighbors, the lengths of shared border, or whether they fall into a specified directional class such as “West.” Classical spatial autocorrelation compares the spatial weights to the covariance relationship at pairs of locations (Anselin, 2003).

Spatial autocorrelation statistics such as global Moran’s *I* and Geary’s C estimates the overall degree of spatial autocorrelation for a dataset. The possibility of spatial heterogeneity suggests that the estimated degree of autocorrelation may vary significantly across geographic space. Local spatial autocorrelation statistics provide estimates disaggregated to the level of the spatial analysis units, allowing assessment of the dependency relationships across space. *G*etis and Ord statistics compare neighborhoods to a global average and identify local regions of strong autocorrelation. Global spatial autocorrelation statistics such as the global Moran's *I* and Geary’s *C* describe the overall spatial dependence of malnutrition (undernutrition) over the entire region, local spatial autocorrelation statistics such as the local Moran's *I* (Anselin, 1995) and Getis and Ord Gi* (Ord & Getis, 1992) are useful in identifying local patterns or hot spots.

Persons, time and place are the basic elements of epidemiologic investigations. Historically, however, the focus of epidemiologic research has been on persons and time with little regard for the implications of place or space even though disease mapping have been done over hundred years. The development of geographic information systems (GIS) over the last 20 years has provided a more powerful and rapid ability to examine spatial patterns and processes. This, in turn, has fostered the discussion of such policy issues as health services and planning (Meade, 1986), as well as the use of GISs for epidemiologic investigations and disease surveillance.

The logic of using geography to study disease or health care is derived from the appreciation of factors causing non-uniformity disease (health issues like undernutrition) distributions (Meade, 1986). These factors include physical and environmental factors such as social, economic, cultural, and genetic factors. For example, disease may be associated with environmental pollution, linked to individual or group behaviours, or associated with genetic predisposition. In turn, all of these factors may have spatial distribution influencing the extent and intensity of a particular disease or health issues like undernutrition.

Nearby locations are likely to possess similar attributes, or in other words, everything is related to everything else and near things are more related than distant things (Murphy, 2018). These features of spatial data creates needs for special analytic techniques so called spatial data analysis and have become familiar methods to be considered every time a project involving geography (i.e., location) is attempted. Exploratory spatial data analysis is an approach consisting of a variety of statistical techniques intended to describe and visualize spatial distributions, identify atypical locations or spatial outliers and discover patterns of spatial association, cluster or hot spot (Paul Longley and Carolina Tobón & Department, 2014).

3.9.2 Spatial autocorrelation

Spatial autocorrelation is quantified in spatial analysis through the use of spatial statistics. Spatial statistics are used to detect patterns of spatial autocorrelation that represent areas of either high or low disease (i.e., undernutrition) risk (Diggle, 2005). These patterns, which often represent areas of significant existence or nonexistence of diseases (i.e, undernutrition), are referred to as clusters. Many spatial statistics that detect the clusters also describe cluster morphology which can be the geographic size.

Deeply rooted in the notion that geographic location matters, one testable assumption is that near things are more related than distant things- a concept often referred to as Tobler's first laws of geography: "Everything is related to everything else, but closer things are more so". Cluster detection within a spatial analysis can be undertaken using a variety of spatial statistical tests, many of which characterized as global or local, where both global and local statistics are used to identify areas of clustering in studies that do not have a predetermined hypothesis about where clusters may be located.

The common principle of different test statistics for spatial autocorrelation is based on the comparison of the value of statistic for a particular dataset to its distribution under the null hypothesis of "H0: no spatial autocorrelation". Such a null hypothesis implies that space does not matter, or in other words, that the assignment of values to particular location is irrelevant. Hence, it is only the values that provide information to the analyst, and "where" they occur does not add any insight. In contrast, under the alternative hypothesis of spatial autocorrelation (Ha: spatial dependence, spatial association), the interest focuses on instances where large values are systematically surrounded by other large values, or where small values are surrounded by other small values (referred to as positive autocorrelation) or where large values are surrounded by small values and vice versa (which is called negative spatial autocorrelation) (Cressie, 1992).

3.9.3 Spatial Weights and Neighborhoods

Spatial autocorrelation measures require a weight matrix that defines a local neighborhood around each geographical area or unit. The value at each areal unit is compared with the weighted average value of it neighborhood. This weight matrix is a square symmetric (RxR) matrix with $(i,j)^{th}$ element equal to "1" (one) if regions i and j are neighbors of one another (or more generally, are spatially related), and "0" (zero) otherwise. The formula for each weight is:

$$Wij = \frac{cij}{\sum_i^N cij}, \quad \text{with } C_{ij} = \begin{cases} 1, if\ i\ and\ j\ are\ linked, and \\ 0,\ otherwise\ (i\ and\ j\ not\ linked\ ) \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

For defining the local neighborhood, we can use the most common method, called the contiguity weight files, which has three subclassifications: Rook, Bishop and their combinations (i.e., Queen Contiguity).

Rook contiguity (so called after the movement of the chess piece): two regions are neighbors if they share (part of) a common border (on any side).

Bishop Contiguity: two regions are spatial neignbors if they meet "at a point". This is spatial analog of two elements of a graph meeting at a vertex.

Queen Contiguity: this is the union of Rook and Bishop Contiguity. Two regions are neighbors in this sense if they share any part of a common border, no matter how short.

Pictorially,

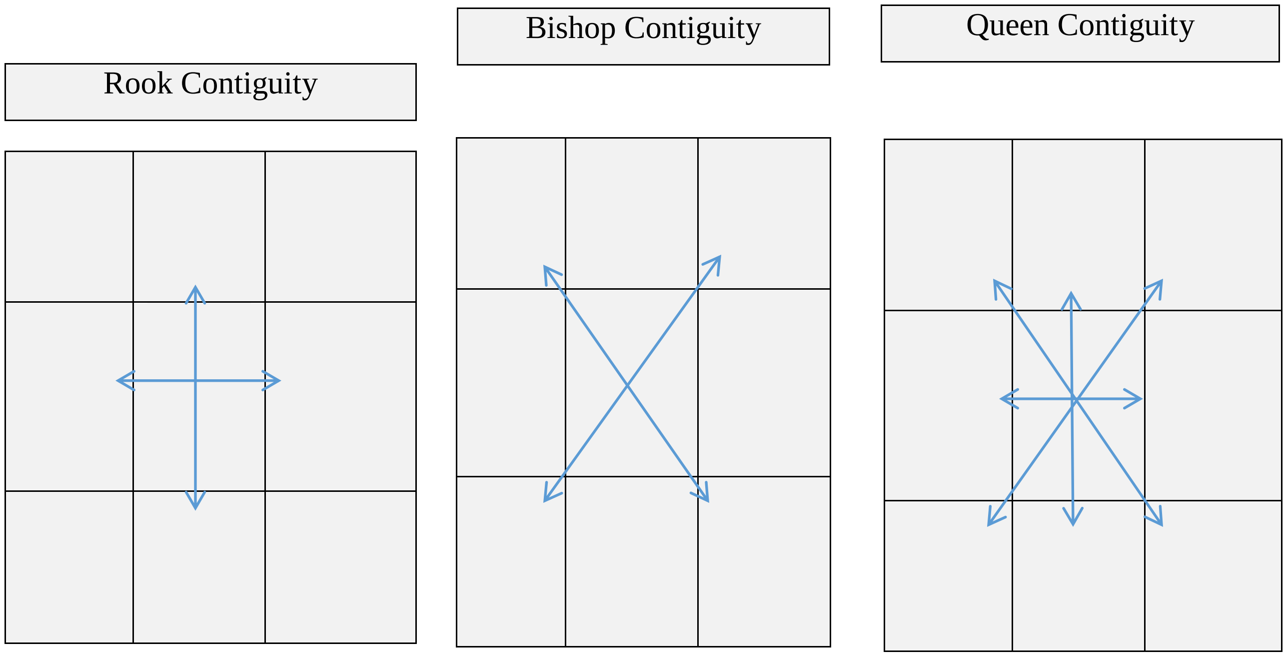

Fig. 2: Contiguity Cases of Representation of Spatial Weight Matrix (TADESSE, 2011) *(adapted), 2019*

3.9.4 Global Measures of Spatial Autocorrelation

The most common techniques for measuring global spatial autocorrelation are Moran's Index statistics (Moran, 1948) and Geary's C statistics (Society & Statistician, 2016). These tests indicate the degree of spatial association as reflected in the dataset as a whole. Moran's Index is based on cross products to measure value association, while Geary's C employs squared differences.

i) Global Moran's I

It provides a single measure of spatial autocorrelation for an attribute in a region as a whole. Formally, Moran's I for N units of a variable y are expressed as:

$$\boldsymbol{I} = \left(\frac{\boldsymbol{N}}{\boldsymbol{Wo}}\right)\frac{\sum\sum \boldsymbol{Wij}(\boldsymbol{yi}-\bar{\boldsymbol{y}})(\boldsymbol{yi}-\bar{\boldsymbol{y}})}{\sum(\boldsymbol{yi}-\bar{\boldsymbol{y}})\boldsymbol{2}} \quad \ldots\ldots\ldots\ldots (2)$$

Where I is Moran's I statistics, N is the total number of units (regions), y is the observed values of attributes (i.e.; undernutrition cases) at each location (region), W is the weight matrix (connectivity) which contains information of the location, and Wo is the normalizing factor equal to the sum of the elements of the weight matrix (Wo=$\sum\sum Wij, i \neq j$).

Under the normal and randomization assumptions, the resulting standardized-values are compared to a table of standard normal critical values to assess the spatial dependence. The null hypothesis (no spatial autocorrelation) will be rejected if the calculated value of $|Z_I| \geq Z\alpha/2$, where

$$Z_{(I)}=\frac{I-E(I)}{\sqrt{Var(I)}} \text{---}(3)$$

$$E(I)_N=\frac{-1}{N-1}=E(I)_R \text{---}(4)$$

The variance of the Moran's varies depending on the assumption of normality and randomization. Under normality assumption:

$$Var(I)_{N=}\ \frac{N^2(N-1)W_1-N(N-1)W_2-2W_0^2}{(N+1)(N-1)W_0^2} \text{---}(5)$$

Where,

$W_0=\sum_{i\neq j}^{N} Wij$; $W_1=\sum(Wij-Wji)^2$; $W_2=\sum_{k=1}^{N}(\sum_{j=1}^{N} Wkj-\sum_{i=1}^{N} Wik)^2$, and $k=\frac{\sum_{i=1}^{N}(yi-\bar{y})4}{\sum_{j=1}^{N}((yi-\bar{y})2)2}$

And with randomization assumption:

$$Var(I)R=\frac{N(W1(N2-3N-3)-NW2+3Wo)2}{(N-1)(N-2)(N-3)Wo2}-\frac{K(W1(N2-N)-2NW2+6Wo)2}{(N-1)(N-2)(N-3)Wo2}-\left(\frac{1}{n-1}\right)2 \text{---------------------}(6)$$

ii) Global Geary's C

Geary's C statistics is given by taking cross product of deviation of each location from its neighbor rather than from its average value. Algebraically according to Geary (1954):

$$C=\left(\frac{N-1}{Wo}\right)\frac{\sum_i\sum_j Wij(yi-yj)2}{\sum_i(yi-\bar{y})2} \text{---}(7)$$

Like Global Moran's Index, the standardized values of the observations will be calculated and the null hypothesis of no spatial autocorrelation will be rejected if:

$/Z_c/\geq Z\alpha_{/2}$, where:

$$\boldsymbol{Z_{(c)}=\frac{C-E(C)}{\sqrt{Var(C)}}} \text{---}(8)$$

$$E(C)_N=E(C)_N=1 \text{---}(9)$$

The variance of Geary's C also varies with the assumptions of normality and randomization:

$$Var(c)N=\frac{(2W1+W2)(N-1)-4Wo2}{2(N+1)Wo} \text{---}(10)$$

And

Var(c)R=$\frac{W1(N-1)(N2-3N+3-K(N-1))}{Wo(N(N-2))(N-3)}+\frac{(N2-3-K(N-1)2)}{N(N-2)(N-3)}-\frac{(N-1)W2(N2+3N-6-K(N2-N+2))}{4N(N-2)(N-3)Wo2}$------(11)

A values of Moran's I that is larger than its theoretical mean of -1/(N-1) or equivalently, a positive Z-value, points to positive spatial autocorrelation. In contrast, for Geary's C, positive spatial autocorrelation is indicated by a value smaller than its mean of 1, or by a negative Z-value.

iii) Moran Scatter Plot

The Moran Scatter plot enables us to visualize the linear correlation between Y and WY. Specifically, WY is plotted against Y and the Moran's I coefficient will be the slope of the regression curve (Anselin, 1998). In additions to this, inspection of global and local spatial instability is carried out by the means of the Moran scatter plot (Anselin, 1996), which plots the spatial lag, WY, against the original values Y. The four different quadrants of the scatter plot correspond to the four types of local spatial association between a region and its neighbors: the first quadrant, (HH) a region with a high value surrounded by regions with high values (top on the right), the second, (LH) a region a with low value surrounded by regions with high values (top on the left),the third (LL) a region with a low value surrounded by regions with low values (bottom on the left) and the last (HL) a region with a high value surrounded by regions with low values (bottom on the right) as shown in the following figure 3 below. The first and the third quadrants refer to positive spatial autocorrelation indicating spatial clustering of similar values whereas the second and the forth quadrants represent negative spatial autocorrelation indicating spatial clustering of dissimilar values. The Moran scatter plot may thus be used to visualize typical localizations, i.e. regions in quadrant two or in the quadrant four.

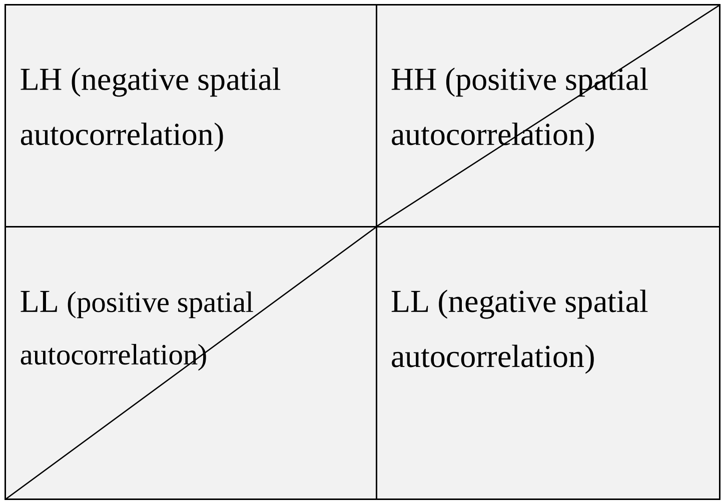

Fig. 3: Moran's I Scatter Plot (Author's own drawing), 2019

3.9.5 Local Measures of Spatial Autocorrelation

In order to observe if there is a local spatial cluster of high or low values, and identify the regions that contribute the most to the clustering (spatial autocorrelation), measures of local spatial autocorrelation such as local Getis and Ord statistics and the local indicator of spatial association are used. Indicators of global spatial autocorrelation (Moran's I or Geary's C) can identify whether or not clustering is occurring. However, they cannot specify the location of clusters or how spatial dependencies vary from one place to another. Local spatial statistics are used to quantify clustering within smaller areas of a large study area, and in many instances, can be seen as smaller partitions of the global spatial statistical analysis (A. Stewart Fotheringham Chris Brunsdon Martin Charlton, 2002).

More generally, Local Indicator of Spatial Autocorrelation (LISA) shows statistically significant groupings of neighbors with high and low values around each region in the study area and, therefore, the aim of using this LISA is to identify 'hot spots' or 'cold spots' (Anselin, 1995). For this study, Local Moran's I and Local Ord and Getis G* statistics will be used for identification of clusters (hot spots) at local level.

i. Local Moran's I

Local Moran's I for each observation measures the extent of significant spatial clustering of similar values around that observation, and algebraically is given as:

$$Ii = \frac{\sum Wij(yi-\bar{y})\,(yj-\bar{y})}{(yi-\bar{y})2},\ \ or\ Ii = Zi\sum WijZj ---------------(12)$$

Zi and Zj are standardized values of attributes (i.e., undernutrition cases) for units 'i' and 'j', where 'j' is among the identified neighbors of 'i' according to the weight matrix and all other notations are as in (2-6).

Analogous to the Global counterpart, the null hypothesis which states 'Ho: no spatial clustering' will be rejected if $/Z_{Ii}/\geq Z\alpha/2$, where:

$$ZIi = \frac{Ii-E(Ii)}{\sqrt{Var(Ii)}} \text{------------------------------------} (13)$$

$$E(Ii) = \frac{\sum_j Wij}{N-1} \text{------------------------------------} (14)$$

$$Var(Ii) = \frac{Wi(N-b2)}{N-1} + \frac{2Wj(2b2-N)}{(N-1)(N-2)} + \frac{Wi2}{(N-1)2} \text{------------------------} (15)$$

b2=M4/M_2^2, $M4 = \frac{\sum_i yi4}{N}, M2\frac{\sum_j yj2}{N};$

$Wi = \sum_{i\neq j}^{N} Wij2$ and $Wj = \sum_{h\neq i}^{N}\sum_{k\neq i}^{N} WikWih$

N.B: The subscript 'i' and 'j' above shows the locations (places) that are used in the computation, and all other notations are the same as in (2-6). The interpretation for the local Moran's I is the same as that of its global counterpart.

In addition to the identification of local spatial clustering, the correspondence between local indicator of spatial association statistics and global spatial autocorrelation measures carries significant additional advantage in decomposing these global measures. Through the estimation of local Moran's I scatter plot, we can identify which observations are consistent with the global pattern of positive or negative spatial autocorrelation and which observations run counter to this global pattern (Anselin, 1992).

ii. Local Ord and Getis G*

The Ord and Getis G* local statistics for measuring spatial autocorrelation (Ord & Getis, 1995) is given as follows:

$$Gi *= \frac{\sum_j Wijyj-(\sum_j Wij+Wii)\bar{y}}{S2x\left[NSi*-\frac{(\sum Wij-Wii)^2}{(N-1)}\right]^{1/2}}$$ -- (16)

The Gi* score ranges from 0 to 1. And**,**

$E(Gi *) = \frac{\sum_{j=1}^{N} W_{ij}}{N}$, and

$Var(Gi *) = \frac{W_i^*(N-E(G_i^*))Y_i^*}{N^2(N-1)Y_k^*}$, where:

$W_i^* = \sum_j W_{ij}$, $Y_i^* = \sum_j Y_j /N$, $Y_k^* = \frac{\sum_{i=1}^{N}\sum_{J=1}^{N}(y_i y_j)^2}{N} - y_i^*$, W_{ij} a weight in case 'i' is in its own neighborhood set, and $\bar{y}$ is the average of the dependent variable (i.e., undernutrition cases), $Si *= \sum_{j=1}^{N}(Wij2 + Wii2$ and S^2 is the sample variance. The formula given in equation (16) shows what portion of the total sum of all values is represented by the values at and near locations 'i'(81**),** (Ord & Getis, 1995).

Positive values of the Gi* statistic indicate that high values are spatially clustered with other high values of the random values. Negative values of Gi* statistic indicate that low values are spatially clustered with other low values of the dependent variable. Note that a consequence of this is that the Gi* statistic, unlike Moran's I, cannot distinguish cases of positive spatial autocorrelation from cases of negative spatial autocorrelation (Getis & Ord, 1992). The contribution of the Gi* statistic, as with other measures of local spatial autocorrelation, is that they aid in identification of local pockets of spatial clustering. Such clustering, moreover, may occur even in the absence of global spatial autocorrelation. Local spatial autocorrelation can exist in the absence of global autocorrelation when the clustering at the local level is limited as a proportion of the overall number of observations or when local patterns are off-setting, producing no global pattern as a consequence (Getis & Ord, 1992). The table below will show a brief comparison of all of the spatial autocorrelation measures dealt above.

Table 3: Summaries and comparison of the four spatial autocorrelation measures described above in terms of their type (global or local), the spatial pattern aspect they measure, their respective value ranges, and the corresponding values' interpretation (Dizon, 2020).

Measure	**Type**	**What is Measured**	**Range**	**Interpretation**
Global Moran's I	Global	Spatial clustering (or dispersion) of a spatial variable for the whole set of area units	-∞ to +∞	Negative values suggest spatial clustering; positive values suggest spatial dispersion
Geary's C			0 to +∞	Values below 1 suggest spatial dispersion; value above 1 suggest spatial clustering
Local Moran's I	Local	Spatial clustering (or dispersion) of a spatial variable for an area unit's neighborhood	-∞ to +∞	Negative values suggest spatial clustering; positive values suggest spatial dispersion
Getis-Ord Gi*		Presence and type (hotspot or cold spot) of spatial clustering of a spatial variable for an area unit's neighborhood	-∞ to +∞	Negative values suggest presence of a cold spot; positive values suggest presence of a hotspot

3.10 Multilevel Logistic Regression Model

In multilevel study, the structure of data in the population is hierarchical, and a sample from such a population can be viewed as a multistage sample. A multilevel model applies to grouped data with two or more hierarchical levels. Multilevel is associated with a nested data structure. The variables in the model can be found at any level of the hierarchy. A hierarchy is a structure of units or individuals grouped in two or more different levels (Hrițcu, 2015).

Many types of data have a hierarchical or nested structure. This hierarchical structure of the society generates a correlation between individuals within the same group. Individuals are influenced by the group they belong to and, in turn, social groups are themselves influenced by the individuals in the group (Harvey Goldstein, n.d.).

The dataset taken for this study was from EDHS 2019. These data are hierarchical structure and surveys are obtained from nested sampling in heterogeneous subgroups or a sampling method was multistage stratified cluster sampling. For multistage clustered samples, the dependence among observations often comes from several levels of the hierarchy. The problem of dependencies between individual observations also occurs in survey research, where the sample is not taken randomly but cluster sampling from geographical areas is used instead. In this case, the use of single-level statistical models is no longer valid and reasonable. Hence, in order to draw appropriate inferences and conclusions from multistage stratified clustered survey data we may require modeling techniques like multilevel modeling.

3.10.1 Two-Level Model

Multilevel models for categorical data that accommodate multiple random effects and allow for a general form for model covariates (Leeuw & Meijer, 2008). A multilevel logistic regression model can account for lack of independence across levels of nested data (i.e., individuals (under five children) nested within regions). Conventional logistic regression assumes that all experimental units are independent in the sense that any variable which affects nutrition status among underfive children has the same effect in all regions, but multilevel models are used to assess whether the effect of predictors vary from region to region.

In this study, the data are collected across regions. In this setting, the region would denote the "j-unit" and the individual/children would denote the "i-unit". The clustering of the data points within geographical regions offers a natural 2-level hierarchical structure of the data, i.e. women are nested within regions. Within each level-2 unit there are n_j women in the j^{th} region. The response variable y_{ij} be the values of dichotomous outcome variable (i.e having undernutrition status), coded '0' as nourished and '1' as undernourished, associated with level-one unit i nested within level two unit j. in other way:

$$y_{ij}=\begin{cases} 1, \text{if the ith children had udernutrition in jth region;} \\ \qquad\qquad 0, \text{if otherwise.} \end{cases} \qquad \text{.......} (17)$$

Also let p_{ij} be the probability that the response variable equals 1, and $p_{ij} = p(y_{ij} = 1)$,is the probability of having undernutrition for children i in region j, and the probability that the response variable equals 0,1 - p_{ij}=p (y_{ij} = 0) ,is the probability of not having undernutrition for children i in region j . Here, y_{ij} follows a Bernoulli distribution. Like the logistic regression p_{ij} is modeled using the logit link function. The two-level logistic regression model can be written as:

$p_{ij} = \log(p_{ij}/1-p_{ij}) = \beta_0 + \beta x_{ij} + u_{0j}$……………………………………………………………(18)

Where, βo and β are unknown regression parameters (coefficients), x_{ij} is covariates or x_{ij} = observation for i^{th} children in j^{th} region, and u_{0j} is the random effect for the j^{th} region (fixed effect). These are assumed to be distributed in the population as $N(0, \sigma_u^2)$. The basic data structure of two level logistic regression is a collection of N groups (units at level-two (regions)) and within group j (*j* = 0, 1, 2,…, *N*) a random sample of n_j level-one units. The outcome variable is dichotomous and denoted by y_{ij} (i = 1, 2… n_j, j = 0, 1, 2,…,N). For level-one unit i nested in level-two group j. The outcome is coded as 0 and 1: 0 for "not having undernutrition", 1 for "having undernutrition", respectively. If one does not take explanatory variables into account, the probability of success is assumed constant in each group.

Let the success probability in group j be denoted by p_j. The dichotomous outcome variable for the individual i in group j, y_{ij}; which is either 0 or 1 can be expressed as sum of the probability in group j, p_j (the average proportion of j levels in group j, $E(y_{ij}) = p_j$) plus some individual dependent residual ε_{ij} , that is, $y_{ij} = p_j + \varepsilon_{ij}$,the residual term is assumed to have mean zero and variance, $var(\varepsilon_{ij}) = p_j (1 - p_j)$. Since the outcome variable is coded 0 and 1, the group sample average is the proportion of successes in group j given by: $\hat{p}_j = \frac{1}{nj}\sum_{i=1}^{nj} yij$, the proportion of children having undernutrition in region j, $\hat{p}j$ is an estimate for the group-dependent probability p_j. Similarly, the overall sample average is the overall proportion of successes, $\hat{p}$ and is given by: $\hat{p} = \frac{1}{M} \sum_{j=0}^{\mathbf{n}} \sum_{i=1}^{\mathbf{nj}} yij$, the overall proportion of children having undernutrition, where, total sample size: $M = \sum_{j=0}^{n} nj$. This is an estimate for the overall probability of success, p (Snijders and Bosker, 2003).

3. 10.2 Testing Heterogeneous Proportions

For the proper application of multilevel analysis, the first logical step is to check where there is heterogeneity proportion of undernutrition between regions in Ethiopia before going to multilevel analysis. The most commonly used test statistic to check for heterogeneity of proportions between groups is the Chi-square (Snijders and Bosker, 2003).To test whether there are indeed systematic differences between the groups, the well-known Chi-square test can be used. The test statistic of the Chi-squared test for contingency table is often given in familiar form. The test statistic of the Chi-squared test for a contingency table is often given in the familiar form:

$$\chi^2 = \sum_{k=1}^{n} \frac{(O_k - E_k)2}{E_k} \qquad (19)$$

Where O is the observed and E is the expected counts in the cell of contingency table. It can also be written as:

$$\chi^2 = \sum_{j=0}^{n} (nj((\hat{p}j - \hat{p}.)2/\hat{p}.(1 - \hat{p}.)) \sim \chi^2_{(N-1)} \qquad (20)$$

The decision will be based on the Chi-square distribution with (N -1) degrees of freedom. This Chi-square distribution is an approximation valid if the expected number of success and of failures in each group, ($n_j\hat{p}_j$) and ($n_j(1 - \hat{p}_j)$), respectively, all are at least 1 while 80 percent of them are at least 5 (Agresti, 2019).

3. 10.3 Estimation of between and within group Variance

The theoretical (true) variance between the group dependent probabilities (Snijders and Bosker, 2003) ,i.e., the population value of $Var(P_j)$, can be estimated by:

$$\tau^2 = S^2_{between} - \frac{S^2_{withi}}{\tilde{n}} \ldots\ldots (21)$$

where, $\tilde{n} = 1/(N1\text{-}1)(M - \sum_{j=1}^{n} n^2_{j/M})$

For dichotomous outcome variables, the observed between-groups variance is closely related to the Chi-squared test statistic. They are connected by the formula:

$$S^2_{between} = \frac{\hat{p}.(1-\hat{p}.)}{\tilde{n}(N-1)} \ldots\ldots (22)$$

And the within-group variance in the dichotomous case is a function of the group averages is given by:

$$S^2_{withi} = \frac{1}{M-N} \sum_{j=0}^{N} nj\hat{p}j(1\text{-}\hat{p}j) \ldots\ldots (23)$$

3. 10.4 The Empty Model

The empty two-level model for a dichotomous outcome variable refers to a population of groups (level-two units, i.e. regions) and specifies the probability distribution for group dependent probabilities p_j in $y_{ij} = p_j + \varepsilon_{ij}$ without taking further explanatory variables into account. We focus on the model that specifies the transformed probabilities $f(p_j)$ to have a normal distribution. This model only contains random groups and random variation within groups. It can be expressed with logit link function as follows:

$$\text{Logit}(p_j) = \beta_0 + u_{0j} \ldots\ldots (24)$$

$u_{0j} \sim IID(0, \sigma_0^2)$, where, β_0 is the population average of the transformed probabilities, and u_{0j} is the random deviation from this average for group j. This model does not include a separate parameter for the level-one variance (Snijders and Bosker, 2003). This is because the level-one residual variance of the dichotomous outcome variable follows directly from the success probability, as indicated by equation var $(\varepsilon_{ij}) = p_j(1 - p_j)$. The probability corresponding to the average value β_0 denoted by π_0 is defined by $f(\pi_0) = \beta_0$. For the logit function, the so-called logistic transformation of β_0 is defined by:

$$\pi_0 = \text{logit}(\beta_0) = \frac{\exp(\beta 0)}{1+\exp(\beta 0)} \ldots\ldots (25)$$

Note that due to the non-linear nature of the logit link function, there is no simple relation between the variance of probabilities and the variances of the deviations u_{0j} (Snijders and Bosker, 2003). According to Snijders and Bosker (Snijders and Bosker, 2003) there is an approximate formula, however, valid when the variances are small. However, there is an approximate formula which is valid when the variances are small given by:

$var\ (p_0) = (\pi_0(1 - \pi_0))^2\sigma_0^2$

The null model also serves as a "baseline model" for purposes of comparison with more complex Models. Note that a model is "conditional" by the presence of predictors at level 1 or level-2. Since a researcher almost always employs predictor variables and is not simply interested in the null model, most mixed models are conditional.

3. 10.5 The Random Intercept multilevel Binary Logistic Regression Model

With grouped data, a regression that includes indicators for groups is called a varying intercept model because it can be interpreted as a model with a different intercept within each group (ANDREW GELMAN, 2007). In the random intercept logistic regression model, the intercept is the only random effect meaning that the groups differ with respect to the average value of the response variable (distribution of undernutrition). A assume that X is predictors data matrix denoted by: X_h, (h = 1, 2, 3,…,k) these variables are denoted by their values indicated by X_{hij} (Snijders and Bosker, 2003). Some or all of those variables could be level one variables, the success probability is not necessarily the same for all individual in a given group (region). It represents the heterogeneity between groups in the overall response. The logistic random intercept model expresses the log-odds, i.e. the logit of p_{ij}, as a sum of a linear function of the explanatory variables and a random group-dependent deviation u_{0j}. That is:

$$\text{Logit}(p_{ij})=\log\left(\frac{pij}{1-pij}\right)= \beta_{0j} + \beta_1x_{1ij} + \beta_2x_{2ij} + \ldots + \beta_kx_{kij}$$

$$\text{logit}(p_{ij})=\log\left(\frac{pij}{1-pij}\right)= \beta_{0j} + \sum_{h=1}^{\mathbf{n}} \beta hxhij \ldots\ldots(26)$$

Where the intercept term β_{oj} is assumed to vary randomly and is given by the sum of an average intercept β_o and group-dependent deviations u_{oj}. That is $\beta_0 = \beta_0 + u_{0j}$. As a result we can show that:

$$\text{Logit }(p_{ij})=\log\left(\frac{pij}{1-pij}\right)= \beta_0 + \sum_{h=1}^{\mathbf{n}} \beta hxhij + u0j \ldots\ldots(27)$$

$u_{0j} \sim IID(0, \sigma_0^2)$

And to solve for p_{ij} which is : $p_{ij} = \frac{e^{\beta 0 + \sum_{h=1}^{n} \beta hxhij + u0j}}{1+e^{\beta 0 + \sum_{h=1}^{n} \beta hxhij + u0j}}$, where β_o (average intercept) is the log-odds that y = 1 when x = 0 and u = 0, β_h is the effect on log-odds of dependent variable in same group or β_h is a unit difference between the X_h values of two individuals in the same group is associated with a difference of β_h in their log-odds (same value of u), exp(β_h) is an odds ratio, comparing odds for individuals in the same group. u_{oj} is the effect of being in group j on the log-odds that $y = 1$ also known as a level 2 residual, σ_0^2 is the level 2 (residual) variance, or the between-group variance in the log-odds that $y = 1$ after accounting for X. Note that the first part of the left-hand side of (equation 27), incorporating the regression coefficients, $\beta_0 + \sum_{h=1}^{n} \beta hxhij$ is the fixed part of the model, because the coefficients are fixed. The remaining part, u_{oj}, is called the random part of the model. The region intercepts measure the differences between the regions, controlling for other effects in the model. Equation (27) is a mixed model because it has both fixed effects and random effects. It is a logistic mixed model, because the link function is logit, and thus, a member of the family of generalized linear mixed models.

3. 10.6 Random Slope multilevel Binary Logistic Regression Model

This is used to assess whether the slope of any of the explanatory variables has a significant variance component between the groups. So far, we have allowed the probability of undernutrition to vary across regions, but we have assumed that the effects of the explanatory variables are the same for each region. We will now modify this assumption by allowing the difference between explanatory variables within a region to vary across regions. To allow for this effect, we will need to introduce a random coefficient for those explanatory variables. So, a random coefficient model represents heterogeneity in relationship between the response and explanatory variables. The intercepts β_{oj} as well as the regression coefficients, or slopes, β_{1j} are group (region) dependent. These group dependent coefficients can be split into an average coefficient and the group dependent deviation. Suppose that there are k level-one explanatory variables X_1, $X_2 \ldots$, X_k and consider the model where all predictor variables have varying slopes and random intercept. That is:

$\beta_0 = \beta_0 + u_{0j}$, $\beta_{1j} = \beta_1 + u_{1j}$ . . . , $\beta_{hj} = \beta h + u_{hj}$, where h = 1, 2,…,k

Thus, by substituting in equation (25) then, logit(p_{ij}) is given as:

$$\text{Logit}(p_{ij}) = \log\left(\frac{pij}{1-pij}\right) = \beta_0 + \sum_{h=1}^{n} \beta hxhij + u0j + \sum_{h=1}^{n} u_{hj}x_{hij}$$

Now, we have $\beta_0 + \sum_{h=1}^{n} \beta hxhij$ is called the fixed part of the model, and $u_{0j} + \sum_{h=1}^{n} \beta hxhij$ called the random part of the model. u_{0j}, u_{1j}, , u_{hj} are random effects at group level, the random intercept u_{0j} and the random slope u_{1j}, , u_{hj} are assumed to be independent between groups but may be correlated within groups. So the components of the vector u_{0j}, u_{1j} , u_{hj} are independently distributed as a multivariate normal distribution with zero mean vector and variances and co-variances Ω given by (u_{0j}, u_{1j}, , u_{hj} ~MVN(0,Ω)):

$$\Omega = \begin{pmatrix} \sigma_0^2 & \sigma_{01} \cdots & \sigma_{k0} \\ \sigma_{01} & \sigma_1^2 \ldots & \sigma_{0k} \\ \vdots & & \\ \sigma_{0k} & \cdots & \sigma_k^2 \end{pmatrix}$$

3. 10.7 Intra-class Correlation Coefficient (ICC)

In this study, we want to estimate the proportion of variability in the chance of having undernutrition rather than not having undernutrition that lies between regions. To do so, we need to run an empty model, that is, a model containing no predictors (also referred to as an "unconditional mean model"), and calculate the intra-class correlation coefficient. The intra-class correlation coefficient (ICC) measures the proportion of variance in the outcome explained by the grouping structure. This ICC is an indication of the correlation of the children having early undernutrition belonging to the same region, i.e. it is an indication of the dependency of the undernutrition among children within the regions. The ICC is defined as the variance between regions divided by the total variance, where the total variance is defined as the summation of the variance between regions and the variance within regions (Goldstein, 2011). Below is the formula of the Intra-class Correlation Coefficient:

$$\text{ICC} = \frac{Var(uoj)}{var(uoj)+var(eij)} = \frac{\sigma_0^2}{\sigma_{uo+\ \pi^{2/3}}^2} \qquad (28)$$

Where var (u_{oj}) is the random intercept variance, that is, the level-2 variance component: The higher var(u_{oj}), the larger the variation of the average log-odds between clusters; var(e_{ij}) is variance of individual (lower) level units. Since the logistic distribution for the level one residual variance implies a variance of: $\pi^{2/3}$ = 3.29 (Snijders and Bosker, 2003). And this formula can be

$$\text{ICC} = \frac{\sigma_0^2}{\sigma_{uo+\ 3.29}^2}$$

The ICC quantifies the degree of homogeneity of the outcome within clusters. The ICC represents the proportion of the between-cluster variation var(u_{oj}) (in this study: the between-region variation of the chances of having undernutrition) in the total variation (in this study: the between- plus the within-region variation of the chances of having undernutrition). The ICC may range from 0 to 1. ICC = 0 indicates perfect independence of residuals. The observations do not depend on cluster membership. The chance of having undernutrition does not differ from one region to another (there is no between-regional variation). When the ICC is not different from zero or negligible, one could consider running traditional one level regression analysis (ANDREW GELMAN, 2007). However, ICC = 1 indicates perfect interdependence of residuals: The observations only vary between clusters. In a given region, either everyone or nobody have undernutrition (there is no within-regional variation).

3. 10.8 Parameter estimation

3. 10.8.1 Maximum Likelihood Estimation via Quadrature

The most common methods for estimating the parameter of multilevel logistic models are Marginal Quasi-Likelihood (Rasbash, 1996), Penalized Quasi-Likelihood (Clayton, 2007) are the two prevailing approximation procedures. The numerical integrations approach and Laplace approximation seem to produce statistically more satisfactory estimates than marginal quasi-likelihood (MQL) and Penalized Quasi-Likelihood (PQL) approaches. After applying these quasi-likelihood methods, the model is then estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) (Goldstein, 2011).

Random intercept and random coefficient multilevel logistic model belongs to the class of Hierarchical Generalized Linear Models (Goldstein, 2011). And the likelihood function for random slope multilevel logistic regression model is described as follows. Let the response vector consist of the entire elements y_{ij}. Assuming that the conditional distribution of y_{ij} given the random effect u_j are independent of each other, the conditional density of y_{ij} is given by:

$f_{uij/uj}^{Yij/Uj}$ ~Bernoulli(p_{ij}) ……………………………………………………………….(29)

The expected value of the Bernoulli distribution equals p_{ij}, after applying the specified link function, modeled as a linear function of the covariates. The distributions of the random effects are multivariate normal (u_1, u_2, , u_N ~$N(0, \Omega)$) which are independent draws from multivariate normal distribution. The likelihood approach is used to estimate the fixed and the random parameters of the model by treating the actual random effect 'U' as nuisance parameters, and work with the marginal likelihood function which is given by:

$L(\beta, \Omega) = \int f(Y \mid U;\ \beta) f(U;\ ) dU$ ……………………………………………………………(30)

Where, $f(Y \mid U; \beta)$ is the distributional function for response conditional on the random effect. Here $f(U;)$ is the distribution function for the random effects. For two-level logistic Bernoulli response model, where random effects are assumed to be multivariate normal and independent across units, the marginal likelihood function is given by:

$L(\beta; \Omega) = \prod_j \int \prod i\ (pij)^{yij}(1 - pij)^{1-yij} f(Uj;) d_{U\,j}$……………………………………………….(31)

$pij = 1 + \exp(-Xij\beta j)^{-1},\ \beta j = \beta + Uj$

Where $f(U_j;)$ is typically assumed to be the multivariate normal density and can be written in the form: $\int_{-\infty}^{\infty} p(uj) f(uj) d(uj)$

Gauss-Hermite quadrature approximates an integral such as the above as:

$\int_{-\infty}^{\infty} p(v)\ e^{-v2} d(v) \approx \sum_{q=1}^{Q} P(xq)wq$ ……………………………………………………… (32)

Where $\sum_{q=1}^{Q} P(xq)wq$ is Gauss-Hermite polynomial evaluated at a series of quadrature point indexed by q. this function is then maximized using a suitable search procedure over the parameter space. If we consider the model with single random intercept at level two have:

$p(Uj) = \prod j\ \frac{e^{(xij\beta)+Uj}}{1+e^{(xij+Uj)^2}}$, $f(uj) = \sigma_u^2 \Phi$

Here Φ is the standard normal density. The standard quadrature method selects points centered on zero, but U_j *is* not centered at zero and we may therefore need a very large number of quadrature points to cover the range. A solution is to use adaptive quadrature (Goldstein, 2011). Quadrature methods have been applied successfully to poisson, binomial and multinomial and ordered category models and have been implemented in software packages (SAS and STATA (xtlogit and xtmelogit)). Nevertheless, successful quadrature, even with the adaptive method, will often require a large number of quadrature points and even in simple cases convergence can be difficult to achieve (Clayton, 2007). This becomes especially important when there are several random coefficients since the quadrature points will now be in several dimensions so that the number of points increases geometrically with the number of random coefficients.

3. 10.9 Multilevel Binary Logistic Regression Model Comparison

3. 10.9.1 Deviance Based on Chi-square

The deviance based on Chi-square value for two models is obtained as two times the difference of log-likelihood value of the two models. It is compared with the probability of deviance based on Chi-square, is greater than critical value distributed to Chi-squared at the difference between numbers of parameter in two models degree of freedom. If P-value is less than 5% level of significance, suggesting that multilevel empty model is significant. The basic concept underlying this procedure is to compare the maximum likelihood under an assumed model with that of a baseline model.

Let $\hat{L}_c$ be the maximized likelihood under the current model. This statistic cannot be used on its own to assess the lack of fit of the current model unless compared with a corresponding statistic of an alternative baseline model for the same data. This latter model is taken to be a model that fits the data perfectly. Such a model will have the same number of unknown parameters as there are observations. The model is termed the full or saturated model and the maximized likelihood under it is denoted by $\hat{L}_f$. The saturated model does not condense the information in the bulk of data into a simple summary, as it is not parsimonious. However, the maximum likelihood under this model is an intuitively appealing reference by which a corresponding value of a given model can be compared to assess the adequacy of the given model. Let the statistics D, be defined as:

$$D = -2\log\frac{\hat{L}c}{\hat{L}f} = -2[\log(\hat{L}c) - \log(\hat{L}f)] \quad \ldots\ldots(33)$$

Large values of D are encountered when $\hat{L}c$ is small relative to $\hat{L}f$, indicating that the current model is a poor one. On the other hand, small values of D are obtained when $\hat{L}_c$ is similar to $\hat{L}f$, indicating that the current model is a good one. The statistic D has Chi-square distribution at degree of freedom equals to the difference between the number of parameter in full model and current model therefore, it measures the extent to which the current model deviates from the full model and is termed the deviance.

3.11 Statistical Software

Data management and analysis will be done using SPSS (25.0), STATA, SatScan, ArcGIS 10.7, and R. Each software was used for specific purpose.

CHAPTER FOUR

Results and Discussion

4.1 Results and Discussion

The Composite Index of Anthropometric Failure (CIAF) was used to determine the overall prevalence of undernutrition in children. In assessing the overall magnitude of undernutrition and identifying children with multiple anthropometric failures, CIAF outperforms conventional anthropometric indices (i.e., stunting, underweight, and wasting). The CIAF classification divides children into seven categories: no failure; stunted only; underweight only; wasted only; stunted and underweight; wasted and underweight; wasted, stunted, and underweight. CIAF is a better index for estimating the prevalence of total childhood undernutrition in a population because it excludes children with no anthropometric failure (Schluth et al., 2020). As a result, the CIAF categories and frequencies are listed in table 4.1 below. Therefore, 15.3 %, 3.24 %, and 3.7 % were stunted, underweight, and wasted, respectively. Moreover, 8.96% of children were stunted and underweight only, 2.95 % wasted and underweight only, and 4.1 % stunted, wasted, and underweight. According to the composite index of failure, at about 38.25 % in Ethiopia were diagnosed with undernutrition. That is, total undernutrition (stunted, wasted, or underweight) affects approximately 38.25% of children. (Table 4.1 and Figure 4.1). This result indicates that undernutrition is a very serious public health problem as malnutrition is considered as serious if it is between 20-29% and very high if prevalence ≥ 30% (Zurnila et al., 2019b).

Table 4.1: Categories of the Composite Indicator of Anthropometric Failure (CIAF) (analysed using Svedberg's Classification system), 2019

	CIAF category	Definition	Stunting (HAZ)	Wasting (WHZ)	Underweight (WAZ)	Frequency (%)
A	Nourished	Normal HAZ, WHZ, and WAZ	No	No	No	3396(61.75)
B	Stunted only	HAZ<-2sd, but normal WAZ and WHZ	Yes	No	No	838(15.3)
C	Underweight only	WAZ<-2sd, but normal HAZ and WHZ	No	No	Yes	178(3.24)
D	Wasted only	WHZ<-2sd,but normal HAZ and WAZ	No	Yes	No	201 (3.7)
E	Stunted and underweight	HAZ and WAZ<-2sd,but normal WHZ	Yes	No	Yes	492 (8.96)
F	Wasted and underweight	WHZ and WAZ<-2sd,but normal HAZ	No	Yes	Yes	162(2.95)
G	Wasted, stunted, and underweight	HAZ, WHZ and WAZ<-2sd	Yes	Yes	Yes	226 (4.1)
	Undernourished	B+C+D+E+F+G				2097(38.25)

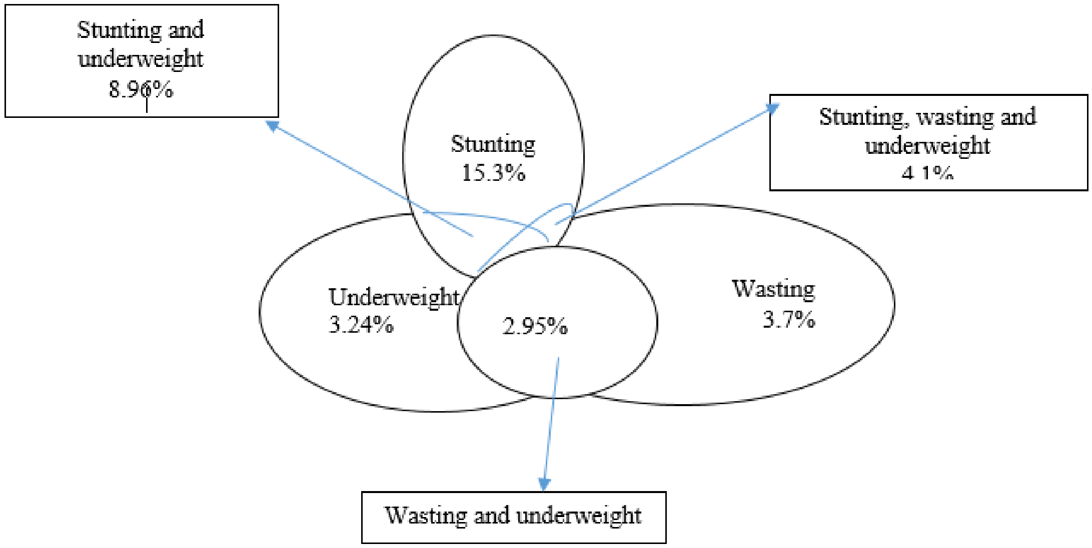

Fig. 4. 1 Percentage distribution of anthropometric indicators, 2019

Table 4.2 shows a cross-tabulation of undernutrition and categorical predictor variables. The proportions of undernourished children in urban and rural areas were 26.5 % and 41.6 %, respectively, based on the newly created nutritional status (binary outcome is recoded from the single composite index of anthropometric indicators). 43.4 % and 24.3 % of the undernourished children in the sample came from the poorest and richest households, respectively. Among undernourished children, 1.6 % does not use additional dietary supplements, and 37.9 percent of mothers had their first child before the age of 20.

Table 4.2 Cross-classification of predictors and nutritional status, 2019

Predictors	**Category**	**Nutritional status**	
		Nourished (%)	**Undernourished (%)**
Place of residence	Urban	73.5	26.5
	Rural	58.4	41.6
Wealth index combined	Poorest	56.6	43.4
	Poorer	57.6	42.4
	Middle	57.8	42.2
	Richer	62.6	37.4
	Richest	75.6	24.3
Dietary diversity	No	98.4	1.6
	Yes	11.1	88.9
Birth order	1^{st}	65.8	34.1
	2-3	63.9	36.1

	4-5	58.9	41.1
	6 and more	58.9	41.1
Multiple birth	Single birth	60.6	39.4
	Multiple	74	26
Sex of child	Male	59.7	40.3
	Female	64	36
ANC visits	No	20.9	79.1
	Yes	71.4	28.6
Place of delivery	Home	62	38
	Health facility	80.3	19.7
Community based health insurance	No	63.1	36.9
	Yes	56.3	43.7
Mother's Age at first birth	Less than 20	62.1	37.9
	20-34	61.3	38.7
	35-49	80	20
Current age of child in months	0-5	81.9	18.1
	6-11	74.8	25.2
	12-23	62.3	37.7
	24-35	53.4	46.6
	36-47	57	43
	48-59	58.1	41.9
Mother's education	No education	56.7	43.3
	Primary	62.8	37.3
	Secondary and higher	73.8	26.2
Source of drinking water	Unimproved source	57.9	42.1
	Improved source	64.5	35.5
Number of household members	1-4	63.6	36.4
	5-9	61.1	38.9
	10 and more	62.1	37.9
Number of children under 5 years in household	1	64.6	35.4
	2	59.2	40.8
	3 and more	62.5	37.5
Husband/partner's education	No education	57.7	37.5
	Primary	65	35
	Secondary and higher	74.1	25.9

4.2 Incremental spatial autocorrelation

Incremental spatial autocorrelation measures autocorrelation for a series of distances increment and optionally creates a line graph of those distances and their corresponding Z-scores. Z-sores reflect the intensity of spatial clustering, and statistically significant peak Z-scores indicate distances where spatial process promoting clustering are most pronounced. A peak in the graph represents the distance at which the clustering is most pronounced. The significance z-score values are indicated by the color of each point on the graph. The result showed that with 10 distance bands beginning at 2.28 km, undernutrition among under five (U5C) children clustered at 2.28 km a significant z-score (7.315036, P-value <0.0001) indicates that clustering of undernutrition among under five (U5C) children was most pronounced at 2.28 Km distance (Fig. 4.2).

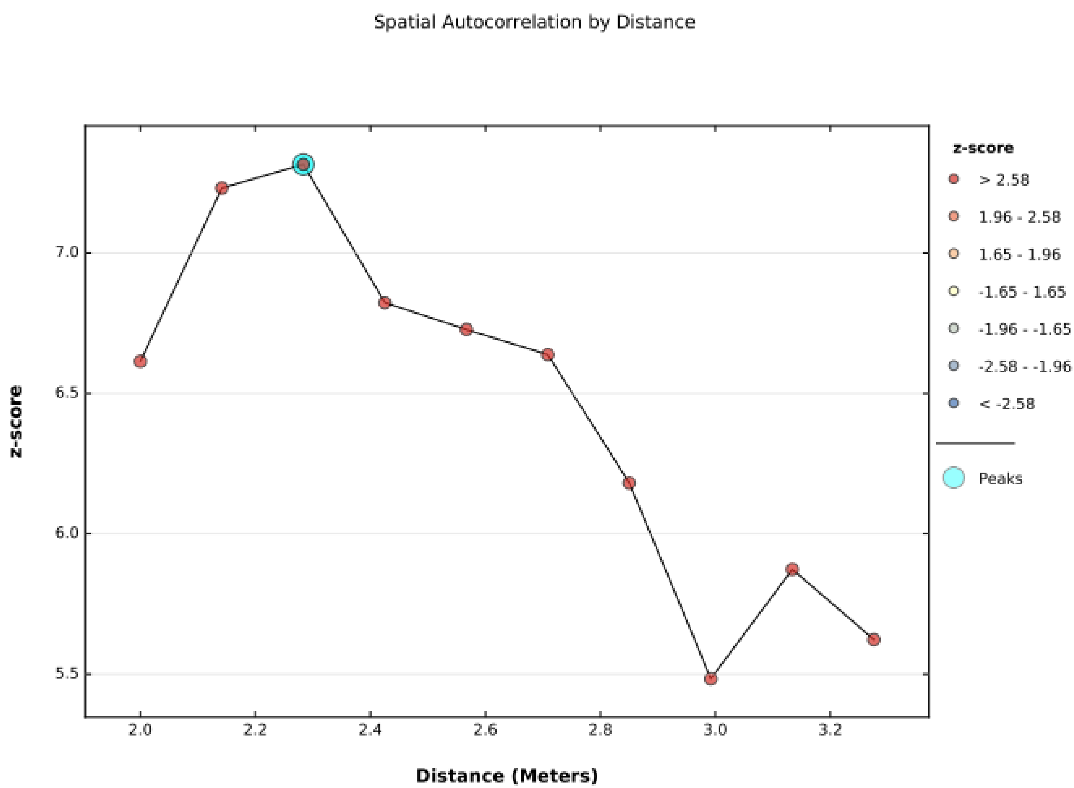

Fig 4.2: Incremental spatial autocorrelation analysis of undernutrition among underfive (U-5) children in Ethiopia,, 2019 EMDHS, 2019

4.3 Spatial distribution of undernutrition among underfive (U5C) children

The spatial distribution of undernutrition among under five (U5C) children in Ethiopia was clustered with Global Moran's I = 0.070888 (z-score = 7.728112, P-value <0.0001). This demonstrated the presence of spatial hotspot and cold spot clustering in Ethiopian regions. With a z-score of 7.728112, there was less than a 1% chance that this high-clustered pattern was due to random chance. The tails' bright red and blue colors indicate a higher level of significance (Fig.4. 3).

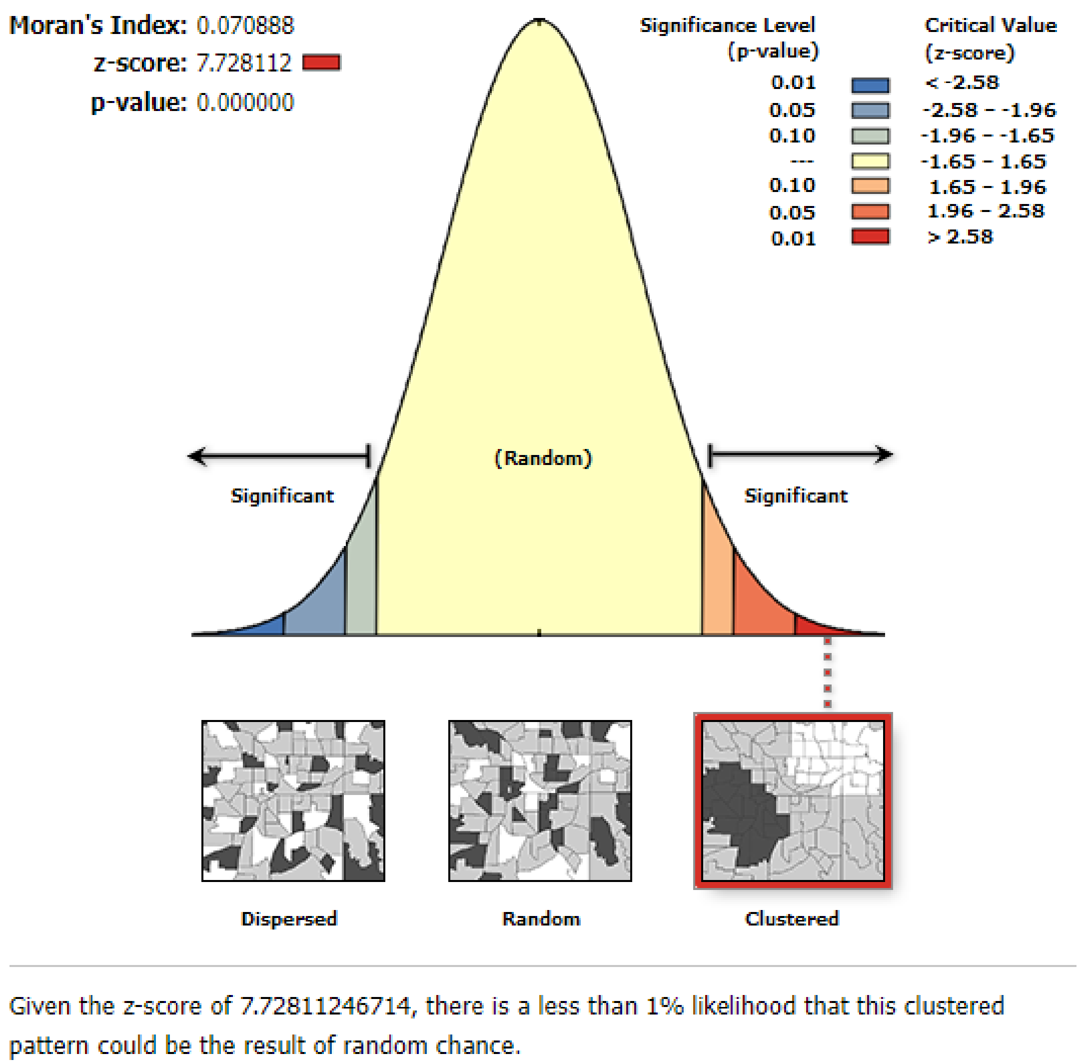

Fig 4.3: Spatial autocorrelation analysis of undernutrition among underfive (U-5) children in Ethiopia, 2019 EMDHS

4.4 Prevalence of undernutrition among underfive (U5C) children in Ethiopia

The red color in the map indicates that the highest prevalence of undernutrition among under five (U5C) children. Therefore, the highest prevalence of undernutrition among underfive (U5C) children was identified in the entire Tigray, Northern Amhara, Somalia, and Afar regions (Fig 4.4).

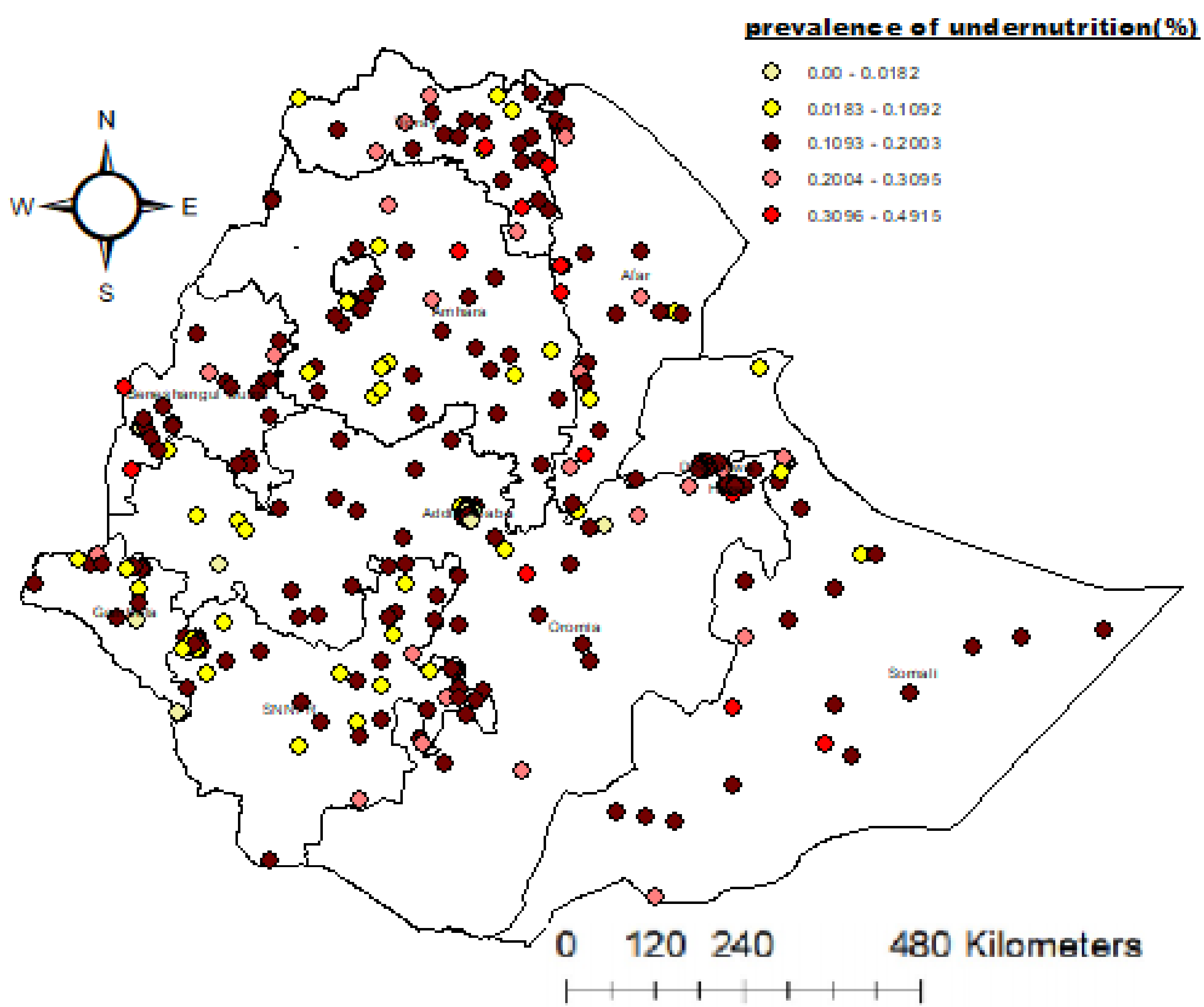

Fig 4.4 Spatial distribution of under-nutrition among underfive (U5C) children in Ethiopia, 2019 EMDHS

4.5 Hot spot analysis (Getis-Ord Gi*) of undernutrition among under five (U5C) children in Ethiopia

The Getis Ord Gi* statistical hotspot analysis showed that the significant hotspot areas of child undernutrition (high prevalence of undernutrition) were located in Tigray, northern Amhara, Afar and somali regional states. The cold spot areas (areas with low prevalence of undernutrition) were found in Central and Eastern Oromia, Southern Afar, Addis Abeba,Gambela and Western and Northern SNNPR regional states (Fig 4.5).

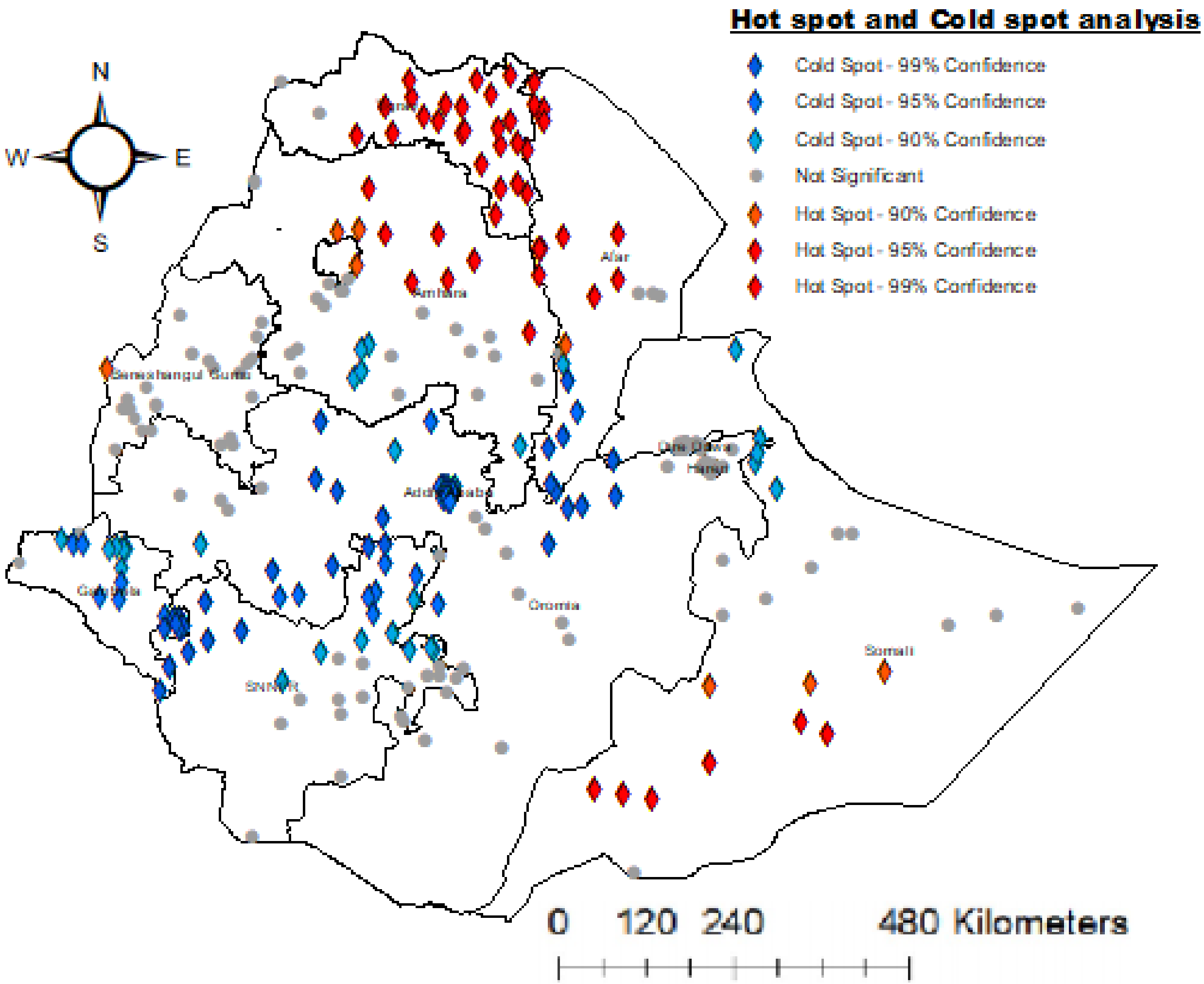

Fig 4.5: Hot Spot Analysis of undernutrition among underfive (U5C) children in Ethiopia, 2019 EMDHS

4.6 Spatial SaTScan analysis of undernutrition among underfive (U5C) Children in Ethiopia

SaTScan is free software developed by Martin Kulldorff that analyzes spatial, temporal and space-time data using the spatial, temporal, or space-time scan statistics. It is designed to detect spatial or space-time disease clusters, and to determine if they are statistically significant (Kulldorff, 2009). In the SaTScan spatial analysis, the cluster with the maximum Log Likelihood Ratio (LLR) was the most likely primary cluster for childhood undernutrition. The SaTScan analysis identified a total of 110 significant hotspot areas of children undernutrition with three significant spatial windows. Of these, 100 clusters were primary (most likely clusters) while 10 were secondary clusters. The most likely clusters were found in Tigray, Amhara, Somalia, Benishangul Gumuz , Northern Oromia and Afar regions, was centered at (13.987653 N, 37.973902 E) / 545.08 km, with a Relative Risk (RR) of 1.39 and a Log-Likelihood ratio (LLR) of 55.275715 at p-value < 0.0001. It showed that children within the spatial window had 1.39 times higher likelihood of undernutrition than children outside the spatial window. The secondary significant clusters were located in the Eastern SNNPR and Southern Oromia (Table 4.3 and Fig. 4.6).

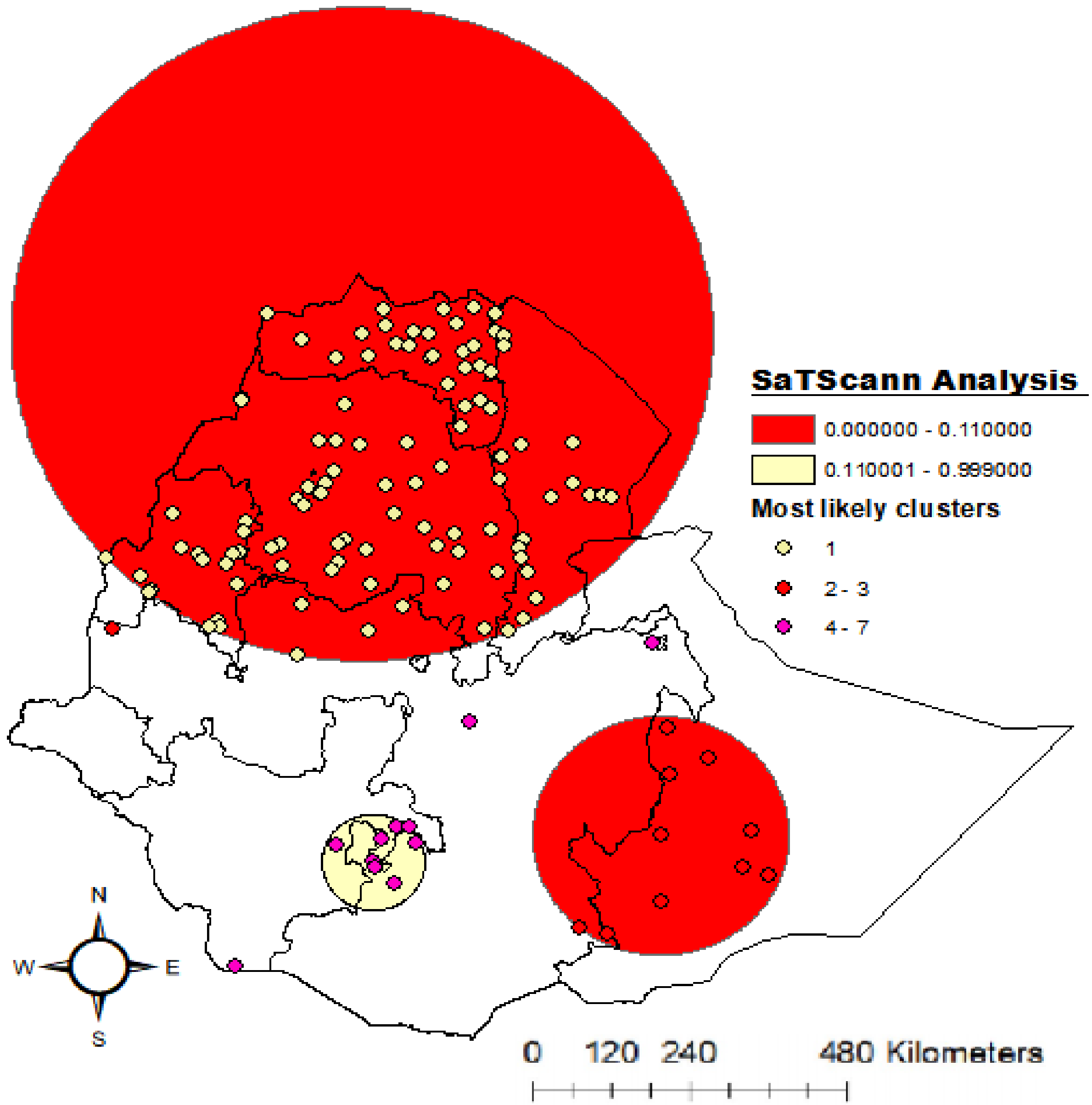

Fig 4.6: SaTScan Analysis for undernutrition among underfive (U5C) children in Ethiopia, 2019_Mini_EDHS

Table 4.3: Significant SaTScan spatial scan clusters of undernutrition among underfive (U5C) children in Ethiopia, 2019 mini EDHS

Most likely clusters	**Primary**	**Secondary**
Significant Enumeration Areas (clusters) detected	8, 1, 9, 6, 7, 22, 13, 12, 21, 11, 2, 14, 56, 10, 16, 4, 23, 17, 5,3, 5, 82, 83, 25, 84, 78, 20, 35, 36, 39, 24, 55, 85, 18, 27, 37, 38, 57, 9, 62, 58, 59, 61, 74, 54, 81, 75, 46, 29, 53, 60, 45, 44,65, 70, 76,65, 71, 63, 79, 51, 34, 162, 80, 64, 72, 66, 52, 33, 7,163, 30, 73, 148, 159, 47, 48, 67, 166, 31, 158, 49, 161, 68, 160, 100, 164, 119, 26, 50, 32, 99, 43, 69, 167, 149, 168, 40, 150, 169, 156, 42, 98, 146	136, 134, 142, 138, 123, 145, 133, 137, 141, 125
Total #of population	1977	258
Total # of cases	1033	146
RR	1.39	1.34
LL	55.275715	10.263789
Coordinates /Radius	(13.987653 N, 37.973902 E) / 545.08 km	(6.459193 N, 42.199432 E) / 199.16 km
P-value	<0.0001	0.0093

Source: Author's/researcher's own work (SaTScan output)

4.7 Spatial interpolation of undernutrition among underfive (U5C) children in Ethiopia

Spatial interpolation is a tool in GIS used to find the values of unknown points. It can be defined as a procedure of estimating the values of properties at unsampled locations based on the set of observed values at known locations. The result of interpolation—usually a surface that represents the real terrain—must be as accurate as possible because it often forms the basis for spatial analysis. In the result of Kriging interpolation, the blue areas represent the highest prediction of undernutrition from unsampled areas among underfive (U5C) children in the regions of Tigray, Afar, North Eastern Amhara, Northern Somali, Western Benishagul Gumuz and South-Estern Oromia, while the lowest rate of undernutrition was predicted in Addis Ababa and its borders of Oromia, Western SNNPR and some parts of the Gambela region. From the figure below the blue and green color represented the highest predicted risk while the yellow color indicated the lowest rates of prediction (Fig. 4.7).

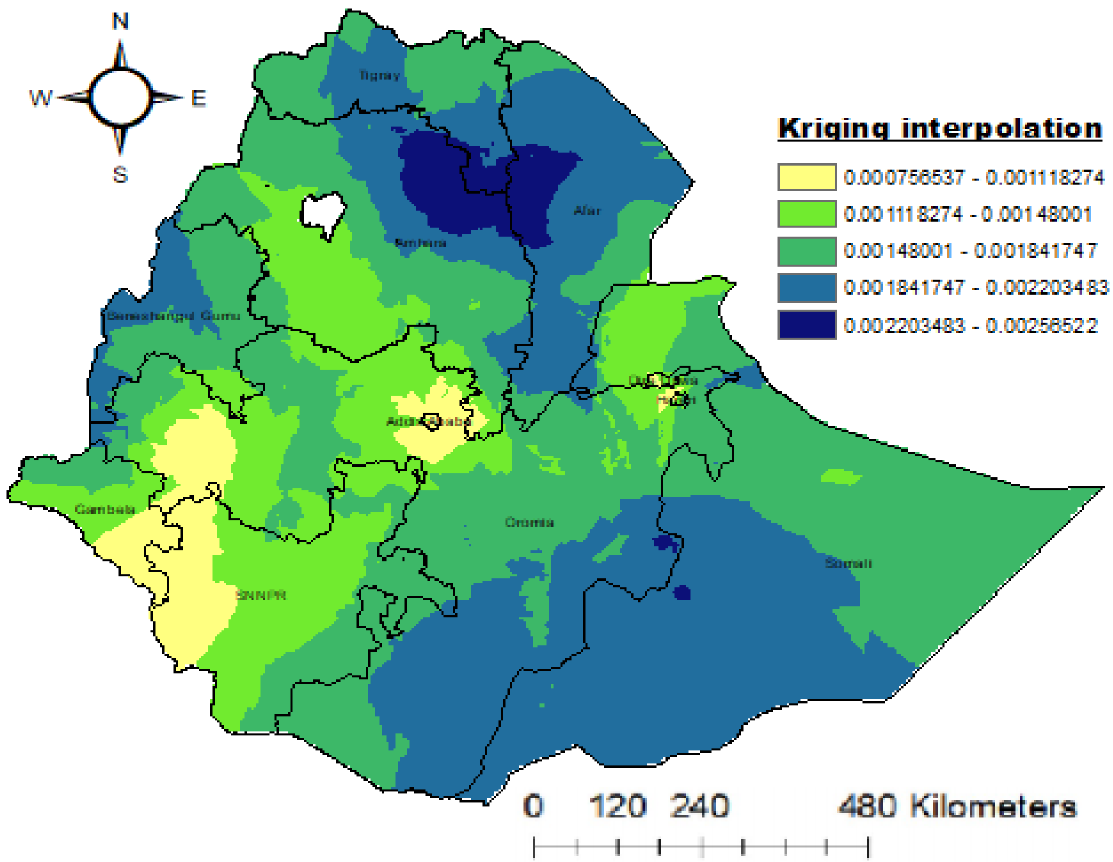

Fig 4.7: Kriging interpolation of undernutrition among under five (U-5) children in Ethiopia, 2019 mini EDHS

4.8 Multilevel Binary Logistic Analysis

Generally the distribution of undernutrition among underfive children (U5C, hereafter) in Ethiopia is clustered, so the usual assumption does not hold. Therefore, it is not appropriate to fit a standard logistic regression model. So this study is also concerned with a multilevel binary logistic regression on determinants of undernutrition among underfive (U5C) children in Ethiopia, from individual women with underfive children (U5C) nested within 305 clusters. The data have a two-level hierarchical structure with 5493 children at level 1, nested within 305 communities (clusters) at level 2. We consider a range of predictors. At level 1, we consider variables such as a wealth index, sex of house hold, source of drinking water, community based health insurance, sex of child, birth order, birth interval, antenatal care visit, multiple child, dietary diversity, number of house hold member, number of children under five years, toilet facility, age of house hold head, age of child, partner education level, place of delivery, woman's age at the time of the first birth and mother education ad Level 2(community) level variables includes regions and residence. The results presented in the subsequent section are obtained using STATA_14.2 version.

The data used in this study have a hierarchical structure. Units at one level are nested within units at the next higher level. Here, the lower level (level-1) units are the individual women with U5C, and the higher level (level-2) units are the regions that constitute the groups into which the women are clustered or nested. Therefore, the multilevel model used to describe the data at both levels, in order to find the effect on undernutrition among underfive (U5C) children in Ethiopia, both the individual woman (i.e with U5C) and the communities.

4.9 Chi-square Test of Heterogeneity

This is done with the expectation that there will be a difference in the number of undernourished children under the age of five (U5C) compared to individual children in the community. As previously stated, multilevel models were created to analyze hierarchically structured data. A random intercept model was used to model the heterogeneity between clusters, which was one of the goals of this study. This enables the overall probability of among children under the age of five (U5C) to vary across clusters. To assess heterogeneity in cluster mean, the chi-square test was used.

The chi-square test yields $\chi 2 = 437.93$ with corresponding P-value= < 0.0001 providing there is evidence of heterogeneity among the communities. It indicates that there is heterogeneity of undernutrition among underfive (U5C) children between clusters. Children in this study were selected from different clusters of Ethiopia. The advantages of using a multilevel model include the ability to fully explore the variability at all levels of the data hierarchy, and estimation of correct standard errors in the presence of clustered data. Children from the same community (cluster) would tend to be more similar compared to children chosen at random from different communities. The model takes into account the correlation structure of the data, enabling correct inferences to be made.

4.10 Random Intercept-Only Model

In multilevel analysis, we first examine the variation due to cluster effects using a random intercept only model. This is the most basic case of a hierarchical two-level model with dichotomous outcome variables and no explanatory variables. Only random groups and random variation within groups are present in this model. Table 4.4 depicts a random intercept or variance components model with cluster random effects (vary across clusters/communities) but no explanatory variables that allow the overall probability of undernutrition. The results show that the average log-odds of undernutrition among children under the age of five (U5C) is significantly different from zero, with the corresponding probability of 0.55/(1 + 0.55) = 0.3548, implying that, in Ethiopia the chance of undernutrition is 35.8 percent on average. The empty model is considered as a parametric version of assessing heterogeneity of communities for undernutrition. According to the result, the between-region variance is 0.407 with its standard error and 95% confidence interval 0.063 and 0.301,0.551 respectively, and the Wald test statistic is 163.15, which is compared with a Chi-squared distribution on 1-degree of freedom, gives a p-value less than 0.0001. Therefore, it indicated that the variation of undernutrition across clusters of Ethiopia was non-zero. We conclude that there is significant variation between clusters/communities in child undernutrition in Ethiopia.

The fundamental reason for applying special statistical techniques in multilevel analysis is the likely existence of intra-class (intra-cluster) correlation arising from similarity of child under-nutrition of the same cluster compared to those of different clusters. The Intra-class Correlation is ratio of the between-cluster variance to the total variance. It tells that, the proportion of the total variance in child undernutrition that is accounted for by the clustering. It can help to determine whether or not a multilevel analysis model is even necessary. If you find that the correlation is zero that means the observations within clusters are no more similar than observations from different clusters. Go ahead and use a simple analysis technique. It can be theoretically meaningful to understand how much of the overall variation in the response is explained simply by clustering.

From the output below, an ICC of 0.1102 can be determined. This implies that, around 11.02% of the variance in undernutrition among children can be explained by differences across clusters or enumeration areas, while 88.98% can be explained by individual differences. And the result of ICC is greater than zero shows that the observations within clusters are more similar than observations from different clusters (Table 4.4).

Table 4.4: Intercept only model.

Undernutrition	Odds ratio	Std.error	Z	P>|Z|	95% CI
Constant (β_0)	0.55	0.027	-12.17	0.000	(0.498,0.605)
Random effect parameter		**Estimate**	**Std. error**		**95% CI**
Variance(β_0)		0.407	0.063		(0.301,0.55)
ICC		0.1102	0.0151		(0.084,0.144)

4.11 Model Comparison

A multilevel process was implemented step by step. The first step involved examining the null model of overall likelihood of undernutrition in children under the age of five in Ethiopia without any predictors. In the second step, we define a multilevel model for analyzing random intercepts and slopes. Lastly, we considered a model for multilevel logistic regression with a random slope (random coefficient) and a random intercept (random intercept). The DIC, AIC and BIC measures should be used to isolate one of them (see Table 4.5). As a result, the random intercept model with fixed coefficients has the best fit to the data, as its DIC, AIC, and BIC are smaller. In explanation of community/cluster differences in child undernutrition, a model with random intercept and fixed slope coefficients was found to be the most appropriate. Based on these findings, the random intercept with fixed coefficient model is the most appropriate model for this study (Table 4.5).

Table 4.5: Model comparison, 2019

Criteria	**Null model**	**Random intercept and fixed effect model**	**Random intercept and slope model**
-2*LL(DIC)	7144.5	1473.2	1482.2
AIC	7148.5	1580.2	1725.2
BIC	7161.7	1904.2	2558.2

4.12 Random Intercept and Fixed Coefficient Analysis

The model is now being extended to account for regional effects on the likelihood of malnutrition. We begin with a random intercept or variance components model, which allows the overall likelihood of nutritional deficiency to differ across clusters. The outcomes of the two-level random intercept and fixed slope models are shown in Table 4.6. In a multilevel logistic regression model with a random intercept and fixed coefficients, we allowed the probability of undernutrition to vary across clusters but assumed that the effects of the explanatory variables were fixed for each cluster. In other words, while the random intercept varies across clusters, the child level explanatory variables remain constant.

According to the result of the random intercept with fixed slope model, the fixed part showed that the variable region, dietary diversity, number of household member, child age in month, mothers age at first birth, partner education level, preceding birth interval, ANC visit were found to be the significant determinant factors of undernutrition among children. The estimated coefficients and odds ratio have similar interpretation like in multiple logistic regression. However, those significant variables did not show any underline variations of undernutrition among clusters.

Children live in Somali(AOR=0.258, 95%CI:0.122,0.55), Benishangul Gumuz (AOR=0.384,95%CI:0.18,0.84), SNNPR(AOR=0.42,95%CI:0.2,0.89), Gambela (AOR=0.24, 95%CI:0.11,0.52), and Dire Dawa (AOR=0.31, 95%CI:0.14,0.696), were less likely to be undernourished as compared to children living in Tigray region. As well, mothers age at first birth between 20 and 35 years (AOR=0.443, 95%CI: 0.334-0.587), children preceding birth intervals over 35 months (AOR=0.644, 95%CI: 0.42, 0.99), and women who had ANC visits were less likely to be undernourished than their reference categories. There was an increase in the odds of undernutrition among children without additional dietary supplementation (AOR=367.12, 95%CI: 182,736.97) compared with those who did not take additional dietary supplementation. However, the odds of undernutrition among children in households with 5-9 members decreased by 0.369 (95%CI: 0.423, 0.943) compared to children with 1-4 members. A child aged 6-11 months, 12-23 months, 24-35 months, 36-47 months, and 48 months had 2.01(95% CI: 1.16,3.5.3), 4.33(95% CI:2.68,7.011), 5.38(95% CI:3.31,8.73), 5.26(95% CI:

3.24,8.54), and 1.889 (95% CI: 1.803, 1.971) times higher odds of undernutrition than a child aged 0-5 months, respectively (Table 4.6).

Table 4.6 Multilevel logistic regression analysis of undernutrition among underfive children in Ethiopia, 2019

Fixed effect	Odds ratio	Std.error	Z	P>|Z|	95%CI
Region(Tigray)					
Afar	.4940165	.188777	-1.85	0.065	.234,1.045
Amhara	.6094911	.2422328	-1.25	0.213	.28,1.323
Oromia	.5932962	.2297139	-1.35	0.178	.278,1.27
Somalia	.2582509	.0994404	-3.52	0.000	.122,.55
Benishangul	.38391	.1527552	-2.41	0.016	.18,.84
SNNPR	.4209384	.1599262	-2.28	0.023	.2,.89
Gambela	.2359212	.0940927	-3.62	0.000	.11,.52
Harari	.8398936	.3745857	-0.39	0.696	.35,2.01
Addis Ababa	.5883245	.3271103	-0.95	0.340	.198,1.745
Dire Dawa	.3069097	.1281807	-2.83	0.005	.14,.696
Residence(Urban)					
Rural	1.294577	.3141574	1.06	0.287	.81,2.083
Sex of house hold head(Male)					
Female	.822991	.144052	-1.11	0.266	.584, 1.16
Wealth index(Poorest)					
Poorer	1.132152	.2636094	0.53	0.594	.72, 1.79
Middle	1.165275	.313486	0.57	0.570	.69, 1.97
Richer	.9528071	.2609343	-0.18	0.860	.56,1.63
Richest	1.146222	.4024403	0.39	0.698	.58,2.28
Health insurance(No)					
Yes	1.076261	.2273085	0.35	0.728	.711,1.63
Sex of child(Male)					
Female	.928952	.1283491	-0.53	0.594	.71,1.22
Multiple birth(single)					
Multiple	.773	.303	-0.848	0.998	0.18,1.37
Dietary diversity(yes)					
No	367.1167	130.5279	16.61	0.000	182.9,736.97
House hold size(1-4)					
5-9	.6305696	.1293411	-2.25	0.025	.423,.943
>=10	.6879784	.2289805	-1.12	0.261	.36,1.32
Number of <5 children(1)					
2	1.20337	.2100856	1.06	0.289	.86,1.69
>=3	.6805132	.1541825	-1.70	0.089	.44,1.06
Toilet facility(No)					
Yes	.9345254	.1751711	-0.36	0.718	.65,1.35
Age of house hold head(15-19)					
20-25	1.102	0.072	0.292	0.77	0.89,1.18
26-30	0.81	0.233	-0.931	0.352	0.51,1.27
31-35	0.922	0.079	-1.03	0.27	0.79,1.08
35+	1.317662	1.4937	0.24	0.808	.143,12.15

Child age (0-5 month)					
6-11	2.01442	.5687233	2.48	0.013	1.16,3.503
12-23	4.332735	1.064152	5.97	0.000	2.68,7.011
24-35	5.37529	1.331357	6.79	0.000	3.31,8.73
36-47	5.258362	1.301316	6.71	0.000	3.24, 8.54
48-59	3.19522	.7448377	4.98	0.000	2.02,5.05
Mother education level(no education)					
Primary	.9052107	.161018	-0.56	0.576	.64,1.28
Secondary and above	.7568525	.1691871	-1.25	0.213	.49,1.173
Birth order(first)					
2-3	.8182762	.1886593	-0.87	0.384	.521,1.29
4-5	.850388	.2168481	-0.64	0.525	.52,1.4
>=6	1.060646	.2635836	0.24	0.813	.652,1.73
Place of delivery(home)					
Health facility	0.891	0.073	-1.59	0.112	0.771,1.027
Age at first birth(<20)					
20-35	.4426461	.0636956	-5.66	0.000	.334,.587
36-49	.3268987	.4204647	-0.87	0.385	.03,4.07
Partner education level(no education)					
Primary	2.177017	.3794011	4.46	0.000	1.55,3.06
Secondary and above	2.15728	.8138888	2.04	0.042	1.03,4.52
Birth interval(<24 month)					
24-35	.6924139	.1525176	-1.67	0.095	.45,1.07
35+	.6437866	.1413558	-2.01	0.045	.42,.99
Source of drinking water(improved)					
Not-improved	1.024148	.1640062	0.15	0.882	.75,1.4
ANC visits(No)					
Yes	.1013571	.0310299	-7.48	0.000	.056,.185
Intercept (B_o)	.2420435	.1441299	-2.38	0.017	.075,.78
Estimation of random effect					
Variance($\boldsymbol{\beta_o}$)	.0855754	.1135797			.0064,1.154
ICC	.0253523	.0327957			.002,.26

In Table 4.4 the variance component representing variation between regions has decreased from 0.1102 in the empty model with random intercept to 0.0856 in the random intercept and fixed slopes multilevel logistic regression model and the significance of it indicates that there is a significant variation between/among communities/clusters in undernutrition among underfive children. The Intra-class (Intra-cluster) correlation coefficient or, in other words, variance partition coefficient can be given as ICC = 0.025, This result shows that 2.5% of the residual variation in the propensity to undernutrition is attributable to differences between clusters the rest 97.5% variation were due to variations within clusters or children factors. This implies that within cluster variations are higher than between cluster variations for undernutrition among children.

4.13 Discussion

This section will address the previous findings and relevant issues surrounding this thesis research. A summary of methodological issues relevant to this thesis will be presented first. Following that, a discussion of the research implications of this study will be provided. Finally, a highlight of the major findings with their policy implications will conclude the section.

Methodologically, this study has used both exploratory spatial statistics and multi-level analysis. It has its own strength and limitations. First, the data used for this study is the 2019_EMDHS which has comparatively a large coverage over Ethiopia, and therefore increases the validity and generalizability of the study. The use of the GIS (Geographic Information System) software to demonstrate the research findings is considered to be an advantage of this study the rationale being that using mapping as a tool to demonstrate the research finding is based on the notion that the distribution of undernutrition of underfive children (U5C) should be monitored and reported in a way that is meaningful to policy makers. Health policy makers are not necessarily trained as epidemiologists or statisticians and thus, may not have a thorough understanding of the results reported by researchers. Researchers should meet the challenge of presenting their results in a way that serves the needs of health policy makers in the most insightful presentation of results through geographic maps in which the rates or distribution of undernutrition are visualized through coloured patterns. Another major advantage of this study is the use of multilevel design. The multilevel design allows the inclusion and analysis of data on both neighbourhood and individual within these neighbourhoods. The combination of individual and neighbourhood variable in one model helps to separate the compositional and contextual effect and increases the validity of the analytical results regarding the neighbourhood impact. Furthermore, it clarifies our understanding of how variances in outcomes are distributed across levels of social hierarchy, which in turn could inform health policy makers and health practitioners to design more effective interventions at different levels of society (i.e., community, family)

The study is not without limitations and all study results must be read with the consideration of these limitations. First, confounding is probably the most important limitation of this study. The potential for confounding by these variables was controlled through the use of logistic multivariate analysis. Because the dataset for this study did not include information on other potentially important risk factors related to the children’s nutritional status, confounding may have affected the parameter estimates of both neighbourhood and individual variables. The data used in this study are cross-sectional and quantitative. With cross sectional data, we are not able to capture the effects of the dynamic changes in the neighbourhood of residence and thus we have ignored potential effects of stability and change in a given community on the health of individual residents. This bias would likely result in an underestimation of the neighbourhood effect. Qualitative neighbourhood data are needed to shed new insight into the mechanism of the neighbourhood effects and how they "get under skin". Also, we cannot fully consider how long people live in their communities which may have most likely led to an underestimation of the neighbourhood impact by which "exposure" for a longer period of time are probably more likely to have their nutrition status affected by their community characteristics than people who recently moved there.

The focus of this study was identifying factors associated with CIAF (i.e., undernutrition) among U5C and mapping the possible spatial pattern of CIAF at regional level. As such, it is the first study in the country that provides the new measures for the prevalence of undernutrition by considering the aggregated indicators of anthropometric failure and applied them to larger nationally representative 2019_EMDHS dataset in Ethiopia.

The geospatial nature of undernutrition in Ethiopia is not random but clustered and most pronounced at 2.28 Km distance. This study indicated that the highest prevalence of undernutrition among underfive children was identified in the entire Tigray, Northern Amhara, Somalia, and Afar regions which is in line with UICEF (2013) estimate of Sub-Saharan Africa report on condition of nutrition (Winter, 2000). This geospatial undernutrition was not accidental and has emerged in cluster form based on a regular occurrence in countries around the world the mean centre being most of the African and Asian countries (Almasi et al., 2019). Similarly, the prevalence map, hot spot analysis and SatScan analysis showed that undernutrition of U5C are consistently seen in Tigray, Northern Amhara, Afar, Somali Regional States, Benishangul Gumuz and Northern Oromia which comply with study done on the 2016-EDHS dataset (Ahmed et al., 2021). This is also affirmed by Kriging interpolation. The spatial SaTScan analysis showed that the primary (containing 100 enumeration areas (EAs)) and secondary cluster (10 EAs) is 1.39 and 1.34 times more likely to have undernutrition than out of the spatial widow, respectively. This consistent tendency of undernutrition in these part of Ethiopia may be due to geospatial factors/covariates or generally geographic factors like low annual precipitation level and enhanced vegetation index, drought episode, high aridity level, low average rainfall amount, etc throughout the year of which none of them were included in the analysis. These factors create food shortage ad occurrence of starvation leading to undernutrition.

This study identified the prevalence and spatial distribution of undernutrition as well as their associated factors among U5C I Ethiopia. The 2019_EMDHS reports that 37% of children under age 5 are stunted (short for their age), 7% are wasted (thin for their height), and 21% are underweight (thin for their age). This report is inconsistent with this study which comes up with 15.3 %, 3.7 %, and 3.24 % stunted, wasted, and underweight, respectively (Demographic & Survey, 2019). Undernutrition status also varies widely temporally, regionally and on types of residence. The Composite Index of Anthropometric Failure (CIAF), however, used in this study determine the overall prevalence of undernutrition in children to be 38.25% which is a very serious public health concern (Svederg, 2001; Zurinila, Saiful and Selvi, 2069a). This demonstrates that the CIAF is significantly higher compared to the prevalence reported by conventional indices of stunting, underweight, and wasting.

Undernutrition in urban and rural areas was 26.5 % and 41.6 %, respectively. This indicates that children dwelling in rural areas are more prone to undernutrition than urban children. This might be because the rural areas are less developed in healthcare facilities and communities lack of awareness of diversified food intake. This finding is consistent with study finding from Nigeria with residence type but inconsistent with percentage distribution of each indicator of undernutrition separately (Gayawan er et al., 2019).

Because of the hierarchical nature of the 2019-EMDHS dataset, a step-wise multilevel analysis was made: the overall likelihood of undernutrition without any predictor (empty model), random intercept and slope analysis and finally multilevel logistic regression with a random slope (random coefficient) and random intercept. This analysis helped to identify the contextual factors related with odds of being undernourished. The random intercept with fixed slope model showed that region, dietary diversity, number of household members, child age in month, mothers' age at first birth, partner education level, preceding birth interval, ANC visit were found to be significant determinant factors for undernutrition among U5C.

Female headed household have 17.7% less likely to have undernourished children compared to male headed ones. This may be that females are more caring and dedicated to their infants and have a full and free decision power on household resource allocation. Similarly, a child from 5-9 household size is 36.9% less likely to be undernourished as compared to households with 1-4 members. This requires a further probe into reasons as to why this happen using qualitative study or other better statistical analytic tool.

There was an increase in the odds of undernutrition among children without additional dietary supplementation (AOR=367.12, 95%CI: 182,736.97) compared to those who did not take additional dietary supplementation. Consumption of a diversified diet was significantly associated with a reduction of stunting, wasting and being underweight in children. The likelihood of being stunted, wasted and underweight was found to decrease as the number of food groups consumed increased. Poor dietary diversity (when people do not eat enough different kinds of food) is a cause of nutritional deficiencies and hence do not get enough macro and micronutrients from their food. These nutritional deficiencies are responsible for impaired physical and mental development; susceptibility to various diseases, premature deaths in children, poor pregnancy outcomes for women may others. So, the odds of being undernourished are most likely in children not fed with diversified food than those fed with optimal quality and quantity of foods. Though the statistical finding is exaggerated highly (because of missed data), it is clinically important to assume that this much odds of undernutrition might be due to not feeding children properly in their golden period of growth and development.

A child aged 6-11 months, 12-23 months, 24-35 months, 36-47 months, and 48 months had 2.01, 4.33, 5.38, 5.26, and 1.889 times higher odds of undernutrition than a child aged 0-5 months, respectively. Adequate nutrition is critical to a child's optimal development, particularly during the first 1,000 days (pregnancy through the child's second birthday), a period of rapid growth where nutrient deficiencies can have long-term consequences. Children born to rural family and even urban family have more chance to be undernourished as the first 2 years and beyond critical growth and development period during which the velocity of growth and development which demands a quality and more quantity of nutritious food may not match the supply. This is also coupled with episodes of childhood illnesses like diarrhea, respiratory disease like pnuemonia, etc resulting in undernutrition (Maalouf-Manasseh et al., 2016).

Children born to 20-35 years old mothers are 55.7% less likely to be undernourished than those born to the extreme of this age group mothers. Experts say the best time to get pregnant is between your late 20s and early 30s. This age range is associated with the best outcomes for both mothers and children. One study pinpointed the ideal age to give birth to a first child as 30.5. Our finding complies with this established scientific fact (Bellieni, 2016). With respect to children born to family having partners' primary, secondary and above educational level, however, the odds of undernutrition is nearly 2.2 times more likely to happen compared to families without partners education. This is against many scientific findings ("WHO Recommendations on Antenatal Care for a Positive Pregnancy Experience," 2015). However, education by itself doesn't contribute much unless translated into income generating activities. Also, almost all learned individuals in Ethiopia are employed in government institution with an income/salary that is not adequate for family expense making food diversification more difficult. Unless accompanied by extra job, income only from employment wouldn't sufficient hence contributing to family undernourishment especially the risky group like children.

Birth spacing/interval ≥35 months has a 35.6% reduction in the likelihood of having undernourished children compared to <24 months of spacing. After a live birth, the recommended interval before attempting the next pregnancy is at least 24 months in order to reduce the risk of adverse maternal, perinatal and infant outcomes. Birth-to-pregnancy intervals of around 18 months or shorter are associated with elevated risk of infant, neonatal and perinatal mortality, low birth weight, small size for gestational age, and pre-term delivery all of which contributes for undernutrition. So, this finding is consistent with many scientific findings (WHO report, 2005). In a similar vein, mothers who had ANC visit (follow up care) have almost a 90% (89.9%) reduced chance of having undernourished children compared to those who had none during their pregnancy. Reasonable use of ANC services for the recommended number of times according to the national guideline for the pregnant women plays a crucial role in ensuring maternal and child safety and reducing the risk of comorbidities, disability, and death in mothers and their infants. Only those maternal women who used prenatal care were able to get medical follow-up, advice and information when needed. ANC also had a psychological effect, preparing the mother to give birth in health institution hence getting broad range of health education throughout gestational period, during and after child birth which in the end contributes to reduction of childhood undernutrition. This finding is in line with studies done in and outside of Ethiopia (Tang et al., 2019) (Pridmore & Hill, 2009).

In general, while the mapping and visualisation of undernutrition was done at regional level, therefore not as granular as what would have been observed if mapping had been done at a lower level such as zonal, district or sub-district level (EAs), there are some clear insights from the findings. In fact, despite spatial analysis or other techniques not being fully applied, the visual observations particularly from mapping patterns of undernutrition across Ethiopia painted a picture which can be further illuminated with previous and further research findings. The mapping visualization showed that Tigray, Northern Amhara, Afar and Somali regions are hot spot while Central ad Easter Oromia, Southern Afar, Addis Ababa, Gambella, and Western and Northern SNNPR regions are cold spot areas for undernutrition. Similarly, multi-level logistic analysis also indicated that having fed non_dieversifed diet, 5-9 household size, all child age categories of underfive children, 20-30 mothers age at first birth, primary ad beyond educational level of partners, 35 and above months of birth spacing, and ANC visit contributed to U5C nutritional status. These findings, together with previous study findings, have valuable policy implications for intervention and program design. The findings have implications and allow interventions to address hot spot areas associated with undernutrition at regional and local administrative levels. Furthermore, these findings are supremely important for the Ministry of Health and Regional Health Bureau to give attention to those hot spot areas for implementing intervention programs to have good progress towards achieving undernutrition free generation.

4.14 Strength and Limitation

4.14.1 Strengths

The study depends on a large population-based study with national coverage. One of the major strengths of this study was the use of different methods to understand child undernutrition problems. The study used the application of geographical information system to identify the spatial patterns of child undernutrition. The spatial scan statistics is one of the methods which is highly efficient in identifying local clusters with good accuracy and can help researchers to evaluate and early detection of the problem and to allocate resources based on need. As a result, using the application of SaTScan in the current study can be mentioned as strength of this study. And also the spatial clustering methods are exploratory tools that help researchers and policy makers make sense of complex geographic patterns of undernutrition.

The second strength is related to the application of multilevel analysis to identify individual and community level determinant factors of child undernutrition. Multilevel analysis has emerged as one analytical strategy that allows the simultaneous examination of group level and individual level determinant factors. Multilevel mixed effects modeling, is very important to control, for unexplained variations and that prevents the misleading association due to correlation within a cluster, which enables to overcome the limitations of the standard regression analysis. So, the application of appropriate statistical modeling can be as well considered as the strength of the current study.

4.14.2 Limitation

The cross sectional nature of the survey, which makes it difficult to see the temporal variation under different seasons, is one of the major limitations of the survey. Especially prevalence and spatial distribution of child undernutrition might vary seasonally. One of the main limitations of this study was that the GPS locations for some areas were missing. Another important limitation has virtually all information collected in DHS surveys are subject to reporting and recall biases. However, in this analysis all covariates were considered fixed during the study period or are constructed based on the state of affairs at the time of the interview.

CHAPTER FIVE

5. Conclusions and Recommendations

5.1 Conclusions

This study intended to perform exploratory spatial analysis of distribution of undernutrition (malnutrition) and its determinants among underfive children (U5C) in Ethiopia based on 2019 Ethiopian Mini-DHS dataset. In this study, the CIAF was utilized to provide an overall estimate of the undernutrition of U5C in Ethiopia. Spatial analysis revealed that spatial distribution of undernutrition among U5C significantly varied across the country. Accordingly, the variable region, dietary diversity, number of household member, child age in month, mothers age at first birth, partner education level, preceding birth interval, ANC visit were significantly associated with undernutrition among U5C in Ethiopia.

The spatial analysis shows that undernutrition of U5C significantly varied across the country, showing that it is not random in Ethiopia. The child undernutrition (high prevalence of undernutrition) were located in Tigray, Northern Amhara, Afar and Somali regions are identified as high-risk (hot spot) areas, whereas cold spot areas were found in Central and Eastern Oromia, Southern Afar, Addis Abeba, Gambela and western and northern SNNPR regional states. In the region Tigray, Amhara, Somalia, Benishangul Gumuz, Northern Oromia and Afar regions, and Afar, SaTscan identified significant primary clusters (most likely clusters). The possible explanation could be related with economic variation, drought, food insecurity and variation in cultivation**.**

The overall magnitude of childhood stunting, underweight and wasting among underfive children were found to be very high with geographical variations across different region. The spatial SaTScan analysis showed clustering of child undernutrition. The spatial variation of child undernutrition in the Spatial SaTScan analysis were observed in the multilevel mixed effects regression after adjusting for individual and community level determinant factors. The study showed heterogeneity in the magnitude of child undernutrition after adjusting for both individual and community level determinant factors in the multilevel analysis. This suggests the need for further spatial analyses concerning the potential factors which influence the spatial distribution.

The determinant factors of child undernutrition operating at individual and community level play a statistically significant role in determining child undernutrition in the study area. The current study have important policy implications which suggest that the challenge to reduce child undernutrition goes beyond addressing individual factors, and requires a better understanding of contextual determinant factors. The multilevel analysis implies that there are unmeasured determinant factors other than those included in the analysis that are causing the clustering of food insecurity and child undernutrition. The presence of spatial heterogeneity in child undernutrition suggests further investigation of left out determinant factors. As a result, child undernutrition variation should be promoted in public health research as efficient means of quantifying the importance of the higher level factors for understanding disparities in child undernutrition.

The spatial variations and determinant factors of child undernutrition in the current study are in agreement with different studies. Some variation could explain the role of determinant factors that influence child undernutrition from area to area. Another possible explanation for difference might be associated with the methodological variations across studies, including, but not limited to, the study design, sample size, sample selection and analysis methods used. Public health planners and programmers should design effective public health interventions to reduce children and women undernutrition in those significant hotspot areas where undernutrition is high.

In conclusion, it was found that undernutrition among U5C varied significantly across Ethiopia. A majority of previous studies assessed undernutrition status by assessing stunting, underweight, and wasting separately. A study conducted here indicates that focusing on any one of these indicators underestimates the overall prevalence of undernutrition, which can be captured more accurately using CIAF.

DIC, AIC, and BIC results indicate that a multilevel binary logistic with random intercept and fixed slope coefficients model provides the best fit to the data, so we use this model to identify the most significant factors associated with undernutrition among U5Cs. There were significant determinants of undernutrition among U5C in Ethiopia: regions, diet diversity, the number of household members, and the age of the child in month, the age of the mother at first birth, the partner's education level, the preceding birth interval, and the ANC visit.

5.2 Recommendation

Based on the above findings the following recommendations are forwarded to reduce undernutrition among U5C in Ethiopia:

To policy makers and nutrition program designer:

- It is recommended to strengthen the existing efforts to reduce the high level child undernutrition in the study area through designing context based interventions-considering the linkages of Agriculture, Nutrition and Health including education should be emphasized in intervention strategies;
- Continued programmatic and policy initiatives aimed at improving children's (and women’s) socioeconomic status and reducing mothers' early age birth culture should be discouraged to reduce childhood undernutrition;
- Health professionals should improve their nutritional education for women and for the community at large of reproductive age and mothers;
- Policy and intervention strategies aiming at mitigating food insecurity and child undernutrition should address the effects of lower level and community level determinant factors using individual/household level and geographical targeting, respectively, and
- In addition, the Ethiopian Federal Ministry of Health (FMOH) should develop nutritional interventions plan for children living in hotspot regions.

To the Academia research institutes:

- In rural communities, where household food consumption depends on own food production from the farmland, the burden of food insecurity and child undernutrition varies seasonally. Understanding temporal variation of food insecurity and child undernutrition, in addition to spatial variability in different agroecosystem areas will guide focused interventions. So, further research is recommended to address the spatiotemporal patterns of food insecurity and child undernutrition;
- To fully understand determinant factors of child undernutrition, program level nutrition sensitive and specific interventional studies are recommended;

- Researchers should focus in searching for additional risk factors that might account for the unexplained variance of child undernutrition, and
- To understand the contribution of spatial analysis results evidence in influencing public health policy to mitigate child undernutrition through geographical targeting interventions shall be tested using interventional studies.

To the community:

- Since the sanitation situation is one of the strongest predictors of child undernutrition, the community should work to improve the situation using local social and religion institutions;
- The farmers should enhance agricultural inputs use to increase crop production to secure household food consumption
- Crop diversity should be taken as one strategy to increase dietary diversity at the household level, and
- Education on child feeding and care practices in the community should be recommended.

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Appendices

Appendix: A

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
[glmerMod]
 Family: binomial  ( logit )
Formula:
undernourished ~ Region + Residance + Sex_of_HH + WI + sex_of_child +
    CBHI + Multiple_Birth + Diatery_diversity + Number_of_HH +
    under_5_child + Toilet_facility + Age_HH + Age_in_month +
    MEDUL + BOR_number + PL_delivary + Age_first_birth + PEDUL +
    Birth_IN + Source_of_drinking + ANC_visit + (1 | Region)
   Data: mydata

     AIC      BIC   logLik deviance df.resid
  1580.2   1904.2   -741.1   1473.2     5444

Scaled residuals:
     Min       1Q   Median       3Q      Max
-10.5963   0.0000   0.0000   0.1573   4.7750

Random effects:
 Groups Name        Variance Std.Dev.
 Region (Intercept) 0        0
Number of obs: 5493, groups:  Region, 11

Fixed effects:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        -1.851e+01  5.339e+02  -0.035 0.972343
Region2            -6.840e-01  3.667e-01  -1.865 0.062128 .
Region3            -4.836e-01  3.858e-01  -1.253 0.210028
Region4            -5.060e-01  3.745e-01  -1.351 0.176617
Region5            -1.316e+00  3.677e-01  -3.579 0.000345 ***
Region6            -9.469e-01  3.837e-01  -2.468 0.013587 *
Region7            -8.527e-01  3.673e-01  -2.321 0.020271 *
Region8            -1.406e+00  3.812e-01  -3.689 0.000225 ***
Region9            -1.483e-01  4.314e-01  -0.344 0.730958
Region10           -5.192e-01  5.403e-01  -0.961 0.336605
Region11           -1.161e+00  4.023e-01  -2.886 0.003900 **
Residance2          2.502e-01  2.304e-01   1.086 0.277393
Sex_of_HH2         -1.929e-01  1.714e-01  -1.125 0.260420
WI2                 1.363e-01  2.283e-01   0.597 0.550399
WI3                 1.623e-01  2.636e-01   0.616 0.538049
WI4                -4.239e-02  2.677e-01  -0.158 0.874200
WI5                 1.497e-01  3.414e-01   0.439 0.661008
sex_of_child2      -7.365e-02  1.366e-01  -0.539 0.589704
```

CBHI1	7.129e-02	2.075e-01	0.344	0.731147	
Multiple_Birth1	-4.257e+00	2.303e+04	0.000	0.999853	
Multiple_Birth2	-4.301e+00	2.379e+04	0.000	0.999856	
Multiple_Birth3	-2.985e+00	4.657e+04	0.000	0.999949	
Diatery_diversity1	5.838e+00	3.424e-01	17.051	< 2e-16	***
Number_of_HH1	-4.585e-01	2.023e-01	-2.267	0.023414	*
Number_of_HH2	-3.514e-01	3.257e-01	-1.079	0.280727	
under_5_child1	1.895e-01	1.724e-01	1.099	0.271829	
under_5_child3	-3.635e-01	2.217e-01	-1.640	0.101109	
Toilet_facility1	-6.721e-02	1.835e-01	-0.366	0.714190	
Age_HH4	2.969e-01	1.122e+00	0.265	0.791359	
Age_in_month1	7.092e-01	2.783e-01	2.548	0.010832	*
Age_in_month2	1.462e+00	2.425e-01	6.029	1.65e-09	***
Age_in_month3	1.668e+00	2.438e-01	6.841	7.87e-12	***
Age_in_month4	1.646e+00	2.438e-01	6.752	1.46e-11	***
Age_in_month5	1.158e+00	2.298e-01	5.040	4.65e-07	***
MEDUL1	-9.473e-02	1.748e-01	-0.542	0.587787	
MEDUL2	-2.811e-01	2.198e-01	-1.279	0.201057	
BOR_number1	-1.903e-01	2.273e-01	-0.837	0.402532	
BOR_number2	-1.548e-01	2.516e-01	-0.615	0.538448	
BOR_number3	6.642e-02	2.447e-01	0.271	0.786073	
PL_delivary1	1.708e+01	5.339e+02	0.032	0.974486	
Age_first_birth1	-8.044e-01	1.416e-01	-5.680	1.35e-08	***
Age_first_birth2	-1.122e+00	1.275e+00	-0.880	0.378708	
PEDUL1	7.742e-01	1.723e-01	4.494	7.00e-06	***
PEDUL2	7.660e-01	3.724e-01	2.057	0.039708	*
Birth_IN1	-3.567e-01	2.175e-01	-1.640	0.101078	
Birth_IN2	-4.228e-01	2.161e-01	-1.956	0.050450	.
Source_of_drinking1	1.833e-02	1.556e-01	0.118	0.906219	
ANC_visit1	-2.276e+00	3.047e-01	-7.470	8.02e-14	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation matrix not shown by default, as p = 48 > 12.

Appendix: B

R_code for UNu5.R

```
library(haven)
mydata<- read_dta("for_analysis_to Stata.dta")
mydata=read.dta("E:/under nutration/for_analysis_to Stata.dta")
str(mydata)
mydata$undernourished = as.factor(mydata$undernourished)
mydata$CLN = as.numeric(mydata$CLN )
mydata$Region = as.factor(mydata$Region )
mydata$Residance = as.factor(mydata$Residance  )
mydata$Sex_of_HH = as.factor(mydata$Sex_of_HH )
mydata$WI= as.factor(mydata$WI)
mydata$sex_of_child= as.factor(mydata$sex_of_child)
mydata$CBHI  = as.factor(mydata$CBHI )
mydata$ Multiple_Birth = as.factor(mydata$ Multiple_Birth )
mydata$Diatery_diversity = as.factor(mydata$Diatery_diversity)
mydata$ Number_of_HH = as.factor(mydata$ Number_of_HH )
mydata$under_5_child = as.factor(mydata$under_5_child )
mydata$Toilet_facility  = as.factor(mydata$Toilet_facility )
mydata$Age_HH = as.factor(mydata$Age_HH)
mydata$Age_in_month  = as.factor(mydata$Age_in_month )
mydata$MEDUL  = as.factor(mydata$MEDUL )
mydata$BOR_number  = as.factor(mydata$BOR_number )
mydata$PL_delivary = as.factor(mydata$PL_delivary)
mydata$Age_first_birth  = as.factor(mydata$Age_first_birth )
mydata$PEDUL = as.factor(mydata$PEDUL)
mydata$Birth_IN  = as.factor(mydata$Birth_IN )
mydata$Source_of_drinking = as.factor(mydata$Source_of_drinking)
mydata$ANC_visit= as.factor(mydata$ANC_visit)
str(mydata)
```

```
library(lme4)
library(VGAM)
naive <- glm(undernourished~ 1, data = mydata, family = binomial("logit"))
null <- glmer(undernourished~ (1 | CLN), family = binomial("logit"), data = mydata)
fixed <- glmer(undernourished~ Region +Residance+Sex_of_HH
    +WI+sex_of_child+CBHI+Multiple_Birth+Diatery_diversity+Number_of_HH+under_5_
    child+Toilet_facility+Age_HH+Age_in_month+MEDUL+BOR_number+PL_delivary+A
    ge_first_birth+PEDUL+Birth_IN+Source_of_drinking +ANC_visit + (1 | Region), family
    = binomial("logit"), data = mydata)
fixed
fit_random <- glmer(undernourished~ Region +Residance+Sex_of_HH
    +WI+sex_of_child+CBHI+Multiple_Birth+Diatery_diversity+Number_of_HH+under_5_
    child+Toilet_facility+Age_HH+Age_in_month+MEDUL+BOR_number+PL_delivary+A
    ge_first_birth+PEDUL+Birth_IN+Source_of_drinking +ANC_visit + (1+ Region +
    Residance | CLN), data = mydata, family = binomial("logit"), glmerControl(calc.derivs =
    FALSE))
summary(fit_random)
summary(fit_random)
anova(null,fixed ,fit_random)
anova(null,fixed ,Rfit_random)
```

Appendix: C

Global Moran's I Summary by Distance

Distance	Moran's Index	Expected Index	Variance	z-score	p-value
2.00	0.081951	-0.003289	0.000166	6.613610	0.000000
2.14	0.084015	-0.003289	0.000146	7.230881	0.000000
2.28	0.079901	-0.003289	0.000129	7.315036	0.000000
2.43	0.069430	-0.003289	0.000114	6.822562	0.000000
2.57	0.064387	-0.003289	0.000101	6.727056	0.000000
2.71	0.059291	-0.003289	0.000089	6.637486	0.000000
2.85	0.052157	-0.003289	0.000080	6.180500	0.000000
2.99	0.043385	-0.003289	0.000072	5.483500	0.000000
3.13	0.043341	-0.003289	0.000063	5.873256	0.000000
3.28	0.038631	-0.003289	0.000056	5.622690	0.000000

First Peak (Distance; Value): 2.28; 7.315036

Max Peak (Distance; Value): 2.28; 7.315036

Distance measured in Meters

Incremental Autocorrelation Parameters

Parameter Name	Input Value
Input Features	Export_Output
Input Field	PROPORTION
Number of Distance Bands	10
Beginning Distance	2.000000
Distance Increment	0.141746
Distance Method	EUCLIDEAN
Row Standardization	True
Selection Set	False