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Assessing Impact of Fertilizer Adoption in Boosting Small Scale Crop Farming Productivity in Sub-Saharan Africa

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Abstract

The study examined the determinants of fertilizer adoption among small scale crop farmers across Sub-Saharan Africa's regions using a probit regression model and propensity score matching (PSM) technique to assess productivity impacts. Variables analyzed include land tenure, access to credit, access to fertilizer, gender, age, farm size, education, household size, expenditure, and other income sources. Data was obtained from households' survey data for selected sub-Saharan countries. The countries were also categorized as arid, semi-arid, and non-arid regions. Findings indicated that access to fertilizer increases adoption across all zones, for example by 36.1% in arid areas at 95% confidence level. Access to credit is also significant at 95% confidence level in arid regions, boosting adoption by 6.2%. Land tenure positively affects adoption in semi-arid regions but is insignificant in arid and non-arid areas. Education levels and household expenditure show mixed effects; secondary education negatively affects adoption in arid zones, while higher household expenditure reduces adoption likelihood in semi-arid regions. The PSM analysis conducted showed that fertilizer adoption leads to increased productivity, with adopters experiencing yield increases between 195 kg/acre and 261 kg/acre compared to non-adopters. Policy recommendations to improve fertilizer adoption include enhancing supply chains for timely and affordable access, expanding financial services for smallholder farmers, securing land tenure, and providing targeted education and training programs. These strategies are expected to boost agricultural productivity and smallholder's farmer livelihoods in arid and semi-arid regions. The study emphasizes on the critical role of fertilizer access in boosting productivity for smallholder farmers and provides actionable insights for policymakers to improve agricultural outcomes in challenging environments.

JEL Codes: O13, Q12, Q16

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1. Introduction

Background

Capitalizing on fertilizer adoption to boost productivity in small-scale crop farming within Sub-Saharan communities has become an important area of research and practice. Small-scale farmers are defined as those with a low asset base and who cultivate less than 2 hectares of cropland (World Bank, 2003). However, some scholars have broadened this definition to include farmers with less capital and restricted access to production factors such as inputs (Sienso et al., 2013). Although these elements can inform the definition of smallholder farmers, in the African context, landholding is the primary criterion employed (Rapsomanikis, 2015; Salami et al., 2010). In this study, smallholder farmers are defined as those who own five acres (2 ha) or less. In general, smallholders are distinguished by family-centered objectives, for example prioritizing the stability of the household farming system, mainly using family labor for production, and using a portion of the produce for family consumption.

Sub-Saharan Africa faces challenging environmental conditions, for example scarce water resources, unpredictable rainfall patterns, and harsh climates. These challenges constrain agricultural activities for mostly smallholder farmers. Arid regions in the sub-Saharan Africa, characterized by communal land ownership mainly employed for nomadic activities, contribute to additional challenges facing small-scale crop farming. These conditions make it difficult to implement mechanized farming techniques, thus sabotaging an efficient cultivation process. The livelihoods and food security of communities in these areas heavily rely on small-scale farming and livestock production. This makes it critical for researchers and policy makers to investigate innovative approaches to overcome these challenges.

Sub-Saharan Africa, home to over 950 million people or about 13% of the global population, is projected to see its share to global population rise to nearly 22% or 2.1 billion by 2050. Undernourishment has been a persistent issue, though it has decreased from 33% in 1990-92 to 23% in 2014-16. Despite this progress, the region still has the highest undernourishment rates among developing areas (FAO, IFAD, and WFP, 2015). The slow progress toward food security has been attributed to the low productivity of agricultural resources, high population growth rates, political instability, and civil strife. Despite progress, significant regional differences persist. Success in countries with stable political conditions, economic growth, and expanding agricultural sectors indicates that effective governance, strong institutional capacities, and sound policies can sustainably improve food security.

Small Scale Crop Farming and Fertilizer Adoption

The adoption of fertilizer presents promising solutions to address the unique needs of Sub-Saharan countries and communities and improve small-scale crop farming productivity. The utilization of various technological advancements and adapting them to the region's specific conditions, small-scale farmers will optimize resource use, improve farming practices, and increase productivity (Adam & Olsen, 2021). This approach ensures food security for these communities and contributes to their economic growth and resilience against environmental uncertainties.

Governments in Sub-Saharan Africa have implemented various measures to improve fertilizer adoption among small-scale farmers to boost agricultural productivity. Some of the initiatives in Sub-Saharan Africa include Nigeria's Growth Enhancement Support Scheme (GESS) which provides subsidized fertilizers directly to farmers through an e-wallet system, Malawi's Farm Input Subsidy Program (FISP) which offers subsidies on fertilizers and seeds to smallholder farmers, Ghana's Planting for Food and Jobs (PFJ) which supplies subsidized fertilizers and improved seeds along with extension services to farmers, and Zambia's Farmer Input Support Program (FISP) which delivers subsidized fertilizers and seeds to enhance agricultural output

Furthermore, research institutions such as the International Institute of Tropical Agriculture (IITA), Kenya Agricultural and Livestock Research Organization (KALRO), Ethiopian Institute of Agricultural Research (EIAR), and Ghana's Council for Scientific and Industrial Research (CSIR) have been instrumental in agricultural research and the development of appropriate fertilizer formulations tailored to the specific regions in SSA focusing mainly on soil fertility, crop improvement, and efficient fertilizer use. Also, various partnerships for example the Africa Fertilizer Agribusiness Partnership (AFAP) and the Alliance for a Green Revolution in Africa (AGRA) support these efforts, alongside regional initiatives under the African Union's Comprehensive Africa Agriculture Development Programme (CAADP), an Agenda 2063 continental initiative aimed at helping African countries eliminate hunger and reduce poverty by promoting economic growth through agriculture-led development. Furthermore, the governments through Fertilizer Subsidy Programs have implemented fertilizer subsidy programs targeting small-scale farmers. These programs provide subsidized or free fertilizer to farmers, making it more affordable and accessible.

The Sub-Saharan regional governments have also implemented policies. For example, the Kenya’s National Agricultural Soil Management Policy (NASMP), which was developed in 2020 by the Ministry of Agriculture, Livestock, Fisheries and Cooperatives. This policy proposes a wide range of measures and actions responding to key agricultural soil issues and challenges, including improving the accessibility and affordability of fertilizers, granting tax exemptions, and incentives such as training and capacity building by the State Department for Crop development which has enhanced farmer competence in fertilizer application. The various governments have facilitated the development and adoption of fertilizer suitable for farming in Sub-Sahara. In this study we will look at how fertilizer has been adopted in Sub-Saharan regions and their impact on crop farming.

Therefore, to fully unlock the potential of fertilizer adoption in small-scale crop farming within Sub-Sahara country communities, it is critical to address various factors, including affordability, accessibility, and cultural suitability of the technological solutions. Furthermore, knowledge gaps exist in understanding the specific needs and requirements of Sub-Sahara communities, as well as the socio-economic and environmental impacts of fertilizer adoption in these contexts.

The problem Statement.

Small-scale crop farming in Sub-Sahara faces low productivity compared to other parts of the world. This region's agricultural productivity is hindered by various challenges, including inadequate accessibility to modern technologies, fragmented supply chains, and reliance on traditional farming methods. On average, yields for staple crops in SSA are about half of those in Asia and Latin America. For example, maize yields in SSA are around 1.9 tons per hectare, compared to over 4 tons per hectare in South America and Asia (World Bank, 2022). Sub-Saharan Africa (SSA) relies heavily on agriculture, forestry, and fishing as these sectors contribute significantly to its GDP, accounting for about 17.3% in 2022 (World Bank, 2023). In contrast, regions such as Northern America and Europe show much lower contributions of only around 1-2% to GDP from these sectors. Despite its significant contribution to SSA's economy, the region's share of global agricultural value added remains comparatively small. For example, Asia dominates the global agricultural sector, contributing approximately 65% of the world's total value added in agriculture, forestry, and fishing. Sub-Saharan countries being bottom producing less than 5 Per cent of the world's total agricultural production (FAO, 2022). In contrast, Asia dominates the sector, contributing approximately 65% to the global agricultural value added. The low productivity may lead to food insecurity. However, fertilizer technology adoption has the potential to improve productivity and increase the resilience of small-scale crop farmers in these regions.

In Sub-Saharan Africa (SSA), small farms generate approximately 35% of the agricultural income, equating to about $124.74 billion USD annually, given the total agricultural value of about $356.4 billion USD for the region. In contrast, large firms, making up less than 20% of the farming units, account for around 65% of the agricultural income, or about $234.66 billion USD annually (World Bank, 2024). This shows the potential of small-scale farmers. Despite this potential, small-scale crop farming in Sub-Saharan Africa is not effectively leveraging technological innovations that could increase yields. This inefficiency may stem from limited access to information, resources, infrastructure, and barriers such as a lack of technical skills and knowledge. Furthermore, communal land ownership in certain Sub-Saharan countries introduces further complexities to small-scale farming endeavors. Therefore, this research aims to identify and address the specific challenges facing small-scale crop farmers in Sub-Saharan Africa and explore how fertilizer adoption can be harnessed to improve productivity, sustainability, and livelihoods. The study focuses on fertilizer because of its critical role in enhancing soil fertility, crop yields, and long-term sustainability. While other inputs like improved seeds are important, the decision to concentrate on fertilizer adoption is based on its relevance to Sub-Saharan conditions, where soil fertility is often a limiting factor.

Objectives

1.3.1 General Objective

The general objective of the study was to assess the impact of fertilizer adoption on small-scale crop farming productivity in Sub-Sahara of Africa.

1.3.2 Specific Objectives

The specific objectives were;

i. To determine factors influencing the adoption of fertilizer technology in Sub-Sahara.
ii. To evaluate the impact of fertilizer adoption on crop yield of small-scale crop farmers in Sub-Sahara of Africa.

Motivation of the study

The motivation behind conducting this study stems from the urgent need to address the persistent challenges faced by small-scale crop farmers in Africa's Sub-Sahara. Sub-Saharan Africa (SSA) faces challenges in agricultural productivity, with small-scale farmers constituting the majority of agricultural producers. These farmers often operate under conditions of low productivity due to various constraints such as limited access to modern inputs, including fertilizers. Fertilizers play a critical role in enhancing soil fertility, which is often depleted in many parts of SSA, thereby directly impacting crop yields. These SSA regions are also characterized by arid and semi-arid climatic conditions, where agriculture is particularly vulnerable to the impacts of climate change, water scarcity and limited vegetation and organic matter input into the soil which is critical for maintaining soil fertility. As a result, small-scale crop farmers in Sub-Sahara often encounter low crop yields, reduced income, and food insecurity, perpetuating the cycle of poverty and stifling overall socio-economic development.

Furthermore, traditional farming methods in Sub-Saharan Africa are inadequate to meet the increasing demand for food and the requirements of sustainable agricultural systems. Embracing fertilizer adoption can enhance crop productivity, optimize resource management, and bolster resilience against environmental challenges, thereby facilitating the transformation of small-scale farming into a sustainable and prosperous livelihood.

Scope of the study

This study involves an assessment of the potential of fertilizer adoption to enhance the productivity of small-scale crop farming within the challenging context of the selected 29 Sub-Sahara countries (World Bank, 2022). The 29 Sub-Saharan African countries selected for the study are chosen to provide a representation of the region's agricultural diversity and challenges. From Central Africa, the countries included are Angola, Burundi, Central African Republic, Chad, Democratic Republic of Congo, and Republic of Congo. Eastern Africa is represented by Ethiopia, Kenya, Madagascar, Somalia, South Sudan, Tanzania, and Uganda. Southern Africa includes Botswana, Malawi, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe. From Western Africa, the selected countries are Benin, Burkina Faso, Cameroon, Ghana, Guinea, Liberia, Mali, Niger, and Nigeria. Each of these nations faces unique agricultural conditions and socio-economic challenges, making them important to understanding the potential impact of fertilizer adoption on small-scale farming productivity across Sub-Saharan Africa. The paper explores the impact of fertilizer adoption with a focus of chosen crops for examination (Maize, Beans and cow peas) that are among the most cultivated crops in the study areas.

Organization of the study

After introducing the topic in Section 1, the paper delves into a review of relevant literature in Section 2. Section 3 then explores the methodology employed for the study. The findings and results are presented in Section 4, followed by concluding remarks and policy recommendations in Section 5.

2. Literature Review

2.1 Theoretical literature

2.1.1. Production Theory

Production theory explains how agriculture contributes to economic growth. Production and technological innovations are closely intertwined and play important roles in driving economic growth (Solow, 1957). Technological innovations includes advancements in knowledge, tools, and techniques that improve productivity and efficiency in the production process (Acemoglu et al., 2009). These innovations can be seen across various sectors, including agriculture, manufacturing, and services.

The production theory states that the quantity of output a firm can generate is determined by the quantity of inputs it utilizes in its production process. This relationship can be mathematically represented using a linear functional form as follows:

$Q = f\,(X1, X2 \ldots\ldots\ldots\ldots Xn)$

Q represents the volume of a company's output, while X1, X2, and Xn denote the quantities of inputs utilized in the process of producing Q.

Technological innovations in agriculture significantly impact production by transforming farming activities. By utilizing new knowledge and technologies, farmers can optimize production systems, achieve higher yields, and enhance overall productivity. These innovations span various areas, including crop breeding and biotechnology, precision farming, mechanization, irrigation systems, and post-harvest handling and processing (FAO, 2022).

To fully harness the potential of technological innovations in production, it is critical to ensure their widespread adoption and accessibility. This necessitates addressing challenges related to knowledge dissemination, affordability, infrastructure development, and capacity building. Policies and programs that promote research and development, technology transfer, and training initiatives will help facilitate the adoption and diffusion of technological innovations across diverse farming communities (Badiane and Ulimwengu, 2013).

2.1.2. The Diffusion of Innovation (DOI) theory

Rogers, the proponent of the diffusion model (Rodgers, 1962), argues that certain characteristics of the innovation itself can facilitate its adoption. Other factors influencing acceptance include promotion by influential role models, the degree of complexity of the change, compatibility with existing values and needs, and the ability to test and modify the new procedure before adopting it (Rogers and Shoemaker, 1971). The diffusion model provides more information into why some practices such as agricultural practices change while others do not and serves as a guide for those attempting to promote the adoption of best-evidence practices (Rodgers, 2003).

The theory of diffusion of innovations examines how agricultural technologies are adopted over time through communication, information sharing, and knowledge transfer (Montes de Oca Munguia et al., 2021). The theory suggests that the decision to adopt an innovation involves a cognitive process that includes stages of knowledge acquisition, persuasion, decision-making, implementation, and confirmation (Meijer et al., 2015; Ntshangase et al., 2018).

In the persuasion and decision stages of the diffusion of innovations theory, the perceived benefits of agricultural technology are critical for adoption. Smallholder farmers, as consumers, have subjective preferences for technology characteristics, and their demand for a specific technology is significantly influenced by their perceptions of its attributes (Adesina & Baidu-Forson, 1995). Teklu et al. (2022) further supports this by showing that farmers' perceptions of a technology's attribute, as well as the benefits related to Climate-Smart Agriculture (CSA) innovations in terms of food security, climate change adaptation, and mitigation, influence the combinations of CSA innovations they choose to adopt.

2.2 Empirical literature

This section reviews several empirical studies related to fertilizer adoption and use. It focusing on the various factors that influence this process. These factors include socio-economic characteristics, access to information, infrastructure, and environmental conditions. The study will help in developing policies and interventions that promote effective fertilizer use among farmers.

Factors Influencing Fertilizer Adoption:

Ouma et al. (2002) utilized cross-sectional data to analyze the effects of agro-ecological variations, gender, manure usage, hired labor, and extension services on the adoption of fertilizer and hybrid seeds for maize productivity in the Embu district. Research by the International Center for Integrated Mountain Development (CIMMYT) in Africa and other East African nations (Doss, 2003) examined factors influencing farmers' decisions regarding new maize seed and fertilizer technology. The study identified several determinants, including household characteristics, farm size, access to credit, extension services, and market conditions. Adoption rates varied across regions and countries, with higher rates in areas with favorable agro-ecological conditions and better infrastructure. These factors positively impacted maize yields, income, and food security for farmers. The research recommended that policies and interventions be tailored to the specific contexts and needs of farmers, with increased attention to the environmental and social implications of new technologies.

Ariga et al. (2008) analyzed data from a household panel survey to investigate changes in fertilizer practices among smallholder maize producers in Africa. Employing Probit and Tobit models, the study identified factors influencing farmers' decisions to enter fertilizer markets and the quantity of fertilizer purchased. The results indicated that location was the most critical factor for smallholders when deciding whether to use fertilizer on maize. While fertilizer purchases for maize were somewhat related to farm size, income did not significantly influence these decisions. In low-potential areas, proximity to fertilizer merchants significantly impacted families' decisions to buy fertilizer for maize. However, the distance between buyers and suppliers did not affect the quantity purchased. The study noted that although tea, coffee, and sugar cane are significant drivers of fertilizer use in Africa, they were not included in the analysis focused on maize fertilizer use.

Kassie et al. (2014) conducted a comparative study on the use of organic and inorganic fertilizers in Ethiopia. Utilizing a multinomial endogenous switching regression model, they identified several factors influencing the adoption decision, including literacy rate, farm size, number of animals, access to extension services, credit availability, and agro-ecological zone. The study found that inorganic fertilizers were more profitable in high-potential areas, whereas organic fertilizers proved more beneficial in low-potential regions. To assess the factors influencing the spread of fertilizer use in Africa, Karanja et al. (1998) analyzed cross-sectional data using a Tobit model.

Their findings revealed that both the distance to the nearest fertilizer market and the cost of fertilizer negatively impacted the adoption rate and intensity of usage. Farmers located closer to markets used more fertilizer. Additionally, the adoption of fertilizer varied with different ecological zones, indicating that fertilizer and hybrid seed usage might complement each other. Factors such as postsecondary education, maize prices, and extension services positively affected fertilizer usage on maize. Educated farmers were more likely to adopt and utilize fertilizer on their crops, likely because they were better equipped to implement recommendations and evaluate the impact of fertilizer on production.

Ogada et al. (2014) investigated the impact of fertilizer adoption on smallholders' commercialization and plot-level production in Sub-Saharan Africa using various methodologies and indicators. The study identified positive and significant effects of fertilizer use on agricultural outcomes. Additionally, the research highlighted the necessity of considering the interdependent choices of adopting inorganic fertilizer and improved maize varieties to avoid biased estimates.

Blessing et al. (2017) evaluated the spread and impact of fertilizer micro-dosing technology in Niger through a randomized controlled study. They found that micro-dosing with fertilizer resulted in a net income gain of 50% and increased grain production by 44% compared to the control group. The adoption decision was influenced by factors such as financial availability, extension services, rainfall unpredictability, and social learning. Marenya and Barrett (2009) examined the determinants of fertilizer usage in Africa and its effects on quality of life. Their research showed that fertilizer usage increased with farm size, soil quality, family wealth, market access, and extension services. Farmers using fertilizer experienced significantly higher corn yields and increased income. In Sub-Saharan Africa, where fertilizer adoption is critical for improving crop yields and ensuring food security, various studies have highlighted the low adoption rate due to factors such as family characteristics, plot-level conditions, institutional challenges, and market issues.

3. Methodology

This section highlights the data and methodology used to achieve the study objectives.

3.1 Theoretical and Empirical Framework

3.1.1 Theoretical Framework

The relative size of the agricultural sector in Sub-Saharan Africa's economy has been steadily declining over the past decades. In 1990, agriculture contributed 20% of the region's GDP, which dropped to 18% by 2000 and 15% by 2015 and 14% in 2021 (FAO, 2023). Projections by the FAO suggest this figure will decrease further to 13% by 2029, even as agricultural trade and production are expected to rise. Similarly, employment in agriculture has decreased, with World Bank estimates showing a reduction from 62% in 1995 to 52% in 2020. Despite this, agricultural production and exports have significantly improved in recent years. The "Africa Agriculture Status Report 2020" by the Alliance for a Green Revolution in Africa (AGRA) highlights that cropland expansion and better access to inputs like fertilizer and high-yield seeds increased gross production value by 11% between 2010 and 2016. Looking ahead, the FAO and OECD project a 21% increase in agricultural and fish production in Sub-Saharan Africa between 2020 and 2029.

Agriculture continues to be an essential economic activity in Sub-Saharan Africa's economy, employing over 40 percent of the total population and more than 70 percent of the rural population. It contributes to 65 percent of export earnings and provides a livelihood for more than 80 percent of Africans (FAO, 2023). Smallholder crop farmers in Africa make numerous production decisions, including the adoption of new farming technologies. According to Rogers and Shoemaker (1971), adoption is the decision to use an invention and continue using it. The widespread use of new technologies can significantly enhance productivity. The theoretical framework for the diffusion of innovation is presented in equation 1.

$$A = f(X, M, C) \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)$$

Where A shows the rate of adoption of fertilizer, indicating the speed at which a household adopts fertilizer. X represents the innovation attribute, in this study, the use of inorganic fertilizer, which is considered innovative compared to traditional fertilizers. M denotes the characteristics of the potential adopters, consisting attributes of individuals or groups considering the innovation, such as age, gender, education level, income, and other demographic and psychographic factors. These characteristics significantly influence how potential adopters perceive and respond to the innovation (Rogers, 2003). C refers to factors such as access to resources, including credit (financial resources) and land tenure (physical resources).

Equation 1 demonstrates that the adoption rate of a specific innovation, such as inorganic fertilizer, depends on three main factors: the attributes of the innovation itself, the characteristics of potential adopters, and external factors related to resource accessibility. The specific functional relationship between these variables varies depending on the context and the nature of the innovation under study. Initially, during the early stages of the study, adoption may be rapid as farmers perceive the potential benefits. However, as more farmers adopt the innovation, the rate of adoption may decrease due to factors such as limited resources or risk aversion.

In this study, productivity was defined as the crop yield obtained per acre of land cultivated by small-scale crop farmers. Following the approach of Donkor and Owusu (2019), the overall production function for the crop yield of small-scale farmers can be represented as

$$Y = f(A, K, L, N) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (2)$$

According to Cobb and Douglas (1928), Equation 2 represents the Cobb-Douglas production function, where Y is a function that increases with factor inputs. In the context of this study, Y represents crop yield, A denotes the rate of adoption aimed at enhancing productivity, K stands for capital input, including investments in technology-related infrastructure and equipment suitable for small-scale crop farming, L represents labor input, which includes farmers and farm workers involved in small-scale crop farming activities, and N denotes land input, referring to the size of land cultivated by small-scale crop farmers in Sub-Saharan Africa.

Considering the influence of these factors, control variables were introduced into this theoretical framework, and the analytical model was summarized as follows.

Crop Yield =f (fertilizer adoption, control variables) ……. (3)

3.1.2 Empirical framework

In this study, a probit model was used to estimate the predicted probabilities (propensity scores) of adopting fertilizer technology to achieve objective one. The probit model, as described by Greene and Hensher (2003), Verbeek (2008), and Willy et al. (2014), is expressed as follows;

$$\mathrm{Pr}(D = 1|X) = G(Z) = {}_{-\infty}^{X^i\beta}\emptyset(Z)dz = \emptyset(X^i\beta) \text{ ...... } (4)$$

In this expression, $G(z)$ is a function that varies between 0 and 1, Φ represents the standard normal probability density function, z is the vector of covariates, and F denotes the standard normal cumulative distribution function.

The empirical probit model estimated is presented below:

$$Y_i^* = \beta X_i + \mu_i, \quad \mu_i \sim N(0,1), \;\; i = 1 \ldots\ldots N, \quad and$$

$$Y_i = \begin{cases} 1, & if\; Y_i^* > 0 \\ 0, & otherwise \end{cases} \qquad \ldots (5)$$

Where Y_i^* refers to the latent variable representing the decision to adopt fertilizer and Y_i refers to the observed status of adopting fertilizer for each household, X denotes a vector of explanatory variables that consist of farmer and farm characteristics, socioeconomic and institutional/policy factors, βs are the estimated parameters, and μ_i is a stochastic error term. The probit model equation can simplify as;

$$\mathrm{Pr}(adoption\ of\ fertilier) = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_r X_r) \ldots\ldots.(6)$$

where Pr (fertilizer adoption) represents the probability of adopting fertilizer. Φ refers to the cumulative distribution function regarding the standard normal distribution and β_0, β_1, β_2, ..., β_r refers to the coefficients to be estimated. X_1, X_2, ..., X_r denotes to the independent variables (e.g. access to fertilizer, land tenure system, access to credit, and other control variables including; household size, gender, age, education level, household expenditure, farm size, other income that influence adoption)

The probit regression model is commonly used to analyze the relationship between the likelihood of adoption and its determining factors. Binary econometric models offer a detailed examination of farmers' adoption of new technology (Enki et al., 2001; Mariano et al., 2012; Muzari et al., 2012). This analysis provides explanations into the characteristics of farmers who are more likely to adopt a specific technology. The probit regression model is chosen for this study due to its advantageous properties, particularly the assumption of a normal distribution (Semykina & Wooldridge, 2010). Consequently, this study employs the probit regression model to identify the factors influencing fertilizer adoption among small-scale crop farmers in Sub-Saharan Africa.

3.2 Model Estimation

Equation 7 specifies the model used to analyze the objectives of the study as follows:

$$
\begin{aligned}
Probability(fertilizer\ adoption = 1) \\
&= \Phi\big(\beta_0 + \beta_1(accesstofertilizer) + \beta_2(Landtenure) + \beta_3(accesstocredit) \\
&+ \beta_4(educationlevel) + \beta_5(Housholdsize) + \beta_6(farmsize) + \beta_7(Otherincome) \\
&+ \beta_8(Gender) + \beta_9(household \exp e nditure) \\
&+ \beta_{10}(Age)\big) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)
\end{aligned}
$$

The utilization of Equation 7 facilitated an examination of the factors influencing the adoption of fertilizer among farmers. Fertilizer adoption, depicted as a binary dependent variable indicating whether a farmer adopts the use of fertilizer or not, was the main point of analysis. The variables considered include access to fertilizer, which evaluates the availability and affordability of fertilizer in the farmer's locality; land tenure, assessing the security and duration of the farmer's land rights; access to credit, indicating the farmer's capability to access financial resources for agricultural inputs; education level, reflecting the farmer's human capital and awareness of new agricultural technologies; household size, which serves as a proxy for the labor supply and consumption needs within the farmer's family; farm size, measuring the scale and intensity of agricultural production; other income, capturing non-farm income sources and diversification strategies; gender, accounting for possible differences in preferences and constraints between male and female farmers; household expenditure, representing the farmer's wealth and liquidity; and age, reflecting the farmer's experience and risk aversion. These variables will collectively shed explore the determinants of fertilizer adoption among small-scale crop farmers in the Sub-Saharan region of Africa. Those were the model's regressors while the coefficients β_1 to β_{10} are respective coefficients associated with each independent variable. The coefficient estimates offer explanations into the relationship between dependent and independent variables. Specifically, these coefficients enable us to predict how the probability of fertilizer adoption changes in response to variations in the respective independent variables.

3.3 Propensity Score Matching (PSM)

To accomplish objective 2, we utilized the Propensity Score Estimation Equation. The propensity score, denoted as Pi, is estimated using probit regression. The equation for estimating the propensity score is as follows:

$P_i = \Pr\,(Treatment_i = 1|X_i)$

Where; P_i refers to the propensity score for the household i (the probability of adopting fertilizer technology). $Treatment_i$ is a binary variable indicating whether household i adopted fertilizer technology (1 for adopters, 0 for non-adopters) and X_i is a vector of covariates (independent variables) for household i that may influence the likelihood of adoption.

In this specific study, Propensity Score Matching (PSM) was employed to estimate the impact of adopting fertilizer on the crop yield of small-scale farmers in the Sub-Saharan region of Africa.

The Propensity Score Matching (PSM) is expressed as;

$$P(X) = \Pr[D = 1|X] = E[D|X]; P(X) = F\{h(X_i)\} \ldots \ldots (8)$$

In this context, p(X) represents the propensity score while Pr is the probability of adopting a technology conditional on the vector of observed covariates (social characteristics), denoted as X. F(.) represents a Probit distribution. The variable D takes the value of 1 if fertilizer is adopted and 0 otherwise.

The main concept behind Propensity Score Matching (PSM), introduced by Rosenbaum and Rubin (1983), is to mitigate self-selection bias by pairing adopters and non-adopters based on their propensity scores. Households that have adopted fertilizer are matched with their counterparts who have not adopted, using the expected probabilities obtained from estimating equation (4). After estimating the propensity scores, various matching algorithms such as nearest neighbor matching (NNM), Kernel-based matching (KBM), and radius matching (RM) were employed to pair each adopter with a non-adopter. The use of different matching algorithms interchangeably aids in validating the accuracy of the estimates. Notably, in the NNM approach, having nearest neighbors with significant differences in propensity scores increases the likelihood of poor matches.

Radius matching is an approach that can address this issue by setting a maximum allowable disparity between propensity scores (Mulugeta & Hundie, 2012). Another example, provided by Becerril and Abdulai (2010), is Kernel-based matching, where all adopter farmers are matched with an average of all non-adopter farmers, with weights inversely proportional to the difference in propensity scores between the two groups. The matching estimations were constructed using the common support, which involves selecting parallel observations from both adopter and non-adopter households in the study. This ensures that comparisons are made only within a range where both groups have sufficient representation, avoiding extrapolation beyond the observed range of propensity scores.

Whether a farmer adopts fertilizer or not, all farmers within the common support region should exhibit similar distributions of observable features. Therefore, it was critical to maintain this balancing aspect of the sample during the study (Villano et al., 2015). The balancing attribute indicates the extent to which the samples are well-matched. In this study, the quality of matching was evaluated using the standardized bias technique, which measures the error in the mean difference of variables between the matched adopter and non-adopter groups. Samples are considered well-matched if the average bias in the mean difference is less than 5 percent. Following the estimation of propensity scores, the average treatment effect on the treated (ATT) was used to assess the impact of fertilizer adoption on crop yield. The mean treatment impact represents the average difference between treatment and control groups that share similar characteristics in terms of propensity scores and common support locations.

The Average Treatment Effect on the Treated (ATT) is specified as follows:

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 0)$$

where Y_1 and Y_0 represent the average quantity of crop yield (in kg/acre) for the adopter and non-adopter farmers, respectively. D is a dummy variable that takes two values: D=1 if

Challenges of Estimation and Remedies

Selection bias and endogeneity may cause significant challenges to measuring effect evaluations in research. These difficulties arise because treatment groups are often chosen non-randomly, leading to the adoption of fertilizer being influenced by both observable and non-observable traits, such as farmers' incentives and risk attitudes. To address these issues, the average treatment effect on the treated (ATT) was estimated using Propensity Score Matching (PSM) methodologies. By matching adopters and non-adopters based on observable traits, PSM reduces self-selection bias and ensures that the estimated technology effect is solely attributable to the treatment (adoption). However, PSM's limitation lies in its inability to account for unobservable factors that may be correlated with the outcome variable. To assess the robustness of the impact estimates obtained from PSM, the Rosenbaum sensitivity test was employed.

3.4 Data Sources

The purpose of this study was to assess the impact of fertilizer technology on small-scale crop farming productivity in Sub-Saharan Africa. To achieve this objective, a cross-sectional analysis of households across 29 Sub-Saharan countries was conducted using data from various household surveys, including the Ethiopia Socioeconomic Survey (ESS), Nigeria General Household Survey (GHS), Uganda National Household Survey (UNHS), Tanzania Household Budget Survey (HBS), Ghana Living Standards Survey (GLSS), South Africa General Household Survey (GHS), Zambia Living Conditions Monitoring Survey (LCMS), Malawi Integrated Household Survey (IHS), Mozambique's Inquérito aos Orçamentos Familiares (IOF), Rwanda Integrated Household Living Conditions Survey (EICV), and Kenya Integrated Household Budget Survey (KIHBS) just to mention a few. The data was collected over a 12-month period for each country from 2015/2016 to 2020/2022 since each country has a unique year that it conducts the survey. The data was analyzed using Stata software.

Table 3.0: Selected African Countries in Sub-Saharan Africa

Central Africa	**Eastern Africa**	**Southern Africa**	**Western Africa**
Angola	Ethiopia	Botswana	Benin
Burundi	Kenya	Malawi	Burkina Faso
Central African Republic	Madagascar	Mozambique	Cameroon
Chad	Somalia	Namibia	Senegal
Democratic Republic of Congo	South Sudan	Zimbabwe	Nigeria
Republic of Congo	Uganda	Zambia	Liberia
	Tanzania	South Africa	Ghana
			Niger

			Guinea
			Mali

Table 3.1.1: Countries Classification based on Aridity

Arid (85%-100%)	Semi-Arid 1 (30%-84%)	Semi-Arid 2 (10%-29%)	Non-Arid
Somalia	Kenya	Central African Republic	Burundi
Namibia	South Sudan	Chad	Democratic Republic of Congo
Niger	Ethiopia	Zimbabwe	Republic of Congo
Chad	Botswana	Zambia	Uganda
Mauritania	Namibia	Benin	Madagascar
Mali	South Africa	Cameroon	Tanzania
Eritrea	Burkina Faso	Senegal	Malawi
Djibouti	Niger	Nigeria	Mozambique
	Mali		Liberia
			Guinea
			Ghana

A description of both dependent and independent variables and their measurement methods are discussed in Table 3.1.

Table 3.1: Variable label, description, and Measurement

Variable	Variable Name	Variable Description	Variable Type	Unit of Measurement
Rate (A)	Fertilizer Adoption	Adoption of fertilizer technology	Dummy	1=Adopters, 0=Non-Adopters
Innovative Attribute (X)	Fertilizer	Fertilizer accessibility, Whether the household had access to fertilizer	Dummy	1=Yes, 0 = No
Actors (C)	Credit accessibility	Whether household had access to credit	Dummy	1=Yes, 0 = No
	Land Tenure System	Whether the household had land tenure	Dummy	1=Yes 0=N0

Characteristic of Adopters (M)	Age	Age of the Household Head	Continuous	Years
	Education level	Education level of the household head	Categorical	1=No-Formal Education 2=Primary Education 3=Secondary Education 4=Higher Education
	Gender	Gender of the Household head	Dummy	1=Male, 0 =Female
	Other income	Whether household had other sources of income	Dummy	1=Yes 0=N0
	Household Size	No of individuals in a Household	Discrete	Individuals
	Expenditure	Household expenditure on agricultural inputs related to crop production	Continuous	Africa Shillings
	Farm size	Size of land cultivated by the households	Continuous	Acres
Yield(outcome) (Y)	Crop yield	yield of crops on the farm	Continuous	Kilograms

Source: *Authors' compilation ,2024*

3.5 Summary statistics

Table 3.2 : Descriptive statistics of variables, Summary statistics: by (Country classification)

Adopters

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Crop yield	29	315.383	528.054	0	4695

Policy/Actor Variables					
land tenure	29	0.742	0.531	0	1
Access credit	29	0.631	0.496	0	1
Access fertilizer	29	0.986	0.144	0	1
Characteristics of Adopters					
Gender	29	0.461	0.541	0	1
age	29	38.362	13.875	18	77
farm size	29	1.750	0.878	1	6
education category	29	1.521	0.942	1	4
Household size	29	2.158	0.939	1	5
log household expenditure	29	5.162	2.656	1	12
other income	29	7.959	1.125	4.525	11.521

Non-Adopters

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Crop yield	29	221.268	357.509	0	3400
Policy/Actor Variables					
land tenure	29	0.758	0.430	0	1
Access credit	29	0.637	0.482	0	1
Access fertilizer	29	0.089	0.316	0	1
Characteristics of Adopters					
Gender	29	0.624	0.512	0	1
age	29	37.524	17.21	18	85
farm size	29	1.521	0.815	1	6
education category	29	2.341	0.845	1	5

Household size	29	5.129	2.876	1	13
log household expenditure	29	7.895	1.115	4.314	11.561
other income	29	0.005	0.070	0	1

4. Results and discussion

4.1. Fertilizer Adoption and its Determinant

Table 4.1 presents the findings of a probit analysis examining the factors influencing farmers' adoption of fertilizer technology in various aridity zones across Africa. Fertilizer adoption serves as a crucial indicator of agricultural productivity and income for rural households. However, adoption rates differ across regions and household characteristics. This study employs a probit regression model to estimate the impact of each factor on the probability of adopting fertilizer, while controlling for other variables.

Table 4.1. Probit analysis on determinants of adoption of fertilizer technology

	Arid (85%-100%)	**Semi-Arid 1 (30%-84%)**	**Semi-Arid 2 (10%-29%)**	**Non-Sub-Sahara**
Fertilizer adoption	Coef.	Coef.	Coef.	Coef.
	(St.Err).	(St.Err.)	(St.Err.)	(St.Err.)
Policy/ Actor Variables				
Land tenure	-0.105	0.326***	0.274*	-0.095
	(0.246)	(0.123)	(0.152)	(0.131)
Access to credit	0.622**	0.141	0.161	-0.091
	(0.352)	(0.191)	(0.181)	(0.173)
Access to fertilizer	3.735***	3.612***	2.952***	3.216***
	(0.315)	(0.217)	(0.175)	(0.131)
Characteristic of Adopter				
Gender	-0.257	0.136	0.131	0.121
	(0.241)	(0.192)	(0.182)	(0.131)
age	-0.021**	-0.004	-0.009*	-0.003
	(0.008)	(0.007)	(0.006)	(0.005)
Farm size	0.095	-0.058	0.141	-0.028
	(0.48)	(0.095)	(0.078)	(0.076)
Primary Education	-0.647	0.182	-0.269	0.127

	(0.520)	(0.248)	(0.228)	(0.168)
Secondary Education	-1.247**	0.338	-0.122	-0.198
	(0.583)	(0.294)	(0.355)	(0.283)
Higher Education	-0.714	0.075	-0.318	-0.484
	(0.617)	(0.497)	(0.328)	(0.360)
Household size	-0.004	-0.041	0.045*	-0.044
	(0.057)	(0.033)	(0.047)	(0.035)
Log household expenditure	0.094	-0.096	-0.138*	-0.022
	(0.127)	(0.078)	(0.034)	(0.062)
Other income	0.956	-0.321	0.575	-0.008
	(1.579)	(0.385)	(0.475)	(0.224)
Constant	-1.799	-1.392*	-.927	-1.322**
	(1.096)	(0.869)	(0.721)	(0.616)
Number of Observation	215	404	332	680
Prob > chi2	0.000	0.000	0.000	0.000
Pseudo r-squared	0.740	0.752	0.619	0.684

Note: *Robust standard errors in Parentheses. *** p<.01, ** p<.05, * p<.1*

Table 4.2. Average Marginal Effect analysis on determinants of adoption of fertilizer technology on the Country classification.

Variable Names	**Arid (85%-100%)**	**Semi-Arid 1 (30%-84%)**	**Semi-Arid 2 (10%-29%)**	**Non-Arid**
	dy/dx	**dy/dx**	**dy/dx**	**dy/dx**
Policy/Actor Variables				
Land tenure	-0.019	0.051***	0.028*	-0.024
	(0.041)	(0.022)	(0.022)	(0.035)
Access to credit	0.062**	0.023	0.024	-0.021
	(0.038)	(0.027)	(0.027)	(0.021)

Access to fertilizer	0.361***	0.328***	0.447***	0.392***
	(0.041)	(0.035)	(0.031)	(0.021)
Characteristic of the Adopter				
Gender	-0.017	0.021	0.021	0.018
	(0.025)	(0.021)	(0.032)	(0.018)
age	-0.004**	0.001	-0.003*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Farm size	0.011	-0.006	0.031	-0.003
	(0.028)	(0.008)	(0.034)	(0.009)
Primary Education	-0.061	0.039	-0.052	0.052
	(0.061)	(0.052)	(0.063)	(0.042)
Secondary Education	-0.131**	0.052	-0.042	-0.039
	(0.051)	(0.038)	(0.061)	(0.031)
Higher Education	-0.068	0.008	-0.058	-0.071
	(0.093)	(0.062)	(0.071)	(0.058)
Household size	-0.003	-0.002	0.011*	-0.001
	(0.005)	(0.004)	(0.009)	(0.003)
Log of household expenditure	0.008 (0.021)	-0.008 (0.009)	-0.031* (0.023)	-0.001 (0.009)
Other income	0.097	-0.041	0.075	-0.003
	(0.260)	(0.055)	(0.068)	(0.033)
Number of Observation	**215**	**404**	**332**	**680**

Note: *dy/dx for factor levels is the discrete change from the base level, Robust standard errors in Parentheses. *** p<.01, ** p<.05, * p<.1*

To clearly understand the factors influencing fertilizer adoption, Table 4.2 presents the estimated coefficients and marginal effects from the Probit model, and shows the impact of various explanatory variables on the dependent variable. The marginal effect values quantify the likelihood of these effects, with their signs indicating the direction of the dependent variables' impact on fertilizer adoption.

The marginal effects indicate how the probability of adopting fertilizer shifts when an independent variable changes by one unit, while keeping all other variables constant at their mean values. These effects are derived as the partial derivatives of the probability function with respect to each independent variable. The standard errors of these marginal effects are provided in parentheses beneath the respective marginal effects values.

Access to fertilizer significantly increases the probability of adoption across all aridity levels. Farmers with access to fertilizer are more likely to adopt the technology than those without it. Specifically, the marginal effects indicate that access to fertilizer raises the probability of adoption by 36.1 percentage points in arid regions, 32.8 percentage points in semi-arid 1 regions, 44.7 percentage points in semi-arid 2 regions, and 39.2 percentage points in non-Arid regions.

Access to credit significantly increases the likelihood of fertilizer adoption in arid areas. Farmers with access to credit are more likely to adopt fertilizer than those without access. The marginal effect of 0.062 indicates that having access to credit raises the probability of adoption by 6.2 percentage points.

The average marginal effect of land tenure is 0.051 in semi-arid 1, indicating that, with other variables held constant at their mean values, secure land tenure increases the likelihood of adopting fertilizer by 5.1 percentage points on average. In semi-arid 2, the average marginal effect of land tenure is 0.028, meaning that secure land tenure raises the probability of adopting fertilizer by 2.8 percentage points, on average, when other variables are held constant. Conversely, log expenditure has a negative and significant impact on the probability of adoption in semi-arid 2 areas. This suggests that farmers with higher expenditure are less likely to adopt the technology compared to those with lower expenditure. The marginal effect is -0.031, indicating that a one percent increase in expenditure reduces the probability of adoption by 3.1 percentage points.

4.2. Treatment effect on fertilizer adoption

The results presented in Table 4.3 are derived from a treatment-effects estimation using propensity-score matching, comparing the average treatment effect on the treated (ATT) between adopters and non-adopters of fertilizer technology. This analysis, which includes 1,474 observations and focuses on individuals between the ages of the household heads, employs a probit model for the treatment variable (fertilizer adoption) to calculate the ATT. The key finding indicates a substantial and statistically significant positive effect of fertilizer adoption on the outcome variable. Fertilizer adopters exhibit an estimated increase of approximately 0.7815 units in the outcome variable compared to non-adopters, a difference that is highly significant at the one percent confidence level. The confidence interval does not include zero, reinforcing the robustness of this effect. These results shows the significant positive impact of fertilizer adoption on the outcome variable among the household heads.

Table 4.3 : Treatment-effects estimation

Propensity Score of fertilizer	Coef.	St.Err.	Sig
Adopter vs Non-adopter	0.781	0.012	***

**** p<.01, ** p<.05, * p<.1*

4.3. Sensitivity and specificity test of adoption

Table 4.4 summarizes the adoption of fertilizer practices in the: Sub-Sahara (Arid and Semi-Arid Lands) and Non arid areas of Sub-Sahara. The table presents the number of farmers categorized as "Non-Adopters" and "Adopters" within each classification with the sensitivity test.

Fertilizer adoption	Country classification by aridity				
	Arid (85%-100%)	**Semi-Arid 1 (30%-84%)**	**Semi-Arid 2 (10%-29%)**	**Non-Sub-Sahara**	Total
Non-Adopters	29	165	150	320	664
Adopters	29	239	182	360	810
Total	215	404	332	680	1474

Table 4.4: Sensitivity test

Sensitivity	Pr(+D)	54.52%	54.27%	58.69%
Specificity	Pr(-~D)	43.52%	44.25%	45.87%
Positive predictive	Pr(D +)	65.65%	63.69%	68.63%

value				
Negative predictive value	Pr(~D -)	37.28%	34.87%	38.79%
Prevalence	Pr(D)	71.25%	63.85%	66.87%

Table 4.4 presents findings on fertilizer adoption rates and the diagnostic accuracy of a test that classifies counties by country classification into arid and non-arid areas. The first part of the table displays the number of fertilizer adopters and non-adopters by country type, along with the total number of countries in each group. The second part provides the test's sensitivity, specificity, positive and negative predictive values, prevalence, and 95 percent confidence intervals.

The test's sensitivity, which measures the percentage of arid countries correctly identified, is 54.52 percent with a 95 percent confidence interval ranging from 54.27 percent to 58.69 percent. This indicates that the test can correctly identify 55 percent of arid counties but fails to detect 45 percent. The moderate sensitivity suggests that the test has a limited ability to identify arid regions accurately.

The specificity, representing the percentage of non-arid countries correctly categorized by the test, is 43.52 percent, with a 95 percent confidence interval from 44.25 percent to 45.87 percent. This means the test correctly identifies 44 percent of non-arid counties but incorrectly classifies 56 percent as arid. The low specificity indicates that the test struggles to accurately exclude non-arid countries.

The positive predictive value (PPV) of the test indicates the percentage of countries identified as dry that are genuinely arid. The PPV is 65.65 percent, with a 95 percent confidence interval between 63.69 percent and 68.63 percent. This means that 66 percent of the counties labeled as dry by the test are truly arid, while 34 percent are false positives. The prevalence of aridity in the population, which affects the PPV, is 71.25 percent, with a 95 percent confidence interval ranging from 63.85 percent to 66.87 percent. This shows that 71 percent of counties are arid regardless of the test results.

The negative predictive value (NPV) of the test reflects the percentage of counties identified as non-arid that are actually non-arid. The NPV is 37.28 percent, with a 95 percent confidence interval from 34.87 percent to 38.79 percent. Thus, about 37 percent of the countries labeled as non-arid by the test are truly non-arid, while 63 percent are false negatives. Similar to the

PPV, the NPV is influenced by the overall prevalence of aridity in the population.

The results indicate that fertilizer adoption rates vary by country type. Furthermore, the test used to classify countries into arid and non-arid regions based on country classification shows moderate sensitivity, low specificity, moderate positive predictive value, and low negative predictive value.

4.4. Effect of fertilizer adoption on productivity

The propensity score matching (PSM) technique was employed to evaluate the effect of fertilizer use/adoption on the productivity of smallholder crop farmers. The results derived from the three algorithms used in the PSM procedure was subjected to quality control assessments. To confirm the integrity of the matching process, the study conducted two diagnostic tests following the prediction of propensity scores for both users and non-users of fertilizer technology.

Table 4.5: Impact of adoption of fertilizer on productivity-PSM.

Arid (85%-100%)

Crop yield	**Treated (Adopters)**	**Controls (Non-Adopters)**	**Difference**	**S.E.**	**T-stat**
Matching algorithms					
Kernel-based matching (KBM)	185.524	93.026	92.498	81.875	2.29
Radius matching (RM)	185.524	96.683	88.841	32.587	2.89
Nearest Neighbor (NNM)	185.524	94.798	90.726	33.687	2.62

Semi-Arid 1 (30%-84%)

Crop yield	**Treated (Adopters)**	**Controls (Non-Adopters)**	**Difference**	**S.E.**	**T-stat**
Matching algorithms					
Kernel-based matching (KBM)	194.523	133.658	60.873	169.314	0.41
Radius matching (RM)	194.523	217.177	-21.723	29.325	-0.81

Nearest Neighbour (NNM)	194.523	125.888	68.635	117.25	0.58

Semi-Arid 2 (10%-29%)

Crop yield	**Treated (Adopters)**	**Controls (Non-Adopters)**	**Difference**	**S.E.**	**T-stat**
Matching algorithms					
Kernel-based matching (KBM)	261.0634	134.9364	126.127	115.241	1.07
Radius matching (RM)	261.0634	179.6404	81.423	51.254	1.51
Nearest Neighbour (NNM)	261.0634	121.4874	139.4874	82.361	1.52

Non- arid regions (less than 10%)

Crop yield	**Treated (Adopters)**	**Controls (Non-Adopters)**	**Difference**	**S.E.**	**T-stat**
Matching algorithms					
Kernel-based matching (KBM)	251.677	228.034	23.647	125.327	0.21
Radius matching (RM)	251.677	268.038	-16.361	36.241	-0.41
Nearest Neighbour (NNM)	251.677	179.136	72.541	157.42	0.38

The estimated average impact of adopting fertilizer on crop yields varies between approximately 195 kg/acre and 261 kg/acre, based on the estimation method used. Adopters of fertilizer technology experienced yield increases of 91 kg in Arid regions, 36 kg in semi-arid1, 116 kg in semi-arid2, and 27 kg in non-arid regions, respectively, indicating improved average productivity across these varied environments. The analysis using different matching methods revealed only slight variations in outcomes, which suggests the robustness of the results. Specifically, the significant impact of fertilizer adoption in Arid regions shows that utilizing fertilizer has led to substantial improvements in yield for small-scale crop farmers.

5. Conclusions and Policy Recommendation

5.1 Conclusion

In summary, this study offers important findings on the determinants that affect the adoption of fertilizer among small-scale crop farmers in Sub-Saharan Africa. Using Probit regression analysis, key factors were identified that greatly influence the uptake of fertilizer. These include access to fertilizers, availability of credit, and land tenure security. Additionally, other control variables like age, household spending, and secondary education level also played a significant role in influencing fertilizer adoption across different country classifications.

The results from the Propensity Score Matching (PSM) indicate that farmers who utilized fertilizer experienced significant gains in productivity, with an increase of between 195 kg/acre to 261kg/acre compared to those who did not adopt fertilizer. This notable improvement justifies the critical role that fertilizer adoption plays in boosting crop productivity and, consequently, enhancing the income levels of farming households. These findings emphasize the necessity for focused policies and initiatives that promote sustainable agricultural methods and improve farmers' living standards.

Given these research findings, there are several policy recommendations that policymakers and stakeholders could consider to encourage wider adoption of fertilizer and increase agricultural productivity in Sub-Saharan Africa. These strategies may include providing greater access to affordable fertilizers through subsidies or financial support, improving credit facilities to allow farmers to invest in necessary agricultural inputs, and strengthening land tenure security to incentivize long-term investments in land productivity. Furthermore, educational programs may be implemented to teach farmers about the benefits of fertilizer use and proper application techniques to maximize yields.
Drawing on the research outcomes, policymakers and stakeholders can utilize the following policy implications to enhance fertilizer adoption and agricultural productivity in Sub-Saharan Africa:

5.2 Recommendation

1. Establishing Clear Land Ownership: Governments in Sub-Saharan Africa, through their respective Ministries of Lands, may consider looking into making the land registration

processes more straightforward and offering legal aid to boost land tenure security. Through establishing clear land ownership, farmers are likely to be more inclined to invest in enduring agricultural technologies, including fertilizers. Furthermore, governments may collaborate with local authorities and community groups to settle land disputes and guarantee a just and transparent distribution of land rights.

2. Enhance Fertilizer Availability: In Sub-Saharan Africa, the related Ministries of Agriculture, Livestock, Fisheries, and Co-operatives may consider prioritizing improving the accessibility and affordability of fertilizers, particularly in underserved regions. They may consider implementing subsidy programs or cooperative models to reduce the cost of fertilizers for farmers and promote group purchasing. Furthermore, forging partnerships with private sector companies and research institutions such as KALRO in Kenya may likely successfully foster the development and distribution of high-quality, climate-resilient fertilizers that are suited to the specific soil conditions and crop varieties of the region.
3. Improved Financial Services: Governments across Sub-Saharan Africa should consider working with financial institutions to broaden access to credit for farmers throughout the region. This initiative would help farmers afford fertilizers and other necessary inputs by alleviating liquidity issues. Additionally, through the Ministry of Public Works, governments could invest in better infrastructure and distribution networks, ensuring fertilizers are reliably and affordably available. Such investments would lower transportation costs and reduce the delays that currently deter farmers from utilizing fertilizers.
4. Focused Educational Initiatives: The findings from the study indicate a clear relationship between education levels and the adoption of fertilizer technology. Farmers with higher education are more inclined to utilize fertilizers. To enhance fertilizer adoption across all areas, governments in Sub-Saharan Africa, through their Ministry of Agriculture, Livestock, Fisheries and Co-operatives in collaboration with the Ministry of Education and private sector partners, may consider launching educational initiatives aimed at farmers with lower educational backgrounds. These initiatives could offer training and disseminate information about the advantages and correct application of fertilizers. Furthermore, leveraging existing agricultural extension services, farmer organizations, and media channels could expand outreach, encouraging peer-to-peer learning and broader adoption.

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