A PREDICTIVE MODEL OF CLIMATE SENSORS EFFECTIVENESS ON SUSTAINABILITY OF SUBSISTENCE AGRICULTURE: THE CASE OF LAIKIPIA COUNTY

BY

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DECLARATION

I declare that this research report is my original work and has not been presented for academic award in any other institution of higher learning. I hereby also declare that this study contains no material written by others except where reference is made and duly acknowledged.

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ABSTRACT

In contrast to many areas of the globe where farmer posses adequate physical, economic and social resources to adapt to and moderate effects of climate variation and climate change, subsistence agriculture in the arid and semi-arid lands (ASALs) of Kenya are particularly affected in an unfavourable manner by the effects of climate change. This is more so because of the increasing dependency of a good number of the population on rain fed agriculture as a source of livelihood and economic income. An effective adaption mechanism to climate change for sustainability of subsistence agriculture in these areas using communication technologies is therefore highly important for food security and protection of livelihoods within the rural areas. The main aim of this study was to model and predict the effectiveness of climate sensors on the sustainability of subsistence agriculture in Laikipia County, one of the ASALs in Kenya. The study hypothesized that the current community based strategies applied by the local farmers are relevant and important to the present-day quest for climate-change adaptation strategies, and that feedback from the stakeholders can generate insight used to generate an improved predictive model to further enhance this adaptation. The study therefore conducted a survey study of rural stakeholders in Laikipia farmlands and assessed the output through descriptive measures. Further, a logistic regression model of variables constructed from the survey study was used to predict the effectiveness of data communication technologies such as climate sensors that are currently employed on the sustainability of subsistence agriculture in these rural areas, using variables such as geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition. The model was be tested through standard measures of goodness of fit such as Chi-square and adjusted goodness-of-fit index. It is expected that results of this study will be useful in policy formulations regarding adaptation mechanisms to climate change for sustainability of rural-based subsistence agriculture.

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LIST OF ABBREVIATIONS

FAO	The Food and Agricultural Organization
CO_2	Carbon dioxide
GDP	Gross Domestic Product
GIS	Geographical Information System
GOK	Government of Kenya
IPCC	Intergovernmental Panel on Climate Change
KALRO	Kenya Agricultural and Livestock Research Organization
LRV	Laikipia Rural Voices
LWF	The Laikipia Wildlife Forum
NWP	Numerical Weather Prediction

DEFINITIONS OF TERMS

Climate Sensors – These are meteorological sensors deployed to record average conditions of key characteristics such as temperature, wind speed, humidity, dissolved oxygen, etc. for measuring climate and weather. Such sensors are typically physical sensors that operate on a variety of different principles and methods, often measuring internal changes in response to changing climatic parameters.

Climate Change – This implies any variation in climate over time and can result from natural variability human activity.

Resilience – This refers to the general tendency to observe integrity when subjected to disturbance.

Sensitivity – This refers to the level with which a system is affected, either positively or negatively, by a climate-related stimulus. The effect may be direct (e.g., a change in crop yield in response to a change in the mean, range, or variation in temperature) or indirect (e.g., damages caused by an increase in the frequency of flooding due to a rise in water levels)

Climate Variability - This refers to variations in the mean state and other statistics (e.g., standard deviations, occurrence of extreme conditions, etc.) of the climate in time and space and extends beyond isolated weather events. Variability may be due to natural internal processes within the climate system (namely, internal variability), or variability in natural or human-initiated external forcing (namely, external variability).

Climate Impact Assessment – This refers to the practice of identifying and evaluating both the positive and negative influences of climate change on natural and human ecosystems.

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

Climate sensors are meteorological sensors deployed to record average conditions of key characteristics such as temperature, wind speed, humidity, dissolved oxygen, etc. for measuring climate and weather. Such sensors are typically physical sensors that operate on a variety of different principles and methods, often measuring internal changes in response to changing climatic parameters. Climate variability and climate change have been identified as the most challenging and complex problem facing the World (Haile et al., 2020). Impacts of climate change have been predicted to significantly increase the challenge of ensuring food safety and to reduce poverty in many African countries (Waaswa et al., 2021). Climate change has affected subsistence agriculture in a number of ways. The first has been the direct effect on reduction in crop productivity (Akoko et al., 2020). As a result, this has hampered the key sustainable development goals (SDGs) of eliminating poverty – SDG 1, zero hunger – SDG 2, good health and well-being – SDG3, and responsible consumption and production – SDG 12 (General Assembly, 2015). A number of factors have added to the increasing poverty, hunger and depreciating development. Among these are the difficulties in coping with variation on climate within a continent that is constantly experiencing floods, droughts and extreme temperatures and the degradation of arable land. To add to these problems, a number of problems associated with socioeconomics, demographics, politics, failed institutions and bad policies continue to further limit the capacity of many African countries to improve adaptation to climate change (Nyika, 2020; Mwangi et al., 2021).

About 80 percent of the East African population resides in rural areas which highly depend on the yearly short- and long-term rains, and on subsistence agriculture (Ogada et al., 2020).

This means that the emergent climate challenges directly affect household wealth, incomes and generally on livelihoods of the majority. According to Kogo et al. (2021), Kenya is of the African countries that are experiencing a lot of changes in weather and rainfall patterns, seawater levels and high concentrations of atmospheric CO_2, factors that directly impact on agriculture and food security. Their findings also showed that climate variability will continue changing the cropping patterns and crop yields in many counties. The rate of droughts encountered in Kenya has kept on increasing, from droughts every 10 years in the 1960s and 70s, to droughts every 5 years in the 1980s, to droughts every 2-3 years in the 1990s, and further to increasing unpredictability in the 2000s. There is prediction of drought-related risks becoming significantly intense by 2050 and affecting many economic segments (Muchiri et al., 2020).

Arid and semi arid regions of Kenya such as Laikipia County have experienced drought even in the past decades. The increasing rate of climate change and Evapotranspiration, because of increase in temperature has caused these arid and semi-arid lands (ASALs) to have extreme climates, increase in soil acidity, water stress and low crop yields, thus heightened food insecurity and malnutrition (Thorton & Lipper, 2015). Given the current problems facing the ASALs as a result of climate change, there is urgent need for adaptation of crop production and food-security systems in the face of the rapid urbanization and constant population increase that Kenya is currently experiencing (Chepkoech et al., 2020). This can only be possible by understanding the level of effectiveness of the ICT tools being used as climate sensors, as well as the factors influencing these levels.

Climate sensors used by the meteorological departments allow real-time tracking of various aspects of climate behaviours such as temperature, wind speed and direction and humidity over space and time. It is important to keep track of all the climate parameters in order to achieve a balance in predicting suitability for subsistence agriculture (Sose & Sayyad, 2016).

Modern weather monitoring technologies are capable of tracking weather and climatic patterns in a cost-effective manner and pinpoint different out-of-range conditions. Space-deployed remote monitoring systems are made up of 2 key components: The satellite which has data-collection sensors, and the data processing system. The latter has the task of getting real-time data from the satellite. It also schedules the tasks needing to be processed. The modern approach uses wireless technologies to monitor climate change and weather patterns. This system has transmitters with different sensing capabilities for temperature, humidity air quality, atmospheric pressure, etc.

The use of machine learning predictive approaches to monitor and predict climate change for subsistence agriculture has the potential to benefit the involved societies as well as to advance the field of machine learning by improving interpretability of outcomes, causal effects and to quantify uncertainty. Different machine-learning methods have been used to predict and manage climate change. One example is computer vision which is applied to process satellite images and generate size and location data for objects such as roof-top solar panels (Gershenson et al., 2019). Time-series analysis has also been used to model events that change over time, such as the degradation of vegetation and forest cover for predicting phenomena such as the management of forests (Bullock et al., 2020). Natural language processing (NLP), network analysis and clustering have also been also used to derive insights from policy-based text data for various applications, akin to automated compliance-checking applied for analysis of social media data in order to derive public opinions and discourse surrounding climate change (Kirilenko & Stepchenkova, 2014; Zhang & El-Gohary, 2015).

Machine learning can also help to integrate data driven knowledge into developed models. For instance, the use of unsupervised learning which do not required labelled data, such and Variational autoencoders and Generative adversarial networks have been applied to observe the salient characteristics which are crucial within a complex modeling environment

(Gunaratne & Garibay, 2020). Supervised ML techniques and fuzzy logic have been used to quantify uncertainty in the field of material science (Butler et al., 2018). Regression models are useful for quantifying non-linear associations between linked variables (Rolnick et al., 2019). While regression techniques have not been popularly used for climate change monitoring, a few studies such as Roberts et al. (2017) and Xie et al. (2019) have applied regression models to predict risk perception of climate risk in the community, as well as to compare crop models with statistical models in understanding climate-change implications.

The World meteorological organization (WMO) categorizes drought into types: 1) Meteorological drought which is characterized by no precipitation over some time, 2) Hydrological drought which refers to a period of time experiencing inadequate subsurface- and surface-water resources, and 3) agricultural drought in which there is a period of decreasing soil moisture and crops fail as a result (Canton, 2021). These definitions are quite ambiguous and not providing detailed measures of drought severeness on a predetermined scale. Neither do they mention the cause and effects of such droughts. While studies such as Muchiri et al. (2020) have tried to analyze historical variation in dry and wet seasons in Laikipia County, they have also not focused on how this variation affects subsistence farming. M'mboroki et al. (2018) looked at the impact of climate change in general vegetation cover but did not concentrate on how this can specifically affect subsistence agriculture.

Kenya's economy is heavily dependent upon subsistence agriculture. However, recent statistics show that subsistence farming has been steadily declining as many frustrated farmers in Laikipia opt to diversify and grow other crop types such as sunflower as reported by Laikipia Rural Voices (LRV, 2018). World Bank estimates a 16 percent drop in African agricultural output by 2050. Rising global temperatures today are putting to an end what little predictability farmers in the past might count on. Specialists predict climate variation will increase the already tough challenges for Kenya in terms of food security.

1.2 Statement of the Problem

A lot of studies on the effect of climate change worldwide have concentrated on commercial agriculture and left the area of climate change effect on subsistence agriculture to remain poorly investigated by researchers. The existing partial investigations have also considered the impacts of climate variation and climate change in isolation and provided insufficient knowledge regarding the degree of awareness of the local weather stations and local farmers on the issue, including which actions are being done, when and how, in order to cope with the changes. Given the fact that subsistence agriculture in most ASALs including Laikipia County depends greatly on climate variability, prolonged dry seasons are one of the most serious climate hazards affecting the agriculture sector, and more research is needed to increase sustainability in this area.

Measures to adapt to climate variation and climate change are not new, but incorporation of present and future climate risk, as well as incorporation of knowledge about the effectiveness of climate sensors into policy making to reduce the risk for subsistence agriculture is little investigated. Even while subsistence farmers have a long history of adapting to climate change at local levels, more sustainable strategic actions are needed for long-term security of the well being for subsistence farmers. Indigenous local knowledge to facilitate adaptation to climate change in rural subsistence communities is critical but has not been incorporated into research, with most adaptation efforts being top-down and not yielding full results at the local rural level (Somah, 2013). To the researcher’s knowledge, there is no research that has engaged multiple stakeholders such as communities, meteorologists, extension agents and subsistence farmers in understanding effective adaptation strategies geared at ensuring the sustainability of subsistence agriculture.

Given the importance of ICT tools such as climatic sensors on predicting suitability periods for agriculture, several studies have attempted to model their effectiveness and impact. Agutu et al. (2017) created land surface models to understand how remote sensing technologies were effective in characterizing drought in East Africa. They found a relative level of effectiveness, but their results were not conclusive. Singo (2018) used digital elevation models (DEMs) to understand how remote sensing techniques impact on predicting land cover changes in South Africa. Fiehn et al. (2018) applied deep learning to predict wet and dry seasons in a smart agriculture system in South Africa. Karst et al. (2020) have applied multiple linear stepwise regression to model subsistence crop yields in Burkina Faso using per-month metrics of vegetation index (VI) and harvest measurements and discovered that yields in four food crops of high-dietary importance, namely millet, sorghum, beans and maize, were the most affected by climate variation. Lately, Dimri et al. (2021) have used GIS-based image analysis models to assess climate variability, precipitation and related influences on agriculture and its related ecosystems in the Indian Himalayan region. They concluded that global warming is expected to increase to above 2.5 degrees Celsius by the end of the 21st Century and cause increase in extreme weather phenomena. While they showed that spatial and temporal models of land coverage are useful for such predictions, they cited as their limitation the lack of direct engagement of communities in predicting localized effects on rural livelihoods.

The two main gaps in existing knowledge that this study has attempted to address are: 1) The lack of localized studies which involve community-based stakeholders to understand effectiveness of climate prediction technologies on subsistence agriculture (Somah, 2013; Zhang & El-Gohary, 2015), and 2) The need to investigate multiple influences on climate variation, though assessment of different types of climate sensors on multi-level characteristics such as precision levels, frequency of use, etc. (Karst et al., 2020)

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study was to model and predict the effectiveness of climate sensors on the sustainability of subsistence agriculture in Laikipia County.

1.3.2 Specific Objectives

The main objective for the study were achieved through the following specific objectives:

i) To determine the factors that affects the effectiveness of sensors for detecting climate variability and suitability for subsistence agriculture in Laikipia.

ii) To design and develop a predictive logistic regression model of climate sensors effectiveness

iii) To test and validate the predictive model developed above.

1.4 Research Questions

The study sought to answer the following research questions:

i) Which are the factors that influence the effectiveness of sensors for detecting climate variability and suitability for subsistence agriculture in Laikipia?

ii) How can these factors be modeled using a predictive logistic regression approach?

iii) What is the validity of the developed model for application to predict climate suitability for subsistence agriculture in the study area?

1.5 Motivation of the Study

The total population of Laikipia County in 2009 was 398,991 people. Later, in 2018 was 505,712 people living within Laikipia County as projected by (KNBS, 2016). Due to this population growth and expanding economies, the demand for Laikipia's agricultural output is expected to grow exponentially over the coming decades. At the same time, climate variation is expected to affect the agricultural sector which will challenge the productivity of the County's subsistence agricultural resources. Figure 1.1. Shows high variation in Laikipia's vegetation condition index (VCI), which has in the recent years remained poor and fluctuating across most of the pastoral zones, mostly as a result of low precipitation level and long sunny periods recorded throughout the County.

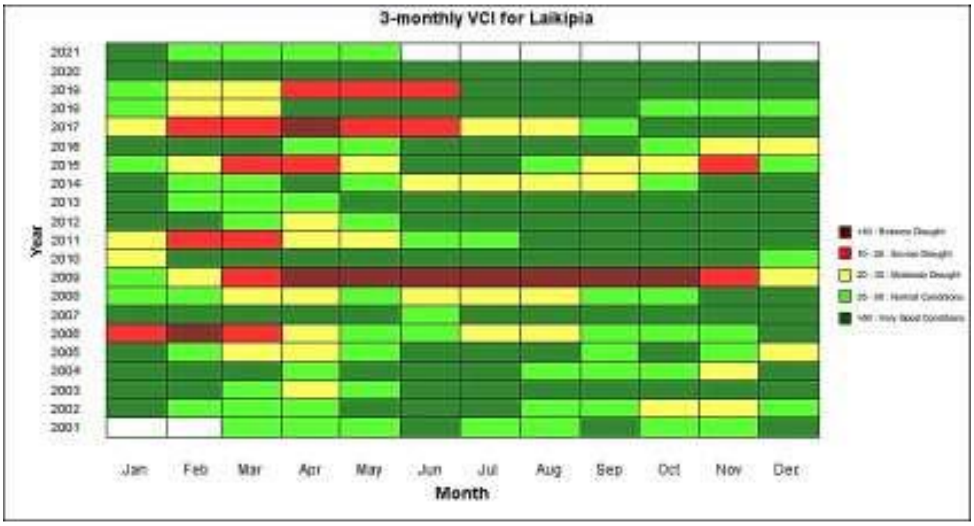

Figure 1.1: Laikipia monthly VCI matrix by May 2021 (Source: NDMA, 2021)

To meet the growing demand for subsistence agriculture, farmers needed to become more skilled in anticipating climate change, variation and finding ways to adapt to these changes. Information about climate prediction has the potential to lessen the impact of adverse weather events. This was anticipated to happen as the advance notice provides the opportunity for decision-makers to implement plans to minimize the impact of weather variations and find planting opportunities within favorable seasons.

As seen in Figure 1.2 below shows that subsistence crops such as maize and beans contribute to the highest percentage of food consumption both on mixed farmers and marginal mixed farmers. However, the income is low among marginal mixed farmers which indicates that the latter does not make a significant income from maize farming probably because it's grown for subsistence farming and not as a cash crop. With a proper prediction of weather variation this low income from marginal mixed farming can be increased

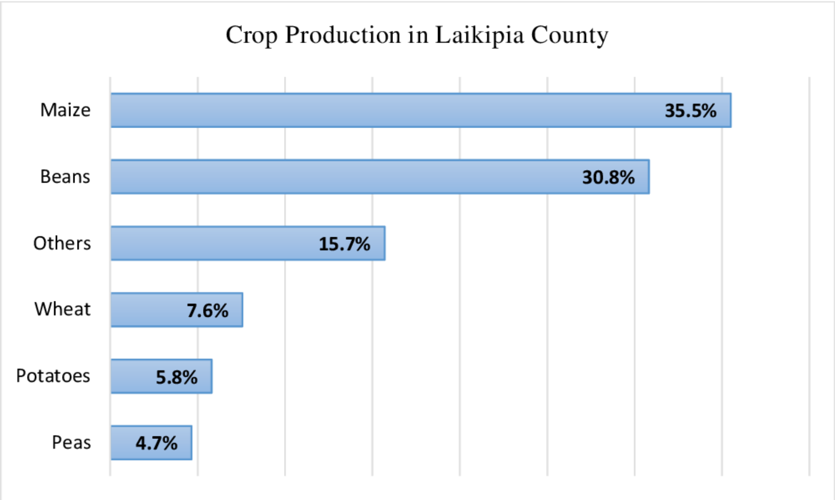

Figure 1.2: Proportion of General Crop Production in Laikipia County. (Source: Gicheru, 2019)

1.6 Significance of the Study

Subsistence farming in Laikipia County contributes majorly to livelihoods with 61-80% of the residents being taking part in the agricultural sector (GOK, 2015). Even though agriculture is the main economic activity in Laikipia County, it continues to be susceptible to climate variability which leads to drought, famine and starvation of the residents every 4 to 5 years (GOK, 2013). Hence this study will create awareness of climate variability among subsistence farmers of Laikipia County and the effectiveness of various predictive mechanisms for sustainable farming.

Apart from that, this study will be of great help to policy makers in the agricultural sector as it will provide them a model that they can utilize to improve adaptability to climate variability and climate change for subsistence farming, for instance coming up with better seeds that can be used in times when there is minimal rainfall and another variety of seeds that can be used when rainfall goes beyond the required amount. The researcher hopes that the findings of this research will be of benefit to other key stakeholders such as Ministry of Agriculture, Kenya Agricultural and Livestock Research Organization (KARLO) by formulating policies, fertilizers and seeds that will cushion farmers from climate variability across Kenya.

To information and communication technology specialists, the study will advise on the relative effectiveness of the different tools, equipment and machinery they employ for predicting climate change for subsistence agriculture, not just at the wide area level but even at the small-scale local level.

In addition, this research addresses existing study gaps and also generates new knowledge on climate variability and subsistence farming that will be beneficial to researchers. Other than that, the researcher will publish this study in a peer review journal which will contribute to growing literature on climate variability and maize production globally.

1.7 Scope of the Study

This study was restricted to Laikipia County which comprises five administrative Wards: Laikipia East, Nyahururu, Laikipia Central, Laikipia North, and Laikipia West. It covers an area of 9,462 square kilometers and supports 518,560 inhabitants (KNBS, 2019). The study was limited to examining the effectiveness of five climate sensors, namely rain gauge, hygrometer, barometer, wind sock and MODIS satellite images. In addition, influence of the following variables on effectiveness of predicting climate change was measured for each: geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition. This study modeled these effects of climate variability using a logistic regression model of survey data in Laikipia County.

1.8 Organization of the Study

The research consists of five chapters. Chapter one provides the general introduction to the study, chapter two involves reviews related studies, critical reviews and research gap estimates. The chapter three articulates the methodology used in the research. This consist of methods of investigating the research design, target populations, sample and sampling procedures, data collection as well as tools used in order to acquire all this information. In addition, chapter four discussed the model formulation and data analysis, how results are presented and the explanation behind the data collected, together with the created model. Chapter five summarizes key outcomes into a broad spectrum of information which are concluded by the research giving recommendations.

CHAPTER TWO

LITERATURE REVIEW

This chapter reviews the literature on climate change and its effect on subsistence farming at the global and local scale. It provides a discussion of existing research on climate prediction and adaptation technologies, models, approaches and variables. The chapter further identifies the gaps on emerging issues associated with the research that have not been exhaustively studied from the literature. It finally conceptualizes a theoretical framework from which the methodology will be designed.

2.1 Introduction

Agriculture has several components such as farming, dairy and poultry rearing among others (Dane, 2020). Farming remains a key contributor to the global economy. A study by Alston & Pardey (2014) revealed that in 2012, farming contributed to 3% of the economy as approximately 19% of the world's population were directly involved in farming. Farming has been recognized as a very influential element in the economy of most countries across the globe. Other than farming contributing to small proportion of the global economic output it employs at least 30% of the global working population. Further farming is seen as a great tool of ending extreme poverty by the year 2030. For instance, according to (World Bank, 2021) studies carried out in 2016 revealed approximately 65% of the poor workforce made a living by engaging in farming. Despite farming accounting for a slightly over a quarter of the global GDP it has a potential to accounting to at least 40% by using irrigation as opposed to relying of rainfed farming, mitigating the risk of climate variation and land use change.

Farming remains the primary economic activity in Africa hence significantly contributing to social and economic well-being of its people. Over 60% of the sub-Saharan Africa populations are small scale farmers and nearly about 25% of the sub-Saharan Africa's GDP output is from farming (Goedde et al., 2019). FAO (2016) assert that, more than half of the total working populations in sub-Saharan Africa engage in farming. In addition, women make up approximately 50% of the labor force. Even though women make a significant contribution in farming they are insignificantly involved in cash crop farming. On the other hand, around 40% of the youth in sub-Saharan Africa continue to work in farms with a majority of them being in rural areas. The number of youths engaging in farming activities in Africa is expected to rise in future (Jimbira & Hathie, 2020).

According to World Bank (2020), subsistence farming contributes greatly to Kenya’s GDP. A World Bank report of 2018 showed that farming contributed to 51% of the total GDP, with 60% of employment and 65% of exports as cited by (Birch, 2018). Farming in Kenya is majorly dominated by poor farmers most of whom reside in rural areas. Even though most of the farmers practice small-scale farming, they account for 78% of total agricultural production in the country and this has helped alleviate food insecurity and poverty. Despite the immense growth in agricultural production, Chepkoech et al. (2020) have noted that Kenya is one of nations within sub-Saharan Africa that has continued to record a general reduction in maize production.

2.2 Climate Variability and Climate Change for Subsistence Agriculture

According to the Justus et al. (2016), climate is defined as describing weather elements by way of average and variation over the period from monthly to decades and century, with thirty years being the classical average period for most of its weather element in order to properly describe the climate of that particular region, while climate variation is defined as differences in the mean state and other figures, such as standard deviations, the frequency of climate anomalies on all spatial and temporal scales outside the weather events (McMichael et al., 2003). Figure 2.1 below shows climate components and how they interact to give climate to a region.

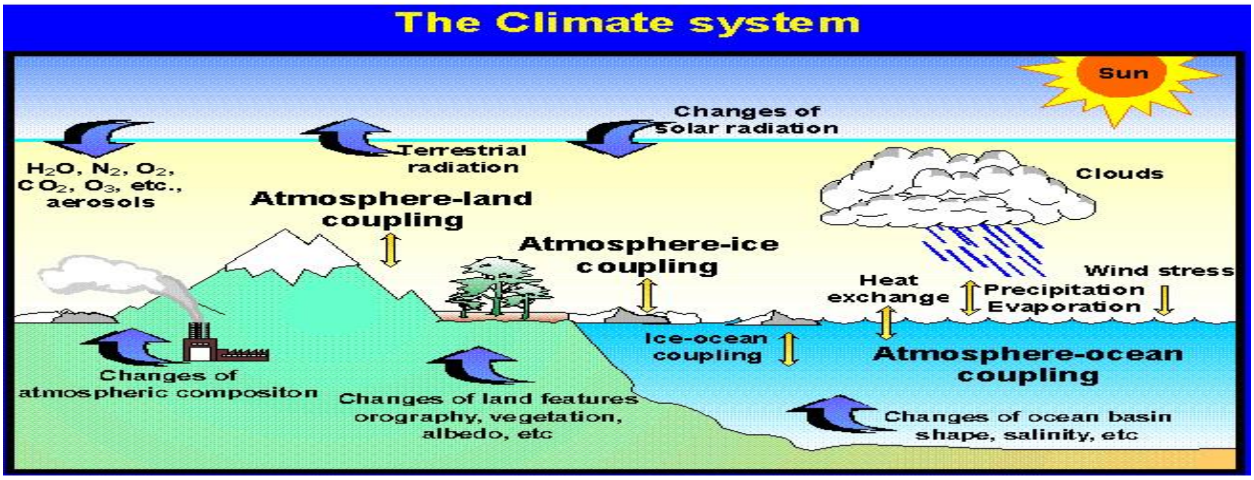

Figure 2.2: Climate System Components: (Source: https://www.windows2universe.org Met)

The global climate variability has over the recent decades heavily impacted on subsistence agriculture and food production systems around the World (Ali et al., 2020). In Africa as a whole, and in East Africa in particular, maize, beans and cassava are among the highest cultivated temporary subsistence crops whose production has been negatively affected by extreme climatic variability. Unexpected spells of drought or heavy rainfall have immediate and long term consequences for subsistence farming, resulting in socioeconomic influences due to the climate related stresses. In East Africa, the risks of extreme weather conditions have been critical as they have heavily affected investments in agriculture and hampered sustainable food security over the long term (Kangalawe et al., 2017). Therefore, research shows that the adversities caused by climate change can significantly affect subsistence farming yields over a given region.

2.2.1 The State of Climate Variability and Climate Change in Kenya

In a study carried out by Xu et al. (2017), they noted that climate variability has a weighty environmental and socioeconomic influence mainly on food security, human well-being, shortage of fresh water and loss of biodiversity. In addition, Omoyo et al. (2015) noted that Arid and Semi-Arid Lands (ASALs) experience severe drought at least once in every five years which leads to rampant food insecurity, increased poverty rates and deduction of agricultural produce. Variability of climate is one of the critical problems in the world and is perceived to be one of the most significant threats to sustainability with adverse environmental effects, food protection, human health, economy and natural resources. Based on a wide range of study regions and plants, climate change had a more significant negative impact on crop yields than positive effects (Kinyanjui, 2019). As Kenya 's economic backbone, agriculture is highly vulnerable to raising temperatures, dryness and floods, which reduce productivity in crops.

(Kilavi et al. (2018) established that across Kenya there are no new droughts and floods. Only a year after drought wreaks havoc on the region, we experience heavy rain. The country is devastated by the damages incurred by the two disasters. Its features, frequency, duration and range vary from event to event. Over time, the frequency and severity of floods and droughts have increased. Hunger relief due to climate extremes is a frequent feature today, with an increased incidence of extended droughts in certain parts of the arid and semiarid counties such as Laikipia. The Laikipia Wildlife Forum (LWF 2018) reported that most of the perennial rivers that flow in and out of Laikipia, including; Ontulili, Nanyuki, Naromoru, Upper Ewaso Nyiro, Mutara, Suguroi, and Pesi, dried up exceptionally quickly, regardless of this being a dry season. The river that flows from Mount Kenya and Abardares Ranges have been depleted by over abstraction by locals, which creates extremely higher demand for household water and irrigating water. The report noted that the identified impacts have already affected food production leading to increased food insecurity, poverty and even loss of human life as farming is the county's main source of livelihoods.

2.2.1 Detection Techniques for Climate Variability and Climate Change

Different communication technologies allow the meteorological departments to track various aspects of climate behaviours such as temperature, wind speed and direction and humidity over space and time. It is important to keep track of all the climate parameters in order to achieve a balance in predicting suitability for subsistence agriculture (Sose & Sayyad, 2016). Modern weather monitoring technologies are designed to track weather and climatic patterns in a cost-effectively and pinpoint out-of-range conditions. Space-deployed remote monitoring systems are made up of 2 key components: The satellite which has data-collection sensors, and the data processing system. The latter has the task of getting real-time data from the satellite. It also schedules the tasks needing to be processed.

The modern approach uses wireless technologies to monitor climate change and weather patterns. The typical design of a modern system is made up of transmitters that have different sensing capabilities for temperature, humidity air quality, atmospheric pressure, etc. For wired systems the output is shown of a liquid crystal display, but the wireless systems use instead a computer monitor that is mounted at a remote location. Figure 2.3 below shows the typical configuration of a modern weather station.

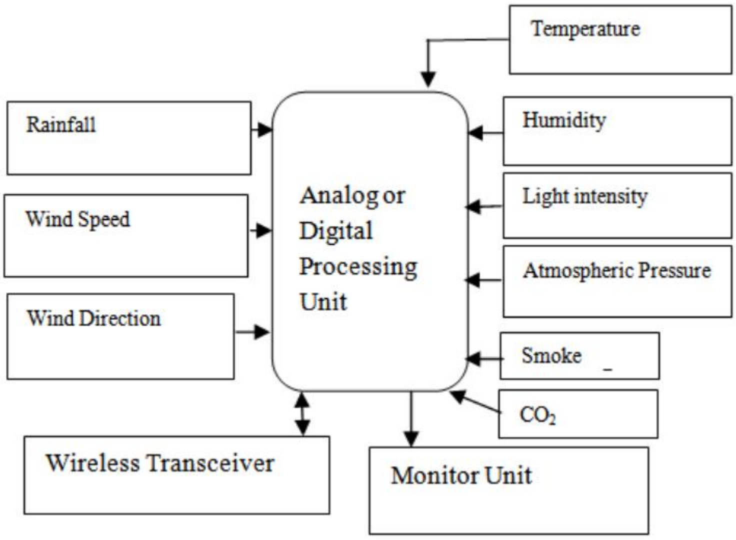

Figure 2.3: Block diagram of a typical weather monitoring station (Source: Sose & Sayyad, 2016)

Different sensors exist with varying capabilities for monitoring weather and climate ranging from simple to complex, such as rain gauge, hygrometer, barometer, wind sock and MODIS satellite images. The *rain gauge* measures the amount of rain over a set time period, usually in millimetres. The total amount of rain that arrives on the ground is deemed as the depth to which it would cover the earth if the earth was level, and in the absence of loss due to evaporating moisture, run-off, or infiltration (Lanre & Umoru, 2012). The *hygrometer* measures an area's humidity, or the amount of atmospheric water vapour. The hygrometer can also take measurement of temperature in degrees Celsius. The measurements can be achieved using a carbon-coated plate (electrical hygrometer) or an infra-red sensor mechanism (infra-red hygrometer). The *barometer* measures atmospheric pressure and can be digital or analogue. The *windsock* is a lightweight and flexible cone or cylindrical instrument that is mounted on a mast and relays the wind direction and strength. Indication of wind direction is by pointing away from the wind as the windsock is blown by wind. Figure 2.4 shows the various instruments used to monitor the weather and climatic trends in a typical weather station.

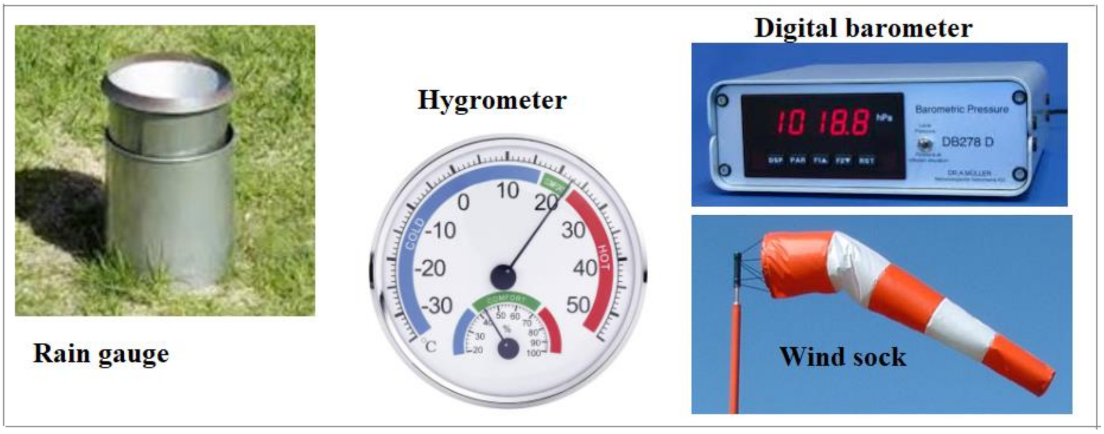

Figure 2.4: Various instruments used to monitor the weather and climatic trends.

Another effective way of monitoring weather and climatic patterns at high-precision spatial and temporal resolution is through the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument which sits on board the National Aeronautics and Space Administration's (NASA) Aqua (EOS-PM1) or Terra (EOS-AM1) satellites (Tomlison et al., 2012). MODIS satellite images can be processed to determine land surface temperatures and other atmospheric variations.

2.3 Theoretical Framework

Climate change studies have increasingly gained importance within academic debates. A number of theories of climate change and climate adaptability exist as proposed by Blast (2010). The most common include anthropogenic global warming, Bio thermostat theory, Cloud formation and Albedo theory, Human forcing besides greenhouse gases theory and Ocean currents theory. Each of these theories is discussed in the sub-sections below.

2.3.1 Anthropogenic Global Warming Theory

This theory postulates that humans emit greenhouse gases such as CO_2, methane and nitrous oxide which cause significant rise in global temperatures through what has been termed as the “enhanced greenhouse effect”. Proponents of the anthropogenic global warming theory agree that the increase in global warming over the past 30 years is largely as a result of manmade greenhouse gases. Researchers using this theory have also applied computerized models to project that the CO_2 in the atmosphere will double by the year 2100 causing the Earth temperatures to rise by an additional 3 degrees centigrade. It has also been proposed that man made CO_2 largely accounts for the presence of droughts, flooding, severe weather patterns, crop yield failure, extinct species, disease spreads famines and a number of other undesirable environmental effects (Blast, 2010). The theory contends that if human emissions are reduced, the rate of global warming will in turn reduce significantly.

2.3.2 Bio thermostat Theory

This theory developed by Blast (2010) and supported by Agba et al. (2017), Rahman and Turay (2018) and Cookey et al. (2020) attempts to mitigate and establish an equilibrium for other negative theoretical formulations. It purports that a number of negative feedbacks arising from biological and chemical processes (such as carbon sequestration by plants, biological carbonyl sulfide emissions from soils, diffuse light, iodinated particles in sea air, biologic dimethyl sulfide from the World oceans, and a number of other aerosols) tend to significantly offset the positive feedback effects which arise from the increasing levels of atmospheric CO_2. It is proposed that these mitigating processes play the role of “global bio thermostat” in maintaining world temperatures at a certain equilibrium. While this theory has been supported by a number of research studies, several others have disputed this theory with evidence that despite the existence of these mitigating mechanisms, the levels of atmospheric CO_2 has continued to rise at a steady level.

2.3.3 Cloud Formation and Albedo Theory

This theory of climate change purports that variation in how albedo clouds are formed can cause negative feedback effects which tend to cancel out a good proportion of the warming effect caused by rising levels of atmospheric CO_2. The basis of the Cloud Formation and Albedo Theory leans more on observed data from a set of research study rather than the formulation of mathematical and computerized models. As early as 1999, a NASA researcher named Yogesh Sud and his team observed that cloud-cover variation within the tropics posed a natural thermostat by maintaining sea-surface temperatures at between 28 and 30 degrees Celsius. The team concluded as a result of their analyses that sea-surface temperature rise causes the air at the cloud cover base to be charged with moist static energy that causes the clouds to the upper troposphere. This cloud cover then causes a reduction in the level of solar radiation arriving at the sea surface and promotes ocean-surface cooling. Lindzen (2001) an MIT meteorological professor of meteorology and his fellow researchers observed that upper level cloud areas inversely affected the average sea surface temperature in the cloudy regions West of the Pacific ocean. The negative feedback effects as computed by Lindzen et al. (2001) was so substantial that it was estimated to cancel out nearly all the positive feedbacks in the current climate models. Later on, Choi et al. (2010) found negative feedback effects in clouds in the tropics and concluded that while indeed research models show climate sensitivity to increased CO_2 levels, the negative feedbacks from clouds against global warming eliminate a good level of the imminent danger posed.

2.3.4 Human Forcing Besides Greenhouse Gases Theory

This theory proposes that even though the natural causes of climate change are crucial, a great influence of man to climate change includes actions such as building cities, cutting down forests, or irrigating deserts. De Laat et al. (2004) observed that by virtue of high concentration of energy emitting machinery, motor vehicles, concentrations of concrete, asphalt and road-building material which absorb solar energy and produce thermal energy, cities naturally tend to be warmer than the rural areas. Additionally, the removal of trees and forests by burning which is commonly done in developing countries causes atmospheric CO_2 to be released thus preventing forests from further sequestering of carbon. Pasture-and or crop-production land which replaces forests does not possess sufficient shade and is thus warmer. Bebber and Butt (2017) estimate that between 0.25 and 0.33 of atmospheric CO_2 emission is caused by deforestation.

2.3.5 Ocean Currents Theory

This theory of climate change has contended that the World temperature variability over the past thirty years have been caused by the slowing down of the ocean's thermohaline circulation (Gray, 2006). Thermohaline circulation occurs when the ocean's water is transferred from the surface-mixed layer to the inner part of the ocean in a process referred to as ventilation. Every 1000-2000 years the ocean ventilates itself completely and the cold saline water moves to the polar region (the Atlantic and Antarctic) while the warmer less saline water moves to the tropics. Data and meteorological experiments have revealed variations over decades and centuries in the thermohaline circulation over the past a thousand years. When this circulation reaches beyond normal strength, the earth incurs a higher level of evaporation or precipitation. When the circulation is weaker than usual (about half the time), then the world experiences rainfall and a reduction in surface evaporation at around 2%.

2.3 Machine-Learning Approaches for Predicting Climate Change Suitability for Subsistence Agriculture

The application of machine learning techniques to monitor and predict climate change for subsistence agriculture has the potential to benefit the involved societies as well as to advance the field of machine learning by improving interpretability of outcomes, causal effects and to quantify uncertainty. Several machine learning approaches have been used in various aspects of predicting and managing climate change. For example, a number of research studies in the past have applied computer vision strategies to process satellite images and generate size and location data for objects such as roof-top solar panels. Such machine learning techniques can also be used to produce information within low data settings with the aid of computer vision alongside graph-search techniques, such as to estimate the layout of sensor and electric grids in regions where they have not been clearly mapped (Gershenson et al., 2019).

The use of time series analysis has in the past been applied to model events that change over time, such as the degradation of vegetation and forest cover (Bullock et al., 2020). Such analyses allow careful monitoring of dynamic events and allow for reliable prediction of phenomena such as the management of forests.

Natural language processing (NLP) is useful in research focused on aligning policy information to be more manageable and relevant to individuals, such as based on the localized environment in which individuals reside. NLP has a potential for deriving comprehensive insights from policy-based text data for various applications, akin to automated compliance-checking [698, 699]. (Zhang & El-Gohary, 2015). Machine language techniques like NLP, network analyses and clustering have also been applied for analysis of social media data in order to derive public opinions and discourse surrounding climate change (Kirilenko & Stepchenkova, 2014). Other common applications of machine language for NLP include identification of climate risks in disclosures generated by companies and the analysis of evolving climate coverage in the social media to dynamically mitigate the risks of climate change (Stanny & Ely, 2008; Vetri & Atanasova, 2017).

Machine learning is also useful for integrating data driven knowledge into developed models. For instance, the use of unsupervised learning which do not required labelled data, such and Variational autoencoders and Generative adversarial networks have been applied to observe the salient characteristics which are crucial within a complex modeling environment (Gunaratne & Garibay, 2020).

Supervised ML techniques and the use of fuzzy logic have been used by researchers in different contexts to quantify uncertainty. Research studies in the field of material science have commonly used supervised learning active learning and generative modeling to model and synthezise different materials (Butler et al., 2018). Other works have applied supervised learning techniques such as decision tree analysis, adaptive-fuzzy logic and support vector machines to classify certainty and forecast events based on past disruption data (Murari et al., 2020).

Regression models are useful for quantifying non-linear associations between linked variables (Rolnick et al., 2019). While regression techniques have not been popularly used for climate change monitoring, a few studies such as Roberts et al. (2017) and Xie et al. (2019) have applied regression models to predict risk perception of climate risk in the community, as well as to compare crop models with statistical models in understanding climate-change implications.

Table 2.1 shows a summary of various applications of machine learning within the context of climate change management:

Table 2.1: Applications of machine learning for climate change modeling and prediction

	Computer vision	Interpretable models	Natural lang. Pr.	Time Series An.	Uncertainty quantification	Unsupervised learning	Supervised learning	Regression	Source
Remote sensing of emissions	•			•			•		Gershenson et al., 2019
Precision agriculture	•			•		•			Gunaratne & Garibay, 2020
Monitoring farmlands	•								Gershenson et al., 2019
Managing forests	•			•					Bullock et al., 2020
Sequestering CO2	•				•	•	•		Murari et al., 2020
Data, ML & climate change	•	•		•	•				Gershenson et al., 2019
Monitoring ecology	•			•					Bullock et al., 2020
Monitoring agricultural crisis	•		•						Vetri & Atanasova, 2017
Modeling impacts				•	•				
Monitoring sensor effect	•			•			•	•	Xie et al. (2019)

2.4 Variables for Determining Effectiveness of Climate Sensors for Subsistence Agriculture

There are several different factors that can be modeled when determining the effectiveness of climate sensors for sustainability of subsistence agriculture. The following are some of the most common factors according to previous research studies:

i) Geographic extent: The refers to the extent of land, often in kilometers, that the sensor measurements can effectively cover in a single snapshot. In a time series analysis of climate change detection with remote sensing techniques, Ayele et al. (2018) showed that the extent of geographic coverage greatly contributes to the effectiveness of a climate sensor in predicting favorable climatic conditions.

ii) Temporal scope: This refers to the length of the time interval used by the sensors to measure climate variation over space and time. Yu et al. (2018) quantified spatial and temporal patterns in predicting extreme bad-weather events and discovered the temporal extent of sensor measurement as a significant factor in quantifying the effectiveness of a given sensor.

iii) Precision level: This refers to the level of detail and accuracy with which the sensor captures and records measurements. Yadav and Congalton (2028) conducted a simulation of crop-yield potential over three continents and concluded that accurate assessments from the sensors are large determinants of sensor effectiveness.

iv) Frequency of usage: This refers to the number of times per minute, hour, day, month, week, etc. that the sensor captures information over the same geographic extent. Merry and Bettinger (2019) observed differing levels in error management and usage effectiveness in smartphone-mounted climate sensors with increased WIFI usage and have suggested this to be an important variable. Massaoudi et al. (2021) have recently observed similar importance of usage frequency through a random forest model of short-term-power forecasting using weather instruments.

v) Cost of acquisition: This refers to the initial cost of deploying the sensor and provides a way of quantifying the affordability of the sensor technology. While many studies have linked cost with precision and effectiveness where sensors are concerned, Gonçalves et al. (2018) and Laporte-Fauret (2019) have shown in their studies that relatively affordable sensors can predict at high resolution over large geographic extents. Nevertheless, cost is a significant factor whose influence is worth examining further.

2.5 Knowledge Gaps

As has been determined by Massaoudi et al. (2021), the problem of determining how effective a climate sensor is at the local geographic scale is a very complex problem and one that has not been sufficiently explored. As was shown in Table 2.1, predictive approaches such as regression have not been fully utilized in predicting effectiveness of weather sensors, particularly within localized subsistence agriculture environments. Unfortunately, the localized subsistence farming is surrounded by a lot of uncertain scenarios emanating from effects of high CO_2 levels and global warming which can lead to incorrect estimation of climate variability. Additionally, to the knowledge of the author, very few studies exist that have incorporated the input from direct stakeholders within localized farming scenarios to provide greater insight into how climate variability is affecting farming at the grassroot level. Researchers according to Awazi et al. (2019), the existing partial investigations have considered the impacts of climate variation and climate change in isolation and provided insufficient knowledge regarding the degree of awareness of the local weather stations and local farmers on the issue, including which actions are being done, when and how, in order to cope with the changes. Given the fact that subsistence agriculture in most ASALs including Laikipia County depends greatly on climate variability, prolonged dry seasons are one of the most serious climate hazards affecting the agriculture sector, and more research incorporating local stakeholders is needed to increase sustainability in this area.

2.6 Conceptual Model

Using knowledge advanced from the examination of previous studies, the study proposes the following conceptual model.

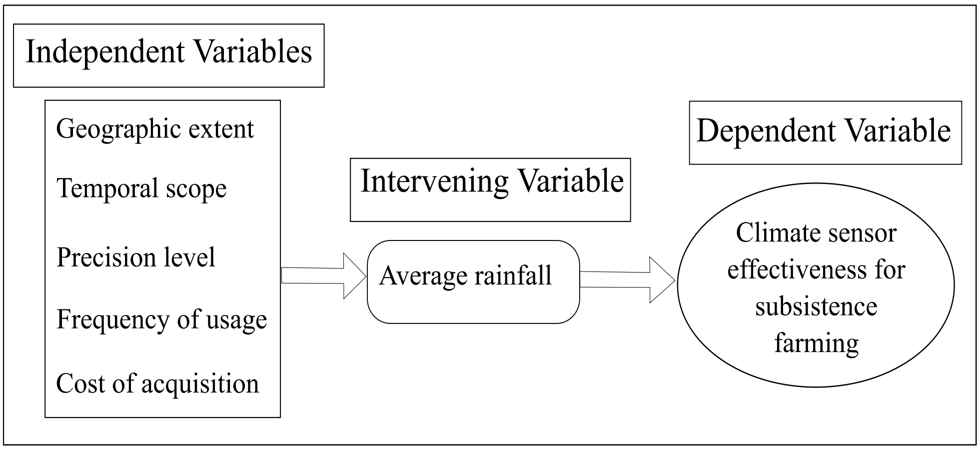

Figure 2.5: Conceptual Model

2.7 Chapter Summary

This chapter has presented a review of the related literature on climate change and its effect on subsistence farming. After establishing the extent of practice and the gaps therein, the chapter has conceptualized a model of dependent, intervening, and independent variables relying on knowledge from existing works. The developed conceptual framework will guide the methodology chapter that follows to map out the analytical framework.

CHAPTER THREE

RESEARCH METHODOLOGY

This chapter outlines the methods and procedures that the research has applied. It describes the research design, target population and sample, study instruments, data collection procedures and data analysis.

3.1 Research Design

The current study adopted a survey research design. This is a set of procedures within quantitative research that involves the investigator administering a survey to a sample or an entire population of study participants in order to quantify and describe attitudes, opinions, characteristics or behavior of the population or aspects of the phenomena that the population experiencing (Braun et al., 2020). In a survey research design, the survey researcher collects quantitative numbered data by means of interviews (usually administered one-on one with or without recording), or through questionnaires which can be physically administered on a drop-and-pick basis, emailed, or administered online. In the current study the researcher conducted an online survey in which the questionnaire was administered online through Google Forms tool.

The data was then analyzed to identify trends about the responses to questions and to test the research questions. As an extension to the survey design, a set of model variables was constructed from survey variables to enable prediction of the effectiveness of sensor data collection techniques for predicting climate suitability for subsistence farming in Laikipia Country in the face of climate change. Figure 3.1 below show a flowchart of the activities which was conducted as part of the survey research design.

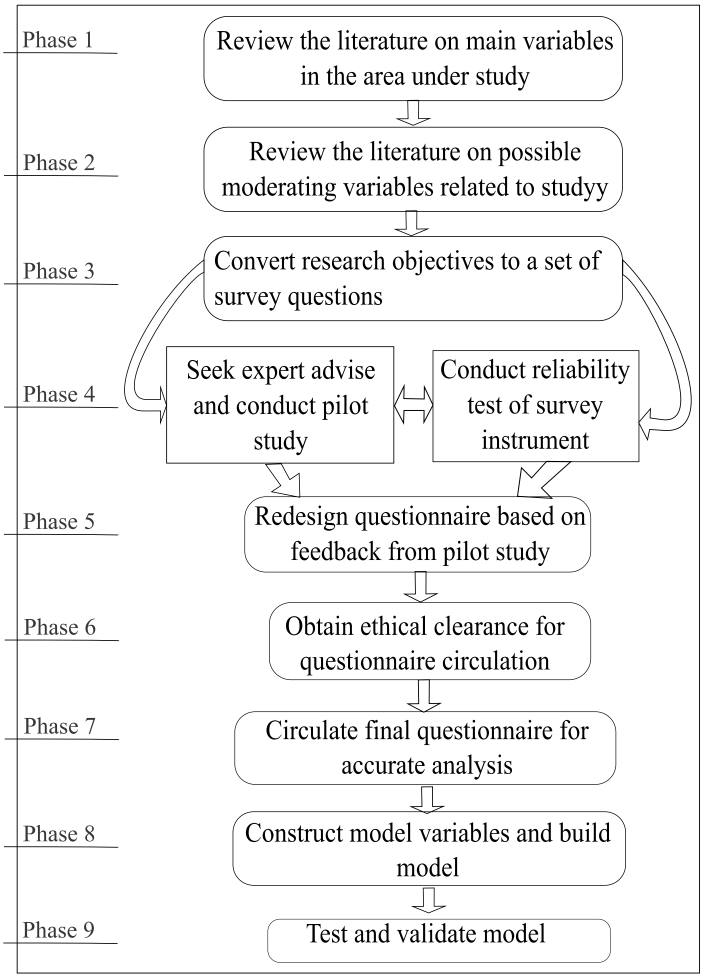

Figure 3.1: Flowchart of the study survey research design

3.2 Target Population

The targeted population for administering the online questionnaire consisted of a total of 86 participants. 18 of these were agricultural extension officers from Laikipia County, six from each of the three administrative sub-counties or constituencies: Laikipia East, Laikipia North and Laikipia West. 10 were from the Meteorological Department in Laikipia and the rest of the participants (i.e., 58 participants) were subsistence farmers who grown at least one of the three most common subsistence crops in Laikipia County: maize, beans and wheat.

3.3 Sampling

The study adopted a mixture of convenience sampling as based on participants who had access to the online questionnaire tool, and snowball sampling, especially for the farmers who were able to refer their fellow farmers to conduct the survey. The sample size of 86 respondents from the three administrative sub-counties in Laikipia County was drawn from a population of about 460 entities, i.e., 128 agricultural extension officers, 72 meteorological officers and 395 subsistence farmers. According to the Neymann Allocation sampling technique (Tarray & Singh, 2017), the sample size *n* was calculated as:

$$n = (\text{Ncv2})/ (\text{cv2} + (\text{N-1})\ e^2)$$

where; *N* is the population, *cv* is coefficient of variation taken to be (0.5) and *e* is tolerance level at 95% confidence level (0.05). This was 14% of the entire population. Table 3.1 shows the summary of the study sample against the population.

Table 3.1: Sample size selected from the relevant population in Laikipia County according to Neymann Allocation sampling technique

	Target Population	Sample size	Sample size as % of population
Agricultural extension officers	128	18	14%
Meteorological officers	72	10	14%
Farmers in Laikipia East	180	27	15%
Farmers in Laikipia North	108	15	14%
Farmers in Laikipia West	107	16	15%
Total	595	86	14%

For convenience and to encourage timely participation, the survey was administered through a carefully structured questionnaire which was deployed online and with links sent to the sample participants through contact persons.

3.5 Research Instruments

The main research instrument for this study was the questionnaire. Document analysis and questionnaire responses were the primary techniques of data gathering in this study. The use of the online questionnaire was important in this research because of its strength in collecting qualitative data and the nature of the research through interaction with experts in the field to obtain their opinions. According to Braun et al. (2020), a fully-qualitative survey that prioritizes qualitative research values and harnesses the rich potential of qualitative data has a lot to offer the qualitative researcher, especially given the online delivery options. While this method has remained highly underused over the recent decades, its use has gained a lot of prominence over the recent year because of the limitations that researchers experienced in reaching the study participants at the onset of the COVID-19 pandemic. The use of qualitative surveys provides an exciting and flexible technique with numerous applications. It offers numerous advantages for researchers and participants alike, such as flexibility, anonymity and freedom.

In this research document analysis, which is a critical examination of public or private recorded information relating to climate change effects on subsistence agriculture in Laikipia County was used as a data collection technique. Document analyses enabled the researcher to access data at his own convenient time, and also to obtain nonobstructive information for the purpose of the research.

3.6 Reliability and Validity of the Instruments

Reliability is a measure of internal consistency with which survey items of the same category are related with each other (Chan & Idris, 2017). Reliability of the research questionnaire instrument was assessed using the 2-way internal consistency Cronbach’s alpha with the Statistical Package for the Social Sciences (SPSS) software. A threshold of 0.6 was set for the Cronbach’s alpha as the level of tolerance for reliability of the items in the questionnaire.

Values of ≥ 0.7 was considered as satisfactory, while a score above 0.8 was used to indicate high reliability of the questionnaire instrument.

On the other hand, the validity of the research questionnaire was tested using exploratory factor analysis. Specifically, the study used principal component analysis to extract the factors that contributed significantly to the study objectives.

3.7 Data Processing and Analysis

In order to achieve objective one, i.e., "to determine the factors that affect the effectiveness of sensors for detecting climate variability and suitability for subsistence agriculture in Laikipia County", the study conducted descriptive analysis of variables extracted from the survey data. This was by means of measures of central tendency in the distribution of the survey data such as mean, median, min, max and standard deviation. The arithmetic mean involved adding all the numbers for each variable and dividing the sum by the number of data points. Min and max was used to define the range of values from the lowest to the highest to help in identifying outliers. Standard deviation computed the variation in distribution of the data values. A small value of the standard deviation indicated a normally distributed data whose values do not deviate from the mean (Kemp et al., 2018). In addition to this, visual output was generated using bar charts and graphs.

Objective two was "to design and develop a predictive logistic regression model of climate sensors effectiveness". This was achieved using mathematical functions provided in the R statistical language (https://www.r-project.org/). R is a free software environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows and MacOS (Allen & Singh, 2012). The model developed was a logistic regression model of the form:

$$\text{logit}(p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5$$

where *logit(p)* is the logit or log odds, β_0 is the model's intercept, β_1, β_2.. β_6 are the independent variables' coefficients, and X_1, X_2, X_3, X_4, and X_5 are the variables geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition respectively.

3.8 Model Validation

The final objective of this study was to test and validate the predictive model. This was achieved using Chi-Square (χ^2), root mean standard error of approximation (RMSEA) and an adjustment for model goodness of fit using the adjusted goodness-of-fit index (AGFI). The χ^2 is the conventional measure for assessing a model's overall fit (Chan & Idris, 2017). The study adopted a threshold value of 0.05 significance level, and values between 0.05 and 0.03 of the χ^2 were considered acceptable, while below this the model was considered as excellent fit. For the root mean standard error of approximation, values between 0.05 and 0.08 was considered as acceptable. Finally, the study set a threshold of 0.85 or higher to indicate a well-fitting model. Adjusted goodness-of-fit index values ranged from 0 to 1, with 0 indicating a poor model and 1 indicating a robust model.

3.9 Ethical Considerations

The study ensured that genuine and accurate results were recorded to the best of the researcher's capacity, achieved though constant communication with study participants and the supervisor and through adherence to study guidelines. Consent, mostly in writing, was sought from respondents before any information was collected. The survey participants were informed of their right not to participate or to withdraw from the survey study. Confidentiality about the respondent identities was protected by treating data in aggregation.

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

This chapter presents an analysis of the findings from the effectiveness of climate sensors for predicting suitability of subsistence agriculture. The IBM Statistical Package for the Social Sciences (SPSS) software version 21 was used for descriptive analysis and the R statistical software was used for building and validating the model.

4.1 Response Rate

Out of the targeted number of 86 survey participants for the study, 73 took part and completed the questionnaire, indicating a response rate of 85%. For the number of meteorological officers the response rate was 90%. For the agricultural extension officers the response rate was 89% while for the subsistence farmers the response rate was 71%. Figure 4.1 below shows the distribution of the participants who successfully took part in the online survey.

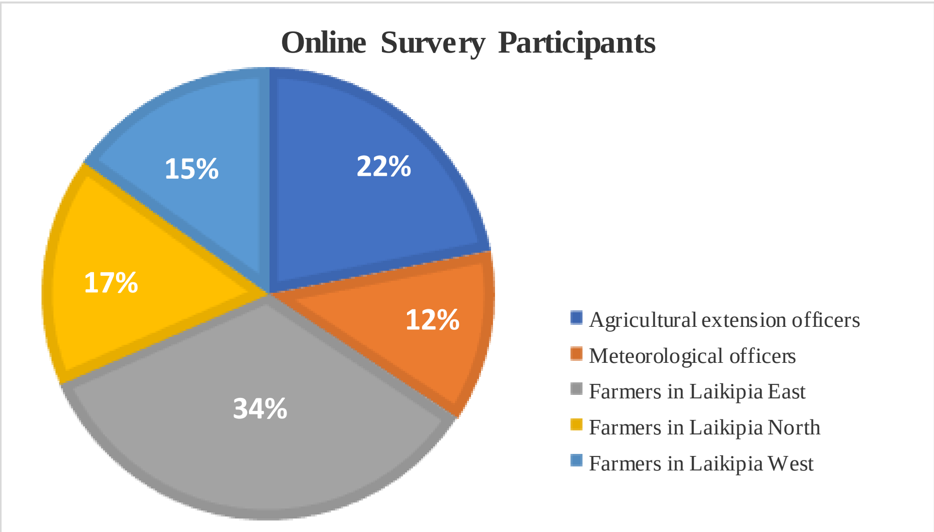

Figure 4.1: Distribution of study participants

4.2 Reliability and Validity of the Survey Instrument

As was stated in chapter 3, reliability is a measure of internal consistency with which survey items of the same category are related with each other. This study assessed reliability using the 2-way internal consistency Cronbach's alpha with the Statistical Package for the Social Sciences (SPSS) software. The Cronbach's Alpha value was 0.865, which showed high reliability of the items in the online questionnaire.

On the other hand, the validity of the research questionnaire was tested using principal component analysis. Table 4.1 below shows the principal components that were adopted for use in this study. These principal components correspond to the factors that contribute significantly to the study objectives. Only one variable cost of sensor acquisition contributed significantly to PC1. Two variables, geographic extent and temporal scope contributed to PC2, while precision level and frequency of usage had a weak contribution to PC3. PC1 was the largest principal component, contributing 32.3% of the explained variance, while PC3 had the weakest contribution of 7.3%.

Table 4.1: Principal Components Analysis of the full dataset (*n*=73 respondents)

ID	Variable Name	PC1	PC2	PC3
1	Geographic extent (**X1**)	0.152	**0.375**	0.318
2	Temporal scope (**X2**)	0.185	**0.398**	0.301
3	Precision level (**X3**)		0.193	**0.325**
4	Frequency of usage (**X4**)		0.232	**0.467**
5	Cost of acquisition (**X5**)	**-0.309**		-0.106
	% Variance Explained	32.3%	12.6%	7.3%

4.3 Descriptive Statistics

Table 4.2 below shows the demographic information for the study participants were male. Most of the study participants (87%) were either using climate sensors or obtaining information from these sensors in order to predict suitability for subsistence farming. Most of the survey candidates who were farmers were not familiar with the MODIS satellite images, although those who were familiar with the technology indicated they had not used it directly.

Table 4.2: Demographic characteristics of Study Survey Participants (*n*=73 respondents)

ID	Variable Name	Description	Min	Max	Mean	SD
1	Age	Number	21	68	52	23.45
2	Gender	Categorical (4 Levels)	1	4	1.57	.611
3	Profession	Categorical (4 Levels)	1	4	2.53	.592

At the same time the survey participants were asked how often they interacted with the different climate sensors, either directly or by getting information from them. The most interaction was with the rain gauge and barometer while the least interaction was from the MODIS satellite images. Table 4.3 below shows the statistical distribution of the responses.

Table 4.3: Descriptive analysis on interaction with different climate sensors (*n*=73 respondents)

ID	Sensor	Description	Min	Max	Mean	SD
1	Rain gauge	Categorical (5 Levels)	1	5	3.38	.412
2	Hygrometer	Categorical (5 Levels)	1	5	2.56	.215
3	Barometer	Categorical (5 Levels)	1	5	3.24	.481
4	Windsock	Categorical (5 Levels)	1	5	2.77	.739
5	Satellite images	Categorical (5 Levels)	1	3	1.09	.285

On the frequency with which the study participants received information on various aspects that influence subsistence farming, the survey respondents responded mainly positively, with most participants rating the aspects on a high scale. Figure 4.2 shows the frequency of communication regarding different information extracted from the climate sensors data.

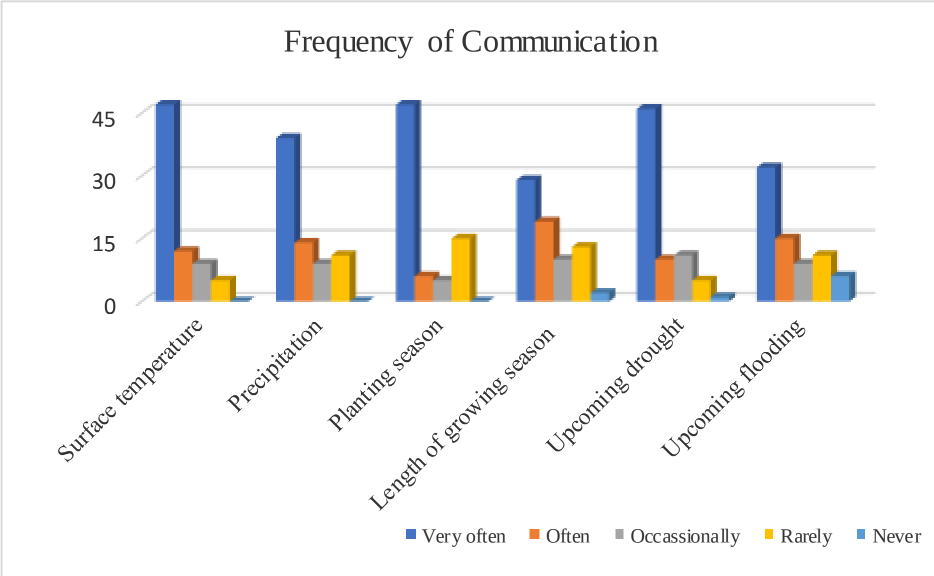

Figure 4.2: Communication frequency on key farming aspects

Participants who interacted with the different climate sensors were asked to rate their general characteristics based on a number of conditions. In general the coverage extent and coverage frequency over the Laikipia wards were the aspects rated quite highly. The cost of acquisition was rated low, especially for the MODIS satellite images and the hygrometer. Similarly, precision of the sensors was only moderately rated. Figure 4.3 shows the rating statistics.

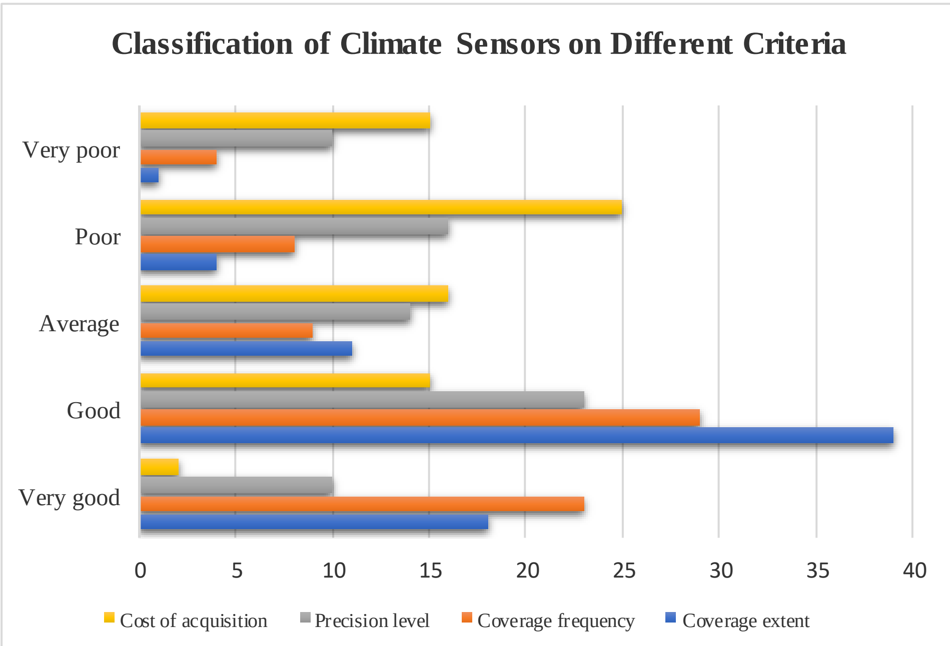

Figure 4.3: Classification of climate sensors by various criteria

Lastly the survey participant classified the effectiveness of the climate sensors based on 5 pre-defined criteria on a 5-points Likert scale. The general opinion was that while the sensors provided timely information, the accuracy of this information was not rated very highly. Table 4.4 shows the statistics of these ratings, while Figure 4.4 below shows the distribution of the effectiveness criteria ratings.

Table 4.4: Descriptive analysis on effectiveness of different climate sensors (*n*=73 respondents)

ID	Criterion	Description	Min	Max	Mean	SD
1	Accurate	Categorical (5 Levels)	1	5	1.87	.651
2	Timely Information	Categorical (5 Levels)	1	5	3.92	.215
3	Suitability for predicting dry season	Categorical (5 Levels)	1	5	1.98	.559
4	Suitability for predicting wet season	Categorical (5 Levels)	1	4	1.52	.239
5	Suitability for predicting length of the growing season	Categorical (5 Levels)	1	4	1.55	.833
6	Suitability for predicting precipitation	Categorical (5 Levels)	1	5	2.32	1.058

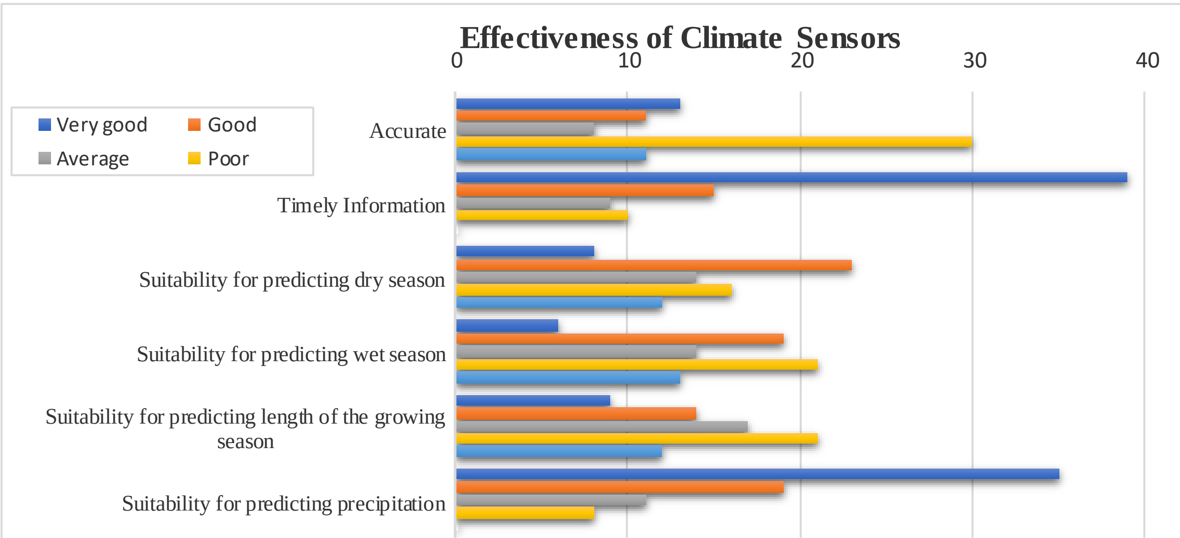

Figure 4.5: Classification of sensor effectiveness parameters

4.4 Predictive Modelling of Climate Change Suitability for Subsistence Agriculture

With the input from the descriptive statistics, the study considered all the variables from the conceptual model into the predictive logistic regression model, i.e., geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition as independent variables for predicting the climate sensor effectiveness. Table 4.5 shows the coefficients of the model variables used for the prediction. The most significant variable was the cost of acquisition (*p*=0.016) which showed that increased cost of acquisition of the climate sensor of sensor data had a significant negative impact on the predictive effectiveness of the climate sensor. Similarly, the variables temporal scope and frequency of sensor usage were positively influencing the predictive effectiveness. Geographic extent of coverage showed the least predictive effectiveness in terms of significance (*p* = 0.057).

Table 4.5: Logistic regression model estimates for sensor effectiveness (n=73 respondents)

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	2.161	1.212		1.783	.100
Geographic extent (**X1**)	.558	.225	.158	1.700	.057
Temporal scope (**X2**)	.605	.108	.142	2.506	.022
Precision level (**X3**)	.452	.119	.352	2.275	.027
Frequency of usage (**X4**)	.407	.121	.454	2.711	.023
Cost of acquisition (**X5**)	-.082	.345	-.059	-2.238	.016

a. Dependent Variable: Effectiveness of climate sensors in predicting suitability levels for subsistence farming

Table 4.6 below shows the model summary. The R-Square in the table suggests that the various variables affecting effectiveness of sensor prediction of farming suitability, i.e., geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition are together contributing 63.7% of the predictive effectiveness.

Table 4.6: Model Summary (n=73 respondents)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.759[a]	.637	.615	.183

a. Predictors: (Constant), geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition

b. Dependent Variable: Effectiveness of climate sensors in predicting suitability levels for subsistence farming

4.5 Predictive Model Validation

The final objective of this study was to test and validate the predictive logistic regression model, using measures such as Chi-Square (χ^2), root mean standard error of approximation (RMSEA) and an adjustment for model goodness of fit using the adjusted goodness-of-fit index (AGFI). Table 4.7 below shows the summary of the validation process. The regression Chi-square value of 0.043 indicated a very good model's overall fit since it was below the threshold value of 0.05. Similarly, the root mean standard error of approximation (RMSEA) showed an acceptable model fit that was below the threshold of 0.05. Finally, the adjusted goodness-of-fit index (AGFI) of 0.819 indicated a robust model since the maximum value for this coefficient is 1 indicating the best model.

Table 4.7: Logistic Model validation of Goodness of fit (n=73 respondents)

Model	Chi-Square (χ^2),	df	RMSEA	AGFI	Sig.
Regression	.043	6	.049	.819	.021[a]
Residual	.067	11	.051		

a. Predictors: (Constant), geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition

b. Dependent Variable: Effectiveness of climate sensors in predicting suitability levels for subsistence farming

4.6 Discussion

This study set out to establish the factors influencing the effectiveness of climate sensors in communicating suitable conditions for subsistence farming in Laikipia County, one of the arid and semiarid lands (ASALs) of Kenya. Further, the study set to develop a predictive model around these factors and to validate the developed model.

The key variable that was found to significantly affect the dependent variable was the cost of sensor acquisition (p=0.016) which showed that increased cost of acquisition of the climate sensor and associated sensor data had a significant negative impact on the predictive effectiveness of the climate sensor. This is in line with other studies e.g., Gonçalves et al. (2018) and Laporte-Fauret (2019) who have shown in their studies that although relatively affordable sensors can predict at moderate resolution over large geographic extents, more precise sensors are extremely expensive to acquire.

The variables with a positive influence on the dependent variable in this study were temporal scope and frequency of sensor usage. In related studies, Merry and Bettinger (2019) observed differing levels in error management and usage effectiveness in smartphone-mounted climate sensors with increased WIFI usage and have suggested this to be an important variable. Massaoudi et al. (2021) have recently observed similar importance of usage frequency through a random forest model of short-term-power forecasting using weather instruments. Yu et al. (2018) quantified spatial and temporal patterns in predicting extreme bad-weather events and discovered the temporal extent of sensor measurement as a significant factor in quantifying the effectiveness of a given sensor.

Although the geographic extent of coverage was not seen in this study to be significant and it showed the least predictive effectiveness (p = 0.057), other studies have uncovered different results. For example, Ayele et al. (2018) showed that the extent of geographic coverage greatly contributes to the effectiveness of a climate sensor in predicting favorable climatic conditions. This was in a time series analysis of climate change detection with remote sensing techniques in Northern Ethiopia. The contrasting findings here may pinpoint the geographical differences that exist between the current study area and Ayele et al. This also means that further studies are needed within the Kenyan context.

4.7 Chapter Summary

In this chapter, the study undertook to present a study analysis on various aspects such as descriptive and inferential analysis. The descriptive statistics consisted of the demographic composition of the respondents, whereas the inferential statistic comprised of logistic regression analysis of the study variables. The study also undertook reliability and validity test of the study variables and data sets to ensure their adherence to internal consistency and stability. The next chapter discusses the key research findings, draws conclusion and postulates recommendations towards enhancement of future study in related areas.

CHAPTER FIVE

RECOMMENDATIONS AND CONCLUSION

5.1 Introduction

The current study was dedicated to climate change and the effectiveness of locally available climate sensors in predicting variability in climate to determine suitability of subsistence farming in an ASAL region of Kenya. The influence of six key independent variables (geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition) was examined through a logistic regression model using survey data from 73 respondents. This chapter highlights the ley findings of the study as well as limitations and recommendations before making concluding remarks.

5.2 Key Findings

The study set out to address the first study objective namely to determine the factors that affects the effectiveness of sensors for detecting climate variability and suitability for subsistence agriculture in Laikipia. Descriptive analysis showed relatively differing effects of the chosen variables, geographic extent, temporal scope, precision level, frequency of usage, and cost of acquisition in determining effectiveness of climate sensor suitability.

Reliability test for the survey instrument showed high consistency among the questionnaire items, with a Cronbach's Alpha value of 0.865, and validity picked 3 principal components as being the most useful, PC1 (32.3%), PC2 (12.6%) and PC3 (7.3%). Together they explained 52.2% of the variance explained. The study found the six variables valid for inclusion into the modeling because of their significant contribution to variance using principal components analysis.

Most of the study participants (87%) were either using climate sensors or obtaining information from these sensors in order to predict suitability for subsistence farming. Most of the survey candidates who were farmers were not familiar with the MODIS satellite images but they were familiar with or had used the other climate sensors or got information from them. Survey participants, including meteorologists and agricultural extension officers were asked to rate the characteristics of different climate sensors that they interacted with. Most rated the cost of acquisition very low, especially for the MODIS satellite images and the hygrometer. Coverage extent and coverage frequency were rated quite high. Similarly, the logistic predictive model showed that cost of acquisition was negatively correlated with effectiveness of climate sensors in predicting suitability levels for subsistence farming, with a significance level of $p=0.016$. Temporal scope and frequency of sensor usage were also significant variables in the model, and they positively influenced the predictive effectiveness. Geographic extent of coverage showed the least predictive effectiveness in terms of significance ($p = 0.057$) but with a positive influence on the effectiveness of climate sensors.

The model summary showed an R-square value of 63.7% meaning that the independent variables were strong and contributing 63.7% of the explained variance in the logistic regression model. This finding was consistent with the PCA test that was carried out to test the validity of the questionnaire. Similarly, measures of the model's goodness-of-fit showed positive results, with a Chi-square value of 0.042, i.e. < 0.05. RMSEA was also showing an acceptable model fit at 0.0489. The adjusted goodness-of-fit index (AGFI) of 0.819 indicated a robust model since the maximum value for this coefficient is 1 indicating the best model. Overall the model variables corresponded very well with previous studies.

5.3 Limitations of the Current Study

This research was not void of limitations. First this was a case study on the effectiveness of climate sensors for predicting suitability of agriculture in Laikipia County and may not apply in another county or country with a totally different set up. Secondly, this research relied on structured questionnaire with minimal touch point of personal opinion hence eliminating potential respondent's personal opinions that may offer important suggestion to the study. The sample size of respondents of 73 was also quite small. Finally the study made an assumption that there is a perfect correlation between independent and dependent variables represented by the principal components analysis, and it therefore used only the identified study variables. It is possible that some additional variables which were relevant for the study predictive model have been left out of the analysis. The study therefore recommends further studies in this aspect of climate change mitigation that has not been of more emphasis to implementation researchers.

5.4 Recommendations for Future Research

Given the identified limitations, the current makes recommendations as follows. First there is need to broaden the scope of research findings by conducting similar research in other counties of Kenya, or even at the country-wide level. Studies can also compare what is happening in Kenya with maybe other neighboring countries.

Secondly, future analytical and predictive studies can extend the study data to include raw data from the sensors and other weather databases instead of relying on a survey of study participants since it is sometimes subjective. Finally the future studies can include an expanded set of independent variables, such as the country's gross domestic product (GDP), soil characteristics, and other intervention measures such as irrigation, soil erosion prevention, etc.

5.5 Conclusions

To combat the effects of climate change on subsistence farming in an arid and semi-arid land of Kenya, i.e. Laikipia County, this study considered the opportunities and challenges to identify the variables that heavily determine the use and effectiveness of climate sensors which communicate information to advice farmers. The study used a set of one dependent variable and six independent variables to identify the influential factors discussed above in a logistic regression approach. The researcher expects that the results of this study will advise farmers, weather experts, extension offices, IT specialists who are responsible for launching and maintaining the sensor systems, and even policy makers and future researchers. The developed logistic regression model has also been found to be effective for prediction and this study highly recommends regression modeling technique for future analysis of variation in climate and suitability of climate sensors for subsistence agriculture.

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Appendix 1: Project Schedule

ID	Task	Start Date	End Date	Duration (Days)
1	Research concept, supervisor assignment and first meeting with supervisor	13/02/2020	22/02/2020	9
2	Prepare research proposal	25/10/2020	13/04/2021	18
3	Get final sign-off from supervisor and present proposal document to SGS	16/04/2021	19/04/2021	3
4	Proposal presentation and feedback			
5	Search, capture and synthesize relevant literature	16/05/2021	30/06/2021	14
6	Prepare draft literature review	23/05/2021	06/07/2021	14
7	Finalize sampling plan	06/07/2021	08/08/2021	2
8	Research proposal presentation/approval	24/04/2021	22/10/2021	1
9	Develop data collection instrument	08/08/2021	01/11/2021	2
10	Pre-test/pilot data collection instrument	10/08/2021	04/11/2021	1
11	Carry out data collection	11/08/2021	25/10/2021	11
12	Prepare data for analysis	22/08/2021	26/10/2021	1
13	Analyze data	22/08/2021	28/10/2021	5
14	Draw conclusions/ recommendations	28/08/2021	28/10/2021	8
15	Prepare final draft of report	07/09/2021	29/10/2021	6
16	Review draft with supervisor	10/09/2021	30/10/2021	7
17	Present report document to SGS	18/09/2021	01/11/2021	2
18	Final dissertation Defense	27/09/2021	02/11/2021	1
19	Final editing	28/09/2021	07/11/2021	7
20	Printing, binding and final submission	05/10/2021	10/11/2021	5

Appendix 2: Budget Plan

Core Activities	Total Cost
Laptop computer	45,000
External HDD/ pen drive	5,000
Operating System	6,000
Office Software	5,000
IBM SPSS Statistics Standard v26	9,500
Analytics software (Open Source)	
Equipment and consolidating of literature	2,500
Design and development of research instruments	2,500
Research Instruction and training	15,000
Finalizing the research instruments, stationery, typing and photocopying	15,000
Main field/ data collection	6,000
Data processing and cleaning	2,000
Data Analysis and model building	7,000
Report writing and Typesetting	5,000
Books, Reams of paper and Telephone	5,000
Contingency cost	5,000
Miscellaneous	2,000
TOTAL	**137,500**

Appendix 3: Online Questionnaire

Climate change on Agriculture

I am John Ndiritu Kariuki, a student and researcher at KCA University doing MSc. Data Communications. My current study deals with mitigation of climate change effects on subsistence agriculture. I invite you to participate in a survey study to shed some light on the effectiveness of climate sensors for predicting suitable climate for local farmers.

The survey questionnaire will take up about 10 minutes of your time. Your valuable and kind support will be highly appreciated.

Disclaimer: Your participation in the survey is completely voluntary and all of your responses will be treated with a high degree of confidentiality and will only be used for research purposes.

Guidance: Please provide the correct information. For any comments, questions or clarification you can reach me on the following email: 1609100@students.kca.ac.ke

* Required

Basic Information

1. Please provide your age group *

Mark only one oval.

- 18-25 years
- 26-35 years
- 36-45 years
- 46-65 years
- 66 years and above
- Other: ______________

2. Please provide your gender *

Mark only one oval.

- Male
- Female
- Prefer not to say

Other: ____________

3. What is your profession? Please select all that apply *

Check all that apply.

- [ ] Meteorological officer
- [ ] Subsistence farmer Extension
- [ ] agent
- [ ] Other: ______________________

4. How often do you receive information about the following? *

Mark only one oval per row.

	Never	Rarely	Occasionally	Often	Very often
Surface temperature	⬭	⬭	⬭	⬭	⬭
Precipitation	⬭	⬭	⬭	⬭	⬭
Planting season	⬭	⬭	⬭	⬭	⬭
Length of the growing season	⬭	⬭	⬭	⬭	⬭
Upcoming drought	⬭	⬭	⬭	⬭	⬭
Upcoming flooding	⬭	⬭	⬭	⬭	⬭

5. How often do you work with the following climate sensors? *

Mark only one oval per row.

	Never	Rarely	Occasionally	Often	Very often
Rain gauge	⬭	⬭	⬭	⬭	⬭
Hygrometer	⬭	⬭	⬭	⬭	⬭
Barometer	⬭	⬭	⬭	⬭	⬭
Wind sock	⬭	⬭	⬭	⬭	⬭
Satellite images	⬭	⬭	⬭	⬭	⬭

6. Please rate the following statements about the sensors that you interact with or receive information from:

Mark only one oval per row.

	Very good	Good	Average	Poor	Very poor
Geographic extent of coverage					
Frequency of coverage					
Precision level					
Cost of acquisition					

7. Please classify the effectiveness of the climate sensors in your area for the following:

Mark only one oval per row.

	Very good	Good	Average	Poor	Very poor
Accurate					
Timely information					
Suitable for predicting dry seasons					
Suitable for predicting wet seasons					
Suitable for predicting length of the growing season					
Suitable for predicting precipitation					

Thank you for taking part in this survey study, your responses have been received