COLLEGE OF DEVELOPMENT STUDIES

CENTER FOR FOOD SECURITY STUDIES

SPATIOTEMPORAL CLUSTERING OF CHILD MALNUTRITION IN ETHIOPIA: EVIDENCE FROM ETHIOPIAN DEMOGRAPHIC AND HEALTH SURVEY

BY:

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A Thesis Submitted to College of Development Studies, Center for Food Security Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Food Security and Development.

DECLARATION

I, the undersigned, affirm that the thesis is my original work, has not been submitted for degrees at any other university, and that all sources of materials utilized in the thesis have been properly acknowledged.

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This thesis has been submitted for the partial fulfillment of the requirments for the Degree of Master of Science in Food Security and Development Complies with the regulations of the University and meets the accepted standards in terms of originality and quality.

Dr. Sitotaw Haile ________________

Advisor's Name Signature

EXAMINING BOARD APPROVAL SHEET

This is to certify that Mesfin Merkebu's thesis entitled "Spatiotemporal Clustering of Child Malnutrition in Ethiopia: Evidence From Ethiopian Demographic And Health Survey (EDHS) data" and submitted for the partial fulfillment of the requirements for the Degree of Master of Science in Food security and development complies with the regulations of the University and meets the accepted standards in terms of originality and quality.

As members of the examining board for this thesis open defense, we attest that we have read, assessed, and suggested that the thesis entitled "Spatiotemporal Clustering of Child Malnutrition in Ethiopia**:** Evidence from Ethiopian Demographic and Health Survey," written by Mesfin Merkebu, be accepted as a thesis required for the degree of master in Food Security and Development.

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Final approval and acceptance of this thesis is contingent upon the candidate's submmission of the final drafts of the thesis, incorporating all the comments by Examining board, to the Council of Graduate Studies(CGS) via the Center Academic Committee(CAC) of the Center.

Signature Date

Chair of the Department of Graduate Program Coordinator

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LIST OF ACRONYMS AND ABBREVIATIONS

AOR	Adjusted Odds Ratio
CI	Confidence Interval
CSA	Central Statistics Agency
DHS	Demographic & Health Survey
EA	Enumeration Area
EDHS	Ethiopian Demographic & Health Survey
EMDHS	Ethiopia Mini Demographic and Health Survey
EPHI	Ethiopian Public Health Institute
GIS	Geographic Information System
GPS	Geographic Positioning System
HHs	Households
ICF	International Child Fund
MDG	Millennium Development Goal
MOF	Ministry of Health
NNP	National Nutrition Program
OMS	Organization Mondial De Sante
SD	Standard Deviation
SDG	Sustainable Development Goal
SSA	Sub Saharan Africa
UNICEF	United Nations International Children Emergency Fund
WB	World Bank
WHO	World Health Organization
ZHA	Z-score of Height-For-Age
ZWA	Z-score of Weight-For-Age
ZWH	Z-score of Weight-For-Height

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ABSTRACTS

Child malnutrition is a major worldwide concern, accounts for 45% of the deaths of children under five. Significant regional differences in child malnutrition rates exist in Ethiopia, a low-income and heavily populated nation in sub-Saharan Africa. This study examines the spatiotemporal clustering of malnutrition in children under five across Ethiopia and explores the associated social and environmental factors. 46,172 weighted samples of children were analyzed using data from five Ethiopian Demographic and Health Surveys (2000–2019). Multivariable logistic regression and spatiotemporal clustering analysis techniques (Getis-Ord G) were employed to identify hotspot clusters of child malnutrition (stunting, underweight, and wasting) and their associated factors. QGIS3.36.0 was applied for visualization, and STATA version 17 was employed for exploratory analysis.*

The major findings indicate that areas like Amhara, Oromia, Sidama, and Central Ethiopia consistently have high rates of malnutrition, while Tigray, Afar, Benishangul-Gumuz, Gambella, Southern SNNP, and Somali regions have emerging clusters. Hotspot clustering has declined country wide over time. Child malnutrition rates were strongly impacted by variables like altitude,marital status, and immunization.

The study reveals significant spatiotemporal clustering of child malnutrition in Ethiopia, particularly in areas of the Amhara, Oromia, and Sidama regions, as well as parts of Central Ethiopia. While malnutrition hotspots have declined over time, socioeconomic and health-related disparities persist. Factors like maternal education, wealth index, and immunization correlate strongly with malnutrition rates. Despite progress, child malnutrition remains high. Targeted actions in food security, economic development, maternal education, and healthcare services are essential for rapid reduction.

Keywords ***:*** Child Malnutrition, Ethiopia, Hotspot cluster Analysis,

Spatiotemporal Clustering, Stunting, Underweight, Wasting.

CHAPTER-ONE: INTRODUCTION

1.1 Background

Malnutrition is a complex condition characterized by an imbalance in nutrient intake and utilization, leading to adverse effects on body composition, physical and mental function, and clinical outcomes. The Global Leadership Initiative on Malnutrition (GLIM) defines malnutrition as a condition that arises from a combination of reduced food intake or assimilation and the presence of disease-related inflammation, which can manifest as involuntary weight loss, low body mass index (BMI), or reduced muscle mass(Jensen et al., 2019; Sobestiansky et al., 2021).

Malnutrition occurs when an individual's dietary intake is not balanced with his or her nutritional needs(Edema, 2006).Undernutrition and overnutrition are both forms of malnutrition(Aheto et al., 2017). Undernutrition is characterized by a deficiency of nutrients resulting from insufficient food consumption and/or illnesses. It includes a variety of illnesses, such as vitamin deficiencies, chronic malnutrition, and acute malnutrition, and overnutrition is the term used to describe conditions where the body receives more nutrients than it needs; diseases linked to this include obesity and overweight(Aheto et al., 2017).

Malnutrition is a common problem with a variety of symptoms. Most individuals on the earth are impacted by it at some point in their life, from early childhood to old age(Edema, 2006). Every country is impacted by malnutrtion, it affects all age groups, regions, wealthy and impoverished, regardless of their sex that made it the most prevalent problem(United Nation, 2018). Malnutrition as a whole causes more illnesses than any other factors; proper nutrition is necessary for optimal health (Alemu et al., 2016). Malnutrition in all its manifestations is linked to a number of illnesses and increased death rates. About 45% of mortality in children under five are attributable to undernutrition, primarily in low and middle-income nations(Alemu et al., 2016; Mesay, 2021)

Currently, a significant body of evidence from various sources suggests that 1in 9 children under the age of five worldwide suffers from one or more forms of malnutrition, and that malnutrition accounts for nearly half of the deaths of this population of children U5 (FAO, 2018). Moreover, the Sub-Saharan African (SSA) area, which includes Ethiopia, significant levels of stunting, wasting, and underweight, as well as notable regional variations influenced by socioeconomic and environmental factors, child malnutrition poses a serious public health concern. According to recent study conducted in Ethiopia by Kuse and Debeko in 2023, the prevalence of stunting, wasting, and underweight in children under five is alarming, at 36.6%, 12.2%, and 25.2%, respectively (Kuse & Debeko, 2023). There is a clear geographic disparity, with urban areas like Addis Ababa reporting much lower rates of wasting, at about 2.26%, while regions like Somali experience extreme levels, at over 21%(Shibeshi & Asfaw, 2021). These variations are mostly explained by regional variations in agricultural methods, access to healthcare, and educational attainment.

In certain regions, there is a dual burden of malnutrition, according to further investigation of regional differences. For example, in the Amhara region, stunting rates reach a startling 46.3% and underweight rates reach 28.4% (Kebede et al., 2021), whereas in the Afar region, 26.7% of children are both stunted and underweight (Kebede, 2021). This draws attention to a persistent problem related to healthcare accessibility and food security.

Food insecurity, maternal education, and household wealth are some of the complex determinants of malnutrition that have been demonstrated to have a major effect on children's nutritional status. Underweight and stunting are strongly correlated with food insecurity, corresponding research, highlighting the need for all-encompassing approaches to address these problems.The Ethiopian Mini Demographic and Health Survey (EMDHS) in 2019 further confirmed these trends, revealing persistent rates of stunting (37%), wasting (7%), and underweight (21%)(Roba et al., 2021). All of these results highlights the need for comprehensive interventions that improve maternal health, improve access to healthcare and education, and increase food security (Kebede & Aynalem, 2021).

Although Ethiopia has made significant progress in lowering its rates of malnutrition over the past 20 years, the magnitude of malnutrition remain so high that the nation still needs to make large investments in nutrition(Atalell et al., 2023; Ethiopian Public Health Institute /EPHI/ & ICF, 2021; Lemessa et al., 2020). The population of Ethiopia is expected to reach 120 million by 2024 projection(Yimam et al., 2024), and represent nearly 1.5% of the world's total population, with a population density of approximately 109 persons per square kilometer(Yimam et al., 2024). Research findings by Almasi et al., (2019) indicated that undernourishment poses a considerable obstacle to the public health system and is associated with a markedly elevated risk of both morbidity and mortality. It results from a dynamic and intricate interplay of various elements, including socioeconomic, environmental, political, and health-related variables (Almasi et al., 2019).

Malnutrition also lowers productivity, raises healthcare costs, and slows economic growth-all of which can prolong the cycle of poverty and disease(Ethiopian Public Health Institute/ EPHI/ & ICF, 2021). Nevertheless, research has demonstrated that the health sciences are becoming more and more interested in spatially oriented research (Marx et al., 2014; Reshadat et al., 2019). Because, recent advancements in spatio-temporal clustering algorithms have significantly improved the efficiency of data extraction from large datasets (Hüsch et al. 2020). Discuss the development of novel algorithms that can handle big spatio-temporal datasets, thereby enhancing the ability to discover patterns that were previously difficult to identify (Hüsch et al., 2020).

Spatiotemporal clustering is a critical area of study that focuses on identifying patterns in data that vary across both space and time. This type of clustering is particularly valuable in various fields, including environmental monitoring, epidemiology, urban planning, and transportation systems. The essence of spatio-temporal clustering lies in its ability to reveal meaningful correlations among spatial and temporal features, which is essential for understanding complex phenomena such as disease outbreaks, traffic patterns, and climate changes (Meshram, 2023; Liu et al., 2021). Furthermore, the ability to visualize and analyze spatio-temporal patterns is thus crucial for decision-making processes across multiple domains (Budde et al., 2014).

In Ethiopia, little has beed studied regarding spatiotemporal clustering of child malnutrition as child malnutrition has still been a critical problem in Ethiopia, spatiotemporal clustering analysis is helpful for evidence-based target intervension and policy processes in health and nutrition sectors. Therefore, this study aim to explore the spatiotemporal patterns and trends of child malnutrition and associated social and environmental factors utilizing the five consecutive (EDHS) survey covering the period from 2000 to 2019 across Ethiopia at cluster level.

1.2 Statement of The Problem

Malnutrition is still a major global health and development issue, not just in developing nations but also in the world (Belaynew, 2014). It is a common public health problem with severe consequences for the death and morbidity of under five children and with physical and cognitive development problems of affected children. Worldwide, there are about 47 million wasted children under five, 14.3 million severely wasted children, 144 million stunted children, and 38.3 million overweight children. Undernutrition is a contributing factor in about 45% of deaths in children under the age of five. These primarily occur in nations with low and middle incomes. In these nations, the prevalence of overweight and obesity in children is also rising (Mesay, 202).

Ethiopia is one of the low-income nations where child malnutrition is still a major issue that the percentage of stunted and severely stunted under five children in the nation is 38% and 18%, respectively (CSA [Ethiopia], 2017; Mesay, 2021). Similarly, 3% and 10% of under five children are severely wasted and wasted, respectively (CSA [Ethiopia], 2017; Mesay, 2021). One of the biggest public health issues in Ethiopia is the estimated 24% underweight prevalence, of which 7% is severely underweight (CSA [Ethiopia], 2017; Mesay, 2021).

Several studies have conducted by different researchers'(Adelo & Temesgen, 2015; Ayana et al., 2015; Belaynew, 2014; Haregewoin, 2012; Mesay, 2021) on child malnutrition in Ethiopia and most of them have focused on understanding its major risk factor and determinants while some of the researches focused on its spatial distribution, hetrogeneity and associatd risk factors and variation (Belay et al., 2023; Belayneh et al., 2021; Gebreyesus & Lindtjorn, 2017; Lemessa et al., 2020). And some others also focused on spatial trends and determinants(Fenta et al., 2020; Jura, 2018; Seboka et al., 2021, 2022) in Ethiopia But, only a few researches were conducted on local spatial clustering of child malnutrition by Gebreyesus et al., (2016) in Ethiopia of SNNP regions in Meskanina Mareko Districts. As under five child malnutrition is a prevalent public health issue and a major contributing factor to child mortality in poor and developing nations, it requires immediate attention.

Even though, the problems of geographic clustering of child malnutrition were been varied in each location, but not sufficiently addressed nationwide. In addition to this, Seasonal variations of malnutrition have also been shown in previous research from southern Ethiopia (Gebreyesus et al., 2016), but little have given attention on the spatiotemporal clustering of under-five child malnutrition at cluster level across the country.

Spatial clustering analysis can provide valuable insights into the geographic distribution of child malnutrition in identifying the high-risk areas and informing targeted interventions.Therefore, this study aimed to investigate the spatiotemporal clustering patterns and trends of child undernutrition and associated social and environmental factors in Ethiopia, with the goal of informing evidence-based policies and interventions to combat malnutrition effectively.

1.3 Objective of The Study

1.3.1 General Objectives

The overarching o. bjective of the study was to examine the spatio-temporal clustering, and assess the key predictors of under-five child malnutrition in Ethiopia based on nationally representative data

1.3.2 Specific Objectives

The study were specifically attempt to:

- Assess the degree of spatio-temporal clustering of child malnutrition in Ethiopia.
- Identify the social determinants of child malnutrition clustering in Ethiopia.
- Identify the environmental determinants of child malnutrition clustering in Ethiopia.

1.4 Research Questions

The present research attempted to answer the following questions:

1.was there spatio-temporal clustering of child malnutrition across Ethiopia? If so,

2. what was the degree of clustering of child malnutrition?

3. What social and environmental factors impacted the clustering of child malnutrition in Ethiopia?

1.5 Significance of The Study

Child malnutrition is a serious issue that requires urgent and comprehensive action. Analyzing the spatial clustering patterns and temporal trends of child malnutrition, along with its social and environmental factors, is crucial in developing targeted interventions and effective policy formations. Moreover, the results of the study might makes a substantial contribution to a number of areas, most notably to exploite the existing knowledge, community welfare, policy formation, and the foundation for future researches.

The results of this research may addresses unanswered questions or unexplored areas within a field, providing new insights that enhance understanding and expanding the body of knowledge or bridging knowledge gaps.

By pinpointing areas with high malnutrition rates, it facilitates the creation of targeted interventions tailored to the needs of vulnerable populations, enhancing the effectiveness of nutrition programs.

This study is significant for policy as it equips policymakers with evidence-based insights into the spatiotemporal dynamics of child malnutrition, enabling informed decision-making and more equitable resource distribution. By highlighting the interconnected factors of healthcare access, sanitation, and socio-economic conditions, emvironmental factors, it encourages the adoption of integrated strategies that tackle multiple determinants of malnutrition. Additionally, the study's recommendations for community engagement can inspire policymakers to back grassroots initiatives, ensuring that interventions are culturally relevant and more likely to succeed.

This study is important for future research because it creates a thorough approach to investigate for child malnutrition, which will serve as a methodological foundation for future investigations look into more variables and long-term trends. It creates opportunities for assessing the efficacy of current interventions and generating new, context-specific tactics, which promotes continued investigation into creative ways to combat malnutrition. Although Ethiopia is the main focus, the methods and findings are more broadly applicable and can be modified for use in other areas dealing with comparable issues, advancing our understanding of malnutrition worldwide.

In general, the significances of this study not only addresses immediate concerns related to child malnutrition in Ethiopia. But also lays the groundwork for sustainable community improvements, informed policymaking, and further academic inquiry into nutritional health.

1.6 Scope of The Study

This research analyzes child malnutrition in Ethiopia, using data from the Ethiopian Demographic and Health Surveys (EDHS) from 2000 to 2019. It covers all regions—Tigray, Afar, Amhara, Oromia, Somali, Benishangul-Gumuz, Harari, Gambela, SNNP—along with Addis Ababa and Dire Dawa, focusing on both urban and rural settings.

Key indicators of malnutrition (stunting, underweight, and wasting) are examined against socio-demographic, economic, environmental, and health factors. The study employs a cross-sectional design and utilizes Getis-Ord G* statistics for cluster analysis, identifying hotspots of malnutrition, while multivariable logistic regression explores influencing factors.

The findings underscore the necessity of community-based initiatives and targeted interventions in high-risk areas, advocating for integrated strategies to tackle the root causes of malnutrition. The research highlights the importance of addressing spatio-temporal disparities and inequalities to design effective nutritional interventions.

1.7 Limitations of The Study

Its cross-sectional design, which makes it impossible to establish a cause-and-effect relationship, is its main drawback. Furthermore, the results are limited by the lack of significant variables, such as dietary consumption and behavioral factors, because the EDHS survey was not designed with the goals of this study in mind. Furthermore, the analysis is limited to variables available in the EDHS. It is possible that many other confounderswere not included in the model. Therefore, readers are advised to caustiouusly interpret these fingings. Inaddition, when examining survey responses, participant recall bias might be taken into consideration. Moreover, the DHS claims that data collection occurs every five years. Consequently, the data on stunting, wasting, and underweight in this study is derived from five consecutive surveys that were carried out in the years 2000, 2005, 2011, 2016, and 2019. This generates doubt on any potential shifts within the five-year time frame. The very limitation of this study was previous literatures regarding spatial clustering of child maluntrition.

1.8 Operational Definition of Key Terms

The following words are operational definitions of key terms to be widely used in this study:

a-Malnutrition: undernutrition or deficiency in nutrition, Lack of proper nutrition, caused by not having enough food, not eating enough food containing substances, and other direct and indirect causes, necessary for growth and health or over consumptions of nutrients(United Nation, 2018; WHO, 2006).

b-Stunting/chronic malnutrition: a low height-for-age in children at < -2 SD of median value of the WHO/NCHS international growth reference. Sever stunting is defined as <-3 SD. It reflects long term cumulative effects of inadequate nutrition, frequent health problem and poverty (WHO, 2006).

c-Wasting/acute malnutrition: a low weight-for-height in children at < -2 SD of the median value of the (NCHS/WHO) international weight-for-height reference. Sever wasting is defined <-3 SD. It refers a nutritional deficit state of recent onset related to sudden food shortage, poor utilization of nutrients and infections which results in rapid weight loss(WHO, 2006).

d-Underweight: low weight-for-age in children at <-2SD of the median value of the WHO/NCHS international reference. Weight for age is influenced by the height and weight of a child and is thus a composite of chronic and acute malnutrition(WHO, 2006).

e-Z-score: “standard Deviation Score(WHO, 2006).

1.9 Organization of The Thesis

The chapters are organized as follows: The introduction components Backgrounds of the study, Statement of the study, Objectives of the Study, Significance of the study, Scope of the study, Limitation of the study, and Operational Definition of Key Terms are covered in Chapter One. Chapter Two encompassed the Theoretical Literature Review, Overwiew of the Literature, Emperical Literature review, and Conceptual Frame Work components. Chapter Three also discusses the methodological aspects of Description of study Area, Study Design and Data Source, Measurement of Study Variables, Data Management and Analysis, Spatiotemporal and Statistical Model Analysis, and Ethical Consideration. Chapter Four Presented Results and Discussions parts. Finally, the Study's Conclusions and Recommendations sections presented in Chapter Five.

CHAPTER TWO : LITERATURE REVIEW

2.1 Theoretical Literature Review

This chapter presentes a review of both theoretical literature, empirical literature reviews, and conceptual framework with correlate of spatio-temporal clustering of child malnutrition. Relevant studies would be reviewed focusing on findings and related issue in developing nations.

2.1.1 Definitions of Malnutrition

Malnutrition in Ethiopia is a complex public health problem that includes undernutrition, overnutrition, and the double burden of malnutrition (DBM). These complexities are reflected in contemporary definitions of malnutrition in Ethiopia, which highlight the growing problems associated with obesity and related conditions in addition to the prevalence of undernutrition among vulnerable groups like women and children (Sahiledengle et al., 2023; Tigabu et al., 2022).

Malnutrition occurs when individuals, particularly children, do not receive adequate nutrients, severely impacting their development and contributing to nearly half of all child deaths worldwide. Early-life malnutrition can stunt mental and cognitive growth, heighten the risk of infections, and lead to increased morbidity and mortality. It also negatively affects academic performance and work productivity while raising the likelihood of chronic diseases in adulthood (Ahmed et al., 2017; Lemessa et al., 2020; United Nation, 2018).

Malnutrition refers to inadequate food intake or nutrient deficiencies beyond mere hunger. It can result from a lack of essential nutrients like iron, protein, and calories, leading to imbalances in nutrient intake. Malnutrition encompasses both "undernutrition," characterized by stunting (low height for age), wasting (low weight for height), underweight(low weight for age), and micronutrient deficiencies, and "over-nutrition," which includes obesity and diet-related non-communicable diseases such as diabetes, cancer, heart disease, and stroke(Saeed et al., 2020; WHO, 2006)

2.2 Overwiew of The Literature

Malnutrition encompasses both undernutrition and overnutrition (United Nation, 2018), but the 2019 Ethiopian Demographic and Health Survey indicates that less than 3% of Ethiopian children under five are overweight. Therefore, this study focuses specifically on undernutrition, which is a major national health issue. This study characterizes malnutrition as undernutrition, which includes stunting, wasting, underweight, and micronutrient deficiencies, all of which are measured in children using anthropometric measurements.

2.2.1 Nutrition of Under Five Years Of Age Children

A proper diet is essential for the survival and thriving of current and future generations, as healthy eating is critical for children's physical and intellectual development (Ahmed et al., 2017; Daniel et al., 2016; Mesay, 2021; United Nation, 2021). Undernutrition, particularly among youth, hinders individuals from reaching their full potential and prevents societies from achieving their goals(Mesay, 2021; United Nation, 2021). Undernurished children often have weakened immune systems, making them more vulnerable to common illnesses like diarrhea and respiratory infections. Even if they survive, they may face a cycle of stunted growth and recurring sickness, often resulting in lasting damage to their social and cognitive development(Haregewoin, 2012; Hurley et al., 2016; Mesay, 2021). Preventing and treating malnutrition in young children, especially those under two years old, can significantly decrease mortality rates and promote optimal physical and mental growth. This age group is particularly responsive to nutrition interventions, making it a crucial time for effective action (Bhutta et al., 2013; Mesay, 2021).

2.2.2 Measuring Under Five Child Malnutrition

Measures of nutritional status for young children can be obtained through anthropometric indicators. WHO advises that the assessment of nutritional status be done by comparing the height and weight of the children participating in the survey with information from a reference group of children who are well-nourished (WHO, 2006). The units of standard deviation from the reference group’s median are used to express the three indices (stunting, wasting, and underweight). Children are classified as moderately malnourished if they are less than minus two standard deviations (-2 SD) from the reference population’s median; severely malnourished if they are less than minus three standard deviations (-3SD) from the reference population’s median. Distinct features of malnutrition are captured by each measure. wasting (weight-for-height), and underweight(weight-for-age) in accordance with World Health Organization(WHO) child growth standards(who, 2006).These anthropometric indices, which are based on measurements to see if the body has grown appropriately, are the widely used markers of malnutrition in children(Edema, 2006; WHO, 2006).

2.2.2.1 Stunting (Height-For-Age)

Stunting in children is measured using height-for-age, a linear growth metric that is less than minus two standard deviations below the reference mean (below -2SD). Chronic malnutrition causes stunting over time, which results in a shorter stature than peers. Poverty, poor feeding habits, recurrent illnesses, and prolonged food shortages are some of the factors that contribute to this condition, which is a reflection of cumulative growth. Stunting is usually found in children under five, but it is most common in those between the ages of 24 and 36 months, after which it stabilizes(Edema, 2006; WHO, 2006).

Stunting prevalence at the population level is useful for tracking malnutrition at the local, state, or federal levels, focusing different interventions on a specific community, and creating long-term plans and policies. A common metric for assessing socioeconomic status and equity is height for age. Since stunting is cumulative and cannot be counteracted by fatness, it is frequently used as a nutritional indicator in poverty analyses. To assess if a child is stunted, their actual height is contrasted with that of a reference child of the same age and sex (Edema, 2006; WHO, 2006).

2.2.2.2 Wasting (Weight-For-Height)

Weight-for-height describes current nutritional status. A child who is below minus two standard deviations (below-2 SD) from the reference mean for weight-for-height is considered too thin for his/her height, or is wasted. Weight-for-height is an indicator of acute malnutrition. It measures body weight relative to height. Because weight can fluctuate rapidly in children due to illness or inadequate food intake, it reflects the current nutritional status of a child, with low weight-for-height indicating current acute malnutrition with failure to gain weight or actual weight loss. However, low weight-for-height can also be a result of a chronic condition in some communities. Weight in individual children and population groups may exhibit marked seasonal patterns associated with changes in food availability or di sease prevalence. In non-emergency situations, the highest prevalence of wasting generally occurs in young children of 12-24 months of age(Mesay, 2021; United Nation, 2021; WHO, 2006). Weight-for-height is a useful index for assessing nutrition status of individual child underfamine conditions and for identifying short-term nutrition problems in non-emergency situations. Wasting is the usual indicator of choice for targeting treatment of diarrheal and other diseases. Weight for height basically is a very good index for short duration malnutrition(Edema, 2006; WHO, 2006).

2.2.2.3 Underweight (Weight-For-Age)

As weight-for-age is a composite index of height-for-age and weight-for-height, it is either a composite indicator of both chronic and acute malnutrition or it does not differentiate between acute malnutrition (wasting) and chronic malnutrition (stunting). A child may be underweighted for his/her age due to either wasted or stunted growth. A population's overall nutritional health can be determined by looking at weight-for-age. Both thinness and height have an impact on weight. Among the three most common indices weight-for age has the highest predictive ability for childhood mortality. Weight-for-age can be used to identify children at risk of becoming malnourished, and guide preventive measures such as nutrition counseling and entry into short-term food supplementation programs(Edema, 2006; WHO, 2006).

The most widely reported anthropometric measure is weight-far-age, which is widely used to track growth, identify kids who may be at risk for growth failure, and evaluate the results of intervention efforts in growth promotion initiatives. One of its benefits is that it only needs one rather basic physical measurement, which is weight. Compared to height, the relative change in weight with age occurs more quickly and is far more responsive to variations in an individual's growth pattern. . A child's real weight is compared to the weight of a reference child of the same sex and age to determine if they are underweight (the international reference standard uses data from the WHO) (WHO, 2006).

2.2.3 Impacts Of Malnutrition On Economic Development.

For people and populations to be healthy, grow, develop, and have economic stability, they must eat a healthy diet. A major public health concern, malnutrition is a factor in the high rates of illness and mortality among mothers and children. It is also more difficult to break the cycle of poverty for undernourished people because they are less likely to reach their full potential in terms of education and economic productivity and because they make less money than their well-nourished peers (Liang & Zeger, 1986).

Economic development is greatly impacted by malnutrition, especially in developing nations where it is closely related to health outcomes, productivity, and educational attainment (Alderman, 2010). Malnutrition has a significant financial cost since it has an impact on both personal health and the expansion of the national economy. Alderman, for example, highlights that investments made to prevent malnutrition yield economic returns equivalent to those from traditional development strategies and that the productivity losses linked to malnutrition are significan(Alderman, 2010). Which is supported by Moench-Pfanner et al, who estimate that malnutrition can cost economies up to 3% of their GDP, highlighting the critical need for targeted interventions(Moench-Pfanner et al., 2016). This result previously explained by WHO and World Bank that the entire economy is weakened by a high percentage of malnutrition, which can lower a nation's gross domestic product (GDP) by as much as 3 percent (WHO, 2006; world bank, 2006).

Moreover, the relationship between malnutrition and economic growth is complex and bidirectional. A dynamic panel data analysis conducted across 26 developing countries by Nafti (Nafti, 2021), revealed that economic growth can lead to reductions in malnutrition rates. However, this relationship is contingent upon effective public health policies and investments in nutrition. Siddiqui et al. further elucidate this connection by arguing that malnutrition adversely affects both the physiological and cognitive capacities of individuals, which in turn hampers productivity levels and increases susceptibility to poverty. This cycle of malnutrition and poverty perpetuates a barrier to economic development, as healthier populations are more productive and capable of contributing to economic growth (Siddiqui et al., 2020). In general, the impacts of malnutrition on economic development are multifaceted, affecting productivity, health, and educational outcomes. Addressing malnutrition through comprehensive public health strategies is essential for fostering economic growth and improving the overall well-being of populations in developing countries.

2.3 Empirical Literature Review

Malnutrition can be caused by a variety of factors, including socio-demographic, socio-economic, and environmental and health-related ones. It is also strongly correlated with living standards and the capacity to meet needs like having access to food, health care, sanitary/hygienic, and housing conditions. This study primarily examine the socio-demographic, socioeconomic, and environmental and health-related factors that contributes to child malnutrition in Ethiopia.The comprehensive reviews of the literature on the socio-demographic, socioeconomic, environmental and health-related factors that influence childhood malnutrition is provided below.

2.3.1 Socio-Demographic Characteristics

Research indicates that socio-demographic factors, such as household income and maternal education, significantly affect children's dietary diversity and nutritional status (Zongrone et al., 2012; Ibe, 2011).

According to the majority of research, birth order, interval, and demographic traits like age and sex play a significant role in determining one's nutritional status. Studies reveal that while the primary causes of malnutrition may vary with age of children, in many instances older kids are found to be correlated with elevated malnutrition. For instance, older children are more likely than younger children to be stunted and underweighted, according to the 2005 WBank report on health and poverty in Ethiopia, which used a descriptive statistical method(WBank, 2005; world bank, 2006).

Children's nutritional status is also more sensitive to factors such as feeding/weaning practices, care, and exposure to infection at specific ages. A cumulative indicator of growth retardation (height-for-age) in children is positively associated with age (Anderson, 1995; Aschalew, 2000). Local and regional studies in Ethiopia have also shown an increase in malnutrition with increase in age of the child (Yimer, 2000; Genebo et al., 1999; Samson and Lakech, 2000). The same results was indicated on research coducted at Madda Waalabu University on "Determinants of malnutrition among under five age of childern in Ethiopa" by Hulle Hassen Aman(Aman, 2020).Additionally, a child's nutritional status is more susceptible to certain factors at a given age. For instance, the mother's ability to care for the child and her feeding habits are the primary factors influencing the child's growth during the first four or six months of life. From the time a child begins receiving supplemental feedings (between the ages of 4 and 6 months) until the child is 2 years old, the main factors are infectious diseases. After the Age of two, the major challenge for the household to be food security(world bank, 2006).

According to the study by Endeshaw (2009) on the factors influencing nutrition security in the Shone District of Hadiya Zone, in the SNNPRS, the age of the child, the interval between the last two births, prenatal care for the chosen child, washing one's hands before handling food, disposing of the child's excreta, and the type of residence were all significant indicators of chiId malnutrition. On the other hand, Christiansen and Alderman (2004) discovered that a child's standardized height decreases until the age of three, at which point it marginally increases(Christiaensen & Alderman, 2004).

Based on descriptive statistics, all four welfare monitoring surveys conducted at the national level between 1996 and 2004 found that, in terms of the three indices of malnutrition (wasting, stunting, and underweight), boys are more susceptible than girls. Several case studies and official surveys (Sentayehu, 1994; Christiaensen and Alderman, 2001; Alemu et al. 2005a) have also reported findings that are similar. Numerous explanations for this gender disparity are provided in the literature. For instance, Alemu et al (2005a). suggested that this might be caused by genetic variations between male and female offspring as well as girls' easier access to food as a result of their gender-specific role in helping with meal preparation. Similarly, Male children have a greater risk of the status of stunting and wasting than female children (Salah E.O. Mahgoubet al., 2006, Mandefroet.al., 2015)**.** On the contrary, (Silva., 2005), found no significant relationship between a child's gender and nutritional status using data from the 2000 Ethiopia Demographic and Health Survey, indicating that gender bias does not affect Ethiopian children's nutritional status. In addition to this, the review and meta analysis result by Ahmed et .al highlighted that among the common factors for child undernutrition were child age, child sex, comlemantry food (cereal based), and diarrhea diseas are presented(Ahmed et al., 2017). Similar findings conducted in Kenya reported that age of child. Sex, maternal education and maternal height(BMI) were among the main determinants of undernutrition (Ahmed et al., 2017).

Abay Asfaw (1995) used longitudinal analysis to report a relatively different result when taking age and gender into account together. Utilizing information gathered from four rural Ethiopian regions, he investigated the relationship between poverty and household health-seeking behaviors. The conclusion is that relationships to the head of the household have a greater impact on health status, demand for medical care, and provider choice of households than do gender and age. Since immediate family members are more likely than other family members to report illness, seek treatment, and visit contemporary healthcare facilities, particularly private clinics.

2.3.2 Socio-Economic And Cultural Characteristics

A National nutritional Program Baseline Survey conducted (2004) in Bangladesh rural, using a multivariable analysis revealed that a mother's educational background is significant because educated mothers are better informed about the health and diet of their children. They can take better advantage of health services, give better care, maintain better hygiene, and occupy a higher position within the family. It is also well known that improved economic circumstances raise families' standards of living and enable them to provide for their children(Adelo & Temesgen, 2015; Ahmed, 2012; Amir et al., 2022).

A study carried out in Nigeria by Ajieroh (2009) identified various factors to be influencing maternal and child nutritional status. These include the economic status of the household, having a primary earner who work in agriculture, the mother's age, her decision-making regarding her income and health, the percentage of children under five in the household, the age and sex of the child, the variety and frequency of meals, and public health services like immunizations and antenatal care. Aditionally, nother findings in Nigeria by Osi et.al., (2010); Atoloye et al., (2015), also suggusts that factors such as education, occupation, income were key determinants of food security as well as environmental conditions such as safe cooking and drinking water, cooking fuel, toilet facilities, electricity, setting and kitchen location and concluded that low socioeconomic conditions are the pridictors of child malnutrition.

According to Christiaensen and Alderman's (2001) research, child malnutrition rates in Ethiopia have remained faltering high for the past few decades. This study determined that key determinants of failing child growth included household resources, parental education, food prices, and maternal nutritional knowledge. Advise launching targeted child growth monitoring and maternal nutrition education programs in tandem with initiatives to support the nation's formal education system and growth in private income in order to significantly and promptly reduce child growth falteringThey. And also a systematic review by Wanden-Berhe et al.,(2009) on the assessment of nutritional status of preschool children of Gumbrit, North West Ethiopia, shows that among the socioeconomic variables household income was significantly associated with malnutrition(Wanden-Berghe et al., 2009). According to a study published in Ethiopia **(**2004), regarding risk factors of malnutrition, one of the main factors contributing to chronic child malnutrition in Ethiopia is parental education(Christiaensen & Alderman, 2004). From the bivariate tests of association, results showed that stunting status of children under age five was significantly associated with socio economic, demographic, and environmental and health factors(Jura, 2018). This result was in harmony with other studies (Danbe and Taye, 2011; workineh and Teshome, 2016).

2.3.3 Environmental And Health Related Characteristics

According to article Reviewed buy Dmello et al, (2023) on geospatial Analysis of Malnutrition among Under-Five Children, the finding shows the nutritional status among U5 children and clusters of stunting, wasting, and underweight are mostly dependent on the mother's literacy, income, food security, household income, seasonal factors, and, rural areas with poor facilities. Most of the study suggests the need of interventional programmes from the government to invest and act towards to improves of health of children under-five (Dmello, 2023). Health and environmental factors, such as diseases, water and sanitation quality, sanitation and medical facilities, immunization coverage, maternal health status, breastfeeding practices, and geographical location at both the community and household levels, are significant because of their direct and indirect effects on child nutrition.

A multivariable logistic regression study carried out in the Eastern Hararge, district of Combolcha identified the following as significant risk factors for child malnutrition: household size, child age, immunization status, gender, and the mother's use of antenatal care, household farm size, water source, latrine use, and incidence of morbidity (Abebaw, 2013). Basic causes of malnutrition include economic systems, human and environmental resources, political and ideological issues. Similar study finding were stated by Takele et al, indicated that child nutritional status is strongly associated with the child‟s age, gender, immunization status and the mother‟s use of antenatal care, farm size, household size, water source, latrine use and incidence of morbidity(Takele et al., 2020). In many nations, natural disasters and made matters worse(UNICEF, 2003). A study findings by Olack et al. (2011) reported that certain health conditions such as tuberculosis (TB), diarrhea, measles, etc., can exacerbate malnutrition in children, and a combination of these health problems can weaken the immune system(Olack et al., 2011).

In sub-tropical and tropical regions, 95% of all malnourished individuals live in relatively stable climate. Thus, climate change is a significant factor to be considered when ensuring substantial availability of food (food security) (Metz, 2011). Latest report has shown that temperature increase in the sub-tropics and tropics are very likely (climate change) (Metz, 2011). A United Nations study carried out in over 40 developing countries showed that climate change directly or indirectly influence the decline in agricultural production and may as a result increase the number of people suffering from hunger each year (Action Against Hunger, 2012). Even a slight change in temperature can affect the weather conditions (Metz, 2011)(. Agricultural production and good nutrition are highly affected by the impact of these events. For instance, during the Central Asian drought, there was about 50% reduction in wheat production and 80% loss of livestock products(Battisti, 2008).

In Sub-saharan Africa, extreme weather conditions such as drought, can diminish productivity of many crop species thereby exacerbating the impact of malnutrition(Battisti, 2008). Poor children often reside in urban slums or very rural areas where there is absolute lack of basic amenities such as water supply and other sanitation facilities which lead to contamination of water bodies which in turn, can cause diarrhoea (Black et al., 2011). Diarrhoea promotes wasting and prevents children from getting enough nutritious food. The spatiotemporal clustering of child malnutrition is significantly influenced by various environmental factors, including climatic conditions, altitude, agricultural vulnerability, and socio-economic contexts, play crucial roles in shaping the nutritional status of children across different regions. Cooper et al demonstrated that drought conditions are associated with increased rates of child stunting, highlighting the direct link between environmental stressors and nutritional outcomes(Link et al., 2019). Similarly, Hagos et al. found that variations in rainfall and temperature significantly correlate with child undernutrition in Ethiopia, indicating that agricultural productivity, which is sensitive to climatic changes, directly impacts food availability and, consequently, child nutrition(Hagos et al., 2014).

Firstly, climatic conditions, particularly drought and precipitation extremes, have been shown to adversely affect child nutrition. For instance, (State & Ph, 2020) demonstrated that drought conditions are associated with increased rates of child stunting, highlighting the direct link between environmental stressors and nutritional outcomes. Similarly, Hagos et al, found that variations in rainfall and temperature significantly correlate with child undernutrition in Ethiopia, indicating that agricultural productivity, which is sensitive to climatic changes, directly impacts food availability and, consequently, child nutrition(Hagos et al., 2014). Alemu et al also emphasized the importance of local area characteristics, including administrative and agronomic conditions, in understanding the spatial inequalities in child malnutrition (Alemu et al., 2016).

Furthermore, the role of environmental sanitation and hygiene cannot be overlooked. Cumming and Cairncross argued that inadequate water, sanitation, and hygiene (WASH) conditions contribute to stunting and other forms of malnutrition(Cumming & Cairncross, 2016). Poor sanitation can lead to increased infections, which exacerbate malnutrition, particularly in vulnerable populations. This interplay between environmental health and child nutrition underscores the need for integrated approaches to address malnutrition.

Research by Cumming & Cairncross (2016), indicates that higher altitudes are associated with increased rates of stunting among children(Cumming & Cairncross, 2016). For instance, Mohammed et al, conducted a study in Ethiopia that demonstrated a significant and progressive increase in the prevalence of stunting with rising altitude, even after controlling for dietary and non-dietary variables(Mohammed et al., 2020). This finding suggests that altitude may directly affect child growth and nutritional status, likely due to the physiological stressors associated with living in hypoxic environments. Similarly, Li et al noted that long-term exposure to high altitude is linked to malnutrition in children under five years old, emphasizing that altitude impacts linear growth and may contribute to chronic malnutrition(Li et al., 2023). Furthermore, Baye and Hirvonen, explored the relationship between altitude and child height deficits, finding that altitude significantly correlates with immediate causes of malnutrition, such as dietary deficiencies and disease prevalence(Baye & Hirvonen, 2020a). Their study utilized regression models to quantify the impact of altitude, suggesting that children living at higher elevations may face unique challenges that exacerbate malnutrition risks. This aligns with findings by Belayneh et al. (2021) identified altitude as one of several predictors of child stunting, alongside wealth index and maternal education(Belayneh et al., 2021). This indicates that while altitude may have direct effects on nutrition, it also interacts with socio-economic conditions, which can vary significantly across different altitudinal zones. The interplay between altitude and socio-economic factors is critical in understanding the spatial distribution of malnutrition.

According to the various publications mentioned above, malnutrition is generally the biggest public health issue, particularly in developing nations. There is more than just a shortage of food to blame for this issue. Numerous variables, such as low family income, larger families, illiterate parents, acute and chronic illnesses, and improper child weaning practices, can either directly or indirectly affect a child's nutritional status. Thus, in order to intervene and prevent malnutrition, it is crucial to take these factors into account in a particular community.

2.4 Conceptual Framework

The conceptual framework for spatiotemporal clustering of malnutrition among children under five years of age integrate socio-demographic, socio-economic, environmental, and health-related variable. These framework is crucial for understanding the multifaceted nature of malnutrition and its variations across different contexts. The socio-demographic charactorstics, such as age, gender, and family structures significantly influences malnutrition rates (Amugsi et al., 2013; Chacon et al., 2021), and socio-economic factors, such as low household income level, lack of resources, clean water and sanitations, poor maternal educations, lack of social supports, and rural vs urban setting are consistently associated with higher rates of malnutrition(Herrador et al., 2014; Saba et al., 2023). Environmental factors, such as geographical location, altitude plays a significant role in exacerbeting malnutrition rates as poor environmental conditions can leads to increased disease burden and malnutrition (Ramesh et al., 2022). And altitude also directly affectes child linear growth and nutritional status that may contribute to immidiate causes of chronic malnutrition through dietary deficiencies and disease prevalence(Amugsi et al., 2013; Baye & Hirvonen, 2020b; Ou et al., 2020). Health related factors, including the prevalence infectious diseases and dietary practices, are essential in malnutrition frameworks(Guan & Han, 2019). And also poor feeding practices and dietary diversity during early childhood linked to higher malnutrition rates (Yang et al., 2019).

In general, the conceptual framework for spatiotemporal clustering of child malnutrition incorporates a comprehensive view of socio-demographic, socio-economic, environmental and health related charactorstics. This multifactorial perspectiv is essential for developing effective strategies to combat malnutrition among vulnerable populations, particularely children under five years of age. As depicted in figure-1, There are a number of closely related and inherited factors that contribute to child malnutrition: Socio-demographic factors directly influence socioeconomic status, healthcare services and nutrition, and socio-economic factors can directly affects health and nutrition. Environment factors can also impactes health outcomes directly and indirecly through socioeconomic status. And health related factors can mediate the effects of socio-demographic, socio-economic, environment factors on health and malnutrition.

Based on the various lituratures, with regards to child undernutrition, the below conceptual framework is prepared for this study.

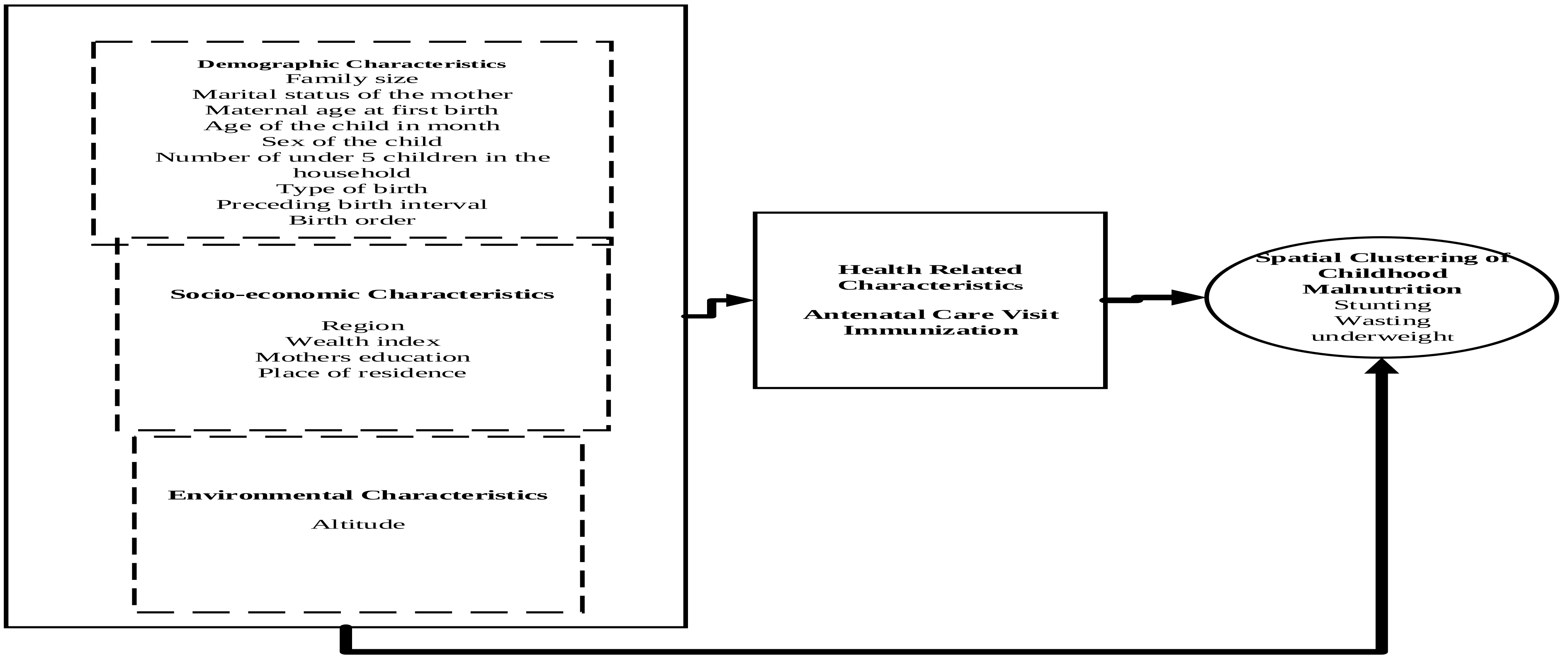

Figure 1: Diagram illustration of the causes of malnutrition.

Source: developed by the researcher based on varioius literature

CHAPTER THREE: METHODS AND MATERIALS

3.1 Description of the Study Area

Ethiopia is a country located in the horn of African continent. Its geographical coordinates are 3 and 15 North latitude and 33 and 48 East longitude or (3°–15° N and 33°–48°E). The total land area is estimated to be 1.13million square kilometer coverage(Billi, 2015). Agriculture is the predominant economic activity accounting for over 83.9% of its GDP, these agricultural activities are mainly dependent on rainfall(Billi, 2015). Administratively Ethiopia is organized into nine regions, namely Tigray, Afar, Amhara, Oromia, Somalia, Benishangul-Gumuz, SNNP, Harari, and Gambela and two city administrations, Addis Ababa and Dire-Dawa (first level), zones (second level), districts/woredas (third level), and kebeles(lowest level) (CSA & Macro, 2001; CSA [Ethiopia], 2006; CSA [Ethiopia] & ICF, 2012). As a land locked country, Ethiopia is shared border with Eritrea in the north, Djibouti and Somalia in the East, Kenya in the South, South Sudan and Sudan in the West (Fetene et al., 2016).

3.2 Study Design and Data Sources

3.2.1 Study Design

This research were employed secondary data obtained from multiple sources, specifically the five rounds of which the four full-scale (2000, 2005, 2011, and 2016) Ethiopian Demographic and Health Survey (EDHS) and the most recent 2019 mini-EDHs surveys. These surveys are comprehensive in nature and provide a wealth of information on various aspects of the Ethiopian population's health, demographic, and socio-economic characteristics(CSA & Macro, 2001; CSA [Ethiopia], 2006, 2017; CSA [Ethiopia] & ICF, 2012; Ethiopian Public Health Institute /EPHI/ & ICF, 2021).

The EDHS employed a population based repeated cross-sectional study design and the sample was designed to provide estimates of key demographic and health variables for the entire country, urban and rural areas separately; each of Ethiopia’s nine regions (Tigray, Afar, Amhara, Oromia, Somalia, Benishangul-gumuze, SNNP, Harari, and Gambela) and two city administrations(Addis Ababa, and Dire-dawa) separately. Every eleven regions were stratified by dividing them into urban and rural areas. In the census frame, each of the 11 administrative areas is subdivided into zones and each zone into woredas which then sub-divided into kebeles which are then further sub divided into convenient areas called census enumeration areas(EAs)(CSA & Macro, 2001; CSA [Ethiopia], 2006, 2017; CSA [Ethiopia] & ICF, 2012; Ethiopian Public Health Institute /EPHI/ & ICF, 2021).

The EDHS employed a two-stage stratified clusters sampling technique in each of the five EDHS surveys. In the first stage, clusters/Enumeration areas(EAs) were selected using probability sampling. In the second stage, households in the selected cluster/EAs were selected using probability sampling. Mothers aged 15–49 years in each selected household were interviewed and anthropometry was taken for all under-five children in each household. In the second round of the selection process, a predetermined number of households per EA were chosen from the list of households. To avoid an uneven sample allocation among regions, the sample was allocated by region in proportion to the square root of the region's population size instead of proportional sample allocation since this procedure yielded a distribution in which 80 percent of the sample came from three regions alone. A thorough sampling methodology was included in the entire EDHS report. Location data (latitude and longitude) coordinates will also be extracted from selected EAs (CSA & Macro, 2001; CSA [Ethiopia], 2006, 2017; CSA [Ethiopia] & ICF, 2012; Ethiopian Public Health Institute /EPHI/ & ICF, 2021).

In EDHS data detailed information were 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. This report presents comprehensive outcomes of the survey at the national level and for Ethiopia's nine regional states and two city administrations separately (CSA & Macro, 2001; CSA[Ethiopia],za 2006, 2017; CSA [Ethiopia] & ICF, 2012; Ethiopian Public Health Institute /EPHI/ & ICF, 2021).

3.2.2 Data Sources

The source of data for this study were obtained from the DHS measures dataset which has been a secondary data that collected in the year 2000, 2005, 2011, 2016, and 2019 in Ethiopia. The EDHS data is nationally representative data conducted every five years (CSA & Macro, 2001; CSA [Ethiopia], 2006, 2017; CSA [Ethiopia] & ICF, 2012; Ethiopian Public Health Institute /EPHI/ & ICF, 2021).

The EDHS data sets and GIS data were downloaded in STATA format from the DHS website (http://www.dhsprogram.com) with permission. The latest Ethiopian administrative boundary shape file (2024) was freely accessed from the UNOCHA-Ethiopia website (https://www.unoch.org). QGIS 3.36.0 was used to link stunting, wasting, and underweight proportions with area-level covariates (https://www.qgis.org). This study analyzed the spatiotemporal clustering patterns and trends of child undernutrition indicators in Ethiopia. The EDHS surveys provide sub-national, regional, urban-rural, and national representation, making them valuable resources for policymakers and stakeholders in addressing child undernutrition.

3.3 Measurement of Study Variables

Determinants And Level of Child Malnutrition are the central theme to be investigated in this study.

3.3.1 Dependent(outcome) Variables

The three undernutrition indicators—stunting (height for age), wasting (weight for height), and underweight (weight for age) in children under the age of five—are the study's outcome variable(s)(Who, 2006). Standardized score units serve as references for these three indicators. While stunting indicates chronic nutritional deprivation, wasting indicates an acute nutritional deficiency in children, and underweight indicates both acute and chronic forms of undernourishment (Mejía-Guevara et al., 2015). A child is considered malnourished if their stunting (ZHA), wasting (ZWH), and underweight (ZWA) are less than −2 SD.

3.3.2 Independent (Explanatory) Variables

The study aimed to identify the key predictors of child undernutrition clustering in Ethiopia by leveraging previous research, including the UNICEF conceptual framework (Young, 2020) and the Lancet series on maternal and child malnutrition (Vu Hoang et al., 2020). It focused on various independent variables such as socio-demographic, socio-economic and cultural, environmental and health-related factors. Specific elements under investigation included altitude, household wealth index, and access to maternal health services (ANC, and Immunizatio), all of which are expected to influence child malnutrition outcomes.

Using prior research, including the UNICEF conceptual framework (Young, 2020) and the Lancet series on maternal and child malnutrition (Vu Hoang et al., 2020), the study sought to determine the major predictors of spatiotemporal clustering of child malnutrition in Ethiopia. Sociodemographic factors, socioeconomic and cultural factors, and environmental and health-related factors are the independent variables that are anticipated to have an impact on child undernutrition. These factors include altitude, household wealth index, and the use of maternal health services (Ayana et al., 2015; Hoq et al., 2019; Khan et al., 2019). Additionally, the survey year and the altitude zone and region of residence will be regarded as independent variables in the analysis. The spatial and temporal clustering of child malnutrition indicators at the cluster level in Ethiopia is thought to be influenced by these geographic and temporal factors. The purpose of the study was to investigate empirically the relative impact of these various predictors on the nationwide distribution of child malnutrition over time.

Ethiopia is characterized by a diverse topography that creates distinict altitude zone, each with unique climatic and ecological characterstics. To understand varying environmental condition, classifying this altitude zone is important.Generally, the recognized classification of altitude zone in ethiopia are catagorized into three main classifications:Low land(below1,500meters asl), Mid-altitude(1,500 to 2,500meters asl), and High lands(above 2,500 meters asl) (Abebe et al., 2010; Zeleke et al., 2023).

Table-1 Dependent and Independent Variables

Dependent variables	Independent variables
Stunting (Height-for-Age) Wasting (Weight-for-Height) Underweight (Weight-for-Age)	**The Socio-demographic variable:** Family size: (Number of HH members) (1: <=5; and 2: >=6); Current marital status of mother: (0: Never married; 1: Married; 2: Widowed 3: Divorced/separated;) Mother's age at first birth (in yrs.): 0: <=20; 1>=21 Sex of child: (1: male, 2: female); Age of child in month: (0: 0-12; 1: 13-24; 2: 25-35; 3: 36+ Number of U5 children in the HHs (in numbers): (0: 1; 1: 2; 2: >=3) Type of birth: (0: Single birth; 1: Multiple birth); Birth order number: (0: 1^{st} birth; 1: 2^{nd} birth; 2: 3^{rd} birth; and 3: 4^{th} +); Preceding birth interval: (1: <=24 months; 2: 25-47months; 3: >=48 months) **The socioeconomic and cultural variable:** Mother's educational level: 0: No education; 1: primary education; and 2: secondary education; 3: higher education Religion: 1: Orthodox; 2: Muslim; 3: Christian; 4: Others Wealth index of the household: 1: Poor; 2: Medium; 3: Rich; Region: (1: Tigray; 2: Afar; 3: Amhara; 4: Oromia; 5: Somali;6: Benishangul-Gumuz; 7: SNNP; 8: Gambella; 9: Harari; 10): Addis Ababa; and 11: Dire-Dawa); Place of residence: (1: urban; 2: rural). **The Environmental and Health related behavior variable:** Altitude (Zones): (1: Low-altitude zone (<1,500m above sea level); 2: Mid-altitude zone (1,500 to 2,500m above sea level); and 3: High-altitude zone (>2,500m abve sea level). Antenatal care visits for pregnancy (ANC): (1: attended at least once; 0: Never attended); Immunization: ((1: yes; 0: else);

Sourc: EDHS 2000, 2005, 2011, 2016, 2019.

3.4 Data Management and Analysis

Data cleaning was performed, and STATA version 17 was used for analysis. Following DHS guidelines, a joining variable linked the EDHS datasets to GPS coordinates. QGIS 3.36.0 facilitated spatial analysis to visualize child malnutrition patterns (underweight, stunting, and wasting) at the cluster level in Ethiopia. Sample weights were computed to restore representativeness due to non-proportional distribution. Descriptive and summary statistics described the study population, while multivariable logistic regression addressed the hierarchical nature of the DHS data. The latest Ethiopian administrative boundary shape file (2024) was accessed from the UNOCHA-Ethiopia website for mapping (https://www.unoch.org)

In order to have an overall picture of spatio-temporal clustering of child malnutrition indicators of stunting, underweight, and wasting at cluster level in Ethiopia, this study employed an exploratory data analysis of the variables included. The total numbers of children under the age of five years covered in the study were 10,752, 9,884, 10,255, 10,179 and 5,101 for the 2000, 2005, 2011, 2016,and 2019 respectively, and weighted to total sampled of 46, 172 children.

3.5 Spatiotemporal and Statistical Model Analysis

3.5.1 Spatiotemporal clustering analysis (Getis–Ord Gi statistic)*

A spatiotemporal hotspot clustering analysis is a scienific approach that combines spatial and temporal data to identify regions/areas/ where events or phenomenen happen much densely than expected(Barro et al., 2015; Deng et al., 2013). This methods enables reseachers to discern not only where events are concentrated but also how these concentration evolve over time. As a result, it can significantly enhance resource allocation and intervention strategies (Barro et al., 2015). Based on a particular attribute, spatial autocorrelation quantifies how similar or dissimilar two locations are from one another. It facilitates the discovery of spatial patterns, clusters, and hotspots in the data. To measure spatial autocorrelation and pinpoint areas with high or low rates of malnutrition, one can employe techniques like Moran's I or Getis-Ord (Profile, 2019). These results' statistical significance was evaluated using Z-scores and P-values. Hotspots for childhood stunting, wasting, and underweightness are shown by a positive Z-score (P-value < 0.05). Whereas children who are not stunted, wasting, or underweight are shown by a negative Z-score (p-value < 0.05).

Thus, in order to identify high concentrations of childhood malnutrition (stunting, wasting, and underweight) in Ethiopia, this study utilized Getis-Ord G* Statistics. These statistics create maps that highlight clusters of malnutrition (Ord & Getis, 1995). Unlike Moran's I, who cannot differentiate between high and low positive spatial autocorrelation, Getis-Ord effectively measures concentrations of values, making it more suitable for this research. The study also explored variations in undernutrition over time and space using spatiotemporal approaches, including trend and emerging hotspot analyses. Spatial maps were produced and analyzed using QGIS 3.36.0 and STATA version 17 software.

3.5.2 Statistical Analysis

Multivariable logistic regression is a statistical method that models the relationship between multiple independent variables and a binary dependent variable. It extends simple logistic regression, focusing on categorical outcomes with two possible results (e.g., success/failure). The main goal is to estimate the probability of an observation falling into one category based on independent variable values. This approach allows researchers to simultaneously assess the impact of multiple predictors, which is essential in fields like epidemiology and social sciences, where outcomes are influenced by various factors (Tang et al., 2021; Tetrault et al., 2008; Wang et al., 2020).

The formula for logistic regression analysis is generally expressed as:

$$ln\left(\frac{P(Y=1)}{P(Y=0)}\right) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + +\beta_k X_k$$

k = is the index for the number of independent variables

Y = is the depedent variable with values 1 representing a hotspot and 0 refers to otherwise.

$P(Y = 1)$is interpreted as the probability of finding a hotspot cluster,

$P(Y = 0)$is interpreted as the probability of not observing a hotspot cluster,

β_o is the intercept,

$\beta_1, \beta_{2,} \dots, \beta_k$ represent the log odds ratio, and

$X_1, X_{2,} \dots, X_k$refer to the predictor variables k.

This approach enhances the model's predictive power and interpretability, as seen in various studies across different domains, including healthcare and social sciences(Qi et al., 2023). Generally, multivariable logistic regression is a powerful analytical tool that enables researchers to explore the relationships between multiple predictors and a binary outcome, providing insights that are critical for decision-making in various fields.

The multivariable logistic regression analysis approach employed in this study was to investigate the cluster-level factors associated with childhood stunting, wasting, and underweight clustering. Initially, a bivariate logistic regression analysis was undertaken to select candidate variables for the multivariable model. Variables that were significant at p-value < 0.25 were considered as potential variables for the final models. An adjusted odd ratio with a 95% CI and a p-value of less than 0.05 was deemed to be statistically significant. Multivariable logistic regression analysis and adjusted odds ratios with corresponding 95% confidence intervals (Cls) were used to model the three indicators of stunting, wasting, and underweight to their independent predictors. The adjusted odds ratio (AOR) and its accompanying 95% confidence intervals (CIs) were supplied in order to assess the strength of the association.

3.6 Ethical Consideration

This study is conducted after obtaining ethical clearance from Addis Ababa

University, College of Development Studies, Center for Food Security studies. And also we requested the DHS Program to grant permission for downloading and utilizing the publicly available Ethiopia Demographic and Health Survey (EDHS) secondary data including the GPS/GIS coordinate reading data and obtained to use freely for this study. Procedures and the study protocols for standard Demographic and Health Surveys have been reviewed and approved by the ICF/ORC Institutional Review Board. In this regard, the names of respondents and individual identifiers were not be included in the final data to ensure respondents' anonymit.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 RESULTS

This chapter presented the Results and Discusion parts of the study.The first section presents the Descriptive Analysis Of The Variables, The Spatiotemporal Analysis, and the Multivriate Logistic Regression Analysis of the results. The second section presents the Discusion parts.

The analysis was based on the Ethiopian Demographic and Health Surveys (EDHSs) data from the survey years of 2000, 2005, 2011, 2016, and 2019 were included. EDHS encompassed an extensive collection of data obtained from a meticulously selected and representative sample households. The present analysis was done using 46,172 children who were below the age of 5 years. Of note, the analysis was carried out using the weighted data. Weights were applied in order to compensate for over/under sampling and non-response. By incorporating data from multiple time points spanning nearly two decades, the analysis enabled us to examine trends and patterns in key indicators related to child health and well-being over an extended period. This approach offered valuable insights into the evolving circumstances and conditions experienced by young children in Ethiopia, shedding light on any changes or developments that occurred over time.

4.1.1 Descriptive Analysis

This sub-section presents descriptive statistics summarizing the characterstics of the study populations over the survey years (2000-2019).

4.1.1.1 The Distributions of Socio-Demographic, Socio-Economic And Cultural Characteristics of The Study Population Over Time

The Socio-Demographic, Socio-economic and cultural characterstics results in Table-2, shows that the largest proportion of the study population was consistently found in Oromia and SNNP regions, comprising approximately 39.78% and 20.34%, respectively, by 2019 (Table-2). Similarly, urbanization trends increased over time, with urban residents growing from 10.61% in 2000 to 25.33% in 2019, reflecting migration and improved urban economic opportunities and access to services (Table-

2). Regarding family size, the proportion of households with family size of 6 or more members decreased slightly from 56.71% in 2000 to 54.38% in 2019, conversly, the proportion of households with 5 or fewer members increased from 43.29% in 2000 to 45.62% in 2019 (Table-2). Withregards to maternal characterstics, the proportion of mothers giving birth at the age of 21 or older increased slightly from 80.96% in 2000 to 82.09% in 2019. While, the proportion of mothers giving birth at the age of 20 or younger decreased from 19.04% in 2000 to 17.91% in 2019 which reflecting a reduction of 5.9% over the years (Table-2).

Interms of education, educational attainment of mothers improved significantly as mothers with no education declined from 81.57% in 2000 to 53.32% in 2019. While, mothers with primary, secondary, and higher education increased markedly, highlighting the influence of education on maternal and child health outcomes (Table-2). Regarding wealth index of the household, An upward shift in household wealth was observed, with an increase in middle and high wealth index households over the study period (Table-2). Overall, the data in Table-2 reveals significant trends in family size, marital status, maternal age, educational attainment, wealth distribution, urbanization, and religious affiliation. These variables are interconnected and can provide insights into the socio-economic conditions affecting families over time.

4.1.1.2 The Distributions of Child Related Demographic Characteristics of the Study Population Over Time.

As vividly described in Table-3, the Child demographic characterstics result demonstrate that the percentage of households with one or fewer children under five years old has increased from 34.59% in 2000 to 40.51% in 2019, which reflecting a growth of 17.11percent. In contrast, households with two or more children have decreased from 65.41% to 59.49 percent in between 2000 to 2019, reflecting a reduction of 9.10%. This trend suggests a move towards smaller family sizes(Table-3). Regarding the current age of child(in month), The largest proportion of children consistently falls in the 36 to 59 months age group (40–43%), followed by lower proportions in the 0 to 11 months (20%) age groups, and (19%) were 12 to 23 months and 24 to 35 months age groups respectely

Table-2 Distribution of Socio-Demographics, Socio-Economics and Cultural Characteristics of Study Population (Weighted, N=46,172).

Variable	Category	Survey year				
		2000 (%)	2005 (%)	2011(%)	2016(%)	2019 (%)
Total (n)	Number	10,752	9,884	10,255	10,179	5,101
Family Size	<=5	43.29	41.01	44.14	43.40	45.62
	>=6	56.71	58.99	55.86	56.60	54.38
Current marital status of mother/care giver	Never married	0.55	0.37	0.69	0.53	0.35
	Married/living together	92.54	94.39	92.66	94.90	94.80
	Widowed	1.46	1.72	1.88	1.08	1.14
	Divorced/separated	5.46	3.53	4.76	3.47	3.70
Age of mothers at the birth of the baby	<=20	19.04	19.32	17.80	16.69	17.91
	>=21	80.96	80.68	82.20	83.31	82.09
Highest educational level the mothers/care givers	No education	81.57	78.54	68.84	65.68	53.32
	Primary education	13.26	16.99	27.44	27.02	35.39
	2ndary education	4.94	4.05	2.20	4.79	7.64
	Higher education	0.22	0.42	1.51	2.51	3.65
Wealth index of the household	Poor	42.48	42.79	44.44	46.73	45.15
	Medium	21.16	21.89	20.63	20.77	18.91
	Rich	36.36	35.32	34.93	32.5	35.93
Place of residence	Urban	10.61	7.41	12.73	11.30	25.33
	Rural	89.39	92.59	87.27	88.70	74.67
Region	Tigray	6.59	6.48	6.63	6.63	6.93
	Afar	1.00	0.94	0.99	1.00	1.52
	Amhara	26.02	22.83	21.48	19.08	19.17
	Oromia	40.51	40.06	43.27	43.72	39.78
	Somali	1.18	4.15	2.80	4.61	7.00
	Ben-Gum	1.00	0.94	1.13	1.10	1.16
	SNNP	21.37	22.37	20.99	20.67	20.34
	Harari	0.21	0.20	0.22	0.23	0.30
	Addis Ababa	1.56	1.41	1.82	2.29	2.83
	Dire Dawa	0.33	0.34	0.32	0.42	0.53
	Gambela	0.23	0.28	0.34	0.25	0.44
Religion	Orthodox	49.23	41.56	37.87	34.68	34.06
	Other Christian	17.04	21.21	24.51	22.12	27.65
	Moslem	29.94	34.77	35.37	41.09	36.66
	Others	3.78	2.46	2.25	2.16	1.62

Source: EDHS 2000, 2005, 2011, 2016, and 2019.

Regarding preceding birth intervals, tabble-3 indicate that the percentage of mothers with a preceding birth interval of 48 months or more has increased from 19.46% in 2000 to 29.91% in 2019, which reflectes a reduction of 53.70%, indicating more mothers are spacing their births further apart. The decrease in the percentage of mothers with a preceding birth interval of 25-47 months from 58.81% to 45.62% further supports this trend towards longer intervals between births(Table-3).

In general, the data in table-3 shows that significant trends in the sex of children, age distribution, family size, birth order, type of birth, and birth spacing. These trends might reflect changing societal norms and family planning practices, indicating a movement towards smaller family sizes and longer intervals between births (Table-3).

Tabel-3 Distributions of Child Related Demographic Characteristics of the Study Population (Weighted, N=46,172)

Variable	**Categories**	**Survey Year**				
		2000 (%)	2005 (%)	2011 (%)	2016 (%)	2019 (%)
Total(n)	Number	10,752	9,883	10,256	10,178	5,101
Sex of child	male	50.78	50.68	51.36	51.01	51.14
	female	49.22	49.32	48.64	48.99	48.86
Current age of child (imonths)	0 to 11	20.31	21.18	20.20	20.62	19.13
	12 to 23	19.95	18.76	17.91	19.79	19.83
	24 to 35	19.38	18.96	18.86	18.74	19.93
	36 to 59	40.37	41.09	43.03	40.84	41.19
Number of U5 children in (HHS)	<=1	34.59	32.99	34.78	38.30	40.51
	>=2	65.41	67.01	65.22	61.70	59.49
Birth Order number	1st Birth	18.44	16.74	18.86	18.84	21.68
	2nd Birth	16.43	15.91	17.03	16.28	18.02
	3rd Birth	13.92	14.69	14.18	14.11	14.16
	4th Birth	51.21	52.66	59.93	50.76	46.14
Type of birth	Single Birth	98.74	98.61	98.13	97.78	97.59
	Multiple Birth	1.26	1.39	1.87	2.22	2.41
Preceding birth interval	<=24months	21.73	22.62	22.57	24.24	24.46
	25-47months	58.81	57	56.1	49.94	45.62
	>=48months	19.46	20.38	21.33	25.82	29.91

Source :EDHS 2000, 2005, 2011, 2016, and 2019.

4.1.1.3 The Distributions of Environmental and Health Related Characterstics of The Study Population Overtime.

As vividly described in table-4, regarding variables related to cluster altitude, antenatal care visits for pregnancy(ANC), and immunization rates:

Results for cluster altitude shows a shift in the distribution of the target population across different altitude zones. The percentage of individuals in the low-altitude zone (<1,500m asl) had increased from 8.30% in 2000 to 23.23% in 2019(Table-4). In contrast, the mid-altitude zone (1,500 to 2,500m asl) had decreased from 60.91% to 53.99%, and the high-altitude zone (>2,500m asl) had also seen a decline from 30.80% to 22.78%. This shift may reflect migration patterns or changes in settlement areas(Table-4). Regarding antenatal care visits(ANC) for pregnancy, there has been a significant decline in the percentage of women with no ANC visits, dropping from 72.45% in 2000 to 24.95% in 2019(Table-4). This indicates a positive trend towards increased awareness and access to antenatal care services. Conversely, the percentage of women who visited at least once for ANC has increased dramatically from 27.07% in 2000 to 74.83% in 2019. This suggests that more women are recognizing the importance of antenatal care for their health and the health of their babies(Table-4).

Interms of Immunization coverage, the data in Table-4 indicates that the vast majority of the population remains unvaccinated, with 95.16% of individuals reporting no immunization in 2000, slightly decreasing to 94.96% in 2019(Table-4). The percentage of individuals who received immunizations has remained low, increasing from 4.84% in 2000 to only 5.04% in 2019. This suggests that while there may be slight improvements in immunization rates, a significant portion of the population is still not receiving necessary vaccinations(Table-4)

Tabel-4 The Distributions of Environmental and Health Related Characteristics of the Study Population(Weighted, N=46,172)

Variables	Categories	Survey year				
		2000 (%)	2005 (%)	2011 (%)	2016 (%)	2019 (%)
Total (n)	Number	10,752	9,883	10,256	10,178	5,101
Antenatal care visits forpregnancy (ANC)	No ANC visits	72.45	71.26	57	36.38	24.95
	Visited at least once	27.07	28.33	42.69	63.44	74.83

	Table-4 Cont'ed					
	Others	0.48	0.40	0.35	0.18	0.21
Cluster altitude (in meters)	Low-altitude zone (<1,500m asl)	8.30	8.59	16.71	17.43	23.23
	Mid-altitude zone (1,500 to 2,500m asl)	60.91	56.47	57	58.27	53.99
	High-altitude zone (>2,500m asl)	30.80	34.93	26.3	24.3	22.78
Immunization	0	95.16	95.67	93.71	93.79	94.96
	Yes	4.84	4.33	6.29	6.21	5.04

Source: EDHS 2000, 2005, 2011, 2016, and 2019.

4.1.2 Spatiotemporal Hotspot Clusters Analysis(Getis-Ord G)*

A spatiotemporal hotspot clustering analysis is a methodological approach that combines spatial and temporal data to identify areas where phenomenen happen much more densely than expected(Barro et al., 2015; Deng et al., 2013). While Getis-Ord G*statistics are used to create maps that identify potential hotspot areas and display clusters of childhood malnutrition (Ord & Getis, 1995).

The key descriptive analysis results of degree of geographical distributions of spatiotemporal patterns and trends of hotspot clustering of under-five childhood stunting across various zones of all regions of Ethiopia at cluster level based on the Getis-Ord G* statistical analysis from EDHS data over different survey years (2000, 2005, 2011, 2016, and 2019) provided bellow.

In the year 2000, the spatiotemporal cluster analysis shown in Figure-2 reveal thatthe hotspot clustering distributions of under-five childhood stunting were predominantly observed in extensive areas of Amhara region of varrious zones like parts of North, Central, and South Gonder Zones, in extensive areas of East and West Gojame Zones as well as western parts of North and South Wollo zones, and in northern parts of North-Showa Zone of Amhara region; In Oromia region: in central parts of North Shewa and eastern and southern parts of West-showa zones, western parts of East Hararge and northern parts of West Hararge

4.1.2.1 Spatiotemporal Hotspot Analysis of Stunting in Under-Five Children in Ethiopia (2000-2019)

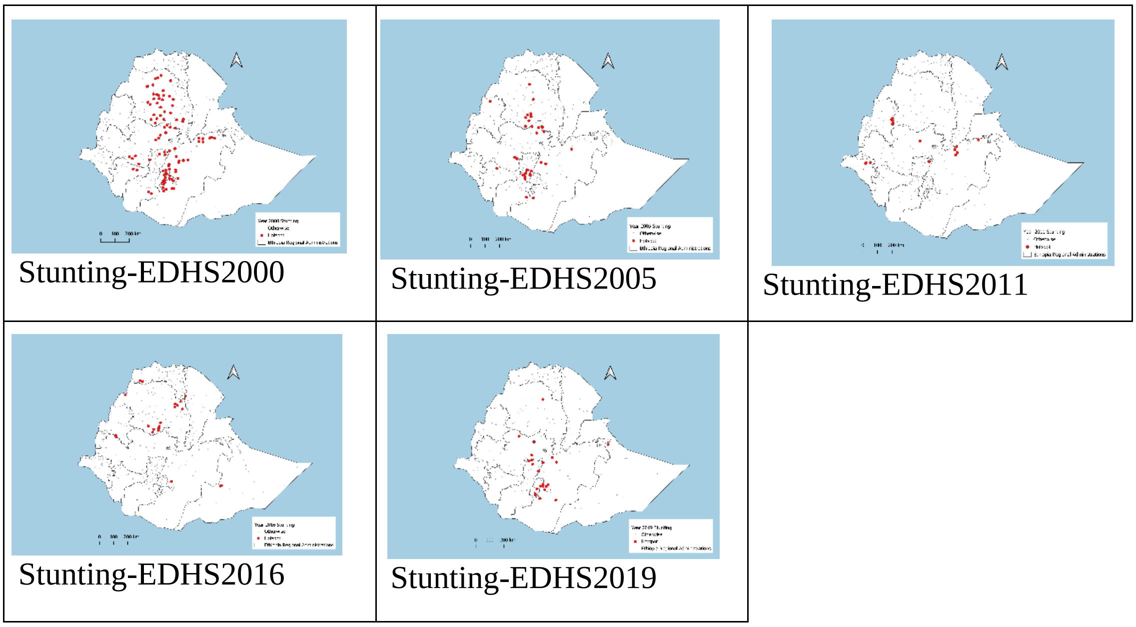

Figure 2: Spatiotemporal Clustering Analysis of Stunting in Under-Five Children in Ethiopia (2000-2019)

Source: EDHS 2000, 2005, 2011, 2016, 2019.

Shapefile:UNOCHA Ethiopia (https://www.unocha.org).

zones, in south-western parts of Arsi and large areas of West-Arsi zones, southern and western parts of Jimma zones as well as central Guji and extensive parts of West Guji zones; in extensive areas of Sidama region, including Gedeo zone, Additionally, hotspot clusters were identified in the eastern parts of Kefa zone of South-West Ethiopia regions as well as in Derashe, and in borders of Burji and Konso zones of SNNP regions.

In the year 2005, the spatiotemporal cluster analysis depicted in Figure-2 indicate that hotspot clusters distribution of under-five childhood stunting observed in Amhara region of various zones such as parts of North, Central, and South Gonder Zones, in extensive areas of East and West Gojam Zones, in south-western parts of South Wollo Zone, parts of North-Showa Zone of Amhara region as well as northern parts of Metekel Zone of Benishangul-Gumuz region. In parts of North Showa Zone of

Oromia regional state, in northwestern parts of West Showa and parts of Jimma Zones, in central parts of West Hararge zone, in Western parts of Arsi and large areas of West-Arsi Zones, in parts of Guji and north-western parts of West Guji Zones of Oromia regions and in parts of Kefa Zone of South-West Ethiopia region as well as extensive areas of Sidam region including Gedeo zone and also Hadiya, Kembata-Tembaro Zones of Central Ethiopia region, and northern parts of Wolayita as well as Amaro and Burji Zones of SNNP region. In this year, hotspot cluster areas were more widely distributed across regions of Amhara, Oromia, Sidama, SNNP, Central Ethiopi, and South-West Ethiopia regions of various zones. A downward trend in hotspot cluster distributions were observed compared to 2000, with newly emerged hotspot clusters locations of northern Metekel Zone of Benishangul-Gumuz region in previously unaffected areas(Figure-2).

In the year 2011, the spatiotemporal clustering analysis in Figure-2 revealed that hotspot clusters of under-five childhood stunting were observed in Benishangul-Gumuz of eastern Metekel zone, northeastern parts of Agnewak Zone of Gambela region, in West and East Shewa Zone of Oromia region, in the southern border of zone-3 of Afar region, as well as northern parts of West Hararge and Arsi Zones, and in eastern parts of Guraghe Zone of Central Ethiopia region. Additionally, the analysis indicate that, along with a continued declining trend, the hotspot clusters of under-five childhood stunting shifted/emerged towards the eastern section of Metekel Zone of Benishangul-Gumuz and the northeastern parts of Agnewak Zone of Gambela region which has previousely unaffected areas with uneven hotspot cluster distribution(Figure-2).

In the year 2016, the spatiotemporal clustering analysis in Figure-2 revealed that hotspot cluster of under-five childhood stunting observed in West-Tigray, West-Gonder Zones, as well as in the northeastern parts Wag Hamra and northern border of North wollo Zones, and in large areas of East-Gojam Zone of Amhara redgion, and also in southwestern parts of Kilbati/Zone-2/ of Afar region, in southern border of Metekel Zone of Benishangul-Gumuz region, in southwestern border of West- Arsi Zone and Sidama region, as well as northern Afder Zone of Somalia region (Figure-2). In this year, Emerging hotspot clusters of new locations were identyfied in West

Gonder, West-Tigray, southern border of Metekel zones of Amhara,Tigray, and Benishangul-Gumuz regions, as well as southwestern borders of Kilbati/Zone-2/of Afar region, and northern parts of Afder Zone of Somalia regions, with continued an overall decline trend of hotspot cluster intensity and with similar uneven distribution as of previous years(Figure-2).

In the year 2019, the spatiotemporal clustering analysis in Figure-2 indicate that hotspot clusters of under-five childhood stunting were found in the northeastern parts of Wag Hamra Zone, in Horoguduru Wollega Zone, in North, West, East, and south-West Shewa Zones, in northern Arsi Zone, as well as in Guji and West-Guji Zones of Oromia region, and in northwestern and southeastern parts of Guraghe Zone of Central-Ethiopia region, and parts central Sidama, including Gedeo Zone, and also in the northern border of Fafen Zone of Somalia region with declining trends in hotspot clustering areas and uneven distribution with similar fashion of previous years pattern(Figure-2). Overall, the Getis-Ord G*statistic analysis of spatiotemporal hotspot clustering distributions of childhood stunting depicted in figure-2 reveal that, (early 2000,2005) degree of hotspot clusters distribution were concentrated in specific regions like Amhara, Oromia, Sidama, and SNNP regions. While, in later years(2011,2016, and 2019), degree of hotspot clusters distribution of childhood stunting distribution shifts, with emerging patterns like Tigray, Afar, Benishangul-Gumuz, Gambela, and Somalia regions with uneven distribution over the years across Ethiopia(Figure-2). Regarding temporal trends, despite regional variation, there has been a gratual reduction in intensity of hotspot clustering distribution of childhood stunting across Ethiopia over the two decades(Figure-2).

4.1.2.2 Spatiotemporal Hotspot Analysis of Wasting in Under-Five Children in Ethiopia (2000-2019)

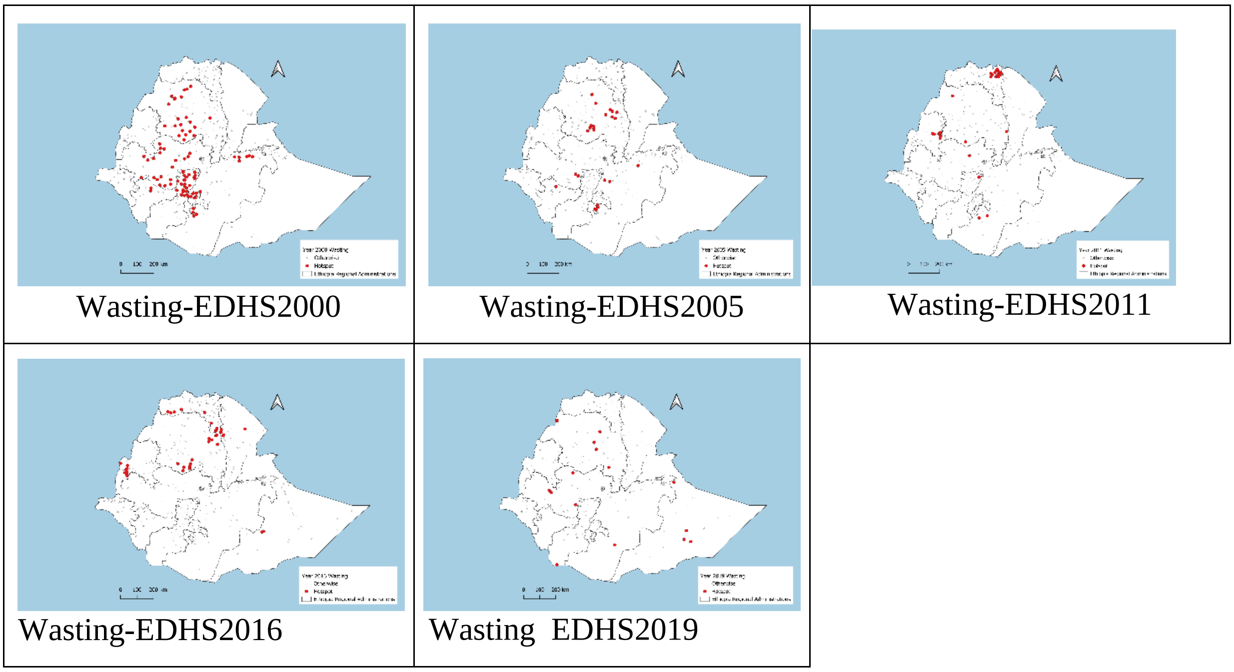

Figure-3 Spatiotemporal Clustering Analysis of Wasting in Under-Five Children in Ethiopia (2000-2019)

Source: EDHS 2000, 2005, 2011, 2016, 2019;
Shapefile:UNOCHA Ethiopia (**https://www.unocha.org**.

The key descriptive analysis results of degree of geographical distributions of spatiotemporal patterns and trends of hotspot clustering of under-five childhood wasting across various zones of all regions of Ethiopia at cluster level, based on the Getis-Ord G*statistical analysis from EDHS data over different survey years (2000, 2005, 2011, 2016, and 2019) provided bellow:

In the year 2000, the spatiotemporal hotspot clusters analysis presented in Figure-3 revealed that hotspot clusters of under-five childhood wasting were primarily concentrated in various zones Amhara regions, such as North, Central, and South Gonder zones, in southern parts of Awi zone, in northern parts of South-Wello zone, as well as in East and West Gojam zones. In Oromia region, the hotspot clustering of under-five childhood wasting were concentrated in various zones, like in the West, East, and Horo Gudru Wellega Zones, in the southern parts of Ilu Aba Bora Zone and large areas of Jimma Zone, in the West and South-West Shewa Zones, as well as East and West Hararge Zones of northern parts; in the central parts of Kefa Zone of South-West Ethiopia region, in southern parts of Yem Special, in the western, southern and eastern parts of Guraghe, eastern Silte, in extensive areas of Hadiya and Kembata-Tembaro Zones of Central Ethiopia region, as well as north-eastern parts of Wolayita Zone of SNNP region as well as Sidama region, including Gedeo Zones(Figure-3). Overall, the hotspot clusters of childhood wasting predominantly concentrated in various zones of Amhara, Oromia, Central-Ethiopia, SNNP, Sidama, and South-West Ethiopia regions of Ethiopia(Figure-3).

By the year 2005, the spatiotemporal hotspot clusters analysis result in Figure-3 indicate that hotspot cluster of under-five childhood wasting more dispersedly observed, particularly in the North, Centraland South Gonder, in the southern border of North and southwestern sections of South Wello Zones of Amhara region; in various zones of Oromia region such as in North, West and South-West Shewa Zones of different parts, in West Hararge, Arsi, and southern parts of Jimma Zones as well as eastern parts of Kefa Zone of South-West Ethiopia region as well as Gedeo Zone of Sidama region. The maps in Figure-3 clearly illustrate that the geographic distribution of the hotspot clustering areas were more spread out,with declining trends compared to 2000, uneven distribution patterns(Figure-3). In the year 2011, the spatiotemporal clustering analysis results provided in Figure-3 revealed that hotspot clusters distribution of under-five childhood wasting were observed in the Eastern-Tigray Zone, in the northern section of Central Gonder zone, in the East-gojam and eastern parts of South Wello Zones as well as in the border of southeastern Metekel Zone of Benishangul-Gumuz region and Awi Zone of Amhara region; in various zones of Oromia region, such as West-Shewa, western Guji and northeastern section of West Guji Zones as well as in Silti Zones of Centra-ethiopia Region. As the maps in Figure-3 illustrate, the geographic distribution of hotspot clusters were shifted to new locations of previously unaffected areas like Eastern-Tigray Zone and Eastern section of Metekel Zone of Benishangul-Gumuz with reflecting an uneven distribution along with declining trends as of previous years over time(Figure-3).

By the year 2016, the spatiotemporal clusterig analysis results shown in Figure-3 indicate that hotspot clusters of childhood wasting identified in the southwestern parts of West-Tigray, northwestern parts of Central Tigray, and southern parts of South-Tigray Zones of Tigray region, northwestern and central parts of Kilbati/Zone-2/ Zones of Afar region, northeastern Wag Hamra and northern parts of North-Welloas well as southern parts of East Gojam Zones of Amhara region; in the northern part of Assossa and Eastern border of Assossa and Kamashi Zones of Benishangul-Gumuz region as well as northern parts of Afder Zone of Somalia region. The maps illustrate that the hotspot clusters distribution for under-five childhood wasting were largely dispersed and emerged to new locations, such as Central and southern Zones of Tigray region, western and central parts of Kilbati/Zone-2/ Zones of Afar region, Southwestern parts of Benishangul-Gumuz as well as western Somalia regions in Ethiopia, all while exhibiting decreasing trends alongwith uneven geographic distribution of hotspot clusters of wasting as of previous years(Figure-3).

In the year 2019, the spatiotemporal clustering analysis results depicted in Figure-3 identified that hotspot clusters of under-five childhood wasting were observed in the northern parts of West-Gonder, Southern parts of Wag Hamra, northern parts of North-Wello as well as southern border of South-Wello Zones of Amhara region; in Horo Gudru Wellega, northwestern and southeastern parts of Jimma, in central Guji zones of Oromia Region; in the southern border of South-Omo Zone of SNNP region as well as in Shebelle and Western parts of Fafen Zones of Somalia region(Figure-3). The maps clearly illustrate that the distributions of hotspot clusters for childhood wasting were more scattered, with some hotspot clusters shifted to the western parts of Amhara region and northern and central Somalia(Figure-3).The overall hotspot clusters distributions exhibited a decline trends over the period alongwith an uneven distributions hotspot cluster as of previous years(Figure-3). Overall, the Getis-Ord G* statistical analysis of childhood wasting hotspots, as shown in Figure 3, reveals that in the early 2000s and 2005, hotspots were primarily concentrated in the Amhara and Oromia regions. However, by 2011, 2016, and 2019, these hotspots shifted to previously unaffected areas, including western Amhara, eastern and western Benishangul-Gumuz, southern SNNP, and northern and central Somalia. This shift demonstrates emerging hotspot clusters with fluctuating distribution patterns over time. Despite an overall decline in childhood wasting, the hotspot clusters exhibited variable distribution trends (figure-3).

4.1.2.3 Spatiotemporal Hotspot Analysis of Underweight in Under-Five Children in Ethiopia (2000-2019)

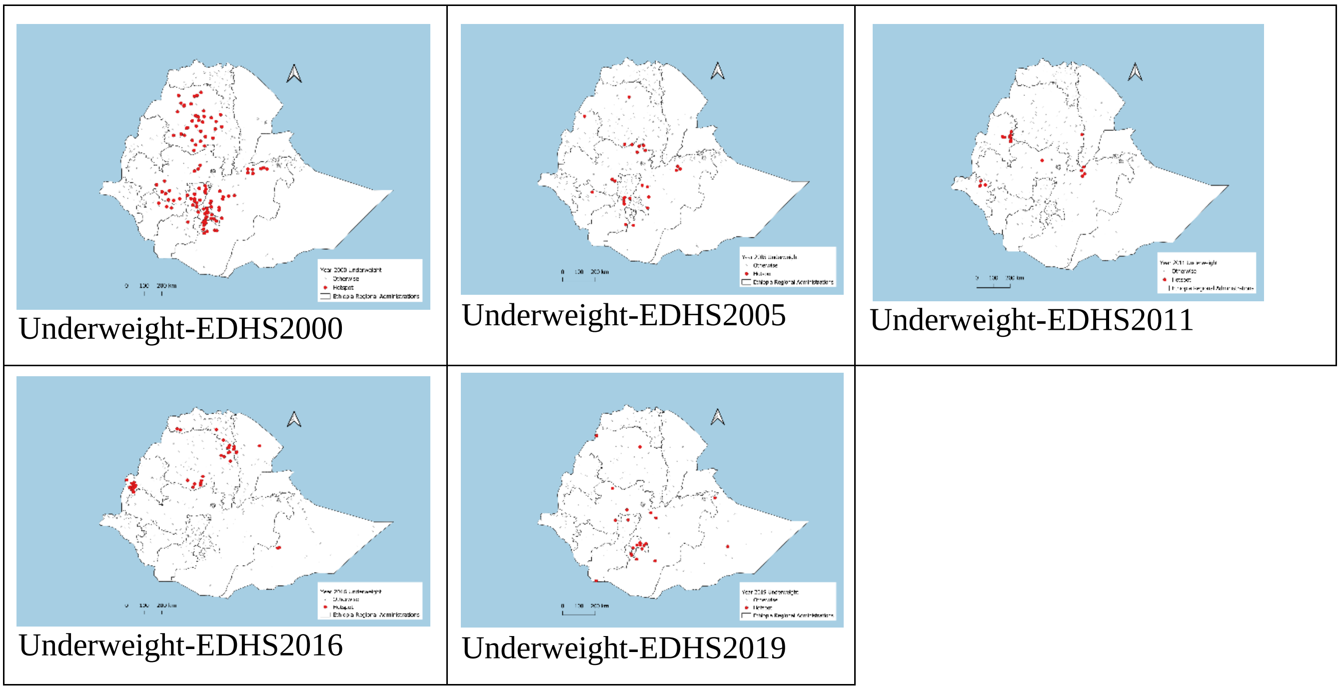

Figure-4: Spatiotemporal Clustering Analysis of underweight in Under-Five Children in Ethiopia (2000-2019)

Source: EDHS 2000, 2005, 2011, 2016, 2019.

Shapefile:UNOCHA Ethiopia (**https://www.unocha.org**

The key descriptive analysis results of degree of geographical distributions of spatiotemporal patterns and trends of hotspot clustering of under-five childhood underweight across various zones of all regions in Ethiopia, at cluster level based on the Getis-Ord G* statistical analysis from EDHS data over different survey years (2000, 2005, 2011, 2016, and 2019)provided bellow:

In the year 2000, the spatiotemporal clustering analysis results depicted in Figure-3 revealed that significant hotspot clusters of under-five childhood underweight across various zones of the Amhara region, such as North, Central, and South Gonder, Awi zones and west and East Gojam Zones as well as North and South Wello Zones of Amhara region; in Oromia region: in West-Shewa, in extensive areas of northern parts of East and West Hararge Zones, in southwestern and southern parts of Jimma Zone as well as southern parts of Arsi, Western and southern parts of West Arsi Zones, and also northeastern parts of West Guji and northeastern parts of Guji Zones; south eastern parts of Ilu Aba Bora and centra parts of Buno Bedelle Zones of oromia region. In northeastern parts of Kefa and Konta special Zones of South-West Ethiopia region; In southern parts of Yem special, Guraghe, and eastern parts of Silti, Hadiya, Kembata-Tembaro Zones of Central Ethiopia region; in Eastern parts of Wolayita Zone of SNNP region as well as extensive areas of Sidama, including Gedeo Zone(Figure-4). Overall, the hotspot clustering of childhood underweight in 2000 were primarily concentrated in Amhara, Oromia, South-West Ethiopia, Central-Ethiopia and Sidama regions(Figure-4).

In the year 2005, the spatiotemporal clustering analysis results shown in Figure-3 revealed that hotspot clusters of under-five childhood underweight were observed in northeasrn parts of central Gonder Zone, in southern borders of East Gojam Zone, and in western borders of North Shewa Zone of Amhara region as well as northern section of Metekel Zone of Benishangul-Gumuz region; in North-Shewa Zone, in northern parts of West Hararge Zone, in northwestern parts of Arsi and southern parts of West Arsi Zones, as well as in western parts of Guji and central parts West Guji Zones and Southeasternparts of Jimma Zone of Oromia Region. Additionally, hotspot clusters were also observed in the northern parts of Kefa Zone of South-West Ethiopia region; in southern Hadiya and northeastern parts of Kembata-Tembaro Zones of Central Ethiopia region as well as in larger areas of Wolayita and adgecent border of Amaro and Burji Zones of SNNP region, as well as southeastern sections of Sidama region of Ethiopia. This analysis revealed that a more dispersed hotspot clustering of underweight and emerging hotspot clusters to new locations of northern parts of Metekel zone of Benishangul-Gumuz region with an uneven distribution patterns and declined trends over time(Figure-4).

In the year 2011, the spatiotemporal clustering analysis results shown in Figure-3 revealed that hotspot clusters of under-five childhood underweight were detected in

Eastern parts of North, West, and eastern borders of East Shewa Zones of Amhara region, the eastern areas of Metekel Zone of Benishangul-Gumuz Region, as well as northern parts of West Hararge Zone of Oromia region and southern border of Gabi/zone-3/ of Afar region, and also eastern parts of Agnewak Zone of Gambela region. Compared to 2000, the 2011 hotspot clusters were more dispersed, with some areas persisting while others shifted to new locations, with reflecting uneven distributions with overall decreasing trends of hotspot cluster distributions over time(Figure-4).

By the year 2016, the spatiotemporal clusterig analysis results shown in Figure-4 indicate that hotspot clusters of childhood underweight found in the southwestern parts of West-Tigray, northwestern parts of Central Tigray, and southern parts of South-Tigray Zones of Tigray region; northwestern and central sections of Kilbati/Zone-2/ of Afar region, northeastern Wag Hamra and northern parts of North-Wello as well as southern parts of East Gojam Zones of Amhara region; in the northern part of Assossa and Eastern border of Assossa and Kamashi Zones of Benishangul-Gumuz region, as well as northern parts of Afder Zone of Somalia region. The maps clearly illustrate that the hotspot clusters distribution of under-five childhood underweight were largely dispersed and emerged to new locations of previously unaffected locations, such as Central and southern Zones of Tigray region, western and central parts of Kilbati/Zone-2/ Zones of Afar region, Southwestern parts of Benishangul-Gumuz as well as western Somalia regions in Ethiopia, all while exhibiting a decreasing trends alongwith uneven geographic distribution of hotspot clusters of wasting as of previous years(Figure-4).

In the year 2019, the spatiotemporal clustering analysis results in Figure-4 revealed that the hotspot clusters of under-five childhood underweight identified in northern parts of West Gonder zone and in northern parts of Wag Hamra Zone of Amhara region, in northern parts of East Wellega, eastern parts of Jimma and South-West and East Shewa Zones as well as northern Arsi, Guji, and West Giji Zones of Oromia region, Aditionally, in extensive areas of Sidama region, including Gedeo Zone and northern parts of Guraghe Zone of Central Ethiopia region as well as southern border of south Omo zone of SNNP region. The maps in Figure-4 clearly illustrate that childhood underweight hotspot clustering were dispersed across specific regions and also migrated to new locations, such as West Amhara, South-Omo Zone of SNNP region, and northern Somalia region, while indicating unevenly distributions alongwith an overall decreasing trends over time(Figure-4). Overall, the Getis-Ord G* statistic analysis of spatiotemporal hotspot clustering of childhood underweight distribution in figure-4 revealed that in the early (2000 and 2005), significant hotspot clusters of childhood underweight were concentrated in regions similar to stunting, such as Amhara, Oromia, Sidama and SNNP regions and persistent hotspot clusters were also remained in Amhara, Oromia and sidama regions. The emergening distribution patterns of childhood underweight hotspot clustering where observed in the years(2011, 2016, and 2019) across regions like Tigray, Afar, Somalia, Benishangul-Gumuz, and Gambela regions(Figure-4). Regarding trend over time, similar to stunting and wasting, the intensity of underweight hotspot clusters has gradually decreased from 2000-2019(Figure-4).

4.1.3 The Multivariable Logistic Regression Analysis.

The multivariable logistic regression analysis depicted in table-5 was performed to examine the association among independent variables (socio-demographic, socio-economic, and environmental factors) and the dependent variables (stunting, wasting, and underweight) in under-five children(table-5). This type of analysis allows for identifying which independent variables are significantly associated with the probability of a child being stunted, wasted, or underweight, while controlling for the effects of other variables. This likely cover factors at the individual, household, and community level that could influence a child's nutritional status, such as the child's age, gender, birth order, mother's age at the birth of the baby and education, family size, wealth index, number of under-five children in the HHs, region, year of survey, urban/rural residence, altitude, and access to health services(ANC and Immunization) (Table-5).

The multivariable logistic regression is run separately for each dependent variable (stunting, wasting, underweight) to examine the unique relationships between the independent variables and each nutrition outcome(Table-5). The results in Table-5 quantify the strength and direction of the associations, providing adjusted odds ratios that indicate how much the odds of the dependent variable change for a one-unit increase in the independent variable, holding all other variables constant. Examining the spatiotemporal clustering and trends over time can provide insights into how these relationships may have changed or stayed the same, which can help identify areas for targeted interventions to address the key drivers of childhood undernutrition.The overall multivariable logistic regression analysis allows for a more comprehensive understanding of complex, multifactorial nature of childhood undernutrition and the contribution of various socio-demographic, socio-economic, and environmental factors(Table-5).

4.1.3.1 Social and Environmental Factors Influencing Under-Five Childhood Stunting in Ethiopia: Multivariable Logistic Regression Analysis (Table-5)

Based on multivariable logistic regression analysis results presented in Table-5, the spatiotemporal clustering patterns and trends in under-five stunting shows a significant association with the majorities of the selected variables: year of survey, number of births, Cluster altitude, and immunization status(Table-5). As evidenced by the multivariable logistic regression analysis, in the year 2005, the odds of stunting was 1.384 times higher compared to 2000(the reference year), and in the year 2011, The odds of stunting were not significantly different from 2000(AOR=1.005), indicating no significant change in hotspot clusters compared to the reference year(Table-5). On the other hand, in the year 2016, the odds of stunting decreases by 12.7% compared to 2000, indicating a slight decrease in hotspot clusters distributions, but this was not statistically significant. Where as in the year 2019, the odds of stunting were significantly decreases by 62.1% than the odds in the year 2000. Overall, The adjusted odds ratio (AOR) for stunting decreased significantly over the survey years, with the lowest odds in 2019, (AOR = 0.379, 95% CI: 0.194-0.744), compared to 2000. This indicates a substantial decline in stunting hotspot clustering distributions(Table-5).

Based on the results of multivariable logistic regression analysis result in table-5, children of married mothers had significantly higher odds of stunting (18.742) times higher (table-5). Higher number of births is associated with an increased risk of stunting (AOR =1.053, 95%; CI:1.046-1.061), indicating highly significant(Table-5).

While higher household wealth had a marginal protective effect(AOR =1.755, 95%; CI: 0.989-3.113)(Table-5). Higher cluster altitude (mid: AOR = 6.992, 95% CI: 3.965-12.328; high: AOR = 9.452, 95% CI: 5.199-17.182), were strong risk factors for the odds of stunting(Table-5). Conversly, immunization was associated with significantly lower odds of stunting (AOR = 0.068, 95% CI: 0.015-0.313). On the other hand, there were no significant association between stunting and the following variables, such as mothers age at conception, family size, sex of child, ANC visits, place of residenc, and maternal education(Table-5). Overall, the rgession analysis shows the key social and environmental factors as follows:

- The key social factors that significantly affect childhood stunting are year of survey, marital status, number of births, and wealth index of the househld. Social factors highlights the influence of marital status, number of birth, and wealth index of the household on clustering of childhood stunting as evidenced by the multivariable logistic regression analysis(Table-5).

- The key environmental factors that significantly affect childhood stunting are cluster altitude and Immunization. So, Environmental factors highlights the influence of altitude, immunization, and living conditions on childhood stunting(Table-5).

4.1.3.2 Social and Environmental Factors Influencing Under-Five Childhood Wasting in Ethiopia: Multivariable Logistic Regression Analysis (Table-5)

Based on multivariable logistic regression analysis results presented in Table-5, the spatiotemporal clustering patterns in wasting hotspot cluster distributions over time showed a significant relationship with some selected variables: such as year of survey, number of births, cluster altitude, immunization status, ANC visits status, wealth index, and number of female births(Table-5). On the other hand, there were no significant associations with the following variables: Place of residence, family size, marital status, maternal education, and age of Mather at the birth of the baby as evidenced by the multivariable logistic regression analysis(Table-5).

Higher cluster altitude (mid: AOR = 2.750, 95% CI: 1.711-4.420); high: AOR = 2.035, 95%CI: 1.188-3.487) were risk factors for wasting. Where as, Immunization was associated with significantly lower odds of wasting (AOR = 0.037, 95% CI: 0.004-0.303), and lack of antenatal care was marginally associated with higher odds of wasting(AOR=0.523, 95%CI: 0.243-1.128)(Table-5). Surprisingly, higher household wealth was associated with increased odds of wasting (AOR=1.905, 95% CI: 1.013-3.584), and female children had marginally lower odds of wasting (AOR = 0.300, 95% CI: 0.089-1.014)(Table-5). The odds of wasting also decreased significantly over the survey years, with the lowest odds in 2019 (AOR=0.383, 95%CI: 0.188-0.783), compared to 2000, representing the largest declining trends in wasting hotspot clusters distribution rates over the study period(Table-5).

The wasting trend based on the multivariable logistic regression analysis shows a consistent and significant decline over the study period, with the odds of wasting decreasing by more than 60% in 2019 compared to the reference year of 2000(Table-5). Moreover, the consistent and significant reduction in wasting contrasts with the more nuanced changes in stunting, suggesting that the study population may have experienced greater improvements in acute malnutrition (wasting) compared to chronic malnutrition (stunting). Overall, this indicates substantial improvements in child nutritional status, specifically with regards to wasting, throughout the years covered in the study period based on the regression analysis(Table-5). Overall, the regression analysis shows the key social and environmental factors as follows:

- The key Social Factors that significantly affect childhood wasting are year of survey, number of birth, ANC, and wealth index of the household. Social factors highlights the influence of year of survey, number of births, marital status, and wealth index of the household on clustering of childhood wasting(Table-5).

- The key environmental factors that significantly affect childhood stunting are cluster altitude and Immunization. Environmental factors highlights the influence of altitude, immunization, and living conditions on childhood wasting(Table-5).

4.1.3.3 Social and Environmental Factors Influencing Under-Five Childhood Underweight in Ethiopia: Multivariable Logistic Regression Analysis(Table-5)

Based on multivariable logistic regression analysis results presented in Table-5, the spatiotemporal patterns of hotspot clusters in under-five child underweight show a significant relationship with some selected variables, Such as year of survey, marital status, number of births, wealth index, cluster altitude, and immunization status,. But, no significant relations with the following variables:Age of mother at birth, antenatal care (ANC) visits, and place of residence(Table-5). Higher cluster altitude (mid: AOR = 4.620, 95% CI: 2.696-7.916, high: AOR = 6.519, 95% CI: 3.682-11.542) were risk factors for underweight(Table-5). Immunization was associated with significantly lower odds of underweight(AOR=0.046, 95% CI: 0.009-0.243)(Table-5). Being married was a significant risk factor for underweight(AOR =11.066, 95%CI: 1.675-73.095)(Table-5). The odds of underweight also decreased significantly over the survey years, with the lowest odds in 2019 (AOR = 0.301, 95% CI: 0.154-0.588), compared to 2000, indicating a declining trend in underweight hotspot clusters(Table-5).

The underweight trends based on the multivariable logistic regression analysis, the underweight odds ratio(AOR) over time: In early 2005, the odds of underweight were decreased by 41.8% when compared to 2000, indicating a significant decrease in underweight hotspot clusters distributions. But, in later 2011, the odds of underweight were decreased by 41.1% compared to 2000 which also showing a notable decline. Similarly in 2016, the odds of underweight were decreased by 52.5% when compared to 2000, a substantial reduction(Table-5). Finally, in 2019, the odds of underweight were decreased by 69.9% than 2000, representing the largest decrease in underweight hotspot clusters rate over the study period(Table-5). Overall, the data shows a consistent and significant decline in underweight hotspot clustering over the study period. The odds of underweight decreased by nearly 70% in 2019 compared to the baseline year(2000), indicating substantial improvements in overall child nutritional status(Table-5). Overall, the regression analysis shows the key social and environmental factors result as follows:

- The key Social Factors that significantly affect childhood underweight are year of survey, marital status. Social factors highlight the influence of these social factors on clustering of childhood underweight (table-5).

- The key environmental factors that significantly affect childhood underweight are cluster altitude and Immunization. Environmental factors highlights the influences of the cluster altitude, immunization, and living conditions on childhood underweight(Table-5).

Table-5 Factors Influencing Childhood Stunting, Wasting, and Underweight in Ethiopia (2000-2019): Multivariable Logistic Regression Analysis

Variables and Categories		STUNTING				WASTING				UNDERWEIGHT			
		AOR	95% Confidence Interval		Sig	AOR	95% Confidence Interval		Sig	AOR	95% Confidence Interval		Sig
Year of survey	2000	1				1				1			
	2005	1.384	.952	2.011	*	.457	.299	.699	***	.582	.395	.859	***
	2011	1.005	.663	1.523		.646	.42	.993	**	.589	.386	.897	**
	2016	.873	.541	1.407		.485	.289	.816	***	.475	.292	.775	***
	2019	.379	.194	.744	***	.383	.188	.783	***	.301	.154	.588	***
Number of births		1.053	1.046	1.061	***	1.038	1.032	1.045	***	1.05	1.043	1.058	
Cluster Altitude	Low	1				1				1			
	Mid	6.992	3.965	12.328	***	2.75	1.711	4.42	***	4.62	2.696	7.916	***
	High	9.452	5.199	17.182	***	2.035	1.188	3.487	***	6.519	3.682	11.542	***
Place of residence	Urban	1				1				1			
	Rural	.844	.446	1.596		1.541	.726	3.271		.705	.358	1.39	
Child immunization coverage		.068	.015	.313	***	.037	.004	.303	***	.046	.009	.243	***

Table-5 Cont'ed													
agemomc22		1.007	.314	3.231		3.075	.787	12.014		1.664	.476	5.813	
Antenatal care visit		.993	.507	1.943		.523	.243	1.128	*	.956	.471	1.942	
Fsmily size		.774	.355	1.688		.764	.312	1.875		.907	.4	2.055	
Maternal education		.414	.113	1.523		.792	.148	4.238		.794	.205	3.069	
Proportion currently married		18.742	3.06	114.805	***	1.042	.155	7.026		11.066	1.675	73.095	**
Household wealth index		1.755	.989	3.113	*	1.905	1.013	3.584	**	1.179	.639	2.173	
Child sex		1.059	.376	2.988		.3	.089	1.014	*	.658	.219	1.976	
Constant		.001	0	.006	***	.022	.002	.199	***	.002	0	.021	***
Fit statistics		Akaike crit. (AIC) = 999.7, Bayesian crit. (BIC) = 1098.6 Chi-sqaure = 367.4, P-value = 0.000				Akaike crit. (AIC) = 1188.7, Bayesian crit. (BIC) = 1287.6 Chi-sqaure = 198.3, P-value = 0.000				Akaike crit. (AIC) = 1158.6, Bayesian crit. (BIC) = 1257.5 Chi-sqaure = 325.6, P-value = 0.000			
*** Sig at p<0.01, **Sig. at p<0.05, *Sig. at p0<0.1													

Source: EDHS-2000, 2005, 2011, 2016, 2019.

4.2 DISCUSSIONS

This study aimed to examine the spatiotemporal clustering of childhood undernutrition indicators (stunting, wasting, and underweight), and the underlying social and environmental drivers influence—among children under five in Ethiopia. The analysis employed data from five consecutive Ethiopian Demographic and Health Surveys (EDHS) data conducted in 2000, 2005, 2011, 2016, and 2019. The focus was on identifying specific regions affected by high concentrated areas of undernutrition cases (hotspot clusters) and its temporal change overtime and to underscoring the socio-demographics, socio-economic, environmental, and health related factors influencing this spatiotemporal clustering and trend events over the past two decades.

According to Getis-Ord G* statistic analysis, the degree of spatiotemporal clustering of childhood stunting findings revealed that stunting exhibits significant and persistent hotspot clustering in regions like Amhara, Oromia, and parts of the Sidama, and SNNP region throughout 2000-2019. This study were suported by geospatial analysis conducted in Ethiopia(Atalell et al., 2023; Hailu et al., 2020; Muche et al., 2021).These regions have been persistent areas of concern, highlighting ongoing challenges in addressing childhood nutrition and health. Similarly, findings by Haile et al confirms that certain areas exhibit high rates of stunting across different regions, suggesting the presence of persistent hotspot clustering that require targeted interventions(Haile et al., 2016). Which is aligned by the research findings of Seboka et al, and ahmed and Hawramei who noted that highlighting the geographical disparities in malnutrition and contextual factors including socioeconomic status and access to healthcare(Ahmed & Hawramei, 2022; Seboka et al., 2021).

On the other hand, new emerging hotspot clustering areas appeared in region such as Benishangul-Gumuz by 2005, with continued trends to eastern parts of Benishangul-Gumuz and northern parts Gambela regions being areas of concenn by 2011.Where as by 2016, new hotspot clusters were identified in the South- western area of Tigray region, as well as the western sections of Amhara, Afar, and Somalia regions. Suggesting a shift in the spatial burden over time. the southern border of the Benishangul-Gumuz and in the northern section of Somalia regions by the year 2019.

Identifying new or shifting clusters is crucial for understanding the dynamics of childhood undernutrition. In certain Ethiopian regions, clustering may result from various factors, including environmental and socioeconomic influences such as climate variability affecting food security, poverty, and limited healthcare access due to inadequate infrastructure. Additionally, instability from conflicts can lead to displacement and resource strain, while government policies may also play a role. Ijaiya (2024) supports this, suggesting that as interventions evolve, the geographical distribution of malnutrition may change (Ijaiya et al., 2024). Furthermore, Mohammed et al. (2020) confirm that shifts in determinants like maternal education and household income can lead to changes in undernutrition hotspot clusters over time (Mohammed et al., 2020).

The intensity of clustering has gradually declined (Fenta et al., 2020), reflecting improvements in long-term nutrition programs. However, reductions are uneven, with some regions maintaining high clustering over decades. This highlights the need for targeted interventions that address specific regional challenges and a comprehensive approach to improving child nutrition and health nationwide. Supporting this, Bharti et al. found that childhood stunting in India is influenced by regional factors like socioeconomic status and healthcare access (Bharti et al., 2019). Similarly, Chuang et al. noted that geographic location reflects environmental and community factors affecting malnutrition, reinforcing the case for localized interventions (Chuang et al., 2019). Addressing these disparities is essential for ensuring that all children in Ethiopia can grow and thrive.

The Getis-Ord G* statistical analysis reveals a complex pattern of spatiotemporal clustering of childhood malnutrition, particularly under-five wasting. Key characteristics include concentration and dispersion, the emergence of new locations, and a declining trend with uneven distribution. Initially, hotspot clusters were

identified in the early 2000s in specific zones of the Amhara region (Central, North, South Gonder, East and West Gojam, South Wello), Oromia region (West, East, Horo-Guduru Wellega, Jimma, West and South West Showa, West Hararge, West Guji), as well as in Sidama (Gedeo Zone), Kefa, Central Ethiopia (Guraghe and Hadiya), and Wolayita (SNNP region). By 2005, geographic distribution began to spread, although Amhara and Oromia continued to show high rates of childhood wasting. By 2011, new hotspots emerged in Benishangul-Gumuz and eastern Tigray, with additional clusters appearing in 2016 and 2019.

The clustering of childhood undernutrition in certain regions of Ethiopia may be attributed to several factors, including: Environmental,Socioeconomic,instability,and government policies were the possible reasons. Almost similar findings were seported by Belay et al(2023) and Seboka et al (2022)in ethiopia.(Belay et al., 2023; Seboka et al., 2022).This changing surroundings implies that environmental conditions, interventions, and socioeconomic status can all have an impact on malnutrition problems, creating new areas of concern.

Trends indicate a general decrease in the severity of hotspot cluster distribution over time, reflecting improvements in some areas while others, such as Benishangul, Tigray, Afar, Somalia, and South Omo Zone, remain vulnerable. Although similar research was conducted in Uganda (Maniragaba et al., 2023), literature on emerging hotspot clusters is limited. Hotspot clustering is uneven, with some regions consistently facing higher rates while others see brief increases. This variability in wasting can be linked to geographic location, socioeconomic conditions, food security, environmental factors, and healthcare access (Alemu et al., 2016). To address these trends effectively, stakeholders must adopt systematic and flexible approaches, enabling targeted resource allocation and policies to reduce childhood wasting and improve health outcomes across Ethiopia.

The Getis-Ord G* statistics spatiotemporal hotspot cluster analysis of childhood underweight in Ethiopia from 2000 to 2019 reveals significant changes over time, aligning with findings by Kasahun Takele (Takele et al., 2020). In 2000, hotspot clusters were concentrated in extensive areas of Amhara, Oromia, southwestern Ethiopia, central regions, and northern SNNP and Sidama, indicating critical concern. By 2005, clustering began to disperse, with new hotspots emerging in northern Benishangul-Gumuz, leading to a decline in intensity and uneven distribution. By 2011, hotspots shifted further to southeastern Amhara and northeastern Gambela, continuing the trend of dispersion.

By 2016 and 2019, new clusters emerged in regions like Tigray, Afar, western Amhara, and southern SNNP, while maintaining an overall decline in hotspot clustering intensity. This reflects a continued dispersion and uneven distribution of childhood underweight, alongside a decrease in concentrated hotspot areas over time, confirmed by a geospatial analysis using a Bayesian framework (Atalell et al., 2022). Persistent hotspots remain in Amhara and Oromia. While literature on emerging hotspot analysis is limited, similar methods have assessed hunger hotspots in sub-Saharan Africa (Liu et al., 2008). These emerging clusters suggest that socio-economic, environmental (such as altitude), and infrastructural factors may contribute to rising underweight rates in these regions.

Despite new hotspots, the overall trend indicates a decrease in hotspot clustering over time (Fenta et al., 2020), suggesting improvements in some regions due to targeted interventions. However, this progress is uneven, revealing disparities in childhood underweight across the country. While some areas improve, others face new challenges, necessitating focused strategies that adapt to regional conditions. Understanding these patterns enables policymakers and health stakeholders to create effective interventions to combat childhood underweight and enhance health outcomes for children in Ethiopia.

Multivariable logistic regression analysis identified key social and environmental factors influencing the spatiotemporal clustering of under-five childhood undernutrition. Social factors include maternal marital status, education, and wealth, while environmental factors involve geographic elements like altitude and immunization. This understanding is vital for implementing targeted public health initiatives.

The analysis shows significant reductions in child undernutrition hotspot clustering rates from 2000 to 2019 across stunting, wasting, and underweight. By 2019, the odds for each type of undernutrition were notably low: stunting (AOR = 0.379), wasting (AOR = 0.383), and underweight (AOR = 0.301), all statistically significant ($p < 0.001$). This trend indicates that public health initiatives have effectively improved child nutrition and health, likely due to better healthcare access, nutritional education, and increased availability of nutritious foods. The decline in malnutrition hotspot clustering highlights the success of sustained public health efforts and the need to continue these initiatives to further enhance child health outcomes.

The multivariable logistic regression analysis shows that children in mid and high-altitude regions have significantly higher odds of malnutrition. The odds for stunting are particularly high (mid-altitude AOR = 6.992; high-altitude AOR = 9.452), with notable odds for wasting (mid-altitude AOR = 2.75; high-altitude AOR = 2.035) and underweight (mid-altitude AOR =4.62; high-altitude AOR = 6.519). These geographic disparities indicate that higher elevations contribute to nutritional challenges, necessitating location-specific health interventions. Previous studies have linked high altitude to stunting and underweight, but not wasting (Bailey et al., 2019; Li et al., 2023; Niermeyer et al., 2009). The elevated risks highlight the need for targeted interventions focused on food security and healthcare access. While maternal healthcare access has improved, challenges persist with low immunization rates and geographic disparities, especially in high-altitude areas. Expanding immunization programs and equitable healthcare services across altitudes is essential for improving health outcomes.

The multivariable logistic regression analysis data indicates that immunization is a critical protective factor against malnutrition indicators (stunting, wasting, and underweight), with non-immunized children exhibiting drastically increased odds of undernutrition (AOR = 0.068, $p < 0.001$). This stark contrast illustrates the protective effect of vaccinations, which not only prevent infectious diseases but also contribute to improved nutritional status. This findings are consistent with previous studies results done (Anekwe & Kumar, 2012; Banerjee et al., 2021; Kristensen et al., 2000; Mcgovern et al., 2015; Rahman & Obaida-Nasrin, 2010; Solis-Soto et al., 2020).

The findings underscore the critical role of strong vaccination programs in child health. The stark differences in undernutrition rates among immunized and non-immunized children reveal health inequalities, with non-immunized children at greater risk of malnutrition. This disparity highlights the need for initiatives to boost vaccination coverage in vulnerable populations. Improving immunization can significantly reduce malnutrition risk, emphasizing the link between vaccination and child wellbeing.

The multivariable logistic regression analysis found that maternal marital status is a significant predictor of child malnutrition, particularly underweight (AOR = 11.066) and stunting (AOR = 18.742). These odds indicate that family dynamics greatly impact child health. Married mothers may encounter unique challenges affecting their children's nutrition, with differences in social support, economic stability, and responsibilities compared to unmarried mothers. This highlights the need for targeted support to improve child nutritional status, aligning with previous findings. (Woldemariam, 2002). Understanding these dynamics is vital for creating effective interventions for mothers and children.

The findings show that wealth and education impact malnutrition rates differently. Wealth is positively linked to stunting (AOR = 1.755), wasting (AOR = 1.905), and underweight (AOR = 1.179), suggesting that economic status significantly affects these issues. Families with fewer resources are more likely to face higher malnutrition rates, while wealthier families can provide better nutrition and healthcare. Thus, economic inequality directly correlates with child health outcomes. Various previous studies results were support this findings(Belay et al., 2023; Belayneh et al., 2021; García Cruz et al., 2017; Gebreyesus & Lindtjorn, 2017; Woldemariam, 2002).

The impact of education on malnutrition is less consistent across the three measures, suggesting it is important but not the sole determinant of child health. Additionally, a higher number of births is positively correlated with malnutrition, indicating that larger families may struggle with resources. Therefore, targeted economic interventions and educational initiatives are crucial for improving child nutritional outcomes. The multivariable logistic regression analysis identifies several social and environmental factors influencing child malnutrition, including the survey year, number of births, marital status, wealth index, immunization coverage, and cluster altitude.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

Based on the study's findings, there is an apparent spatiotemporal clustering of child undernutrition (stunting, underweight, and wasting) in Ethiopia, with recurring hotspot clusterings in areas like various zones of certain regions, Amhara region(North, South, and Central Gonder, East Gojam, Wag Hamra, North and South Wello, North Shew zones), In Oromia region(West, East, Horoguduru Wellga, Jimma, West and South West Shewa, West Hararge, Arsi and West Guji zones), In Sidama region including Gedeo zone, and portions of Central Ethiopia region(Guraghe, Hadiya, Kembata Tembaro, and Yem Special zones). Where as in regions such as Tigray, Afar, Benishangul-Gumuz, Gambella, Southern border of SNNP, and Somalia regions, emerging hotspot clusters were also noted. undernutrition hotspot clustering has declined across Ethiopia over time, but socioeconomic, environmental and health-related factors carry on to contribute to disparities. Child undernutrition rates were found to be significantly correlated with factors like maternal education, marital status, wealth endex, number of births, immunization, and cluster altitude.

5.2 RECOMMENDATIONS

As has already been mentioned out the primary objectives of this study were to examine the spatiotemporal clustering of child undernutrition and look at related environmental and social factors in Ethiopia. The researcher suggests the following points be given critical attention in light of the study's empirical findings.

- Despite significant progress, the rate of child undernutrition remains elevated. It is necessary to pay attention to and take methodical action in the areas of food security, economic development, maternal education, and healthcare services in order to reduce child undernutrition rapidly

- The study's findings concerning about the environmental and socioeconomic factors associated with child undernutrition in Ethiopia have policy ramifications.

The findings must be translated into actions of pertinent interventions that focus on terminating or reducing child undernutrition in Ethiopia.

- The results of the study on child undernutrition in Ethiopia emphasize the necessity of focused interventions, especially in emerging regions like Tigray, Afar, Benishangul, Southern zone of SNNP and Somalia regions as well as enduring hotspots clusterings like Amhara, Oromia, Sidama, and Central Ethiopia regions of the mentioned zones. Effectively allocating resources to these areas can aid in halting additional declines in children's nutrition. Furthermore, strengthening maternal education through health programs and community workshops can enable mothers' to make knowledgeable choices regarding the diet and general health of their children.
- Reducing rates of undernutrition requires broadening access to healthcare services. Strengthening immunization programs and spent in healthcare infrastructure, especially in remote areas, might ensure that mothers and children receive vital health services. Additionally, addressing socioeconomic inequalities through income support programs and job creation can enhance families' capability to afford nutritious food, thereby increasing child nutrition results.
- Since altitude has an impact on undernutrition rates, environmental factors must be taken into account. Food security can be increased by promoting sustainable agricultural practices and designing interventions to address these particular issues. Regular monitoring and evaluation of undernutrition trends might help adapt strategies as needed, while community engagement ensures culturally relevant and effective solutions are implemented.

Finally, the study's conclusions have policy implications for social and environmental factors that are linked to child malnutrition in Ethiopia. The findings must be incorporated into the development of pertinent interventions aimed at ending child undernutrition in Ethiopia.

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Appendix

Annex-1

Table-4.1 Demographic, socio-economic and cultural charactorstics of the study population(Weighted, N=46,172)

Variable	Category	Survey year 2000 (%)	2005(%)	2011(%)	2016(%)	2019(%)	Code
Totale (n)	Number	10,752	9,884	10,255	10,179	5,101	
family Size	<=5	43.29	41.01	44.14	43.40	45.62	fsize
	>=6	56.71	58.99	55.86	56.60	54.38	
Current maritial status of the mother/care giver	Never married	0.55	0.37	0.69	0.53	0.35	v501V4
	Married/living together	92.54	94.39	92.66	94.90	94.80	
	Widowed	1.46	1.72	1.88	1.08	1.14	
	Divorced/separated	5.46	3.53	4.76	3.47	3.70	
Age of mather's at the birth of the baby	<=20	19.04	19.32	17.80	16.69	17.91	agemomc22
	>=21	80.96	80.68	82.20	83.31	82.09	
Highest educational level the mothers/care givers	No education	81.57	78.54	68.84	65.68	53.32	v106
	Primary education	13.26	16.99	27.44	27.02	35.39	
	Secondary education	4.94	4.05	2.20	4.79	7.64	
	Higher education	0.22	0.42	1.51	2.51	3.65	
Wealth index of the household	Poor	42.48	42.79	44.44	46.73	45.15	v190c3
	Medium	21.16	21.89	20.63	20.77	18.91	
	Rich	36.36	35.32	34.93	32.5	35.93	
Place of residencde	Urban	10.61	7.41	12.73	11.30	25.33	v025
	Rural	89.39	92.59	87.27	88.70	74.67	
Region	Tigray	6.59	6.48	6.63	6.63	6.93	v024C11
	Afar	1.00	0.94	0.99	1.00	1.52	
	Amhara	26.02	22.83	21.48	19.08	19.17	
	Oromiya	40.51	40.06	43.27	43.72	39.78	
	Somali	1.18	4.15	2.80	4.61	7.00	
	Ben-Gum	1.00	0.94	1.13	1.10	1.16	
	SNNP	21.37	22.37	20.99	20.67	20.34	
	Harari	0.21	0.20	0.22	0.23	0.30	
	Addis Ababa	1.56	1.41	1.82	2.29	2.83	
	Dire Dawa	0.33	0.34	0.32	0.42	0.53	
	Gambela	0.23	0.28	0.34	0.25	0.44	
Religion	Orthodox	49.23	41.56	37.87	34.68	34.06	v130C4
	Other chrstian	17.04	21.21	24.51	22.12	27.65	
	Moslem	29.94	34.77	35.37	41.09	36.66	
	Others	3.78	2.46	2.25	2.16	1.62	

Annex-2

Table 4. 2 - Child relaated-Demographic charactersstics of the study population(Weighted, N=46,172)							
		Survey Year					
Variable	**Catagories**	**2000 (%)**	**2005 (%)**	**2011 (%)**	**2016 (%)**	**2019 (%)**	**Code**
Totale(n)	Number	10,752	9,883	10,256	10,178	5,101	
Sex of child	male	50.78	50.68	51.36	51.01	51.14	**b4**
	female	49.22	49.32	48.64	48.99	48.86	
Current age of child (in months)	0 to 11	20.31	21.18	20.20	20.62	19.13	**chagegr**
	12 to 23	19.95	18.76	17.91	19.79	19.83	
	24 to 35	19.38	18.96	18.86	18.74	19.93	
	36 to 59	40.37	41.09	43.03	40.84	41.19	
number of U5 children in the HHs	<=1	34.59	32.99	34.78	38.30	40.51	**v137c2**
	>=2	65.41	67.01	65.22	61.70	59.49	
Birth Order number	1st Birth	18.44	16.74	18.86	18.84	21.68	**bordC4**
	2nd Birth	16.43	15.91	17.03	16.28	18.02	
	3rd Birth	13.92	14.69	14.18	14.11	14.16	
	4th Birth	51.21	52.66	59.93	50.76	46.14	
Type of birth	Single Birth	98.74	98.61	98.13	97.78	97.59	**boc2**
	Multiple Birth	1.26	1.39	1.87	2.22	2.41	
Preceding birth interval	<=24months	21.73	22.62	22.57	24.24	24.46	**b11C4**
	25-47months	58.81	57	56.1	49.94	45.62	
	>=48months	19.46	20.38	21.33	25.82	29.91	

Annex-3

Tabel-4.3 Environmental and Health services behavior charactorstics of the study Population(Weighted, N=46,172)							
		Survey year					
Variables	**Catagories**	**2000%**	**2005%**	**2011%**	**2016%**	**2019%**	Code
Totale (n)	Number	10,752	9,883	10,256	10,178	10,179	
Antinatal care visits for pregnancy(ANC)	No ANC visits	72.45	71.26	56.97	36.38	24.95	**m14C4**
	Visited at list once	27.07	28.33	42.69	63.44	74.83	
	Others	0.48	0.40	0.35	0.18	0.21	
Cluster altitude (in meters)	Low-altitude zones	8.30	8.59	16.71	17.43	23.23	**v040C3**
	Mid-altitude zone	60.91	56.47	56.99	58.27	53.99	
	High- altitude zone	30.80	34.93	26.3	24.3	22.78	
Child Immunization Coverage	0	95.16	95.67	93.71	93.79	94.96	**immunized**
	Yes	4.84	4.33	6.29	6.21	5.04	