MODELING KEY DRIVERS OF UNDER-FIVE CHILD MALNUTRITION IN MARSABIT COUNTY, KENYA USING GENERALIZED LINEAR MODELS

BY

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DECLARATION

Declaration by the Candidate

This thesis is my original work and has not been submitted for any academic award in any academic award in any institution; and shall not be reproduced in part or in full, or in any format without prior written permission from the author and/or University of Eldoret.

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Declaration by the Supervisors

This thesis has been submitted with our approval as University supervisors.

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DEDICATION

To the Almighty God, my supervisors, and my family, I dedicate this thesis report to you.

ABSTRACT

Malnutrition remains one of the major problems in developing countries affecting people of all age groups. The severity of the crisis varies among specific groups, such as children under the age of five years. In Kenya, Marsabit County suffers high rates of acute malnutrition (wasting) above recommended levels by the World Health Organization for children between the ages of 6-59 months. The main determinants of wasting include but are not limited to poor nutrition of women during pre-conception, pregnancy status and lactation; poor infant feeding; poor environmental conditions within households where children live; poor health-seeking behaviors among women in the reproductive age and poor maternal health. Therefore, this study aimed at investigating the underlying factors that affect childhood nutritional status and specifically to determine; the prevalence rates of wasting in North Horr and Laisamis study sites, the correlation between household food security status and wasting, fit a logit model to determine factors that significantly affect wasting and a mixed-effects model on factors associated with wasting with site as a random factor for children between 6-59 months in Marsabit County, Kenya and propose appropriate interventions in Marsabit County and other ASAL counties in Kenya. The study utilized retrospective data of the Standardized Monitoring and Assessment in Relief and Transition (SMART) survey collected in Marsabit County in July 2019. Results showed that 29.3 percent of the children were acutely malnourished and that there was an insignificant difference between household food security and child malnutrition status (p-value = 0.842). Factors such as the age and level of education of caregivers, household size, the gender of the child, , if the child was weighed at birth, source of income, the occupation status, and the distance to the water source remained insignificant at a multivariate level. However, factors such as full-term maternal pregnancy, the child being ill for the past two weeks, and the study site were strong significant factors affecting the status of childhood wasting. Moreover, mothers with full-term pregnancy up to the birth were 53 percent less likely to have malnourished infants when compared to their counterparts whose pregnancy was not term. Caregivers who were herders were 1.29 times more likely to have their children undernourished than their counterparts in other occupations [AOR=1.29, 95% CI=0.546-3.057]. The other important results were that mothers/caregivers who traveled more than half a kilometer were twice more likely to have their children wasted than those who had traveled less than half a kilometer [AOR=2.00, 95% CI=1.282-3.190]. Based on the findings, the study makes recommendations that the policymakers and the entire county government of Marsabit should build more social amenities that provide pregnant women with full-term maternal checkups for both antenatal and postnatal care. Moreover, the County government of Marsabit should lobby and mobilize resources for food aid or cash transfers to households with severely or moderately malnourished to curb the high rate of wasting, make water available close to households so that the women/caregivers minimize the distance to a water source and have sufficient time to be with their infants.

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LIST OF ACRONYMS

AIC	-	Akaike Information Criterion
AM	-	Acute malnutrition
AOR	-	Adjusted Odds Ratio
ASAL	-	Arid and Semi-Arid Lands
BDHS	-	Bangladesh demographic and health survey
BLR	-	Binary Logistic Regression
BMI	-	Body Mass Index
CI	-	Confidence Interval
CLTS	-	Community-Led Total Sanitation
CRM	-	Continuous Ratio Model
DF	-	Degree of Freedom
EBF	-	Exclusive breastfeeding
EDHS	-	Ethiopia Demographic and Health Survey
FAO	-	Food and Agriculture Organization
FEWS NET	-	Famine Early Warning Systems Network
FHI	-	Family Health International
GAM	-	Global Acute Malnutrition
GDP	-	Gross Domestic Product
GLM	-	Generalized Linear Model
GLMM	-	Generalized Linear Mixed Models
HAZ	-	Height-for-Age Z-scores
HDDS	-	Household Dietary Diversity Score
HH	-	Household
HHS	-	Household Hunger Score

IPC	-	Integrated Food Security Phase Classification
KDHS	-	Kenya Demographic and Health Survey
KNBS	-	Kenya National Bureau of Statistics
LBW	-	Low-Birth Weight
LM	-	Linear Models
LR	-	Logistic Regression
MAM	-	Moderate Acute Malnutrition
MD	-	Micronutrient deficiency disease
MDG	-	Millennium Development Goals
MLE	-	Maximum Likelihood Estimate
MOH	-	Ministry of Health
MUAC	-	Mid Upper Arm Circumference
NDMA	-	National Drought Management Authority
NNP	-	National Nutrition Program
OLR	-	Ordinal Logistic Regression
OLS	-	Ordinary Least Squares
PEM	-	Protein-energy malnutrition
POM	-	Proportional Odds Model
PPOM	-	Partial Proportional Odds Model
RUSF	-	Ready-to-use Supplementary Food
RUTF	-	Ready-to-use therapeutic foods
SAM	-	Severe Acute Malnutrition
SDG	-	Sustainable Development Goals
SM	-	Stereotype Model

SMART	-	Standardized Monitoring and Assessment in Relief and Transitions
UNICEF	-	United Nations Children's Fund
UOR	-	Unadjusted Odds Ratio
WASH	-	Water Sanitation and Hygiene
WAZ	-	Weight-for-Age Z-scores
WDDS	-	Women Dietary Diversity Score
WFP	-	World Food Programme
WHO	-	World Health Organization
WHZ	-	Weight-for-Height Z-scores

DEFINITION OF KEY TERMS

Child mortality: The probability of dying between the 1st and 5th birthdays

Global Acute Malnutrition (GAM): GAM is the percentage of children in a population suffering from either MAM or SAM in a given population.

Infant mortality: The probability of dying before the 1st birthday

Moderate Acute Malnutrition (MAM): MAM is defined as moderate wasting.

Neonatal mortality: The probability of dying within the 1st month of life.

Post neonatal mortality: The difference between infant and neonatal mortality

Severe Acute Malnutrition *(SAM):*Very Low Weight-for-Height z-score (WHZ).

Stunting: Is a symptom of chronic malnutrition and evidenced in Poor linear growth or low height for age Z score

The Integrated Food Security Phase Classification (IPC): This refers to a groundbreaking effort to enhance the study and decision-making of food security and nutrition in order to assess the severity and magnitude food insecurity and serious malnutrition in a region, in compliance with globally recognize science criteria.

Under-five mortality: The probability of dying before the fifth birthday

Wasting: Is a symptom of *acute* under nutrition, usually as a consequence of insufficient food intake or a high incidence of infectious diseases.

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

The background information, problem statement, and hypothesis formulation, objectives of the study, justification of the study, and limitations of the study are discussed in this chapter.

1.2 Background of the Study

Marsabit County experiences poor health and nutrition outcomes which are thought mainly to be related to household food insecurity as a result of recurrent droughts. According to Marsabit County Long Rains Food Security Assessment Report (2017), the prevalence of Global Acute Malnutrition (GAM) for the county as per the weighted average was 16.9 percent, classifying the county as Critical, Nutrition Integrated Food Security Phase Classification (IPC). There are major variances, though, between the two sub-counties. North Horr has a 31.0 percent Global Acute Malnutrition (GAM) incidence, which is IPC Phase 5: Extremely critical and 4.8 percent GAM rate (IPC Phase 4) in Laisamis (Marsabit County SMART Survey, 2017).

Improving nutrition leads to efficiency, economic development, and poverty reduction by enhancing physical work ability, cognitive growth, school results, and wellbeing by reducing illness and mortality, (Demment *et al.*, 2003). Besides its important contribution to economic development and poverty reduction, nutrition is recognized as a basic human right. Nutrition has been recognized as a basic human right dating as far back as 1948according to article 25 of the convention of the universal declaration of human rights. Furthermore, in 2017, the United Nations Standing Committee on Nutrition (UNSCN) published a “global narrative” on nutrition, entitled by 2030 end all forms of malnutrition and leave no one behind (Watkins, 2014).

The convention ensures that all persons have the right to a good living standard adequate for the health and well-being of himself and his family (Benson, 2005). The under-five mortality rate in Marsabit County is 52 per1000 live births and crude mortality rates stand at 10.4 per 10,000 live births per day in the County (KDHS, 2014). The mortality rate of under the age of five years is the most important indicator of the development of any nation in the world since it indicates the environmental, the social and the economic situations where the children live in their societies comprising the quality of health received (Kandala, *et al.*, 2011).

In Kenya, despite all steps taken by the government, UNICEF, WHO, health initiatives such as building health facilities, infant deaths are on the rise, especially in a rural community with socio-economic factors as the key issue (Ali, A. (2021).). In addition, a large number of children born had high infant mortality in the past. The figures, however, have decreased dramatically in developing countries, primarily due to enhanced basic health care (Zhang & Kanbur, 2009).

In several villages where there are unsatisfactory/inadequate health centers, maternal and infant mortality remains high, and the available ones do not adequately meet the demand of villagers. In 2000, infant mortality was estimated at 82 deaths per 1,000 live births, approximately one out of 10 children do not live to have their first birthday (Kamilius, 2010). The reduction in infant mortality is therefore a high priority in Kenya's national public health strategy. A number of interrelated factors, such as age at first birth, schooling, and economic class, have been known to affect infant mortality. Since the relative impact of each factor varies from one population to another, it is of interest to research its relationship and contribution to the effect of under nutrition on children six (6) months and above but below 5 years of age, in Marsabit County, Kenya since it is amongst the counties with the highest Global Acute Malnutrition (GAM) rates.

1.3 Problem Statement

The acute malnutrition rates in Northern Kenya have often remained at or above emergency levels. For instance, in Marsabit County the wasting status of children is 21.4 percent (Haider *et al.*, 2021). The interventions of emergency nutrition-specific activities in Kenya and elsewhere have historically employed short-term, malnutrition treatment-focused methods. These approaches have been critical in averting excess mortality, but they have been unable to sustainably prevent acute malnutrition due to limited project timelines and a relative lack of focus on addressing its key drivers. Hence, in Marsabit County, it is not well known since the underlying causes can have varied relative impacts depending on the county under study. Therefore, to design interventions that achieve sustainable results in Northern Kenya, this study seeks to understand the key drivers of under-five acute malnutrition with specific focus to Marsabit County, Kenya.

1.4 The General Objective

This study in general seeks to find specific drivers of acute malnutrition in Marsabit County, Kenya.

1.4.1 Specific Objectives of the Study

The objectives of this study are specifically:

i. Determine the prevalence rates of acute malnutrition (wasting) using WHO standards between the two study sites, in Marsabit County, Kenya.
ii. Determine the correlation between household food security and acute malnutrition status of under five years children in Marsabit County, Kenya.

iii. Fit a Logit model to determine factors that significantly affect the acute malnutrition status of under-five children in Marsabit County, Kenya.

iv. Fit a mixed-effects model on the factors associated with malnutrition with the site as a random factor in Marsabit County, Kenya

1.4.2 The Study Hypotheses

H_{01}: The prevalence of malnutrition is significantly different across the two study sites in Marsabit County, Kenya

H_{02}: There is a strong correlation between household food security indicators of Household Hunger Scale (HHS) and Women dietary diversity Score and the wasting of children between the ages of 6-59 months in Marsabit County, Kenya

H_{03}: Many important factors affect wasting of children between the ages of 6-59 months in Marsabit County, Kenya

H_{04}: The wasting of children between the ages of 6-59 months vary significantly across the study sites in Marsabit County, Kenya

1.5 Scope of the Study

This study investigated differential impact of demographic, socio-economic, environmental, livelihoods and health related factors on wasting status among under-five years of age of children in Marsabit county, Kenya. The research investigated the key causes/drivers of malnutrition in North Horr and Laisamis Sub-Couties by use of logistics regression model using retrospective data collected during Marsabit County SMART survey data.

1.6 Justification of the Study

Under-nutrition of children is a significant issue recognized internationally in the (United Nations Department of Economic and Social Affairs, 2018). However, relatively significant numbers of children wasting of children between the ages of 6-59 months are still malnourished, especially in Kenya's ASAL counties, such as Marsabit. For successful policy action within the country at large, a thorough knowledge as to why such a significant percentage of children are still malnourished is necessary. There are factors that affect under nutrition among children under five years, for instance, lack of exclusive breast feeding, close birth spacing and household income. Previous research have been unable to capture their full results and therefore this study will help contribute to key factors affecting wasting of children between the ages of 6-59 months in Marsabit County. The results of the study will provide a base of reference for other research in the future.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

Related literature review on the different types of malnutrition, management guidelines on malnutrition, the theoretical and conceptual framework are discussed in this chapter.

2.2 Malnutrition in the General Population

Research shows that malnutrition is categorized into Protein-Energy Malnutrition (PEM) and micronutrient deficiency disease (Abubakar *et al.*, 2017). PEM is caused by absences of some or all nutrients, while the Micronutrient deficiency disease (MDD) is caused by a lack of specific nutrients. This research focuses on the protein-energy malnutrition category. Moreover, there are three types of PEM in children: 1) acute malnutrition; 2) chronic malnutrition; and 3) a combination of acute malnutrition and chronic malnutrition, respectively. The figures below explain this in more detail:
These kinds of protein-energy malnutrition in children can be pictured like this:

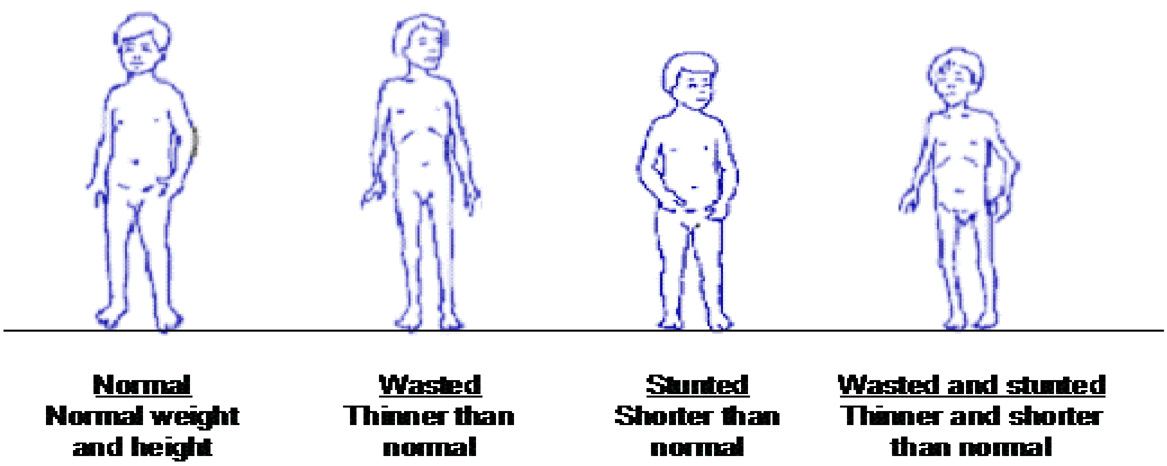

Figure 1: Forms of Protein-energy Malnutrition in Children

Wasting is a sign of acute malnutrition in children, mainly caused by inadequate food consumption or a high occurrence of infectious diseases mainly diarrhea. It, in essence, weakens the immune system's operation which may lead to an increased severity and period of infectious disease vulnerability and thus an increased risk of mortality. The wasting indicator is measured using Weight-for-Height Z-scores (WHZ). Wasting can be moderate or severe and helps detect children between the ages 6-59 months suffering from current under-nutrition. Wasting is usually suitable for analyzing short-term changes, such as seasonal changes in the availability of food or short-term dietary stress related to sickness. The Stunting, or poor linear growth, on the other hand, is a symptom of chronic malnutrition. It is a measure of low Height-for-Age (HAZ <-2), rather than low Weight-for-Height, whereas wasting is the best indicator for current nutritional status, stunting reflects past episodes. Stunting also indicates the total effects of under-nutrition and infection over time since conception. This rate may be viewed as an indicator of poor environmental circumstances or a long-term reduction of the growth capacity of a child. Children experiencing stunting due to inadequate diets or chronic sickness appear to be at increased risk of disease and death. Stunting is caused by dietary deficiencies in the long term which frequently results in slow mental development, low success in education, and lowered intellectual ability. This, in essence, influences the national level of economic productivity.

Studies suggest that stunted mothers are often at increased risk of producing a low-birth-weight child, leading to a vicious circle of intergenerational malnutrition (Martorell & Zongrone, 2012).

Furthermore, a symptom of acute or chronic malnutrition or a mixture of the two is Underweight. Underweight is measured using Weight-for-Age Z-scores (WAZ) and reflects body mass relative to chronological age. As both the height of the child and its weight impact underweight, the measure represents both historical (chronic) and/or current (acute) under-nutrition. In a population, this indicator is also a predictor of health and nutritional risk. In order to measure improvements in the severity of malnutrition over time, underweight is advocated as an indicator.

The Severe Acute Malnutrition (SAM): SAM is marked by an exceptionally low Weight-for-Height z-score (WHZ) (below -3 Z scores/ standard deviations from the mean World Health Organization growth standards), by evident severe wasting, or by the existence of bilateral pitting nutritional edema. Along with WHZ, Mid-Upper Arm Circumference (MUAC) can also be used to identify SAM for children who are between 6 months and 59 months of age. A MUAC of<115mm (or 11.5cm) is classified as severe. A child with SAM is highly vulnerable and has a high risk of death, with a median under-five case-fatality rate of 30-50%.

Treatment of SAM must be managed through an inpatient setting/ stabilization center. Once the child is stabilized without complications or edema, SAM can be managed in an outpatient setting using Ready-to-Use Therapeutic Foods (RUTF).

Moderate wasting marks Moderate Acute Malnutrition (MAM) with a Weight-for-Height not more than -2 and not less than -3 Z-scores of the WHO Child Growth Standards median. MUAC greater or equal to 115mm and less than 125mm can also be used to identify MAM. Moderate malnutrition contributes more to the overall disease burden than SAM, since it affects a greater percentage of children.

The dietary management of children with MAM is focused on the optimal use of locally available foods in order to boost their nutritional status and to prevent the worsening of the condition to SAM. Ready-to-use supplementary foods (RUSF) can be used to manage MAM in circumstances of food deficits, or when those nutrients are not readily accessible by local foods.

The Global Acute Malnutrition (GAM): GAM is the percentage of children in a population suffering from either MAM or SAM in a given population. An emergency is indicated by a GAM value of over 10 percent. A clear cause for alarm is high prevalence rates outside of the seasonal norm. The commonly used threshold for GAM is the following (WHO, 2000).

Table 1: Normally Used Threshold for GAM

Prevalence of wasting	Severity of malnutrition
<2.5%	Very Low
2.5% to <5%	Low
5% to <10%	Medium
10 to <15%	High
≥15	Very High

Source: De Onis *et al* (2019)

Impact Indicator for Wasting: Percent of wasted (moderate and severe) children above six months but below five years of age that have a Weight-for-Height Z-score that is less then <-2. Wasting is a measurement of acute malnutrition and is the best measurement for the current status and rapid changes.

2.3 Theoretical Framework

Mother’s health influences the health of a child implying that when the mother is malnourished, her chance of giving birth to low-birth-weight babies increases. According to the 2014 Kenya Demographic and Health Survey (KDHS), 27 percent of women aged 15 to 49 years in Marsabit are underweight (body mass index <18.5). Additionally, 9 percent of the cohorts are “moderately or severely thin,” with a BMI of fewer than 17. Nationally, 9 percent of women were found to have a BMI under 18.5 and 2.5 percent were moderately or severely thin (KDHS, 2014). It is well known that women’s nutrition is negatively affected by cultural factors such as hierarchical eating and the belief that eating too much while pregnant will result in a large baby and make delivery complicated (Ugwa, 2016). The same survey found that according to mothers' recollection, 18 percent of babies in the North Eastern Region (Isiolo and Marsabit) are "very small" or "smaller than average" at birth; (KDHS, 2014) the national average was 12 percent. Babies with low birth weight or who are born small for their gestational age are more likely to be ill in the short term and those who are female are more likely to give birth to small babies as adults, fueling an intergenerational cycle of malnutrition. While babies under six months are not included in nutrition surveys, shortly after birth the nutritional shortages that contribute to stunting and wasting are likely to begin.

According to Kimwele & Ochola (2017), 99 percent of children in Kenya had ever been breastfed, with only 61 percent of children below six months of age having been exclusively breastfed and just 22 percent of children were fed per recommended dietary diversity and normal practices. Other studies elsewhere have also found out that the rate of exclusive breastfeeding and appropriate complementary feeding is even lower in the ASALs (Mohamed *et al.*, 2018). On the other hand, since breastfeeding for up to twenty months is common in the North Eastern region of Kenya, less than one percent of infants are exclusively breastfed until six months of age (Grobler, 2006). A study of reasons associated with chronic malnutrition in children less than 24 months in Kenya and Cambodia found a higher risk for stunting among males compared with females and reported that boys under the age of 12 months have a chance to be stunted, while girls are probable to be chronically malnourished after their first birthday. They hypothesize that mothers are more likely to practice inappropriate weaning and complementary feeding practices with male infants (Ettyang & Sawe, 2016). Not only does the early introduction of complementary food reduce an infant's consumption of breastmilk, which has the ideal nutritional content, but it also increases the risk of infection, particularly diarrheal disease. In children in Turkana, early weaning was found to be closely associated with acute malnutrition. Increased exclusive breastfeeding practice could immediately decrease child mortality by 20% (Grobler, 2006). Many other researchers have shown that gender of the child (Liben *et al*., 2016; Demissie & Worku, 2013), maternal education (Yoseph *et al* (2020) fathers education (Amare *et al*., 2016), maternal occupation of the mother (Ma'alin *et al.,* 2016; Fikadu *et al*., 2014), household income (Liben *et al*., 2016; Mousley., 2015), antenatal care service utilization (Ma'alin *et al*., 2016; Bergen *et al*.,2015), source of water (Girma, Fikadu & Abdisa (2019)., feeding the child with colostrum (Teshome *et al*.,2009) and methods of feeding (Derso *et al.,* 2017; Teshome *et* al., 2009) contribute extensively to chronic malnutrition. Many studies, however, have so far put emphasis on factors affecting wasting specific to individual child ignoring factors related to community. Studies concentrating on fixed-effect variables on an individual child could disregard the membership of the child within a specific group and concentrates entirely on differences within individual children and characteristics at the individual level thus having the downside of ignoring the possible relevance of group-level qualities in affecting individual-level findings in this scenario. Also, if results are correlated for people within groups, incorrect standard errors or estimates that are not efficient are obtained since the assumption of independence of observations is infringed.

Similarly, a mother's health, both physical and mental, continues to correlate with her children's nutritional outcomes, even after birth. A study done in Kenyatta National Hospital found that 64 percent of women whose babies were in hospital for wasting were moderate to severely depressed. Just five percent of women with children of expected weight admitted to the hospital for other serious illnesses met the criteria for depression (Haithar *et al*., 2018). Other researchers suggest that maternal depression correlates with nonresponsive caregiving practices and a lower likelihood of breastfeeding. The correlation between state of the mothers' mental health and infant health can be mutual, according to Surkan *et al*., (2011), and the poor health of a child could cause the depression of the mother.

Similarly, one study found that 15 percent of children born to mothers who had received no formal education were wasted and 5 percent of these children were severely affected (Grote, 2014).

Milk is an essential staple food for pastoralists, especially for children in ASAL areas. A study undertaken in the Somali Region of Ethiopia found out that during the wet season, the average one-year-old child consumes 100 percent of her protein requirements and about two-thirds of her energy requirements from milk (Nyariki & Amwata, 2019). By the end of a normal wet season, children's milk consumption fell by more than 70 percent and was replaced by grains, cooked with water, which provides little protein, fatty acids, or micronutrients (Fekadu *et al*., 2015). Similarly, Action Against Hunger's Causal Analysis report (2014) found that inadequate access to milk and animal products was a major cause of acute malnutrition during dry seasons in the ASALs. When men migrate away from their families to find pasture and water, they bring most of their herd with them. Women have little access to money or credit to buy food in the market, thus they cope with the milk from just one or two goats left behind, and whose production is often slowed by the lack of water and grass for foraging. As there is little land in the area suitable for farming, few fruits and vegetables are grown at home or available in the markets.

Many households in the targeted counties depend on government rations during times of food insecurity. However, the amount provided is aimed at covering just 75 percent of household's needs, for 80 percent of the population in pastoral districts. Additionally, targeting at the community level is often uneven and inequitable. Grobler, 2006 observed that, despite the awareness that households with children admitted to therapeutic feeding services should be related to the general allocation of rations but this was not often practiced.

The rural landscape and historic neglect of the ASALs by the national government have left the region with limited infrastructure and human resources for health care. Marsabit has just one referral hospital, three sub-county hospitals, and 63 dispensaries that serve a population of nearly 300,000 people which spread across 70,000 square kilometers (KNDS, 2018).

2.4 Water and Sanitation (WASH)

The Kenya Environmental Sanitation and Hygiene Policy state that community-led total sanitation (CLTS) is the model to use in ending open defecation in Kenya (Musyoki, 2010). However, literature reports that pastoralists prefer not to use latrine due to cleanliness and accessibility. According to Aful & Danga (2013), latrine coverage is 34 percent in Marsabit. Open defecation leads to a higher risk of both acute and chronic illness in children. The use of improved water supplies has been shown to decrease diarrhea deaths by within the interval 6-25 percent, while improved sanitation will decrease diarrhea morbidity by 32 percent.

2.5 Social and Cultural Norms and Trends

Unlike many other parts of Kenya, where mixed and diversified farming practices are common, pastoralism remains the predominant livelihood strategy in the ASALs. In spite of the sensitivity and the exposure and to repeated droughts, the pastoralist economy in the Northern parts of Kenya contributes 95 % of family livelihoods and 90

% of employment (Kenya ASAL Policy, 2012). Therefore, with the effect of climate change, the ASALs are expected to experience more frequent climatic extremes which will cause reduced yields from rain-fed agriculture and increased food insecurity and malnutrition (Thornton & Lipper, 2014). While it is reasonable to believe that livelihood diversification would provide residents with some insurance against shocks, some research suggests that pastoralist dropouts those who are living in towns and seeking income from non-agricultural sources, fare worse than pastoralists with productive herds.

However, women in the ASALs bear the brunt of household work and have little access to or control over resources or income. Some women engage in trade of small ruminants and processed milk, but these activities rarely generate enough income to provide independence. Women's lack of decision-making power and financial resources hinders their ability to seek health and sanitation services for themselves and their children and limits their ability to purchase food in the markets (Kinati & Mulema, 2018). The population in the ASAL counties is young and growing where 47 percent of Marsabit residents are under 15 years (Mutua *et al.*, 2015). Literacy is 25-58 percent among women in the ASALs, compared to 88 percent nationally (Sussman, 2011). The analogous statistics for men demonstrate large gender gaps, as well as the divergence of the ASALs from national averages.

2.6 Economic, Political, Security, Market, and Infrastructure

The viability of the pastoralist way of life has been weakened by a reduction in pastoralists' rights to own and manage rangeland, commercialization of the livestock sector, the concentration of herd ownership, privatization of rangeland, and increased conflict over access to water, land, and fodder for their herd.

Furthermore, Mosley &Watson (2016) contends that the potential of the ASALs counties on energy, trade and tourism are considered important to the national policy and planning in the ‘Vision 2030 Development Strategy for Northern Kenya and Other Arid Lands'. Similarly, according to Elmi & Birch (2013), stopping further marginalization of pastoral areas and therefore making the ASALs regions equal partakers of the ‘National cake’ is envisioned in Vision 2030 through promotion of inclusion of pastoralists in national development. Furthermore, Livestock farming accounts for more than 80 percent of income in the ASALs. Market transportation infrastructure is limited, which reduces households’ ability to purchase food and other commodities and trade livestock (Barrett, 2010). Livestock prices decrease during drought, a function of increased supply, and worsening animal conditions and at at the same time that other food prices increase.

2.7 Key Drivers of Malnutrition in the World

Breastfeeding of children that is not optimal, deficiencies in vitamins and minerals causes poor fetal growth which in turn results in stunting and wasting in children. This causes 3.1 million children to die or attributed to 50% of all deaths under age 5 years every year. This is distinctly higher among delicate and conflict-affected regions (Kim *et al.,* 2020). When children are under-nourished, their social, mental and even physical development are impacted and therefore, the drivers of child under-nutrition need to be studied regularly in order to continuously monitor the situation and recommend the most appropriate interventions to prevent more children from getting malnourished (Adel *et al*., 2007; Kariuki *et al*., 2002).

According to De Onis & Branca (2016), stunting presents the most common form of under nutrition globally. Research has shown that approximately 165 million children under the age 5 years are severely stunted but a higher number of children moderately stunted and are therefore suffering poor linear growth (UNICEF, WHO, World Bank, 2012). The under nutrition underlies 45% of all child deaths among children < 5 years (Black *et al*., 2013). However, owing to its longer-term effect on cognitive function and adult economic productivity, stunting more commonly hinders the developmental ability and human resources of whole societies; it is thus considered the strongest proxy predictor of inequality in infant welfare (Prendergast & Humphrey, 2014).

Many researchers are still interested in identifying factors for child malnutrition. To uncover the variables of child malnutrition, various techniques are applied. Among them, logistic regression analysis has got the most reference from previous scholars. For majority of the scholars, the response factor was considered either nourished or malnourished and therefore binary logistic regression (BLR) has been used. The nutritional condition of a child is however categorized as nourished, moderately malnourished, and severely malnourished. Key drivers that could influence moderate and severe malnutrition could be different. Therefore, using BLR would entail the creation of two distinct models by classifying the response variable into two groups. The response variable can be considered as ordinal and thus ordinal logistic regression (ORL) can be applied to recognize the predictors of child under nutrition. ORL model is always preferred when response variables are in levels as in the case with malnutrition and other medical and epidemiological studies.

Abitew *et al.*, (2020) utilized information from Gondar referral emergency clinic in Ethiopia by utilizing logistic regression (both bivariate and multivariable) to inspect the risk variables of severe acute malnutrition (SAM). The discoveries affirmed that there is huge relationship between wasting of children below five years of age and poor feeding practice. Further logistic regression analysis indicated that the risk of wasting was profoundly correlated with the absence of exclusive breastfeeding for the initial half-year of life and the late initiation of complementary feeding after the consequences of other essential risk factors were managed.

Correspondingly, Heita (2020) draw investigation on information gathered from a panel survey conducted in Bangladesh by utilizing a BLR model to contrast children with weight for age Z-score (wasting) >= -2 with that of children with weight for age Z-score (wasting) < -2 and consequently recognize the potential determinants/risk factors of malnutrition. The investigation shows that the age of the child, educational status, and sex of head of household, household facility, and area of residence are substantially correlated with malnutrition of children under five years of age.

Singh *et al* (2011) on the other hand, analyzed the spatial distribution of Indian children's nutritional status and found that there are gender disparities and spatial variations in children's weight-for-age (underweight) status Similarly, closely spaced pregnancies are often associated with the mother having a short period of time to retrieve lost fat and supplement stores (ACC/SCN, 2008). As the mother gets sufficient and ideal opportunity for appropriate childcare, higher birth spacing is also responsible for enhancing child nutrition. Studies in developing countries showed that in most countries where DHS has been done, children born after a shorter birth period (less than 24 months) have higher underweight levels (Magadi, 2011).

Wondafrash Kibebew (2018) performed bivariate and multinomial logistic regression on information obtained from the National Nutrition Program (NNP) research done in Bangladesh in 2004. The outcome was that 40.5 percent of the children had poor linear growth with about 16 percent having severe linear growth. It was also found out that about 35 percent were underweight with 12 percent being severely underweight. The same study found that about 18 percent were moderately wasted with 3 percent being severely wasted. Female children were 30 percent and 21 percent less likely than their male counterparts, respectively, to appear moderately and severely stunted. Girls who had not attained under five years of age, conversely, had a 20% to 21% lower risk of becoming underweight. A higher percentage of elderly and malnourished women had moderately underweight babies.

Rytter (2017) applied logistic regression, χ^2 and T-tests on data collected from children under five years of age with complicated acute malnutrition (AM) admitted to the Zambia university teaching hospital's stabilization center from August to December 2009. The study revealed that diarrhea is the highest contributing factor to deaths of severely wasted children even if all other factors were held constant.

Das & Rahman (2011) applied (OLR)-proportional odds model (POM) and partial proportional odds model (PPOM) rather than conventional binary logistic regression to information from the Bangladesh demographic and health survey (BDHS, 2004) to survey the potential probable variables of under-nutrition. As indicated by the discoveries of the author, household wealth status, child feeding status, Mother’s BMI, incidence of diarrhea, mother's antenatal and/or postnatal care status, mother's education, child feeding practice, birth interval and age of the child are risk factors that that fundamentally influence the nutritional status of children under five years of age. The examiners also suggested that ordinal logistic regression (OLR)-proportional odds model (POM) or partial proportional odds model (PPOM) are fitting to distinguish the potential risk factors of malnutrition on children of five years of age than/to that of traditional binary logistic regression.

Mothers should be helped to begin giving breast milk to their babies as soon as the baby is delivered but not exceeding half an hour upon delivery per the World Health Organization and UNICEF (Zakarija *et al*., 2012). In the first hours after birth, babies are usually in a calm, alert state. This is the perfect moment for bonding and breastfeeding to start. The WHO advised in 2001 that babies are to be fed only with breast milk in their initial half year, thereafter, complimentary feeding with adequate nutritional component to be introduced after six months. Feeding the baby with breast milk is beneficial to both the baby as it has all the required nutrients for proper growth of the baby. In addition, feeding the baby with breast milk guards against sicknesses that are common in childhood such as diarrhea and pneumonia as well as being associated with longer-term wellness which include; reduction of obesity in childhood and in adolescence. Early initiation to breastfeeding refers to the infant being provided with mothers' breast milk within one hour upon delivery and this facilitates that the baby gets the colostrum that contains many protective factors. The report by Cochrane Review supports using immediate or early skin-to-skin contact to promote breastfeeding (Moore *et al.*, 2016). Advantages for the mother include earlier expulsion of the placenta reduced bleeding and increased breastfeeding self-efficacy (Essa & Ismail, 2015).

The key risk factor affecting nutritional malnutrition among children under five in Ethiopia's food surplus zones is inadequate feeding practices. Therefore, even in food surplus areas, the importance of proper feeding during infancy and childhood need to be emphasized. The high prevalence of malnutrition in Ethiopia points out that the belief kept by many individuals that malnutrition is not an issue in food surplus areas needs to be revisited, and therefore, improvement and execution of preventive strategies aimed at addressing child malnutrition ought to be considered even in food surplus regions of the nation (Yalew *et al*., 2014).

The implementation of feeding the baby with only breast milk up to the age of six months is advised by WHO as optimum way of feeding the child as it provides the baby with adequate diet and protects the baby against infections such as diarrhea (Talbert *et al.,* 2020). Feeding the baby with only breast milk is however affected by variables interacting at various levels which include; cultural factors, individual factors affecting the mother and the baby, the social-economic factors and also political factors (Rollins *et al.,* 2016). According to Kenya National Bureau of Statistics (2014), mothers feeding their babies with only breast milk up to the age of six months increase from 32 percent to 61 percent between 2008 and 2014.

The availability of household resources such as income is believed to be among the important factors in the prediction of child health and nutritional status. Nevertheless, there is a lack of consistency across studies over the significance of these variables. For instance, utilizing information from 2006 Brazilian Demographic and Health Survey, Kim & Schneider (2005) reported that utilizing multinomial logistic regression that total income impacts the weight of the baby in a marked and favorable way in both rural and urban regions. Conversely, as the family size gets bigger there is an opportunity of a lifetime of having monetarily idle individuals in the family unit and this prompts an unfavorable effect on the accessible assets and accordingly on child nutrition outcomes.

Hong (2020), utilizing Chi-square and t-test investigation in India found that babies born to mothers under the age of eighteen years had a higher chance of being under-nourished than those born to mothers above the age of eighteen years. The outcomes additionally indicated that 73 percent of the babies delivered had their mother married early, which is before 18 years. The bivariate examination of this investigation additionally demonstrated that there are critical relationship between in babies whose mothers were married early and the child's risk of conducting illnesses such as diarrhea or getting malnourished, low birth weight, and deaths.

Anin *et al.,* (2020) utilized BLR analysis highlighted that the employment of mothers can have both positive and negative repercussions on children's dietary intake. Small babies, with birth weight below 2,500g are malnourished and have higher odds of dying in their early life. This is a critical indicator since it reflects the status of the newborn and the nutritional status of the mother. Factors such as smoking, consumption of alcohol while the mother is expectant, genetically inherited factors and environmental factors are some of the reasons thought to affect low birth weight of children but also a good indicator for mother's weight gain and the development of the children during pregnancy.

Babies' growth and development are impacted by the previous nutritional intake of their mother. At the age of 5 years, a low-birth-weight child is more likely to remain stunted. This will lead to the child having inadequate nutrition and therefore, sustained poor health leading to a stunted adolescent up until adulthood. Chronically malnourished mothers have higher odds of giving birth to underweight children therefore perpetuating malnutrition from one generation to another hence a sustained pattern of high infant mortality rate.

2.8 Conceptual Framework

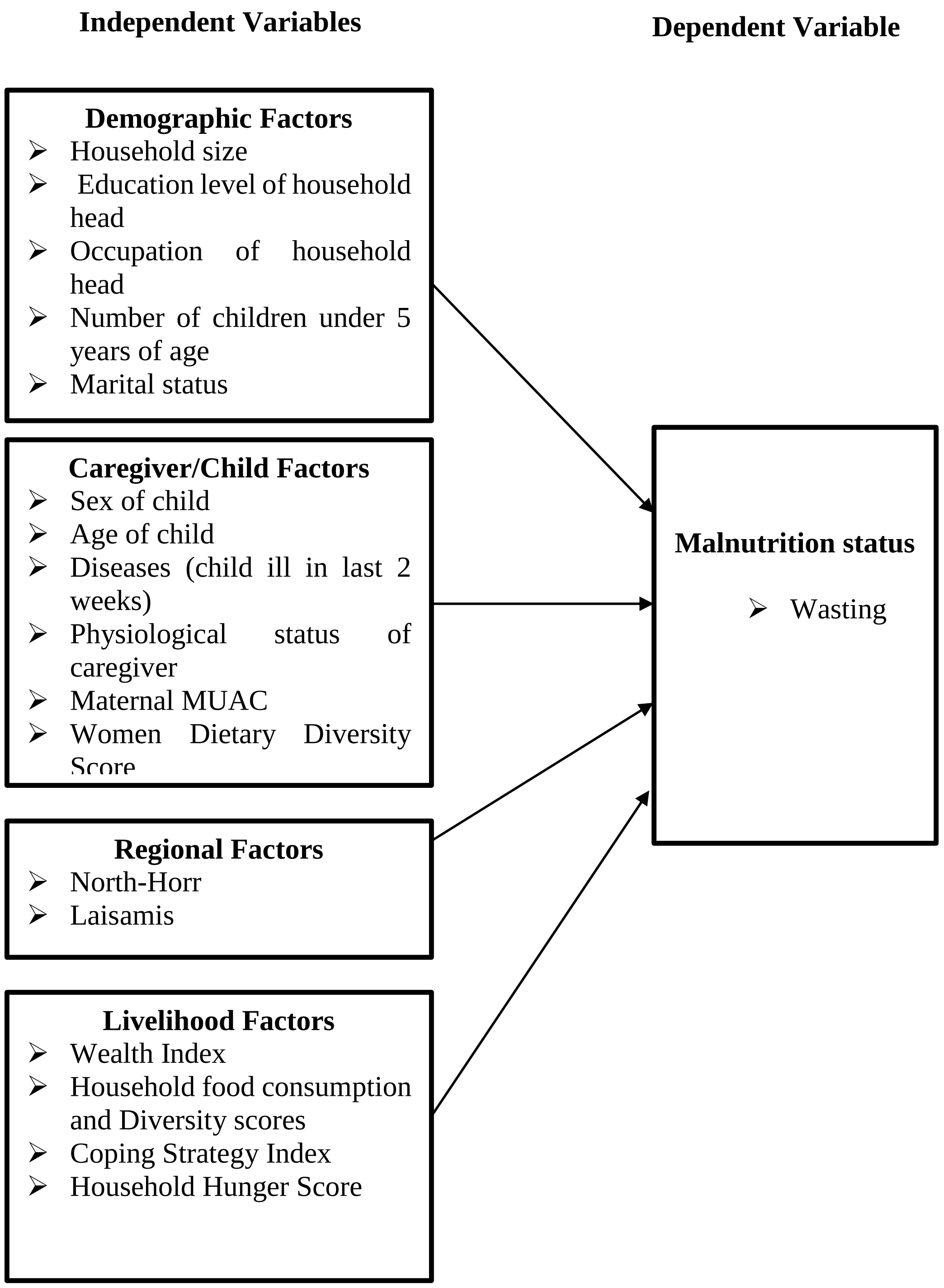

Figure 2: Relationship between Independent and Dependent Variables

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter covers the methods used in the research that include the site in which the study was conducted, the sources of data, the sample size and sampling procedure, statistical analysis and the models used to analyze and interpret results.

3.2 Study Site

The study site was North Horr and Laisamis Sub-Counties of Marsabit County. Marsabit County is located in Kenya's central north. It is located on the eastern shore of Turkana Lake. The OlDonyo range (2,066M) in the southwest, Mount Marsabit (1,865M) in the central part of the county, the Hurri Hills (1,685M) in the northeastern part of the county, Mount Kulal (2,235M) in the northwest, and the mountains surrounding Sololo-M are all significant topographical features. According to the Kenya National Bureau of Statistics Census (KNBS) report of 2019, Marsabit county population was 459785 persons (243548 male, 216219 female and 18 intersex) with with average household size of 5.8 person. The same reports show the county being the most sparsely populated county in the country having an average of 6 persons per square kilometer. Livestock farming (mainly pastoralism) accounts for more than 80 percent of income of residents of the county ((Kenya Food Security Brief, 2013).

This study used retrospective data collected among under 5 years children in Marsabit, County Kenya in July 2019 from Standardized Monitoring and Assessment of Relief and Transition (SMART) survey where anthropometric data was captured. The primary objective of the study is to give current evidence for planning, policy formulation, monitoring and evaluation of population and health programs in the Marsabit County. To this effect representative sample of 451 households with children between 6 - 59 months were selected and all women aged 15-49 years qualified for the individual interview module of the survey.

3.3 Data Sources

The research extracted data from the SMART survey of Marsabit County conducted in July 2019. The study employed a retrospective study design that utilized information on the malnutrition categories of children which included the indicators of height, weight, and age of all children under age five which was used to calculate weight-for-height (WHZ) anthropometric indicator. The index was expressed as standard deviation unit from the median for the reference group. Children's nutritional status was calculated using revised growth criteria released in 2006 by the World Health Organization (WHO). Children who had less than -2 SD of the median reference populace were counted were termed as too thin for the respective heights (wasted). This variable was deemed to be response variable during statistical investigations. The two-level response variable wasting was defined as 1= for AM and 0= for not AM, (Abera *et al*., 2017; WHO, 2006).

The child's nutrition status was grouped into three classes which are namely; 1)-Severely under-nourished (< -3.0 Z-score), 2) Moderately under-nourished (-3.0 to -2.01 Z-score) and 3) Nourished (≥-2.0 Z-Score). Thus, malnutrition status variable is a categorical variable which was modeled using a linear model where the Logit and the mixed effects models were employed to predict factors linked with under nutrition among children above six months but less than 59 months.

3.4 Sample Size and Sampling Procedure

The sample size utilized a single proportion population formula as per Lawson & Comstock (2020) as shown below;

$$n = \frac{\left(Z_{\alpha/2}\right)^2 PQ}{D^2} * Deff \text{ .... } 3.1$$

n is the desired sample size and P is the estimated probability of the acutely malnourished children in the target population

Z=Std. normal deviation which is usually assumed to be 1.96

D=degree of precision which is set at 0.05

Deff=Design Effect, which is an adjustment due to the data being used in the different strata (North Horr and Laisamis). Calculated as;

$$Deff = 1 + \delta(n_1 - 1)$$

δ is the inter study site correlation for the GAM prevalence and n_1 is the average size of each study site.

The following assumptions were considered:

95% confidence level, Design Effect taken as 1.4, estimated proportion (P) of wasting (29.9%) taken from published Master of Science thesis which was conducted in Marsabit County [Saddio, 2017] and a 5 percent error margin. When this formular was adopted, the computed size of the sample for the incidence of wasting was comparatively higher and this gave the required size of the sample of 451 survey caregivers that the current study utilized where information on children were also utilized, that is, $\frac{1.96*1.96*0.299*0.701*1.4}{0.05*0.05}$ =451

3.5 Statistical Analysis

Statistical Package for Social Sciences (SPSS) version 21.0 and Microsoft office excel 2007 was utilized for entry and analysis of data. 2006 WHO Anthro 3.2.1 Software and SAS version 9.3 were used to determine WHZ anthropometric index. To explain the proportions and frequencies of socio-demographic features and other applicable factors in the research, outputs from descriptive analysis were used. Outputs obtained from the analysis of Bivariate and multivariable logistic regression analysis identified the variables related to under 5 child under-nutrition status. In order to see the extent of the correlation between the result and the chosen independent variables of interest, both the crude and adjusted odds ratios and their corresponding 95 percent confidence intervals were calculated. A p value of < 0.05 was considered to be statistically significant. The Hosmer–Lemeshow test was also performed to check for model fit while using the logit model. To measure the effect of variation across the two selected study sites, mixed effects model was employed to help compare the results of the parameter estimates with the logit model.

3.6 Ethical Considerations.

There was no Ethical clearance required since data that was used was a retrospective source. However, study data will be de-identified to have only household ID numbers and the study variables of interest to the researcher. Moreover, confidentiality of the extracted data was enhanced by using password protected computer.

3.7 Statistical models

3.7.1 Generalized Linear Model

To model factors such as wasting in children, assuming independence of nutritional outcomes of children in the sample, the most commonly used model in statistics is the probit or logistic regression. However, if there exists clustering, as in the case of children been nested within household and household within a community, in child nutritional outcome, then the assumption of independence is violated since they share attributes such as; how they are cared by their parents, household environment for example, the space and health cares are expected to contrast in different households but be the same in the household. Therefore, children's nutritional status can be expected to be clustered in the household. In addition, since they have common features that include accessibility to health technologies, vulnerability to diseases, economic, and climatic environments, that are similar to households in similar regions but vary across regions; households may be grouped within the region. This illustrates that the result of child feeding is likely to vary at the same time at the level of the child, household, and society. Generalized least square estimates which bases on the accurate structure of residual covariance matrix in the presence of clustering of child nutritional data, produces more accurate predictions than those produced by logistic or probit regression models. These methodologies do not allow for exploring clustering structure (Bostrom & Holmberg, 2011).

The unidentified factors are considered in the fixed effects and random effects model. According to Hill *et al* (2020). However, given that the nutrition result is measured dichotomously, the estimators of fixed effects are expected to suffer from the accompanying parameters problem. This can happen since estimators of fixed effects depend on how the constants are estimated, which are fixed and can be very small, based on cluster observations leading to poor estimation of constants and parameters. Similarly, the estimation bias is likely if observations are small in the clusters. In the other hand, the predicted value of differences within cluster is believed to be zero in the random effects models, the term of idiosyncratic error and the covariance that exists in the heterogeneity of the cluster and idiosyncratic error. Simulation using random-intercept specification model at several levels would be implemented given the dichotomously calculated nutrition factor and a limited number of cluster observations, which is described in section that follows.

3.7.2 Mixed Effects Model, Variables and Estimation

Raudenbush & Bryk (2002), proposed that unobserved differences within household and community are accounted for by using three level model of random-intercept logistic regression.

$$log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{000} + \sum_{p}^{p}\beta_{pjk}\,C_{ijk} + \sum_{q=1}^{Q_p}\beta_{0qk}\,H_{qjk} + \sum_{s=1}^{S_{pq}}\beta_{p0s}V_{sk} + \gamma_{0jk} + \mu_{00k} + \varepsilon_{ijk} \quad \text{...3.2}$$

The parameters presented are as follows;

π_{ijk} is the probability of i^{th} child being malnourished in k^{th} community and j^{th} household. Fixed effect components which includes; the p=1,…,P, q=1,…,Q_p and s=1,…,S_{pq} predicts the log odds of malnutrition status of i^{th} child. (C_{ijk}) is child-level characteristics while H_{qjk} is household-level characteristics and V_{sk} is features at the community-level. ε_{ijk} denotes the components of the random effects that describe the difference of nutrition status of children within households, γ_{0jk} is the random effect component that describes differences of households in the communities and μ_{00k} represents inter-community random effect components. When the intercept of the child level has been decomposed with regard to household features, and also the intercept of the household level decomposed with regard to the features at the community level, β_{000} is the intercept for the community-level model.

Schielzeth (2020) suggested that the random variables are assumed to be independent in all levels and have zero mean and variance distributed as; ε_{ijk} N (0, σ2c), $\gamma0_{jk}$ N(0, σ2h), μ_{00k} N(0, σ2v) and are assumed to be independent across levels.

The specified variances are not known and therefore, the goal of modelling at different levels seeks to find the estimates multi-level modeling is to find the estimates of those variances or unobserved differences in the various levels (Ayalew, 2020). This procedure proposes the method of adaptive quadrature to get the maximum likelihood estimates of a discrete response factor having nested random effect. Relationships within classes which assess the extent of association of children both at household and community level is analyzed based on the effects of random components (Rabe-Hesketh & Skrondal, 2005).

The child-specific variables to be included in the models are sex of child, if the pregnancy was full term or not, and whether birth weight was recorded or not. The determined birth size is also argued to be closely associated with nutritional effects, such as malnutrition. The gender of the baby is treated as a two-level factor, that is, '0' if the gender of the child is female and '1' if the gender of the child is male. Age of child is expected to account for the duration of breastfeeding and its effects and therefore, it is controlled in these models and the relationship is recognized. The covariate at the level of the household that are controlled in the models are; the education level of the caregiver (mother), the caregiver's age, food security at the household, household dietary diversity score and study site. Education level of the mother is categorized in to two classes; ever attended school and never attended school. The mother's age is treated as a continuous variable. The scores of household hunger and household dietary diversity were used to control for the household differential capability to take care of the health of the child and was categorized either as high dietary or low dietary (for HDDS) and secure and not secure (for HHS). Similarly, the caregivers and child ability to assess health care is important in describing the health of the child. The response will be recoded dichotomously as '1' if child's weight at birth was recorded and '0' otherwise.

3.7.3 Generalized Linear Mixed Effects Model

Generalized linear model (GLM) is unable to handle correlation in clustered data. To accommodate it into the model, GLM has been extended to generalized linear mixed model (GLMM) (Stroup, 2012), which includes random effect component along with fixed effects. Following this model, generalized linear model is extended by including random effect term along with explanatory variables in the linear predictor for non-normal responses.

GLMM combine the features of GLM and mixed models, therefore, is are more robust statistical models. There are an extension of GLM where the random effect are factored to the linear predictors therefore allowing modelling of related and possibly not normally distributed data and covariates can be accommodated. GLMM sorts modeling problem of data with high variances thus accommodating the population heterogeneity. GLMMs are important tools for clustered data especially in public health and community-based research have become important tools for clustered data, particularly in public health and many community-based researches.

3.7.4 Logistic Regression Model

This model allows categorical response variables which have binomial errors to be modeled using a regression analysis by extending the techniques of multiple regression analysis for categorical outcome variables. According to Fernée & Trimmis (2021), discrete outcome as in the case of membership of a group can be predicted when there exist predictor variables that are discrete or continuous or a mix. Binary logistic regression is often used when the response factor is at two levels for instance, high or low, absence or presence, among others. Pohar *et al* found out that logistic regression is preferrable to multiple regression and discriminant analysis since its mathematically flexible and simple requiring fewer assumptions. When the response variable has three or more categories and are ordered according to their importance, ordinal logistic regression (POM or PPOM) should be applied to analyze the relationship between the response and the independent variables. In logistic regression, independent variables do not need to be normally distributed, unlike in the case of discriminant analysis. Furthermore, it does not need to meet the requirements of same variances or linearly related (homoscedasticity) independent variables within each group (Antonogeorgos *et al.*, 2009). One unique property of logistic regression is the ability to estimate logit differences for data collected retrospectively and prospectively quite simply (Armangue *et al*,. 2018). Therefore, logistic regression is mainly used to predict group membership and to provide insights of the associations and strengths among variables. Logistic regression has two main purposes, that is, to predict membership of a group and to provide insights of the associations and strengths among the factors.

3.7.5 Binary Logistic Regression Model Description

Consider a random variable Y that can take on one of two possible values. Given a data set with total sample of n, where each observation is independent, Y can be considered as a column vector of n Bernoulli random variables y_i. Let $X_i = (x_{0i}, x_{1i}, \ldots x_{ki})'$ be a vector of factors (explanatory variables) corresponding to the i th subject, $i = 1,2, \ldots n$, where $x_{0i} = 1$. Suppose y_i takes on the value 1 with probability$\prod(\mathrm{x_i}) = \mathrm{p}\left(Y_i = 1 | X_i = x_i\right)$ and the value 0 with probability $1 - \prod(\mathrm{x_i})$. In logistic regression the response probability $\prod(\mathrm{x_i})$ evaluated as:

$$\prod(\mathrm{x_i}) = \mathrm{p}\left(Y_i = 1 | X_i = x_i\right) = \frac{e^{\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki}}}{1 + e^{\beta_0 + \beta_1 X_{1i} + \ldots + \beta_k X_{ki}}} = \frac{\exp(\beta' X_i)}{1 + \exp(\beta' X_i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

In which β=$(\beta_0, \beta_1, \beta_2, \ldots, \beta_k)'$ refers to a column vector of coefficients of regression that are not known. The odds of success are defined as:

$$\frac{\prod(\mathrm{X_i})}{1 - \prod(\mathrm{X_i})} = \quad exp\{\beta' \mathrm{X_i}\}(2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

The log-odds (logit) are then given by:

$$\log\left(\frac{\prod(\mathrm{x_i})}{1-\prod(\mathrm{x_i})}\right) = \beta' X_i \text{ , i1,2,3, ... , n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.5$$

A key feature of the multiple binary logistic regression models is that the odds that an outcome will happen when a specific category of a given covariate compared to the odds of the outcome happening given the reference category, adjusted for all other covariates, can be calculated directly from the logistic coefficients by $OR = \exp\ (\beta_k)$. However, this simple relationship is true only if the relationship between the logit and X_k is in fact linear and there are no interactions between the covariates.

3.7.6 Interpretation of Logistic Regression

The change in the log-odds of an event of success per unit increment in the corresponding covariate keeping other covariates constant is taken as the coefficient of a continuous covariate. When we have a predictor variable that is categorical, it would be taken to mean the log-odds of an event of success for a specified class taken in comparison to the class of reference.

It is not advisable to predict the response variable using OLS regression with categorical dependent variables for the following reasons;

- ✓ Ordinal Logistic Regression analysis may result in probabilities that are greater than one or in negative probabilities. These do not make sense.
- ✓ Ordinal Logistic Regression normally assumes that the residuals are normally distributed. However, predicting categorical dependent variables using OLS will have residuals that are not normally distributed as they can only take on one of a number of values for each mixture of levels of the independent variables.

- ✓ The coding is entirely random for nominal dependent variables, and it is arbitrary for ordinal response factors up to a monotonic transformation. However, recoding the response factors yields very distinct outcomes.

3.7.7 Assumptions of logistic regression

For Logistic Regression to be efficient, sustain assumptions should be satisfied thereby making the model valid. Al-Fugara (2020), put forward that the following should hold:

i. Variables are coded meaningfully to aid in interpretation of logistic coefficients. The dependent class of the greater interest is coded as 1 while the class of lesser interest is coded as 0.

ii. The log-odds of a logistic regression model have a linear relationship but linear relationships between the dependent and independent variable is not assumed.

iii. The response variable characteristically takes a distribution from an exponential family such as binomial, Poisson, and multinomial and not necessarily normally distributed.

iv. Only one group should be a case and each case must be a part of one of the groups; the groups must be mutually exclusive and exhaustive.

v. As compared to linear regression, logistic regressions require larger samples since the maximum likelihood coefficients converges in probability to the value been estimated.

vi. There should not be severe co-linearity among predictor variables.

3.7.8 Odds Ratios

This refers to the ratio of the odds of an event happening in a group compared to the odds of the event happening in another group. In a study, odds ratio is computed by calculating the odds of a risk factor among individuals with the event of interest divided by the odds of a risk factor among individuals without the event of interest (Stare &

Maucort, 2016). It is the exponential of the estimated coefficients $\hat{\beta}$ ($\exp(\hat{\beta})$) in binary logistics regression while it is the predicted change in the odds of being acutely malnourished for a unit increase in an independent factor for continuous covariate such as age of the mother. When the odds ratio is one (1), it means that the explanatory variable do not affect the response variable. For independent variables that are in categories, $\exp(\hat{\beta})$ denotes the expected change in the odds of being undernourished with respect to the reference category for a given category of the independent factor. Since more variables are included in the analysis, Adjusted Odds Ratio is computed to explain the effects due to the additional variables included in the analysis.

3.7.9 Model Building and Variable Selection for Logistic Regression

A balance needs to be fitted while selecting a model to use, so as to ensure that the model used is sufficiently complex to fitting the data well as well as maintaining the simplicity to enable interpretation, smoothing, and avoiding over fitting of the data (Agresti, 2002). When the number of independent variables increases, it will be expected that the interactions also increase and subsequently possible effects of interactions increasing making model selection process complicated.

All covariates significant in the uni-variate analysis at the p-value 0.2 to 0.25 level and any other that are thought to be of clinical importance should be contained in a multivariable model from the beginning. According to any covariate that has the potential to be a significant confounder should also be included. P-values from the Wald tests of the individual coefficients are used to classify covariates that may be omitted from the formula, as a result of the fit of the multivariate model. To confirm that the covariate which is removed is not significant, partial likelihood ratio test is utilized. We can also verify if covariate elimination induces a 'major' shift in the coefficient of any of the remaining covariates in the model. We proceed until no covariate can be excluded from the model (Bursac *et al*., 2008).

3.8 Goodness of Fit of the Model

3.8.1 Deviance and Pearson's Goodness-of-Fit Test

The goodness of fit of a statistical model refers to how well the model describes. To assess goodness of fit entails analysis of how the predicted values are close to that of the observed values (Fernando & Sooriyarachchi, 2020). We can compare the likelihood of the current model (**L**$_c$) with that of the full model or saturated model (**L**$_f$). The scaled deviance is often defined, in generalized linear model (GLM) terminology, as:

$$D(c,f) = -2\log(\frac{l_c}{l_f}) \qquad \text{3.6}$$

where the full model is the model that has as many location parameters as observations, that is, *n* linearly independent parameters thereby reproducing same data that is not simplified hence limiting its use for interpretation. This current model lies in between of the maximal and the minimal model. When the deviance is large it implies that the data fits less to the model (Celeux *et al*., 2006). The deviance has a chi-squared asymptotic null distribution with degrees of freedom equivalent to the difference between parameter values of saturated and unsaturated models.

In addition, Pearson's goodness-of-fit test helps in determining whether a model fits well, or a pair of categorical variables is associated. It is computed as:

$$X^2 = \sum_{i=1}^{C} \frac{(O_i - E_i)^2}{E_i}, \qquad \text{3.7}$$

Where O_i represents the number of observed items in the i^{th} category, E_i is the expected number of items in i^{th} category and ‘C’ represents the number of categories.

The estimated number of items in a group is determined by the expected value of a binomial random variable, since the binomial formula forms the basis of this test. This implies, $E_i = np_i$ where *n* represents total observations and p_i represents the chance of getting an observation in the i^{th} category (Allison, 2014). The Pearson chi-square statistics has an asymptotic X^2-distribution with (C-1) degrees of freedom when it is used to test several proportions simultaneously (Rempala & Wesolowski, 2016).

3.8.2 Likelihood-Ratio Test

Another commonly used technique of testing the significance of many independent variables is the likelihood ratio test as it is appropriate for many statistical models. Agrresti (1990) maintains that the likelihood ratio test is preferable especially when the sample size is small or in case of many parameters. The test uses the ratio of the maximized value of the likelihood function of the full model (L_f), instead of the maximized value of the likelihood function for the null model (L_0) (Lewis *et al*., 2011). The likelihood-ratio formula is as below:

$$\mathrm{G}^2 = -2ln\left[\frac{L_0}{L_f}\right] = -2\{\ln L_0 - \ln L_f\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.8$$

In which L_0 denotes the likelihood function of the null model, L_f denotes the likelihood function of the full model that is evaluated at the maximum likelihood estimates. According to Gbur *et al* (2020), an asymptotically chi-squared statistic with degree of freedom equal to the difference between the numbers of parameters estimated in the two models is yielded by the natural log transformation of the likelihood functions. The null hypothesis under consideration is that all coefficients for the population logistic regression are zero except the constant one. i.e., it tests:

$H_o: \beta_1 = \beta_2 = \beta_3 = \cdots = \beta_k = 0$ Vs$H_1: \beta_j \neq 0$ for at least one j, $\mathrm{j} = 1,2, \ldots, \mathrm{k}$

3.8.3 The Wald Test

Alongside the likelihood ratio (LR) and Lagrange multiplier (LM) tests, the Wald test is one of the most critical likelihood testing procedure. Its commonly used to test statistical significance of each coefficient in logistic regression. Wald X^2(chi-square) statistics is calculated as:

$$Z_j^2=\left(\frac{\hat{\beta}_j}{se(\hat{\beta}_j)}\right)^2, j=1,2,\ldots,k \qquad \text{3.9}$$

Individual Wald statistic is likened with a chi-square distribution with 1 degree of freedom. It is simple to determine although it has questionable reliability particularly when the sample size is small thereby giving likelihood ratio test more reliability (Woods *et al*., 2013).

CHAPTER FOUR

RESULTS

4.1 Introduction

This section covers the finding of the study which includes the demographic characteristics of the study subjects, the prevalence rates of wasting both in Laisamis and North Horr Sub-counties and by the gender of child, finding the correlation between wasting status of children and the household food security status, fitting the logit model on factors that significantly affect wasting for the children 6-59 months and a mixed-effects model on the factors that are significantly associated with wasting with study site a random factor.

4.2 Demographic Characteristics of Study Subjects.

Sample children under 5 years of age were used in the study. The study details of children were matched with those of caregivers of reproductive age groups between 15-49 years of age. The total study sample used was 451. The mean age of caregivers was 24.68 years with a standard deviation of 7.29 years with a mean household size of 5.83 members and a standard deviation of 2.16 members. This summary was drawn up based on the parametric distribution assumptions, since the age of the caregivers, fulfilled the normality assumption.

As far as marital status is concerned, a very low percentage of women were single 5 (1.1%), while 400 (88.7%) were married, and 35 (7.8%) were widowed. With regards to the education level of the caregiver, 370 (82.0 %) did not attend school, while (6.9 % vs. 2.7 %) attended primary and pre-primary school respectively, with 21 (4.7 %) having tertiary education. The women, who were lactating, however, had the highest proportion of 306 (67.9%), those who were pregnant and lactating had 103 (22.8%), and those who were pregnant had the lowest proportion.

Conversely, concerning the occupation status of caregivers, the majority were in the informal sector, with 347 (76.9 %) herders, 44 (9.8 %) casual workers and 26 (5.8 %) traders respectively, while the least occupation was farming with only two farm workers (0.4 %). Furthermore, the North Horr study site appears to have slightly more subjects than the Laisamis site (51.0% vs 49%) respectively.

Table 2: Study Participants Caregivers' Socio-demographic Characteristics, n=451

Study variables	Statistic
Mean household size, SD	5.83 (SD=2.16)
Mean age caregivers, SD	24.68 (SD=7.29)
Education level	
Pre-primary	12 (2.7%)
Primary	31 (6.9%)
Secondary	17 (3.8%)
Tertiary	21 (4.7%)
None	370 (82.0%)
Marital status	
Single/never married	5 (1.1%)
Married	400 (88.7%)
Widowed	35 (7.8%)
Separated	8 (1.8%)
Divorced	3 (0.7&)
Physiological status of women	
Pregnant	32 (9.9%)
Lactating	201 (62.4%)
Not pregnant and not lactating	2 (0.6%)
Pregnant and lactating	87 (27.0%)
Occupation of the caregiver	
Farm labor	2 (0.4%)
Employed (salaried)	20 (4.4%)
Waged labor (casual)	44 (9.8%)
Trader	26 (5.8%)
Study Site	
North Horr	230(51%)
Laisamis	221(49%)

The demographic characteristics of children above six months and below 59 months of age are shown in Table 3. As the distribution of the child age was not normally distributed, the presentation of the parameters was made using a non-parametric distribution. The median age of the child was 31.19 months, and the age range was 53.83 months. It was clear that the average child size per household was approximately 1.0 In terms of gender distribution; male subjects appear to have a higher percentage than female subjects. On the other hand, the measurement of the child MUAC distribution ranged from 9.60 cm to 23 cm, with a median of 14.2 cm. Also, 136 (30.2 %) of children were reported to have been ill in the last two weeks. A higher percentage of caregivers were known not to have taken any water treatment measures before drinking as compared to 109 (24.2%) who made attempts to treat water.

A quarter, 112 (24.8%) of the caregivers have been walking for more than 2 km to the main source of water, while 202 (44.8%) have been walking for less than 1/2 km. Besides, only 74 (16.4 %) of infant birth weights were taken at birth meaning 337 (74.7 %) of infant birth weights were not taken, and some of their birth weight measurements were unknown at 40 (8.9 %) as summarized in Table 3.

Table 3: Table showing child demographic /caregivers factors, n=451

Child study variables	**Statistic**
Child median age(months), range	31.19 (range=53.83, min=6,max=59.83)
Median child-size per household	1
Mean child weight (Kg)	10.87 (SD=2.45)
Gender of child	
Male	260 (57.6%)
Female	191 (42.4%)
Child MUAC distribution	
Minimum	9.60
Lower quartile	13.50
Median	14.2
Upper quartile	15.00
Mean (SD)	14.21 (SD=1.20)
If birth weight was taken at birth	
Yes	174 (16.4%)
No	337 (74.7%)
Don’t know	40 (8.9%)
Whether your child been ill in the past two weeks?	
Yes	136 (30.2%)
No	315 (69.8%)
Do you do anything to your water before drinking?	
Yes	109 (24.2%)
No	342 (75.8%)
Trekking distance to the water source	
<1/2 km	202 (44.8%)
>1/2 km to less than 2 km	137 (30.4%)
>2 km	112 (24.8%)

4.3 Determining the Acute Malnutrition Prevalence Rates

The overall acute malnutrition status of children over the age of 6 months but under the age of 59 months using WHO standards in Laisamis and North Horr study sites of Marsabit County, Kenya was investigated, and results are as shown in Table 3. A proportion of 29.3 percent of children was undernourished (wasted) and a relatively higher percentage of the study cohort of children was nourished (70.7 percent)

Table 4: Overall Malnutrition Status of Children using WHZ Scores, n=451

Malnutrition status	N, percent (%)
Wasting (malnourished)	132 (29.3%)
Normal (Healthy)	319 (70.7%)
Total	**451 (100.0%)**

The results presented in Table 5 show the status of acute malnutrition on the site of the study. The Laisamis study site in Marsabit is shown to have a higher number of acutely malnourished children compared to North-Horr (33.0 % vs. 25.6 %) respectively.

Table 5: Malnutrition Status by Study Site, n=451

	Study site		p-value
Malnutrition status	**North-Horr, n (%)**	**Laisamis, n (%)**	
Wasting (malnourished)	59 (25.6)	73 (33.0%)	
Normal (Healthy)	171 (74.4)	148 (67.0%)	0.0851
Total	**230**	**221**	**451**

Table 6 shows the status of acute malnutrition by the sex of the child. The status of sex-wide wasting was statistically insignificant (p-value=0.3526). However, relative to their male counterparts, a significantly higher proportion of females were severely and moderately malnourished (33.5 % vs. 26.2 %), respectively.

Table 6: Malnutrition Status by Gender of the Child, n=451

	Gender of child		
Malnutrition status	**Male, n (%)**	**Female, n (%)**	**p-value**
Wasting/malnourished	68 (26.2%)	64 (33.5%)	
Healthy	192 (73.8%)	127 (66.5%)	0.089
Total	**260**	**191**	**451**

4.4 Determining the Correlation between Household Food Security and Childhood Malnutrition Status

The Women Dietary Diversity score (WDDS) and Household Hunger Score (HHS) were used as proxy indicators to access the food security status of households. Households with Hunger Score less than one (HHS<1) were considered to be more food secure than those with HHS>1. Similarly, women with dietary diversity score greater than 5 (WDDS>5) were also considered to be more food secure than those with a score of 5 or less (WDDS<=5).

Table 7 below shows the impact of food security in the household versus acute malnutrition status in children. There is no significant difference between household food security and child malnutrition status (p-value=0.842). However, there was a slight difference in malnutrition status with households considered to be food secure having 28.8% of children being undernourished as compared to 29.6% of children from food-insecure households.

Table 7: Correlation between Household Food Security and Malnutrition Status, n=451

Malnutrition status	Household food security status(using the household hunger Scale-HHS)		p-value
	Secure, n (%)	Not secure, n (%)	
Wasting/malnourished	57 (28.8%)	75 (29.6%)	
Healthy	141 (71.2%)	178 (70.4%)	0.842
Total	**198**	**253**	**451**

***Food Secure Households (HHS of between 0 and 1) & food insecure households HHS> 1.**

Table 8 below shows the impact of households' women's dietary diversity index versus childhood malnutrition status. There is no significant difference between household dietary diversity index and child malnutrition status (p-value=0.241). However, it was in line with the fact that households with low dietary diversity scores had a higher proportion of children undernourished compared to households with high dietary diversity scores (30.1% vs. 21.4%) correspondingly.

Table 8: Correlation between Women's Dietary Diversity Score versus Malnutrition Status, n=451

Malnutrition status	Women dietary diversity status		p-value
	High dietary diversity (score>=6) n (%)	Low dietary diversity(score<6) n (%)	
Wasting/malnourished	9 (21.4%)	123 (30.1%)	
Healthy	33 (78.6%)	286 (69.9%)	0.241
Total	**42**	**409**	**451**

***Women dietary diversity Score (score>=6), high dietary diversity.**

4.5 The Fitted Logit Model on Factors that significantly affect Acute Malnutrition Status of Under-Five Children in Marsabit County, Kenya

At the Univariate level, only child disease status in the past two weeks shows a strong effect with acute malnutrition status in children under 5 years of age with children having been ill in the past two weeks being more acutely malnourished than nourished children [UOR=1.91, 95% CI=1.243-2. 929]. However, the gender of the child and the study site [UOR=0.70, 95% CI=0.465-1.052] were of marginal significance, with boys less likely to be acute malnourished compared to the girls [UOR=0.70, 95% CI=0.467-1.057], On the other hand, the study subjects from North-Horr were less likely to be malnourished compared to the study group from Laisamis region [UOR=0.70, 95% CI=0.465-1.052]. Additionally, the other variables of the sample remained statistically insignificant.

Table 9: Unadjusted Logistic Regression Model versus Wasting status for Children above six months but below five years of age using WHZ scores, n=451

Factors	Estimate	Std error	Wald Chi-Square	P-value	UOR	95% CI
Caregivers age (years)	-0.0146	0.0142	1.0567	0.3040	0.98	0.958-1.013
Household size		0.0490	0.6683	0.4137	0.96	0.873-1.058
Child gender						
Male vs. female (Ref)	-0.3527	0.2084	2.8652	**0.0905****	0.70	0.467-1.057
Education level						
Ever attended school vs. never attended school (Ref)	-0.3609	0.2855	1.5983	0.2062	0.70	0.398-1.220

Child weight taken at birth						
Yes vs. No (Ref)	-0.4766	0.3036	2.4639	0.1165	0.62	0.342-1.126
Distance to the water point						
>1/2 km vs. <1/2 km (Ref)	0.1357	0.2089	0.4219	0.5160	1.15	0.761-1.725
Women physiological status						
Lactating vs. pregnant (Ref)	0.3027	0.3843	0.6202	0.4310	1.35	0.637-2.875
Pregnant and Lactating vs pregnant (Ref)	0.1946	0.4246	0.2101	0.6467	1.22	0.529-2.792
Full term pregnancy						
Yes vs. No (Ref)	-0.2352	0.2147	1.2008	0.2732	0.79	0.519-1.204
Child ill in the past two weeks						
Yes vs. no (Ref)	0.6459	0.2187	8.7269	**0.0031***	1.91	1.243-2.929
Occupation status						
Herders vs. other categories (Ref)	0.2772	0.2547	1.1849	0.2764	1.32	0.801-2.174
Income						
Has income vs. No income (Ref)	0.1001	0.2290	0.1912	0.6620	0.91	0.578-1.417
Study site						
North-Horr vs. Laisamis (Ref)	-0.3574	0.2080	2.9527	**0.0857****	0.70	**0.465-1.052**

UOR=Unadjusted Odds Ratio, Ref=Reference Category, *(Significant at 5%), ** (Significant at 10%)

The results of the adjusted regression model are shown in table 9 below. Factors such as the age of caregivers, the size of the household, the gender of the child and the level of education of caregivers, if the child was weighed at birth, the source of income, the occupation and the distance to the water source remained insignificant at a multivariate level. However, factors such as full-term maternal pregnancy, child ill for the last two weeks, and the study site have been significant factors affecting the status of childhood malnutrition.

As expected, mothers with full-term pregnancy up to the birth were 53 percent less likely to have malnourished infants compared to their counterparts whose pregnancy was not term [AOR=0.47, 95% CI=0.276-0.804]. Similarly, children of caregivers at the North-Horr study site were shown to be less affected by malnutrition compared to children at the Laisamis study site [AOR=0.57, 95 percent CI=0.354-0.931]. On the other hand, children's disease among children has been associated twofold times with malnutrition status [AOR=2.00, 95% CI=1.282-3.190]. Similarly, observations have also been made on the occupation status of caregivers. Caregivers who are herders are therefore 1.29 times more likely to have their children undernourished than their counterparts in other occupations [AOR=1.29, 95% CI=0.546-3.057].

Table 10: Adjusted Logistic Regression Model with Factors Related to the Overall Wasting Status for Children above six months but below five years of age using WHZ scores, n=451

Factors	Estimate	Std error	Wald Chi-Square	P-value	AOR	95% CI
Intercept	-0.0774	0.7116	0.0118	0.9134	0.93	
Caregivers age (years)	-0.0180	0.0149	1.4569	0.2274	0.98	0.954-1.011
Household size	-0.0445	0.0537	0.6862	0.4074	0.96	0.861-1.063
Child gender						
Male vs. female (Ref)	-0.3253	0.2166	2.2563	0.1331	0.72	0.472-1.104
Education level						
Ever attended school vs. never attended school (Ref)	-0.2562	0.3440	0.5549	0.4563	0.77	0.394-1.519
If child weight taken at birth						
Yes vs. No (Ref)	-0.3403	0.3416	0.9922	0.3192	0.71	0.364-1.390
Distance to the water point						
>1/2 km vs. <1/2 km (Ref)	0.1305	0.2327	0.3143	0.5751	1.14	0.722-1.798
Women physiological status						
Lactating vs. Pregnant (Ref)	0.7505	0.4204	3.1862	0.0743**	2.12	0.929-4.828
Pregnant and Lactating vs Pregnant (Ref)	0.2255	0.4546	0.2460	0.6199	1.25	0.514-3.054
Full term pregnancy						
Yes vs. No (Ref)	-0.7537	0.2730	7.6191	0.0058**	0.47	0.276-0.804
Child ill in the past two weeks						
Yes vs. no (Ref)	0.7042	0.2326	9.1680	0.0025*	2.00	1.282-3.190
Occupation status						
Herders vs. other categories (Ref)	0.2560	0.4394	0.3394	0.5602	1.29	0.546-3.057
Income						
Has income vs. No income (Ref)	-0.2003	0.3786	0.2799	0.5968	0.82	0.390-1.719

			Study site			
North-Horr vs. Laisamis (Ref)	-0.5552	0.2470	5.0500	0.0246*	0.57	0.354-0.931

***AOR=Adjusted Odds Ratio, Ref=Reference Category, *(Significant at 5%), ** (Significant at 10%)**

The other important results are that mothers/caregivers who have traveled more than half a kilometer are 1.14 times more likely to have their children malnourished than those who have traveled less than half a kilometer [AOR=1.14, 95% CI=0.722-1.798.] Another finding was that caregivers who had ever attended school were less likely to suffer from malnutrition than those in the community who had never attended school [AOR=0.77, 95% CI=0.394-1.519].

4.6 A Fitted Mixed-Effects Model on the Factors Associated with Malnutrition with the site as a Random Factor in Marsabit County, Kenya.

The results below show the output of a mixed-effects model while controlling the study site as a random variable. It is evident that, by adjusting for other factors of interest in the regression model, factors such as full-term pregnancy between women and children who have been ill for the past two weeks were identified as strong significant factors associated with malnutrition status of children. The residual variance due to the impact of the study site was 0.2010. However, when the Akaike information criterion (AIC) was compared, the standard logistic regression model showed a better fit model than the mixed-effects model (544.564 vs. 596.9) respectively. This is true since the smaller the value of the AIC, the better the model fit.

4.6.1 The Mixed Procedure

Model Information

Data Set	WORK.OVERAL_DATA_5
Dependent Variable	whz status
Covariance Structure	Variance Components
Subject Effect	Sub county
Estimation Method	REML
Residual Variance Method	Profile
Fixed Effects SE Method	Model-Based
Degrees of Freedom Method	Containment

Class Level Information

Class	Levels	Values		
Child sex	2	Female	Male	
Education level	2	0	1	
Weight taken at birth	2	0	1	
A full-term pregnancy	2	1	2	
Income	2	0	1	
Distance to water point	2	1	2	
Occupation status	2	1	2	
Child ill in the past two weeks	2	1	2	
Physiological status of women	3	1	2	3
Sub county	2	Laisamis	North Horr	

Dimensions

Covariance Parameters	2
Columns in X	22
Columns in Z Per Subject	1
Subjects	2
Max Obs Per Subject	229
Observations Used	450
Observations Not Used	1
Total Observations	451

Iteration History

Iteration	Evaluations	-2 Res Log Like	Criterion
0	1	592.88146664	
1	1	592.88146664	0.00000000

The Mixed Procedure

Convergence criteria met but final hessian is not positive definite.

4.6.2 Covariance Parameter Estimates

CovParm	Subject	Estimate
Intercept	Sub county	0.04162
Residual		**0.2010**

Fit Statistics

-2 Res Log Likelihood	592.9
AIC (smaller is better)	596.9
AICC (smaller is better)	596.9
BIC (smaller is better)	594.3

4.6.3 Type 3 Tests of Fixed Effects

Table 11: Adjusted Mixed-effects Model for less than 5 years of Childhood Malnutrition Status with Study Site as a Random Factor

Effect	DF	DF	F Value	Pr> F
Child sex (male vs. female)	1	438	2.43	0.1197
Education level	1	438	0.41	0.5198
Weight taken at birth (yes vs. no)	1	438	1.01	0.3145
Full term pregnancy	1	438	7.41	**0.0067**
Source of income	1	438	0.42	0.5167
Distance to water point	1	438	0.22	0.6360
Occupation status	1	438	0.59	0.4425
Child ill past two weeks	1	438	9.85	**0.0018**
Physiological status of women	2	438	2.10	0.1241
Sub county	1	0	0.11	.

CHAPTER FIVE

DISCUSSION

5.1 Estimated Rates of Acute Malnutrition (wasting) Rates

In this study, we investigated; the prevalence rates of acute malnutrition (wasting) by obtaining the heights and weights of children 6-59 months and comparing them against a healthy reference population using WHO standards (2006) in Laisamis and North Horr Sub-Counties.

It was a cross-sectional study with a sample size of 451 children aged 6-59 months. Standardized Monitoring and Assessment in Relief and Transitions (SMART) survey data conducted in July 2019 was utilized for the analysis. The study found out that the mean age of caregivers and children was 24.68 years and 31.19 months, respectively. Each household had a mean of 5.83 members. 88.7 percent of the women were married, 7.7 percent were widowed and 1.1 percent single. 82 percent of the caregivers did not attend school while only 4.7 percent had a post-secondary qualification. On the physiological status of women, the majority (69.9 %) were lactating. The main occupation of the respondent was livestock keeping with 76.9 percent of households being herders. North-Horr study site had slightly more respondents than Laisamis with 51perecnt and 49 percent, respectively. A Chi-square test was used to examine the association between the nutritional status between two study sites and between boys and girls in Laisamis and North Horr Sub-Counties of Marsabit County.

In KDHS (2014), the prevalence of wasting (Weight-for Height) was 21.4 percent in Marsabit County.

Our study revealed that 29.3 percent. This is means that 70.7 percent of the children were considered to be nourished. According to KDHS (2014), the national total on the prevalence of wasting was 4.9 percent. Our study revealed that North Horr and Laisamis sub-counties had 25.6 percent and 33 percent of the children 6-59 months were wasted, respectively.

Similarly, our study found out that girls aged 6-59 months were more wasted compared to boys counterparts with prevalence rates of 33.5 percent vs 26.2 percent respectively which was however not significant (P-Value=0.089). This contradicts the study conducted in India (Jith & Bedamatta, 2021).) and from DHS of Sub Saharan African countries (Asuma *et al.*, 2020) which indicated that boys are more likely to be malnourished than girls. Similar patterns of malnutrition among boys and girls have been noticed in some parts of Ethiopia (Berhane *et al.*, 2020). These studies postulate that boys are more likely to have repeated infections and are more exposed to risk factors such as an unhygienic environment. In our study, this could be attributed to the gender inequality in the society where boys are preferred to girls and therefore, where the boys are given more attention by their caregivers and the society in general.

5.2 Determining association between food security and malnutrition status of children below 5 years of age Marsabit County.

On our second objective, we used binary logistic regression to determine the association between food security and malnutrition status of children below 5 years of age. We used the household hunger scale (Nkegbe *et al.*, 2017) and women's dietary diversity score (FAO, 2016) as a proxy to the food security of households. Our study found that there was no significant difference between household hunger and malnutrition status of children 6-59 months (P-Value=0.842). Similarly, there was no significant difference between women's dietary diversity score and child malnutrition status (p-value=0.241). However, households considered to be more food secure had a slightly lower proportion of undernourished children than those of less food secure households with 28.8% vs

29.6% and 21.4% vs 30.1% for HHS and WDDS, respectively. Studies have shown that household food security play important roles in preventing under nutrition (Drennen *et al* (2019). Evidence in our study to support or contradict these studies is feeble. This can be attributed to the cultural set up of these communities where households share their resources among each other where the lesser privileged households are supported by those households who fare a little better. Interventions that target to address malnutrition issues need to target community factors rather than household factors.

5.3 Investigating factors that influence malnutrition status of children less than 5 years of age in Marsabit County

The adjusted Logit regression model was fitted to investigate factors that significantly affect malnutrition status of children below 5 years of age. At a multivariate level, children who have been ill in the past two weeks preceding the survey were twice more likely to be acutely malnourished compared to children who have never been sick (AOR=2.00, 95% CI=1.282-3.19). Other studies have reported environmental factors that have a significant impact on the preference of body weight deficiencies to include the impact of previous illness (Larson *et al.*, 2018).

Place of residence has also been shown to have significant effects of under 5 years children under nutrition (Larson *et al*., 2018). Our study also found out that children in North Horr sub-county were less likely to be affected by under nutrition compared to their counterparts in the Laisamis sub-county (AOR=0.57, 95 percent CI=0.354-0.91). The implication here is that the various sub-counties have a significant difference in acute malnutrition levels and more interventions are required to curb the problem of acute malnutrition in Laisamis Sub-County. It is critical to note that North Horr sub-county also has a way higher level of malnutrition when compared with the national average of 4.9% (KDHS, 2014).

Mothers with full-term pregnancy were 53 percent less likely to have undernourished children compared to those mothers whose pregnancy was not full term (AOR=0.47, 95% CI=0.276-0.804). This observed association is consistent with the findings of other studies (WHO, 2009), (Islam *et al*., 2013), (Mishra et al., 2014), (Masiye *et al*., 2010), (Jesmin et al., 2011), (Dhar *et al*., 2002) and (Correia *et al*., 2014).

Another finding was that children from mothers who were lactating were twice as likely to be acutely malnourished compared to those who children whose mothers were pregnant but not lactating (AOR=2.12, 95% CI=0.929-4.828). This is an interesting finding since it is an acknowledged fact that breastfeeding plays important role in prevention of various form of childhood malnutrition including acute malnutrition (Scherbaum & Srour., 2016) as it is associated with a lower risk of infectious diseases particularly in lower-income countries (Solomons, 2007) where feeding the child with breast milk is expected to disrupt diseases and malnutrition in children. This needs to be investigated further in future studies.

Other important results were that mothers who often trekked more than half a kilometer to fetch water were 1.14 times more likely to have their children malnourished than those who trekked less than half a kilometer (AOR=1.14, 95% CI=0.722-1.798). This is aligned to study by Action Against Hunger where it found out that mothers having more time with their children were less likely to have malnourished children (Bizoueme *et al*., 2012). Distant water sources also compromised household hygiene (Paul.., 2018) and this would contribute to child under nutrition.

As compared to other studies (Frost *et al*., 2005; Glewwe, 1999; Desai & Alva, 1998), our study also found that caregivers who had ever attended school were less likely to have acutely malnourished children than those in the community who had never attended school (AOR = 0.77, 95% CI = 0.394 – 1.519). Paul *et al.*, (2018), also found out that a mother's education was related to child illness which can also lead to children under the age of 5 being acutely malnourished.

5.4 Effect of factors that influence malnutrition status of children less than 5 years of age assuming study site to be a random factor Marsabit County.

On fitting the mixed-effects model while controlling for study site as a random variable, children born before full term and children being ill in the past two weeks were factors considered significant factors that contribute to a child being acutely malnourished which is consistent with other findings.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The broad scope of this study was to find specific drivers of acute malnutrition in Marsabit County, Kenya. The survey results described in Chapter four and five show that the specific objectives outlined in chapter one have been achieved. The major conclusions were that; the study found the prevalence rates of acute malnutrition in Laisamis and North Horr sub-counties as 29.3% which is 24.4% higher than the national total. Similarly, contrary to many studies where boys are more acutely malnourished than girls, the study found out that girls were more malnourished in these sites, also, the association between household food security and acute malnutrition status of under five years children was not significant although these factors remain key important indicators for maternal health and that factors like child health, maternal pregnancies, and trekking distance to water sources negatively affected malnutrition status among caregivers in the current study.

6.2 Recommendations

- The experiences gained from the conduct of the study and through literature review has recommended that; Marsabit County to Lobby and resource mobilize for food aid or cash transfers to households with SAM and MAM cases to curb the high rate of acute malnutrition and expected mortality as a result. Secondly, gender inequality appears to exist in the communities studied since high proportions of girls are acutely malnourished contrary to many similar studies. Therefore, broad-based interventions will be needed to improve girls' health and nutritional status. The third recommendation is that there should be fundraising to rehabilitate and construct more sources of water to reduce trekking distance hence enabling mothers to have more time with their children. Finally, there should be existence of health and nutrition interventions to promote health pregnancies, hence enhancing full-term pregnancies.

6.3 Limitation of the Study

The study was only conducted in two study sites in Marsabit County. The findings may not be generalized to other counties

6.4 Suggestion for Future Studies

The findings and related literature review of the study recommends that more research needed on the long-term effects of malnutrition in other ASAL counties so that ministry of health can use it a policy framework document among its citizens. Moreover, a prospective study is needed to investigate why a critical factor such household food security was not a significant factor that influence the wasting status of children between the ages of 6-59 months.

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APPENDICES

APPENDIX I : ANALYSIS SYNTAXES

libname malnut "F:\BENJAMIN ROP MSC. THESIS 5TH AUGUST 2019";

**Benjamin MSC thesis analysis-25th/06/2020;

**Data set used for malnutrition analysis;

**Analysis approach

*Present descriptive summaries of demographic variables for both mother and child;

*Test for bivariate associations with selected outcome variables of interest;

*Perform binary logistic regression model with selected covariates of interest with malnutrition status as an outcome of interest;

```
data malnut_1; set     MALNUT.A;

run;

*generate a unique identifier in an analysis data set;

  data malnut_2; set malnut_1;

  id = _N_;

   run;

 *check frequency distribution of study sites;

  proc freq data=malnut_2;

  tables Sub_county;

  run;

**pick the two sub-county study sites (north-horr and saku) as the study sample;

data malnut_3; set malnut_2;where (Sub_county= "north_horr"|Sub_county=
"laisamis");

run;

*percent distribution of sub-county study site before randomization;

proc freq data=malnut_3;

title 'percent distribution per Sub_county study site';

tables Sub_county;

run;


**selecting required study samples per site using probability proportional to size
sampling technique;

*NOTH-HORR=16.5%, proportion of under 5 children;
```

*LAISAMIS=15.7% , proportion of under 5 children(change study site of interest);

*North-horr data set;

proc surveyselect data=malnut_3 (where=(Sub_county='north_horr')) out=data1 sampsize=**230** method=srs stats seed=**2334**;

run;

*LAISAMIS data set;

proc surveyselect data=malnut_3 (where=(Sub_county='laisamis')) out=data2 sampsize=**221** method=srs stats seed=**2334**;

run;

**generate combined analysis data set;

data overal_data;

set data1

data2;

run;

**descriptive statistics for the malnutrition data;

*Average hhold size per sudy site;

proc means data=overal_data;

var Household_size;

run;

*average hhold size by study site;

proc means DATA=overal_data;

by Sub_county;

var Household_size;

run;

*percentage distribution on the level of education;

proc freq data=overal_data;

title 'education level of hhold head';

tables Highest_Education_level_of_the_H;

run;

```
*percent distribution on marital status;
proc freq data=overal_data;
title 'marital status of caregiver';
tables Marital_status;
run;

*percent distribution on the main source of income;
proc freq data=overal_data;
title 'main source of income';
tables Main_source_of_income;
run;
*percent distribution on the occupation of caregiver;
proc freq data=overal_data;
title 'occupation of caregiver';
tables Occupation;
run;
*percentage distribution per study site;
proc freq data=overal_data;
title 'study site';
tables Sub_county;
run;

*percentage of women physiological status
proc freq data=overal_data;
title 'women physiological status';
tables physiological_status;
run;

*child demographic characteristics;
proc means n mean median stddev range min max data =overal_data;
var _age_months_;
run;
```

```
proc means n mean median stddev range min max data =overal_data;
title'mean child size per hhold';
var Out_of_these_how_many_are_childr;
run;
proc means n mean median stddev range min max data =overal_data;
title'mean childbirth weight';
var Weight_KG_;
run;
*oedema;
proc freq data=overal_data;
title'presence of oedema';
tables Oedema;
run;

*child weighed at birth;
proc freq data=overal_data;
title'child weighed at birth';
tables weighed_at_birth__;
run;

*child weighed at birth;
proc freq data=overal_data;
title'if the child has been ill for the past two weeks';
tables ill_two_weeks;
run;
proc freq data=overal_data;
title 'if mother used mosquito net';
tables Mosquito_net;
run;

proc freq data=overal_data;
title 'if anything was done to water before drinking';
```

```
tables Anything_done_water;
run;

proc freq data=overal_data;
title'What is the trekking distance to the current main water source? ';
tables Trekking_distance/missing;
run;

proc means n mean p25 p75  median stddev range min max data =overal_data;
title'child MUAC distribution-descriptive summaries';
var MUAC__in_CM;
run;

proc freq data=overal_data;
title 'sex of the child';
tables child_sex;
run;

*main source of income;
proc freq data=overal_data;
tables Main_source_of_income;
run;

*if child was weighed at birth;
proc freq data=overal_data;
title'if child was weighed at birth';
tables weighed_at_birth__;
run;

**Revised place of birth variable;
*generate new occup variable;
```

data overal_data_1; set overal_data;

*edu level of hhold head/caregiver;

if (Highest_Education_level_of_the_H=**1**|Highest_Education_level_of_the_H=**2**|Highest_Education_level_of_the_H=**3**|

Highest_Education_level_of_the_H=**4**) then edu_ct=**1**;*ever attended school;

else if Highest_Education_level_of_the_H=**5** then edu_ct=**0**;*none-never attended school;

*marital status;

if Marital_status=**2** then marstatus_ct=**1**;*married;

else if (Marital_status=**1**|Marital_status=**3**|Marital_status=**4**|Marital_status=**5**) then marstatus_ct=**0**;*not married;

*main source of income;

if Main_source_of_income="other" then Main_source_of_income=**10**;

if Main_source_of_income=**1** then income_ct=**1**;else income_ct=**0**;*(no income vs. having source of income) for hhold head;

*treking distance to water source;

if Trekking_distance=**1** then dist_ct=**1**;*<1/2 km;

else if (Trekking_distance=**2**|Trekking_distance=**3**|Trekking_distance=**.**) then dist_ct=**2**;*>1/2 km;

*occupation;

if Occupation=**1** then occup_ct=**1**;*herders;

else if (Occupation=**2**|Occupation=**3**|Occupation=**4**|Occupation=**5**|Occupation=**6**|Occupation=**8**|Occupation='other')

then occup_ct=**2**;*other categories;

*if child was weighed at birth;

if weighed_at_birth__=**1** then wt_ct=**1**;else wt_ct=**0**;

*physiological status of children;

if physiological_status=**3** then physiological_status=**.**;

if physiological_status=**1** then physio_ct=**1**;*pregnant;

else if physiological_status=**2** then physio_ct=**2**;*lactating;

else if physiological_status=**4** then physio_ct=**3**;*preg & lactating;

```
run;
proc freq data=overal_data_1;
tables dist_ct edu_ct occup_ct wt_ct physio_ct;
run;
*generate malnutrition status for children using WHO recommended MUAC cut offs;
data overal_data_2; set overal_data_1;
if MUAC__in_CM<11.5 then child_muac_cat=1;*severely malnourished;
else if 11.5<=MUAC__in_CM<=12.4 then child_muac_cat=2;*moderately malnourished;
else if MUAC__in_CM>12.4 then child_muac_cat=3;*normal-healthy;

*whz category/wasting malnutrition status*;
if whz<=-2 then whz_status=1;*stunting/malnutrition*;
else if whz>-2 then whz_status=0;*normal*;
run;
*overal prevalence of malnutrition;
*malnutrition using muac;
proc freq data=overal_data_2;
title 'percent distribution of child MUAC';
tables child_muac_cat edu_ct/missing;
run;

proc freq data=overal_data_2;
title 'percent distribution of child MUAC';
tables whz_status/missing;
run;

*malnutrition across the study sites;
proc freq data=overal_data_2;
title 'child malnutrition status by study site';
tables whz_status*Sub_county/chisq;
run;
```

```
**malnutrition status vs gender of child;
proc freq data=overal_data_2;
title 'child malnutrition status by study site';
tables whz_status*child_sex/chisq;
run;

**to employ logistic regression method;
**start with unadjusted logistic regression model;
**run adjusted logistic regression model;

data overal_data_3; set overal_data_2;
if (child_muac_cat=1|child_muac_cat=2) then malnut_ct=1;else malnut_ct=0;

*food dietary score;
if Women_dietery_diversity_Score>=6 then diet_score_ct=1;else diet_score_ct=0;

*household hunger score;
if (0=<HH_Hunger__Score<=1) then secure_ct=1;*food secure hhold;
else if HH_Hunger__Score>1 then secure_ct=0;*household food insecure;

*house hold hunger score2;
if (HH_Hunger__Score=0|HH_Hunger__Score=1) then secure_ct2=1;*food secure
hhold;
else if HH_Hunger__Score>1 then secure_ct2=0;*household food insecure;
run;
proc freq data=overal_data_3;
title 'combined outcome on malnutrition status';
tables malnut_ct diet_score_ct secure_ct secure_ct2;
run;
```

```
**descriptive analysis check;
proc freq data=overal_data_5;
title 'study site';
tables Sub_county caregiver_sex whz_status edu_ct;
run;

proc means n mean median p25 p50 p75 min max std range data=overal_data_5;
var caregiver_age_1;
run;

**perform unadjusted logistic regression modelbivariate analysis);
**starting with caregivers selected factors;
proc logistic data=overal_data_5 desc;
title 'unadjusted logistic model for caregivers age';
model  whz_status=caregiver_age_1/expb;
run;
proc logistic data=overal_data_5 desc;
class caregiver_sex/param=ref ref=first;
title 'unadjusted logistic model for caregivers gender';
model  whz_status= caregiver_sex/expb;
run;

proc logistic data=overal_data_5 desc;
title 'unadjusted logistic model for caregivers hhold size';
model  whz_status= Household_size/expb;
run;

proc logistic data=overal_data_5 desc;
class marstatus_ct/param=ref ref=first;
title 'unadjusted logistic model for place of birth';
model  whz_status= marstatus_ct/expb;
run;
```

```
proc logistic data=overal_data_5 desc;
class edu_ct/param=ref ref=first;
title 'unadjusted logistic model for edu level caregivers';
model whz_status= edu_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class income_ct/param=ref ref=last;
title 'unadjusted logistic model for income';
model  whz_status= income_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class occup_ct/param=ref ref=first;
title 'unadjusted logistic model for income';
model  whz_status= occup_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class child_sex/param=ref ref=first;
title 'unadjusted logistic model for child sex';
model  whz_status= child_sex/expb;
run;

proc logistic data=overal_data_5 desc;
class Sub_county/param=ref ref=first;
title 'unadjusted logistic model for study site';
model  whz_status= Sub_county/expb;
run;

proc logistic data=overal_data_5 desc;
class dist_ct/param=ref ref=first;
title 'unadjusted logistic model for trekking distance to water point';
```

```
model  whz_status= dist_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class wt_ct/param=ref ref=first;
title 'unadjusted logistic model for trekking distance to water point';
model  whz_status= wt_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class full_term_pregnancy/param=ref ref=first;
title 'unadjusted logistic model for water treatment';
model  whz_status= full_term_pregnancy/expb;
run;

proc logistic data=overal_data_5 desc;
class physio_ct/param=ref ref=first;
title 'unadjusted logistic model for physiological status of lactating mums';
model  whz_status= physio_ct/expb;
run;

proc logistic data=overal_data_5 desc;
class ill_two_weeks/param=ref ref=first;
title 'unadjusted logistic model for food secure hholds';
model  whz_status= ill_two_weeks/expb;
run;

proc freq data=overal_data_5;
tables physio_ct*secure_ct/chisq;
run;
****Objective two-association between hhold food security and malnutrition status;
proc freq data=overal_data_5;
title 'child malnutrition status by hhold food security';
```

tables whz_status*secure_ct/chisq;

run;

proc freq data=overal_data_5;

title 'child malnutrition status by women diatary habits';

tables whz_status*diet_score_ct/chisq;

run;

****objective 3-The logit model;
**Fit adjusted logistic regression model for malnutrition status;
*potential covariates of interest;

proc logistic data=overal_data_5 desc;

class child_sex edu_ct wt_ct full_term_pregnancy(ref=last) income_ct dist_ct occup_ct(ref=last)ill_two_weeks(ref=last)

physio_ct Sub_county/param=ref ref=first;

title'unadjusted logistic model for transactional sex';

model whz_status=caregiver_age_1 Household_size child_sex edu_ct wt_ct full_term_pregnancy

income_ct dist_ct occup_ct ill_two_weeks physio_ct Sub_county/expb;

run;

****objective 4-The mixed effects model;

Title "predicting malnutrion with site as a random factor ";

proc MIXED data=overal_data_5 ;

class child_sex edu_ct wt_ct full_term_pregnancy income_ct dist_ct occup_ct ill_two_weeks physio_ct sub_county;

model whz_status = child_sex edu_ct wt_ct full_term_pregnancy income_ct dist_ct occup_ct ill_two_weeks

physio_ct sub_county;

random int / subject=sub_county;

run;

APPENDIX II: OUTPUT (Do files)

Model Convergence Status
Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	546.598	544.564
SC	550.708	602.093
-2 Log L	544.598	516.564

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	28.0347	13	0.0089
Score	27.3582	13	0.0111
Wald	25.8015	13	0.0181

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
caregiver_age_1	1	1.4569	0.2274
Household_size	1	0.6862	0.4074
child_sex	1	2.2563	0.1331
edu_ct	1	0.5549	0.4563
wt_ct	1	0.9922	0.3192
full_term_pregnancy	1	7.6191	0.0058
income_ct	1	0.2799	0.5968
dist_ct	1	0.3143	0.5751
occup_ct	1	0.3394	0.5602
ill_two_weeks	1	9.1680	0.0025
physio_ct	2	4.6905	0.0958
Sub_county	1	5.0500	0.0246

Analysis of Maximum Likelihood Estimates							
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Exp(Est)
Intercept		1	-0.0774	0.7116	0.0118	0.9134	0.926
caregiver_age_1		1	-0.0180	0.0149	1.4569	0.2274	0.982
Household_size		1	-0.0445	0.0537	0.6862	0.4074	0.956
child_sex	Male	1	-0.3253	0.2166	2.2563	0.1331	0.722
edu_ct	1	1	-0.2562	0.3440	0.5549	0.4563	0.774
wt_ct	1	1	-0.3403	0.3416	0.9922	0.3192	0.712
full_term_pregnancy	1	1	-0.7537	0.2730	7.6191	0.0058	0.471
income_ct	1	1	-0.2003	0.3786	0.2799	0.5968	0.818
dist_ct	2	1	0.1305	0.2327	0.3143	0.5751	1.139
occup_ct	1	1	0.2560	0.4394	0.3394	0.5602	1.292
ill_two_weeks	1	1	0.7042	0.2326	9.1680	0.0025	2.022
physio_ct	2	1	0.7505	0.4204	3.1862	0.0743	2.118
physio_ct	3	1	0.2255	0.4546	0.2460	0.6199	1.253
Sub_county	north_horr	1	-0.5552	0.2470	5.0500	0.0246	0.574

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
caregiver_age_1	0.982	0.954	1.011
Household_size	0.956	0.861	1.063
child_sex Male vs Female	0.722	0.472	1.104
edu_ct 1 vs 0	0.774	0.394	1.519
wt_ct 1 vs 0	0.712	0.364	1.390
full_term_pregnancy 1 vs 2	0.471	0.276	0.804
income_ct 1 vs 0	0.818	0.390	1.719
dist_ct 2 vs 1	1.139	0.722	1.798
occup_ct 1 vs 2	1.292	0.546	3.057
ill_two_weeks 1 vs 2	2.022	1.282	3.190
physio_ct 2 vs 1	2.118	0.929	4.828
physio_ct 3 vs 1	1.253	0.514	3.054
Sub_county north_horr vs laisamis	0.574	0.354	0.931

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.2	Somers' D	0.289
Percent Discordant	35.3	Gamma	0.290
Percent Tied	0.5	Tau-a	0.120
Pairs	41976	c	0.644

Model Information	
Data Set	WORK.OVERAL_DATA_5
Dependent Variable	whz_status
Covariance Structure	Variance Components
Subject Effect	Sub_county
Estimation Method	REML
Residual Variance Method	Profile
Fixed Effects SE Method	Model-Based
Degrees of Freedom Method	Containment

Class Level Information		
Class	Levels	Values
child_sex	2	Female Male
edu_ct	2	0 1
wt_ct	2	0 1
full_term_pregnancy	2	1 2
income_ct	2	0 1
dist_ct	2	1 2
occup_ct	2	1 2
ill_two_weeks	2	1 2
physio_ct	3	1 2 3
Sub_county	2	laisamis north_horr

Dimensions	
Covariance Parameters	2
Columns in X	22
Columns in Z Per Subject	1
Subjects	2
Max Obs Per Subject	229
Observations Used	450
Observations Not Used	1
Total Observations	451

Iteration History			
Iteration	Evaluations	-2 Res Log Like	Criterion
0	1	592.88146664	
1	1	592.88146664	0.00000000

Covariance Parameter Estimates		
Cov Parm	Subject	Estimate
Intercept	Sub_county	0.04162
Residual		0.2010

Fit Statistics	
-2 Res Log Likelihood	592.9
AIC (smaller is better)	596.9
AICC (smaller is better)	596.9
BIC (smaller is better)	594.3

Type 3 Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
child_sex	1	438	2.43	0.1197
edu_ct	1	438	0.41	0.5198
wt_ct	1	438	1.01	0.3145
full_term_pregnancy	1	438	7.41	0.0067
income_ct	1	438	0.42	0.5167
dist_ct	1	438	0.22	0.6360
occup_ct	1	438	0.59	0.4425
ill_two_weeks	1	438	9.85	0.0018
physio_ct	2	438	2.10	0.1241
Sub_county	1	0	0.11	.

APPENDIX III: SIMILARITY REPORT

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