ANALYSIS OF EXTENT AND EFFECTS OF MOBILE PHONE USE ON PRODUCTIVITY OF CLIMATE-SMART HORTICULTURE FARMERS IN TAITA-TAVETA COUNTY, KENYA

BY

MWIKAMBA JIMSON NYAMBU

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This thesis is my original work and has not been submitted for award of a degree in any other University.

Signature: ________ Date: 06^{th} December 2022

Mwikamba Jimson Nyambu

Reg. No. A56/35968/2019

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

1. Dr. David Jakinda Otieno

Signature: ____________________ Date: 06^{th} December 2022

Department of Agricultural Economics, University of Nairobi

2. Prof. Willis Oluoch-Kosura

Signature: Date: 06^{th} December 2022

Department of Agricultural Economics, University of Nairobi

UNIVERSITY OF NAIROBI

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Registration Number: A56/35968/2019

School/Faculty/Institute: Agriculture

Department: Agricultural Economics

Course Name: MSc. Agricultural and Applied Economics

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I dedicate this work to my wife Vivian and sister Caroline.

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LIST OF ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of Variance
CAK	Communication Authority of Kenya
CSA	Climate-smart Agriculture
CSAP	Climate-smart Agriculture Practices
CSH	Climate-smart Horticulture
FAO	Food and Agriculture Organization of the United Nations
GB	Gigabyte
HCDA	Horticultural Crops Directorate Authority
HFCS	Household Food Consumption Score
ICT	Information and Communication Technology
IPCC	Intergovernmental Panel on Climate Change
KALRO	Kenya Agricultural and Livestock Research Organization
KCSAP	Kenya Climate Smart Agriculture Project
KNBS	Kenya National Bureau of Statistics
MoALF	Ministry of Agriculture Livestock and Fisheries
NBRM	Negative Binomial Regression Model
NGO	Non-governmental Organization

PBC	Perceived Behavioral Control
PFP	Partial Factor Productivity
PSM	Propensity Score Matching
RAM	Random Access Memory
RUM	Random Utility Model
RUT	Random Utility Theory
SMS	Short Messaging Service
SSA	Sub-Saharan Africa
TFP	Total Factor Productivity
TPB	Theory of Planned Behavior
TTCIDP	Taita-Taveta County Integrated Development Plan
UNDP	United Nations Development Programme
WHO	World Health Organization

ABSTRACT

Horticulture farmers continue to experience climate change-related problems despite advancement in technologies such as mobile phones. Currently, mobile phone is the most commonly used tool in communication. Previous studies have shown that application of mobile phones in farming helps to reduce information asymmetry and improve productivity. However, there is little evidence on whether farmers are using their phones to build resilience and improve horticultural productivity within the context of climate change, commonly referred to as climate-smart horticulture (CSH). This study analyzed the extent and effect of mobile phone use on productivity of climate-smart horticulture farmers in Taita-Taveta County. Primary data was collected from a random sample of 403 green gram and tomato farmers. Paired *t-test* statistics were used to characterize the adoption of climate-smart horticulture practices between users of mobile phone and non-users. Binary logit model was applied to examine the factors influencing mobile phone use on climate-smart horticulture. Negative binomial regression was applied to assess the determinants of adoption of the number of climate-smart horticulture practices. Productivity was measured using partial factor productivity. Tobit model (censored from below) was applied to analyze the effect of mobile phone use on productivity of climate-smart horticulture farmers. Results show that a significantly higher percentage of mobile phone users adopted climate-smart horticulture practices than non-users. Trust on the information transmitted through mobile phones, access to electricity (hydro-electricity and solar power), access to credit and the number of CSH practices adopted significantly influenced the use of mobile phone on climate-smart horticulture. Gender (being a male farmer), education, farming experience, mobile phone use on CSH and CSH awareness positively determined the number of CSH practices adopted.

However, farm size and climate change awareness negatively affected the number of CSH practices adopted by farmers. Partial factor productivity scores showed that farmers who produced tomatoes were more productive than green gram and both crop producers. Tobit regression (censored from below) results showed that mobile phone use improved productivity of climate-smart horticulture farmers by 90%. Other factors including education, gender, farming experience and climate-smart horticulture awareness positively influenced productivity. There is need to develop a mobile phone supported digital hub that will provide specific climate-smart horticulture information to farmers to build resilience to climate change and improve productivity. The County government of Taita-Taveta should also collaborate with other development partners such as Kenya climate smart agriculture project (KCSAP) to build the capacity of agricultural extension workers to improve dissemination of climate-smart horticulture knowledge and skills to farmers.

Key words: Mobile phone, climate-smart horticulture, productivity, tomato, green gram.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background information

Globally, the development of horticulture production contributes to improved household nutrition and diversification of incomes (Davies, 2015). In Kenya, the horticulture sector (flowers, vegetables and fruits) is the largest foreign exchange earner that contributes 30% of all domestic exports (Kenya national Bureau of Statistics (KNBS), 2022). It is largely concentrated among fifteen Counties (located in Coast, South Eastern, Central, South Rift and Western parts of Kenya) that contribute about 74% of the total national horticultural output (HCDA, 2018). Between the year 2019 and 2020, the total value of domestic exports of horticulture, in Kenya, grew by 5%, compared to the previous year, due to increased area under production and demand for flowers and vegetables (KNBS, 2022).

However, horticulture productivity is directly influenced by variability in climate (rainfall and temperatures) patterns which lead to low quantity and quality of output (Hirpo and Gebeyehu, 2019). This sector is mainly dominated by small-scale farmers who own less than 10 acres of land and contribute between 50 and 60% of total horticultural output (UNEP, 2015; World Bank and CIAT, 2015). Climate change has continued to be the main challenge affecting horticulture in Africa. It is likely to prolong severe effects on; soil health, water availability, disease control and production planning (AgriProFocus and Verbos Business Development, 2018; Patrick *et al.*, 2020). Horticulture farmers are at risk of climate change incidences such as prolonged drought, poor spatial and temporal rainfall distribution and increased temperature variability.

This is likely to cause damage of between 15% and 50% decline in crop productivity (Nhemachena *et al.*, 2020). In addition, Kenya is likely to suffer from severe food insecurity by the year 2100 if considerable adaptation and mitigation measures on climate change are not put in place. This is due to a significant decline in maize, beans, millet and sorghum yields that is likely to be experienced (Kabubo-Mariara and Kabara, 2015). The Northern and Eastern regions will need humanitarian food assistance and livelihood support throughout the year 2022 (FEWSNET, 2021). In Taita-Taveta County, production of most horticultural crops (such as green grams, onions and tomatoes) contribute on average 10% and 90% of household food requirements and income, respectively. However, production is projected to decline by between 37% and 46%, respectively due to climate change (Mohamed and Chege, 2019; Osano *et al.*, 2018).

In an effort to reduce adverse effects of climate change on agriculture, the government of Kenya initiated Kenya climate-smart agriculture project (KCSAP) covering 24 Counties, including Taita-Taveta in 2017. Climate-smart agriculture (CSA) is a system that seeks to improve adaptation to climate change, productivity, improve food security and decrease emission of greenhouse gases (Government of Kenya, 2017). Therefore, the approaches (new and indigenous) applied by farmers to build resilience and adapt farming to local climate variabilities are included in considered, in this study, as ‘climate-smart’. Climate-smart horticulture (CSH) draws from this definition but confines it to horticulture (Sahu, 2016).

There are four main categories of CSA approaches that entail innovative ways of: managing field, crop management, reducing farm risk and conserving the soil (Thornton *et al.*, 2018; Wekesa *et al.*, 2018). Crop management methods include innovative; integrated pest management, crop irrigation, use of improved seed varieties that are well adapted to local climate, crop rotation, matching planting dates to climate conditions and efficient use of inorganic fertilizers (Pooniya *et al.,* 2015; Shah and Wu, 2019).

General field management practices include use of terraces, agroforestry and use of live barriers – which are strips of crops (such as grass) planted along a contour to prevent soil erosion (Caulfield *et al.,* 2020; Hellin and Haigh, 2002). Soil conservation practices entail the use of organic fertilizers, cover crops, composting, mulching and conservation agriculture (Baumhardt and Blanco-Canqui, 2018). On the other hand, farm risk reduction practices include crop diversification, use of farm water ponds, use of information technologies to guide farm activities and crop insurance (Filan and Fake, 2012; FAO, 2018).

Previous studies have shown that farmers who adopted all the four practices had higher household food consumption scores (HFCS) than non-adopters (Wekesa *et al.,* 2018). Specifically, adopting crops that are well adapted to local climate, sustainable water-use and management practices and technology use in production planning are important strategies for horticulture farmers facing climate change problems (FAO, 2017).

Another way of strengthening the capacity of horticulture farmers to deal with climate-related risks is through giving them information that is accurate, reliable, and timely to enable them to make informed decisions. This is because farm productivity and agricultural transformation have been traditionally suppressed by information asymmetry, inadequate access to markets, low use of improved technologies, low access to relevant infrastructure, high costs of production and transport (Government of Kenya, 2019; Ogutu, *et al.,* 2014).

Mobile phone use in horticulture enables the transmission of knowledge and information on CSH practices (Mehar and Mittal, 2014). The use of mobile phone on CSH means that the farmer uses the phone to make and receive payments for inputs and output, respectively, search for horticulture-related information and weather information. For example, rapid growth in application of mobile phones in agriculture is reducing information deficit by making it possible for farmers to obtain relevant information about weather, credit, farm inputs and output market at lower costs than traditional agricultural extension services (Etwire *et al.*, 2017; Kirui *et al.*, 2013).

In Kenya, mobile phone penetration rate was estimated to be 95% in 2019 (CAK, 2019). About 53% of farmers own smartphones (a mobile phone that has capacity to support other applications apart from voice calls and short message services (SMS)) while 47% have basic feature phone with SMS (Geopoll, 2018). However, the extent and effect of use of mobile phone on CSH is not well known (Mittal and Hariharan, 2018; Government of Kenya, 2017).

1.2 Research problem statement

Climate change effects including prolonged droughts, unpredictable rainfall pattern and floods are causing damage to the world food system (IPCC, 2020). For example, between the years 2006 and 2016 prolonged droughts caused 30% of total agricultural losses in the world (costing over USD 29 billion). Specifically, 83% of these losses were reported in Africa (FAO, 2018). In the past 100 years, Sub-Saharan Africa (SSA) surface temperatures rose by 0.5 to 2^0C and drought and floods have also become more frequent (Government of Kenya, 2018). It is further projected that temperatures will rise by 4.5^0C by the year 2100 in Kenya if climate change measures are not implemented (WHO, 2016).

Consequently, incidences of pests and diseases will increase, while there will be little natural water available for irrigation; hence reducing the quantity and quality of crop produce (especially for fruits and vegetables) (Azam *et al.*, 2017). This means that the livelihoods of 80% of rural and 70% of the total populations in Kenya and Taita-Taveta County, respectively, will be adversely affected as they rely mainly on agriculture (Taita-Taveta County Integrated Development Plan, TTCIDP, 2018).

Further, it is anticipated that climate change will cause an increase in prices of basic foods such as maize, rice and wheat by 4%, 7% and 15%, respectively, in SSA and between 1 and 29% globally by the year 2050 hence negatively affecting household food security (IPCC, 2019). To control these consequences of climate change, the Government of Kenya has been promoting CSA practices in 24 counties since the year 2017. However, farmers in Taita-Taveta County are still facing climate change problems (Mohamed and Chege, 2019). Elsewhere, low uptake of CSA technologies in Tanzania and South Africa have been attributed to lack of information (Abegunde et al, 2019; Jha *et al.*, 2020).

There is a growing empirical evidence that mobile phones can be utilized to obtain and share information on CSA technologies hence contributing to solve the problem of climate change among farmers (Chhachhar *et al.*, 2016; Tadesse and Bahiigwa, 2015). For instance, in Taita-Taveta county, mobile phone penetration rate was estimated to be over 80% in the year 2018 with farmers using it to access information online (TTCIDP, 2018).

Also, Etwire *et al.* (2017) and Ogbeide and Ele (2015) showed that Ghanaian and Nigerian farmers applied mobile phone technology to obtain timely weather and market information. This underscores the importance of mobile phone as an enabler of agricultural development.

In addition, studies such as Amir *et al.* (2016), Baba (2017), Jairath and Yadav (2012) and Ogutu *et al.* (2014) showed positive effect of mobile phones on agricultural marketing, use of fertilizers and improved seeds in Kenya and Ethiopia. However, these studies did not focus on CSH and economic implication of the mobile phone on CSH farmers. Also, most impact studies concentrate on projects and often ignore farmers' decisions which are mostly dependent on self-innovation and information gathered from other farmers (Mehar and Mittal, 2014).

This affects sustainability of such project impacts (Jha *et al.*, 2020). In addition, the government of Kenya suggests that there is need to integrate ICTs in climate smart farming systems (Government of Kenya, 2017 and 2018). But, there is still a gap in existing literature on whether farmers are using their phones to access information on CSH and if such use has any effect on adoption of CSH practices and crop productivity. Therefore, this study sought to provide insights on mobile phone use and its effects on productivity of CSH farmers in Taita-Taveta County with specific attention to green grams and tomato farmers.

1.3 Objectives of the study

The study sought to evaluate the extent and effects of mobile phone use on productivity of climate-smart horticulture farmers in Taita-Taveta County. The following specific objectives were pursued:

i. To characterize adoption of climate-smart horticulture practices and use of mobile phones in accessing related information.

ii. To examine the factors influencing the use of mobile phones on climate-smart horticulture.

iii. To analyze the determinants of extent of adoption of climate-smart horticulture practices.

iv. To evaluate the effect of mobile phone use on productivity of climate-smart horticulture farmers.

1.4 Research hypotheses

i. There are no differences in climate-smart practices between mobile phone users and non-users.

ii. Infrastructural, socio-economic and institutional factors do not affect mobile phone use on climate-smart horticulture.

iii. Socio-economic, infrastructural and institutional factors do not affect the extent of adoption of climate-smart horticulture practices.

iv. Mobile phone use does not affect the productivity of climate-smart horticulture farmers.

1.5 Justification

This study examined the use of mobile phone on CSH. This will help the Kenyan national government and other stakeholders to develop policies and interventions that will benefit farmers through knowledge transfer and real time weather information. This is in line with recommendation(s) 1 and 2 of eTransform Africa: Agricultural sector study report, 2012 (Deloitte, 2012). This is because mobile phone use helps to reduce information gaps and cost hence improving adoption of climate-smart horticulture practices (Jha *et al.*, 2020; Mittal and Hariharan, 2018).

Information on the factors affecting mobile phone use in climate-smart horticulture will assist the county government of Taita-Taveta, non-governmental organizations (NGOs) and private entities (such as Microsoft) to address the specific challenges that affect the farming population in Taita-Taveta County hence saving on extension costs.

It will also contribute to achievement of Kenya agricultural sector growth and transformation strategy 2019-2029 flagships 8 and 9 on strengthening digital and data use cases for improved decision making and sustainable and climate smart natural resource management (MoALFI, 2019).

Information on the influence of mobile phone use on CSH productivity will benefit Taita-Taveta county government by enhancing agricultural service delivery hence improving livelihoods of the community through agriculture (TTCIDP, 2018). It will contribute towards achieving the African Union agenda 2063 aspiration one – section(s) 9, 13 and 16 on eradicating poverty, modernize agriculture and address climate change challenges through technological transformation (African Union, 2015). It also contributes to attainment of the sustainable development goals number 1 and 2 on ending extreme poverty and achieving zero hunger, respectively (UNDP, 2015).

1.6 Study area

The study was done in Taita-Taveta County, Kenya, because it has been implementing CSA project since the year 2018 and has different agro-ecological zones; lower highland zone (altitude of above 1680 m) to lowland zone (altitude of below 610 m). The area is also susceptible to climate changes including high temperatures and unpredictable rainfall (MoALF, 2016; Motaroki *et al.*, 2021). The main economic activity in the region is agriculture, however, poverty levels range between 50 and 70% (TTCIDP, 2018). Taita-Taveta County is among the six counties of the Coast region. It is the top County in horticulture production relative to all counties in the Coast region. The county has four sub-counties and twenty administrative wards as shown in Figure 1.1.

The study covered Wundanyi, Taveta and Mwatate sub-counties because they have high output and acreage of land under tomato and green grams (Mohamed and Chege, 2019; Moranga, 2016).

This study focused on green grams and tomato crops because they are widely grown for both subsistence and commercial purposes in Taita-Taveta County.

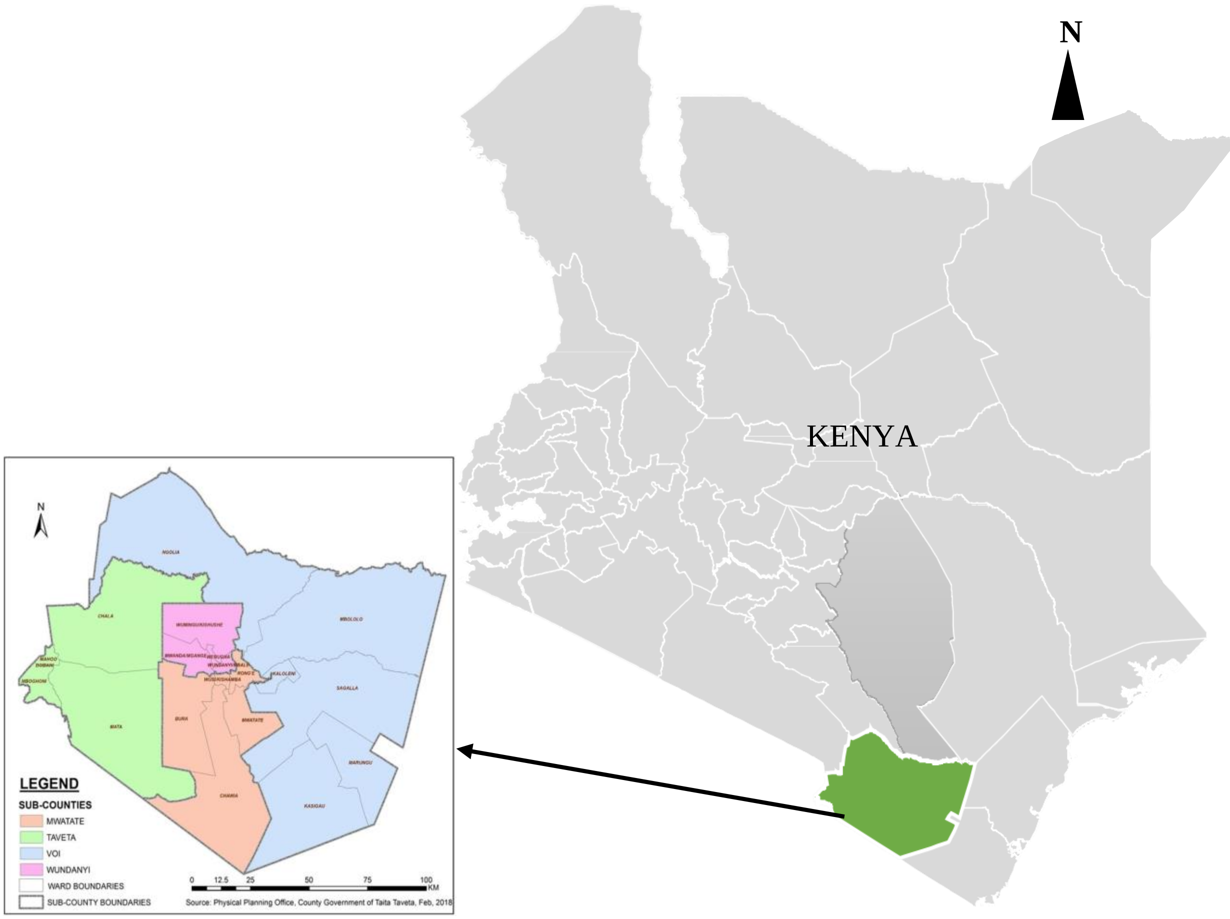

Figure 1.1: A map of the research site (Taita-Taveta County)
Source: TTCIDP (2018-2022).

In addition, green gram is a drought tolerant seed vegetable prioritized in CSA project within the county (Balasubramanian, 2014; Blair *et al.*, 2016; Goodman, 2004; KCSAP, 2018). The average land area under green grams in the county is 843 hectares and contributes an average of 0.6% of total output in Kenya (International Trade Centre, ITC, 2016; Osano *et al.*, 2018).

On the other hand, tomato production covers 755 hectares of the County’s crop land and contributes, on average, 6% of total value of tomatoes sold in Kenya (HCDA, 2018). About 90% of green grams and tomatoes produced in Taita-Taveta are sold for income thus contributing to household poverty alleviation (MoALF, 2014; Mohamed and Chege, 2019).

1.7 Organization of the thesis

This thesis includes six chapters. Chapter one provides background information, research problem statement, objectives of the study, hypotheses, justification and describes the study area. Chapter two provides a review of climate-smart horticulture concept, application of mobile phones in farming, factors influencing mobile phone use in climate-smart horticulture and knowledge gaps on the influence of mobile phone use on horticulture productivity. This chapter also presents the conceptual and theoretical frameworks. Chapter three, four and five present the methodology, results and conclusions of the respective specific objectives. Finally, chapter six provides the conclusion and recommendations derived from the study.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 The climate-smart horticulture concept

According to Sahu (2016), horticulture is considered to be "climate-smart" when it contributes to improving productivity, food and nutritional security, adapting horticulture to climate change and reducing greenhouse gas emission. The Food and Agriculture Organization (FAO) encourages small-scale farmers to practice CSA so as to adapt to climate change effects and sustainably improve food security.

Wekesa *et al.* (2018) noted that CSA practices can be categorized into four groups which include innovative farm risk reduction, field, crop and soil management practices. Climate-smart agriculture has multiple entry points ranging from improvement of technologies and practices to insurance schemes, information technologies, political and institutional environment (Thornton, *et al.*, 2018). It is also context-specific since no interventions can be applied uniformly in all situations. This is because CSA integrates various climate change measures across different food systems, agricultural value chains and government policies (Lipper *et al.*, 2014).

2.2 Review of mobile phone use in agriculture

Mobile phone is currently the most commonly used communication tool and has a great potential to transform agriculture in the SSA region. Its ability to effectively facilitate transfer of knowledge and information offers good prospect for agriculture development (Sekabira and Qaim, 2016). For instance, Kiberiti *et al.* (2016) showed that mobile phones offered Tanzanian farmers a better solution to their information requirements hence reducing costs in searching for extension services. However, the effect of mobile phone use varies from one sector to another hence there is need to identify the sector-specific effects to provide specific solutions. The current study addressed this by focusing on mobile phone use on horticulture productivity with specific attention to tomatoes and green gram farmers.

A study by Angelo (2015) in Tanzania found that, among all the ICT tools available, majority of livestock farmers used mobile phone to learn and disseminate information about livestock husbandry practices. In addition, Emeana *et al.* (2020) noted two benefits of mobile phone-supported services related to agriculture *(m-Agri services);* facilitating access of financial services by farmers and agricultural-related information such as farm inputs, farming practices and market prices. This contributes to solving the market failure problems that farmers face more often (Kirui *et al.,* 2013). However, both Angelo (2015) and Emeana (2020) lacked statistical evidence on the extent to which the mobile phones benefited farmers considered in their studies. The current study filled this gap by using regression techniques to examine the extent to which the use of mobile phones affects farmers' productivity.

A study by Baumuller (2015) found that *m-services* helped Kenyan farmers plan their production process better by offering market price information. The study used a case study approach, which involved collection of farmers' perceptions on mobile phone use. However, the problem with this approach is that it may not give a quantified measure of the impact of mobile phones and perceptions vary from one person to another which may sometimes be misleading (Rahman, 2017).

Krell *et al.* (2020) found that nearly all farmers in Central Kenya owned mobile phones. However, very few of them used the mobile phones to access crop, livestock and market information. In addition to this, the study noted that smartphone ownership significantly increased access to and use of *m-services*.

While these studies showed the extent to which farmers used and value information from mobile phones, they lack statistical evidence on the effect of such information on crop or livestock productivity.

2.3 A review of factors influencing mobile phone use on climate-smart horticulture

Mobile phone technology is mainly used to transmit information and other services in the developing countries because it is user friendly and highly portable (Qiang *et al.,* 2011; Jairath and Yadav, 2012). Most farmers have taken advantage of this development and use their phones to obtain information at different levels of the horticulture value chains. For example, in Pakistan, Jehan *et al.* (2014) found that application of mobile phones in farming helped farmers to choose markets and set base prices. This provides valuable insights on mobile phone use in horticulture. However, the study does not provide any information on the extent of mobile phone impact on output or income.

Similarly, an empirical review by Chhachhar and Hassan (2013) on the usage of mobile phone for agriculture development indicated that most farmers use their phones to obtain weather, input and output price information. They observed that farmers appreciate mobile phone as an easy and convenient way of obtaining information. However, the conclusion that mobile phone improved farmers' income was only theoretical and lacked quantitative evidence.

Further, a survey by Chhachhar *et al.* (2014) in Malaysia, on the application of mobile phone amongst farmers for agriculture information found that most farmers did not use their phones for agricultural purposes. This contradicts the earlier claims that farmers use mobile phones hence the need to conduct more studies on the use of mobile phone among farming community to clarify this controversy.

Mobile phone is a vital tool in facilitating technology adoption. For instance, Baumuller (2012) argued that mobile phone services can be used to overcome some limitations to technology adoption by enabling easy access to information, knowledge, input and output market and financial services. This underlines the role of mobile phones on adoption of CSH technologies.

Also, most farmers use mobile phone technology in accessing weather, price and input information (quality of seeds and its price) to plan their production (Chhachhar *et al.*, 2016; Jairath and Yadav, 2012). For example, Baumuller (2016) showed that farmers were using price information obtained through m-services to make key farm decisions pertaining to production and marketing. Although the above study did not apply any statistical methods and was limited to only *m-services*, it offers a glimpse on the importance of delivering timely information to farmers and the effect it can have on productivity and incomes. The current study evaluated the influence of mobile phone use on climate smart horticulture productivity.

Despite mobile phones improving efficiency in agricultural supply chains by connecting farmers to high-end markets and through significant reduction of information asymmetry, its potential has not been fully exploited due to infrastructural, socio-economic and other institutional constraints (Amir *et al.*, 2016; Baumuller, 2016). For instance, Amir *et al.* (2016) showed that the level of off-farm income, education, family size and mobile phone use perception significantly determined mobile phone use in agriculture. The study also noted that there was higher likelihood of using a mobile phone by farmers with access to off-farm income than those without. Although this study provided a good measure of factors affecting mobile phone use, it did not demonstrate any link with CSH.

Another study by Mugwimi (2015) revealed that horticulture farmers face a myriad of challenges in using their mobile phones. Using descriptive statistics, the study demonstrated that lack of training on mobile phone use contributed to 85% of the farmers not using the phone in horticulture production activities. Other factors identified include cost, awareness, complexity and lack of trust in mobile phone technology. However, both Baumuller (2016) and Mugwimi (2015) ignored the fact that climate change would have an effect on mobile phone use.

On the other hand, membership to farmer group, education, distance to commercial bank, distance to banking agent and financial and physical asset endowment of the farmer significantly determine the extent of use of mobile money services (Kirui *et al.*, 2013; Okello *et al.*, 2014). These studies employed negative binomial regression model, which is suitable for dependent variables that are countable finitely. However, the studies drew their samples from farmers who participated in ICT projects. Considering that farmers may not continue using the ICT services after the project period ends, the current study focused on mobile phone use (without tying it in an ICT project) on CSH so as to allow analysis of the effects beyond project duration. In addition, this study addressed the suggestion by Mittal and Hariharan (2018) on the need for further research on enablers of CSA practices adoption by farmers as means of building resilience to climate change risks to improve farm incomes.

Moranga (2016) found that gender, age, group membership, access to credit and income determined the willingness of tomato farmers to adopt innovative timing approaches. Further, he revealed that farmers in Taita-Taveta matched planting dates and used early maturing varieties to cope with climate variability. These approaches are classified as climate-smart practices under the current study. This study extends that of Moranga (2016) by addressing mobile phone use on adoption of climate-smart practices.

2.4 Knowledge gaps on the effect of mobile phone use on horticulture productivity

The mobile (sim) penetration was estimated at 126% of the total population in Kenya (CAK, 2020). This is because some people opt to have more than one sim card. It is generally considered among precision agriculture scholars that mobile phone use positively impacts income and poverty reduction practices among farming communities. This can be traced back to Bayes *et al.* (1999) who concluded that mobile phones can be used as production goods hence lowering transaction costs and delivering significant positive impacts on poverty reduction. Prior studies such as Masuki *et al.* (2007), Mittal and Tripathi (2009) and Qiang *et al.* (2011) confirm these assertions. This study sought to ascertain the validity of these claims by examining the effect of mobile phone use on climate-smart horticulture productivity using econometric methods.

A study by Baumuller (2016) on the role of mobile phones in service delivery suggested that mobile services can be useful in overcoming some obstacles faced by farmers in technology adoption through facilitating access to; learning, information sharing, financial service provision and access to input and output markets. Although the current study was based on the premise that mobile phone plays a critical role in agriculture, it focused more on the effect of mobile phone use on productivity.

In India, Jairath and Yadav (2012) explored the effects of short messaging services (SMS) on production, marketing and communication using descriptive statistics. The study revealed that 45% of the farmers received better knowledge about crop and disease management, which improved productivity and profitability. However, the descriptive methodology applied in the above study does not provide a rigorous basis for cause-effect analysis of mobile phone use.

Participating in ICT-based market information and money transfer services by farmers has also been shown to positively contribute to land and labor productivity, and hence improving income. For example, a study by Ogutu *et al.* (2014) using propensity score matching (PSM) revealed that land and labor productivity of farmers who participated in ICT-based market information service (MIS) was higher than non-participants. Additionally, using mobile money transfer services (such as M-pesa) increases farmer's household income significantly (Kirui *et al.,* 2013). The current study places more emphasis on the usage of mobile phone in facilitating adoption of CSH technologies.

Mittal and Mehar (2012) found that farmers who applied mobile phones in farming had better connection to markets, got better prices and accurate information that enabled them to improve their yields. Likewise, through empirical review, Mehar and Mittal (2014) found that mobile phones led to reduced production costs, improved productivity and income. However, these studies lack statistical basis for demonstrating the effect of mobile phone use on farmers' productivity.

Adoption of mobile phone reduces costs in the agricultural supply chain thereby improving efficiency (Ogbeide and Ele, 2015). In their analysis, Ogbeide and Ele revealed that mobile phones were applied by most farmers to search for market information but there was less application of it in gathering weather information. However, the study did not demonstrate any link between mobile phone use and productivity. On the contrary, Tadesse and Bahiigwa (2015) in their evaluation of how mobile phone impacts farmers' marketing decisions in Ethiopia noted that it is only a small fraction of farmers who used it to search for market information. They concluded that adoption of new technology (mobile phone) does not necessarily mean that farmers are using it to maximize its benefits. The inconclusive observations from these studies were addressed by use of an econometric model to isolate the contribution of mobile phone use on horticulture productivity.

Mittal and Hariharan (2018) in a study on the impact of mobile phone-based services on Indian farmers' ability to manage risk found that there was a huge gap between technology awareness and adoption by farmers. This is because the benefits realized from the application of mobile phone in marketing may accrue more to traders than farmers due to information asymmetry and differences in bargaining power. Also, the realization of full benefits of a technology may require additional support such as training and infrastructure (Tadesse and Bahiigwa, 2015; Mittal and Hariharan, 2018).

Similarly, Aminou *et al.* (2018) noted that a mobile phone is a consumer good if it is purchased to call friends and play games since such uses do not make the individual more productive but only increase utility costs. However, Aminou *et al.* (2018) showed that mobile phone ownership significantly increased maize productivity of farmers in Benin by 26%. Further, an empirical review by Emeana *et al.* (2020) revealed that *m-agriservices* facilitated access to information and farmers' extension services hence improving farmers' livelihoods. This means that mobile phone ownership improves climate-smart agricultural productivity only when used for agriculture related purpose.

Another study by van Baardewijk (2017) on the impact of mobile phone in India found that its use improved social networks, cognitive assets and lowered transaction costs (such as travelling and search costs). Moreover, Nsabimana and Amuakwa-Mensah (2018) found that mobile phones greatly reduced price distortions (difference in world market price and prices received by farmers due to taxes or subsidies by the government) in Ghana. This implies that use of a mobile phone can improve crop productivity and farmers' income through technology and knowledge transfer services.

In conclusion, the extant literature shows that much work has been done in the field of mobile phone and agriculture. However, most studies such as Baumüller (2015), Etwire *et al.* (2017) Mittal (2016), Tadesse and Bahiigwa (2015), focused on the role of mobile phones in farming.

Further, the studies that assessed the effect and impact of mobile phone in agriculture used non-econometric methods (Jehan *et al.*, 2014; Mehar and Mittal, 2014; Mittal and Hariharan, 2018; van Baardewijk, 2017). This makes it difficult to identify the effect of mobile phone use on agricultural production. Therefore, a considerable empirical gap still exists on the determinants of mobile phone use by farmers, its effect on adoption of CSA practices and productivity (Baumuller, 2016; Mittal and Hariharan, 2018; Ogbeide and Ele, 2015). To address this gap, the current study focused on analysis of extent and effects of mobile phone use on productivity of climate-smart horticulture farmers.

2.5 Conceptual framework

Following Pambo (2013), this study presents both the conceptual and theoretical frameworks in the literature review to allow subsequent chapters to document the methods applicable to specific objectives of the study. Climate change problems such as poor rainfall pattern and high temperatures leading to floods and prolonged droughts, often result in huge losses of agricultural output (FAO, 2018). In order to reduce this damage, farmers in the horticultural sector are adopting climate smart practices such as innovative timing of planting and harvesting periods, using seed varieties adapted to the local environment, crop rotation and diversification, integrated pest management, conservation agriculture and using weather information to plan farm activities that build resilience and improve farm productivity (Amadu *et al.*, 2020; FAO, 2017; Moranga, 2016; Wekesa *et al.*, 2018).

Mobile phones are useful tools in transferring valuable information and knowledge on weather and climate smart practices to farmers and hence improve productivity (Etwire *et al.,* 2017; Mittal and Hariharan, 2018). It also helps farmers to reduce transaction costs and obtain higher market prices (in real terms) hence improving farmers' income (Nsabimana and Amuakwa-Mensah, 2018).

However, to improve horticulture productivity by use of mobile phone in CSH depends on several factors such as education, gender, family size, awareness, farmer's financial and physical asset endowment, off-farm income, access to mobile phone network infrastructure, access to extension services, electricity, distance from farm to agricultural market, level of trust on information conveyed via mobile phone and group membership (Khan *et al.,* 2019; Mugwimi, 2015; Quandt *et al.*, 2020; Tadesse and Bahiigwa, 2015). The interaction of these factors and how they influence horticultural productivity through use of mobile phones in CSH are presented in Figure 2.1.

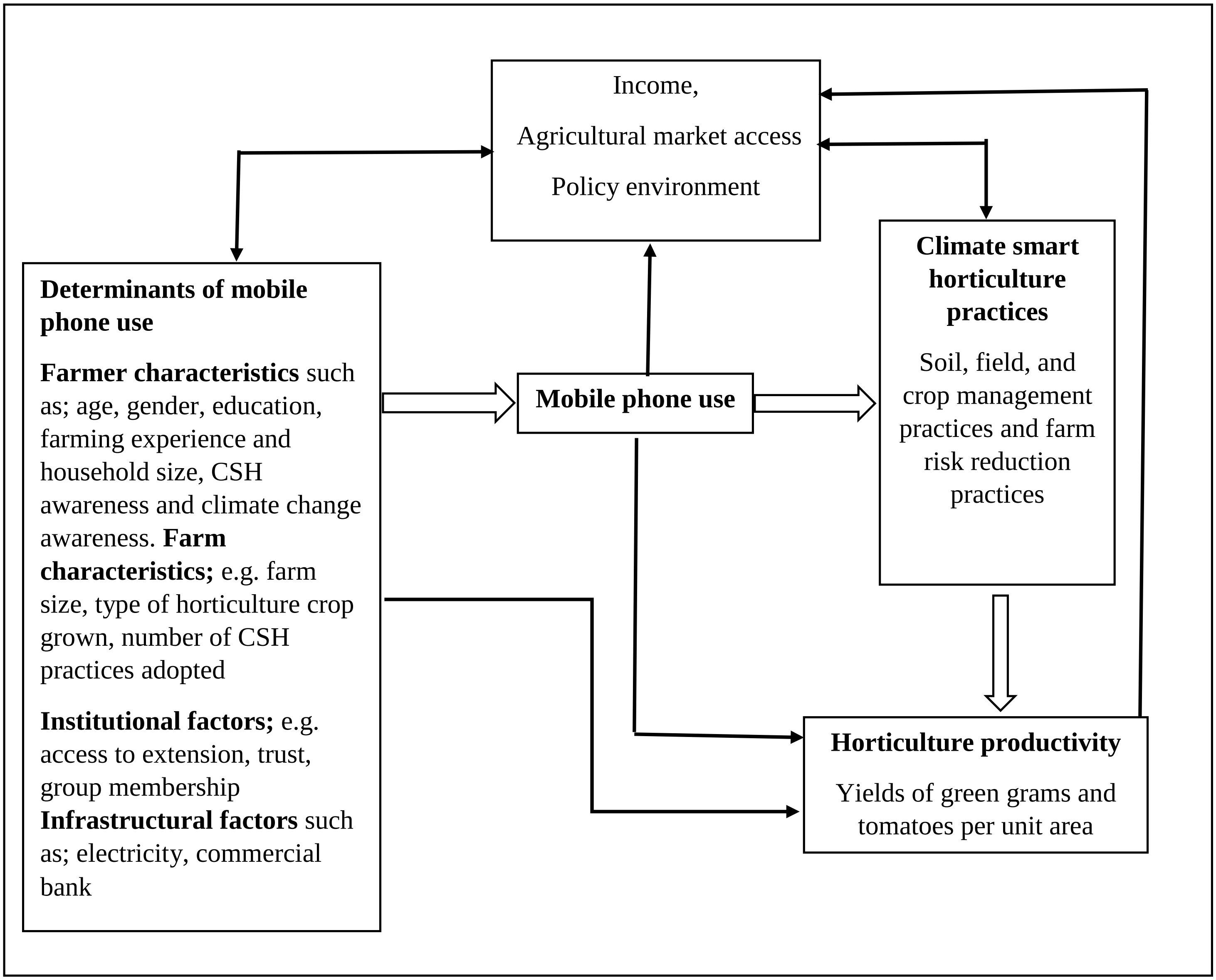

Figure 2.1: A framework on determinants of mobile phone use on CSH and its effects on productivity
Source: Adapted from Mittal and Hariharan (2018).

2.6 Theoretical framework

This study was anchored on diffusion of innovation theory, theory of planned behavior and random utility theory.

2.6.1 Diffusion of innovation theory

Characterizing mobile phone use among CSH farmers was centered on diffusion of innovation theory. The term diffusion refers to the process where innovation is transferred through specific channels over time between members of a social system (Rogers, 1983). Diffusion of innovation is the process followed as people embrace a new idea, practice or product. Its major components include; innovation characteristics, adopter characteristics and the innovation decision process (Hamed, 2018).

Adopter characteristics can further be categorized into innovators, early adopters, early majority, late majority and laggards, as shown in Figure 3 (Kaminski, 2011).

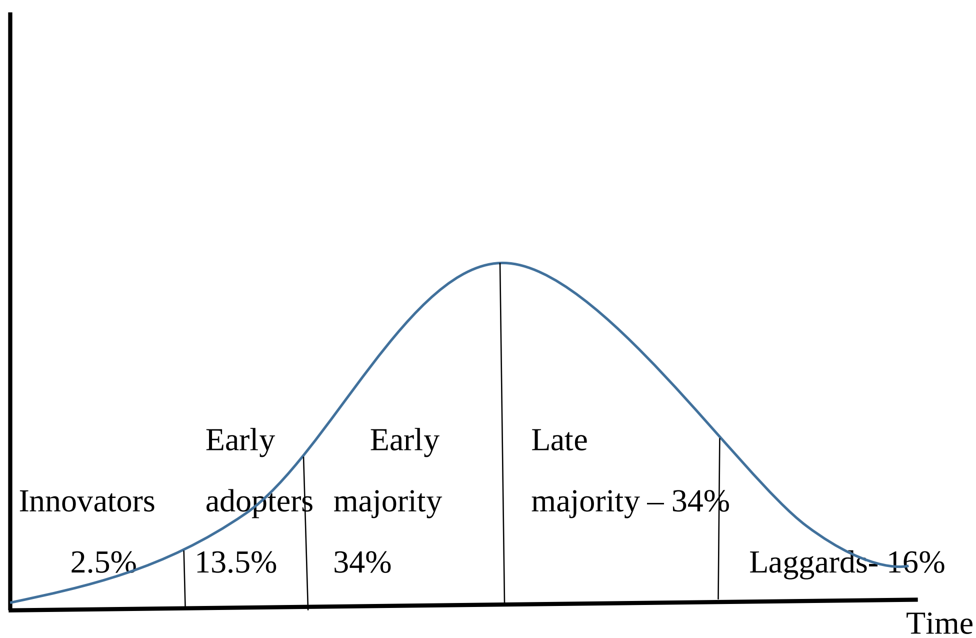

Figure 2.2: Innovation adopters' characteristics
Source: Rogers (1983).

According to Rogers (1983), innovators are individuals who are venturesome, have financial resources, requisite knowledge and are very ready to try out new ideas. Early adopters are seen as opinion leaders. They are looked upon by others to provide information before an idea is implemented. The early majority are those who often take some time before they adopt an innovation. They are between the early adopters and late majority. The late majority are cautious and more skeptical about the innovation. They do not adopt an innovation before other people in their social system have done so. Laggards are the last one to adopt an innovation. They base their decisions on what has been done in previous generations and often wait to see extent of benefits or losses; in other words, they are risk averse or avoiders.

In agriculture, diffusion of innovation theory is widely applied to describe the manner in which innovation spreads from one point to another in the community; the process of change (Peshin *et al.*, 2009). Simin and Janković (2014) concluded that diffusion of innovation theory can be used to study organic farming systems with respect to all characteristics and specifications of organic farming.

In this study, diffusion of innovation theory was applied to describe the use of mobile phones in CSH. The relationship between these two technologies (mobile phone and CSH) was analyzed through descriptive statistics. The study adapted Krell *et al.* (2020) categorization of mobile phones to suit current trends in mobile phone technology. According to Krell *et al.* (2020), mobile phones can be classified into three distinct categories, which include; *basic phone* – which support voice calls, SMS and money transfer services only, *feature phone* –which can access limited internet services and cannot download applications and *smartphone* – which include mobile phones that can easily access internet services and download various applications.

The CSH technology adoption was evaluated following a list of CSH practices shown in Table 2.1.

Table 2.1: Categorization of selected CSH practices

CSH Category	CSH Practice	Source
Crop management	Use of improved and well adapted seed variety	Agripofocus (2018); FAO (2017), Wekesa *et al.* (2018) and Netherlands Enterprise Agency (2019)
	Integrated Pest Management	
	Crop rotation	
	Crop irrigation	
	Use of cover crops	
	Efficient use of fertilizers	
Field management practices	Use of terraces	Caulfield *et al.* (2020), Hellin and Haigh (2002) and Thornton *et al.* (2018)
	Agroforestry	
	Contour cultivation	
	Use of live barriers – strips of crops (grass) along contours	
Farm risk reduction	Integrated farming system (mixed farming)	Filan and Fake (2012), FAO (2017), Thornton *et al.* (2018) and Amadu *et al.* (2020)
	Crop insurance	
	Crop diversification	
	Water harvesting	
	Matching planting dates to weather condition	
Soil management	Use of mulching	Baumhardt and Blanco-Canqui, (2018), FAO (2017) and Wekesa *et al.* (2018)
	Minimum tillage	
	Composting	
	Use of organic manure and fertilizers	

2.6.2 Theory of planned behavior

This theory was suggested by Ajzen (1991) as an improved version of the theory of reasoned action by taking into account perceived behavioral control (PBC). The theory of reasoned action was anchored on an assumption that a person’s intention to behave (not behave) in a certain manner actually determines that action (Ajzen, 1985). The theory of planned behavior (TPB) assumes that an individual’s norms, attitudes and PBC affects his/her behavior (action) by shaping his/her intentions.

Intentions are defined as the extent to which people are willing to put in effort to perform a certain behavior. Stronger intentions likely result into performance of that behavior (Ajzen, 1991). The TPB revolves around the attitudes, subjective norms and PBC. These greatly determine the intensions necessary for performance of a behavior (Ajzen, 1991). Figure 4 shows a diagram of the TPB. Perceived behavioral control is largely affected by opportunities, skills, availability of resources and their significance in achieving the desired outcome (Hamed, 2018). These factors affect the extent of mobile phone usage by farmers in their activities and adoption of CSH practices.

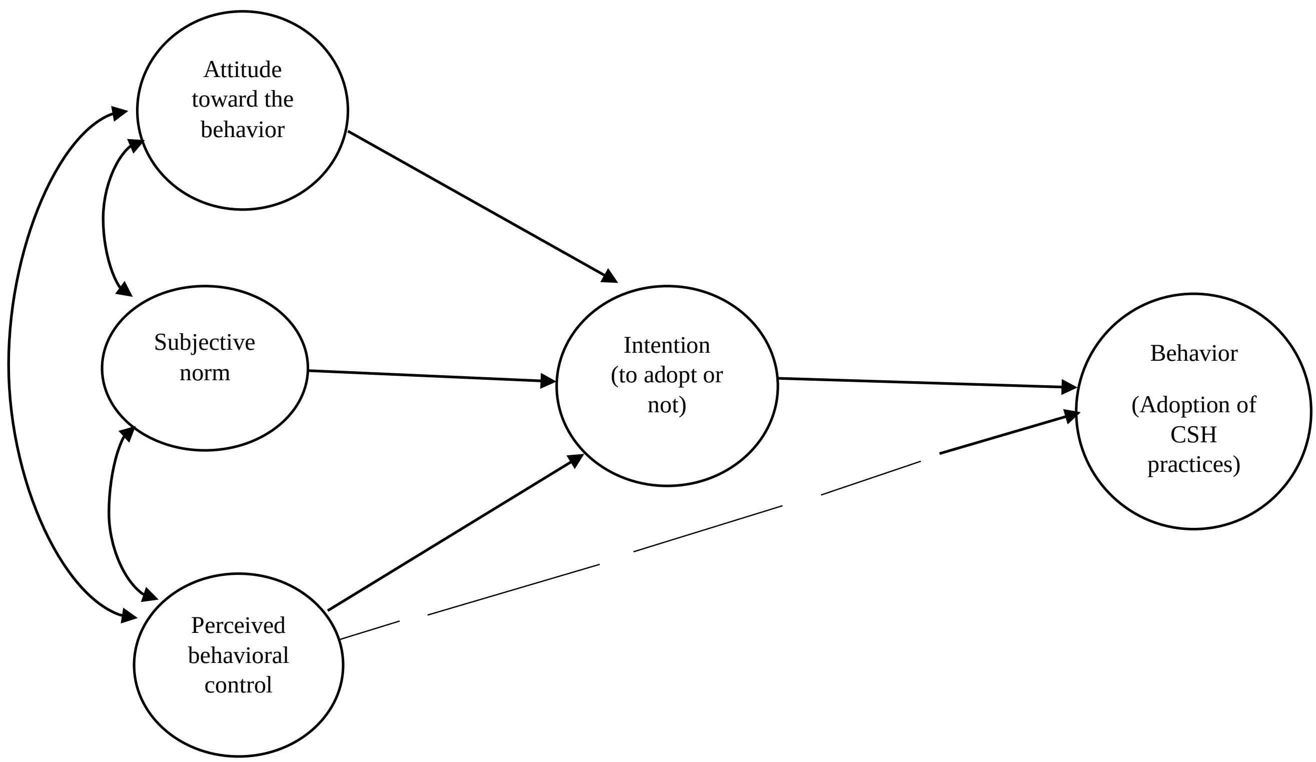

Figure 2.3: A diagrammatic presentation of the theory of planned behavior

Source: Adapted from Ajzen (1991).

The TPB has been widely used in empirical studies involving choices and adoption of innovations. For example, Ajzen (2015) used the TPB to explain consumer intentions and behavior.

He found that TPB goes beyond product attributes to include alternative choices available to the consumer and the effect of PBC and perceived social norms. Likewise, Ansari and Tabassum, 2018 and Mutyasira *et al.,* 2018 in their studies on adoption of improved agricultural practices found that the TPB provided a comprehensive framework for investigating farmers' adoption decisions.

However, if TPB is not well applied, the research may not provide useful information about attitudes and intentions that shape farmer's decision to adopt an innovation (Sok *et al.,* 2020). The TPB was applied in this study as a fundamental concept on modeling farmers' decision to adopt CSH practices. The farmers' adoption behavior (when to adopt and the number of CSH practices adopted) are influenced by their beliefs and attitudes and other background factors such as age, education, physical assets and group membership (social capital) (Ansari and Tabassum, 2018).

2.6.3 Random utility theory

The random utility theory (RUT) models an individual's preferences on alternatives by independently drawing a real-valued score on each alternative from a parameter distribution (Azari *et al.,* 2012). These alternatives are then ranked according to the identified scores. In this case the farmer is assumed to be a rational decision maker and maximizes farm income or profit relative to his/her choices subject to his/her socio-economic, institutional and infrastructural characteristics (Cascetta, 2009). This theory has been widely used for modelling choices among discrete alternatives (Amadu *et al.,* 2020; Cascetta, 2009; Soufiani *et al.,* 2012). For example, Amadu *et al.* (2020) used the RUT to conceptualize household's participation in CSA intervention. He postulated that a farmer would undertake to adopt CSA practices if the utility derived from adoption is greater than non-adoption.

In the current study, it was assumed that farmer's decision to use mobile phone in CSH can be modelled as a choice, given the farmer's socio-economic, institutional and infrastructural factors. Therefore, the farmer chooses an alternative with the greatest perceived utility. It was assumed that the utility U_{ij} of alternative *i* for individual *j* can be decomposed in two terms, that is, a deterministic term, V_{ij}, which is associated with the measured attributes of the alternative choice and a stochastic term, ε_{ij} representing the difference between the measurable utility and the true utility of the alternative choice for individual *j*. The stochastic term (ε_{ij}) accounts for omitted and unobservable factors that affect the utility of alternative choice.

The probability that individual *j* chooses alternative *i* from available alternatives n_j is given as;

$$P_j(i) = P\left(U_{ij} \geq U_{nj},\ \forall\, n \in n_j\right) = P(V_{ij} + \varepsilon_{ij} \geq\ V_{nj} + \varepsilon_{nj}, \forall\, n) \quad \text{.............................. (1)}$$

Equation (1) can be re-arranged as;

$$P_j(i) = (\varepsilon_{nj} - \varepsilon_{ij}\ \geq\ V_{ij} - V_{nj}, \forall\, n \in n_j) \quad \text{.. (2)}$$

Equation (2) means that the probability that a particular alternative is chosen depends on the joint distribution of the differences between the stochastic terms (Abegunde *et al.*, 2019; Shefer *et al.*, 2004).

Subsequently, chapter three, four and five present in paper form, the specific methods applied, and results obtained for the respective objectives of the study, while the conclusions from the various results are all provided in the last chapter.

CHAPTER THREE

3.0 ADOPTION OF CLIMATE-SMART HORTICULTURE PRACTICES AND USE OF MOBILE PHONES BY SMALLHOLDER FARMERS

3.1 Abstract

This chapter characterizes the implementation of climate-smart horticulture (CSH) practices and mobile phone use among farmers using frequency tables, bar graphs, correlation analysis, t-test and one-way analogous analysis of variance (ANOVA). The study used primary data drawn from a focus group discussion (FGD) with key informants and a survey of 403 randomly selected green gram and tomato farmers. Pooled results reveal that 71% of the farmers adopted crop rotation while only 2% adopted crop insurance practices. One-way analogous ANOVA results show that more farmers who produced both green grams and tomatoes adopted seed varieties adapted to local climate, matched planting date, practiced crop rotation, agro-forestry and mulching. On the other hand, more tomato crop producers adopted cover cropping (42%), terracing (73%), used live barriers (such as napier grass) (54%) and used organic manure and fertilizers (71%). Similarly, both crops (tomato and green gram) producers mainly used their mobile phones on CSH than the single crop producers. Also, the results show that 97% of the farmers owned mobile phones with 100% using it for social calls while less than 44% use it for CSH. Correlation analysis results revealed that use of smartphone is positively related to the number of CSH practices adopted. Paired *t-test* statistics also show that the adoption of CSH practices was relatively higher among mobile phone users compared to the non-users.

Key words: mobile phone, climate-smart horticulture, green grams, tomatoes

3.2 Introduction

Horticulture is described as production of vegetables, flowers, fruits, and ornamental crops. In Kenyan agriculture sector, horticulture is the leading income earner to farmers contributing 31% of total value earned from agriculture (KNBS, 2020). On the other hand, vegetables (including tomatoes) contribute 18% to domestic value of marketed horticultural crops (HCD, 2019). Specifically, 90% of tomatoes and green grams produced by smallholder farmers in Taita-Taveta county are sold for household income (Mohamed and Chege, 2019).

However, negative effects of climate change such as prolonged droughts and unpredictable rainfall distribution affects crop productivity (Nhemachena *et al.*, 2020). For example, Northern and Western parts of Kenya may not be suitable for green gram production during March to May season due to shifts in climatic conditions (Mugo *et al.,* 2020). This requires specific interventions such as use of well-adapted seed variety, sustainable farming systems and agroforestry to make the area(s) conducive for tomato and green gram production. These interventions are referred to as climate-smart horticulture (CSH), since they have been shown to improve resilience to climate change effects and crop productivity (Amadu *et al.,* 2020; Sahu, 2016; Thornton *et al.*, 2018).

Mobile phones assist farmers to understand and adopt climate-smart horticulture practices (Baumuller, 2016; Mittal and Hariharan, 2018). They reduce information gaps by allowing farmers to access real time information that fit their specific contexts (Etwire *et al.*, 2017). Precisely, farmers with smartphones have been shown to access a wide range of information (including technology simulations) related to modern farming techniques (Krell, Giroux, Guido, Hannah, Lopus, Caylor, & Evans, 2020).

Therefore, mobile phone can become an asset in climate-smart horticulture if well utilized. For instance, it has been shown that mobile phones are used by farmers to access information concerning weather, input (such as seeds and fertilizer) and output prices, money transfer services, connect to other farmers and contacting extension agents (Etwire *et al.*, 2017; Kirui *et al.*, 2012; Mittal and Mehar, 2014).

In Taita-Taveta County, about 80% of farmers own a mobile phone (CGTT, 2018). However, little is known about how they apply their mobile phones in horticulture. Besides, there are different agro-ecological zones under which farmers produce different crops and require different CSH interventions (Anuga *et al.*, 2013; Jaetzold *et al.*, 2010). This has not been well documented. Characterizing the adoption of CSH practices and mobile phone use among green gram and tomato farmers would help reduce the knowledge gap and contribute to agricultural development in the area.

3.3 Methodology

3.3.1 Data sources and sampling procedure

The study used primary data collected through a field survey conducted in Wundanyi, Mwatate and Taveta sub-counties in Taita-Taveta county. The three sub-counties were purposively selected due to high concentration of tomato and green gram farmers. Also, green grams and tomatoes are important crops that contribute 10% and 90% to household food and income generation, respectively, in the area (Mohamed and Chege, 2019).

The sample size was calculated using a formula adapted from Cochran (1977). The formula is presented in Equation (3).

$$n_o = \frac{Z^2 pq}{e^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where; $\boldsymbol{n_0}$ represent the sample size, ***Z*** is the *Z-critical* value at a particular confidence level, ***p*** is the maximum level of variance, ***q*** represents *(1-p)* and ***e*** is the preferred margin of error.

The study used 95.1% confidence level and 0.049 desired margin of error to attain a sample size of 400; which would be large enough to draw generalization on the population with +/-4.9%. The ***p*** was assumed to take a value of 0.5, since the disparity among CSH farmers was not known and the fact that green gram crop characteristics are slightly different from tomatoes. Therefore, the sample size was calculated as shown in equation (4);

$$n_o = \frac{1.96^2 \times 0.5 \times 0.5}{0.049^2} = 400 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (4)$$

This sample size was proportionately distributed among the three sub-counties according the 2019 Kenya population and housing census and additional 20 (equivalent to 5% of sample size) farmers were added to cater for incomplete questionnaires and potential non-response (Bujang, 2021).

Data was collected through an FGD checklist questionnaire (Appendix 1) and a structured questionnaire (Appendix 2). The FGD had eleven (11) members comprising of tomato and green gram farmers, agricultural officers, agricultural input dealers, local administrator and credit provider. The discussion focused on the meaning of climate change and climate-smart horticulture (CSH), CSH practices adopted in the area, evolution of mobile phone and its use in agriculture. This helped to gain broader insights on the study area and validate the information collected in the survey.

Subsequently, individual tomato and green gram farmers were randomly selected and interviewed using semi-structured questionnaires. The questionnaire was used to collect information on socio-economic characteristics of the farmers, mobile phone use and climate-smart horticulture. Four hundred and fifteen (415) farmers participated in the household survey.

However, during data cleaning, 12 questionnaires were found to be incomplete and hence not included in the analysis. Therefore, this study used a total of 403 filled questionnaires (59 from Wundanyi, 122 from Mwatate and 222 from Taveta sub-counties); 115 respondents were tomato farmers, 259 green gram farmers and 29 farmers produced both crops.

3.3.2 Test for multicollinearity

The test for multicollinearity was done using variance inflation factor (VIF) to determine the variance of the independent variables (Gujarati, 2004) as shown in equation (5).

$$VIF = \frac{1}{(1-R_j^2)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

where, R_j^2 is the coefficient of determination.

The average VIF shown in Appendix 3 was 1.9, meaning that there were no serious issues of multicollinearity between the independent variables. All the variables had a VIF of less than 4 indicating that there was a low level of multicollinearity (Gujarati, 2003). According to Garson *et al.* (2016), multicollinearity become problematic when the VIF is greater than 4. On the other hand, Gujarati and Porter (2009) suggested that a value greater than one indicates a risk of multicollinearity while VIF greater than 10.0 shows there is serious multicollinearity and that variable may need to be dropped.

In addition, partial correlation analysis was conducted to determine whether there is correlation between any two independent variables (Gujarati and Porter, 2009). The results showed that there was strong correlation between some variables such as the farm size under crop and total farm size (0.6170), distance from farm to the market and distance from farm to the bank (0.5087) (Appendix 4).

Therefore, total farm size and distance from farm to the agricultural market were dropped in the regression model(s) in favor of farm size (under crop) and distance from farm to the bank, respectively.

3.3.3 Test for heteroscedasticity

Heteroscedasticity is said to exist if the error term does not exhibit equal variance given the values of independent variables (Wooldridge, 2013). This causes the model to produce biased standard errors and test statistics which may result to inaccurate conclusion in hypothesis testing (Olvera and Zumbo, 2019). This study applied Breusch-Pagan test and obtained a chi-square (χ^2) value of 33.18 with a *p-value* of 0.0000. The *p-value* obtained means that we reject the null hypothesis and conclude that there was presence of heteroscedasticity in the independent variables used to estimate Tobit model. To address this problem, the study used robust standard errors in the Tobit model (Gujarati, 2004; Olvera and Zumbo, 2019). Robust standard errors are unbiased and provides a more accurate measure of the true standard error of a regression coefficient (Gujarati and Porter, 2009).

3.3.4 Test for endogeneity

Endogeneity problem arises when some of the independent variables are correlated with the error term in the model (Ao, 2009). This occurs under various circumstances including omitting important variables from the model (omitted variable bias) and when a regressor is a regressand (simultaneity bias) (Lynch and Brown, 2011).

In the presence of simultaneity, OLS estimators are biased and inconsistent – leads to overestimation of co-efficients in the model (Ao, 2009; Lynch and Brown, 2011). To test for endogeneity, one can apply Hausman specification test (Gujarati & Porter, 2009).

The test is done under a null hypothesis that the regressor is exogenous and alternative hypothesis that the regressor is endogenous. This study suspected that the mobile phone use and the number of CSH practices were endogenous under the models. The study used stata software to test for endogeneity and obtained the output shown below;

```
. estat endog

  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)          =  .786565  (p = 0.3751)
  Wu-Hausman F(1,397)             =  .776369  (p = 0.3788)
```

The p-value is 0.38, implying that we fail to reject the null hypothesis and conclude that the regressor (mobile phone use on CSH) is exogenous.

3.3.5 Data analysis

Bar graphs and tables were used to show the percentage of farmers who adopted CSH practices and used mobile phones for different purposes including CSH. On the other hand, Pearson's correlation analysis (Hung *et al.,* 2018) was used to show the relationship between the type of mobile phone used (whether basic feature phone, low-end smartphone or high-end smartphone) and the number of CSH practices adopted. To show this, the study applied Pearson's correlation coefficient(r_{xy}) shown in Equation (6):

Given paired data $(x_1, y_1), \ldots, (x_n y_n)$ consisting of n pairs, r_{xy} was defined as;

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

where;

n is a sample size

x_i is the type of mobile phone and y_i is the number of CSH practices adopted.

$\bar{x}, \bar{y}$ are the means of x and y variables, respectively.

Equation (6) can be re-written as;

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{\sqrt{(\sum x_i^2 - n\bar{x}^2)}\sqrt{(\sum y_i^2 - n\bar{y}^2)}} \text{ ……………………………………….. (7)}$$

In addition, one-way analogous analysis of variance (ANOVA) (Mai and Zhang, 2017) was used to compare the proportions of three groups of farmers dealing with tomato, green gram and both crops. The method uses maximum likelihood method to estimate variation between and within groups. According to Mai and Zhang (2017), comparing group proportions for binary data has the same hypothesis as one-way ANOVA for continuous data but apply different models because the outcome variable (for binary data) does not have a normal distribution. Following this logic, one-way analogous ANOVA table was used (Table 3.1).

Table 3.1: One-way analogous ANOVA for the three groups of farmers

Source	Sum of variance	Degree of freedom	Test statistic	p-value
Between group	$SS_B = -2(\ell_{Mo} - \ell_{M1})$	$k-1$	$\tilde{D} = -2(\ell_{Mo} - \ell_{M1})$	$\Pr[\chi^2(k-1) \geq \tilde{D}]$
Within group	$SS_W = -2\ell_{M1}$	$n-k$		
Total	$SS_T = -2\ell_{Mo}$	$n-1$		

Source: Mai and Zhang (2017).

Paired t-test was used to measure the differences in CSH adoption between mobile phone users and non-users. The differences between mobile phone users and non-users were treated as a random sample drawn from a normal population with mean of $\mu_D = \mu max - \mu min$ and unknown standard deviation.

The hypothesis tested using t-test was given as; H_o: There are no differences in climate-smart practice(s) adoption between mobile phone users and non-users ($\mu max = \mu min$) and H_1: More mobile phone users adopt climate-smart practice(s) than non-users ($\mu max > \mu min$).

3.4 Results and discussion

3.4.1 Climate-smart horticulture adoption characteristics

Table 3.2 presents one-way analogous ANOVA results. The results indicate that there is high relationship between adoption of CSH practices and different farmer types. For instance, significant differences were revealed in the use of well adapted seed variety, matching planting dates with weather information received, crop rotation, terracing, agroforestry, use of live barriers, organic manure, mulching, farm ponds for water harvesting and storage and contour cultivation between the three types of farmers (green grams, tomatoes and both crops producers). This is because farmers adopt CSH practices based on the environment in which they operate (Lipper *et al.*, 2014; Thornton *et al.*, 2018). In addition, the results imply that the type of crop produced largely determines the CSH practice(s) adopted.

Farmers who produced tomatoes only and those who produced both green grams and tomatoes adopted more CSH practices than those who produced green grams only (Table 3.2). But, there was no significant difference in adoption of crop insurance, crop diversification and mixed farming practices between the three types of farmers.

Table 3.2: Climate-smart horticulture practices adopted by different types of farmers

CSH practices	Type of farmer		
	Green grams (%) (n =259)	*Tomatoes (%) (n=115)*	*Both green grams and tomatoes (%) (n =29)*
Well adapted seed variety	40.93[c]	66.09[b]	72.41[a]
Matching planting dates to weather information received	16.22[c]	36.52[b]	41.38[a]
Crop rotation	62.93[c]	85.22[b]	93.10[a]
Use of cover crops	27.80[c]	42.61[a]	41.38[b]
Soil testing before fertilizer application	8.49[c]	30.43[b]	34.48[a]
Terracing	44.02[c]	73.04[a]	65.52[b]
Agro-forestry	41.70[c]	53.91[b]	65.52[a]
Live barriers such as napier grass	16.60[c]	53.91[a]	27.59[b]
Mixed farming	44.02	52.17	55.17
Crop insurance	2.70	1.74	3.45
Crop diversification	46.72	51.30	58.62
Use of compost manure and organic fertilizers	33.98[c]	71.30[a]	55.17[b]
Mulching	27.80[c]	60.87[b]	65.52[a]
Minimum tillage	24.32[c]	24.35[b]	44.83[a]
Farm ponds for water storage	12.36[c]	42.61[b]	44.83[a]
Integrated Pest Management (IPM)	13.90[c]	48.70[a]	17.24[b]
Contour cultivation	23.55[c]	48.70[a]	44.83[b]

Note: [a, b, c] denote significant differences (at 10% level or better) in climate-smart practice(s) between different types of crop farmers in descending order of magnitude
Source: Survey Data (2021).

Combined results (all the three types of farmers) in Figure 3.1 show that Taita-Taveta County farmers adopted CSH practices to different extents. This is because each type of crop and agro-ecological zone requires different interventions in terms of CSH practices (Aryal *et al.*, 2018).

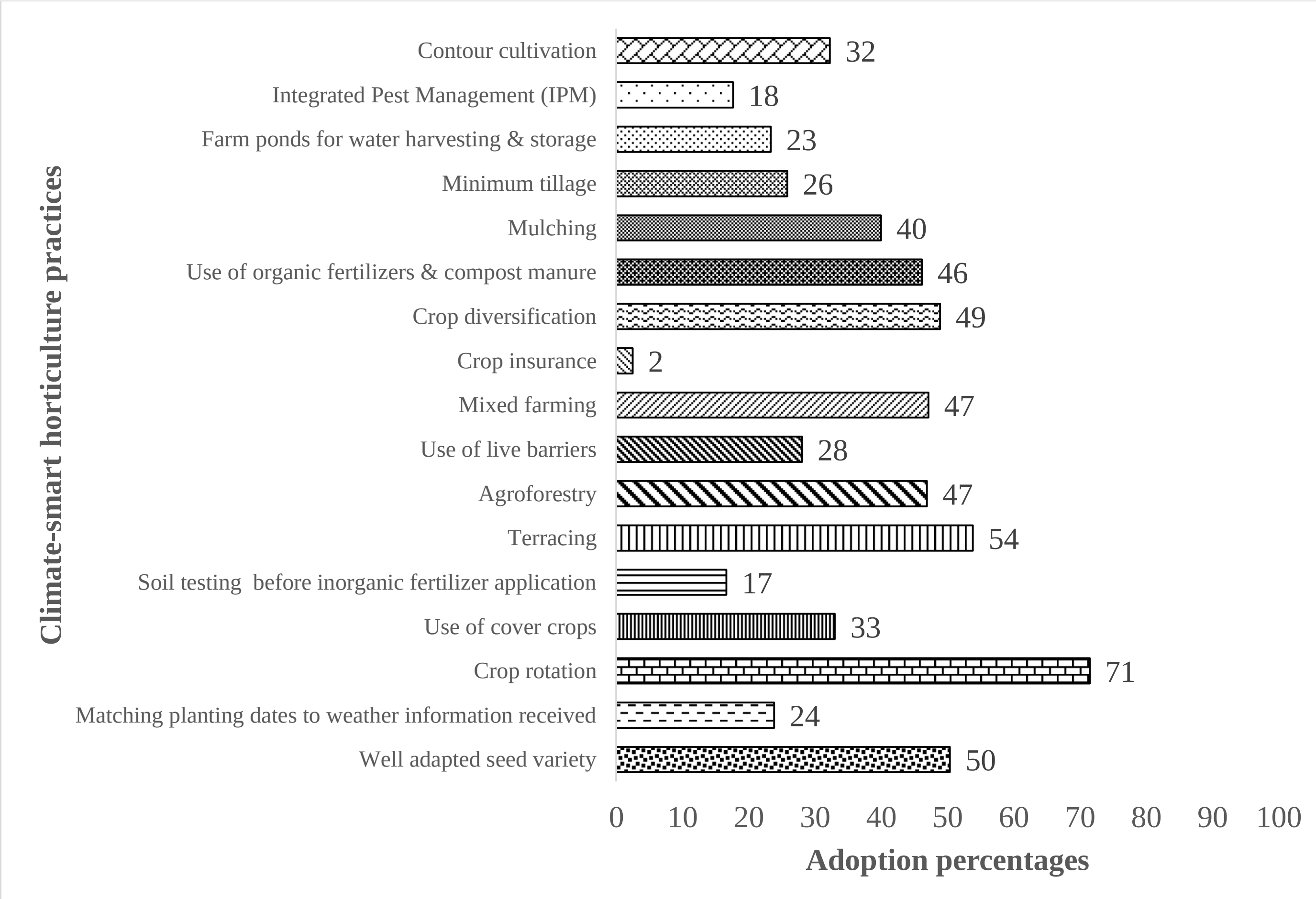

Figure 3.1: Percentage of farmers who adopted climate smart horticulture practices in Taita-Taveta County
Source: Survey Data (2021).

The results demonstrate that crop rotation was the most adopted practice with 71% of farmers practicing it. The high adoption of crop rotation practice is attributed to; low income of farmers – since it requires less capital and technical knowledge to implement and the farmers' perception that crop rotation is the most effective method of controlling weeds, diseases and pests (Acheampong *et al.*, 2021; He *et al.*, 2008).

On the other hand, only 2% of the farmers adopted crop insurance (Figure 3.1). Similar results were obtained by Nyabochwa (2015) who revealed that low uptake of crop insurance was due to lack of awareness of such facility by the farmers. Other practices such as terracing and use of well adapted seed variety were adopted by 54% and 50% of the farmers, respectively.

Crop diversification, mixed farming, agroforestry, use of compost manure, mulching, among others, were practiced by less than 50% of the farmers. This is because most farmers in the area rely on rain-fed agriculture, have low access to extension services and low income, which limits their farm practices (Fliegel and Kivlin, 1966; Kassie, 2014; Kemboi *et al.*, 2020).

3.4.2 Climate-smart horticulture adoption behavior exhibited by farmers

Figure 3.2 shows CSH adoption pattern exhibited by tomatoes and green gram farmers in Taita-Taveta County. The results revealed that about 55% of the farmers took less than 3 months while 33% took more than 12 months to adopt the practice(s). This diverges from earlier claim by Rogers (1983) that majority of adopters lie between early majority and late majority. The results show a different pattern from that which was proposed by Rodgers (1983), since less farmers lie between innovators and laggards.

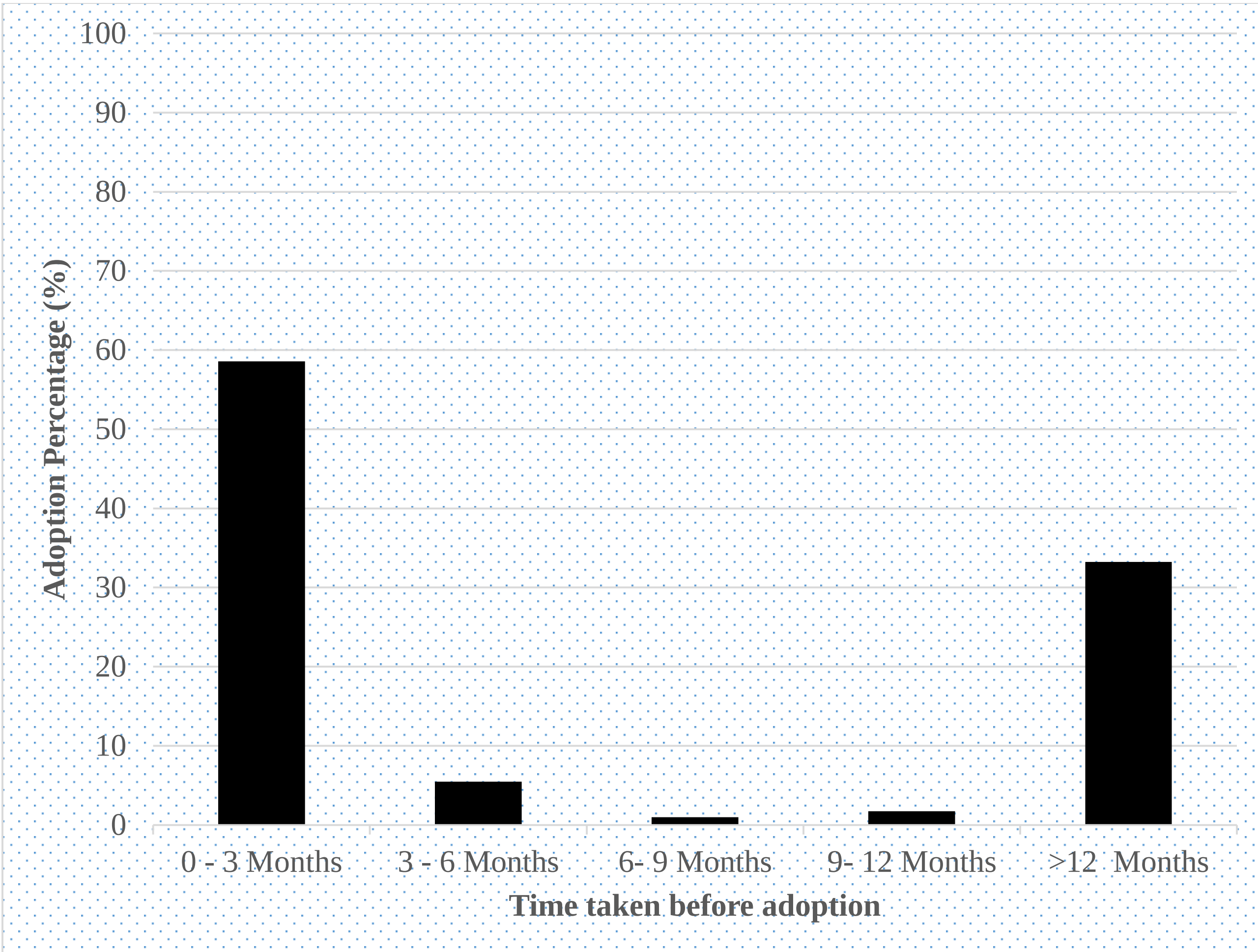

Figure 3.2: Climate-smart horticulture practice(s) adoption pattern among farmers in Taita-Taveta County
Source: Survey Data (2021).

Some factors that may have led to high number of early adopters include; awareness of climate change and climate-smart horticulture, social factors such as indigenous knowledge and farming experience (Pagliacci *et al.*, 2020). In addition, Fliegel and Kivlin (1966) noted that innovations that are perceived to be less risky but rewarding are accepted swiftly and practiced by farmers. This was also observed in the study area where most farmers adopted innovations, which blended with their existing farming systems and had low costs attached. However, farmers who hesitate to put their money in agricultural innovations end up being laggards (Diederen *et al.*, 2003).

3.4.3 Evolution and key drivers of mobile phone use among farming community in Taita-Taveta County

In a FGD that involved tomato and green gram farmers, agro-input dealers, local administrators and credit service providers, the participants described the evolution of mobile phone use and key drivers as shown in Table 3.3. The focus group comprised of 53% and 47% male and female, respectively, distributed between 24 and 57 years of age.

Table 3.3: Evolution of mobile phone use and key drivers from 1980 – 2021

Period	Changes in mobile phone use	Key drivers of change
1980 -1990	• There were no mobile phones in the area during this period • People used to queue at telephone booths (which were also limited in number) to communicate using landline phones • The landline phones could not support messaging services. Therefore, users were limited to calls only	• Underdeveloped mobile phone technology • Very few people were educated • Mobile phones were not in the country during this period
1991 -2000	• Mobile phones were introduced in the country during this period • It was very difficult to get a mobile phone because it was not easily accessible and had a high cost of operation • It was possible to make calls and send limited (characters) short text messages using mobile phone during this period	• High level of poverty • No network connectivity in the area • Improved mobile phone technology relative to the previous period • Few mobile phone producing companies (such as Nokia and Motorola) were available

2001 -2010	• Mobile phone penetration improved and poor households could afford but low-end smartphones were accessible to wealthier households only • It was mainly used for social communication through calls and text messaging • It was difficult to find network connectivity. • Commercial farmers would sometimes use their phones for agricultural purposes • Text messages were mainly used to communicate to farmers • It was rarely used to pass climate change information from government and non-governmental organizations • Introduction of mobile money transfer services such as M-Pesa	• Introduction of more network service providers such as Safaricom Ltd and Celtel, who improved network access to rural areas • Reduced cost of acquiring and operating a mobile phone (in terms of airtime and electric power access) relative to previous period. • Improved education levels among households compared to previous periods
2011 -2021	• It was cheap to acquire a mobile phone (one can get it with only Kshs. 1,000) compared to earlier periods. • Network connectivity was readily available due to introduction of different network service providers. • Introduction of high-end smartphones which can handle multiple tasks and applications • Easy to access farming-related information through mobile phones and most farmers were using them • Many social media platforms such as whatsapp, facebook and twitter where farmers can interact • Mobile phones were used for multiple tasks such as marketing, obtaining weather forecast information, teleconferencing, making and receiving payments and entertainment	• High number of mobile phone shop outlets and brands (such as Nokia, Samsung, Huawei, Oppo, Apple, Itel and Tecno) • Accessibility of high quality network (4th generation (4G)) in most areas • Increased demand for high-end smartphones with ability to perform multiple tasks such as money account management, teleconferencing, document processing and filing and e-commerce. • Low cost of operation (in terms of airtime, technical knowledge and power access). • High literacy level compared to earlier periods • Increased youthful population demanding new types of phone with better features

Source: Survey Data (2021).

The results show that the application of mobile phones in farming became more evident from the period 2001. These findings are consistent with Bayes *et al.* (1999), Masuki *et al.* (2007) and Mittal and Tripathi (2009) on the role and application of mobile phone in improving farm productivity. The findings also show that the application of mobile phones in climate-smart horticulture has continued to grow and currently include; real time weather information, agricultural market information and information on crop husbandry practices. Similarly, previous studies such as Baumuller (2016), Krell *et al.* (2020) and Mittal and Hariharan (2018) showed that mobile phones were being applied by farmers to get market, weather and crop husbandry information.

3.4.4 Mobile phone use characteristics among climate-smart horticulture farmers

Mobile phones are the most widely used tools for communication in Kenya (CAK, 2019). Similarly, farmers own different types of mobile phones, which they use to communicate as shown in Table 3.4.

Table 3.4: Farmer classification based on type of phone used in climate-smart horticulture

Type of mobile phone owned	Mobile phone ownership among farmers (%)
None	3.47
Basic feature phone	57.32
Low-end smartphone	23.82
High-end smartphone	15.38

Source: Survey Data (2021).

In this study, *none* means that the farmer does not own any mobile phone. A *basic feature phone* was defined as a mobile phone that supports voice call, messaging and money transfer services only. On the other hand, *low-end smartphones* included mobile phones that support voice calls, operate on second and/or 3rd generation network, limited applications and memory size of less than one gigabyte (GB) random access memory (RAM).

High-end smartphones comprised of personal digital assistants, more than one GB RAM, mobile phones that support graphics, 3rd generation network and above and can support teleconferencing applications. Results show that 96% of farmers in Taita-Taveta County own a mobile phone; over half of them having basic feature phone compared to low-end and high-end smartphones. This implies that a high number of farmers have low access to mobile phone-based agricultural information services. This finding follows the observation by Quandt *et al.* (2020) that majority of farmers in Tanzania had basic feature phones which limited their use of agricultural information services.

Table 3.5 shows one-way analogous ANOVA results on the difference in the use of mobile phone between the three types of farmers (green grams, tomatoes and both crops). The results reveal that most farmers used their mobile phones for social calls, entertainment and social chats (facebook, whatsapp and twitter). However, there are differences in usage of mobile phones between the different types of farmers. For instance, farmers who produced tomatoes and both crops mainly used their mobile phones for social chats, searching information on output markets and making and receiving payments compared to green gram producers.

Table 3.5: Mobile phone use characteristics among different crop farmers

Use of mobile phone	Type of farmer		
	Green grams (%) (n = 259)	*Tomatoes (%) (n = 115)*	*Both green grams and tomatoes (%) (n = 29)*
Social calls	95.37	96.52	100.00
Play games	8.88[c]	18.26[a]	10.34[b]
Entertainment	55.60	65.22	68.97
Social chats (facebook, WhatsApp and twitter)	57.14[c]	70.43[b]	79.31[a]
Search for information on farm laborers	3.47[c]	8.70[b]	13.79[a]
Search for weather information	10.04	9.57	10.34
Search for agricultural input information	18.53[c]	36.52[b]	44.83[a]
Search for agricultural output information	33.98[c]	59.13[b]	62.07[a]
Making and receiving payments	32.82[c]	62.61[b]	65.52[a]
Contact agricultural extension agent	20.08[c]	33.91[b]	34.48[a]
Search for agronomic information	22.01[c]	46.09[b]	51.72[a]
Search for farm transport information	25.10[c]	39.13[b]	41.38[a]
Search for non-agricultural information	16.22[c]	29.57[b]	34.48[a]

Note: [a, b, c] denote significant statistical differences (at 10% level or better) in the use of mobile phone between different types of crop farmers in descending order of magnitude
Source: Survey Data (2021).

The results also reveal that there was less application of mobile phones in searching for information on weather, agricultural inputs and contacting agricultural extension agent(s) among all the three types of farmers. This is attributed to lack of awareness of such services and skills to use them (Khan *et al.,* 2019). In addition, majority of farmers had basic feature phones, which limited their access to agricultural information services (Quandt *et al.*, 2020).

Pooled results in Figure 3.3 indicate that over 96% of Taita-Taveta county farmers (tomato and green grams) use their mobile phones for social calls while 63% and 59% use it for social chats (through whatsapp, facebook and twitter) and entertainment, respectively.

However, less than 44% use their phones for agricultural purpose such as searching for; price, agronomic, weather and farm transport information and making and receiving payments. These results are consistent with Chhachhar *et al.* (2014) who found that ownership of mobile phones by farmers did not necessarily reflect their application for agricultural purposes.

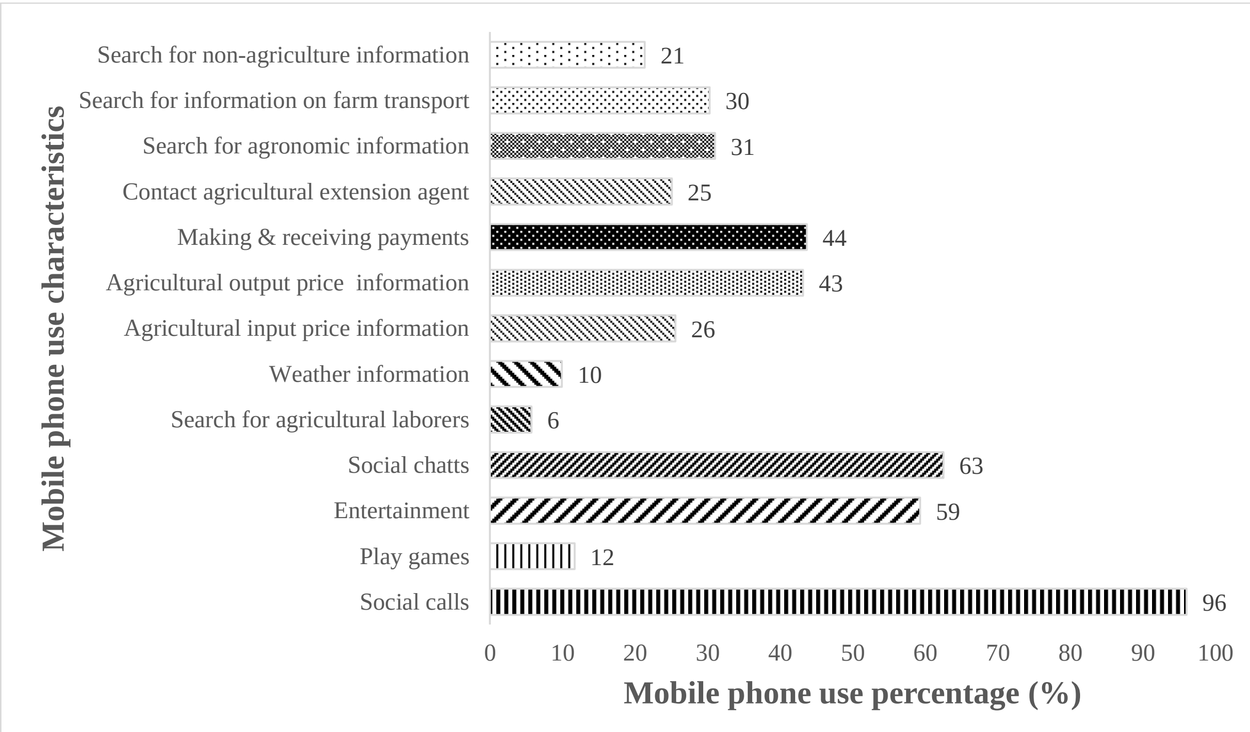

Figure 3.3: Extent to which climate-smart horticulture farmers use their mobile phones

Source: Survey Data (2021).

3.4.5 Correlation between the type of mobile phone used and the number of climate-smart horticulture practices adopted

From Figure 3.4, there is positive correlation between the types of mobile phone the farmers use and the number of CSH practices adopted. Farmers who use high-end smart phone adopt more CSH practices. This is because farmers with smartphones are able to access a wide range of information and technologies (including simulations) that are useful to agricultural production.

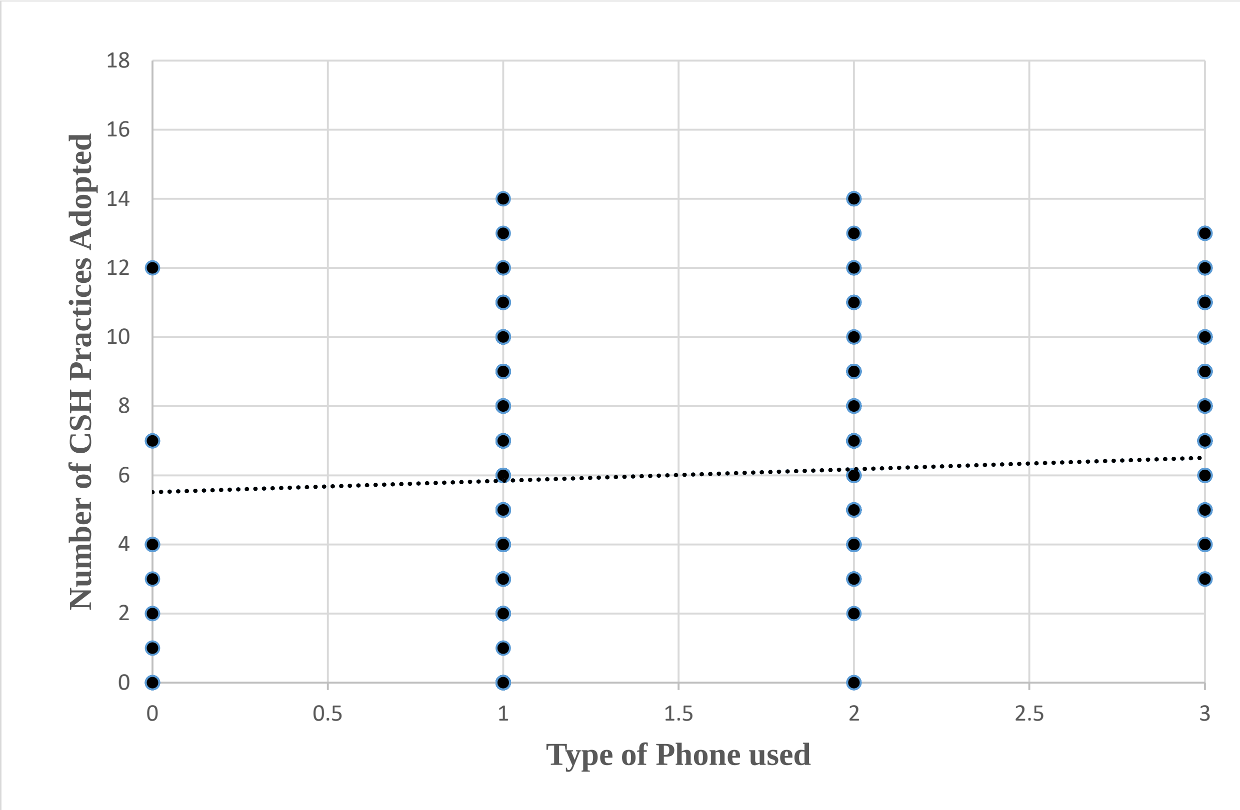

Figure 3.4: Pearson's correlation analysis of type of phone used against the number of climate-smart horticulture practices adopted

Note: X-axis; 0 =non-use of mobile phone, 1 = basic-feature phone, 2 = low-end smartphone, 3 = high-end smartphone

Source: Survey Data (2021).

3.4.6 Differences in climate-smart horticulture adoption characteristics between mobile phone users and non-users

Table 3.6 presents the adoption of CSH practices between mobile phone users and non-users on CSH. Mobile phone users on CSH was used to mean farmers who applied their mobile phones in searching for any climate-smart horticulture information and/or using the phone to pay (or receive money) for related products and services. Using t-test statistic, results show that a significantly higher number of mobile phone users in horticulture adopted most CSH practices compared to non-users.

For example, the difference in adoption of agroforestry, use of terraces, cover crops and crop rotation was 38%, 32%, 29% and 25%, respectively between mobile phone users and non-users. These results are consistent with those of Mittal (2016) who found that mobile phone users adopted new farming practices and technologies due to improved awareness.

Table 3.6: Mean differences in adoption of climate-smart horticulture practices between mobile phone users and non-users

CSH practice	*Mobile phone users (n = 224)*	*Mobile phone non-users (n = 179)*	*Mean difference*
Use of improved and well adapted seed variety	0.59	0.39	0.20***
Matching planting dates to weather information received	0.31	0.15	0.16***
Crop rotation	0.83	0.58	0.25***
Use of cover crops	0.46	0.17	0.29***
Efficient use of inorganic fertilizers through soil testing	0.19	0.14	0.05
Use of terraces	0.68	0.36	0.32***
Agroforestry	0.64	0.26	0.38***
Use of live barriers such as Napier grass	0.38	0.16	0.22***
Mixed farming	0.48	0.46	0.02
Crop insurance	0.03	0.02	0.01
Crop diversification	0.47	0.51	-0.04
Use of organic fertilizers and compost manure	0.54	0.37	0.17***
Mulching	0.50	0.27	0.23***
Minimum tillage	0.33	0.17	0.16***
Farm ponds (water harvesting and storage)	0.30	0.15	0.15***
Integrated Pest Management	0.18	0.17	0.01
Contour cultivation	0.42	0.21	0.21***

*Note: *** 1% statistical significance level.*

Source: Survey Data (2021).

Previous research has also shown that majority of digital device users on CSA adopt at least one such practice (Shrader *et al.*, 2020). Similarly, the results reveal that crop diversification was the only highly adopted practice by mobile phone non-users compared to users, with a difference of 4%.

This is because most mobile phone non-users were older in terms of age (relative to mobile phone users) implying that they were more concerned with household food security, which to a large extent can be assured through diversification (Dembele *et al.*, 2018; Kemboi *et al.*, 2020). It also implies that the older farmers had larger sizes of land that allowed for diversification compared to younger farmers – who may not have ownership rights (Aikins *et al.*, 2021). As noted in Table 3.2, most farmers (64%) were green gram farmers who mainly depended on rainfall for their farming activities. This has been shown to enhance crop diversification to reduce the risk of loss (Kassie, 2014).

CHAPTER FOUR

4.0 FACTORS INFLUENCING MOBILE PHONE USE AND ADOPTION OF CLIMATE-SMART HORTICULTURE PRACTICES

4.1 Abstract

Mobile phone is an important tool for farmers. Its role in reducing agricultural information gaps and improving access to wide range of services cannot be underestimated. While climate change poses a serious threat to crop production, mobile phones have steadily attempted to provide a solution by facilitating sharing of real time information and enhancing virtual networks beneficial to farmers. However, there is still low application of mobile phone in horticulture. This study analyzed the factors affecting mobile phone use on climate-smart horticulture (CSH). The study surveyed 403 tomato and green gram farmers randomly drawn from three sub-counties (Wundanyi, Mwatate and Taveta) in Taita-Taveta County. Binary logit model was applied to examine the factors influencing mobile phone use on CSH. Negative binomial model was used to assess the determinants of the number of CSH practices adopted. Binary logit results indicate that male farmers were 84% more likely to use mobile phones on CSH compared to female farmers. Likewise, trust on accuracy of information received, access to electric power (solar and hydro-electricity) and access to credit increases the likelihood of using mobile phones on CSH by 1.08, 1.38, 1.44 times, respectively. Farmer's age negatively influenced mobile phone use on CSH. The results from the negative binomial regression model show that being a male farmer (gender), education, farming experience, mobile phone use and awareness on CSH positively determined the number of CSH practices adopted. However, an increase in farm size under crop and awareness of climate change negatively affects the number of CSH practices adopted.

Other factors such as agricultural extension and trust on information received positively determined the number of CSH practices. Based on the findings, it is suggested that government institutions should partner with local telecommunication service providers to educate farmers and extension agents on mobile phone use on farming and develop a one-stop app that would provide real time and credible weather, agronomic, market and price information.

Key words: Mobile phone, climate-smart, binary logit, negative binomial regression, Taita-Taveta County.

4.2 Introduction

Mobile phone penetration has rapidly grown in Kenya since 1999 (Malack *et al.*, 2015) and is currently estimated at 126% (CAK, 2020). Similarly, mobile phone ownership and use among smallholder farmers increased (GeoPoll, 2018). The farmers use mobile phones to access a wide range of agricultural information including input and output prices, weather and agronomic information (Akinola, 2017). According to GeoPoll (2018), all farmers under their study owned mobile phones with more than half of them using smartphones.

As the mobile phones and telecommunication sector continues to grow, more customized features also emerge. For instance, there are more than 50 mobile phone-supported agricultural applications that serve different sections of farmers (Qiang *et al.*, 2011). With these developments, farmers are able to reduce information gaps and transaction costs along agricultural value chains through their mobile phones (Ogutu *et al.*, 2014; Suarez and Suarez, 2013). However, Okello *et al.* (2014) argue that mobile phone use is dependent on farmer-specific and capital endowment factors. Specifically, Krell *et al.* (2020) showed that smartphone ownership and high level of education significantly affected the usage of mobile phone-based agricultural services *(m-services)*.

In horticulture, mobile phone plays a key role in linking farmers to the markets, since most crops (including tomatoes) are highly perishable (Pokhrel, 2021; Tadesse and Bahiigwa, 2015). Likewise, they can also be viewed as enablers in achieving CSH objectives including increased productivity and building resilience to climate change (Sahu, 2016). This is because they enable transmission of real time weather, price and market information to farmers (Mittal, 2016).

Despite the perceived importance of mobile phone use in horticulture, there is still low evidence of mobile phone use for agricultural purposes. Aminou *et al.* (2018) suggested that mobile phone is a consumer good if not used for production purposes. Chhachhar *et al.* (2014) also found that most farmers were not using their mobile phones for agricultural information despite owning one. In addition, previous studies have shown how application of mobile phones would help farmers address climate change challenges including weather (Etwire *et al.,* 2017; Mittal and Hariharan, 2018). However, there is scanty evidence on the factors affecting application of mobile phones in horticulture. This study contributes to addressing this knowledge gap by providing such evidence.

4.3 Methodology

4.3.1 Data analysis

The study applied a two-step approach in analyzing the factors that influence mobile phone use in CSH. In the first step, a binary logit model (Corlett and Aigner, 1972) was used to analyze the determinants of mobile phone use on CSH. In this case, the variable, *mobile phone use*, was equated to 1 if the farmer was using mobile phone on CSH and 0 otherwise. The use of either logit or probit models in analysis depends on researcher's preference since they yield similar results and does not affect interpretation (Udimal *et al.,* 2017).

The logit model was preferred because of its closed mathematical form and it was assumed that the error term is logistically distributed (Wooldridge, 2013). In this study, the likelihood *(p)* that a farmer uses mobile phone in CSH is expressed by the logistic distribution function shown in equation (8) (Gujarati and Porter, 2009). A *'climate-smart farmer'* was defined as a farmer who was actively practicing one or more of the CSH techniques.

$$P_i = \frac{e^z}{1+e^z} \text{ where, } Z_i = \beta_1 + \beta_2 X_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (8)$$

If P_i is the probability of using mobile phone in CSH (as shown in equation 8), then *(1-P_i)*, the probability of not using it, is expressed as;

$$(1 - P_i) = {}^{1}/_{1 + e^{z_i}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Equation (9) can be expressed as;

$$\frac{P_i}{1-P_i} = e^{z_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

where, (P_i/1-P_i) is the odds ratio in favor of using a mobile phone in CSH.

Taking the natural log of equation (10) we get;

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_1 + \beta_2 X_i + \varepsilon \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (11)$$

where,

L_i is the logit transformation and Z_i is the latent variable that takes the value of 1 if a farmer is using mobile phone in climate smart horticulture and 0 otherwise.

X_i is a group of independent variables which include; education, age, gender, land size, electricity connection, off-farm income, group membership, access to credit, geographic location and access to extension services.

$\boldsymbol{\varepsilon}$ is the error term that is assumed to have a logistic distribution.

In the second step, a negative binomial regression model (NBRM) was applied to examine the determinants of the extent of adoption of CSH practices (in which mobile phones are used). Since the dependent variable is a non-negative count variable, either a Poisson model or NBRM could be used (Greene, 2003; Wooldridge, 2013). The NBRM was preferred in this study because it generalizes the Poisson model by introducing unobserved effect into the conditional mean and relaxes its assumption of the equality between conditional mean and variance. It also does better for over-dispersed data than the Poisson model (Greene, 2003; Yang and Berdine, 2015). Therefore, the NBRM applied in this study was expressed as shown in equation (12);

$$(y_i|x_i,\ \varepsilon) = \frac{e^{-\lambda_i \varepsilon_i}(\lambda_i \varepsilon_i)^{y_i}}{y_i!} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where λ_i is distribution parameter, $y_i = 0,\ 1,\ 2,\ 3,\ \ldots..$ (countable variable that takes non-negative integer), x_i is a vector of independent variables and ε_i is the stochastic term. Equation (12) can be expressed as;

$$E(y_i|x_i,\ \varepsilon) = \exp(\boldsymbol{X'\beta} + \boldsymbol{\varepsilon}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (13)$$

Taking logs on Equation (13);

$$\log E(y_i|x_i,\ \varepsilon) = \boldsymbol{X'\beta} + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

4.3.2 Expected signs for variables in the binary logit and negative binomial regression models

Table 4.1 presents expected signs for determinants of mobile phone use and the number of CSH practices adopted.

Table 4.1: Variables included in the binary logit, negative binomial regression model and their expected signs

Variable	Description	Binary logit	Negative binomial regression model
Farmer's age	Number of years	-	+/-
Gender of the farmer	Male = 1, female = 0	+/-	+/-
Farmer's education level	Number of years spent in school	+	+
Household size	Number of dependants in a household	+	+
Farming experience	Years spent in active farming	+	+/-
Farm size	Number of acres under the crop	+	+
Access to electricity (either solar and hydro-electric power)	Yes = 1, Otherwise =0	+	
Group membership	If in a farmer group (Yes =1, No = 0)	+/-	+
Access to credit	Has the farmer obtained credit in the past 2 years (Yes =1, No = 0)	+	+
Trust on information received	Believes in information received through mobile phone = 1, Otherwise =0	+	
Access to agricultural extension services	If the farmer has received training within the last one year (Yes =1, No = 0)	+	+
Distance from farm to commercial banking services	Kilometers	+	
Mobile phone use in CSH	Yes =1, No = 0		+
Climate change awareness	If the farmer is aware of climate change (yes =1, No =0)	+	+
CSH awareness	Yes =1, No =0	+/-	+
Number of CSH practices adopted	Count	+	

Source: Survey Data (2021).

Age was expected to either positively or negatively influence mobile phone use, number of CSH practices adopted and horticulture productivity. A study by Akrofi-Atitianti *et al.* (2018) showed that the likelihood of adopting CSA practices increased with age but eventually drops with further age increase due to reduced capacity to work. Conversely, Andone *et al.* (2016) found that young people used smartphone more on entertainment and social interactions while older people used it for getting agricultural-related information. On the other hand, Krell *et al.* (2020) found that age was not a significant determinant of mobile phone use in farming. This was because most farmers owned feature phones, which have limited access to multiple agricultural services.

Owusu *et al.* (2017) showed that fewer number of females own mobile phones and use internet compared to their male counterparts. Gezimu *et al.* (2019) and Gebissa *et al.* (2019) found that male farmers realized higher agricultural productivity relative to female counterparts. However, under similar environment the productivity for females was higher than males. Therefore, gender was expected to either positively or negatively influence CSH productivity based on the usage of mobile phones in farming.

This study categorizes education according to the number of years completed in school. According to Okello *et al.* (2014), increasing years spent in education increases the likelihood of mobile phone use. Likewise, Akrofi-Atitianti *et al.* (2018) and Aryal *et al.* (2018) indicated that literate household heads were likely to adopt CSA practices. Based on these findings, educated farmers were likely to use their mobile phones in farming, adopt CSH practices and have higher productivity due to their ability to access wide range of services.

Household size was measured in terms of number of dependents in a household during the time of survey. A study by Akinola (2017) showed that increase in family size significantly increased the use of mobile phone in agriculture. Urgessa (2015) and Kabubo-Mariara and Mulwa (2019) found that increased household size significantly improved agricultural productivity.

On the other hand, Mwalupaso *et al.* (2019) got mixed evidence on the effect of household size on attitude to use mobile phone. Consequently, the expected effect of household size on mobile phone use and CSH productivity was positive. This was based on the premise that a larger household would provide labor for CSH activities, which improve productivity.

Farming experience was estimated in terms of the number of years the respondent spent in active farming. According to Kirui *et al.* (2012), the likelihood of more experienced farmers adopting mobile money transfer services was low relative to their less experienced counterparts. However, Abegunde *et al.* (2019) showed that farming experience has significant positive effect on adopting the CSA practices. Therefore, the expected effect of farming experience on mobile phone use and number of CSH adopted was negative and positive, respectively. This is because experienced farmers tend to spend less time searching for new information.

The farm size was measured in acres under green grams and/or tomatoes. Akinola (2017) revealed that farm size has a positive effect on mobile phone use in agriculture. Similarly, as farm size increases, so is the likelihood of adopting CSA practices (Abegunde *et al.*, 2019; Aryal *et al.*, 2018). However, Ladvenicová and Miklovičová (2015) and Sheng *et al.* (2019) established a negative correlation between farm size and productivity.

This is because large farm size makes it difficult for crop husbandry practices since most have lack capacity. Hence the expected effect of size of farmland on mobile phone use and number of CSH practices adopted was positive while on productivity was negative.

In this study, mobile phone use is a dummy variable that take a value of 1 if the farmer uses mobile phone on CSH and 0 otherwise. Ali *et al.* (2016) and Aminou *et al.* (2018) showed a positive relationship between mobile phone use and agricultural productivity. Following this finding, mobile phone use was assumed to have a positive effect on CSH productivity because it improves the farmer's (user) production skills.

Access to credit was a dummy variable that takes a value of 1 if the farmer accessed credit for the last twelve months and 0 otherwise. Anang (2019) showed that credit is positively related to productivity. Therefore, the expected effect of credit on productivity was assumed to be positive because it improves productive capacity of farmers – in terms of required agricultural assets and inputs.

Kirui *et al.* (2012) and Okello *et al.* (2014) showed that being a member to a farmer organization increased the likelihood of using market information and mobile phone-based money transfer services. However, Mwaura (2014) found mixed effects of membership to a farmer group on adoption of agricultural technology and productivity. So, the effect of group membership in CSH can be either positive or negative. This is because farmer groups make it possible to transfer information and technologies from one farmer to another, which means that if they get the right information they will do well while wrong information would affect their productivity negatively.

On access to agricultural extension services, previous studies such as Aryal *et al.* (2018) and Komarek and Msangi (2019) showed that accessing agricultural extension services was positively related to the number of CSA practices adopted and agricultural productivity. Thus, access to extension services was postulated to have a positive effect on the number of CSH practices adopted and productivity in the area of study. This is because agricultural extension builds up the farmer's skills thereby improving productivity.

4.4 Results and discussion

4.4.1 Characteristics of mobile phone users and non-users on climate-smart horticulture

Table 4.2 presents the characteristics of CSH farmers in Taita-Taveta County with respect to mobile phone use. In terms of gender, results show that there is a significant difference in gender between mobile phone users in CSH and non-users. This means that more male farmers used their mobile phones in CSH than their female counterparts. The finding is attributed to the fact that more male farmers owned smartphones, which improved their access to CSH information.

The average age of mobile phone users and non-users was 45 and 50 years, respectively, which indicates that more young farmers used their mobile phones in CSH than old farmers. This is because young people have the capacity to access various internet sites and access the information they need compared to older farmers who mainly depend on guidance from agricultural extension officers. Similar results were obtained by Andone *et al.* (2016) who showed that young people used their phones more than their older counterparts. Also, mobile phone users had spent two more years in education than non-users. This finding is consistent with Antoun (2015) who found that most mobile internet users were more educated.

Similarly, the difference between mobile phone users and non-users in CSH was very significant in agricultural extension services, access to electric power, number of CSH practices adopted, trust on information received through mobile phone, climate change and climate-smart awareness. In addition, to a smaller extent, there was a difference between users of mobile phones in CSH and non-users in amount of off-farm income, farming experience and access to credit. Access to agricultural extension, electric power and trust on information received encouraged the use of mobile phones among farmers. Furthermore, having off-farm income increased the capacity of the farmer(s) to own a mobile phone hence improving its use.

Table 4.2: Mean differences in socio-economic and institutional characteristics between mobile phone users and non-users on climate-smart horticulture.

Variables	*Mobile phone users (n=224)*	*Mobile phone non-users (n= 179)*	*Mean difference*	*Pooled (N=403)*
Gender of the farmer (male =1)	0.71	0.46	0.25^{***}	0.60
Farmer’s age (years)	44.71	50.04	-5.33^{***}	47.08
Farmer’s education level (years)	9.20	7.22	1.98^{***}	8.32
Household size (count)	5.33	5.37	-0.04	5.35
Off-farm income (Kshs)	5425.89	3526.26	1899.64^{*}	4582.13
Farming Experience (years)	8.56	10.48	-1.92^{**}	9.41
Farm size (under crop) (acres)	1.42	1.35	0.07	1.39
Access to agricultural extension service (yes =1)	0.69	0.55	0.13^{***}	0.63
Group membership (yes =1)	0.46	0.39	0.07	0.43
Credit access (yes =1)	0.13	0.07	0.07^{**}	0.10
Electric power access (yes =1)	0.94	0.78	0.16^{***}	0.87
Distance from farm to bank (Km)	19.63	18.13	1.50	18.97
Number of CSH practices (count)	7.25	4.53	2.72^{***}	6.03
Trust on information received (yes =1)	0.64	0.36	0.28^{***}	0.51
Climate change awareness (yes =1)	0.96	0.88	0.08^{***}	0.92
CSH awareness (yes =1)	0.79	0.56	0.23^{***}	0.69

*, ** and *** denote 10%, 5% and 1% statistical significance levels, respectively

Note: pooled sample includes the total number of respondents from the 3 crop categories (403).

Source: Survey Data (2021).

4.4.2 Factors influencing the use of mobile phone and adoption of climate-smart horticulture practices

Table 4.3 presents binary logit regression model results, which is the first stage analysis, of the factors influencing mobile phone use on CSH. Mobile phone usage on CSH was interpreted as the application of mobile phone in searching for any climate-smart horticulture information and/or using the phone to pay (or receive money) for related products and services. The pseudo-R^2 shows that the model fits the data well (Wooldridge, 2013). Pooled results (which includes all farmers under the study) indicate that household level features such as farmer's gender, age and education significantly affect the likelihood of using a mobile phone on CSH.

The findings show that (gender) male farmers are 84% more likely to use a mobile phone on CSH than their female counterparts. This is because more male farmers own smartphones and have internet access more than their female counterparts (Krell *et al.*, 2020). An increase in farmer's age by one year decreases the likelihood of using a mobile phone on CSH by 3%. This is due to the fact that older people had little knowledge on climate-smart horticulture and related information that can be accessed through mobile phones. This reduced their capacity to use their phones on CSH.

The study shows that farmer's education level significantly influences the likelihood of using mobile phone on CSH by 8%. This finding conform with Kirui *et al.* (2012) and Krell *et al.* (2020) who found that farmers with higher levels of education were more likely to use mobile phone-based agricultural services. This is because educated farmers are able to read and navigate through various information services available in the mobile platform and find what they need to improve farming.

Table 4.3: Binary logit regression results on factors influencing mobile phone use on climate-smart horticulture

Variables	Tomato farmers (n = 115)		Green gram farmers (n = 259)		Pooled (n = 403)	
	Co-efficient	*Std. Error*	*Co-efficient*	*Std. Error*	*Co-efficient*	*Std. Error*
Dependent variable						
Mobile phone use in CSH (yes =1)						
Independent variables						
Gender of the farmer (male =1)	0.658	0.666	0.838**	0.344	0.841***	0.272
Farmer's age (years)	-0.006	0.027	-0.036**	0.015	-0.027**	0.011
Household size (count)	-0.069	0.127	0.060	0.073	0.032	0.059
Farmer's education level (years)	0.056	0.095	0.111**	0.050	0.076*	0.040
Farming experience (years)	-0.062	0.041	-0.0004	-0.026	-0.013	0.019
Farm size under crop (acres)	-0.313	0.206	0.165	0.105	0.025	0.083
Trust on information received (yes =1)	0.724	0.491	0.919**	0.368	1.075***	0.268
Group membership (yes =1)	0.234	0.658	0.886*	0.470	0.340	0.309
Access to agricultural extension service (yes =1)	0.771	0.646	-0.829	0.559	-0.465	0.376
Access to credit (yes =1)	1.896*	1.105	1.527***	0.559	1.437***	0.447
Climate change awareness (yes =1)	-0.579	1.072	0.644	0.725	0.321	0.535
CSH awareness (yes =1)	-0.226	0.793	0.330	0.494	0.465	0.364
Access to electricity (yes =1)	2.680**	1.179	1.278**	0.561	1.383***	0.449
Distance from farm to commercial bank (km)	0.010	0.022	0.001	0.011	-0.004	0.008
Number of CSH practices adopted (count)	0.283**	0.133	0.279***	0.077	0.237***	0.052
	*Constant = -3.9525**		*Constant = -4.167****		*Constant =-3.452****	
	Pseudo R^2 = 0.2019		*Pseudo R^2 = 0.2863*		*Pseudo R^2 = 0.2649*	
	Prob >chi2 = 0.0185		*Prob >chi2 = 0.0000*		*Prob >chi2 = 0.0000*	
	Log likelihood = -56.40		*Log likelihood = -127.82*		*Log likelihood = -203.48*	

Note: *, ** *and* *** *represent 10%, 5% and 1% statistical significance, respectively*

Source: Survey Data (2021).

Further, the results reveal that trust on information received through mobile phone increases the likelihood of mobile phone use on CSH by 1.08 times. This is because farmers who believe the information received tend to use their phone more often to access current information on weather, crop husbandry and market information. Similar results have been shown by Mahatanankoon *et al.* (2006), Masrek *et al.* (2015) and Xin *et al.* (2013) who found that trust plays a critical role in the use of mobile phone device and its related services. Farmers who had access to credit were 1.48 times likely to use their mobile phones on CSH. This is because credit accessibility allows farmers to access farm assets and mobile phone can be viewed as such if used for farm activities (Aminou *et al.,* 2018).

Farmers who had access to electricity (hydro-electric and/or solar power) were 1.38 times more likely to use mobile phones in CSH than those who had no access. This can be attributed to the fact that power is an essential ingredient in a mobile phone and high-end smartphones are high power consumers. Thus, accessing electricity improves farmer's convenience and reduces mobile phone battery charging costs hence likely to use it.

The number of CSH practices adopted by farmers are likely to influence mobile phone use in CSH by 24%. This can be seen as reverse causality since most studies have provided evidence on the effect of mobile phone on farming practices (Krell *et al.,* 2021; Mittal and Hariharan, 2018; Mittal and Tripathi, 2009; Quandt, *et al.,* 2020). However, this effect may be attributed to the fact that most farmers who adopted CSH practices were more enlightened, had more assets and were curious to learn more on improving their farm productivity in the context of climate change. Enlightened farmers have been revealed to use a mix of technologies in a bid to improve farm productivity (Li *et al.,* 2020; Wordofa *et al.,* 2021).

A comparison between green gram and tomato farmers shows that factors such as; gender, farmer's age, education, trust on information received (both weather and agronomic information) and group membership significantly affected the likelihood of using a mobile phone in green gram farming. On the other hand, access to credit, electricity (hydro-electric power and solar) and number of CSH practices influenced the likelihood of using mobile phones on CSH for both green gram and tomato farmers. The differences in mobile phone use may be ascribed to systems of production for the two crops, where tomatoes are mainly produced under irrigation system while green grams are mainly produced under rain-fed system.

Table 4.4 presents the second stage analysis results from the NBRM, which provide evidence on the determinants of the number of CSH practices adopted. In this study, a CSH farmer was described as a farmer who adopted at least one of CSH practices listed in Figure 6. Using a mobile phone on CSH increased the number of CSH practices adopted by 24%. This may be attributed to reduced costs in searching for climate-smart related information and easy connectivity with other farmers through the mobile phone. The finding is consistent with Mittal and Hariharan (2018) who showed that farmers who used mobile phones in farming had adopted at least one improved technology to deal with climate change consequences.

Farmers who were aware of CSH were 54% more likely adopt more CSH practices compared to farmers who were unaware. This is because farmers who were aware of CSH had knowledge on which practices were best suited to their farms. However, being aware of climate change decreased the likelihood of adopting CSH practices by 29%. This implies that being aware of climate change does not mean that a farmer will adopt the CSH practices.

The study found that increasing education level and farming experience by a year increases the number of CSH practices adopted by 4% and 1%, respectively. These results imply that adoption of CSH practices depends on the skills accumulated through education system and farmers' own experience in farming. This finding conforms with Akrofi-Atitianti *et al.* (2018) and Li *et al.* (2020) who showed that farmers' education level and experience increased the odds of practicing CSA.

Accessing agricultural extension services and trust on the information received increased the number of CSH practices adopted by 17% and 12%, respectively. This means that extension services coupled with farmers' perception and belief on the information received would have a great effect in shaping agricultural practices and technology adoption. Similar findings were obtained by Anuga *et al.* (2013) and Li *et al.* (2020) who noted that institutional factors, including trust, shaped the adoption of agricultural innovations.

On the other hand, increasing farm size under green grams and tomatoes by one acre, decreases the number of CSH practices adopted by 4%. This may be attributed to inadequate resources required to meet the CSH costs due to increased farm size(s). This finding diverges from Wekesa *et al.* (2018) who noted that increasing farm size increased the adoption of climate-smart agriculture practices.

A comparison between green gram and tomato farmers show that factors such as gender of the farmer, mobile phone use in CSH, trust on information received, group membership, access to agricultural extension services, climate change awareness and distance from the farm to the nearest commercial bank had significant effects on the number of CSH practices adopted by green gram farmers relative to tomato farmers.

Table 4.4: Negative binomial regression results for determinants of the number of CSH practices adopted

Variable	Tomato farmers (n = 115)		Green gram farmers (n = 259)		Pooled (n = 403)	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*	*Co-efficient*	*Std. Error*
Dependent variable						
Number of CSH practices (count)						
Independent variables						
Gender of the farmer (male =1)	-0.076	0.101	0.150**	0.062	0.184***	0.047
Household size (count)	0.009	0.018	0.014	0.013	0.014	0.001
Farmer's education level (years)	0.022*	0.013	0.020**	0.009	0.035***	0.006
Farming experience (years)	0.008*	0.005	0.006	0.004	0.010***	0.003
Farm size under crop (acres)	0.016	0.030	-0.008	0.023	-0.044***	0.015
Trust on information received (yes =1)	0.061	0.069	0.253***	0.069	0.115***	0.045
Mobile phone use in CSH (yes =1)	0.108	0.080	0.206***	0.066	0.241***	0.048
Group membership (yes =1)	0.082	0.078	0.248***	0.083	0.045	0.047
Received agricultural extension service (yes =1)	-0.065	0.096	0.225**	0.094	0.170***	0.060
Access to credit (yes =1)	-0.051	0.119	0.026	0.099	-0.029	0.070
Climate change awareness (yes =1)	0.119	0.187	-0.356***	0.116	-0.291***	0.090
CSH awareness (yes =1)	0.240**	0.103	0.705***	0.087	0.544***	0.063
Distance from farm to commercial bank (km)	-0.005	0.003	0.008***	0.002	0.003**	0.001
	*Constant = 1.512**** *Log likelihood = -256.08* *Pseudo-R^2 = 0.0584* *Prob > chi^2 = 0.0026*		*Constant = 0.335** *Log likelihood = -562.64* *Pseudo-R^2 = 0.1514* *Prob>chi^2 = 0.0000*		*Constant = 0.725**** *Log likelihood = -956.99* *Pseudo-R^2 = 0.1150* *Prob > chi^2 = 0.0000*	

*Note: *, ** and *** indicate 10%, 5% and 1% statistical significance, respectively.*

Source: Survey Data (2021).

CHAPTER FIVE

5.0 EFFECT OF MOBILE PHONE USE ON PRODUCTIVITY OF CLIMATE-SMART HORTICULTURE FARMERS

5.1 Abstract

Horticulture is the largest sub-sector contributing to foreign exchange earned in Kenya. However, its productivity is highly affected by climate change. Various measures including climate-smart horticulture practice(s) are applied by farmers to curb the severity of climate change. Additionally, some farmers use mobile phones to enhance flow of information and access to knowledge and skills relating to climate-smart horticulture production. However, the effect of mobile phone use on productivity of climate-smart horticulture farmers is not well known. To determine this, the study used primary data from a random sample of 403 tomato and green gram farmers. Partial factor productivity (PFP) was used to measure productivity of climate-smart horticulture farmers. Tobit model (censored from below) was applied to determine the effect of mobile phone use on productivity of climate-smart horticulture farmers. The PFP results showed that the productivity levels of tomato and green gram farmers dropped by 62% and 49%, respectively, in 2021 compared to the year 2017. On the other hand, the Tobit model results showed that mobile phone use on CSH improved land productivity by 90%. Other factors such as gender (being male), education, farming experience, membership to a farmer group and climate-smart horticulture awareness positively influenced land productivity. Horticulture stakeholders should develop a mobile phone-supported application that would provide customized horticulture information to farmers. The study also recommends capacity building of farmers on various mobile phone-based information services that are useful to CSH farming.

Key words: climate-smart horticulture, productivity, mobile phone, data envelop analysis, Tobit.

5.2 Introduction

Horticulture sector (fruits, vegetables and flowers) is the leading foreign exchange earner in Kenya (HCD, 2018). The sector employs over 60% smallholder farmers (Kangai and Gwademba, 2016). Over the years, cut flowers have been the highest contributors to Kenyan's foreign exchange basket and provides a large pool of formal employment. On the other hand, vegetables (including tomatoes and green grams) provides employment and nutrition to many smallholder farmers and traders along the value chain (HCD 2017 and 2018; ITC, 2016; KNBS, 2020).

However, the quantity produced decreased by 6% in 2019 despite an increase in the area of land used (KNBS, 2020). This is attributed to adverse climate change consequences such as excess rainfall, extreme temperatures, prolonged droughts and low soil fertility (Pipitpukdee *et al.,* 2020). To reduce the severity of these consequences, there have been efforts by the Government of Kenya to improve farm productivity through implementing CSA practices. For example, the government financed Kenya Agricultural Productivity and Agri-business Project (KAPAP) in 2009 and Kenya climate-smart agricultural project (KCSAP) in 2017 to improve productivity of smallholder farmers (Government of Kenya, 2009 and 2017).

The integration of technology in modern farming has also been proven to enhance farmer productivity. For example, previous studies have shown that ownership and use of mobile phone in farming has a positive impact on crop productivity (Aminou *et al.,* 2018; Chhachhar *et al.,* 2016; Kirui *et al.,* 2013). Further, Krell *et al.* (2020) showed that the type of mobile phone owned influences access to quality of information by farmers. On the other hand, Etwire *et al.* (2017) and Mittal and Hariharan (2018) noted that mobile phones were useful tools for farmers in accessing real-time weather information.

In Taita-Taveta County, most green gram and tomato farmers sell up to 90% of their produce for household income (MoALF, 2014). However, these crops are highly affected by climate change effects such as prolonged droughts, unpredictable rainfall patterns and high temperatures (MoALF, 2016; Mohamed and Chege, 2019). These effects contribute to high prevalence of crop pests and diseases (Skendžić *et al.*, 2021). It has been shown that mobile phones can be used to improve farming practices by facilitating real-time flow of information (Baumuller, 2016; Mittal, 2016). However, the effect of mobile phone use on productivity of horticulture farmers remains unexplored. Therefore, this study examined the effect of mobile phone use on productivity of CSH farmers.

5.3 Methodology

This study is premised on Bayes *et al.* (1999) and Aminou *et al.* (2018) that mobile phone is a production good if used for productive activities. The study adopted a two-step approach in measuring the effect of mobile phone use on climate-smart horticulture productivity. Previous studies show that there are two main approaches to measuring productivity; partial factor productivity (PFP) and total factor productivity (TFP).

The PFP measures the efficiency of specific resource of interest (single input) while TFP focuses on an index of output to combined index of all inputs. Both approaches can be used for specific analytical purposes (Murray, 2016). Total factor productivity is the share of total output relative to total input (Frija *et al.*, 2015). It measures input productivity applied in the production process and is often accounted for by changes in technology such as information and communications technology (Aswathy, 2017). The main weaknesses of TFP method include challenges in empirical measurement and interpretation (Murray, 2016).

The TFP can be measured using two main approaches; parametric and non-parametric approaches (Giang, *et al.*, 2019). Parametric approaches include econometric models such as stochastic frontier and production function while non-parametric include data envelop analysis, Solow index and Malmquist productivity index (Aswathy, 2017; Frija *et al.*, 2015). The parametric approaches introduces a functional form and uses econometric techniques in estimating a production function whereas non-parametric method does not (Suphannachart and Warr, 2010).

Essentially, TFP can be viewed as an index of total output with respect to total conventional inputs (Frija *et al.*, 2015; Fuglie, 2010; Suphannachart and Warr, 2010) as expressed in equation 15.

$$TFP = {}^{Q}\!/_{X} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. \quad (15)$$

where *TFP* is the total factor productivity (yield), Q is the yield of green grams and tomatoes in kilograms and *X* is an aggregate of conventional inputs such as capital, land and labor.

The common methods applied in measuring productivity using PFP approach include data envelopment analysis (DEA), stochastic frontier analysis (SFA) and Cobb-Douglas production function (Ali, 2016; Aminou *et al.*, 2018; Theodoridis and Anwar, 2011).

Cobb-Douglas production function is expressed using econometric techniques. For example, following (Giang *et al.*, 2019), equation 15 can be expressed as follows:

$$TFP_j = \frac{Q_j}{f(K_j, L_j)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (16)$$

where: TFP_j is total factor productivity of firm j relative to other firms.

Q_j is total yield of firm j in kilograms

K_j is capital input of firm j in Kshs

L_j is the value of total labor input in Kshs

Equation 16 can be re-arranged to define Q_j:

$$Q_j = f(K_j, L_j)TFP_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (17)$$

Equation 17 can be analyzed using different methods, such as Translog production function and Cobb-Douglas production function. Therefore, equation 17 can be expressed in Cobb-Douglas form as shown in equation (18);

$$Q_j = AK_j^{\alpha}L_j^{\beta}TFP_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (18)$$

Linearizing equation 18 through logarithmic approach yields:

$$LnQ_j = LnA + \alpha LnK_j + \beta LnL_j + LnTFP_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (19)$$

Assuming $TFP_j = e^{u_j}$, equation 19 can be re-written as:

$$LnQ_j = LnA + \alpha LnK_j + \beta LnL_j + u_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (20)$$

It has been argued that Cobb-Douglas production function has good mathematical properties and can be interpreted easily (Giang *et al.*, 2019). However, when applied in measuring productivity, the error term (Equation 20) is automatically considered as a measure of productivity (Aminou *et al.*, 2018; Giang *et al.*, 2019; Suphannachart and Warr, 2010).

Stochastic frontier analysis (SFA) can also be used to measure productivity. This method involves transformation of a dataset into logarithm form then running it in a frontier software (Coelli, 1995). Following Alulu *et al.* (2021), SFA model can be estimated using equation (21) derived from equation (15);

$$Q_i = \beta X_i + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (21)$$

where, Q_i is the log of i^{th} farmer's output, X_i is the vector of input quantities of i^{th} farmer, β is a vector of parameters to be estimated, ε_i is a composite error term consisting of random error and inefficiency component, that is, $v_i + u_i$, respectively.

This means that for decision-making units (farmers) who realized zero output and those that have less than one acre of land would result to missing data and negative values that may require transformation before further analysis is done. However, this would make it difficult to draw conclusions regarding the original data and addition of positive constant can affect statistical significance in testing hypothesis (Feng *et al.,* 2014). Therefore, there has been introduction of various customized techniques such as generalized estimating equation methods, deterministic frontier analysis (DFA), range directional model (RDM) and generalized maximum entropy (GME) to address this problem (Campbell *et al.,* 2008; Feng *et al.,* 2014; Hjalmarsson *et al.,* 1996; Portela *et al.,* 2004).

Several attempts have been made to compare different productivity measurement models. For instance, Hjalmarsson *et al.* (1996) compared DEA, DFA and SFA. They found a high rank correlation between them implying that there was no much difference in the models' results. Similarly, a study by Weill (2004) on comparison of different frontier approaches, was unable to conclude on the best frontier approach since SFA and DEA results were correlated.

On the other hand, it has been shown that DEA provides more satisfactory productivity measurement than SFA (Lovell, 1996; Wadud, 2003). Existing literature show that most of these productivity methods are suitable for panel and time series data. Specifically, Ali (2016), Pantzios *et al.* (2011) and Saikia (2014) used Malmquist index to measure productivity while others such as Lovell, (1996), Mujasi *et al.* (2016) and Rajasekar and Deo (2014) applied DEA and SFA methods to measure efficiency.

In this study, productivity was measured using partial factor productivity method. This is because of data limitations; where it was difficult to measure all the factors of production that farmers used in production, there were no records of labor and various capital inputs such as fertilizer, seeds and pesticides used. Land was used as an input for two reason; 1) its measurement is standard in all locations (acre or hectare) and 2) the study focused on CSH, which largely affects the land (in terms of soil and water). Also, the study focused specifically on determining the effect of mobile phone use on climate-smart horticulture productivity – because mobile phone was viewed as a production good (when applied in CSH) (Aminou *et al.,* 2018; Bayes *et al.,* 1999). The choice of this method was also based on Murray (2016) suggestion that PFP measure is suitable when the analyst's objective is on specific policy issue – in this case, mobile phone use. Equation (22) shows the method applied in this study.

$$PFP_i = \frac{Q_i}{X_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (22)$$

where; PFP_i is the partial factor productivity score for farm i, Q_i is the value of output from farm i and X_i represents size of the farm (under crop) i in acres.

The productivity measurements obtained from equation (22) were then transformed into logarithms as shown in equation (23).

$$PFP_i = ln\left(\frac{Q_i}{X_i}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (23)$$

This reduced skewness of PFP scores and gave better estimates compared to non-transformed data (West, 2022). Similar recommendation was made by Lütkepohl and Xu (2009) who suggested that precision of the results improves if log transformation makes the variance more consistent throughout the sample. The transformed PFP scores can be regressed against various independent variables using ordinary least squares (OLS) or Tobit model (Wooldridge, 2013).

In a case of censored dependent variable, OLS results leads to biased estimates and in that case a two-limit Tobit model is more efficient (Ahmad *et al.,* 2017; Mcmillen and Mcdonald, 1990). The Tobit model has also been applied by Alulu *et al.* (2021) and Miriti *et al.* (2021) in assessing the factors influencing technical efficiency of vegetable and sorghum growers. Since efficiency scores are distributed between zero and one, they argued that OLS was not the most appropriate method to use (Mcmillen and Mcdonald, 1990). Instead, Heckman two-step procedure or Tobit models provide better results given the data set (Carson and Sun, 2007; Sigelman *et al.,* 2000). However, Gujarati and Porter (2013) specify that Tobit model produces more efficient estimates of the parameters relative to Heckman two-step procedure.

Additionally, different arguments have been advanced by researchers on the use of Tobit and OLS models. For example, Foster and Kalenkoski (2013) claim that the Tobit model is a bit sensitive to certain types of data (such as qualitative data) and gives higher estimates compared to OLS. However, they concluded that the two methods are similar. Conversely, Stewart (2013) noted that even though Tobit model performs significantly better, compared to OLS.

This study used productivity value, which is bound at zero in the lower limit. Therefore, considering the foregoing arguments, the study applied a Tobit model (censored from below) (Greene, 2003) to assess the determinants of climate-smart horticulture productivity and specifically identify the effect of mobile phone use on climate-smart horticulture productivity. This is because the Tobit model fitted the data well than OLS.

Following Carson and Sun (2007) and Sigelman *et al*. (2000), the following Tobit model was specified and estimated:

$$Y^* = \beta_0 + \beta X + \varepsilon, \varepsilon|X \sim N(0, \delta^2) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (24)$$

where, Y^* is the latent variable *($lnPFP_i$)* that satisfies classical linear model assumptions (no perfect multicollinearity, homoscedasticity and linearity assumptions), β is a vector of coefficients to be estimated, X is a vector independent variables and ε is the error term assumed to be normally distributed.

$$Y = 0 \ if \ Y^* \leq 0$$
$$Y = Y^* \ if \ 0 < Y^*$$

Since the dependent variable was log-transformed, interpretation and reporting of the results (in section 5.4.2) was based on normalized values using the formula:

$$100 \times (e^{\widehat{\beta}} - 1) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. \qquad (25)$$

where; $\hat{\beta}$ is the coefficient of estimation obtained from Equation (24).

Table 5.1: Variables included in the Tobit model and expected signs

Variable	Description	Tobit model
Gender of the farmer	Male = 1, female = 0	
Farmer's age	Years	+/-
Farmer's education level	Number of years spent in school	+
Household size	Number of people in a household at the time of survey	+
Farming experience	Number of years spent in active farming	
Mobile phone use in CSH	Yes = 1, No = 0	+
CSH participation	Yes = 1, No = 0	+
Farm size	Number of acres under crop covered in this study	
Group membership	In a farmer group (Yes=1, No = 0)	+
Access to agricultural extension services	If the farmer received agricultural training within the last one year (Yes = 1, No = 0)	+
Distance from farm to the bank	Distance in kilometers	-
Climate change awareness	Yes = 1, No =0	+
Climate-smart horticulture awareness	Yes =1, No =0	+

Source: Survey Data (2021).

Climate change awareness was expected to have a positive sign on productivity. This is because farmers who had acquired information about climate change were able to adapt easily (Abbasi and Nawaz, 2020). Climate-smart horticulture awareness was expected to exhibit a positive sign on productivity because farmers who were aware of these practices were better off in using the practice(s) that are best suited to their context. This has been proven to positively influence productivity (Jelagat, 2019; Rohila *et al.*, 2018).

5.4 Results and discussion

5.4.1 Technical efficiency scores for tomato and green gram farmers

Table 5.2 presents the input-oriented DEA results. The results show that the mean technical efficiency (TE) of the tomato and green gram farmers in Taita-Taveta County was 34% and 25%, respectively.

This means that tomato and green gram farmers could still produce the same level of output by reducing all inputs (on average) by 66% and 75%, respectively (Huguenin, 2012; Månsson, 2003). It also implies that farmers who produced tomatoes or green grams only were highly inefficient. This may be attributed to high infestation of crop pests *(Tuta absoluta)* for the case of tomato farmers and drought experienced in the area due to climate change. On the other hand, farmers who produced both crops under study exhibited an efficiency score of 54%. This suggests that farmers who produced both crops under study could reduce all inputs by 46% to be fully efficient.

Table 5.2: Technical efficiency scores for green grams and tomato farmers

Variable	Tomatoes (n = 115)	Green grams (n = 259)	Both green grams and tomatoes (n = 29)	Pooled (n = 403)
Mean	0.343	0.249	0.543	0.297
Max.	1.000	0.992	1.000	1.000
Min.	0.000	0.000	0.027	0.000
Std. Deviation	0.333	0.305	0.318	0.323

5.4.2 Productivity score for climate-smart horticulture farmers in Taita-Taveta County

Table 5.3 presents the first-step analysis (partial factor productivity) results. The results show that the mean productivity score of tomato and green gram farmers in Taita-Taveta County was 4,817 kgs/acre and 143 kgs/acre, respectively. This productivity level is low compared to previous years. For example, the mean quantity of tomato and green grams per acre in Taita-Taveta County was 12,667 and 280 kgs, respectively, in the year 2017 (Government of Kenya, 2020; HCDA, 2018).

This represents 62% and 49% decline in tomato and green gram productivity, respectively, in the year 2021 relative to 2017.

Table 5.3: Productivity scores (Kgs per acre) for green grams and tomato farmers

Variable	Mean	Std. Deviation	Min.	Max.
Tomatoes (n = 115)	4,817.12	5,736.50	50.00	32,000
Green grams (n = 259)	143.30	215.42	0.00	1,800
Both tomatoes and green grams (n = 29)	2,716.03	2508.18	24.59	11,500
Pooled (n = 403)	1,661.00	3,770.55	0.00	32,000

Source: Survey Data (2021).

The low productivity in the study area was attributed to high infestation of crop pests *(Tuta absoluta)* for the case of tomato farmers, prolonged drought and unpredictable rainfall distribution (seasons) experienced in the area due to climate change. Farmers also cited soil nutrient degradation as a contributing factor to low crop performance. Other factors that contributed to low output per acre included disruption of horticultural supply chain and markets by Covid-19 pandemic and low purchasing power of inputs by farmers. On the other hand, Table 5.4 shows productivity scores based on geographical distribution. Wundanyi exhibited higher productivity relative to Taveta and Mwatate sub-counties because it is on high altitude area with greater agricultural potential and most farmers were tomato producers, which has high output per unit area compared to green grams.

Table 5.4: Productivity scores (Kgs per acre) for green grams and tomatoes in the three sub-counties

Sub-county	Mean	Std. Deviation	Min.	Max.
Wundanyi (n = 59)	3,591.97	3,700.53	200	20,000
Mwatate (n = 122)	394.47	1,203.81	0	11,000
Taveta (n = 222)	1,843.84	4,422.56	0	32,000
Pooled (n= 403)	1,661.00	3,770.55	0	32,000

5.4.2 Effect of mobile phone use on productivity of climate-smart horticulture farmers

Table 5.5 and 5.6 presents Tobit model results on the effect of mobile phone use on productivity of climate-smart horticulture farmers based on the crop and geographical location, respectively.

The coefficients shown below were normalized using equation (25) for easy reporting – since the dependent variable was log-transformed (Feng *et al.,* 2014; Yang *et al.,* 2017).

Pooled results show that social characteristics including gender, education, and farming experience positively affected (land) productivity by 1.5 times, 17% and 5%, respectively. This implies that male farmers achieved higher productivity compared to their female counterparts both terms of the crop enterprise and geographical location. Gebissa *et al.* (2019) noted that male households realized higher productivity than their female counterparts due to low access to inputs by female farmers. Education and farming experience expands the farmer's knowledge and skills to deal with the changing environment and use a mix of production technologies for higher productivity.

However, it was noted that an increase in farmer's age by a year reduced productivity by 3%. Meaning that older farmers were likely to get low output per unit area. This is attributed to reduced capacity of production – in terms of labor, access to credit and production technologies, which are essential inputs to achieving higher productivity. Similar findings were made by Guo *et al.* (2015) and Myeni *et al.* (2019) who noted that productively was low among the aged population compared to middle-aged farmers.

Table 5.5: Tobit regression results for climate-smart horticulture farmers based on the type of crop produced

Variable	Green grams (n=259)		Tomatoes (n =115)		Pooled (n = 403)	
	Coefficient	*Robust Std. Error*	*Coefficient*	*Robust Std. Error*	*Coefficient*	*Robust Std. Error*
Dependent variable						
Partial productivity (kgs/acre)						
Independent variables						
Gender of the farmer (male = 1)	0.325	0.322	0.823***	0.287	1.492***	0.278
Farmer's age (years)	0.001	0.014	-0.024**	0.010	-0.028**	0.012
Farmer's education level (years of schooling)	0.122***	0.040	0.053	0.036	0.169***	0.037
Household size (count)	0.014	0.068	0.045	0.051	0.027	0.060
Farming experience (years of farming)	0.011	0.020	0.026	0.018	0.050***	0.018
Farm size (acres under crop)	-0.279**	0.124	0.088	0.057	-0.233**	0.112
Access to agricultural extension services (yes = 1)	-0.559	0.488	-0.433	0.307	0.126	0.371
Membership to a farmer group (yes = 1)	-0.874*	0.454	0.073	0.221	-1.376***	0.323
Distance from farm to com. bank (km)	0.011	0.009	0.019**	0.008	0.010	0.008
Mobile phone use in CSH (yes = 1)	0.939***	0.318	0.073	0.248	0.903***	0.294
Participation in CSH (yes =1)	-0.234	0.594	-0.561	0.574	0.618	0.542
Climate change awareness (yes =1)	0.279	0.546	-0.482	0.406	-0.239	0.529
CSH awareness (yes =1)	0.787**	0.469	0.490	0.306	0.808**	0.390
	*Constant =1.995***		*Constant = 7.670****		*Constant = 2.607****	
	Prob. >F = 0.0000		*Prob. >F = 0.0000*		*Prob.>F = 0.0000*	
	Pseudo R^2 = 0.0532		*Pseudo R^2 = 0.0926*		*Pseudo R^2 = 0.0825*	
	Log likelihood = -523.75		*Log likelihood = -173.52*		*Log likelihood = -882.01*	

*Note: *, ** and *** means 10%, 5% and 1% levels of significance, respectively. CSH stands for climate-smart horticulture.*

Pseudo R^2 shows that the covariates have explanatory power – the model fits the data.

Source: Survey Data (2021).

Table 5.6: Tobit regression results for climate-smart horticulture farmers in three different sub-counties

Variable	Wundanyi (n= 59)		Mwatate (n = 122)		Taveta (n = 222)		Pooled (n=403)	
	Coef.	*Robust SE*	*Coef.*	*Robust SE*	*Coef.*	*Robust SE*	*Coef.*	*Robust SE*
Dependent variable								
Partial productivity (kgs/acre)								
Independent variables								
Gender of the farmer (male = 1)	0.634*	0.256	-0.073	0.280	1.656***	0.269	1.492***	0.278
Farmer's age (years)	-0.008	0.009	-0.014	0.012	-0.073	0.011	-0.028**	0.012
Farmer's education level (years of schooling)	0.020	0.021	0.063**	0.030	0.086**	0.038	0.169***	0.037
Household size (count)	-0.003	0.037	-0.057	0.063	0.024	0.055	0.027	0.060
Farming experience (years of farming)	0.040**	0.018	0.038**	0.018	0.087	0.014	0.050***	0.018
Farm size (acres under crop)	-0.183	0.215	-0.220	0.257	-0.051	0.081	-0.233**	0.112
Access to agricultural extension services (yes = 1)	-0.140	0.385	-0.528	0.502	0.027	0.285	0.126	0.371
Membership to a farmer group (yes = 1)	-0.030	0.144	-0.463*	0.368	-0.518**	0.312	-1.376***	0.323
Distance from farm to commercial bank (km)	-0.267*	0.018	-0.004	0.019	0.024***	0.007	0.010	0.008
Mobile phone use in CSH (yes = 1)	0.508	0.251	0.253	0.238	1.204***	0.261	0.903***	0.294
Participation in CSH (yes =1)	0	omitted	1.874	0.801	-0.444	0.425	0.618	0.542
Climate change awareness (yes =1)	-0.457	0.527	1.092	0.554	-0.598**	0.385	-0.239	0.529
CSH awareness (yes =1)	0.640*	0.261	2.281**	0.539	0.805*	0.346	0.808**	0.390
	*Constant =4.507****		*Constant =4.507***		*Constant =2.506****		*Constant = 2.607****	
	Prob. >F =0.0134		*Prob. >F = 0.0038*		*Prob.>F =0.000*		*Prob.>F = 0.0000*	
	Pseudo R^2 =0.1186		*Pseudo R^2 = 0.0829*		*Pseudo R^2=0.0885*		*Pseudo R^2 = 0.0825*	
	L. likelihood =-65.34		*L. likelihood=-200.59*		*L. likelihood =-402.05*		*L. likelihood = -882.01*	

*Note: *, ** and *** represent statistical significance levels at 10%, 5% and 1%, respectively. CSH stands for climate-smart horticulture.*

Source: Survey Data (2021).

An increase in farm size (under crop) by one acre resulted to decrease in (land) productivity by 23%. This finding diverges from Barbier, (1984) and Helfand and Taylor (2020) who claim that there is no inverse relationship between farm size and productivity. The inverse relationship exhibited in this study was due to destruction of crops by diseases (*Tuta absoluta* - in the case of tomatoes), extreme drought and decreasing returns to scale (due to tomatoes and green grams output) (Sanchez *et al.,* 2019).

According to the results, being in a farmer group was shown to negatively affect productivity by 1.4 times. This finding is in line with Mwaura (2014) who noted that the effect of farmer group membership on productivity varied with the type of crop enterprise. But it differs from Adekunle (2018) who found that membership to group-farming cooperative had a positive effect on food production. The negative effect of group farming was attributed to the type of crop enterprise and poor quality of agricultural information passed from one farmer to the other. Majority of group members (74%) in the study were green gram farmers, majority of whom were located in Mwatate sub-county. The lower parts of this sub-county usually experience longer dry seasons compared to Wundanyi and Taveta. It was also noted that group members did not have the right information on rainfall distribution and the right agro-chemicals - in the case of tomatoes. Likewise, the green gram farming groups depended on the seeds provided by the KCSAP, which fetched lower market prices compared to non-members.

On the other hand, mobile phone use on climate-smart horticulture increases productivity by 90%. This finding is consistent with literature where it was determined that mobile phone ownership and use improved agricultural productivity (Aminou *et al.,* 2018; Quandt *et al.,* 2020).

This is attributed to the fact that application of mobile phones in agriculture reduces information gaps, improves agricultural extension service delivery, adoption of improved technology and access to cognitive assets that lead to increase in horticultural productivity (Kiberiti *et al.*, 2016; Mittal and Hariharan, 2018; Mittal and Mehar, 2012; van Baardewijk, 2017).

Being aware of climate-smart horticulture (what it means and practices) increased (land) productivity by 81%. Therefore, it implies that most farmers who are aware about climate-smart horticulture (both in concept and practice) adopt practices that are best suited to their environment (Abegunde *et al.*, 2020; Anuga *et al.*, 2013; Pagliacci *et al.*, 2020). This leads to improved productivity.

CHAPTER SIX

6.0 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This study analyzed the extent and effects of mobile phone use on productivity of climate-smart horticulture farmers. Characterization of adoption of CSH practices and mobile phone use on CSH showed that farmers adopted at least one CSH practice while 96% of them owned a mobile phone (whether a high-end smartphone, low-end smartphone or basic feature phone). All farmers used their phones for social calls but very few of them used the phone to search for climate-smart horticulture related information – on weather, best agronomic practices, agricultural input and output and contacting agricultural extensionists. Smartphone owners adopted more CSH practices compared to low-end smartphone and basic feature phone owners.

Different types of farmers (tomato, green gram and both crop) adopted CSH practices to different extent. Tomato producers and both crop (green gram and tomato) farmers adopted more CSH practices than only green gram farmers. Crop rotation was the most adopted practice while crop insurance was the least adopted. The use of well adapted seed varieties, mulching, agroforestry and terracing were also adopted by more than 65% of the farmers. Most farmers adopted took less than three months to adopt the CSH practices due to indigenous knowledge and less capital required to implement.

Social factors such as gender, education and farming experience influences mobile phone use, number of climate-smart horticulture practices adopted and productivity. Other factors that positively affect adoption of CSH include access to credit, trust on climate-smart horticulture information received and climate-smart horticulture awareness.

Mobile phone use had positive effect on adoption of CSH practices and productivity. It was therefore concluded that mobile phone use improves climate-smart horticulture farmers' productivity.

6.2 Recommendations

6.2.1 Policy recommendations

Despite the efforts by the Government of Kenya to promote CSH practices among farmers, some practices such as crop insurance were not well adopted. They also exhibited low productivity levels. Both the County and Central governments should partner with insurance service providers (such as APA insurance company and KCB Ltd) to develop crop insurance regulations within the country and conduct awareness campaigns in the farming communities to enhance uptake by farmers. The two levels of government and NGOs should also strengthen agricultural extension services within the country to help farmers implement CSH technologies.

The national government, through KCSAP, should partner with Kenya Agricultural Research Organization (KALRO), County governments and private companies (such as Microsoft and telecommunication service providers) to develop farmer-friendly communication regulations and build a climate-smart Technological Innovation Management Practices (TIMPs) hub digital platform that will facilitate real time interaction of farmers with agriculture-related service providers, input and output markets and meteorological department for early warning systems.

This will help farmers to build resilience to climate change and/or adapt to improve productivity. It will also help farmers to access both domestic and international markets easily. This recommendation is similar to Arid Lands Information Network (ALIN) that exists in four counties of Kenya (Nairobi, Kajiado, Laikipia and Kisumu).

However, the information hub does not provide real-time information and is based on particular station where may not be accessible by all farmers. The implementation of climate-smart TIMPs hub digital platform will contribute to solving this problem.

There is also need for agricultural development partners to empower women –in terms of agricultural education, mentorship and credit access in order to improve their farm productivity, since their productivity was low compared to male farmers in all analyses conducted in this study. In addition, the agricultural development partners, including county government(s), should operationalize the county climate change fund, customize and implement the climate change action plan 2021-2025 by World Bank (2021) for horticultural development.

6.2.2 Recommendations for further research

Having assessed the effects of mobile phone use on climate-smart horticulture, there are still gaps that need to be filled by future research. For example, the study analyzed the effect of mobile phone use on CSH farmers' productivity. However, there is need to determine the impact of climate-smart agriculture project participation on horticulture farmers' productivity. This will make it possible to identify the long-term contribution of the project to farmers' livelihood.

There is need to conduct more research on adaptation of horticulture to climate change to determine whether the current climate-smart agricultural interventions have impact on farmers in the long run.

This study characterized the adoption of CSH practices and use of mobile phones in accessing related information. There is need to characterize the role of indigenous knowledge on CSH and its effect on the extent of adoption, since this was not fully addressed by the current study.

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APPENDICES

Appendix 1: Focus group discussion guide

Location of the meeting ………………………………. Date …………………

Number of participants; Male ……. Female ……. Time ……………….

1. Is the community aware of climate smart horticulture? How do they define and perceive it?
2. Are there any differences between conventional and climate smart agricultural practices?
3. What is the extent of mobile phone penetration and how they are used in horticulture?
4. Who are the main stakeholders involved in climate smart horticulture and their roles? *(e.g. government extension agents, private sector, NGOs, farmers, policy makers).*
5. What are the trends and key drivers for the last 40 years regarding evolution of climate smart practices and use of different interventions (including ICTs like mobile phones) to address the various challenges over time?
6. What climate smart practices are considered most suitable in; Wundanyi, Mwatate and Taveta sub-counties?
7. How did Covid-19 affect implementation of climate smart agriculture practices and horticulture practices? To what extent?

Thank you for participating in this discussion.

Appendix 2: Household survey questionnaire

ANALYSIS OF EXTENT AND EFFECTS OF MOBILE PHONE USE ON PRODUCTIVITY OF CLIMATE-SMART HORTICULTURE FARMERS IN TAITA-TAVETA COUNTY, KENYA

FEBRUARY 2021

<u>INTRODUCTION</u>

This survey is part of a course requirement for the award of a Master's degree in Agricultural and Applied Economics, University of Nairobi. The purpose of this survey is to get your experiences and information on mobile phone use and its effect on horticulture productivity. The findings from this survey will be used to make relevant policy recommendations for improving mobile phone use in agriculture and climate smart horticulture in the country. Respondents to this survey will be tomato and/or green gram farmers who are 18 years of age and above. Further, information obtained from this survey will be confidential and used for academic purposes only. This interview will take one hour only. Kindly allow me to begin the interview.

Respondents' screening question

1. Are you a tomato farmer? (Yes = 1, No = 0) …………….
2. Are you a green gram farmer? (Yes = 1, No = 0) ……………….
3. Have you planted any of the above crops for the past one year? (Yes =1, No = 0) ….

If yes for questions (1, 2 or both) and 3, proceed with the interview, otherwise, stop and thank the respondent for his/her time.

PERSONAL INFORMATION

Interviewer's name ………………………. Date ……………

Interviewee's phone no. …………………….

Sub-county: Wundanyi ☐ Mwatate ☐ Taveta ☐

GPS co-ordinates …………………….

SECTION A: Respondent's Socio-economic Characteristics

1. Gender (Male = 1, Female = 0) ……
2. Age of the respondent in years ………..
3. Who is the head of the household? (Male = 1, Female = 0)
4. Kindly fill the table below on family size:

Family members	Number of **male** members	Number of **female** members
Children (under 18 years)		
Adults (18 years and above)		

5. Who makes decisions on horticulture enterprise? (male = 1, female = 2, joint = 3) ……….
6. What is your level of education? Fill in the table below.

None =1, Primary =2, Secondary =3, post-secondary = 4, Others =5	Number of years spent in school

7. Kindly state the amount of income earned from the following enterprises per month:

S/No	Enterprise	Income (Kshs)
1.	Green grams	
2.	Tomatoes	
3.	Livestock	
4.	Off-farm enterprises	
5.	Leasing farm equipment	
6.	Other farm enterprises	

8. Do you have other employment apart from the farm? (Yes = 1, No = 0) ………

9. If yes, what is the average off-farm income per month? Kshs …………

10. Kindly fill the table below on land issues:

S/No.	Question	Response
1.	How many acres of land do you have?	
2.	How many acres do you farm?	
3.	How many acres are under green grams crop?	
4.	How many acres are under tomatoes?	
5.	What is your ownership status? (Owner with title =1, Owner without title =2, long term lease (>5 years) = 3, Short term lease (<5 years) =4, Family land =5, Given to farm while owner is away = 6	
6.	Have you done any onsite land improvement such as terracing, planting trees, etc. (Yes =1, No = 0)	

SECTION B: Production Characteristics

1. Which crop do you produce? (Tomatoes = 1, green grams = 0, both = 2) ……….

2. Who makes most decisions on tomato production (Male person = 1, Female person = 2, Joint male & female = 3) ……….

3. Who makes most decisions on green gram production (Male person = 1, Female person = 2, Joint male & female = 3) …….

4. Decision maker's position in the household (1 = husband, 2 = wife, 3 = both husband & wife, 4 = other members) tomato…………green gram…………

5. What is the age bracket (in years) of the decision maker? (0 – 35) …... (36 – 45) …... (46 – 55) …. (>55) …...

6. How many years have you been practicing tomato farming …... green gram farming …..

7. Kindly tick appropriately in the following table:

S/No.	**Input Description**	**Tomatoes**	**Green grams**	**Cost per acre (Kshs)**	
				Tomatoes	**Green grams**
1.	Quantity of planting fertilizer used per acre(kgs)				
2.	Quantity of top-dressing fertilizer used per acre (kgs)				
3.	Quantity of organic manure used per acre (tonnes)				
4.	Quantity of herbicides used per acre (litres)				
5.	Quantity of pesticides applied per acre (litres)				
6.	Hired labor per acre (man days)				
7.	Family labor used per acre (man days)				
8.	Type of planting material used (own seeds =1, certified seeds = 2, purchased ready seedlings = 3)				
9.	Quantity of certified seeds used per acre				
10.	Quantity of own seeds used per acre				
11.	Number of seedlings used per acre				
12.	Land in acres planted in the last season				

8. How much do you pay for hired labor per acre? Specify in the following table:

Activity/crop	Land Preparation (Kshs)	Weeding, Spraying & other crop husbandry (Kshs)	Harvesting (Kshs)
Tomatoes			
Green grams			

9. How many kilograms did you produce per acre in the last season? Tomatoes ……. Green grams …….

10. Kindly fill the following table:

S/No.	**Description**	**Response**	
		Tomatoes	**Green grams**
1.	How many kilograms were consumed?		
2.	How many kilograms were retained for planting in the next season?		

3.	How many kilograms were sold out?		
4.	Amount received per kilogram sold (Kshs)		

11. If you sold some output, where did you sell it? Tick appropriately.

Market	Open air	middlemen	Wholesale	Supermarkets	Online/Virtual
Tick					

12. How do you access the market? Through: face to face (physical) = 0, Mobile phone = 1 ……………..
13. Why did you choose the outlet in 11 above? Low transaction cost = 1, flexible = 2, predictable = 3, simplicity = 4, high price received = 5 ……………..

<u>SECTION C: Institutional Characteristics</u>

14. Kindly fill the table below on extension services.

S/No	Type of extension service received in the last 12 months	Extension service provider (1. Government, 2. Private, 3. NGO)	How many times	Crop	
				Green grams	Tomatoes
1.	Input services				
2.	Agronomic advisory services				
3.	Pest management services				
4.	Any other service (please specify)				

15. What channel did you use to receive extension services?

Channel/Type of service	Face to face	Radio	Television	Mobile Phone	Print media (eg. Newspaper, books, newsletters, etc)		
						Green grams	Tomatoes
Input services							

Agronomic advisory services							
Pest management services							
Any other service (please specify)							

16. Are you in a farmer group? (Yes = 1, No = 0) ……….

17. Have you received a loan in the past 12 months? (Yes = 1, No = 0) …….

18. If yes, please fill the table below:

Source of loan	**Amount applied for (Kshs)**	**Amount received (Kshs)**	**If not received, why?** 1. Defaulter, 2. No security, 3. Inability to repay, 4. Lack of business plan, 5. Others (specify) ….	**Main use**: 1. farm inputs, 2. purchase of land, 3. domestic consumption, 4. Boost other business, 5. school fees, 6. Others (specify) …..	**Amount repaid (Kshs)**
Family/friends					
Micro-finance					
Commercial bank					
SACCOS					
Farmer groups					
Table banking					
Others (specify) …………….					

SECTION D: Infrastructural Characteristics

1. Are you connected to electricity? (Yes = 1, No = 0) ………..

2. Are you connected to solar power? (Yes = 1, No = 0) …………

3. What is the average distance to the nearest tarmac road (in Kilometers)? ………….
4. What is the average distance from your farm to the input market (in Kilometers)? ………
5. What is the average distance from your farm to the output market (in Kilometers)? ………
6. What is the average distance from your home to commercial banking services (in Kilometers)? …………..
7. Can you access mobile phone communication network from your area of residence? (Yes =1, No =0) ……………
8. If no (in 7 above), what is the average distance to the nearest mobile phone communication network (in Kilometers)? …….

SECTION E: Mobile Phone Use Characteristics

1. Do you own a mobile phone? (Yes = 1, No = 0) ………….
2. What type of mobile phone do you own? Tick in the table below.

Code	Type of phone	Description	Tick appropriately
1.	Basic-feature phone	Support voice calls, SMS, money transfer services & cannot download applications	
2.	Low-end smartphone	RAM of less than one GB, downloads limited applications, low memory capacity (less than 8 GB)	
3.	High-end smartphones	RAM of more than one GB, high memory capacity (more than 8GB), can support video-conferencing apps, etc	

3. Do you use your phone to access any agricultural-related information? (Yes = 1, No= 0) ….

4. Kindly tick the boxes below according to how you use your mobile phone.

Mobile phone use	**Tomatoes farmer**	**Green grams farmer**	**Frequency (**1= never, 2 = once a day, 3 = 2 - 4 times a day, 4= more than four times a day**)**
Call relatives and friends			
Play games			
Listening to radio/ watch movies/news for recreation/entertainment			
Chat with relatives and friends (via SMS, whatsapp, twitter, facebook, etc)			
Search for information on farm laborers/ workers			
Weather information (from various mobile phone-based platforms)			
Agricultural input price and market information			
Agricultural output price and market information			
Making payments for agricultural-related transactions			
Contact agricultural extension agent			
Search for agronomic information			
Search for information on transport of farm produce			
Search for non-agricultural information (e.g. school work, sports, shopping for household items, etc.)			

5. Whose mobile phone is mainly used for: tomato information……. green gram information …...? (1 = husband, 2 = wife, 3 = both husband & wife, 4 = other members)
6. Are you aware of any mobile phone-supported agricultural applications or information service? (Yes =1, No = 0) …….
7. If yes, which one? 1. DrumNet, 2. I-Shamba, 3. Kenya Commodity Exchange, 4. Kenya Agricultural Observatory Platform (KAOP), 5. Kilimo Salama. 6. Any other …………….

8. Do you use any of the agricultural information service mentioned in 8 above? ………. If yes, which one(s)? ………………..

9. Kindly indicate in the boxes below on how you perceive information received through mobile phone:

Respondent's Perception on information provided through mobile phone	1. Agree	2. Not sure	3. Disagree
Relevant			
Reliable			
Timely			
Complex			

<u>SECTION F: Climate Smart Horticulture Data</u>

1. Are you aware of climate change? (Yes = 1, No = 0) …..
2. Which of the following statements do you strongly agree with?
    a) Climate change refers to extreme climatic events that significantly reduce agricultural productivity.
    b) Climate change refers to the changes in climatic patterns such as unpredictable rainfall, droughts, changing agro-ecological zones that significantly affect agricultural practices.
    c) Climate change refers to negative climatic conditions only.
3. What is the source(s) of climate change information? 1. Extension officer, 2. Other famers, 3. Books and printed materials, 4. Any other (specify) …..
4. Which channel do you use to access climate change information? 1. Mobile phone, 2. Radio, 3. Television, 4. Written media, 5. Any other (please specify) ………………….
5. What climate change problems do you face in your farm activities?

Type of problem	Tick appropriately
Prolonged drought	
Frequent floods	
Poor rainfall distribution	
High temperatures	
Land degradation	
Unpredictable rainfall	
Desertification	
Water scarcity	
Any other (please specify)	

6. Do you receive any information on weather forecast? (Yes = 1, Otherwise = 0) ……………

7. If yes, what channel do you use to access weather information? Tick in the box below.

Radio	Television	Mobile phone	Printed media	Others (specify)

8. Do you trust the information you receive on weather forecast? (Yes = 1, No = 0) ….

9. Are you aware of climate smart horticulture? (Yes =1, No = 0) ………..

10. Which of the following statements do you strongly agree with?

    a) Climate smart horticulture are those practices that help climate change adaptation and improve food security.

    b) Climate smart horticulture are those practices that adapt horticulture to climate change and improve productivity.

    c) Climate smart horticulture are practices that improve horticulture adaptation to climate change, improve productivity and reduce greenhouse gas emissions.

11. Which channel(s) do you use to access climate smart horticulture information? Tick appropriately

Radio	Television	Mobile Phone	Printed media (e.g. Newsletters, etc.)

12. How long did it take you to implement climate smart horticulture information received?

1) 0 – 3 months	2) 3-6 months	3) 6 -9 months	4) 9 –12 months	5) More than 12 months

13. Based on question 10 above, what climate smart horticulture practices have you implemented in your farm to reduce negative effects of climate change? Tick in the box below.

S/No	**Climate smart horticulture Practice**	**Tick appropriately**	
		Tomatoes	**Green grams**
1.	Use of improved and well adapted seed variety		
2.	Matching planting dates to weather information received		
3.	Crop rotation		
4.	Use of cover crops		
5.	Efficient use of inorganic fertilizer through soil testing		
6.	Use of terraces		
7.	Agroforestry		
8.	Use of live barriers – strips of crops (grass) along contours		
9.	Integrated farming system (mixed farming)		
10.	Crop insurance		
11.	Crop diversification		
12.	Use of organic fertilizers		
13.	Use of mulching		
14.	Minimum tillage		
15.	Farm ponds (water harvesting)		
16.	Integrated pest management		
17.	Contour cultivation		
18.	Any other (please specify)		

14. To what extent have you adopted climate smart horticulture practices? Tick appropriately.

Adoption behavior	**Tick appropriately**	**Duration of adoption**
Adopted and continuing		
Adopted and stopped		
Never adopted		

15. How well did the adopted practices work? Kindly share your views.

……………………………………………………………………………………………..........................

....

16. Kindly share your opinion on why you are still using or stopped using some climate smart horticulture practices.

………

………

17. Were there any yield differences before and after adoption of climate smart horticulture practices? (Yes = 1, No =0) …………

18. If yes, what was the magnitude of the difference (in kilograms/acre)? ………………….

19. Were there changes in your farm activities due to Covid-19? (Yes = 1, No =0) ………

20. If yes, to what extent did covid-19 affect your farm activities and output?

S/No	Effect	Agree/Disagree	Extent
1.	Inputs became expensive		
2.	Extension visits were cut-off		
3.	There was low output per acre planted		
4.	Transport services from farm to input and output markets became expensive		
5.	Output prices significantly reduced due to low demand		
6.	Any other (specify)		

-- THE END –

Thank you for your responses.

Appendix 3: Variance inflation factor(s) (VIFs)

Variable	**VIF**	**1/VIF**
Number of CSH practices adopted	3.10	0.322658
Farm size under crop	2.95	0.339194
Expenditure on fertilizer	2.95	0.339237
Total Farm size	2.89	0.345909

Distance from farm to the bank	2.46	0.406778
CSH participation	2.43	0.411778
Agricultural extension services	2.42	0.413239
Expenditure on seeds	2.19	0.456930
CSH awareness	2.13	0.470076
Distance from farm to the market	2.09	0.477403
Age	1.88	0.532069
Horticulture crop	1.87	0.536070
Hired labor	1.82	0.548942
Type of phone owned	1.67	0.597164
Gender	1.63	0.613250
Group membership	1.62	0.615726
Mobile phone use in CSH	1.60	0.623168
Education	1.55	0.645166
Farming experience	1.54	0.650492
Head of the household	1.49	0.672531
Electric power access	1.44	0.696206
Decision maker	1.42	0.705360
Trust on weather information	1.37	0.731367
Climate change awareness	1.35	0.741249
Household size	1.31	0.762558
Land ownership status	1.30	0.770652
Credit Access	1.22	0.822975
Mean VIF	**1.90**	

Appendix 4: Partial correlation coefficients for all variables

	Gender	Age	Head of household	Decision maker	Education	Household size	Off-farm income	Horticulture crop	Farming experience
Gender									
Age	0.0793								
Head of the household	0.3611***	-0.1940***							
Decision maker	-0.2414***	-0.0094	0.1198**						
Education	0.0426	-0.1098**	0.1148**	-0.1021**					
Household size	-0.0464	0.2514***	0.0577	0.1419***	-0.0590				
Off-farm income	0.0510	-0.0927*	0.0010	0.0381	0.1901***	-0.0569			
Horticulture crop	0.1296***	-0.0347	-0.0177	-0.0753	0.0024	-0.0345	0.0263		
Farming Experience	0.0158	0.4178***	-0.0426	-0.0246	-0.0789	0.0247	0.0727	0.0316	
Farm size (under crop)	0.0752	-0.0110	-0.0234	0.0931*	-0.1159**	-0.0413	-0.0887*	-0.0151	0.0456
Total farm size	0.0371	0.0676	0.0254	-0.0471	0.0991*	0.0529	0.2802***	-0.1468***	-0.0011
Land ownership status	-0.0832	-0.1611***	0.0258	-0.0701	0.0080	0.1408***	0.0711	0.0020	-0.0460
Access to extension services	-0.0163	0.0020	-0.0224	-0.2392***	0.0049	0.0726	0.0302	0.0375	-0.0490
Group Membership	-0.0838	0.1315**	0.0495	0.1390***	-0.0392	0.0026	-0.0197	-0.1460***	-0.1521***
Access to credit	-0.1199**	-0.0418	-0.0318	-0.0208	0.0277	0.1063**	-0.0640	-0.0101	0.0589
Electric power access	-0.0610	-0.0625	0.0750	-0.1048**	0.0192	0.1384***	0.0471	0.0639	-0.0619
Distance from farm to market	-0.0972*	0.0124	0.0155	-0.0134	-0.0099	-0.0283	0.0493	-0.0269	0.0346

Distance from farm to bank	0.0618	-0.1334***	0.0744	0.0599	-0.0027	0.1087**	-0.0827	-0.0175	-0.0016
Type of phone owned	-0.0168	-0.1178**	-0.0440	0.1472***	0.1615***	-0.1154**	0.0581	-0.0007	-0.0485
Number of CSH practices	0.0909*	0.0083	-0.0286	0.0638	0.1953***	0.0735	-0.0664	0.3455***	0.1450***
Mobile phone use in CSH	0.1178**	-0.0741	0.0792	0.0296	0.0402	0.0547	0.0214	-0.0126	0.0016
Trust	0.0080	0.0494	0.0360	0.0050	0.0044	0.0009	-0.0400	-0.1046**	-0.0908*
CSH participation	0.0434	0.0525	0.032	0.1294**	-0.0470	-0.0443	-0.0439	-0.0969*	0.0001
Climate change awareness	0.0924*	-0.0142	0.0936*	0.0446	0.0299	0.0571	0.0233	-0.0260	-0.0104
CSH awareness	-0.1006*	0.0449	-0.0166	-0.0172	-0.0568	-0.0128	0.0610	-0.0334	-0.1055**
Hired labor	-0.0182	-0.0228	-0.0134	-0.0829	0.1020*	0.0180	0.0918*	0.1143**	-0.0307
Expenditure on seeds	-0.0441	-0.0450	0.0056	0.0944*	0.0832	0.0914*	0.0126	-0.0859*	0.0537
Expenditure on fertilizer	0.0296	-0.0484	-0.0501	0.0261	-0.1096**	-0.0731	-0.0473	0.3707***	-0.0194
Value of output	0.0033	0.0142	0.0070	-0.0150	0.0025	-0.0111	-0.1092**	-0.0799	-0.0460
Value of output per acre	0.0343	-0.0437	0.0373	-0.0678	-0.0210	0.0219	0.0204	0.0764	0.1538***

	Farm size (under crop)	Total farm size	Land ownership status	Access to extension services	Group Membership	Access to credit	Electric power access	Disance from farm to market	Distance from farm to bank
Farm size (under crop)									
Total farm size	0.6170***								
Land ownership status	-0.0577	-0.0655							
Access to extension services	-0.0582	-0.0168	0.0595						
Group Membership	-0.0307	0.0554	-0.0979*	0.2871***					
Access to credit	-0.0779	0.1538***	0.0213	0.1379***	0.0195				

Electric power access	0.0287	0.0213	-0.0371	0.0577	0.0736	-0.0027			
Distance from farm to market	-0.0341	0.1663***	0.0564	0.0556	-0.0292	-0.0297	-0.2465***		
Distance from farm to bank	0.0080	-0.0483	-0.1264**	-0.3199***	-0.1357***	0.0889*	-0.0464	0.5087***	
Type of phone owned	-0.0401	-0.0233	-0.1741***	0.0834	0.0005	-0.0116	0.0212	0.0684	-0.0693
Number of CSH practices	-0.1867***	0.1590***	-0.0032	-0.0539	0.0695	-0.0642	-0.0589	-0.0261	-0.0491
Mobile phone use in CSH	0.0859*	-0.0893*	-0.0834	-0.0001	0.0208	0.1770***	0.1264**	0.0255	-0.0213
Trust	0.0848	-0.0640	-0.1451***	-0.0296	-0.0603	-0.1502***	0.0553	0.0853*	0.0965*
CSH participation	0.0278	-0.0682	0.0805	0.2281***	-0.0122	0.0663	0.1629***	0.1454***	0.1054**
Climate change awareness	0.0829	-0.0273	0.0177	0.0927*	-0.0803	0.0671	0.1644***	0.1489***	-0.1186**
CSH awareness	0.0509	-0.0399	0.0073	0.2949***	0.0875*	-0.0754	-0.0547	-0.1455***	0.2151***
Hired labor	0.2783***	-0.0397	0.0505	0.0090	0.0753	0.1352***	-0.0405	-0.2000***	0.1569***
Expenditure on seeds	0.0850	0.0539	0.0029	0.0409	0.0461	-0.0176	-0.0692	-0.1552***	0.0501
Expenditure on fertilizer	0.0997*	0.1049**	0.0438	0.1237**	-0.0370	0.0152	0.0690	0.1246**	0.0923*
Value of output	-0.0315	0.0871*	-0.0135	-0.0054	-0.0213	-0.1189**	0.0252	0.0715	0.0070
Value of output per acre	-0.0583	-0.0659	-0.0255	-0.1551***	0.0634	0.1663***	0.0135	0.0372	-0.1137**

	Expenditure on fertilizer	Value of output
Expenditure on fertilizer		
Value of output	0.3403***	
Value of output per acre	-0.0305	0.3156***

Note:

1. ***, ** and * denotes significance level(s) of 1%, 5% and 10% respectively.
2. show high level of association between the two variables under consideration