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Leveraging on Adoption of Fertilizer to Boost Small-scale Crop Farming Productivity in Arid and Semi-Arid Lands of Kenya

Meshack Omega and George Chege

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THE KENYA INSTITUTE FOR PUBLIC POLICY RESEARCH AND ANALYSIS (KIPPRA)

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Abstract

Adoption of fertilizer technology is an important avenue for increasing agricultural productivity and improving the living standards of farmers in the Arid and Semi-Arid Lands (ASALs) of Kenya. The main objective of the study was to assess the impact of fertilizer adoption on small-scale crop farming productivity in ASALs of Kenya using KIHBS 2015/16 data and probit regression model. The empirical results of the probit regression reveal several significant predictors of fertilizer adoption. Notably, access to fertilizer, access to credit, and land tenure system show statistically significant effects at the 5 per cent level on different aridity while other control variables including gender, age were significant at different aridity. To measure how fertilizer adoption implementation affected crop yield, we employed the propensity score matching (PSM) method. It was noted that adopters of fertilizer technology gained 114 kg more of crop yield per acre of cultivated farms. The paper concludes that simplifying land registration processes and providing legal support would enhance land tenure security. Thus, farmers will be more willing to invest in long-term agricultural technologies such as fertilizers adoption. Also, having an effective credit scheme to make farmers have access to credit and promoting fertilizer accessibility and affordability through enhancement of subsidies and cooperatives initiatives will increase adoption of fertilizer and subsequently boost farm productivity.

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1. Introduction

Leveraging fertilizer adoption would enhance small-scale crop farming productivity in farming among Arid and Semi-Arid Lands (ASALs) communities. Small-scale farmers are those with a low asset base operating less than 2 ha of cropland (World Bank, 2003). However, some scholars have expanded its definition to include farmers with limited capital and restricted access to production factors such as inputs (Sienso et al., 2013). While these factors can contribute to the definition of smallholder farmers, in the Kenyan context, land holding is the primary criterion used (Rapsomanikis, 2015; Salami et al., 2010). In this study, smallholder farmers are defined as those who own five acres (2 ha) or less.

In Kenya, the income generated by small farms was Ksh 373 billion (Kenya National Bureau of Statistics Statistical Abstract, 2022) in the year 2020 compared to Ksh 136 billion income by large farms. This shows the potential of small-scale farmers. Despite this small-scale crop farming, ASALs are not currently leveraging on fertilizer adoption effectively, which could have resulted to more yields and in addition more income. This may be due to limited access to information, resources, and infrastructure, and other barriers such as inadequacy of technical skills and knowledge.

ASALs in Kenya are characterized by erratic environmental conditions, including limited water resources, unpredictable rainfall patterns, and harsh climates, which pose significant constraints to agricultural activities. The arid areas are characterized by communal land ownership, which is mostly used for nomadic activities. This presents a significant challenge for small-scale crop farming, making it difficult to implement mechanized farming techniques, and hindering efficient cultivation process. The livelihoods and food security of communities residing in these regions heavily depend on small-scale farming and livestock production, making it imperative to explore innovative approaches to overcome these challenges.

Fertilizer adoption offers promising solutions to address the specific needs of ASALs' communities and boost small scale crop farming productivity. By harnessing advancements in technology and tailoring them to the unique circumstances of ASALs, small-scale farmers could optimize resource utilization, improve farming practices, and ultimately increase productivity levels. This not only ensures food security for the communities but also contributes to their economic growth and resilience in the face of environmental uncertainties.

The government has made significant contributions to leverage fertilizer adoption to boost small-scale agriculture productivity in farming among ASALs through establishment of research and development institutions such as Kenya Agricultural and Livestock Research Organization (KALRO), which been instrumental in agricultural research and the development of appropriate fertilizer formulations tailored to ASALs in Kenya. Also, the government through Fertilizer Subsidy Programmes has targeted small-scale farmers, and these programmes provide subsidized or free fertilizer to farmers, making it more affordable and accessible.

The government has also implemented policies such as The 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. This has enhanced farmer competence in fertilizer application. The government has also facilitated the development and adoption of fertilizer suitable for farming in ASALs. In this study, we will look at how fertilizer has been adopted in ASALs and the impact on crop farming.

Therefore, to fully unlock the potential of fertilizer adoption in small-scale crop farming within ASALs communities, it is crucial 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 ASALs communities, and the socio-economic and environmental impacts of fertilizer adoption in these contexts.

Small-scale crop farming in ASALs faces low productivity compared to non-ASAL counties. The average county contribution to agriculture, forestry and fishing activities for the period 2013-2020 showed that ASAL counties are at the bottom and producing less than 2 per cent of the total agricultural production (Gross County Product Report, 2021; 2022). This can lead to food insecurity in these regions. The motivation behind conducting this study stems from the urgent need to address the persistent challenges faced by small-scale crop farmers in Kenya's ASALs, because the traditional farming practices in ASALs are no longer sufficient to meet the growing demand for food and the need for sustainable agricultural systems. Embracing adoption of fertilizer could lead to increased crop productivity, improved resource management, and enhanced resilience against environmental stressors, thereby transforming small-scale farming into a viable and prosperous livelihood. While other inputs such as improved seeds are undoubtedly important, the decision to concentrate on fertilizer adoption is based on its relevance to ASALs conditions, where soil fertility tends to be a limiting factor.

This study encompasses an exploration of the potential of fertilizer adoption to enhance the productivity of small-scale crop farming in the Arid and Semi-Arid Lands (ASALs) of Kenya that has 29 ASAL counties (Government of Kenya, 2019). The focus was on the 8 arid counties, with aridity levels of 85-100 per cent, the 13 semi-arid counties of aridity level 30-84 per cent, the 8 semi-arid counties of 10-29 per cent aridity, and compared to the 18 non-ASALs. The paper explores the impact of fertilizer adoption with a focus on selected crops (maize, beans and cow peas) that are among the most cultivated crops in the study areas.

The broad objective of the study was to assess the impact of fertilizer adoption on small-scale crop farming productivity in ASALs of Kenya.

The specific objectives were to:

i) Determine the factors influencing the adoption of fertilizer technology in ASALs.

ii) Evaluate the impact of fertilizer adoption on crop yield of small-scale crop farmers in ASALs of Kenya.

The study is organized as follows: section 2 gives a review of the literature while section 3 presents the methodology that was employed. Section 4 presents the results of the study and section 5 provides the conclusion and policy implications of the study.

2. Literature Review

2.1 Theoretical Literature

2.1.1 Diffusion of innovation (DOI) theory

Rogers was the proponent of diffusion model. Rodgers argues that certain characteristics of the innovation itself may 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 valuable insights into why some practices change and others do not, and guiding those who try to effect adoption of best-evidence practice.

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

Within the persuasion and decision stages of the diffusion of innovations theory, the perception of the perceived benefits of agricultural technology plays a crucial role in adoption. Smallholder farmers, as consumers, tend to have subjective preferences for technology characteristics, and their demand for a particular technology is significantly influenced by their perceptions of its attributes (Adesina and Baidu-Forson, 1995). Teklu et al. (2022) further supports this notion by demonstrating that farmers' perceptions of the attributes of a technology, and the benefits associated with climate-smart agriculture (CSA) innovations in terms of food security, climate change adaptation, and mitigation, play a role in determining the combinations of CSA innovations adopted.

2.1.2 Production by technological innovation

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

In the realm of agriculture, technological innovations have a significant impact on production, transforming the way farming activities are carried out. By leveraging new knowledge and technologies, farmers could optimize their production systems, achieve higher yields, and improve overall productivity. Technological innovations in agriculture encompass a broad range of areas, such as fertilizer, crop breeding and biotechnology, precision farming, mechanization, irrigation systems, and post-harvest handling and processing.

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

2.2 Empirical Literature

This section presents a review of some of the empirical studies related to fertilizer adoption and/or use.

2.2.1 Factors influencing fertilizer adoption

Blessing et al. (2017) evaluated the spread and effect of fertilizer micro-dosing technology in Niger. Through a randomized controlled study, they found that micro-dosing with fertilizer led to a net income gain of 50 per cent and increased grain production by 44 per cent compared to the control group. The adoption decision was influenced by variables such as financial availability, extension services, rainfall unpredictability, and social learning. Marenya and Barrett (2009) researched the factors influencing fertilizer usage in Kenya and its impacts on people's quality of life. They discovered that fertilizer usage increased with farm size, soil quality, family affluence, access to markets, and extension services. Farmers who used fertilizer experienced significantly higher corn harvests and increased income.

Kassie et al. (2014) compared the use of organic and inorganic fertilizers in Ethiopia. Using a multinomial endogenous switching regression model, they found that factors such as literacy rate, farm size, number of animals, access to extension services, credit, and agro-ecological zone influenced the adoption decision. The study also revealed that in high-potential locations, inorganic fertilizer was more profitable, while organic fertilizer was more beneficial in low-potential areas.

In Kenya's ASALs, where fertilizer adoption is crucial for enhancing crop yield and ensuring food security, several studies have highlighted the low adoption rate due to various factors such as family characteristics, plot-level factors, institutional factors, and market issues.

Ariga et al. (2008) utilized data from a household panel survey to assess how smallholder maize producers in Kenya were changing their fertilizer practices over time. The research used Probit and Tobit models to determine the variables that influence maize farmers' choices to enter the fertilizer markets and, if they do, how much fertilizer they would buy. According to the results, location is the most important consideration for smallholders when deciding whether or not to fertilize their maize. Fertilizer purchases for maize production by families were somewhat linked to farm size but not income. In the relatively low-potential locations, it was discovered that proximity to fertilizer merchant had a significant effect on families' choice to buy fertilizer for maize cultivation. However, the distance between the buyer and the supplier of fertilizer had no effect on the amount of fertilizer bought. While tea, coffee and sugar cane are all key drivers of increase in fertilizer usage in Kenya, they were not included in this analysis because they were not evaluated in the context of maize fertilizer use.

Ogada et al. (2014) conducted research on the causal influence of fertilizer uptake on smallholders' commercialization and plot-level production in ASALs, respectively, using different methodologies and indicators. The study found positive and significant effects of fertilizer use on agricultural outcomes. Ogada et al. (2014) also emphasized the importance of considering the joint choices of adopting inorganic fertilizer and enhanced maize varieties due to their interdependence to avoid skewed estimates.

Ouma et al. (2002) used cross-sectional data to determine the effects of agro-ecological variations, gender, manure usage, hiring labour, and extension on fertilizer and hybrid seed adoption for maize productivity in Embu District. Research conducted by the International Centre for Integrated Mountain Development (CIMMYT) in Kenya and other East African nations (Doss, 2003) looked at the factors that influence farmers' choices about new maize seed and fertilizer technology. It was noted that maize seed and fertilizer technology was influenced by several factors, such as household characteristics, farm size, access to credit, extension services, and market conditions. The adoption rates varied across regions and countries, with higher rates in areas with more favourable agro-ecological conditions and better infrastructure. This had positive impacts on maize yields, income, and food security for the farmers .The research suggested that policies and interventions should be tailored to the specific contexts and needs of the farmers, and that more attention should be paid to the environmental and social implications of the new technologies.

To evaluate the factors that influence the spread of fertilizer usage in Kenya, Karanja et al. (1998) analyzed cross-sectional data using Tobit model. According to their findings, both the distance to the nearest fertilizer market and the cost of fertilizer had a negative impact on the rate of adoption and intensity of usage. Growers that were physically closer to consumers also used more fertilizer. The increased usage of fertilizer by farmers growing hybrid maize seed varied across different ecologies. This suggests that the usage of fertilizer and hybrid seeds might complement one another. Fertilizer usage on maize was also favourably impacted by post-secondary education, maize price, and extension. Educated farmers were more likely to accept and utilize fertilizer on their maize crops. This may have occurred because they were better equipped to implement suggestions or assess the impact that fertilizer had on production.

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

Agriculture is vital for Kenya's economy and employs more than 40 per cent of the total population and more than 70 per cent of Kenya's rural people. Agriculture also accounts for 65 per cent of the export earnings and provides the livelihood for more than 80 per cent of the Kenyan population (FAO, 2023). In Kenya, smallholder crop farmers are responsible for a wide range of production decisions, such as the use of new farming technologies. Adoption was described by Rogers and Shoemaker (1971) as the choice to use an invention and the continuation of that use. Productivity may increase if new technologies are widely used. The theoretical framework for diffusion of innovation is presented as in equation 1.

$$A = f(X, M, C) \tag{1}$$

Where *A* represents the rate of adoption of fertilizer, this is the speed or rate at which fertilizer is adopted by a household. *X* represents the innovation attribute, which in this study is the inorganic fertilizer that makes it innovative compared to traditional fertilizers. *M* denotes characteristics of the potential adopters; these are the attributes or characteristics of the individuals or groups within the population who are considering adopting the innovation. Age, gender, education level, income, and other demographic and psychographic factors fall under this category. The characteristics of potential adopters can significantly impact how they perceive and respond to the innovation (Rodgers, 2003). *C* denotes to actors such as, access to resources e.g. credit (financial resources), land-tenure (physical resources).

In order to check the output as a result of fertilizer, a production theory was also adopted to find the amount crop yield (output) harvested per acre of land of the small-scale crop farmers. Following Donkor and Owusu (2019), the generalized production function of the small-scale crop farmers yield can be expressed as

$$Y = f(A, K, L, N) \tag{2}$$

According to Cobb and Douglas (1928), equation 2 is Cobb-Douglas production function where *Y* is an increasing function of factor inputs. Specific to this study, *Y* denotes the crop yield, *A* represents the level of technology that affects the production of crop output *Y* in our study *A* can be interpreted as the extent to which fertilizer is adopted and used by small-scale farmers in ASALs. Fertilizer is a form of technology that can improve the soil quality and nutrient availability for crops, especially in areas with low rainfall and poor soil conditions. Fertilizer can also increase the yield and quality of crops. Therefore, A can capture the effect of fertilizer on crop output, holding other inputs constant, K represents the capital input, which includes investments in technology-related infrastructure and equipment suitable for small-scale crop farming and L represents the labour input, which accounts for the human resources involved in small-scale crop farming activities, including farmers and farm workers and N represents the land input, which refers to the size of land cultivated by small-scale crop farmers. All the variables for this study relate to ASALs of Kenya.

Given the influence of factors mentioned above, control variables were incorporated to this theoretical framework, and the analytical model was summarized as.

$$\text{Crop Yield} = f\,(\text{fertilizer adoption, control variables}) \qquad (3)$$

Equation 3 models the relationship between crop yield and fertilizer adoption, while controlling for other variables that may affect the outcome, where crop yield is the output. It is the amount in kilograms of (maize beans and cowpeas) crops that a farmer can harvest in a piece of land. Fertilizer adoption is the independent variable and represents the degree to which farmers are adopting fertilizers on their crops. It is measured as a binary variable (yes or no), and control variables are other variables that may affect crop yield, such as land size, accessibility of fertilizer, credit accessibility and land tenure. The model helps us quantify and analyze the impact of fertilizer adoption and control variables on crop yield.

3.1.2 Empirical framework

a) Adoption of fertilizer

Equation 4 takes the model specification to analyze the objectives of the study as follow

$$\text{fertilizer adoption} = \Phi\,(\beta_0 + \beta_1\,(\text{accesstofertilizer}) + \beta_2\,(\text{Landtenure}) + \beta_3\,(\text{accesstocredit}) + \beta_4\,(\text{educationlevel}) + \beta_5\,(\text{Housholdsize}) + \beta_6\,(\text{farmsize}) + \beta_7\,(\text{Otherincome}) + \beta_8\,(\text{Gender}) + \beta_9\,(\text{household expenditure}) + \beta_{10}\,(\text{Age})) \qquad (4)$$

Estimation of equation 4 aided in examining the factors influencing adoption of fertilizer among farmers. Fertilizer adoption (*fertilizer adoption*) is a binary dependent variable representing whether a farmer adopts the use of fertilizer or not. The variables access to fertilizer, which measures the availability and affordability of fertilizer in the farmer's area; land tenure, which captures the security and duration of the farmer's land rights; access to credit, which indicates the farmer's ability to borrow money for agricultural inputs; education level, which reflects the farmer's human capital and awareness of new technologies;

household size, which proxies the labour supply and consumption needs of the farmer's family; farm size, which measures the scale and intensity of the farmer's production; other income, which captures the farmer's non-farm income sources and diversification strategies; gender, which accounts for the possible differences in preferences and constraints between male and female farmers; household expenditure, which proxies the farmer's wealth and liquidity; and age, which reflects the farmer's experience and risk aversion are the model's regressors while the coefficients β_1 to β_{10} are respective coefficients associated with each independent variable. Coefficients estimates provide information on the relationship between dependent and independent variables. In particular, these coefficients can be used to predict the change in probability of fertilizer adoption as a result of changes in the respective independent variables.

A probit model was employed in the study to estimate the predicted probabilities (propensity scores) of adopting fertilizer technology so as to be able to achieve objective one. Following (Greene and Hensher, 2003), (Verbeek, 2008) and (Willy et al., 2014), the probit model is expressed as;

$$Pr\ (D=1 \mid X) = G(Z) = {}^{X^i\beta}{}_{-\infty}\emptyset\ (Z)dz = \emptyset\ (X^i\ \beta) \qquad (5)$$

where *G(z)* is a function taking values between 0 and 1, ∅ is the standard normal probability density function, *z* is the vector of covariates and *f* is the standard normal cumulative distribution function.

The empirical probit model estimated is expressed below:

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

$$Y_i = \begin{cases} 1, & if\ Y_i^* > 0 \\ 0, & otherwise \end{cases} \qquad \ldots(6)$$

Where Y_i^* is a latent variable representing the decision to adopt fertilizer and Y_i is the observed status of adopting fertilizer for each household, *X* is a vector of explanatory variables that include farmer and farm characteristics, socio-economic and institutional/policy factors, *βs* are the estimated parameters, and μ_i is a stochastic error term.

Probit regression model has been widely utilized to evaluate the functional association among the probability of adoption and its determining elements. The binary econometric models enable a more specific analysis of farmers' adoption of new technology (Enki et al., 2001; Mariano et al., 2012; Muzari et al., 2012). This type of analysis provides more detailed information on the characteristics of the farmers who tend to adopt a specific technology. The probit regression model is preferred in this study over the others because of its good properties, especially the assumption of normal distribution (Semykina and Wooldridge, 2010). Thus, this study used probit regression model to identify the factors influencing fertilizer adoption among small-scale crop farmers in the ASALs of Kenya.

b) Implications of adoption of fertilizer on crop yield

The adoption of fertilizer in agriculture carries profound implications for crop yield, playing a pivotal role in the quest for enhanced food production and food security. Moreover, the implications of fertilizer adoption extend beyond immediate crop yield improvements. Increased yields can have cascading effects on food security, income generation for farmers, and rural development. By enhancing crop production, fertilizer use can contribute to meeting the nutritional needs of local communities and reducing food shortages. Additionally, higher crop yields can generate surplus produce for sale in the market, leading to increased income for farmers and improved livelihoods. This, in turn, can stimulate economic growth in rural areas and reduce poverty.

However, the adoption of fertilizer is not a simple decision that depends only on the availability and affordability of the input. There are many other factors that influence the adoption behaviour of farmers, such as their socio-economic characteristics, farm characteristics, access to information and extension services, risk preferences, and environmental conditions. Therefore, to measure the causal effect of fertilizer adoption on crop yield, we need to account for these factors and isolate the effect of the treatment variable (fertilizer adoption) from the confounding variables (control variables).

One way to achieve this is to use a statistical technique called propensity score matching (PSM). PSM is a method that matches farmers who adopted fertilizer with farmers who did not adopt fertilizer, but have similar characteristics in terms of the confounding variables. By doing so, PSM creates a counterfactual scenario that allows us to compare the outcomes of the two groups of farmers as if they were randomly assigned to adopt or not adopt fertilizer. This way, we can estimate the average treatment effect (ATE) of fertilizer adoption on crop yield, which is the difference in crop yield between the treated group (fertilizer adopters) and the control group (non-adopters) after matching.

To achieve objective 2, we employed Propensity Score Estimation Equation: The propensity score (denoted as P_i) 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 is the propensity score for 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 that may influence the likelihood of adoption. In this particular study, PSM was applied to estimate the impact of adopting fertilizer on the crop yield of small-scale crop farmers in the ASALs of Kenya.

The PSM is expressed as;

$$P(X) = Pr\ [D{=}1 \mid X] = E\ [D \mid X];\ P(X) = F\ \{h(X_i)\} \qquad (7)$$

Where *P(X)* is a propensity score and *Pr* is the probability of adopting a technology conditional on the vector of observed covariates (social characteristics), *X* and *F{.}* is a probit distribution. D=1 if fertilizer is adopted and zero (0) otherwise. The key idea behind PSM, introduced by Rosenbaum and Rubin (1983), is to adjust for self-selection bias by matching adopters and non-adopters based on their propensity scores. Households who have adopted fertilizer are paired with their counterparts who have noted adopted based on the expected probabilities obtained from estimating equation (4). After the estimation of propensity scores, different matching algorithm, which are nearest neighbour matching (NNM), Kernel-based matching (KBM), and radius matching (RM) were utilized to pair each adopter with a non-adopter. The use of different matching algorithms interchangeably helps in validating the accuracy of the estimates. In the NNM's approach having nearest neighbours with very far away in terms of propensity score differences increase the likelihood of poor matches.

Radius matching is an approach that can be used to fix this problem by setting a maximum allowable disparity between propensity scores (Mulugeta and Hundie, 2012). Matching all adopter farmers with an average of all non-adopter farmers, where the weight is inversely proportional to the difference in propensity ratings between the two groups Becerril and Abdulai (2010) is an example of a Kernel-based matching approach. The matching estimations were built using the common support. Selecting parallel observations from the adopters and non-adopters' households in the study constitutes the common support condition.

Whether or not a farmer adopts fertilizer, all farmers in the common support region should share the same distribution of observable features, hence it was important to keep this balancing aspect of the sample in mind when conducting the study (Villano et al., 2015). The balancing attribute represents the degree to which the samples are well matched. The quality of the matching was evaluated in this study 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 to be well-matched if the average bias in the mean difference is less than 5 per cent. Following the estimation of propensity scores, the average treatment effect on the treated (ATT) was used to determine the impact of fertilizer adoption on crop yield. The mean treatment impact is the average disparity between treatment and control groups that share similar characteristics on propensity scores and common support locations.

The ATT is specified as follows.

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

Where Y_1 and Y_0 are the average quantity of crop yield (kg/acre) for the adopter and non-adopter farmers respectively, D is a dummy variable that takes two values: $D = 1$ if farmers adopt technology and $D = 0$ if farmers do not adopt a technology.

Selection bias and endogeneity are two major obstacles to measuring effect evaluations in research. These difficulties result from the treatment groups being chosen non-randomly, which causes the adoption of fertilizer to be influenced by both observable and non-observable traits, such as farmers' incentives and risk attitudes. The average treatment effect on the treated (ATT) was estimated using Propensity Score Matching (PSM) methodologies to overcome these problems. By matching adopters and non-adopters based on observable traits, PSM reduces self-selection bias and makes sure that the estimated technology effect is purely attributable to the treatment (adoption). However, PSM's weakness lies in its inability to account for unobservable factors that may be correlated with the outcome variable. To address this concern, the Rosenbaum sensitivity test was employed to assess the impact estimates obtained from PSM.

3.2 Data and Data Sources

The purpose of this study was to assess the impact of fertilizer technology on small-scale crop farming productivity in ASALs of Kenya. To achieve this objective, a cross-sectional analysis of households across the ASAL counties in Kenya was done using data from the 2015/16 Kenya Integrated Household Budget Survey (KIHBS). The data was collected for 12 months from September 2015 to August 2016 for all the 47 counties in Kenya and was analyzed with the help of Stata software. A description of both dependent and independent variables and how they are measured 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
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=No
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=No
	Household size	No. of individuals in a household	Discrete	Individuals
	Expenditure	Household expenditure on agricultural inputs related to crop production	Continuous	Kenya Shillings
	Farm size	Size of land cultivated by the households	Continuous	Acres
Yield (outcome) (Y)	Crop yield	Yield of crops on the farm	Continuous	Kilogrammes

Source: Authors' compilation (2023)

3.3 Definition of Variables and Summary Statistics

The definitions of variables and summary statistics of the sampled farm households in the study are presented in Table 3.1.

The study examines fertilizer adoption behaviour and its influencing factors among small-scale crop farmers in the ASALs. Table 3.1 show the descriptive statistics of various variables for the adopters and non-adopters of fertilizer in four county classifications: arid (85-100%), semi-arid 1 (30-84%), semi-arid 2 (10-29%), and non-ASALs (less than 10%). The variables include crop yield, characteristics of adopters, and policy/actor variables. The tables also show the number of observations, the mean, the standard deviation, the minimum, and the maximum values for each variable and group. Some of the main findings from the tables are:

The mean crop yield of adopters is higher than that of non-adopters in all aridity zones except for non-ASALs, where the difference is negligible. This suggests that fertilizer adoption has a positive impact on crop productivity, especially in arid and semi-arid areas where there is limited access to water, and unpredictable rainfall is a major constraint.

On the policy/actor variables, the proportion of adopters who have secure land tenure is higher than that of non-adopters in all aridity zones except for semi-arid 2, where the difference is negligible. This may imply land tenure security, or that households with secure land tenure are more likely to adopt fertilizer due to lower transaction costs or higher incentives to invest in land improvement. Adopters who have access to credit are lower than that of non-adopters in all categories except for arid and semi-arid 1, where the difference is negligible. This may indicate that households with access to credit are likely to adopt fertilizer, because it ensures that farmers can acquire fertilizers when they are needed, rather than having to wait until they have saved enough money, potentially missing the optimal window for application.

The proportion of adopters who have access to fertilizer is higher than that of non-adopters in all aridities except for semi-arid 2, where the difference is reversed. This may suggest that household farmers who have access to fertilizers can experience a significant increase in crop yields and quality. This immediate benefit serves as a strong incentive for them to continue using fertilizer.

On the characteristic of the adopter, the gender distribution of adopters and non-adopters is similar in all aridities, indicating that fertilizer adoption is not biased by gender. However, the proportion of female adopters is slightly higher than that of male adopters in arid and semi-arid 1 zones, which may reflect the greater vulnerability of women to drought and food insecurity. The mean age of adopters and non-adopters is also similar in all aridity's, implying that fertilizer adoption is not influenced by age. However, the standard deviation of age is higher for non-adopters than for adopters, suggesting that there is more variation in the age profile of non-adopters than adopters.

The mean farm size of adopters is slightly larger than that of non-adopters in all aridity's except for arid, where the difference is reversed. This may indicate that farm size is not a major determinant of fertilizer adoption.

The mean education category of adopters is lower than that of non-adopters in all aridity's except for semi-arid 2, where the difference is negligible. This may suggest that fertilizer adoption does not require a high level of education, or that education does not have a strong effect on fertilizer adoption. Alternatively, it may reflect the lower availability or quality of education in arid and semi-arid areas compared to non-ASALs.

The proportion of adopters who have other income sources is higher than that of non-adopters in all aridity's except for arid, where the difference is negligible. This may suggest that households with diversified income sources are more likely to adopt fertilizer.

Table 3.1: Descriptive statistics of variables

Summary statistics: by (County classification)

Arid (85-100%): Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	206	318.383	539.064	0	3595
Policy/Actor Variables					
Land tenure	206	0.772	0.421	0	1
Access credit	206	0.621	0.486	0	1
Access fertilizer	206	0.976	0.154	0	1
Characteristics of Adopters					
Gender	206	0.471	0.500	0	1
Age	206	35.262	14.745	18	87
Farm size	206	1.570	0.788	1	5
Education category	206	1.631	0.802	1	5
Household size	206	2.248	0.879	1	4
Log household expenditure	206	5.252	2.786	1	13
Other income	206	7.869	1.135	4.605	11.438

Arid (85-100%): Non-Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	157	221.268	357.509	0	3500
Policy/Actor Variables					
Land tenure	157	0.758	0.430	0	1
Access credit	157	0.637	0.482	0	1
Access fertilizer	157	0.089	0.286	0	1
Characteristics of Adopters					
Gender	157	0.554	0.499	0	1
Age	157	38.439	16.31	18	86
Farm size	157	1.490	0.765	1	5
Education category	157	2.242	0.835	1	4
Household size	157	5.089	2.676	1	12
Log household expenditure	157	7.944	1.095	4.248	11.472
Other income	157	0.006	0.080	0	1

Semi-Arid 1 (30-84%): Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	405	317.533	853.79	0	13060
Policy/Actor Variables					
Land tenure	405	0.780	0.415	0	1
Access credit	405	0.570	0.496	0	1
Access fertilizer	405	0.970	0.170	0	1
Characteristics of Adopters					
Gender	405	0.504	0.501	0	1
Age	405	38.541	16.882	18	88
Farm size	405	1.597	0.868	1	5
Education category	405	1.588	0.876	1	5
Household size	405	2.037	0.896	1	4
Log household expenditure	405	4.254	2.568	1	16
Other income	405	7.914	1.135	4.605	11.608

Semi-Arid 1 (30-84%): Non-Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	278	265.432	641.248	0	7900
Policy/Actor Variables					
Land tenure	278	0.687	0.465	0	1
Access credit	278	0.532	0.500	0	1
Access fertilizer	278	0.065	0.247	0	1
Characteristics of Adopters					
Gender	278	0.468	0.500	0	1
Age	278	38.59	17.014	18	89
Farm size	278	1.612	0.858	1	5
Education category	278	2.140	0.902	1	4
Household size	278	4.471	2.829	1	17
Log household expenditure	278	7.939	1.122	4.605	10.597
Other income	278	0.054	0.226	0	1

Semi-Arid 2 (10-29%): Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	299	425.682	1515.11	0	18000
Policy/Actor Variables					
Land tenure	299	0.776	0.418	0	1
Access credit	299	0.338	0.474	0	1
Access fertilizer	299	0.957	0.204	0	1
Characteristics of Adopters					
Gender	299	0.502	0.501	0	1
Age	299	38.191	16.004	18	85
Farm size	299	1.643	0.955	1	5
Education category	299	1.709	0.999	1	5
Household size	299	2.201	0.927	1	4
Log household expenditure	299	3.819	2.333	1	12
Other income	299	7.965	1.192	4.094	11.503

Semi-Arid 2 (10-29%): Non-Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	245	240.498	469.086	0	5400
Policy/Actor Variables					
Land tenure	245	0.714	0.453	0	1
Access credit	245	0.261	0.440	0	1
Access fertilizer	245	0.139	0.346	0	1
Characteristics of Adopters					
Gender	245	0.453	0.499	0	1
Age	245	39.629	16.946	18	85
Farm size	245	1.563	0.892	1	5
Education category	245	2.094	0.907	1	4
Household size	245	3.931	2.443	1	13
Log household expenditure	245	8.066	1.085	4.605	11.29
Other income	245	0.049	0.216	0	1

Non-ASALs : Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	582	363.387	1104.894	0	13000
Policy/Actor Variables					
Land tenure	582	0.732	0.443	0	1
Access credit	582	0.144	0.352	0	1
Access fertilizer	582	0.952	0.214	0	1
Characteristics of Adopters					
Gender	582	0.452	0.498	0	1
Age	582	37.904	15.651	18	87
Farm size	582	1.633	0.914	1	5
Education category	582	1.596	0.874	1	5
Household size	582	2.149	0.858	1	4
Log household expenditure	582	4.160	2.421	1	15
Other income	582	7.933	1.151	4.605	11.385

Non-ASALs: Non- Adopters

Variable	Obs	Mean	Std. Dev.	Min	Max
Crop yield	520	399.333	1338.615	0	18420
Policy/Actor Variables					
Land tenure	520	0.762	0.427	0	1
Access credit	520	0.181	0.385	0	1
Access fertilizer	520	0.081	0.273	0	1
Characteristics of Adopters					
Gender	520	0.438	0.497	0	1
Age	520	38.612	17.026	18	88
Farm size	520	1.675	0.956	1	5
Education category	520	2.204	0.885	1	4
Household size	520	4.129	2.424	1	12
Log household expenditure	520	7.877	1.193	4.382	12.112
Other income	520	0.098	0.298	0	1

4. Factors Influencing Fertilizer Adoption and Impact on Crop Production

4.1 Determinants of Adoption of Fertilizer

Table 4.1 provided shows the marginal results of a probit analysis on the determinants of adoption of fertilizer technology by farmers in different aridity zones of Kenya. The adoption of fertilizer is an important indicator of agricultural productivity and income for rural households. However, the adoption rate of fertilizer varies across different regions and household characteristics. The paper uses a probit regression model to estimate the effect of each factor on the probability of adopting fertilizer, controlling for other variables.

Table 2. Average marginal effect analysis on determinants of adoption of fertilizer technology on the county classification

Variable Names	Arid (85%-100%)	Semi-Arid 1 (30%-84%)	Semi-Arid 2 (10%-29%)	Non-ASALs
	dy/dx	dy/dx	dy/dx	dy/dx
Policy/Actor Variables				
Land tenure	-0.010 (0.783)	0.035*** (0.001)	0.034* (0.069)	-0.016 (0.361)
Access to credit	0.051** (0.047)	0.013 (0.451)	0.024 (0.372)	-0.011 (0.594)
Access to fertilizer	0.352*** (0.000)	0.317*** (0.000)	0.438*** (0.000)	0.381*** (0.000)
Characteristic of the Adopter				
Gender	-0.015 (0.507)	0.011 (0.471)	0.019 (0.438)	0.015 (0.327)
Age	-0.001** (0.050)	0.002 (0.876)	-0.001* (0.086)	-0.000 (0.451)
Farm size	0.008 (0.611)	-0.004 (0.602)	0.020 (0.129)	-0.002 (0.807)
Primary education	-0.048 (0.194)	0.017 (0.417)	-0.028 (0.359)	0.012 (0.519)
Secondary education	-0.106** (0.029)	0.029 (0.234)	-0.019 (0.569)	-0.014 (0.526)
Higher education	-0.054 (0.296)	0.007 (0.857)	-0.036 (0.446)	-0.049 (0.162)
Household size	-0.001 (0.898)	-0.004 (0.234)	0.010* (0.076)	-0.004 (0.168)
Log of household expenditure	0.008 (0.420)	-0.008 (0.267)	-0.019* (0.087)	-0.001 (0.826)

Other income	0.087 (0.535)	-0.028 (0.410)	0.083 (0.145)	-0.001 (0.966)
Number of observations	**363**	**683**	**544**	**1102**

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

The estimated coefficients and marginal effects of the probit estimates used to describe the impact of various explanatory factors on the dependent variable. Marginal effect values represent the amount of the likelihood of effects, while their sign indicates the direction of the impact of the explanatory factors on the dependent variable (adoption of fertilizer).

The marginal effects show how the probability of adopting fertilizer changes when one of the independent variables changes by one unit, holding all other variables constant at their means. They are calculated as the partial derivatives of the probability function with respect to each independent variable. The standard errors of the marginal effects are reported in parentheses below the marginal effects.

Access to fertilizer has a positive and significant effect on the probability of adoption in all aridity, meaning that farmers who have access to fertilizer are more likely to adopt the technology than farmers who do not have access to fertilizer. The marginal effects mean that having access to fertilizer increases the probability of adoption by 35.2, 31.7, 43.8, and 38.1 percentage points in arid, semi-arid 1, semi-arid 2 and non-ASALs, respectively.

Access to credit has a positive and significant effect on the probability of adoption in arid areas, meaning that farmers who have access to credit are more likely to adopt the fertilizer than farmers who do not have access to credit. The marginal effect is 0.051, which means that having access to credit increases the probability of adoption by 5.1 percentage points.

The average marginal effect of land tenure is 0.035 in semi-arid 1, which means that holding other variables constant at their mean values, having secure land tenure increases the probability of adopting fertilizer by 3.5 percentage points, on average. While on semi-arid 2, the average marginal effect of land tenure is 0.034, which means that holding other variables constant at their mean values, having secure land tenure increases the probability of adopting fertilizer by 3.4 percentage points, on average.

Log expenditure has a negative and significant effect on the probability of adoption in semi-arid 2 areas, meaning that farmers with higher expenditure are less likely to adopt the technology than farmers with lower expenditure. The marginal effect is -0.019, which means that for every one percent increase in expenditure, the probability of adoption decreases by 1.9 percentage points.

4.2 Impact of Fertilizer Adoption on Productivity

The results presented in Table 3 are from a treatment-effects estimation using propensity-score matching. The analysis compares the average treatment effect on the treated (ATE) between adopters and non-adopters of fertilizer technology. The analysis employs propensity-score matching to investigate the impact of fertilizer adoption on (maize, beans and cowpeas) crops and includes 2,692 observations and focuses on individuals household heads. Using a probit model for the treatment variable (fertilizer adoption), the analysis calculates the Average Treatment Effect on the Treated (ATE). The key finding reveals a substantial and highly statistically significant positive effect of fertilizer adoption on the outcome variable. Fertilizer adopters, compared to non-adopters, exhibit an estimated increase of approximately 0.7765 units in the outcome variable, and this difference is found to be highly significant at one percent confidence level. The confidence interval does not include zero, further affirming the robustness of this effect. The results indicate that fertilizer adoption is associated with a significantly positive impact on the outcome variable among household heads.

Table 3: Treatment-effects estimation

Propensity Score of fertilizer	Coefficient	Standard Error	P-Value	Significance
Adopter vs Non-adopter	0.776	0.013	0.000	***
Mean dependent var	0.560	SD dependent var	0.444	
*** p<.01, ** p<.05, * p<.1				

Sensitivity and specificity test of adoption

Table 5 summarizes the adoption of fertilizer practices in the: ASALs (Arid and Semi-Arid Lands) and non-ASALs. The table presents the number of farmers categorized as "non-Adopters" and "Adopters" within each classification. Table 6 presents the results of a sensitivity test assessing the accuracy with confidence intervals at the 95 per cent level.

Table 5: Fertilizer adoption by county classification

Fertilizer adoption	County classification				
	Arid	Semi_ Arid1	Semi_ Arid 2	Non_ ASALs	Total
Non-Adopters	157	278	245	520	**1200**
Adopters	206	405	299	582	**1492**
Total	**363**	**683**	**544**	**1102**	**2692**

Table 6: Sensitivity test

Sensitivity	Pr(+D)	55.77%	54.11%	57.44%
Specificity	Pr(-~D)	42.82%	41.16%	44.48%
Positive predictive value	Pr(D +)	63.55%	61.93%	65.16%
Negative predictive value	Pr(~D -)	35.14%	33.54%	36.74%
Prevalence	Pr(D)	64.12%	62.51%	65.73%

In Table 5, the findings reveal fertilizer adoption rates and the diagnostic accuracy of a test that classifies counties by county classification into arid and non-arid areas. The first table displays fertilizer adopters and non-adopters by county type and the total number of counties in each group. Table 6 provides the test's sensitivity, specificity, positive and negative predictive values, prevalence, and 95 per cent confidence intervals. The test's sensitivity is the percentage of arid counties properly categorized. The sensitivity is 55.77 per cent, with a 95 per cent confidence range of 54.11 per cent to 57.44 per cent. This indicates the test can detect 56 per cent of arid counties but misses 44 per cent. This modest sensitivity suggests the test may discover dry regions.

The percentage of non-arid counties properly categorized by the test is its specificity. The specificity is 42.82 per cent, with a 95.00 per cent confidence range of 41.16 per cent to 44.48 per cent. This indicates the test can detect 43 per cent of non-arid counties but misclassifies 57 per cent as arid. This poor specificity suggests the test cannot exclude non-arid counties well.

The test's positive predictive value (PPV) is the percentage of dry counties that are genuinely arid. The PPV is 63.55 per cent, with a 95 per cent confidence range of 61.93 per cent to 65.16 per cent. This suggests that 64 per cent of test-labelled dry counties are indeed arid and 36 per cent are false positives. The prevalence of aridity in the population is 64.12 per cent, with a 95 per cent confidence range of 62.51 per cent to 65.73 per cent, determining the PPV. This indicates 64 per cent of counties are dry regardless of test results.

The test's negative predictive value (NPV) is the percentage of non-arid counties that are identified as so. The NPV is 35.14 per cent, with a 95 per cent confidence range of 33.54 per cent to 36.74 per cent. About 35 per cent of counties designated non-arid by the test are actually non-arid, whereas 65 per cent are false negatives. The same as above, population aridity affects NPV.

The results show that fertilizer adoption rates vary by county type and that the test that classifies counties into arid and non-arid regions based on county classification has moderate sensitivity, low specificity, moderate positive predictive value, and low negative predictive value.

The propensity score matching (PSM) method was used in estimating the impact of fertilizer adoption on smallholder crop farmers' productivity. The estimates obtained by the three algorithms through the PSM process were subjected to quality control tests. The study performed two diagnostic tests to ensure the quality of the matching process after predicting the propensity score for both adopters and non-adopters of fertilizer technology.

Table 7: Impact of adoption of fertilizer on productivity-PSM

Arid

Crop yield Matching algorithms	Treated (Adopters)	Controls (Non-Adopters)	Difference	S.E.	T-stat
Kernel-based matching (KBM)	304.686	172.026	132.660	84.420	2.17
Radius matching (RM)	304.686	220.683	84.003	29.615	2.84
Nearest neighbour (NNM)	304.686	180.798	123.888	32.717	2.66

Semi-Arid 1

Crop yield Matching algorithms	Treated (Adopters)	Controls (Non-Adopters)	Difference	S.E.	T-stat
Kernel-based matching (KBM)	318.593	257.799	60.794	173.014	0.35
Radius matching (RM)	318.593	340.317	-21.723	29.511	-0.74
Nearest neighbuor (NNM)	318.593	248.862	69.731	112.245	0.62

Semi-Arid 2

Crop yield Matching algorithms	Treated (Adopters)	Controls (Non-Adopters)	Difference	S.E.	T-stat
Kernel-based matching (KBM)	401.636	274.319	127.117	117.355	1.08
Radius matching (RM)	401.636	319.317	82.523	50.270	1.64
Nearest Neighbor (NNM)	401.636	260.415	141.220	83.576	1.69

Non- ASALs

Crop yield Matching algorithms	Treated (Adopters)	Controls (Non-Adopters)	Difference	S.E.	T-stat
Kernel-based matching (KBM)	387.195	365.045	22.149	131.327	0.17
Radius matching (RM)	387.195	401.777	-14.582	37.595	-0.39
Nearest neighbour (NNM)	387.195	315.802	71.393	165.84	0.43

Based on these results, it was found that: For Arid counties, all three matching algorithms show a positive and statistically significant after treatment effect (ATE) of fertilizer adoption on crop yield. This means that adopting fertilizer increases crop yield by an average of 84 to 133 kilogrammes per acre in arid regions, compared to not adopting fertilizer. This is a large and meaningful effect, given that the average crop yield in arid region is only 172 kilogrammes per acre for non-adopters. For semi-arid 1, none of the matching algorithms showed a statistically significant ATE of fertilizer adoption on crop yield. This means that adopting fertilizer does not have a clear or consistent effect on crop yield in semi-arid, compared to not adopting fertilizer. The estimated ATE ranges from -22 to 70 kilogrammes per acre, but they are not different from zero at 5 per cent significance level.

For semi-arid 2 regions, all three matching algorithms show a slightly positive and statistically significant ATE of fertilizer adoption on crop yield. This means that adopting fertilizer increases crop yield by an average of 83 to 141 kilogrammes per hectare in semi-arid 2 counties, compared to not adopting fertilizer. This is also a large and meaningful effect, given that the average crop yield in semi-arid 2 AEZ is only 274 kilogrammes per acre for non-adopters.

For non-ASALs counties, none of the matching algorithms showed a statistically significant ATE of fertilizer adoption on crop yield. This means that adopting fertilizer does not have a clear or consistent effect on crop yield in non-ASALs, compared to not adopting fertilizer. The estimated ATE ranges from -15 to 71 kilogrammes per acre.

These results suggest that fertilizer adoption has a heterogeneous effect on crop yield across different aridity's. Fertilizer adoption seems to have a positive and significant impact on crop yield in arid and semi-arid 2 counties, where crop production is more constrained by low soil fertility and water availability. However, fertilizer adoption does not seem to have a significant impact on crop yield in semi-arid 1 and non-ASALs counties, where crop production may be more influenced by other factors such as pest infestation and use of organic fertilizers.

The estimated average impact of fertilizer technology adoption on yield ranges from about 304 kg/ha to about 401 kg/ha depending on the estimation techniques. Thus, adopters of fertilizer obtained between 84 and 132 kg more yield per hectare of farmland, yielding an average productivity reduction of about 114 kg/acre less if they had not adopted fertilizer. The values of the estimated matching methods showed minimal differences in the outcomes, which implies that the results are robust.

5. Conclusion and Policy Recommendations

5.1 Conclusion

In conclusion, this research provides valuable insights into the factors influencing fertilizer adoption among small-scale crop farmers in the Arid and Semi-Arid Lands (ASALs) of Kenya. Through probit regression analysis, we identified significant predictors, including access to fertilizer, access to credit and land tenure that highly contributed to the adoption of fertilizer, other control variables such as age, household expenditure and secondary education also had a significant effect in some of the county classification. The PSM results show that farmers who adopted fertilizer in the arid counties had a significant increase in productivity and that they would have had 114 kg/acre less if they had not adopted it. The findings support the view that adoption of fertilizer plays a vital role in increasing crop productivity, which in turn increases the income of farm households. These findings underscore the importance of targeted policies and interventions to promote sustainable agricultural practices and enhance farmers' livelihoods.

Based on the research findings, policy makers and stakeholders can leverage the following policy recommendations to boost fertilizer adoption and agricultural productivity in the ASALs:

5.2 Recommendations

i) Formalizing Land Ownership: The government through the Ministry of Lands to simplify land registration processes and provide legal support to enhance land tenure security. By formalizing land ownership, farmers will be more willing to invest in long-term agricultural technologies such fertilizers. The government will also work with local authorities and communities to resolve any land disputes and ensure fair and transparent allocation of land rights.

ii) Promote Fertilizer Access: The government through Ministry of Agriculture, Livestock, Fisheries and Co-operatives to focus on improving the accessibility and affordability of fertilizers, particularly in regions where access is limited. Subsidy programmes or cooperative initiatives can be explored to reduce the cost of fertilizers for farmers and encourage bulk purchasing. The government can also partner with private sector actors and research institutions to promote the development and dissemination of high-quality and climate-smart fertilizers that suit the local soil conditions and crop varieties.

iii) Enhanced Financial Services: The government to collaborate with financial institutions to improve access to credit for farmers across ASALs. This will enable farmers to purchase fertilizers and other inputs without facing liquidity constraints. Additionally, the government can invest in infrastructure and distribution networks to ensure the reliable and affordable availability of fertilizers. This will reduce transportation costs and delays that often discourage farmers from using fertilizers.

iv) Targeted Education Programmes: The results show that education levels have a significant impact on fertilizer adoption. Farmers with higher levels of education are more likely to adopt fertilizer technology. To promote fertilizer adoption in all regions, the Ministry of Agriculture, Livestock, Fisheries and Co-operatives in partnership with the Ministry of Education and private actors could consider implementing education programmes that specifically target farmers with lower levels of education. These programmes can provide training and information on the benefits and proper use of fertilizers. They can also leverage existing extension services, farmer groups, and media platforms to reach a wider audience and foster peer learning.

Finally, by implementing these evidence-based policy implications, policy makers can create an enabling environment for fertilizer technology adoption, leading to increased crop productivity, food security, and enhanced incomes for farmers in the ASALs of Kenya. Strengthening the agricultural sector will contribute to sustainable development, poverty alleviation, and overall socio-economic progress in the region.

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Annex

Annex 1: Probit analysis on determinants of adoption of fertilizer technology

	Arid (85%-100%)	**Semi-Arid 1 (30%-84%)**	**Semi-Arid 2 (10%-29%)**	**Non-ASALs**
Fertilizer adoption	Coef. (P-value).	Coef. (P-value).	Coef. (P-value).	Coef. (P-value).
Policy/ Actor Variables				
Land tenure	-0.105 (0.780)	0.346*** (0.001)	0.334* (0.067)	-0.084 (0.355)
Access to credit	0.533** (0.044)	0.139 (0.449)	0.154 (0.387)	-0.087 (0.591)
Access to fertilizer	3.625*** (0.000)	3.504*** (0.000)	2.948*** (0.000)	3.116*** (0.000)
Characteristic of Adopter				
Gender	-0.153 (0.520)	0.126 (0.471)	0.127 (0.435)	0.118 (0.331)
Age	-0.020** (0.023)	-0.003 (0.938)	-0.009* (0.097)	-0.002 (0.669)
Farm size	0.084 (0.593)	-0.049 (0.603)	0.130 (0.140)	-0.018 (0.788)
Primary Education	-0.557 (0.164)	0.181 (0.429)	-0.159 (0.444)	0.117 (0.460)
Secondary Education	-1.107** (0.019)	0.318 (0.260)	-0.102 (0.665)	-0.098 (0.593)
Higher Education	-0.645 (.557)	0.064 (0.872)	-0.208 (0.551)	-0.364 (0.161)
Household size	-0.005 (0.903)	-0.039 (0.228)	0.065* (0.078)	-0.034 (0.173)
Log household expenditure	0.092 (0.391)	-0.086 (0.262)	-0.128* (0.085)	-0.012 (0.819)
Other income	0.946 (0.520)	-0.311 (0.406)	0.555 (0.149)	-0.009 (0.966)
Constant	-1.699 (0.118)	-1.292* (0.093)	-.916 (0.191)	-1.242** (0.014)
Number of Observation	363	683	544	1102
Prob > chi2	0.000	0.000	0.000	0.000
Pseudo r-squared	0.730	0.742	0.599	0.664

Note: *P-value in Parentheses. *** p<.01, ** p<.05, * p<.1*

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