A DATA-DRIVEN MODEL FOR SUSTAINABLE DEPLOYMENT AND ADOPTION OF CLIMATE SMART AGRICULTURE PRACTICES AMONG SMALLHOLDER FARMERS IN KAKAMEGA COUNTY

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DECLARATION

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CERTIFICATION

The undersigned certify that they have read and recommend for acceptance of Masinde Muliro University of Science and Technology a thesis entitled **"A Data-Driven Model for Sustainable Deployment and Adoption of Climate Smart Agriculture Practices Among Smallholder Farmers in Kakamega County"**

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DEDICATION

In remembrance of my late parents, Rebecca Muthoni Ndung'u and John Ndung'u Ndirangu. I regret that they were unable to witness my graduation after giving everything they had to support my education.

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ABSTRACT

Kenya's agriculture is dominated by 4.5 million smallholder farmers who produce over 75% of the national agricultural production. These farmers are the most vulnerable to climate change because of various socioeconomics, demography, and policy trends limiting their capacity to adapt to the change. To mitigate the negative effects of climate change on smallholder farmers, numerous interventions in the form of Climate Smart Agriculture (CSA) Technologies have been developed and promoted by various organizations. The current deployment of CSA practices, however, does not consider individual farm-level biophysical and socio-economic characteristics during the design and implementation of the interventions. This study, therefore, enhances smallholder farmers adaptation to climate change by development, prototyping and evaluating the suitability of a data-driven model for the sustainable deployment and adoption of CSA practices. Through a quantitative survey of 428 respondents, this study investigated the major socio-economic and biophysical characteristics of smallholder CSA farmers and developed a predictive tool for sustainable deployment of CSA practices. Supervised Machine Learning using the Scikit-Learn library of Python Programming language was used to build, pilot, and review Decision Tree and Random Forest Classifier models. The predictive tool was piloted among 15 smallholder CSA farmers and validated by key stakeholders in the CSA ecosystem through a Focus Group Discussion. While agroforestry, composting, and soil and water conservation structures were the most adopted, push-pull technology, conservation agriculture, and vermiculture were the least adopted CSA technologies. This study, further, established that smallholder farmers' level of education, membership to a farmers' group, interaction with extension officers and farming experience influenced adoption of CSA technologies. Factors that increase household productive resources, such as land ownership, household income, and access to agricultural credit also influenced adoption of CSA practices. The classifier model produced a Mean Squared Error of 0.16. The model predicted smallholder farmer adoption at an accuracy of 89.53% and 80.0% with test data and pilot data, respectively. Through the study, it was possible to predict which smallholder farmers would be CSA technology adopters using their farm specific characteristics. This study, therefore, develops a model for the optimal selection of Climate Smart Agriculture intervention beneficiaries.

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LIST OF ACRONYMS AND ABBREVIATIONS

ACT	African Conservation Tillage Network
AEZ	Agroecological Zones
AUC	Area under Curve
CA	Conservation Agriculture
CGK	County Government of Kakamega
CSA	Climate Smart Agriculture
DANIDA	Danish International Development Agency
DSS	Decision Support System
FAO	Food and Agriculture Organization of the United Nations
FAW	Fall armyworm
GHG	Greenhouse Gas
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GPFARM	Great Plains Framework for Agricultural Resource Management
ICRAF	World Agroforestry Centre
ICT	Information and Communication Technologies
IPM	Integrated Pest Management
ISFM	Integrated Soil Fertility Management
ISLM	Integrated Sustainable Land Management
KARI/KALRO	Kenya Agricultural Research Institute, now Kenya Agricultural and Livestock Research Organization
KCSAP	Kenya Climate Smart Agriculture Project
LPG	Liquified Petroleum Gas
MEA	Mean Absolute Error
ML	Machine Learning
MSE	Mean Squared Error
NALEP	National Agriculture & Livestock Extension Programme
NERICA	New Rice for Africa
NGO	Non-Governmental Organization
PPT	Push-Pull Technology
RMSE	Root Mean Squared Error
ROC	Receiver Operating Characteristic Curve
SWC	Soil and Water Conservation

TIMPS	Technologies, Innovations, and Management Practices
WKCDD-FD	Western Kenya Community Driven Development and Flood Mitigation Project
WSU	Washington State University

OPERATIONAL DEFINITION OF KEY TERMS

Agroforestry	Land use practice in which woody perennials are deliberately integrated with crops varying from simple and sparse to very complex and dense systems
Climate Change	A change in climate systems which is caused by significant changes in the concentration of greenhouse gases because of human activity and which is in addition to natural climate change that has been observed during a considerable period
Climate Change Adaptation	Adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities
Climate Change Mitigation	Efforts that seek to prevent or slow down the increase of atmospheric greenhouse gas concentration by limiting current or future emissions and enhancing potential sinks for greenhouse gases
Climate Change Resilience	The capability to maintain competent function and return to some normal range of function even when faced with adverse impact of climate change
Climate Smart Agriculture	Agricultural production method of combining various sustainable methods to address a specific community's climate challenges. CSAs, agricultural practices that consider both resilience and adaptation to climate change, assists those who manage agricultural systems in responding effectively to challenges of climate change.

Composting	A Climate Smart Agriculture Practice that involves the putting together of a mixture of crop and organic residue, manure, soil, and water to form humus.
Conservation Agriculture	A Climate Smart Agriculture Practice that is based on the three principles of minimal soil disturbance, permanent crop cover, and crop rotation to create a more sustainable cultivation system for the future
Data-driven agriculture	The set of approaches using digital technology to source, analyse and translate data into timely, practical, and context-specific information to help farmers make the best choices for their farms
Greenhouse	A Climate Smart Agriculture Practice in which an enclosed space that, due to the confinement of the air and the absorption of shortwave solar radiation, creates a different environment than that found outside
Greenhouse Gas	A gas that absorbs and emits radiant energy within the thermal infrared range causing the greenhouse effect. Greenhouse gas includes carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulphur hexafluoride and indirect greenhouse gases
Integrated Sustainable Forest Management	Various degrees of human intervention, ranging from actions aimed at safeguarding and maintaining forest ecosystems and their functions to those favouring specific socially or economically valuable species or groups of species for the improved production of goods and services
Integrated Sustainable Land Management	Application of soil fertility management practices, and the knowledge to adapt these to local conditions

	which maximize fertilizer and organic resource use efficiency and crop productivity
Machine Learning	The use of computer programs to learn about the characteristics and features of given targets and then use the learning in identifying other related targets using the data previously collected from the previous target
Push-Pull Technology	A Climate Smart Agriculture Practice for managing stem borers, which primarily affect maize, sorghum, and other grasses. The technology attracts stem borers to trap plants, while repellent non-host crops repel them from cereal crops
Smallholder farmers	Refers to rural producers predominantly in developing countries who mainly farm using family labour and for whom the farm provides the principal source of food and income. In Kenya, smallholder farmers refer to those farmers who work and own land ranging from 0.5 to 5 hectares
Sustainable agriculture	Refers to farming practices that meet society's current food and fibre needs without jeopardizing current and future generations' ability to meet their own. Sustainable agriculture is to be economically viable, socially supportive, and ecologically sound in that it seeks to support farmers, resources, and communities by promoting profitable, environmentally sound, and community-friendly farming practices and methods
Water harvesting	The collection of surface runoff from a catchment caused by rains. It entails collecting, concentrating, and storing surface runoff water for crops, livestock, and humans.

CHAPTER ONE
INTRODUCTION

1.1 Introduction

This chapter introduces the reader and other researchers to the problem of the study. First, this chapter gives a background of the problem and smallholder agriculture in Kakamega County. It, further, elaborates on the problem statement, objectives, limitations, and the scope of the study. This study's significance and limitations are also discussed. The chapter concludes with a justification for the study and why it was necessary to conduct it.

1.2 Background Information

1.2.1 Agriculture and Food Security

Smallholder farmers in Kenya are estimated at 4.5 million, and they account for more than 75% of the country's agricultural output (GOK, 2018; Kirimi et al., 2011). The contribution of smallholder farmers to Kenya's agricultural development, therefore, cannot be underestimated as they play a significant role in the food security of the country. Available reports indicate that smallholder farmers produce over 80% of the food produced in Africa (Mpandeli, 2020). In addition, they produce for their households thereby reducing the burden on the government to provide food for them. World Bank reports by Luc (2018) indicate that agriculture is two to three times more effective in eradicating poverty than other interventions.

Kenyan smallholder farmers face several challenges. First, because of their small landholdings, they produce only enough food to feed their families and have little to sell (Giller et al., 2021). As a result, their ability to generate income is reduced, and their poverty levels rise. Second, smallholder farmers cannot obtain agricultural credit to improve their farming practices because they lack adequate data to support their creditworthiness (Maru et al., 2018). Third, because the majority of these smallholder farmers live in remote and rural areas, they do not have access to the necessary infrastructure and other services that would enable them to access farm inputs and agricultural markets (Aaron, 2012). Fourth, smallholder farmers face pest and disease outbreaks, droughts, and a scarcity of arable land to both live in and carry out their farming practices (Mpandeli, 2020). Lastly, a report by Kenya Agricultural Research Institute (KARI) (2009) indicates that smallholder farmers are faced with the major challenge of climate change. The report indicates, further, that the zones that are considered semi-arid may become arid areas or too dry for any agricultural activity to take place.

The Government of Kenya has put in place several policy documents to sustainably increase agricultural productivity in the presence of climate change. First, is the Agricultural Sector Transformation and Growth Strategy, a 10-year plan that seeks to raise the incomes of smallholder farmers, pastoralists, and fishermen; boost agricultural productivity and value addition; and strengthen household food resilience to climate change. Second, is the National Adaptation Plan (2015–2030). This plan aims to: Improve the resilience of public and private sector investment in the national transformation, economic and social, and pillars of Vision 2030 to climate shocks; increase synergies between adaptation and mitigation actions to attain a low-carbon, climate-resilient economy; and integrate climate change adaptation into national and county level development planning and budgeting processes. The Kenya Climate Smart Agriculture Strategy (KCSAS) was created to direct investments in and the execution of climate-smart agriculture (CSA) initiatives that ensure food security and production while addressing adaptation and mitigation of climate change. Through the Kenya

National Climate Change Action Plan 2018–2022, Kenya aims to sequester up to 4.1 metric tonnes of carbon dioxide by 2030 by establishing 281,000 Hectares of agroforestry between 2015 and 2030. Finally, Kenya has developed the National Agroforestry Strategy 2021–2030 with the aim of restoring agricultural productive capacity and mitigating climate change through enhanced agroforestry practices.

1.2.2 Agriculture Production in Kakamega County.

The County Government of Kakamega (CGK) estimates that more than 80% of the working population works in agriculture, primarily in rural regions (CGK, 2018). This population mostly work in the production, delivery, and processing of agricultural goods. The County's primary agricultural products are sugarcane, tea, coffee, maize, beans, sweet potatoes, bananas, upland rice, cassava, sorghum, finger millet, native vegetables, and other horticulture products (CGK, 2020). While all other crops are typically produced as food crops and are primarily grown for subsistence, sugarcane, tea, and coffee are cash crops. The county also raises a significant amount of livestock, primarily cattle, fowl, sheep, goats, and pigs (CGK, 2020). The County Government's initiatives along provision of subsidized aquaculture inputs and the establishment of the Fish Processing Factory have resulted to increased fish production in the County. Currently, the County is home to around 6,300 smallholder aquaculture farmers who raise more than 700,000 kilograms of fish each year (CGK, 2020). As a result, the County has a great potential for agriculture, which is expected to grow in importance and generate more jobs in future.

Smallholder farmers, who primarily farm for subsistence, account for most of the agricultural activity in the County (CGK, 2020). Available reports indicate that the county's smallholder farmers own an average of 1.5 acres of land, while medium-scale farmers own an average of 10 acres (CGK, 2020). There are, however, large-scale farmers in that area because of the county's northern region's bigger landholding.

Despite the County's ample rainfall, fertile soils, and significant agricultural potential, there are high rates of extreme poverty and low levels of household food self-sufficiency. Reviewed literature indicates that the county has a 57% poverty rate, with some sources ranking it as the 20th poorest county out of the country's 47 counties (TrendinginKenya, 2020). Additionally, despite the various initiatives taken by the national government, county government, and aid organizations, agricultural productivity remains poor.

Detailed strategies have been outlined by the County Government of Kakamega for integrating climate change adaptation and mitigation into development initiatives for sustainable development, as envisioned in the development strategy and governor's manifesto. Since 2013, the County Government of Kakamega has implemented the farm inputs subsidy project to boost maize production and food security. The flagship project involves availing non acidifying fertilizer and certified maize seeds to farmer in all the 60 administrative wards (CGK, 2020). In addition, Kakamega is one of the 24 counties in Kenya that implemented the Kenya Climate Smart Agriculture Project between 2018 and 2022. This World Bank funded project was implemented under the framework of the Agriculture Sector Development Strategy (2010-2020) and National Climate Change Response Strategy (2010). KCSAP has funded major irrigation and drainage systems such as the rehabilitation on water dams, construction of water pans and support to smallholder irrigation systems cross the county (CGK, 2020).

From the foregoing, efforts are being put to support climate adaptation among Kakamega County residents. The government and her partners have supported several climate action initiatives that will go a long way to help residents adapt to the changing climate. There are, however, gaps in the adoption of CSA practices as

1.2.3 Climate Change and Agriculture

Climate change studies have identified rising temperatures, more variable rainfall, and changes in the onset and offset of rainfall as some of the major challenges facing agriculture today (Harvey & Pilgrim, 2011). In addition, high temperatures and drought conditions have been reported to harm maize and bean production, flowering, and yields in many tropical countries (Eitzinger et al., 2013). In addition, climate change has been documented to have negative effects on tropical agricultural production, because of increased insect pests and crop disease incidences. Paudel et al. (2022), associates the invasion of fall armyworms (FAW) in Africa with climate change indicating that Eastern and Central Africa will have the optimal climate for FAW persistence. The foregoing notwithstanding, climate change has impacted negatively on smallholder agriculture through unpredictable weather and intensified drought cycles making farming unpredictable and reducing agricultural productivity (Ahmad et al., 2022). As a result, smallholder farmers must develop coping strategies such as sustainable agriculture, climate-smart agriculture (CSA), precision agriculture, and other interventions.

Previous studies in indicate that the Kakamega county experiences unpredictable rainfall, with the planting seasons being marked by unusually early showers that are then followed by weeks of dry weather (Ochenje et al., 2016). According to Ochenje et al. (2016), smallholder farmers in Kakamega are becoming increasingly exposed to climate risk as a result of the increased rainfall intensity and delayed rainstorm onset, both of which tend to harm agricultural production. Comparable studies by Liru and Heinecken (2021) suggest that the main climate changes affecting the livelihoods of smallholder farmers in Kakamega County are changes in weather patterns, including temperature variations, variability in precipitation, and prolonged dry periods. The authors assert that these consequences are influenced by extreme climatic occurrences, such as floods, droughts, and the associated natural catastrophes that have an impact on cattle and crops.

Climate Smart Agriculture (CSA) practices consider both resilience and adaptation to climate change. The Food and Agriculture Organization of the United Nations (FAO) defines CSA as an approach that aims to assist those who manage agricultural systems in responding effectively to climate change (FAO,2020a). The triple wins of climate-smart agriculture are the sustainable increase in productivity and income, adaptation to climate change, and reduction in greenhouse gas emissions (FAO,2020a). Thus, CSA helps guide actions to transform agrifood systems towards green and climate resilient practices.

There is enough evidence that sustainable adoption of CSA practices by smallholder farmers leads to diverse benefits ranging from increased yields to reduction of costs of production. Reviewed literature reveals that some of the benefits that accrue to adopting farmers include enhanced and efficient use of fertilizer and improved output productivity (Fairhurst, 2012; Lambrecht et al., 2014b). Similar studies by Kamau et al. (2013), indicate that sustainable adoption of CSA practices reduce the need for chemical fertilizers owing to their ability to raise the efficiency of the applied nutrients. In addition, the use of organic fertilizers such as compost manure, green manures, crop residues, and legume integration in farming systems improve soil organic matter, nutrient and water retention in soils thus increasing agricultural productivity (Wezi G Mhango et al., 2013). Overall, there are economic benefits such as profits maximization realized when the farm productivity exceeds the cost of CSA adoption.

From the foregoing, CSA can indeed help smallholder farmers to achieve household food self-sufficiency and at the same time increase their incomes from their farming activities. This, however, has not been realized and there is a need to re-think the process of deployment of the technologies among smallholder farmers.

1.2.4 Data Driven Agriculture and CSA Models

Current systems for deployment of CSA among smallholder farmers are not based on statistical models and, therefore, fail to systematically incorporate readily available data on prices, weather and demographics Lentz et al. (2019). The current practice is that farms in each locality are given blanket recommendations. This may or may not work as individual farms are different ranging from management practices in each farm, soil characteristics, and other farm-based characteristics such as household income, land holding, and decision making. Rao (2018), argues that CSA requires farm-specific knowledge of local climate conditions, risks, and detailed knowledge of other conditions at the farm level. This knowledge, if available, supports decision-making in the choice of crop variety, planting dates, fertilizer application, and the efficient use of water. This, therefore, implies that farm data is of paramount importance as far as the sustainability of CSA is concerned.

Data-driven agriculture is the deliberate application of big data to augment on-farm precision agriculture. It entails having the appropriate farm data at the appropriate time to make better decisions (Hayden, 2020). Data-driven agriculture is also defined as a system for supplementing on-farm precision agriculture with the right farm data, at the right time, and in the right format to make better decisions (Sourcetrace, 2019). Data-driven agriculture is also defined as a set of approaches that use digital technology to source, analyse, and translate data into timely, practical, and context-specific information to assist farmers in making the best decisions for their farms (CGIAR, 2020). The use of data-driven agriculture increases productivity and makes better use of farm inputs.

Many studies have been conducted to model agricultural production. First, Johann et al. (2016) estimated the soil moisture content using an autoregressive error function. This model is suitable to estimate soil moisture in controlled systems applied no no-till machinery. A similar study by Chen, et al. (2014) designed a Wireless Sensor Network (WSN) to monitor multi-layer soil temperature and moisture in a farmland field to improve water utilization and to collect basic data for research on soil water infiltration variations for intelligent precision irrigation. Muangprathub et al. (2019) developed a model for optimally irrigating crops based on a Wireless Sensor Network (WSN). In this model, a soil moisture sensor is used to monitor the field and connecting to the control box. A web-based application is designed to manipulate crop data and field information. This application applies data mining to analyze the data for predicting suitable temperature, humidity, and soil moisture for optimal future management of crops growth. A mobile smart phone app is then developed to control crop watering.

Another notable model developed in the recent past is the Climate Smart Village Approach by Aggarwal et al (2018). This model provides a means of performing agricultural research for development through testing technological and institutional options for dealing with climate variability and climate change using participatory methods. According to Aggarwal et al. (2018), an ideal CSV approach gives guidance before and during the planting season on the most suitable CSA practices, technologies, services, processes, and institutional options considering market and resource availability such as capital, labor and markets.

The Climate Smart Decision Support system for analysing the water demand of a large-scale rice irrigation scheme is one of the models that have been developed to inform Climate Smart Agricultural decisions. This model by Rowshon et al. (2019), was applied to evaluate the impacts of climate change on irrigation water demand and other key hydro-climatic parameters in the Tanjung Karang Irrigation Scheme in Malaysia for the period 2010-2099. This model which has been used for analysing the water demand of a large-scale rice irrigation scheme helps promote adaptation and mitigation strategies that can lead to more sustainable water use at the farm level.

Ascough Li et al. (2002), developed the Great Plains Framework for Agricultural Resource Management (GPFARM), to provide crop and livestock management support at the whole farm level in the Great Plains of the United States. This DSS provides producers, consultants, action agencies, and scientists with information for making management decisions that promote sustainable agriculture. GPFARM contains risk analyses that combine projected crop yield and animal production data with concurrent environmental impact data. Another DSS was developed by Bseiso et al. (2015) targeting greenhouse farmers in low-resource settings. The DSS provides farmers with slides of decision information which is only read through printed papers or in a PDF format. This means that this DSS tool can be made into an app instead of paperwork.

Fourati et al. (2014) present a climatic monitoring system for farmers. Using an integrated WSN weather station, farmers can display weather measures relative to temperature, humidity, wind and solar radiation. These measures allow the DSS to precisely calculate the water requirement in a daily calendar. Another DSS is by Panchard et al. (2007), known as Commonsense net. This DSS is a wireless sensor network for resource-poor agriculture in the semiarid areas of developing countries. This sensor network system aims at improving resource poor farmers' farming strategies in the wake of highly variable conditions. The risk management strategies include choice of crop varieties, planting and harvesting, pests and disease control and efficient use of irrigation water. This decision Support System uses WSN for the improvement of farming strategies in the face of highly variable conditions.

From the foregoing, no study was found that specifically targets sustainable deployment and adoption of CSA practices among smallholder farmers in Kakamega County or globally. It has been proven that data-driven agriculture informs the smallholder farmers on the critical decisions of including what to produce, how much to produce and when and how much to produce (Maru et al., 2018). In addition, with the supporting data, farmers can effectively plan for farm activities that produce more yields. For this reason, it is important to develop a data-driven model for sustainable deployment and adoption of CSA technologies in Kakamega County.

1.2.5 Climate Smart Projects in Kakamega County

Smallholder farmers in Kakamega County implement CSA practices through various projects. The Kenya Climate Smart Agriculture Project (KCSAP) is one of the major projects working with smallholder farmers within the county. This is a World Bank-funded project, implemented by the County Government of Kakamega, works with smallholder farmers in three sub-counties and six wards across the county. Previously, the county government and her partners worked on several projects. The Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) is one of the most important CSA partners in Kakamega County through their ProSoil Program. ProSoil Program has rehabilitated over 166,000 hectares in three counties, Kakamega, Siaya, and Bungoma, through CSA interventions such as Conservation Agriculture, agroforestry, composting, and the implementation of soil conservation structures through their Soil Protection and Rehabilitation of Degraded Soil for Food Security Project (GIZ, 2020).

Another major CSA project recently implemented in Kakamega is the Scaling up Sustainable Land Management and Agro-Biodiversity Conservation to Reduce Environmental Degradation in Small Scale Agriculture in Western Kenya. This project which was implemented by the Kenya Agricultural and Livestock Research Organization (KALRO) and other partners in the counties of Nandi, Kakamega, and Vihiga used a micro-catchment approach to increase the incomes of smallholder farmers in the Kakamega forest by implementing sustainable land/forest management technologies (AGRA, 2020) . These projects, among others, indicate the role that has been played by development partners in promoting CSA practices in the county.

While development partners and donors have played a vital role in promoting CSA practices, many of these interventions have been short-lived, with most farmers abandoning these practices once donor funding ends. Reviewed literature reveals that most projects aimed at smallholder farmers become unsustainable after donor funding is withdrawn (Olang, 2016). According to Olang (2016), several donor-funded projects in Kakamega County have failed to be sustainable following the donor agency's withdrawal. These include the two dairy cooperatives that were revived with Danish International Development Agency, milk chilling plants in Tombo and Kimangeti dairies that were established by the Western Kenya Community Driven Development and Flood Mitigation Project, 21 community cattle dips revived by the Malava Constituency Development Fund and the Dairy animals that were given out to community members by Send a Cow. Other studies by Akuto (2020) have linked institutional factors such as low community participation, weak managerial capacities and low extension services to lack of sustainability of donor funded projects

Similar studies by Okumu (2023) indicate that poor rural households occupy marginal despite the promotion of CSAs by different partners and players, poverty rates in

Kakamega are still high with 51% of the residents living below the poverty line. A study by Shilomboleni et al. (2019), suggests that rural poor households face ecological and socio-economic uncertainties making it difficult for them to uptake agricultural innovations after end of donor funded projects. This suggests that donor-funded projects have a higher likelihood of failing to continue after the donor organizations stop financing.

The foregoing notwithstanding, smallholder farmers have different resource endowment in the form of smallholder farmer level of education, household income, labour availability, individual smallholder farmer interest and other farm-based characteristics such as soil characteristics, types of crop and livestock enterprises and the different farm management practices. In addition, these smallholder farmers may face challenges including lack of credit facilities, small land holdings, limited access to necessary infrastructure and support services such as extension, farm inputs and markets. These challenges coupled with the supporting CSA projects coming to an end may result in CSA technology dis-adoption among smallholder farmers.

1.3 Problem Statement

Climate change has been identified as one of the major challenges in Kenya's agriculture with expected losses in the production of basic staples like maize and beans, and livestock products. This results in high food prices which in effect lower food accessibility and lower per capita calorie availability. Climate Smart Agriculture (CSA) interventions have been developed to increase smallholder farmers' resilience to climate change, reduce Greenhouse Gas (GHG) emissions, and increase agricultural productivity. Through climate finance and other sources of funding, numerous governmental and non-governmental organizations have been promoting CSA practices among smallholder farmers in Kakamega for a long time. The current deployment of CSA practices among smallholder farmers, however, may not achieve the intended goals because it does not consider individual farm-level biophysical and socio-economic characteristics during the design and implementation of the interventions. For this reason, the lack of information, insights, and data-driven decisions leads to losses and reduced yields forcing some smallholder farmers to abandon CSA practices with the winding up of supporting projects.

This study, therefore, seeks to establish the different biophysical and socio-economic characteristics of the Kakamega County's smallholder farmers that influence their sustainable adoption of CSA practices. The resultant data driven agriculture model will allow smallholder farmers to base their farming systems and farming practices on tailored and salient climate information; thus, increasing their resilience and adaptability to climate change using big data. Providing farmers with more accurate, accessible, timely information, from large agricultural groups and ecosystems to the individual smallholders, will help to ensure smallholder farmers produce their crops optimally.

1.4 Objectives of the Study

1.4.1 Main Objective

The main goal of this study was to enhance smallholder farmers adaptation to climate change through sustainable deployment of climate smart agricultural practices in Kakamega County

1.4.2 Specific Objective

i. To establish the different biophysical and socio-economic characteristics of the Kakamega County's smallholder farmers that influence their sustainable adoption of CSA practices.

ii. To develop a suitable data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega county's smallholder farmers.

iii. To prototype the data-driven model for the deployment and adoption of CSA practices among Kakamega county's smallholder farmers.

iv. To evaluate the applicability and suitability of the data-driven model for the deployment and adaptation of CSA practices among Kakamega county's smallholder farmers.

1.4.3 Research Questions

i. What are the different biophysical and socio-economic characteristics of the Kakamega County's smallholder farmers that influence their sustainable adoption of CSA practices?

ii. What is a suitable design of the data-driven model for deployment and adaptation of CSA practices among Kakamega county's smallholder farmers?

iii. How can the data-driven model be implemented in the form of a prototype for the deployment and adoption of CSA practices among Kakamega county's smallholder farmers?

iv. What is the applicability and suitability of a data-driven model prototype for deployment and adoption of CSA practices among Kakamega county's smallholder farmers?

1.5 Justification of the Study

Kakamega County was purposely selected for it was one of the 24 implementing counties of KCSAP, which was funded by the World Bank and implemented under the National Climate Change Response Strategy and the Agriculture Sector Development Strategy (2010-2020). Moreover, Kakamega County has been implementing the GIZ ProSoil project since 2015 and has been working with smallholder farmers to apply climate-smart, agroecological techniques to prevent soil erosion and preserve soil fertility. Lastly, Kakamega County is one of the three counties in Western Kenya that implemented the Scaling up Sustainable Land Management and Agro-Biodiversity Conservation to Reduce Environmental Degradation in Small Scale Agriculture in Western Kenya project.

Most of the CSA technologies that are promoted among the smallholder farmers require that they give up the conventional agricultural production methods that they are used to in favour of the new production methods. In addition, smallholder farmers may not fully understand the non-financial benefits of modern technologies and the markets of the associated products. Although most organizations will train and capacity-build the smallholder farmers on modern technologies, most of these technologies are abandoned as the technology-promoting programs are short-term in nature and the programs would often wind up once the donor support is stopped. This could be because of high technology establishment costs, culture and belief systems, and other pressures associated with smallholder farmers and the people in the farming business.

The smallholder farmers who sustainably adopt these practices beyond the project period reap the benefits that accrue from the successful implementation of CSA technologies including reduced chemical fertilizer use, increased yields, increased soil fertility, increased wood, and non-wood forestry products, and increased soil and water conservation. CSA interventions and the resultant benefits go a long way in reducing GHG emissions and thus reducing global warming that leads to climate change. From the foregoing, smallholder farmers have diverse interests, information, and financial capability thus influencing the adoption of CSA technologies to different extents and ways. It is of utmost importance, therefore, to establish the various biophysical and socio-economic characteristics of the smallholder farmers that influence their sustainable adoption of CSA technologies. This would then inform the identification of target smallholder farmers for CSA technology interventions.

This study develops a decision support system model for the sustainable deployment of CSA technologies among smallholder farmers based on their farm-specific biophysical and socioeconomic data. With this model, the government's, donor agencies', and development partners' CSA resources will be properly invested because their CSA interventions will be deployed among the appropriate smallholder farms. The successful implementation of this model will increase agricultural productivity and incomes while also increasing smallholder resilience to climate change and lowering GHG emissions. Eventually, smallholder farmers' household food self-sufficiency will increase, leading to increased food security in the country.

1.6 Significance of the Study

This study developed a decision support model for sustainable deployment and adoption of CSA technologies among of smallholder farmers based on their farm-specific biophysical and socioeconomic data. The model is aimed at aiding CSA promoting projects, donor programs and extension officers in targeting of suitable smallholder farmer candidates for implementation of various CSA interventions in the county. The model shifts away from traditional "supply-driven" interventions and tends toward individual farm biophysical and socioeconomic-specific interventions. When well utilized, this model results in increased smallholder agricultural production and productivity, as well as sustainable adoption of CSA technologies among smallholder farmers in Kakamega County.

The study and the resultant data-driven model has many benefits not only to smallholder farmers but also to the government and donor agencies. First, the utilization of this model will lead to increased adoption of CSA interventions by target smallholder farmers as the interventions will be tailormade based on their farm-specific biophysical and socioeconomic characteristics. Secondly, the study makes CSA interventions more sustainable as they are deployed to the appropriately targeted smallholder farms whose probability to sustainably adopt the technologies are high. Lastly, employment of this model will lead to better utilization of CSA funding and investments as the smallholder CSA farmers will be rightfully targeted thus achieving CSA project objectives. Ultimately, this model will go a long way in achieving the triple wins of Climate Smart Agriculture which are to sustainably increase agricultural productivity and incomes, adapt to climate change, and reduce greenhouse gas emissions.

1.7 Scope of the Study

The main goal of the study was to develop a data-driven model for the sustainable deployment and adoption of CSA practices among smallholder farmers in Kakamega County based on farm-specific biophysical and socio-economic data. It was not possible, however, for the study to develop the solution beyond a prototype.

Smallholder farmers have different farm enterprises with varying levels of investments in terms of land, labour, and capital intensity. The study, therefore, was not able to cover all aspects of smallholder farmers including livestock and aquaculture practices, but rather, was limited to crop production. In addition, the study, which was conducted in Kakamega County, was limited by the number of farmers to work with and the crop enterprises.

1.8 Assumptions of the study

The study made several assumptions:

i. The selection criteria and sampling strategy gave a representative sample of the study population, and the respondents had similar characteristics.
ii. The development of smallholder farm-specific data CSA decision model required a lot of data from smallholder farmers, agricultural extension officers, research Organizations, donor organizations, and the meteorological department. The study assumed that the data was readily available and accessible to use.
iii. The study worked closely with smallholder farmers to implement CSA practices using the model. The study assumed that most of the smallholder farmers are fairly computer literate with the ability to use smartphone apps.

1.9 Limitations of this study

The research was carried out in Kakamega County. Though the findings of the study and the model developed, as a result, can be used by smallholder farmers in other locations, some features may be limited to Kakamega County characteristics. Furthermore, while the focus of the study was on smallholder farmers in Kakamega, some of the study's findings and developments may or may not apply to large-scale farmers. Because the study was designed to use farm data, the model's application may not work perfectly in farms and ecosystems with limited data

CHAPTER TWO

LITERATURE REVIEW

2.1.Introduction

This chapter examines the literature from earlier studies on the topic conducted worldwide, in Africa, Kenya, and Kakamega County. The chapter discusses the common themes of smallholder agriculture in Kenya, the effects of climate change on smallholder agriculture in Kenya, climate-smart agriculture techniques, Information and Communication Technologies (ICTs) for agriculture, and the application of big and open data for these practices. The models of Climate Smart Agriculture and their application in various agricultural fields are also thoroughly examined in this chapter.

2.2.Climate change as a global market failure

Market failure is a situation that occurs when the inefficiencies in a market fail to account for the benefits and costs necessary to produce and consume a product or service. Harris et al. (2017) site the atmosphere as a global common into which individuals and firms can release pollution into without paying for it. The absence of costs to polluting the atmosphere leads individuals and firms to continue polluting. This continuous pollution creates a negative externality that all individuals and firms across the globe must pay for through climate change and its negative effects. According to Fang (2018), this negative externality is not experienced by those who continually cause the problem and is not reflected on the prices of the goods and services produced and consumed. Climate change affects all people globally including the ones that that do not lead to emissions of greenhouse gases. Climate change can be said to be a public bad as it is non-excludable and non-depletable. Anthropogenic climate change is contributed by a few people while everyone in the globe suffers the repercussions. Of all global Green House Gas

Emissions, the top twenty countries that emitted the most carbon dioxide gas in 2016, accounted to 78% of all emissions while the rest of the world contributed 22% (Liu et al., 2019). China, for example, the leading GHG emitter in 2016 contributes to 28% of all global emissions (Wang et al., 2019). The effects of Climate change on the other hand, are felt by all people across the globe.

2.3.Effects of Climate Change Globally

Studies have shown that Climate change impacts negatively on agriculture and food production. According to Dudu & Çakmak (2018), though climate shocks are introduced in agricultural sector, climate change affects all sectors significantly as a result of complex interactions among the sectors. It is therefore expected that other sectors of the economy are affected negatively by the impacts of climate change. Climate change may increase the incidences of crop pests and diseases as a result of favorable weather conditions. According to Khan et al (2009), there is observed crop stagnation in intensive cultivation of crops in North West India as a result of frequent floods and droughts in the area. Khan et al. (2009) further argue that a rise in winter temperatures reduces the hibernation period of pests thus increasing their activities. In addition, gradual climate warming will lead to changes in pest fauna in different areas resulting in high population growth rate of many pest species.

Scientists have found that the rising deep-water temperatures cause coral bleaching and the loss of breeding grounds for marine fishes and mammals (Smithsonian, 2020) Studies have shown that the ocean absorbs close to half of the carbon produced by burning fossil fuels making sea water more acidic (Kline et al., 2019). According to Kline et al. (2019), both living and dead corals declined to almost zero while the rate of dissolution of dead colonies almost doubled with increase in carbon dioxide levels.

2.4.Effects of climate change in Kenya

Being a tropical country and along the equator, Kenya is highly likely to encounter negative impacts of climate change. Available reports indicate that deep water temperatures of Lake Victoria have warmed by 0.2 to 0.7 degrees Celsius since the early 1900 (Nassali et al., 2020). It is predicted that climate change will result into decrease in the production of the most important staple crops in Kenya such as maize and beans. This may lead to increased food security issues in the country (Kogo et al., 2021). According to Herrero, et al. (2010), Kenya is expected to experience losses in the production of basic staples like maize and beans and that of livestock products. This will result in high food prices which in effect will lower food accessibility and lower per capita calorie availability.

It has been reported that climate change has led to more frequent droughts in Kenya. Marthews, et al. (2015), link the 2014 drought on the Greater Horn of Africa region to anthropogenic activities. According to them, human influence and activities resulted in higher temperatures and incoming net radiation at the surface over the Greater Horn of Africa Region which includes Kenya. Another study by Lott et al. (2013), also linked anthropogenic activities to the severe drought that hit the region during the 2011 long rains season. Their study found an enhanced risk of failure of the 2011 long rains in the greater Horn of Africa region to human induced climate change. These and many more studies insinuate a region that is prone to climate change shocks whose major impact is more droughts and less rainfall.

2.5.Measures Taken to Stop Climate Change

Governments and Organizations have realized the negative effects that Climate Change is having on the lives of the public. One of the methods that Governments are using to combat emissions is the use of carbon pricing. Carbon Pricing is a government instrument that captures the external costs of GHG emissions. Carbon pricing works by setting per ton of carbon emissions to be paid by GHG emitters. According to Fang (2018), the added price makes the carbon intensive goods and services more expensive while carbon efficient goods and services become more relatively cheaper and thus more competitive. This system, however, may be expensive to implement as it requires a high level of monitoring with fines and punishments system in place for noncompliance.

Since Climate change is a global "Public Bad", Governments have come with International Agreements in order to have governments participate in reduction of GHG gas emissions in their respective countries. The Kyoto Protocol is an agreement between nations which aims at reducing their respective GHG emissions. The framework pledges to stabilize GHG concentration in the atmosphere to a level that would prevent dangerous anthropogenic interference with the climate system. From these global agreements, governments are putting in place legislation or enacting specific laws to mitigate the effects of climate change.

2.6.Climate smart agriculture technologies and practices

The farming community employs CSA practices in a variety of ways. Smart farming is one of the farming management concepts that employ modern technology to increase both the quantity and quality of agricultural products (Schuttelaar & Parners, 2017). Thus, smart farming employs available Information and Communication Technologies (ICTs) to boost agricultural productivity, reduce production costs, and reduce GHG emissions. This includes simple forms such as farmers receiving market and weather information for their areas through mobile phones or the internet (Krell et al., 2021). In modern days, improved technology-based agricultural practices such as the use of drones, robots, sensors, and other smart devices are replacing old-fashioned farming practices (Virk et al., 2020). These smart farming technologies involve integration of Information and Communication Technology (ICT) in agricultural processes such as planting, irrigation, pesticide application, transportation, and marketing of agricultural produce.

Crop insurance is a new CSA practice that is taking shape in the County and around the globe as increasing temperatures and changing rainfall patterns have had complex impacts on agricultural production. Available reports indicate that there are 198 million smallholder farmers under some form of crop insurance in developing countries (Ghosh et al., 2021). In Nepal, for example, existing crop insurance products include traditional indemnity-based crop insurance, primarily targeted at medium and large-scale commercial cereal farmers (Budhathoki et al., 2019). Other developing countries that have implemented crop insurance schemes include Mexico, India, China, Pakistan, Morocco, Malawi and Peru (Ghosh et al., 2021; Smith & Watts, 2019).

The government of Kenya, in cooperation with seven insurance companies developed a crop insurance scheme for farmers to insure their crops (Adhikari et al., 2015). This program was developed with assistance from the World Bank Group and built on the experience of similar programs in Mexico, India, and China (World Bank, 2022). This product provided multi-peril micro-insurance products that covered smallholder farmers for crop yields that fell below 80% of the expected harvest due to climate, disease, insect damage, and other factors. This weather-indexed insurance uses collected data on weather from satellites and automated weather stations to estimate farmers' harvests. At the end of each growing season, the collected weather data was automatically compared to an index of historical weather data (Chantarat et al., 2013;

Sandmark et al., 2013). If there existed a difference, the insurance payout owed to client farmers was calculated and sent to them without necessarily claiming it.

Studies conducted on the adoption of crop insurance in Kenya indicate that the levels of adoption are low (Binswanger-Mkhize, 2012; Carter et al., 2015; Cole et al., 2013; Mahul & Stutley, 2010; Njue et al., 2018). This has been attributed to the lack of knowledge and information about the mechanism of purchase of agriculture insurance, program limitations on the scope of cover, unfavourable pricing of insurance, and the untrustworthiness of insurance companies (Baagøe et al., 2020). Other reports indicate that the insurance pay-outs were often much smaller than the losses incurred and in some instances, farmers were not compensated at all for the losses incurred Oxford (Oxford Business Group, 2017). There is a need, therefore, to involve all stakeholders in the designing and development of crop insurance products and the selection of target crop enterprises.

Sustainable agriculture has in the last few decades gained popularity as a strategy to cope with climate change. The term sustainable agriculture has been used to refer to farming practices that meet society's current food and fibre needs without jeopardizing current and future generations' ability to meet their own (SAREP, 2018). Sustainable agriculture is, thus, said to be economically viable, socially supportive, and ecologically sound in that it seeks to support farmers, resources, and communities by promoting profitable, environmentally sound, and community-friendly farming practices and methods (SARE, 2010). Furthermore, sustainable agriculture promotes healthy ecosystems and aids in the management of land, water, and natural resources, all while ensuring global food security (FAO, 2020). As a result, sustainable agriculture is a viable practice that smallholder farmers can employ to mitigate the effects of climate change in their farming operations.

Sustainable agriculture has four components: soil management, crop management, water management, and pest and disease control. While soil management encompasses crop rotation and generous feeding of the farm with both compost and green manure to maintain and improve the soil, crop management discourages monocropping but encourages the cultivation of a wide range of crops using crop rotation to ensure that soil nutrients are replenished naturally and that pests and diseases do not proliferate (Roos, 2020). The water management component entails reducing erosion and evaporation by using modern technologies such as drip irrigation while the final component of pest and disease control encourages animals and crop enterprises to use natural resistance rather than chemical solutions (Roos, 2020).

Organic farming is a well-known sustainable agricultural practice. Organic agriculture has been defined as a holistic production management system that promotes and improves the health of the agroecosystem (Templer et al., 2018). It emphasizes management practices over off-farm inputs because regional conditions necessitate locally adapted systems (FAO 2020) .

2.7.CSA technologies widely disseminated in Africa

Several CSA practices have been successfully deployed among smallholder farmers in Africa. As discussed in the sections below, each technology and practice have different farm requirements and is meant to achieve a specific goal on the farm.

2.7.1. Conservation agriculture

Conservation Agriculture is a major CSA technology that is being promoted not only in Kenya but throughout the world. CA is defined as a farming practice that is based on the three principles of minimal soil disturbance, permanent crop cover, and crop rotation to create a more sustainable cultivation system for the future (Hobbs, 2007).

CA covers approximately 1.2 million hectares in Africa, with South Africa accounting for approximately 30% of the total land area. Other African countries with significant CA land areas include Zimbabwe, Zambia, Mozambique, and Malawi, which have 332,000, 200,000, 152,000, and 65,000 hectares, respectively (Mkomwa et al., 2017). CA promotion in Africa has primarily relied on donor funding. Through the Norwegian Agency for Development Cooperation, Norway has been at the forefront of promoting CA in Africa NORAD (NORAD, 2020). The United Kingdom's Department for International Development (DFID), the International Fund for Agricultural Development (IFAD), GIZ, the World Agroforestry Centre (ICRAF), and the International Maize and Wheat Improvement Centre (CIMMYT) are among the other donors assisting with the expansion of CA (Mkomwa et al., 2017). These donors promote CA technologies through local and international NGOs such as Concern Worldwide, Care International, the African Conservation Tillage Network (ACT), the Rockefeller Foundation, the Alliance for the Green Revolution in Africa (AGRA), and the Canadian Food Grains Bank.

Conservation agriculture has been practised in all agroecological zones, and the three principles must be applied concurrently to reap the full benefits (Infonet-Biovision, 2020). However, for farmers to reap the benefits of CA, they must practice it for an extended period. According to Martinsen et al (2017), a small difference in soil quality parameters between CA and conventional practices at smallholder farms was only realized 12 years after CA adoption. Another limitation of CA is the difficulty of planting crops with small seeds, such as finger millet and sesame, without disturbing the soil. Furthermore, CA farmers who also raise livestock face the challenge of feeding their animals on crop residues that are needed on the farm as a cover crop or as mulch (Infonet-Biovision, 2020).

Another factor that has been shown to affect CA effectiveness is soil type, as measured by soil bulk density (Palm et al., 2014). According to Piccoli et al. (2020), increased soil compaction and permeability slow the adoption of CA technology because it reduces yields. Furthermore, due to the fine texture of the soil, low soil organic carbon and clay contents make loamy soils prone to compaction. According to FAO and MOALF (2018), the land must be well-conserved with biological and physical structures

The success or failure of CA to increase crop yields may be influenced by climatic conditions and the amount of rainfall received on a farm. Previous research on the effectiveness of CA has found that it increases crop productivity under low rainfall conditions while decreasing yields under high rainfall conditions (Gatere et al., 2013). Kabirigi et al. (2015) discovered that when herbicides are not used, yields are reduced in high-rainfall areas and labour requirements are increased. CA's potential for drought mitigation, however, has not been demonstrated in areas or seasons with no significant drought incidences (Thierfelder & Wall, 2009). CA technology may be best practised in dry areas such as Zambia, as indicated by the report by Conservation Farming Unit (2019). In drier areas, there is insufficient moisture to grow a cover crop; as a result, farmers rely on mulch and restrict livestock grazing in the fields (Infonet-Biovision, 2020). Other empirical studies on conservation agriculture suggest that mulching, an aspect of CA, reduces yields in high rainfall areas but is an important success factor in drier areas (Pannell et al., 2014). The best practice of CA will thus be dependent on the climatic conditions in which the farm is located.

Farm topography is a major factor in the success of CA in individual farms (Palm et al., 2014). CA can be practised in steep and sloping farms to conserve the soil and prevent soil erosion. Studies conducted on the effect of CA on sloping farms have shown significant improvement in the retention of soil nutrients. According to Yang et al. (2020), no-till practised in sloping upland reduces surface Nitrogen (N) losses in both Carbon (C) and N-poor soils. In addition, CA should be combined with vegetative barriers, fruit and timber trees, and cover crops involving food and fodder species.

Another important characteristic is soil fertility, which is determined by the number of crop residues produced in a field. Studies have shown that smallholder farms in Africa are faced with the challenge of managing this sustainably (Erenstein, 2002; Palm et al., 2014). This point of view is shared by Pannell et al. (2014) who discovered that other farm-level and cultural needs, such as the right to use the residue and the pressure to feed livestock, impede crop residue retention among smallholder farmers. CA, on the other hand, has the potential to produce high agricultural yields when crop residue is kept on the farm and soil fertility is maintained.

There are many organizations that promote CA at community levels. KCSAP, a World Bank-funded project, works with 18,900 smallholder farmers in three sub-counties of Lurambi, Navakholo and Malava to implement various CSA practices in Kakamega County, including CA. Through CSA interventions such as CA, GIZ Soil Protection and Rehabilitation of Degraded Soil for Food Security Project has promoted CSA technologies among 19,097 smallholder farmers in Kakamega County (GIZ, 2020). The Integrated Soil Fertility Management Program that was implemented by KALRO, Alupe Centre, between 2015 to 2018 reached over 30,765 smallholder farmers through trainings and capacity building on the various CSA practices including CA (Alupe, 2020; ROA 2020). Report by Muteithia (2021) indicate that the African Community Leadership and Development also promoted CA to 58 smallholder farmers in Kakamega between the years 2020 and 2021. The main practice of promoting CA among smallholder farmers by the CA promoting Organizations has been to establish quarter an acre demonstration plots which are then divided into two. One portion is put under conventional agriculture while the other is put under CA. On Agricultural research, the Kakamega Centre of the Kenya Agriculture and Livestock Research Organization (KALRO) has been on the forefront to study the impacts of CA on the soil and other matters. According to Ayuke et al. (2019), CA increases soil fauna taxonomic richness and abundance because of long-term addition of organic residues. There is scanty information on the actual number of smallholders farmers practicing CA in Kakamega County and relevant the drivers of adoption.

2.7.2. Agro-Forestry

Agroforestry is often used to describe the cultivation of crop-friendly trees alongside field crops. Branca et al (2011) define agroforestry as *"the land use practices in which woody perennials are deliberately integrated with crops varying from simple and sparse to very complex and dense systems".* Agroforestry is primarily practised because trees are an essential component of the natural ecosystem, providing numerous benefits to the soil, other plant species, and overall biodiversity. In addition, practising farmers gain greatly from the fruits and medicines they produce, as well as the wood which they use for a variety of uses as well as increasing their resilience to unfavourable weather events like strong storms and droughts (McCabe, 2013). Another fundamental reason for agroforestry is to absorb carbon dioxide gas from the atmosphere, thereby regulating global warming (Montagnini & Nair, 2004). Lastly, according to Jemal et al. (2018), agroforestry has numerous social benefits, including poverty and hunger eradication, improved living standards for practising farmers through job creation, food security, tourism development, and cultural preservation through local activities.

Agroforestry is widespread in Kakamega County though there is scanty information on the actual number of smallholders farmers practicing it. Available reports, however, indicate that *Grevillea robusta* and *Eucalyptus saligna* are the two most popular tree species in Kakamega due to their quicker growth rates (Agevi et al., 2019). Other agroforestry trees adopted by smallholder farmers are Calliandra (*Calliandra calothyrsus*) and Sesbania (*Sesbania sesban)* which are also used as fodder crops for livestock (Gupta et al., 2023) This improves the farmers' livelihoods by providing them with a greater economic value. Other tree species are, however, adopted by smallholder farmers to meet their other needs. Community Empowerment Initiative Network, a local NGO, has been involved in the planting of over 15,000 *Moringa oleifera* seedlings among smallholder farm families affected by HIV/AIDS (ITF, 2023).

The importance of agroforestry in the county cannot be overemphasized as 79.2% of the inhabitants use wood as their main source of energy (Chisika et al., 2022). Published literature, however, indicate that the shortage of wood fuel in the county has resulted to households adopting agroforestry and planting of trees to ease the problem (Sikei et al., 2009). Other arising needs for agroforestry include fodder for livestock, shade, medicinal and ornamental purposes and as a measure to conserve both water and the environment in the farms (Awazi & Tchamba, 2019).

The County has an estimated 32,713 hectares of gazetted forests which influences biodiversity and farming practices among community members CGK (CGK, 2018). Reviewed literature indicates that the local population perform important religious ceremonies and gather medicinal plants, grass for thatching, and fuel wood from the forest (Ondiba & Matsui, 2021). The restoration and conservation of Kakamega forest, Kenya’s only tropical rain forest has attracted many partners thus promoting agroforestry in the county.

The promotion of agroforestry among smallholder farmers is mainly donor supported. Available literature suggests that bilateral and multilateral aids provide backing for African forestry (Blanchez & Dube, 1997). The World Agroforestry Centre (ICRAF) is one of the major supporters of agroforestry in Africa. Its' support is on scientific knowledge, germplasm, networking, capacity building, and operations funds while governments contribute infrastructure, executive power, personnel, and tax rebates. Other important donors in agroforestry include Canadian International Development Agency, IFAD, United Nations Development Program, European Development Fund, World Food Programme (WFP), Global Environmental Fund (GEF), World Bank, and the United Nations Environment Programme (UNEP) (Blanchez & Dube, 1997; Böhringer, 2001). There are many organizations promoting agroforestry at community levels in Kakamega. VI agroforestry, a Swedish NGO, promotes the integration of woody perennials in smallholder farming systems in Kakamega to improve soil fertility, reduce soil erosion and increase water infiltration (Hughes et al., 2020). Other programs that have promoted agroforestry include GIZ ProSoil Program, KCSAP and the Scaling up Sustainable Land Management and Agro-Biodiversity Conservation to Reduce Environmental Degradation in Small Scale Agriculture in Western Kenya project.

While agroforestry is widespread in Kakamega County there is scanty information on the actual number of smallholders farmers practicing it. The forms and types of agroforestry practiced by the smallholder farmers in Kakamega has not been documented.

2.7.3. Integrated soil fertility management

Kakamega County has experienced rapid population growth over the past 10 years, which has increased demand for housing, food, water, energy, and, to some extent, rubbish removal (Olunga, 2017). Integrated Soil Fertility Management (ISFM) was introduced in the county to conserve biodiversity and reduce environmental degradation in smallholder farms surrounding Kakamega forest. ISFM is not widespread in the county as compared to the other CSA practices with reports putting adoption rates at 36% (Adolwa et al., 2019). This technology has been promoted mainly on the farms surrounding Kakamega forest to reduce encroachment of the forest.

Integrated Soil Fertility Management is primarily used by smallholder farmers to increase production and make better use of farm inputs. Sanginga and Woomer (2009) define ISFM as the "*application of soil fertility management practices, and the knowledge to adapt these to local conditions which maximize fertilizer and organic resource use efficiency and crop productivity*". ISFM principles are based on the idea that neither practices based solely on mineral fertilizers nor practices based solely on organic matter management are sufficient for long-term agricultural production. While ISFM promotion in Africa is heavily reliant on donor funding, reports indicate that the technology has increased average maize yields from 2.0 tons to 4.6 tons per hectare (Roobroeck et al., 2015). The adoption of ISFM is, however, limited by a few factors. On a community level, these include low crop yields, weak markets, and low livestock yields. On a farm level, these include inadequate soil nutrient amelioration, improper soil residue management, and subpar tillage systems.

Soil fertility decline is one major problem farmers are experiencing and this has resulted in continuous low production. This has led to a mismatch between food supply and food demand. Studies have identified ISFM interventions that would help farmers mitigate problems of food insecurity and improve the resilience of the soil's productive capacity (Bationo et al., 2003). ISFM represents one of the sustainable and intensified nutrient concepts that have proven to be successful in the farmer's field (Ollenburger, 2012; Sommer et al., 2013). Therefore, the contrast between food supply to demand is attributed to soil nutrients. This is supported by Vanlauwe (2015) who defined ISFM as a set of soil fertility management practices that include; the use of fertilizer, organic inputs, improved germplasm, and knowledge on how to adapt these practices to local conditions to optimize agronomic use efficiency of the applied nutrients and improve crop productivity. Mhango et al (2013) and Ollenburger (2012) note that integrating legumes is key to the implementation of ISFM.

Smallholder farmers can benefit from using ISFM technologies in a variety of ways. To begin, ISFM technologies boost fertilizer efficiency and agricultural productivity (Fairhurst, 2012; Lambrecht et al., 2014a; Marenya & Barrett, 2007). Second, because of their ability to increase the efficiency of applied nutrients, ISLM technologies have the potential to reduce the need for chemical fertilizers (Kamau et al., 2014). Third, economic benefits such as profit maximization can be realized when input productivity exceeds the cost of adoption. Fourth, ISFM technologies have a positive environmental impact because efficient fertilizer use reduces nitrogen residues in the soil, reducing run-off and nitrate leaching into the environment (Wezi G. Mhango et al., 2013). These organic fertilizers improve soil organic matter, nutrients, and water retention in soils. In addition, the incorporation of legumes and crop residues increases soil organic matter, which improves the relationship between plants and applied nutrients.

While the benefits of adoption of ISFM have been well documented and discussed, there is little literature on the adoption rates of ISFM among smallholder farmers. Available literature has discussed the number of smallholder farmers who have been reached with extension messages about ISFM but no study has been conducted to describe the adoption of the technology after the end of the project.

2.7.4. Small-scale water harvesting

Kakamega County is a high rainfall area with annual precipitation ranging between 1280.1mm and 2214.1mm (CGK, 2018; C. G. o. K. CGK, 2023). This creates a high potential for both rainwater and surface runoff water harvesting. Available reports, however, indicate that water harvesting is not yet a common practice in the county (Nthuni et al., 2014). The main practice is rainwater harvesting for domestic use and small-scale irrigation. Other forms of water harvesting in the county include zai basins, water pans and fishponds.

Water harvesting is the collection of surface runoff from a catchment caused by rains. It entails collecting, concentrating, and storing surface runoff water for crops, livestock, and humans (Alamerew et al., 2002). Rainwater harvesting is important because it helps to mitigate the effects of temporary rain shortages by providing water for both household needs and productive use, thereby reducing water scarcity issues. It has been used to improve access to water and sanitation, aid in groundwater recharge, and boost agricultural production, all of which have contributed to poverty alleviation. It also helps recharge groundwater, and address floods and droughts by storing runoff. Water harvesting is thus an excellent CSA technology, particularly in areas where rains are not consistent.

Water scarcity is a major development problem in most places in Kenya. Generally, Kenya is a water-scarce country, with less than 600 cubic meters per capita, which is less than the global average of 1000 cubic meters per capita (Kenya, 2019). As a result, water harvesting is a viable solution for rural homesteads and drought-prone areas where water scarcity is observed. Rural homesteads require low-cost water harvesting technologies, whereas, in urban areas, dam construction and long-distance water conveyance ensure their availability (Hillel & Hatfield, 2005; Pandey et al., 2003). As a result, water harvesting is a viable solution for rural homesteads and drought-prone areas where water scarcity is observed. Water harvesting technologies, therefore, have the potential to increase agricultural productivity while also assisting in meeting the water needs of urban households.

The level of food production is usually determined by the quality and quantity of available water as a resource. Furthermore, government policies recognize water as a basic need and an important catalyst for both the economic and social development of a country (GOK, 2006). In adopting the Millennium Development Goals (MDGs) in 2002, for example, countries committed to halving the proportion of people without access to safe drinking water and basic sanitation by the year 2015. Simple and low-cost small-scale water harvesting technologies available to community members can help mitigate the effects of erratic rainfall, reliance on food aid, and the risks of dry spells that characterize water-scarce regions (Munyao, 2014).

Small-scale water harvesting technologies have been promoted among smallholder farmers to protect them from erratic weather and its effects on crop and livestock production. Available reports indicate that farmers harvest rainwater and store it in reservoirs and tanks during the rainy season, then use it during the dry season (Popescu, 2018). Water harvesting technology adoption, however, is hampered by several factors. According to Mwangi (2003), a lack of understanding of the social structure within which the technology is to be implemented and maintained may pose a major problem. In addition, poor understanding of technologies by the farmers and lack of proper information transfer to them may hinder its adoption.

Most smallholder farmers use Zai Basin for water harvesting. Although Zai Basins in CA fields have been reported to improve water availability in drier regions with less than 1000mm of rainfall, they are not required and may even be detrimental in regions with adequate rainfall (Gatere et al., 2013). Furthermore, basins perform well in situations where moisture is limited and farmers have manure or compost available to apply to the basins (Thierfelder et al., 2016). Since Zai basins are inexpensive to build, as compared to other water harvesting structures, resource-constrained smallholder farmers can use them to boost agricultural output.

While studies have shown the importance of small-scale water harvesting technologies and the government and her partners effort to promote them, it is not clear on the adoption of the technology among smallholder farmers.

2.7.5. Greenhouse Farming

Farmers must adopt modern technologies to increase agricultural productivity, one of which is greenhouse farming. A greenhouse is an enclosed space that, due to the confinement of the air and the absorption of shortwave solar radiation, creates a different environment than that found outside (El Ghoumari et al., 2005; Liu & Nyalala, 2002; Liu et al., 2005). Greenhouse crop cultivation is, thus, a high-intensity technology that gives crop yields that are up to ten times greater than in an open field.

Greenhouse farming is a smart way to manage a changing climate by growing crops in a controlled environment. Tomatoes, cucumbers, onions, black nightshade, brinjals, butternut, cabbages, peppers, herbs, spices, watermelon, cowpeas, strawberries, and flowers have all been successfully grown in greenhouses. When combined with a greenhouse, a drip irrigation system produces higher yields. Furthermore, growing crops in a greenhouse with a drip irrigation system save water improves pest and disease control, and protects crops from flooding and drought (Schubert, 2020).

Control of the environment, control of evapotranspiration rate, and production outside of regular production seasons are some of the benefits associated with this technology that has prompted its spread to the tropics (Nordey et al., 2017; Panwar et al., 2014). Greenhouses reduce production risks due to controlled conditions, ensuring returns on investments (Nikolaou et al., 2021). Other advantages include reduced land use to achieve the same results, low labour input, and market timing (Liu et al., 2005). Overall, greenhouse farming techniques may result in more food for the world and aid in the reduction of world hunger.

Many studies have identified several factors that limit smallholder farmers' adoption of greenhouse farming. High investment costs, intensive management, and greenhouse pests are some of the factors identified as impediments to the adoption of this technology among smallholder farmers (Liu & Nyalala, 2002; Liu et al., 2005). Similarly, inadequate farmer support systems, such as a lack of farm inputs and water, is a major constraint for smallholder farmers attempting to diversify into advanced technologies (Mwendia, 2019). To ensure the long-term viability of greenhouse farming technology among smallholder farmers, Awiti (2013) advocates for the enhancement of Integrated Pest Management (IPM) in greenhouse disease and pest management, as well as the use of renewable energy sources to reduce the cost of fuel used in greenhouse farming.

In Kenya, most greenhouses are in the Rift Valley near lake Naivasha and tea estates in Kericho and Nandi hills. Large-scale flower farming is for the international market and the small local market. Other parts of the country with high greenhouse adoption rates are in the central region (Omoro et al., 2014). According to Omoro (2014), greenhouse farming has spread countrywide with many players promoting the technology as providers of materials, equipment, and products.

In Kakamega County, greenhouses are used to grow high value crops such as tomatoes, sweet pepper and lettuce. Though greenhouse technology has been tried by many farmers, studies have shown that their rate of dis-adoption is quite high. According to Awiti (2013), only 5% of smallholder farmers in Kakamega sustainably adopt the technology beyond three years. This indicates that adoption of greenhouse may be out of reach to the thousands of smallholder farmers in the county.

For greenhouse farming to be successful several factors must be considered. FarmLINK Kenya (2019) has cited some of the tips for successful greenhouse farming. First, there should be a consistent supply of water sufficient to maintain drip irrigation throughout the season. The source of this water influences whether or not a farmer can produce all year, and the source of water should not be dependent on precipitation levels (Van der Spijk, 2018). Second, the greenhouse should always be bio-secured to keep outside pathogens from attacking the crops. Secondly, the farmers who are interested in the project must have sufficient financial resources to purchase the materials and cover the construction costs. This puts greenhouse farming out of reach for most resource-constrained farmers (Bseiso et al., 2015). The major greenhouse costs include the purchase of polythene coverings, drip lines, water tanks, and installation costs. Third, the type of crop to be cultivated should be considered since different crops require different amounts of water and nutrients, nurturing techniques, and dictate the length of growing seasons (Bseiso et al., 2015). Fourth, the soil type of an area is also important as it informs the farmer of the nutrition that is required by the crop to be farmed. Overall, the soil should be well-drained, medium-textured, and fertile with high organic matter and should not be prone to surface water or lack sunlight (Bseiso et al., 2015; Morgan, 2022).

Reviewed literature points to 5% adoption of greenhouse technology in Kakamega county. The studies, however, do not show the biophysical and socio-economic characteristics associated with smallholder farmers adoption of the technology.

2.7.6. Composting

Composting is one of the CSA technologies that need to be embraced by farmers to transform agriculture into a more vibrant activity and business. Inorganic fertilizers have been used in agricultural production although it is a challenge to small-scale farmers because of their prohibitive costs (Diacono & Montemurro, 2011; Kassie et al., 2009). It is therefore recommended that smallholder farmers use organic fertilizer or use a mix of the two (Negassa et al., 2005). On-farm composting is a controlled and microbially mediated decomposition process that converts biodegradable waste into a stable product that is ultimately used as a soil amendment (Nigussie et al., 2015). Composting involves the putting together of a mixture of residue, manure, soil, and water to form humus (Hulit, 2011). The compost manure is then used as a fertilizer in the production of crops.

Small-scale on-farm composting has been practiced by many smallholder farmers in Kakamega. Though there are a lot of organizations that promote on-farm composting, smallholder farmers mostly heap their organic waste in one point and later use it in their farms. Other common practice among smallholder farmers is to spread the organic wate and ash in their kitchen garden where vegetables and other early maturing crops are grown. Smallholder farmer gardens that employ organic manure and compost and the ones that don't differ noticeably from one another. GIZ, a development partner in Kakamega, has established a farmer demonstration plot at Bukura Agricultural Training Centre where best composting practice is showcased. In addition, there are composting demonstration plots in all the lead farmers.

There are three main categories of composting methods. Thermal compost vermicompost and static compost are the most cost-effective composting methods for small-scale farmers. While vermicomposting produces an excellent product, it is not weed-free and requires many worms. Static compost, on the other hand, is the simplest but least reliable due to the uncontrolled environment that exposes pathogens (Abbasi et al., 2015). Thus, thermal compost is the most suitable method.

On-farm composting has been shown to improve soil structure, increase soil buffering capacity and moisture holding capacity, add organic matter to the soil, stimulate biological activity, and provide a liming effect on the soil (DPI&RD, 2020). In addition, composts are used to improve soil fertility by providing minerals and nutrients required by plants and microorganisms, as well as to keep farming lands productive by preserving soil organic matter, improving soil chemicals, and improving soil physical and biological properties (Hargreaves et al., 2008; Negassa et al., 2005; Peltre et al., 2015; Plaza et al., 2004). Composting is, thus, an important practice at the farm level regardless of the scale of production.

The adoption of on-farm composting, however, is hampered by several factors. Even though the technology has numerous advantages, due to the high demand for fuel and animal feed, smallholder farmers are unable to retain a large amount of crop residue on their farmlands which is required for composting (Baudron et al., 2014). According to Baudron et al (2014), only a small number of farmers apply the composting technique because the crop wastes are used as fuel and fodder, so only a small portion of crop residue remains. This has been identified as a major cause of the slow adoption of composting in sub-Saharan Africa (Mekonnen & Köhlin, 2009). This challenge, further, limits the amount of compost that is produced and used on the farm. In addition, there is low production of animal manure, and the little produced is not well used to form compost (Baudron et al., 2014; Kassie et al., 2009; Tittonell et al., 2005). For these reasons, the intensity of on-farm composting continues to lag that of other CSA technologies.

Although composting can be done in any climatic condition, certain conditions must be met to ensure the quality of the compost manure. According to Washington State University (WSU) Whatcom County Extension (2020), to ensure quality compost manures, the moisture content of the materials should be between 40 and 60%. WSU Whatcom (2020) further states that the optimum conditions for composting include a temperature range between 135 to 160^{o}C, particles being shredded to a maximum of two inches, and, the compost pits should be between three and four feet deep. Moreover, composting requires sufficient aeration to maintain aerobic conditions and frequent mixing of materials (Cooperband, 2002; Mohee & Mudhoo, 2005). Mixing the pile once or twice a month provides the necessary oxygen and increases the composting process. A pile that is not mixed may take three to four times longer to decompose.

While it is possible to tell the major requirements for composting at household levels, reviewed literature do not address the extent of composting adoption in Kakamega County. In addition, it is not clear on the major forms of composting adopted and possible reasons for their adoption.

2.7.7. Push-Pull Technology

Push-Pull Technology (PPT) is an IPM strategy for managing stem borers, which primarily affect maize, sorghum, and other grasses. This technology was developed for smallholder farmers in Africa, the vast majority of whom are resource-constrained subsistence farmers. Proponents of this approach argue that using pesticides on smallholder farms to combat stem borers is both uneconomical and impractical (Gwada, 2019; Mishra et al., 2022). The technology attracts stem borers to trap plants, while repellent non-host crops repel them from cereal crops (Chatterjee & Kundu, 2022). Available literature indicates that the trap crops emit chemicals that are attractive to female moths but are not suitable for the survival of the pest's larval stage, resulting in high mortality rates and delayed larval development (Chatterjee & Kundu, 2022; Kumar et al., 2022). This push-pull mechanism, therefore, acts as a natural way to manage pests and other diseases.

Push-pull technology is widely promoted and widely tried by smallholder farmers in Kakamega. There is, however, little research on the practice and adoption of the technology in the county. GFA Consulting group, an implementing partner of GIZ in Kakamega, has established a push-pull technology demonstration plot at Bukura Agricultural Training Centre where best PPT practice is showcased. In addition, GIZ CSA implementing agencies such as Weltungerhilfe and GFA Consulting group have set up PPT demonstration sites in all the lead farmers of the farmer groups supported. Studies have, however, showed that PPT, one of the skill intensive CSAs is one of the least adopted technologies among smallholder farmers in Kakamega (Nyairo et al., 2021). The foregoing notwithstanding, the technology has been shown to be effective in the control of crop pests.

Push-pull technology provides numerous benefits to farmers in the field. First, smallholder farmers can increase milk output and diversify their revenue streams by using companion plants (desmodium and Napier grass) as animal feed (Chepchirchir et al., 2016; Khan et al., 2014). Secondly, desmodium has been shown to improve soil fertility through nitrogen fixation, erosion prevention, and increased soil organic matter (Khan et al., 2014). Third, studies have shown that PPT is effective in preventing Striga weed growth on farms because the desmodium releases substances that prevent the plant from germinating (Midega et al., 2018). Fourth, this method decreases the number of pesticides that are sprayed on a crop since it uses crops that are suitable for farmers while also utilizing and taking advantage of natural enemies to ward against pests (Kumela et al., 2019).

Aside from stem borers, PPT has been used to control other pests in various crops by utilizing different repellents and trap crops. With the arrival and invasion of FAW in African farms in recent years, studies have shown that PPT was effective in pest control, just as it was in the control of stem borers (Gebreziher & Gebreziher, 2020; Midega et al., 2018). This may be explained by the fact that FAW belongs to the same family as some of the stem borers.

PPT is considered effective when all three components, the main crop, the trap crop, and the repellent crop, are used together. Maize is usually the host/main crop in most cases. According to Khan et al. (2014), though the technology is easily adaptable to most African farms due to its effectiveness and low cost, its effectiveness is dependent on companion crop establishment and management. Other studies attribute the success of PPT to the intensity of practice, implying that the technology's success is dependent on the land size used, with larger push-pull plots yielding higher yields than smaller plots (Chepchirchir et al., 2016). Although no specific land size has been assigned to push-pull technology, Chepchirchir et al. (2016) propose that one acre is the optimal land size for a successful push-pull plot.

Studies have been conducted on the adoption of PPT among smallholder farmers. These studies, however, fall short of describing the adoption of PPT in Kakamega county. More research is required to inform on this dimension.

2.8.General Factors Driving Smallholder Farmers to abandon CSA technologies.

Several studies have identified the reason smallholder farmers abandon CSA practices after donor-funded projects are completed. First, according to the study by Khatri-Chhetri (2017), smallholder farmers' preferences and willingness to pay for CSA technologies are determined by the potential benefits and costs of the technologies. As a result, when there is insufficient data to support the benefits of CSA on their farms, smallholder farmers may abandon CSA technologies. The lack of sufficient funds to support the adopted technologies is another reason donor-funded CSA practices are abandoned. According to Milder et al. (2011), when compared to conventional farming, CSA technologies are frequently more profitable eventually. As a result, smallholder farmers need supporting data to demonstrate the profitability and benefits of CSA. Furthermore, CSA technologies necessitate initial investments that are frequently prohibitively expensive for smallholder farmers to obtain and they are hesitant to accept long transition periods because they want to see tangible results quickly (Mizik, 2021).

One of the major challenges identified by scholars that hinder the sustainable adoption of CSA practices is that most practices are capital-intensive. Drip irrigation, for example, necessitates a significant capital investment that smallholder farmers may not be able to afford (Valenzuela, 2020). Second, farmers who produce organically must be certified for their agricultural products to be labelled organic. Certification procedures are time-consuming and thus discouraging for smallholder farmers (Riddle, 2020). Finally, in developing economies with incomplete agricultural value chains, getting a premium price for agricultural produce from sustainable agriculture is difficult. For these reasons, sustainable agricultural practices are not widely used in Kenya.

2.9. Farm-Specific Socioeconomic Factors that influence CSA Technology Adoption

2.9.1. Land tenure

Studies have indicated that land tenure is a key factor in the sustainable adoption of various CSAs such as planting date, crop diversification, and changing the crops cultivated (Fosu-Mensah et al., 2012). Other supporting literature indicates that land ownership encourages the sustainable adoption of CSA technologies such as agroforestry (Foresta, 2013). A study by Bryan et al. (Bryan et al., 2009), found that farmers with land ownership had the incentive to invest in their farms while those with leasing farmlands recorded lower profits thus negatively influencing adoption. For this reason, it is important to consider land ownership before promoting certain CSA technologies among smallholder farmers.

There is agreement among scholars that where the farmers do not own land, they may not invest in agroforestry as the benefits of the investments may not accrue to them (Dlamini, 2020; Foresta, 2013). This view is further supported by Glover et al. (2013) who indicated that for Agroforestry to be well adopted by smallholder farmers, they must have access to land on which they have the right to plant trees; the rights over the trees must be sufficient to justify the effort of planting them and the right to harvest and utilize them must be exclusive enough to give a return on investment.

Regarding such technologies like ISFM which are aimed at increasing soil fertility, studies have found that households with secure land tenure rights are more likely to invest in soil fertility-enhancing technologies because of the guaranteed benefits despite the length of the return period, while those with insecure land tenure are more likely to abandon them (Kamau et al., 2014; Teklewold et al., 2013). These findings are in concurrence with those of Lu et al. (2019) who observed that land entitlement does not only encourage farmers to invest in their farmlands but also encourages them to allocate large quantities of agricultural waste to soil amendment. Information on land tenure is important but may not independently predict adoption or disadoption of CSA practices among smallholder farmers. A predictive model is, therefore, required to inform the right target beneficiaries for various CSA technologies.

2.9.2. Land Size

Land size may influence the type and the number of CSA technologies that a smallholder farmer may adopt. Exceedingly small land sizes may limit some technologies such as agroforestry and soil and water conservation structures that may require bigger lands to implement. According to Janssen (2018), big investments such as farm vehicles and large farm machinery would not be profitable once applied on small farms but are more profitable when applied on larger farms. These findings are in agreement with those of Fosu-Mensah et al. (2012) who report that smallholder farmers are less likely to adopt a CSA technology that has a high fixed cost given the uncertainty and the fixed production costs associated with such technologies.

Independently, information on land size may not reliably inform adoption of CSA technologies by smallholder farmers. Smallholder farmers are faced with information decisions that are influenced by other biophysical and socio-economic factors. For this reason, a predictive model would solve the challenge of beneficiary targeting.

2.9.3. Access to Credit and Financial Services

Financing agricultural technologies is often an issue for small and medium-scale farmers because their incomes are low. Purchasing expensive inputs or technology therefore often requires the use of credit. Makate et al. (2019) found that the availability of credit increases soil conservation measures, the use of different crop varieties, planting trees, and the ability to irrigate crops to address the adverse effects of climate change on crop production. Furthermore, access to credit provides starting capital for farmers who have constraints in accessing resources (Lambrecht et al., 2014a). Thus, those farmers with access to credit are more likely to adopt CSA technologies than those farmers without access to credit.

Farm inputs may be expensive and sometimes beyond the reach of many smallholder farmers. Smallholder farmers who have access to agricultural credit, however, can purchase farm inputs to boost crop production and hence the negative impact of climate change on their crops (Fosu-Mensah et al., 2012). These findings are in concurrence with those of Roncoli et al. (2010) who found that lack of access to credit, capital, and financial services hinders the availability of farm inputs as they become unaffordable. In addition, Kijima et al. (2011), opined that lack of access to credit limits the sustainable adoption of modern technology since such adoption needs to be accompanied by increased use of farm inputs such as fertilizers, herbicides, labour, and pesticides.

Apart from increasing access to farm inputs, access to agricultural credit enables smallholder farmers to purchase agricultural tools and other modern agricultural technologies allowing them to manage shocks without selling their hard-earned assets. Scholars have noted that modern technologies such as mechanization require higher capital inputs and that small-scale farmers may be at a disadvantage unless they are helped in reducing their transaction costs to access inputs, credit, and marketing facilities.

Access to financial services and agricultural credit goes a long way to supporting smallholder farmers to adopt CSA practices such as crop and livestock insurance. Available literature indicates that agricultural credit, income, and increased access to other financial capital like saving capital are positively correlated with index insurance uptake (Amare et al., 2019; Fonta et al., 2018; Njue et al., 2018; Sibiko et al., 2018). Farmers, however, still need income to pay for the insurance and the plans may be expensive for them to adopt the technologies (Baagøe et al., 2020).

While access to credit may empower smallholder farmers to access productive resources such as fertilizer and seed, not all smallholder farmers have access to required credit. In addition, independently, credit access may not inform whether a smallholder farmer will adopt CSA technologies. A predictive model, therefore, goes a long way to identify the right smallholder farmers for adoption of CSA practices.

2.9.4. Availability of Agricultural Equipment and Implements

Agricultural equipment and implements make agricultural work easier, especially among smallholder farmers. Studies by Mutuku et al. (2017) revealed that an increase and access to labour-enhancing machines and implements leads to an increase in the adoption of CSA technologies and practices. These findings are similar to those by Zakari (2019) who found a positive relationship between the possession of agricultural equipment and the adoption of CSA technologies. Foresta (2013), however, found that there may be limitations in the adoption of some CSA technologies such as agroforestry when smallholder farmers' ability to use large farm equipment is limited.

2.9.5. Number of adults in the household and Labour availability

The number of adults in the household can explain the adoption of labour-intensive CSA technologies. The number of adults in a household is captured as the number of persons in the household older or equal to 18 years. According to Lahiri and Daramola (2023), households with more adult residents are normally associated with a higher labour endowment that would enable a household to accomplish various agricultural tasks on a timely basis. Conversely, households with more adult members may be forced to divert a part of the labour force to off-farm activities to earn income to ease the consumption pressure imposed by many adults. With the availability of family labour, it may be more encouraging to adopt a profitable production system than in a situation where family labour is inadequate. In instances where family labour is not available, labour to implement CSA technologies must be hired. Studies by Ngoma (Ngoma et al., 2021) found that labour availability and labour bottlenecks were two of the most important types of diagnostic information that aid in selecting appropriate technologies.

2.9.6. Smallholder Farmer's education level

Many studies that have been conducted on drivers of adoption of CSA technologies indicate that education has a positive effect on adoption with the probability of adoption getting higher with higher levels of education. According to Abegunde et al. (2019), education provides a better understanding of ideas thus households with high education levels are more likely to adopt CSA technologies, as opposed to households with low levels of education. Other studies by Ninh (2021) indicate that an educated farmer optimizes the use of the available scarce resources to increase productivity and that they allocate much of their waste to composting.

Knowledge and understanding of the decision-maker have been shown to determine the adoption of CSA technologies (Neill & Lee, 2001). This can be through the level of education achieved by the farmers or the training the farmer may have achieved through training and exposure. High literacy levels among smallholder farmers not only give them the ability to adopt new and advanced technologies but also helps them in the identification of Climate change risks and how to adapt accordingly (Israr et al., 2020). In addition, it has been inferred that higher literacy levels among household heads enable them to better understand and analyse the benefits accrued with high knowledge-based technologies whose immediate gains may not be visible (Chepchirchir et al., 2016). This view is supported by Kijima et al. (2011), who reported that the ability of the farmer to decode the latest information and rice production knowledge affected the adoption of upland New Rice for Africa (NERICA) rice technologies.

Studies have shown that some technologies may require higher literacy levels than others. According to Bseiso et al. (2015), technical information such as crop spacing, watering, and timeliness of activities in the production and management of certain crops such as greenhouse tomatoes requires high educational levels as compared to open-field tomato production.

2.9.7. Availability of Extension Service Providers

The availability of extension service providers to reinforce the adoption of CSA technologies is paramount to their adoption and continuous utilization as extension services enhance the flow of knowledge, awareness, and understanding to farmers. The role of extension officers is mainly to educate farmers on climate change and how to mitigate its impact on crop yield (Fosu-Mensah et al., 2012). Studies conducted on on-farm composting indicate that farmers who had access to extension services allocated manure and crop residues mainly to soil amendment (Baudron et al., 2014). These findings are in agreement with those of Danso et al. (2006) who found that urban farmers who had access to extension services were more willing to participate in urban waste compost as the extension services increased the farmers’ awareness of the benefits of compost.

Other studies have indicated that access to extension service providers does not only help the farmers with technical training but also with group formation and institutional mechanisms allowing better distribution of Government aid and services (Roncoli et al., 2010). In addition, extension service providers provide technical information to the farmers and help them access government-subsidized farm inputs (Chepchirchir et al., 2016). These studies, therefore, imply that the lack of access to extension services may lead to the dis-adoption of CSA technologies by the farmers as was found by (Oladele, 2005). According to Oladele (2005), the lack of visits to the CSA adopting farmers by extension service providers led to the discontinuance of the adoption of the technologies.

The availability of agricultural extension service providers increases the farmers' access to training and capacity-building opportunities. Scholars have opined that farmers' participation in agricultural field days, farm trials, agricultural seminars, and workshops explain the farmers' adoption of CSA technologies (Makokha et al., 1999). Further to this Fosu-Mensah et al (2012) cited the lack of weather information, CSA technologies, and their implementation as major barriers to the adoption of the CSA technologies. This could be because of a lack of an adequate national and county extension framework. Scholars have cited the lack of strong national extension support and lack of information as factors that have limited the adoption and uptake of PPT in Africa Khan (Khan et al., 2014). This, therefore, confirms the importance of smallholder farmers' access to agricultural extension services in the adoption and continuous utilization of CSA technologies.

2.9.8. Reliability and availability of CSA technologies

The reliability in supply, availability, and cost of CSA technologies has been cited to significantly influence the adoption of CSA technologies (Fosu-Mensah et al., 2012;

Makokha et al., 1999). The shortage of desmodium seeds, for example, has been cited as a factor that has limited the adoption and uptake of PPT in Africa (Khan et al., 2014). First, farmers need access to input markets for them to adopt these varieties. According to Roncoli et al. (2010), timely access to seeds and seedlings of the appropriate crop varieties is a key resource needed for climate change adaptation. Dlamini (2020) also cites the lack and unavailability of appropriate tree seedlings as one of the major limitations of the adoption of agroforestry in developing countries. Market failures, such as limited access to input markets, have been cited as one of the major determinants of the adoption or abandonment of climate-smart seed varieties with farmers located in remote areas having little access to them (Simtowe & Mausch, 2019). Other studies by Kijima et al. (2011), found that limited NERICA seed availability hindered the adoption of upland rice technology especially when small amounts of rice seed are produced by the companies and distributed mainly through seed distribution programs.

Foresta (2013) argues that to succeed in agroforestry, some underlying conditions must first be met. The first conditions as explained by Foresta (2013) are technical conditions that include the use of suitable tree species and practices. This is informed by the fact that some tree species may compete for water while some practices may harbour crop pests. This view is supported by Dlamini (2020) who argued that fast-growing and early-maturing tree species are preferred to the ones that have a long maturity period.

2.9.9. The Period of Return on Investment in CSA technologies

For the sustainability of CSA technologies, it is paramount that the technologies being promoted make economic sense to smallholder farmers. Studies have shown that resource-poor farmers who are food insecure and low-income are not able to adopt innovations and adaptations as they require shorter-term tangible benefits (Roncoli et al., 2010). This view is supported by Stevenson et al. (2014) and Corbeels et al. (2014) who argue that long-term productivity and environmental benefits from CA do not drive the adoption in contexts where the smallholder farmers are resource-poor. This may be explained by the time taken by the technologies to generate immediate income as some technologies like agroforestry may give returns on investments after several years (Foresta, 2013). In addition, the CSA interventions must make economic sense to the farmers for them to be widely adopted. A study by Stevenson et al. (2014), for example, cited the lack of economic incentives, such as reduced costs, to be a major cause of the low adoption of CA in Sub Sahara Africa. Stevenson et al. (2014) further argued that the process of converting to CA from conventional agriculture is not profitable over the planning horizons of most resource-poor farmers.

2.9.10. Availability of Market for surplus Produce

Smallholder farmers are always rational, and they make rational decisions on their farms. Most farmers adopt modern technologies to increase their farm production and productivity. Available literature suggests that when the out-put market is not well-established farmers are unwilling to adopt a technology (Barrett et al., 2002). Other studies have shown that the input and output market affect the adoption/dis-adoption of CSA technologies. According to Nambiro et al. (2013), the long distance between the farm and input and output markets has a negative influence on ISFM adoption. These findings concur with those of Odendo et al. (2010) who reported that improved market access can be the driving force for the sustainable intensification of agriculture.

Once agricultural productivity is increased because of the adoption of CSA technologies, the farmers will produce surplus produce thereby necessitating a market. Lack of market and opportunities to market surplus produce has been cited as one of the limitations towards the adoption of CSA technologies. According to Oladele (2005), the lack of market for surplus produce market realized after the adoption of improved cowpea varieties led to the discontinuation of the technology. Similar findings were reported by Kijima et al., (2011) who found that the lack of rice millers in nearby towns resulted in the abandonment of the cultivation of upland NERICA rice in Uganda. Other studies by Foresta (2013) showed that the lack of well-developed markets for agroforestry products and the non-inclusion of tree products in market information systems forced many farmers to rule out agroforestry as a viable investment option. Similar findings were found by Glover et al. (2013) who reported that when agroforestry product prices are stable and high enough to secure profit margin, farmers are attracted and adopt but when the prices are low and unreliable the farmers dis-adopt the technology.

2.9.11. Knowledge, experience, and understanding of decision-makers

Experienced farmers are assumed to have tried out several technologies and have identified the ones suitable to their situations. In addition, the older household heads may have gathered, with time, more resources required for technology adoption than younger household heads (Nchinda et al., 2010; Woldenhanna & Oskam, 2001). Scholars have reported that farming experience increases the likelihood of adoption of CSA technologies as the farmers have much knowledge and information on climatic changes and the best crop management practices to adopt (Fosu-Mensah et al., 2012). In addition, farmers with more farming experience are more knowledgeable about weather patterns and their implications on crop production (Israr et al., 2020).

Studies conducted on agricultural waste utilization indicate that experience in on-farm composting influenced the utilization of agricultural waste for soil amendment due to the farmers' awareness of the benefits of organic amendments (Nigussie et al., 2015). Available literature suggests that experience in farming influences the planning horizon. Yirga & Hassan (2008), for instance, found that more experienced farmers were reluctant to switch from their norm to new practices. These findings were similar to those of Marenya and Barrett (2007) who inferred that young farmers with little experience easily change to a new production method than older and more experienced farmers.

2.9.12. Membership in Community Groups or Organizations

The membership of a farmer in a group or organization has been shown to have a positive correlation with the adoption of CSA technologies (Chepchirchir et al., 2016; Sidibé, 2005). This has been attributed to the sharing of information among group members, participation in field days, and access to agricultural extension providers (Chepchirchir et al., 2016). Studies by Baagøe et al. (2020) found that farmers were exposed to agricultural insurance schemes through interactions with other members of their groups during their meetings and gatherings. Baagøe et al. (2020) further found that farmers who had taken agricultural insurance belonged to a specific group or cooperative. Thus, membership in a farmers’ group is a valuable source of information and knowledge and has an impact on farmers' attitudes toward CSA technology uptake such as agricultural insurance.

Other studies have found that farmer groups and organizations are used as a proxy for farmer-to-farmer information sharing and access to extension service packages (Nchinda et al., 2010). According to Nchinda (2010) farmers in groups and farmer organizations engage in such activities as inputs acquisition and selling of produce thus improving their profits. These findings concur with those of Kassie et al (2013) who point out that groups are a form of social capital and that group membership facilitates the exchange of information, enables farmers to access inputs on time, and helps them overcome credit constraints and shocks. Kassie et al (2013) point out, further, that farmer group membership helps reduce transaction costs and increase farmers' bargaining power, thus positively influencing technology adoption.

2.9.13. Gender of the Household Head

Gender issues in agricultural production systems and technology adoption have been investigated by many scholars. Household heads make major decisions regarding farming activities and the utilization of household resources. Studies have found that male-headed households are more likely to adopt new agricultural technologies than female-headed households (Deressa et al., 2009). According to Akudugu et al. (2012), the gender of the household head indicates differential access to productive resources that are critical for the adoption of CSA technologies. Studies by Kamau et al. (2014) found that male headship has a positive influence on investment in sustainable agricultural technologies due to access to productive resources. These findings are similar to those of Mwangi and Kariuki (2015), who found that male farmers often have better access to technologies and information than their female counterparts.

2.9.14. Age of the household head

Just like gender issues, studies along the age of the household head in the adoption of CSA technologies has attracted many scholars. Although there is much literature about the effect of age on the adoption of modern agricultural technologies, there is no agreement among scholars on the influence of age on CSA technology adoption. Chiputwa et al. (2010), for instance, found that age has a positive effect on the adoption of CSA technologies and indicated that older farmers had experience in beneficial technologies and were shown to adopt them. While studies by Deressa et al. (2009) also found a positive correlation between age and the adoption of CSA technologies, Bryan et al. (2009) found no effect of age on adapting to climate change through the uptake of agricultural technology. Other studies found that young farmers are more willing to take in new CSA technologies as compared to old farmers (Abdulai & Huffman, 2005; Tiamiyu et al., 2009). Other studies by Moges and Taye (2017) found that older farmers were reluctant to participate and invest in Soil and Water Conservation (SWC) technologies as compared to younger farmers. This view is further supported by Bett (2004) and Tizale (2007) who reasoned that older farmers have shorter planning horizons and are more reluctant to invest in soil conservation technologies as it takes a long time before benefits are realized.

2.9.15. Government Policies and Incentives

Government policies play a leading role in the sustainable adoption of various CSA agricultural technologies. Studies have found that a lack of supportive policy frameworks limits the adoption of CSA technologies, such as agroforestry. According to Foresta (2013), agroforestry is disadvantaged by adverse policies, legal constraints, and a lack of coordination between the government sectors to which it contributes including agriculture, forestry, environment, and trade. Sardar et al. (2021) opined that government policy including support programmes influence innovation, investment, and adoption of CSA by farmers.

2.9.16. Type of Crop to be Grown

The type of crop to be grown dictates the type of CSA technology to be adopted by the smallholder farmer. Though the type of crop grown in the farmland under CSA has not been studied widely, crops are an important factor to consider as they determine the type of technology to be adopted. Push-pull technology, for example, involves intercropping maize (main crop) with desmodium which acts as a stemborer repellent and Napier Grass as a trap crop around the maize crop field (Khan et al., 2008). Other technologies such as greenhouse are normally used for growing as tomatoes, capsicum and other horticultural crops. Available literature around sustainable CSA practices indicate that a CSA practice is not sustainable if it is not associated with a crop that will remain important to the household (Neill & Lee, 2001). For this reason, the type of crop to be grown under a CSA technology must be considered before the identification of the technology to be employed.

2.9.17. Soil Fertility

Different soils have different fertilities and therefore call for different CSA practices. Studies conducted in this area have found that smallholder farmers with perceived less fertile soils are likely to abandon their farms or will not invest in external inputs like fertilizers as lower yields do not justify increased use of inputs (Fosu-Mensah et al., 2012). Foster and Rosenzweig (2010) note that the marginal product of inorganic fertilizer tends to be higher in ‘better’ soils than in poor soils. Thus, farmers' perception of fertile soils is expected to influence the adoption of ISFM technologies such as inorganic fertilizers and improved seeds (Ngetich et al., 2012).

2.9.18. Livestock Ownership

Most smallholder farmers are mixed farmers who grow various crops and rear livestock. Available literature suggests that the number of animals on a farm influences the adoption of CSA technologies such as ISFM. Studies by Nigussie et al. (2015) showed that smallholder farmers with a higher number of animals used crop residues as feed for their animals. This implies that high cattle density in field crop production systems is the reason to retain only a small fraction of crop residues on farmlands. These findings are in concurrence with those of Mugwe et al. (2009) who revealed that farmers with zero or fewer mature cattle, plus little manure, will have a higher probability of adopting new ISFM technologies than one with many mature cattle. This may be because of lesser competition for crop residues which is an important ingredient for ISFM.

2.9.19. Costs of inputs

The more the cost/price of inputs increases, the more farmers become unwilling to purchase the inputs. Therefore, as the prevailing prices of improved seed and organic fertilizers increase, the farmers in Arid and Semi-Arid Lands (ASALs) become more reluctant to adopt them (Ajayi et al.; Humphreys et al., 2008).

2.9.20. Radio Access

An increase in radio accessibility increases farmers' adoption. Agricultural radio programs disseminate crucial information including modern technologies, pest and disease outbreaks, and weather information. According to Lwoga et al. (2011), radio is cost-friendly and it covers a huge number of farmers, therefore, increasing access to knowledge and information on Agricultural practices and technologies. Studies by Djido et al. (2021) indicate that source of agricultural information such as radios influences smallholder farmers perceptions of climate change and the subsequent adaptation measures.

2.9.21. Household Food Self-Sufficiency Situation

The level of household food self-sufficiency may affect the adoption of CSA technologies among smallholder farmers. Most smallholder farmers produce for subsistence and have little for sale. For this reason, some of the smallholder farmer households are not food self-sufficient and this impacts their adoption of CSA technologies. The importance of food security is in agreement with the findings of Pilbeam et al. (2005) who linked the adoption of soil fertility management practices with food insufficiency among households in Nepal.

2.9.22. Smallholder farmer uses the CSA Products

Various products come along with different CSA practices. Household composting, for example, produces compost manure while water harvesting structures produce water that could be used for irrigation or other household activities. Other CSA practices such as CA produce a wide range of products other things from the cover crops that are grown with the technology. Studies conducted in agroforestry indicate that farmers' interest in the trees must be considered as some farmers may be interested in wood products only when they do not decrease crop production (Duguma, 2010). This view concurs with that of Dlamini (2020), who reports that agroforestry only thrives where it is beneficial to the farmers with multipurpose trees being preferred to single-purpose tree species.

2.10. Data-Driven Agriculture

There is enough evidence that most CSA interventions that have been developed and implemented by smallholder farmers lack the necessary data to support the benefits. This may lead to the non-sustainability of these interventions.

Data-driven agriculture is the thoughtful use of big data to supplement on-farm precision agriculture. It means having the right farm data, at the right time, to make better decisions (Hayden, 2020). Sourcetrace (2019) defines data-driven agriculture as the system of using big data to supplement on-farm precision agriculture by using the right farm data, at the right time and in the right formats to make better decisions. Data-driven agriculture has also been defined as the set of approaches using digital technology to source, analyse and translate data into timely, practical, and context-specific information to help farmers make the best choices for their farms (CGIAR, 2020). Data-driven agriculture results in increased productivity and efficient use of farm inputs

Data-driven agriculture provides a lot of opportunities for smallholder farmers. First, Data-driven agriculture creates an opportunity for planning. Data-driven agriculture informs smallholder farmers on the critical decisions of including what to produce, how to produce and for whom and how much to produce (Maru et al., 2018). With the supporting data, farmers can effectively plan for farm activities that produce more yields. Secondly, apart from enabling farmers to monitor and assess the status of natural agricultural resources including land and resource use practices, data-driven agriculture also helps secure controlled environment agriculture and monitor soil and plant physicochemical parameters (Maru et al., 2018; Paul et al., 2022). Thirdly, data-driven agriculture enables farmers to manage their events and farm interventions. Farmers can use such external data as weather forecasts, growth models and market prices, and the occurrence of new pests and diseases to manage their farm operations and events such as when to spray, harvest, and even irrigate the farms (Maru et al., 2018; Sørensen et al., 2019). Fourthly, using farm-specific data, farmers can do autonomous on-farm actions such as auto-feeding animals, closing or opening windows, and switching on or off irrigation pumps when soil humidity levels get to a target amount through ICTs (Maru et al., 2018; Paul et al., 2022). Lastly, data-driven agriculture helps farmers and other value chain actors track and trace agricultural products. According to Maru et al. (2018), the data shared from the farm is essential in tracking data flows such as farm identification, farming practices and agricultural inputs used. For these reasons, data-driven agriculture enables farmers not only to increase their farm productivity but also to improve efficient production systems thereby increasing farming profitability.

Data-driven agriculture, however, comes with challenges for smallholder farmers. First, big data solutions are expensive and unaffordable to many smallholder farmers. Available reports suggest that most smallholder farmers are poor and food insecure with limited access to markets and services (FAO, 2020b; Maru et al., 2018). This hinders smallholder farmers' ability to adopt these data-driven CSA technologies. Secondly, smallholder farmers are challenged in finding, understanding, interpreting, and using the data effectively. According to Maru et al. (2018), while most data are useful, some cannot be used either because they are in inappropriate formats or the farmer is not able to make sense of them. It is, therefore, necessary to develop relevant and affordable data-driven solutions that are within the reach and understanding of smallholder farmers.

2.11. Machine Learning for Agriculture

Machine Learning (ML) is a form of data-driven problem-solving using computer programming. While Mitchell (1997) defines ML as data-driven programming that gathers many well-defined disciplines each of which aims to solve its way a problem, Jagtap et al. (2022) define it as the process of extracting useful information from various types of data. In other definitions, ML has been described as the scientific field that gives machines the ability to learn without being strictly programmed (Samuel, 2000). ML, therefore, could be defined as the use of computer programs to learn about the characteristics and features of given targets and then use the learning in identifying other related targets using the data previously collected from the previous target.

ML has been used in several disciplines such as image processing, customer evaluation, and robotics. In agriculture, ML has been used in yield prediction, pests and disease recognition and prevention, water management, and soil management (Liakos et al., 2018). Computer vision and ML algorithms have been used to detect and discriminate weeds at a low cost with no environmental issues (Arakeri et al., 2017 ; Dadashzadeh et al., 2020). ML has also been used in the detection of crop disease and precision agriculture management where agrochemicals are targeted to specific affected plants (Alam et al., 2020). In irrigation systems, ML-based applications are connected with periodical evapotranspiration estimation to identify expected weather phenomena and estimate evapotranspiration and evaporation (Liu et al., 2020). ML has also been used by researchers to develop climate-smart models (Rosenstock et al., 2020).

ML uses mathematical algorithms to learn data and make a prediction. Machine Learning algorithms are programs of data-driven inference tools that offer an automated means of recognizing patterns in high-dimensional data (El Bouchefry & de Souza, 2020). Many ML algorithms help to do better data analysis. This section describes the three ML algorithms that have been used in the data analysis and modelling of this study.

2.11.1. Linear Regression

One of the simplest ML algorithms is Linear Regression. Linear Regression finds linear relationships between one or more predictors where the independent variables predict the dependent variables. According to Maulud and Abdulazeez (2020), linear regression is a mathematical test used for evaluating and quantifying the relationship between the considered variables. Linear regression establishes linear relationships between variables that are dependent and independent (Maulud & Abdulazeez, 2020). Thus, given several variables, linear regression could be used to estimate the dependent variables once the independent variables are known.

2.11.2. Decision Trees for Agriculture

Another major machine learning algorithm is the use of decision trees. Decision trees are supervised machine ML algorithms and are useful tools for mimicking human decision-making in a variety of settings through predictive modelling (Keboola, 2022). According to Dreiseitl and Ohno-Machado (2002), decision trees repeatedly splits the data according to a criterion that maximizes the separation of the data resulting in a tree-like structure. The main advantage of decision trees is that they can be expressed as rules.

2.11.3. Random Forest

Another commonly used ML algorithm is the Random Forest (RF). According to El Bouchefry and de Souza (2020), the RF algorithm utilizes a majority vote to predict classes based on the partition of data from multiple decision trees. Other scholars indicate that RF uses various decision trees, collects predictions from each of them, and then finds the best solution to a problem (Asif et al., 2021). It could, therefore, be argued that RF is an ML algorithm that utilizes multiple decision trees to identify the best solution to a problem.

2.12. Modelling for Climate Smart Agriculture

Many studies have been conducted to model agricultural production. First, Johann et al. (2016) estimated the soil moisture content using an autoregressive error function. This model is suitable to estimate soil moisture in controlled systems applied no no-till machinery. A similar study by Chen, et al (2014) designed a Wireless Sensor Network (WSN) to monitor multi-layer soil temperature and moisture in a farmland field to improve water utilization and to collect basic data for research on soil water infiltration variations for intelligent precision irrigation. Muangprathub et al. (2019) has developed a model for optimally irrigating crops based on a Wireless Sensor Network (WSN). In this model, a soil moisture sensor is used to monitor the field and connecting to the control box. A web-based application is designed to manipulate crop data and field information. This application applies data mining to analyze the data for predicting suitable temperature, humidity and soil moisture for optimal future management of crops growth. A mobile smart phone app is then developed to control crop watering.

The Climate Smart Village Approach by Aggarwal et al (2018) provides a means of performing agricultural research for development through testing technological and institutional options for dealing with climate variability and climate change using participatory methods. According to Aggarwal et al (2018), an ideal CSV approach gives guidance before and during the planting season on the most suitable CSA practices, technologies, services, processes, and institutional options considering market and resource availability such as capital, labor and markets.

2.13. Decision Support System

A Decision Support System (DSS) is a computer-based system that helps in the planning, operations, and management decisions based on the available information. A Decision Support System is defined as a computerized system used to support determinations, judgments, and courses of action in an organization (Segal, 2020). DSS at the farm level is used to make critical day and long-term planning on farm management. Power (2002) defines DSS as interactive computer-based systems that help people use computer communications, data, documents, knowledge, and models to solve problems and make decisions. Other scholars have defined DSS as an interactive computer-based information system that is designed to support solutions to decision problems (Bhatt & Zaveri, 2002; Lee & Huh, 2006). From these definitions, DSS supports managers to make informed decisions given complex situations. However, these decisions cannot be made without sufficient information and data.

Many Decision Support Systems have been developed to aid decision-making in agricultural disciplines. The Climate Smart Decision Support system for analysing the water demand of a large-scale rice irrigation scheme is one of the models that have been developed to inform Climate Smart Agricultural decisions. This model by Rowshon et al. (2019), was applied to evaluate the impacts of climate change on irrigation water demand and other key hydro-climatic parameters in the Tanjung Karang Irrigation Scheme in Malaysia for the period 2010-2099. This model which has been used for analysing the water demand of a large-scale rice irrigation scheme helps promote adaptation and mitigation strategies that can lead to more sustainable water use at the farm level.

Ascough Li et al. (2002), developed the Great Plains Framework for Agricultural Resource Management (GPFARM), to provide crop and livestock management support at the whole farm level in the Great Plains of the United States. This DSS provides producers, consultants, action agencies, and scientists with information for making management decisions that promote sustainable agriculture. GPFARM contains risk analyses that combine projected crop yield and animal production data with concurrent environmental impact data. Another DSS was developed by Bseiso et al. (2015) targeting greenhouse farmers in low-resource settings. The DSS provides farmers with slides of decision information which is only read through printed papers or in a PDF format. This means that this DSS tool can be made into an app instead of paperwork.

Fourati et al (2014) present a climatic monitoring system for farmers. Using an integrated WSN weather station, farmers can display weather measures relative to temperature, humidity, wind, and solar radiation. These measures allow the DSS to precisely calculate the water requirement in a daily calendar. Another DSS is by Panchard, et al.(2007) known as Commonsense net. This DSS is a wireless sensor network for resource-poor agriculture in the semiarid areas of developing countries. This sensor network system aims at improving resource poor farmers' farming strategies in the wake of highly variable conditions. The risk management strategies include choice of crop varieties, planting and harvesting, pests and disease control and efficient use of irrigation water. This decision Support System uses WSN for the improvement of farming strategies in the face of highly variable conditions.

From the foregoing, it is apparent that efforts have been put to assist farmers adapt to climate change. From the models discussed, it is not clear on the drivers of smallholder farmers adoption of CSA technologies and the possible interventions. The models further do not consider farm specific characteristics of the smallholder farmers in their adoption of CSA practices. A data-driven model for the sustainable deployment and adoption of CSA practices in Kakamega will inform policy makers and CSA promoting organizations on the right target beneficially for CSA adoption. On their part, smallholder farmers can effectively plan for farm activities that produce more yields thus increasing their incomes and improving their livelihoods. Apart from informing the policy makers and CSA promoting organizations on the right target beneficiaries, this model will go a long way to reduce GHG emissions as well as help the smallholder farmers to adapt to climate change.

2.14. Conceptual Framework

The sustainable CSA model has the following components:

1. **Knowledge Base:** this is the store of information or data that is available to draw on. This knowledge is gathered from farm-specific data provided by the farmers and the climate and weather information provided by the Meteorological department.
2. **Decision Support System:** This is the information system that supports decision-making on sustainable CSA approaches. DSS are software-based systems that gather and analyses agricultural data from a variety of sources. A

CSA decision support system helps farmers solve complex issues related to climate-smart agriculture practices.

3. **Sustainable CSA Practices:** these are the output of the decision support system. At this level, the smallholder farmers and agricultural officers can get a combination of appropriate CSA practices for a given location.
4. **Evaluation:** The model will be continuously evaluated, and feedback given back to the knowledge base to increase efficiency and effectiveness.

Primary Players

These players provide primary information (data) to the knowledge base. These include:

i. **Smallholder Farmers:** these players play a key role as they are the ones who own the farms. For this reason, they are the primary users and beneficiaries. They provide information regarding soil characteristics, existing CSA practices, main crop enterprises, other crop and livestock enterprises, land tenure, farm management practices, and the land size in which the CSA practices will be employed.

ii. **Meteorological Department:** CSA approaches are concerned with changing climate and weather information. This department will be the primary provider of this information.

Secondary Players

These players play other roles in the decision support system. The major players at this level are:

i. **Research Institutions:** Their key role revolves around developing CSA Technologies, Innovations, and Management Practices (TIMPS). These TIMPS are generated by research Organizations through site-specific adaptation trials.

These TIMPS include Conservation Agriculture, Composting, Organic and Inorganic inputs, water harvesting technologies, greenhouse farming, soil and water conservation structures, and Integrated Pest Management.

ii. **Private Extension service providers and NGOs:** These are private extension service providers. They will draw important findings from the decision support system that supports the farmers involved in their projects and programs.

Primary Beneficiaries

These are the beneficiaries who draw benefits directly from the model. These include:

i. **Agricultural Officers:** The key role of agricultural officers is to give information to farmers on appropriate CSA approaches. These officers also conduct farm trials and demonstrations on various crop enterprises, and they report back to the knowledge base to enrich its usability.

ii. **Donor Agencies**: These agencies are the main supporters of CSA approaches in the county through their programs and projects. They will draw appropriate CSA approaches to be disseminated to specific farmers who are implementing their projects.

Support Players

These players offer support in form of policy and legal frameworks. Policies, strategies, and programs are formulated and implemented at this level. The players involved in this stage include the County Government of Kakamega, The Ministry of Agriculture, the Ministry of Environment, and the Ministry of Livestock Development.

Figure 2.1 depicts the conceptual framework for sustainable deployment and adoption of CSA practices in Kakamega county as developed by the researcher based on empirical literature reviewed.

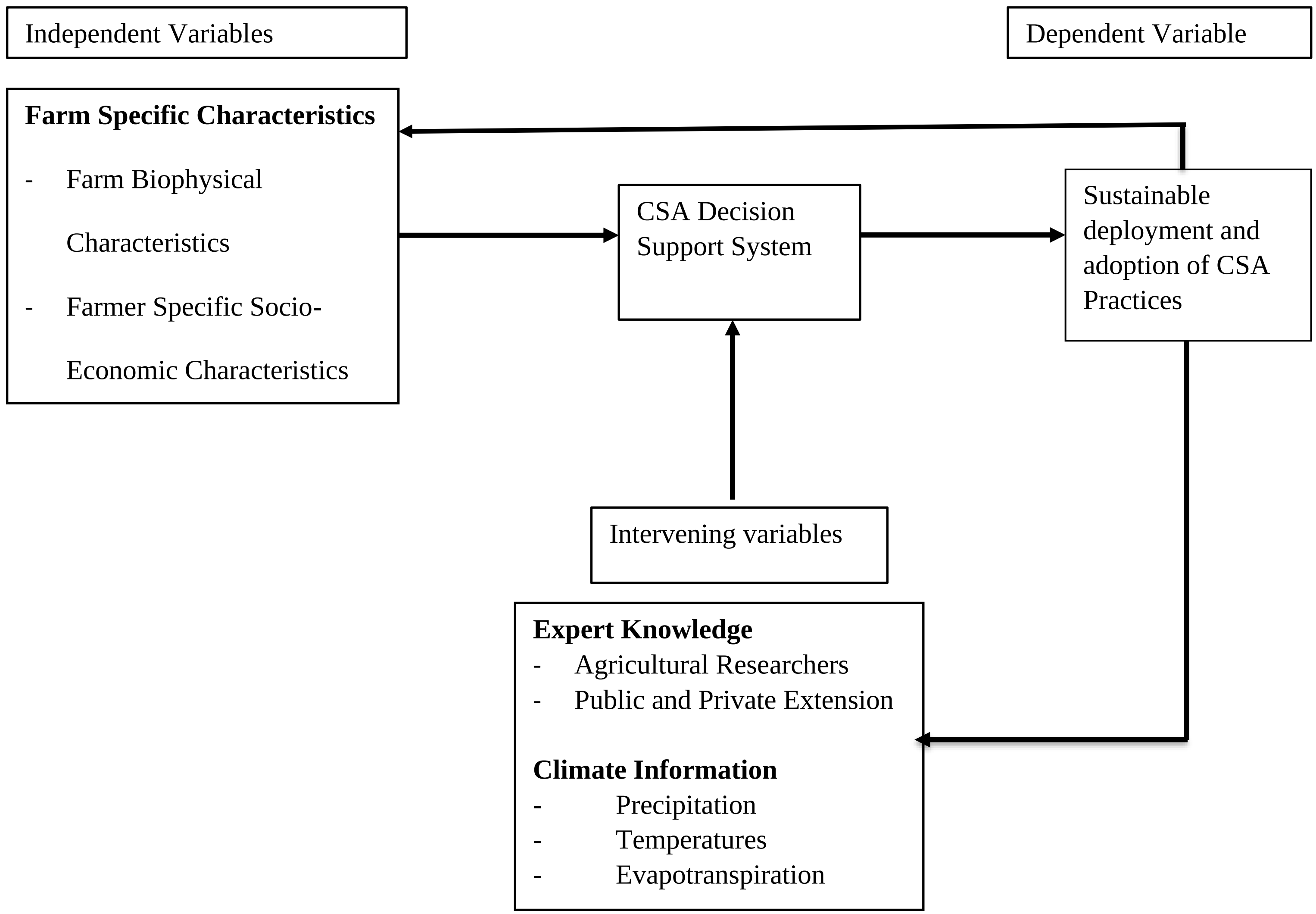


Figure 2.1: Conceptual Framework for Sustainable Deployment of CSA Practices

CHAPTER THREE

MATERIALS AND METHODS

3.1.Introduction

This chapter gives a brief overview of design and methodology of this study, including study location, data collection and analysis.

3.2.The Study Area

3.2.1. Location and Size

This study was undertaken in Kakamega, one of the Forty-Seven Counties in Kenya. The County lies between longitudes 34 and 35 degrees East and Latitudes 0 and 1 degrees North (MoALF, 2017). The county covers an area of 3051.3 KM^2 and borders Trans Nzoia and Bungoma counties to the North, Siaya and Vihiga counties to the South, Nandi and Uasin Gishu counties to the East, and Busia county to the West (CGK, 2018). Figure 3.1 below shows the location of the study area.

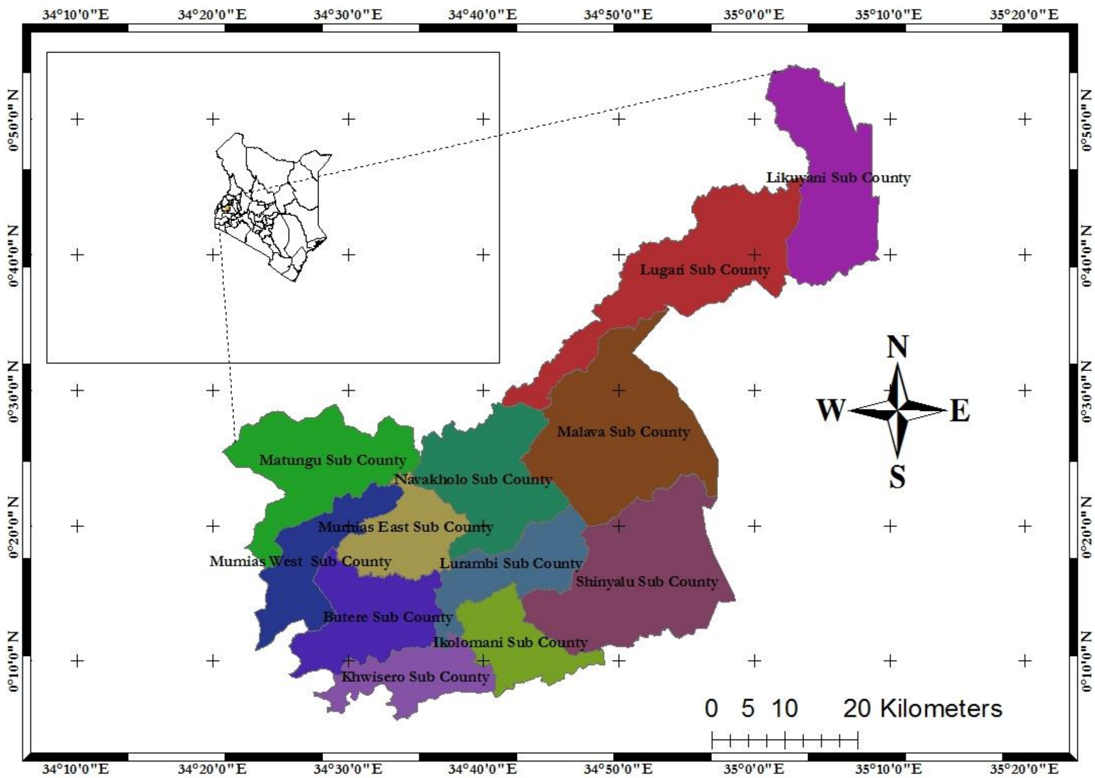


Figure 3.1 Map of Kakamega County, the study area

The county is the fourth most populous in Kenya with a population of 1,867,759 persons comprising 897,133 males and 970,406 females (KNBS, 2019). It comprises of 12 Sub-counties and 60 wards. As shown on Table 3.1, the sub-counties are grouped to form the three regions of Southern, Central, and Northern. The Southern Region covers Matungu, Mumias West, Mumias East, Butere, and Khwisero sub-counties. While the Central Region covers the sub-counties of Navakholo, Ikolomani, Shinyalu, and Lurambi; the northern Region covers Malava, Lugari, and Likuyani sub-counties.

Table 3.1: Kakamega County Wards and Population per sub-counties

Region	Sub County	No. of Wards	Population
Central	Lurambi	6	188,212
	Shinyalu	6	167,641
	Ikolomani	4	111,743
	Navakholo	5	153,977
Southern	Butere	5	154,100
	Matungu	5	166,940
	Mumias East	3	116,851
	Mumias West	4	115,354
	Khwisero	4	113,476
Northern	Malava	7	238,330
	Lugari	6	188,900
	Likuyani	5	152,055
County		**60**	**1,867,579**

Source: CGK (2018)

3.2.2. Major Livelihood Sources

It is estimated that over 80% of the working population in the county is employed in agriculture, and is mainly in rural areas (CGK, 2018). The main crops grown in the county include sugarcane, tea, coffee, maize, beans, sweet potatoes, bananas, upland rice, cassava, sorghum, finger millet, local vegetables, and other horticultural crops. Reports by the County Government of Kakamega indicate that the county has a total of 255,483.30 hectares under food and cash crop production. Table 3.2 below shows the production of the major crops in the county.

Table 3.2:Major Crop Production in the County

Crop	Production (Tons)
Dry Maize	168,256.71
Beans	25, 353.45
Tea	2,797
Sweet Potatoes	32,370

Source: CGK (2018)

Apart from crop production, the county also produces various livestock. Reports from the County Government of Kakamega indicate that cattle, poultry, pigs, goats, sheep, rabbits, and bees are the main livestock reared in the County. Table 3.3 below shows the major livestock population in the county.

Table 3.3: Kakamega County Livestock Population

Product	**Population (Numbers)**
Cattle	377,910
Sheep	88790
Goats	74,405
Pigs	24,604
Chicken	1,033,622

Source: CGK (2018)

3.2.3. Soil Characteristics

The county is characterized by different soils and drainage characteristics. A study by Sigunga and Wandahwa et al. (2015) highlighted the major soil characteristics of Kakamega County. According to them, the different soil and drainage characteristics influence the county inhabitants' livelihoods, farming systems, and farming enterprises. The authors point out further that soils in the county are generally shallow and poor in fertility implying that they may not support some crop and livestock enterprises. Other Studies by Rota et al. (2006) indicate that most of the soils in Kakamega are well-drained and range in texture from clay to sandy loam. Rota et al. (2006), however, argue that heavy rains make these soils susceptible to erosion, which lowers agricultural productivity. This may explain why the soils area acidic and of low fertility.

3.2.4. Climate Information

Kakamega's climate is classified as tropical and has year-round rainfall**,** which helps to sustain agricultural output (CGK, 2023). According to weather reports, the driest month is January with an average rainfall of 61 millimetres, and the wettest month is May with an average precipitation of 273 millimetres (Climata-Data, 2020). However, the distribution of rainfall varies across the County, with the Southern Region of the County receiving a greater amount of precipitation than the Central and Northern Regions. The diverse agroecological zones in the county are caused by this variation in rainfall and other factors. The rainfall pattern in the county is bimodal with two peaks. The long rains season peaks during May while the short rains season peaks during September. The annual rainfall in the county ranges from 1280 mm to 2214 mm per year with the average annual rainfall being 1971mm (CGK 2018; CGK 2023). Figure 3.2, below, depicts the mean annual rainfall in the various parts of the county.

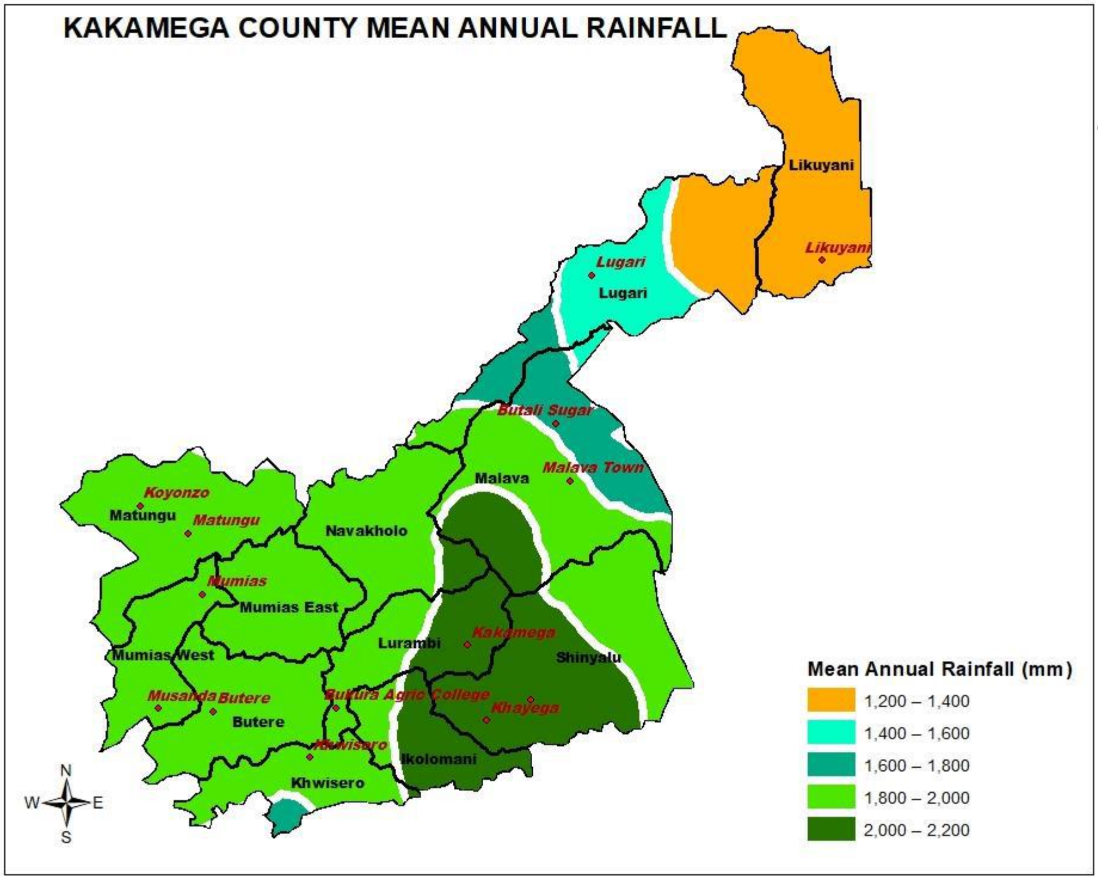


Figure 3.2: Kakamega County Mean Annual Rainfall

(Source: CGK (2018)

The temperatures range from 18 degrees Celsius to 29 degrees Celsius with the annual mean temperatures being 24 degrees Celsius (Climata-Data, 2020). Climata-Data (2020) reports indicate that February is the hottest month in the County with a mean temperature of 22.5 degrees Celsius while July is the coolest month with a mean temperature of 19.7 degrees Celsius. In addition, the county has an average humidity of 67% (Climata-Data, 2020).

Kakamega County has a high potential for agricultural production gauging from the high average rainfall received and the different soil and water conditions (Nyairo et al., 2021; Ochenje et al., 2016). The County's diverse soil and drainage features have an impact on the livelihoods, farming practices, and agricultural enterprises of the residents. The Southern region is characterized by flat landscape and well-drained soils. Nonetheless, the area is vulnerable to flooding due to the region's flat geography (Wambugu & Karugia, 2014). Fertile soils, forestry, and cattle farming, on the other hand, define the central region, which borders the lush Nandi Escarpment. The county's northern region, which has well-drained soils, is where most of the maize and beans that are sold to other sub-counties are produced (Wambugu & Karugia, 2014). Because of this, the county has a lot of potential to produce food for humans, and feeds for livestock including fish.

3.2.5. Agroecological Zones and Landforms

The county has two main agroecological zones namely, the Upper Midland (UM) and the Lower Midland (LM). The UM Zone which covers the Central and Northern regions of the county is suitable for forestry, dairying and the production of maize, beans, tea, coffee, sunflower, bananas, grain amaranth, sugarcane, and Horticulture (MOALFC, 2018). The LM Zone which covers the Southern region of the County is suitable to produce sweet potatoes, cassava, sugarcane, maize, groundnuts, oil palm, dairy, horticulture, and pineapples (MOALFC, 2018).

The county lies between 1,240 metres to 2,000 metres above sea level. The southern part is hilly and made up of rugged granites rising in places to 1,950 metres above sea level. The county has several hills including Eregi, Butieri, Eshikhokhochole, Misango, Imanga, Lirhanda, Kiming'ini and Mawe Tatu hills (CGK 2023). The county landform is also characterized by the Nandi escarpment to the North. This escarpment, which rises over one kilometre above the general elevation, forms a prominent boundary feature of the county and is the source of several streams that flow into the main rivers (Chepkosgei, 2016).

3.3. Sampling

3.3.1. Target Population

Data collection focused on smallholder farmers who have received training from several CSA promotion programs. This study focused on both CSA technology adopters and dis-adopters among the trained smallholder farmers. Table 3.4 shows the programs that have been started by various organizations to promote CSA technologies and the number of beneficiaries reached by December 2021. As a result, 68,762 makes up the study's target population.

Table 3.4: CSA beneficiaries as of December 2021

Organization	Beneficiaries as of December 2021
KCSAP	18,900
GIZ ProSoil Project (Welthungerhilfe)	8,263
GIZ ProSoil Project (GOPA)	7,500
GIZ ProSoil Project (GFA)	3,334
MOALFC/ADS/KALRO (ISLM/ISFM)	30,765
Total (N)	**68,762**

Source: KCSAP, GIZ and MOALFC Reports

3.3.2. Sample Size Calculation

In Kakamega County, there are 168,029 smallholder farmers, according to Department of Agriculture data (CGK, 2018). As depicted in Table 3.4, above, CSA-promoting organizations had provided CSA technologies to 68,762 smallholder farmers by December 2021. As a result, 68,762 makes up the study's target population. Yamane's (1967)'s formula was used to calculate the sample size, as follows:

$$n = N/1 + N(e)^2$$

Where:

n is the required sample size from the population under study

N is the whole population that is under study e is the precision or sampling error

Thus, for a study population of 68,762, the sampling size was calculated as follows:

$n = 68{,}762/1+68762(0.05)^2$

$n = 397.68$

The sample size calculation gave a sample size of 397.68 respondents. These respondents were distributed uniformly as shown on Table 3.5, below.

Table 3.5: Target Respondents per Sub County

Region of the County	Sub County	Target Respondents
Northern	Malava	66.28
	Lugari	66.28
Central	Lurambi	66.28
	Navakholo	66.28
Southern	Matungu	66.28
	Mumias West	66.28
Total	**County**	**397.68**

3.3.3. Sampling Strategy

The selection of the study respondents followed a multistage random sampling approach. The first stage involved clustering the county into three regions: northern, central, and southern. The northern region comprised of Likuyani, Lugari, and Malava sub-counties. The central region comprised Lurambi, Ikolomani, Shinyalu, and Navakholo sub-counties, while the southern region comprised Butere, Mumias West, Mumias East, Matungu, and Khwisero sub-counties. This was followed by randomly selecting two sub-counties from each region to represent the county's various agroecological zones and regions for the research sample. Lugari and Malava sub-counties were randomly selected to represent the Northern Region, while Lurambi and Navakholo sub-counties were randomly selected to represent the Central Region. For the Southern Region, Matungu and Mumias West sub-counties were randomly selected. The second stage involved the selection of farmer groups that had been trained in CSA practices. In each sub-county, all the groups that participated in CSA training were listed, and six groups were randomly selected. The final stage involved the selection of CSA adopters and dis-adopters. The lists of the group members were obtained and grouped into CSA technology adopters and dis-adopters. In each farmer's group, six CSA technology adopters and six CSA technology dis-adopters were randomly selected and interviewed. This exercise yielded 428 respondents whose farm specific biophysical and socioeconomic characteristics were collected.

3.4.Data collection

Before the actual fieldwork and data collection, an ecosystem mapping exercise was carried out to understand the players and the roles they play in CSA adoption and promotion. The various players were also informed about the study, its objectives, and its significance. The stakeholders include both National Government and County Government Administration Officials. Other relevant stakeholders who were visited included Agriculture Department officials and project officers dealing with Climate Smart Agriculture in the County.

3.4.1. Primary Data Collection

Primary data was collected using online-created mobile phone questionnaires. The study made use of the Kobo Collect software. A personal account was created on the publicly accessible instance of Researchers, Aid Workers, and Everyone Else. Using the Toolbox form creator feature of Kobo Collect, an interview guide was created from scratch. The questionnaire was assessed several times using the Kobo Collect App, and feedback was used to improve the questionnaire before collecting field data. Data collection targeted smallholder farmers who were utilizing CSA technologies and those who had given up and abandoned the CSA technologies. The selected respondents' farm specific biophysical and socioeconomic characteristics were collected using the online-created mobile phone interview guide (For a copy of the Study Interview Guide for Smallholder CSA Farmers, see Appendix A).

3.4.2. Secondary Data Collection

Secondary data was obtained from various scholarly articles, government publications, project reports, and other relevant works that were reviewed systematically. Government publications used include the Kenya Climate Change Act of 2016, Agriculture Sector Transformation and Growth Strategy, Kakamega County Integrated Development Plan (2013-2022), Department of Agriculture Annual Reports, National Government Ministry of Agriculture website and the Kakamega County Government website. Project reports reviewed included the Kenya Climate Smart Agriculture Project Reports, GIZ's Soil Protection and Rehabilitation (ProSoil) Project implementing agencies' reports, Rural Outreach Africa Reports and KALRO Alupe's Integrated Sustainable Land Management Project Reports.

3.5.Data Analysis

3.5.1. Data Processing

Microsoft Excel was used to download data from the Kobo Collect software. The downloaded data yielded 549 variables. Table 3.6 shows an example of the variables as downloaded from Kobo Collect.

Table 4.6: Format of Downloaded Survey Questionnaire

Farmer Number	Gender	Age Bracket	Marital Status	Are you the Household Head	Main farm decision maker	Gender of the Household Head	Type of Farmer
1	Male	56 – 65 years	widowed	Yes	Self	Male	Dis-adopter
2	Female	46 – 55 years	widowed	Yes	Self	Female	Dis-adopter
3	Female	≤ 35 years_	married	No	Other	Male	Dis-adopter
4	Female	36 – 45_years	married	No	Other	Male	adopter
5	Female	46 – 55 years	married	No	Other	Male	adopter
6	Female	36 – 45 years	married	No	Other	Male	Dis-adopter
7	Male	56 – 65 years	married	Yes	Self	Male	adopter
8	Female	≤ 35_years	married	No	Other	Male	Dis-adopter
9	Female	36 – 45 years	married	No	Other	Male	Dis-adopter
10	Male	56 – 65 years	married	Yes	Self	Male	adopter
11	Male	≥66 years	widowed	Yes	Self	Male	adopter
12	Female	46___55_years	married	Yes	Self	Female	adopter
13	Female	56___65_years	married	No	Self	Male	Dis-adopter

The downloaded data, both for the variables and the responses, was coded, from V1 to V610 and the responses assigned numerical values, for ease of analysis and manipulation as shown on Table 3.7 **(see Appendix B for more details).**

Table 3.7: Sample of variable and data coding

V3	V4	V5	V6	V7	V8	V9	V12
1	1	4	1	1	1	1	2
2	2	5	1	1	1	2	2
3	2	1	1	2	1	1	2
4	2	3	1	2	1	1	1
5	2	2	1	2	1	1	1
6	2	4	1	2	2	1	2
7	1	1	1	1	2	1	1
8	2	5	1	2	1	1	2
9	2	4	1	2	1	1	2
10	1	4	1	1	1	1	1
11	1	2	1	1	1	1	1
12	2	1	1	1	2	2	1
13	2	3	1	2	2	1	2

Note: V3: Respondents from 1 to 428 in the study, V4: Gender of the smallholder CSA farmer, V5: Respondent Age V6: Marital Status, V7: Whether Respondent is the Household Head, V8: Whether the Respondent is the Main Farm decision maker, V9: Gender of the Household Head, V12: Farmer type.

The data were analysed using both descriptive and inferential statistics. Microsoft Excel and the Statistical Package for Social Sciences were used to process and analyse the data. The findings were incorporated into interpretations based on the reviewed literature and were eventually used in report writing, including discussions and conclusions. To summarize how the variables of interest were distributed in the sample, descriptive statistics like frequencies, percentages, and means of population demographics, CSA farmer characteristics, general farm characteristics and group information, extent of adoption of CSA technologies and respondents' perception of CSA were computed. The result of the analysis was presented using tables, charts, diagrams, and discussions.

3.5.2. Variable Correlation Coefficients

The coded variables were subjected to Pearson's pairwise correlation to identify the variables that were associated with smallholder farmers' adoption and dis-adoption of CSA technologies. Correlation Coefficients of these data were used to select variables for Machine Learning.

Variable V12 represented the CSA farmer type which was either a CSA technology adopting or a dis-adopting smallholder farmer. It was, for this reason, was identified as the dependent variable whose value was dependent on other variables. In this study, therefore, the correlations identified for are those affecting V12 against all the other variables. Variables with significant correlations at the 0.05 and 0.01 levels (2-tailed) were identified and investigated further using machine learning. Table 3.8 below shows an example of pairwise correlation coefficients from the variables. For more details on the study variables and their correlations, **see Appendix B**.

Table 3.8: Pearson pairwise correlation coefficients for selected variables

Correlations

		V3	V4	V5	V6	V7	V8	V9	V12
V3	Pearson Correlation	1	.006	-.034	.039	.011	.012	.023	-.003
	Sig. (2-tailed)		.909	.478	.424	.814	.811	.632	.952
	N	428	428	428	428	428	428	428	428
V4	Pearson Correlation	.006	1	-.167**	.204**	.603**	.473**	.567**	.216**
	Sig. (2-tailed)	.909		.001	.000	.000	.000	.000	.000
	N	428	428	428	428	428	428	428	428
V5	Pearson Correlation	-.034	-.167**	1	.128**	-.255**	-.240**	-.228**	-.124*
	Sig. (2-tailed)	.478	.001		.008	.000	.000	.000	.010
	N	428	428	428	428	428	428	428	428
V6	Pearson Correlation	.039	.204**	.128**	1	-.354**	-.246**	-.335**	.217**
	Sig. (2-tailed)	.424	.000	.008		.000	.000	.000	.000
	N	428	428	428	428	428	428	428	428
V7	Pearson Correlation	.011	.603**	-.255**	-.354**	1	.706**	.948**	.077
	Sig. (2-tailed)	.814	.000	.000	.000		.000	.000	.112
	N	428	428	428	428	428	428	428	428
V8	Pearson Correlation	.012	.473**	-.240**	-.246**	.706**	1	.603**	.128**
	Sig. (2-tailed)	.811	.000	.000	.000	.000		.000	.008
	N	428	428	428	428	428	428	428	428
V9	Pearson Correlation	.023	.567**	-.228**	-.335**	.948**	.603**	1	.070
	Sig. (2-tailed)	.632	.000	.000	.000	.000	.000		.147
	N	428	428	428	428	428	428	428	428
V12	Pearson Correlation	-.003	.216**	-.124*	.217**	.077	.128**	.070	1
	Sig. (2-tailed)	.952	.000	.010	.000	.112	.008	.147	
	N	428	428	428	428	428	428	428	428

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

3.5.3. Reliability of the Research Instruments

Cronbach's alpha was used to measure the internal consistency. Table 3.9 below, depicts the Cronbach's alpha coefficient.

Table 3.9: Summary of Reliability Test Results

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
V10	36.198458	48.506	.167	.740
V4	38.196121	54.232	-.049	.733
V5	36.829299	49.066	.197	.731
V6	38.612009	55.075	-.169	.737
V8	38.513879	54.288	-.057	.733
V17	39.247523	51.307	.360	.717
V18	39.191449	50.854	.437	.714
V19	39.810607	54.102	.014	.728
V22	39.376028	50.852	.426	.715
V25	39.805935	54.047	.049	.728
V29	39.387710	50.949	.413	.715
V34	38.165748	57.206	-.459	.748
V37	38.911075	53.122	.208	.725
V38	38.883037	53.502	.146	.726
V40	39.081636	51.427	.391	.717
V41	38.883037	53.281	.206	.725
V43	39.499860	49.893	.611	.708
V44	39.518551	51.044	.439	.715
V47	39.429766	50.080	.551	.710
V51	37.997523	55.005	-.181	.736
V58	37.932243	47.112	.263	.727
V68	39.322290	50.372	.491	.712
V75	39.392383	50.586	.467	.713
V76	39.616682	50.885	.541	.713
V77	39.562944	51.397	.407	.717
V80	39.527897	51.383	.390	.717
V103	38.775561	54.416	-.121	.731
V104	39.724159	54.859	-.137	.736
V107	39.796589	54.210	-.060	.729
V115	38.894720	53.239	.200	.725
V119	38.857336	53.856	.071	.728
V120	39.392383	51.108	.391	.716
V129	37.165748	45.282	.519	.698
V130	38.224159	57.351	-.466	.749

V133	39.406402	51.352	.358	.717
V134	39.597991	49.993	.679	.708
V135	39.600327	49.903	.699	.707
V136	38.583972	55.047	-.178	.736
V138	39.397056	55.116	-.170	.738
V139	39.427430	52.465	.200	.724
V140	39.637710	54.515	-.097	.733
V141	39.326963	52.211	.229	.723
V143	39.537243	50.055	.610	.709
V144	39.553598	50.152	.607	.709
V145	39.682103	54.497	-.100	.732
V146	39.446121	51.078	.406	.716
V160	39.366682	52.793	.148	.726
V161	39.090981	52.962	.146	.726
V162	39.705467	53.634	.085	.727
V163	38.992850	53.677	.051	.729
V164	38.936776	53.022	.205	.724
V165	39.668084	54.473	-.093	.733
V167	39.719486	53.191	.197	.725
V168	39.784907	54.290	-.084	.730
V169	39.712477	55.170	-.256	.735

3.5.4. Overall Model

As indicated on Table 3.10 below, the research instruments were reliable as the constructs had Cronbach's alpha values above 0.7.

Table 3.10 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No of Items
0.728	0.725	55

3.6.Data-Driven Model for CSA Adoption

Decision Tree Classifier and Random Forest Classifier models were used for prediction of adoption or dis-adoption of CSA practices. In the primary data collection exercise, 182 smallholder CSA farmers were adopters while 246 were dis-adopters. The purpose of the models, therefore, was to aid in decision-making through prediction on which smallholder farmers would be CSA adopters and who would be CSA dis-adopters using the different variables identified in the study.

3.6.1. Dependent and Independent Variables for Prediction

The Dependent Variable (Y) was identified as the variable whose value was dependent on other variables. Y represented the CSA farmer type which was either be a CSA technology adopting or a dis-adopting smallholder farmer. The identified classification models, therefore, sought to predict the value of Y (CSA Technology adopter or dis-adopter) given the various farm-specific biophysical and socioeconomic characteristics (X).

3.6.2. Training the ML Algorithm

This was the first step in the CSA model's development. The Supervised Machine Learning paradigm was used in this study, in which previously labelled data (both dependent and independent variables) with known answers were fed into the ML algorithm. The ML Algorithm examined the various characteristics of each CSA adopter and dis-adopter and identified the patterns in the data. Thus, the algorithm was trained on which independent variables when combined resulted in CSA technology adopters and which resulted in CSA technology dis-adopters (output). The ML algorithm was trained using 70% of the total data.

3.6.3. Testing the ML Algorithm

The algorithm was evaluated to see how well it could predict a new data set based on the training data. The ML algorithm was fed with a dataset of independent variables without labelling the dependent variables, adopters, and dis-adopters. The ML algorithm was supposed to determine which variables while combined resulted in a CSA technology adopter and which resulted in a CSA technology dis-adopter. Thirty% of a completely different data set from the one used for training was used to test the algorithm.

3.6.4. Machine Learning Classification Algorithms

In machine learning, classification deals with a class of issues where algorithms are used to categorize test data. It locates entities in the training dataset and attempts to determine how those entities ought to be labelled or defined. Linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbours, and random forests are a few examples of classification algorithms (Bhavsar & Panchal, 2012). This study made use of random forest and decision tree classifiers.

3.6.5. Machine Learning Tools

The Google Collaboratory notebook was used for the model development and testing processes. The Google Collaboratory notebook is a free hosted Jupyter notebook service that is provided by Google. It gives users access to memory and computing resources that are free (Google, 2022).

3.6.6. Libraries and tools used in machine learning

ML libraries are an interface of a set of rules or optimized functions that are written in a given language to perform repetitive work such as arithmetic computation, visualizing data sets, and reading images (Pedamkar, 2019). In addition, a Library is a collection of functions that can be added to Python code and called as necessary, just like any other function. The first step in ML involved importing libraries into the Collaboratory notebook. The following are the ML libraries that were used in the modelling:

3.6.6.1.Pandas

This is an open-source data analysis and manipulation tool that is built on top of the Python programming language and is quick, strong, adaptable, and simple to use (McKinney, 2012; Nagpal & Gabrani).

3.6.6.2.Numpy

This is a Python library that offers a multidimensional array object, several derived objects (like masked arrays and matrices), and a selection of routines for quick operations on arrays, including among others discrete Fourier transforms, basic linear algebra, basic statistical operations, shape manipulation, sorting, and random simulation (Oliphant, 2006; Wang et al., 2022).

3.6.6.3.Matplotlib

This is a comprehensive Python library for producing animated, interactive, and static visualizations (Matplotlib Development Team, 2022). This Library was customized to plot charts, axis, and figures.

3.6.6.4.Scikit-learn

This is an open-source machine-learning library that supports both supervised and unsupervised learning. Additionally, it offers numerous utilities, including tools for data pre-processing, model evaluation, model selection, and model fitting (scikit-learn, 2022).

3.6.6.5.Seaborn

This is a Python data visualization library built on the matplotlib framework. It offers a high-level interface for creating appealing and instructive statistical graphics (Waskom, 2021). The ML libraries were imported into the Collaboratory notebook as follows:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
import seaborn as sns
```

Source: Quiroz (2023)

3.6.7. Import the data into the notebook.

This was the second step which involved loading the dataset into a pandas data frame using the read_csv function. The dataset was loaded as follows:

```
df = pd.read_csv("/content/Whole Data Set_549 Variables.csv")
```

Source: Quiroz (2023)

3.6.8. Define the X and Y variables

This third step involved defining the X and Y variables using all of the 549 variables collected from the 428 smallholder CSA respondents. The dependent variable, V12, was defined as the smallholder CSA respondent categorization in terms of adopters and dis-adopters. The independent variables (X) were all the other variables that influenced the smallholder farmer to be either an adopter or a dis-adopter. The dependent variable (Y) and the independent variables (Y) were then defined as follows:

```
X = df[["V17" , "V25" , "V44" , "V144" , "V48" , "V50" , "V133" , "V130" ,
"V135" , "V38" , "V143" , "V120" , "V107" , "V43" , "V169" , "V77" , "V40" ,
"V22" , "V47" , "V104" , "V76" , "V5" , "V112" , "V134" , "V8" , "V57" ,
"V75" , "V80" , "V119" , "V37" , "V165" , "V103" , "V68" , "V121" , "V18" ,
"V29" , "V58" , "V41" , "V28" , "V34" , "V164" , "V115" , "V146" , "V129" ,
"V141" , "V10" , "V168" , "V4" , "V49" , "V6" , "V140" , "V145" , "V167" ,
"V163" , "V139" , "V162" , "V136" , "V161" , "V51" , "V138" , "V160"]]
y = df['V12']
```

Source: Quiroz (2023)

3.6.9. Splitting the data into training and test data sets

The data were randomly split into two datasets, one for training the model and the other one for testing the model. The model was trained with the dataset comprising 70% of the smallholder CSA farmers while the test datasets were developed comprising 30% of the data set as follows:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=0)
```

Source: Quiroz (2023)

3.6.10. Fitting the models

Model fitting was done to measure how well the ML models generalize to similar data to that on which they were trained. A good model fit accurately predicts the output of unknown input when it is input with unknowable inputs. The models were defined and fit as follows:

Decision Tree.

```
clf = DecisionTreeClassifier (max_depth = 5, random_state = 0)
model = clf.fit(X_train, y_train)
```

Random Forest.

```
clf=RandomForestClassifier (n_estimators=10)
model = clf.fit(X_train, y_train)
```

Source: Quiroz (2023)

3.6.11. Making predictions on the test data set

The test data set was to be used to gauge the ability of the model to learn from the training data and make accurate predictions when input with new data. The fitted models were used to fit the test data as follows:

```
y_pred = clf.predict(X_test)
```

Source: Quiroz (2023)

3.6.12. Comparison of the Actual and predicted values

The actual values were the values that were obtained during the primary data collection exercise. They were compared with the predicted values as per the ML model. The actual values and the predicted values were compared as follows:

```
df=pd.DataFrame('Actual':y_test, 'Predicted':y_pred)
```

Source: Quiroz (2023)

3.6.13. Model Evaluation

Model Evaluation was the process of using different evaluation metrics to understand the machine learning model's performance, strengths, and weaknesses. The models were evaluated using the following metrics:

3.6.13.1. Confusion Matrix.

A confusion matrix is a performance measurement for machine learning classification. This metric measures how well a model performed when tested on real data. It implies the number of times the model got confused before arriving at the various solutions amongst which some were correct, and others were incorrect. A confusion matrix is useful in measuring recall, precision, specificity, accuracy, and AUC-ROC curves. The confusion matrix was developed for the models as follows:

```
metrics.confusion_matrix(y_test, y_pred, labels = [1, 2]).
```

Source: Quiroz (2023)

3.6.13.2. Training Accuracy.

Training accuracy is the resultant model accuracy given when the model is applied to the training data implying that the model is tested on the examples it was constructed on.

3.6.13.3. Prediction Accuracy.

This is given by the ratio of the variables that are correctly predicted to the number of times the variables have been predicted in total. Prediction accuracy is the accuracy of the model on data it has not seen before.

3.6.13.4. Precision/Sensitivity.

This is the proportion of observed positives that are predicted to be positives. This metric is used when the objective is to reduce the number of false negatives in the confusion matrix.

3.6.13.5. Recall.

This metric tells the frequency of the correct predictions that are positive values. Recall metric is used when the objective is to reduce the number of false negatives in the confusion matrix.

3.6.13.6. Specificity.

This metric determines the proportion of actual negatives that were correctly predicted to be negatives.

3.6.13.7. F1- Score.

This is the harmonic mean of recall and precision. It is used when both precision and recall are used as metrics in analysing a model's performance. The F1 Score is a statistical measure of the accuracy of a test or a model. An F1 score of 1 represents perfect accuracy and recall of the model while a score of 0 represents the worst values.

3.6.13.8. Receiver Operating Characteristic Curve (ROC) and Area Under Curve (AUC).

ROC Curve presents the visual way of measuring the performance of a binary classifier. It is the ratio of the true positive rate (TPR) and the false positive rate (FPR). AUC-ROC graphs were used to represent the connection and trade-off between sensitivity and specificity for every cut-off for a test being performed or a combination of tests being performed. The Model AUC-ROC graphs were developed for the models as follows:

```
from sklearn.metrics import roc_curve, AUC
from sklearn.metrics import RocCurveDisplay
ax = plt.gca()
rfc_disp = RocCurveDisplay.from_estimator(model, X_test, y_test, ax=ax,
alpha=0.8)
plt.show().
```

Source: Quiroz (2023)

3.6.13.9. The area under Curve (AUC).

This is the metric used to find the area under the ROC curve. A larger area under the curve indicates that the algorithm gives high recall and precision values. An excellent model has an AUC near one meaning that it has a good measure of separability while a poor model has an AUC near zero meaning it has the worst measure of separability. When the AUC is zero (0), the model is deemed to have no class separation capacity whatsoever.

3.6.13.10. Classification Report.

A Classification report was used to measure the quality of predictions from a classification algorithm in terms of how many predictions were true and how many predictions were wrong. The Precision measured the ability of a classifier not to label an instance positive that is negative and gives the% of the correct predictions. While the Recall gives the percentage of positive cases, the F1 Score gives the percentage of correct positive predictions. The Classification Report was developed for the models as follows:

```
from sklearn.metrics import classification_report
target_names = ['Adopt', 'Dis-Adopt']
print(classification_report(y_test, y_pred, target_names=target_names))
```

Source: Quiroz (2023)

3.6.14. Computing Model Accuracy

Several approaches were used to calculate the accuracy of the classification and regression model. These approaches are the following:

3.6.14.1. Mean Absolute Error (MEA) Approach.

This approach was used to give the absolute value of the difference between the actual values and the values that were predicted. MEA was given by the average difference between the observations (true values) and model output (predictions). In simple terms, MEA informs how big an error is expected from the prediction on average.

3.6.14.2. Mean Squared Error (MSE) approach.

This was calculated by taking the average of the square of the difference between the original and predicted values of the data. When the Model has no error, the MSE equals zero. As model error increases MSE value increases.

3.6.14.3. Root Mean Squared Error (RMSE) Approach.

RMSE was calculated by finding the Standard Deviation of the errors which occur when a prediction is made on a data set. RMSE aggregates the magnitudes of the errors in predicting various times into a single measure of predictive power. A lower RMSE value indicates a better fit while a higher RMSE value indicates a poor fit.

3.6.14.4. Accuracy.

Model accuracy was given by the number of classifications that a model predicted accurately divided by the number of predictions made. The model accuracy, using the various approaches, was computed as follows.

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred)))

# Calculate the absolute errors
errors = abs(y_pred - y_test)
```

```
# Print out the mean absolute error (MAE)
print('Mean Absolute Error:', round(np.mean(errors), 2))
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

Source: Quiroz (2023)

3.6.15. Plotting the Actual vs Predicted Values

The actual and predicted values were plotted together for visualizing and analysing how the actual data correlate with those predicted by the model. The actual and predicted values were plotted as follows:

```
import seaborn as sns
plt.figure(figsize=(5, 7))
ax = sns.distplot(y, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values", ax=ax)
plt.title('Actual vs Fitted Values for Adoption vs Dis-adoption')
plt.show()
plt.close()
```

Source: Quiroz (2023)

3.6.16. Identification of important Features

Important features were the variables that were majorly important for generating the model that could predict the adoption of CSA technologies among smallholder farmers in Kakamega County. A key features matrix was generated to provide details about each feature and its percentage importance in generating the model. The key features were identified as follows:

```
pd.DataFrame(model.feature_importances_,index=features).sort_values(by=0,
ascending=False)
model.feature_importances_
sorted_idx = model.feature_importances_.argsort()
features = X.columns
plt.figure(figsize=(10, 15))
```

```
plt.barh(features[sorted_idx], model.feature_importances_[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
plt.ylabel("Variables")
```

Source: Quiroz (2023)

3.6.17. Visualizing the Random Forest and the Decision Tree Classifier Models

Tree visualization in form of a flowchart was used to illustrate how underlying variables (data) predict a chosen target and highlights key insights about the Random Forest Classifier and the decision tree. The Gini index was used to measure the impurity or purity of the decision tree in the Classification and Regression Tree (CART) algorithm. An attribute with a low Gini index was preferred to the one with a high Gini Index. The resulting trees were visualized as follows:

3.6.17.1. Decision Tree Visualization

```
cn = ["Adopt","Disadopt"]
fig = plt.figure(figsize=(30,10))
_ = tree.plot_tree(model,
feature_names=features,
class_names=cn,
filled=True, fontsize=12)
```

Source: Quiroz (2023)

3.6.17.2. Random Forest Classifier Visualization.

```
from sklearn import tree
cn = ["Adopt","Disadopt"]
#plt.figure(figsize=(25,15))
estimator = model.estimators_[5]

from sklearn.tree import export_graphviz
# Export as dot file
export_graphviz(estimator, out_file='tree.dot',
        feature_names = features,
        class_names = cn,
        rounded = True, proportion = False,
        precision = 2, filled = True)

# Convert to png using system command (requires Graphviz)
```

```
from subprocess import call
call(['dot', '-Tpng', 'tree.dot', '-o', 'tree.png', '-Gdpi=600'])

# Display in jupyter notebook
from IPython.display import Image
Image(filename = 'tree.png')
```

Source: Quiroz (2023)

3.7.Rapid Prototyping of the Data-Driven Model

Rapid Prototyping is the first stage of product development, and it gives the potential users a complete idea of how the final product will look like. The main aim of the prototype was to attract and inform potential users of a product that they could invest in before allocating resources to and implementation of CSA technologies in Kakamega County.

The prototype developed was used to simulate a real ground situation. This step involved the development of a of a web interface that users could interact with, key in important features resulting in a prediction whether a smallholder farmer will either adopt or dis-adopt CSA technologies. The following steps were followed in this process.

3.7.1. Development of a data collection guide

An online data collection tool was developed for the top 18 variables as identified in Objective 2 as being the most important in influencing the adoption of CSA technologies in Kakamega.

3.7.2. Primary Data Collection

A random sample of 15 smallholder farmers, 8 adopters, and 7 dis-adopters, was identified from Butere Subcounty. Their farm biophysical and socioeconomic data were collected based on the top 18 variables identified in objective 2.

3.7.3. Fitting the Model

The Google Collaboratory notebook was used for the model fitting and testing process. The prediction capabilities of the model were tested as follows:

3.7.3.1. **Import the data into the notebook.**

The dataset was loaded into a pandas data frame using the read_csv function as follows:

```
df_test= pd.read_csv("/content/drive/MyDrive/Model_Testing_15092022.csv")
```

Source: Quiroz (2023)

3.7.3.2. **Define the X and Y variables.**

This step involved the use of all 18 variables and the resultant secondary independent variables. The independent variable, V12, was defined as the smallholder farmer categorization in terms of adopters and dis-adopters. The independent variables comprised the 18 important variables that were under investigation and the secondary independent variables resulting from the data collection exercise. The independent variables (X) and dependent variables (y) were then defined as follows.

```
X_test=
df_test[["V5","V6","V10","V37","V38","V39","V40","V41","V42","V43","V
44","V45","V46","V47","V49","V50","V51","V58","V59","V103","V104","
V107","V115","V119","V120","V112","V129","V136","V138","V139","V14
0","V141","V143","V144","V145","V146","V160","V161","V162","V163","
V164","V165","V166","V167","V168","V169"]]
y_test = df_test['V12']
```

Source: Quiroz (2023)

3.7.3.3. Split the data into training and test data sets.

The data was split into two datasets, 70% for training the model and 30% for testing the model. The data was split as follows:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

Source: Quiroz (2023)

3.7.3.4. Make predictions on the test data set.

The test data set was used to gauge the ability of the model to learn from the training data and make accurate predictions when input with new data. The fitted models were used to fit the test data as follows:

```
y_pred = model.predict(X_test)
```

Source: Quiroz (2023)

3.7.3.5. Compare the Actual and predicted values.

The actual values are the values that were obtained during data collection. In the model testing data collection exercise, 15 smallholder CSA farmers were sampled out of which eight were adopters while seven were dis-adopters. The main goal of this step was to compare the ML Model predictions versus these actual values. The actual values and the predicted values were compared as follows:

```
df=pd.DataFrame('Actual':y_test, 'Predicted':y_pred)
```

Source: Quiroz (2023)

3.7.3.6. Model Evaluation.

The model was evaluated using the following metrics:

3.7.3.7.Calculate Absolute Errors.

Absolute errors were used to give the difference between the actual observation and the predicted observation. Getting absolute errors involves treating the positive and negative errors as absolute. The absolute errors were calculated as follows:

```
# Calculate the absolute errors
errors = abs(y_pred - y_test)
```

Source: Quiroz (2023)

The Mean Absolute Error (MEA) was given by the average difference between the observations (true values) and model output (predictions). The MEA was calculated as follows:

```
# Print out the mean absolute error (MAE)
print('Mean Absolute Error:', round(np.mean(errors), 2))
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / y_test)
```

Source: Quiroz (2023)

3.7.3.8.Model Accuracy:

Model accuracy is given by the number of classifications that a model predicts accurately divided by the number of predictions made. The model accuracy was calculated as follows:

```
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%')
```

Source: Quiroz (2023)

3.7.3.9.Precision/Sensitivity.

This is the proportion of observed positives that are predicted to be positives. This metric is used when the objective is to reduce the number of false negatives in the confusion matrix. The model Precision/Sensitivity was calculated as follows:

```
# Precision
print('Precision:',precision_score(y_test,y_pred))
```

Source: Quiroz (2023)

3.7.3.10. Recall (also known as sensitivity or true positive rate):

tells the frequency of the correct predictions that are positive values. Recall metric is used when the objective is to reduce the number of false negatives in the confusion matrix. The model recall was calculated as follows:

```
# Recall
print('Recall:',recall_score(y_test,y_pred))
```

Source: Quiroz (2023)

3.7.3.11. Specificity.

This is the proportion of observed negatives that were predicted to be negatives. The specificity of the model was calculated as follows:

```
# Specificity
tn, fp, fn, tp = confusion_matrix.ravel()
specificity = tn / (tn+fp)
print('Specificity:',specificity)
```

Source: Quiroz (2023)

3.7.3.12. F1- Score.

This is the harmonic mean of recall and precision. It is used when both precision and recall are used as metrics in analysing a model's performance. The f1 score was calculated as follows:

```
# f1 Score
```

```
print('f1 Score:',f1_score(y_test,y_pred))
```

Source: Quiroz (2023)

3.7.3.13. Confusion Matrix.

This metric was used to measure how well the model performed when tested on real data. It implies the number of times the model got confused before arriving at the various solutions amongst which some were correct, and others were incorrect. A confusion matrix is useful in measuring recall, precision, specificity, accuracy, and AUC-ROC curves. The confusion matrix was developed for the models as follows:

```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred, labels = [1,
2])
print('Confusion_Matrix')
print(confusion_matrix)
```

Source: Quiroz (2023)

3.7.3.14. Classification Report

A Classification report was used to measure the quality of predictions from a classification algorithm in terms of how many predictions were true and how many predictions were wrong. The Precision measured the ability of a classifier not to label an instance positive that is negative and gives the% of the correct predictions. While the Recall gives the% of positive cases, the F1 Score gives the percentage of correct positive predictions. The Classification Report was developed for the models as follows:

```
# Classification Report
target_names = ['Adopt', 'Dis-Adopt']
print(classification_report(y_test, y_pred, target_names=target_names))
```

Source: Quiroz (2023)

3.7.4. Web Interface Development

An interactive web interface was developed using the key features identified by the model. The aim of this interface is to give users an opportunity to interact with the ML model and other content through a web browser. In addition, this web interface was used in simulation sessions where users could key in important features resulting in a prediction.

3.8.Data-Driven Prototype Evaluation and Piloting

The objective of this stage of the study was to assess the applicability and suitability of the data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega County's smallholder farmers. This step involved conducting a focus group discussion with key stakeholders in the CSA ecosystem to get their input in the model development process. This step was important as it brought out the potential users' expectations about the model and the challenges it was meant to solve. In addition, this step was used to determine whether the model was useful to the potential users and to gauge its user-friendliness. The following activities were conducted.

3.8.1. Presentation of the data-driven model and piloting

A seminar was organized to validate the data-driven model for sustainable deployment and adoption of CSA technologies in Kakamega County. Participants included the University academic staff and students, Research Organizations, County Government Agricultural Extension Staff, Smallholder CSA farmers and Organizations promoting CSA technologies among smallholder farmers in Kakamega County.

3.8.2. Demonstration of the model working

A demonstration was conducted to show the workings of the data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega County's smallholder farmers. Dummy farmer biophysical and socio-economic data was used to predict the possibility of adoption of CSA technologies.

3.8.3. Eliciting of Feedback on the Model Workability

The objective of this exercise was to elicit feedback on the applicability and suitability of the data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega County's smallholder farmers. The feedback from the workshop was used to improve the model to increase user friendliness.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1. Objective 1: To establish the different biophysical and socio-economic characteristics of the Kakamega County's smallholder farmers that influence their sustainable adoption of CSA practices.

4.1.1. CSA Technologies Trained, Adopted, and Abandoned by Smallholder Farmers

Smallholder CSA farmers were trained in a variety of CSA technologies and implemented what they could. As shown in Table 4.1, close to all (96.5%, 93%, 93%, and 90.2%) respondents had received training in on-farm composting, SWC, agroforestry, and CA, respectively. While agroforestry, composting, and SWC were the least abandoned, vermiculture and green housing were the most abandoned, (dis-adopted by 93.1% and 85.1% of the trained farmers, respectively). Other technologies with high dis-adoption rates included fallowing (73.1%), water harvesting (67.6%), PPT (66.8%), ISLM/ISFM (66.1%), and CA (46.4%).

Composting may have been highly adopted as it is uncomplicated for smallholder CSA farmers as the materials needed to create one are readily available at the household level as reported by Dandeniya and Caucci (2020). Soil and water conservation structures are permanent farm structures that conserve soil and prevent water erosion. Their permanent presence on farmlands may help to prevent abandonment. Agroforestry adoption, like SWC structures, involves the planting of perennial trees on the farm, making it difficult to abandon. CA may be widely disadopted because most smallholder farmers are accustomed to intensive tillage of the land, in contrast to CA, which advocates for zero tillage on farmlands. The difficulty in weed control on CA farmlands may also have contributed to the high dis-adoption rate of the technology. A similar view is held by Chinseu et al. (2019) who found that smallholder farmers grapple with the challenge of weeds, poor crop emergence and pests and disease incidences and thus they disadopt.

The least adopted practices were water harvesting (16.8%), PPT (14.4%), Green housing (8.1%) and vermiculture (6.9%). The unavailability of desmodium seeds and the perceived low pest infestation in farmlands may account for the high dis-adoption rate in PPT. Similar view was held by Gwada (2019) who reported that PPT was embraced and used by farmers who saw Striga infestation as one of the main issues facing agriculture, as opposed to the others who did not. Gwada (2019) also holds the view that desmodium seeds are unavailable and expensive, thus, out of reach for most smallholder CSA farmers.Similar studies by Maguza-Tembo, et al. (2017) indicate that SWC was adopted more than other CSA practices.

Table 4.1: Adoption of Various Field CSA Technologies by Smallholder CSA Farmers

Variable	Frequencies		Farmer Type (No.)		No Attempt	CSA Adoption Rate (%)	
CSA Practice	*Respondents Trained (No)*	*Proportion (%)*	*Adopters*	*Dis-adopters*		*Adopters*	*Dis-adopters*
Composting	413	96.5	351	56	6	85.0	13.6
SWC	398	93.0	309	75	14	77.6	18.8
Agroforestry	398	93.0	376	16	6	94.5	4.0
CA	386	90.2	190	179	17	49.2	46.4
PPT	313	73.1	45	209	59	14.4	66.8
Water Harvesting	244	57.0	41	165	38	16.8	67.6
Vermiculture	160	37.4	11	149	0	6.9	93.1
Green housing	135	31.5	11	110	14	8.1	81.5
ISFM	127	29.7	43	84	0	33.9	66.1
Fallowing	119	27.8	32	87	0	26.9	73.1

4.1.2. Smallholder Farmer Demographics Characteristics and adoption of CSA in Kakamega County

The study included 428 respondents who had received training on various CSA practices, of which 182 (42.5%) were adopters and 246 (57.5%) were dis-adopters (Table 4.2). The smallholder CSA adopting farmers had sustainably adopted more than four CSA practices while the dis-adopters had either completely or partially abandoned most CSA practices.

Table 4.2: Demographic Characteristics of Smallholder farmers adopting CSA practices in Kakamega County

Variable	Frequencies		Farmer Type (no.)		Adoption Rate (%)	
	Respondents	Proportion (%)	Adopters	Dis-adopters	Adoption	Dis-adoption
Sample Size	428	100	182	246	42.5	57.5
Gender of the respondents						
Male	164	38.3	92	72	56.1	43.9
Female	264	61.7	90	174	34.1	65.9
Farmer's Age (in Years)						
Average Age	50.3					
≤ 35	57	13.3	11	46	19.3	80.7
36 – 45	106	24.8	47	59	44.3	55.7
46 – 55	115	26.9	52	63	45.2	54.8
56 – 65	87	20.3	45	42	51.7	48.3
≥66	63	14.7	27	36	42.9	57.1
Main farm decision maker						
Male	291	68.0	136	155	46.7	53.3
Female	137	32.0	46	91	33.6	66.4

4.1.2.1.Gender of the Smallholder CSA Farmers.

As depicted on Table 4.2 (above) the study respondents comprised 164 (38.3%) males and 264 (61.7%) females. The gender distribution of the sample size indicates that female smallholder farmers participated more on CSA technologies than male smallholder farmers. However, the female smallholder CSA farmers dis-adopted at a higher rate (65.9%) than their male counterparts (43.9%). This could be explained by male farmers having greater access to resources, land, and decision-making than female farmers. In addition, CSA adoption was higher (46.7%) when the main farm decision-maker was male, than when the main farm decision-maker was female (33.6%) (Table 4.1). Similar studies found that male smallholder farmers have greater access to resources, land, and decision-making than their female counterparts (Akudugu et al., 2012; Kamau et al., 2014; Mwangi & Kariuki, 2015). These findings are also consistent with those of Deressa et al. (2009)

who reported that male-headed households are more likely to adopt new agricultural technologies than female-headed households.

4.1.2.2.Gender of the household head

The gender of the household head influenced CSA technology adoption in the same way that the gender of the smallholder farmer influenced technology adoption. As shown on Table 4.2, male-headed households had a higher rate of technology adoption (47.4%) than female-headed households (32.1%). These findings imply that, while women are the most trained and capacity built on CSA technologies, they are not the main farm decision-makers or household heads and thus easily dis-adopt. This may be due to gender roles in the local culture, in which males perform more field work while females perform more household chores (Jayachandran, 2021).

Similar studies have found that male-headed households adopt new agricultural technologies than female-headed households. According to Akudugu et al (2012) and Deressa, et al. (2009), the gender of the household head indicates differential access to productive resources that are critical for the adoption of CSA technologies. Other scholars have found that male farmers often have better access to technologies and information thus have a positive influence on investment in sustainable agricultural technologies (Kamau et al., 2014; Mwangi & Kariuki, 2015). This gives the male farmers added advantage in CSA technology adoption than their female counterparts, and thus adopt more.

4.1.2.3. Relationship between Smallholder Farmers Age and Adoption of CSA in Kakamega County

Different farmer age groups had different farming experiences, information and interests which may have influenced their adoption of CSA technologies. Table 4.2 depicts smallholder CSA adoption among the different age groups. The rate of CSA technology adoption increased with age, peaking in the 56-65 age bracket. CSA technologies were least adopted (19.3%) by smallholder farmers under the age of 35.

These findings imply that agriculture may be unappealing to young people but appealing to the older generation. Chiputwa et al. (2010) and Deressa et al. (2009), found similar results, indicating that older farmers are more familiar with beneficial technologies and can thus easily adopt them. These findings, however, contradict those of Bryan et al. (2009) who found no effect of age on climate change adaptation through agricultural technology adoption. According to other studies, young farmers are more willing to adopt new CSA technologies than older farmers (Abdulai & Huffman, 2005; Moges & Taye, 2017; Tiamiyu et al., 2009). According to these studies, older farmers have shorter planning horizons and are more hesitant to invest in technologies that take a long time to reap benefits.

4.1.2.4. Relationship between Age and Land Ownership among CSA farmers in Kakamega County

Land ownership increased with farmer age. As shown on Table 4.3, only 77.2% of respondents aged 35 and under, owned land compared to 100% of those aged 66 and up. It could, therefore, be argued that land ownership encourages smallholder farmers to invest in and adopt CSA technologies. The lack of land ownership among young people may also explain why they are less interested in agriculture, particularly CSA technologies. Similar studies have found that land tenure has a significant influence on the adoption of CSA practices such as planting date, crop diversification, and crop rotation (Fosu-Mensah et al., 2012). According to Fosu-Mensah et al. (2012), farmers who own land have the incentive to invest in their farms, whereas those who lease farmland have lower profits, influencing adoption of CSA technologies negatively.

Table 4.3: Relationship between Age and Land Ownership among CSA farmers in Kakamega County

Age Bracket (Years)	Respondents (No.)	Land Ownership (No)	Proportion (%)
≤35	57	44	77.2
36 – 45	106	100	94.3
46 – 55	115	110	95.7
56 – 65	87	84	96.6
≥66	63	63	100.0

4.1.2.5. Highest level of education completed by the household head and adoption of CSA in Kakamega County

Most respondents who were household heads (70.8%) had completed at least primary school (9.3% tertiary, 25.5% secondary and 36% primary school), and 34.8% had completed at least secondary school (9.3% tertiary education and 25.5% secondary school). Only a few household heads (9.3%) had completed tertiary education. The highest level of education completed by the household head was had an inverse relationship with CSA adoption rates. As shown on Table 4.4, respondents whose household heads had completed tertiary education had higher rates of technology adoption (65%) whereas the respondents whose household heads had not completed primary school had lower (30.4%) technology adoption rates.

It could be argued, therefore, that education improves understanding of training instructions and increases access to necessary information. Yirga & Hassan (2008), found similar results, arguing that education provides a better understanding of ideas, and thus households with higher levels of education adopt CSA technologies more than households with lower levels of education. Other studies by Messer & Townsley (2003), show that an educated farmer makes the best use of scarce resources and composts a large portion of their waste. These findings, however, contradict those of Bryan et al. (2009), who found no significant effect of the household head's level of education on climate change adaptation measures.

Table 4.4: Relationship between the highest level of education completed by the Household Head and adoption of CSA in Kakamega County

Variable	Frequencies		Farmer Type (no.)		Adoption rate (%)	
Highest level of education completed	Respondents	Proportion (%)	Adopters	Dis-adopters	Adopters	Dis-adopters
Completed Tertiary	40	9.3	26	14	65.0	35.0
Completed Secondary	109	25.5	60	49	55.0	45.0
Completed Primary	154	36.0	58	96	37.7	62.3
Not Completed Primary	125	29.2	38	87	30.4	69.6

4.1.2.6. Effect of Support by funding agencies on adoption of CSA in Kakamega County

A little more than a third (35.3%) of the respondents received assistance from CSA-promoting NGOs while 64.7% did not. This assistance was in form of monetary assistance, climate information, extension information, and training. Such incentives allowed smallholder farmers to obtain inputs such as desmodium seeds and irrigation equipment that are otherwise out of reach for most smallholder farmers due to their prohibitive cost. As shown in Table 4.5, respondents who were supported by NGOs adopted more (53.6%) than those who were not. It is possible that smallholder CSA farmers were more interested in monetary and material support from NGOs than in the benefits of CSA technologies, and thus dis-adopt after CSA promoting programs end. This view is supported by Tanti, et al. (2022) who opine that NGOs and other supporting organizations support farmers in various ways including training and follow-up SMSs thus increasing adoption rates. Other studies by Vincent and Balasubramani (2021) indicate that NGOs support the testing and scaling up of CSA technologies by providing extension advisory services through such models as participatory approaches and climate field schools. Given the role of NGOs in promoting CSA technologies, coming to an end of CSA projects that are supported by NGOs leads to the disadoption of the practices (Khoza et al., 2022). For sustainable adoption of CSA technologies, the selection of participants in the donor and NGO-funded CSA initiatives should, therefore, be data-driven gauging from the individual farmer's biophysical and socio-economic characteristics.

Table 4.5: Effect of Support by funding agencies on adoption of CSA in Kakamega County

Variable	Frequencies		Farmer Type (no.)		CSA Adoption Rate (%)	
Response	Frequencies	Proportion (%)	Adopters	Dis-adopters	Adoption	Dis-adoption
Yes	151	35.3	81	70	53.6	46.4
No	277	64.7	101	176	36.5	63.5

4.1.3. Farmer CSA Characteristics in relation to CSA practices

4.1.3.1. Major agricultural information sources

Extension officers; public *barazas* and field days; and radios and televisions were the top three sources of agricultural information for respondents, accounting for 72.9%, 62.1%, and 56.5%, respectively (Table 4.6). These findings suggest that most respondents obtain agricultural information from CSA technology-promoting organization trainers who collaborate with extension officers to organize public *barazas* and farmers' field days. Respondents who used the internet to obtain agricultural information, however, adopted more (59.1%), than those who received agricultural information from the other sources such as radios and televisions (46.7%), extension officers (44.9%), public *barazas* and field days (48.5%) and newspapers (48.8%). It could be argued that having access to the internet puts smallholder farmers in a better position to access agricultural information and other services at any given time and location, influencing adoption. Similar results were reported by Kurgat et al. (2020) who report that the farmers with internet connectivity are able to get information on new technologies as compared to their counterparts who do not have internet connectivity.

Table 4.6: Major Sources of Agricultural Information and adoption of CSA in Kakamega County

Variable	Frequencies		Farmer Type (no.)		CSA Adoption Rate (%)	
Source of Agric Information	*Respondents*	*Proportion (%)*	*Adopters*	*Dis-adopters*	*Adopters*	*Dis-adopters*
Internet Sources	22	5.1	13	9	59.1	40.9
Radios & T.V.	242	56.5	113	129	46.7	53.3
Extension Officers	312	72.9	140	172	44.9	55.1
Public *Barazas* & Field Days	266	62.1	129	137	48.5	51.5
Newspapers	80	18.7	39	41	48.8	51.3

4.1.3.2.Access to information and communication technology devices and adoption of CSA in Kakamega

Information and communication technology devices increase smallholder farmers' access to agricultural information, resulting in better farming practices. Radios were the most accessible ICT devices to 90.7% of respondents, followed by basic mobile phones at 51.9%. Less than half of the respondents (43.7%) had access to televisions. Smartphones and tablets were only accessible to 20.1% of the respondents while 1.6% had access to computers (see Table 4.7). In terms of adoption of CSA technologies, however, farmers with smart devices had higher adoption rates (50%) followed by those with televisions (49.2%). Although the majority had radios and basic mobile phones, these did not significantly affect the adoption rates.

Access to and ownership of ICT devices may, therefore, influence the adoption of CSA technologies among smallholder farmers. Studies conducted on the role of ICT devices in agricultural technology adoption indicate that they assist farmers to stay updated with recent information including weather information and better ways of agricultural production to improve quality and productivity (Cropin, 2022). According to Saidu et al. (2017), ICTs facilitate agricultural growth through the improvement of market activities, the exchange of information, and networking with other global players. As noted by Saidu et al. (2017), however, poor internet connectivity, insufficient power supply and lack of basic ICT skills among rural farmers hinder the successful reaping of the fruits of ICT application in rural agricultural activities.

Table 4.7: Ownership of ICT Devices and the adoption of CSA in Kakamega County

Ownership of ICT Devices			Adopters/Dis-adopters (No.)		Adoption/Dis-adoption Rate (%)	
ICT Device	Frequencies	Proportion (%)	Adopters	Dis-adopters	Adopters	Dis-adopters
Radio	388	90.7	163	225	42.0	58.0
Television	187	43.7	92	95	49.2	50.8
Basic Mobile Phone	222	51.9	99	123	44.6	55.4
Smart Devices	86	20.1	43	43	50.0	50.0
Computer	7	1.6	3	4	42.9	57.1
None	5	1.2	2	3	40.0	60.0

4.1.3.3. Smallholder Farmers' Farming Experience and adoption of CSA in Kakamega County

Smallholder farmers adoption of CSA technologies increased with years of farming experience (Figure 4.4). It could be argued that more experienced farmers have a better chance of selecting the right technologies and thus making informed farming decisions. Farmers with less farming experience, on the other hand, may be unsure about the best technologies for their farms, resulting in higher rates of dis-adoption.

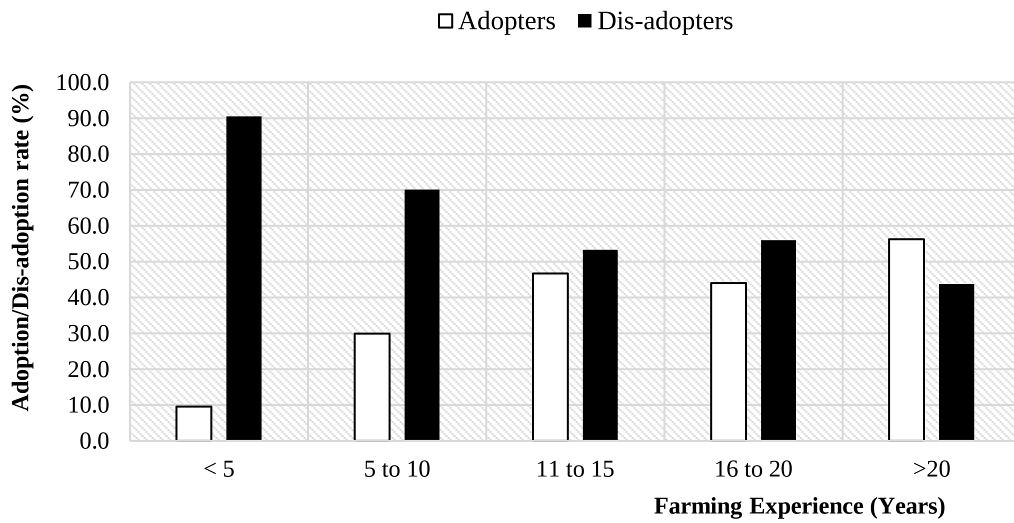


Figure 4.1: Farming Experience and the adoption of CSA in Kakamega County

These findings are in agreement with those of Fosu-Mensah et al. (2012), who reported that farming experience increased the likelihood of CSA technology adoption because farmers have a wealth of knowledge and information on climatic changes and the best crop management practices to implement. Other studies, such as those conducted by Israr et al. (2020), support this viewpoint by demonstrating that farmers with more farming experience are more knowledgeable about weather patterns and their implications for crop production, resulting in a high rate of adoption.

4.1.4. General Farm Characteristics and Group Information

4.1.4.1. Relationship between Average Land Size and adoption of CSA in Kakamega County

It has been established that the respondents with larger farm sizes adopted CSAs more than farmers with smaller land sizes. From Table 4.8, the average land size in the study area was 1.88 acres with a standard deviation of 1.39. The results of the study, further, indicate that respondents with farm sizes between three and four acres had higher CSA technology adoption rates (66.7%) than those with land sizes less than or equal to one acre (33.9%). This finding implies that land size is an important factor to consider when promoting the adoption of CSA technologies. Smallholder farmers with larger land holdings may have more space to experiment with new technologies than farmers with smaller land holdings. However, smallholder farmers with very large land holdings may have already committed their land to other enterprises and are unwilling to adopt the new CSA practices. These findings are consistent with those of Fosu-Mensah, et al. (2012) who found that smallholder farmers with small land sizes are less likely to adopt CSA technologies due to the high fixed costs and the uncertainty associated with such technologies. Regarding the smallholder farmers with very large farmlands, these findings, agree with those of Maguza-Tembo, et al. (Maguza-Tembo et al., 2017) who argue that an increase in land ownership entails an introduction of additional costs to the farmer which they may fail to cover given their resource base and thus low adoption rates.

Table 4.8: Relationship between land size and adoption of CSA in Kakamega County

Variable	**Frequencies**		**Farmer type (No)**		**Adoption rate (%)**	
	Respondents (no)	**Proportion (%)**	**Adopters**	**Dis-adopters**	**Adopters**	**Disadopters**
≤1	168	39.3	57	111	33.9	66.1
1.1-2	134	31.3	55	79	41.0	59.0
2.1-3	84	19.6	44	40	52.4	47.6
3.1-4	21	4.9	14	7	66.7	33.3
> 4	21	4.9	12	9	57.1	42.9
$\bar{X} = 1.88$						
$\sigma = 1.39$						

4.1.4.2.Land tenure system and the adoption of CSA technologies in Kakamega County

As shown in Table 4.9, a significant number (93.7%) of the respondents owned land but only 42.2% had title deeds. Those who did not own land farmed on leased farmland or on farms to which they had been granted rights but did not own. All (100%) of those who leased farmland disadopted CSA technologies. This could be attributed to leased lands' lack of ownership and decision-making ability. Furthermore, lands are leased for shorter periods, such as one year, preventing lessees from investing in such technologies. Secure land tenure encourages adoption of CSA practices such as Agroforestry and SWC practices. These findings are consistent with many studies that find that land ownership influences the adoption of CSA practices (Dlamini, 2020; Foresta, 2013). According to Bryan, et al. (2009), smallholder farmers with land ownership have the incentive to invest in their farms while those with leasing farmlands record lower profits thus negatively influencing their adoption of CSAs.

Table 4.9: Land tenure system and adoption of CSA in Kakamega County

Variable		**Frequencies**		**Adoption rate (%)**	
Land Tenure		***Respondents (no)***	***Proportion (%)***	***Adopters***	***Disadopters***
Type of land ownership	Owned	401	93.7	42.9	57.1
	Leased	5	1.2	0.0	100.0
	Rights to farm	22	5.1	45.5	54.5
Title Deed Held	Yes	173	40.4	42.2	56.1
	No	255	59.6	42.7	57.3

4.1.4.3.Main Livestock Reared and the adoption of CSA in Kakamega County

Most of the smallholder CSA farmers reached were mixed farmers who grew a wide range of crops and reared different livestock (Table 4.10). While indigenous poultry was reared by a sizeable proportion of the respondents (65.4%), exotic poultry was reared by a small proportion (7.7%). Crossbreed cows and local cows were the other major livestock reared by 49.5% and 32.7% of the respondents, respectively. Respondents with high value livestock such as pure dairy cows, dairy goats, or exotic poultry had higher adoption rates than those with lower value livestock such as meat goat, sheep, indigenous poultry, and other livestock such as rabbits and ducks.

These findings contradict many studies that focus on the number of livestock rather than the value of the livestock reared. Studies by Nigussie et al. (2015), for example, showed that smallholder farmers with a larger number of animals fed crop residues to their animals, preventing the adoption of CSA technologies. Moreover, Mugwe et al. (2009) discovered that farmers with fewer or no mature cattle were more likely to adopt new CSA technologies than farmers with many mature cattle.

Table 4.10: Relationship between Main Livestock reared and adoption of CSA in Kakamega County

Variable	**Respondents**		**Farmer Type (no.)**		**CSA Adoption Rate (%)**	
Major Livestock	Frequencies	Proportion (%)	Adopters	Dis-adopters	Adopters	Dis-adopters
Dairy Cow	72	16.8	36	36	50.0	50.0
Crossbreed Cow	212	49.5	93	119	43.9	56.1
Local Cow	140	32.7	65	75	46.4	53.6
Oxen	36	8.4	17	19	47.2	52.8
Dairy Goats	43	10.0	22	21	51.2	48.8
Meat Goats	28	6.5	11	17	39.3	60.7
Sheep	80	18.7	33	47	41.3	58.8
Pigs	62	14.5	29	33	46.8	53.2
Local Poultry	280	65.4	118	162	42.1	57.9
Exotic Poultry	33	7.7	17	16	51.5	48.5
Other Livestock	27	6.3	11	16	40.7	59.3

4.1.4.4. Interaction with Agricultural Officers and adoption of CSA in Kakamega County

This study investigated the interactions between respondents and agricultural officers as extension plays a significant role in promoting CSA practices. Table 4.11 shows that respondents who had their most recent interaction with agricultural officers within the previous year had higher CSA adoption rates (47.1%) followed by those with between 1 and 2 years (41.4%) while those with between 2 and 5 years had 27.3%. The respondents who interacted with agricultural officers more than five years ago had the least CSA adoption rate (16.7%). It could be argued, therefore, that frequent contact with agricultural officers allows farmers to gain access to agricultural information and modern farming technologies required for CSA technology adoption. Furthermore, frequent contact with agricultural officers indicates increased access to government services such as subsidized farm inputs, grants, and other farmer support systems thus higher CSA adoption rates.

Table 4.11: Interaction with extension officers and the adoption of CSA

Variable	CSA Adoption Rate (%)	
Last interaction with extension officers (years)	Adopters	Dis-adopters
<1	47.1	52.9
1 – 2	41.4	58.6
2 – 5	27.3	72.7
>5	16.7	83.3

These findings are consistent with those of Danso et al. (2006), who reported that farmers with access to extension services were more willing to participate in CSA technologies because the extension services raised farmers' awareness of the benefits. Other studies by Roncoli et al. (2010) found that access to extension service providers not only helps farmers with technical training but also with group formation and institutional mechanisms that allow for better distribution of government aid and services. Studies by Oladele (2005), found that a lack of visits to CSA-adopting farmers by extension service providers resulted in the discontinuation of the technologies' adoption.

4.1.4.5.Relationship between formal employment and adoption of CSA in Kakamega County

This study investigated the impact of formal employment on the adoption of CSA technologies in the study area. Table 4.12 illustrates the different CSA adoption rates among respondents who had household members in formal employment and those that did not. Most respondents (75.7%) did not have household members in formal employment, while a small proportion (24.3%) did. Respondents from households with members in formal employment had higher adoption rates (48.1%) than those who did not (40.7%).

These findings imply that formal employment may influence CSA adoption. It could be argued that formal employment encourages households to adopt CSA technologies because regular income increases the household's ability to obtain necessary farm inputs. These findings contradict those of Antwi and Antwi-Agyei (2023) who opine that farmers with a choices for non-farming livelihoods are not likely to adopt CSA practices on their farms

Table 4.12: Relationship between formal employment and adoption of CSA in Kakamega County

Variable	**CSA Adoption Rate (%)**	
Are there members of this household who are in formal employment?		
Response	Adopters	Dis-adopters
Yes	48.1	51.9
No	40.7	59.3

4.1.4.6.Main sources of household income and adoption of CSA in Kakamega County

The main sources of household income were farming, business, casual labour, formal employment, and remittances. As shown on Table 4.13, households with employment as their main source of income had a higher CSA adoption rate (54.1%) than households who had other activities as their main source of income. It could be argued, therefore, that regular income from employment increases a household's ability to purchase necessary farm inputs as well as modern agricultural technologies and equipment, assisting in the adoption of CSA technologies. This finding contradicts that of Abegunde et al. (2019) who opine that a robust alternate revenue stream, such trading, handwork, cleaning and remittances, could lead to an apathetic attitude towards agricultural productivity.

Table 4.13: Relationship between Sources of household income and adoption of CSA in Kakamega County

Variable	CSA Adoption Rate (%)	
Main Source of Household Income	**Adopters**	**Dis-adopters**
Farming	42.7	57.3
Employment	54.1	45.9
Remittances	42.9	57.1
Business	38.8	61.2
Casual Labour	38.6	61.4

4.1.4.7.Household level of monthly income and adoption of CSA in Kakamega County

Majority 45.3% of the respondents earned less than KES. 5,000 followed by those who earned between KES. 5001 and 10,000. However, as illustrated in Table 4.14, respondents from households earning between KES 10,000 and 20,000 per month had a higher adoption rate (54.7%) as compared to those earning less than KES. 5,000 per month (32%). These findings imply that households with higher incomes had more resources to invest both in farming and other activities. CSA practices may require investments in farm inputs, labour and other services which would be out of reach of households with lesser incomes. These findings are consistent with those of Sardar et al. (2021) who opine that higher resource endowment enables smallholder farmers to adopt more measures to mitigate the adverse effects of climate change.

Table 4.14: Level of monthly income and the adoption of CSA in Kakamega County

Variable	CSA Adoption Rate (%)	
Monthly Income (KES)	**Adopters**	**Dis-adopters**
≤5,000	32.0	68.0
5,001- 10,000	48.1	51.9
10,000 - 20,000	54.7	45.3
>20,000	53.3	46.7

4.1.4.8. Smallholder farmer access to agricultural credit and adoption of CSA in Kakamega County

Access to agricultural credit is an important consideration when farming profitably. According to the findings of this study, more than half (58.9%) of the respondents did not have access to agricultural credit. The low access to agricultural credit could be attributed to the high interest rates on loans and the lack of collateral by most smallholder farmers. As shown in Table 4.15, there were higher CSA adoption rates (48.9%) among the respondents who had access to agricultural credit as compared to those who did not (38.1%). These findings are similar to those of Sardar et al. (2021) who found that lower interest rates motivates farmers to invest more and save more money in order to implement CSA. Other studies by Makate et al. (2019) indicate that a farmer's ability to obtain credit enhances their economic prospects and is the primary means by which they can obtain essential supplementary inputs for CSA such as seed and fertilisers.

Table 4.15: Smallholder farmer access to agricultural credit and adoption of CSA in Kakamega County

Variable	Frequencies		Farmer Type (no.)		CSA Adoption Rate (%)	
Do you have access to credit?	Respondents	Proportion (%)	Adopters	Dis-adopters	Adopters	Dis-adopters
Yes	176	41.1	86	90	48.9	51.1
No	252	58.9	96	156	38.1	61.9

4.1.4.9. Group Membership

This study established that close to all (96.9%) of the respondents were members of agricultural groups (Table 4.16). It was, further, established that CSA technology adoption rates were higher (43.9%) among respondents in groups than among those who were not (6.2%).

Table 4.16: Group membership, involvement, and Leadership and adoption of CSA in Kakamega County

Variable	Respondents		Farmer Type (no.)		CSA Adoption Rate (%)	
Group Membership	**Frequencies**	**Proportion (%)**	**Adopters**	**Dis-adopters**	**Adopters**	**Dis-adopters**
Yes	412	96.3	181	231	43.9	56.1
No	16	3.7	1	15	6.2	93.8
Type of group						
Agricultural	400	96.9	181	219	45.3	54.8
Non-agricultural	13	3.1	1	12	7.7	92.3
Level of Involvement in Group Activities						
Active: 1	277	67.2	133	144	48.0	52.0
Active: 2	121	29.4	47	74	38.8	61.2
Passive: 1	13	3.2	1	12	7.7	92.3
Passive: 2	1	0.2	0	1	0.0	100.0
Group Leadership Position						
Chairperson	49	11.9	34	15	69.4	30.6
Vice Chairman	10	2.4	4	6	40.0	60.0
Secretary	32	7.8	17	15	53.1	46.9
Treasurer	22	5.3	13	9	59.1	40.9
Other Position	50	12.1	26	24	52.0	48.0
No position	249	60.4	87	162	34.9	65.1

Note. Active 1: Always involved; Active 2: sometimes involved; Passive 1: Aware of group activities but not involved; Passive 2: Not aware of group activities and not involved

The adoption rate of CSA technology was higher (48%) among active group members and lower (7.7%) among passive group members. This could be explained by the fact that active group members are more likely to be exposed to current information on good agricultural practices through such activities as agricultural training, demonstrations, and financial literacy capacity-building activities. Passive members, on the other hand, may not participate in most group activities and thus miss capacity building and group credit and therefore they dis-adopt more.

These findings are similar to those of Chepchirchir, et al. (2016) who found a positive correlation between a farmer's group membership and adoption of CSA technologies. They attribute higher adoption rate among group members to sharing of information, participating in field days, and having access to agricultural extension providers. Other literature by Kassie et al. (2013) argue that groups are a type of social capital that facilitates the exchange of information, allows farmers to access inputs on time, and assists them in overcoming credit constraints and shocks.

As shown in Table 4.16, group members who held chairperson positions had a higher CSA adoption rate (69.4%), whereas those who did not hold any leadership positions had a high dis-adoption rate (65.1%). While the respondents who held Vice-Chairperson positions in their groups had higher CSA technology adoption rates than regular farmers, this study finds that farmers in Vice-Chairperson positions had a lower adoption rate (40%) than respondents holding other group leadership positions. These findings may be explained by the role of group dynamics in the promotion and implementation of CSA technologies. As a result, it could be argued that group leaders have greater access to agricultural training, group loans, demonstration materials, and demonstration fields than other group members. It is also possible that group leaders have a higher level of education and income than their peers, resulting in higher rates of adoption.

4.1.4.10. CSA Farmer Categorization

Smallholder CSA farmers are organized to facilitate training, demonstrations, and capacity building, as shown in Table 4.17. On the one hand, lead farmers are typically group leaders who provide a demonstration plot for group members to learn about various CSA technologies. Follower farmers, on the other hand, are mostly other group members who learn from the demonstration plot in the hopes of implementing the technologies learned on their farms.

Table 4.17: Smallholder farmer categorization and adoption of CSA in Kakamega County

Variable	Respondents		Farmer Type (no.)		CSA Adoption Rate (%)	
Farmer Category	Frequencies	Proportion (%)	Adopters	Dis-adopters	Adopters	Dis-adopters
Follower Farmer	349	81.5	118	231	33.8	66.2
Lead Farmer	79	18.5	64	15	81.0	19.0

This study found that lead farmers had higher CSA adoption rates (81%) while follower farmers had lower CSA adoption rates (33.8%). Similar findings by Maguza-Tembo, et al. (2017) indicate that being a lead farmer increases the probability of adopting CSA practices by implying that the farmer category may influence CSA technology adoption. In addition, lead farmers may be given demonstration materials and other types of assistance on behalf of their groups, incentivizing them to adopt more than regular group members. This view is supported by Kadzamira and Ajayi (2019) who report that the lead farmer is the main contact for CSA promotion, they are given materials and they train other farmers in their locality.

4.1.5. Identification of Drivers of CSA Adoption - Correlation Analysis

This study sought to identify the factors that influence the adoption of CSA practices in Kakamega County. Pearson correlation coefficients were used to identify the factors associated with farmers adoption of CSA practices. It is, however, acknowledged that association does not imply causation. Table 4.18 shows the variables that were found to have a significant correlation at the 0.05 and 0.01 levels (2-tailed). P values were used to measure the significance of the variables.

The main drivers of CSA adoption as identified by this study include being a member of a farmers' group, being a group leader and possibly a lead farmer. This may be occasioned by the access to training and productive resources thus higher CSA adoption rates. The gender of the farmer was also a major driver with higher adoption rates found among male farmers than female farmers. This may be associated with access to productive resources, decision making and access to education and training. Other major drivers include land ownership, household income and access to agricultural credit. This increases the household productive resources and thus higher CSA adoption rates. Finally, support from CSA promoting NGOs and education level played a major role in the adoption of CSA technologies. Climate-smart agriculture technologies in Kakamega are mainly promoted by development partners and therefore access to NGO support goes a long way to increase CSA adoption.

The findings of this study indicate that practicing CA is a major node for CSA adoption. The smallholder farmers who sustainably adopted CA were also found to have sustainably adopted other CSA technologies. The CSA practices in their order of importance are CA, SWC, PPT, composting, small-scale water harvesting , vermiculture and agroforestry.

Table 4.18 Variable Importance (P Values) in adoption of CSA in Kakamega County

Variable Code	Variable	Correlation	P-Values	Variable Code	Variable	Correlation	P-Values
V17	Radio & TV	-.096*	0.047	V103	Group membership	.145**	0.003
V25	Computer	-.098*	0.043	V68	Solar Radio owned	-.148**	0.002
V44	ISLM/ISFM Trained	-.098*	0.043	V121	Ext. officer interaction	.152**	0.002
V48	CSA Organization	.099*	0.041	V18	Barazas	-.155**	0.001
V144	G/House abandoned	.099*	0.040	V29	Bicycle owned	-.159**	0.001
V50	Year Trained	.106*	0.029	V58	Land Size	-.161**	0.001
V133	Farming	-.106*	0.028	V41	Agroforestry Trained	-.162**	0.001
V130	Access to agric. credit?	.107*	0.027	V28	W/Barrow owned	-.163**	0.001
V38	SWC Trained	-.107*	0.027	V34	NGO Support?	.166**	0.001
V135	Other HH Activities	-.107*	0.026	V164	Agroforestry practised	-.166**	0.001
V143	ISLM/ISFM abandoned	.108*	0.026	V115	The Main Group activity is Farming	-.170**	0.000
V120	Agric credit	-.110*	0.023	V146	Vermiculture abandoned	.174**	0.000
V107	Left Group	.111*	0.022	V129	HH Monthly income	-.183**	0.000
V43	G/House Trained	-.112*	0.020	V141	PPT Abandoned	.193**	0.000
V169	Fallowing Practised	.115*	0.018	V10	Education	-.193**	0.000
V77	G/Nuts grown	-.115*	0.018	V168	Vermiculture Practised	-.197**	0.000
V40	PPT Trained	-.116*	0.016	V4	Sex	.216**	0.000

V22	TV Owned	-.119*	0.014	V49	Farming Experience	.216**	0.000
V47	Mulching Trained	-.119*	0.014	V6	Marital	.217**	0.000
V104	Reason not in a group	.120*	0.013	V140	SWC Abandoned	.235**	0.000
V76	Soybean grown	-.122*	0.011	V145	Composting Abandoned	.250**	0.000
V5	Age	-.124*	0.010	V167	W/Harvesting Practised	-.276**	0.000
V112	Position held	.125**	0.010	V163	Composting practised	-.304**	0.000
V134	Sch. Fees	-.125**	0.010	V139	W/Harvesting abandoned	.322**	0.000
V8	Decision Maker	.128**	0.008	V162	PPT Practised	-.327**	0.000
V75	Cassava grown	-.129**	0.008	V136	Abandoned CSA Practices?	-.341**	0.000
V80	Fruit Trees Grown	-.137**	0.004	V161	SWC Practised	-.344**	0.000
V119	Agric Trainings	-.139**	0.004	V51	Farmer Category	.370**	0.000
V37	CA Trained	-.141**	0.004	V138	CA Abandoned	.429**	0.000
V165	ISLM/ISFM Practised	-.143**	0.003	V160	CA Practised	-.549**	0.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

4.2. Objective 2: To develop a suitable data-driven model for the deployment and adoption of CSA practices among smallholder farmers in Kakamega County

4.2.1. Modelling Variables Selection

The study yielded 549 variables (See Appendix B). The variables were then defined as the Y and X variables. The adoption/dis-adoption of CSA technology (Y) was dependent on several independent variables (X), including land ownership, access to training, and membership in farmers' organizations, among others. The variables that were found to have a significant correlation at the 0.05 and 0.01 levels (2-tailed) in Objective 1 were identified and used in ML Model.

4.2.2. Modelling for CSA Adoption

Decision tree Classifier and Random Forest Classifier Models for the Prediction of Adoption or Dis-adoption of CSA Practices were considered for prediction and behaviour analysis **(See Appendix C).** In the primary data collection exercise, 182 smallholder CSA farmers were adopters while 246 were dis-adopters. The ML Model predictions were compared with these actual values to determine their predictive accuracy. **Appendix D shows the results of this Comparison.**

4.2.3. Model Evaluation

The models were evaluated using the following metrics:

4.2.3.1. Confusion Matrix.

The confusion matrix was used to visualize the performance of the ML Algorithms. As shown in Table 4.19 below, the Decision Tree Classifier gave 45 True positives, 11 False Positives, 7 False negatives and 66 True Negatives. This gives a prediction accuracy of

86.05%. The Random Forest Classifier gave 45 True positives, 13 False Positives, 7 False negatives and 64 True Negatives, giving a prediction accuracy of 84.50%.

Table 4.19: Decision Tree and Random Forest Classifier Models Evaluation using Confusion Matrix

		Decision Tree Classifier			***Random Forest Classifier***	
		Predicted Values			*Predicted Values*	
		Adopter	Dis-adopter		Adopter	Dis-adopter
Actual	Adopter	45 (TP)	7 (FN)	Adopter	45(TP)	7 (FN)
Values	Dis-adopter	11 (FP)	66 (TN)	Dis-adopter	13(FP)	64 (TN)

4.2.3.2.Model AUC-ROC graphs.

Figure 4.2 (below) depicts the model AUC-ROC graphs. This metric was used to find the area under the ROC curve. A larger area under the curve indicates that the algorithm gives high recall and precision values. According to Vujović (2021), AUC-ROC Score indicates a model's ability to rank predictions with the best score being 0.9 and the worst being 0.5. The models under review produced AUCs of 0.89 and 0.91 under the Decision Tree Classifier and Random Forest Classifier, respectively. This metric implies that the models produced the best scores indicating good measure of separability.

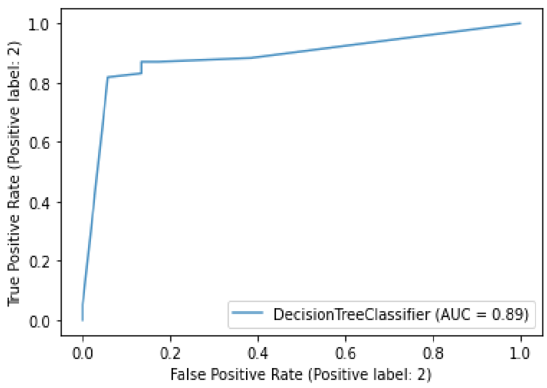
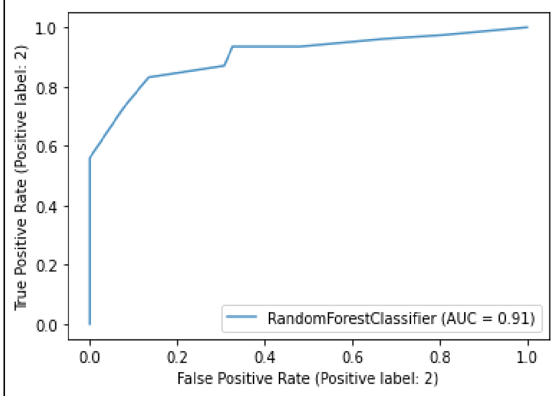
<table>
<tr><th>Decision Tree Classifier</th><th>Random Forest Classifier</th></tr>
<tr><td>
</td><td>
</td></tr>
</table>

Figure 4.2: AUC-ROC graphs

4.2.3.3.Training Accuracy.

Training accuracy is the resultant model accuracy given when the model is applied to the training data. This implies that the model is tested on the examples it was constructed on. The model was trained on 70% of the data and had a training accuracy of 94.3% and 99.6% for the decision tree and random forest classifiers respectively. These results imply that the model could predict accurately a high number of smallholder CSA farmers.

4.2.3.4.Prediction Accuracy.

This is given by the ratio of the variables that are correctly predicted to the number of times the variables have been predicted in total. Prediction accuracy is the accuracy of the model on data it has not seen before. The model prediction accuracy was tested on 30% of the data. The prediction accuracy was 86% and 84.5% for the decision tree and random forest classifier, respectively. According to Vujović (2021), the best accuracy is 1 (100%) while the worst is 0. The prediction accuracy results of the models, therefore, indicate that the model have high prediction ability given that the testing data was completely new to it.

4.2.3.5.Precision.

Precision is a measure of correctly predicted positive observations divided by the total number of predicted positive observations. Decision Tree Precision was calculated by TP/(TP+FP) = 45/(45+11)x100 = 80.357%. Random Forest Precision was calculated by TP/(TP+FP) = 45/(45+13)x100 = 77.586% (Table 4.69). According to Vujović (2021), the best model precision is 1 while the worst is 0.0. These model precisions are close to 1 implying that that the models have good prediction ability.

4.2.3.6.Recall.

The Model Recall implies how well the model was able to correctly predict all possible positive observations. In other words, Recall is the proportion of actual positives identified correctly. Recall = TP/(TP+FN) = 45/(45+7) = 86.538 As illustrated on Table 4.69 below, the model had a Recall of 0.86 for both decision tree classifier and random forest classifier. According to Vujović (2021), the best model Recall is 1 and the worst is 0.0. The scores of the classifier models are close to 1 implying that the models could accurately predict positive events.

4.2.3.7.Specificity.

Specificity is the ability of the model to identify smallholder CSA adopters. The Model evaluation gave a specificity of 0.865 for both the decision tree and random forest classifiers. Decision tree specificity score is given by TN/(TN+FP) = 66/ (66+11)x100 = 85.71% while that of the random forest is 83.11% (64/ (64+13)x100 = 83.12%). According to Vujović (2021), the best specificity score is 1 while the worst is 0.0. These results imply that the model could accurately predict a significant number of the smallholder CSA adopting and disadopting farmers.

4.2.3.8.F1 Score.

F1 Score implies the overall model performance. F1 Score is given by 2x (Precision x Recall) / (Precision + Recall). An F1 score above 0.9 is interpreted as a very good score for the model, while a score between 0.8 and 0.9 is interpreted as good. According to Vujović (2021), an F1 score between 0.5 to 0.8 is deemed OK while the one below 0.5 is deemed not good. From Table 4.20, this model had an F1 score of 0.833 and 0.818 for the decision tree classifier and random forest classifier, respectively. These results imply that the model is a good one in predicting smallholder CSA farmer ability to adopt or dis-adopt CSA technologies.

Table 4.20: Model Metrics

Metric	Decision Tree Classifier	Random Forest Classifier
Training Accuracy	0.9431438127090301	0.9966555183946488
Prediction Accuracy	0.8604651162790697	0.8449612403100775
Precision / Sensitivity	0.8035714285714286	0.7758620689655172
Recall	0.8653846153846154	0.8653846153846154
Specificity	0.8571428571428	0.83116883116883
F1- Score	0.8333333333333334	0.8181818181818181
AUC – ROC	0.89	0.91

4.2.3.9.Classification Report.

A Classification report was used to measure the quality of predictions from a classification algorithm in terms of how many predictions were true and how many predictions were wrong. Table 4.21, below, depicts the model classification report.

Table 4.21: Model Classification Report

	Decision Tree Classifier				Random Forest Classifier			
	Precision	*Recall*	*F1-Score*	*Support*	*Precision*	*Recall*	*F1-Score*	*Support*
Adopt	0.80	0.87	0.83	52	0.78	0.87	0.82	52
Dis-Adopt	0.90	0.86	0.88	77	0.90	0.83	0.86	77
Accuracy			0.86	129			0.84	129
macro avg	0.85	0.86	0.86	129	0.84	0.85	0.84	129
weighted avg	0.86	0.86	0.86	129	0.85	0.84	0.85	129

4.2.4. Computing Model Accuracy

Several approaches were used to calculate the accuracy of the classification and regression model. These approaches are the following:

4.2.4.1.Mean Absolute Error (MEA) Approach.

As indicated in Table 4.22, this model had MEAs of 0.13953488372093023 and 0.15503875968992248 for the Decision Tree Classifier and Random Forest Classifier, respectively. This implies that this model had only a few errors.

4.2.4.2.Mean Squared Error (MSE) approach.

As indicated in Table 4.22, this model had MSEs of 0.13953488372093023 and 0.15503875968992248 for the Decision Tree Classifier and Random Forest Classifier, respectively. This implies that this model had only a few errors.

4.2.4.3.Root Mean Squared Error (RMSE).

As depicted in Table 4.22, the RMSEs for the Decision Tree Classifier and Random Forest Classifier were 0.3735436838188142 and 0.3937496154790789, respectively.

4.2.4.4.Accuracy.

As depicted in Table 4.22, the Accuracy Values for the Decision Tree Classifier and Random Forest Classifier were 90.31% and 89.53%, respectively. These results indicate that the model has high accuracy and is therefore a good model to predict the adoption and dis-adoption of CSA technologies among smallholder farmers in Kakamega County.

Table 4.22: Model Accuracy using different approaches

Approach	Explanation	Decision Tree	Random Forest
Mean Absolute Error	Sum of absolute errors divided by the sample size	0.14	0.16
Mean Squared Error	Average squared difference between the estimated values and the actual value	0.14	0.16
Root Mean Squared Error	Standard deviation of the prediction errors	0.37	0.39
Accuracy		90.31%	89.53%

4.2.4.5.Plotting the Actual vs Predicted Values.

The actual and predicted values were plotted together for visualizing and analysing how the actual data correlate with those predicted by the model. As depicted in Figure 4.3 below, the plots displayed identical distributions both for the decision tree classifier and the random forest classifier. These plots further imply that the model could accurately predict the adoption or dis-adoption (V12).

Decision Tree Classifier	Random Forest Classifier

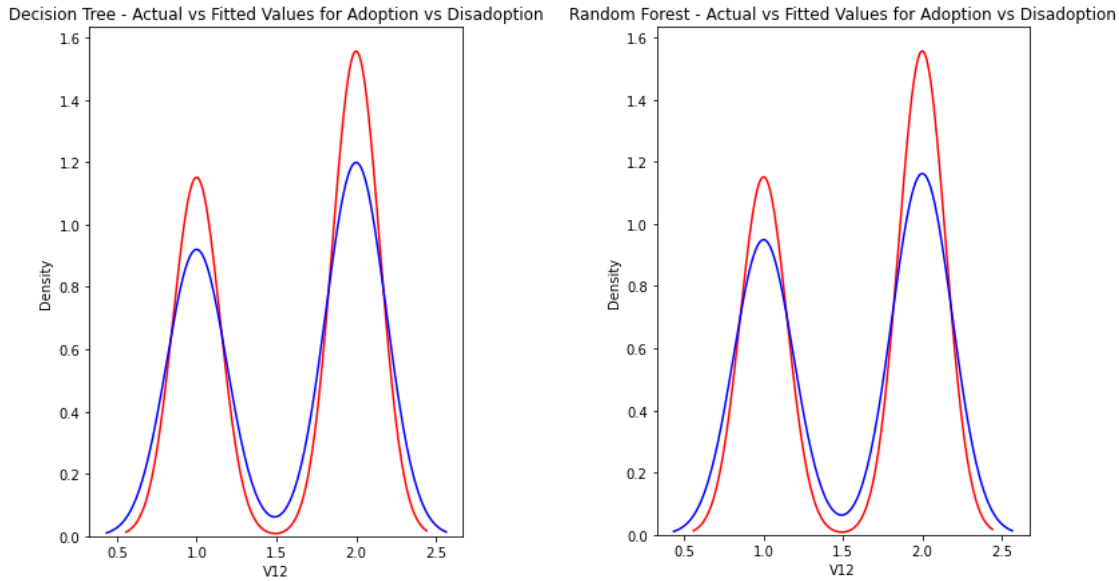


Figure 4.3: Actual vs Fitted Values for Adoption and Disadoption

4.2.4.6.Identification of important Features using Decision Tree.

The model identified and ranked the selected variables (features) from the most important to the least important in Predicting the adoption and dis-adoption of CSA practices among smallholder farmers in Kakamega County (Table 4.23). The Model identified 14 important variables with the most important one being V160 (CA Practiced). The importance of this variable implies that the smallholders who practice CA sustainably are well able to adopt other CSA practices. Other important variables identified by the Decision Tree include SWC practice (V161), PPT practice (V162), Composting Practiced (V163), ISLM/ISFM Practiced (V165), Water Harvesting practice (V167), Year of CSA Practice Training (V50) and the Farmer Category (V51) in terms of a Lead farmer or Follower farmer.

Table 4.23: Decision Tree Feature (Variable) Importance

Variable	Contribution (%)	Variable	Contribution (%)	Variable	Contribution (%)
V160	0.345985	V4	0	V120	0
V161	0.185694	V168	0	V107	0
V162	0.13754	V18	0	V43	0
V163	0.113938	V6	0	V169	0
V165	0.05611	V140	0	V77	0
V167	0.029799	V145	0	V40	0
V50	0.026095	V48	0	V22	0
V51	0.024686	V139	0	V47	0
V164	0.023641	V144	0	V104	0
V28	0.022019	V136	0	V76	0
V129	0.013212	V44	0	V5	0
V57	0.008783	V138	0	V112	0
V49	0.007431	V29	0	V134	0
V8	0.005067	V121	0	V75	0
V10	0	V133	0	V80	0
V58	0	V68	0	V119	0
V41	0	V130	0	V37	0
V34	0	V135	0	V25	0
V115	0	V38	0	V103	0
V146	0	V143	0	V17	0
V141	0				

4.2.4.7.Identification of important Features using Random Forest Classifier Model.

The model identified and ranked the selected variables from the most important to the least important in Predicting the adoption and dis-adoption of CSA technologies among smallholder farmers in Kakamega County (Table 4.24). The Random Forest Classifier Model identified 47 variables that were associated with farmers adoption or dis-adoption of CSA practices. Variables V160 (CA Practiced) and V161 SWC practice, just like in the Decision Tree, were identified by this model as influencing sustainable adoption of CSA practices. The other important variables with a contribution of 0.030 %and above include V138 (CA Abandoned), V10 (education Level), V5 (Smallholder Farmers Age), V163 (Composting Practiced), V162 (PPT practiced), V139 (Water Harvesting abandoned), V58 (Land Size) and V49 (Farming Experience). From the foregoing, the Random Forest

Classifier Model identified more variables and thus identified as the better model for this study purposes.

Table 4.24: Random Forest Classifier Feature (Variable) Importance

Variable	Contribution (%)	Variable	Contribution (%)	Variable	Contribution (%)
V160	0.15765086	V136	0.01898321	V38	0.00384722
V161	0.10778454	V140	0.01819589	V43	0.00328322
V138	0.08937059	V6	0.01659587	V164	0.00292064
V10	0.03544279	V145	0.01502669	V119	0.00233905
V5	0.03502229	V51	0.01404221	V40	0.00221336
V163	0.03405033	V59	0.01121503	V103	0.00215789
V162	0.03392181	V44	0.01049681	V115	0.00212019
V139	0.03362288	V46	0.0102526	V39	0.00184252
V58	0.0317778	V42	0.01008639	V166	0.00178529
V49	0.030106	V146	0.0095861	V168	0.00166549
V112	0.02888547	V117	0.0095354	V107	0.00158925
V4	0.02571036	V116	0.00940684	V105	0
V120	0.02330297	V41	0.00869023	V109	0
V165	0.02226637	V114	0.00831827	V106	0
V167	0.02223764	V144	0.00711218	V108	0
V50	0.02166705	V45	0.00619122		
V129	0.02114275	V169	0.00610769		
V141	0.02027508	V143	0.00499815		

4.2.4.8.Visualizing important Features identified in the 2 ML Algorithms.

Figure 4.4, below, depict the graphical representation of the key features from the most important to the least important.

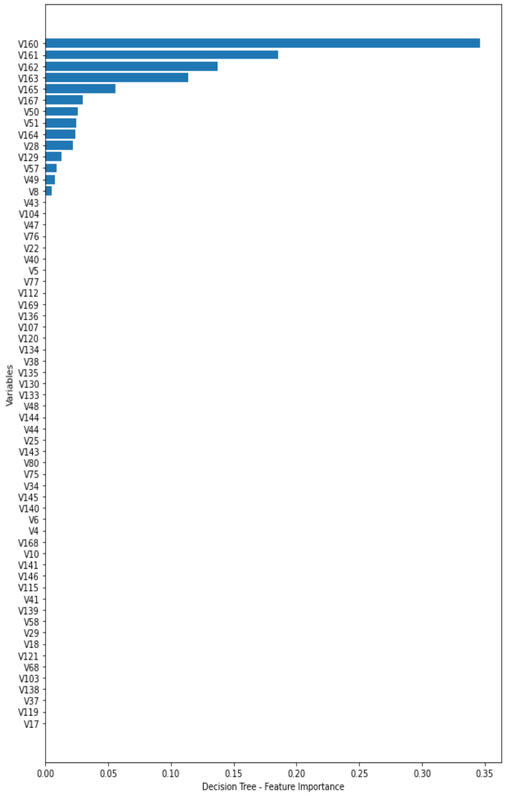
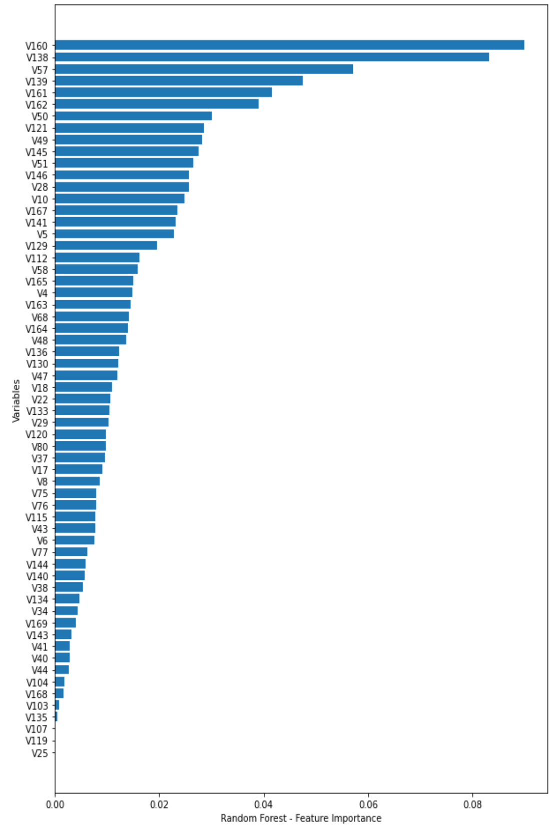
Decision Tree Classifier	Random Forest Classifier
	

Figure 4.4: Visualization of important features of the different classifier models

4.2.4.9.Visualizing the Decision Tree Classifier

The Classifier was visualized to illustrate how underlying variables (data) predict a chosen target. Figure 4.5 depicts the decision tree visualization. The visualization of the classifiers gives the various levels of importance of the different variables in predicting the farmer categorization. For the decision tree, the root node is V160 (CA Practiced) with 299 samples of which 137 are adopters and 162 are dis-adopters. This root node points to the close association of practising CA with the adoption of CSA practices. This further implies that the smallholders who practice CA sustainably are well able to adopt other CSA practices while those who are not able to sustainably adopt it end up dis-adopting the CSA practices.

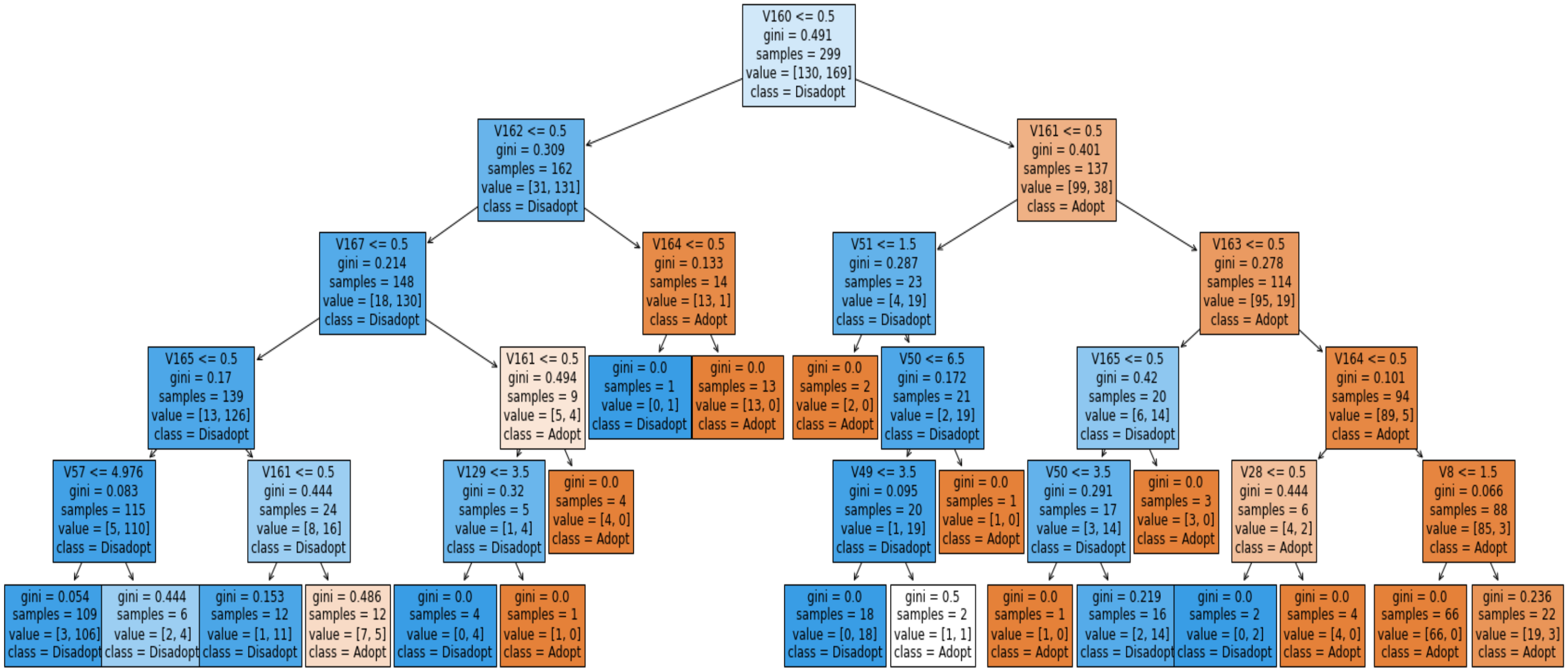


Figure 4.5: Decision Tree Visualization

The intermediate nodes were V161 (SWC practised), V162 (PPT practised), V167 (Water Harvesting practised), V164 (Agroforestry Practiced), V51 (Farmer Category) and V163 (Composting Practiced). Variables V57, V161, V164, V129, V49, V50, V28 and V8 were leaf nodes where the model could not further split the data.

4.2.4.10. Visualizing the Random Forest Classifier.

The Classifier was visualized to illustrate how underlying variables (data) predict a chosen target. Figure 4.6 below, depicts the Random Forest Classifier. V138 (CA abandoned) was the root node in this classification model. This implies that the sustainable adoption of CA significantly contributed to the adoption of other CSA practices. It also implies that the dis-adoption of CA may lead to the dis-adoption of other CSA practices. The decision nodes are V161, V162, V167, V51, V163, V165, V50, V57, V129, V49, V28, V8, V120, V129, and V139. The leaf nodes are V136, V112, V58, V107, V4, V119, V160, V10, V46, V5, V58 and V49.

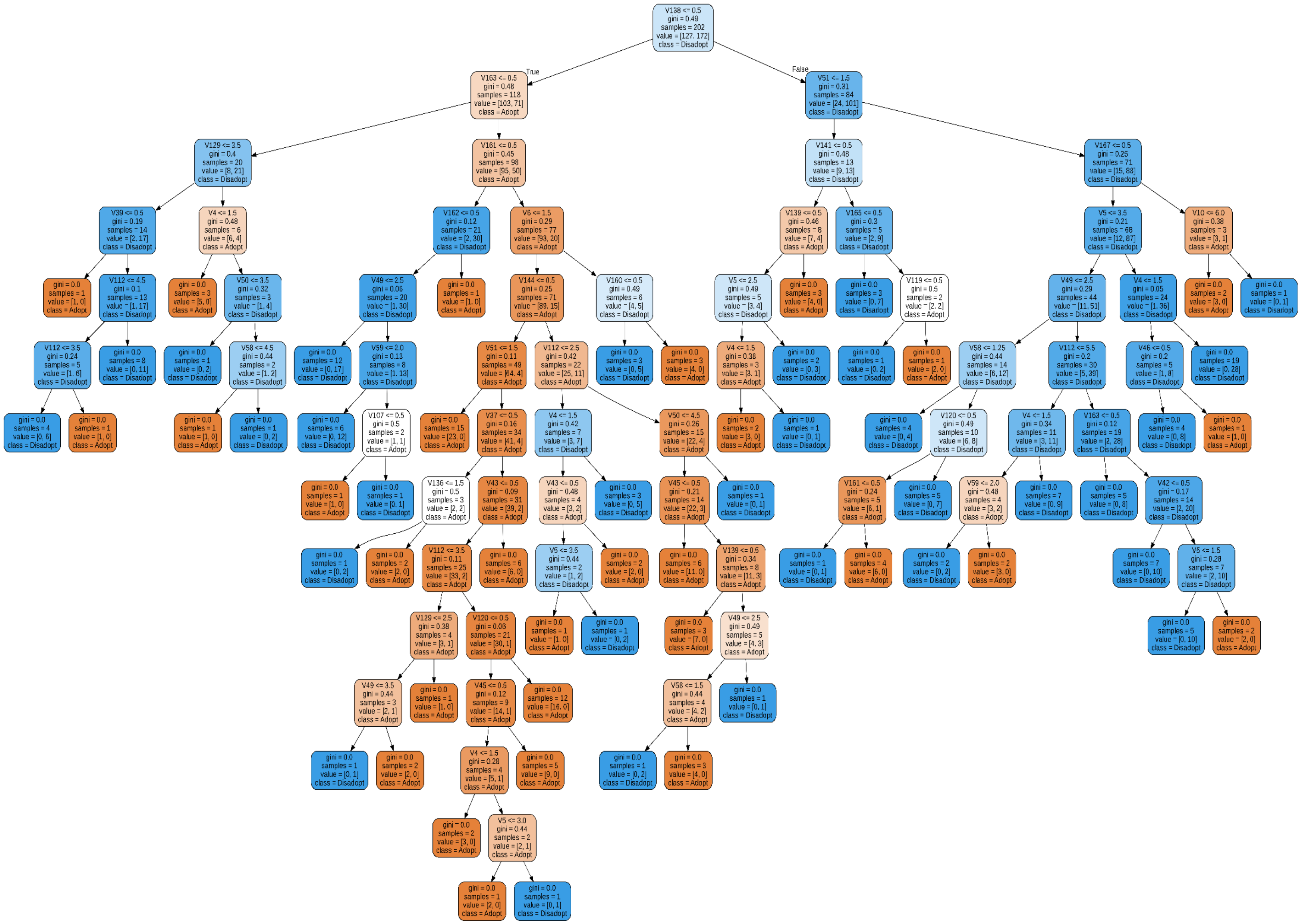
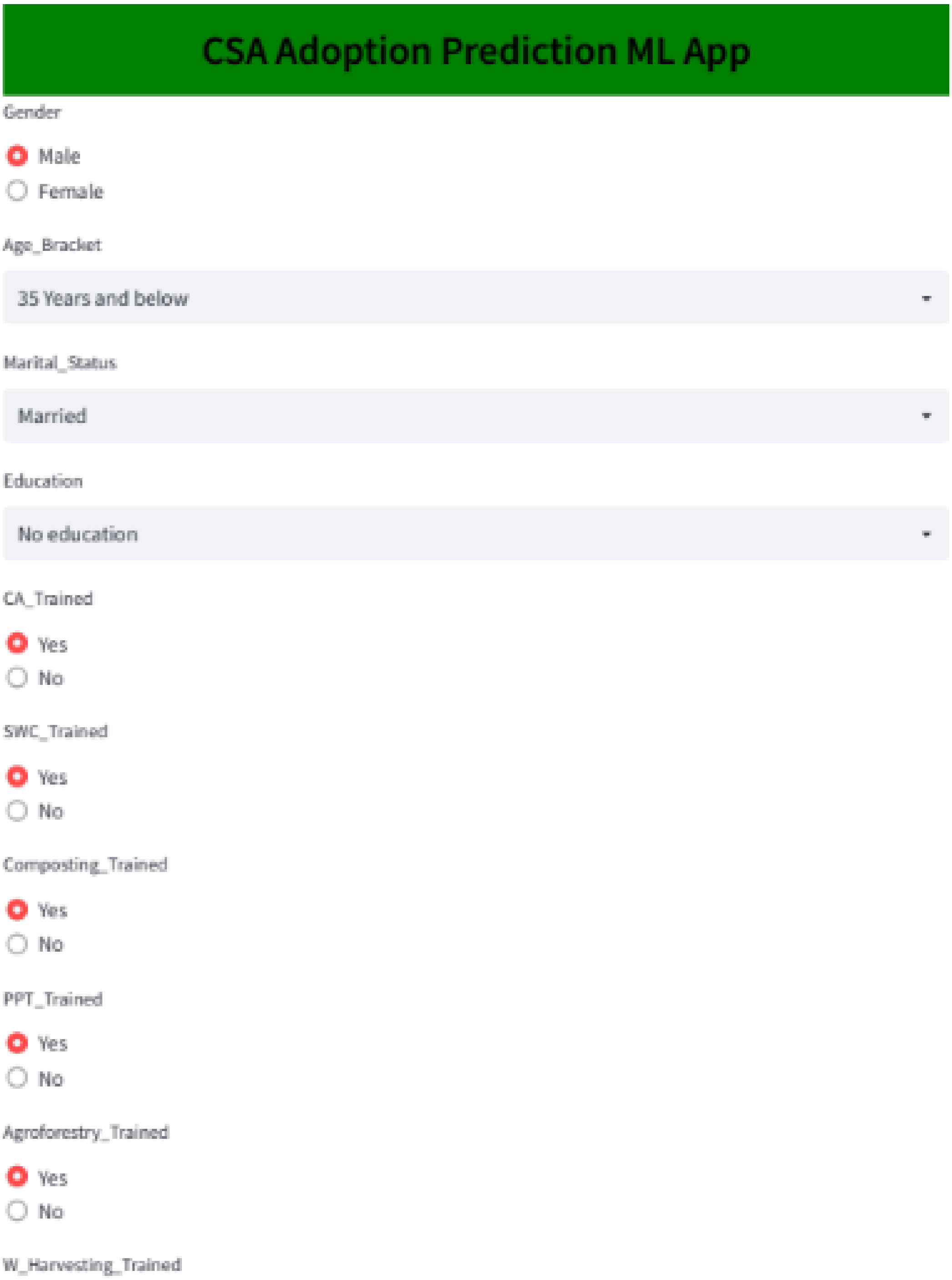


Figure 4.6: Random Forest Visualization

4.3. Objective Three: To prototype and pilot the data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega county's smallholder farmers.

4.3.1. Rapid Prototyping

This step involved the development of a web-based prototype that predicts whether a smallholder farmer will either adopt or dis-adopt CSA technologies. The main aim of the prototype was to attract and inform potential users of a product that they could invest in before allocating resources to and implementation of CSA technologies in Kakamega County. Figure 4.7 represents the web interphase of the predictive model.


CSA Adoption Prediction ML App
Gender
Male
Female
Age_Bracket
35 Years and below
Marital_Status
Married
Education
No education
CA_Trained
Yes
No
SWC_Trained
Yes
No
Composting_Trained
Yes
No
PPT_Trained
Yes
No
Agroforestry_Trained
Yes
No
W_Harvesting_Trained

- (•) Yes
- ( ) No

G/House_Trained

- (•) Yes
- ( ) No

ISLM/ISFM_Trained

- (•) Yes
- ( ) No

Vermiculture_Trained

- (•) Yes
- ( ) No

Fallowing_Trained

- (•) Yes
- ( ) No

Farming_Experience

Over 20 Years

Year_Trained

Before 2015

Farmer_Category

- (•) Model Farmer
- ( ) Follower Farmer

Land_Size

≤1 Acre

Type_of_land_ownership

Owned

Group_membership

- (•) Yes
- ( ) No

Not_Interested

- (selected) Yes
- No

G/House_Trained

- (selected) Yes
- No

ISLM/ISFM_Trained

- (selected) Yes
- No

Vermiculture_Trained

- (selected) Yes
- No

Fallowing_Trained

- (selected) Yes
- No

Farming_Experience

Over 20 Years

Year_Trained

Before 2015

Farmer_Category

- (selected) Model Farmer
- Follower Farmer

Land_Size

≤1 Acre

Type_of_land_ownership

Owned

Group_membership

- (selected) Yes
- No

Not_Interested

Yes

No

Not_aware

Yes

No

Left_Group

Yes

No

Not_involved

Yes

No

Group_dissolved

Yes

No

Position_held

Chairman

Table_Banking

Yes

No

Farming

Yes

No

M_G_Rounds

Yes

No

Welfare

Yes

No

Agric_Trainings

Yes

No

Agric_credit

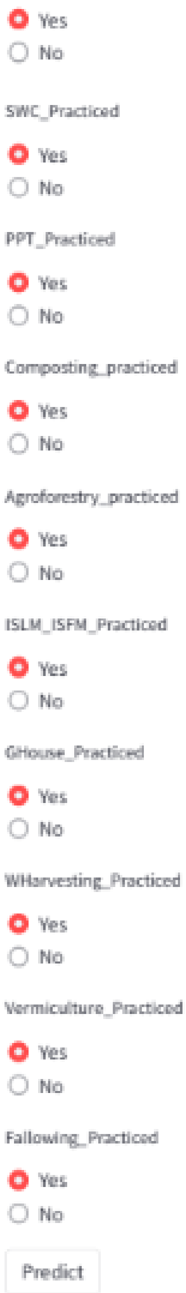


Figure 4.7: web interphase of the predictive model

The ML model was piloted with 15 randomly selected smallholder CSA farmers from Butere Sub County. According to Vujović (2021), a model accuracy is given by the total of true positive (TP) and true negative (TN) events. As depicted in Table 4.25 below, the model accurately predicted 12 out of the 15 farmers. This implies that, given a new data set, the ML model could accurately predict 80% of smallholder CSA farmers ability to adopt CSA technologies.

Table 4.25: Comparison between Actual and Predicted Values

Index	Actual	Predicted	Type of Prediction
0	2	2	Accurate
1	1	1	Accurate
2	1	1	Accurate
3	1	1	Accurate
4	1	1	Accurate
5	1	1	Accurate
6	1	1	Accurate
7	2	1	Non-accurate
8	2	2	Accurate
9	1	1	Accurate
10	2	1	Non-accurate
11	2	2	Accurate
12	1	1	Accurate
13	2	1	Non-accurate
14	2	2	Accurate

4.3.2. Model Evaluation

4.3.2.1.Confusion Matrix

The confusion matrix was used to visualize the performance of the ML Algorithm. As shown in Table 4.26 below, the Model gave 8 True positives, 3 False Positives, 0 False negatives and 4 True Negatives. These values were used to calculate model metrics such as model accuracy, F1 score, specificity, recall and precision. According to Vujović (2021), a model accuracy is given by the total of true positive (TP) and true negative (TN) events. The pilot model prediction accuracy in this case was 80%.

Table 4.26: Confusion Matrix

		Predicted Values	
Actual Values		Adopter	Dis-adopter
	Adopter	8 (TP)	0 (FN)
	Dis-adopter	3 (FP)	4 (TN)

4.3.2.2.Classification report

Table 4.27 below depicts the model classification report. The support gives values of the different categories of farmers. In this case the model was tested with eight adopters and seven dis-adopters.

Table 4.27: Model Classification Report

	Precision	**Recall**	**F1-Score**	**Support**
Adopt	0.73	1.00	0.84	8
Dis-Adopt	1.00	0.57	0.73	7
Accuracy			0.80	15
macro avg	0.86	0.79	0.78	15
weighted avg	0.85	0.80	0.79	15

The piloting of the model gave a precision of 73%. Precision = TP/(TP+FP) = 8/(8+3) *100 = 73%. Precision is a measure of correctly predicted positive observations divided by the total number of predicted positive observations. According to Vujović (2021), the best metric value for precision is 1 while the worst is 0.0. This model has, therefore, given close to the best precision.

The model Evaluation gave a Recall of 1. Recall is the proportion of actual positives identified correctly. Recall = TP/(TP+FN) = 8/(8+0) = 1. According to Vujović (2021), the best Recall value is 1 while the worst is 0.0. In this case this model gave a Recall of 1 implying best prediction of CSA practice adoption.

The Model evaluation, further, gave a specificity of 0.571 implying that the model could accurately predict all the smallholder CSA adopting farmers. Specificity = TN/(TN+FP) = 4/(4+3) = 0.57143.

F1 Score implies the overall model performance. F1 Score is given by 2 * (Precision * Recall) / (Precision + Recall). According to Vujović (2021), the best possible F1 score is 1 while the worst is 0.0. From Table 4.28, this model had an F1 score of 0.8421 implying that it is a good model in predicting smallholder CSA farmer ability to adopt or dis-adopt CSA technologies.

Table 4.28: Model Metrics

Metric	**Random Forest Classifier**
Precision / Sensitivity	0.7272727272727273
Recall	1.0
Specificity	0.57
F1- Score	0.8421052631578948
Accuracy	80.0%

4.4. Objective Four: To assess the applicability and suitability of the data-driven model for the sustainable deployment and adoption of CSA practices among Kakamega County's smallholder farmers.

4.4.1. Focus Group Discussion

This step involved conducting a focus group discussion with key stakeholders in the CSA ecosystem to get their input in the model development process. The objective of this exercise was to elicit feedback on the applicability and suitability of the data-driven model for the deployment and adoption of CSA practices among Kakamega County's smallholder farmers. The participants included the 8 members of MMUST academic staff, 9 university postgraduate students, 1 research organization, 2 County Government agricultural extension staff, 2 smallholder CSA farmers and 4 representatives of the organizations promoting CSA technologies among smallholder farmers in Kakamega County. A demonstration was conducted to show the workings of the data-driven model for the deployment and adaptation of CSA practices among Kakamega County's smallholder farmers. Dummy farmer biophysical and socio-economic data was used to predict the possibility of adoption of CSA technologies.

4.4.2. Feedback and Concerns raised in the Focus Group Discussion

The Focus Group Discussion with key stakeholders in the CSA ecosystem raised concerns and feedback around the following issues:

i. How the model will address the small farm sizes that characterize smallholder farmers. The most important model variables, which land was one of them, were explained.

ii. How the model will address the challenge of different seed varieties in the market today. It was explained that the model was a decision support system for on-farm CSA practices such as CA and agroforestry among others

iii. The participants agreed with the presenter that the availability of credit, farmer training, and extension services play a key role in the adoption and dis-adoption of CSA practices once the donors leave.
iv. The participants requested the presenter to clearly outline the problem being addressed by the model as the problem statement was not clear. The student presenter promised to work on the problem statement to make it clearer.
v. The participants sought to know why the study sampling design targeted an equal number of respondents in the sampled sub-Counties. It was explained that this study is exploratory in nature and thus required an equal number of respondents in each clustered sub-county
vi. The participants sought to know if the model was the presenter's original innovation, or if it was a build-up of an existing model. It was confirmed that the model was a new Ph.D. study output and was not a build-up of another existing model. However, it was clearly explained that the model used a Random Forest Machine Learning algorithm. The presenter was advised to register the innovation with the Property rights authority.
vii. The participants sought to know how the model will tackle the adoption of various CSA technologies in different seasons. It was explained that the technologies and practices under review were perennial and may not be affected by seasons.
viii. The participants sought to know the importance of the model beyond academics. It was explained that the model would support decision-making on the right smallholder farmers to target during the promotion of CSA technologies.
ix. Participants were interested to know the reasons why some of the CSA practices are adopted or dis-adopted. It was explained that the study collected socioeconomic and biophysical characteristics from 428 farmers. These characteristics were

analyzed through machine learning to identify the characteristics that are associated with adoption and dis-adoption.

x. The participants sought to know whether the study was based only on a cropping system or a combined system of crops and livestock. It was explained that smallholder farmers in the study area are mixed farmers producing both crops and livestock. While the technologies under review are field-based, the study collected both biophysical and socioeconomic characteristics of the adopters and dis-adopters, including livestock and crop enterprises.

xi. Participants sought to know whether the CSA practices targeted were crop enterprise specific. It was explained that CSA practices are field practices that cut across many farm enterprises and may not be linked to specific crops.

xii. The participants sought clarity on the target recipients and beneficiaries of the model and how the adopters and dis-adopters would be managed afterwards. It was explained that the main beneficiaries of the model were CSA technology promoters including development partners, the government, and agricultural extension service providers. They would use this tool to identify the right target smallholder farmers for the various CSA initiatives being promoted in the county.

xiii. The participants urged the presenter to look at the following variables that affect the adoption of CA among other CSA technologies: Professionalism, Source of Agricultural information, Main crops grown on the farms, Major agricultural activities on the farm, and Formal employment.

4.4.3. Achievements of the Validation Process

i. There was sensitization and awareness creation of the model and its usefulness in the modern-day agricultural technology adoption process

ii. The stakeholders present viewed the prototype as a potential baseline survey toolkit that would determine and help identify the smallholder farmers who had the highest chance of CSA technologies adoption. These smallholder farmers would then be targeted with the right CSA interventions.
iii. The model was identified as an innovation that could revolutionize the roll-out and implementation of CSA technologies among smallholder farmers in Kakamega County
iv. Model and thesis improvements were suggested

CHAPTER FIVE

CONCLUSIONS AND AREAS OF FUTURE RESEARCH

5.1.Conclusions

5.1.1. Objective 1: To establish the different biophysical and socio-economic characteristics of the Kakamega County's smallholder farmers that influence their sustainable adoption of CSA practices

This study sought to understand the current adoption of CSA practices among smallholder farmers in Kakamega County. This study found that agroforestry, composting, and Soil and Water Conservation Structures are the most adopted CSA practices while push-pull technology, Conservation Agriculture and Vermiculture are the most dis-adopted practices. It was, further, established that group membership, interaction with extension officers, gender of the farmer and farming experience are the main drivers of adoption of CSA technologies. In addition, higher CSA adoption rates were low among young farmers and among the elderly in the community.

5.1.2. Objective 2: To develop a suitable data-driven model for the deployment and adaptation of CSA practices among Kakamega county's smallholder farmers

This study designed a data-driven model for the sustainable deployment and adoption of CSA practices among smallholder farmers in Kakamega county. Using data collected from 428 farmers, categorized into adopters and dis-adopters, and from the six sampled Sub-Counties, this study found that it is possible to predict which smallholder farmers will adopt and the ones will dis-adopt CSA technologies. The machine learning algorithm was trained with 70% of the data and tested on 30% of the data. The test results indicated that the model could predict the farmer category with 91% accuracy**.** Using the random forest classifier and decision tree, it was found that it was possible to predict which smallholder farmers would be CSA technology adopters and which ones would be dis-adopters. The random forest classifier was identified.

5.1.3. Objective 3: To prototype the data-driven model for the deployment and adaptation of CSA practices among Kakamega county's smallholder farmers

The ML model was first piloted with 15 farmers from Butere, an area that was outside the six sampled sub-counties. With this new data, the model was able to predict the farmer category with 90% accuracy. The ML algorithm was, further, prototyped in an interactive web interface where users could input the key features resulting into a prediction. The high prediction accuracy and precision of this model implies that it is a suitable decision support system that could be used for the identification of smallholder farmers that are most likely to adopt the promoted CSA technologies.

5.1.4. Objective 4: To assess the applicability and suitability of the data-driven model for the deployment and adaptation of CSA practices among Kakamega County's smallholder farmers

Though the web interface, the model was presented to the stakeholders drawn from the academia, agricultural research, Agricultural Extension, smallholder CSA farmers and CSA promoting agencies. A simulation was conducted on the model’s ability to predict smallholder farmer CSA technologies adoption. The stakeholders present viewed the prototype as a potential baseline survey toolkit that would determine and help identify the smallholder farmers who had the highest chance of CSA technologies adoption. These smallholder farmers would then be targeted with the right CSA interventions. In addition, the model was identified as an innovation that could revolutionize the roll-out and implementation of CSA technologies among smallholder farmers in Kakamega County

5.2.Areas of Further Research

This study had limited scope in terms of target beneficiaries and study population. The model was developed for and used data from smallholder farmers in Kakamega County, who farm for subsistence purposes. For this reason, the model may not apply to large-scale and commercial farmers in Kakamega County and beyond. A study that targets commercial and large-scale farmers in Kakamega and other areas is therefore encouraged as it would enhance the findings of this study and support the United Nations Sustainable Development Cooperation framework principle of Leaving No One Behind.

This study was limited to Smallholder Farmers in Kakamega County and, therefore, the model developed may not be suitable for use in other areas with different agroecological and socio-economic characteristics. Future research should, therefore, seek to model the adoption of CSA technologies through larger samples that would cover bigger regions such as the former Western Province or the Western Region including the former Nyanza Province.

This study considered the adoption of bundled CSA technologies among smallholder farmers in Kakamega County. The adoption of individual CSA technologies may be influenced by the different biophysical and socio-economic characteristics that are specific to the technology. For this reason, future studies, and the development of models for the sustainable deployment of specific CSA technologies should be considered.

Smallholder farmers have different farm enterprises with varying levels of investments. This study, however, was not able to cover all aspects of smallholder farmers including livestock and aquaculture practices, rather, it was limited to crop production. Future studies should model the adoption of CSA practices among livestock farmers, fish farmers, and other livelihoods.

This study was limited to the number of CSA technologies. The study was limited to field CSA technologies such as Conservation Agriculture, Push-Pull Technology, Water Harvesting, Soil and Water Conservation Structures, Agroforestry, Composting Greenhouse Technology, and Vermiculture. Future studies may investigate other CSA technologies such as Improved Seed Varieties and Smart Farming Technologies such as hydroponics, the use of drones, mobile apps, and other recent agricultural developments. In addition, the technologies under review were long-term on-farm investments and were neither seasonal nor crop specific. Future studies may, therefore, focus on seasonal and crop-specific CSA technologies.

This study used Random Forest and Decision Tree Classifier Models to predict the adoption of CSA practices among smallholder farmers in Kakamega County. Though the models have high accuracy levels in prediction of smallholder farmers adoption of CSA technologies, future studies should seek to use other models and classifiers.

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APPENDICES

APPENDIX 1: INTERVIEW GUIDE FOR SMALLHOLDER CSA FARMERS

Question	Response Code	Variables
Enumerators Names	1	Cecilia Bunoro
	2	Nolega Kuyonzo
	3	Dorothy Makayoto
	4	Phaustine Ambunya
	5	Irene Muthoni
Introduction	1	OK. Please Continue
Gender	1	Male
	2	Female
Age Bracket	1	35 years and below
	2	36 - 45 Years
	3	46 - 55 Years
	4	56 - 65 Years
	5	66 Years and Above
Marital Status	1	Married
	2	Widowed
	3	Single
Are you HH Head?	1	Yes
	2	No
Who is the main farm decision-maker?	1	Self
	2	Other (Spouse, parent, etc.)
Education Completed	1	No Education
	2	Not Completed Primary
	3	Completed Primary
	4	Not Completed Secondary
	5	Completed Secondary
	6	Completed College/University
	7	Not Completed College/University
Farmer Type	1	Adopting Farmer
	2	Dis-adopting Farmer
3c. What are the other main sources of agricultural information?	1	Extension Officers
	2	Newspapers
	3	Internet sources such as Facebook, websites, etc.
	4	Radios and TVs
	5	Public Barazas and Field days
	6	Agricultural magazines such as The Organic Farmer
Which of the following	1	Radio

Information communication devices do you have?	2	Television
	3	Basic Mobile phone
	4	Smart Devices (tablets, smartphones, i-pads, etc.)
	5	Computer (laptop, desktop, etc.)
	6	None
Which of the following tools do you have?	1	Wheelbarrow
	2	Bicycle
	3	Tuk-tuk
	4	Vehicle
	5	Hoes
	6	Motorcycle
3f. Do you currently receive support from NGOs (such as GIZ, FAO, Sustainet, etc.)	1	Yes
	2	No
How many meals does your household have in a day?	1	1 Meal
	2	2 meals
	3	3 Meals
	4	More than 3 meals
3h. Which of the following CSA practices have you ever been trained on?	1	Conservation Agriculture (CA)
	2	Soil and Water Conservation Structures such as Cut off Drains, Grass Strips, etc.
	3	Push Pull Technology
	4	Composting
	5	Water Harvesting
	6	Agroforestry
	7	Integrated Soil Fertility Management/ Integrated Sustainable Forest Management (ISLM/ISFM)
	8	Vermiculture
	9	Fallowing
	10	Mulching
	11	Green House Farming
3i. Who are the main promoters of CSA practices on your farm?	1	GIZ (or their agents Welthungerhilfe, GOPA, GFA, CESSUD, Shibuye CHWs)
	2	KALRO
	3	Ministry of Agriculture
	4	KCSAP (Kenya Climate Smart Agriculture Project)

	5	Anglican Development Services (ADS)
	6	V.I. Agroforestry
	7	Other Government Extension Service Provider
	8	Other Private Extension Service Providers
	9	Other Practicing Farmer
	10	World Vision
For how many years have you been a farmer?	1	Over 20 years
	2	Between 16 and 20 years
	3	Between 11 and 15 Years
	4	Between 5 and 10 Years
	5	Below 5 Years
Which year did you join or were you first trained on CSA (by the training organization, say GIZ, KALRO, etc.)	1	Before 2015
	2	2015
	3	2016
	4	2017
	5	2018
	6	2019
	7	2020
	8	After 2020
During the CSA training and implementation period, which farmer category were you in?	1	Demo Farmer/Lead Farmer/Model Farmer
	2	Follower Farmer
Sub County	1	Lurambi
	2	Navakholo
	3	Mumias West
	4	Matungu
	5	Malava
	6	Lugari
Is the land owned or leased?	1	Owned
	2	Leased
	3	Granted rights to farm but not owned
Do you have a Title Deed?	1	Yes
	2	No
Which of the following is the major source of energy in your household?	1	Wood Fuel
	2	Charcoal
	3	Kerosene
	4	Electricity
	5	Solar Energy devices
	6	LPG

5f. Which of the following Energy Saving Devices do you have?	1	Maendeleo Jikos
	2	Solar Lighting
	3	Fireless Cookers
	4	Energy Saving Bulbs
	5	Solar TVs
	6	Solar Radios
	7	None of the above
5g. What are the main crops grown? (Tick Appropriately)	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Soybeans
	7	Ground Nuts
	8	Tea
	9	Tomatoes
	10	Fruit Trees e.g., Mangos, Avocados, Papaya
	11	Finger Millet
	12	Sorghum
	13	Coffee
	14	Sweet Potatoes
	15	Bambara Nuts (Njugu Mawe)
	16	Sesame (Sim sim)
	17	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	18	Local Vegetables e.g., Mrenda, Miro, Kunde, etc.
	19	Fodder Crops (e.g., Napier, Bracharia, etc.)
What are the main livestock types reared?	1	Dairy Cow (pure grade)
	2	Crossbreed Cow
	3	Local Cow
	4	Oxen
	5	Dairy Goats
	6	Meat Goats
	7	Sheep
	8	Pigs
	9	Indigenous Poultry (Kienyeji and improved)
	10	Exotic Poultry
	11	Rabbits

When did you carry out soil sampling and testing on your farm?	1	Never
	2	During the last year
	3	2-5 Years ago,
	4	6-10 Years ago,
	5	Over 10 years ago
Are you a member of a group?	1	Yes
	2	No
5k. Why are you not in a group kindly give us your reasons	1	The Group dissolved
	2	Aware of the existence of groups but am not involved
	3	Left Group/Organization
	4	Not aware of the existence of groups/organizations
If yes, what type of group do you belong to?	1	agricultural group
	2	non-agricultural group
What is the level of your involvement in Group Activities?	1	Active member (Always involved)
	2	Active member (sometimes involved)
	3	Passive member (Aware of group activities but not involved)
	4	Passive member (Not aware of group activities and not involved)
What leadership position do you hold in the farmers' group or organization?	1	Chairman
	2	Vice Chairman
	3	Secretary
	4	Treasurer
	5	Other Committee Position
	6	No Leadership position
Main Group Activities	1	Table Banking
	2	Farming
	3	Merry Go Rounds
	4	Welfare and Benevolent
	5	Others
What is the importance of the group to your farming?	1	Source of Agricultural Training
	2	Agricultural Credit
	3	Other (Specify)
Last Interaction with agricultural Officer	1	1 Year and below
	2	Between 1 and 2 years ago
	3	Between 2 and 4 years ago
	4	Between 3 and 4 years ago
	5	Over 5 years ago
	6	Never

Are there members of this household who are in formal employment?	1	Yes
	2	No
Main Source of Household Income	1	Farming
	2	Employment
	3	Remittances
	4	Business
	5	Casual Labour
What is the estimated monthly level of your household income from all sources?	1	Below Ksh. 3,000 monthly
	2	Between Ksh. 3,001 and 5,000 monthly
	3	Between Ksh. 5,001 and 10,000 monthly
	4	Between Ksh. 10,000 and 20,000 monthly
	5	Between Ksh. 20,001 and 30,000 monthly
	6	Above Ksh. 30,0000 monthly
Do you access agricultural credit for your farming activities?	1	Yes
	2	No
5u. If yes, what are the main sources of your agricultural credit?	1	Farmer Group Loans
	2	Shylocks
	3	Commercial Banks
	4	Farm Inputs Organization e.g., One Acre Fund, AGRICS, etc.
	5	Mobile phone loan providers (such as Tala, Mshwari, Mkopa, Fuuliza, etc.)
5v. Where do you mainly invest the agricultural credit on?	1	Farming
	2	School Fees for the children
	3	Household activities, say, feeding, clothing, funerals, ceremonies, etc.
Have you left/abandoned CSA Practices	1	Yes
	2	No
Which CSA Practice have you abandoned?	1	Conservation Agriculture
	2	Soil and Water Conservation Structures
	3	Push Pull Technology
	4	Composting
	5	Agroforestry
	6	ISLM/ISFM
	7	Greenhouse farming
	8	Small-scale water Harvesting
	9	Vermiculture

	10	Fallowing
	11	Other (Specify)
What are the reasons that you left/abandoned CSA technologies?	1	Found better opportunities
	2	My expectations were not met
	3	I incurred losses
	4	I was disappointed by the group leadership/organization in general
	5	It was not beneficial
	6	Lacked capital to implement
	7	Lost Interest
	8	The Project Promoting CSA came to an end
	9	Lack of support from NGOs
	10	Other (Specify)
Which of the following CSA practices do you practice?	1	Conservation Agriculture (CA)
	2	Soil and Water Conservation Structures
	3	Push Pull Technology
	4	Composting
	5	Agroforestry
	6	Integrated Soil Fertility Management
	7	Greenhouse farming
	8	Small Scale Water Harvesting
	9	Vermiculture
	10	Fallowing
	11	Other (Specify)
What are the main CA principles that the farmer is practicing.	1	Zero Tillage
	2	Permanent Soil Cover
	3	Crop Rotation
	4	Mulching
	5	None
7a (iii) What specific farm characteristics did you consider before establishing CA on your farm?	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Agro-Ecological Zones
	6	Type of Crop to be planted
	7	Types of Livestock reared
	8	Wind
	9	Pests and Disease Incidences
	10	Land Availability
7a (iv) What is the main	1	Maize

crop grown in the CA field?	2	Sugarcane
	3	Bananas
	4	Cassava
	5	Coffee
	6	Local Vegetables e.g., e.g., Mrenda, Miro, Kunde, etc.
	7	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	8	Mucuna
7a (v) What are the other crops grown in the CA field?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Ground Nuts
	7	Fruit Trees e.g., Mangos, avocados, papaya
	8	Sorghum
	9	Sweet Potatoes
	10	Fodder Crops (e.g., Napier, Bracharia, etc.)
	11	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	12	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	13	Soybeans
	14	Finger Millet
7a (vi) Which Cover crop do you use under CA?	1	Mucuna
	2	Dolichos lab lab (Njahi)
	3	Beans and other legumes
	4	Canavalia
	5	Banana Leaves
Specify other Cover Crops under CA	1	Sweet Potatoes
	3	Desmodium
	4	Other mulching materials
How many years have you practiced CA on the current plot?	1	0-5 years
	2	6-10 years
	3	Above 10 years
What are your main benefits after implementing CA on your farm?	1	Increased Yields
	2	Reduced Production Costs
	3	Low Labour Requirements

	4	Reduced Soil Erosion
	5	Reduced Pests and Disease Incidences
	6	Increased Soil Fertility
What are your main challenges in implementing CA on your farm?	1	High Labour Requirements
	2	Small Land Size
	3	Lack of information and knowledge on implementation
	4	High weed incidences
	5	Poor Soils (e.g., Too Rocky, too sandy, etc.)
	6	Inability to use CA equipment
	7	Inaccessibility of farm implements
	8	Coming to the end of the CA promoting project
	9	Lack of support from CA promoting NGO
	10	Lack of Resources
	11	Rodents and other pests
	12	Cover Crop issues such as poor performance and climbing on maize
7a (xii) Do you intend to increase the land size under CA in the next few years?	1	Yes
	2	No
Reasons for increasing or Reducing Land size under CA.	1	It will encourage behavior change.
	2	To increase production
	3	Increase diversity
	4	Protect the soil
	5	Limited land size
7b (ii) What are the main soil and water conservation measures/structures that the farmer practices	1	Cut Off Drains
	2	Grass Strips
	3	Fanya Juu
	4	Fanya Chini
	5	Stone Strips
	6	Mulching
7b (iii) What specific farm characteristics did you consider before establishing Soil and Water Conservation Structures on your farm?	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Agro-Ecological Zones
	6	Type of Crop to be planted
	7	Types of Livestock reared

	8	Wind
	9	Land Availability
7b (iv) What is the main crop grown in Soil and Water Conservation Structures on your farm?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Fruit Trees e.g., Mangos, avocados, papaya
	7	Sweet Potatoes
	8	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	9	Local Vegetables e.g., e.g., Mrenda, Miro, Kunde, etc.
	10	Arrow roots
	11	Tomatoes
7b (v) What are the other crops grown in the Soil and Water Conservation field?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Ground Nuts
	7	Fruit Trees e.g., Mangos, avocados, papaya
	8	Sorghum
	9	Sweet Potatoes
	10	Fodder Crops (e.g., Napier, Bracharia, etc.)
	11	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	12	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	13	Tomatoes
	14	Finger Millet
	15	Soybeans
	16	Coffee
7b (vi) What are your main benefits after implementing Soil and Water Conservation Structures on your farm?	1	Increased Yields
	2	Reduced Production Costs
	3	Low Labour Requirements
	4	Reduced Soil Erosion
	5	Boosting Soil Fertility

	6	Other Products such as Fodder
7b (vii) What are your main challenges in implementing Soil and Water Conservation Structures on your farm	1	The cost of labor required to implement is prohibitive
	2	Inaccessibility of requisite planting materials such as Napier grass
	3	Small land sizes limit implementation
	4	Poor Soils (e.g., Too Rocky, too sandy, etc.)
	5	High rainfalls thus damage the structures
	6	Lack of information and knowledge on implementation
	7	Lack of requisite equipment and tools
	8	Lack of support from the promoting NGOs
	9	Lack of Resources to implement
	10	Ending of the project
7b (viii) Do you intend to increase the land size under Soil and Water Conservation Structures in the next few years?	1	Yes
	2	No
7c (ii) What are the main Push Pull Technologies practiced on the farm?	1	Grass Crop
	2	Desmodium
	3	Napier Grass/Bracharia
7c (iii) What are the specific farm characteristics did you consider before establishing Push Pull Technology on your farm?	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Agro-Ecological Zones
	6	Type of Crop to be planted
	7	Need for fodder
	8	Prevalence of stem borers and other pests
	9	Land Availability
7c (iv) What is the main crop grown under Push Pull Technology on your farm?	1	Maize
	2	Bananas
	3	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
7c (v) What are the other crops grown in the Push-Pull Technology field?	1	Fodder Crops (e.g., Napier, Bracharia, etc.)
	2	Bananas

	3	Fruit Trees e.g., Mangos, Avocados, Papaya
	4	Maize
	5	Beans
	6	Sweet Potatoes
	7	Ground Nuts
	8	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	9	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	10	Cassava
	11	Sugarcane
	12	Soybeans
	13	Tea
7c (v) How many years have you practiced Push Pull Technology on the current plot?	1	0-5 years
	2	6-10 years
	3	Above 10 years
7c (ix) What are your main benefits after implementing Push Pull Technology on your farm?	1	Increased Yields
	2	Reduced Production Costs
	3	Low Labour Requirements
	4	Reduced Soil Erosion
	5	Soil Moisture retention during dry spells
	6	Suppression of Weeds
	7	Fodder from the Napier and desmodium
	8	Reduction of Striga weed infestation
	9	Reduction of stem borer infestation incidences
7 (x) What are your main challenges in implementing Push Pull Technology on your farm?	1	Control of weeds in the plot under PPT
	2	Some Napier grass harbors rodents
	3	Small land sizes to warrant profitable PPT farming
	4	Non-availability of planting material especially desmodium seed
	5	High cost of desmodium seed
	6	The promoting project coming to an end
	7	Lack of support from the technology-promoting NGO
	8	Lack of Resources to implement
	9	Other (Specify)

	10	Germination of desmodium seeds during the dry season
	11	Grass border rows take up essential crop-growing areas of small fields
	12	Control of weeds in the plot under PPT
7c (xi) Do you intend to increase the land size under Push-Pull Technology in the next few years?	1	Yes
	2	No
What is the main method of composting by the farmer	1	Compost Heap - Compostable materials are heaped on top of the soil surface
	2	Compost pit - Compostable materials are thrown in a pit on the ground
	3	Garbage Heap - Compostable materials plus other non-compostable materials are heaped
	4	Professional Composting - compostable materials are well layered under shade and turned frequently
7d (ii) What materials do you use while composting?	1	Green Matter
	2	Ash
	3	Livestock Manure
	4	Kitchen waste
7d (iii) What are the specific farm characteristics did you consider before establishing Composting on your farm and on	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Agro-Ecological Zones
	6	Type of Crop to be planted
	7	Availability of raw materials
	8	Availability of land
	9	Types of Livestock reared
	10	Nearness to the farm
7d (iv) What is the main crop grown under Compost manure on your farm?	1	Maize
	2	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	3	Fruit Trees e.g., Mangos, avocados, papaya
	4	Sugarcane
	5	Local Vegetables e.g., e.g., Mrenda, Miro, Kunde, etc.
	6	Bananas

	7	Tomatoes
7d (v) What are the other crops grown under compost manure on your farm?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Ground Nuts
	7	Fruit Trees e.g., Mangos, avocados, papaya
	8	Sorghum
	9	Sweet Potatoes
	10	Fodder Crops (e.g., Napier, Bracharia, etc.)
	11	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	12	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	13	Tomatoes
	14	Soybeans
	15	Finger Millet
	16	Sesame (simsim)
	17	Bambara Nuts (Njugu mawe)
7d (vi) How many years have you practiced Compost manure use on the current plot?	1	0-5 years
	2	6-10 years
	3	Above 10 years
7d (ix) What are your main benefits after implementing Composting on your farm?	1	Increased Yields
	2	Low Labour Requirements
	3	Reduced Soil Erosion
	4	Reduced chemical fertilizer requirements
	5	Helps make use of agricultural waste
	6	Helps Suppressing weeds, diseases, and pests
7d (x) What are your main challenges in implementing Composting on your farm?	1	Lack of information and knowledge on implementation
	2	Shortage or lack of composting materials such as manure, green matter, ash, etc.
	3	High transportation costs to the farm
	4	High-time requirements for composting
	5	High Labour Requirements

	6	Coming to the end of the technology promoting project
	7	Lack of support from the technology-promoting NGO
	8	Lack of raw materials
	9	Lack of storage facilities
	10	Lack of market
	11	Other Reasons
7d (xi) Do you intend to increase the land size under Compost manure use in the next few years?	1	Yes
	2	No
7e (ii) What type of small-scale water harvesting technologies do you implement on your farm?	1	Zai Basins
	2	Water Storage Tanks
	3	Fishponds
	4	Ground Water
7e (iii) Which are your main ways of harvesting water	1	Surface runoff harvesting
	2	Rooftop rainwater harvesting
	3	Ground Water
7e (iv) What are the farm-specific characteristics that you considered before establishing small-scale water harvesting technologies on your farm and this plot	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Availability of land
	6	Availability of water sources
	7	The type of crops
7e (v) What is the main crop grown under small-scale water harvesting technologies on your farm?	1	Maize
	2	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	3	Tomatoes
	4	Fruit Trees e.g., Mangos, avocados, papaya
	5	Local Vegetables e.g., e.g., Mrenda, Miro, Kunde, etc.
	6	Tree Nursery
7d (v) What are the other crops grown under small-scale water harvesting technologies on your farm?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Ground Nuts

	7	Fruit Trees e.g., Mangos, avocados, papaya
	8	Sweet Potatoes
	9	Fodder Crops (e.g., Napier, Bracharia, etc.)
	10	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	11	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	12	Tomatoes
	13	Soybeans
	14	Finger Millet
	15	Other (Specify)
7e (vi) Apart from irrigation, which other uses do you put the harvested water into?	1	Household use e.g., cooking, bathing, washing
	2	Livestock
	3	Fish farming
7e (vii) How many years have you irrigated the current plot using small-scale water	1	0-5 years
	2	6-10 years
	3	Above 10 years
What are your main benefits after implementing small-scale water harvesting on your farm?	1	Source of irrigation water
	2	Increased farm productivity
7e (x) What are your main challenges in implementing small-scale water harvesting on your farm?	1	Limited land size
	2	Lack of sufficient water storage facilities
	3	Lack of enough rainwater
	4	High rainfall breaching the storage facilities
	5	Ending of the technology-promoting project
	6	Lack of support from the technology-promoting NGO
	7	Lack of Resources to implement
	8	Inaccessibility to water and irrigation implements
	9	Other (Specify)
7e (xi) Do you intend to increase the land size under irrigated using small-scale water harvesting in the next	1	Yes
	2	No

few years?		
7f (ii) Which is your main form of agroforestry?	1	Woodlot
	2	Compound Trees
	3	Fruit Trees
	4	Trees planted along the fence
	5	Trees planted along farm contours
	6	Trees intercropped with food crops
7f (iii) What type of agroforestry trees do you have on your farm?	1	Grevillea Robusta
	2	Blue Gum/Eucalyptus
	3	Cyprus
	4	Casuarina
	5	Sesbania Sesbania
	6	Calliandra
	7	Fruit Trees such as mangos, avocados, oranges, etc.
	8	Other (Specify)
7f (iv) Which are the main uses of your agroforestry?	1	Wood fuel
	2	Fodder
	3	Timber, poles, and posts
	4	Ornamental and medicinal
	5	Shade
	6	Fruits
	7	Medicinal
What are the farm-specific characteristics that you considered before establishing agroforestry on your farm?	1	None
	2	Soil Type
	3	Farm Topography (Slope, etc.)
	4	Climatic Conditions
	5	Need for wood fuel and other needs
	6	Other (Specify)
7f (vi) What is the main crop grown under Agroforestry on your farm?	1	Maize
	2	Sugarcane
	3	Bananas
	4	Cassava
	5	Fruit Trees e.g., Mangos, avocados, papaya
	6	Tomatoes
	7	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	8	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	9	Sweet Potatoes

	10	Other (Specify)
7f (v) What are the other crops grown under agroforestry on your farm?	1	Maize
	2	Beans
	3	Sugarcane
	4	Bananas
	5	Cassava
	6	Ground Nuts
	7	Fruit Trees e.g., Mangos, avocados, papaya
	8	Sweet Potatoes
	9	Fodder Crops (e.g., Napier, Bracharia, etc.)
	10	Exotic Vegetables e.g., Kales, Cabbages, Capsicum, Onions, etc.
	11	Local vegetables e.g., Mrenda, Miro, Kunde, etc.
	12	Soybeans
	13	Tomatoes
	14	Sorghum
	15	Bambara Nuts (Njugu mawe)
	16	Finger Millet
	17	Tea
	18	Tea
7f (vii) How many years have you implemented agroforestry in the current plot?	1	0-5 years
	2	6-10 years
	3	Above 10 years
7f (viii) What are your main benefits after implementing Agroforestry on your farm?	1	Source of diverse products such as wood fuel timber posts and poles
	2	Serves as a wind break
	3	Increased soil fertility
	4	Provision of shade
	5	Other (Specify)
7f (x) What are your main challenges in implementing agroforestry on your farm?	1	Low survival rate of certain tree species
	2	Long Waiting time before realizing benefits
	3	Lack of resources to implement
	4	Lack of requisite seed and seedlings
	5	Effect of tree shade on crops
	6	Coming to an end of the technology promoting Project

	7	Lack of support from the technology-promoting NGO
	8	Theft
	9	Lack of knowledge and information to implement
7f (xi) Do you intend to increase the land size under agroforestry in the next few years?	1	Yes
	2	No
7g (ii) Which is your main form of ISFM/ISLM?	1	Use of compost/organic manure
	2	Use of well-adapted pest and disease-resistant seed varieties
	3	Use of chemical fertilizer
	4	Good Agricultural Practices
7g (iii) What type of agroforestry trees do you have on your farm for ISM/IFM?	1	Grevillea Robusta
	2	Blue Gum/Eucalyptus
	3	Fruit Trees
	4	Cyprus
	5	Calliandra
	6	Sesbania Sesban
	7	Casuarina
	8	Mugombera
7g (iv) Which are the main products/uses of your ISFM/IFM?	1	Forest non-wood products such as honey mushrooms mugombera etc.
	2	Fodder Crops
	3	Wood and other forest products such as timber
	4	Food Crops
What are the farm specific Characteristics that you considered before establishing ISLM/ISFM on your farm?	1	Need for wood fuel and other needs
	2	Climatic Conditions
	3	Topography (Slope etc.)
	4	Nearness to Government Forest
	5	Need for Livestock Feeds
	6	Need for forest products such as mugombera and other herbs
	7	Soil type
	8	None
7g (vi) What is the main crop grown under ISLM/ISFM on your farm?	1	Fruit Trees e.g., Mango's avocados papaya
	2	Maize
	3	Bananas

	4	Tomatoes
	5	Sugarcane
	6	Exotic Vegetables e.g., Kales Cabbages Capsicum Onions, etc.
7f (v) What are the other crops grown under ISLM/ISFM on your farm?	1	Bananas
	2	Exotic Vegetables e.g., Kales Cabbages Capsicum Onions, etc.
	3	Sweet Potatoes
	4	Beans
	5	Maize
	6	Cassava
	7	Fodder Crops (e.g., Napier Bracharia etc.)
	8	Fruit Trees e.g., Mangos Avocados Papaya
	9	Sugarcane
	10	Tea
7g (vii) How many years have you implemented ISLM/ISFM in the current plot?	1	0-5 years
	2	6-10 years
	3	Above 10 years
What are the main benefits of implementing ISFM/ISLM on your farm?	1	Source of diverse products such as honey fodder etc.
	2	Reduced requirement for chemical fertilizer
	3	Making use of locally available materials
	4	Increased soil fertility
7g (x) What are your main challenges in implementing ISLM/ISFM on your farm	1	Lack of technical knowledge and information
	2	Lack of financial resources to buy requisite farm inputs
	3	Coming to the end of the technology-promoting Project
	4	Lack of support from the technology-promoting NGO
	5	Lack of resources to implement
	6	Small land size
7g (xi) Do you intend to increase the land size under ISLM/ISFM in the next few years?	1	Yes
	2	No
What is the main crop	1	Tree Nursery

grown in the greenhouse	2	Tomatoes
	3	Exotic Vegetables such as hot pepper, kales
For how many years have you practiced greenhouse farming technology on your farm?	1	0 - 5 Years
	2	6 - 10 Years
What type of greenhouse does the farmer has	1	Wooden Greenhouse
	2	Metallic Greenhouse
	3	Both wooden and metallic Greenhouses
Have you been supported by an organization say an NGO or the government to set up the greenhouse?	1	Yes
	2	No
For how many years have you practiced vermiculture on your farm	1	0 - 5 Years
Have you been supported by an organization say an NGO or the government to set up the vermiculture technology?	1	Yes
	2	No
What are the main benefits of vermiculture technology on your farm	1	Source of organic manure
	2	Source of organic pesticides
On a scale of 1 to 5, where 1 is the least and 5 is the most, has CSA practices improved your household income?	1	CSA has least improved my household income
	2	CSA has to a small extent improved my household income
	3	indifferent on whether CSA has improved my household income
	4	CSA has to some extent improved my household income
	5	CSA has to a great extent improved my household income
On a scale of 1 to 5, how likely are you to recommend CSA practices to another farmer	1	least likely
	2	not likely
	3	indifferent
	4	likely
	5	most likely

APPENDIX 2: STUDY VARIABLES, CODES, AND CORRELATIONS

Question	Variable Code	Variable	Pearson Correlation
Demographics	V1	Enum #	.066
	V2	Consent	.[a]
	V3	Farm #	-.003
	V4	Sex	.216**
	V5	Age	-.124*
	V6	Marital	.217**
	V7	HH Head?	.077
	V8	Decision Maker	.128**
	V9	HH Head Sex	.070
	V10	Education	-.193**
	V11	HH Size	-.010
Agri-information Sources	V14	Ext. Office	-.078
	V15	N/Papers	-.054
	V16	Internet	-.078
	V17	Radio & TV	-.096*
	V18	Barazas	-.155**
	V19	Agri magazines	-.056
ICT Devices	V21	Radio	.032
	V22	TV	-.119*
	V23	Basic Phone	-.043
	V24	Smart Devices	-.076
	V25	Computer	-.098*
	V26	None	.006
Farm Tools	V28	W/Barrow	-.163**
	V29	Bicycle	-.159**
	V30	Tuk-tuk	-.064
	V31	Vehicle	-.069
	V32	Hoes	.020
	V33	Motorcycle	-.060
	V34	NGO Support?	.166**
	V35	Meals per Day	-.046
CSA Practices Trained	V37	CA Trained	-.141**
	V38	SWC Trained	-.107*
	V39	Composting Trained	-.035
	V40	PPT Trained	-.116*
	V41	Agroforestry Trained	-.162**
	V42	W. Harvesting Trained	-.045
	V43	G/House Trained	-.112*
	V44	ISLM/ISFM Trained	-.098*

	V45	Vermiculture Trained	.000
	V46	Fallowing Trained	-.036
	V47	Mulching Trained	-.119*
	V48	CSA Organization	.099*
	V49	Farming Experience	.216**
	V50	Year Trained	.106*
	V51	Farmer Category	.370**
Farm Location	V52	Sub County	.072
	V54	Latitude	.041
	V55	Longitude	.083
	V56	Altitude	.022
	V57	Precision	-.128**
	V58	Land Size	-.161**
	V59	Land Ownership	.009
	V60	Title Deed?	-.017
	V61	Energy Source	.071
Energy Saving Devices	V63	M. Jiko	-.001
	V64	Solar Lighting	-.076
	V65	F. Cooker	-.055
	V66	Energy S. Bulbs	-.018
	V67	Solar TV	-.089
	V68	Solar Radio	-.148**
	V69	None	.010
Crops Grown	V71	Maize	-.052
	V72	Beans	-.068
	V73	Sugarcane	-.044
	V74	Bananas	-.007
	V75	Cassava	-.129**
	V76	Soyabean	-.122*
	V77	G/Nuts	-.115*
	V78	Tea	-.082
	V79	Tomatoes	-.041
	V80	Fruit Trees	-.137**
	V81	F/Millet	-.021
	V82	Sorghum	.006
	V83	Coffee	-.056
	V84	S/Potatoes	-.093
	V85	B/Nuts	-.010
	V86	Simsim	-.015
	V87	E. Veges	-.089
	V88	L. Veges	-.066
	V89	Fodder Crops	-.060

Livestock Reared	V91	Pure B. Cow	-.068
	V92	Cross B. Cow	-.027
	V93	L. Cow	-.055
	V94	Oxen	-.019
	V95	D. Goats	-.058
	V96	M. Goats	.017
	V97	Sheep	.012
	V98	Pigs	-.043
	V99	L. Chicken	.016
	V100	E. Chicken	-.053
	V101	Rabbits	.009
Soil Sampling	V102	Soil Sampling Year	-.032
Group Involvement	V103	Group membership	.145**
	V104	Reason not in a group	.120*
	V105	Not Interested	.c
	V106	Not aware	-.056
	V107	Left Group	.111*
	V108	Not involved	.094
	V109	Group dissolved	.072
	V110	Group Type	-.023
	V111	Level of involvement	.070
	V112	Position held	.125**
Group Activities	V114	Table Banking	-.086
	V115	Farming	-.170**
	V116	M/G Rounds	-.088
	V117	Welfare	-.019
Group Importance	V119	Agric Trainings	-.139**
	V120	Agric credit	-.110*
	V121	Ext. officer interaction	.152**
	V122	Formal Employment?	.064
HH Income Source?	V124	Farming	-.034
	V125	Employment	-.072
	V126	Remittances	-.002
	V127	Business	.057
	V128	Casual Labour	.030
	V129	HH Monthly income	-.183**
	V130	Access Agri credit?	.107*
	V131	Agric Credit Sources	-.066
Agric credit uses	V133	Farming	-.106*
	V134	Sch. Fees	-.125**
	V135	Other HH Activities	-.107*
	V136	Abandoned CSA Practices?	-.341**

CSA Practices Abandoned	V138	CA Abandoned	.429**
	V139	W/Harvesting abandoned	.322**
	V140	SWC Abandoned	.235**
	V141	PPT Abandoned	.193**
	V142	Agroforestry abandoned	.095
	V143	ISLM/ISFM abandoned	.108*
	V144	G/House abandoned	.099*
	V145	Composting Abandoned	.250**
	V146	Vermiculture abandoned	.174**
	V147	Fallowing abandoned	.049
Reasons CSAs abandoned	V149	For better opportunities	.039
	V150	Expectations not met	.026
	V151	Incurred losses	-.032
	V152	Disappointed	.084
	V153	Not Beneficial	.031
	V154	Lacked Capital	.064
	V155	Lost interest	.086
	V156	Project ended	.093
	V157	Lack NGO support	.035
	V158	Other Reasons	.071
CSA Practiced	V160	CA Practiced	-.549**
	V161	SWC Practiced	-.344**
	V162	PPT Practiced	-.327**
	V163	Composting practiced	-.304**
	V164	Agroforestry practiced	-.166**
	V165	ISLM/ISFM Practiced	-.143**
	V166	G/House Practiced	-.023
	V167	W/Harvesting Practiced	-.276**
	V168	Vermiculture Practiced	-.197**
	V169	Fallowing Practiced	.115*
	V170	CA Land size	.040
CA Principles	V172	Zero Tillage	-.291**
	V173	P. Soil Cover	-.496**
	V174	C. Rotation	-.537**
	V175	Mulching	-.404**
	V176	None	-.072
CA Farm Xtics Considered	V178	None	-.215**
	V179	Soil Type	-.286**
	V180	Topography	-.317**
	V181	Climatic conditions	-.225**
	V182	AEZs	-.137**
	V183	Crop type	-.202**

	V184	Livestock type	-.260**
	V185	Wind	-.064
	V186	Pests & Diseases	-.334**
	V187	Land availability	-.317**
	V188	Main CA Crop	-.381**
	V190	Maize	-.333**
	V191	Beans	-.405**
	V192	Sugarcane	-.169**
	V193	Bananas	-.238**
	V194	Cassavas	-.158**
	V195	Soybeans	-.159**
	V196	G/Nuts	-.117*
	V197	Tea	.^{c}
	V198	Tomatoes	.^{c}
	V199	Fruit Trees	-.118*
	V200	F/Millet	-.010
	V201	Sorghum	-.080
	V202	S/Potatoes	-.197**
	V203	B/Nuts	.^{c}
	V204	Simsim	.^{c}
	V205	E. Veges	-.264**
	V206	L. Veges	-.307**
	V207	Fodder Crops	-.202**
CA Cover crop	V209	Mucuna	-.326**
	V210	Dolichos	-.139**
	V211	Beans and Legumes	-.331**
	V212	Canavalia	-.170**
	V213	Banana leaves	-.068
	V214	Other Crops	-.039
	V216	Increased Yields	-.532**
	V217	Reduced Costs	-.314**
	V218	Low Labour costs	-.254**
	V219	Reduced erosion	-.352**
	V220	Reduced Pests & Diseases	-.359**
	V221	Soil Fertility	-.334**
CA Challenges	V223	High Labour requirements	-.321**
	V224	Small land size	-.348**
	V225	Lack of information	-.222**
	V226	High Weed incidences	-.238**
	V227	Poor Soils	-.199**
	V228	Inability to use CA equipment	-.230**

	V229	Inaccessibility of farm implements	-.271**
	V230	Project Ended	-.232**
	V231	Lack of NGO Support	-.289**
	V232	Lack of resources	-.221**
	V233	Rodents and pests	-.306**
	V234	Cover crop issues	-.080
CA Land increment?	V236	SWC Land Size	-.291**
SWC Structures	V238	CODs	-.110*
	V239	Grass Strips	-.314**
	V240	Fanya Juu	-.188**
	V241	Fanya Chini	-.186**
	V242	Stone Strips	.016
	V243	Mulching	-.145**
SWC Xtics	V245	None	.003
	V246	Soil Type	-.147**
	V247	Topography	-.306**
	V248	Climatic Conditions	-.195**
	V249	AEZs	-.029
	V250	Crop to be planted	-.122*
	V251	Livestock type	-.114*
	V252	Wind	-.125**
	V253	Land Availability	-.114*
	V254	Main SWC Crop	-.201**
Other SWC Crops	V256	Maize	-.143**
	V257	Beans	-.217**
	V258	Sugarcane	-.103*
	V259	Bananas	-.136**
	V260	Cassava	-.170**
	V261	Soybeans	-.123*
	V262	G/Nuts	-.171**
	V263	Tea	.[c]
	V264	Tomatoes	-.080
	V265	Fruit Trees	-.159**
	V266	F/Millet	-.098*
	V267	Sorghum	-.010
	V268	Coffee	.042
	V269	S/Potatoes	-.073
	V270	B/Nuts	.[c]
	V271	Simsim	.[c]
	V272	E. Veges	-.166**
	V273	L. Veges	-.173**

	V274	Fodder Crops	-.099*
SWC Benefits	V276	Increased Yields	-.263**
	V277	Reduced Production Costs	-.170**
	V278	Low Labour Requirements	-.146**
	V279	Reduces S. Erosion	-.360**
	V280	Soil Fertility	-.194**
	V281	Other Products	-.153**
SWC Challenges	V283	High Labour Cost	-.212**
	V284	Lack of planting materials	-.184**
	V285	Small land size	-.122*
	V286	Poor Soils	-.059
	V287	High Rainfall	-.167**
	V288	Lack of information	-.099*
	V289	Lack of implements	-.108*
	V290	Lack of NGO Support	-.106*
	V291	Lack of Resources	-.139**
	V292	Project Ended	-.076
	V293	Intention to increase SWC	-.360**
	V294	PPT Land Size	-.293**
PPT Principles	V296	Grass Crop	-.251**
	V297	Desmodium	-.362**
	V298	Napier/Bracharia	-.368**
PPT Xtics	V300	None	-.126**
	V301	Soil Type	-.236**
	V302	Topography	-.169**
	V303	Climatic Conditions	-.160**
	V304	AEZs	-.126**
	V305	Type of Crop	-.214**
	V306	Need for Fodder	-.263**
	V307	Stem borers Presence	-.295**
	V308	Land Availability	-.204**
	V309	Main PPT Crop	-.363**
Other PPT Crops	V311	Maize	-.229**
	V312	Beans	-.271**
	V313	Sugarcane	-.160**
	V314	Bananas	-.189**
	V315	Cassava	-.126**
	V316	Soybeans	-.098*
	V317	G/Nuts	-.080
	V318	Tea	-.056
	V319	Tomatoes	.[c]
	V320	Fruit Trees	-.126**

	V321	F/Millet	.[c]
	V322	Sorghum	.[c]
	V323	Coffee	.[c]
	V324	S/Potatoes	-.126**
	V325	B/Nuts	.[c]
	V326	Simsim	.[c]
	V327	E. Veges	-.160**
	V328	L. Veges	-.180**
	V329	Fodder Crops	-.249**
	V330	PPT Experience	-.338**
PPT Benefits	V332	Increased Yields	-.308**
	V333	Reduced P. Costs	-.244**
	V334	Low Labour Requirements	-.214**
	V335	Reduced S. Erosion	-.229**
	V336	Moisture Retention	-.257**
	V337	Weeds Control	-.242**
	V338	Fodder	-.263**
	V339	Reduced Striga	-.236**
	V340	Reduced S. Borers	-.313**
PPT Challenges	V342	Weeds control	-.229**
	V343	Desmodium Germination	-.222**
	V344	Grass takes up Cropland	-.196**
	V345	Rodents	-.235**
	V346	Small land size	-.159**
	V347	Limited access to Desmodium	-.214**
	V348	Desmodium High Cost	-.220**
	V349	Project Ending	-.180**
	V350	Lack NGO Support	-.169**
	V351	Lack of Resources	-.214**
	V352	Intention to Increase PPT	-.346**
	V353	Compost Land Size	-.287**
	V354	Composting Technique	-.236**
Composting Materials	V356	Green Matter	-.329**
	V357	Ash	-.304**
	V358	Manure	-.331**
	V359	Kitchen Waste	-.198**
Composting Xtics	V361	None	-.066
	V362	Soil Type	-.238**
	V363	Topography	-.026
	V364	Climatic Conditions	-.112*
	V365	AEZs	-.031

	V366	Type of Crop	$-.107^{*}$
	V367	Type of Livestock	$-.101^{*}$
	V368	Land Availability	$-.097^{*}$
	V369	R. Materials availability	$-.189^{**}$
	V370	Nearness to Farm	-.010
	V371	Composting Main Crop	$-.190^{**}$
Other Composting Crops	V373	Maize	$-.177^{**}$
	V374	Beans	$-.192^{**}$
	V375	Sugarcane	$-.144^{**}$
	V376	Bananas	$-.106^{*}$
	V377	Cassava	$-.111^{*}$
	V378	Soybeans	$-.148^{**}$
	V379	G/Nuts	$-.098^{*}$
	V380	Tea	$.^{c}$
	V381	Tomatoes	-.064
	V382	Fruit Trees	$-.143^{**}$
	V383	F/Millet	-.075
	V384	Sorghum	$-.098^{*}$
	V385	Coffee	$.^{c}$
	V386	S/Potatoes	$-.100^{*}$
	V387	B/Nuts	-.010
	V388	Simsim	.042
	V389	E. Veges	$-.137^{**}$
	V390	L. Veges	-.077
	V391	Fodder Crops	$-.135^{**}$
	V392	Composting Experience	$-.231^{**}$
Composting Benefits	V394	Increased Yields	$-.278^{**}$
	V395	Low Labour Requirements	$-.113^{*}$
	V396	Reduced S. Erosion	$-.149^{**}$
	V397	Low Fertilizer needs	$-.127^{**}$
	V398	Agricultural waste use	$-.177^{**}$
	V399	Suppressing Pests & Diseases	$-.109^{*}$
Composting Challenges	V401	Lack of information	$-.113^{*}$
	V402	Lack of materials	.000
	V403	High Transport Costs	-.074
	V404	Time Consuming	$-.173^{**}$
	V405	High Labour Requirements	$-.167^{**}$
	V406	End of Project	-.076
	V407	Lack NGO Support	-.054
	V408	Lack of raw materials	-.076
	V409	Lack of storage	$-.122^{*}$

	V410	Lack of market	-.061
	V411	Other Reasons	-.038
	V412	Intention to increase composting	-.218**
	V413	Irrigated Land Size	-.220**
Water harvesting Techs	V415	Zai Basins	-.080
	V416	Water Pans	.c
	V417	Water Tanks	-.274**
	V418	Fishponds	-.038
	V419	Ground Water	-.080
Ways of Water Harvesting	V421	Run-Off	-.190**
	V422	Rooftop Rainwater	-.276**
	V423	Others	-.038
Water Harvesting Xtics	V425	None	.042
	V426	Soil Type	-.217**
	V427	Topography	-.235**
	V428	Climatic Conditions	-.206**
	V429	Type of Crops	-.198**
	V430	Land Availability	-.220**
	V431	Water Sources	-.227**
	V432	Irrigated Crops	-.234**
Other Irrigated Crops	V434	Maize	-.236**
	V435	Beans	-.179**
	V436	Sugarcane	-.113*
	V437	Bananas	-.117*
	V438	Cassava	-.113*
	V439	Soybeans	-.056
	V440	G/nuts	-.080
	V441	Tea	.c
	V442	Tomatoes	-.098*
	V443	Fruit Trees	-.159**
	V444	F/Millet	-.056
	V445	Sorghum	.c
	V446	Coffee	.c
	V447	S/Potatoes	-.197**
	V448	B/Nuts	.c
	V449	Simsim	.c
	V450	E. Veges	-.198**
	V451	L. Veges	-.254**
	V452	Fodder Crops	-.204**
Other Harvested Water Uses	V454	Household Uses	-.274**
	V455	Livestock	-.257**

	V456	Fish Farming	-.072
	V457	Irrigation Experience	-.245**
Water Harvesting Benefits	V459	Source of water	-.243**
	V460	Increased Productivity	-.272**
Water Harvesting Challenges	V462	Limited Land Size	-.193**
	V463	Lack of Storage Facilities	-.201**
	V464	Lack of enough rainwater	-.197**
	V465	Very high rainfall	-.220**
	V466	Project ending	-.149**
	V467	Lack of NGO Support	-.188**
	V468	Lack of Resources	-.220**
	V469	Water Inaccessibility	-.235**
	V470	Intention to Increase irrigation	-.246**
	V471	Agroforestry Land Size	-.160**
Agroforestry Forms	V473	Woodlot	-.087
	V474	Compound Trees	-.198**
	V475	Fruit Trees	-.165**
	V476	Fence Trees	-.156**
	V477	Farm Contour Tress	-.249**
	V478	Intercropped with food crops	-.154**
Agroforestry tree types	V480	Grevillea	-.153**
	V481	Eucalyptus	-.068
	V482	Cyprus	-.092
	V483	Casuarina	-.150**
	V484	Sesbania Sesban	-.134**
	V485	Calliandra	-.300**
	V486	Fruit Trees	-.114*
Agroforestry Uses	V488	Wood Fuel	-.183**
	V489	Fodder	-.220**
	V490	Timber, Poles & Posts	-.169**
	V491	Ornamental	-.104*
	V492	Shade	-.112*
	V493	Fruits	-.153**
Agroforestry Characteristics	V495	None	.002
	V496	Topography	-.072
	V497	Soil Type	-.044
	V498	Climatic Conditions	-.115*
	V499	Need for wood fuel	-.104*
	V500	Agroforestry Crop	-.047
Other Agroforestry Crops	V502	Maize	-.108*
	V503	Beans	-.079

	V504	Sugarcane	-.073
	V505	Bananas	-.083
	V506	Cassava	-.077
	V507	Soyabeans	-.098*
	V508	G/Nuts	-.047
	V509	Tea	.042
	V510	Tomatoes	-.010
	V511	Fruit Trees	.038
	V512	F/Millet	-.010
	V513	Sorghum	-.056
	V514	Coffee	.[c]
	V515	S/Potatoes	-.001
	V516	B/Nuts	-.056
	V517	Simsim	.[c]
	V518	E. Veges	-.049
	V519	L. Veges	-.058
	V520	Fodder Crops	-.126**
	V521	Agroforestry Experience	-.192**
Agroforestry Benefits	V523	Soil Fertility	-.135**
	V524	Shade	-.113*
	V525	Diverse Products	-.143**
	V526	Wind Break	-.168**
Agroforestry Challenges	V528	Long waiting time	-.035
	V529	Lack of information	-.058
	V530	Lack of Resources	-.061
	V531	Lack of seeds and seedlings	-.157**
	V532	Effect of shade on crops	-.007
	V533	Project Ending	-.044
	V534	Lack of NGO Support	-.045
	V535	Low survival of some species	-.014
	V536	Theft	-.050
	V537	Intention to increase agroforestry	-.193**
	V538	ISLM/ISFM Land Size	-.101*
ISLM/ISFM Forms	V540	Adapted Seed Varieties	-.115*
	V541	Organic Manure use	-.159**
	V542	Chemical Fertilizer Use	-.090
	V543	GAPs	-.107*
Agroforestry Trees	V545	Grevillea	-.107*
	V546	Eucalyptus	-.078
	V547	Cyprus	-.154**

	V548	Casuarina	-.056
	V549	Sesbania Sesban	-.038
	V550	Calliandra	-.126**
	V551	Fruit Trees	-.137**
	V552	Mogumber	.059
ISLM/ISFM Products	V554	Forest non-wood Products	-.159**
	V555	Wood Products	-.121*
	V556	Food Crops	-.179**
	V557	Fodder Crops	-.198**
ISLM/ISFM Xtics	V559	None	.042
	V560	Soil Type	-.075
	V561	Nearness to Forest	-.091
	V562	Need for Fodder	-.082
	V563	Topography	-.080
	V564	Climatic Conditions	-.096*
	V565	Need for wood fuel	-.137**
	V566	Need for Forest Products	-.098*
	V567	ISLM/ISFM Main Crop	-.113*
Other ISLM/ISFM Crops	V569	Maize	.022
	V570	Beans	-.006
	V571	Sugarcane	.042
	V572	Bananas	-.102*
	V573	Cassava	-.117*
	V574	Soyabeans	.[c]
	V575	G/Nuts	.[c]
	V576	Tea	.042
	V577	Tomatoes	.[c]
	V578	Fruit Trees	-.126**
	V579	F/Millet	.[c]
	V580	Sorghum	.[c]
	V581	Coffee	.[c]
	V582	S/Potatoes	-.021
	V583	B/Nuts	.[c]
	V584	Simsim	.[c]
	V585	E. Veges	-.099*
	V586	L. Veges	-.102*
	V587	Fodder Crops	-.139**
	V588	ISLM/ISFM Experience	-.150**
ISLM/ISFM Benefits	V590	Use of locally available materials	-.121*
	V591	Diverse Products	-.116*
	V592	Reduced C. Fertilizer Use	-.127**

	V593	Soil Fertility	-.136**
ISLM/ISFM Challenges	V595	Small Land Size	-.026
	V596	Lack Requisite Inputs	-.102*
	V597	Lack of information	-.054
	V598	Project Ending	-.121*
	V599	Lack NGO Support	-.102*
	V600	Lack of Resources	-.055
	V601	Intent to Increase ISLM/ISFM	-.137**
Greenhouse Crop	V603	Greenhouse Experience	-.110*
	V604	Greenhouse Type	-.106*
	V605	Support from NGO or Govt?	-.107*
	V606	Vermiculture Experience	-.180**
	V607	Support from NGO or Govt?	-.180**
Vermiculture Benefits	V609	CSAs improved HH Income?	-.118*
	V610	Recommend CSA to others?	-.195**

APPENDIX 3: MACHINE LEARNING LAGORITHM

```
Use /tmp/tmp8wsg48cm as a temporary training directory
Reading training dataset...
Training dataset read in 0:00:05.535409. Found 292 examples.
Training model...
The model trained in 0:00:00.342664
Compiling model...


Model compiled.
1/1 [==============================] - 1s 509ms/step - loss: 0.0000e+00 -
accuracy: 0.9118

loss: 0.0000
accuracy: 0.9118
Model: "random_forest_model"
_________________________________________________________________
 Layer (type)     Output Shape            Param #
=================================================================
====
=================================================================
====
Total params: 1
Trainable params: 0
Non-trainable params: 1
_________________________________________________________________
Type: "RANDOM_FOREST"
Task: CLASSIFICATION
Label: "__LABEL"

Input Features (61):
	V10
	V103
	V104
	V107
	V112
	V115
	V119
	V120
	V121
	V129
	V130
	V133
	V134
	V135
	V136
	V138
	V139
	V140
```

V141
V143
V144
V145
V146
V160
V161
V162
V163
V164
V165
V167
V168
V169
V17
V18
V22
V25
V28
V29
V34
V37
V38
V4
V40
V41
V43
V44
V47
V48
V49
V5
V50
V51
V57
V58
V6
V68
V75
V76
V77
V8
V80

No weights

Variable Importance: MEAN_MIN_DEPTH:
1. "V107" 6.061888 ################
2. "__LABEL" 6.061888 ################
3. "V25" 6.056942 ###############

4. "V135” 6.035393 ###############
5. "V119” 6.003965 ###############
6. "V38” 5.994976 ###############
7. "V133” 5.991609 ###############
8. "V77” 5.989445 ###############
9. "V134” 5.989209 ###############
10. "V37” 5.982509 ###############
11. "V17” 5.980798 ###############
12. "V168” 5.978922 ###############
13. "V43” 5.978855 ###############
14. "V47” 5.973464 ###############
15. "V8” 5.972321 ###############
16. "V75” 5.969374 ###############
17. "V103” 5.966159 ###############
18. "V143” 5.964396 ###############
19. "V76” 5.963249 ###############
20. "V29” 5.956429 ###############
21. "V169” 5.953642 ###############
22. "V40” 5.947487 ###############
23. "V41” 5.945617 ###############
24. "V44” 5.941678 ###############
25. "V130” 5.940983 ###############
26. "V104” 5.940503 ###############
27. "V18” 5.930401 ###############
28. "V22” 5.929931 ###############
29. "V120” 5.919561 ###############
30. "V68” 5.909852 ##############
31. "V115” 5.905641 ##############
32. "V28” 5.904334 ##############
33. "V80” 5.895449 ##############
34. "V34” 5.881757 ##############
35. "V144” 5.868709 ##############
36. "V48” 5.850789 ##############
37. "V146” 5.790208 ##############
38. "V121” 5.789006 ##############
39. "V165” 5.766902 #############
40. "V49” 5.753222 #############
41. "V50” 5.719735 #############
42. "V129” 5.718946 #############
43. "V141” 5.718069 #############
44. "V164” 5.688086 #############
45. "V4” 5.669920 #############
46. "V145” 5.639934 #############
47. "V5” 5.624090 ############
48. "V140” 5.605900 ############
49. "V112” 5.567714 ############
50. "V6” 5.553842 ############
51. "V58” 5.493566 ############
52. "V10” 5.347317 ###########
53. "V167” 5.262791 ##########

54. "V57” 5.005407 ########
55. "V139” 4.998652 ########
56. "V136” 4.934415 ########
57. "V162” 4.840022 #######
58. "V51” 4.838302 #######
59. "V163” 4.776970 #######
60. "V161” 4.584071 #####
61. "V138” 4.569554 #####
62. "V160” 3.760022

Variable Importance: NUM_AS_ROOT:

1. "V160" 49.000000 #################
2. "V136" 31.000000 ##########
3. "V138" 29.000000 #########
4. "V161" 28.000000 #########
5. "V163" 23.000000 #######
6. "V162" 21.000000 ######
7. "V51" 20.000000 ######
8. "V139" 18.000000 #####
9. "V167" 16.000000 #####
10. "V140” 8.000000 ##
11. "V145” 6.000000 #
12. "V10” 5.000000 #
13. "V112” 5.000000 #
14. "V164” 5.000000 #
15. "V6” 4.000000 #
16. "V103” 3.000000
17. "V104” 2.000000
18. "V129” 2.000000
19. "V141” 2.000000
20. "V4” 2.000000
21. "V49” 2.000000
22. "V57” 2.000000
23. "V58” 2.000000
24. "V115” 1.000000
25. "V119” 1.000000
26. "V121” 1.000000
27. "V144” 1.000000
28. "V146” 1.000000
29. "V168” 1.000000
30. "V18” 1.000000
31. "V28” 1.000000
32. "V29” 1.000000
33. "V34” 1.000000
34. "V38” 1.000000
35. "V40” 1.000000
36. "V5” 1.000000
37. "V50” 1.000000
38. "V80” 1.000000

Variable Importance: NUM_NODES:

1. "V57" 730.000000 ################
2. "V58" 427.000000 #########
3. "V10" 363.000000 #######
4. "V161" 344.000000 #######
5. "V160" 328.000000 #######
6. "V5" 325.000000 #######
7. "V50" 275.000000 ######
8. "V112" 254.000000 #####
9. "V129" 253.000000 #####
10. "V163" 242.000000 #####
11. "V49" 240.000000 #####
12. "V139" 230.000000 #####
13. "V51" 207.000000 ####
14. "V138" 203.000000 ####
15. "V4" 200.000000 ####
16. "V162" 180.000000 ###
17. "V121" 169.000000 ###
18. "V136" 149.000000 ###
19. "V165" 133.000000 ##
20. "V146" 130.000000 ##
21. "V34" 128.000000 ##
22. "V44" 127.000000 ##
23. "V6" 125.000000 ##
24. "V120" 119.000000 ##
25. "V80" 118.000000 ##
26. "V75" 116.000000 ##
27. "V18" 115.000000 ##
28. "V17" 113.000000 ##
29. "V28" 113.000000 ##
30. "V141" 111.000000 ##
31. "V29" 110.000000 ##
32. "V22" 109.000000 ##
33. "V8" 103.000000 ##
34. "V167" 99.000000 ##
35. "V68" 99.000000 ##
36. "V48" 96.000000 ##
37. "V140" 86.000000 #
38. "V164" 86.000000 #
39. "V40" 86.000000 #
40. "V47" 84.000000 #
41. "V130" 83.000000 #
42. "V133" 77.000000 #
43. "V145" 77.000000 #
44. "V76" 72.000000 #
45. "V77" 70.000000 #
46. "V144" 68.000000 #
47. "V43" 67.000000 #
48. "V143" 58.000000 #
49. "V37" 44.000000

50. "V134" 39.000000
51. "V169" 37.000000
52. "V135" 28.000000
53. "V115" 27.000000
54. "V41" 26.000000
55. "V104" 13.000000
56. "V38" 12.000000
57. "V103" 8.000000
58. "V119" 7.000000
59. "V168" 7.000000
60. "V25" 1.000000

Variable Importance: SUM_SCORE:

```
 1. "V160" 5825.239255 ################
 2. "V161" 3719.850065 ###########
 3.  "V57" 3241.338325 #########
 4. "V138" 2576.847617 #######
 5. "V163" 2204.881587 ######
 6.  "V51" 1678.370579 ####
 7. "V139" 1650.825271 ####
 8.  "V58" 1647.063799 ####
 9. "V162" 1621.465199 ####
10.  "V10" 1532.849280 ####
11. "V136" 1392.575787 ###
12.   "V5" 1043.849442 ##
13. "V112" 989.692286 ##
14. "V129" 954.665801 ##
15.  "V50" 934.233853 ##
16. "V167" 849.080579 ##
17.   "V4" 802.876516 ##
18. "V165" 800.435553 ##
19.  "V49" 793.969601 ##
20. "V121" 611.113882 #
21. "V140" 578.875881 #
22. "V146" 576.390751 #
23.   "V6" 572.912016 #
24. "V164" 540.616078 #
25. "V145" 520.472480 #
26.  "V34" 479.588043 #
27. "V141" 471.581074 #
28.  "V80" 447.801415 #
29.  "V44" 433.808388 #
30. "V120" 416.474847 #
31.  "V48" 372.789322 #
32.  "V28" 364.102392
33.  "V18" 358.959782
34.  "V29" 345.959497
35.  "V75" 342.601542
36.  "V22" 327.830028
37.  "V68" 319.680118
```

38. "V144" 310.812498
39. "V17" 308.474778
40. "V8" 303.415275
41. "V40" 261.649665
42. "V47" 257.534607
43. "V130" 246.949546
44. "V76" 239.706320
45. "V77" 236.073723
46. "V169" 220.400257
47. "V133" 216.195251
48. "V43" 210.584552
49. "V143" 203.317245
50. "V37" 178.491523
51. "V134" 139.460715
52. "V41" 121.985184
53. "V115" 107.150135
54. "V135" 84.782175
55. "V104" 74.921918
56. "V38" 60.145175
57. "V103" 54.104019
58. "V168" 35.802962
59. "V119" 28.905943
60. "V25" 2.905542

Winner take all: true
Out-of-bag evaluation: accuracy:0.828767 logloss:0.396494
Number of trees: 300
Total number of nodes: 16992

The number of nodes by tree:
Count: 300 Average: 56.64 StdDev: 5.41144
Min: 41 Max: 69 Ignored: 0

[41, 42) 1 0.33% 0.33%
[42, 43) 0 0.00% 0.33%
[43, 45) 1 0.33% 0.67%
[45, 46) 8 2.67% 3.33% ##
[46, 48) 12 4.00% 7.33% ###
[48, 49) 0 0.00% 7.33%
[49, 51) 15 5.00% 12.33% ###
[51, 52) 26 8.67% 21.00% ######
[52, 54) 25 8.33% 29.33% ######
[54, 55) 0 0.00% 29.33%
[55, 56) 41 13.67% 43.00% ##########
[56, 58) 43 14.33% 57.33% ##########
[58, 59) 0 0.00% 57.33%
[59, 61) 39 13.00% 70.33% #########
[61, 62) 42 14.00% 84.33% ##########

```
[ 62, 64) 22   7.33% 91.67% #####
[ 64, 65) 0   0.00% 91.67%
[ 65, 67) 18   6.00% 97.67% ####
[ 67, 68) 5   1.67% 99.33% #
[ 68, 69] 2   0.67% 100.00%

Depth by leaves:
Count: 8646 Average: 6.07622 StdDev: 2.03221
Min: 1 Max: 14 Ignored: 0
----------------------------------------------
[ 1, 2)   12   0.14%   0.14%
[ 2, 3) 209   2.42%   2.56% #
[ 3, 4) 654   7.56% 10.12% ####
[ 4, 5) 1133 13.10% 23.22% #######
[ 5, 6) 1515 17.52% 40.75% #########
[ 6, 7) 1600 18.51% 59.25% ##########
[ 7, 8) 1432 16.56% 75.82% #########
[ 8, 9) 1066 12.33% 88.14% #######
[ 9, 10) 601   6.95% 95.10% ####
[ 10, 11) 258   2.98% 98.08% ##
[ 11, 12) 114   1.32% 99.40% #
[ 12, 13)   37   0.43% 99.83%
[ 13, 14)   13   0.15% 99.98%
[ 14, 14]    2   0.02% 100.00%

The number of training obs by leaf:
Count: 8646 Average: 10.1319 StdDev: 7.95418
Min: 5 Max: 89 Ignored: 0
----------------------------------------------
[ 5, 9) 5425 62.75% 62.75% ##########
[ 9, 13) 1444 16.70% 79.45% ###
[ 13, 17) 555   6.42% 85.87% #
[ 17, 22) 453   5.24% 91.11% #
[ 22, 26) 264   3.05% 94.16%
[ 26, 30) 165   1.91% 96.07%
[ 30, 34) 120   1.39% 97.46%
[ 34, 39)   87   1.01% 98.46%
[ 39, 43)   41   0.47% 98.94%
[ 43, 47)   33   0.38% 99.32%
[ 47, 51)   32   0.37% 99.69%
[ 51, 56)   10   0.12% 99.80%
[ 56, 60)    4   0.05% 99.85%
[ 60, 64)    5   0.06% 99.91%
[ 64, 68)    4   0.05% 99.95%
[ 68, 73)    2   0.02% 99.98%
[ 73, 77)    0   0.00% 99.98%
[ 77, 81)    1   0.01% 99.99%
[ 81, 85)    0   0.00% 99.99%
[ 85, 89]    1   0.01% 100.00%
```

The attribute in nodes:

730: V57 [NUMERICAL]
427: V58 [NUMERICAL]
363: V10 [NUMERICAL]
344: V161 [NUMERICAL]
328: V160 [NUMERICAL]
325: V5 [NUMERICAL]
275: V50 [NUMERICAL]
254: V112 [NUMERICAL]
253: V129 [NUMERICAL]
242: V163 [NUMERICAL]
240: V49 [NUMERICAL]
230: V139 [NUMERICAL]
207: V51 [NUMERICAL]
203: V138 [NUMERICAL]
200: V4 [NUMERICAL]
180: V162 [NUMERICAL]
169: V121 [NUMERICAL]
149: V136 [NUMERICAL]
133: V165 [NUMERICAL]
130: V146 [NUMERICAL]
128: V34 [NUMERICAL]
127: V44 [NUMERICAL]
125: V6 [NUMERICAL]
119: V120 [NUMERICAL]
118: V80 [NUMERICAL]
116: V75 [NUMERICAL]
115: V18 [NUMERICAL]
113: V28 [NUMERICAL]
113: V17 [NUMERICAL]
111: V141 [NUMERICAL]
110: V29 [NUMERICAL]
109: V22 [NUMERICAL]
103: V8 [NUMERICAL]
99: V68 [NUMERICAL]
99: V167 [NUMERICAL]
96: V48 [NUMERICAL]
86: V40 [NUMERICAL]
86: V164 [NUMERICAL]
86: V140 [NUMERICAL]
84: V47 [NUMERICAL]
83: V130 [NUMERICAL]
77: V145 [NUMERICAL]
77: V133 [NUMERICAL]
72: V76 [NUMERICAL]
70: V77 [NUMERICAL]
68: V144 [NUMERICAL]
67: V43 [NUMERICAL]
58: V143 [NUMERICAL]
44: V37 [NUMERICAL]

39: V134 [NUMERICAL]
37: V169 [NUMERICAL]
28: V135 [NUMERICAL]
27: V115 [NUMERICAL]
26: V41 [NUMERICAL]
13: V104 [NUMERICAL]
12: V38 [NUMERICAL]
8: V103 [NUMERICAL]
7: V168 [NUMERICAL]
7: V119 [NUMERICAL]
1: V25 [NUMERICAL]

The attribute in nodes with depth <= 0:
49: V160 [NUMERICAL]
31: V136 [NUMERICAL]
29: V138 [NUMERICAL]
28: V161 [NUMERICAL]
23: V163 [NUMERICAL]
21: V162 [NUMERICAL]
20: V51 [NUMERICAL]
18: V139 [NUMERICAL]
16: V167 [NUMERICAL]
8: V140 [NUMERICAL]
6: V145 [NUMERICAL]
5: V164 [NUMERICAL]
5: V112 [NUMERICAL]
5: V10 [NUMERICAL]
4: V6 [NUMERICAL]
3: V103 [NUMERICAL]
2: V58 [NUMERICAL]
2: V57 [NUMERICAL]
2: V49 [NUMERICAL]
2: V4 [NUMERICAL]
2: V141 [NUMERICAL]
2: V129 [NUMERICAL]
2: V104 [NUMERICAL]
1: V80 [NUMERICAL]
1: V50 [NUMERICAL]
1: V5 [NUMERICAL]
1: V40 [NUMERICAL]
1: V38 [NUMERICAL]
1: V34 [NUMERICAL]
1: V29 [NUMERICAL]
1: V28 [NUMERICAL]
1: V18 [NUMERICAL]
1: V168 [NUMERICAL]
1: V146 [NUMERICAL]
1: V144 [NUMERICAL]
1: V121 [NUMERICAL]
1: V119 [NUMERICAL]

1: V115 [NUMERICAL]

The attribute in nodes with depth <= 1:
100: V160 [NUMERICAL]
64: V161 [NUMERICAL]
64: V138 [NUMERICAL]
57: V51 [NUMERICAL]
52: V163 [NUMERICAL]
50: V139 [NUMERICAL]
48: V162 [NUMERICAL]
48: V136 [NUMERICAL]
43: V57 [NUMERICAL]
34: V167 [NUMERICAL]
29: V10 [NUMERICAL]
20: V58 [NUMERICAL]
20: V4 [NUMERICAL]
19: V112 [NUMERICAL]
17: V145 [NUMERICAL]
14: V5 [NUMERICAL]
14: V34 [NUMERICAL]
14: V165 [NUMERICAL]
14: V129 [NUMERICAL]
13: V6 [NUMERICAL]
12: V140 [NUMERICAL]
11: V164 [NUMERICAL]
11: V141 [NUMERICAL]
10: V80 [NUMERICAL]
10: V121 [NUMERICAL]
8: V146 [NUMERICAL]
7: V68 [NUMERICAL]
7: V50 [NUMERICAL]
6: V49 [NUMERICAL]
6: V144 [NUMERICAL]
5: V48 [NUMERICAL]
5: V115 [NUMERICAL]
5: V103 [NUMERICAL]
4: V168 [NUMERICAL]
4: V104 [NUMERICAL]
3: V43 [NUMERICAL]
3: V41 [NUMERICAL]
3: V29 [NUMERICAL]
3: V28 [NUMERICAL]
3: V18 [NUMERICAL]
3: V143 [NUMERICAL]
3: V134 [NUMERICAL]
3: V120 [NUMERICAL]
2: V76 [NUMERICAL]
2: V40 [NUMERICAL]
2: V22 [NUMERICAL]
2: V17 [NUMERICAL]

2: V130 [NUMERICAL]
1: V8 [NUMERICAL]
1: V77 [NUMERICAL]
1: V75 [NUMERICAL]
1: V38 [NUMERICAL]
1: V37 [NUMERICAL]
1: V169 [NUMERICAL]
1: V135 [NUMERICAL]
1: V133 [NUMERICAL]
1: V119 [NUMERICAL]

The attribute in nodes with depth <= 2:
163: V160 [NUMERICAL]
108: V161 [NUMERICAL]
105: V57 [NUMERICAL]
98: V163 [NUMERICAL]
95: V138 [NUMERICAL]
87: V51 [NUMERICAL]
86: V139 [NUMERICAL]
77: V162 [NUMERICAL]
76: V10 [NUMERICAL]
68: V136 [NUMERICAL]
58: V58 [NUMERICAL]
52: V167 [NUMERICAL]
47: V129 [NUMERICAL]
46: V112 [NUMERICAL]
42: V4 [NUMERICAL]
36: V5 [NUMERICAL]
33: V6 [NUMERICAL]
33: V165 [NUMERICAL]
32: V145 [NUMERICAL]
31: V50 [NUMERICAL]
29: V34 [NUMERICAL]
28: V121 [NUMERICAL]
27: V164 [NUMERICAL]
26: V146 [NUMERICAL]
26: V141 [NUMERICAL]
26: V140 [NUMERICAL]
25: V49 [NUMERICAL]
19: V80 [NUMERICAL]
16: V22 [NUMERICAL]
14: V144 [NUMERICAL]
13: V68 [NUMERICAL]
13: V48 [NUMERICAL]
12: V134 [NUMERICAL]
11: V76 [NUMERICAL]
11: V75 [NUMERICAL]
11: V40 [NUMERICAL]
11: V18 [NUMERICAL]
11: V143 [NUMERICAL]

11: V120 [NUMERICAL]
10: V77 [NUMERICAL]
10: V17 [NUMERICAL]
10: V133 [NUMERICAL]
10: V115 [NUMERICAL]
9: V37 [NUMERICAL]
9: V28 [NUMERICAL]
9: V130 [NUMERICAL]
8: V41 [NUMERICAL]
8: V29 [NUMERICAL]
8: V169 [NUMERICAL]
7: V8 [NUMERICAL]
7: V43 [NUMERICAL]
7: V103 [NUMERICAL]
5: V44 [NUMERICAL]
5: V168 [NUMERICAL]
5: V104 [NUMERICAL]
4: V47 [NUMERICAL]
4: V38 [NUMERICAL]
4: V119 [NUMERICAL]
2: V135 [NUMERICAL]
1: V25 [NUMERICAL]

The attribute in nodes with depth <= 3:
212: V57 [NUMERICAL]
210: V160 [NUMERICAL]
172: V161 [NUMERICAL]
139: V10 [NUMERICAL]
133: V163 [NUMERICAL]
131: V51 [NUMERICAL]
124: V138 [NUMERICAL]
120: V58 [NUMERICAL]
120: V139 [NUMERICAL]
113: V162 [NUMERICAL]
88: V136 [NUMERICAL]
84: V129 [NUMERICAL]
82: V112 [NUMERICAL]
75: V5 [NUMERICAL]
67: V4 [NUMERICAL]
67: V167 [NUMERICAL]
64: V50 [NUMERICAL]
62: V49 [NUMERICAL]
58: V165 [NUMERICAL]
53: V6 [NUMERICAL]
52: V146 [NUMERICAL]
52: V121 [NUMERICAL]
51: V145 [NUMERICAL]
50: V164 [NUMERICAL]
47: V34 [NUMERICAL]
46: V141 [NUMERICAL]

39: V140 [NUMERICAL]
32: V22 [NUMERICAL]
30: V28 [NUMERICAL]
30: V144 [NUMERICAL]
29: V80 [NUMERICAL]
28: V120 [NUMERICAL]
27: V17 [NUMERICAL]
26: V48 [NUMERICAL]
26: V133 [NUMERICAL]
23: V76 [NUMERICAL]
23: V68 [NUMERICAL]
23: V40 [NUMERICAL]
23: V29 [NUMERICAL]
23: V143 [NUMERICAL]
23: V130 [NUMERICAL]
22: V8 [NUMERICAL]
22: V75 [NUMERICAL]
21: V44 [NUMERICAL]
20: V47 [NUMERICAL]
20: V18 [NUMERICAL]
18: V77 [NUMERICAL]
18: V37 [NUMERICAL]
16: V43 [NUMERICAL]
16: V169 [NUMERICAL]
16: V134 [NUMERICAL]
15: V41 [NUMERICAL]
11: V115 [NUMERICAL]
11: V104 [NUMERICAL]
8: V135 [NUMERICAL]
7: V103 [NUMERICAL]
6: V38 [NUMERICAL]
5: V168 [NUMERICAL]
5: V119 [NUMERICAL]
1: V25 [NUMERICAL]

The attribute in nodes with depth <= 5:
458: V57 [NUMERICAL]
290: V160 [NUMERICAL]
280: V161 [NUMERICAL]
266: V58 [NUMERICAL]
249: V10 [NUMERICAL]
202: V163 [NUMERICAL]
186: V51 [NUMERICAL]
183: V5 [NUMERICAL]
179: V138 [NUMERICAL]
176: V139 [NUMERICAL]
173: V50 [NUMERICAL]
171: V112 [NUMERICAL]
160: V162 [NUMERICAL]
160: V129 [NUMERICAL]

150: V49 [NUMERICAL]
144: V4 [NUMERICAL]
122: V136 [NUMERICAL]
109: V165 [NUMERICAL]
106: V121 [NUMERICAL]
101: V146 [NUMERICAL]
99: V6 [NUMERICAL]
95: V34 [NUMERICAL]
90: V167 [NUMERICAL]
83: V141 [NUMERICAL]
78: V80 [NUMERICAL]
77: V44 [NUMERICAL]
76: V140 [NUMERICAL]
76: V120 [NUMERICAL]
73: V145 [NUMERICAL]
72: V22 [NUMERICAL]
71: V28 [NUMERICAL]
69: V48 [NUMERICAL]
69: V164 [NUMERICAL]
68: V18 [NUMERICAL]
66: V17 [NUMERICAL]
63: V68 [NUMERICAL]
63: V29 [NUMERICAL]
59: V47 [NUMERICAL]
58: V75 [NUMERICAL]
55: V8 [NUMERICAL]
53: V40 [NUMERICAL]
53: V144 [NUMERICAL]
53: V130 [NUMERICAL]
49: V133 [NUMERICAL]
44: V77 [NUMERICAL]
44: V76 [NUMERICAL]
44: V43 [NUMERICAL]
39: V143 [NUMERICAL]
31: V134 [NUMERICAL]
30: V37 [NUMERICAL]
30: V169 [NUMERICAL]
23: V41 [NUMERICAL]
21: V115 [NUMERICAL]
19: V135 [NUMERICAL]
13: V104 [NUMERICAL]
10: V38 [NUMERICAL]
7: V119 [NUMERICAL]
7: V103 [NUMERICAL]
5: V168 [NUMERICAL]
1: V25 [NUMERICAL]

Condition type in nodes:
8346: HigherCondition
Condition type in nodes with depth <= 0:

300: HigherCondition
Condition type in nodes with depth <= 1:
888: HigherCondition
Condition type in nodes with depth <= 2:
1855: HigherCondition
Condition type in nodes with depth <= 3:
3135: HigherCondition
Condition type in nodes with depth <= 5:
5901: HigherCondition
Node format: NOT_SET

Training OOB:
trees: 1, Out-of-bag evaluation: accuracy:0.8 logloss:7.20873
trees: 11, Out-of-bag evaluation: accuracy:0.80756 logloss:1.40343
trees: 21, Out-of-bag evaluation: accuracy:0.839041 logloss:0.818687
trees: 31, Out-of-bag evaluation: accuracy:0.85274 logloss:0.698837
trees: 41, Out-of-bag evaluation: accuracy:0.869863 logloss:0.696616
trees: 51, Out-of-bag evaluation: accuracy:0.863014 logloss:0.583953
trees: 61, Out-of-bag evaluation: accuracy:0.856164 logloss:0.597861
trees: 71, Out-of-bag evaluation: accuracy:0.84589 logloss:0.601112
trees: 81, Out-of-bag evaluation: accuracy:0.842466 logloss:0.600812
trees: 91, Out-of-bag evaluation: accuracy:0.842466 logloss:0.602873
trees: 101, Out-of-bag evaluation: accuracy:0.842466 logloss:0.608823
trees: 111, Out-of-bag evaluation: accuracy:0.842466 logloss:0.61046
trees: 121, Out-of-bag evaluation: accuracy:0.835616 logloss:0.614605
trees: 131, Out-of-bag evaluation: accuracy:0.839041 logloss:0.612815
trees: 141, Out-of-bag evaluation: accuracy:0.839041 logloss:0.505777
trees: 151, Out-of-bag evaluation: accuracy:0.835616 logloss:0.503939
trees: 161, Out-of-bag evaluation: accuracy:0.832192 logloss:0.502576
trees: 171, Out-of-bag evaluation: accuracy:0.818493 logloss:0.504734
trees: 181, Out-of-bag evaluation: accuracy:0.825342 logloss:0.505728
trees: 191, Out-of-bag evaluation: accuracy:0.825342 logloss:0.50347
trees: 201, Out-of-bag evaluation: accuracy:0.828767 logloss:0.504074
trees: 211, Out-of-bag evaluation: accuracy:0.828767 logloss:0.504811
trees: 221, Out-of-bag evaluation: accuracy:0.825342 logloss:0.504921
trees: 231, Out-of-bag evaluation: accuracy:0.825342 logloss:0.504618
trees: 241, Out-of-bag evaluation: accuracy:0.828767 logloss:0.50523
trees: 251, Out-of-bag evaluation: accuracy:0.821918 logloss:0.505803
trees: 261, Out-of-bag evaluation: accuracy:0.821918 logloss:0.50702
trees: 271, Out-of-bag evaluation: accuracy:0.828767 logloss:0.506287
trees: 281, Out-of-bag evaluation: accuracy:0.825342 logloss:0.397176
trees: 291, Out-of-bag evaluation: accuracy:0.828767 logloss:0.396277
trees: 300, Out-of-bag evaluation: accuracy:0.828767 logloss:0.396494

APPENDIX 4: COMPARISON BETWEEN THE TEST VALUES AND THE PREDICTED VALUES

Random Forest Classifier			Random Forest Classifier		
index	**Actual**	**Predicted**	**index**	**Actual**	**Predicted**
78	1	1	274	2	2
271	1	1	159	2	2
141	2	2	54	2	2
388	1	2	310	1	1
155	1	1	10	1	1
160	2	1	368	2	2
107	1	1	176	1	1
392	2	2	329	1	2
342	2	2	259	1	1
124	1	1	190	2	2
49	1	2	21	2	2
52	1	1	316	2	2
74	2	1	122	2	2
26	2	2	421	2	2
45	2	2	221	2	2
144	2	2	252	2	1
4	2	2	354	1	1
225	2	2	219	1	1
369	1	1	318	2	2
100	2	2	401	1	2
255	2	2	346	1	1
410	1	2	191	1	1
229	2	2	350	2	2
5	2	2	1	2	2
427	2	2	37	1	1
188	2	2	134	2	2
398	2	1	65	1	1
7	1	1	158	1	2
200	1	1	309	2	2
22	2	2	12	1	1
68	2	2	194	2	2
313	1	1	186	1	1

20	1	1	417	2	2
135	1	1	320	2	1
272	2	2	198	1	1
14	2	2	154	2	2
360	2	2	96	2	1
357	1	2	317	1	1
220	2	2	347	1	1
278	2	2	218	2	1
142	1	1	289	2	2
75	2	2	153	2	2
64	1	1	361	1	1
55	2	2	224	2	2
81	2	1	15	2	2
306	1	1	339	1	1
390	2	2	60	2	2
391	2	2	170	1	1
71	2	2	196	1	1
400	1	1	113	1	1
287	1	1	420	2	2
282	1	1	377	1	1
407	2	2	6	2	2
303	2	2	90	1	1
424	2	2	150	2	2
157	2	2	336	1	1
56	2	2	102	1	1
8	1	1	76	2	2
231	2	2	376	2	1
164	2	2	145	2	1
132	2	2	199	2	2
233	1	1	59	2	1
239	2	2	348	1	1
404	2	1	175	2	2
413	2	1			