THE IMPACT OF PRODUCTION RISK ON THE CHOICE OF THE OPTIMAL LEVEL OF INPUTS, ADOPTION, AND WELFARE OF SMALL HOLDER INTERGRATED AGRICULTURE AQUACULTURE FARMERS IN KENYA

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A99/CTY/27585/2019

A THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF DOCTOR OF PHILOSOPHY (AGRICULTURAL ECONOMICS) IN THE SCHOOL OF AGRICULTURE AND ENVIRONMENTAL SCIENCES, KENYATTA UNIVERSITY

NOVEMBER, 2025

DECLARATION

I, Fonda Jane Awuor, declare that this thesis is my original work and has not been presented for the award of a degree in any other university or any other award

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DEDICATION

This work is dedicated to my grandmother Wilkista Angaya Ong'ondo

ACKNOWLEDGEMENT

I wish to express my profound gratitude to individuals and institutions whose unwavering support made this thesis possible. My deepest appreciation goes to my supervisors and mentors, Dr. Ibrahim Macharia Ndegwa and Prof. Richard Mulwa, for their invaluable academic guidance, personal encouragement, and for nurturing my growth as a scholar. I am also indebted to Prof. Maurice Ogada for his insightful methodological input. Dr. Chrispine Nyamweya, Dr. Jonathan Munguti, Prof. Deo Namwira, and Prof. Karlijn van den Broek are appreciated for their candid discussions. Special thanks to Prof. Henry Mutembei for his mentorship. I am thankful for the financial support from the Kenya Climate Smart Agriculture Project (KCSAP) for financing my studies. My fieldwork was immensely supported by the county leadership and fisheries officers of Kirinyaga, Busia, Siaya, Kakamega, and Nyeri. I extend sincere thanks to Mr. Timothy Odende, Mrs. Anne Kimotho, Dr. Elizabeth Odhiambo, Mrs. Maureen Muriuki and Mr. Zephaniah Otieno for facilitating my research. My gratitude also goes to the dedicated county fisheries officers and my exceptional research assistants, Evelyn Ndanu, Angela Achieng, and Alvin Ambunya. Most importantly, I thank the 427 fish farming households who shared their experiences, making this study possible. I acknowledge the Kenya Marine and Fisheries Research Institute (KMFRI) for providing a conducive work environment. I thank Dr. Mary Opiyo for her constant encouragement. Special thanks to Dr. Philip Ochieng, Dr. Basil Ajer, Kevin Mureti, Dr. Nancy Momanyi, Joel Nyongesa, Elly Kyallo, Perpetua Mutinda, Joseph Kiuna and Calvince Ocharo for their vital insights. To my family, I owe everything. My heartfelt thanks to my mother, Anne Ong'ondo and my sister for their steadfast support. To Arianne Wonder Hawi, thank you for your inspiration, patience, and for being my ray of hope. Finally, I give all glory to the Almighty God for the blessing of health, guidance, and mental tranquility throughout this journey.

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OPERATIONAL DEFINITION OF TERMS

Integrated Agriculture Aquaculture (IAA): A farming system that combines fish production with crop and/or livestock enterprises on the same farm, allowing recycling of nutrients, shared use of inputs, and improved overall farm productivity and household income.

IAA Adopter: A household that maintains at least one functional fishpond and practices resource recycling across farm enterprises (fish–crop, fish–livestock, or fish–crop–livestock integration).

Non-Adopter: A household that practices aquaculture but does not integrate fishponds with crop or livestock enterprises for resource recycling.

Risk-Increasing Input: A production input whose increased use leads to greater variability (variance) of output, thereby raising production risk.

Risk-Decreasing Input: A production input whose increased use lowers the variability (variance) of output, thereby reducing production risk.

Welfare (Farmer Welfare): In this study, welfare refers to the economic well-being of the farming household. Although welfare can be measured using several indicators such as consumption expenditure, assets, food security, or multidimensional household indices this study uses household income and Inter-spatial Total Factor Productivity (ITPF) as practical and reliable proxies. Income captures the immediate monetary gains from IAA adoption, while TFP reflects improvements in production efficiency and resource use. Together, they provide a comprehensive assessment of household welfare consistent with agricultural economics literature, especially for smallholder systems characterized by mixed enterprises and production risk.

Endogenous Switching Regression (ESR): An econometric model used to compare two groups such as farmers who adopt a technology and those who do not while recognizing that farmers choose whether to adopt based on their own characteristics (for example, skills, resources, or risk attitudes). It helps estimate what would have happened to each group under the opposite choice (their counterfactual). ESR model offers a stronger and more reliable approach because it controls for both observable and unobservable factors that influence adoption. It corrects for self-selection bias and estimates counterfactual outcomes, allowing for a clearer understanding of the true impact in this study, of IAA adoption on productivity, income, and production risk. ESR also permits separate outcome equations for adopters and non-adopters, capturing behavioral and production differences that simpler models cannot.

Inter-spatial Total Factor Productivity (ITPF): A measure of farm-level productivity that accounts for multiple inputs and outputs across different enterprises in an integrated system.

Smallholder Farmer: A farming household operating on limited landholding typically less than two hectares and relying primarily on family labor, typically producing for both subsistence and the market.

LIST OF ACRONYMS AND ABBREVIATIONS

ASDS Agricultural Sector Development Strategy

CIDP County Integrated Development Plan

ESP-FFEPP Economic Stimulus Project-Fish Farming and Enterprise Productivity Program

ESR Endogenous Switching Regression

FIML Full Information Maximum Likelihood

FOC First Order Condition

IAA Integrated Agriculture Aquaculture

IMR Inverse Mills Ratio

KCSAP Kenya Climate Smart Agriculture Project

KMFRI Kenya Marine and Fisheries Research Institute

KNBS Kenya National Bureau of Statistics

OLS Ordinary Least Squares

RTS Returns To Scale

SDGs Sustainable Development Goals

TFP Total Factor Productivity

TH Transitional Heterogeneity

TI	Tornqvist Index
TVET	Technical and Vocational Education and Training
VE	Variance Elasticity
VIF	Variance Inflation Factor

ABSTRACT

Integrated Agriculture Aquaculture has been promoted in Kenya as a climate-smart approach capable of increasing productivity, stabilizing incomes, and improving the welfare of smallholder farmers. Despite these potential benefits, adoption remains low, largely because farmers operate under significant production risk. This study examined how production risk influences optimal input-use decisions, adoption, and welfare outcomes, measured through productivity and household income, among 427 smallholder farmers across Busia, Kakamega, Siaya and Nyeri counties. Using the Just–Pope stochastic production framework, the Heckman selection model, and the Endogenous Switching Regression model, the study estimated the risk properties of key production inputs used in integrated agriculture aquaculture systems, analyzed how risk shapes adoption choices, and evaluated the effect of production risk on productivity and income variability. Results from the first objective revealed that inputs have distinct risk characteristics which influence how farmers allocate resources. Among adopters, seeds and organic fertilizer increase output variability due to the complexity of managing integrated systems, while non-adopters experience risk-reducing effects from labor, chemical fertilizer, and organic fertilizer. Overall, adopters face lower total variance elasticity, showing that integrated aquaculture stabilizes production by diversifying output streams. Results from the second objective showed that production risk emerges as a major determinant of adoption. Higher expected profits encourage farmers to adopt and intensify integrated agriculture aquaculture use, whereas greater profit variability and downside risk significantly discourage adoption. Adoption is further shaped by a farmer's education level, labor availability, training, land ownership status, topography, irrigation access, and distance to markets, with awareness consistently appearing as one of the strongest predictors of adoption. Objective three showed that integrated agriculture aquaculture adoption significantly enhances productivity, with adopters achieving higher Interspatial Total Factor Productivity due to more effective use of seed, labor, organic fertilizer, capital, and irrigation. Non-adopters would experience higher productivity if they adopted integrated aquaculture, as evidenced by a negative and significant treatment effect showing that they forgo productivity gains by not adopting. Results from the fourth objective showed that adoption also improves household income and reduces its variability, driven by diversified revenue streams, nutrient recycling efficiencies, and improved labor utilization. Factors such as education, credit access, labor availability, organic fertilizer use, capital investment, irrigation access, and closer market proximity further increase income among adopters. These findings indicate that production risk is a central but often overlooked determinant of farmer behavior, influencing both the decision to adopt integrated agriculture aquaculture and the welfare gains that follow. Although integrated agriculture aquaculture clearly improves productivity and income stability, farmers' risk perceptions continue to limit widespread adoption. To address these constraints, the study recommends targeted risk-aware interventions. These include training to manage inputs that are risk-increasing within integrated systems, improved extension services that focus specifically on risk mitigation, better market access, and tailored credit products for integrated farming. Promoting enterprise diversification (fish, crop, livestock) and developing financial safety nets such as insurance or guarantee schemes would further enhance the stability and effectiveness of integrated agriculture aquaculture.

CHAPTER ONE: INTRODUCTION

1.0 Background

Smallholder farmers form the backbone of Kenya's agricultural economy, contributing approximately 78% of total agricultural production and playing a central role in ensuring household-level food and nutrition security (Wahome et al., 2024). Despite this importance, they operate under significant constraints limited land, inadequate access to credit, low adoption of modern technologies, and vulnerability to climatic and market shocks (Obiero et al., 2019; Waite et al., 2014). These structural limitations have intensified the need for alternative or complementary livelihood strategies that can boost productivity, enhance resilience, and increase incomes.

Aquaculture has been identified as one of the priority growth subsectors due to its potential to increase fish supply, create employment, reduce poverty, and support food security (Obiero et al., 2019; ole-MoiYoi, 2017). Kenya's inland waters particularly Lake Victoria, Lake Turkana, and several smaller lakes continue to contribute significantly to the fisheries sector (KNBS, 2025). While production in Lake Victoria has fluctuated, the lake remains the largest source of freshwater fish, followed by increasing activity in Lake Turkana and aquaculture farms nationwide (Fisheries Statistical Bulletin, 2024). Variability in smaller systems such as Lake Naivasha and Lake Baringo reflects the spatial and environmental heterogeneity of the country's aquatic ecosystems. Meanwhile, aquaculture production has grown steadily in both volume and value over the years, illustrating expanding investments and growing farmer participation (KNBS, 2025). These trends highlight aquaculture's rising strategic importance for addressing Kenya's protein deficit, employment needs, and household incomes (Golden et al., 2017).

From the early 2000s, aquaculture has been promoted as the main pathway to reduce this deficit. The government's “Eat More Fish” campaigns, followed by the rapid expansion of pond construction under the 2009 Economic Stimulus Programme (ESP-FFEPP), marked critical inflection points in the sector’s growth (ole-MoiYoi, 2017). As a result, aquaculture production rose from below 5,000 MT in the mid-2000s to over 24,000 MT in 2014 (Obiero et al., 2019). Nevertheless, production later declined due to persistent challenges such as inadequate water retention in ponds, poor extension services, limited access to quality inputs, weak markets, and overreliance on subsidies (Opiyo et al., 2018).

Recognizing these vulnerabilities, the Kenya Climate-Smart Agriculture Project (KCSAP) prioritized aquaculture as a key climate-smart value chain to strengthen resilience, enhance productivity, and promote rural incomes. The project aligned with Kenya’s Vision 2030, the Agricultural Sector Development Strategy (ASDS), and the Medium-Term Plans, which emphasize diversification, sustainable intensification, and improved natural resource management (KCSAP, 2018). Devolution has further enabled counties to support aquaculture through investments in infrastructure, feed support, and extension services, though implementation varies widely.

Within this evolving policy landscape, Integrated Agriculture-Aquaculture (IAA) has gained prominence as a promising pathway for sustainable intensification (Ogello et al., 2023). Originating from Asia farming systems and adapted for smallholder conditions in Sub-Saharan Africa, IAA integrates fish production with crop and livestock enterprises, allowing farmers to recycle nutrients, optimize land and water use, increase overall productivity, and diversify income streams (Dey et al., 2010; Ogello et al., 2013). In Kenya, three main IAA systems crop-fish, livestock-fish, and crop-fish-livestock have been adopted, each offering complementary benefits such as enhanced soil fertility, reduced waste, and improved farm output, and resilience to climate variability (Ogello et al., 2013). These attributes align with national ambitions on food security, climate adaptation, and rural development. Despite its benefits, adoption remains relatively low, suggesting persistent barriers that warrant systematic investigation (Obiero et al., 2019; Ogello et al., 2023).

A critical yet underexplored barrier to wider adoption of IAA is production risk. Smallholders operate in environments characterized by high uncertainty climatic variability, input price fluctuations, market volatility, disease outbreaks, and inconsistent policy support (Juma et al., 2022; Opiyo et al., 2018). Production and price risks significantly shape farmers' decisions on input use, technology adoption, enterprise diversification, and investment. Risk-averse farmers often underinvest in productivity-enhancing technologies, preferring stability over potentially higher but uncertain returns (Komarek et al., 2020). Research has shown that smallholders frequently choose sub-optimal input bundles and rely on risk-reducing strategies rather than profitability-maximizing ones. This behavior has important implications, it affects the level of adoption of innovative technologies, the productivity of aquaculture systems, and ultimately the welfare of farming households.

The economics of production under risk provides important insights into these farmer decisions. The Just–Pope production framework demonstrates that inputs influence both the mean and variance of output, implying that farmers consider not only expected productivity but also risk exposure when choosing input levels (Just & Pope, 1979). Similarly, Antle's (1983) flexible moment-based approach shows that variance and skewness of output are central parameters shaping optimal production choices under uncertainty. Empirical evidence from developing countries confirms that production risk critically affects technology adoption. Koundouri et al. (2006) reported that farmers adopt modern technologies as hedges against risk, Juma et al. (2022) showed that yield variability discourages technology uptake in Kenya's semi-arid areas, and Ogada et al. (2014) demonstrated that risk and market imperfections jointly constrain adoption of improved agricultural technologies in Kenya.

In aquaculture specifically, production risk stems from factors such as water quality fluctuations, feed costs, disease outbreaks, fingerling quality, and technical knowledge gaps (Khan et al., 2021). Price risk arises from volatile market prices, input price changes, demand shifts, and policy-influenced market distortions (Asche et al., 2015; Assouto et al., 2020; Broll et al., 2013; Khan et al., 2021; Roheim et al., 2011). These risks influence whether farmers adopt IAA, how they allocate inputs, and how much they produce. Because IAA systems involve interlinked enterprises, they may expose farmers to multidimensional risks that shape their input allocation, investment strategies, and adoption behavior differently from standalone aquaculture systems.

The implications of production risk extend beyond adoption and directly affects household welfare outcomes. Welfare in smallholder systems is commonly measured through income, consumption, food security, and productivity indicators such as Interspatial Total Factor Productivity (TFP). High production risk reduces expected farm income, increases vulnerability to shocks, and constrains investment in welfare-enhancing activities. Households facing higher risk tend to maintain low-input systems, diversify into low-return enterprises, or exit productive aquaculture altogether limiting their ability to improve incomes and living standards. Conversely, risk mitigation through integrated systems like IAA can enhance overall farm resilience, stabilize incomes, and contribute to improved household welfare (Dey et al., 2010; Ogello et al., 2023). Understanding how production risk shapes these welfare pathways is therefore critical for designing evidence-based strategies to support smallholder aquaculture development. These dynamics underscore the need to empirically examine how production risk shapes smallholder decisions regarding input optimization, IAA adoption and welfare outcomes (Juma et al., 2022). Understanding the role of production risk is therefore critical for designing policies and interventions that promote uptake of sustainable technologies, reduce vulnerability, and enhance household well-being (Ogada et al., 2014).

While existing national and county policies support aquaculture expansion, they offer limited guidance on risk management for smallholder IAA systems. Existing frameworks emphasize productivity and commercialization but provide minimal guidance on how farmers can manage or adapt to production risks that constrain optimal input use, adoption and welfare impacts. This gap underscores the need for empirical evidence to inform risk-sensitive aquaculture policy design. Against this backdrop, the present study investigated how production risk influences optimal input use, adoption, and welfare outcomes specifically productivity and income variability among smallholder farmers in Kenya. By examining these interlinked relationships, the study contributes to evidence necessary for promoting sustainable aquaculture practices, enhancing resilience, and improving rural livelihoods.

1.1 Statement of the Problem

Smallholder farmers in Kenya operate in an environment characterized by substantial production uncertainty arising from weather variability, water constraints, fluctuating input quality, disease outbreaks, and imperfect markets (Komarek et al., 2020). These conditions heighten risk aversion and strongly influence how farmers allocate inputs and whether they adopt new technologies. Although IAA has been promoted as a climate-smart option that can raise productivity, diversify income, and improve resource-use efficiency, its adoption at national level remains low and uneven across counties (Dey et al., 2010; Ogello et al., 2023). This pattern suggests that conventional determinants such as socio-economic characteristics and access to services do not fully explain farmers' adoption behavior (Ogada et al., 2014).

Existing studies on aquaculture and IAA in Kenya and the region have largely focused on average effects such as mean yields, profits, or household incomes (Dey et al., 2010). They provide limited evidence on how specific IAA production inputs (for example seed, labor, organic fertilizer, irrigation, land and capital) are either risk-increasing or risk-reducing, yet such information is essential for understanding farmers' optimal input-use choices under uncertainty. In addition, the welfare benefits of IAA have mostly been assessed in terms of mean outcomes, without explicitly accounting for the variability of productivity and income under risk. This omission is critical because smallholder welfare is determined not only by average performance but also by the stability of productivity and income over time.

As a result, critical questions remain unanswered: How do the risk properties of different IAA inputs influence smallholder optimal input-use decision What is the impact of production risk on the choice of the optimal level of input use? In what ways does production risk affect farmers' decisions to adopt IAA technologies? To what extent does production risk contribute to variability in farmers' productivity and income? Without answers to these questions, policies and programmes aimed at scaling up IAA may overlook key constraints that affect smallholder decision-making and welfare outcomes, thereby limiting their effectiveness.

This study therefore addresses these knowledge gaps by jointly analyzing production risk in optimal input use, adoption, and welfare outcomes within IAA systems. Specifically, it assesses the impact of production risk on the choice of the optimal level of input use, examines how production risk affects the adoption of IAA, and assesses how production risk contributes to variability in productivity and household income. In doing so, the study provides new evidence on the role of production risk in smallholder IAA systems and generates policy-relevant insights for aquaculture development in Kenya.

1.2 Objectives of the Study

1.2.1 General Objective

The overall objective of the study was to assess the impact of production risk on the choice of the optimal level of input use, adoption, and welfare of small holder integrated agriculture aquaculture farmers in Kenya.

1.2.2 Specific Objectives

The specific objectives were*:*

i. To estimate the risk properties of IAA production inputs to determine how these risk characteristics influence farmers' optimal input-use decisions in Kenya.

ii. To analyze how production risk affects smallholder farmers' likelihood of adopting IAA.
iii. To evaluate the effect of production risk on the variability of productivity among smallholder IAA farmers.
iv. To evaluate the effect of production risk on the variability of household income among smallholder IAA farmers.

1.3 Research Hypotheses

The study was guided by the following hypotheses, which were formulated directly from the specific objectives. These hypotheses were designed to statistically test the influence of production risk on farmers' optimal input-use decisions, adoption behavior, productivity outcomes, and income outcomes within IAA systems. Each hypothesis reflected a testable relationship that allowed examination of how production risk shapes smallholder decision-making under uncertainty.

Hypothesis 1: Input-Use Decisions (Objective i)

H_{01}: The risk properties of IAA production inputs have no significant influence on farmers' optimal input-use decisions.

H_{11}: The risk properties of IAA production inputs significantly influence farmers' optimal input-use decisions.

Hypothesis 2: Adoption of IAA Technologies (Objective ii)

H_{02}: Production risk has no significant effect on smallholder farmers' likelihood of adopting IAA technologies.

H_{12}: Production risk significantly affects smallholder farmers' likelihood of adopting IAA technologies.

Hypothesis 3: Productivity Variability (Objective iii)

H_{03}: Production risk does not significantly contribute to variability in farmers' productivity within IAA systems.

H_{13}: Production risk significantly contributes to variability in farmers' productivity within IAA systems.

Hypothesis 4: Income Variability (Objective iv)

H_{04}: Production risk has no significant effect on the variability of household income among smallholder IAA farmers.

H_{14}: Production risk significantly affects the variability of household income among smallholder IAA farmers.

1.4 Significance of the Study

The pursuit of sustainable intensification in Kenya has positioned IAA as enhancing food security and elevating the livelihoods of smallholder farmers. Yet, despite its demonstrated potential, the adoption of IAA remains low. This study looked at a fundamental, yet largely unaddressed, obstacle to its widespread uptake, production risk. While previous research has extensively documented socio-economic and structural factors influencing adoption, the profound influence of production risk and uncertainty on farmer decision-making has been overlooked. Without a clear understanding of how production risks shape optimal choice of production inputs, adoption decisions and outcomes, policies and promotion strategies are designed with a critical blind spot, leading to interventions that are often misaligned with the realities faced by the intended beneficiaries.

If this research were not undertaken, the development of Kenya's small holder aquaculture would likely follow a suboptimal trajectory. Policymakers and development partners would lack the crucial evidence required to craft truly effective support systems. This could result in the continued stagnation of IAA adoption, as risk-averse farmers, without viable strategies to manage uncertainty, would understandably shy away from investing their limited resources. Consequently, the opportunity to improve household nutrition, diversify income streams, and build climate resilience would be squandered, and the cycle of low productivity and poverty could be perpetuated. For the farmers who do adopt IAA without adequate risk-mitigating support, exposure to high variability in yields and incomes could lead to financial strain and eventual abandonment of the practice, worsening their welfare instead of improving it.

The significance of this study, therefore, extends across a wide spectrum of stakeholders who are central to aquaculture development. For national and county-level policymakers, the findings provide an empirical basis for designing smarter, risk-informed financial and institutional policies. This includes the development of targeted credit schemes, index-based insurance products, and extension programs specifically focused on risk management, ensuring that public resources are invested in mechanisms that genuinely address farmers' core constraints. For the smallholder farmers themselves, who are the ultimate agents of change, this research offers practical insights. By identifying which inputs are risk-increasing and which are risk-decreasing, the study empowers farmers with the knowledge to make more informed decisions, optimize their input use, and stabilize their production and incomes, thereby enabling them to engage with IAA with greater confidence and resilience.

Finally, for the academic community, this study makes a substantive contribution by bridging a critical gap in the literature. It moves the discourse beyond conventional adoption determinants by explicitly integrating production risk into the analysis of IAA, thereby providing an economically sound framework for understanding farmer behavior. This scholarly contribution is poised to inform future research and policy not only in Kenya but throughout similar smallholder contexts in Sub-Saharan Africa.

1.5 Theoretical Framework

The expected utility maximization theory informed this study. This theory is based on the idea that farmers in developing countries like Kenya work in significant market imperfections and uncertainty (Ogada et al., 2014). Smallholders tend to be less willing to take risks, so they are not likely to be the first to use new technologies (Obiero et al., 2019). They instead take a "wait-and-see" approach. A farmer may face production risks, such as bad weather. Risk is shown by ε, and the distribution $G(\cdot)$ is independent of what the farmer does. Assuming risk-averse farmers who use conventional inputs $\boldsymbol{x}$ and water x_w in a given production season to produce output q in a well-behaved production function $f(\cdot)$. In IAA, water is an essential input. Areas with a lot of water are good places to raise fish and, by extension, to combine with crops/livestock. Smallholder farmers could utilize water to cultivate high-value crops that helped them make more money on their farms (Dey et al., 2010). A function $l(\alpha)$ is added to the production function to account for how efficiently water is used. The fact that water efficiency depends on management practices and the characteristics of the farmer shows how different farmers are. Unobserved heterogeneity may include unreported farm management skills, land fertility, measures to reduce risk, and discount rates, which have the potential to affect how much inputs are used and how productive a farm is. So, the production function is written as follows:

$$y = f\left[l(\alpha)x_{w,}\boldsymbol{x}, \varepsilon\right] \tag{1a}$$

Given a risk aversion scenario, maximization of the expected profit utility is denoted as:

$$\max_{x,x_w} E[U(\overline{\omega})] = \max_{x,x_w} \int \left\{U\left[pf\left(\varepsilon, l(\alpha)x_{w,}\boldsymbol{x}\right) - r_w x_w - \acute{r}\boldsymbol{x}\right]\right\} dG(\varepsilon) \tag{1b}$$

Where $U(\cdot)$is the von Neumann-Morgenstern utility function. Getting the first-order condition for water input choice. Where $\acute{U} = \partial U(\overline{\omega})/\partial(\overline{\omega})$ is:

$$E\left[r_w \acute{U}\right] = E\left\{p\frac{\partial f\left(\varepsilon, l(\alpha)X_{w,}x\right)}{\partial x_w}\acute{U}\right\} \Leftrightarrow \tag{2a}$$

$$\frac{r_w}{p} = E\left\{\frac{\partial f\left(\varepsilon, l(\alpha)x_{w,}\boldsymbol{x}\right)}{\partial x_w}\right\} + \frac{cov\left[\acute{U}; \partial f\left(\varepsilon, l(\alpha)x_{w,}\boldsymbol{x}\right)/\partial x_w\right]}{E\left[\acute{U}\right]} \tag{2b}$$

Where p and r are the prices of output and the vector of inputs, respectively, assumed to be non-random (meaning farmers do not influence prices in the markets). The First Order Condition (FOC) for the other variables in equation (1) are derived similarly. The farmer's choices are demonstrated as a binary choice such that $P = 1$ to adopt or not to adopt $P = 0$. The optimum input choices upon adoption or otherwise were represented as x^1 and x^0 respectively for adopters and non-adopters. An IAA adopter is characterized as a farmer who includes a fishpond in their farming operations and practices resource recycling across various enterprises. The expected utility of an individual who adopts an improved farming system is higher than for a non-adopter and is given by:

$$E[U(\overline{\omega}^1)] - E[U(\overline{\omega}^0)] > 0 \tag{3}$$

$$\max_{X^1, X_w^1} E[U(\bar{\omega})] = \max_{X^1, X_w^1} \int \{U[pf(\varepsilon, l^1(\alpha)x_w^1 x^1) - r_w^1 r_w^1 - \acute{r}x^1 - I^1]\} dG(\varepsilon) \tag{4}$$

and

$$\max_{X^0, X_w^0} E[U(\bar{\omega})] = \max_{X^0, X_w^0} \int \{U[pf(\varepsilon, l^0(\alpha)x_w^0 x^0) - r_w^0 r_w^0 - \acute{r}x^0 - I^0]\} dG(\varepsilon) \tag{5}$$

Equations (4) and equation (5) are the expected utility for adoption and non-adoption

$$\frac{r_w^1}{p} = E\left\{\frac{\partial f(\varepsilon, l(\alpha)x_w^1 x^1)}{\partial x_w^1}\right\} + \frac{cov[\acute{U}; \partial f(\varepsilon, l(\alpha)x_w^1 x^1)/\partial x_w^1]}{E[\acute{U}]} \tag{6}$$

$$\frac{r_w^0}{p} = E\left\{\frac{\partial f(\varepsilon, l(\alpha)x_w^0 x^0)}{\partial x_w^0}\right\} + \frac{cov[\acute{U}; \partial f(\varepsilon, l(\alpha)x_w^0 x^0)/\partial x_w^0]}{E[\acute{U}]} \tag{7}$$

Equations (6) and (7) show the FOC for a risk-averse farmer's water input, considering whether or not to adopt. The exact process is used to find the FOC for the other variables. Assuming that the farmers do not know how well the technology works or are more likely to make mistakes when using it, future profit flows are unknown after the farmers adopt it. The investment cost is fixed, meaning the extra information may be worth more than it costs. Because of this, farmers who use the technology may be hesitant to learn more about it. Assuming $VI \geq 0$ is a value of new knowledge that depends on the fixed investment cost, the level of risk attached to technology utilization, and the farmer's features, the farmer will adopt if and only if:

$$E[U(\bar{\omega}^1)] - E[U(\bar{\omega}^0)] > VI\ ;\ VI > 0 \tag{8}$$

1.6 Conceptual Framework

The conceptual framework, adopted from Dey et al. (2010) and modified for this study, illustrates the hypothesized pathways through which production inputs, production risk, adoption of IAA, and welfare outcomes interact among smallholder farmers in Kenya. The framework is structured around four main components: independent variables, moderating factors, mediating variables, the decision variable, and dependent variables. The independent variables include all inputs required for agricultural and aquacultural production such as seed (fish, crop, livestock), labor, feed, chemical fertilizer, organic fertilizer, land, capital, water, and irrigation (Dey et al., 2010). These inputs directly determine the level of output but also shape the variability of production outcomes. In the Just-Pope framework, inputs may be risk-increasing or risk-reducing, meaning they influence not only mean output but also output variance (Just & Pope, 1979). Thus, the first pathway shows that production inputs influence production risk, which becomes central in the farmer's decision-making (Amondo & Simtowe, 2018; Juma et al., 2022; Kassie et al., 2008; Ogada et al., 2014). The moderating factors including the socioeconomic, farm and institutional characteristics are age, education, gender of household head, household labor availability, farm size, land ownership, access to extension, IAA awareness, number of farm enterprises, irrigation access, wetland presence, soil type, farm topography, distance to input markets, and access to credit (Dey et al., 2010). These factors do not directly produce output, but modify the strength and direction of the relationship between inputs, production risk, adoption, and welfare outcomes. For example, access to extension may reduce perceived risk, while long distance to input markets may increase it. These factors therefore influence the magnitude of production risk, the likelihood of adopting IAA and eventual welfare outcomes. The mediating variable which is the production risk measured through mean variance, downside risk, and kurtosis (of profits) acts as the mediating mechanism between production inputs and adoption decisions. Inputs create variability in yields and profits, and smallholder farmers who are generally risk-averse evaluate whether adopting IAA reduces or increases that risk.

Production risk therefore mediates the pathway from production inputs to adoption decisions, and welfare outcomes (productivity and income). Because farmers maximize expected utility rather than expected profits, their risk perceptions play a decisive role in technology uptake (Mendola, 2007). The decision variable which is adoption of IAA represents the farmer's choice to adopt or not adopt IAA. Adoption is shaped by both the level of production risk and the moderating socioeconomic and institutional conditions (Dey et al., 2010; Juma et al., 2022; Kumar et al., 2018; Obiero et al., 2019; Ogada et al., 2014). If farmers perceive that IAA reduces risk or improves efficiency, they are more likely to adopt. Conversely, risk-increasing conditions discourage adoption. Adoption is the key behavioral outcome in the framework, linking risk to welfare. The dependent variable, welfare outcomes is captured through two indicators, Farmer Productivity and Farmer Income. IAA adoption is expected to positively influence welfare through increased efficiency and diversified production. However, the actual welfare outcomes depend on how production risk is managed or amplified within the system (Figure 1).

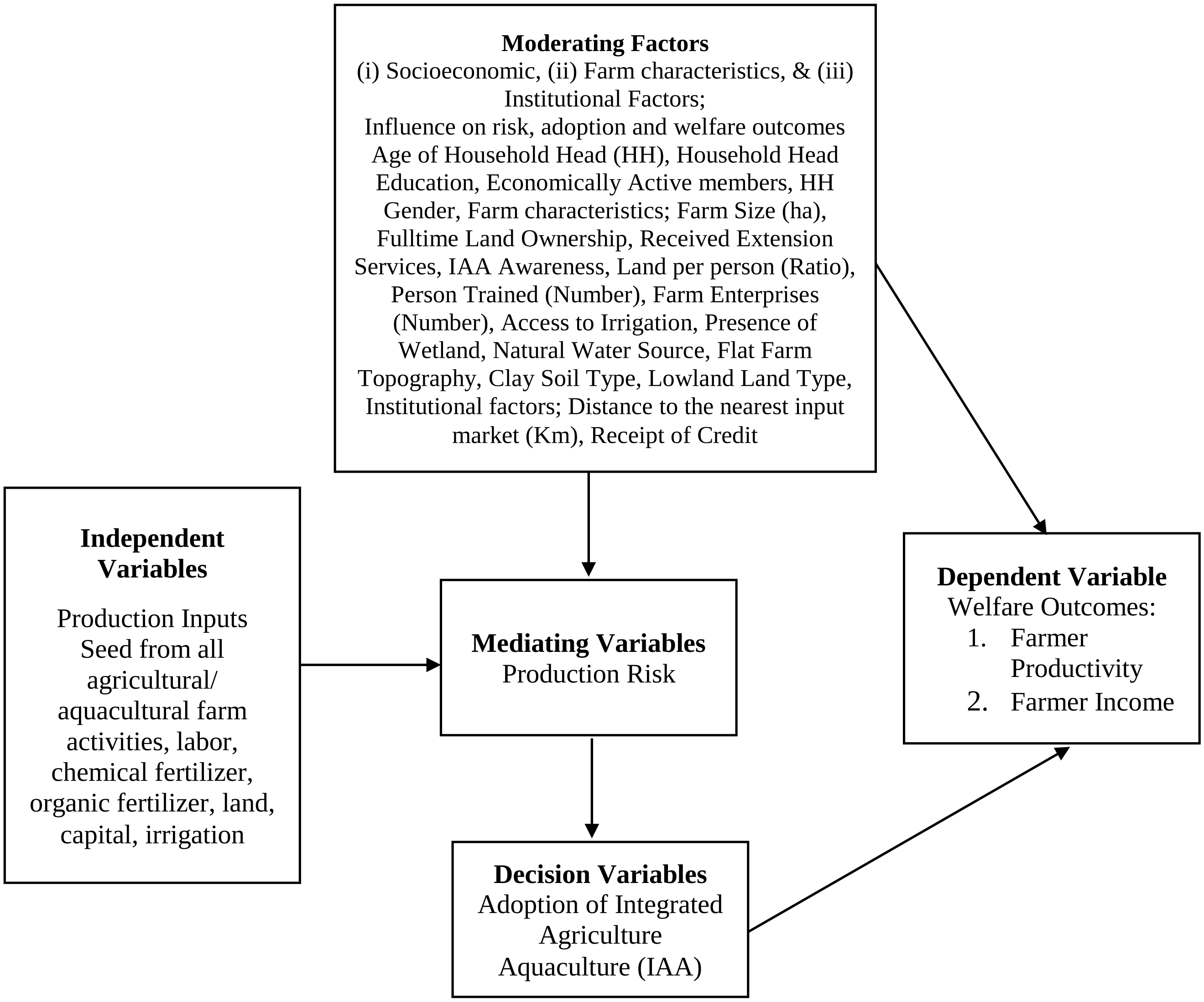

Figure 1: Conceptual Framework of the Study

Adapted and modified (Dey et al., 2010)

1.7 Scope of the Study

This study assessed the impact of production risk on the choice of the optimal level of input use, adoption, and welfare of small holder IAA farmers in Kenya. The work was limited Busia, Kakamega, Siaya and Nyeri counties. The selection of counties followed the Kenya Climate Smart Agriculture Project (KCSAP) framework, which identified specific priority intervention counties for climate-smart research and development activities. These counties also exhibit strong potential for aquaculture development, characterized by high production capacity, established infrastructure such as research and processing facilities, adequate water resources, ongoing aquaculture programmes, and well-developed market linkages. The study relied on the Kenya Population and Housing Census, Volume V (Socio-Economic Characteristics) that formed the study population and offered the most complete and nationally representative dataset on the number of households engaged in fish farming in Kenya (KNBS, 2019). As such, the findings reflect the conditions and realities of farmers operating in these geographical locations. The study focused on four main areas including the risk properties of IAA production inputs on small holder farmers' optimal input-use decisions, how production risk affects smallholder farmers' likelihood of adopting IAA technology, the effect of production risk on the variability in productivity levels among smallholder IAA farmers and the effect of production risk on the variability of household income among smallholder IAA farmers. Data used was collected during in the second quarter of 2021 that targeted farmers' August 2020-March 2021 production season/cycle and the results therefore apply to the circumstances and agricultural conditions that prevailed during that time. Because the study was based on cross-sectional data, the analysis reflects outcomes at a single point in time rather than changes over multiple years. The research design was guided by the resources available, including time, funding, and field logistics.

CHAPTER TWO: LITERATURE REVIEW

2.0 Chapter Overview

This chapter provides a critical review of theoretical and empirical literature relevant to production risk, technology adoption, and welfare outcomes in smallholder IAA systems. The aim was to synthesize existing knowledge, highlight what was already well established in the literature, and identify the gaps that justified the current study. The chapter begins by outlining the theoretical foundations that explain farmer decision-making under risk, including expected utility theory, risk aversion, innovation diffusion, and household production models. These theories help explain why smallholders often adopt technologies, allocate inputs conservatively, and behave differently from profit-maximizing firms. The empirical section reviews studies on adoption, production risk, and welfare outcomes.

2.1 Theoretical Literature Review

Theoretical viewpoints on household decision-making behavior and the adoption of innovations were examined in this section. The theories include profit maximization, risk aversion, utility maximization, Rogers' innovation-diffusion, and the social learning theory.

2.1.1 Profit Maximization Theory

According to the profit maximization theory, peasant households operate as rational producers in perfectly competitive markets and are therefore expected to manage their scarce resources efficiently despite their poverty (Mendola, 2007). However, several scholars have questioned the allocative efficiency of such households. In practice, peasant households often balance profitability with other equally important though not purely economic objectives, which means they do not always behave as ordinary profit maximizers. Traditional profit-maximization theory also fails to account for the uncertainty and complexity inherent in peasant production decisions. Smallholders routinely confront significant risks, including price volatility, weather shocks, and social uncertainties, which shape their resource allocation patterns. As Mendola (2007) shows, farm households are not risk-neutral, and their production choices cannot be fully understood within simplified objective functions or constraints that ignore market imperfections and institutional limitations. Given these realities, evaluating how regulatory or policy interventions influence farm households' input choices and expected profits without incorporating risk considerations may yield misleading conclusions for policymakers. An accurate understanding of smallholder decision-making therefore requires models that explicitly incorporate risk, uncertainty, and the broader institutional environment in which farm households operate.

2.1.2 Risk Aversion Theory

Decision-making by peasant households is examined using the risk aversion model from two connected viewpoints which are the expected utility viewpoint and the disaster-avoidance method. According to the disaster-avoidance model, households with uncertain income sources will identify secure options before deciding based on their projected utility (Mendola, 2007). The key priority of the decision-maker is to keep their income above the subsistence level. This emphasis on safety may lead a household to favor risky or less risky activities. According to the anticipated utility approach, sometimes called the entire optimality perspective, a farm household chooses amidst risky alternatives established on its desire for the potential outcomes and the likelihood that they would occur. Farm households are thought of as utility maximizers with risk constraints. Households select low-risk, high-utility productive activities, *ceteris paribus*. Due to this, analysis employing the Von Neumann-Morgenstern anticipated utility model is pertinent.

2.1.3 Utility Maximizing Theory

Risk aversion theory examines peasant household decision-making from two complementary perspectives: the expected utility framework and the disaster-avoidance (safety-first) approach. According to the disaster-avoidance model, households facing uncertain and volatile income sources first identify production choices that ensure survival, prioritizing activities that keep income above a minimum subsistence threshold (Chiappori & Lewbel, 2015). Only after securing this "safety margin" do they compare the remaining options based on expected utility (Mendola, 2007). This survival-driven logic implies that households may choose either low-risk or, in some contexts, high-risk activities depending on which option minimizes the likelihood of falling below the disaster level of income. In contrast, the expected utility or full optimality approach assumes that farm households evaluate risky alternatives by weighing the desirability of potential outcomes against the subjective probabilities of their occurrence. Within this framework, households behave as utility maximizers whose choices are shaped by their degree of risk aversion. Consequently, risk-averse households tend to select production activities that provide lower variability but relatively stable expected utility. The Von Neumann–Morgenstern expected utility model is therefore widely applied in analyzing household behavior under risk, though its assumptions may oversimplify real-world decision processes in settings characterized by market imperfections and severe uncertainty (Thorbecke, 1993).

2.1.4 Innovation Diffusion Theory

Innovation Diffusion Theory highlights the critical role of information flow in shaping farmers' technology adoption decisions. According to Rogers (1983), adoption occurs through a series of sequential stages. The process begins with the knowledge stage, where a farmer becomes aware of a new technology and gains an initial understanding of how it works. This is followed by the persuasion stage, during which the farmer develops a favorable or unfavorable attitude toward the innovation. The third step is the decision stage, where the farmer chooses whether to adopt or reject the technology. Adopters are assumed to act rationally, selecting the option that maximizes expected benefits. Once a favorable decision is made, the farmer enters the implementation stage, during which the innovation is put into use. At this stage, the technology may be adapted or modified to suit local production conditions. The final confirmation stage involves reinforcement of the adoption decision. If the outcomes of implementation are satisfactory, the farmer continues using the innovation; if not, the farmer may discontinue it. Throughout this process, the diffusion of credible, timely, and accessible information plays a central role in shaping adoption behavior.

However, while Innovation Diffusion Theory contributes important insights for understanding adoption pathways, it focuses primarily on information dissemination and behavioral stages. It does not explicitly account for other critical determinants of adoption such as socio-demographic characteristics, institutional factors, credit access, or production risk which may significantly influence smallholders' decisions in real-world settings.

2.1.5 Social Learning Theory

Social Learning Theory posits that individuals acquire knowledge and skills by observing the behavior of others and the consequences of those behaviors (Bandura, 1977). Whether observation translates into behavioral change depends on the individual's cognitive capacity to understand the behavior, their ability to replicate it, and their motivation to act on it. In the context of agricultural innovation, adoption is therefore viewed as a socially embedded process in which farmers learn through both formal and informal channels such as observing peers, sharing experiences, imitating successful farmers, or adhering to prevailing social norms. Through these social interactions, farmers evaluate the perceived benefits, risks, and appropriateness of new technologies. This makes observation and peer influence powerful drivers of adoption behavior, particularly in settings where information is imperfect or where formal extension services are weak. However, while Social Learning Theory provides valuable insight into how farmers acquire and internalize new knowledge, it does not fully account for additional determinants of adoption. Factors such as socio-demographic characteristics, institutional support, and production risk also significantly influence whether and how smallholders adopt innovations elements that the theory does not explicitly incorporate.

2.2 Empirical Literature Review

This section reviews empirical studies that have examined production risk, optimal input use, technology adoption, and welfare outcomes in smallholder farming systems. The focus is on evidence from agriculture and aquaculture and IAA to establish what is already known, where consensus exists, and where gaps remain. By synthesizing findings from previous work, this section provides the foundation for understanding how farmers respond to risk, the factors influencing adoption decisions, and the impacts of integrated systems on productivity and income. The empirical insights reviewed here justify the methodological approach used in this study and highlight the specific contributions it makes to the existing body of knowledge.

Just and Pope (1979) challenged the traditional multiplicative stochastic production function, which assumes that any input that increases output must also increase output variance. They argued that this assumption is overly restrictive and does not reflect real production environments where some inputs may reduce risk for example, irrigation, machinery, or protective technologies. To address this, they proposed a more flexible production structure that separates the mean and variance functions, allowing inputs to affect expected output and production risk independently. Using fertilizer response data, they demonstrated that conventional log-linear models exaggerate risk effects and generate misleading standard errors, potentially biasing policy and input-use recommendations. Their contribution is foundational, as it provides the theoretical basis for modern risk-sensitive production modelling such as the Just–Pope and flexible stochastic frontier frameworks. Their critique of traditional Cobb–Douglas and translog risk specifications remains highly influential, and their flexible model provides a more realistic foundation for analyzing production risk particularly useful in smallholder aquaculture and agriculture research where risk varies across inputs.

Antle (1983) argues that agricultural economists have made limited progress in analyzing production risk in ways that meaningfully inform farmers' decisions. He critiques the conventional use of neoclassical production models which typically incorporate uncertainty only through the Arrow–Pratt risk-aversion framework for failing to capture how risk truly affects production behavior. Antle (1983) proposed a shift toward a more flexible, moment-based approach that focuses on the functional relationship between inputs and the distribution of output under uncertainty. Rather than assuming risk neutrality or risk aversion through utility functions, he emphasizes analyzing how inputs influence the mean, variance, and higher-order moments of output. This allows risk to be incorporated directly into empirical production models without imposing restrictive assumptions about farmer preferences. Antle's (1983) work is foundational because it provides a practical and flexible way to integrate risk into production analysis. However, his framework also abstracts from institutional and behavioral factors that influence how smallholders perceive and respond to risk. Additionally, by focusing on the statistical properties of output rather than explicit utility-based decision-making, the model simplifies the behavioral complexity of risk responses. Despite these limitations, Antle's (1983) moment-based approach remains widely used and offers a strong methodological foundation for analyzing production risk in smallholder agriculture.

Dey et al. (2010) assessed the adoption and farm-level impacts of IAA systems in Southern Malawi using survey data from 315 households (166 adopters and 149 non-adopters). The study used a two-stage adoption model and applied a stochastic frontier to estimate technical efficiency, along with total factor productivity and income analysis. The results show that access to extension, age, farm size, and number of enterprises significantly increased the likelihood of adoption. IAA adopters were substantially more productive, recording an 11% higher total factor productivity and a 134% higher farm income per hectare than non-adopters. Technical efficiency was also much higher among adopters (90%) than non-adopters (65%), largely due to improved recycling of on-farm resources, better nutrient management, and higher human and social capital through participatory training. Propensity Score Matching (PSM) and Heckman selection models confirmed that IAA adoption raised total farm income by about 22–60%. Although the study provides strong evidence of positive productivity and income gains from IAA it does not explicitly model production risk, despite IAA's potential to reduce vulnerability to shocks. While the stochastic frontier identifies technical efficiency differences, it does not address possible endogeneity in adoption, especially where adopters may differ from non-adopters in unobservable traits such as motivation or management ability. In addition, the context Malawi's participatory extension system and specific agroecological setting may limit generalizability to regions where extension systems are weaker. Despite these limitations, the study provides important empirical support for integrated farming as a pathway to improved productivity and welfare among smallholder farmers.

Kumar et al. (2018) provide a comprehensive review of the factors influencing aquaculture technology adoption globally. They group adoption drivers into five major categories including information sources, technology characteristics, economic incentives, farm characteristics, and socio-demographic and institutional factors. The authors highlight that successful adoption depends heavily on access to credible information through extension, farmer field schools, and peer learning. They also emphasize that technologies with clear relative advantage such as higher productivity, lower cost, risk reduction, ease of use, and compatibility with existing practices are adopted more readily. Economic factors such as profit expectations, stable input–output prices, labor availability, and access to credit strongly shape farmers' willingness to adopt new technologies. Farm-level attributes including size, resource endowments, tenure security, and proximity to input/output markets also influence adoption decisions. Institutional elements like regulation, training, policy incentives, and cooperatives further condition adoption outcomes. Although this review offers a valuable synthesis for understanding aquaculture adoption, its nature as a broad narrative review limits its empirical depth. The paper does not provide quantitative estimates, making it difficult to assess the relative importance of each factor. Risk both production and market are acknowledged but not rigorously analyzed, despite being central to adoption in aquaculture. The wide range of global examples improves coverage but reduces contextual specificity, making generalization to smallholder settings (e.g. Africa) challenging. Because the review relies heavily on secondary literature, it reflects existing gaps, particularly the limited empirical evidence on how constraints such as risk preferences, gender dynamics, and environmental shocks shape aquaculture adoption. Despite these limitations, the review provides a useful conceptual foundation for understanding the multi-dimensional nature of technology adoption in aquaculture.

Khan et al. (2021) examined production risk, technical efficiency, and input-use patterns in Bangladesh's pond aquaculture using a flexible stochastic frontier model that incorporated a mean production function, a variance (risk) function, and an inefficiency function. The study found that feed, labor, and capital significantly increased output, while fingerling density and farm size increased production risk. In contrast, feed and capital investment reduced risk. Technical efficiency was high (0.92), and access to extension services, training, and credit significantly reduced inefficiency. Larger farms were found to be more productive and efficient than smaller ones, contradicting the inverse farm size–productivity hypothesis. Although the study provides valuable insights into aquaculture production risk and efficiency, the analysis does not fully integrate institutional or behavioral factors into the risk function, and the results may have limited applicability beyond pangas farming in a high-production district. Despite these limitations, the study contributes important evidence on how input choices influence risk and efficiency in aquaculture.

Lower adoption rates are generally linked to imperfect credit markets, information, input and output markets, agroecological characteristics, and low incentives related to farm tenure arrangements, most of which are noticed in developing countries. Elsewhere, Feder et al. (1985) undertook an extensive survey that summarized the influencers of the adoption of farm technologies and agricultural innovations. The choice to adopt or otherwise the case depends on its profitability, farmer training, and other variances among farmers and across farming systems.

Using a cross-sectional study, Obiero et al. (2019) scrutinized what influences fish farmers' perceptions, attitudes, and mannerisms in aquaculture technology adoption in Kenya. However, the authors failed to consider whether technology's riskiness or the farmer's attitudes to risk influence adoption. Though the study is quite appealing, it needs economic intuition. Since smallholders are not solely consumers, some of their produce is meant for the market to get non-farm produce. Providing empirical evidence on how production risks affect expected farm profits is relevant for production and technology adoption decisions.

Ogada et al. (2014) examined the joint adoption of inorganic fertilizer and improved maize varieties among Kenyan smallholders using nationally representative panel data. Recognizing that these technologies are complementary, the authors applied a bivariate probit model to correct for simultaneity in adoption decisions. They incorporated production risk measured through expected yield and yield variance derived using Antle's moment-based approach. The results show strong interdependence between the two technologies, with unobserved household factors influencing both decisions. Adoption was positively associated with education, secure land tenure, larger plot size, good soil drainage, proximity to markets, credit access, and higher expected yield. Higher yield variability significantly reduced the likelihood of joint adoption, indicating that farmers are risk averse and avoid technologies perceived as risky. Although the study makes a valuable methodological contribution by modelling joint adoption and incorporating production risk, it faces several limitations. First, risk measures are estimated from only two waves of panel data (2004 and 2007), which may not adequately capture long-term production variability. Second, while the Mundlak–Chamberlain approach addresses unobserved heterogeneity, the model may still suffer from residual endogeneity, especially where unobserved managerial ability influences both risk and adoption. Third, multicollinearity issues forced the removal of downside risk (skewness), meaning the study does not fully capture farmers' exposure to catastrophic losses. Despite these constraints, the study provides important insights into how risk, market imperfections, and complementary input requirements shape technology adoption among smallholders in Kenya.

Juma et al. (2022) analyzed how production risk affects the adoption of soil-conserving and soil-conditioning technologies in rain-fed semi-arid areas of Kenya using detailed plot-level data from Machakos and Taita Taveta districts. Using Antle's moment-based approach, they first estimated plot-level mean yield, yield variance, and downside risk (skewness), then incorporated these moments into a pseudo-fixed effects probit model to explain adoption decisions. Their results show that higher expected yield increases the likelihood of adopting fertilizer and manure, while greater yield variability discourages manure use and reduces the intensity of fertilizer application. Higher downside risk increases terracing and manure intensity but reduces fertilizer adoption, suggesting that farmers treat manure and terracing as risk-reducing investments, whereas fertilizer is viewed as risk-increasing. Additional factors influencing adoption include household size, gender, education, social capital, plot distance, tenure security, extension visits, and district differences. The study offers rigorous analysis by integrating production risk into adoption decisions and addressing heterogeneity using Mundlak's approach. This study provides important empirical evidence on how risk shapes technology uptake in low-income, rain-fed systems an issue highly relevant to smallholder decision-making.

Amondo and Simtowe (2018) examined the effects of adopting Drought-Tolerant Maize Varieties on productivity and production risk in rural Zambia using an Endogenous Switching Regression (ESR) model that controls for both observable and unobservable heterogeneity. Using moment-based measures, they assessed the impact of Drought-Tolerant Maize Varieties adoption on mean yield, yield variance, and downside risk. The study found that adoption increased maize yield by 8%, while significantly reducing yield variance by 35% and downside risk exposure by 27%. These results indicate that Drought-Tolerant Maize Varieties provide both productivity gains and strong risk-mitigating benefits, particularly in drought-prone regions. While the study demonstrates strong risk-reducing effects, it does not explore how institutional constraints such as information gaps, seed market access, or input timing shape adoption outcomes. Despite these limitations, the authors offer valuable insights into how risk-reducing technologies influence smallholder production decisions under climate stress.

A growing body of work has examined IAA systems and their contribution to productivity and household welfare. In Bangladesh, Murshed-E-Jahan and Pemsl (2011) showed that IAA adoption significantly increases farm productivity, profitability, and food and fish consumption, leading to improved nutrition outcomes. Similar conclusions are drawn from studies in East Africa and the Great Lakes region, where IAA is framed as a promising strategy for sustainable intensification and resilience, though the empirical focus is often on mean yields and incomes rather than on risk. While these studies provide strong evidence that IAA is beneficial on average, they do not decompose productivity or income into systematic and risk components, nor do they examine how the variability of outcomes influences smallholders' willingness to adopt and intensify IAA.

Kassie et al. (2011) evaluated the impact of adopting improved groundnut varieties on crop income and poverty in rural Uganda using survey data from 927 households across seven districts. They applied PSM to address observable selection bias in adoption decisions. The results show that adoption significantly increased net crop income and reduced poverty, supporting the role of improved agricultural technologies in enhancing rural livelihoods. The study also demonstrated heterogeneous effects both smaller and larger farmers benefitted from adoption, though the magnitude differed by education level and farm size. Although PSM corrects for selection on observable characteristics, the study remains vulnerable to unobserved heterogeneity, such as managerial ability or risk attitudes, which may influence both adoption and income. Additionally, the model does not incorporate production risk, despite its importance in smallholder decision-making.

Beyond Africa, Sanglestsawai et al. (2017) analyzed Bt maize adoption in the Philippines and found that the technology reduced downside yield risk and improved farmer welfare by stabilizing income, rather than solely through higher mean yields. These findings underline the importance of integrating risk into analyses of technology adoption and welfare. However, they were still rooted in crop agriculture and do not address complex, integrated systems where aquaculture and terrestrial enterprises interact, as is the case with IAA.

2.3 Conclusion

This chapter reviewed the theoretical and empirical foundations relevant to production risk, technology adoption, and welfare outcomes. The theoretical review highlighted that while traditional profit-maximization frameworks assume rational behavior under perfect markets, smallholders operate under pervasive risk, imperfect information, and institutional constraints that shape their production choices. Risk aversion, expected utility, innovation diffusion, and social learning theories jointly demonstrate that farmers evaluate technologies not only on profitability but also on risk, information access, social networks, and perceived fit within existing production systems. These frameworks underscore the need to incorporate risk, uncertainty, and behavioral considerations when analyzing technology adoption among smallholder households.

The empirical literature further reveals substantial progress in modelling production risk and understanding adoption behavior across agriculture and aquaculture. Foundational contributions by Just and Pope (1979) and Antle (1983) advanced flexible methods for capturing input-specific risk effects, moving beyond restrictive traditional production functions. Subsequent studies across Africa and Asia demonstrate that production risk significantly affects adoption decisions, input use, technical efficiency, and welfare outcomes. Evidence consistently shows that technologies such as improved varieties, drought-tolerant crops, soil and water conservation practices, and IAA systems enhance productivity and reduce risk exposure. However, the majority of studies remain crop-focused and seldom examine integrated systems where interactions between aquaculture and terrestrial enterprises jointly shape risk and welfare. Many also inadequately address endogeneity and unobserved heterogeneity. Importantly, only a limited number of studies explicitly decompose welfare outcomes into mean and risk components, despite the centrality of risk in smallholder decision-making. The review reveals three key gaps that this study seeks to address. First, there is limited empirical evidence on how production risk influences input choices, adoption, and welfare in IAA systems. Second, few studies incorporate flexible risk-sensitive production models within integrated farming contexts. Third, the limited application of ESR in aquaculture or IAA settings leaves unaddressed the challenge of separating true adoption effects from selection bias. These gaps justify the present study, which employs a risk-sensitive analytical framework and ESR to examine how production risk affects optimal input use, adoption behavior, and welfare outcomes among smallholder IAA farmers in Kenya.

CHAPTER THREE: METHODOLOGY

3.0 Overview

This chapter details the methodological framework utilized in the study. The selection of the study area, determination of sample size, and the data collection and analysis techniques were all methodically planned to facilitate a thorough and rigorous exploration of the study's objectives. The methods applied were tailored to the specific objectives and were designed comprehensively.

3.1 Study Site

The study was implemented in four counties, namely Kakamega, Nyeri, Busia, and Siaya (Figure 2). The areas were selected based on agroecological zone typologies, which depend on climate, altitude, and soil. These counties are distinguished by significant aquaculture activity, high production potential, existing infrastructure like processing and research facilities, sufficient water resources, and strong marketing opportunities.

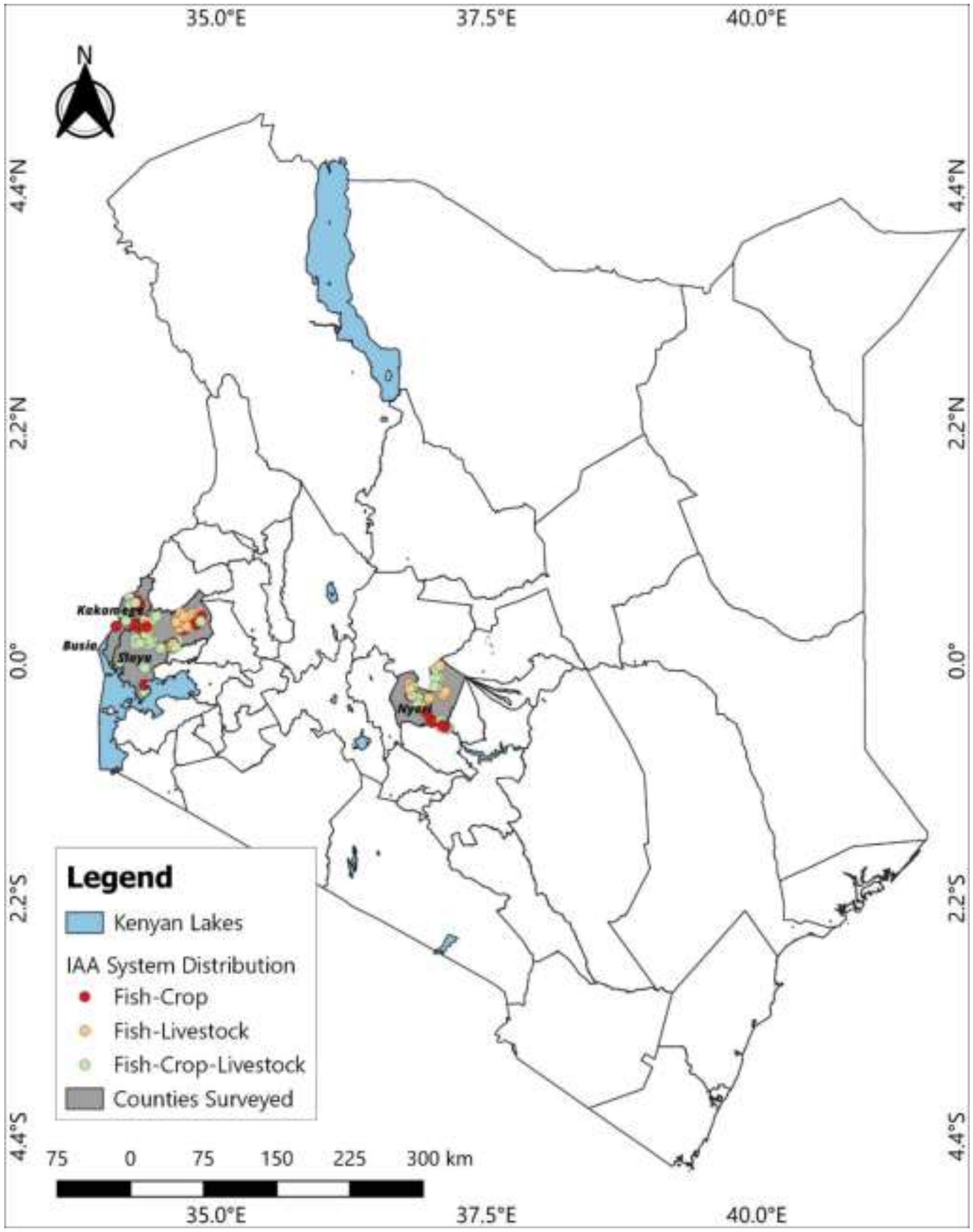

Figure 2: Map of the Study Areas

3.2 Research Philosophy

Research philosophy explains the assumptions that guide how knowledge is created and interpreted in a study (Creswell, 2009). The philosophical orientation guiding this study was grounded in positivism, which assumes that reality is objective, observable, and measurable, and that knowledge can be generated through systematic empirical investigation (Bryman, 2016). This philosophy was appropriate because the study sought to quantify the influence of production risk on input-use decisions, technology adoption, productivity, and income among smallholder farmers, relationships that can be rigorously examined using statistical and econometric models. Under the positivist paradigm, social phenomena such as farmer behaviour are treated as patterned and governed by causal mechanisms that can be identified through empirical analysis. The study further aligns with objectivist epistemology, which holds that researcher and phenomenon are independent, and that valid knowledge emerges from observable data rather than subjective interpretation (Kothari, 2004). This is consistent with the study's reliance on primary quantitative data from 427 farming households and the application of econometric frameworks such as the Just–Pope stochastic production function, the two-stage Heckman selection model, and the ESR model. These methods assume stable, measurable relationships among variables and allow for hypothesis testing, which is central to positivist inquiry. In addition, the study reflects aspects of determinism, as it assumes that farmer decisions regarding input allocation and adoption of IAA are shaped by identifiable factors including production risk, household characteristics, and farm attributes. Production risk is treated not as a random occurrence but as a quantifiable variable whose influence can be estimated and modelled. This philosophical stance supports the study's objective to determine how risk-increasing and risk-reducing inputs affect both behaviour and welfare outcomes. Given that the study sought to generalize findings to the wider population of smallholder IAA farmers in Kenya, positivism provides a coherent and defensible foundation. It justifies the use of structured questionnaires, numerical data, and statistical inference as tools to uncover regularities in farmer behaviour. The cross-sectional design, the use of probability sampling, and the emphasis on measurable indicators such as input levels, productivity, income, and risk moments further reinforce this philosophical position.

3.3 Research Design

The study followed an analytical study design given that there were comparison groups of study that is, adopters and non-adopters. The models in the three study objectives were assessed on cross-sectional data from a survey of Kenya's smallholder fish farmers in the Busia, Siaya, Kakamega and Nyeri counties following Koundouri et al. (2006) and Di Falco and Veronesi (2014).

3.4 Sampling and Sample Size Determination

The study population was all fish farmers in the selected study areas. The sampling frame selected a list of adopters and non-adopters of IAA in four sub-counties with the highest aquaculture production in each of the four counties. To achieve the sampling size, the study employed the computation formula proposed by Kothari (2004) for a finite population (9), stated as:

$$n = \frac{Z^2 \cdot p \cdot q \cdot N}{e^2(N-1) + Z^2 \cdot p \cdot q} \quad (9)$$

Where: n = sample size; p = Sample proportion; q =1- p; N is the estimated population which comprises all pond-based fish farming households from the four selected counties (approximately 2500 active fish farming households); e is the acceptable margin of error/precision rate: Hence, the desired precision was 100/23=4.34. Say, e=4%. Z= 1.96; The estimated standard variation at 95% confidence interval. Therefore, the estimated sample size was 484.

The selection of counties followed the KCSAP framework, which identified specific priority intervention counties for climate-smart research and development activities. Accordingly, the study purposively selected Nyeri, Kakamega, Busia, and Siaya, all of which were officially designated KCSAP project counties. These counties also exhibit strong potential for aquaculture development, characterized by high production capacity, established infrastructure such as research and processing facilities, adequate water resources, ongoing aquaculture programmes, and well-developed market linkages. After identifying the counties based on project alignment, an appropriate sampling approach was required for household selection within each county. The study relied on the Kenya Population and Housing Census, Volume V (Socio-Economic Characteristics), which offered the most complete and nationally representative dataset on the number of households engaged in fish farming (KNBS, 2019). This dataset provided a reliable measure of the target population across counties.

To recruit the 484 individuals, automated randomization was adopted for the 2,500-population size of active fish farming households in the four study areas. The study employed the RAND Function in Microsoft Excel. An Excel worksheet sorted per study area (counties). All the participants of the population in each county were listed. A blank row was inserted where each location ended on the Excel sheet and where the new location started. Using the function, "=RAND () ENTER," random numbers were generated for each household in each location (i.e., the study population per study area). Auto-fill was employed to ensure each member of the population had a randomly generated number. This was repeated for each study area. To ensure that the generated random numbers do not change in the future, the study selected the command "CONTROL ALL" (for the column with the random numbers), THEN CONTROL C to copy the column, THEN CONTROL, ALT, and V simultaneously to get the option "VALUES." The worksheet was sorted per location and by random numbers in ascending order. To have a representative sample, the proportion contribution to the four regions' total population was calculated to determine how many people are sampled per county (i.e., 40% Kakamega, 19% Siaya, 17% Busia, and 24% Nyeri). The randomly selected households were highlighted for interview. All the selected households were interviewed. However, they were replaced in unlikely cases of missing households after repeat visits. The study employed a margin between 5-10 households for replacements per county.

3.5 Data Needs, Types and Sources

Table 1 outlines the comprehensive approach that was taken to gather and analyze data to meet each study's objectives.

Table 1: Objective specific Data needs, Type and Sources

Objectives	Data needs	Type	Sources
1	Input levels (seed from all agricultural/ aquacultural farm activities, labor, chemical fertilizer, organic fertilizer, land, capital, irrigation), output quantities and values	Primary	Literature Search, Survey
2	Production risk indicators (mean, variance, skewness of profits), Adoption decisions, variables affecting adoption i.e Household characteristics including, Age of Household Head (HH) in Years, Household Head Education in Number of years, Economically Active members, HH Gender, Farm characteristics, Farm Size (ha), Fulltime Land Ownership, Received Extension Services, IAA Awareness, Land per person (Ratio), Person Trained (Number), Farm Enterprises (Number), Access to Irrigation, Presence of Wetland, Natural Water Source, Flat Farm Topography, Clay Soil Type, Lowland Land Type, Institutional factors including Distance to the nearest input market (Km), Receipt of Credit	Primary	Literature Search, Survey, Key informant interviews
3	Productivity measure, Production risk indicators, Age of Household Head in Years, HH Education in Number of years, Economically Active, HH Gender, Farm Size (ha), Fulltime Land Own, Received Credit, IAA Aware, Distance to the nearest input market (Km), Land per person (Ratio), Number Farm Enterprise, Access to Irrigation, Presence of Wetland, Natural Water Source, Flat Farm Topography, Clay Soil Type, Land Type, Seed Input, Labor Input, Chemical Fertilizer Input, Organic Fertilizer Input, Land Input, Capital Input, Irrigation Input	Primary	Literature search, Survey
4	Income level, Production risk indicators, Age of Household Head in Years, HH Education in Number of years, Economically Active, HH Gender, Farm Size (ha), Fulltime Land Own, Received Credit, IAA Aware, Distance to the nearest input market (Km), Land per person (Ratio), Number Farm Enterprise, Access to Irrigation, Presence of Wetland, Natural Water Source, Flat Farm Topography, Clay Soil Type, Land Type, Seed Input, Labor Input, Chemical Fertilizer Input, Organic Fertilizer Input, Land Input, Capital Input, Irrigation Input	Primary	Literature search, Survey

3.6 Data Collection

A highly competent team of three research assistants with vast experience in the research industry were engaged during data collection. A lean team was used for ease of team management. A standard recruitment process adhered to with a strict emphasis on Overall comprehension and/or knowledge of social science research methodologies and study methods, Experience in conducting comparable studies, Knowledge of the selected study sites, Ability to read and write in English, Kiswahili and local language to properly administer the study tool, Capability of troubleshooting during data collection, Proven abilities in teamwork, Possessing post-secondary education level, more so mid-level college education and above, Ability to exercise discretion during data collection, Attentive to detail and Available during the study execution period. The recruited team was trained with the overall objectives of putting a firm understanding of the study objectives, key expectations, and role-play sessions to practice administering the research instrument. The role-play sessions served as a second check on the flow of the study instruments before use in the field. A five (5) days centralized training session was held at the Kenya Marine and Fisheries Research Institute (KMFRI-Sagana). Similarly, a pilot exercise with fish farmers was undertaken in Kirinyaga County (not part of the study areas) to give the research assistants an additional opportunity to practice administering the instrument in natural settings. After the practice interviews, a debrief session was held with the data collection team to address existing gaps before the primary data collection exercise. Key insights from the training sessions were used to revise the study instrument and inform the planning phase before data collection.

Data collection was undertaken in the second quarter of 2021 using digitized semi-structured questionnaires. Key informant interviews with different stakeholders supplemented survey data by exploring the subject matter thoroughly and uncovering information that might not be revealed through a survey alone. Focus group discussions were adopted to triangulate and interpret results from the survey. Requisite primary data from a cross-section of households was collected on geolocation, sociodemographic, conventional inputs, social and human capital, detailed production data, and risk exposure. This was collected through farm visits (face to face) and using an open-access Kobo Toolbox application installed on Android smartphones to ensure quality checks and data safety. Secondary data was garnered from various sources like case studies, peer-reviewed journal articles, books, national government publications, County Integrated Development Plans, and grey literature.

3.7 Data Analysis

3.7.1 Risk properties of IAA Production Inputs

To address the first objective, this study adopted the Just and Pope (1979) framework to estimate production risk and test for the risk properties of the inputs (i.e. if they are risk increasing or decreasing). Measurement of the production risk was the primary objective of using the Just-Pope framework rather than the more traditional homoscedastic approach. The requirement for heteroskedastic production technology was implied by production risk. Therefore, the initial step was to determine whether there was any production risk. The JP framework function took the following functional form:

$$y = f(x; \alpha) + h(z; \beta)\varepsilon \tag{10}$$

Where $f(.)$ and $h(.)$ are mean production and variance (or risk) functions respectively. x and z denote the input vectors; ε is the exogenous stochastic disturbance, such that $E\ (\varepsilon) = 0$ and var (ε)=δ_ε^2. The mean output was:

$$E(y) = f(x; \alpha) + \mu \tag{11a}$$

while output variance:

$$var(\mu) = [h(z; \beta)]^2 \delta_\varepsilon^2 \tag{11b}$$

This study began by examining the existence of consequential production risk. Considering the specification of production risk as heteroskedastic in the JP context, it was vital to test for the presence of heteroscedasticity. Non-detection of heteroscedasticity pointed to the absence of production risk. If detected, $f(.)$ and $h(.)$ become of interest and the production function necessitates re-estimation using maximum likelihood estimator. In the study, to estimate the production and variance functions, a specified linear quadratic functional form was used. This specific functional form gave room for variation of input levels in $f(.)$ and in $h(.)$ by input elasticities.

$$y = a_0 + \sum_k \alpha_k x_k + 0.5 \sum_j \sum_k \alpha_{jk} x_j x_k + \mu \tag{12}$$

The subscripts j and k are inputs. An ideal scenario in estimating the production function would be having the quantity of output, but given the case of IAA characterized by multiple farms produce, there could be aggregation challenges. To that end, two models were estimated, and the robust one sought. Following Kabubo-Mariara et al. (2017) the study employed aggregation of all quantities produced into a single unit. All farm produce by the targeted farmers were converted into fish equivalent units to work with one output, that is, converting each kilo of produce (vegetable, poultry etc) to a kilo fish equivalent then converting to per hectare basis. In this case, the dependent variable employed was kg/ha. Similarly, the output value was converted into monetary terms (the price of output). Here the dependent variable was price/ha. The advantage of the abovementioned approaches is that they permit the determination of the value of output. This is based on the premise that smallholders are not solely producers, part of their produce is meant for the market to get products that are not produced on-farm. Separate OLS models using the two measurements of output were estimated. OLS estimation of the production function using fish equivalent and output value as the outcome variables showed that the model with output value was the robust one, with an R-square of 0.90 as compared to the model with fish equivalent as the outcome value with R-square of 0.01. In the proceeding estimations, the value of output was the main outcome variable in estimating the production function.

The production function was specified with the following inputs; seed, labor, chemical fertilizer, organic fertilizer, land, capital and irrigation. To ensure that aquaculture was not "masked" in the investigation, the study investigated the inputs risk properties for both adoption and non-adoption scenarios. Empirical findings were presented in terms of elasticities to get an expressive explanation of the estimated input parameters. The output elasticity for input k was given by:

$$E_k = \left[\left(\alpha_k + 0.5\sum_j \alpha_{jk} x_j\right)\left(\frac{x_k}{f(x)}\right)\right] \tag{13}$$

The returns to scale (RTS) specified as:

$$RTS = \sum_k E_k = \sum_k \left[\frac{\partial y}{\partial x_k} x \frac{x_k}{f(x)}\right] \quad (14)$$

The variance function was specified as:

$$var(u) = h(z) = exp[z\beta] \quad (15)$$

Where z values are input levels. In the JP model, var $(y) = var\ (u)$. The exponent's justification was:

$$\mathrm{v}ar(y) = exp.[\beta_0 + \sum_k \beta_k x_k] \quad (16a)$$

The total output variance elasticity in inputs was:

$$TVE = \sum_k VE_k = \sum_k \beta_k \quad (16b)$$

3.7.2 Effect of Production Risk on Smallholder Farmers' Likelihood of Adopting IAA

To address objective two, the mean, variance, skewness and kurtosis of profits which were indicators of production risk were calculated. These variables, along with the socioeconomic, farm characteristics and institutional variables were then used in a discrete choice model to examine how production risks influence adoption decisions. Following the technique fronted by Koundouri et al. (2006) considering a risk-averse farm household seeking output y by employing inputs x in the presence of risk in a well-behaved stochastic production function $y = h(x, m)$. m is a vector of random risk variables. Consider:

$$h(x, m) = f_i(x, \beta_i) + u \quad (17)$$

Where: $f_i(x, \beta_i) \equiv E[h(x, m)]$ is the mean of (x, m) (first central moment); and $u = h(x, m) - f_i(x, \beta_i)$ is a random variable having a zero mean zero with an exogenous distribution to farmers' actions. To get higher moments, the study followed:

$$E\{[h(x,m) - f_1(x,\beta_1)]^k|x\} = f_k(x,\beta_k) \tag{18}$$

For k=2,3 implying $f_2(x,\beta_2)$ the second central moment (variance), and $f_3(x,\beta_3)$ is the third (skewness). A rise in skewness implied a lessening in exposure to downside risk such that:

$$\hat{\mu}_i^2 = h(x_{wi}, x_i, z_i; \delta) + \hat{\mu}_i \tag{19}$$

Applying Ordinary Least Square (OLS) to equation (19) gives consistent estimates δ. $\hat{\mu}_i^2$ are consistent estimates of the variance. The same criteria was applied to estimate the third and fourth central moments. The four estimated moments and other variables were plugged in the discrete adoption model. To get the discrete model, the i^{th} household was assumed to face the decision to adopt or not IAA. Let P^* symbolize the benefit difference derived from the adoption U_{iA} and non-adoption U_{i0}. A household adopts IAA if P^*=U_{iA}-$U_{i0} > 0$. $P^*$is unobservable and can be denoted as:

$$P_i^* = Z_i\beta + m_i + \varepsilon_i; P_i = 1\ if P_i^*\ > 0\ and\ P_i^* = 0, otherwise \tag{20}$$

The first stage of the analysis employed a selection model, estimated using the probit model, to determine the factors affecting IAA adoption. The two-step Heckman estimation was conducted, and the coefficient of the Mills ratio (used to correct for selection bias). Consequently, the IV2SLS model was used to estimate the relationship between technology adoption and the intensity of adoption while accounting for suspected endogeneity and heterogeneity. The variable description, measure and probable outcomes for objective two are indicated in Table 2.

Table 2: Variables Description, Measurement, and Probable Outcomes for Objective 2

Variable	Description and Measurement Type	Probable Outcome
	Dependent Variable	
Stage 1: Adoption	1 if adopter, 0 otherwise (non-adopter)	
Stage 2: Intensity of integration	Proportion of bio resource flows quantity to the overall quantity of each farm's enterprises. 1 for higher integration (defined as integration of 0.75 or above) and 0 if otherwise (Low)	
	Independent Variables	
Age of respondents	Years	+
Level of education	Number of years	+
Economically active members	proportion	+
Gender	1 for male, 0 otherwise (female)	+
Farm size/land area	Ha	+
Land ownership status	1 for Full-time owner, 0 otherwise (part-owner)	+
Credit	Whether household received credit services. 1 if household had received credit, 0 otherwise;	+
Extension contact	Whether household received extension service. 1 if household has received to extension service, 0 otherwise	+
IAA Awareness	1 for Yes, 0 otherwise (No)	+
Access to irrigation	Whether household had gained irrigation services. 1 if household has gained irrigation services, 0 otherwise	-
Farmer group membership	1 for farmer ascribes to a group, 0 otherwise	+
Market distance to nearest input market	Km	+
Person: land ratio (n/ha)	Person: Economically active members in the household Land: The Area in (ha)	+
Number of household members trained in IAA	Number of family members	+
Number of on-farm enterprises	Number of enterprises in the farm	+
Presence of wetland area on the farm	1 for present, 0 otherwise (not present)	+
Water source	1 for Natural sources, i.e., rivers, springs, lakes, etc, 0 otherwise (rainfall)	+
Topography	1 for flat, 0 otherwise (gently sloping)	-
Soil type	1 for Clay, 0 otherwise	+
Land type	1 for lowland, 0 otherwise (highland)	+
Production risk	Four Profit moments	+/-

To detect the problem of multicollinearity, the study employed the Variance Inflation Factor (VIF) and the White test to test for Heteroscedasticity.

3.7.3 Effect of Production Risk on the Variability of Farmers' Productivity Levels

Welfare can be measured using several indicators such as consumption expenditure, assets, food security, or multidimensional household indices. This study used household income and TFP as practical and reliable proxies.

Income captures the household's ability to meet basic needs and participate in economic activities, and is widely used in agricultural welfare studies. TFP reflects how efficiently households convert multiple inputs into outputs across enterprises. Higher TFP indicates better use of resources, improved technology adoption, and stronger production performance all of which directly influence household well-being.

The first outcome variable, objective three, was TFP. To measure TFP, the study used the generalized Interspatial Tornqvist Index (TI) (Dey et al., 2010). TI is a versatile tool for measuring TFP in a multifactor, multi-output production process, allowing for comparison of productivity for each farm with the average farm. TI is flexible in the choice of inputs, outputs, and technology assumptions, and it is robust to measurement errors and noise in the data, making it a reliable method for measuring TFP across different sectors and time periods. The interspatial Tornqvist index (Eq. 21) was defined as follows:

$$TI_j = \frac{\sum_l ln\left[\frac{M_{jl}}{M_l}\right]\left(s_{mjl} + s_{ml}\right)}{2} - \frac{\sum_v ln\left[\frac{N_{jv}}{N_v}\right]\left(s_{njv} + s_{nv}\right)}{2} \quad (21)$$

Where: TI_j is the interspatial Tornqvist index; j is the j^{th} farmer, l is l^{th} output (fish, vegetables, other), v is the v^{th}input that is (seed, fertilizer, labor), M_{jl} is output quantity (measured in kg/ha/year); M_l = mean across farmers; N_{jv} = input quantity; s_{mjl} portion of the l^{th} output to sum of gross return; s_{njv} is the portion of v^{th} input to total input cost; s_{ml}& s_{nv} = mean portion of the l^{th} output and the v^{th} input. TI_j exponential is the variance in productivity between the j^{th} farmer and the average farmer TFP_j .The ESR was used to model this objective including calculating the average treatment effects/ Counterfactual Analysis.

The ESR model, a two-stage approach designed to account for selection bias that may result from unobserved farm or household variables influencing both the adoption decision and the outcome variables was used. In the first stage, the adoption decision was modeled using a selection equation (Eq. 22). The second stage involved specifying separate outcome equations for adopters and non-adopters (see Eq. 27 and Eq. 28). The ESR model operates under the assumption that farmers choose between options based on the anticipated benefits of adoption, such as expected farm net income. By addressing selection bias, the ESR model provided a more accurate estimation of adoption's impact on the outcome variable. In the first stage, a selection model was employed in which a typical farm household decides whether or not to adopt IAA. This decision is made based on whether the anticipated utility of adopting $U(\overline{\omega}^1)$ surpasses the expected utility of not adopting ($U(\overline{\omega}^0)$)

$$E[U(\overline{\omega}^1)] - E[U(\overline{\omega}^0)] > 0 \tag{22}$$

Here, E represents the expectation operator based on the subjective distribution of the uncertain variables that the decision maker encounters, while $U(.)$ denotes the von Neumann-Morgenstern utility function, which reflects the farm household's preferences in the presence of risk. The latent variable (Wi*) was specified as:

$$W_i^* = g(l, x, m, n, o, \Omega) + \mu_1 \; with \; W = 1\{W_i^* > 0\} \tag{23}$$

Where: l connotes the adoption of integrated aquaculture, x stands for other conventional inputs, m denotes a vector of institutional, socio-economic and farm variables, n is a vector of random variables for uncontrollable like weather conditions, o represents the instrument variables; Ω is a set of parameters to be estimated. Instrumental variables are commonly employed to address potential endogeneity issues. Endogeneity can arise due to various reasons, such as measurement errors in the variables, omitted variables, or simultaneity.

In the second stage, risk exposure functions that account for endogenous selection were estimated. To remain consistent with previous research in this area, specific functional forms were chosen (Di Falco et al., 2011). The analysis used a moment-based specification frequently employed in agricultural risk management studies (Di Falco & Veronesi, 2014). Consider a risk-averse farm household that produces output y using inputs x within a stochastic production function $y = h(x, m)$, where m represents a vector of risk-related random variables. The probability distribution of the stochastic production function $h(x, m)$ was analyzed using a moment-based approach (Antle, 1983), with risk exposure being characterized by the moments of the production function $h(x, m)$. The following econometric specification was used for $h(x, m)$:

$$h(x, m) = f_i(x, \beta_i) + u \quad (24)$$

where: $f_i(x, \beta_i) \equiv E[h(x, m)]$ is the mean of (x, m) (first central moment); and $u = h(x, m) - f_i(x, \beta_i)$ is a random variable having a zero mean with an exogenous distribution to farmers' actions. To get higher moments, the study employed the equation below:

$$E\{[h(x, m) - f_1(x, \beta_1)]^k | x\} = f_k(x, \beta_k) \quad (25)$$

For k=2,3 implying $f_2(x, \beta_2)$ the second central moment (variance), and $f_3(x, \beta_3)$ is the third.

$$\hat{\mu}_i^2 = h(x_{wi}, x_i, z_i; \delta) + \hat{\mu}_i \quad (26)$$

Profit moments are also applicable (objective one) following Koundouri et al. (2006) in determining production risk indicators. Applying OLS to equation (26) gives consistent estimates δ. $\hat{\mu}_i^2$ are consistent estimates of the variance. The same criterion was applied to estimate the succeeding moments. To address selection biases, ESR model was employed that evaluates the exposure to downside risks by farmers who have two regimes: to adopt, and not to adopt that is:

$$Regime\ 1 = Y_{1i} = g(l, x, m, n, \beta_1) + \varepsilon_{1i}\ if\ W_i = 1 \quad (27)$$

$$Regime\ 2 = Y_{2i} = g(l, x, m, n, \beta_2) + \varepsilon_{2i}\ if\ W_i = 0 \quad (28)$$

Where Y_{1i}, Y_{2i} are the dependent variables in the outcome variable. The error terms (μ_1, ε_{1i} and ε_{2i}) in Equations (26), (27) and (28) are presumed to follow a trivariate normal distribution with covariance matrix below and a mean of zero:

$$\ddot{\Upsilon} = \begin{bmatrix} \sigma^2{}_{\mu} & \sigma_{\mu 1} & \sigma_{\mu 2} \\ \sigma_{1\mu} & \sigma^2{}_{1} & . \\ \sigma_{2\mu} & . & \sigma^2{}_{2} \end{bmatrix} \tag{29}$$

Before estimating the model, an instrumental variable was identified (see Appendix 1). According to Baum (2006), a valid instrument must meet two criteria (i) it should not be correlated with the error term and (ii) it should be correlated with the endogenous variable (in this case, the adoption of IAA). The Full Information Maximum Likelihood (FIML) method was then applied to estimate both Stage I and Stage II simultaneously, as this approach is effective for estimating ESR models (Lokshin & Sajaia, 2004). FIML allows for the simultaneous estimation of parameters in both the selection equation and the outcome equations, taking into account the correlation between the error terms in these equations. In this study, the outcome equations included the Inverse Mills Ratio (IMR) and a covariance term to address selection bias. The IMR captured the correlation between the adoption decision and the outcome variable by incorporating the error term from the selection equation. By including the IMR and covariance term in the outcome equation, the study addressed potential selection bias resulting from unobserved variables that influence both the decision to adopt and the outcome variable.

3.7.3.1 Average Treatment Effects/ Counterfactual Analysis

This study employed the ESR model to estimate the impact of IAA on TPF. Unlike PSM, which requires explicit matching and balance checks, the ESR model inherently accounts for selection bias by modeling the decision to adopt IAA and the subsequent outcome simultaneously. The ESR model begins with a selection equation that models the adoption decision based on observable covariates, ensuring that the comparison between adopters and non-adopters is made on a like-for-like basis. This approach mitigates potential biases arising from both observed and unobserved factors, providing a more accurate estimation of the Average Treatment Effects (ATT and ATU). Furthermore, the ESR model's structure ensures that the covariates are balanced between the treated and control groups without the need for separate balance checks. The overlap between treated and control groups is addressed through the model's estimation process, ensuring that the estimated treatment effects are based on comparable groups within the region of common support. By estimating separate outcome equations for adopters and non-adopters, the ESR model allows for a robust counterfactual analysis, providing insights into what the outcomes would have been under alternative scenarios of adoption and non-adoption. This analysis is critical for understanding the true impact of IAA adoption on smallholder farmers in Kenya.

The Average Treatment Effect on the Treated (ATT) is a measure that assesses the expected difference in outcome, (productivity, in the case of objective three), between households that have adopted IAA and those that have not, specifically focusing on the adopters. It quantifies the disparity by comparing the expected outcome of the adopters to those of similar non-adopters in terms of observable characteristics. On the other hand, the Average

Treatment Effect on the Untreated (ATU) measures the expected difference in outcome between households that have adopted IAA and those that have not, emphasizing the non-adopters. It calculates the difference between the expected outcome of the non-adopters and those of similar adopters in terms of observable characteristics. By comparing the ATT and ATU the overall impact of IAA can be evaluated. A positive ATT that exceeds the ATU indicates a positive net impact resulting from IAA adoption. Conversely, if the ATT is positive but smaller than the ATU, it suggests that IAA has a positive impact on the adopters. However, the overall net impact is diminished due to the foregone benefits of non-adoption. Cases (30a) and (30b) in the analysis represent the observed expectations in the sample, while cases (30c) and (30d) depict hypothetical expected outcomes. Additionally, the treatment effect of "to adopt" on the treated (TT) was calculated by subtracting (30c) from (30a). Similarly, the effect of the treatment on the untreated (TU) households that did not adopt IAA was determined by subtracting (30d) from (30b). These calculations were specified as follows:

$$E(Y_1|W_i = 1) = g(l, x, m, e, n, \beta_1) + \lambda_{1i}\, \sigma_{1\mu} \tag{30 a}$$

$$E(Y_2|W_i = 0) = g(l, x, m, e, n, \beta_2) + \lambda_{2i}\, \sigma_{2\mu} \tag{30 b}$$

$$E(Y_2|W_i = 1) = g(l, x, m, e, n, \beta_2) + \lambda_{1i}\, \sigma_{2\mu} \tag{30 c}$$

$$E(Y_1|W_i = 0) = g(l, x, m, e, n, \beta_1) + \lambda_{2i}\, \sigma_{1\mu} \tag{30 d}$$

ATT and ATU of the outcome variables were defined as:

$$ATT = E(Y_{1i} | W_i = 1) - E(Y_{2i} | W_i = 1) \tag{31 a}$$

$$ATU = E(Y_{1i} | W_i = 0) - E(Y_{2i} | W_i = 0) \tag{31 b}$$

By utilizing the expected outcomes depicted in (30a) - (30d), the impact of heterogeneity was estimated as well. For instance, farm households that did not adopt might have been subjected to lower downside risk compared to the ones who adopted, not because of their decision not to adopt, but due to unobservable factors like their abilities. To determine the effect of base heterogeneity for the group of farm households that chose to adopt approach was adopted to compute the difference between (30a) and (30d) i.e. (BH1). (BH2) was the difference between (30c) and (30b) (Carter & Milon, 2005). Finally, the study investigated the transitional heterogeneity (TH), which refers to whether the impact of adopting IAA is greater or lesser for the adopters or non-adopters if they had decided to adopt, indicated by the difference between equations (TT) and (TU).

Defining the ATT and ATU of variance:

$$ATT = E(\mu_{1i}^2 \middle| W_i = 1) - E(\mu_{2i}^2 \middle| W_i = 1) \tag{32 a}$$

$$ATU = E(\mu_{1i}^2 \middle| W_i = 0) - E(\mu_{2i}^2 \middle| W_i = 0) \tag{32 b}$$

Defining the ATT and ATU of skewness:

$$ATT = E(\mu_{1i}^3 \middle| W_i = 1) - E(\mu_{2i}^3 \middle| W_i = 1) \tag{32c}$$

$$ATU = E(\mu_{1i}^3 \middle| W_i = 0) - E(\mu_{2i}^3 \middle| W_i = 0) \tag{32d}$$

3.7.4 Effect of Production Risk on the Variability of Household Income

The fourth objective assessed how production risk influences the variability of household income. Farm net income was calculated as the difference between the total value of farm output and the variable production costs, expressed in KES/ha/year. After deriving household income, the analysis applied the ESR model in exactly the same manner as was done for TFP under Objective 3. Using ESR allowed the study to control for selection bias arising from both observed and unobserved factors that jointly affect IAA adoption and income outcomes, and to conduct counterfactual analysis (ATT and ATU) to estimate the true impact of adopting IAA on household income under production risk. This ensured that the second welfare measure, household income, was evaluated consistently within the same risk-sensitive analytical framework used for TFP.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.0 Introduction

This chapter presents the main findings of this study. It starts by presenting the summary statistics of the study sample. The chapter then presents detailed research findings for each of the research objectives. Further, it interprets the implications of these findings for policy, practice, and future research.

4.1 Summary Statistics

Out of the target sample size of 484 households, data on 427 representing 88% was obtained which implied a good response rate. Proceeding household-level data analysis was carried out on these 427 households. 209 households had adopted the IAA. Table 3 presents the distribution of IAA among adopters in the study areas, categorized by county, depicting the prevalence and regional variations in the adoption of these sustainable and integrated farming techniques, contributing to the overall understanding of IAA practice in the study areas. The table shows the number of adopters engaged in different combinations of IAA within each sampled area in the counties. In Busia County, a total of 42 adopters were identified, and they were engaged in various IAA combinations. Specifically, 18 adopters implemented a combination of fish crops, 5 adopters practiced fish-livestock integration, and 19 adopters adopted crop-fish-livestock. In Kakamega County, a larger number of adopters were observed, totaling 69. Among these adopters, 7 individuals adopted fish crops, 28 individuals implemented fish-livestock integration, and 34 individuals embraced the holistic crop-fish-livestock IAA. In Nyeri County, a total of 48 adopters were identified. Out of these, 9 adopters were engaged in fish-crop IAA, 12 adopters practiced fish-livestock integration, and 27 adopters embraced the comprehensive crop-fish-livestock IAA approach. Siaya County had a total of 49 adopters. Among them, 11 adopters practiced fish-crop IAA, 8 adopters implemented fish-livestock integration, and 30 adopters followed the holistic crop-fish-livestock IAA. Overall, among these, 46 adopters were engaged in fish-crop IAA, 53 adopters implemented fish-livestock integration, and the largest group, consisting of 110 adopters, adopted the comprehensive crop-fish-livestock IAA.

Table 3: Distribution of IAA among Adopters in the Study Areas

County	**County**				
IAA	**Busia**	**Kakamega**	**Nyeri**	**Siaya**	**Grand Total**
Fish-Crop	18	7	9	11	46
Fish-Livestock	5	28	12	8	53
Crop-Fish- Livestock	19	34	27	30	110
Grand Total	**42**	**69**	**48**	**49**	**209**

Table 4 shows the average differences between people who use IAA (adopters) and those who do not (non-adopters) in the study area. Adopters had bigger farms, more educated household heads, more economically active members, more farm businesses, and were more aware of IAA. The average household head age of non-adopters was 64 years while adopters was 66 years. Adopters (KES 239,733.3) made significantly higher profits compared to non-adopters (KES 224,943.3). The analysis of input variables such as seed and irrigation inputs reveal a high degree of variability, as indicated by the large standard deviations relative to the mean values. This suggests significant heterogeneity within the sample, likely reflecting the diverse conditions and practices among the farmers included in the study.

Table 4: Descriptive Statistics of Survey Data

Variable	Non-Adopters		Adopters		Difference	Pr (|T| > |t|)
Age of Household Head (HH) (Years)	64.27	(21.67)	65.88	(20.24)	-1.61	0.30
Household Head Education (Number of years)	2.56	(1.2)	2.69	(1.44)	-0.13	0.18
Economically Active members	0.60	(0.24)	0.64	(0.27)	-0.04*	0.03
HH Male Gender (1/0)	0.37	(0.48)	0.44	(0.5)	-0.07*	0.05
Farm Size (ha)	2.54	(2.74)	3.38	(3.67)	-0.84***	0.00
Fulltime Land Ownership (1/0)	0.14	(0.35)	0.27	(0.45)	-0.13***	0.00
Received Credit (1/0)	0.24	(0.43)	0.29	(0.45)	-0.05	0.13
IAA Awareness (1/0)	0.46	(0.5)	0.66	(0.47)	-0.2***	0.00
Distance to the nearest input market (Km)	3.45	(6.63)	3.16	(3.03)	0.29	0.41
Land per person (Ratio)	1.37	(1.39)	1.14	(1.39)	0.23*	0.02
Number Farm Enterprise	0.00	(0.00)	2.29	(0.06)	-2.29*	0.00
Access to Irrigation	0.22	(0.42)	0.38	(0.49)	-0.16***	0.00
Presence of Wetland (1/0)	0.51	(0.5)	0.68	(0.47)	-0.17***	0.00
Natural Water Source (1/0)	0.55	(0.5)	0.49	(0.5)	0.06	0.12
Flat Farm Topography (1/0)	0.36	(0.48)	0.40	(0.49)	-0.04	0.33
Clay Soil Type (1/0)	0.31	(0.46)	0.24	(0.43)	0.07*	0.02
Land Type	0.51	(0.5)	0.43	(0.49)	0.08*	0.03
Seed Input (KES)	8,641.88	(10,683.99)	20,059.92	(64,987.25)	-11418**	0.00
Labor Input	58.49	(42.08)	81.19	(97.5)	-22.7***	0.00
Chemical Fertilizer Input (KES)	12,960.46	(21,651.82)	20,624.64	(46,425.35)	-7664.18**	0.00
Organic Fertilizer Input (KES)	5,320.82	(5,648.47)	10,687.98	(12,669.49)	-5367.16**	0.00

Land Input	20.89	(98.15)	14.6	(188.73)	6.29	0.60
Capital Input (KES)	6,024.46	(28,585.33)	3,589.47	(32,195.45)	2434.99	0.29
Irrigation Input (KES)	1,617.75	(8,645.45)	2,120.98	(15,799.56)	-503.23	0.62
Net Farm Income (KES)	224,943.3	(867,995.5)	239,733.3	(2.28E+06)	-14790**	0.00
Expected profit (Mean Profit)	357,775.4	(769,610.6)	361,464.4	(557,556.4)	-3688.98*	0.02
Profit Variance (Profit variability)	197,189.4	(355,783.4)	168,853.9	(915,428.9)	28335.53*	0.01
Downside risk (Skewness of Profit Moment)	1	(2.19)	0.26	(1.97)	0.74	0.00

4.2 Risk Properties of Production Inputs Used by Smallholder Adopters of IAA

This section presents the results of objective 1 which aimed to estimate the risk properties of IAA production inputs to determine how these risk characteristics influence farmers' input-use decisions in Kenya.

4.2.1 Comparison of Production Inputs and Output Between Adopters and Non-Adopters

Table 5 compares the mean levels of key production inputs and output between adopters and non-adopters of IAA using a two-sample t-test with unequal variances. The results reveal systematic differences between the two groups, suggesting that adoption is associated with distinct input-use patterns. Adopters, on average, spent significantly more on seeds (KES 13,585) compared to non-adopters (KES 7,435), and the difference was statistically significant. This indicates that adopters invested more in seed inputs, consistent with the integrated nature of IAA systems which often require diversified and higher-quality seed varieties (Dey et al., 2010). Similarly, adopters used significantly more labor hours per week (225 hours) relative to non-adopters (182 hours). IAA systems require additional labor for coordinated management of fish ponds, manure handling, crop cultivation, pond monitoring, and harvesting. The willingness to allocate more labor suggests that adopters perceive labor as low-risk and high-return consistent with integrated systems where labor can be substituted flexibly across enterprises. Labor is a key complementary input in integrated systems, and adopters' readiness to allocate more labor echoes the argument by Kumar et al. (2018) that farmers adopt technologies perceived to be manageable and profitable, particularly when labor is readily available as a low-cost resource.

Adopters also applied more organic fertilizer (KES 9,607) compared to non-adopters (KES 7,378), with a statistically significant mean difference. This reflects the integrated recycling processes embedded in IAA systems where manure, compost, and farm by-products are commonly used to fertilize ponds and crop fields. Organic fertilizer use is therefore a key complementarity factor facilitating the synergy between fish and crop enterprises. This reflects a behavioral shift, since adopters choose organic fertilizer because its availability within the system reduces both cost and risk, making it preferable to riskier cash-dependent chemical fertilizers. The observed greater use of organic fertilizer by adopters reinforces earlier evidence that IAA enhances nutrient recycling across enterprises, leading to higher uptake of farm-based manure and compost. Dey et al. (2010) demonstrated that IAA households rely heavily on organic inputs because pond–crop interactions naturally generate manure, sediments, and biomass that can be reused within the system. This lowers cash expenses, reduces chemical fertilizer dependency, and cushions farmers against input-price risk. This supports the interpretation that adopters prefer organic fertilizer partly as a risk-reducing strategy, consistent with adoption literature showing that farmers gravitate toward inputs that enhance stability and reduce uncertainty.

Differences in chemical fertilizer use, and irrigation expenditure were not statistically significant. This suggests that these inputs do not strongly distinguish adopters from non-adopters in the sample, possibly because fertilizer use patterns are shaped more by agroecological factors than by adoption status. There was a significantly higher capital expenditure among adopters compared to non-adopters. This is consistent with IAA systems requiring higher upfront investment in infrastructure such as fishponds, water management systems, and integrated farm structures. Finally, adopters exhibited substantially higher output value (KES 523,399) than non-adopters (KES 300,174), and the difference is statistically significant. This finding reinforces previous evidence that IAA enhances overall farm productivity by generating multiple streams of output from integrated enterprises. Higher output further reduces risk by providing multiple income pathways, helping farmers smooth consumption and withstand shocks (Murshed-E-Jahan & Pemsl, 2011). Dey et al. (2010) reported that adopters achieved higher total factor productivity and substantially higher farm income due to resource recycling, diversified output streams, and improved efficiency.

Table 5: Two-sample t-test with unequal variances between Adopters and Non-Adopters

Variable	Non-Adopters	Adopters	Difference	t-Value
Value of Seeds	7,434.88	13,585.35	-6,150.46	-1.75**
Labor (Hours/Week)	182.00	224.89	-42.89	-1.36*
Chemical Fertilizer	14,013.54	17,322.87	-3,309.34	-0.76
Organic Fertilizer	7,377.58	9,607.14	-2,229.55	-1.86*
Land (ha)	4.13	4.37	-0.23	-0.50
Capital	3,669.90	8,915.58	-5,245.67	-0.94*
Irrigation	27,080.00	21,982.05	5,097.95	0.34
Output	300,173.81	523,399.48	-223,225.70	-0.83**

(Variable in KES)

4.2.2 Mean Production Function Elasticities Estimates

Estimated Production Function

In line with the Just–Pope stochastic production framework described in Chapter Three, the production function for IAA was estimated using a log-linear specification that separates the mean production effects from the production risk effects of each input. The mean production function was specified as a Cobb–Douglas–type log-linear function as:

$$ln\, Y_i = \beta_0 + \beta_1 ln\,(Seed_i) + \beta_2 ln\,(Labor_i) + \beta_3 ln\,(\mathrm{ChemFert}_i) + \beta_4 ln\,(\mathrm{Land}_i) + \beta_5 ln\,(Capital_i) + \beta_6 ln\,(\mathrm{Irrigation}_i) + \mu_i \quad (33)$$

Where:

$Seed_i$ = seed input costs (KES) from all agricultural and aquaculture activities

$Labor_i$ = family and hired labor (hours per week)

$\mathrm{ChemFert}_i$ = expenditure on chemical fertilizer (KES)

Land_i = cultivated land area (ha)

$Capital_i$ = capital expenditure on IAA infrastructure (KES)

Irrigation_i= dummy variable taking the value 1 if the household has access to irrigation and 0 otherwise

μ_i = a random error term with zero mean

In this specification, the coefficients $\beta_k\ for\ k\ =\ 1, \ldots\ldots\ldots 6$ are output elasticities with respect to each input.

The average elasticities estimations for adopters, non-adopters and the overall estimates are presented in Table 6. The values of the variables were all standardized by transforming them into natural logarithms. This implies that the partial production elasticities were viewed from a Cobb-Douglas production function perspective. These elasticities show how responsive farm output is to changes in each input. An elasticity value indicates the percentage change in output resulting from a 1% change in an input, holding all other factors constant. The findings reveal important differences in how inputs contribute to output under integrated versus non-integrated systems, and they help explain the production-risk environment shaping farmers' decisions.

Land had a positive and significant effect on output among adopters, meaning that increasing land area by 1% raises output by about 0.10%. For non-adopters, the effect was positive but smaller and statistically insignificant. This implies that IAA systems make better and more efficient use of land because integrated farms combine ponds, crops, and livestock. This means land is more productive per unit among adopters. Non-adopters rely on more traditional, single-enterprise production where land contributes less to output.

Labor contributed positively to output for both groups, but the effects were not statistically significant. This means that although IAA systems use more labor, the marginal contribution of labor to output is low. This suggests that farms may already be labor-intensive, and adding more labor does not proportionally raise output. It also reflects the smallholder context, where labor is abundant relative to land and capital. There farmers would benefit from labor-saving innovations (e.g. simple aerators, automated feeders), youth labor programs for aquaculture, and training to improve labor productivity rather than labor quantity.

Seed elasticity was low for both adopters (0.04) and non-adopters (0.01), with only the non-adopters' estimate being statistically significant. This imply that smallholders often use low quantities or low-quality seed. In IAA systems, the effect may be diluted because output is multi-sourced (crops, fish and livestock), unlike in conventional farms that depend heavily on crop seed. To that end, improving access to improved, affordable, and certified seeds can strengthen productivity. Chemical fertilizer had a positive but very minimal effect on output for both groups, and these results were not significant. This reinforces earlier findings that organic fertilizer use is more important in IAA systems (Dey et al., 2010). Chemical fertilizers do not seem to be a major driver of productivity in either system possibly due to low application rates or inappropriate usage. Low chemical fertilizer use may be due to cost constraints or inappropriate application rates and farmers may benefit from optimal fertilizer application to avoid wastage.

The elasticity for irrigation was highly significant among non-adopters. This implies in IAA systems, water is naturally managed through ponds and farm-level recycling of wastewater, making irrigation a less distinct or influential input. There is need to promote

IAA water recycling systems in water-scarce regions and expand training on integrated water–soil–pond management.

Capital contributed marginally and insignificantly to output in both cases. This implies that smallholder capital investment remains low, and most farmers do not invest enough for capital to strongly influence productivity. Among adopters, capital expenses such pond construction or pumps may take several seasons before significantly influencing output. Capital investments in smallholder systems are limited and often insufficient to drive large productivity gains. Therefore, small holder farmers need affordable aquaculture loans, matching grants for pond infrastructure, and microcredit targeting productive capital investments. Both groups (Adopters: 0.24) and (Non-adopters: 0.09) exhibited decreasing returns to scale (RTS < 1), but the effect was much stronger among adopters. An RTS of 0.24 means that doubling all inputs raises output by only 24% for adopters. For non-adopters, doubling inputs raises output by just 8%. This implies that small holder farmers still operate below the scale needed to achieve efficiency. IAA farms are more productive per unit of input but still constrained by small scale. Non-adopters are highly constrained and additional inputs contribute very little to output. IAA adoption therefore improves productivity but does not eliminate scale-related inefficiencies common in smallholder systems.

Table 6: Mean Production Function Elasticities Estimates

Parameter	LP Model Adopters (n=209)	LP Model Non-Adopters(n=218)
ln Land	0.105*	0.0592
	(0.049)	(0.0454)
ln Seed	0.0404	0.00902*
	(0.0339)	(0.00448)
ln Labor	0.0885	0.0104
	(0.0904)	(0.0211)
ln Chem Fert	0.00661	0.00325
	(0.0173)	(0.00561)
Irrigation	0.00000947	0.0000126***
	(0.00000496)	(0.00000287)
ln Capital	0.00277	0.00447
	(0.0110)	(0.00969)
Sum/RTS	0.2433***	0.0865***
	(0.5525)	(0.4532)

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.3 Risk Function Model Results

Similarly, the variance (risk) function associated with the Just–Pope framework was modelled as a log-linear function as:

$$ln\,\sigma_i^2 = \delta_0 + \delta_1 ln\,(Seed_i) + \delta_2 ln\,(Labor_i) + \delta_3 ln\,(\mathrm{ChemFert}_i) + \delta_4 ln\,(\mathrm{Land}_i) + \delta_5 ln\,(Capital_i) + \delta_6 ln\,(\mathrm{Irrigation}_i) + \delta_7 ln\,(\mathrm{OrgFert}_i) \tag{34}$$

Where σ_i^2 is the conditional variance of output for household i and the parameters δ_k measure the variance elasticity (risk effect) of each input. A positive δ_k indicates that the corresponding input is risk-increasing (it raises output variability), while a negative δ_k indicates that the input is risk-reducing (it stabilizes output).

These variance elasticities are summarized in Table 7. Understanding which inputs are risk-increasing or risk-reducing is critical because farmers' behavior under uncertainty depends on these risk properties. TVE was 0.12 for adopters and 0.70 for non-adopters.

This indicates IAA systems dampen overall production variability because of enterprise diversification and internal recycling. Hence, promoting IAA adoption particularly in high-risk environments can play a major role in stabilizing smallholder livelihoods and reducing vulnerability to shocks. This indicates that IAA systems substantially reduce output variability, consistent with literature that highlights diversification as a natural hedge against production risk (Antle, 1983; Di Falco & Veronesi, 2014). The Just & Pope model also emphasizes that systems with multiple interacting enterprises spread risk across outputs, reducing overall variance. Khan et al. (2021) similarly observed lower variability in integrated farms due to recycling of inputs and resource complementarities.

Non-adopters, who depend on single or limited enterprises, experience much greater fluctuations in output. Capital investment tends to slightly stabilize output for both groups, though the effects are weak and insignificant. This indicates that smallholder capital levels are low and inconsistent, so investment does not substantially change production variability. However, the negative sign implies that when capital is used effectively, it contributes to more stable production, especially through improved structures and equipment. Policies should focus on improving access to affordable capital such aquaculture loans or matching grants to strengthen farmers' resilience and improve management quality.

The elasticity estimate for land was negative for adopters but positive for non-adopters. Land reduces risk among adopters but increases risk among non-adopters. This indicated that in IAA systems, land is used more efficiently because activities are integrated. This reduces exposure to shocks on any one enterprise. For non-adopters, expanding land under low-diversity systems increases exposure to pests, disease, and weather shocks therefore increasing risk. Small holder farmers should thus be encouraged to integrated land–water resource management to reduce exposure to shocks. Similarly, smallholders should be supported in optimizing not expanding land use.

Organic fertilizer was found to have a risk-increasing effect on production for adopters, while it had a risk-reducing effect for non-adopters. Both effects were statistically significant, though at different significance levels, indicating that the impact varies depending on adoption status. Among adopters, organic fertilizer increases risk likely due to pond–field nutrient cycling. If poorly managed, excessive manure may reduce water quality, cause fish stress, or lead to variable crop responses. This reflects a key complexity of IAA that nutrient recycling is productive but can introduce biological and water-related risks if not well managed. These results are consistent with the findings of Khan et al. (2021). Among non-adopters, organic fertilizer stabilizes output because it supplements soil nutrients in simple cropping systems. Chemical fertilizer is risk-reducing for both groups, significantly so for non-adopters. The stabilizing effect reflects that fertilizer helps smooth production by maintaining soil fertility. For adopters, the effect is smaller because their systems rely more on organic recycling, and fertilizer is not the main driver of stability.

Labor reduces risk significantly for non-adopters but increases it for adopters. Non-adopters rely heavily on labor for routine crop management, which helps reduce production variability. Adopters manage multiple subsystems (fish, crops, livestock). Adding labor may introduce variability due to uneven task allocation, skill gaps, or inconsistent management practices across components. More labor stabilizes sole fish farms but introduces management complexity in IAA farms. To that end, small holder IAA farmers need targeted technical training, labor planning tools, and standard operating procedures to reduce management mistakes.

Seed input had a statistically significant risk-increasing effect for the adopters and a non-significant risk-reducing effect for the non-adopters. For the risk-increasing scenario, the use of non-commercial seed leads to more variation in output quantity and quality. Similarly, for fingerlings (that is aquaculture seeds) the risk-increasing effect is attributed to the fact that a higher density of fingerlings can negatively impact water quality by lowering the oxygen levels in the pond. Thus, certified seed systems for crops, livestock and fish fingerlings, training on optimal stocking densities in ponds should be promoted. Irrigation was highly significant and risk-increasing for both adopters and non-adopters. Water access does not automatically stabilize production, instead, variability in water supply (timing, quantity, quality) introduces risk. Also, using irrigation in production is very costly hence it is likely to consume more financial resources exposing farmers to more production risks. In IAA systems, irrigation interacts with pond water levels, increasing biological and management risks. For non-adopters, dependence on rainfall and inconsistent irrigation sources causes fluctuating yields.

Table 7: Modelling Risk Function-Variance Function Elasticity Estimates

	Adopters(n=209) Output Variance	**Non-Adopters(n=218)** Output Variance
ln Capital	-0.00179	-0.000260
	(0.00102)	(0.00172)
ln Land	-0.00535	0.0192
	(0.00608)	(0.0101)
ln Organ Fert	0.00631^{*}	-0.0170^{***}
	(0.00319)	(0.00293)
ln Chem Fert	-0.00505	-0.0215^{***}
	(0.00417)	(0.00358)
ln Labor	0.00280	-0.0320^{***}
	(0.00627)	(0.00818)
ln Seed	0.0122^{*}	-0.00794
	(0.00517)	(0.00751)
Irrigation	0.00000291^{***}	0.00000660^{***}
	(0.000000718)	(0.00000121)
Constant	0.107^{*}	0.752^{***}
	(0.0497)	(0.0885)
TVE	0.1161***	0.6925***
lnsigma2	5.143^{***}	2.002^{***}
	(0.355)	(0.381)
Log-likelihood	230.7636	205.1507
Wald chi2(6)	31.51	114.60
Prob > chi2	0.0000	0.0000

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Influence of Production Risk on the Choice of IAA

This section presents the findings for Objective 2, which aimed to analyze how production risk influences smallholder farmers' likelihood of adopting IAA technology in Kenya. The analysis involved estimating the profit moments (mean, variance, skewness, and kurtosis), followed by a Probit regression to model the adoption decision and a Heckman selection model to analyze the intensity of adoption while correcting for selection bias. Prior to presenting these model estimation results, key diagnostic tests were undertaken to ensure that the data satisfied the assumptions required for valid inference.

4.3.1 Diagnostic Tests

4.3.1.1 Multicollinearity Test in Production Risk and Choice of IAA

Multicollinearity was examined using the Variance Inflation Factor (VIF). High multicollinearity inflates the variance of estimated coefficients and can distort inference on the determinants of adoption. Results in Table 8 show that the mean VIF was 1.70, well below the commonly accepted threshold of 8.0 (and much lower than the conservative threshold of 10). None of the individual VIF values exceeded 2.31. This demonstrates that predictors included in the Probit and Heckman models do not exhibit harmful collinearity, and therefore the estimated coefficients can be interpreted with confidence. The low VIF values imply that explanatory variables such as profit moments, land characteristics, institutional factors, and household attributes provide unique, non-overlapping information in explaining adoption. This strengthens the reliability of subsequent findings because the model is not affected by unstable or inflated coefficient estimates.

Table 8: Multicollinearity Test in Production Risk and Choice of IAA

Variable	VIF	1/VIF
Variance Profit Moment	2.31	0.43
Mean Profit Moment	2.22	0.45
Farm Topography	2.08	0.48
Skewness Profit Moment	2.07	0.48
Land Type	2.03	0.49
Kurtosis Profit Moment	2.00	0.50
IAA Awareness	1.90	0.53
Number of Farm Enterprises	1.87	0.54
Wetland	1.80	0.55
Presence of Wetland	1.77	0.56
Fulltime Land Ownership	1.75	0.57
Farm Size	1.69	0.59
Received Extension Services	1.68	0.59
Received Credit	1.68	0.60
Clay Soil Type	1.58	0.63
Natural Water Source	1.50	0.67
Age	1.44	0.69
Gained Access to Irrigation	1.43	0.701
Education	1.40	0.71
Economic Active Members	1.36	0.73
Person Trained	1.26	0.80
Distance to the nearest input market (Km)	1.16	0.86
Gender	1.15	0.87
Mean VIF	**1.70**	

4.3.1.2 Heteroscedasticity Test in Production Risk and Choice of IAA

Heteroscedasticity which is the non-constant variance of the error term was tested using both the Breusch–Pagan test and White test. The results, shown in Table 9, led to the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, indicating the presence of heteroscedasticity. The presence of heteroscedasticity meant that the variance of the regression errors differs across observations typical in cross-sectional farm data where farms vary widely in size, risk exposure, and resource endowments. If unaddressed, heteroscedasticity could lead to inefficient estimates and biased standard errors. To address this issue, all subsequent Probit and Heckman model estimations were conducted using robust standard errors, ensuring valid inference.

Table 9: Heteroscedasticity Test in Production Risk and Choice of IAA

Test	**H_0**	**Chi^2 (1)**	**Prob > chi^2**
Breusch–Pagan/Cook–Weisberg	Homoscedasticity	13.83	0.00
White's test	Homoscedasticity	344.88	0.00

4.3.2 Model results on the Influence of Production Risk on the Choice of IAA

This section presents the model results of Objective 2, which sought to determine how production risk influences smallholder farmers' likelihood of adopting IAA. The analysis used a two-stage approach, a Probit model to estimate the adoption decision and an IV-2SLS/Heckman model to estimate the intensity of adoption while correcting for selection bias. The first moment, representing mean profit, had a highly significant positive impact on the adoption of IAA (Table 10). This indicates that smallholder farmers are motivated by profit maximization and are inclined to adopt profit-enhancing practices when higher returns are assured (Ogada et al., 2014). Higher returns can encourage farmers to invest in the necessary resources, technology, and training for successful IAA adoption. This positive effect was also observed in the intensity of IAA application. Although farmers seek to maximize profits, they tend to be risk-averse and are reluctant to make significant investments in uncertain outcomes. To that end, training and extension should emphasize the demonstrated profitability of IAA systems to encourage uptake.

In contrast, the second moment, which reflects profit variability, showed a negative impact on both IAA adoption and the intensity of its use. The negative and significant effect of profit variability reinforces findings from Ogada et al. (2014) and Juma et al. (2022), who showed that higher variability discourages adoption. These results indicate that farmers avoid IAA when profit outcomes are unstable. This is consistent with the broader risk literature, which posits that in environments with market imperfections, liquidity constraints, and absence of insurance, farmers systematically choose lower-risk technologies even when high-risk technologies offer higher average returns (Antle, 1983).

A unit increase in skewness reduced the likelihood of adopting IAA. The statistical insignificance of the third moment of profit (skewness) suggests that farmers consider downside yield uncertainty when deciding whether to adopt IAA. An increase in skewness indicates a decrease in downside risk exposure, which in turn implies a higher probability of failure, leading to a lower likelihood of adoption and intensity of use (Ogada et al., 2014). Hence, IAA promotion programs should provide risk management tools and training to minimize management-related failures. This is consistent with Khan et al. (2021), who observed that in aquaculture production, certain inputs sharply increase downside yield risk, discouraging adoption of improved practice.

Beyond production risk variables, factors such as age, education, the proportion of economically active members, farm size, full-time land ownership, access to credit services, awareness of IAA, number of trained individuals per household, number of farm enterprises, accessibility to irrigation, natural water sources and flat farm topography were all found to positively influence the probability of adopting the technology. Among these, the proportion of economically active members, full-time land ownership, awareness of IAA, accessibility to irrigation, and flat farm topography were statistically significant in positively influencing the intensity of IAA use. Teklewold et al. (2013) showed that older farmers were more likely to adopt multiple sustainable practices due to experience. The current literature offers mixed evidence regarding the relationship between age and aquaculture technology adoption. For instance, Obiero et al. (2019) found a negative association between age and aquaculture technology adoption, whereas this study found age to positively influence the likelihood of adopting IAA. Aquaculture technology adoption is influenced by a complex interplay of various factors, including economic, social, and cultural aspects. Different regions, contexts, and types of technology can yield different results. In the case of IAA, the positive impact of age on adoption could be due to several factors. Older farmers may have accumulated more experience and knowledge in traditional farming practices, making them more receptive to innovative approaches like IAA. Additionally, older farmers might have better access to resources, networks, and support systems that facilitate adoption. It is also possible that the positive correlation between age and IAA adoption is specific to the study area and its unique characteristics. Factors such as the availability of training and extension services, the presence of government incentives, and the existence of local markets can all influence adoption decisions (Kumar et al., 2018).

The finding that education positively influenced the likelihood of adopting IAA aligns with existing research and supports the general understanding of technology adoption in aquaculture (Läpple et al., 2015) Education plays a crucial role in shaping farmers' attitudes, knowledge, and skills, making them more open to new and innovative practices. Farmers with higher levels of education are more likely to recognize the benefits and potential of IAA, leading to a greater interest in adopting these practices. Educated farmers often have better access to information, extension services, and training programs, which can enhance their understanding and implementation of IAA. They are also more inclined to try new approaches and adapt their farming methods based on scientific evidence and recommendations. Kumar et al. (2018) also emphasize that aquaculture adoption depends on the farmer’s ability to understand technical requirements. Furthermore, education empowers farmers to critically evaluate the potential risks and benefits associated with adopting IAA (Cofre-Bravo et al., 2019). Educated farmers can better assess the economic viability, resource requirements, and potential returns on investment essential factors in the decision-making process. Education also contributes to the adoption of sustainable and environmentally friendly practices. In the case of IAA, educated farmers may be more aware of the importance of conserving natural resources, reducing waste, and promoting ecological balance, all of which are crucial for the successful and sustainable implementation of IAA. Education alone may not guarantee technology adoption (Amankwah-Amoah, 2016). Other factors, such as access to resources, market opportunities, institutional support, and risk considerations, also play a role in influencing adoption decisions. However, education can act as a catalyst, helping farmers overcome barriers and embrace innovative practices like IAA.

The finding that an increase in the proportion of economically active household members positively impacts the likelihood of adopting IAA highlights the significance of family dynamics and labor availability in aquacultural decision-making. The positive relationship between the proportion of economically active members and IAA adoption can be explained by several factors. A higher number of economically active members within a household increases the available labor force for agricultural activities, including the implementation and management of IAA practices (Suvedi et al., 2017). With sufficient labor, farmers may feel more confident in adopting labor-intensive practices like aquaculture, which can require regular attention and care. Teklewold et al. (2013) showed that labor availability is a major driver of adopting multi-enterprise technologies. Economic activities of family members can contribute to the pooling of resources, which can then be invested in agricultural diversification, including IAA. Financial resources from the economically active members can facilitate the purchase of necessary inputs, infrastructure, and training required for successful IAA adoption. With more economically active members, there may be a higher ability to share risks associated with IAA ventures. Diversifying income sources through IAA can provide a safety net in case of output failure or market fluctuations, reducing the overall financial risk for the household. Economically active members who have exposure to external markets, information, and new ideas may bring valuable knowledge and insights to the household. This can facilitate the adoption of innovative practices like IAA, as they can better understand its potential benefits.

The finding that the number of persons trained per household positively influenced the adoption of IAA suggests that training plays a significant role in promoting the uptake of this agricultural practice (Kumar et al., 2018). Training programs are crucial in equipping farmers with the knowledge, skills, and technical know-how required to implement IAA effectively (Kuehne et al., 2017). When more members of a household receive training in IAA techniques, the overall capacity and understanding of the family increase, leading to a higher probability of adoption.

The finding that distance from the nearest input market was inversely proportional to the likelihood of adoption and the extent to which IAA is used emphasizes the significant influence of market proximity on farmers' decisions. This proximity offers several advantages that impact IAA adoption. Ogada et al. (2014) showed that better market access increased adoption of improved inputs and Obiero et al. (2019) also argued that proximity to markets reduces transaction costs and facilitates aquaculture adoption. For instance, farmers near the market can easily transport and sell their produce, reducing transportation costs and post-harvest losses. This accessibility encourages farmers to engage in IAA, knowing that their products can be readily sold and fetch better prices. Proximity to the market often means a steady demand for agricultural products. Farmers are more confident in adopting IAA when they can count on consistent demand and stable prices for their products. Being close to the market means easier access to inputs, such as fish fingerlings, feed, and crop seeds. This availability of resources facilitates the adoption and ongoing management of IAA practices. Farmers near the market can access timely information on market trends, consumer preferences, and price fluctuations. This information empowers them to make informed decisions about the adoption of IAA.

Other covariates were also found to positively and significantly influence the intensity of IAA integration. These factors included the number of economically active members, age, education level, flat farm topography, full-time land ownership, clay soil type and awareness of IAA. These findings align with studies which identified a positive and significant relationship between technology adoption and variables such as education, age, and flat farm topography (Kassie et al., 2011; Mukasa, 2018; Teklewold et al., 2013). Older farmers are more inclined to engage in fish farming due to their accumulated skills, resources, and experience (Dey et al., 2010). The positive effect of economically active household members on IAA integration can be attributed to the increased labor availability, which facilitates greater integration of IAA practices (Asfaw et al., 2014). Conversely, the variables that were found to be statistically and significantly negatively affecting the integration of IAA included farm size, presence of wetlands and person-to-land ratio. Similarly, Dey et al. (2010) established that a unit increase in the ratio of person to land led to a reduction in the levels of IAA integration by 38%. However, Mukasa (2018) found a positive impact of land size on IAA integration. This study found that an increase in farm size by one hectare reduced the level of technology integration by 17%, implying that the land may be used for other non-farm activities.

Table 10 : Selection Model for Technology Adoption

Variable	First Stage Probit Model Adoption (1/0)	Marginal Effects Results	IV2SLS Model Intensity
Household characteristics			
Age of Household Head (HH) (Years)	0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)
Household Head Education (Number of years)	0.06 (0.04)	0.02 (0.01)	0.20*** (0.07)
Economically Active members	1.17*** (0.28)	0.32*** (0.07)	1.09** (0.51)
HH Male Gender (1/0)	-0.01 (0.11)	-0.00 (0.03)	0.00 (0.13)
Farm characteristics			
Farm Size (ha)	0.00 (0.03)	0.00 (0.01)	-0.17** (0.07)
Fulltime Land Ownership (1/0)	1.21*** (0.17)	0.33*** (0.04)	0.94*** (0.24)
Received Extension Services (1/0)	-0.06 (0.14)	-0.02 (0.04)	--
IAA Awareness (1/0)	1.23*** (0.15)	0.33*** (0.03)	3.61*** (0.90)
Land per person (Ratio)	-0.10** (0.03)	-0.03*** (0.01)	-0.38*** (0.14)
Person Trained (Number)	0.18*** (0.05)	0.04** (0.01)	--
Farm Enterprises (Number)	0.02 (0.09)	0.01 (0.02)	--
Gained Access to Irrigation (1/0)	0.46*** (0.14)	0.13*** (0.04)	--
Presence of Wetland (1/0)	0.11 (0.17)	0.03 (0.05)	-0.72*** (0.28)
Natural Water Source (1/0)	0.27 (0.14)	0.07* (0.04)	0.10 (0.17)
Flat Farm Topography (1/0)	0.39** (0.15)	0.11*** (0.04)	0.51*** (0.19)
Clay Soil Type (1/0)	-0.39** (0.14)	-0.11*** (0.04)	0.88*** (0.17)
Lowland Land Type (1/0)	-0.72*** (0.15)	-0.19*** (0.04)	--
Institutional factors			
Distance to the nearest input market (Km)	-0.02* (0.01)	-0.01** (0.00)	-0.04 (0.03)
Received Credit (1/0)	0.20 (0.14)	0.05 (0.04)	0.12 (0.17)
Production Risk Measures			
Expected profit (Mean Profit)	0.00* (0.00)	9.78e-08** (4.62e-08)	1.04e-07* (3.73e-07)
Profit Variance (Profit variability)	-0.00** (0.00)	-3.23e-08** (3.56e-08)	-5.88e-07*** (2.23e-07)
Downside risk (Skewness of Profit Moment)	-0.09*** (0.02)	-0.02*** (0.01)	-0.21*** (0.04)
Constant	-1.76*** (0.46)	--	-2.16** (1.06)

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4 Effect of Production Risk on the Variability of Farmers' Productivity

This section begins by explaining the results for the third objective. Table 11 presents the correlation coefficients (rho values) from the ESR model. The presence of a negative and statistically significant rho_2 indicates the existence of selection bias, which justifies the use of ESR as a method to obtain consistent impact estimates, in line with previous applications of ESR models in technology adoption and risk analysis (Amondo & Simtowe, 2018; Di Falco & Veronesi, 2014; Kabubo-Mariara et al., 2017).

Table 11: Summary of Correlation Coefficients in ESR

	Adopters (rho_1)	**Non-Adopters (rho_2)**
Mean Profit Moment	-0.23*	-0.57***
Variance	0.19	-0.39***
Kurtosis	0.63***	-0.41***
Skewness	0.39***	-0.36***
Farmer’s Income	0.41***	-0.02

Table 12 provides estimates of the factors that influence IAA adoption and its impact on farmers' ITPF, objective three, one of the welfare outcome indicators. The key determinants of IAA adoption and increased productivity were access to credit, the number of economically active members, full-time land ownership, awareness of IAA, the education level of the household head, and the number of farm enterprises. Access to credit, in particular, plays a vital role in enabling IAA adoption and boosting productivity. Access to credit allows adopters to invest in necessary inputs, equipment, and technologies, thereby enhancing their productivity levels. Kassie et al. (2011) showed that liquidity relaxes investment constraints and enhances the uptake of high-return technologies. In aquaculture, credit is especially important given the upfront capital demand, aligning with findings by Khan et al. (2021) that financial access improves both efficiency and risk management.

Similarly, full-time land ownership provides adopters with greater control and flexibility in implementing IAA practices, leading to increased productivity (Kumar et al., 2018). IAA awareness and household head education level also exhibit a positive association with adoption and productivity. Adequate awareness about IAA practices equips adopters with the knowledge and skills required to effectively implement and manage the system, resulting in enhanced productivity levels. Furthermore, a higher education level of the household head signifies a greater understanding of agricultural techniques, management strategies, and market dynamics, contributing to increased productivity within the IAA framework (Obiero et al., 2019).

The number of economically active members and farm enterprises are additional factors positively influencing productivity. A larger number of economically active members indicates a greater availability of labor resources, enabling adopters to carry out diverse farming activities and improve productivity. Similarly, engaging in multiple farm enterprises allows adopters to leverage different revenue streams, optimize resource utilization, and enhance overall productivity (Hasimuna et al., 2023).

Seed input, labor input, organic fertilizer input, capital input, and irrigation input all positively and significantly influence the productivity of IAA adopters. Conversely, larger farm size negatively impacts the productivity of these farmers. It is important for IAA farmers to optimize their farm size to ensure effective resource utilization and maximize productivity. Seed input plays a crucial role in determining yields and overall productivity. By using quality seeds, IAA farmers can enhance their outputs and achieve higher productivity. Additionally, increased labor input allows for more efficient farm management and cultivation practices, leading to improved productivity outcomes. The use of organic fertilizer input proves beneficial in IAA systems as it enhances nutrient availability and promotes sustainable farming practices (Ahmed et al., 2014).

A larger pool of economically active household members significantly raises productivity by easing labor constraints. IAA is labor-intensive (pond monitoring, composting, integrating livestock–manure use, irrigation management), and this aligns with the conclusions of Asfaw et al. (2014) and Suvedi et al. (2017) who found labor availability to be a key driver of adoption and efficiency in mixed agricultural systems.

Capital input plays a crucial role in providing the necessary financial resources for IAA farmers to invest in infrastructure, equipment, and technological advancements. Access to capital enables them to adopt efficient production techniques, thereby positively impacting productivity. Similarly, irrigation input is vital as adequate water supply through irrigation systems enhances productivity and minimizes yield fluctuations due to water stress (Ahmed et al., 2014).

Table 12: Determinants of IAA Technology Adoption and its Impact on Farmer's ITPF

	ITFP					
	Adopters		Non-Adopters		Selection	
Age of Household Head (Years)	2.27e-06	(1.96e-0)	-1.95e-05	(3.03e-5)	0.00	(0.01)
HH Education (Number of years)	4.91e-05*	(3.15e-05)	0.00	(0.00)	0.02*	(0.05)
Econ Active	0.00**	(0.00)	0.00	(0.00)	0.54*	(0.28)
HH Male Gender (1/0)	-0.00	(7.18e-05)	-0.00	(0.00)	0.28*	(0.15)
Farm Size (ha)	-5.2e-05***	(1.83e-05)	-0.00**	(0.00)	-0.05	(0.03)
Fulltime Land Own (1/0)	4.75e-05**	(9.89e-05)	-0.00**	(0.00)	0.41**	(0.16)
Received Credit (1/0)	2.23e-05**	(8.95e-05)	0.00	(0.00)	0.33**	(0.15)
IAA Aware (1/0)	0.00***	(9.61e-05)	-0.00**	(0.00)	0.47***	(0.15)

Distance to the nearest input market (Km)	-3.25e-05**	(1.21e-05)	2.05e-05	(7.43e-05)	-0.01	(0.01)
Land per person (Ratio)	6.44e-05**	(2.76e-05)	0.00	(0.00)	-0.01	(0.05)
Number Farm Enterprise	5.00e-05*	(5.19e-05)	6.24e-05	(0.00)	0.03*	(0.10)
Access to Irrigation	-1.48e-05	(8.63e-05)	0.01***	(0.00)	0.24	(0.16)
Presence of Wetland (1/0)	-0.00	(9.18e-05)	0.00	(0.00)	0.17	(0.16)
Natural Water Source (1/0)	4.85e-05	(8.19e-05)	-0.00	(0.00)	0.12	(0.15)
Flat Farm Topography (1/0)	-0.01***	(9.33e-05)	-0.01***	(0.00)	-0.19	(0.17)
Clay Soil Type (1/0)	-7.48e-05	(9.56e-05)	-0.01***	(0.00)	-0.13	(0.16)
Land Type	7.19e-05	(8.93e-05)	-0.00	(0.00)	-0.14	(0.15)
Seed Input	0.00**	(2.75e-05)	0.00**	(0.00)	0.01	(0.05)
Labor Input	8.49e-05*	(4.77e-05)	0.00	(0.00)	0.10	(0.07)
Chemical Fertilizer Input	-8.48e-2**	(1.85e-05)	-0.00***	(0.00)	0.03	(0.03)
Organic Fertilizer Input	4.1e-05***	(1.57e-05)	-0.00***	(0.00)	0.03	(0.03)
Land Input	0.00**	(7.57e-05)	0.00**	(0.00)	0.09	(0.11)
Capital Input	7.99e-06	(1.02e-05)	0.00***	(0.00)	0.01	(0.02)
Irrigation Input	2.95e-05**	(1.38e-05)	-0.00	(0.00)	0.06**	(0.03)
IV_Adoption					4.36***	(0.22)
lns1					-7.02***	(0.03)
lns2					-4.23***	(0.03)
r1					0.21*	(0.13)
r2					-0.01	(0.08)
Wald $\chi 2$					184.09***	
Log-likelihood					5286.49	
Constant	6.04e-06	(0.00)	0.00	(0.00)	-4.03***	(0.65)
Observations	1,290		1,290		1,290	

*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level

4.4.1 Average Treatment Effects

The results presented in Table 13 show the ATT showing how much adopting IAA improved productivity compared to if the same farmers had not adopted it. The results show that farmers who adopted IAA recorded a higher level of productivity (ITFP = 0.0009194) compared to the productivity they would have achieved if they had chosen not to adopt (0.0007518). The difference (ATT = 0.000168) is positive and statistically significant. This means IAA directly raises productivity for those who adopt it. For non-adopters, their actual productivity (0.0037781) was lower than the productivity they would have achieved had they adopted IAA (0.0048879). The treatment effect for non-adopters (ATU = –0.0011) was negative and significant. This means that non-adopters are missing out on higher productivity by not adopting IAA. There is a strong positive heterogeneous effect. That is the difference between adopters and non-adopters (2.2543) shows that the gain from adopting IAA is not uniform; adopters benefit more than non-adopters would under the same conditions. This suggests that adopters are using the technology more effectively, possibly due to better awareness, training, resource access, or management skills. To that end, IAA adoption clearly improves farmers' productivity. Adopters are not only better off compared to themselves had they not adopted, but they also outperform non-adopters by a considerable margin.

Table 13: The Observed Treatment Effect of IAA Technology

Outcome	Household type	Decision stage		AverageTreatment Effect (ATE)
		To adopt	Not to adopt	
Farmer ITFP	Adopters (ATT)	0.0009194	0.0007518	0.000168**
	Non-adopters (ATU)	0.0037781	0.0048879	-0.0011**
	Heterogenous effect	-0.0028	-0.0041	0.00127

4.5 Production Risk and The Level of Variance of Farmers’ Income

Objective 4, the second welfare outcome, aimed to assess production risk and the level of variance of farmers’ income under IAA system. Table 14 presents the determinants of net return volatility for adopters and non-adopters of IAA using FIML estimation framework. The first two columns show the outcome equations (variance of net returns), while the last column represents the selection equation identifying the factors influencing adoption. The results provide important insights into how household, farm, institutional and input-related characteristics shape income stability under IAA and non-IAA farming systems.

4.5.1 Volatility

Several variables significantly reduce volatility among adopters, suggesting that IAA systems benefit from stabilizing features. For instance, older farmers exhibit significantly lower net return volatility. This suggests that experience accumulated over many years improves management of integrated systems, enabling farmers to better coordinate crops, fish ponds, and livestock. Experienced farmers may also be more skilled at managing biological risks, resources, and seasonal variations. The finding is consistent with the notion that experience promotes resilience and stable performance. A higher number of able household members substantially lowers volatility. IAA systems are labor-intensive thus, households with more working members can manage ponds, crops, manure recycling, and feeding schedules more consistently. This reduces operational shocks and stabilizes net returns. These findings are consistent with evidence that managerial experience, human capital and family labor improve decision-making and reduce both production and income risk (Dey et al., 2010; Juma et al., 2022; Ma & Abdulai, 2019). In labor-intensive systems such as IAA, abundant family labor enhances timely pond management, manure recycling and crop husbandry, which smooths production and dampens shocks.

Education significantly reduces volatility among adopters. More educated farmers are better able to understand IAA techniques, implement best management practices, and respond to crop–pond interactions. This mirrors findings by Ma and Abdulai (2019) who show that education improves managerial ability and lowers production and income risk. Education therefore enhances farmers' ability to coordinate multiple subsystems, leading to more predictable returns.

The findings on land from Objective 1 on the risk properties of production inputs and Objective 3 on are consistent and mutually reinforcing. In the variance function (objective one), land was found to reduce production risk among adopters but increase risk among non-adopters. This is because IAA systems make more efficient use of land by integrating ponds, crops, and livestock within the same physical space, which spreads risk and buffers shocks. This echoes Juma et al. (2022) and Ogada et al. (2014), who show that in low-diversity systems, expanding cultivated area often increases exposure to climatic shocks. In contrast, IAA adopters use land more intensively and diversify within the same space (fish, crops, livestock), so marginal land increments spread risk across enterprises and stabilize returns. These results reinforce the argument that integrated land–water management can be a more effective risk-management strategy than simple area expansion (Murshed-E-Jahan & Pemsl, 2011). Conversely, non-adopters typically operate low-diversity systems where expanding land increases exposure to climatic shocks, pests, and monitoring challenges. In the volatility model, larger farm size similarly reduced net return volatility among adopters. Therefore, these findings show that while land expansion increased risk for non-adopters, both marginal increases in land and overall larger farm sizes contribute to risk reduction among IAA adopters. As such, policy interventions should prioritize integrated land–water resource management and support farmers to optimize, rather than simply expand land use. Encouraging smallholders to integrate aquaculture with crops and livestock enhances the buffering capacity of their farms and reduces vulnerability to shocks.

Factors such as IAA awareness, use of organic fertilizer, access to irrigation, and the use of seed inputs had negative and statistically significant impacts on net returns volatility. These findings suggest that greater knowledge and awareness of IAA practices, along with adequate access to essential resources and inputs, contribute to more stable and sustainable net returns. These results underscore the importance of targeted interventions and support programs that promote IAA awareness, improve access to irrigation facilities, and encourage the use of high-quality seed inputs and organic fertilizers. In IAA, organic fertilizers are part of internal nutrient recycling between ponds and fields when combined with adequate knowledge and water control, this recycling stabilizes yields and income. By addressing these factors, farmers can potentially mitigate the risks and uncertainties associated with IAA systems, leading to more stable and sustainable net returns. None the less, non-adopters exhibit a different risk profile that reflects the fragility low-diversity farming systems that highlight that non-adopters lack the buffering advantages of integrated subsystems, making them more vulnerable to shocks.

Table 14: Determinants of IAA Adoption and its Impact on Net Return Volatility

	Variance (Volatility)					
	Adopters		Non-Adopters		Selection	
Age of Household Head (Years)	-0.01**	(0.00)	0.00	(0.00)	0.00	(0.00)
HH Education (Number of years)	-0.14**	(0.06)	0.05	(0.05)	-0.03	(0.06)
Econ Active	-1.07***	(0.36)	1.23***	(0.29)	0.63**	(0.30)
HH Male Gender (1/0)	-0.09	(0.15)	-0.41***	(0.14)	0.33**	(0.16)
Farm Size (ha)	-0.17***	(0.06)	0.04	(0.04)	-0.08*	(0.04)
Fulltime Land Own (1/0)	-0.17	(0.20)	-0.22	(0.18)	0.43**	(0.17)
Received Credit (1/0)	0.33*	(0.19)	-0.16	(0.16)	0.40**	(0.16)
IAA Aware (1/0)	-0.15	(0.20)	0.57***	(0.17)	0.48***	(0.16)
Distance to the nearest input market (Km)	0.05*	(0.03)	-0.03***	(0.01)	-0.02	(0.02)
Land per person (Ratio)	-0.13	(0.08)	-0.14**	(0.06)	-0.06	(0.06)
Number Farm Enterprise	-0.22**	(0.11)	-0.26**	(0.11)	0.00	(0.11)
Access to Irrigation	-0.45**	(0.19)	0.28	(0.20)	0.04	(0.17)
Presence of Wetland (1/0)	-0.24	(0.20)	-0.67***	(0.19)	0.23	(0.18)
Natural Water Source (1/0)	0.07	(0.18)	-0.52***	(0.16)	0.23	(0.15)
Flat Farm Topography (1/0)	-0.03	(0.22)	-0.41**	(0.17)	-0.12	(0.18)
Clay Soil Type (1/0)	0.35*	(0.19)	-0.05	(0.17)	0.01	(0.18)
Land Type	-0.31	(0.20)	-0.11	(0.17)	-0.23	(0.16)
Seed Input	-0.11*	(0.06)	0.13***	(0.05)	-0.02	(0.05)
Labor Input	-0.14	(0.09)	0.06	(0.06)	0.10	(0.07)
Chemical Fertilizer Input	0.01	(0.04)	0.01	(0.03)	0.05*	(0.03)
Organic Fertilizer Input	-0.09***	(0.03)	0.09***	(0.02)	0.02	(0.03)
Land Input	0.37**	(0.17)	-0.31***	(0.12)	0.06	(0.13)
Capital Input	0.09***	(0.02)	0.05**	(0.02)	0.02	(0.02)
Irrigation Input	0.08***	(0.03)	-0.00	(0.04)	0.09***	(0.03)
IV_Adoption					3.50***	(0.25)
lns1					0.30***	(0.04)
lns2					0.21***	(0.04)
r1					0.55***	(0.20)
r2					-0.32**	(0.16)
Wald χ2					147.21***	
Log-likelihood					-1414.03	
Constant	13.66***	(0.82)	9.87***	(0.621)	-3.58***	(0.71)
Observations	731		731		731	

*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level

4.5.2 Downside Risk Exposure

Downside risk simply refers to a farmer's chance of experiencing very bad outcomes, such as extremely low net return. Unlike general variability which includes both good and bad fluctuations downside risk focus only on the worst-case scenarios. For farmers who adopted IAA, there were factors that helped protect them from very low yields or major losses. Table 15 shows which factors reduce or increase this downside risk for farmers who adopt IAA and for those who do not.

Results show that male-headed households, farm size, IAA awareness, natural water sources, flat land topography, and seed input had a negative and statistically significant impact on skewness for farmers who adopted IAA, while these factors positively influenced skewness for non-adopters. Male-headed households showed lower downside risk. This may be because men often have easier access to labor, credit, and physical strength for demanding farm tasks, which helps them avoid severe crop or fish losses. Bigger farms had fewer extreme losses among adopters. Large IAA farms usually combine several activities (fish, crops, livestock), which helps them absorb shocks. If one activity fails, others can compensate. Farmers who understand how IAA works are better able to manage water, manure, ponds, and crops. Better knowledge reduces the chance of serious failures. Reliable water reduces the chance of complete crop or fish loss, especially during droughts. Using good-quality seed reduces the chance of total crop failure. It improves overall performance. Together, these factors show that well-informed farmers with better land and water conditions are less likely to face extreme production losses when using IAA.

Additionally, the results indicate that the number of enterprises among adopters has a positive and significant effect on skewness, thereby reducing the risk of output failure. For farmers using IAA, having more enterprises (e.g. fish, crops and livestock) significantly reduced downside risk. The income generated from different enterprises can be used to fulfil immediate credit needs for purchasing inputs, thereby alleviating credit constraints. This diversification strategy provides adopters with greater financial stability and resilience, reducing the likelihood of complete crop failure impacting their livelihoods. Moreover, the produce from various enterprises can serve as an asset during periods of poor yield seasons. By selling the products from other enterprises, adopters can generate income even when the main crop yield is low (Murshed-E-Jahan & Pemsl, 2011). This flexibility enhances their ability to cope with adverse weather conditions or market fluctuations, reducing the overall vulnerability of their agricultural operations. Secondly, the adoption of IAA offers additional benefits through the use of animal manure as an organic alternative to chemical fertilizers and promote sustainable farming practices. This reduces expenses on chemical inputs and simultaneously improves soil texture and fertility.

The distance to the nearest input market was found to have a negative and significant effect for adopters, indicating that greater distances to the market increase farmers' exposure to downside risk. Longer distances can create transportation challenges, raise transportation costs, and make it more difficult to access timely market information and opportunities (Di Falco & Veronesi, 2014). On the other hand, IAA awareness had a positive and significant impact on increasing skewness for both adopters and non-adopters, thereby reducing the risk of output failure. Awareness of IAA is essential in promoting sustainable farming practices and enhancing aquacultural outcomes. For adopters, increased awareness about IAA enables them to effectively implement and manage integrated systems, leading to more balanced and resilient production. The positive effect on skewness suggests that IAA awareness contributes to a more stable and predictable distribution of returns, reducing the risk of extreme output failures. To enhance the adoption and spread of IAA practices, it is important to prioritize awareness-raising efforts. These patterns align with the broader literature on risk-reducing technologies, which shows that diversification, better information and favorable biophysical conditions reduce the probability of catastrophic losses (Amondo & Simtowe, 2018). Providing farmers with information, training, and education programs that highlight the benefits and techniques of IAA can contribute to increased awareness and improved agricultural outcomes. This confirms the central role of information and training emphasized in diffusion and social learning theories and documented empirically in aquaculture adoption studies (Kumar et al., 2018). Labor, capital and land input for adopters had a positive and significant effect in increasing skewness hence reducing output failure. For adopters of IAA, the allocation of sufficient labor, capital, and land resources plays a vital role in achieving successful outcomes. Adequate labor input enables efficient farm management, timely interventions, and effective utilization of resources, resulting in a more balanced and resilient agricultural production system. Furthermore, the availability of capital resources allows adopters to invest in necessary inputs, infrastructure, and technology, enhancing productivity and reducing the risk of output failure. Capital investment enables farmers to improve their production capabilities, adopt innovative practices, and mitigate the negative effects of external shocks. Allocating appropriate land resources for different enterprises within the system enables better diversification, optimized resource utilization, and reduced vulnerability to output failures or market fluctuations.

Table 15: Determinants of IAA Adoption and its Impact on Downward Risk Exposure

	Skewness					
	Adopters		Non-Adopters		Selection	
Age of Household Head (Years)	-0.00	(0.00)	-0.00	(0.00)	0.00	(0.00)
HH Education (Number of years)	0.06	(0.06)	0.18***	(0.06)	-0.02	(0.05)
Econ Active	-0.19	(0.31)	-0.25	(0.29)	0.56**	(0.28)
HH Male Gender (1/0)	-0.37***	(0.13)	-0.87***	(0.16)	0.28*	(0.15)
Farm Size (ha)	-0.12***	(0.03)	0.14***	(0.04)	-0.06*	(0.03)
Fulltime Land Own (1/0)	-0.29	(0.18)	-0.13	(0.21)	0.43***	(0.16)
Received Credit (1/0)	-0.14	(0.16)	0.31	(0.19)	0.28*	(0.15)
IAA Aware (1/0)	0.460***	(0.17)	1.08***	(0.17)	0.43***	(0.15)
Distance to the nearest input market (Km)	-0.10***	(0.02)	0.01	(0.01)	-0.01	(0.01)
Land per person (Ratio)	0.00	(0.05)	0.02	(0.07)	-0.01	(0.05)
Number Farm Enterprise	0.20**	(0.10)	-0.12	(0.13)	0.01	(0.11)
Access to Irrigation	-0.05	(0.16)	-0.04	(0.21)	0.25	(0.16)
Presence of Wetland (1/0)	-0.21	(0.17)	0.35*	(0.19)	0.16	(0.16)
Natural Water Source (1/0)	-0.39***	(0.15)	0.10	(0.18)	0.07	(0.15)
Flat Farm Topography (1/0)	-1.37***	(0.17)	-0.11	(0.18)	-0.24	(0.16)
Clay Soil Type (1/0)	0.13	(0.17)	0.99***	(0.19)	-0.16	(0.16)
Land Type	0.58***	(0.16)	-0.04	(0.18)	-0.13	(0.15)
Seed Input	-0.35***	(0.05)	-0.13***	(0.05)	-0.03	(0.05)
Labor Input	0.22**	(0.09)	-0.23***	(0.06)	0.11	(0.07)
Chemical Fertilizer Input	-0.02	(0.03)	-0.02	(0.03)	0.02	(0.03)
Organic Fertilizer Input	0.03	(0.03)	0.10***	(0.03)	0.05**	(0.03)
Land Input	0.38***	(0.14)	-0.11	(0.11)	0.09	(0.11)

Capital Input	0.05**	(0.02)	-0.01	(0.02)	0.01	(0.02)
Irrigation Input	0.03	(0.03)	0.04	(0.04)	0.05*	(0.03)
IV_Adoption					4.26***	(0.21)
lns1					0.50***	(0.01)
lns2					0.61***	(0.03)
Rho 1					0.48***	(0.09)
Rho 2					-0.48***	(0.11)
Wald $\chi2$					252.15***	
Log-likelihood					-2735.09	
Constant	3.52***	(0.64)	1.09*	(0.62)	-3.87**	(0.62)
Observations	1,290		1,290		1,290	

*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level

4.5.3 Kurtosis

Kurtosis shows how extreme the worst outcomes can get. While downside risk (skewness) focuses only on the chance of bad outcomes, kurtosis is how severe those bad outcomes can be if they occur. A high kurtosis value means the farmer is more likely to experience very big losses or extremely bad harvests. Table 16 shows which factors make these extreme outcomes more or less likely for adopters and non-adopters. For farmers who adopted IAA, the following factors reduced the chance of severe losses: Factors such as education, labor input, organic fertilizer, and irrigation contributed to reducing the risk of extreme outcomes for adopters. Educated farmers with sufficient labor, good soil management, and reliable water supply face fewer extreme crashes when practicing IAA. This suggests that these factors contribute to reducing the likelihood of extreme outcomes and enhancing the stability of profit distribution within the IAA systems, while factors like age, farm topography, and chemical fertilizer increase the risk for non-adopters. The mitigating effect of education on extreme losses is consistent with earlier results on volatility and with the literature that links human capital to better risk management and smoother income profiles (Ma & Abdulai, 2019). Non-adopters remain vulnerable to extreme losses because their systems lack diversification. These factors employ a negative effect on the distribution of profits, indicating a higher probability of extreme outcomes and increased vulnerability to severe losses.

Table 16: Determinants of IAA Technology Adoption and its Impact on Kurtosis

	Kurtosis					
	Adopters		Non-Adopters		Selection	
Age of Household Head (Years)	-0.02	(0.01)	-0.02*	(0.02)	0.00	(0.00)
HH Education (Number of years)	0.45**	(0.22)	0.69***	(0.23)	0.01	(0.05)
Econ Active	1.86	(1.19)	-1.43	(1.15)	0.56**	(0.28)
HH Male Gender (1/0)	-2.31***	(0.51)	-3.25***	(0.61)	0.3**	(0.15)
Farm Size (ha)	-0.12	(0.13)	0.10	(0.17)	-0.0`4	(0.03)
Fulltime Land Own (1/0)	0.49	(0.70)	1.44*	(0.82)	0.41**	(0.16)
Received Credit (1/0)	-0.78	(0.63)	3.62***	(0.74)	0.39***	(0.15)
IAA Aware (1/0)	0.21	(0.67)	0.90	(0.68)	0.51***	(0.15)
Distance to the nearest input market (Km)	-0.07	(0.09)	-0.03	(0.04)	-0.01	(0.01)
Land per person (Ratio)	-0.07	(0.20)	0.44*	(0.26)	-0.03	(0.05)
Number Farm Enterprise	0.42	(0.37)	-0.60	(0.51)	-0.04	(0.10)
Access to Irrigation	-0.50	(0.61)	-0.83	(0.80)	0.18	(0.15)
Presence of Wetland (1/0)	0.67	(0.65)	2.288***	(0.73)	0.11	(0.16)
Natural Water Source (1/0)	0.14	(0.58)	0.32	(0.69)	0.15	(0.15)
Flat Farm Topography (1/0)	-3.97***	(0.66)	-5.03***	(0.69)	-0.16	(0.16)
Clay Soil Type (1/0)	-0.68	(0.67)	2.08***	(0.74)	-0.01	(0.16)
Land Type	1.42**	(0.63)	1.10	(0.72)	-0.15	(0.15)
Seed Input	-1.04***	(0.19)	0.27	(0.19)	-0.01	(0.05)
Labor Input	1.76***	(0.34)	0.49**	(0.25)	0.10	(0.07)
Chemical Fertilizer Input	0.16	(0.13)	-0.43***	(0.11)	0.04	(0.03)
Organic Fertilizer Input	0.24**	(0.11)	-0.16	(0.11)	0.04	(0.03)
Land Input	0.28	(0.54)	0.40	(0.41)	-0.01	(0.13)
Capital Input	0.09	(0.07)	0.22**	(0.09)	0.01	(0.02)
Irrigation Input	0.64***	(0.10)	0.29*	(0.17)	0.06**	(0.03)
IV_Adoption					4.19***	(0.24)
lns1					1.86***	(0.03)
lns2					1.97***	(0.03)
r1					0.62***	(0.13)
r2					-0.47***	(0.12)
Wald $\chi 2$					176.35***	
Log-likelihood					-4481.46	
Constant	2.32	(2.48)	4.55*	(2.43)	-4.00***	(0.65)
Observations	1,290		1,290		1,290	

*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level

4.5.4 Net Incomes

This section explains what determines farmers' incomes and how adopting IAA affects earnings. Table 17 compares what drives income for farmers who adopt IAA and those who do not. The results show that IAA adopters generally earn more and are influenced by different factors than non-adopters. The education level of the household head, who is typically the primary decision-maker, plays a crucial role in the decision-making process. An educated household head is better equipped to access and understand information about various technologies, their benefits, and the risks of not adopting them. Educated farmers tend to adopt more efficient farming practices, maintain accurate records, and use smart technology, all of which enhance net farm returns. These findings are consistent with those of Ogada et al. (2014) who also identified education as a key factor in technology adoption among farmers.

The impact of credit constraints differs between adopters and non-adopters. For non-adopters, the negative and statistically significant coefficient of the credit constraint variable suggests that limited access to credit significantly hampers their farm net returns. This indicates that non-adopters, facing greater credit constraints, may find it difficult to adopt climate-smart technologies due to the associated costs. Their income from aquaculture may be fully committed to traditional farming, leaving little room for adopting new practices. In contrast, for adopters, the positive and statistically significant relationship between credit availability and farm net returns highlights the importance of credit in enhancing profitability (Dey et al., 2010; Kumar et al., 2018). Additionally, the presence of positive and significant coefficients for the number of economically active members suggests that IAA adoption is labor-intensive and is more likely to be embraced by households with sufficient labor resources. In households that rely on family labor, a larger household size positively correlates with the adoption of IAA. The contribution of labor input significantly boosts the incomes of adopters while having a lesser impact on non-adopters. In this study, it appears that more farmers are leveraging the availability of family labor, leading to increased income.

Other factors, such as clay soil type, land per person ratio, and capital input were found to positively influence net incomes for adopters compared to non-adopters. The positive and statistically significant coefficient associated with the number of enterprises owned by a household indicates that having more farm enterprises tends to be linked with higher net returns for adopters. This suggests that diversification and involvement in multiple activities contribute to better financial outcomes for adopters. By broadening their scope of operations and engaging in various compatible enterprises, adopters are likely to experience increased income generation and reduced risks associated with dependence on a single enterprise. This finding is consistent with previous research highlighting the positive effects of diversification on farm profitability (Kumar et al., 2018). Owning multiple enterprises allows households to take advantage of different market opportunities, effectively utilize their resources, and mitigate potential negative impacts of market fluctuations or crop failures.

Table 17: Determinants of IAA Technology Adoption and its Impact on Farmer's Incomes

	Net Farm Income					
	Adopters		Non-Adopters		Selection	
Age of Household Head (Years)	-0.02**	(0.01)	-0.01	(0.01)	0.00	(0.00)
HH Education (Number of years)	0.32*	(0.18)	0.35**	(0.15)	0.01*	(0.05)
Econ Active	1.36**	(0.96)	0.14	(0.75)	0.55**	(0.28)
HH Male Gender (1/0)	-0.14	(0.41)	0.51	(0.40)	0.27*	(0.15)
Farm Size (ha)	-0.17	(0.10)	0.02	(0.11)	-0.05	(0.03)
Fulltime Land Own (1/0)	3.28***	(0.56)	-0.71	(0.54)	0.44***	(0.17)
Received Credit (1/0)	0.86*	(0.51)	-1.90***	(0.49)	0.33**	(0.15)
IAA Aware (1/0)	1.12**	(0.55)	-3.10***	(0.45)	0.47***	(0.15)
Distance to the nearest input market (Km)	0.11	(0.07)	0.06***	(0.024)	-0.01	(0.01)
Land per person (Ratio)	0.52***	(0.16)	-0.10	(0.17)	-0.02	(0.05)
Number Farm Enterprise	0.38***	(0.30)	-1.54***	(0.34)	0.03***	(0.10)
Access to Irrigation	0.16	(0.49)	1.06**	(0.53)	0.20	(0.16)
Presence of Wetland (1/0)	-1.91***	(0.52)	0.26	(0.48)	0.18	(0.17)
Natural Water Source (1/0)	-0.10	(0.47)	0.83*	(0.45)	0.09	(0.15)
Flat Farm Topography (1/0)	0.79	(0.53)	-1.78***	(0.45)	-0.17	(0.17)
Clay Soil Type (1/0)	2.16***	(0.54)	-0.31	(0.49)	-0.13	(0.16)
Land Type	-0.49	(0.51)	-0.25	(0.47)	-0.17	(0.15)
Seed Input	0.08	(0.16)	0.29**	(0.12)	-0.00	(0.05)
Labor Input	0.15	(0.27)	-0.34**	(0.16)	0.09	(0.07)
Chemical Fertilizer Input	-0.13	(0.11)	0.14*	(0.07)	0.03	(0.03)
Organic Fertilizer Input	0.35***	(0.10)	-0.13*	(0.07)	0.03	(0.03)
Land Input	1.03**	(0.43)	0.28	(0.27	0.08	(0.11)
Capital Input	0.15**	(0.06)	0.08	(0.06)	0.01	(0.02)
Irrigation Input	-0.30***	(0.08)	-0.04	(0.11)	0.08***	(0.03)
IV_Adoption					4.40***	(0.22)
lns1					1.63***	(0.03)
lns2					1.54***	(0.03)
r1					-0.07	(0.11)
r2					0.06	(0.12)
Wald $\chi 2$					158.66***	
Log-likelihood					-4102.82	
Constant	10.92***	(2.03)	11.40***	(1.593)	-4.04***	(0.65)
Observations	1,290		1,290		1,290	

*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level

4.5.5 Average Treatment Effects

Table 18 shows how much better (or worse) farmers performed after adopting IAA, compared to if they had not adopted it. This was measured using the ATT, which shows how adoption changed income for farmers who actually adopted the technology. The results show that farmers who adopted IAA earned significantly more income than they would have earned if they had chosen not to adopt. IAA adoption made farmers better off. The ATT confirms that IAA adoption significantly increased household income. Adopters earned substantially higher net farm income than they would have earned in the counterfactual scenario of non-adoption, indicating a clear welfare gain from IAA. This result is in line with previous studies that find strong income and poverty-reducing effects of improved agricultural technologies and IAA systems (Dey et al., 2010; Kassie et al., 2011; Khan et al., 2021; Mukasa, 2018; Murshed-E-Jahan & Pemsl, 2011). For farmers who did not adopt, forcing them to adopt IAA would have made them worse off. This suggests non-adopters may lack the resources, skills, labor, or proper conditions needed to benefit from IAA. The heterogeneous effect shows how much more IAA benefited adopters compared to non-adopters. IAA benefits are not uniform. It works very well for those who adopt voluntarily (adopters). It does not benefit those who choose not to adopt (non-adopters). Meaning farmers self-select into IAA based on their readiness, access to resources, or favorable conditions. Those who choose to adopt are the ones most able to benefit from it. To that end, the results indicate that adopting IAA significantly increases income for farmers who choose it. However, farmers who do not adopt would not automatically benefit if they were pushed to adopt. This means IAA is best suited for farmers who have the right conditions such as access to training, water, labor, and knowledge. Policies should therefore focus on supporting willing and prepared farmers, rather than encouraging all farmers to adopt IAA blindly.

Table 18: The Observed Treatment Effect of IAA Technology on Farmer Income

Outcome	Household type	Decision stage		AverageTreatment Effect (ATE)
		To adopt	Not to adopt	
Farmer income	Adopters (ATT)	9.2103	7.5780	1.6323***
	Non-adopters (ATU)	7.4770	8.099	-0.622**
	Heterogenous effect	1.733	-0.521	2.2543

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.0 Introduction

This final chapter presents the conclusions from the study, offers recommendations based on the findings and areas of further research.

5.1 Conclusions

This study had four objectives, including (i) to estimate the risk properties of IAA production inputs to determine how these risk characteristics influence farmers' optimal input-use in Kenya, (ii) to analyze how production risk affects smallholder farmers' likelihood of adopting IAA, (iii) to evaluate the effect of production risk on the variability of productivity among smallholder IAA farmers in Kenya and (iv) to evaluate the effect of production risk on the variability of household income among smallholder IAA farmers in Kenya. With regard to the first objective, the study found that IAA adopters use significantly more seeds, organic fertilizer, labor, and capital than non-adopters, and they consequently achieve higher output levels. The production function results indicate that inputs such as land, seed, and organic fertilizer was more productive among adopters, reflecting the efficient resource recycling and complementary interactions inherent in integrated systems. Although both adopters and non-adopters operate under decreasing returns to scale, adopters still achieve higher productivity per unit of input. In terms of risk properties, some inputs such as organic fertilizer and seeds increase output variability for adopters because their systems are more complex to manage, whereas non-adopters benefit from risk-reducing effects of labor, chemical fertilizer, and organic fertilizer. Importantly, adopters exhibited substantially lower total variance elasticity, indicating that IAA systems help stabilize production through diversification.

The second objective examined how production risk affects the choice to adopt IAA. The results show that farmers were highly responsive to risk. Higher expected profits significantly increased adoption while greater profit variability reduced the likelihood of adoption. Downside risk, which represents the possibility of extremely low returns, also discouraged adoption. The decision to adopt IAA was further shaped by household characteristics such as age, education, labor availability, and training, as well as farm attributes including full-time land ownership, flat topography, and access to irrigation. Market access emerged as an important constraint, as longer distances to input markets negatively affect adoption. Awareness of IAA consistently appeared as one of the strongest predictors of both adoption and intensity, underscoring the role of information in reducing uncertainty.

In this study, farmers' welfare was assessed using two complementary indicators, (i) productivity and (ii) income. These welfare outcomes were captured through the third and fourth objectives. Objective three examined the effect of production risk on farmers' productivity, measured through ITPF, which reflected the efficiency with which farmers convert inputs into output. Objective four evaluated the influence of production risk on household income variability, thereby providing insight into the financial well-being and resilience of smallholder farmers practicing IAA. Together, these two objectives provided a comprehensive measure of how production risk shapes overall welfare, recognizing that improvements in productivity and stable incomes are central to enhancing the livelihoods of smallholder farmers in Kenya. For objective three, the results indicate that adopters achieved higher productivity than non-adopters, driven by the effective use of seed, labor, organic fertilizer, capital, and irrigation. Productivity gains among adopters reflect better resource coordination and complementarities across enterprises. Conversely, chemical fertilizer uses and larger farm sizes reduced productivity, suggesting inefficiencies in input allocation and management challenges at larger scales. Education, access to credit, awareness of IAA, and the number of economically active household members all contributed positively to productivity, highlighting the importance of knowledge, financial resources, and labor in enhancing farm efficiency. Diversification through multiple farm enterprises also raised productivity, as farmers can better utilize shared resources and spread production risks.

Finally, the fourth objective examined the effect of production risk on farmers' incomes. The results showed that IAA adoption significantly increases household income and reduces vulnerability to income fluctuations. Adopters benefitted from higher and more stable incomes due to enterprise diversification, better nutrient recycling, and efficient use of labor. Key factors that raised income for adopters included education, labor availability, access to credit, organic fertilizer use, capital investment, and engagement in multiple enterprises. Non-adopters, on the other hand, faced stronger credit constraints, which depress their income and limit their ability to adopt new technologies. Irrigation access and market proximity also supported higher incomes, particularly by improving production consistency and market participation. IAA adoption clearly enhanced household welfare by boosting incomes and reducing exposure to financial shocks.

Overall, the study established that production risk is a critical but often underestimated factor influencing smallholder IAA performance. Production risk affects how farmers choose inputs optimally, whether they adopt the technology, and how their productivity and income evolve. Although IAA offered clear benefits in terms of higher productivity and incomes, these welfare gains were moderated by the level of production risk farmers face. Further, IAA improved productivity and income and reduced some aspects of risk but only when farmers had adequate institutional support, training, labor, and financial resources. Production risk remains central in shaping smallholder decisions, but broader structural factors such as market access, education, land ownership, and enterprise diversity determine how effectively households benefit from IAA. Policies that reduce risk exposure therefore have the potential to substantially increase adoption and enhance welfare outcomes in smallholder aquaculture systems.

5.2 Recommendations

The findings of this study carry important policy and practical implications for improving production efficiency, reducing production risk, and strengthening welfare outcomes for smallholder IAA farmers in Kenya. Because the study demonstrated that IAA systems improve productivity and income while lowering exposure to production risk, policy and development efforts should prioritize strategies that address the constraints identified in adoption and performance. The study therefore recommends the following: -

First, the need to strengthen efficiency-focused, risk-aware, and skills-based extension and training services. Because adopters operate under decreasing returns to scale, long-term growth cannot be achieved by simply expanding land or increasing input use. Instead, productivity gains must come from improved technical efficiency and better management of integrated systems. National and county governments, in collaboration with research institutes and training colleges, should establish comprehensive IAA capacity-building programmes. These programmes should equip farmers with practical skills in land–water optimization, nutrient recycling, pond–water–crop interactions, irrigation management, and risk diagnostics. Demonstration farms should be used to showcase best practices, while agricultural and Technical and Vocational Education and Training (TVET) institutions ought to integrate IAA modules into their curricula to build long-term technical capacity across farming communities.

Second, access to finance and input availability were shown to be critical drivers of adoption, income growth, and productivity. Microfinance institutions and development partners should develop aquaculture-specific financial products that align with production cycles. Counties governments should also bring inputs closer to farmers by establishing local aquaculture input centers. Coupling finance with training will ensure that investments translate into real productivity gains.

Third, diversification within the IAA system was found to reduce downside risk and stabilize incomes. County governments and producer organizations should therefore encourage enterprise bundling such as fish–crop–livestock combinations because they enhance resilience, nutrient recycling and resource efficiency. Promoting integrated land–water resource management will support stable production systems and protect farmers from shocks.

Fourth, the study revealed considerable downside risk and income volatility, especially among non-adopters. Because such risks discourage adoption and investment, aquaculture-focused insurance products are needed. The Insurance Regulatory Authority and private insurers should design index-based aquaculture insurance covering water-level fluctuations, disease outbreaks and yield failure. County governments may subsidize premiums for vulnerable households as part of climate-smart agriculture initiatives.

Finally, the Average Treatment Effects demonstrated that IAA adoption significantly improves both productivity and income. Policymakers should therefore position IAA as a priority pathway for smallholder welfare improvement within agricultural and climate-smart policy frameworks. Programmes should specifically target households with labor availability, training potential and interest in enterprise diversification, as these are the farmers most likely to translate IAA into tangible welfare gains.

5.3 Suggestions for Further Research

While this study provides important evidence on how production risk influences optimal input use, adoption, and welfare outcomes of IAA systems among smallholder farmers in Kenya, several areas remain open for further investigation. First, future studies should explore the long-term impacts of IAA, particularly how production risk, optimal input use, adoption, productivity, and income evolve over extended periods. Because this study relied on cross-sectional data, it was not possible to fully capture dynamic changes that occur as farmers gain experience, adjust enterprise combinations, or respond to climatic and market shocks. Longitudinal or panel data would allow researchers to assess whether the benefits observed such as reduced downside risk and improved welfare are sustained, diminish, or increase over time. Second, there is need for season-by-season performance tracking of adopters and non-adopters. Monitoring farmers across multiple production cycles would help confirm whether the short-term gains documented in this study such as income improvements, reduced volatility, and higher total factor productivity persist in the long run. This is particularly relevant given the study's finding of decreasing returns to scale, which suggests that productivity gains may plateau without complementary innovations or policy interventions.

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APPENDICES

Appendix 1: Ethical Clearance

KENYATTA UNIVERSITY
DIRECTORATE OF ETHICS REVIEW COMMITTEE

Fax: 8711242/8711575
Email: chairman.kuerc@ku.ac.ke
Nairobi, 00100

Website: www.ku.ac.ke
Our Ref: **KU/ERC/APPROVAL/VOL.1**

P. O. Box 43844,

Tel: 8710901/12

Date: 12th August, 2021

Jane Fonda Awuor

P.O BOX 43844-00100
Nairobi.

Dear Ms. Awuor

APPLICATION NUMBER: PKU/2290/I1431 IMPACT OF PRODUCTION RISK ON WELFARE OF SMALL HOLDER ADOPTERS OF INTEGRATED AQUACULTURE FARMING SYSTEM IN WESTERN AND CENTRAL REGIONS OF KENYA

This is to inform you that ***KENYATTA UNIVERSITY DIRECTORATE OF ETHICS REVIEW COMMITTEE*** has approved version 4 of the study protocol together with the attached consent forms dated 12.09.2020. Your application approval number is **PKU/2290/I1431.** The approval period is ***12th August, 2021 TO 12th August, 2022.***

This approval is subject to compliance with the following requirements;

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by ***KENYATTA UNIVERSITY DIRECTORATE OF ETHICS REVIEW COMMITTEE.***
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to ***KENYATTA UNIVERSITY DIRECTORATE OF ETHICS REVIEW COMMITTEE*** within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be

reported to ***KENYATTA UNIVERSITY DIRECTORATE OF ETHICS REVIEW COMMITTEE*** within 72 hours

v. Clearance for export of biological specimens must be obtained from relevant institutions.

vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.

vii. Submission of an executive summary report within 90 days upon completion of the study to ***KENYATTA UNIVERSITY DIRECTORATE OF ETHICS REVIEW COMMITTEE***.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

To serve you better, researchers are kindly requested to access and complete a customer feedback form and sent it back online as you continue with research and upon completion of data collection found on the following websitelink;(https://docs.google.com/forms/d/1ytWefDwvyz5h1oz_Vln0xbxg3uGdIDzMXFWNDsMrRPQ/edit?usp=sharing

Yours sincerely

KENYATTA UNIVERSITY
OFFICE OF THE CHAIRMAN
12 AUG 2021
ETHICS REVIEW COMMITTEE
P.O. BOX 43844 - 00100 NAIROBI

Prof. Judith Kimiywe

DIRECTOR - KENYATTA UNIVERSITY ETHICS REVIEW COMMITTEE.

Appendix 2: Research License

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **295677**

Date of Issue: **23/June/2021**

RESEARCH LICENSE

This is to Certify that Miss.. Fonda Jane Awuor of Kenyatta University, has been licensed to conduct research in Busia, Kakamega, Nyeri, Siaya on the topic: IMPACT OF PRODUCTION RISK ON WELFARE OF SMALLHOLDER ADOPTERS OF INTEGRATED AQUACULTURE FARMING SYSTEM IN WESTERN AND CENTRAL REGIONS OF KENYA for the period ending : 23/June/2022.

License No: **NACOSTI/P/21/11329**

295677

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is Guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014

CONDITIONS

1. The License is valid for the proposed research, location and specified period
2. The License any rights thereunder are non-transferable
3. The Licensee shall inform the relevant County Director of Education, County Commissioner and County Governor before commencement of the research
4. Excavation, filming and collection of specimens are subject to further necessary clearence from relevant Government Agencies
5. The License does not give authority to tranfer research materials
6. NACOSTI may monitor and evaluate the licensed research project
7. The Licensee shall submit one hard copy and upload a soft copy of their final report (thesis) within one year of completion of the research
8. NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice

National Commission for Science, Technology and Innovation
off Waiyaki Way, Upper Kabete,
P. O. Box 30623, 00100 Nairobi, KENYA
Land line: 020 4007000, 020 2241349, 020 3310571, 020 8001077
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E-mail: dg@nacosti.go.ke / registry@nacosti.go.ke
Website: www.nacosti.go.ke

Appendix 3: Informed Consent

KENYATTA UNIVERSITY
OFFICE OF THE CHAIRMAN ETHICS REVIEW COMMITTEE

Informed Consent

My name is Fonda Jane Awuor from Kenya Marine and Fisheries Research Institute (KMFRI). I am a Ph.D. Student from Kenyatta University. I am conducting a study titled *"The Impact Of Production Risk On The Choice Of The Optimal Level Of Inputs, Adoption, And Welfare Of Small Holder Integrated Agriculture Aquaculture System Farmers In Kenya"* The information you will provide will be used in formulation of suitable programmes and policies to promote climate smart aquaculture in the country.

Procedures to be followed

The study population will be all fish farmers in the selected study counties namely Busia, Kakamega, Nyeri and Siaya. The sampling frame will select a list of adopters and non-adopters of integrated aquaculture farming systems in four sub counties with priority be given to KCSAP working sites. The sample size has been computed by a formula. Each county will have a total of 120 fish farmers. From each of the four sub counties, a total of 30 adopters and non-adopters is therefore envisaged and will be randomly selected. A good working relationship will be established with the community leadership, fisheries officers, the County Directors of Fisheries and the KCSAP county coordination units in the study areas. Participation in this study will require that I ask you some questions and also examine you and your household (0-59 months) and all members of your household in order to screen for child health (child nutrition, feeding patterns, dietary diversity, breast feeding, delivery care and health status of children) and anthropometry (for height and weight measurements). This will be collected through farm visits and using an open access Kobo tool Box application installed on android smartphones to ensure quality check and data safety.

Voluntarism

You have the right to refuse participation in this study. You will get the same services and care whether you agree to join the study or not and your decision will not change the care you will receive. Please remember the participation in this study is voluntarily. You may ask questions related to the study at any time.

You may refuse to respond to any questions and you may stop an interview at any time. You may also stop being in the study at any time without any consequences to the services you receive or any other organization now or in the future.

Discomfort and Risks

Some of the questions you will be asked are on intimate subject and may be embarrassing or make you uncomfortable. If this happens you may refuse to answer these questions if you so choose. You may also stop the interview at any time.

Benefits

If you participate in this study, the information you will provide will be pooled with that from other respondents and analyzed. The findings from the study will inform policymakers' need to include the projected gains that farmers obtain from lowering their exposure to risk in the applicable cost-benefit examinations. The technology developers of integrated aquaculture farming systems will have a further advantage of feedback on the technologies performance for improvement and or marketing. Smallholders will know the risk decreasing and increasing inputs, whether they are operating profitably and their welfare improving and or whether they need to change the technology. You will also contribute to learning how to monitor the nutritional status of children. You will be enlightened on Community-based nutrition programmes which have the potential of creating awareness on proper nutrition practices in the community and lower child malnutrition incidences. Growth monitoring will be critical in identifying growth related concerns hence provide a preventive and or corrective actions.

Reward

There are no rewards or any payments to you if you participate.

Confidentiality

The questionnaires will be kept safe at Kenyatta University. Everything will be kept private and only shared with the study team.

Contact Information

If you have any questions about the study call the Dr. Macharia Ibrahim Ndegwa Tel +254 722 574 172 or Prof. Richard. M. Mulwa Tel +254 710 561 626.

However, if you have questions about your rights as a study participant: You may contact Kenyatta University Ethical Review Committee Secretariat on chairman.kuerc@ku.ac.ke or secretary.kuerc@ku.ac.ke

Participant's statement

The above participation regarding my participation in the study is clear to me. The study has been explained to me and I have been given a chance to ask questions and my questions have been answered to my satisfaction. My participation in this study is entirely voluntary. I understand that my records will be kept private and that I can leave the study at any time. I understand that I will still get the same service whether I decide to leave the study or not and my decision will not change the service that I will receive.

Name of participant____

________________________________ ________________________________

Signature or thumbprint Date

________________________________ ________________________________

Name of representative/Witness (where necessary) Relationship to subject

Investigator's statement

I, the undersigned, have explained to the volunteer in a language s/he understands, the procedures to be followed in the study and the risks and benefits involved.

____
Name of interviewer

____

____
Signature Date

Appendix 4: Informed Consent for Children

KENYATTA UNIVERSITY
OFFICE OF THE CHAIRMAN ETHICS REVIEW COMMITTEE

Project Title: The Impact Of Production Risk On The Choice Of The Optimal Level Of Inputs, Adoption, And Welfare Of Small Holder Integrated Agriculture Aquaculture System Farmers In Kenya

Protocol Number: N/A

Principal Investigator: Fonda Jane Awuor

The investigator named above is doing a research study.

<u>These are the things we want you to know about research studies:</u>

We are asking you to be in a research study. Research is a way to test new ideas. Research helps us learn new things. Whether or not to be in this research is your choice. You can say Yes or No. Whatever you decide is OK. You will still receive services.

<u>What is the study about?</u>

This research study forms part of an intervention within the Kenya Climate Smart Agriculture Project (KCSAP) framework on supporting the generation and dissemination of improved agricultural Technologies, Innovations, and Management Practices (TIMPs). A section of this study will require that I ask you some questions and also examine you and your household (0-59 months) and all members of your household in order to screen for child health (child nutrition, feeding patterns, dietary diversity, breast feeding, delivery care and health status of children) and anthropometry (for height and weight measurements). The nutritional status of a population forms one of the critical indicators of the population's general welfare. To that end, child growth is perceived as a vital indicator of nutritional status and health.

<u>Why am I being asked to be in this research study?</u>

The study population will be all fish farmers in the selected study counties namely Busia, Kakamega, Nyeri and Siaya. The sampling frame will select a list of adopters and non-adopters of integrated aquaculture farming systems in four sub counties with priority will be given to KCSAP working sites. The sample size has been computed by a formula. Each county will have a total of 120 fish farmers. From each of the four sub counties, a total of 30 adopters and non-adopters are therefore envisaged and will be randomly selected for interviews and that is how you have been selected. A good working relationship will be established with the community leadership, fisheries officers, the County Directors of Fisheries and the KCSAP county coordination units in the study areas.

<u>What will happen during this study?</u>

I will ask you some questions and also examine you and your household (0-59 months) and all members of your household in order to screen for child health (child nutrition, feeding patterns, dietary diversity, breast feeding, delivery care and health status of children) and anthropometry (for height and weight measurements). This will be collected through farm visits and using an open access Kobo tool Box application installed on android smartphones to ensure quality check and data safety. If you agree to be in this study, you will help contribute to learning how to monitor the nutritional status of children and steps achieved towards attaining the Sustainable Development Goal (SDG) targets of culminating hunger, and achieving food security and improved nutrition.

Will the study hurt/risks?

The anthropometry section will be administered to all household members except the sick, pregnant women and those abled differently.

What else should I know about the study?

According to the 2010 Kenyan Constitution, all Kenyans have the right to basic nutrition, safe and clean water in acceptable amounts and acceptable quantities of food. Nutrition refers to food intake in relation to dietary needs. The nutritional status of a population forms one of the critical indicators of the population's general welfare. To that end, child growth is perceived as a vital indicator of nutritional status and health.

What are the good things /benefits that might happen?

If you agree to be in this study, the information you will provide will be pooled with that from other respondents and analyzed. The findings from the study will inform policymakers' need to include the projected gains that farmers obtain from lowering their exposure to risk in the applicable cost-benefit examinations. The technology developers of integrated aquaculture farming systems will have a further advantage of feedback on the technologies performance for improvement and or marketing. Smallholders will know the risk decreasing and increasing inputs, whether they are operating profitably and their welfare improving and or whether they need to change the technology. You will also contribute to learning how to monitor the nutritional status of children. You will be enlightened on Community-based nutrition programmes which have the potential of creating awareness on proper nutrition practices in the community and lower child malnutrition incidences. Growth monitoring will be critical in identifying growth related concerns hence provide a preventive and or corrective actions.

What if I don't want to be in this study?

You do not have to be in the study if you do not want to. You will not lose any care or service.

Who should I ask if I have any questions?

If you have any questions about this study, you or your parents can call Dr. Macharia Ibrahim Ndegwa Supervisor 1 on Tel +254 722 574 172 or Supervisor 2 on Prof. Richard .M. Mulwa Tel +254 710 561 626 or the Kenyatta University Ethical Review Committee Secretariat on **chairman.kuerc@ku.ac.ke or secretary.kuerc@ku.ac.ke**

Do I have to be in the study?

No, you do not have to be in the study. Even if you say yes now, you can change your mind later. It is up to you. No one will be mad at you if you don't want to do this.

Signatures

Before deciding if you want to be in the study, ask any questions you have. You can also ask questions during the time you are in the study.

If you sign your name or put a mark below, it means that you agree to take part in this research study.

Your Name (Printed) Age

Your Signature Date

Signature of Person Obtaining Consent Date

Signature of Witness Date

Appendix 5: Study Questionnaire

KENYATTA UNIVERSITY
SCHOOL OF AGRICULTURE AND ENVIRONMENTAL SCIENCES
DEPARTMENT OF AGRICULTURAL ECONOMICS
FISH FARMER STUDY QUESTIONNAIRE

Household ID (HHID)_

SECTION A: PRELIMINARIES

Date of Interview:	Geo - points (compulsory)
Enumerator Name:	County:
Enumerator Tel:	Sub county:
Ward:	Location
Respondent Name:	Village
Respondent Telephone:	Name of the farm:

SECTION B: DEMOGRAPIC AND SOCIO-ECONOMIC BACKGROUND

Please fill in the Table below for details of the household members starting with the household head. The appropriate respondent is the household head or spouse. A household is defined as a person or a group of people living in the same compound, answerable to the same head and share a common source of food and or income as a single unit. When filling the table, go row by row.

B.1 How many members belong to your household including yourself	B2. Name of HH Member (Start with the Household Head)	B.3 Year of birth	B.4 Gender (Codes)	B.5 Marital status (Codes)	B.6 Years of Education [1] None [2] Primary [3] Secondary [4] Mid-level	B.7 Relation to HH (Codes) [1] Household head [2] Spouse [3] Son/daughter [4] Parent [5] Sister/brother [6] Grandchild [7] Other relative [8] Non-Relative (including employees who live in the house)	B.7a How many members are (>18 years)	B.7b Number of Children < 18 years	B.8 Household community/ ethnicity [1] Luo [2] Kalenjin [3] Luyha [4] Kisii

					colleges [5] Vocational [6] Undergraduate [7] Postgraduate	[9] Other, specify__			[5] Kikuyu [6] Other, specify
			[1] Male [0] Female	[1] Single [2] Married [3] Widowed [4] Separated/ Divorced [4] Child					
	1.								
	2.								
	3.								
	4.								
	5.								
	6.								

SECTION C: FARM PROFILE

C1. a. Does your household have land for fish, crop and/or livestock production? [1] Yes [0] No

C1. b. How many parcels of land does this household own? ______

C2. What is the tenure of this land? *(Multiple response)*

[1] Own land w/ title deed [2] Owned w/o title deed [3] Family land [4] Communal [5] Leased land [5] Other, Specify_________________

C3. Who owns this land?

[1] Husband [2] Wife [3] Both husband and wife) [4] Other family member (specify) ____

C4. Please indicate the areas in acres of land allocated to the following:

What is the **total agricultural area** of your farm in Acres?	How many acres are allocated for **fish farming?**	How many acres are allocated for **crop/vegetable farming?** *e.g* Beans, Lentils, Tomatoes, etc	How many acres are allocated for **livestock keeping?** Livestock include cattle, sheep, goats, poultry, pigs or rabbit	How many acres are allocated for **other activity?**

C5 What is the main source of farm labor for the household? (*Single response*)
[1] Family [2] Casual [3] Permanent [4] Other specify
C6. How many members of your household are 18 years and above offer farm labor?

Men	Hours worked per week	Women	Hours worked per week

C7. How many members of your household are below 18 years of age offer farm labor?

Men	Hours worked per week	Women	Hours worked per week

C8. Is there a wetland area on the farm? [1] Yes [0] No
C9. Did this household have any irrigated land between (August 2020-March 2021)?
[1] Yes [0] No
C10. What is the main source of water in your farm?
[1] Wells [2] Borehole [3] Stream [4] Canal [5] River [6] Tap water [7] Harvested rain water [8] Lake [9] Man-made lake/Dam [10] Other (specify)……………………………………………….

SECTION D: FISH PRODUCTION

D1. When did you start farming fish? (Indicate the month and year) _________________
D2. Why did you start fish farming? (*Select only one*)
[1] Income [2] Food [3] Income & food [4] Hobby [5] Create employment
[6] Benefit from Economic Stimulus Programme [7] Utilize idle land [8] Other, specify ____________
D3. Do you raise fish as an individual or as a group? *(Single choice)*
[1] Individual; *If farmer answers individual skip to D6* [2] Group
D4. What is the name of the fish farming group? _________________

D5. How many members are in the fish farming group?

Men	Women	Total

D6. Please select the fish species you culture, the culture facility (ies), the source of fingerlings and the culture period for each.

D6a. Fish species cultured (*Select all that apply)* (Code A)	D6b. Are these fish mono-sex or mixed sex? [1] Mono - sex [2] Mixed sex [3] Combination (varies by species/pond)	D6c. Culture Facility (Code B)	D6d. Source of fingerling (Code C)	D6e. Culture period (Code D)
1.				
2.				
3.				

Species code A: [1] Tilapia [2] Catfish [3] Other, specify________________
Culture Facility B: [1] Earthen ponds [2] Liner ponds [3] Concrete ponds [4] Wooden raised ponds [5] Other, specify ________________
Source of fingerlings code C: [1] Government hatchery [2] Private hatchery [3] Farmers [4] Self-production [5] Group/Cluster farm [6] Other, specify________________
Culture period code D: [1] ≤4 months [2] 6 months [3] 6-12 months [4] ≥ 1 year

D7a. What type of aquaculture farming system do you practice? Integrated Aquaculture farmer is defined as a farmer who has a fishpond as part of his/her farming operations and who recycles resources among various enterprises (Please tick only one)
[1] Integrated Aquaculture farming system [2] Sole Aquaculture farming system

D7b. *Ask both adopters and non-adopters*: Are there some enterprises mainly managed by women in your farm (not only fish farming)? [1] Yes [0] No
(Where Enterprises include e.g. fish farming, poultry keeping, diary keeping, crop farming etc)

D7c. If yes to D7b, please state the enterprises managed by women in your farm?
1. ____
2. ____
3. ____
4. ____

Ask D8-D9 to integrated aquaculture farmers only

D8a. Please specify the type of integrated aquaculture farming system you practice. Then list each crop produced and each livestock reared where applicable during the period August 2020-March 2021. *(Livestock include cattle, sheep, goats, poultry, pigs or rabbit).*

(a) [1] Fish-Crop [2] Fish-Livestock [3] Fish-Crop-Livestock [4] Other, specify_____ (*Select only one option*)

(b) Livestock (s) reared (*Multiple response)* ______________

____

(c) i. Crop (s) reared (*Multiple response*)______________

____

D8b. Ask (c) ii and (c) iii. both Integrated Aquaculture farming system and Sole Aquaculture farming system

(c) ii Did the food grown by the family last the entire year? [1] Yes [0] No

(c) iii. If no, which months of the year did the family run short of food? ______________

D9a. (Ask only non-adopters of integrated aquaculture farming system)

If you do not practice integrated aquaculture farming system, are you willing to adopt it in future? [1] Yes [0] No

D9b. If yes please give reasons:

1. ____
2. ____

D9c. If NO please give reasons:

1. ____
2. ____

SECTION E: FARM RECORDS

E1. Do you keep farm records? [1] Yes [0] No

E2. If yes, in what form?

[1] Book [2] Loose Sheet [3] Computer [4] Other, Specify_________________

E3. What type of records do you keep?

[1] Stocking records [2] Feeding records [3] Production [4] Accounting records, [5] Pond fertilization [6] Other records, specify________________

E4. *Enumerator to Observe*: How are the records?

[1] Minimal [2] Medium – some records [3] Good - up to date records [4] Excellent, comprehensive, computer-based records [5] Notes

E5. Enumerator take photo of records

SECTION F: FARM PRODUCTION

F1. With reference to August 2020-March 2021, please indicate the quantity and the total cost of the inputs purchased for production? Probe and ensure ALL inputs are captured (*When filling the table, go row by row).*

		This season is suitable for fish farming due to the favorable temperatures (August 2020-March 2021) Plot size …………………total farm size		
Item/Input	Quantity	Unit	Total (KES)	
Fingerlings 1. Tilapia				
2. Catfish				

3. Other fish species (Specify)				
Fish Feeds (Types, *If applicable)* 1.				
2.				
3.				
4.				
5. Other (Specify)				
Seeds/Crop Seedlings *e.g. spinach, kales, tomatoes etc.* 1.				
2.				
3.				
4.				
5. Other (Specify)				
Livestock **(**cattle, sheep, goats, poultry, pigs or rabbit) 1.				
2.				
3.				
4.				
5. Other (Specify)				
Hay/Napier grass/animal feed				
poultry feeds 1. Poultry Starter Mash				
2. Poultry Grower Feed				
3. Poultry Finisher Feed				
4. Other (Specify)				
Inorganic/Chemical Fertilizers Type; 1. DAP				
2. CAN				
3. Urea				
4. NPK				
5.Other specify				
Organic/Manure				

1. Goat manure				
2. Cow dung manure				
3. Pig manure				
4. Chicken manure				
5. Duck manure				
6. Combination of manure				
7. Other (Specify)				
Lime				
Labor (Family labor)				
1.Ploughing (Number of people)				
2.Number of people planting				
3.Number of people per weeding				
4.Number of weeding				
5.Number of people harvesting				
6.Number of people Threshing/shelling				
7.No. of people other labor, specify				
Labor (Off farm/Hired labor)				
1.Ploughing (Number of people)				
2.Number of people planting				
3.Number of people per weeding				
4.Number of weeding				
5.Number of people harvesting				
6.Number of people Threshing/shelling				
7.No. of people other labor, specify				
Land				
Pesticides (indicate names and quantities below) if applicable/Used 1.Pesticide 1				

2. Pesticide 2				
3. Pesticide 3				
4. Pesticide 4				
5. Pesticide Other (Specify)				
Irrigation				
Herbicide **1.** Herbicide 1				
2. Herbicide 2				
3. Herbicide 3				
Farm Machinery/Equipment repair				
Electricity				
Fuel and lubricant				
Hire of Machinery				
Other, Specify				

F2. Please indicate the quantity (Kg) and value (KES) of each produce harvested, consumed, gifted and or sold between (August 2020-March 2021). *When filling the table, go row by row.*

F2.1. Produce Write the list of all produce before filling in the succeeding columns	F2.2Total Production			F2.3. Own consumption		F2.4. Gift (kg)		F2.5Sales	If yes, F2.5a. who is the buyer type of {produce	F2.6. Who mainly controls the income from each enterprise? (Fill for each enterprise) Code:
	Produce **(kg)**	Qnty (kg)	Total Value (KES)	Quantity in	Value (KES)	Quantity	Value (KES)	F2.5a. Did you sell part of your harvest? 1=Yes 2=No G2.5b. If yes, how much of each product did you sell during the last cycle of production?	1. Company 2. Small traders 3. Large scale traders 4. Hotels /restaurants 5. Consumers/ neighbors 6. Government	

												7. Other, specify	[1] Husband [2] Wife [3] Both Husband and wife [4] Child [5] Other, Specify
									Quantity	(Price	Total Value (Ksh)		
Fish	Tilapia												
	Catfish												
	Other, Specified												
Crop Enterprises	1.												
	2.												
	3.												
	4.												
Livestock Enterprises	1.												
	2.												
	3.												
	4.												
	5.												
	6.												
Other specify…													

SECTION G: INCOME FROM OTHER SOURCES AND USE OF INCOME

G1. Think about **all your household income**, could you please provide an estimate of the contribution of the different household members in total household income in the past 12 months [KES]
[1] Husband [2] Wife [3] Child [4] Other, Specify
[1] Less than 20,000 [2] 20,001- 40,000 [3] 40,001- 60,000 [4] 60,001- 80,000
[5] 80,001-100,000 [6] 100,001- 150,000 [7] 150,001- 200,000 [8] 200,001-300,000
[9] above 300,001

G2. Did any member of the household earn some income from other sources in the past 12 months (*indicate income from all members of the household*) *When filling the table, go row by row.*

S/No	Source	Estimated income/year (KES (in case the income was earned once within a year) [1] Less than 20,000 [2] 20,001- 40,000 [3] 40,001- 60,000 [4] 60,001- 80,000 [5] 80,001-100,000 [6] 100,001- 150,000 [7] 150,001- 200,000 [8] 200,001-300,000 [9] above 300,001	Who mainly controls this other source of income? Code: [1] Husband [2] Wife [3] Both Husband and wife [4] Child [5] Other, Specify
1.	Remittances		
2.	Salaried employment such as civil servant, private sector employee		
3.	Non-farm income e.g. business within the homestead/non agricultural		
4.	Pensions, social welfare grants and insurance payments		
5.	Other, specify		
6	TOTAL		

G3. What do you use your last fish income for? (*two main)*
[1] Reinvest in fish farming operation [2] Invest in crop farming operation [3] Invest in livestock farming operation [4] Pay off debts [5] Purchase food [6] Medical expenses [7] Pay School fees [8] Purchase assets like TV, motor vehicle, motorcycle, Radio, vehicle etc. [9] Other: ____________

SECTION H: ACCESS TO EXTENSION AND ADVISORY SERVICES

H1. What is the distance from your household to the nearest extension office *(Km)* ___________?
H2. What is the distance from your home to the nearest Motorable road/paved road? *(Km)* _____?
H3. What is the distance from your home to the nearest Local food market? *(Km)* ____________?
H4. What is the time taken to the nearest Motorable road? (on foot-walking) *(In mins)* ________?
H5. What is the time taken to the nearest Local food market? (on motor bike) *(In mins)* _________?

Training: Think about the trainings you have had.
H6. How often do extension agents/advisory agents visit your farm?
[1] Never [2] Once a week [3] Once a month [4] Every three months [5] Every six months [6] Once a year [7] On demand
H7a. Have you had any training? REFER TO TOPICS OF TRAINING LIST.

H7b. Topics of training received (list) [1] Yes [0] No	H8. If Yes, who in the household has received the training? [1] Husband [2] Wife [3] Both husband and wife) [4] Child [5] Farm manger [6] Other, specify	H9. If YES, which was the last year training occurred?	H10. If Yes indicate the most important training provider (s) (Codes)	H11. If yes, after receiving the advice, did you follow it or adopt the practices? [1] Yes [0] No	H12. If yes, did you have to pay to receive for this service advice? [1] Yes [0] No	H13. If you paid, how much did you pay? (KES)	H14.Have you trained other farmers [1] Yes [0] No	H15.Is there anything you have modified from the training? [1] Yes [0] No	H16If yes, what have you modified?
Fish pond construction									
Fish breeding and genetics									
Pond Fertilization and Liming									
Fish feed formulation, storage and administration									
Water Quality Management									

Record Keeping and Enterprise Budgeting									
Post-Harvest, Value Addition and Marketing									
Co-operative/group formation and management									
Input usage									
Predator control									
Integrated Aquaculture Farming System									
Credit/microfinance									

H17. Who provided this advice?
[1] County Fisheries Extension Department [2] NGO/CBO/FBO
[3] Research Institutions [4] Input service provider
[5] Universities/Mid-level Colleges [6] Micro finance institution
[7] Farmer Organizations [8] Neighbors / family / friends in village
[9] Neighbors / family / friends outside village [10] Other (specify)
H18. In future, are you willing to pay for your own training in aquaculture?
[1] Yes [0] No
H18. If yes, why? (multiple response)
[1] For increased profits [2] For increased yields [3] For Adoption of new technologies [4] To Increase financial capability [5] Other (specify)____________________

***Ask both adopters and non-adopters*: Information on integrated aquaculture farming system**

H19. Have you heard or do you know any farmer who is practicing integrated aquaculture farming system? [1] Yes [0] No
H20. Do you think it is necessary to have training on integrated fish farming? [1] Yes [0] No
H21. Are you willing to pay for your own training on integrated fish farming? [1] Yes [0] No
H22a. Has the adoption of integrated aquaculture farming system' affected women in any way in this area? [1] Yes [0] No

H22b. If yes, to question, I19a how so? Please list
1. ____
2. ____
3. ____

SECTION I: ACCESS TO INSITUTIONAL AND SUPPORT SERVICES

I1. Do you or any member of your household belong to a farmer's association /Co-operative?
[1] Yes[0] No
I2. If yes, what motivated you to join? *Mention three reasons*
1. ____
2. ____
3. ____
I3. What type of a farmer's association /Co-operative does you /household member belong? *Tick all that apply*
[1] Agricultural (crop/livestock/fish) [2] Credit/savings group/merry go-round
[3] Traders/business group [4] Community based/neighborhood group
[5] Self-help [6] Other, specify
I4. How many members are in the association /Co-operative?

Men	Women	Total

I5. If yes, when did you join the association/cooperative? *Indicate month and year*_____________
I6. When was the cooperative/association formed? *Indicate month and year* _________________
I7. Did you pay for registration/subscription fee to join? [1] Yes [0] No
I8. If Yes, how much KES annually? _ ________________________
I9a. Is there an annual renewal charge? [1] Yes [0] No
I9b. If YES, how much KES annually? ___________________
I10a. Do you or any member of your household hold any position in the association /Co-operative? [1] Yes [0] No
I10b. Which position do you hold? [1] Chairman [2] Treasurer [3] Secretary
I11. Do you feel represented by the leadership of the group?
[1] fully [2] somewhat [3] almost never [4] never
I12. Does the farmer's association /Co-operative consult on common strategies? [1] Yes [0] No
I13. How many group meetings do you have per year? *Indicate number* ___________________

I14. Do you think you have benefited from joining the association /Co-operative? [1] Yes [0] No
I15. If yes, what are the main benefits have you accrued from the farmer's associations /Co-operatives?
[1] Access to credit
[3] Have better access to markets [4] Training and skill development
[5] Joint purchase of inputs [6] Access to training and extension services
[7] Learn new methods of farming [8] Policy lobbying/advocacy
[9] Collective production activities (labor [10] Better prices
[12] Low cost of transport [13] Other ____________________
I20. Do you sell your farm produce as a group? [1] Yes [0] No
I16. If no, why?
1. ____
2. ____

I17. What are the major bottlenecks encountered in implementing your collective action activities?
1. ____
2. ____
3. ____
I18. How do you view the future of the group in five years?
[1] Group will still be here in 5 years,
[2] Group will probably will be here in 5 years
[3] Group will probably not be here in 5 years,
[4] Group will definitely not be here in 5 years
I19a. If no to I1, please tell me why neither you nor any member of your household does not belong to a farmer's association /Co-operative?
1. ____
2. ____
3. ____
I19b. Do you plan to join any farmer's association /Co-operative? [1] Yes [0] No

Financial Liabilities
Let me now ask you about your current financial situation.
I20. Does this household have any outstanding loans? [*Probe for formal and informal loans*]

[1] Yes[0] No, *if no skip to I31*
I21. When did you borrow the loan? *Indicate month and year* ___________
I22. Does this loan have any interest? [1] Yes [0] No
I23. If yes, is the interest monthly or annual? [1] Monthly [0] Annual
I24. What is the interest rate? ______________ *allow decimal point*
I25. Who in the household received the credit/loan?
[1] Husband [2] Wife [3] Joint husband and wife [4] Other, specify _______________
I26. What was the source of credit?
[1] Commercial Bank [2] Microfinance Institution /SACCO
[3] NGO/CBO/FBO [4] Producer Association / Cooperative
[5] Family / friends [6] Input provider
[7] Informal credit/merry go round [8] Mobile money [9] Other, specify _______________
I27. What is the repayment period (at start of loan) (months)? ____________
I28. What collateral was required?
[1] None [2] livestock [3] land [4] household items [5] crop harvest [6] fish harvest [7] Other, specify
I29. Did you receive the amount asked for? [1] Yes [0] No
I30. What did you or any other household member use the credit for? *Choose all that apply*
[1] Purchase Food [2] Purchase inputs for aquaculture/agriculture
[3] Doctor / Medicine [4] Special occasion (wedding / funeral / birth / etc.)
[5] Purchase other goods [6] Purchase inputs for business
[7] Purchase land [8] Education/School Fees
[9] Build / reconstruct house [10] Solve family quarrel
[11] Buy motorbike [12] Migrate
[13] Pay debts [14] Other specify ___________________
I31. Why did you not request for credit? (*Single selection*)
[1] Do not need [2] Too expensive
[3] Cannot pay back [4] Do not have collateral
[5] Do not want to risk collateral [6] Too complicated
[7] Do not know where to request [8] Will not get it (still in debts) [9] Other (specify) _____________

SECTION J: FARMERS KNOWLEDGE, ATTITUDE AND PRACTICE OF PRODUCTION

J1. For each statement below, please rate the level to which you agree or disagree with regards to your understanding of production risk. *When filling the table, go row by row. The section should be made compulsory*

S/No	Attitudinal Statements	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)
1.	I am confident that there are various risks and uncertainties in production					
2.	I feel that the severity of individual risks differs among individuals and are likely to change depending on when each is encountered during the production cycle					
3.	For me, production risk relates to the possibility that the yield/output levels could be lower than the projected.					
4.	For me, sound and updated information that is relevant for farming to control for production risk is a good idea					
5.	I feel that a farmer willing to adopt new proven production practices has a less risk association to production loss					

J2. For each statement below, please rate the level to which you agree or disagree with each statement below.

S/No	Subjective norm Statements	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strong Agree (5)
1.	My family think that I am more willing to adopt aquacultural innovations (new					

	ways of doing things) compared to other people					
2.	My friends think that I am reluctant to adopt aquacultural innovations, until I see their advantages and disadvantages from farmers around me					
3.	Professionals in the field think that to implement my farm plan goals, it is important for me to take more risks than others					
4.	My peers think that I avoid decisions which will bring severe losses or high profits in the next production cycle					
5.	My family thinks that I am concerned with an existing profit more than several predicted and non-guaranteed profit					
6.	Most people whose opinion I value think that I should take my farm decisions without hesitation regardless of their probable risks					
7.	Before I take high risk probability decisions, I prefer to discuss them with my family					

J3. Please indicate how likely you would be to do the following

S/No	**Intentions**	**Strongly disagree (1)**	**Disagree (2)**	**Neutral (3)**	**Agree (4)**	**Strong Agree (5)**
1.	I plan to diversify my production to help lower production risks					

2.	I intend to diversify my income sources in order to lower the effect of a negative shock to any one of my other incomes					
3.	I expect to have Extension contact and attend training to control production risk through having up to date farming information					
4.	I intend to have the requisite technical skills/knowledge and management practices and applying them in production					
5.	I plan to use quality seeds from authenticated suppliers					
6.	I intend to get into a group to mitigate risk					
7.	I will make an effort to reallocate my labor resources to off-farm labor activities in the next production cycle					

SECTION K: HOUSEHOLD FOOD SECURITY SCORE (FCS)

AND DIETARY DIVERSITY SCORE (HDDS)

I now kindly ask you about the different types of food that the adults and children in your household have eaten in the past 7 days and last 24hours. *When filling the table, go row by row.*Food Group and Food list	K1. How **many days over the last 7 days** did **adults (18 and above)** in your household eat these foods prepared and/or consumed at home (Indicate number of days)	K2. What was the **main source of food** for the past 7days? Source of food codes [1] Own production [2] Purchase (cash) [3] Purchase (credit) [4] Food assistance [5] Gifts [6] Exchange for labor [7] Beg [8] Others, specify	K3. Did adults of your household eat these foods **yesterday** during the day and at night? [1] Yes [0] No	K4. How **many days over the last 7 days** did **children 6-23 months** in your household eat these foods prepared and/or consumed at home (Indicate number of days) IF HH DOESN'T HAVE CHILDREN 6-23, CODE '99'	K5. What was the **main source of food** for the past 7days? Source of food codes [1] Own production [2] Purchase (cash) [3] Purchase (credit) [4] Food assistance [5] Gifts [6] Exchange for labor [7] Beg [8] Others, specify	K6. How **many days over the last 7 days** did **children 24-59 months** in your household eat these foods prepared and/or consumed at home (Indicate number of days) IF HH DOESN'T HAVE CHILDREN 24-59, CODE '99'	K7. What was the **main source of food** for the past 7days? Source of food codes [1] Own production [2] Purchase (cash) [3] Purchase (credit) [4] Food assistance [5] Gifts [6] Exchange for labor [7] Beg [8] Others, specify	K8. Did **children 0-59 months** of your household eat these foods **yesterday** during the day and at night? [1] Yes [0] No IF HH DOESN'T CHILDREN 0-59, CODE '99'

1	**Cereals & grains:** Ugali, Githeri, mukimo, motokoi, noodles, spaghettis, biscuits, bread, mandazis and others								
2	**Roots & Tubers:** potatoes, yams, cassava, white flesh sweet potatoes,								
3	**Legumes& nuts:** Beans, soy, pigeon pea, peanuts, lentils (Kamande),								
4	**Orange veges (Rich in Vit. A):** Carrots, red/yellow pepper (hoho), pumpkin, orange sweet potatoes.								
5	**Greeny leafy veges:** Spinach, broccoli, amaranth, cassava leaves/other dark green leaves**.**								
6	**Other vegetables:** Onions, tomatoes, cucumber, radishes, green beans, peas (minji), French beans (muchiri), lettuce, cabbage								

7	**Orange fruits (Rich in Vit.A)**: Mangoes, papaya, passion fruits, kiwi, apricot, peach, loquates, melon, guavas.								
8	**Other fruits:** Pears, banana, apple, lemon, tangerine, pineapple, plums, grapes, pears, others								
9	**Meat:** Goat, beef, chicken, pork (in large quantities, not as condiments)								
10	Organ meat (Rich in hem iron): Liver, kidney, heart and/or other organ meats								
11	**Fish/shellfish:** Fish (including canned tuna, in large quantities, not as condiments) (Specify source) i.e. Cultured, captured (Wild) or Imported fish								
12	Eggs								

13	**Milk &dairy products:** Fresh milk, yoghurt, cheese and other dairy products (exclude margarine, butter /small amounts of milk for tea and coffee)								
14	**Oil/fat/butter:** Vegetable oil, margarine, palm oil, shea butter and other fats/oils.								
15	**Sugar/sweets:** Sugar, honey, jam, cakes, cookies, pastries and other sugary drinks.								
16	**Condiments/spice:** Tea, coffee, cocoa, salt, garlic, yeast /backing powder, tomato sauce, meat /fish condiments, others								

K9. I would like to know more about how you mainly consume your fish. Please select: [1] Dried [2] Fresh [3] Smoked [4] Fried [5] Frozen [6] Filleted

K10. Where do you mostly source your fish from? [1] Wild caught [2] Cage reared fish [3] Pond reared fish [4] Imported (frozen) fish (specify where) _________

SECTION L: COMMUNITY BASED NUTRITION PROGRAMMES

CHILD HEALTH AND ANTHROPOMETRY

L1. Measure all children younger than 5 years of age. In case the household has more than one child, please repeat this for every eligible child under 5 years of age *When filling the table, go row by row.*

L2. How many children under 5 are in this household?

Child's List as child 1,2,3 etc.	Child Age	Where was [] delivered? [1] Hospital [2] Health center [3] Clinic/ dispensary [4] Maternity home [5] At home [6] Other specify	Who assisted in []'s delivery? [1] Doctor [2] Midwife/Nurse [3] Traditional Birth Attendance [4] Trained Traditional Birth Attendant [5] Self	Has [] ever breastfed? [1] yes [0] no	How long after birth was [] first put to breast? [1] Immediately [1] Hours [1] Days (Indicate days)	Is this child still breast feeding? [1] yes [0] no	For how long was [] breastfed? Fill in the Completed Months	For how many months was [] exclusively breastfed? Fill in the Completed Months	What FIRST supplement was [] given [1] Milk Other Than Breast [2] Commercial Infant Food/ Formula [3] Porridge [4] Fortified Porridge	Has [] ever participated in any community nutrition programs? [1] yes [0] no	Has [] participated in the Growth Monitoring Clinic? [1] yes [0] no	Has [] had diarrhea in the last 14 days? [1] yes [0] no	What type of Fluid/Food was [] given during diarrhea? **Food** [1] Nothing [2] Commercial infant/food/formula/yoghurt [3] Semi solids foods [4] Fruits [1] Other, specify **Fluids** [1] Nothing [2] Breast milk [3] Porridge [4] Water only [5] Milk other than breast milk	Weight (kg)	Height (cm)	How was this child's height measured? (Code A)

			[6] Other, specif y						[5] Semi-Solids [6] Water [7] Other				[] Other, specify			

Measurement (Code A) [1] Lying down [2] Standing up [3] No measurement was taken

L3. Reason for not being measured?

[1] Not at home during survey period [2] Too ill [3] Unwilling [4] Other, specify

L4. When you are not home or cannot feed the baby yourself, who does it?

[1] Husband [2] Grandmother [3] Other children [4] Other, Specify

SECTION M: HOUSEHOLD ASSETS

M1. Please allow me to ask you a few questions on the household items. Some of these items are important for agricultural development while others are purely for the welfare of the household members. Please confirm whether you own the following assets and estimate their number and current value. The current value is estimated as the price the asset would fetch if sold now in its current state.

No	**Asset**	**Qty How many?**	**Total Current value (KES)**	**No**	**Asset**	**Qty**	**Total Current value (KES)**
	HOUSEHOLD ITEMS				Fishing equipment e.g. seine nets, waders etc.		
	Gas/electric cooker				Screens on water inlet/outlet		
	Refrigerator				Grinding machine		
	Radio				Wheel barrow		
	Television				Weighing machine		
	Generator				Solar panels		
	Pressing iron				Water pump		
	Fan				Spray pump		
	Computer				Irrigation equipment		
	Blender				Water tanks		
	Deep freezer				Sewing/knitting machine		
	Wall clock				Mobile phone		
	Bed				Poultry houses		
	Buckets				Power saw		
	Mobile phone				Fenced farm		
	Sofa set				Pond cover/cover nets		
	Sewing machine				Stores		
	Mosquito nets				Houses (residential)		

	TRANSPORT				Borehole		
	Truck				Well		
	Car				FOOD		
	Motorcycle				Maize		
	Bicycle				Beans		
	Cart (Animal drawn)				Nuts		
					Dried fish/value added fish/processed fish		
	Farm implements				Potatoes		
	Animal traction plough				Peas		
	Water trough				Dried meat		
	Tractor				Dried fruits		
					Bottled water		
					Sweet potatoes		
					Chicken		

SECTION N: LIVELIHOOD INFORMATION

N1. Finally, have the following indicators improved, decreased, or not changed since you started participating in sole aquaculture/integrated aquaculture farming activities *(tick appropriately, probe and record) When filling the table, go row by row.*

S/N	Indicators	Improved	Decreased	No change
1.	Fish consumption			
2.	Consumption of other food crops/vegetables			
3.	Consumption of other animal protein e.g. beef, mutton etc.			
4.	Incomes and profits			
5.	Yield (Fish/Crop/Livestock)			
6.	Technology adoption (aquaculture)			
7.	Market linkages (crop/fish/livestock)			
8.	Collaboration and partnership e.g. groups/associations etc.			
9.	Housing (type)			
10.	Payment of school fee			
11.	Enterprise diversification			

12.	Possession of household assets such as TV, motor vehicle, motorcycle, Radio, vehicle etc.			
13.	Social status			
14.	Any other (specify)			

THANK YOU FOR YOUR TIME!

Appendix 6: Instrumental Variables Validation Test (OLS)

Var	Mean	Variance	Skewness	Kurtosis	Net Income	Productivity
Inst_Var_Adoption	0.25***	-0.57***	-0.89***	-3.11***	0.50***	-0.00*
	(0.07)	(0.21)	(0.18)	(0.79)	(0.04)	(0.00)
Age	0.00	-0.00	-0.01**	-0.06***	-0.01***	2.76e-05
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(2.50e-05)
Education	0.03	0.02	0.05	0.37	-0.40***	0.00
	(0.02)	(0.05)	(0.06)	(0.24)	(0.01)	(0.00)
Econ Active	0.36***	0.31	-1.33***	0.90	2.60***	0.00
	(0.12)	(0.28)	(0.29)	(1.26)	(0.06)	(0.00)
Gender	-0.00	-0.28**	-0.74***	-3.95***	-0.43***	-0.00
	(0.06)	(0.13)	(0.14)	(0.59)	(0.03)	(0.00)
Farm Size	-0.03**	-0.06*	-0.08***	0.04	-0.10***	-0.00*
	(0.01)	(0.04)	(0.03)	(0.13)	(0.01)	(0.00)
Land Own	-0.45***	0.45***	0.49***	1.50*	-2.84***	-0.00
	(0.08)	(0.16)	(0.19)	(0.80)	(0.04)	(0.00)
Credit	0.03	0.22	0.63***	2.82***	1.23***	0.00
	(0.07)	(0.15)	(0.16)	(0.69)	(0.04)	(0.00)
IAA Aware	0.04	0.48***	0.14	-0.89	0.56***	-0.00***
	(0.06)	(0.14)	(0.16)	(0.67)	(0.03)	(0.00)
Mark_Dist	-0.00	-0.01	-0.01	-0.07	0.12***	-8.73e-05
	(0.01)	(0.01)	(0.01)	(0.06)	(01)	(0.00)
Per_Land_R	0.07***	0.23***	0.02	-0.41	0.88***	0.00*
	(0.03)	(0.08)	(0.06)	(0.27)	(0.01)	(0.00)
Num_Farm_Entep	0.09**	-0.39***	-0.19*	0.15	0.01	0.00
	(0.04)	(0.09)	(0.01)	(0.43)	(0.02)	(0.00)
Access_Irrig	0.42***	-0.07	-0.25	-0.50	0.38***	0.00***
	(0.06)	(0.15)	(0.16)	(0.68)	(0.04)	(0.00)
Wetland	-0.08	0.35**	0.64***	2.41***	1.77***	0.00
	(0.07)	(0.17)	(0.17)	(0.75)	(0.04)	(0.00)
Water_Source	0.06	0.14	0.16	-0.89	0.64***	-0.00
	(0.06)	(0.14)	(0.16)	(0.69)	(0.04)	(0.00)
Farm_Topography	-0.29***	-0.49***	-0.97***	-4.57***	-2.09***	-0.00**
	(0.07)	(0.17)	(0.17)	(0.75)	(0.04)	(0.00)
Soil_Type	-0.02	0.17	0.55***	-0.27	-2.30***	-0.00***
	(0.07)	(0.16)	(0.17)	(0.72)	(0.04)	(0.00)

Land_Type	0.01	-0.12	0.41*	1.33*	0.92***	-0.00***
	(0.07)	(0.15)	(0.16)	(0.69)	(0.04)	(0.00)
Ln_Seed_Input	0.08***	-0.00	-0.03	-0.23	0.62***	0.00*
	(0.03)	(0.06)	(0.07)	(0.29)	(0.02)	(0.00)
Ln_Labor_Input	0.07**	0.03	0.16*	0.65**	-0.89***	-0.00
	(0.03)	(0.05)	(0.07)	(0.31)	(0.02)	(0.00)
Ln_Chem_Fert_Input	0.08***	-0.02	-0.10***	-0.23*	-0.13***	-0.00**
	(0.01)	(0.03)	(0.03)	(0.13)	(0.01)	(0.00)
Ln_Organ_Fert_Input	-0.06***	-0.06**	-0.04	0.10	-0.68***	-0.00***
	(0.01)	(0.03)	(0.03)	(0.12)	(0.01)	(0.00)
Ln_Land_Input	0.20***	0.32**	0.20*	0.18	0.88***	0.00
	(0.05)	(0.14)	(0.11)	(0.48)	(0.02)	(0.00)
Ln_Capital_Input	0.04***	0.08***	0.10***	0.28***	-0.06***	0.00***
	(0.01)	(0.02)	(0.02)	(0.08)	(0.00)	(0.00)
Ln_Irrigation_Input	-0.04***	0.06***	0.13***	0.63***	-0.51***	-0.00
	(0.01)	(0.02)	(0.03)	(0.11)	(0.01)	(0.00)
Constant	10.15***	11.61***	2.43***	10.37***	9.58***	0.01
	(0.29)	(0.66)	(0.72)	(3.11)	(0.15)	(0.01)
Observations	784	420	784	784	784	784
R-squared	0.48	0.52	0.47	0.44	0.50	0.37

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Inst_Var_Adoption is statistically significant for all the models. This is the instrumental variable used in the ESR model identification.

Appendix 7: Quantity and Value of Fish Landings 2017 – 2021

	2017		2018		2019		2020		2021	
Fresh Water	**M. Tons**	**Value '000 KES**	**M. Tons**	**Value '000 KES**	**M. Tons**	**Value '000 KES**	**M. Tons**	**Value '000 KES**	**M. Tons**	**Value '000 KES**
Lake Victoria	92,727	13,976,586	98,150	14,487,650	90,743	11,640,537	88,223	12,687,298	94,349	14,082,375
Lake Turkana	4,021	486,540	7,587	564,739	7,031	645,107	13,190	1,177,193	15,644	1,478,953
Lake Naivasha	1,689	222,579	2,287	287,194	3,087	391,719	2,216	238,638	1,804	216,974
Lake Baringo	155	46,606	145	43,442	203	49,499	162	39,502	406	118,590
Lake Jipe	112	21,756	131	38,260	157	45,957	197	57,549	227	66,051
Lake Kanyaboli	127	26,346	203	29,656	300	43,826	264	60,201	286	70,074
Lake Kenyatta	45	3,473	14	1,330	32	2,725	72	7,295	68	6,816
Tana River Dams	422	84,500	297	37,373	394	60,571	283	50,960	197	28,563
Tana River Delta	115	9,296	46	5,069	202	17,595	158	20,360	135	13,048
Aquaculture	12,356	3,691,046	15,120	4,480,875	18,542	5,581,142	19,945	6,303,617	20,973	6,711,360
Turkwel	35	9,905	34	9,822	50	12,850	107	16,112	98	14,750
Riverine	10	2,368	320	86,400	380	106,371	411	115,049	393	109,454
Small Dams	300	75,120	339	42,015	459	126,455	358	95,022	380	83,465
Total Fresh Water	**112,114**	**18,656,121**	**124,673**	**20,113,825**	**121,580**	**18,724,354**	**125,586**	**20,868,796**	**136,326**	**23,335,961**
Marine (Artisanal)	23,286	4,375,822	23,145	4,246,962	25,670	4,477,577	23,684	4,831,948	25,380	5,491,800
Mariculture	51	1,530	64	1,920	76	1,895	85	2,119	103	2,568
Industrial (Marine)										
Shallow prawn trawl fishery	346	115,486	520	189,605	535	185,900	273	177,446	330	115,231
Deep water trawl fishery	41	9,102	10	42,341	626	170,089	943	518,385	1,026	350,933
Deep water crab pottery	-	-	1	251	38	19,072	86	71,295	137	119,680
Deep sea longlining	62	1,788	508	20,362	795	30,759	670	26,855	432.6	170,965
Total Industrial	**449**	**126,376**	**1,039**	**252,559**	**1,994**	**405,820**	**1,972**	**793,981**	**1,926**	**756,809**
Marine Aquarium		28,701		42,414		38,575		34,516		809,219
Total Marine	**23,786**	**4,532,429**	**24,248**	**4,543,855**	**27,740**	**4,923,867**	**25,741**	**5,662,564**	**27,409**	**7,060,396**
Grand Total	**135,900**	**23,188,550**	**148,921**	**24,657,680**	**149,320**	**23,648,221**	**151,327**	**26,531,360**	**163,735**	**30,396,357**
EXPORTS										
Fish and fish products	3,554	2,253,644	7,250	2,974,980	8,821	3,407,548	8,387	2,740,678	10,782	3,412,116
Aquarium fish (Numbers)	323,691	22,866	366,776	34,241	297,367	31,219	272,696	27,583	498,908	609,668
Aquarium invertebrates (Numbers)	176,130	5,835	191,672	8,173	133,844	7,356	124,856	6,933	350,309	199,551
TOTAL		**2,282,345**		**3,017,394**		**3,446,123**		**2,775,194**		**4,221,335**
Imports	19,127	1,568,565	26,383	2,974,678	22,813	2,798,951	19,892	2,251,861	19,601	2,478,751

Balance of Trade		**713,780**		**42,716**		**647,172**		**523,333**		**1,742,584**

Appendix 8: List of Conferences Attended


THE WORLD BANK

Kenya Climate Smart Agriculture Project

Certificate of Participation

This is to certify that

Fonda Jane Awuor

Actively Participated as a Poster Paper Presenter in
the Kenya Climate Smart Agriculture Project (KCSAP) Scientific Conference

Venue: Lake Naivasha Resort
Dates: 22nd - 26th November 2021

Steering Committee Chairperson

KCSAP National Coordinator

Website: www.kcsap.go.ke

INTERNATIONAL YEAR OF
ARTISANAL FISHERIES AND AQUACULTURE
2022

THE INTERNATIONAL CONFERENCE ON
ARTISANAL FISHERIES & AQUACULTURE
(ICAFA) **2022**

"**Breaking new grounds** to recognize and celebrate the contribution of **small scale fisheries** towards **food security** and nutrition"

CERTIFICATE
OF APPRECIATION

PROUDLY PRESENTED TO

Fonda Jane Awuor

For his/her contribution in THE INTERNATIONAL CONFERENCE ON ARTISANAL FISHERIES & AQUACULTURE (ICAFA) 2022

Signature Organiser

02-09-2022
DATE

Appendix 9: List of Publications

1. Awuor, F. J., Macharia, I. N., & Mulwa, R. M. (2023). Adoption and intensity of integrated agriculture aquaculture among smallholder fish farmers in Kenya. Frontiers in Sustainable Food Systems, 7, 1181502. https://doi.org/10.3389/fsufs.2023.1181502
2. Awuor, F.J., Macharia, I.N., Mulwa, R.M. et al. Adoption and impact of integrated agriculture aquaculture on income and productivity of smallholder fish farmers in Kenya. SN Bus Econ 4, 18 (2024). https://doi.org/10.1007/s43546-023-00607-0