UPTAKE AND EFFECTS OF CLIMATE SMART AQUACULTURAL PRACTICES ON PRODUCTIVITY AMONG SMALLHOLDER FISH FARMERS IN KAKAMEGA COUNTY, KENYA

BOKE CHRISTOPHER MAGESI

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DECLARATION AND RECOMMENDATION

Declaration

I hereby declare that this is my original work and has not been presented for examination in this or any other university.

Signature: Date: 14/07/2025

Boke Christopher Magesi

KM17/13002/21

Recommendation

This thesis has been submitted to Egerton university graduate school with our approval as university supervisors.

Signature: Date: 14/07/2025

Prof. Hillary Bett, PhD

Department of Agricultural Economics and Agribusiness Management

Egerton University

Signature…. Date: 14/07/2025

Dr. Augustus Muluvi, PhD

Department of Economics

Egerton University

DEDICATION

This work is lovingly dedicated to my late Dad John Linus Magesi, my mother Rahab Gati Sessan and my siblings; Fred Chacha, Joseph Muniko, Robi Esther, Mercy Weirungu and Angel Hillary.

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ABSTRACT

Climate change and its negative impacts on livelihoods and ecosystems are a major global concern. The aquaculture segment has also been disfranchised due to climatic variabilities, posing a risk to its sustainability in light of increasing population demands. To tackle this, climate smart aquaculture strategies have been escalated for acceptance and implementation by aquafarmers. Nevertheless, it is unknown whether fish farmers prefer these practices, and little is known about their contribution to productivity. This study aimed to determine fish farmers' preferences for climate smart aquaculture practices, determine the socio-economic and institutional drivers of choice of climate smart aquacultural practices, and determine how these practices affect productivity among farmers in Kakamega county, Kenya. Through multistage sampling approach, 220 fish farmers were selected with data collected applying semi-structured questionnaires. A best-worst scaling technique served to identify preferences for CSA interventions. In relation to the factors influencing the choice of CSA practices, the study adopted a multivariate probit model, and the effects of climate smart aquaculture practices on productivity were determined using a multinomial endogenous switching regression. The results posited that most fish farmers highly preferred the use of solar power, water reuse, and water harvesting climate smart aquaculture goals, while the use of wind power, dam liners, and improved feeds were the least preferred. On the second objective age of the respondent, level of education, gender, farmers' experience, household size, land size, extension services, and training pointedly influenced the uptake of climate smart aquaculture practices. Finally, the results demonstrated high productivity among farmers who used CSA practices in combinations (Da_Ta_St at 3665.96 Kgs/Ha) as compared to the single application of these practices (Adjusted stocking 489.99 and Dam lines at 196.63). In conclusion, the uptake of climate smart aquaculture strategies by fish farmers significantly contributed to an upsurge in productivity. The study recommends policies that prioritize the preferences of aqua farmers in the development of climate smart aquaculture interventions, the revitalization of the aquaculture sector through enhanced access to extension and knowledge diffusion aimed at promoting the uptake of these innovations. The findings of this study contribute to the current body of literature on climate-smart aquaculture and will inform policy formulation and the development of strategies intended to promote aquatic farming.

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LIST OF ABBREVIATIONS AND ACRONYMS

ATE	Average Treatment Effect
ATH	Average Treatment Heterogeneity
ATU	Average Treatment Effect on the Untreated
CSAq	Climate Smart Aquaculture
EUT	Expected Utility Theory
FAO	Food and Agricultural Organisation
GOK	Government of Kenya
HH	Household
IPCC	Intergovernmental Panel on Climate Change
KNBS	Kenya National Bureau of Statistics
MALFI	Ministry of Agriculture, Livestock, Fisheries and Irrigation
MESR	Multinomial Endogenous Switching Regression
MVP	Multivariate Probit Model
RUM	Random utility Theory
SDGs	Sustainable Development Goals
SOFIA	The State of World Fisheries and Aquaculture
SSA	Sub-Saharan Africa
VIF	Variance Inflation Factor
WTP	Willingness to Pay

CHAPTER ONE
INTRODUCTION

1.1 Background Information

Consequences of climate change in global governance and development strategies have garnered a substantial attention in recent times. This heightened attention arises from its profound implications for critical aspects in particular food and nutritional security, poverty alleviation, livelihood and inequality reduction. Efforts aimed at achieving the Paris treaty and attainment of sustainable development goals (SDGs) have been stalled owing to the far-reaching impact of climate change (FAO, 2020). Amid the diverse challenges posed by climate change, global warming and droughts have emerged as the most formidable threats to a wide array of livelihood resources, including, livestock, agriculture and fisheries.

It is undeniable that the fisheries sector plays is central to enhancing livelihood and ensuring food and nutrition security (Garlock *et al.,* 2020). Nonetheless, this sector continues to face ongoing disruptions due to bearings of climate change. According to Barange *et al.* (2018) and Lubembe *et al.* (2022), factors such as rising temperatures, salinity, deoxygenation and extreme climatic events have exerted detrimental effects on production and the delicate ecosystems upon which the fish activities depend on. Affecting the fishing industry through invasion of non-native species, altered fish distribution, declined catchability and diseases infestation (Macusi *et al.*, 2020). With the world population projected at 9.8 billion by 2050, debates continue over the sustainability of the fishing industry in the long-run, calling for mitigation and adaptive responses to realize a self-sustaining system (IPCC, 2022).

The global fish production has struggled to meet the mounting demand resulting from population upsurge and shifting dietary predilections. As a result, aquatic farming has gained a significant attention as a means to bridge this gap. According to FAO (2022), global capture fisheries have plateaued for decades with approximately 90 MT of fish caught annually. The aquaculture sector which accounts for 87MT of total fish production, recorded a growth rate of 2.7% in 2020. However, this has remained below the annualized rate of growth of 4.5% achieved in previous years. Asian countries have dominated this industry accounting for about 89% of the global aquaculture production. America is the second highest producer accounting for about 4.6%, closely followed by Europe at 3.8% (Garlock *et al.,* 2020 & Rocha *et al.,* 2022). African countries produce a mere 2.7%, with Egypt and Nigeria leading in production (Kaleem & Sabi, 2021).

According to the Kenya National Bureau of statistics (KNBS, 2020), fish output is approximated at 180,000 tonnes per year in which aquaculture accounts for approximately 13% resulting in a demand deficit of about 373, 000 tonnes per year This substantial deficient requires a better emphasis on aquatic farming to realize the suggested per capita consumption of 20 kilograms per person annually. Furthermore, over dependence on imported frozen fish highpoints the earnestness on augmenting national production securing sustainable and secure fish stream (Adekola *et al.*, 2022 & Ogello *et al.,* 2022). Efforts to leverage aquatic farming such as the initiation of economic stimulus programs and the establishment of the Fish Farming Enterprise Productivity Program (FFEPP) aim at increasing fish production, enhancing food security, and improving the livelihood of fish farmers (GoK, 2009). Nevertheless, the aquaculture sector still grapples with climate change challenges, including flooding, extreme temperatures, and drought resulting in increased disease vulnerability, fish stock losses, and infrastructure destructions (Obiero *et al.,* 2019).

Due to abundance of aquatic resources in Kakamega County, aquaculture has enormous growth potential. In light of this, the County Integrated Development Plan prioritizes aquaculture as a key value chain for economic transformation. Nevertheless, the growing variability in climate presents a major risk to the growth of this industry. Adekola *et al.* (2022) projects that the full effects of climate change reduce up to 40 % of the latent progress in aquaculture as a result of both the primary and secondary effects of climate change. The county's reliance on rainfed agriculture affects productivity and subject farmers to the vagaries of changes in climate. In the greater western Kenya, evidence of climate change, which include prolonged droughts and unpredictable rainfall has intensified, with rising temperatures, worsening agricultural droughts and results in low yields, as emphasised by Chepkoech *et al.* (2018). Such climatic pressures are not only compromising fish farming but also present a complex challenge for agricultural policy makers, researchers, extension officers, and other stakeholders in designing and implement farmer-friendly innovations and adaptive technologies that increase resilience and protects the aquaculture sector against the negative effects of climate change.

Climate adaptation strategies have been developed to address the challenges arising from climatic vulnerabilities (Oparinde *et al.,* 2021). Moreover, as a possible remedy to food security, climate-smart agricultural practices (CSA) are proving to be effective interventions to address climate alterations since it has been found to enhance agricultural productivity (Bai *et al.,* 2019;

Finizola & Passel, 2020). Likewise, CSA practices have played a crucial role in enhancing food security and changing livelihood in the aquaculture sector (Funge & Bennett, 2019). The introduction CSA into aquaculture farming, is essential to attainably address the growing demand for food and buffer farmers against the adverse climate change. Key CSA practices incorporated in this context are recirculating aquaculture system, water management and re-use, use of dam liner, embankment creation, improved feeds and seeds, utilization of green energy and post-harvest handling of fish (Aswathy & Joseph, 2020; Onyeneke *et al.,* 2020); Oparinde, 2021). Nevertheless, additional development and validation of CSA practices applied to aquaculture farming is required to achieve higher productivity (Hussain *et al.,* 2022).

The government has implemented the Kenya climate smart agricultural projects (KCSAP) in partnership with world bank to conduct research and come-up with technologies meant to empower fish agriculturalists against the effects of climate change and speed up resilience while boosting production (MALFI, 2018; Dinesh *et al.,* 2017). There have been three major trends in the development of aquaculture industry. To begin with, there has been a consistent increase in value chains of freshwater aquaculture in both production scale and market value, reflecting a growing demand for fish products. Secondly, feed processing technology and formulations have been enhanced significantly, which have contributed to improving the efficacy and resilience of aquaculture developments. Thirdly, the development of fish breeding and genetics has been significant, particularly focusing on freshwater species such as the Nile tilapia and African catfish, aiming to enhance traits like growth rate and disease resistance (KMFRI, 2021). These trends are indicative of the dynamic development and growing sophistication of the aquaculture sector due to such developments.

Aquaculture has emerged from relative obscurity to become a vital supply system of fish to consumers, mostly in rural and urban areas (Aura *et al.,* 2018). Notwithstanding the outlined benefits, integration of CSA's technologies among smallholder fish farmers continues to lag. Similarly, there is limited evidence on the contribution of CSA interventions on fish productivity. This study, therefore, sought to answer following questions: what are the preferences for CSA techniques among aquatic farmers? what are the factors influencing uptake of CSA practices? and how CSA practices affect fish productivity in Kakamega County.

1.2 Statement of the Problem

Kenya's aquaculture sector serves as a cornerstone in improving food and nutrition security and fostering economic growth. With its abundant aquatic resources, Kenya holds the capacity to meet the increasing demand and changing dietary preferences through fish farming. However, this sector has been severely impacted by the adverse effects of climate change. The heightened risks of drought, extreme temperatures, shifting rainfall patterns and amplified human activities have made fish farmers more vulnerable. To confront these bottlenecks, climate smart aquaculture innovations have been developed. Despite the vital role these strategies play in augmenting productivity of aquaculture farming, limited research has been conducted in this field. Existing studies have primarily focused on the factors influencing the adoption of climate smart-aquaculture practices without considering their effect on fish productivity. Against this backdrop, the present study aims to determine the impact of climate smart-aquaculture strategies on the productivity of fish farming among aqua farmers in Kakamega County, Kenya.

1.3 Objectives of the Study

1.3.1 General Objective

To contribute towards increased food security, climate resilience and improved livelihood through uptake of CSA practices among fish farmers in Kakamega County.

1.3.2 Specific Objectives

i. To determine fish farmers preferences for climate smart aqua cultural practices in Kakamega County.

ii. To determine socio-economic and institutional factors influencing the choice of CSA practices among fish farmers in Kakamega county.

iii. To determine the effects of climate-smart aquaculture on productivity of aquaculture farming in Kakamega county.

1.4 Research Questions

i. What are the fish farmer’s preferences for climate smart aqua cultural practices in Kakamega County?
ii. What socio-economic and institutional factors influence fish farmer’s choice of CSA practices in Kakamega County?
iii. What are the effects of CSA practices on productivity of aquaculture farming among fish farmers in Kakamega County?

1.5 Justification of the Study

This present study aligns with major agricultural development initiatives in Kakamega County. The county has identified aquaculture farming as a vital chain of economic value. Hence this study will bolster efforts to promote food and nutritional security, coupled with improve farmers’ livelihoods and further contribute towards achieving the strategic goals outlined in Kakamega County Integrated Development Plan (CIDP) 2023-2027. Further, the study is congruous with larger-scale efforts such as Agricultural Sector Transformation and Growth strategies as proposed in the Kenya Vision 2030, the Bottom-up Economic transformation, and strategic framework for Climate Smart Agricultural technology 2018-2027. By aligning with these objectives, this research will help to advance the African Agenda 2063, especially on pillar one that advocate for blue economies, environmental sustainability and climate resilience and also the UN’s Sustainable Development Goals (SDGs) of eradicating poverty (SDG 1), eradicating hunger (SDG 2), and combating climate change (SDG 13) in Kakamega County and beyond.

The investigation of institutional and socio-economic aspects in aquaculture proved crucial insights into the decision-making process underlying the choice of climate-smart agricultural initiatives. This understanding will inform the County’s policy formulation and strategic planning in responding to climate variability. Moreover, an in-depth examination on the impact of CSA strategies on productivity will guide the development of approaches to expedite the implementation of CSA techniques by local fish farmers. This acceleration will play a critical role in augmenting fish production, and addressing the current deficit in demand across counties and national levels. The study will also help policy formulation at the national level and augment the scholarly work on aquaculture.

1.6 Scope and Limitation of the Study

The study was conducted in Kakamega County and focused on smallholder aquaculture farmers. It gathered information on fish production as well as socio-economic and institutional factors to assess their influence preferences, the adoption of climate-smart aquaculture (CSA) goals and its subsequent impacts on productivity. This study was however not without limitations, primarily the reliance on cross-sectional dataset which might not capture a true picture of the effects of CSA practices over time. Secondly the study relied on recall among aqua farmers hence we might have had cases of misinformation. Lastly, the study focused on the household level and specifically focused on small-scale aquafarmers in Kakamega County due to financial constraints in conjunction with time limits, therefore it might not be a true representation of the entire country, especially in regions where large-scale operations are more common.

1.7 Definition of Terms

Aquaculture: It is the practice of growing and raising fish in fish ponds.

Climate change: refers to long-term, persistent changes in the mean and/or variability of climatic variables that are either natural or human-induced.

Climate change adoption: the state of using strategies that align and caution fish farmers against the negative shocks caused by changes in climatic conditions.

Climate-smart agriculture: it is an integrated approach that ensures efficient use of resources to meet the growing demand for food while reducing negative spill over to the environment.

Climate-smart agriculture packages: A set of related (have a joint combination) climate-smart agricultural practices.

Climate-smart aquaculture: it entails incorporating climate change adaptation strategies to minimize environmental impacts and enhance the resilience of fish farmers to maximize productivity.

Fish pond: It is a man-made body of water that is designed and used for the purposes of raising and breeding fish

Productivity: It is the ratio of production in kilograms to the pond area of each farm in hectares

Uptake: the willingness and action taken by aquafarmers to acquire and utilize a new practice, a technology or an innovation directed at improving fish production and strengthening the aptitude of fish schemes to and withstand vagaries of climate change.

CHAPTER TWO
LITERATURE REVIEW

2.1. Kenya's Aquaculture Sector

Kenya boasts a vast aquatic resource, yet its aquaculture sector remains underutilized despite its potential to produce up to 14 million tons of fish (KMFRI, 2021). The sector has immensely contributed to food security, employment and export albeit dismal, its contribution cannot be overemphasized. Aquaculture farming has increased exponentially, Kenyan fisheries segment underwrote about 0.8% to the country's GDP in 2019, surmounting to 461milion USD, in the economy, The initiative directly and indirectly improves the living standards of over four million people (Wanja *et al.,* 2020).

The swiftly growing preference for fish and its products in Kenya, which cannot be met by wild fish stock, requires a consented effort to attenuate the demand gaps. Fish farming therefore compliments the wild catchability fish supplies (Obiero *et al.,* 2019a). To leverage this sector, the government is actively endorsing the progress of fish value chain segments, largely over the proposal intended to escalate policy frameworks aligned to aquaculture farming, mainly by the implementation of the Kenya Climate Smart technological innovation Enactment plan-2018-2027' in 2018, Fisheries Management and Development Act, 2016 in effort to ensure a sustainable aquaculture system.

In an effort to cushion farmers against climatic variability, the Kenyan government in collaboration with the world bank has promoted climate smart aquaculture technologies, innovations and management practices (CSA-TIMPs). Climate smart practices intend to address synergies and trade-off in agriculture towards achieving a "Triple win" effect that is anchored on three pillars; productivity, adaptation and mitigation (Ellis *et al.,* 2019; Yatsenko, 2021). The project is critical and at the right time when Kenya is faced with threats of climate change. Calling for the need to improve on productivity, increased resilience and concerted efforts to sustainably use our resources taking cue of the negative spill-overs (Adekola *et al.,*2022; Obiero *et al.,* 2019).

CSA-TIMPs bring together important tools and methods that improve the fish value chain and support aquaculture farmers. Among the innovations and technologies developed include; fish breed and breading and reproduction, culture systems, fish feeds and feeding programs, market linkages, post-harvest reduction among others. To help farmers successfully adopt these practices in Kenya, there is a strong need for joint efforts from all relevant stakeholders. This includes creating supportive policies and building the skills and knowledge of farmers through training and capacity building programs (Waaswa *et al.,* 2022).

2.2. Empirical Literature

2.2.1 Preferences for Climate Smart Aquacultural Practices Realized Among Farmers

Research on evaluating smallholder farmers selection tendencies for CSA innovations in Ethiopia, Wassie and Pauline (2018) used a conjoint experiment. The findings indicate that farmers preferred practices that had high climate resilience and high yields to those, which had high greenhouse gas emissions (GHG) and low climate resilient. The study further asserted that unreliable climate information and low funds are some of the factors contributing to low uptake of climate smart agricultural practices among farmers. This study corroborated with Mussa (2015) on eliciting trade-offs and preferences in Tanzania, suggested positive utility on farming systems that are highly productive, highly resilient to climate change and with low greenhouse gas emissions while low productivity and high greenhouse gas emissions had a disutility. Nevertheless, modelling using choice experiment presume that all farmers share the same predilection for CSA practices over time and that the farmers have similar preferences and make decisions based on a common set of underlying factors.

Geda and Kühl (2021) used a multinomial logit model to assess farmers preferences for climate smart seed innovations in Ethiopia. The findings revealed that farmers have high preferences for drought tolerate seeds while colour of the seeds had a disutility among farmers. The study further asserted that there is need to develop CSA technologies that encapsulate farmer's preferences in efforts to boost uptake of these innovations. However, the multinomial logit model assumes that all farmers have the same underlying preferences, which is not in most cases. The model also tends to relay on observed variables to determine preferences and it therefore does not consider cases where preferences are due to latent factors such as social norms. The proposed study will overcome this challenge by using best-worst scaling technique to elicit preferences.

Martey *et al.* (2020) utilized a random parameter logit to determine farmers' preference for climate smart cowpea varieties in Ghana. The study posits that farmers preferred varieties that are high yielding with high maturity rate and low pricing. The assertions are in line with Miriti *et al.* (2022) which posit that high yielding; early maturity had significant heterogeneity and influenced farmers' preferences to use improved varieties. This model bests suits this study due to its ability to capture preference dynamics and overcome preference heterogeneity among farmers. However, it is greatly affected by cognitive biases and response fatigue exhibited by respondents in the process of eliciting preferences. To overcome these challenges, a best-worst scaling technique will be utilized to elicit farmers preferences for climate smart aquaculture innovations.

Research to determine integration of carbon farming activities among farmers in Australia, Dumbrell *et al.* (2016) used a best-worst scaling approach. The results posited that farmers had high preferences for reduced soil erosion and minimum tillage cropping strategies while agroforestry and use of biochar had relatively lower level of preference among farmers. On contrary, a study by Shittu *et al.* (2018) in Nigeria showed that farmers had a high preference for agroforestry and manure management. The best-worst scaling technique unlike the traditional discrete choice has the ability to provide more information on relative preferences of attributes with higher efficiency and it also reduces the cognitive bias of the respondent.

2.2.2 Factors Swaying the Choice of Climate Smart Agricultural Innovations Among Fish Farmers

A number of factors stimulating the use of climate smart agricultural initiatives among farmers including institutional factors in particular access to credit, group membership, access to extension services among others or socio-economic factors such as age, gender and off-farm employment among others. Different researchers have outlined how these factors impacting how farmers embrace diverse CSA goals.

Aswathy and Joseph (2020) used a binary logit model to determine the factors affecting cage fish farming adoption decisions in India. The findings posited that the odds of adopting to climate smart technological innovations practice are positively inclined to occupation, household income, access to farm information, training and personal education. However, family size, farmers experience, perception on climate change and whether one is a group member did not significantly impact uptake of cage farming. The study corroborates with N'souvi *et al.* (2021) asserted that education level was positively associated with the adoption of CSA innovations among fish farmers in China. The drawback of this model is that it assumes a binary outcome. Its application is limited where multiple strategies are adopted. To overcome this the proposed study will use a multivariate probit model to account for instances where a farmer adopts more than one strategy.

In a study to assess the role of institution in influencing technology adoption among small-holder farmers in India, Tanti *et al.* (2022) modelled using a bivariate probit. The assertions indicated access to extensionists, access to information, labour availability and economic efficiency positively and significantly influenced adoption. These contentions are agreeable with Oparinde *et al.* (2021) on a assertions conducted in Nigeria positing education, off-farm income, age, household size and credit access significantly influence adoption of climate smart agricultural practices among fish farmers. The application of probit model is limited to a binary outcome; hence it does not apply to instances where more than one outcome variable is used.

In Nigeria, Onyeneke *et al.* (2020) in determined fish farmers adoption decisions on climate variation strategies utilizing a multivariate probit model. The findings denoted that farmers experience, regularity of extension visits, number of years spent in school, off-farm income, access to credit and age of the household leader were the key causality of the decision to integrate climate change initiatives. These findings are in line with Gnanasubramaniam and Hemachandra (2020), which also found that extension services contributed to the skill and knowledge for farmer hence adopting improved technology to enhance fish production. Further, the assertions outlined by Obiero *et al.* (2019), on behavioural orientation amongst fish farmers on aquaculture technologies in Kenya further cemented that farm size, the level of education, training, diversified farm activities and ease handling of technologies underscored how farmers perceived aquaculture technology. The multivariate probit mode is suitable where the outcome variable is multi-level. The proposed study therefore used this model to determine the factors influencing uptake of CSA practices among fish farmers.

In examining how CSA innovations affect food security, Wekesa *et al.* (2018) deployed a Poisson regression to determine the social-economic and institutional aspects impacting the use of CSA practices in Kenya. The assertions of the study pointed that the application of specific CSA practices were swayed by age, gender, family size, off-farm job, group participation, credit availability, and frequency of extension services. The poison model assumes that the counts are independent of each other. Nevertheless, there may be correlation between the CSA practices where farmers use more than one practice. Therefore, this limitation was addressed by a multivariate probit model as proposed by the study.

Boateng *et al.* (2022) used a two stage Heckman regression in determining the factors influencing the adoption and intensity of technology adoption among fish farmers in Ghana. The finding indicates that gender, frequency of extension services, farm groups, farm size and the level of education exerted a significant and positive impact on uptake and the level of technology use among fish farmers. Similarly, a study conducted in Ghana, in assessing the parameters likely to influence usage of technology amongst fish farmers, Mantey *et al.* (2020) posited that credit admittance among fish farmers and extension visits suggestively and positively influenced the implementation of climate smart agricultural practices.

Muriithi (2020) used a multinomial logit model in the study of selected climate smart technology amongst small-scale farmers in Kenya. The research revealed that access to credit and income derived from off-farm activities significantly contributed the adoption of CSA technology. Further, households led by male farmers posited high chances of integration as opposed to female headed households. The assertions are in line with research on the position of climate resilient aquaculture in Kenya by, Adekola *et al.* (2022) posited the need for the government to design policies intended to improve farmers knowledge and increase information dissemination systems to enable farmers cope up with the changing climatic conditions. The multinomial logit is suitable when individuals choose a single alternative from a set of set of distinct choices. The model also assumes that each choice is independent prohibiting any correlation between the options, disregarding the adoption of multiple CSA practices, a significant limitation for this study.

Using a double hurdle in the study of aquaculture feed adoption among small-holder farmers in Ghana, Amankwah and Quagrainie (2019), found that small-holder decisions to adopt these arrangements was influenced by years of education, fish-farming training, access to credit, fish-farm size, total land holding, number of extension contacts and water sources. The marginal effect in the first hurdle indicated the probability of feed adoption as a result of these variables. Further, extension contacts and credit access increased adoption probability by 5% and 18% respectively. However, this study posited a setback in that it only focused on fish feeds as a CSA practice, therefore the proposed study will include other CSA practices in the analysis to inform policies appropriately.

2.2.3 Assessing the Effects of Climate Smart Agricultural Practices on Productivity of Aquaculture Farming

To boost production in the aquaculture sector, CSA has emerged as a promising approach to address the challenges posed by climate change and improve production in the aquaculture sector. The use of CSA practices in aquaculture farming has been shown to advance productivity, condense environmental impacts and augment resilience of aquaculture farming systems to climate dynamics. Different researches have outlined the extent to which CSA practices can be implemented in different aquaculture systems and how it affects the welfare of farmers.

Rahman *et al.* (2021), applied a propensity score matching in ascertaining how climate change strategies bearing on income and food security among aquafarmers in Indonesia. The impacts were assessed using near matching and kernel-based matching. The average treatment effect asserted that the adaptive initiatives positively impact on income and food security among fish farmers. The study corroborated with Amankwah *et al.* (2018) who assessed the impact of climate smart feed technology on fish farmer's income and poverty in Kenya, the findings posit that adopters had high income and reduced poverty as opposed to non-adopters. Matching on propensity score is advocated to be a reliable approach with possibly extensive pertinent features. Nevertheless, the model fails to consider selection bias of unobserved variables such as farmer behavioural orientation and risk aversion which might impact on the findings. To overcome the selectivity bias exhibited by farmers in choosing certain combinations of CSA practices the study proposed adopting a multinomial endogenous switching regression.

In a study to assess the impacts of sustainable aquatic farming technology on the welfare of fish farmers, Aung *et al.* (2023) used an endogenous switching regression. The findings indicate that age of the respondent and income from off-farm activities significantly and positively influenced productivity. Climate shocks were also found to have an effect on productivity of non-adopters since adopters had better mechanisms to respond to these shocks. The treated and untreated effect accounts for self-selection probably due to differences exhibited by adopters and non-adopters. The average treatment effect (ATT) of the technology adoption among the adopters was 25.2% while the average treatment effects on the untreated (ATU) of the non-adopters was at 53.2%. The study further revealed that the implementation of aquaculture technology has positive and significant in-flood on aquaculture productivity among fish farmers. Karim *et al.* (2020) pointed out similar results in a study on performance of aquaculture technology in Myanmar. This model is essential where the outcome variables are binary, it does not therefore consider the possibilities of simultaneous options. The proposed study will use multinomial endogenous switching regression (MESR) because it accounts for both monolithic and collective alternative selection.

In a study to review the influence of CSA practices on household income among farmers in South Africa, Mango *et al.* (2018) used the ordinary least squares regression method. Standard treatment model was employed to address potential biasness that might ascend when comparing the outputs of mutually implementors and non- implementors of CSA strategies. The farmers were faced with a dichotomous choice between adoption and rejection. The study revealed a significant and positive impact on income among adopters. A number of recommendations were suggested which include; policy formulation to caution farmers against total loss due to climatic variability, support the extension services in knowledge dissemination, and the need to put more emphasize on semi and intensive agriculture. The linear relationship assumed by ordinary least square regression model may not hold true in some cases.

In the assessing the impact of climate change strategies on poverty and food security in Nigeria, Oparinde (2021) deployed multinomial endogenous switching regression. The results denoted that all the combination of climate change strategies, (ATT) and (ATU) constructively suggested that fish farmers receive high products with adopter having over 70% more in comparison to non-adopters. The findings corroborated with Wekesa *et al.* (2018) in a study on the effects of CSA practices on food security in Kenya which highlighted that farmers who had adopted different CSA combinations were more food secure than the non-adopters. The multinomial endogenous switching regression model accounts for selection bias of both observed and unobserved factors especially were more than two option are used, hence it is the most ideal for this study.

Multiple regression model was used to access the impact of CSA practices on food security of farmers in Bangladesh by Hasan *et al.* (2018). The study findings posited a positive relationship between adoption of CSA practice and household food security. The research likewise asserted that the number of years spent in school and credit access are central towards establishing that households are food secure. The study recommended that there is need to accelerate information dissemination to farmers on adoption of CSA practices, increase access to capital, improve the capacity of research institutions and regular information dissemination by the extensionists enable farmers to make sound production decisions.

An appraisal of previous studies asserted that, although much research has been conducted on Climate-Smart Aquaculture (CSA) practices, most of it has focused broadly on awareness and adoption, without paying close attention to farmers’ preferences for specific practices or the actual outcomes of adoption. In particular, there is a paucity of evidence on how different CSA practices whether used alone or in combination affects aquaculture productivity of smallholder fish farmers in Kenya. While CSA practices are widely recognized for their potential to improve resilience to climate change and enhance livelihoods, existing studies rarely explore how farmers choose among accessible technologies and hoe they impact on productivity. The paucity in the literature confines the aptitude of policymakers and practitioners to design targeted interventions that reflect the realities and needs of small-scale fish farmers. Therefore, this study sought to examine farmers' preferences for CSA practices, their adoption patterns, and the resulting effects on productivity. Providing insights that are essential for informed decision-making and sustainable aquaculture development in the face of climate change.

2.3 Theoretical Framework

This research is hinged on modelling the choice under uncertainty, anchored within the framework of both Random utility theory (RUT) and Expected Utility Theory (EUT). Whereas EUT interprets uncertainty as objective risk, RUT suggests preferences are shaped by both objective and random factors and individual specific characteristics (Chambers *et al.,* 2000).

The study therefore was guided by random utility maximization theory as it delves into how farmers might value distinct climate-smart agricultural CSA) practices. This was based on theory's assertion that choices are influenced by random elements and that choice's utility integrates both deterministic and random components (McFadden, 1973). Essentially, the utility that a fish farmer perceives from choosing a CSA practice is a combination of a defined component and a random residual. The utility equation can be presented as;

$$U_j^i = V_j^i + \varepsilon_j^i \qquad (1)$$

Where U_{ij} is the total utility,V_{ij} postulated an explanatory element while E_{ij} denoted the residual. Farmers value derived from the product is influenced by a set of CSA practices and their attributes as well as farmer characteristics (Cascetta, 2009). Denoting a utility function form by:

$$U = f(CSA_{Attributes}, Farmers_{Attributes}) \qquad (2)$$

A farmer aiming for maximum benefits chooses among a set of CSA practices based on that which provides the highest utility. Provided that the utility gained from one practice U_j prevails over another $U_{j'}$, farmer will select practice j. When rationality might not lead a farmer to an obvious choice, an error term accounts for randomness in the utility function. The likelihood that a farmer chooses a specific CSA strategy can be defined by;

$$P[j(PA) = P[U_j > U_{j'}] \quad (3)$$

with several assumptions in play, including that the error term distribution is independent, identical and follows Gumble distribution (McFadden, 1973).

2.4 Conceptual Framework

This research adopts a conceptual framework illustrated in Figure 1, which establishes a relationship between socio-economic and institutional factors and their influence on the uptake of Climate Smart Aquaculture (CSA) practices. It underscores that socio-economic and institutional factors constitute regressors that shape fish farmers' preferences for CSA innovations, as well as adoption of CSA strategies and subsequent fish productivity.

Socio-economic aspects particularly age, education level, household size, off-farm income, and experiential knowledge are vital in influencing aquafarmers' uptake decisions of CSA initiatives. These factors reflect the individual and household characteristics that affect a farmer's willingness and ability to embrace climate-smart strategies. Institutional factors, including access to credit and extension services, are also pivotal in supporting the uptake of CSA practices. These factors provide essential resources, knowledge, and assistance, which facilitate the adoption process and help fish farmers to better manage climate risks.

The framework posits that the uptake of CSA initiatives ultimately brings about increased fish productivity, which in turn contributes to heightened food security, greater climate resilience, and upgraded livelihoods for fish farmers. By considering both socio-economic and institutional factors, this study offers comprehensive insights into the influences driving the adoption of CSA practices and highlights the relevance of both individual decisions and external institutional support in fostering sustainable aquaculture in the face of climate change.

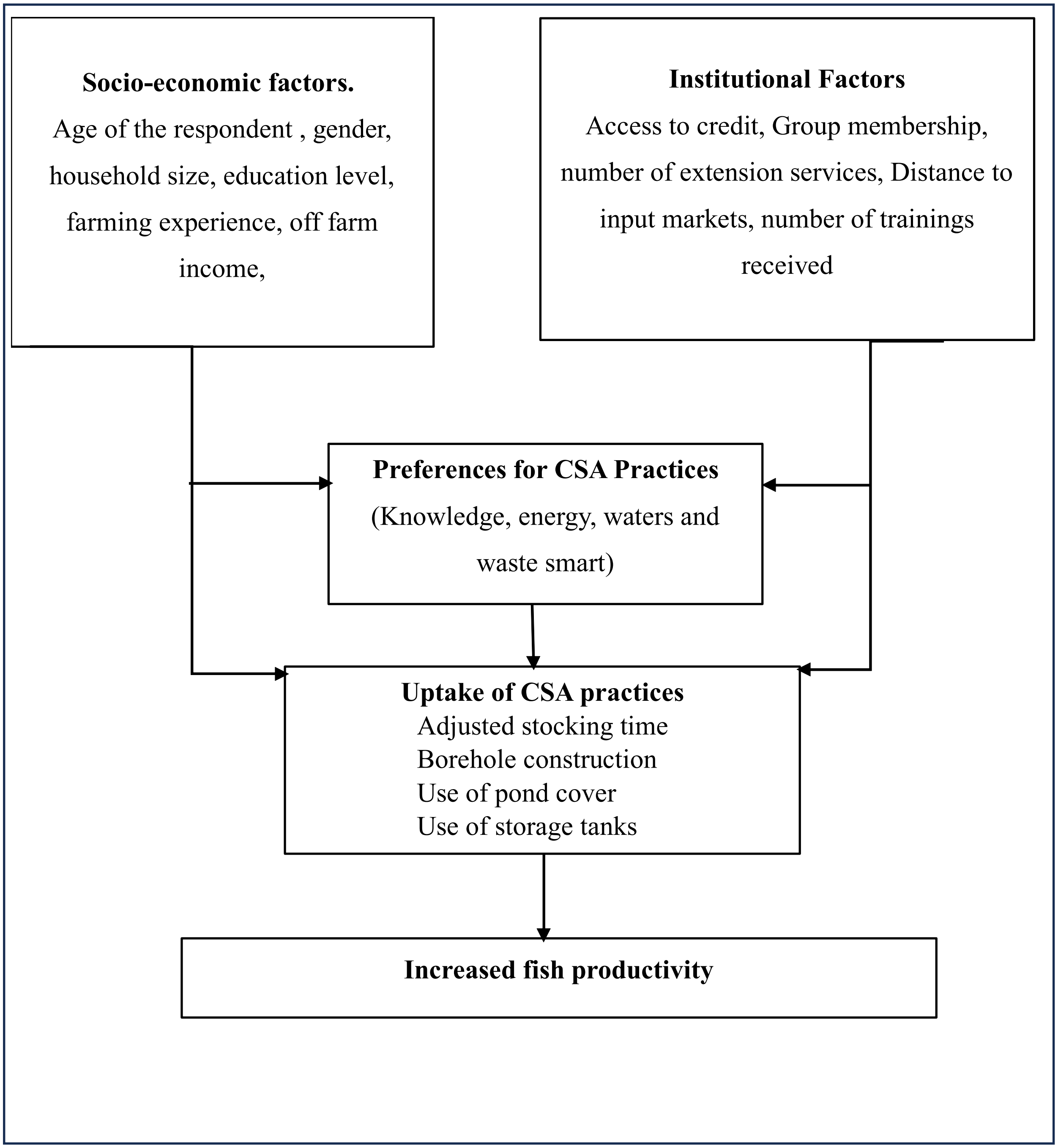

Figure 1: Conceptual Framework

CHAPTER THREE
METHODOLOGY

3.1 Study Area

This work utilized data collected from farmers in Kakamega County, located in western Kenya. The county shares borders with Uasin Gishu County on the Eastern side, Siaya County to the western side, Vihiga County to the south, and Trans Nzoia County to the north. Administratively, Kakamega County comprises twelve sub-counties: Lugari, Lukuyani, Ikolomani, Shinyalu, Navakholo, Mumias East, Mumias West, Matungu, Butere, Kwisero, Lurambi, and Malava. The focus of this study was on Matungu Sub- County. According to the Kakamega County Integrated Development Plan (CIDP, 2023), Matungu Sub- County covers approximately 367 square kilometres and has a population of 167,014 (KNBS, 2019). Geographically, it is situated amid longitudes 34º 52’ 34.36” East and latitude 0º 39’ 4.17” North. The sub-county encompasses five administrative wards: Namamali, Mayoni, Koyonzo, Kholera, and Khalaba. On average, the area records annual rainfall of 1,747 mm and experiences a mean yearly temperature of 23.5ºC. The long rains occur from March to May, while short rains are typically received between October and November.

Agriculture serves as the primary economic activity in Kakamega County, with key crops including maize, beans, sweet potatoes, sorghum, and cassava (MALFI, 2018). In recent years, the county has also emerged as a leader in aquaculture, boasting approximately 9,000 fish farmers. This development underscores a strategic shift toward promoting fish farming as a high-potential value chain. Given that Kakamega is the second most populous county in Kenya with the highest rural population (CIDP, 2023), increasing pressure on land resources has necessitated the exploration of alternative livelihood option to supply the heightened demand for protein. In this context, fish farming has gaining traction not only as a reliable source of protein for the growing population but also as a means of improving household incomes and enhancing overall livelihood resilience.

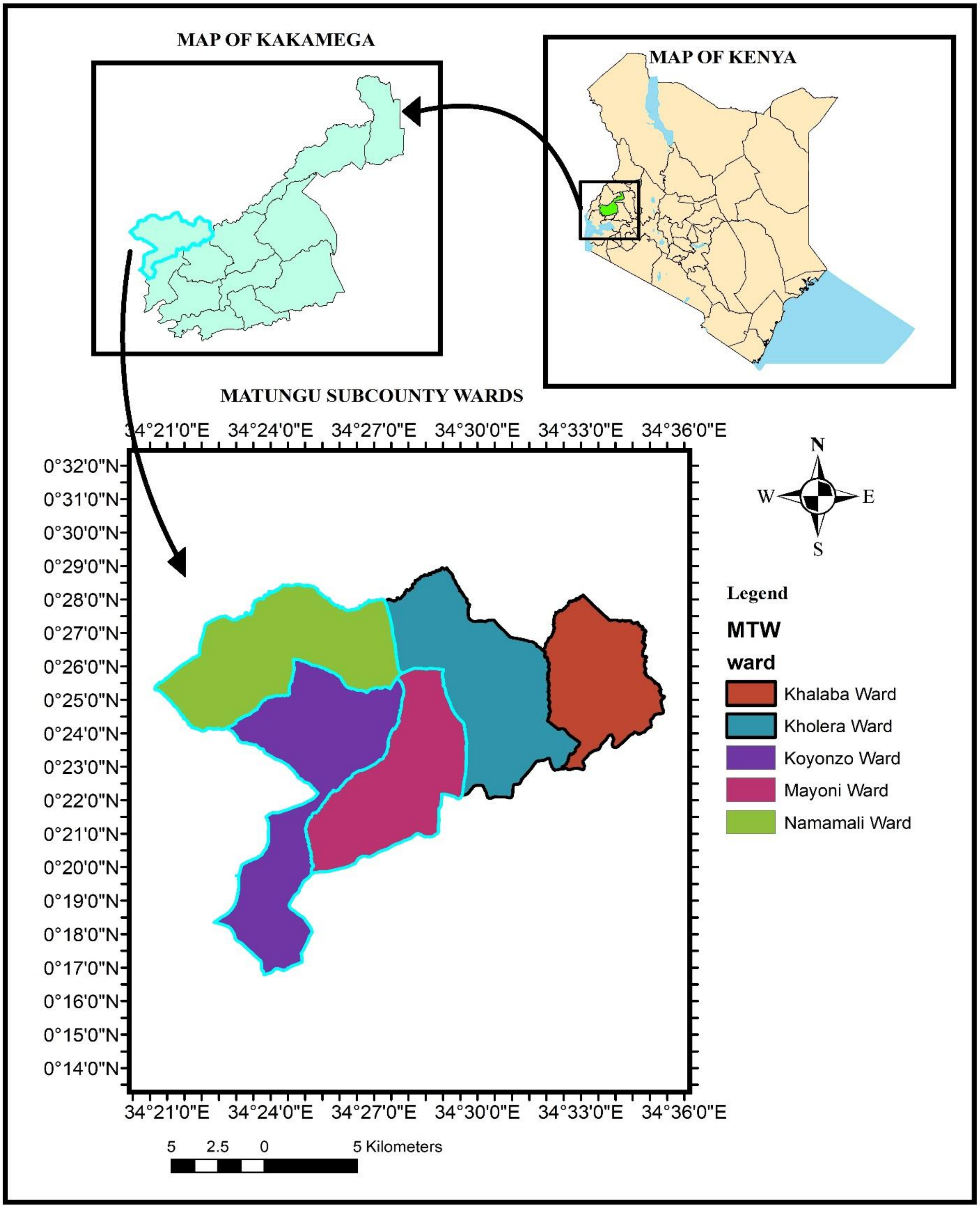

Figure 2: Map of Kakamega County

Source: Survey of Kenya, (2020)

3.2 Research Design

The study adopted a cross-sectional research design, which was suitable for several reasons. This design allowed data to be collected from different groups of fish farmers at a particular point in time, providing a clear picture of their practices given their experiences. It was also time-efficient and cost-effective, making it practical for the study. Additionally, since data collection was done within a relatively short period, the design ensured that the research process was manageable and efficient.

3.3 Target Population

Aquafarmers in Matungu Sub-County constituted the unit of analysis. The sample consisted of male and female farmers who are core decision makers in their households. Their selection ensured that the study captured firsthand insights into aquaculture practices and household decision-making dynamics.

3.4 Sampling Procedure

Aquatic farmers were selected using a multistage sampling approach. At the initial stage, Kakamega County was decisively sampled since it is one of the counties where fish farming has been recognized as an import value chain. Secondly, Matungu sub-county was purposively designated particularly due to it positing humungous fish production potential in Kakamega County. Thirdly, three wards (Namamali, Mayoni and Koyonza) were arbitrarily sampled. In the final stage of sampling, a systematic random sampling procedure was used to select 220 fish farmers for the study.

A complete list of registered fish farmers was first obtained from the office of the County Director in the Fisheries Department. To begin the selection process, the first respondent was randomly chosen from this list to ensure an unbiased starting point. Subsequently, the remaining respondents were selected at a fixed intervals from the list. The sampling interval, was determined by distributing the whole figure of 489 registered fish farmers as per the required sample size of 220. By following this approach, every fish farmer in the list had an equal and predictable chance of being selected, ensuring that there was a reflective sample of aquatic farming populace within the study locality.

3.5 Sample Size Determination

The formula advanced by Yamane (1967) was employed to determine the sample size as shown below;

$$n = \frac{N}{1+N(e^2)} \tag{4}$$

the formula incorporated key statistical parameters to ensure accuracy and representativeness. Here, *n* represents the required sample size, *Z* denotes the critical value corresponding to the chosen confidence level (α = 0.05), *N* refers to the total populace of aquafarmers in the study site, and *E* signifies the tolerable margin of error. For this study, an acceptable error of 5% was used, ensuring that the sample size provides reliable estimates while minimizing potential inaccuracies in data collection and analysis. Characterized by a population size of 489 registered fish farmers in Matungu sub-county, a representative sample of 220 respondents was obtained using the formula above (Table 3.1).

Table 3.1: Target Population and Distribution in each Ward

Sub-county	Ward	Target population	Proportions	Sample
Matungu	Namamali	162	0.33	72
Sub- county	Mayoni	132	0.27	60
	Koyanza	195	0.40	88
Total		489	1.0	220

3.6 Data Collection and Analysis

The study utilized primary data collected by interviewing aqua farmers employing semi-structured questionnaires in elicitation. Trained enumerators conducted the interviews to guarantee precision, steadiness, and dependability in data gathering. Prior to the actual survey, a pre-test was carried out in Mumias East Sub-County to assess the credibility and precision of the questionnaire. This exercise helped identify ambiguities, refine question wording, and ensure that the research instrument effectively captured the required information. Additionally, the pilot study served as a training opportunity for enumerators, equipping them with the necessary skills in data collection, interview techniques, and ethical considerations to enhance the quality of responses.

A research permit was secured from the National Commission for Science, Technology and Innovation, with permit number [Licence No: NACOSTI/P/24/33966] before the onset of data collection exercise. During the main survey, aquafarmers were asked to state their preferences for different climate-smart aquaculture (CSA) practices and indicate which practices they had implemented on their farms. The collected data was then analysed using STATA version 18.

3.7 Analytical Framework

3.7.1 Modelling of Preferences for Climate Smart Aquaculture Practices Among Fish Farmers

In determining preference for climate smart aquacultural practices among fish farmers, A number of different analytical methods could be used. This includes contingent ranking, contingent rating, pairwise comparison, choice modelling techniques and best-worst scaling approach among others. These approaches allow the valuation and or estimation of the characteristics or attributes of a good and of marginal changes in these characteristics. While contingent rating and pairwise comparison use a deterministic utility function. Contingent ranking, choice experiment and best-worst scaling relays in application of random utility functions. The study employed the use of a best-worst scaling technique since it integrates both deterministic and random utility functions. Further, the approach is preferred since it indicates preferences of respondents over attribute levels within each scenario unlike the traditional discrete choice experiment methods that considers preferences between scenarios (Rogers *et al.,* 2021; Thiene *et al*., 2015).

This study applied a best-worst scaling technique as proposed by Marley and Louviere (2005). A multi-profile case technique was adopted to elicit best and worst scenarios. The multi-profile was suitable for this study since it combines critical features of objective (case 1) and profile cases (case 2). Hence, individual fish farmers were required to make a choice within each scenario by selecting an attribute that was most preferred and least preferred. The variation nature of this model offers deeper insights onto relative preferences of attributes with large efficacy due to a large quantity of choice data from every interviewee. The best-worst technique therefore aided in elicitation of more information on individual preferences for climate smart aquacultural practices since it tends to clearly capture key propensities of individuals regarding their best and worst preferred options (Louviere *et al*., 2008).

The study focused on the following four bundles of climate smart aquacultural practices: knowledge smart technology (improved seeds, improved feeds, adjusted stocking time), water-smart technologies (water reuse, embankments, dam line), Energy smart technology (Solar power, wind power, electricity) and waste-smart technologies (water treatment, water reuse, usage of antibiotics). The orthogonal main-effect plan (OMEPs) was employed to generate CSA choice sets using statistical analysis software (SAS). Attributes and attribute-levels were combined into 16 choice tasks. These tasks were then grouped into 4 profiles each profile constituted of 4 choice cards that were presented for eliciting preferences for CSA practices among farmers. An initial efficient design using zero priori was used. The attributes and attribute-levels were determined using relevant literature (Anugwa *et al.,* 2022), and further complimented with a focused group discussion with relevant stakeholders. The fractional factorial design was adopted to reduce cognitive bias and costs that would otherwise have been incurred as a result of using a full factorial design. The fractional factorial design is essential in eliminating the biases while curating the designs efficacy. Table 3.2 presents the attribute and attribute levels used to generate choice sets.

Table 3.2: Description of Attributes and Attribute-Levels

Attribute	Description	Level
Knowledge Smart	Does the CSA meet the demands of the farmer	Improved feeds, Improved seeds, Adjusted stocking time
Energy Smart Tech	Whether the technology is energy efficient	Use of solar, Wind power, Electricity
Water Smart	Whether the practice meet the water demands of the farm	Dam liner, water harvesting, embankments
Waste-Smart	Whether the CSA is environmentally friendly	Water treatment, antibiotics use, water re-use

The potential best-worst preference for CSA was defined as a pair as used by Marley and Louviere, (2005). The probability of a best-worst scenario took the form: let T signify a predetermined pair of hypothetically existing choices. Let $B_X(x)$ symbolize that alternative x is chosen as most preferred in X, $W_X(y)$ denote that alternate y is selected as the least preferred in X and $BW_X(x,y)$ denote a joint likelihood of choosing goal x as most preferred and goal y as least preferred. Hence, the probabilities such that a farmer picks a best or a worst option are as shown below.

$0 \leq B_X(x), W_X(y), BW_X(x,y) \leq 1$

The selection process of respondents choosing among the best and worst options resulted in a best-worst choice probability as denoted by equation 5.

$$PBW_X(x,y) = \frac{\exp\left(\delta\left(\sum_{t=1}^{n}(B_X(x) - W_X(y)\right)\right)}{\sum_{k \neq k} \exp\left(\delta\left(\sum_{t=1}^{n}(B_X(x) - W_X(y)\right)\right)} \tag{5}$$

where δ denote the parameter that determines the scale of utilities, B_X parameter vector associated with best option and W_X parameter estimate associated with worst estimates.

The count and average ranking analysis were obtained from a pooled set of choices elicited from the respondents. Indicators from each attribute-level selected from each respondent were determined. B denoted the frequency a goal was ranked highest, W: the count of occurrence it was chosen as least. A best minus worst score $BWS = (B - W)$; was determined by the differences of best and worst. A standard score $SS = (B - W)(N * 4)$ was determined, with N denoting the sample size, with four signifying the number of choice cards presented to a household. Finally, the analytical best worst $ABW = \log(1 + SS)/(1 - SS)$ according to (Mueller Loose & Lockshin, 2013) and a ratio score$RS = \sqrt{B}/W$ were determined and finally a standardized scale as used by Marley and Louviere, (2005) was adopted where the most important goal takes the value of 100 and multiplying each ration score by a factor given in;

$$Scale = \frac{100}{Max(RS)} \tag{6}$$

From the aforementioned indicators, heterogeneity in preferences was assessed based on the standard deviations of individual BWS scores. These deviations highlighted the variability in farmers' choices regarding CSA goals, indicating both uniformity and diversity in their decision-making. A quotient of the standard deviation to the individual means $Std/mean$ was calculated. With high ratios indicated high variations in heterogeneity while small ratios that tended towards zero denoted low levels of variation among fish farmers were identified as the most important attributes. Table 3.3 depicts a choice set used to elicit preferences among farmers.

Table 3.3: An Example of a Choice Card used in Elicitation

Attributes	**Alternative A**	**Alternative B**	**Alternative C**	**Alternative D**
Knowledge Smart	Adjusted Stocking	Adjusted Stocking	Improved Feeds	Improved Seeds
Energy Smart	Solar Power	Solar Power	Electricity	Wind Power
Water Smart	Water Harvesting	Dam Liner	Embankments	Embankments
Waste Smart	Water Treatment	Water Reuse	Antibiotics Use	Antibiotics Use
Best Preferred				
Worst preferred				

3.7.2 Modelling the Socio-Economic, Institutional and Climate Related Factors Influencing the Use of CSA Practices Among Fish Farmers

Grounded on the reviewed empirical studies, a Multivariate probit (MVP) model was adopted for this study. This model was best preferred since it could simultaneously set out the stimuli of socio-economic and institutional aspects on the use of CSA strategies while allowing the unobserved disturbances as well as different climate smart practices to be correlated. Fish farmers in this study were faced with different CSA practices such as adjusted stocking time, covering of fishponds, use of improved feeds and embankments among others. Therefore, considering the possibilities of different CSA practices, this work adopted a multivariate probit model. Even though a number of CSA practices have been adopted, this study was limited to borehole construction, adjusted stocking time, erection of pond cover, use of storage tanks and the use of dam lines. The innovations were adopted for this work due to the prevalence uptake among fish farmers in Kenya.

Several studies have employed bivariate models to determine the decision to use a certain practice (Aswathy & Joseph 2020, N'souvi *et al*., 2021 & Saha *et al*., 2020). However, these researches do not differentiate the diverse CSA practice that a farmer undertakes. While others have employed multinomial logit (Murithi, 2020), which tends to assume independence of occurrences necessitating the choice of mutually exclusive variables. The assumption of multinomial logit that the practice is mutually exclusive possesses a caveat especially where a household adopts more than one strategy. This study overcame the independence of irrelevant assumptions and in instances where more than one strategy was adopted by using a multivariate probit model (MVP).

A diagnostic test to check for multicollinearity and heteroscedasticity was undertaken using the variance inflation factor (VIF) and Breusch-pagan tests, while the model goodness of fit was assessed using Wald test and also likelihood ratios were used to test for correlation coefficients. The assumption that given a set of regressors, the multivariate rejoinders are indicators, holds for MVP. Let W denote unobserved latent variables, MVP assumed where every object has k distinct dual rejoinders, $i = 1, \ldots\ldots n$ are independent observation (Household characteristics), $k = 1, \ldots . k$ are the available dual outcomes and that *Xi* denotes a matrix of covariates containing any distinct or incessant choice indicators.

$Y_{ik} = (Y_{i1}, \ldots., Y_{ik})$ signify vectors of dimension *k* of observed in dual responses with the value of {0,1} regarding the ith farmer. $W_{ik} = (W_{i1}, \ldots\ldots W_{ik})$ represent a *k* variate ordinary vector of unobserved outcome, subject to: $W_{ik} = X_i B + E_i, i = 1, \ldots \ldots, n$, in which $B = (\dot{\mathrm{B}}_1, \ldots\ldots \dot{\mathrm{B}}_k)$ is a matrix of unspecified regression parameters. E_i is a vector of error terms following a multivariate normal distribution with a mean of zero and a variance of one $\mathcal{E}_i \sim N(0, \phi)$. ϕ denote the second-moment matrix with a value of 1 and leading diagonally. The off-diagonal components in the association matrix, P_{jk} represented the overlooked association between the idiosyncratic component of the j^{th} and k^{th}options.

The vector between the latent variable (W_{ik}) and the vector of observable ordinary responses (Y_{ik}) in the MVP was given by;

$$\mathrm{Y_{ik}} = \{1 \text{ if } \mathrm{Z_{ik}} > 0, 0 \text{ if not}\} \quad \mathrm{i} = 1, \ldots\ldots, \mathrm{n} \text{ and } \mathrm{k} = 1, \ldots \ldots, \mathrm{k}$$

The possibility of observable discrete data was then determined by embedding over the dormant variable *w* as shown by the equation 7.

$$P(Y_{ik} = 1 | X_i, B, \phi) = \int D_{ik}, \ldots, \int D_{i1} S_v (W_{ik} | X_i, B, \phi) dW_{ik} \tag{7}$$

The probability of observing a particular set of multivariate outcomes given the explanatory variables, was calculated using a cumulative distribution function (CDF) of the multivariate normal distribution.

$$P(Y = 1_1, Y_2 = 1, .. Y_k = 1 | X_1, X_2, .. X_K = \iint \ldots . \int \emptyset\, (\tau_1 - X_1 B_1, \ldots\ldots \tau_K - 1 - X_K - 1 B_K - 1, \infty) d\epsilon_1, d\epsilon_2 \ldots\ldots d\epsilon_k \tag{8}$$

where $\emptyset(.)$ is the CDF and ϵ_1, ϵ_2 and ϵ_k are the correlation outcome coefficients between the residual per observation.

The system of equations of the MVP model was calculated using simulated maximum likelihood which is the joint probability of observing the set of multivariate outcomes conditional on set of regressors. Based on equation (7), in determining the socioeconomic and institutional aspects prompting the use of CSA initiatives among fish farmers, an estimated model was specified as follows.

The variables used in Table 3.4 were designated from correlated literature and particular variables of interest.

Table 3.4: Model Variables Hypothesized to Influence the Use of CSA Practices

Variable	Description	Measurement	Sign
CSA Practices; Pond Cover, Dam Lines, Tanks, Adjusted Stocking, Boreholes	**Dependent Variable** The adoption of CSA practices		
	Independent Variables		
Age	Age of household in years	Discrete	+/-
Gender	Household gender (male=1, female=0)	Dummy	+/-
HH Size	The size of the household	Discrete	+/-
Level of Education	Number of years spent in school.	Discrete	+/-
Level of Experience	Experience of farmers in years	Continous	+/-
Off-Farm Income	Income from non-farm activities	Continuous	+/-
Training	Number of trainings received in a year	Discrete	+/-
Credit Access	Whether fish farmers have access to credit	Dummy (1=yes,0=otherwise)	+/-
Number of Ponds	Number of ponds owned	Continuous	+/-
Distance	Distance to input markets	Continuous	+/-
Awareness	If the respondent is aware of climate changes	Dummy (1=yes, 0=otherwise)	+/-
Duration Of Practice	Number of years CSA has been used	Continuous	+/-
Extension	Whether fish farmers access extension services	Dummy (1=yes,0=otherwise)	+/-
GMSHP	If one belongs to a fish farmer association/group	Dummy(1=yes,0=otherwise)	+/-

3.7.3 Modelling the Effect of Climate Smart Agricultural Practices on Productivity of Aquaculture Farming

A number of climate smart aquaculture practices undertaken by fish farmers as reviewed by previous studies. This includes; creation of embarkments, use of well-structured drainage systems, site selection, use of tanks, use of boreholes, adjusted stocking schedules, covering of fish ponds, use of dam lines, recirculating aquaculture systems, use of improved seeds and feeds among others (Aswathy & Joseph, 2020; Olawale, 2016; Onyeneke *et al.,* 2020); Oparinde, 2021). The study determined all the possible combinations of the CSA practices outlined. Since these combinations are mutually exclusive, a two-stage multinomial endogenous regression was employed to model the determinants of choice and effect of climate smart agricultural practices on productivity of aquaculture farming. Productivity was estimated on farmers that have adopted and those that have not adopted any CSA practice. In the first stage, households are assumed to select from *K* mutually exclusive initiatives to adjust to climate dynamics and then proceed through the second stage where the impacts of CSA practices on productivity are evaluated.

In accounting for self-selection and endogeneity a number of frameworks in particular instrumental variables, propensity score matching and multinomial endogenous switching regression (MESR) are often used. However, instrumental variables and propensity score matching do not apply in circumstances that do not exhibit mutual exclusiveness. Following Durbin and McFadden (1984) and Bourguignons *et al.* (2007), the study adopted a MESR treatment effect to account for self-selection. Access to climate information was used as an instrumental variable as used by previous researches. Instruments validity was checked, and admissible tests were undertaken to test the joint effect of the variables. MESR is superior since it allows assessment of monolithic as well as joint effects of CSA strategies on productivity.

A multinomial logit was employed within the first step to examine the drivers of choice of CSA innovations. Farmers were presumed to maximize their utility, Yi through comparison of productivity that will be realized by *K* alternate CSA techniques. The obligation for a farmer to select any approach j over other substitutes K is that $Y_{ij} > Y_{ik}$, $k \neq j$ that is j provides high productivity than any other strategy. This study presumed that productivity is a quotient of production in kilograms per hectare as used by Sandip *et al.* (2019) (Productivity=production/hectare).

Y_{ij}^{*} is a latent variable that represents the expected productivity which contains both the observable household and pond characteristics and unobservable features expressed as:

$$Yij^{*} = BjXi + Eij \qquad (9)$$

Xi denotes the observed exogenous variables (Household and pond characteristics) and the error term E_{ij} denotes the unobserved characteristics. The Xi is a covariate that is assumed to be uncorrelated with the idiosyncratic unobserved disturbance term E_{ij} such that $E\left(E_{y}\middle|X_{i}\right) = 0$ under the assumption that E_{ij} are independent and identically Gumbel distributed that is under the independent irrelevant alternatives (IIA) hypothesis. The likelihood that an individual i picked approach j was quantified using a multinomial logit model (McFadden, 1993).

$$P_{ij} = r\left(E_{ij} < 0\middle|X_{i}\right) = \frac{\exp\left(B_{j}X_{i}\right)}{\sum_{K=1}^{j}\exp\left(B_{k}X_{i}\right)} \qquad (10)$$

P_{ij} denotes the likelihood that respondent i choose variant j, X_{i} is the i household attributes and $B_{j}$is the vector of coefficients related to choice j.

In the second step, a pathway to analyse the effects of CSA was resolute using a multinomial endogenous switching regression model as projected by Bourguignon *et al.* (2007) was used to investigate the impact of each response practice on productivity. The farm household was subjected to a number of K regimes with regime $j = 1$ being the reference category (non-responsive). Productivity status for each possible regime was defined as:

$$Regime1: Q_{1R} = B_{iR}Z_{iR} + E_{iR} \qquad if \quad i = 1$$

$$\begin{matrix} . & & . \\ . & & . \end{matrix}$$

$$Regimej: Q_{inR} = B_{iR}Z_{iR} + E_{iR} \qquad if \quad i = j$$

From the above equation $Q_{inR}{}'s$ represents productivity where the i^{th} farmer in regime j and the error terms $E_{iR}'{}'s$ are distributed with $E(E_{iR}|X,Z) = 0$ and variance $\left(E_{ij}\middle|X,Z\right) = \sigma_{j}^{2}$. Q_{iR} is realized and contingent upon, CSA strategies were implemented. This occurred where $Y_{ij}^{*} > \underset{K\neq1}{max}(Y_{ik})$ if the error terms in regime 1 and regime j are not independent. A consistent estimation of B_{iR} was required inclusion of the selection correction terms of the alternative options in the above equation. MESR assumes the following linearity assumption and that the correlation between the two error terms will be equal to zero.

$$E\left(U_{ij} \middle| \mathcal{E}_{i1} \ldots \ldots \mathcal{E}_{ij}\right) = \sigma_j \sum_{k \neq j}^{j} rj(\mathcal{E}_{ik} - E(\mathcal{E}_{ik})) \quad (11)$$

Using the above assumption, equation (9) will be expressed as follows

$$Regime 1: Q_{i1} = Z_i \alpha_1 + \gamma_1 \delta_1 \qquad if\ i = 1$$

$$\vdots$$

$$Regime\ j: Q_{ij} = Z_i \alpha_j + \gamma_j \delta_j \qquad if\ i = j$$

γ_j is the covariance between error terms while δ_j is the inverse Mills ratio computed from the estimated probabilities in equation (8) as follows:

$$\delta_j = \sum_{k \neq j}^{j} Pj[\frac{P_{ik} \ln(P_{ik})}{1 - P_{ik}} + \ln(P_{ij})] \quad (12)$$

P in equation (12), represents the correlation coefficient of error terms while $\gamma_j \delta_j$ are error terms with an expected value of zero. In the multinomial choice setting expressed earlier, there were $j - 1$ selection correction term, one for each alternative CSA practices. To take into consideration heteroskedasticity ascending as a result of predictors (δ_j) we used bootstrapped standard errors and statistical tests were as well computed to justify the model choice. Variance Inflation Factor (VIF) was also conducted to percept the issue of multicollinearity.

The treatment effect on the treated due to uptake of CSA practices was computed by comparing the expected value of the outcome of adopters and non-adopters in actual and counterfactual scenarios as shown by the two regimes below.

Productivity status with usage

$$E(Q_{i1} | i = 2) = Z_i \alpha_1 + \sigma_i \Lambda_2 \quad (13a)$$

$$E(Q_{i1} | i = j) = Z_i \alpha_1 + \sigma_j \Lambda_j \quad (13b)$$

Productivity status without usage

$$E(Q_{i1} | i = 2) = Z_i \alpha_1 + \sigma_i \Lambda_2 \quad (14a)$$

$$E(Q_{i1} | i = j) = Z_i \alpha_1 + \sigma_1 \Lambda_j \quad (14b)$$

ATT was defined by the difference between (13a) and (14a) which was given by:

$$ATT = E(Q_{i2}|i = 2) - E(Q_{i1}|i = 2)$$
$$= Z_i(\alpha_1\alpha_2)$$
$$+ \Lambda_2(p_2$$
$$- p_1) \tag{15}$$

The right-hand side denoted the expected change in adopters' productivity if the adopters' characteristics had the same return as non-adopters. The parameters as per Table 3.5 were chosen as per the available literature (Oparinde, 2021) and particular variables of interest.

Table 3.5: Model Variables Hypothesized on the Impact of CSA on Productivity

Variables	Description	Measurement	Sign
Dependent			
Productivity	Productivity of fish	Ratio of production to area of pond in meter	
Independent			
Age	Age of household in years	Discrete	+/-
Gender	Household gender (male=1, female=0)	Dummy	+/-
HH size	The household size	Discrete	+/-
Education	Years spent in school.	Discrete	+/-
Experience	Experience of farmers in years	Discrete	+/-
Off-farm income	Income from non-farm activities	Discrete	+/-
Training	Number of trainings received in a year	Continuous	+/-
Credit acc	Whether fish farmers have access to credit	Dummy(1=yes,0=otherwise)	+/-
N.o of ponds	Number of ponds owned	Continuous	+/-
Stocking Density	Number of fingerlings stocked in a pond	Continuous	+/-
Source of seed	Source of the fingerlings used	Dummy (1=Government hatchery,2=Private,3=Both	+/-
Feeds	Quantity of feeds in the reference period	Discrete	+/-
Awareness	Farmer is aware of climate changes	Dummy (1=yes, 0=otherwise)	+/-
Duration of practice	Number of years CSA has been used	Discrete	+/-
Extension	Fish farmer access extension services	Dummy(1=yes,0=otherwise)	+/-
GMSHP	Fish farmer association/group	Dummy(1=yes,0=otherwise)	+/-
Water system	The system of water used by the farmer.	Categorical (1=Flow through,2=stagnant pond,3=RAS	+/-
Fertilizer	Quantity of lime used	Continuous	+/-
Pond size	The size of the pond in (square meters)	Continuous	+/-
Labour	No of adult present in the HH.	Continuous	+/-
Gov't subsidies	Access to government subsidies	Dummy (1=Yes, 0= otherwise)	+/-

CHAPTER FOUR
RESULTS AND DISCUSSIONS

The results of the three objectives are discussed in this chapter. The first section outlines results of the first objective whereby fish farmers' preferences for climate smart aquacultural practices were identified and ranked. Secondly, the chapter also addressed the determinants of the acceptance of different CSA stratagems and finally, the results of the effect of various CSA practices on fish productivity are presented.

4.1 Descriptive Statistics of Variables used in Econometric Model

The study assessed fish farmer's socio-economic and institutional characteristics. The results in Table 4.1 shows the averages and standard deviations of different characteristics of fish farmers.

Table 4.1: Means and Standard Deviation of Variables Used in the Analysis

Variables	Mean	Standard Deviation
Age	48.76	12.03
Education	10.32	3.52
Household size	6.34	2.37
Land size	3.92	2.47
Experience	7.9	6.2
Number of ponds	1.9	1.1
Year of CSA implementation	3.8	4.26
Number of extension contacts	4.98	3.59
Household labour	3.45	2.10
Gender	.62	.49
Off farm income	.48	.50
Training	.67	.47
Group membership	.65	.49
Credit access	.36	.48
Government subsidies	.75	.43

The mean age of the respondents was 49 years. Suggesting that fish farmers were agile and within the economic productive age. The respondents had received at least 10 years of schooling, showing that most of the farmers were literate. On average, the farmers had 8 years of experience on fish farming, indicating a great foundation on this sector. It is sensibly assumed that elderly farmers endowed resources, wealth of knowledgeable, are more likely to invest in aquaculture farming owing to its huge startup also the risks related with changes in climatic conditions. Youths lack resources to invest in fish farming, a plausible explanation why they are crowded-out from this venture. Oparinde (2021) revealed similar results on age and experience distribution among fish farmers in Nigeria, where majority of the participating farmers average age was 50 years with experience of 7 years and above.

The results on gender imply that 62% of the respondents were male implying that there were more males than females involved in fish farming. A plausible explanation could be that fish farming requires production resources which are mostly owned by male-headed households. The findings corroborate with Obayelu *et al.* (2014) which indicated that male-headed households were more involved in fish farming due to its demand for production resources and high start-up costs.

The results further revealed that 67% of the respondents had access to training, therefore, farmers had knowledge on the process of fish farming. 75% of these farmers had access to subsidies, postulating the reason why they had adopted different CSA practices in fish farming. Plausibly, training accelerates information diffusion among fish farmers therefore increasing the easy with which a certain practice is incorporated in fish farming. Additionally, government subsidies help alleviate production costs, making fish farming a more viable option among farmers. The results agree with Tanti *et al.* (2022) which posited that training influenced farmers involvement in farming.

The frequency of extension contacts received by most fish farmers was averagely 5 contacts annually. Extensionists play a pivotal role educating farmers on the best farming practices and different CSA practices to implement to their farms to realize high outputs. Through extension services, most farmers are able to implement different CSA practices in the farming process. Extension services are key to ensuring farmers acclimate with the effects of climate change through the utilization of CSA practices in their farming activities (Tanti & Jena, 2023).

The uptake of CSA innovations is influenced by the household size. On average, each household comprised of seven members. The findings corroborated a study by Marie *et al.* (2020)

and Wekesa *et al.* (2018), revealing that larger household sizes correlate with increased family labour availability, essential for embracing labour-intensive CSA practices. Additionally, they exert substantial influence on crucial decision-making processes within the family unit through easy access of information.

Group membership had the potential to influence uptake of CSA goals among aquatic farmers. The assertions indicate that 65% of aquafarmers were affiliated to different farmer groups. These assertions find backing in previous studies which emphasised the significance of teamwork and information sharing among farmers on acceptance and application of CSA techniques (Mensah *et al.,* 2024 & Waaswa *et al.,* 2022).

4.2 Farmers Preferences for Climate Smart Aquaculture Practices

The ranking of relative importance of climate smart aquaculture (CSA) attributes using utility scores of most and least preferred CSA practices are presented in Table 4.2. The results postulate that aqua culturalists prefer a number of CSA goals. The attributes with the highest scores are the most preferred and those with the lowest scores have a below average preference. CSA attributes such as solar power, water harvesting, water reuse, adjusted stocking time and improved seeds had the highest scores suggesting averagely high level of utility derived from these practices by farmers. Low utility scores were exhibited by wind power, water treatment, use of antibiotics, and use of dam lines since they had relatively the highest worst scores.

From the count scores of the attribute levels in knowledge smart practices, adjusted stocking time had the highest score (339), followed by improved seeds (311) suggesting that they are the most preferred practices while improved feeds had the highest worst score (312) positing a disutility among farmers. On energy smart practices solar power was highly preferred with a score of 507, the use of electricity among farmers was averagely preferred by fish farmers with a score of 7 while wind power had a relatively below average preference with the highest worst score (542). On water smart technologies, water harvesting (389) was the most preferred practice whereas the use of dam lines and embankments creation had relatively low utility as denoted by their highest worst counts of 80 and 62 scores respectively. Water reuse was ranked highly among the waste smart goals with a score of 174, water treatment and use of antibiotics had relatively lower average scores of 114 and 60 respectively.

Table 4.2: Count Analysis of Multiple Climate Smart Aquaculture Practices Attributes

Attribute	Level	Best	Worst	B-W	SS	ABW	RS	Index
Knowledge smart	Improved seeds	311	271	40	0.045	-0.956	1.068	97.3
	Improved feeds	230	312	(82)	-0.093	-1.098	0.859	77.14
	Adjusted stocking	339	297	42	0.048	-0.953	1.071	100.0
Energy smart	Solar power	507	72	395	0.449	-0.622	2.654	100.0
	Electricity	233	226	7	0.008	-0.922	0.936	88.59
	Wind power	140	542	(402)	-0.457	-1.622	0.508	70.46
Water smart	Water harvesting	389	240	142	0.161	-0.850	1.273	100.0
	Dam lines	267	397	(80)	-0.091	-1.095	0.877	84.89
	Embankments	224	286	(62)	-0.070	-1.073	0.685	56.37
Waste smart	Water treatment	273	387	(114)	-0.130	-1.139	0.840	89.91
	Water reuse	358	184	174	0.198	-0.818	1.394	100.0
	Antibiotics usage	249	314	(60)	-0.068	-1.070	0.891	92.32

((B-W) Best-Worst, (SS) standard scores, (ABW) Analytical Best-Worst, (RS) Ratio scale)

4.2.1 Average Preference of CSA Goals

The results of the average best-worst scores denoted on average the number of times an attribute is selected as most or least vital. The average CSA preferences are as shown in Table 4.3. The results highlights that the use of solar power was selected as the most important attribute among fish farmers with an average score of 45%. The high utility stems from its advantageous features including low operation costs and widespread accessibility plausibly playing a vital role in fish farming. The findings are in line with Birhanu *et al.* (2023) who emphasized the efficacy of solar-based technologies in enhancing the livelihoods of fish farmers, cushioning them against the effects of climate changes. This underscores the growing recognition of the value of adopting sustainable and cost-effective CSA attributes.

Table 4.3: Average CSA Preferences and Standardized Importance Weights

Attribute-level	BW scores	Average BW	Ranking A.BW	Squaroot (BW)	Standardized Importance Weights
Solar power	395	0.449	1	2.654	20.02
Water reuse	174	0.198	2	1.394	10.52
Water harvesting	142	0.161	3	1.273	9.60
Adjusted stocking	42	0.048	4	1.071	8.08
Improved seeds	40	0.045	5	1.068	8.06
Electricity	7	0.008	6	0.936	7.06
Antibiotics usage	(60)	-0.068	7	0.891	6.72
Embarkments	(62)	-0.070	8	0.885	6.68
Dam lines	(80)	-0.091	9	0.877	6.62
Improved feeds	(82)	-0.093	10	0.859	6.48
Water treatment	(114)	-0.130	11	0.840	6.33
Wind power	(402)	-0.457	12	0.508	3.83

The second most favoured attribute among fish farmers is water reuse with an average score of 20%. The preference for this attribute is primarily because of its substantive utility in promoting sustainable water utilization to optimize on productivity within a unified system. The findings cement the significance of water reuse strategies in fostering efficient resource utilization and socioeconomic development within the aquaculture sector (Farrant *et al.,* 2021). The study results corroborate with a study by Ibrahim *et al.* (2023) underscoring the positive effects of water reuse in the aquaculture sector on enhancing both income generation and food security within fish farming communities.

Water harvesting was another important attribute within the framework of CSA goals identified by fish farmers with a relative average importance of 16%. Presumably, fish farmers consciousness on the need for water in aquaculture underscores the pronounced utility for this attribute in mitigate the effects of droughts. This perspective solidifies the pivotal role of water harvesting as a goal in advancing aquaculture practices and mitigating environmental challenges. The findings align with Shahzad *et al.* (2021) who outlined how management agriculture water is a pathway to improving fish productivity and enhance their resilience against climate change.

Fish farmers placed an average relative importance of 5% on adjusted stocking time, indicating it is a vital attribute in fish farming. The assumption is that strategically timing fish stocking, farmers may mitigate the adverse effects of environmental stressors such as drought to enhance productivity and sustainability of aquaculture (Ahmed *et al.,* 2023). Notably, timely adjusted stocking schedules can optimize stocking densities and ensure optimal conditions for fish growth. Adjusted stocking is effective in reducing the effects of drought on agriculture (Cheng *et al.,* 2022).

Improved seeds were another important attribute goal identified by most farmers. Improved fingerlings are associated with high maturity and survival rates, resistance to diseases and improved feed conversion ratios. This attribute holds significant importance to farmers as evinced through a study conducted in India. The study highlighted strong preferences for high maturity and survival rates of fingerlings, which not only amplify yields but also serves as a buffer in contradiction of the adverse effects of climate change (Manyise *et al.,* 2024).

The results indicate that electricity was a moderate important goal identified among fish farmers with a relative importance of 1%. The lower levels of relative importance are attributed to the predominantly small-scale operations of most fish farms where the high costs of electricity are a concern. Moreover, reliance on alternative energy sources that offer consistency and availability is advocated for as posited by the high preference for solar power among aqua farmers. The reflexion brings into line insights of Gorjian *et al.* (2022) who emphasized the need for energy solutions characterised with low cost of installation and maintenance, coupled with minimal environmental impact to foster sustainable aquaculture practices.

Another CSA goal selected as less important among fish farmers was the use of antibiotics. Notably, for small-scale fish farmers application of antibiotics presents a distinguished challenge primarily stemming from constrained access and inadequate understanding of its application. A study by Dang *et al.* (2021) on usage and knowledge of antibiotics of fish farming in fresh water aquaculture underscores the prevailing knowledge gap regarding antibiotics application, unreliable sources and heightened environmental concerns that aggravates the risk of misuse and abuse within the aquaculture sector.

The use of embankments in fish farming had a relatively lower preference. This is likely due to the varying effectiveness of embankments creation, which depends on drivers such as the land surface, the source of water and pond types adopted by most farmers. embankments are particularly important to areas prone to flooding. As a result, aqua farmers perceive that embankments offer limited or insignificant benefits compared to other goals. This nuanced perception creates a disutility among armers regarding this attribute.

Farmers attached less efficacy to the use of dam lines as CSA attribute in the farming process. This is surprising because drought significantly affects most Kenyan fish farmers and the use of dam lines serves as a buffer against the effects of drought. However, its reduced importance can be linked to the fact that dam lines are costly. Therefore, most farmers tend to shy away from this technological attribute resorting to other conventional methods that are cheap. These findings are agreeable with Autio *et al.* (2021) who argued that a lot farmers are resource constrained and are therefore unwilling to invest in CSA technologies.

Improved feeds were another less important attribute fish farming technology preferred among aqua farmers. Notwithstanding improved feeds are an important factor of production; most fish farmers attached a disutility. This could be attributed to the perception towards this goal, its effectiveness, and the sources of this product. Brugere *et al.* (2021) argued that farmers opinions, uncertainties about the results and how beneficial the novel aquafeeds are informed why fish farmers consider using the novel aquafeeds.

Similarly, water treatment was identified as another less important goal preferred by aquafarmers. One important factor that might influence aquafarmers to attach low utility to this goal is the small-scale nature of pond operation that does not guarantee high returns. These farmers, therefore, due to their less resource endowment they are unable to invest in this new technology. Additionally, absence of extension services and knowledge bottlenecks their ability and perception on this CSA goal. The findings corroborate the results of Msaki *et al.* (2022) on wastewater treatment in Tanzania, emphasized the need for public education regarding wastewater treatment to promote its adoption.

Another least important CSA goal was the use of wind power with a standardized importance weight of 3.83. The low preference may stem from the fact that this technology is not widely spread and therefore it is not well known to most farmers. Presumably, the reason why it had a high disutility among fish farmers. Additionally, this technology is crippled with dwindling demand, underdeveloped infrastructure, and low societal approval in Kenya (Pueyo, 2018).

4.2.2 Heterogeneity in the Preferences for CSA Attributes

The results in Table 4.4 shows the heterogeneity in preferences regarding the choices of different CSA attributes made by individual fish farmers. The means, variances, standard deviations and the coefficient of variations (SD/Mean) of CSA goals are presented.

Table 4.4: Variance and Standard Deviation of Important CSA Practices

CSA goals	Mean	Variance	Standard deviation	Ratio (SD/Mean)
Solar power	1.80	1.49	2.21	0.83
Water reuse	0.79	1.40	1.95	1.76
Water harvesting	0.65	1.73	2.99	2.68
Improved seeds	0.18	1.26	1.58	6.92
Adjusted stocking time	0.19	1.49	2.23	7.82
Electricity	-0.03	1.24	1.55	-39.09
Antibiotic use	-0.28	1.68	2.83	-5.97
Embankments	-0.27	1.22	1.48	-4.46
Dam line use	-0.36	1.46	2.13	-4.02
Improved feeds	-0.37	1.39	1.94	-3.74
Water treatment	-0.52	1.65	2.71	-3.18
Wind power	-1.83	1.64	2.26	-0.90

The CSA attributes with low coefficient of variations (Low Ratio) indicates low variations in heterogeneity among respondents. Positive ratios indicate the most important attributes while the negative ratios indicate the least important attributes. The results show that the use of solar power, water reuse and water harvesting goals were selected as the most important attributes in fish farming due to their small ratios posited low variations in heterogeneity among farmers on the choice of these attributes. Likewise, the use of wind power, water treatment and improved feeds were identified as the least important CSA goals identified by farmers since they had low ratios of standard deviations to the individual means.

High variations in heterogeneity as denoted by high ratios of standard deviation to each corresponding mean were reported on CSA goals such as; improved seeds, adjusted stocking time, use of electricity, use of antibiotics, creation of embankments and us for dam lines among fish farmers. This is because they had very high coefficients of variations as denoted by the results in

Table 4.4. Hence, the variability on the relative importance of these attributes among fish farmers. The importance of these attributes is context specific and is also dependent on individual farmer knowledge on applicability and the household resource endowment. for instance, the importance of improved seeds varies depending on whether farmers afford and access this goal with easy and whether this goal is from a reliable source. According to Obiero *et al.* (2019) most farmers in Kenya are faced with high input costs, inadequate supply of quality and affordable feeds and fingerlings and further limited financial access.

The importance of adjusted stocking time is highly variable due to the variations in aqua farmers adopting to changes in weather patterns. The variability of weather patterns calls for adoption of this attribute to improve on productivity. Resistance to change, productivity will be affected by the weather variations. Therefore, more farmers tend to attach more utility to this attribute. However, where farmers practice changes with variations in the weather patterns, their productivity will not be highly affected and therefore they will not attach high importance to this attribute in selecting their appropriate CSA choices.

The relative importance attributed to the application of antibiotics is highly heterogenous, as evidenced by a high coefficient of variation of 5.97. This variability can be attributed to differences in farmers' technical know-how regarding the applicability of this strategy, as well as the perceived level of risk associated with fish farming. Many smallholder farmers lack formal training and access to extension visits, impedes farmers capacity to apply antibiotics effectively and appropriately. As a result, farmers assess production risks differently; those with prior experience of disease outbreaks tend to place higher value on antibiotic use, while others who have not encountered such challenges may perceive it as less important. This leads to substantial variation in the importance attached to antibiotic use among fish farmers.

The high coefficient of variation observed for electricity among fish farmers suggests considerable differences in the value placed on this input. This disparity is likely influenced by variations in income levels and diverse access to electricity across farming households. Farmers with reliable access are better positioned to integrate electricity dependent technologies into their production systems. In contrast, those lacking such access are often compelled to rely on alternative energy sources. Consequently, wealthier farmers tend to perceive electricity as a more critical component of their operations, while those with limited resources may assign it lower importance due to cost constraints.

4.3 Factors Influencing the Choice of CSA Practices among Fish Farmers

Findings denoted on Table 4.5 indicate the CSA practices that were undertaken by most fish farmers.

Table 4.5: CSA Practices Adopted by Smallholder Fish Farmers in Kakamega County

Variable	Frequency	Percent
Dam lines	137	62
Adjusted stocking	115	52
Use of tank	104	47
Pond cover	84	38
Boreholes	68	31

Considering the application of CSA technologies, dam lines were highly adopted CSA attributes among fish farmers at 62%, followed by utilization of adjusted stocking time, use of tanks, pond cover practice and boreholes at 52%, 47%, 38% and 31% respectively. Adekola *et al.* (2022) highlighted significant water shortages on aquaculture farming in Kenya particularly during drought periods. The increased utilization of dam lines, adjusted stocking schedules, boreholes and tanks among aquatic farmers stems from the need to ensure consistent water availability throughout the production cycle.

Preliminary diagnostic tests, Multicollinearity and heteroscedasticity as per the parameters adopted in the analysis were conducted. Testing for multicollinearity among the variables used, a variance inflation factor (VIF) was conducted on continuous variables and a contingency coefficients was used for dummy explanatory variables. The results of Table 4.6 revealed that there was no multicollinearity amongst the continuous explanatory variables tested since the VIF for the continuous explanatory variables had a mean of 1.11 affirming independence among explanatory parameters.

Table 4.6: Variance Inflation Factors of Continuous Explanatory Variables

Variables	VIF	1/VIF
Years of schooling	1.06	0.947472
Household size	1.20	0.835688
Land size	1.12	0.893308
Experience	1.13	0.886021
Age of the respondent	1.23	0.813078
Number of ponds	1.06	0.943972
Extension service received	1.09	0.913337
Mean VIF	1.11	

Further, results on Table 4.7 on contingency coefficients showed no evidence of serious linear association amongst dummy regressors. Variables had below 0.75 contingency coefficients. In light of the empirical observation, there was not a notable correlation amongst the dummy regressor parameters. Consequently, all the proposed regressor parameters were included in the regressions analysis.

Table 4.7: Contingency Coefficients for Dummy Explanatory Variables

Variables	Gender	Off-farm Income	Government Subsidies	Credit Access	Training
Gender	1.0000				
Off-farm Income	0.0115	1.0000			
Government Subsidies	0.2534	0.0375	1.0000		
Credit access	0.0620	0.1101	0.0359	1.0000	
Training	0.1566	0.0652	0.4801	0.1849	1.0000

4.3.1 Factors Influencing the Choice of CSA Practices Among Fish Farmers

The multivariate probit model was used to estimate five binary dependent variables; Dam lines, adjusted stocking time, use of tanks, pond cover and boreholes. These CSA practices were used because they are the most widely adopted practices among fish farmers. Significant results from the Wild Chi test at the 1% level indicated that certain groups of coefficients in the model were collectively significant. This suggests that the explanatory variables effectively explained the outcomes. Table 4.8 further illustrates significant likelihood ratio tests and correlations among all estimated coefficients, emphasizing the independence of decisions regarding CSA practice uptake.

The results of multivariate probit regression analysis on factors influencing the choice of different climate smart aquacultural practices among fish farmers are presented in Table 4.6. The results shows that both socio-economic and institutional aspects influenced the choice of different CSA practices. They include gender, age of the respondent and number of years spent in school by the household head, size of the household, land size, aquatic farming experiential knowledge, frequency of extension contacts received as well as number of training services offered to fish farmers.

Gender of the household head was positively associated with the choice of pond cover and dam line practices at 5% and 10% level of significance respectively. The likelihood of choosing these practices were high among male as compared to females. Positing that male aquafarmers were more probable to implement the usage of dam line and pond cover than their female counterparts. A plausible explanation would be that productive resources were more accessible to male farmers coupled with security of tenure which gave them an upper-hand in accessing credit facilities. Notably, men hold the prerogative rights to decision making unlike their female counterparts. These results find backing by the assertions of Unekwu *et al.* (2020) holding sway that female farmers have limited access to productive resources also that decision making is solely mandated by the household head crowding out female farmers.

Education level of the respondent was positive and significant at 5% for both dam lines and usage of tanks and 10% sinking of boreholes. This finding implied that attainment of high education increased the probability of utilizing the use of dam lines, use of tanks and sinking of boreholes among fish farmers. Fish farmers that are more educated are in a position to decipher the overall benefits of adopting these practices to cushion them against climatic variability. Further, attainment of high education accelerates information diffusion among farmers hence removing barriers on implementation of different CSA practices on their farms. These results correspond with Onyeneke *et al*. (2020) who postulated that education attainment among aquatic farmers positively influenced uptake of different climate change adoption strategies as such; use of boreholes, site selection, and diversification of fish and livelihood in efforts to caution them against climatic variability.

Age of the respondents emerged as a substantial aspect with a positive association on the choice of adjusted stocking time achieving a notable significant level of 5%. The findings suggested an increase in the likelihood to adopt adjusted stocking time was positively associated with respondent's age. This posited that older farmers exhibited greater propensity to adopt such a strategy compared to their younger counterparts. A plausible explanation will be that old farmers have had a long production period through which they have appraised the benefits of different CSA practices. These contentions are in line with Tanti *et al.* (2022) who noted that age positively correlated with the adoption of CSA practices. Their rationale suggested that older farmers inclined to possess greater knowledge having been in fish farming over a long time swaying the acceptance of CSA innovations.

Experience showed a notable significant association at 1% level on adoption of adjusted stocking time. Findings revealed that probability of selecting adjusted stocking time escalated with an increase in experiential knowledge. Suggesting that as farmers gain more experience in aquaculture, they tend to implement adjusted stocking time more frequently. Remarkably, experience reflected a greater propensity for knowledge diffusion and willingness to take risks among farmers. Negera *et al.* (2022) pointed out that experience positively contributed to the demand for CSA initiatives. As farmers gained hand-on experience, they become more capable of discerning the advantages linked to the implementation of various CSA strategies.

Household size was negatively associated with the choice of adjusted stocking time and dam line usage at 1% and 5% significant level respectively. The findings posited that as the number of members in household increase, the likelihood of implementing the use of adjusted stocking time and dam lines tends to decline. A plausible explanation would be that an increase in the size of the household increases the demand on basic necessities such as food and clothing resulting in less disposable income. Household heads are forced to divert their resources to necessities thus decreasing demand for CSA goals. Contrary, Marie *et al.* (2020) emphasised that a large number of active household members tended to embrace CSA practices more readily in efforts to reduce the impact of climate change through increased information access on the probable gains of using CSA practice.

A negative correlation was revealed between the land size owned by fish farmers and the demand for dam lines at 5% level of significance. As the size of land for aquaculture use rose, the probability of choosing dam lines among aquafarmers showed a downward trend. This suggests that farmers with extensive land holdings where fish ponds were situated were less inclined to utilizing dam lines in their production practices. A plausible explanation will be the costs of purchase and installing the dam lines resulted in less demand. Notably, the high demand for basic necessities limit farmers escalating the use of CSA. The results contrast a study by Obiero *et al.* (2019) which revealed that fish farmers with large tracts of land adopted improved aquaculture technologies than aquafarmers with small parcels of land.

Contact with extensionists was positively associated with the use of pond covers and dam lines at 1% and 10% level of significance. The results suggested that the frequency of extension services accessed by farmers demonstrated greater likelihood in implementing various CSA technologies compared to those who had limited or no contact. Extension services play a crucial role in providing the necessary information and technical support required for successful CSA practices adoption (Sisay *et al.,* 2023). Contrarily, Kifle *et al.* (2022) reported that farmers without contact with extension services had a high propensity to adopting a CSA technology on their farms due to reliance on indigenous knowledge than that offered by the extensionists.

Finally, access to training positively influenced the prospect of usage for dam lines at 5% significance level, use of tanks and adjusted stoking time at 10% level of significance. An upsurge in training programs received by aquafarmers increased the likelihood to adopt dam lines, tanks and adjusted stocking time at 5%, 4% and 6% respectively. Training enhances knowledge transfer, risk reduction, skill development and peer learning among fish farmers. Similarly, Onyeneke *et al.* (2020) noted that training and workshops on climate change accelerated usage of different CSA initiatives among aquafarmers.

Table 4.8: Determinants of Usage of Climate Smart Aquacultural Practices Among Aquafarmers

Variable for CSA	Dam line		Borehole		Pond cover		Tanks		Ad_stocking	
Strategies	dy/dx	Std	dy/dx	Std	dy/dx	Std	dy/dx	Std	dy/dx	Std
Gender	0.367	0.203*	-0.077	0.198	0.411	0.227*	0.192	0.201	0.371	0.295
Education	0.054	0.028**	0.048	0.026*	0.042	0.029	0.053	0.026**	-0.011	0.036
Age	0.002	0.000	0.004	0.000	0.005	0.000	0.003	0.000	0.021	0.011**
House size	-0.103	0.044**	0.045	0.040	-0.043	0.047	0.005	0.042	-0.255	0.078
Off farm income	0.023	0.194	0.214	0.190	-0.121	0.214	-0.045	0.194	0.071	0.262
Land size	-0.078	0.039**	0.016	0.040	0.057	0.041	-0.046	0.039	-0.089	0.066
Experience	0.006	0.015	0.017	0.016	0.018	0.017	0.002	0.015	0.070	0.021***
Number of ponds	-0.053	0.086	0.067	0.085	-0.114	0.096	0.052	0.081	-0.004	0.111
Extension	0.048	0.028*	0.026	0.029	0.120	0.032**	0.034	0.028	-0.012	0.038
Credit Access	0.181	0.204	0.046	0.196	-0.024	0.204	-0.027	0.194	0.188	0.253
Training	0.516	0.212**	0.313	0.206	0.353	0.235	0.407	0.213*	0.575	0.318*

chi2(10) = 23.7799 Prob > chi2 = 0.000 Note: *, **, *** represents 10%, 5% and 1% levels of significance respectively.

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4.4 Determinant of Choice of CSA Combinations and its Effects on Fish Productivity

The results are discussed in a two-pronged analytical framework. First, we delve into the features stimulating farmers' preference for various CSA combinations. Secondly, we examine the effects of these CSA combinations on productivity. Since the integration and use of CSA practices is not a monolithic process but rather a complex decision influenced by individual farmer taste and preferences and its application are specific to an enterprise (Oparinde, 2021). The multifaceted uptake pattern underscores the critical need to understand the factors driving the selection of different CSA combinations. Underscoring its pivotal role in formulation of policy interventions that are tailored to enhance uptake of CSA practices effectively.

There are a number of different CSA practices that were adopted by farmers such as embankments creation, pond covers, site selection, use of dykes, dam lines, building of ponds close to water sources, use of boreholes, use of tanks, adjusted stocking time among others. The conventional practices such as site selection, use of dykes, embankments creation and building of ponds close to water sources were not considered in this objective. The investigation focused solely on the utilization of dam lines, tanks, and adjusted stocking time. These specific CSA were singled out due to their widespread adoption among farmers, representing proactive measures aimed at mitigating the adverse effects of climate variability.

The results presented in Table 4.9 indicate that aqua farmers used the CSA practices both singularly and in combinations. A majority of the farmers had adopted CSA practices, with only 25 % who had not implemented any of the combinations in their ponds. On the adopters, 25 % of the farmers had adopted combination of dam lines and use of tank (Dam_tank), 29 % of the farmers had adopted the use of dam lines, 12 % had adopted the use of adjusted stocking time, 5 % had implemented combination that involved the use of dam lines, tanks and adjusted stocking schedule (Da_Ta_St) and finally 5 % of the farmers also had adopted combination of dam line and adjusted stocking schedule (Dam_Stock). These results show that 75 % of aquafarmers had used at the minimum a combination in the production process. Majority of the farmers had used combination Dam_tank and dam lines while few had used combination Da_Ta_St and Dam_Stock.

Table 4.9: Combinations of CSA Practices Adopted by Farmers

Combination	Frequency	Percent
Non_adopters	55	25.00
Dam_tank	54	24.55
Dam lines	63	28.64
Adjusted stocking time	26	11.82
Da_Ta_St	12	5.45
Dam_Stock	10	4.55
Total	220	100.00

4.4.1 Determinants of Factors Influencing the Choice of CSA Combinations Among Fish Farmers

This section presents the results of the multinomial endogenous switching regression. This model is a two-step model where in the first part outcomes of a multinomial logit model (MNL) are reported, showing results of the factors that influenced the choice of different CSA combinations. This step is paramount as it informs the necessary intervention aimed at accelerating uptake of CSA practices. The marginal effects of the MNL depicted a unit change in the independent variables resulted in the predictable change in likelihood of the choices on CSA packages selected among respondents. The non-adopters were used as a base category. The outputs are outlined in Table 4.10. The second and the final stage denoted the impacts of CSA strategies on productivity.

Education was significant and positively influenced the choice of combination involving the use of dam lines and tanks (Dam_tank) at 1 % significant level. Educated farmers were more likely to use combination Dam_tank as opposed to non-users of any package. An increase in one year of schooling, increases the probability of choice of this combination by 21 %. Sardar *et al.* (2021), observed that farmers with a high level of literacy are better equipped to navigate the challenges posed by climatic variability. They are more adept at accessing and evaluating information, enabling them to implement CSA practices that align with individual preferences.

The findings indicated a statistically significant and positive correlation between group membership and the adoption of combination that involved the use of dam lines, tanks and adjusted stocking time (Da_Ta_St) at 1% significance level. Specifically, a one unit rise in group membership was positively allied with the probability of integrating CSA among adopters. It is noteworthy that group membership facilitates access to credit by pooling of resources, thereby potentially expediting the adoption of CSA practices. These contentions are in line with the findings by Oparinde (2021), who indicated that group membership enhanced easy access to resources and knowledge sharing resulting in increased adoption of CSA practices among adopters as compared to non-adopters.

Experiential knowledge exhibited a positive and significant association on the choice of adjusted stocking time and combination Da_Ta_St at 5% significance level. Experienced farmers were more likely to use this combination as opposed to non-use of any combination. Precisely, the probability of using adjusted stocking time and combination Da_Ta_St increased by 1% and 3% for experienced farmers. This is likely because experiential knowledge allows them to adopt and redefine their approaches overtime (Do & Ho, 2022). Further, they are better equipped to anticipate and manage risks associated with climatic variability drawing through their experiences to make informed decisions on adoption of CSA practices. Notably, Ojo and Baiyegunhi (2020), posited that farming experience showed a significant variation on net income between the implementors and non-implementors of climate innovative strategies.

The findings revealed the number of members in a household had a varying impact on the adoption of different combinations; one involving the use of Dam lines and adjusted stocking time (Dam_stock), Da_Ta_St and Dam_tank in fish farming. It showed an inverse relationship between household size and the choice of Dam_stock and Da_Ta_St while the choice of Dam_tank, had a positive influence. The results revealed that an increase in household size by one member reduced the probabilities of adopting Dam_stock and Da_Ta_St by 33% and 28% respectively while increasing the likelihood of selecting Dam_tank by 44%. Large household are faced with decision making dynamics that can either facilitate or impede the adoption of these combinations depending on the level of consensus and preferences at a family unit. Additionally, large households may have access to a broader social network, potentially increasing their exposure to information about CSA practices and credit access. The results corroborate research by Onyenekwe *et al.* (2023), which outlined that large households are inclined to implement multiple climate adaptation strategies as a precautionary measure against adverse climatic events.

The number of ponds owned by fish farmers was negatively correlated with uptake of combination Da_Ta_St at 10% significant level. A rise in the number of ponds by one reduces probability of adoption of this package by 35%. It follows therefore that farmers with a large number of fish ponds had little capacity to use this combination as opposed to non-usage of any combination. This is due to increased opportunity costs associated with managing multiple ponds which require a significant amount of capital, efforts and time. A likely reason the decreasing adoption of this combination. Contrary, Oparinde (2021) observed that the number of fishponds owned by farmers resulted to an increased uptake of CSA techniques.

Findings indicated a positive and significant relationship between the stocking density of fingerlings and the likelihood of adopting combination Da_Ta_St and use of dam lines with probabilities at 1% and 5% significant levels correspondingly. Marginal effects of 0.003 and 0.0001 suggested that a one unit increase in the quantity of fingerlings stocked increased the probability of using these combinations by 0.3% and 0.01% respectively ceteris paribus. These assertions find support in a study conducted by Mensah *et al.* (2024) who reported that stocking density was associated with integration of climate insurance products among smallholder fish farmers.

The number of extension services received among fish farmers positively and significantly influenced their preference for a combination that involved the choice of dam lines. Presumably, an increase in the number of extension services received by a unit had a probability of influencing the choice of this combination by 2% holding other factors constant. Extension services escalate information sharing and knowledge transfer among farmers. Informed farmers stand a better chance to adopt a number of CSA practices and technologies that are intended to caution them against climatic variabilities. Kolapo and Kolapo (2023), argues in which the propensity of uptake of agricultural technology was positively impacted by information services offered by extensionists to farmers.

The estimated marginal effects indicated a statistically significant and positive relationship between training and adoption of combination Da_Ta_St at 5% significant level. Seemingly, the high the frequency of training programs received among fish farmers, increased the probability of choosing CSA practices among users of this combination by 13.1% as opposed to non-usage of any combination. Training escalates the level of awareness and capacity building which are a prerequisite to adoption and implementation of CSA practices. Through training farmers are able to understand the overall benefits linked with embracing of climate smart strategies (Ahmed *et al.,* 2023).

Table 4.10: Marginal Effects of the Determinants of Choice of CSA Practices

Variable	Adj_Stock		Dam_Stock		Da_Ta_St		Dam_Tank		Dam Lines	
	Dy/dx	P-value	Dy/dx	P-value	Dy/dx	P-value	Dy/dx	P-value	Dy/dx	P-value
Age	-.001	0.791	-.000	0.802	.002	0.778	-.001	0.778	-.003	0.284
Gender	-.019	0.737	.026	0.439	-.001	0.971	.034	0.588	.034	0.623
Education	-.005	0.531	-.005	0.199	.000	0.880	.021	0.014**	-.000	0.980
Group Mshp	.000	0.993	.002	0.709	.010	0.000***	.011	0.126	-.018	0.124
Land size	-.006	0.632	-.003	0.577	.000	0.932	-.005	0.719	-.013	0.339
Experience	.001	0.059*	.000	0.146	.003	0.026**	-.000	0.434	.000	0.571
HH_size	-.024	0.275	-.033	0.047**	-.028	0.066*	.044	0.007***	.007	0.697
No_ponds	.014	0.553	-.016	0.455	-.035	0.077*	-.015	0.714	-.036	0.479
Subsidies	.065	0.419	.021	0.621	.018	0.724	.110	0.143	-.121	0.163
Stocking density	.000	0.247	-.000	0.351	.003	0.008***	.000	0.431	.000	0.085*
Extension	.003	0.609	-.000	0.424	.001	0.704	.004	0.644	.002	0.044**
Credit access	-.000	0.560	.000	0.149	.000	0.292	.000	0.158	-.000	0.710
Training	-.051	0.356	.035	0.453	.131	0.014**	.006	0.922	-.010	0.899
Distance	.004	0.148	-.002	0.115	.001	0.427	.003	0.922	.004	0.415

Note: *, **, *** represents 10%, 5% and 1% significant levels correspondingly

4.4.2 Treatment Effects for Adoption of CSA Combination on Productivity

Table 4.11 presents the results of the multinomial endogenous switching regression (MESR). The empirical results of the treatment effects delineated from effects of specific CSA combinations on fish productivity are presented. Productivity was defined as a ratio of fish output to the area of fish ponds in hectares. The average treatment effect on the treated (ATT) and average treatment effects on the untreated (ATU) were both positive and negative, suggesting that fish farmers realized both high and low productivity depending on CSA combination adopted. The results denoted that there was a significant increase in productivity among aquafarmers who used CSA combinations; adjusted stocking time, dam line and the combination involving the use of dam lines, tanks and adjusted stocking time (Da_Ta_St).

Table 4.11: Effects of CSA Packages on Fish Productivity

			Productivity	
Combination	Scenario	Productivity of actual scenario (A)	Productivity of counterfactual scenario (B)	Treatment effects ATT/ATU (A-B)
Adjusted stocking	Adopters	7265.04	6783.05	481.99*
	Non-Adopters	6579.63	6624.47	-47.84
	Heterogeneity effects	686.42	158.58	527.84
Da_Ta_St	Adopters	12656.96	8991.00	3665.96***
	Non-Adopters	6455.69	7011.45	-555.76***
	Heterogeneity effects	6201.27	1979.56	4221.71
Dam_tank	Adopters	6321.69	6564.42	-242.73
	Non-Adopters	6425.41	7066.22	-640.81***
	Heterogeneity effects	-103.72	-501.80	398.08
Dam lines	Adopters	7171.38	6974.75	196.63*
	Non-Adopters	6580.23	6645.84	-65.61
	Heterogeneity effects	592.15	328.91	263.24
Dam_Stock	Adopters	6212.13	4702.69	1509.44
	Non-Adopters	6988.91	6754.63	234.28
	Heterogeneity effects	-776.73	-2046.96	1270.23

Note: *, *** represents 10% and 1% levels of significance respectively

Among the fish farmers who adopted different combinations, high productivity (ATT) was reported among farmers that used Da_Ta_St (a combination involving the use of dam lines, tanks and adjusted stocking time) followed by Adj_stock (adjusted stocking time) and lastly the use of dam lines. For instance, productivity was high among farmers who used combination Da_Ta_St by 3665.96 kilograms per hectare (kgs/ha), maximum productivity was realised through the adoption of Adj_stock was 481.99 Kgs/ha while adoption of dam lines resulted in an increase in productivity by 196.63 Kgs/ha. The joint application of CSA practices realized high productivity as opposed to the single use of the practices. Amankwah and Gwatidzo (2024) highlighted the need for joint application of agricultural technologies to realize high output among small-holder farmers in Zimbabwe. Overly, the application of dam lines, tanks and adjusted stocking time as a combination or singularly could significantly increase productivity. Cementing the central role of water is to aquaculture. The findings corroborate with Oparinde (2021) who reported similar findings on utilization of climate smart techniques and food security amongst aqua culturalists in Nigeria. On non-adopters of any CSA combinations, the average treatment effects on the untreated showed that, fish farmers were worse off on adoption of Dam_tank and Da_Ta_St at 640.81 Kgs/ha and 555.76 Kgs/ha respectively. Suggesting the need to promote adoption of Da_Ta_St and Dam_tank among the non-adopters to significantly boost productivity.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

From the study findings, the following conclusions emerge:

i. Farmers ranked the use of solar power, water reuse, water harvesting and adjusted stocking time highly among the CSA attributes. This ranking reflects famers prioritization on cost-effective and resource efficient technologies intended to reduce dependence on costly energy sources and address water scarcity issues as the most pressing constraints in aquaculture.

ii. Access to education, trainings and extension services revealed a significant positive impact across various CSA practices such as dam lines, use of tanks, pond covers, adjusted stocking time and boreholes. This indicates that more educated and trained farmers are probable to implement these strategies, highlighting the vital role of literacy as well as training programs in endorsing CSA technologies. However, the negative effect of the size of the household on CSA technologies is likely due to increased financial pressure and limited disposable income in large household which constrains the ability to invest in CSA technologies.

iii. Uptake of various CSA techniques has productivity effects in aquaculture farming among small-holder farmers. Joint adoption of CSA technologies demonstrated high productivity as compared to the usage of a single CSA technologies among farmers. however, not all CSA practices resulted in high productivity among farmers positing availability of other better options in fish farming.

5.2 Recommendations

In light of the study findings, the following recommendations are suggested:

i. Prioritize scaling up of low-cost high impact CSA technologies, like the use of solar energy and water harvest kits through provision of subsidies, enhanced financial access, extension programs and training to build on resilience in the face of climate variability.

ii. Targeted training and education programs should be prioritized to boost cognizance and application of CSA innovations especially for less educated farmers. Further, there is need for implementation of gender sensitive policies to promote equitable access to resources and CSA technologies across different genders.

iii. To achieve desired productivity at both the County and National level, there is need to focus on joint adoption of CSA technologies through training and input support around proven combinations. Further, strengthen extension services to escalate guidance on CSA implementation and feedback platforms for farmers.

5.3 Areas for Further Research

The research highlights the following gaps for further studies.

i. To determine gender dynamics on preferences for climate smart aquaculture (CSA) practices among fish farmers.

ii. To assess the effects of CSA practices on post-harvest fish losses among farmers.

REFERENCES

Abegunde, V. O., & Obi, A. (2022). The role and perspective of climate smart agriculture in Africa: A Scientific Review. *Sustainability*, *14*(4), Article, 2317. https://doi.org/10.3390/su14042

Adekola, O., Gatonye, M., & Orina, P. (2022). Status and outlook for climate resilient Aquaculture in Kenya. *Case Studies in the Environment*, *6*(1), Article, 1544759. https://doi.org/10.1525/cse.2022.1544759.

Ahmed, B., Haji, J., Ketema, M., & Jemal, K. (2023). Impacts and adaptation extents of climate smart agricultural practices among smallholder farmers of Ethiopia: Implication to food and nutrition security. *Cogent Economics & Finance*, *11*(1), Article, 2210911. https://doi.org/10.1080/23322039.2023.2210911

Amankwah, A., & Gwatidzo, T. (2024). Food security and poverty reduction effects of agricultural technologies adoption. A multinomial endogenous switching regression application in rural Zimbabwe. *Food Policy*, *125*, Article, 102629. https://doi.org/10.1016/j.foodpol.2024.102629

Amankwah, A., & Quagrainie, K. K. (2019). Aquaculture feed technology adoption and smallholder household welfare in Ghana. *Journal of the World Aquaculture Society*, *50*(4), 827–841. https://doi.org/10.1111/jwas.12544

Amankwah, A., Quagrainie, K. K., & Preckel, P. V. (2018). Impact of aquaculture feed technology on fish income and poverty in Kenya. *Aquaculture Economics & Management*, *22*(4), 410–430. https://doi.org/10.1080/13657305.2017.1413689

Anugwa, I. Q., Onwubuya, E. A., Chah, J. M., Abonyi, C. C., & Nduka, E. K. (2022). Farmers' preferences and willingness to pay for climate-smart agricultural technologies on rice production in Nigeria. *Climate Policy*, *22*(1), 112–131. https://doi.org/10.1080/14693062.2021.1953435

Aswathy, N., & Joseph, I. (2020). A Logit analysis of the factors affecting cage fish farming adoption decisions in the Southwest Coast of India. *Current Journal of Applied Science and Technology*, 29–34. https://doi.org/10.9734/cjast/2020/v39i4031109

Aung, Y. M., Khor, L. Y., Tran, N., Akester, M., & Zeller, M. (2023). The impact of sustainable aquaculture technologies on the welfare of small-scale fish farming households in

Myanmar. *Aquaculture Economics & Management*, *27*(1), 66–95. https://doi.org/10.1080/13657305.2021.2011988

Aura, C. M., Musa, S., Yongo, E., Okechi, J. K., Njiru, J. M., Ogari, Z., Wanyama, R., Charo-Karisa, H., Mbugua, H., Kidera, S., Ombwa, V., & Oucho, J. A. (2018). Integration of mapping and socio-economic status of cage culture: Towards balancing lake-use and culture fisheries in Lake Victoria, Kenya. *Aquaculture Research*, *49*(1), 532–545. https://doi.org/10.1111/are.13484

Autio, A., Johansson, T., Motaroki, L., Minoia, P., & Pellikka, P. (2021). Constraints for adopting climate-smart agricultural practices among smallholder farmers in Southeast Kenya. *Agricultural Systems*, *194*, Article, 103284. https://doi.org/10.1016/j.agsy.2021.103284

Bai, X., Huang, Y., Ren, W., Coyne, M., Jacinthe, P., Tao, B., Hui, D., Yang, J., & Matocha, C. (2019). Responses of soil carbon sequestration to climate-smart agriculture practices: A meta-analysis. *Global Change Biology*, *25*(8), 2591–2606. https://doi.org/10.1111/gcb.14658

Barange, T. Bahri, M.C. Beveridge, K. L. Cochrane, S. Funge-Smith, & F. Poulain, (2018), *Impacts of climate change on fisheries and aquaculture*. United Nations' Food and Agriculture Organization, Italy. *12*(4) 628-635. https://www.fao.org/3/i9705en.pdf

Birhanu, B. Z., Sanogo, K., Traore, S. S., Thai, M., & Kizito, F. (2023). Solar-based irrigation systems as a game changer to improve agricultural practices in sub-Sahara Africa: A case study from Mali. *Frontiers in Sustainable Food Systems*, *7*, Article, 1085335. https://doi.org/10.3389/fsufs.2023.1085335

Boateng, C. N., Mtethiwa, A., & Agyakwah, S. K. (2022). Drivers of adoption intensity of pond aquaculture: The case of Ghana. *Aquaculture*, *560*, Article, 738597. https://doi.org/10.1016/j.aquaculture.2022.738597

Brugere, C., Padmakumar, K. P., Leschen, W., & Tocher, D. R. (2021). What influences the intention to adopt aquaculture innovations? Concepts and empirical assessment of fish farmers' perceptions and beliefs about aquafeed containing non-conventional ingredients. *Aquaculture Economics & Management*, *25*(3), 339–366. https://doi.org/10.1080/13657305.2020.1840661

Cascetta, E., & Cascetta, E. (2009). Methods for the evaluation and comparison of transportation system projects. *Transportation Systems Analysis: Models and Applications*, 621-681. https://doi.org/10.1007/978-0-387-75857-2_10

Chambers, R. G., & Quiggin, J. (2000). *Uncertainty, Production, Choice, and Agency: The state-contingent approach*. Cambridge University Press. https://doi.org/10.1111/j.1467-8489.2006.00320.

CGOK. (2022). *Kakamega County Integrated Development Plan 2022-2027*. https://repository.kippra.or.ke/handle/123456789/3577

Cheng, M., McCarl, B., & Fei, C. (2022). Climate change and livestock production: A Literature review. *Atmosphere*, *13*(1), 140. https://doi.org/10.3390/atmos13010140

Chepkoech, W., Mungai, N. W., Stöber, S., Bett, H. K., & Lotze-Campen, H. (2018). Farmers' perspectives: Impact of climate change on African indigenous vegetable production in Kenya. *International Journal of Climate Change Strategies and Management*, *10*(4), 551–579. https://doi.org/10.1108/IJCCSM-07-2017-0160

Chia, S. Y., Macharia, J., Diiro, G. M., Kassie, M., Ekesi, S., van Loon, J. J., ... & Tanga, C. M. (2020). Smallholder farmers' knowledge and willingness to pay for insect-based feeds in Kenya. *PloS One*, *15*(3), Article, e0230552. https://doi.org/10.1371/journal.pone.0230552

Dang, L. T., Nguyen, L. T., Pham, V. T., & Bui, H. T. T. (2021). Usage and knowledge of antibiotics of fish farmers in small-scale freshwater aquaculture in the Red River Delta, Vietnam. *Aquaculture Research*, *52*(8), 3580–3590. https://doi.org/10.1111/are.15201

Dinesh, D., Aggarwal, P. K., Khatri-Chhetri, A., Loboguerrero Rodriguez, A. M., Mungai, C., Radeny, M. A., & Zougmoré, R. B. (2017). The rise in Climate-Smart Agriculture strategies, policies, partnerships and investments across the globe. *Agriculture for Development* (pp. 4-9). https://cgspace.cgiar.org/handle/10568/81372

Do, H.-L., & Ho, T. Q. (2022). Climate change adaptation strategies and shrimp aquaculture: Empirical evidence from the Mekong Delta of Vietnam. *Ecological Economics*, *196*, Article, 107411. https://doi.org/10.1016/j.ecolecon.2022.107411

Doherty, E., Mellett, S., Norton, D., McDermott, T. K., O'Hora, D., & Ryan, M. (2021). A discrete choice experiment exploring farmer preferences for insurance against extreme weather events. *Journal of Environmental Management*, *290*, Article, 112607. https://doi.org/10.1016/j.jenvman.2021.112607

Dumbrell, N. P., Kragt, M. E., & Gibson, F. L. (2016). What carbon farming activities are farmers likely to adopt? A best–worst scaling survey. *Land Use Policy*, *54*, 29–37.https://doi.org/10.1016/j.landusepol.2016.02.002

Ellis, N. R., & Tschakert, P. (2019). Triple-wins as pathways to transformation? A critical review. *Geoforum*, *103*, 167-170. https://doi.org/10.1016/j.geoforum.2018.12.006

FAO. (2020). *The state of world fisheries and aquaculture*. *Meeting the sustainable development goals*. FAO. Rome, Italy. https://www.fao.org/3/ca9229en/ca9229en.pdf

Farrant, D. N., Frank, K. L., & Larsen, A. E. (2021). Reuse and recycle: Integrating aquaculture and agricultural systems to increase production and reduce nutrient pollution. *Science of The Total Environment*, *785*, Article, 146859. https://doi.org/10.1016/j.scitotenv.2021.146859

Finizola e Silva, M., & Van Passel, S. (2020). Climate-smart agriculture in the Northeast of Brazil: *An Integrated Assessment of the Aquaponics Technology. Sustainability*, *12*(9), 3734. https://doi.org/10.3390/su12093734

Funge-Smith, S., & Bennett, A. (2019). A fresh look at inland fisheries and their role in food security and livelihoods. *Fish and Fisheries*, *20*(6), 1176–1195. https://doi.org/10.1111/faf.12403

Garlock, T., Asche, F., Anderson, J., Bjørndal, T., Kumar, G., Lorenzen, K., Ropicki, A., Smith, M. D., & Tveterås, R. (2020). A Global blue revolution: Aquaculture growth across regions, species, and countries. *Reviews in Fisheries Science & Aquaculture*, *28*(1), 107–116. https://doi.org/10.1080/23308249.2019.1678111

Geda, S. A., & Kühl, R. (2021). Exploring smallholder farmers' preferences for climate-smart seed innovations: empirical evidence from Southern Ethiopia. *Sustainability*, *13*(5), Article, 2786. https://doi.org/10.3390/su13052786

Gnanasubramaniam, S., & Hemachandra, D. (2020). Perception of climate change and farmers' adaptation: an analysis for effective policy implementation. *Asia-Pacific Journal of Rural Development*, *30*(2), 27–54. https://doi.org/10.1177/1018529120946177

Gorjian, S., Kamrani, F., Fakhraei, O., Samadi, H., & Emami, P. (2022). Emerging applications of solar energy in agriculture and aquaculture systems. In Gorjian, S., Ebadi, H., Jathar, L. D., & Savoldi, L. (2022). Solar energy for sustainable food and agriculture: Developments, barriers, and policies. (pp. 425–469). Elsevier. https://doi.org/10.1016/B978-0-323-89866-9.00008-0

Government of Kenya (2009 August Edition) Economic stimulus Program; Office of the Deputy Prime Minister and Ministry of Finance, Quarterly Economic and Budgetary, Review Fourth Quarter 2008/2009, Source: Central Bank of Kenya. https://www.treasury.go.ke/wp-content/uploads/2021/05/FY2015-16-Programme-Based-Budget.pdf

GOK. (2018). *National Adaptation Plan 2015-2030 - Kenya - Climate Change Laws of the World*. https://www.climate-laws.org/geographies/kenya/policies/national-adaptation-plan-2015-2030

Halwart, M. (2022). Aquaculture in SOFIA 2022. *FAO Aquaculture Newsletter*, (66), 7-8. https://search.proquest.com/openview/e2b6f956dc1ff83e4143291ac23c8022/1?pq-origsite=gscholar&cbl=237326

Hanemann, M., Loomis, J., & Kanninen, B. (1991). Statistical efficiency of double-bounded dichotomous choice contingent valuation. *American Journal of Agricultural Economics*, *73*(4), 1255–1263. https://doi.org/10.2307/1242453

Hasan, M. K., Desiere, S., D'Haese, M., & Kumar, L. (2018). Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. *Food Security*, *10*(4), 1073–1088. https://doi.org/10.1007/s12571-018-0824-1

Hussain, S., Amin, A., Mubeen, M., Khaliq, T., Shahid, M., Hammad, H. M., & Nasim, W. (2022). Climate smart agriculture (CSA) technologies. *Building Climate Resilience in Agriculture: Theory, Practice and Future Perspective*, 319-338. https://link.springer.com/chapter/10.1007/978-3-030-79408-8_20

Ibrahim, L. A., Abu-Hashim, M., Shaghaleh, H., Elsadek, E., Hamad, A. A. A., & Alhaj Hamoud, Y. (2023). A Comprehensive Review of the Multiple Uses of Water in Aquaculture-Integrated Agriculture Based on International and National Experiences. *Water*, *15*(2), Article, 367. https://doi.org/10.3390/w15020367

IPCC, 2022: Summary for policymakers. In: Climate change 2020: Mitigation of climate change. contribution of working group III to the *Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* https://www.ipcc.ch/report/ar6/wg2/chapter/chapter-9/

Kaleem, O., & Bio Singou Sabi, A.-F. (2021). Overview of aquaculture systems in Egypt and Nigeria, prospects, potentials, and constraints. *Aquaculture and Fisheries*, *6*(6), 535–547. https://doi.org/10.1016/j.aaf.2020.07.017

Karim, M., Leemans, K., Akester, M., & Phillips, M. (2020). Performance of emergent aquaculture technologies in Myanmar; challenges and opportunities. *Aquaculture*, *519*, Article, 734875. https://doi.org/10.1016/j.aquaculture.2019.734875

Kifle, T., Ayal, D. Y., & Mulugeta, M. (2022). Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, Central highland of Ethiopia. *Climate Services*, *26*, Article, 100290. https://doi.org/10.1016/j.cliser.2022.100290

Kim, Jeong-Dae. (2014). An overview of Kenyan aquaculture: current status, challenges, and opportunities for future development. *Fisheries and Aquatic Sciences*, *17*(1), 1–11. https://doi.org/10.5657/FAS.2014.0001

Kimathi, S. M., Ayuya, O. I., & Mutai, B. (2022). Stated Farmers' Preferences and Willingness to Pay for Climate Resilient Potato Varieties in Kenya: *A Discrete Choice Experiment*. https://doi.org/10.22004/AG.ECON.321220

KNBS (2020). Economic survey 2020. Kenya national bureau of statistics https://dc.sourceafrica.net/documents/119905-KNBS-Economic-Survey-2020.html

Kolapo, A., & Kolapo, A. J. (2023). Implementation of conservation agricultural practices as an effective response to mitigate climate change impact and boost crop productivity in Nigeria. *Journal of Agriculture and Food Research*, *12*, Article, 100557. https://doi.org/10.1016/j.jafr.2023.100557

Lancaster, K. 1966. "A New Approach to Consumer Theory." *Journal of Political Economy*, *74* (2), 132–157. https://www.journals.uchicago.edu/doi/abs/10.1086/259131

Louviere, J. J., Street, D., Burgess, L., Wasi, N., Islam, T., & Marley, A. A. J. (2008). Modeling the choices of individual decision-makers by combining efficient choice experiment designs with extra preference information. *Journal of Choice Modelling*, *1*(1), 128–164. https://doi.org/10.1016/S1755-5345(13)70025-3

Lubembe, S. I., Turyasingura, B., & Chavula, P. (2022). *Reflection on Impacts of Climate Change on Fisheries and Aquaculture: Sub-Sahara Africa*. *6*(10). https://www.academia.edu/download/93431776/IJAPR221010_2.pdf

Macusi, E. D., Macusi, E. S., Jimenez, L. A., & Catam-isan, J. P. (2020). Climate change vulnerability and perceived impacts on small-scale fisheries in eastern Mindanao. *Ocean & Coastal Management*, *189*, Article 105143. https://doi.org/10.1016/j.ocecoaman.2020.105143

Mango, N., Makate, C., Tamene, L., Mponela, P., & Ndengu, G. (2018). Adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on household income in the Chinyanja triangle, Southern Africa. *Land*, *7*(2), Article 49. https://doi.org/10.3390/land7020049

Mantey, V., Mburu, J., & Chumo, C. (2020). Determinants of adoption and disadoption of cage tilapia farming in southern Ghana. *Aquaculture*, *525*, Article 735325. https://doi.org/10.1016/j.aquaculture.2020.735325

Manyise, T., Lam, R. D., Lozano Lazo, D. P., Padiyar, A., Shenoy, N., Chadag, M. V., Benzie, J. A. H., & Rossignoli, C. M. (2024). Exploring preferences for improved fish species among farmers: A discrete choice experiment applied in rural Odisha, India. *Aquaculture*, *583*, Article 740627. https://doi.org/10.1016/j.aquaculture.2024.740627

Marie, M., Yirga, F., Haile, M., & Tquabo, F. (2020). Farmers' choices and factors affecting adoption of climate change adaptation strategies: Evidence from northwestern Ethiopia. *Heliyon*, *6*(4), Article e03867. https://doi.org/10.1016/j.heliyon.2020.e03867

Marley, A. A. J., & Louviere, J. J. (2005). Some probabilistic models of best, worst, and best–worst choices. *Journal of Mathematical Psychology*, *49*(6), 464–480. https://doi.org/10.1016/j.jmp.2005.05.003

Martey, E., Etwire, P. M., & Abdoulaye, T. (2020). Welfare impacts of climate-smart agriculture in Ghana: Does row planting and drought-tolerant maize varieties matter? *Land Use Policy*, *95*, Article 104622. https://doi.org/10.1016/j.landusepol.2020.104622

McFadden D. Conditional logit analysis of qualitative choice behaviour. Frontiers in Econometrics (1973) New York: Academic press. https://doi.org/10.1108/eb028592.

Mensah, N. O., Asare, J. K., Mensah, E. T.-D., Amrago, E. C., Tutu, F. O., & Donkor, A. (2024). Determinants and framework for implementing sustainable climate-smart aquaculture insurance system for fish farmers: Evidence from Ghana. *Aquaculture*, *581*, Article 740354. https://doi.org/10.1016/j.aquaculture.2023.740354

Ministry of Agriculture L, Fisheries and Irrigation. Kenya Climate Smart Agriculture Implementation Framework 2018-2027. Nairobi, Kenya: Ministry of Agriculture, Livestock, Fisheries and Irrigation 2018. https://kilimo.go.ke/page/30/

Miriti, P., Regassa, M. D., Ojiewo, C. O., & Melesse, M. B. (2022). Farmers' preferences and willingness to pay for traits of sorghum varieties: Informing product development and breeding programs in Tanzania. *Journal of Crop Improvement*, 1–20. https://doi.org/10.1080/15427528.2022.207903

Msaki, G. L., Njau, K. N., Treydte, A. C., & Lyimo, T. (2022). Social knowledge, attitudes, and perceptions on wastewater treatment, technologies, and reuse in Tanzania. *Journal of Water Reuse and Desalination*, *12*(2), 223–241. https://doi.org/10.2166/wrd.2022.096

Mueller Loose, S., & Lockshin, L. (2013). Testing the robustness of best worst scaling for cross-national segmentation with different numbers of choice sets. *Food Quality and Preference*, *27*(2), 230–242. https://doi.org/10.1016/j.foodqual.2012.02.002

Mujeyi, A., Mudhara, M., & Mutenje, M. J. (2020). Adoption determinants of multiple climate smart agricultural technologies in Zimbabwe: Considerations for scaling-up and out. *African Journal of Science, Technology, Innovation and Development*, *12*(6),735-746. https://journals.co.za/doi/abs/10.1080/20421338.2019.1694780

Munene, B., & Wanjiku, A. (2020). *Contribution of fisheries to job creation among the youth in Kenya*. Kenya Institute for Public Research and Analysis. https://repository.kippra.or.ke/handle/123456789/2518

Munguti J., Obiero, K., Musa S., Mwaluma J., Orina, P., Opiyo M., Kyule D., Mirera D., and]Ochiewo J. James M. Njiru., Ogello E., Hagiwara A (Eds) (2020). State of Aquaculture Report 2020: Towards Nutrition Sensitive Fish Food Production Systems. Kenya Marine and Fisheries Research Institute, Mombasa, Kenya http://repository.tharaka.ac.ke/xmlui/handle/1/3212

Muriithi, L. N. (2020). *Adoption of Selected Climate Smart Agriculture Technologies Among Smallholder Farmers in Lower Eastern Kenya*. http://www.repository.embuni.ac.ke/handle/embuni/3879

Mussa, K. (2015). Eliciting smallholder farmers' tradeoffs and preferences on the attributes of climate smart agriculture in the breadbasket areas of Tanzania using a conjoint experiment method. *International Journal of Environmental Protection and Policy*, *3*(6), Article 188. https://doi.org/10.11648/j.ijepp.20150306.12

N'souvi, K., Sun, C., & Che, B. (2021). Aquaculture technology adoption and profitability of the polyculture system practiced by prawn and crab farmers: Case study of Anhui province in China. *Aquaculture Reports*, *21*, Article 100896. https://doi.org/10.1016/j.aqrep.2021.100896

Negera, M., Alemu, T., Hagos, F., & Haileslassie, A. (2022). Determinants of adoption of climate smart agricultural practices among farmers in Bale-Eco region, Ethiopia. *Heliyon*, *8*(7), Article e09824. https://doi.org/10.1016/j.heliyon.2022.e09824

Njiru, J.M., Omukoto, J.O., Kimani, E.N., Aura, C.M., & van der Knaap, M. (2021). Kenya marine fisheries: The next frontier for economic growth? *Aquatic Ecosystem Health and Management*, *24*, 97 – 104. https://doi.org/10.14321/aehm.024.01.14

Obayelu, O. A., Adepoju, A. O., & Idowu, T. (2014). Factors influencing farmers' choices of adaptation to climate change in Ekiti State, Nigeria. *Journal of Agriculture and Environment for International Development*, *108*(1). https://doi.org/10.12895/jaeid.20141.140

Obiero, K. O., Waidbacher, H., Nyawanda, B. O., Munguti, J. M., Manyala, J. O., & Kaunda-Arara, B. (2019). Predicting uptake of aquaculture technologies among smallholder fish farmers in Kenya. *Aquaculture International*, *27*(6), 1689–1707. https://doi.org/10.1007/s10499-019-00423-0

Obwanga B, Soma K, Ayuya OI, Rurangwa E, van Wonderen D, Beekman G, et al. Exploring enabling factors for commercializing the aquaculture sector in Kenya. Centre for Development Innovation (2020). https://library.wur.nl/WebQuery/wurpubs/563180

OECD & Food and Agriculture Organization of the United Nations. (2020). *OECD-FAO Agricultural Outlook 2020-2029*. OECD. https://doi.org/10.1787/1112c23b-en

Ogello, E., & Outa, N. (2022). *Socio-economic consequences of imported frozen tilapia in the Kenyan aquaculture value chain: Strategies for optimizing local unexploited potential*. https://doi.org/10.14293/111.000/000018.v2

Ojo, T. O., & Baiyegunhi, L. J. S. (2020). Determinants of climate change adaptation strategies and its impact on the net farm income of rice farmers in south-west Nigeria. *Land Use Policy*, *95*, Article 103946. https://doi.org/10.1016/j.landusepol.2019.04.007

Okello, A. O., Otieno, D. J., Nzuma, J. M., Kidoido, M. M., & Tanga, C. M. (2023). Smallholder farmers' willingness to pay for commercial insect-based chicken feed in Kenya. *International Food and Agribusiness Management Review*, *26*(1),67-87. https://doi.org/10.22434/IFAMR2022.0047

Onada Olawale, A. (2016). Climate Smart Aquaculture: A Sustainable Approach to increasing fish production in the face of climate change in Nigeria. *International Journal of Aquaculture and Fishery Sciences*, 012–017. https://doi.org/10.17352/2455-8400.000013

Onyeneke, R. U., Igberi, C. O., Aligbe, J. O., Iruo, F. A., Amadi, M. U., Iheanacho, S. C., Osuji, E. E., Munonye, J., & Uwadoka, C. (2020). Climate change adaptation actions by fish farmers: Evidence from the Niger Delta Region of Nigeria. *Australian Journal of Agricultural and Resource Economics*, *64*(2), 347–375. https://doi.org/10.1111/1467-8489.12359

Onyenekwe, C. S., Opata, P. I., Ume, C. O., Sarpong, D. B., & Egyir, I. S. (2023). Heterogeneity of adaptation strategies to climate shocks: Evidence from the Niger Delta region of Nigeria. *Bio-Based and Applied Economics*, *12*(1), 17–35. https://doi.org/10.36253/bae-13436

Oparinde, L. O. (2021). Fish farmers' welfare and climate change adaptation strategies in southwest, Nigeria: Application of multinomial endogenous switching regression model. *Aquaculture Economics & Management*, *25*(4), 450–471. https://doi.org/10.1080/13657305.2021.1893863

Orina PS, Maina JG, Wangia SM, Karuri EG, Mbuthia PG, Omolo B, Owiti GO, Musa S, Munguti JM (2014). Situational analysis of Nile tilapia and African catfish hatcheries management: a case study of Kisii and Kirinyaga counties in Kenya. Livest Res Rural Dev 26:168–169 https://aquadocs.org/handle/1834/7343

Ortiz, C. A., Avila-Santamaría, J. J., & Martinez-Cruz, A. L. (2023). Dairy farmers' willingness to adopt cleaner production practices for water conservation: A discrete choice experiment in Mejia, Ecuador. *Agricultural Water Management*, *278*, Article 108168. https://doi.org/10.1016/j.agwat.2023.108168

Pueyo, A. (2018). What constrains renewable energy investment in Sub-Saharan Africa? A comparison of Kenya and Ghana. *World Development*, *109*, 85–100. https://doi.org/10.1016/j.worlddev.2018.04.008

Rahman, Moh. S., Toiba, H., & Huang, W.-C. (2021). The Impact of climate change adaptation strategies on income and food security: empirical evidence from small-scale fishers in Indonesia. *Sustainability*, *13*(14), Article 7905. https://doi.org/10.3390/su13147905

Republic of Kenya. (2019). Agricultural sector transformation and growth strategy: Towards sustainable agricultural transformation and food security in Kenya. Nairobi: Republic of Kenya. https://cgspace.cgiar.org/handle/10568/99040

Rogers, H. J., Marshman, Z., Rodd, H., & Rowen, D. (2021). Discrete choice experiments or best-worst scaling? A qualitative study to determine the suitability of preference elicitation tasks in research with children and young people. *Journal of Patient-reported Outcomes*, *5*, 1-11. https://doi.org/10.1186/s41687-021-00302-4

Rocha, C. P., Cabral, H. N., Marques, J. C., & Gonçalves, A. M. M. (2022). A Global overview of aquaculture food production with a focus on the activity's development in transitional systems. The Case Study of a South European Country (Portugal). *Journal of Marine Science and Engineering*, *10*(3), Article 417. https://doi.org/10.3390/jmse10030417

Sandip Mitra, Md. Akhtaruzzaman Khan & Rasmus Nielsen (2019) Credit constraints and aquaculture productivity, *Aquaculture Economics & Management, 23*(4), 410-427, doi: 10.1080/13657305.2019.1641571

Sardar, A., Kiani, A. K., & Kuslu, Y. (2021). Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan. *Environment, Development and Sustainability*, *23*(7), 10119–10140. https://doi.org/10.1007/s10668-020-01049-6

Sebatta, C., Ssepuuya, G., Sikahwa, E., Mugisha, J., Diiro, G., Sengendo, M., & Nakimbugwe, D. (2018). Farmers' acceptance of insects as an alternative protein source in poultry feeds. *International Journal of Agricultural Research, Innovation and Technology*, *8*(2), 32-41. https://doi.org/10.3329/ijarit.v8i2.40553

Shahzad, M. F., Abdulai, A., & Issahaku, G. (2021). Adaptation Implications of Climate-Smart Agriculture in Rural Pakistan. *Sustainability*, *13*(21), Article 11702. https://doi.org/10.3390/su132111702

Shittu, A., Kehinde, M., Shittu, A., & Kehinde, M. (2018). *Willingness to Accept Incentives for a Shift to Climate – Smart Agriculture among Smallholder Farmers in Southwest and Northcentral Nigeria*. https://doi.org/10.22004/AG.ECON.275983

Sisay, T., Tesfaye, K., Ketema, M., Dechassa, N., & Getnet, M. (2023). Climate-Smart Agriculture Technologies and Determinants of Farmers' Adoption Decisions in the Great Rift Valley of Ethiopia. *Sustainability*, *15*(4), Article 3471. https://doi.org/10.3390/su15043471

Tanti, P. C., & Jena, P. R. (2023). Perception on climate change, access to extension service and energy sources determining adoption of climate-smart practices: A multivariate approach. *Journal of Arid Environments*, *212*, Article 104961. https://doi.org/10.1016/j.jaridenv.2023.104961

Tanti, P. C., Jena, P. R., Aryal, J. P., & Rahut, D. B. (2022). Role of institutional factors in climate-smart technology adoption in agriculture: Evidence from an Eastern Indian state. *Environmental Challenges*, *7*, Article 100498. https://doi.org/10.1016/j.envc.2022.100498

Teferi, E. T., Kassie, G. T., Pe, M. E., & Fadda, C. (2020). Are farmers willing to pay for climate related traits of wheat? Evidence from rural parts of Ethiopia. *Agricultural Systems*, *185*, Article 102947. https://doi.org/10.1016/j.agsy.2020.102947

Thiene, M., Scarpa, R., & Louviere, J. J. (2015). Addressing preference heterogeneity, multiple scales and attribute attendance with a correlated finite mixing model of tap water choice. *Environmental and Resource Economics*, *62*(3), 637–656. https://doi.org/10.1007/s10640-014-9838-0

Unekwu, O., Mojisola, A. O., Tina, E., & Ogala, D. (2020). Perception and uptake of aquaculture technologies in Kogi state, central Nigeria: Imperative for Improved Management practices for sustainable aquaculture development. *African Journal of Agricultural Research*, *16*(6), 819–828. https://doi.org/10.5897/AJAR2019.14558

Waaswa, A., Oywaya Nkurumwa, A., Mwangi Kibe, A., & Ngeno Kipkemoi, J. (2022). Climate-Smart agriculture and potato production in Kenya: Review of the determinants of practice. *Climate and Development*, *14*(1), 75–90. https://doi.org/10.1080/17565529.2021.1885336

Wanja, D. W., Mbuthia, P. G., Waruiru, R. M., Bebora, L. C., Ngowi, H. A., & Nyaga, P. N. (2020). Antibiotic and disinfectant susceptibility patterns of bacteria isolated from farmed fish in Kirinyaga county, Kenya. *International Journal of Microbiology*, *2020*, 1–8. https://doi.org/10.1155/2020/8897338

Wassie, A., & Pauline, N. (2018). Evaluating smallholder farmers' preferences for climate smart agricultural practices in Tehuledere District, North Eastern Ethiopia: Evaluating smallholder farmers' preferences. *Singapore Journal of Tropical Geography*, *39*(2), 300–316. https://doi.org/10.1111/sjtg.12240

Wekesa, B. M., Ayuya, O. I., & Lagat, J. K. (2018). Effect of climate-smart agricultural practices on household food security in smallholder production systems: Micro-level evidence from Kenya. *Agriculture & Food Security*, *7*(1), Article 80. https://doi.org/10.1186/s40066-018-0230-0

Yamane, Taro. 1967. Statistics, An Introductory Analysis, 2nd Ed., New York: Harper and Row. *Mathematical formula for sample size determination*. http://www.sciepub.com/reference/180098

Yatsenko, Y. (2021). Aquaculture: An Emerging Research Area. Academia Letters. https://doi.org/10.20935/AL680

Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., Ericksen, P., Said, M., & Jalloh, A. (2016). Toward climate-smart agriculture in West Africa: A review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture & Food Security*, *5*(1), Article 26. https://doi.org/10.1186/s40066-016-0075-3

APPENDICES

APPENDIX A: HOUSEHOLD QUESTIONNAIRE

A. QUESTIONNAIRE IDENTIFICATION

Questionnaire Number………

Name of Enumerator………..

Dear respondent,

I am Christopher Magesi, a student at Egerton University pursuing a Master's degree in Agriculture and Applied Economics. We are doing research on the **Uptake and Effects of Climate Smart Aquaculture Practices on Productivity among fish farmers in Kakamega County, Kenya**. Th end goal of this research is to escalate adoption of climate smart aquaculture practices in efforts to improve the livelihood of small-holder fish farmers. Taking part in this research will help researchers and policy makes in designing interventions that provide an enabling environment on socio-economic and institutional development of aqua farmers. You have been selected to participate in this interview however your participation is voluntary. The information you provide will be confidential and your name will not appear at any level on reporting of the results. The interview will take approximately 50 minutes. Notes and responses will be recorded on Open Data Kit (ODK). If you agree to participate you will be asked about socio-demographic aspects, institutional and support services on fish farming, Preferences for CSA practices and Production. **Please note that this study does not involve any physical or emotional risks to you or any of your fish project. Thank you.**

DO YOU AGREE TO PARTICIPATE IN THIS STUDY?

Name of interviewer [___________ ____________]

Household number [_________________]

Ward [_________________]

Village [_________________]

Date of interview [_________________]

2. Household Characteristics

2.0 Name of the household head [__________ __________]

2.1 Year of birth of the household head [______________]

2.3 Gender of the household head[______________] 1=male,0=female

2.4 What is the relationship of the respondent to the household head [________]

1=Son,2=Daughter,3=Wife,4=Parent,5=Grandchild,6=Brother,7=Others(specify)

2.5 What is the level of education of respondent [_________] Number of school-going years

2.6 Gender of the respondent [______________] 1=male,0=female

2.7 Age of the respondent [______________]

2.8 What is the size of the household [______________]

2.9 Number of Adults present in the household? [______________]

2.10 Who is the key decision maker? [_________]1=HH,2=Spouse,3=Both

2.11 Does the Household head participate in off-farm employment? [_________] 1=yes,0=no

(***If yes, continue, if no go to question 3)***

2.12 What is the source of your off-farm income?

Business **[ ]** Civil servant **[ ]** Casual labour [ ] others (specify) [_________]

2.13 How much time do you spend doing the off-farm work? [_________]

2.14 What is the average monthly income for the off-farm employment? [_________]

3. Property Rights

3.1 Do you own land? 1=Yes[ ] 2= No[ ] (if **yes** continue, if **no** go to question **3.3)**

3.2 What is the total land owned? [_________] (in acres)

3.3 Do you rent-in land? 1=Yes[ ] 2=No[ ]

3.4 If **yes** what is the total land size rented in? [_________]

3.5 If rented, how much do you pay in **2022/2023** for a farm year? [_________]

3.5 What is the total land size? [______________] (both owned and rented)

4. Information on fish production

4.1 what is the size of your aquaculture farm? [_________] in acres

4.2 How many years have you been involved in aquaculture farming? [_________]

4.3 Income from aquaculture farming (in the reference period) [_______________]

4.4 Are you or any of your household member aware of the following practices? [_________]1=Yes, 0=No

(**Adjusted stocking time, embarkments, use of boreholes, tanks, covering of fish pond, dam liner, Recirculating fish systems, use of improved seeds, use of improved feeds, site selection, construction of drainage systems)**

4.5 Has any member of the HH received training on any of the following CSA practices? [_________]1=Yes, 0=No

5. Climate information

5.1 Would you say that there have been severe changes in climate in the last 10 year? [_________]1=Yes,0=No

5.2 If yes, what bad incidences related to climate have you experienced in this area in the last 10 years? [_________]1=Drought,2=Hailstorms,3=Floods, 4=Tempareture,5=Others(specify)

5.2 Did your fish production decline due to such incidences? [_______________] 1=Yes,0=No

5.3 Have you made any changes on your pond following the bad incidences [_________]1=Yes,0=No

5.4 If yes, which one of the following practices have you adopted? [_________]

Adjusted stocking time [ ]
Embarkment creation [ ]
Use of boreholes [ ]
Use of tanks [ ]
Covering of fish ponds [ ]
Use of dam liner [ ]
Recirculating fish systems [ ]

Use of improved seeds [ ]

Use of improved feeds [ ]

Smoking Kiln [ ]

Integrated system [ ]

Use of solar power [ ]

Waste-water treatment [ ]

Dykes construction [ ]

Water- reuse [ ]

5.5 How has the application of this CSA affected your productivity? [_________]

5.6

Number of fish ponds	Quantity of fish stocked	Area of pond (in meters)	Quantity of fish harvested	Quantity of fish feeds used (Kgs)

5.7 How long have you implemented CSA practices on your farm? (years)

[_______________]

5.8 What are the challenges involved in the use of the above strategies?

1=Lack of capital,2=lack of information,3=lack of access, 4=shortage of labour,5=others(specify)

5.9 How often do you seek information on CSA practices? [_________] 1= weekly, 2=Monthly, 3= Annually, 4= Rarely, 5=Never

5.10 Are there local or national policies supporting CSA uptake?

[_______________]1=Yes, 2=No ***(if yes, continue if No go to 5.13)***

5.11 If Yes, have these policies influenced your decision about CSA?

Strongly influence [ ]

Somewhat influence [ ]

No influence [ ]

Not aware of any policies

5.11 Have you received any incentives or support from the government or NGOs to implement CSA practices? [_________]1=Yes, 0=No

5.12 If Yes, what kind

Feeds [ ]

Fingerlings [ ]

Others [ ] (specify) [_________]

5.13 How did you learn about climate smart aquaculture practices? [_________]

(1=family/friends,2=Gov't programs,3=Media,4=NGO's,5=others(specify))

5.14 How supportive are the channels in promoting CSA practices?

1=very supportive, =somewhat supportive, 3=Neutral, 4=Not supportive, 5=Don't Know

5.15 Have you incurred any additional cost as a result of implementing CSA practices?

[_________]1=Yes, 0=No

5.16 If yes, how much [_________]

6. Information on Institutional Factors

6.1 Have you received any extension services in the last 1 year? [_________]1=Yes,0=N0

(If Yes continue, if No go to 6.4)

6.2 During your production period on average how many times do you access extension services? [_________]

6.3 what is the mode of extension delivery? 1=farm visits,2=field day,3=office visits, 4=others (specify)

6.4 Is the household head a member of a formal group? [_________]1=Yes,0=No this is missing

(If yes, continue if no go to question 6.8)

6.5 How many groups is he/she in? [_________]

6.6 Does the HH head have any leadership in the group? [_________]1=Yes,0=N0

6.7 What benefit does the HH head derive from the group

1=information on credit,2=advice on farming,3=information on climate change,4=help on credit access,5=others(specify)

6.8 Do you have access to credit? [_________]1=Yes,0=No

(If yes, continue if no go to question 6.11)

6.9 what amount have you received during the reference period [_________]Ksh

1,000- 10,000 [ ]

10,000-50,000 [ ]

50,000 and above [ ]

6.10 What is the source of credit received?

Bank [ ]

Friends/family [ ]

ROSCAS [ ]

Others (specify) [ ]

6.11 Is the credit used in fish farming? [_________] 1=Yes,0=No

6.12 Have you attended any training on climate smart aquacultural practices? [_________]1=Yes,0=No (***If Yes, continue if No go to 6.14)***

6.13 How many trainings on CSA practices have you attended in the last one year [_________]

6.14 Social influence:

i. Those in my social circle influence my access to climate information [_________]

ii. Those in my social circle influence the choice of CSA practice [_________]

iii. Those in my social class influence the use of CSA [_________]

(1=strongly disagree,2=disagree,3=neutral,4=agree,5=strongly agree)

6.15 What is the distance from homestead to….?

	Distance in KM	Mode used	Cost incurred	Time spent
Input markets				
Extension office				
Tarmac road				

(Mode: 1=Bodaboda, 2=Matatu, 3=Walking, 4=Others(specify)

7. Asset Endowment

What assets do you own?

Asset	unit	Approximated unit value
Cow		
Goat		
Sheep		
Pig		
Chicken		
Donkey		
Land		
Tank		
Water pump		
Radio		
Tv		
Mobile phone		

9. Choice Experiment

The following choice cards are constructed based on the attributes and attribute levels of climate smart aquacultural practices. A farmer will only be presented with one profile which contains four choice cards each. In each card there are four alternatives that are presented to the farmer for eliciting preferences. A farmer will then be required to choose the best and worst preferred alternatives from the four alternatives. Then from the remaining two alternatives, He/she will be required to select that which is preferred to other. The aim of this experiment is to be able to determine the optimal options of climate smart aquacultural practices that are most and least preferred by the fish farmers.

Attributes and levels of climate smart aquacultural practices

Attribute	Description	Level
Knowledge smart	Does the CSA meet the demands of the farmer	Improved feeds, Improved seeds, Adjusted stocking time

Energy smart tech	Whether the technology is energy efficient	Use of solar, Wind power, Electricity
Water smart	Whether the practice meet the water demands of the farm	Dam liner, water harvesting, embarkments
Waste-smart	Whether the CSA is environmentally friendly	Water treatment, low antibiotics, water re-use

Profile 1

Choice card one

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved seeds	Adjusted stocking time	Improved feed	Improved feeds
Energy smart	Solar power	Wind power	Electricity	Wind power
Water smart	Water harvesting	Dam liner	embarkments	Water harvesting
Waste smart	Low antibiotics	Water reuse	Water treatment	Water reuse
Best preferred				
Worst preferred				

Choice card two

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Adjusted stocking time	Adjusted stocking time	Improved feeds	Improved seeds
Energy smart	Solar power	Solar power	electricity	Wind power
Water smart	Water harvesting	Dam liner	embarkments	Embarkments

Waste smart	Water treatment	Water reuse	Low antibiotics	Low antibiotics
Best preferred				
Worst preferred				

Choice card three

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Adjusted stocking time	Improved feed	Improved seeds	Improved seeds
Energy smart	Solar power	Wind power	electricity	electricity
Water smart	Water harvesting	Dam liner	Dam liner	Embarkment
Waste smart	Water treatment	Low antibiotics	Water treatment	Water reuse
Best preferred				
Worst preferred				

Choice card four

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Adjusted stocking time	Improved feed	Improved seeds	Adjusted stocking time
Energy smart	electricity	Solar power	Wind power	Wind power
Water smart	Embarkment	Water harvesting	Dam liner	Embarkment

Waste smart	Water reuse	Water treatment	Water reuse	Water treatment
Best preferred				
Worst preferred				

Profile 2

Choice card one

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Adjusted stocking time	Improved feed	Improved seeds
Energy smart	Solar power	Wind power	electricity	electricity
Water smart	Dam liner	Water harvesting	Dam liner	Embarkment
Waste smart	Water treatment	Water reuse	Low antibiotics	Water treatment
Best preferred				
Worst preferred				

Choice card two

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Improved seeds	Improved feed	Improved seeds
Energy smart	Wind power	Solar power	Solar power	Electricity
Water smart	Dam liner	Water harvesting	Embarkment	Water harvesting

Waste smart	Water reuse	Water treatment	Low antibiotics	Low antibiotics
Best preferred				
Worst preferred				

Choice card three

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Adjusted stocking time	Improved seeds	Adjusted stocking time
Energy smart	Wind power	electricity	electricity	Wind power
Water smart	Water harvesting	Water harvesting	Dam liner	Dam liner
Waste smart	Water treatment	Low antibiotics	Water reuse	Low antibiotics
Best preferred				
Worst preferred				

Choice card four

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved seeds	Improved seeds	Adjusted stocking time	Improved feed
Energy smart	Electricity	Wind power	Electricity	Solar power
Water smart	Dam liner	Embarkment	Embarkment	Water harvesting
Waste smart	Water treatment	Water treatment	Water reuse	Water reuse
Best preferred				

Worst preferred

Profile 3

Choice card one

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Improved feeds	Improved seeds	Adjusted stocking time
Energy smart	Wind power	Solar power	electricity	Solar power
Water smart	Embarkment	Dam liner	Embarkment	Water harvesting
Waste smart	Water treatment	Low antibiotics	Low antibiotics	Water reuse
Best preferred				
Worst preferred				

Choice card two

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Adjusted stocking time	Adjusted stocking time	Improved feed	Improved seeds
Energy smart	electricity	Solar power	Wind power	Solar power
Water smart	Water harvesting	Dam liner	Embarkment	Water harvesting
Waste smart	Low antibiotics	Low antibiotics	Water reuse	Water treatment

Best preferred				
Worst preferred				

Choice card three

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved seeds	Adjusted stocking time	Adjusted stocking time	Improved feed
Energy smart	Electricity	Solar power	Wind power	electricity
Water smart	Dam liner	Embarkment	Embarkment	Water harvesting
Waste smart	Low antibiotics	Water reuse	Water treatment	Water reuse
Best preferred				
Worst preferred				

Choice card four

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Improved seeds	Improved feed	Improved seeds
Energy smart	Wind power	Solar power	Electricity	Wind power
Water smart	Dam liner	Water harvesting	Dam liner	Water harvesting
Waste smart	Low antibiotics	Low antibiotics	Water treatment	Water reuse

Best preferred				
Worst preferred				

Profile 4

Choice card one

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved seeds	Improved feed	Improved feed	Adjusted stocking time
Energy smart	Wind power	Electricity	Electricity	Wind power
Water smart	Dam liner	Water harvesting	Dam liner	Embarkment
Waste smart	Water treatment	Water reuse	Water treatment	Low antibiotics
Best preferred				
Worst preferred				

Choice card two

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Adjusted stocking time	Adjusted stocking time	Improved seeds
Energy smart	Wind power	electricity	Wind power	Solar power
Water smart	Dam liner	Embarkment	Water harvesting	Embarkment

Waste smart	Water reuse	Water treatment	Water treatment	Water reuse
Best preferred				
Worst preferred				

Choice card three

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Adjusted stocking time	Improved seeds	Adjusted stocking time	Improved feed
Energy smart	Wind power	Solar power	Electricity	Solar power
Water smart	Water harvesting	Embarkment	Dam liner	Embarkment
Waste smart	Low antibiotics	Water treatment	Low antibiotics	Water reuse
Best preferred				
Worst preferred				

Choice card four

Attributes	Alternative A	Alternative B	Alternative C	Alternative D
Knowledge smart	Improved feed	Adjusted stocking time	Adjusted stocking time	Improved seeds
Energy smart	Electricity	Solar power	Solar power	Wind power
Water smart	Water harvesting	Dam liner	Dam liner	Water harvesting

Waste smart	Low antibiotics	Water reuse	Water treatment	Low antibiotics
Best preferred				
Worst preferred				

APPENDIX B: VARIANCE INFLATION FACTOR FOR CONTINUOUS EXPLANATORY VARIABLES

Variables	VIF	1/VIF
Years of schooling	1.06	0.947472
Household size	1.20	0.835688
Land size	1.12	0.893308
Experience	1.13	0.886021
Age of the respondent	1.23	0.813078
Number of ponds owned	1.06	0.943972
Extension service received	1.09	0.913337
Mean VIF	1.11	

APPENDIX C: CONTINGENCY COEFFICIENTS FOR DUMMY EXPLANATORY VARIABLES

Variables	Gender	Off-farm income	Government subsidies	Credit access	Training
Gender	1.0000				
Off-farm income	0.0115	1.0000			
Government subsidies	0.2534	0.0375	1.0000		
Credit access	0.0620	0.1101	0.0359	1.0000	
Training	0.1566	0.0652	0.4801	0.1849	1.0000

APPENDIX D: MULTIVARIATE RESULTS OF THE FACTORS INFLUENCING UPTAKE OF CSA PRACTICES AMONG SMALL-HOLDER FISH FARMERS

```
Multivariate probit (SML, # draws = 5)          Number of obs   =        220
                                                Wald chi2(55)   =     151.67
Log pseudolikelihood = -578.21418               Prob > chi2     =     0.0000
```

	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
damline						
gender	.368708	.2087457	1.77	0.077	-.0404261	.7778421
EDUC	.053157	.0260859	2.04	0.042	.0020297	.1042843
Age	.0015277	.0092833	0.16	0.869	-.0166673	.0197227
HH_size	-.1040474	.0414352	-2.51	0.012	-.185259	-.0228358
offfarm	.0163996	.203226	0.08	0.936	-.3819161	.4147152
Lsize	-.0790604	.0411078	-1.92	0.054	-.1596302	.0015094
exper	.0068337	.0150609	0.45	0.650	-.0226852	.0363526
No_ponds	-.056721	.0902193	-0.63	0.530	-.2335477	.1201056
NO_EXT	.0493156	.0300846	1.64	0.101	-.0096492	.1082804
Crdt_access	.1831888	.2064868	0.89	0.375	-.2215179	.5878954
CSA_train	.5141111	.2088702	2.46	0.014	.104733	.9234892
_cons	-1.230903	.7672443	-1.60	0.109	-2.734675	.2728679
borehole						
gender	-.052145	.1953112	-0.27	0.789	-.434948	.330658
EDUC	.0464689	.0254596	1.83	0.068	-.003431	.0963689
Age	.0042852	.008165	0.52	0.600	-.011718	.0202883
HH_size	.0446195	.0422435	1.06	0.291	-.0381762	.1274152
offfarm	.2280643	.1937661	1.18	0.239	-.1517103	.6078389
Lsize	.0167347	.0369272	0.45	0.650	-.0556413	.0891107
exper	.0189377	.0146543	1.29	0.196	-.0097843	.0476596
No_ponds	.0671242	.0784953	0.86	0.392	-.0867238	.2209723
NO_EXT	.025115	.0272087	0.92	0.356	-.028213	.078443
Crdt_access	.0629705	.1980981	0.32	0.751	-.3252947	.4512357
CSA_train	.3019716	.2011005	1.50	0.133	-.0921782	.6961213
_cons	-1.953192	.7508465	-2.60	0.009	-3.424824	-.4815597
pondcover						
gender	.4163941	.1999707	2.08	0.037	.0244588	.8083294
EDUC	.0395198	.0283423	1.39	0.163	-.0160301	.0950698
Age	.0061671	.0087431	0.71	0.481	-.0109691	.0233032
HH_size	-.0509081	.0452011	-1.13	0.260	-.1395007	.0376844
offfarm	-.1287991	.2022429	-0.64	0.524	-.525188	.2675897
Lsize	.0602837	.0416806	1.45	0.148	-.0214089	.1419762
exper	.017068	.0142422	1.20	0.231	-.0108461	.0449821
No_ponds	-.1127139	.0898757	-1.25	0.210	-.288867	.0634393
NO_EXT	.115327	.0330178	3.49	0.000	.0506134	.1800406
Crdt_access	.3089462	.2034474	1.52	0.129	-.0898034	.7076959
CSA_train	.3374477	.2258093	1.49	0.135	-.1051305	.7800258
_cons	-3.160658	.8465903	-3.73	0.000	-4.819945	-1.501372
tank						
gender	.2421218	.191275	1.27	0.206	-.1327704	.6170139
EDUC	.0473921	.0268277	1.77	0.077	-.0051893	.0999735
Age	.0046726	.0086197	0.54	0.588	-.0122218	.021567
HH_size	-.0031592	.0403619	-0.08	0.938	-.0822671	.0759487
offfarm	.0062741	.1902719	0.03	0.974	-.366652	.3792002
Lsize	-.0609732	.0422196	-1.44	0.149	-.143722	.0217757
exper	.0075495	.0166474	0.45	0.650	-.0250787	.0401778
No_ponds	.047205	.0888016	0.53	0.595	-.1268429	.221253
NO_EXT	.0390092	.0277891	1.40	0.160	-.0154565	.0934749
Crdt_access	-.0483476	.1907731	-0.25	0.800	-.4222561	.3255609
CSA_train	.3366739	.2017412	1.67	0.095	-.0587317	.7320794
_cons	-2.024301	.7835558	-2.58	0.010	-3.560042	-.4885594
Adj_stock						
gender	.3898613	.2465708	1.58	0.114	-.0934086	.8731313
EDUC	-.0097218	.0360064	-0.27	0.787	-.0802931	.0608495
Age	.0208338	.0106179	1.96	0.050	.0000231	.0416445
HH_size	-.2528799	.0629674	-4.02	0.000	-.3762937	-.1294661
offfarm	.0662491	.2396723	0.28	0.782	-.4035001	.5359982
Lsize	-.1039941	.0550987	-1.89	0.059	-.2119856	.0039975
exper	.0719188	.0166427	4.32	0.000	.0392997	.1045378
No_ponds	-.0135417	.1144303	-0.12	0.906	-.237821	.2107377
NO_EXT	-.0074965	.0397803	-0.19	0.851	-.0854645	.0704715
Crdt_access	.1550373	.2438223	0.64	0.525	-.3228457	.6329203
CSA_train	.5572382	.3475614	1.60	0.109	-.1239697	1.238446
_cons	-2.658297	1.036876	-2.56	0.010	-4.690537	-.6260565

APPENDIX E: NACOSTI PERMIT

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APPENDIX F: PUBLICATION ABSTRACT

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How does climate-smart aquaculture affect fish productivity among smallholder farmers in Kakamega County, Kenya? A multinomial endogenous switching regression

Boke Christopher Magesi*
Department of Agricultural Economics and Agribusiness Management, Egerton University, Egerton, Kenya. E-mail: bokechris5@gmail.com

Hillary Bett
Department of Agricultural Economics and Agribusiness Management, Egerton University, Egerton, Kenya. E-mail: Hillary.bett@egerton.ac.ke

Augustus Muluvi
Department of Economics, Egerton University, Egerton, Kenya. E-mail: amuluvi@egerton.ac.ke

* Corresponding author