EFFECT OF CLIMATE EXTREMES ON HEALTH OUTCOMES IN KENYA

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DECLARATION

This research project is my original work and has not been presented for a degree in any other university.

Signed ……….   Date………………

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This research project has been submitted for examination with my approval as the University supervisor.

Signed ………….   Date ………………….

Dr. Michael Ndwiga Jairo

DEDICATION

I dedicate this project to My Family; My Amazing Mum Loise, My ddBrother Peter Gatundu and My Late Dad Kamuyu. To my mum specifically, you gave me all the support and encouragement I needed while I was doing my masters. For the interest you showed and sacrifices you made am forever grateful.

Special Gratitude to my favorite person and Fiancé Fwamba Nakitare for believing in me so much, that was enough to push me to finish my masters.

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LIST OF ABBREVIATIONS

AEZs: Agro-Ecological Zones.

ANOVA: Analysis of Variance

GDP: Gross Domestic Product

IPCC: Intergovernmental Panel on Climate Change

KNBS: Kenya National Bureau of Statistics

LMICs: Low Middle and Income Countries

NCCAP: National Climate Change Action Plan

NCCRS: National Climate Change Response Strategy.

NMCP: National Malaria Response Strategy

ROK: Republic of Kenya

VIF: Variance Inflation factor.

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ABSTRACT

Malaria and pneumonia mortality rates are still high in proportion compared to the growing population. These diseases are of grave concern in developing countries and their burden is quite high even with the notable efforts from the government. There are expectations that malaria could infest new ecological zones that have low immunity towards the disease. This could lead to endemic morbidity and mortality of the disease. In Kenya, pneumonia deaths are on the rise. There are several studies in Sub-Saharan Africa that aimed at understanding the covariates of morbidity and mortality of malaria and pneumonia. Scanty of these literatures sought to understand the effects of climate change on morbidity and mortality of malaria and pneumonia but none tried to investigate the effects of climate extremes on morbidity and mortality of malaria and pneumonia. This study sought to bridge this gap by analyzing the effects climate extremes on mortality of malaria and pneumonia in Kenya. The study used three waves of household survey data from Tegemeo Institute for period of 2004, 2007 and 2010. Climate extremes data was sourced from Kenya meteorological department for a period of 1980 to 2010. To estimate climate extremes at household level, weather data was extrapolated and merged with the Tegemeo data using the GPS coordinate of the households. The study utilized random effects Poisson regression model to estimate the effects of extreme precipitation, minimum, and maximum temperature on mortality of malaria and pneumonia. The study found that climate extreme events do negatively affect outcomes of malaria and pneumonia mortality though not all. As for pneumonia extreme minimum temperature and extreme maximum temperatures, negatively affected mortality. Whereas malaria mortality was found to be affected by extreme minimum temperature and extreme precipitation. The findings further show that social interactions have significant effects on household health outcomes. This study recommends that the health care system in Kenya needs to invest in disease surveillance that focusses on the climate extremes events and their effect on disease burden of malaria and pneumonia mortality.

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

In many regions, worldwide climate extremes and weather events are a contemporary issue with attention drawn towards the impacts of these events on human health and wellbeing (IPCC, 2012). In Low and Middle-income countries in Africa the relationship between climate and health which varies geographically is still an area not well explored. Presently, if the severity and health burden resulting from impacts of climate extremes could be mitigated, then public health policy and practice would have strategic improvements (IPCC, 2012). In the developed world, there are several studies on climate extremes and how they affect different diseases. Thus, this helps in preparing for disaster management and research efforts that ensure public health infrastructural improvements. In Africa such research efforts are repressed by the absence of reliable data on climate and health (Hondula, Joackim & Sankoh, 2012).

The day-to-day economic development of Africa, is affected by climate extrmes particularly in traditional rain-fed agriculture, pastoralism, and water resources at all scales. Extreme events can render sustainable development impossible some locations inhabitable for long and repeated periods (Thornton, Jones, Opiyo &Orindi, 2006). The groups most vulnerable to climate related illness are those with less ability to adapt thus poor and marginalized causing concern of health inequalities because of climate extremes. The elderly, women and children are most vulnerable to extreme climate but also residents in urban towns and cities who are characterized by poor living conditions, overcrowding, poor housing, lack of access to clean water poor sanitation as well as lack of adequate medical care (Hashizume et al., 2008). The Intergovernmental Panel on Climate Change(IPCC) acknowledges that there is evidence of trends for some health outcomes that have direct or indirect implications for vulnerability to extreme climate events. Additionally, the Panel observed trends in public health threats including infectious or communicable diseases resulting from climate extremes (IPCC, 2012).

Households living in rural areas in developing countries are prone to many risks including illness or mortality of household members, losses in agricultural produce which also cause income loss caused by natural phenomena such as extreme weather events or shocks. In addition, the effects of any shocks, say health shocks can be left even decades later thus causing concern for public policy. The impacts could be indirect, in that they affect other outcomes such as education attainment which in turn affects long run wellbeing. Most rural communities are at the risk of facing low agricultural produce, low fisheries produce, water scarcity, drought, loss of biological resources and destruction in infrastructure due to events of climate extremes. Moreover, these communities have poor access to health services which aggravates their health problems causing illnesses such as malaria, cholera, diarrhea and malnutrition to result to death (Maccini & Yang, 2009).

Increased temperatures globally have often been accompanied by extreme weather events causing shocking environmental, economic, demographic, and social (Zhao, Zhu & Tu, 2015). Vector borne diseases can be prolonged in peak periods due to increased average temperatures while extreme precipitation can create ideal conditions for spread of malaria which is a vector borne disease, though it is preventable (Mrema, Shamte, Selemani & Masanja, 2012). Mortality caused by heat extremes has reduced due to various forms of adaptation brought about by technology more so air conditioners in America (IPCC, 2012). However, even with all the precautions in place especially with the advantage of advanced technology the effects of extreme temperatures are dangerous especially when it comes to drought and water unavailability. The impact of hot temperatures on mortality are more instantaneous compared to cold temperatures whose effects tend to accumulate over time (Barreca, Deschenes & Shapiro, 2016).

Events of extreme precipitation tend to cause flooding resulting to concerns of infectious diseases thus affecting their chances of being epidemics. Flooding then causes pools of stagnant water which act as a breeding site for vectors and hosts such as mosquitoes. Thus, it is imperative to know the effects of extreme precipitation on disease occurrence that could leads to possible mortality so as that the effects can be mitigated (Chen, Lin, Wu, Chih, Lung & Su, 2012).

The Centre for diseases control in America analyzed the impacts of extreme temperature on diseases in North America between 2006 and 2010 and found 31% of deaths were related to heat exposure while 63% were attributed to cold exposure (Hajat & Kosatky, 2010). The Intergovernmental Panel on Climate Change (IPCC, 2012) argue that extremely cold period deaths are largely associated with respiratory infections more so pneumonia. Additionally, there are also incidences of heat related, vector borne, and water borne diseases and deaths that may result due to climate extremes (Seltenrich, 2015). In 2011, 1.3 million children aged below five years were reported do have died from pneumonia which was the leading killer amongst children. Globally with the increasing earth's average surface temperature this trend is said to increase (Walker, Rudan, Liu, Nair & Theodoratou, 2013) yet the true scale of extreme temperature on childhood pneumonia is largely unidentified (Xu, Liu, Ma, Li, Hu & Tong, 2014).

Kenya experiences serious threats to socio-economic development due to climate related events such as prolonged drought, flash floods unpredictability of rain and extreme and weather (Republic of Kenya, 2015a). Although Kenya's contribution to global emissions of greenhouses is minimal it experiences the impacts through extreme and harsh climate conditions. Noted impacts of the harsh conditions include widespread disease epidemics, destruction of infrastructure, loss of livestock, human mortality and destruction of agricultural produce. Extreme climate events account for more than seventy percent of natural disasters in Kenya (Republic of Kenya, 2009a). Close to one million people were affected in the 1997/98 floods that costed Kenya US$ 0.8-1.2 million. Roads, buildings, communication systems, public health disasters and crops loss were among the severe outcomes of these floods. With current increasing temperatures and change of precipitation patterns malaria is foreseen to be endemic in new areas due to climate extremes (Republic of Kenya, 2013a).

The National Climate Change Action Plan of Kenya (Republic of Kenya, 2012a) highlights that there is need to prioritize adaptation activities that increase individuals' climate resilience measures in the health sector. More importantly is monitoring the malaria disease and trying to evaluate its movement to non-endemic regions. Nevertheless, surveillance of

disease epidemics resulting from climate extremes has not been done. Correspondingly there are no health policies that guide in dissemination of information on health risks and how to respond to disease related to climate (Republic of Kenya, 2013a).

Malaria on one hand still accounts for majority of reported deaths and diseases with close to 70% of individuals at risk of contracting the disease in Kenya. This disease continually poses social and economic burden to households. Households lose a substantial amount of their wages when they suffer from malaria (Kioko, Mwabu & Kimuyu, 2013). The epidemiology of malaria in Kenya is characterized by different epidemiological zones with diversity in risks largely determined by altitude, rainfall patterns and temperature. Climate extremes could cause rampant outbreaks more so in vulnerable populations or non-endemic regions thus resulting to death. In addition, due to the different epidemiological zones malaria interventions cannot be evenly applied across all counties (Republic of Kenya, 2015a).

Pneumonia deaths amongst children on the other hand accounts for about 19-23% of children aged under 5years in developing countries (Jeffrey, Ayub, Norbert, Stewart, Robert & Daniel, 2007). The economic survey report 2016, reported 22,473 pneumonia deaths which were higher than the deaths resulting from malaria at 20,691 in 2015. The report indicating that from 2011 to 2015 malaria and pneumonia had been the leading causes of death in Kenya (Republic of Kenya, 2016a). Respiratory tract infections cases are said to increase with significant drop in temperatures (IPCC, 2012). Pneumonia mortality patterns from many studies in Kenya seem to correspond to temperature patterns annually. However, at the Ministry of Health with the initiative of Global Action Plan for Prevention and Control of Pneumonia claim that there is need for more research evidence on epidemiology of the disease (Ye, Zulu, Mutisya, Orindi, Emina & Kyobutungi, 2009).

Malaria has been an economic burden that has brought about poverty and deaths more so in the poorer population in Kenya due huge costs on households. However, geographical and epidemiological differences are not accounted due to limited data to help approximate the cost of malaria both socially and economically (Chuma, Okungu & Molyneux 2010).

1.2 Problem Statement

From the National Climate change response strategy (Republic of Kenya, 2010a), tremendous efforts have been made to reduce the burden of this disease. However, from the economic survey report 2016 of malaria is still one of the leading causes of morbidity and mortality in the country (Republic of Kenya, 2016a). The strategy depicts that malaria already accounts for 50% of household expenditures on health and this will increase with increased incidence of the disease and consequently increase the number of deaths. Additionally, the disease is spreading to areas where managing the cost of the disease will be disproportionately higher due to lower immunity compared to the endemic regions. Although the deaths of malaria have reduced in number considering the growing population the proportions are still high.

The economic survey (Republic of Kenya, 2016a) reported higher incidences and deaths of pneumonia compared to malaria. In addition, respiratory infection morbidity was on the rise. The infants and the elderly were said to be the most affected by respiratory infections. Pneumonia is respiratory disease and is easily preventable and treatable compared to other diseases. Risk factors, incidences and mortality in Kenya have not been well defined to explain the epidemiology of pneumonia in Kenya (Jeffrey et al., 2007). The low attention and prioritization of climate extreme unlike climate change impacts on malaria and pneumonia mortality prevention and control in Kenya may be attributed to lack of evidence or empirical limitations on the impact of these extreme on individuals' health outcomes.

In addition, there have been few studies that have explored extreme precipitation and climate-related infectious diseases (Chen et al., 2012). In Low and Middle-income countries studies on extreme temperatures and its impact on population health and mortality is still difficult to find as its not, detailed and systematic (Zhao et al., 2015). Kenya approximates about US$ 500 million that amounts to 2.6% of its annual GDP as the cost due to the burden of extreme climate events annually that depletes resources for investment for long term growth. Most of the country's population about 65.5% is based in the rural areas where their main source of livelihood is farming (Republic of Kenya, 2012a). The impact of these climate and weather shocks have more impact in the rural

areas because the households have less weather reliant forms of production. Affecting their main source of livelihood means an overall effect on their ability to access other services including health, education and good nutrition (Republic of Kenya, 2013; Burgess, Deschenes, Donaldson & Greenstone, 2009).

The economic impacts of known disasters tend to fall under 10% of the GDP however this impact of climate extreme events can be greater at local scales but due to lack of good data it is difficult for to assess the increased frequency of these events and their impact on GDP growth in the future (IPCC, 2012; Wilbanks et al., 2007). There are no clear-cut policies to help with adaptation and mitigation of these climate extremes which could have an impact on the occurrence of these diseases. Thus, if mitigated for maybe the disease burden would reduce and in turn reduce mortalities as well as overall costs of treatment of these diseases.

There are few studies relating extreme climates effects on malaria and pneumonia mortality in Kenya and developing countries at large. The country will continue to experience these extremes in the future and with the present mortalities in malaria and pneumonia still leading causes of death in the country, this study addresses the gap of epidemiology of these diseases with inclusion of climate extremes. The Intergovernmental panel on climate change (IPCC, 2012) notes that lack of information on impact of climate extremes on health outcomes in developing countries in general to be the largest gap. This includes the mortality or morbidity data and information on other contributing factors such as disease episodes, nutritional status or access to safe water and medical facilities. Over a long period of time lack of reasonable quality health data studies examining health effects of climate extreme events (hot or cold) have been far less in developing countries (Alam et al., 2012).

1.3 Objectives of the study
1.3.1 General Objective
The main objective of this study was to investigate the effect of climate extremes on health outcomes in Kenya.

1.3.2 Specific Objectives

The specific objectives were to:

i. Estimate the effects of climate extremes on malaria mortality amongst households in Kenya.

ii. Estimate the effects of climate extremes on pneumonia mortality amongst households in Kenya.

1.4 Study Hypothesis

The hypothesis of this study is:

i. H_{01}: Climate extremes do not significantly affect malaria mortality amongst households in Kenya.

ii. H_{02}: Climate extremes do significantly affect malaria mortality amongst households in Kenya.

iii. H_{01}: Climate extremes do not significantly affect pneumonia mortality amongst households in Kenya.

iv. H_{02}: Climate extremes do significantly affect pneumonia mortality amongst households in Kenya.

1.5 Contribution of the Study

The National change action plan insists on prioritizing increased climate resilience in the health sector with improvement of disease surveillance especially malaria epidemics to observe early warnings and ensure dissemination of information to households on changing health risks (Republic of Kenya, 2012a). The Action plan justifies that climate change should be priority for Kenya to reduce vulnerability caused by disasters by using climate risk information in development planning and policy making. Additionally, the Climate change framework policy depicts that human health has been affected by climate, but it is not clear to what extent. Moreover, these policies recognize a gap on disease surveillance research due to climate extremes. This paper will help shed light on the current state of mortality of malaria and pneumonia caused by climate extreme and thus help inform on policy.

There is only limited information on the magnitude of the problem of climate extremes, particularly in developing countries. According to the Intergovernmental panel on climate change most research focuses on climate change with very few studies concentrating on impacts of climate extremes more so in Kenya. Any climate extreme or shocks tends to widen inequality gap leaving the poor and vulnerable groups most affected taking into consideration that more than 70% of natural disasters in Kenya are related to extreme climate events.

Climate extreme adaptation and mitigation is a priority as in the Sustainable Development Goals on climate change action (Griggs, Smith& Noble 2013). As a developmental and global issue of serious concern, adaptation and mitigation of these occurrences deserve to be prioritized by governments and health care agencies. Thus, this study adds on to frontier literature on this area. This study employs panel data that accounts for heterogeneity (Cao& Chiang, 2001) as opposed to most studies that use time series data for the analysis of these climate extremes and their effects on health outcomes.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter provides some of the theories on health and empirical literature discussing determinants of health outcomes and the impacts of climate extremes on health outcomes of malaria and pneumonia.

2.2 Theoretical Literature Review

2.2.1 Social Model of Health

Dahlgren and Whitehead (1991) explained a socio-ecological theory on health using grouped social determinants that influenced health. The social determinants were grouped into layers including; individual specific, lifestyle choices, social and community factors and lastly general socio-economic, cultural and environmental factors. Individual factors include age, gender, genetics factors. Lifestyle choices by the individual are influenced by community customs and behaviors from friends. Social and community factors considers the benefits of inclusion and integration in the society. General, socio-economic, cultural and environmental is a broad category that includes; education, water, unemployment, sanitation, work environment.

2.2.2 Health Belief Model

This model was initially known as health utilization framework before it was later renamed to be the health belief model. The Health Belief model was proposed by Rosenstock, Strecher and Becker (1994) model focusses on individual behavioral change. The model suggests that individuals make decisions of health change by focusing on the benefits they could obtain by doing so. The model outlines four aspects of assessments that individuals ought to use to make these decisions. These assessments include; the risk perception that they could contract the illness, Severity of the illness that could affect their productivity and cause death which will affect their households, Perceived benefits of changing their behavior because of belief that they could be better off health wise if they conformed to

some health actions, Perceived barriers such as costs, side effects and time where a cost-benefit analysis would be required.

2.2.3 Health as Human Capital Theory

From an economic perspective Becker (1962) explained human behavior and more so their desire to have tangible and intangible goods in his theory on human capital According to Becker health was one of the intangible goods that individuals invest in to increase value of their life. Becker (1965) argued that individuals were both producers and consumers of commodities in his theory of the allocation of time. The households desire being to maximize their utility subject their budget which is a constraint that gives rise to demand functions for goods consumed by the household, including leisure. Hence, the utility associated with a market good is conditional on the time that is allocated to its consumption. However, the assumption that one household welfare function represents the preferences of all household members has been criticized as incompatible with individual choices of household members.

Grossman (1972) from Becker (1965) further developed the health production function using the 'shadow price'. He explained how resources could be allocated by individuals to produce good health. The model utilized the individual as a producer of health and not just a consumer, in that individuals invest in health for the consumption benefits as well as production benefits that good health provides. Health was defined by Grossman as a capital stock that varied over time and that produced an output of healthy time. The observed variation health stock was justified by investments in health that increased the capital stock and by depreciation of the stock as the individuals aged.

In the Grossman model, one indirectly derives the demand for medical care and other market goods from the commodities that households choose to produce. The level of health capital that is optimal is then determined by the equality of the marginal cost of investment in health capital to that of the marginal utility of healthy days for any individual. The essentiality of this model being that health can be viewed as a durable capital stock that produces an output of healthy time. A key criticism of the model by Hren (2012) was that

did to consider the uncertainty of the future health status and the uncertainty of the effects of investments in health production.

Ehrlich and Chuma, (1990) criticized this model from an assumption made by Grossman that health investment is produced through a constant-returns-to-scale. This brought about an indeterminacy problem especially with the introduction to technology causing a problem of with respect to optimal investment and health maintenance. The critics assume that the production function of gross investment in health exhibits diminishing returns to scale with the marginal cost of gross or net investment being a positive function of the amount of investment. Thus, suggested an incentive to reach the desired stock gradually rather than instantaneously.

Muurinen (1982) further developed the Grossman model to incorporate the role of education, lifestyle and environmental factors in the model as Grossman was unspecific about their effects on health outcome. Using health outcome as general concept she viewed productive benefits generated by health stocks at home or labor force as increased capacity to perform tasks. However, she abandoned the household production and assumed that medical care requires a fixed amount of time. Cropper (1997) also made some modifications from the Grossman model though in the context of promoting health. Cropper (1997) suggested that investment in health was so as individuals to avoid disutility related to illness to avoid monetary loss. She allowed for uncertainty just as Grossman pointing out that illness cannot be avoided just because there is high level of health capital. She assumed short illnesses did not affect heath stock. In addition, she modelled decisions to choose occupations where an individual is exposed to pollutants with a higher wage.

Grossman (2000) responded to this criticism suggesting great complexity of the model with introduction of diminishing returns to scale. Arguing that the marginal cost of gross investment and its percentage rate of change over time become endogenous variables that depend on the quantity of investment and its rate of change. He concludes by saying that the modification ought not to be necessary. However, Galama (2015) suggests that the possible solution to this indeterminacy which he referred to a mathematical degeneracy

should be solved by allowing for a more flexible functional form of the production process. Grossman (2004) further added that if an individual's health is improved it does not just their productivity but also the households' productivity.

2.3 Empirical Literature Review
2.3.1 Determinants of Health Outcomes

Maccini and Yang (2009) assessed the impact of rural household incomes and its effect on health outcomes of females in the rural area due to rainfall shocks. Similarly, Solar and Irwin found income a necessary and direct determinant of health through expenditures to access health commodities. Macinko, Shi, Starfield and Wulu (2003) from their critical literature review that poverty does not make one ill but instead being sick makes one's ability to earn income low. Galobarges, Shaw, Lawlor, Lynch and Smith (2006) alike argued that income affects access to other services that could affect income determinants such as education as well as a reverse causality which is level of income can be affected by the health status of an individual.

Burton et al. (2011), studied determinants of health care seeking behavior in rural Kenya for common infectious diseases such as Pneumonia in Kenya. They found that the distance to the health facility and the cost involved determined whether the households would visit the hospital. Tanser (2006) and Angel-Urdinola, Cortez and Tanabe (2008) efound that those households who lived closed to the health facilty were more likry to visit the faciltities and get treated when sick compared to those who were farther from them. A similar study by Okeke and Okeibunor, (2010) revealed that income availability, distance to health facility for information as well as quality of services determined the health care seeking of rural households. In both studies, the health seeking behavior determined health outcomes of the households.

Solar et al. (2009), on social determinants of health argue that the kind of occupation affects health through one's environmental exposure and income which has a direct effect as it influences one's income which in turn directly affects the type of health care accessed. In another study by Paavola's (2008) women majorly relied on climate sensitive agriculture

as they occupation due to lack of other income streams which left them vulnerable because of climate change and extremes which affects their produce affecting their income thus when ill they are not able to access the best health care.

Similarly, gender affects the health due to inequity in access to resources for women compared to men a factor studied by (Maccini and Yang, 2009). Solar et al., (2009) similarly found that women faced discrimination in accessing power, prestige and resources. Prevalence in some gender divisions in society also affect health through less visible biosocial processes. Lack of control over resources by girls' and women's due to the perceived lower social status exposes them to health risks. Doyal (2000), alike found that policies of removal of gender inequities especially in resource accessibility would help achieve gender equity in health.

Black et al. (2010) finds that infant mortality resulting from malaria is common in children under the age of five like (Kudamtsu et al. (2012) who found that children under the age of five died of malaria as a result of climate change. Egondi et al. (2012) finds older people vulnerable to anything extreme due to their ability to cope and underlying chronic diseases can worsen if they experience any adversity.

Oladipo (2014) found that in seeking of health care in the rural and urban settings the dominant predictors in the rural areas were household size, age sex, disease and proximity to the facility. Similar findings by Adam and Awunor (2014) found that perception of poor quality of health care, inaccessibility to health facility and high costs of drugs determined the utilization of care by residents and their overall health outcome in rural areas. Cohen and Syme (2013) saw that educational attainment was a well-established social health determinant which is also a major determinant of health according to (Solar, 2010). Solar (2010) found the level of education influencing health choices and the ability to obtain resources which influenced health outcomes of individuals. Currie (2009) studied the effect of parental socioeconomic status with a focus on income, education, occupation and area of residence on child health. Further she explored how then the child's health further

influenced future education and labor outcomes. She found that the socioeconomic status of the parents was vital to a child's health outcomes.

2.3.2 Effects of Climate Extremes on Health Outcomes.

Mata, Amaya and Mauricio (2014) exploited incidence of malaria in Colombia under climate extremes. They investigated health impacts of severe climate shocks using panel data and a difference in difference estimation model. They found that in municipalities that experienced extreme precipitation levels, there was significance of increased malaria morbidity and mortality. This study however ignored the impact of shocks from extreme temperature and only explored precipitation only.

Hunter (2011) noted that heavier rainfall increased vegetation thus leading to increased animal host population more so in tropical countries. However, he acknowledged that also there were cases where heavy rainfall events reduced mosquito population. Moreover, he noted that although some studies have demonstrated a relationship between abnormal precipitation or temperature levels and a subsequently higher incidence of malaria, many other studies relating the impact of El nino southern oscillation (ENSO) events and malaria cases are known to suffer from endogeneity. Paaijmans, Blanford, Bell, Blanford, Read and Thomas (2010) using univariate analysis of variance approach found that at the extreme fluctuations of lower mean temperatures transmission of malaria is made more possible than has been previously predicted using maximum mean temperatures.

Baylis and Risley (2013) reviewed literature that based on the increase and decreases of the disease caused by vectors due to climate change and its extreme events. El Niño Southern Oscillation (ENSO) is said to be the main cause of climate change that has increased frequency of extreme climate events. Rainfall variations that have greater intra- or inter-annual capacity caused by El nino southern oscillation or otherwise have led to increased occurrence of vector-borne diseases and deaths. Xu, Etzel, Su, Huang, Guo and Tong (2012) did a similar review on children's health and found extreme hot and cold temperatures mainly affect cases of infectious diseases among children including gastrointestinal diseases, malaria, hand foot and mouth disease and respiratory diseases.

They pointed out that future research is needed to examine the extent of disease burden as result of these extremes.

Kudamtsu et al. (2012) showed that weather shocks in 28 African countries rose malaria exposure of expectant mothers. In turn increasing infant deaths more so if the shocks cause a malaria epidemic where malaria is rare. The impact of drought shocks was more distinct for those babies born in the hungry season, whose parents were not educated, did not depend on agriculture thus causing infant mortality. Floods also caused a malaria epidemic however incidences of drought were more likely to cause high numbers of infant mortality. Chuma et al. (2010) found significant differences in epidemiology of malaria that caused the economic costs to differ in Makueni, Kwale and Bondo. In Makueni which is regarded a high endemic but low acute transmission district the disease episodes lasted longer than in Kwale which is an intense transmission and Bondo a high perennial transmission.

Mrema et al. (2012) in Rufiji rural Tanzania to assessed extreme weather and mortality using time series data. Using a Poisson regression model and a distributed lag model they estimated the delayed association of monthly extreme weather by age on all-cause mortality. Infant deaths incidences rose in locations that experienced tropical climate due to increased malaria exposure. The increased exposure being blamed on extreme weather which also affected the elderly more so extreme temperatures. They used quartiles to measure the events of extreme weather that could affect mortality. However, the in this analysis was based on all-cause mortality, but since the causes of death are usually driven by different mechanisms they also respond differently to monthly weather.

Likewise, Luis, Mendes, Pianho and Zacarias (2017) in Chimoio, Mozambique using an Auto regressive moving average model found that malaria mortality was significantly different from January to March as they recorded highest percentage of mortality from malaria due to increased precipitation than dryer seasons. In addition, urban areas recorded lower malaria crude mortality rate compared to the rural side. Equally, Ngomane and Jager (2012) found floods in South Africa having a significant impact on mortality of malaria but there was no significant effect in the changes in extreme temperature. Additionally, a

study done in China found floods to have increased the disease burden of malaria (Ding, Gao, Li, Zhou, Liu, Ren & Jiang, 2014).

Oluleye and Akinbobola (2010) studied the role of increased temperature and rainfall in relation to malaria and pneumonia in Lagos Nigeria. Their findings show profound effects of extreme climate on individuals illnesses. This is because they aggravate the disease severity, increase hospitalization and cause accelerated death. Applying the Mann-Whitney method cases of malaria occurrences during very dry periods were more prevalent. In the case of pneumonia, temperature indicated a weak and negative correction during warmer periods. Increased cases or reported pneumonia infection during the rainy season was said to have been caused by overall reduction in diurnal temperature and not precipitation. Though there was no definite relationship between malaria and increased rainfall as indicated by irregular and weak correlation between the two variables.

Chen, Chen, Guo, Chen and Su (2014) investigated on Sporadic Legionnaires Disease (LD) an acute form of pneumonia due to increased Precipitation in Taiwan. Using a conditional logistic regression analysis, they measured the extreme level of precipitation through quartiles that would increase episodes of pneumonia. The results showed increased precipitations of 21-40 and 61-80 mm and an 11-day lag increased Legionnaires Disease (LD) occurrence. This particularly causing deaths in male and elderly groups in Taiwan. Davis, Rossier and Enfield (2012) found that in days or periods of unusually low temperature and humidity, pneumonia and influenza mortalities were high more so in those aged above 65 in New York. However, in the years of non-pandemic pneumonia and influenza was skewed by age extremes.

Kim et al. (2016) in New Guinea studied occurrence of childhood pneumonia caused by climatic variables. Applying a generalized linear model using time series data they found heightened vulnerability to pneumonia to be related to food shortage during the dry season. They argued that risk of pneumonia development in the area was determined by heterogeneity of direction and size of the response to the specific climate factors in a specific area indicates the different distribution of the main determinants. This study

however did not show the size of the climate factors and to what extreme they would account for child pneumonia.

Egondi et al. (2012) using a time series analysis studied weather patterns and mortality in Nairobi Informal settlements. They used a distributed lag approach to model the delayed effect of weather on mortality, stratified by cause of death, age, and sex. Increased temperatures above the 75th percentile caused child mortality and Non-Communicable Diseases (NCD) deaths. In addition, results showed very heavy rainfall was associated with mortality with cumulative lagged effect in all ages and pneumonia. Ye, Zulu, Mutisya, Orindi, Emina and Kyobutungi (2009) studied the seasonal pattern of pneumonia-related mortality among children younger than age 5, their evidence provided that mortality in this age group in Nairobi's slums peaks during the rainy season.

2.4 Overview of Literature

According to IPCC (2007), severe weather shocks, such as floods, drought are known to affect the epidemiology of some vector-borne diseases, especially in the aftermath of events by modifying the number of mosquitoes. The reviewed literature relates to effects of climatic extremes and change on health outcomes of malaria and pneumonia mortality as well as determinants of health outcomes. The burden of these diseases worsens the socio-economic status of households. In general, Hunter (2011) concludes that there is good evidence of the relationship between climate change and its impacts on health. However, the issue of climate shocks/ extremes is still not explicitly studied yet they have a greater impact.

Most of the reviewed studies use time series data, with socio-economic and community variables to determine health outcomes. In this sense, this research will contribute to the existing literature providing new evidence using panel data and climate extreme variables to study health outcomes. Nevertheless, there is need for a better understanding of health responses to weather conditions to ensure better health services and policies formulation (Mrema et al., 2012).

CHAPTER THREE
METHODOLOGY

3.1 Introduction

This chapter discusses the methodological approach used to guide on how models have been estimated to ensure the best results. It includes the theoretical model, specific model that will be used to estimate the results, data source utilized in the study and a table having the variables and their measurement. In addition, the Panel data estimation approaches and issues are highlighted.

3.2 Theoretical Framework

This study adopted the Grossman's (1972) health human capital model where demand for health care utilizes the idea of the individual as a producer of health. Individuals as producers of health consume market inputs combined with non-market environmental inputs to produce health, it these inputs that they consume to derive some utility. Health production function describe how an individual household combine various inputs to produce some level of health, these inputs may vary by household and could include: environmental factors the household is exposed to; household social economic status (education level, income, occupation, social class, household size, gender, marital status, household size).

Every individual is characterized by the ultimate desire to maximize his own health and utility at large(Becker,1965). Health outcome being a function of inputs of variables such as household characteristics, socio demographic characteristics and environmental variables. Households consume both health good and non-health to derive some level of utility. Hence a household with members i {1, 2...n} is faced with the following utility maximization problem:

$$\text{Max } U = U(X, H) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Subject to

$$Y = \sum_{i=1}^{n} l_i \, w_i + \sum_{i=1}^{n} y_i + y_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where U is utility, J represents non-health goods, H represents health goods, Y is the total household income measured by the sum of incomes earned by each household member (labor income $l_i w_i$ and non-labor income y_i), and the income earned by the household members jointly, y_j (Becker, 1974).

Assuming household members have identical preferences and income is pooled and the constraint is redefined as;

$$Y = \alpha J + \beta H \quad \text{..} \quad (3)$$

Using the Lagrangean approach to find the FOC

$$L = U(J, H) + \lambda \quad \text{..} \quad (4)$$

By differentiating L with respect to J and H,

$$\frac{\partial L}{\partial J} = U'(J, H) = 0 \quad \text{..} \quad (5)$$

$$\frac{\partial L}{\partial H} = U'(J, H) = 0 \quad \text{..} \quad (6)$$

Therefore, the health production function translates into behavioral choices adopted by household that affect their health outcomes. The household production function provides a framework to analyze factors that influence health status of an individual/ household (Davanzo & Gertler, 1990; McCrary & Royer, 2011).

$$H = f(M) \quad \text{..} \quad (7)$$

H is the health outcome; while M is a vector representing socio-economic variables, community characteristics and environmental factors.

3.3 Model Specification

To estimate the effect of climate extreme on household health outcome this study adopted a health production function in line with (McCrary & Royer, 2011). As shown in equation (7) in the theoretical framework and with few adjustments, this study specifies health production function as;

$$H = f(S, C, E) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (8)$$

Where H is the health outcome (mortality of pneumonia and malaria), S represents socio-economic and community factors including age, sex, education, working status, gender, household size and marital status C represents distance to health facility, presence of piped water, agro-ecological zone, E represents the environmental variables. The environment variables being climate extremes (extreme minimum temperature, extreme maximum temperature and extreme precipitation). Based on the Grossman Health production specification with climate extreme variables, to estimate the effect of climate extreme events on health outcomes amongst households with modifications, the model to be estimated is as follows:

$$H_{ijt} = \beta_o + X_{it}\beta_1 + E_{it}\theta_2 + \varepsilon_{it}\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. \quad (9)$$

Where;

H_{ijt} is Mortality rate of the health outcome, j malaria and pneumonia for households i at year t, X is a vector of socio-economic and community characteristics, E is an environmental vector representing extreme maximum temperature, extreme minimum temperature and extreme precipitation, ϵ is the error term, $\beta 0$, $\beta 1$ and θ are parameters to be estimated.

This study adopted the Poisson regression model because the dependent variable mortality is a count and can only take non-negative values. The main assumption of the Poisson model is that the mean should be equal to the variance but in some cases due to over dispersion this assumption does not hold. Thus, Negative Binomial Distribution may avail a better model.

3.4 Measurement of Variables

Table 3.1 shows the variables that will be used in analysis of this study. The dependent variable is health outcome measured by mortality and several independent variables have been used to estimate the model.

Table 3.1: Measurement of Variables

Variable	Measurement	Expected sign	Literature source
Dependent variable			
Health outcome	Mortality of Pneumonia and Malaria		Kudamtsu et al. (2012) Mrema et al. (2012); Dibuolo et al. (2012)
Independent Variables			
Age	Age in years	Positive/negative	Kudamtsu et al. (2012); Rocha & Soares (2012); Black et al. (2010); Egondi et al (2012)
Age squared	Age squared	Positive/negative	Pscharopoulous, (1994); Egondi et al. (2012)
Extreme minimum Temperature	Extreme minimum temperature will be measured as a dummy variable.1-if minimum temperature is below the Long term mean or above the long-term mean, 0- otherwise.	Positive/negative	Burgess et al. (2014); Egondi et al. (2012); Lindebool et al, (2012)
Extreme Maximum Temperature	Extreme maximum temperature will be measured as a dummy variable1-if maximum temperature is above the long term mean, 0- otherwise.	Positive/negative	Burgess et al. (2014); Egondi et al. (2012); Lindebool et al. (2012)
Extreme Precipitation	Extreme precipitation will be as a dummy variable. 1 if extreme precipitation is above the long term mean, 0 -otherwise.	Positive/negative	Mrema et al. (2012); Burgess et al. (2014), Egondi et al. (2012), Lindebool et al. (2012)
Income	Total sum of income from crop, livestock and off farm activities.	Negative	Solar & Irwin (2010); Maccini &Yang (2009); Burgess et al. (2014)
Education	Measured as a categorical variable 1-primary 0-otherwise, 2 -secondary 0-otherwise, 3-tertiary 0-other	Negative	Solar& Irwin (2010), Cohem and Syme (2013)
Gender	Dummy, female =1, 0 otherwise	Positive/negative	Maccini & Yang 2009, Egondi et al. 2012 Doyal 2000
Distance to health facility	Distance to the nearest health facility from the household home in kilometers	Positive/negative	Burton et al. (2011); Okeke et al. (2010); Adam & Awunor (2014).
Household size	Total number of members of a household	Positive/negative	Oladipo (2014)
Marital status	Measured as a categorical variable. 1=if married, 0 – otherwise 1-if single 0-otherwise, 1-divorced 0 -otherwise 1-if separated 0-otherwise	Positive	Solar & Irwin (2010)
Working status	Dummy, 1if in formal employment, 0 otherwise	Positive	Paavola (2008), Solar & Irwin (2010)
Asset value	Value of the household's assets	Negative	Solar & Irwin (2010); Maccini &Yang (2009); Burgess et al., (2014)
Group Membership	Dummy, 1 if one is a member of a group, 0-Otherwise	Positive/negative	Mata&Amaya (2014), Dibuolo et al., (2012)

3.5 Data Types and Sources

The study sourced data from the Tegemeo Institute of Agriculture and Policy Development. Tegemeo institute surveys for years 2004, 2007 and 2010 are aimed at monitoring households' agricultural growth, health and economic status. The surveys were representative as they were carried out in the whole country. However, Turkana and Garissa were excluded due to the nature pastoralism of most households and for Garissa households were engaged in irrigation which gave an indication that the area was highly productive. The sampling method used was similar across all the sites in all years where they considered Agro Ecological Zones (AEZ) population and districts. They considered the spatial distribution in the zones to enable capture diverse conditions in the sampling. They divided the districts to divisions that were then randomly picked incorporating the idea of diversity the same was done for into locations, sub locations and then villages.

From the randomly selected villages a list of all household units within the village using household heads was made. There were many cases where the list exceeded the sample size and thus the universal KAMPAP sampling technique was to select the households. The universal KAMPAP sampling technique used by Tegemeo is explained, for instance if there exists a total list of 90 households in an area provided by the administration and they needed 9 households to interview in that village they would select every 10th household to get 9 households they needed. They then wrote number 1 to 10 on papers, mix them up and ask a villager to pick. If the number 5 is picked then they would pick households from the 5th on the list i.e., 5,10,15,20,25 and so on. Income collected from the households was deflated using the Consumer price index given by the Central bank for years 2004, 2007 and 2010.

Climate data was sourced from the Kenya Meteorological Department for the period between 1980 and 2010. This climate data was collected from 26 weather stations located in the whole country. The data included daily minimum temperature, daily maximum temperature and precipitation. Household data was collected yearly and thus the climate data was averaged annually as well. To get climate data for each household, we first mapped the weather stations as they had Global Positioning System (GPS) coordinates.

The mapping was done through QGIS, after mapping an inverse distance interpolation method still in QGIS will be used to interpolate climate data (minimum temperature, maximum temperature and precipitation). The household data from Tegemeo contains Global Positioning System (GPS) coordinates which were used to extract climate data at household level giving minimum temperature, maximum temperature and precipitation at household level.

To then get climate extremes, from the averaged annually distribution of minimum temperature, maximum temperature and precipitation data long term means were used as a threshold. Any value of minimum temperature below the long-term mean was regarded as extreme, any value of maximum temperature above the long-term mean was viewed as extreme and any value above of precipitation above the long-term mean was said to be extreme.

3.6 Estimation Issues

To ensure effective results from panel data, the assumptions of classical linear regression model should hold to guarantee that the OLS estimator is the Best Linear Unbiased Estimator (BLUE). If the assumptions are violated, then it leads to unsuitable results. The consequences of the assumptions being violated could lead to the following estimation issues;

3.6.1 Autocorrelation

Autocorrelation is correlation across the observations in the groups in a panel likely to be a substantive feature of the model. That is, nonzero covariances across observations in a group or similarity between observations as a function of the time lag between them This problem causes inefficiency of the model where parameter estimates are thought to be more precise than they really are. This was tested using the Woodridge test for autocorrelation in panel data (Woodridge, 2002).

3.6.2 Omitted variable bias

One must properly account for the relationship between dependent and independent variables failure to do so makes a multiple regression model suffer from functional form

misspecification. These misspecifications can lead to biased coefficients and error terms, which in turn can lead to incorrect inference and incorrect models. To detect this problem, the study used the Ramsey's RESET test to detect if there are any neglected nonlinearities in the model (Ramsey & Schmidt, 1976)

3.6.3 Multicollinearity

Multicollinearity is a problem often encountered due to inaccurate use of dummy variables thus resulting in unstable parameter estimates which make it very difficult to assess the effect of independent variables on dependent variables. When there are two or more predictor variables highly correlated in multiple regression model then there could be multicollinearity. However, this study used Variance Inflation factor (VIF) to test for multicollinearity (Wooldridge, 2002).

3.6.4 Fixed Effects or Random Effects

In analyzing panel data, a Hausman test is run to choose between using the fixed effects or the random effects as was done in this study. The null hypothesis being the random effects and the alternative hypothesis the fixed effects (Greene, 2008). Fixed effects are used when one is only interested in analyzing the impact of variables varying over time.

An assumption made in the fixed effects is that something within the individual may impact or bias the predictor or outcome variables and we need to control for this. An additional assumption is that those time-invariant characteristics are unique to the individual and should not be correlated with other individuals. However, the features of fixed-effects models cannot be used to investigate time-invariant causes of the dependent variables. If there is chance of differences across entities having some influence on the dependent variable, then one should use random effects.

An advantage of using random effects is that one can include time invariant variables like gender. It basically tests whether the unique errors are correlated with the regressors, the null hypothesis is they are not. In the random effects, a pool-ability test is done to decide between a pooled OLS model or random effects. However, in most panel techniques of

estimation they fixed effects method estimator that includes time invariant effect and individual-invariant effect.

3.6.5 Equal Variance Test

It is important to test the equality of variances between populations or factor levels. Many statistical procedures, assume homogeneity of variance more so in analysis of variance meaning the variances of the observations in the individual groups are equal. The susceptibility of different procedures to unequal variances varies greatly, hence the need to do a test for equal variances. This study adopted the Bartlett's test for equality of variance to test whether the variance between the populations were equal which is an assumption in the analysis of variance.

CHAPTER FOUR
DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

In this section, the results from the empirical estimation and their economic interpretations are presented. The section begins by presenting the descriptive statistics of all the variables in the estimable model and then goes further to establish the panel data properties of the variables. Finally, the two Poisson regression model for pneumonia and malaria estimations are presented succeeded by a discussion and interpretation of the results.

4.2 Descriptive Statistics

To determine the statistical properties of the data, a descriptive analysis was conducted. A summary of the analysis which gives the number of observations, the mean and the standard deviation for the years 2004, 2007 and 2010 is shown in table 4.1. The descriptive statistics are for the dependent and independent variables for the panel data for the years 2004, 2007,2010 used in estimating the model. The household heads who were the respondents in the survey had a mean age of was 57.54, 60, 62.39 years for the years 2004, 2007 and 2010 respectively. In 2009 from the census the household heads had a mean age of 47 where the variation could be explained by a larger sample size in the census (Republic of Kenya 2010, a). There was a decrease in the mean of extreme minimum temperature however, extreme precipitation and extreme maximum temperature means increased over the years. This to mean that there was more rainfall experienced as well as more heat. The mean of real income increased to mean that the households standards of living improved over the years.

Additionally, the mean of the asset value increased over the years which could also imply that the households were continually doing well economically. However, enrollment in groups seemed to decline over the years. On average household members travelled 0.54 kilometers to access health services to the nearest health facility. There was a huge marginal difference in the number of male household heads and female household heads in the survey with 87.32 per cent of the respondent's being female and 12.68 were male in

2004 which was also the case in 2007 and 2010. From the 2009 population census 32.1% of the household heads were female while 67.9% were male (Republic of Kenya 2010a). This variation could be attributed to the fact that the census had a larger sample size compared to this survey. Additionally, the survey here focuses a bit more on the rural dwellers where the ratio of men to women is normally higher. About 71% of the household's heads went to primary school in 2004, 53% in 2007 and 64% in 2010. From the 2009 national census the number of household heads that reported primary education was 41.1%. The difference from the census and the survey could be that most household respondents in the survey were residing in rural areas compared to the larger census sample size which had a majority share of urban dwellers. School enrollment and the number of educated people continues to have an upward trend with more women enrolling in schools (Republic of Kenya, 2010a). In 2004, 43% of the household heads were in formal employment with a small increase in 2007 at 43.4% but in 2010 it increased to 48%. From the census 83.3% of the household heads reported to have formal employment. This difference could be attributed to the fact that this data focused on a population that was engaging in agricultural activities. Similarly, though unemployment rates are still high more people are moving into urban town to get formal employment. As for the marital status in 2004, 84% who were the majority were married with a declining trend in 2007 of 83% and 82% in 2010. In the 2009 census 70.05% of the household heads reported that they were married the slight disparity could be attributed to the larger sample size in the census compared to the Tegemeo survey data (Republic of Kenya, 2010a). The average household size in 2007 was 7 compared to that of the census which was 4 but it is argued in the census report that rural dwellers have larger households (Republic of Kenya, 2010, a).Further statistics are provided in Table 4.1.

Table 4.1: Descriptive Statistics

Variable		Mean	SD	Min	Max
Pneumonia Mortality	2004	.0108	.1106	0	2
	2007	.0062	.0784	0	1
	2010	.0046	.0680	0	1
Malaria Mortality	2004	.0270	.1769	0	2
	2007	.0209	.1483	0	2
	2010	.0070	.0832	0	1
Age (in years)	2004	57.541	13.343	25	108
	2007	60.008	12.937	29	107
	2010	62.390	12.711	19	110
Age squared	2004	3488.848	1600.705	625	11664
	2007	3768.169	1602.161	841	11449
	2010	4053.91	1627.477	361	12100
Extreme minimum temperature	2004	.3839	.487	0	1
	2007	.307	.461	0	1
	2010	.103	.304	0	1
Extreme maximum temperature	2004	.257	.437	0	1
	2007	.580	.494	0	1
	2010	.619	.486	0	1
Extreme precipitation	2004	.447	.498	0	1
	2007	.595	.491	0	1
	2010	.743	.437	0	1
Real income (Kenya Shillings)	2004	14939.67	21155.49	107.561	467483.9
	2007	19987.6	36025.38	5.123538	1006465
	2010	73362.23	123905.2	383.4851	2616912
Working Status of the Household head	2004	.430	.495	0	1
	2007	.435	.496	0	1
	2010	.482	.500	0	1
Gender of the Household head	2004	.870	.337	0	1
	2007	.865	.342	0	1
	2010	.861	.346	0	1
Distance to the nearest health facility (in kms)	2004	.542	.852	.0523	4.19
	2007	.542	.852	.0523	4.19
	2010	.542	.852	.0523	4.19
Household size	2004	5.228	2.403	1	16
	2007	7.006	3.184	1	24
	2010	6.807	3.256	1	27

Group membership	2004	.760	.428	0	1
	2007	.752	.432	0	1
	2010	.708	.455	0	1
Assets value (Kenya Shillings)	2004	200984.8	1071298	1200	3.66e+07
	2007	250809.9	944896.6	5000	3.07e+07
	2010	297137.3	791730.6	3000	1.85e+07
Education1 (primary level)	2004	.717	.451	0	1
	2007	.537	.499	0	1
	2010	.643	.479	0	1
Education2 (secondary level)	2004	.225	.418	0	1
	2007	.230	.421	0	1
	2010	.276	.447	0	1
Education3 (Tertiary level)	2004	.058	.234	0	1
	2007	.056	.235	0	1
	2010	.081	.274	0	1
Education4 (No education)	2004	0	0	0	0
	2007	.174	.380	0	1
	2010	0	0	0	0
Marital status1 (single)	2004	.008	.092	0	1
	2007	.006	.079	0	1
	2010	.004	.062	0	1
Marital status2 (Widowed)	2004	.127	.333	0	1
	2007	.144	.351	0	1
	2010	.162	.368	0	1
Marital status3 (married)	2004	.850	.358	0	1
	2007	.834	.373	0	1
	2010	.822	.383	0	1
Marital status4 (separated/divorced)	2004	.015	.122	0	1
	2007	.016	.125	0	1
	2010	.013	.112	0	1

4.3   Diagnostic Tests

4.3.1   Fixed effects and Random Effects Analysis

To select the right model for analysis, a Hausman test was carried under both pneumonia mortality and malaria mortality models under the null hypothesis of random effect model is the appropriate model. Under the pneumonia mortality model, the results from the Hausman test gave a chi-square probability of 21.88 % which is far above 5%. This implies

that we fail to reject the null hypothesis and conclude that the random effect model was appropriate for pneumonia mortality analysis. For malaria mortality model, the results from the Hausman test gave a chi-square probability of 95.75 % which was far above 5%. This implied that we failed to reject the null hypothesis and conclude that the random effect model was appropriate for malaria mortality analysis. The results of both models are shown in Table 4.2.

Table 4.2: Hausman Test for fixed and random effect

Model	Chi squared statistic	Prob>chi2	Comment
Pneumonia mortality	15.43	0.2188	Fail to reject H_0
Malaria mortality	5.01	0.9575	Fail to reject H_0

4.3.2 Multicollinearity test.

In testing for multicollinearity Variance Inflation factor (VIF) test was used. (Greene, 2012). Furthermore, if the VIF is considerably higher than 1 say 5 then there is multicollinearity across all the predictors.

Upon carrying out a VIF test, it indicated that multicollinearity existed between variables age and age squared and marital status widowed. Furthermore, the mean VIF appeared to be higher at 11.14. To address the problem, age squared and marital status widowed were removed from the model and the test carried out again. The retest results indicated no multicollinearity between variables and the mean VIF value was at 1.89 which shows that multicollinearity problem has been addressed.

Table 4.3 Multicollinearity Test - VIF

Variable	Model with Multicollinearity		Model without multicollinearity	
	VIF	1/VIF	VIF	1/VIF
Age squared	64.71	0.015453		
Maritalstatus~2 widowed	18.78	0.053252		
Age	64.61	0.015478	5.22	0.191633
Maritalstatus~3 married	22.52	0.044395	5.20	0.192226
Education1	5.28	0.189264	2.63	0.379927
Education2	5.25	0.190322	2.57	0.389500
Maritalstatus4 divorced	3.64	0.274702	2.27	0.440356
Education3	2.66	0.376263	1.56	0.642709
gender	2.28	0.438497	1.41	0.709916
Real income	1.56	0.642009	1.27	0.787969
Extreme Minimum temperature	1.41	0.709630	1.20	0.836224
Extreme Maximum temperature	1.20	0.836153	1.19	0.841421
Household size	1.17	0.853916	1.14	0.880845
Employed	1.12	0.896344	1.12	0.896463
Extreme precipitation	1.11	0.903778	1.11	0.904436
Asset value	1.10	0.909296	1.10	0.909404
Group membership	1.10	0.912352	1.09	0.920238
Distance to health facility in Kilometers	1.03	0.971629	1.07	0.972404
Mean VIF	**11.14**		1.89	

4.3.3 Autocorrelation Test

This study carried out the Woolridge test for autocorrelation to check for autocorrelation which occurs when error terms from different time periods (or cross-section observations) are correlated. The test for autocorrelation in panel data was carried out under the null hypothesis of no serial correlation. Upon carrying out the test, we failed to reject the null hypothesis of no serial correlation because the value of p which was 0.3601 was greater

than 0.05 and thus concluded that the data does not have first-order autocorrelation. Thus, to mean that the deviations of observations from their expected values are uncorrelated.

4.3.4   Homogeneity of variance test

The study adopted the Bartlett's test for equality of variance. From the results the chi square probability was 499.33 and the probability of the chi square was 0.000. From the Bartlett's chi-squared statistic the study rejected the null hypothesis of equal variance at the 0.01 level. This implied that heteroscedasticity or unequal variances existed in the population. To address this problem, robust standard errors were used.

4.3.5   Omitted variable bias test

The RAMSEY RESET test was carried out under the null hypothesis of the model has no omitted variables. The test results outcome indicated the F calculated value of 6.46 and Probability > F of 0.0002 which was significant at 0.05 significance level. Consequently, the study failed to reject the null hypothesis and concluded that the model did not suffer from an omitted variable problem.

4.4   Regression results

Table 4.7 presents results of the Poisson regression from the random effects model having more significant results compared to the pooled OLS model. From the earlier test of equal variance across units results we rejected the null hypothesis of no significant differences across units, therefore there are panel effects and the random effects model is most appropriate. Similarly, a pooled OLS model was estimated and found almost all the variables were not significant compared to the Poisson model which were significant. The dispersion parameter was zero and thus there was no need to avert to the negative binomial model but instead the Poisson model was used.

The constant which was -5.39 determines the Poisson estimate when all other variables are evaluated at zero in the pneumonia model. Table 4.7 presents these results. From the results on the model on pneumonia mortality, the coefficient of age of the household head was -0.005. The coefficient was significant at 0.001 significance level. Thus, an additional year

in age will lead to corresponding decrease in the expected log count of the pneumonia mortality by 0.005. The results are comparable to those of Walker et al. (2013) who found out that children under the age of five years, more so those aged 2 years died of severe pneumonia.

Extreme temperatures both minimum and maximum were found to be significant in influencing the pneumonia mortality rate at 0.001 significance level. The coefficient of extreme maximum temperature was 0.522. On one hand, a one-degree celsius increase in extreme maximum temperatures, increases cases of Pneumonia mortality log counts by 0.522. This is in concurrent with Egondi et al (2013) who found that pneumonia increased with higher temperatures in Nairobi settlements. Similarly, Oluleye and Akinbobola (2010), found that in Nigeria, temperature indicated a weak and negative correlation during warmer periods for pneumonia mortality.

On the other hand, the coefficient for extreme minimum temperature was 0.329 with and was significant at 0.001 significance level. Therefore, a one-degree celsius increase in extreme minimum temperature increases the log counts of pneumonia mortality by 0.329. This was consistent with Davis et al., (2012) found that unusually low temperatures to cause increased cases of pneumonia and influenza deaths more so for the elderly.

The coefficient for extreme precipitation was -0.129 and was found to be significant at 0.001 significance level. Thus, a one-degree celsius increase in extreme precipitation will lead to a decrease in the pneumonia mortality rate by 0.129. This was in contrast with Egondi et al., (2012) who observed that an increase in rainfall above the normal threshold was significantly associated with pneumonia deaths. In addition, Ye et al., (2009) found that in Nairobi slums seasonal pattern of pneumonia related mortality among children under the age of 5 years was on the peak during the increased rainy season.

The coefficient for log of real income of the household head was -0.376 and was significant at 0.001 significant level. Therefore, a shilling increase in income causes 0.376 decrease in the log count of pneumonia mortality. From most literature, it is argued that income affects

the kind of health quality services one could seek when sick and poor health affects one's income (Macinko et al., 2003 & Galobarges et al., 2006). Kioko et al. (2012) argue that most of the households who have income canaccess better health services.

The coefficient for tertiary education of the household head was -17.98 thus a unit increase in the households with tertiary education leads to a decrease in expected log count of pneumonia by 17.98 compared to those with no education. Similarly, Currie (2009) found that higher education of parents resulted to better health outcomes of their other household members. However, the coefficient for primary education was 5.681 meaning a unit increase in the households with primary education led to an increase in pneumonia mortality by 5.681 compared with those with no education. However most studies in literature find any level of education to have positive health impacts compared to no education (Mrema et al., 2012, Solar &Irwin, 2010, Kudamtsu et al., 2012).

The coefficient for gender was 0.490 and was significant at 0.001 significance level. Females are more prone to pneumonia compared to the males. A unit increase in females shows an increase in the log count pneumonia mortality by 0.490 compared to the male gender. This would mean that women were more prone to Pneumonia deaths. This showing similarity from Yang et al. (2009) and Solar et al. (2010) who argue that women face discrimination, lack of access to resources and power and thus could expose them to lower social status which could then cause health risk and death. However, there has been significant efforts to bring about gender equity and empowerment. Donor agencies and governments have rolled programmes for women which could bring about the change. However, form the economic survey report 2016 male adults' deaths resulting from pneumonia is attributed to motorcycle transportation (Republic of Kenya, 2016a)

The coefficient for distance to the nearest health facility was 0.131 which was significant at 0.001 significance level. A one kilometer increase in the distance to the nearest health facility leads to an increase in the expected log count of pneumonia mortality by 0.131. An increase of an extra kilometer in the distance between a household and the nearest health facility leads to an increase in the expected log count of pneumonia mortality by 0.13.

Distance reduces access to health services. Lack of access to health services bundles including health promotion and preventing information increase the odds of a household reporting pneumonia. The results are in line with Tanser (2006) and Angel-Urdinola et al. (2008). These studies have it that spatial dimensions are important in determining health care utilization. Accessibility is a strategic factor contributing to the use of health care facilities. Thus, the greater the distance to the nearest health facility the less likely are users to seek medical services.

The coefficient for household size was -0.027 and was significant at 0.001 significance level. Thus, an additional household member would leads to a decrease in the expected log count of pneumonia mortality by 0.027. This was different from O'Donnell et al, (2005) who found that larger households had a chance of getting sick. However, in many developing countries large families act as insurances against catastrophic expenditure. The pool of resources from family members cushions the household from the negative consequences as well as raises health expenses.

The coefficient for marital status of the household heads being married was -1.089 which was significant at 0.001 significant level. Consequently, a unit increase in the number of married households leads to a decrease in pneumonia mortality by 1.089 compared to the single households. This is in line with Solar and Irwin (2010) who argues that married households could have a pull of resources and access better health care. Additionally, being married. The coefficient for marital status for those household who reported they were divorced was -24.95 with and was significant at 0.01 significance level. A unit increase in the number of widowed household heads leads to a decrease in the log count of pneumonia mortality by 24.95 compared to the single household heads. The coefficient for group membership is -0.006 and significant at 0.001 significance level. Thus, a unit increase in group membership led to decrease in expected log count of pneumonia mortality by 0.006. This to imply that if a household is part of a group they could get information from other affected households on pneumonia mortality and could thus take precaution. This to mean that social interactions had a effects in the health choices or information that households share or get as a result of the group memberships (Mata & Amaya, 2014).

The coefficient of working status of the household head was -0.674 and was significant at 0.001 significance level. Therefore, a unit increase employed households heads would lead to a decrease in the expected log count of pneumonia by 0.623. The working status here to formal employment. Comparable, to Currie (2009) who found that formal employment reduces mortality due to the accessibility to health insurance and information.

As for the malaria model different variables affected the mortality differently. The coefficient for age was 1.031 and was significant at 0.001 significance level. An additional year in terms of age will lead to an increase in expected log count of malaria by 1.031. Mrema et al. (2012) and Ye et al. (2009) in a similar study found that in Tanzania malaria mortality was most common among children under five years of age, the older people and among pregnant women. Thus, the increase in age could be explained by pregnant mothers. However, most studies find malaria to affect children under the age of five years (Kudamtsu et al., 2012, & Kim et al., 2016).

The coefficient for extreme maximum temperature was -1.107 and was significant at 0.001 significance level. A one degree celsius increase in extreme minimum temperature will lead to a decrease in the expected log count of malaria mortality by 1.107. However, Oluleye and Akinbobola (2010) found increased temperatures led to increased episodes of malaria mortality in Nigeria. Kudamtsu et al. (2012) also found children under 5 years to be severely affected by malaria causing deaths during very hot periods as they also led to a season of hunger.

The coefficient for extreme minimum temperature was 17.10 and was significant at 0.001. Therefore, a one degree celsius increase in extreme minimum temperature leads to an increase in the expected log count of malaria by 17.1. Similarly, Paaijmans, Blanford, Bell, Blanford, Read and Thomas (2010) found extreme fluctuations of lower mean temperatures transmission of malaria is made more possible than has been previously predicted using maximum mean temperatures.

The coefficient of extreme precipitation is 1.028 and is significant at 0.001 significance level. A one degree celsius increase in extreme precipitation increases the log count of

malaria by 1.028. These findings are comparable to those of Mrema et al. (2012) and Ngomane et al. (2012) found increased precipitation to bring about floods thus increasing the disease burden of malaria.

The coefficient for real income was -6.447 and was significant at 0.001 significance level. A shilling increase in real income decreases the expected log count of malaria by 6.447. Income is a major determinant of health outcomes because it enables one access health services get education which also gives them information on prevention of diseases. These are the similar findings with by Okeke and Okeibunor, (2010) and Currie (2009). The coefficient for those household heads with tertiary education was -4.161, thus a unit increase in the level of tertiary education led to a decrease in expected log counts of malaria by 4.161 compared to those with no education. This is in line with Cohem and Syme (2013) who found that household heads with higher education had more information on seeking better healthcare.

The coefficient for distance to health facility was -0.845 and was significant at 0.001 significance level. Thus, a kilometer increase to the nearest health facility leads to a decrease in the expected log count of malaria. These results are different from those of Burton et al., (2011) and Angel-Urdinola et al., (2008) who found that the nearer one was to the hospital the higher the chances of visiting it when ill. However, there are those who still live close to hospital but do not visit the hospital to avoid being diagnosed with diseases.

The coefficient for household size was -1.08 and was significant at 0.001 significance level. An additional household member will lead to a decrease in the expected log count of malaria by 1.08. This was different from O'Donnell et al, (2005) who found that larger households had a chance of getting sick. However, in many developing countries large families act as insurances against catastrophic expenditure. The pool of resources from family members cushions the household from the negative consequences as well as raises health expenses. The coefficient for marital status (married) was -7.227 and is significant at 0.001 significance level. A unit increase in the number of married households leads to a decrease in the expected log count of malaria by 7.23 compared to the single ones.

The coefficient for household heads who had group membership was 3.253 and was significant at 0.01 significant level. Thus, an additional membership led to increase in expected log count of malaria by 3.253. This is different from Dibuolo et al. (2012) who found group membership to reduce malaria mortality.

The coefficient for those household's heads who were employed was 1.364 which was significant at 0.01 percent. Thus, a unit increase in employed household heads leads to an increase in expected log count of malaria by 1.364. However, this is in contrast with Solar et al. (2010), who finds that the type of employment influences one's income which in turn directly affects the type of health care accessed. However, they argue that environmental exposure due to the type of occupation could affect one's health.

Table 4.4 Regression Results for Pneumonia Mortality and Malaria Mortality

Variable	Poisson RE Pneumonia mortality	Poisson RE Malaria mortality	
Age	**-0.005*****	**1.031*****	
	(0.000)	(0.009)	
Extreme maximum temperature	**0.522*****	**-1.107*****	
	(0.001)	(0.005)	
Extreme minimum temperature	**0.329*****	**17.10*****	
	(0.001)	(0.016)	
Extreme precipitation	**-0.129*****	**1.028*****	
	(0.001)	(0.0161)	
Real income	**-0.376*****	**-6.447*****	
	(0.000)	(0.045)	
Education Level			
Secondary level	**6.075*****	**6.358*****	
	(0.201)	(0.084)	
Tertiary level	**-17.98*****	**-4.161*****	
	(0.201)	(0.171)	
Primary level	**5.681*****	**17.99*****	
	(0.201)	(0.054)	
Gender	**0.490*****		
	(0.001)		
Distance	**0.131*****	**-0.845*****	
	(0.000)	**(0.004)**	
Household Size	**-0.027*****	**-1.089*****	
	(0.000)	(0.010)	
Marital Status			
Married	**-1.089*****	**-7.227*****	
	(0.029)	(0.045)	
Divorced/Separated	**-24.95**		
	(15318.8)		
Employed	**-0.674*****	**1.364*****	
	(0.001)	(0.011)	
Group Membership	**-0.006*****	**3.253*****	
	(0.001)	(0.036)	
Constant	**-5.390*****		
	(0.198)		
lnalpha Constant		0.554***	
		(0.00618)	
Observations	1985	1985	1985
Adjusted R^2			

Standard errors in parentheses $^*\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

CHAPTER FIVE
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter gives a summary of the study and the conclusions drawn. It provides the policy outcomes of the study and recommendations. It also outlines the study's limitations and highlights areas for further research.

5.2 Summary

This study sought to investigate the effect of climate extremes on health outcomes in Kenya. The study was based on the Grossman Health production function because it describes how households combine various inputs to produce some level of health outcome. The health outcomes in this study were malaria mortality and pneumonia mortality. To achieve this the study used Tegemeo Institute Household Panel data for the periods 2004, 2007 and 2010. The data was used to fit two Poisson regression model and coefficients of the independent variables discussed against the dependent variables.

A Poisson regression model was adopted because the dependent variable was count. From the results, the extreme climate factors that were significant and adversely or negatively affected pneumonia mortality were extreme minimum temperature and extreme maximum temperature. This to mean that minimum and maximum temperature experienced by the households was above (extreme maximum temperature) and below (extreme minimum temperature) the threshold value of the range of observed values of the variables. Thus, the occurrence of these extremes was found to negatively have affected pneumonia mortality.

Other factors that affected pneumonia mortality negatively included increased distance to the health facility. Also, it was observed more males were affected by pneumonia mortality than the females. Additionally, from the findings extreme precipitation, an increase in age, being married, higher level of education (tertiary), increased household size, group membership, and having formal employment decreased pneumonia mortality.

As for malaria, extreme minimum temperature and extreme precipitation were found to significantly and negatively affect malaria mortality. This to mean that households experienced days that were colder than usual and increased rains above the threshold value. Other factors from the model that negatively affected malaria include increased age, group membership, working status. However, some these other factors are found to affect malaria mortality different in other studies. From the same model some factors were found to reduce malaria mortality including extreme minimum temperature, higher incomes, higher level of education (tertiary), higher asset value, increased household size and being married.

5.3 Conclusion

Malaria and Pneumonia mortality account for a higher percentage of disease burden in Kenya. Though these diseases are said to majorly affect children under the age of 5 years there are still older people who die from these diseases. Most studies have estimated the effect of climate change on malaria and pneumonia mortality. However very few have studied the effect of climate extremes on these diseases. The main aim of this study was to estimate the effect of extreme maximum temperature, extreme minimum temperature and extreme precipitation on malaria and pneumonia. As for pneumonia mortality, extreme maximum temperature and extreme minimum temperature were found to significantly and negatively affect the outcome of the disease. As such the government through the Ministry of health should factor in extreme maximum temperature and extreme minimum temperature while coming up with interventions to reduce the burden of pneumonia mortality in the country.

As for malaria mortality, extreme minimum temperature and extreme precipitation were found to significantly and negatively affect the malaria mortality. Thus, the government through the malaria control programme should monitor these climate extreme variables during surveillance of the disease as well as implementing interventions for the disease. Therefore, the results of this study forms basis for various policies on the effect of the climatic extremes on the health outcomes in Kenya. First, this study provides basis to policy makers in understanding the role of climatic extremes on the health outcomes and

particularly Malaria Mortality rate and Pneumonia Mortality rate. Secondly, this study provides solution to Policy makers on health sector to the role of various climatic factors on Malaria and Pneumonia Mortality. There is need for the government to have up to date data on climate variables and point out climate extreme variables being experienced and giving prior information to the ministry of health to ensure there are no outbreaks of diseases due to these climate extremes.

Moreover, the Ministry of Environment and Natural Resources is currently drafting policies on Climate Change and Climate extremes thus this research can be used to add information that can be used by environmental experts to mitigate the impacts of climate extremes specifically to the health sector.

Finally, this study could be used by policy makers to enable them allocate budgets that could help towards mitigating the negative effects of the extreme climate factors on health outcomes.

5.4 Recommendation

This study has pointed out that climate extremes have a significant effect on health outcomes at household level in Kenya. As demonstrated by the findings households in Kenya face climate extremes and thus are at risk of pneumonia and malaria mortality. As for pneumonia mortality extreme maximum temperature and extreme minimum temperature negatively, affected mortality. As for malaria mortality extreme minimum temperature and extreme precipitation were found to negatively affect mortality. Kudamtsu et al. (2012) in a study on weather and mortality in Africa recommended that climate variab/fles should be studied on the effect they have on disease burden in Africa. As climate experienced by households continues to change over time it is important that the ministry of health invests in disease surveillance, with a focus on the effect climate extreme variables have on pneumonia and malaria and preventive measures to ensure no resurgence of the disease that could be a result of climate extremes.

The United Nations (2016) recommend that climate change action is an important goal in achieving sustainable development in the world. While money is being used to help mitigate climate extreme disasters in developing countries it is important to integrate disaster risk measures into national policies. The policies should be sector specific in this case to the health sector, where the ministry should take into consideration the effect climate extremes have on malaria mortality and pneumonia mortality.

5.5 Further Areas of Research

Extreme climatic conditions play an important role in defining health outcomes and in this case Kenya. The study notes that it has not exhausted the climate factors which can be considered extreme and affect health outcomes such as humidity ad wind speed and hence the call for further research. Additionally, there are still very few studies in Kenya which have examined the effect of climate extremes on health outcomes and therefore there is need for more studies. Malaria and pneumonia mortalities are still high in Kenya and climate patterns have in the recent times become unpredictable with warmer days, floods in some parts of the country and colder days. With the changing climate patterns, it is important to see how diseases such as malaria and pneumonia could be changing with the climate extremes. Further studies could focus on the rate of pneumonia and malaria mortality because of climate extremes with very current data.

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