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# Adoption and the Role of Fertilizer Trees and Shrubs as a Climate Smart Agriculture Practice: The Case of Salima District in Malawi

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**Abstract:** Fertilizer trees and shrubs can improve degraded soil and avert the impacts of climate change on smallholder farmers in Malawi. This paper analyses the roles of fertilizer trees and shrubs and factors that determine adoption, as well as the intensity of use of fertilizer on trees and shrubs in maize-based farming systems using the Tobit model. A household survey involving 250 smallholder farmers was conducted in Salima district, Malawi. The analysis shows that adopters of fertilizer trees and shrubs considered fertility improvement, shade, source of food and erosion control as main roles of fertilizer trees and shrubs. The Tobit model shows that households with relatively more land are more likely to adopt fertilizer trees and shrubs than those with small land sizes. Adoption is higher among farmers who had been exposed to fertilizer trees and shrubs for longer periods than others had. Land tenure, education and availability of labor also influence the adoption of fertilizer trees and shrubs. Results further show that household and farm characteristics and availability of extension services explain the current adoption rates of tree-fertilizer technologies. Our findings can guide effective targeting of farmers to ensure higher adoption and sustainability of fertilizer-tree and shrub technology for climate-smart agriculture among the smallholder farmers.

**Keywords:** fertilizer trees and shrubs; Tobit model; adoption; climate change

## 1. Introduction

Based on the 5th Assessment report of the Intergovernmental Panel on Climate Change (IPCCC), there has been an increased pattern of prolonged dry spells and erratic precipitation in Africa, adversely affecting livelihoods and food security of people [1]. Smallholder farmers in Sub Saharan Africa depend on rain-fed agriculture and, thus, the impacts of climate related shocks are resulting in a decline in food production and causing persistent food insecurity [2]. Other challenges facing smallholder farmers in the region include high rates of soil erosion and depletion of fertility that have undermined efforts to attain food security [3].

Like most countries in sub-Saharan Africa, in Malawi, climate change is already exerting negative impacts on agriculture. Smallholder farmers already experience the adverse impacts, especially in most vulnerable areas, including along the lakeshore areas and the Shire River valley [4]. This study focused on Salima district, one of the lakeshore districts, because a worsening pattern of prolonged dry spells and floods threatens food production, especially the staple, maize [5]. Among the responses, agriculture policy, development agencies, non-governmental organizations (NGOs) and researchers

have promoted climate-smart agricultural practices and strategies to enhance food security while adapting and mitigating the adverse impacts of climate change (CC).

Climate-smart agriculture (CSA) encompasses agricultural practices that contribute to the achievement of sustainable development goals by integrating economic, social and environmental dimensions of the farming system to adapt to the impacts of climate change and improve food security [2]. CSA comprises of field-proven agricultural practices, such as agroforestry, that contribute to enhancing household food security for the smallholder farmers [6]. The CSA approach seeks to identify and operationalize sustainable agricultural development within the explicit parameters of climate variability and change [7].

Research shows that the integration of trees on farmlands through agroforestry can enhance farm productivity while contributing to climate change mitigation through carbon sequestration and enhance adaptation to alleviate adverse impacts of climate change [8]. In particular, fertilizer-tree technologies form one of the sustainable solutions to nutrient depletion, high costs of inorganic fertilizer and soil erosion [3]. Fertilizer-tree technologies include leguminous tree and shrubs incorporated in crop fields to enhance fertility by incorporating biomass and/or fixing nitrogen through the root nodules. Fertilizer-trees and shrubs maintain soil cover, improve nutrient levels and soil organic matter and provide shade, food, fiber and fuel [9]. Although agroforestry can work in various cropping systems, this research focused on maize-based systems because of their importance to food security in Malawi.

The key questions of this paper are: (1) What role and level of importance do farmers assign to fertilizer trees and shrubs in their crop production? (2) What factors determine the decision to adopt and expand land allocated to fertilizer trees and shrubs? (3) What are the broader implications for the promotion of fertilizer-tree and shrubs technologies into smallholder farming systems for the broader goals of enhancing food security and promoting climate-smart agriculture? Answering these questions is vital for establishing critical factors that need to be considered for up-scaling fertilizer-tree and shrubs technologies and ultimately increasing the resilience of farming systems to CC and the adaptability of farming families. Findings from this study can guide project and program design to ensure high adoption, use and sustainability of fertilizer trees and shrubs to minimize vulnerability of smallholder farmers to the adverse impacts of CC.

### *1.1. Research Background*

Agroforestry is a collective name for land-use systems and technologies where land managers/farmers deliberately incorporate woody perennials on the same land management unit as agricultural crops and/or animals, in some form of spatial arrangement or temporal sequence to harness both ecological and economic benefits from the interactions between the different components [10–12]. In this research, the definition narrows down to the deliberate introduction and management of leguminous trees and herbaceous legumes. These tree species are commonly termed as fertilizer trees and shrubs and farmers introduce them in crop fields mainly to increase nitrogen and biomass in the soil to enhance crop production [13].

Despite the known benefits of fertilizer trees and shrubs, adoption rates among the smallholder farmers, particularly in Salima district, are generally low [14]. Fertilizer trees and shrubs can also minimize impacts of climate change and conserve soil because of their vital ecological roles [15]. The current low levels of adoption of fertilizer trees and shrubs show the need for reliable information on the factors that determine adoption and expansion of fertilizer trees and shrubs interventions among smallholder farmers. Some scholars, for example, Sanchez (1995) [16], highlight a need to develop predictive understanding of how farming households make decisions regarding land use, including the choice and levels of investment in fertilizer trees and shrubs adoption and management to ensure sustainability of agroforestry.

## 1.2. Previous Studies

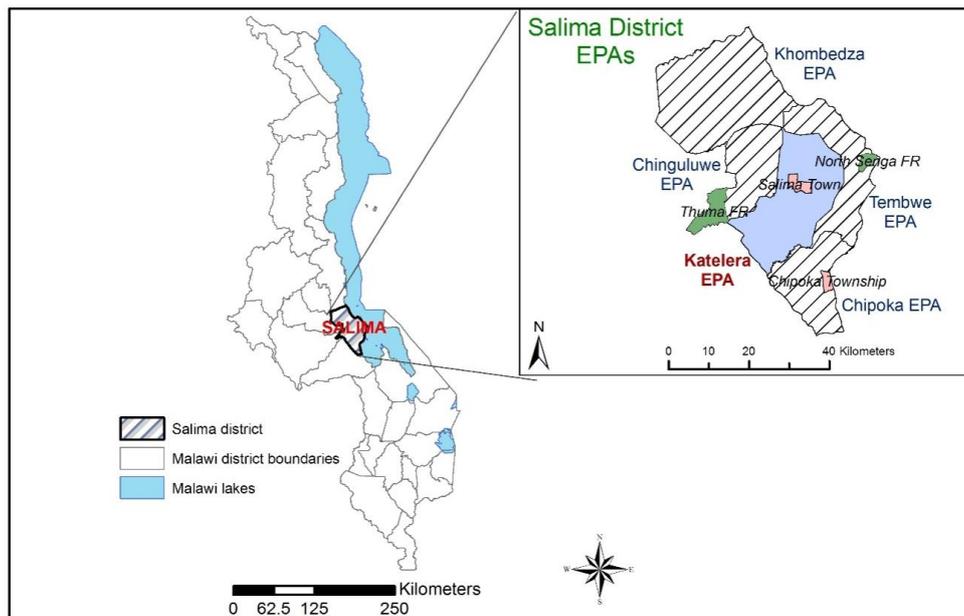
Farmers adopt fertilizer-trees and shrubs technologies to provide shade and a steady supply of food throughout the year, to arrest soil degradation and maintain soil fertility [17]. Based on research on the role of agroforestry as a climate-change adaptation strategy conducted in Akwa Ibom State in Nigeria [8], farmers identified increasing soil nutrients, providing shade to crops, soil erosion control and income generation as the important roles of tree species. According to Verchot et al. (2006) [18], agroforestry maintains productivity during drier years because deep-root systems of the tree or herb extract larger volumes of soil water from depths not normally reached by the shallower roots of annual crops and help during moisture stress periods. Other benefits of fertilizer trees and shrubs include incorporation of organic matter, minimizing soil erosion and supplementing food requirements [19].

Research on factors that influence adoption of fertilizer-trees and shrubs technologies in particular settings remains insufficient. However, some research [20] suggests contact with extension agents and availability of labor positively influences their adoption, while increase in the age of the household head negatively influences adoption. A recent synthesis [21] shows that several factors shape adoption of agroforestry, including the type of the technology; socio economic household characteristics; policy and institutional context within which the technologies are disseminated; and geo-spatial characteristics, such as tree species performance across biophysical conditions and agroecological zones. In Malawi however, there is little information on determinants of fertilizer trees and shrubs adoption in areas prone to climate change shocks such as prolonged dry spells and floods. This study therefore seeks to identify the types, relative importance and configuration of factors that influence the decision to adopt fertilizer trees and shrubs technologies in the central lakeshore district of Salima, in Malawi.

## 2. Methodology

### 2.1. Study Area

The study site, Katelera Extension Planning Area (EPA), is a sub-district administrative unit for agriculture extension in Salima district (Figure 1). Salima Rural Development Program has five EPAs—namely, Katelera, Chipoka, Tembwe, Chinguluwe and Khombedza. This district is located along the lakeshore agroecological zone. It has a total land area of 2196 square kilometers and a population of 337,895 [22]. The district is located in Malawi's rift valley floor, which comprises of scattered hilly upland areas lying between 200 and 1000 m above sea level in elevation. Soils vary from clay-loam, alluvial deposits and deep dark clay and black to red shallow stony soils. The district experiences a generally warm tropical climate with mean annual temperatures of 22 degrees Celsius. Salima district experiences unimodal rainfall. Data for the past 30 years show mean precipitation of 1188.11 mm. Agriculture in the district, as in most of Malawi, is virtually all rainfall dependent. The main source of livelihood for the district is smallholder agriculture covering about 107,400 hectares of customary farmland.



**Figure 1.** Map of Malawi showing the location of the study site in Salima District and Extension Planning Area (EPA).

## 2.2. Data Sources

We collected household survey data using questionnaires. Researchers interviewed household heads or the spouse. Through the questionnaire, we sought data on socio-demographic characteristics of the farming households, farming in general, fertilizer trees and shrubs adoption and perception of farmers on fertilizer trees and shrubs. The study also collected data on biophysical attributes of the farms using the questionnaire as well as Global Position System (GPS) devices in the case of information location and elevation used in deriving slope.

We employed a multistage, stratified probability sampling design. The researchers selected EPA purposively because it had the highest proportion of farmers with fertilizer trees and shrubs species in the district. Ten villages were randomly selected from the list of villages in the EPA. Households within the sampled villages were then stratified into adopters and non-adopters of fertilizer trees and shrubs and 250 households were randomly selected from all the sampled villages. The number of households in each stratum was determined in proportion to the size of the stratum and sample size was determined using the power sampling formula below.

$$n = \frac{[Z^2(1-p)p]}{e^2} \quad (1)$$

where:  $n$  is the sample size,  $z = 1.96$  (2-tailed test),  $e = 0.05$  (margin of error) and  $p =$  proportion of farmers practicing agroforestry. Out of the total population of 6780 for the EPA, the researchers interviewed a sample of 154 adopters and 96 non-adopters. According to Government of Malawi (2014) [23], the adoption rate of fertilizer trees and shrubs is about 10% in Salima district.

## 2.3. Theoretical Framework

How much utility a household gains from its decision can drive the decision to adopt fertilizer trees and shrubs. Binary dependent variable models are most appropriate to the theory of random utility, in which observed discrete choices are the result of optimizing behavior where the decision maker has two alternatives to choose from during the decision process [24]. Utility is an unobserved index determined by a set of explanatory variables that an individual uses to rank a set of decision alternatives. Because utility is unobserved, it behaves as a random variable and a dichotomous choice

decision to adopt or not. We therefore used the random utility model to evaluate the probability that a household will decide to adopt fertilizer trees and shrubs based on the set of explanatory variables.

We envision an indirect utility function where utility depends on a vector of personal attributes of the *i*th household head  $H_i$ , such as age, gender and education level; and a vector of the *i*th household features  $Z_i$ , such as available household labor, land size and land tenure.

The indirect utility function  $F$  for the *i*th household can be expressed as:

$$U_{ti} = \beta_t F(X_{ti}) + \varepsilon_{ti}, \text{ where } t = 1, 0; \text{ and } i = 1 \dots n; X_{ti} \in (H_{ti}, Z_{ti}) \tag{2}$$

where  $t$  represents the household choice to adopt agroforestry ( $t = 1$ ) or not ( $t = 0$ );  $U_{ti}$  is the indirect utility function  $F$  for the household;  $X_i$  is a vector of characteristics of the *i*th household ( $H_i$  and  $Z_i$  defined above);  $\beta$  is a vector of parameter of the model and  $\varepsilon$  is the error term.

The utilities ( $U_{ti}$ ) are random and the *i*th household chooses to participate if  $U_{1i} > U_{0i}$ ; the latent random variable  $y_i^* = 1$  if  $(U_{1i} - U_{0i}) > 0$ ,  $y_i^* = 0$  otherwise. The probability that the latent variable equals 1 can be expressed as:

$$P_i = Pr (y_i = 1) = Pr (U_{1i} > U_{0i}) \tag{3}$$

where  $P_i$  is the probability of the *i*th household participating while  $Pr$  stands for probability.

This can further be expressed in Equations (4) and (5) below as function of the independent variables, that is,

$$\begin{aligned} P_i &= \beta_1 F(X_{1i}) + \varepsilon_{1i} > \beta_0 F(X_{0i}) + \varepsilon_{0i} \\ &= Pr \{(\varepsilon_{1i} - \varepsilon_{0i}) > \beta_1 F(X_{1i}) - \beta_0 F(X_{0i})\} \end{aligned} \tag{4}$$

$$\begin{aligned} P_i &= Pr \{\mu_i > \alpha F(X_i)\} \\ &= F(H_i' \alpha) \end{aligned} \tag{5}$$

where  $\mu_i = (\varepsilon_{1i} - \varepsilon_{0i})$  is a random error term,  $\alpha = (\beta_1 - \beta_0)$  is a vector of parameters to be estimated;  $X_{1i}$  represents characteristics of an adopter *i* while  $X_{0i}$  represents characteristics of a non-adopter *i*; and  $F(H_i' \alpha)$  is the cumulative distribution function of the error term  $\mu_i$  evaluated at  $X_i' \beta$ . Thus, Equation (4) measures the probability of change from the status quo (no adoption) to new status (adoption).

#### 2.4. Empirical Models

This study used the Tobit model [25], which assumes that the dependent variable has a number of its values clustered at a limiting value, usually zero. In this study, the Tobit model estimates the factors that determine adoption and the extent of adoption. In order to determine the extent of adoption, the study used the McDonald-Moffit decomposition extension. This was used to estimate the total marginal effect of change in an independent variable on the expected value of land allocated to fertilizer trees and shrubs being equal to a weighted sum of the change in the probability of adoption by non-adopters and the percentage change in the amount of land under adoption. The Tobit model is as follows:

$$y_{ti} = X_{ti}\beta_t + \tau_{ti}, y_{ti} = \begin{cases} X_{1i}\beta_1 + \tau_1 > 0 \\ X_{0i}\beta_0 + \tau_0 \leq 0 \end{cases} = 0 \tag{6}$$

where  $i = 1, 2, \dots, n$

where  $n$  is the number of observations,  $y_{ti}$  is the dependent variable,  $X$  is a vector of independent variables,  $\beta_t$  is a vector of unknown coefficients and  $\tau_{ti}$  is an independently distributed error term assumed to be normal with zero mean and constant variance  $\sigma^2$ . Thus, the model assumes that an underlying, stochastic index equal to  $(X_{ti}\beta_t + \tau_{ti})$  is observed only when it is positive. According to Tobin (1958) [25], the expected value of  $y$  in the model is:

$$Ey = X\beta F(z) + \sigma f(z) \tag{7}$$

where  $z = X\beta/\sigma$ ,  $f(z)$  is the unit normal density and  $F(z)$  is the cumulative normal distribution function. The expected value of  $y$  for observations above the limit ( $y^*$ ),  $Ey^*$ , is the expected value of the truncated normal error term:

$$\begin{aligned}
 Ey^* &= E(y|y > 0) \\
 &= E(y|y > -X\beta) \\
 &= X\beta + \sigma f(z)/f(z)
 \end{aligned}
 \tag{8}$$

Consequently, the basic relationship between the expected value of all observations,  $Ey$ , the expected value conditional upon being above the limit,  $Ey^*$ , the probability of being above the limit,  $F(z)$ , is

$$Ey = F(z)Ey^*
 \tag{9}$$

The useful decomposition is derived by considering the effect of a change in the  $i$ th variable of  $X$  on  $y$ :

$$\frac{\partial Ey}{\partial X_i} = F(z) \left( \frac{\partial Ey^*}{\partial X_i} \right) + Ey^* \left( \frac{\partial F(z)}{\partial X_i} \right)
 \tag{10}$$

Thus, the total change in  $y$  can be disaggregated into the change in  $y$  of those above the limit (zero in this case) and the change in the probability of being above the limit, weighted by the expected value of  $y$  if above. Assuming that one has estimates  $\delta f/\beta$  and  $\sigma$  (see below), each of the terms in Equation (10) can be evaluated at some value of  $X\beta$ , usually at the mean of the  $X$ 's,  $\bar{X}$ .  $X$  is the vector in an independent variable, and here  $X$ 's indicates that there are several independent variables, each a vector  $X$ . The value of  $Ey^*$  can therefore be calculated from Equation (8) and the value of  $F(z)$  can be obtained directly from statistical tables.

### 2.5. Choice of Variables

Explanatory variables that influence household choices fall into five broad categories: household preferences, resource endowments, market incentives, risk and uncertainty and biophysical characteristics [26]. Household preferences include variables that measure household specific characteristics such as risk tolerance, innovativeness and household homogeneity. Many of these factors cannot be measured directly. However, demographic and socioeconomic variables obtained from the household-survey (see Table 1) can provide (indirect) estimate. The age of the household head reflects the experience of the farmer. We assume that younger farmers are more risk-taking in trying new technologies than older farmers and that educated farmers understand better the tree growing requirements, possess the capacity to analyze the net benefits of newly introduced technologies before they make final adoption decisions and to have more access to non-farm cash income to invest in such a technology.

**Table 1.** Variables expected signs and their description.

| Variable  | Sign | Description  |
|-----------|------|--|
| GENDER    | -    | Dummy variable: 1 = male, 0 = female headed household. Gender of a household head significantly influenced agroforestry adoption [27].   |
| EDUCATION | +    | Measure: Attainment of formal education (primary, secondary and tertiary level). Education enhances adoption of agroforestry [28].   |
| LABOUR    | +    | Labor: Person-days allocated to farming activities in a season. Tree growing needs labor and many smallholder farmers rely on household labor. Therefore, labor availability influences adoption [29]. |
| LANDSIZE  | +    | Landholding size: The total land the farmer has. Landholding size can influence agroforestry adoption [30].  |
| EXTENSION | +    | Number of contacts between the extension officer and the farmers in a week. Farmers' contact with extension agents helps them to pursue new practices [31].  |
| EXPOSURE  | +    | Measure: The number of years the farmer has taken to evaluate the possible benefits of the technology [32].  |
| HHAGE     | -    | The age of household head (years) can influence production and adoption [3].   |
| TENURE    | +    | Dummy variable: 1 = owned land, 0 = land not owned. Ownership enhances tenure security can enhance agroforestry adoption [32].   |
| AGE       | -    | Measure: The age of the household head in the farming household. Farmers become more risk averse with age [33].  |

Resource endowments such as land and labor may induce or deter people from investing in a new technology. Consideration of family labor is important because households with more labor are more likely cope with additional workloads, whereas larger land sizes can induce adoption because of the extra available land for other uses. Market factors such as prices were not included because fertilizer trees and shrubs have no clear market that can depict their real market value. Risk and uncertainty, such as pests and diseases were not included. The analysis also examined potential effects of other factors, such as age and education, as they indicate one's ability to overcome or cope with these risks. Land size is important because it can determine how much land a farmer can "sacrifice" to fertilizer trees and shrubs given that land holding sizes are already generally low. In fact, households are increasingly renting land parcels (paying the owners on an annual basis) in order to increase landholding size and enhance food security. Tenure security is also an important consideration in the decision to invest in tree/shrubs, some of which may take years before bearing dividends to the farmer. This explains the assumed positive correlation between these two land variables (landholding size and tenure security) and the decision to plant and the extent of its cultivation. Biophysical factors relate to influences on the physical production process associated with farming and forestry. Examples include the slope of farmland and plot size. In general, poorer Biophysical production conditions (for instance greater slope or potential for high erosion) create a positive incentive to adopt fertilizer-tree and shrubs technologies, legume intercropping and other soil and water conservation technologies in order to alleviate adverse impacts of these barriers [34,35]. Table 1 shows the definitions, measurements and a priori expected effects of the independent variables on the decision to adopt fertilizer trees and shrubs, based on the literature.

### 3. Results and Discussion

#### 3.1. The Roles of Fertilizer Tree Species in Adaptation to Climate Change

This section presents the common tree species and their perceived roles on adaptation to the adverse impacts of climate change. Adopters of the fertilizer tree species attributed soil conservation, soil fertility enhancement, shade, source of food and wood to various tree species. The roles reported by the farmers depended primarily on their experience on their individual farms rather than some knowledge from training.

Table 2 shows that 43.3% of the adopters indicated that the tree species (identified as trees by the World Agroforestry Centre-ICRAF) have increased soil fertility for maize production. Farmers indicated that *Gliricidia sepium* (21.5%), *Cajanus cajan* (11.6%) and *Tephrosia vogelii* (8.8%) were the main tree species that enhance soil fertility. Our results show that 14.3% of the adopters reported that fertilizer tree species control soil erosion on their farms. Farmers in some studies have used fertilizer trees as a sustainable solution to soil erosion, for example, Ajayi et al. (2008) [3]. Table 2 shows that provision of shade is another role that the fertilizer tree species play. Salima district experiences frequent incidences of extreme heat, erratic rains and dry spells during critical stages of crop development; hence, they found these tree species to be vital when moisture levels decline. Adopters reported that *Cajanus Cajan* (7.5%), *Gliricidia sepium* (6.8%), *Acacia polyacantha* (2.0%), *Senna siamea* (2.0%) and *Tephrosia vogelii* (1.4%) minimized impacts of extreme heat, erratic rains and dry spells. Agroforestry improves the risk of losing crops due to high solar radiation by lowering the risks associated with prolonged dry spells and droughts [36]. Another main importance of the fertilizer tree species is the provision of food as shown in Table 2. *Cajanus cajan* and *Leuceana leucocephala* were identified by 13.6% and 0.7% of the farmers, respectively, as sources of food adopters used *Cajanus cajan* for food as relish or ate it as a main meal, especially during lean periods, while *Leuceana leucocephala* was identified as the source of local medicine.

**Table 2.** Percentages of the perception of farmers on fertilizer trees and shrubs and their use.

| Fertilizer Trees and Shrubs Species | Roles of Fertilizer Trees and Shrubs Species (n = 154) |                 |       |                |      |           |       | Total |
|-------------------------------------|--|-----------------|-------|----------------|------|-----------|-------|-------|
|                                     | Soil Fertility   | Prevent Erosion | Shade | Source of Food | Feed | Fuel Wood | Fence |       |
| <i>Sesbania sesban</i>              | 0.7  | 0.7             | 0.0   | 0.0            | 0.0  | 0.0       | 0.0   | 1.4   |
| <i>Tephrosia vogelii</i>            | 8.8  | 1.4             | 1.4   | 0.7            | 0.0  | 0.0       | 0.7   | 13.0  |
| <i>Cajanus cajan</i>                | 11.6   | 2.0             | 7.5   | 13.6           | 0.0  | 0.0       | 0.0   | 34.7  |
| <i>Leucena leucocephala</i>         | 0.0  | 2.0             | 0.0   | 0.7            | 1.4  | 0.7       | 0.0   | 4.8   |
| <i>Gliricidia sepium</i>            | 21.5   | 7.5             | 6.8   | 0.0            | 0.0  | 0.0       | 1.4   | 37.2  |
| <i>Acacia polyacantha</i>           | 0.7  | 0.7             | 2.0   | 0.0            | 0.0  | 1.4       | 0.0   | 4.8   |
| <i>Senna siamea</i>                 | 0.0  | 0.0             | 2.0   | 0.0            | 0.0  | 2.1       | 0.0   | 4.1   |
| Total                               | 43.3   | 14.3            | 19.7  | 15.0           | 1.4  | 4.2       | 2.1   | 100   |

In sum, farmers also indicated a clear preference for three main fertilizer trees and shrubs species, *Gliricidia sepium* being the most popular by far (21.5% of adopters), followed by *Cajanus cajan* (11.6%) and *Tephrosia vogelii* (8.8%). These species, including others that farmers specifically linked to heat mitigation/adaptation strategies, can also be used by policy makers, extension workers and project implementers in their guidance to farmers in the promotion of the adoption and scaling up of fertilizer-tree technologies to meet the diverse, more immediate provisioning needs for food, wood, nutrients and shade. In terms of sustainability and the attainment of climate-smart agriculture, the findings also offer an entry point for promoting the attainment of the longer-term agroecological benefits that enhance the resilience of smallholder farming systems and reduce their socioeconomic vulnerability to the adverse impacts of climate change.

### 3.2. Descriptive Statistics

Chi square estimation in Table 3 shows that attainment of secondary education and land tenure exhibited a significant association with the decision to adopt fertilizer trees and shrubs. However, main occupation, slope of the land where the farmers had their fields and primary education attainment did not significantly correlate with the decision to adopt fertilizer trees and shrubs.

**Table 3.** Chi Square estimation of the association of socioeconomic variables with adoption.

| Socio-Economic Factors | Sample Size = 250 |    |                     |                |
|------------------------|-------------------|----|---------------------|----------------|
|                        | $\chi^2$          | df | p-Value             | Phi/Cramer's V |
| Main Occupation        | 4.459             | 2  | 0.108 <sup>ns</sup> | 0.134          |
| Slope                  | 2.041             | 2  | 0.360 <sup>ns</sup> | 0.052          |
| Primary Education      | 0.213             | 1  | 0.645 <sup>ns</sup> | −0.028         |
| Secondary Education    | 8.859             | 1  | 0.003 <sup>**</sup> | −0.188         |
| Tenure                 | 9.872             | 2  | 0.007 <sup>**</sup> | 0.199          |

ns = Not significant, \*\* significant at 5% ( $p < 0.05$ ).

Table 4 shows a significant difference in the mean age for the adopters and non-adopters ( $p < 0.05$ ). While household size between the two groups is comparable, adopters have a higher land-holding size compared to the non-adopters ( $p < 0.05$ ). Table 4 further shows a significant difference ( $p < 0.01$ ) on period exposure to fertilizer trees and shrubs. Adopters on average had reported exposure to fertilizer trees and shrubs of 5.73 years on average while non-adopters reported exposures of 4.33 years on average. Table 4 also shows that a significant difference ( $p < 0.05$ ) on contact with extension agents.

**Table 4.** Mean values for predictors between adopters and non-adopters ( $n = 250$ ).

| Variable                         | Adopters                      | Non-Adopters                  | Total            |
|----------------------------------|-------------------------------|-------------------------------|------------------|
| Household size                   | 2.15 <sup>ns</sup><br>(0.91)  | 1.99 <sup>ns</sup><br>(0.64)  | 2.09<br>(0.82)   |
| Age of household head            | 39.79 <sup>*</sup><br>(13.37) | 42.51 <sup>*</sup><br>(15.44) | 39.07<br>(14.42) |
| Land size (hectares)             | 1.30 <sup>**</sup><br>(2.31)  | 1.05 <sup>**</sup><br>(1.32)  | 1.2<br>(2.01)    |
| Exposure to agroforestry (years) | 5.73 <sup>***</sup><br>(3.68) | 4.32 <sup>***</sup><br>(2.41) | 5.15<br>(3.33)   |
| Extension contact (per month)    | 5.68 <sup>**</sup><br>(3.29)  | 4.33 <sup>**</sup><br>(4.09)  | 5.16<br>(3.67)   |

ns = Not significant, \* significant at 10% ( $p < 0.1$ ), \*\* significant at 5% ( $p < 0.05$ ), \*\*\* significant at 1% ( $p < 0.01$ ) figures in brackets are standard deviation (SD).

### 3.3. Empirical Results

#### Tobit Model Output

Table 5 shows that land size, education, exposure to fertilizer trees and shrubs, land tenure and labor significantly influenced adoption of fertilizer trees and shrubs. The Likelihood Ratio (LR) Chi-Square test LR  $\chi^2$  for the model is 107.57. The Prob>  $\chi^2$  is 0.000. The Pseudo  $R^2$  for the Tobit model is about 15% but this level of explanatory power is consistent with other studies using censored data to explain technology adoption decisions (see, for instance [37]).

**Table 5.** Determinants of household decisions to adopt fertilizer trees and shrubs.

| Variable            | Description                  | Coeff   | Std. Error | p-Value              |
|---------------------|------------------------------|---------|------------|----------------------|
| Age                 | Years                        | 0.0103  | 0.0121     | 0.394                |
| Gender              | Dummy (1 Male, 0 Female)     | −0.3822 | 0.2882     | 0.186                |
| Land size           | Hectares                     | 1.2685  | 0.1798     | 0.000 <sup>***</sup> |
| Secondary Education | Dummy (1 Yes, 0 Otherwise)   | 1.2022  | 0.05272    | 0.023 <sup>**</sup>  |
| Primary Education   | Dummy (1 Yes, 0 Otherwise)   | 0.8662  | 0.8412     | 0.073 <sup>*</sup>   |
| Extension           | Number of visits per week    | 0.0508  | 0.0345     | 0.143                |
| Exposure            | Years                        | 0.1721  | 0.0361     | 0.000 <sup>***</sup> |
| Non-Household Labor | Dummy (1 Owned, 0 Otherwise) | −0.0041 | 0.0019     | 0.039 <sup>**</sup>  |
| Land Ownership      | Man-days to farming          | 1.5244  | 0.6875     | 0.028 <sup>**</sup>  |
| Slope               | Slope of the field           | 0.3443  | 0.2538     | 0.176                |
| Constant            | Constant                     | −4.8204 | 1.1017     | 0.000 <sup>***</sup> |
| Sigma               | Sigma                        | 1.6414  | 1.1017     |                      |
|                     | Observations ( $n$ ) = 248   |         |            |                      |
|                     | Log likelihood = −297.801    |         |            |                      |
|                     | LR $\chi^2$ (10) = 107.57    |         |            |                      |
|                     | Prob > $\chi^2$ = 0.000      |         |            |                      |
|                     | Pseudo $R^2$ = 0.1530        |         |            |                      |

Significance levels \* significant at 10%, \*\* Significant at 5%, \*\*\* Significant at 1%. LR  $\chi^2$ : the Likelihood Ratio (LR) Chi-Square test.

Landholding size of significantly influenced a household's adoption of fertilizer trees and shrubs ( $p < 0.01$ ). According to Parwada et al. [29], agroforestry adoption increases with the amount of land owned by the farmer. Exploratory assessment of the Pearson chi-square association showed a very weak and statistically insignificant association (based on the Phi/Cramer's V statistic) between attainment of primary education (relative to those with no formal education) and adoption of fertilizer trees and shrubs. However, findings revealed a much stronger though modest association for attainment of secondary education relative to those with no formal education. However, use of more sophisticated statistical analysis using the Tobit model revealed statistically significant associations for both primary and secondary education attainment in relation to tree-fertilizer adoption, with a higher level of significance ( $p < 0.05$ ) for

secondary education than for primary education ( $p < 0.1$ ). This suggests that the potential influence of education in promoting fertilizer-tree and shrubs adoption is more likely and manifest for those who have attained secondary education than among those with primary education.

The relationship between the amount of available household labor and fertilizer tree/shrub adoption was not what was expected. Household size exhibited a negative relation significant at  $p < 0.05$  (Table 5).

Table 6 shows the McDonald-Moffit decomposition for the Tobit model with two components of the elasticity. The first component indicates the probability of adoption by non-adopters of the fertilizer trees and shrubs is to changes in size,  $E(y)$ , is 1.3095. The second component indicates the proportional change in hectareage under adoption by current fertilizer-tree adopters relative to the expected amount of land to be planted by those who already have the fertilizer-tree species,  $E(y^*)$ , which is 0.4999. These findings show that every increase in landholding size at the mean by one hectare increases the probability of adoption (for the non-adopters) by 46% and increase the amount of land allocated to fertilizer trees and shrubs by 0.3 hectares. The results further show the importance of education. Thus, relative to those that are not educated, the attainment of secondary education increases the probability of adopting fertilizer tree species by 45% and the amount of land allocated to fertilizer tree species by adopters by about 0.3 hectares. Likewise, primary education increased the probability of adopting fertilizer tree species by 32% and would increase amount of land allocated to fertilizer trees and shrubs by adopters by about 0.2 hectares. According to Rogers [38], education level affects the decision to adoption agroforestry because effective management of fertilizer trees and shrubs requires understanding of information, which educated farmers can do more easily. Similarly, the level of education affects the use of reading materials by the respondents [39].

**Table 6.** Decomposition effect of the Tobit model.

| Variable            | Description                  | $E(y)$ dy/dx      | $E(y^*)$ dy/dx | p-Value   | X       |
|---------------------|------------------------------|-------------------|----------------|-----------|---------|
| Age                 | Years                        | 0.0038            | 0.0025         | 0.394     | 40.927  |
| Gender              | Dummy (1 Male, 0 Female)     | -0.1441           | -0.0925        | 0.201     | 0.7621  |
| Land size           | Hectares                     | 0.4610            | 0.3083         | 0.000 *** | 1.2035  |
| Secondary Education | Dummy (1 Yes, 0 Otherwise)   | 0.4499            | 0.2856         | 0.026 **  | 0.4476  |
| Primary Education   | Dummy (1 Yes, 0 Otherwise)   | 0.3215            | 0.2080         | 0.077 *   | 0.4435  |
| Extension           | Number of visits per week    | 0.0185            | 0.0124         | 0.141     | 5.1452  |
| Exposure            | Years                        | 0.0626            | 0.0418         | 0.000 *** | 5.1492  |
| Total labor         | Man-days to farming          | -0.0015           | -0.0010        | 0.038 **  | 116.919 |
| Land Ownership      | Dummy (1 Owned, 0 Otherwise) | 0.4375            | 0.3304         | 0.004 *** | 0.9435  |
| Slope               | Slope of the field           | 0.1270            | 0.0835         | 0.182     | 0.3871  |
|                     |                              | $E(y) = 1.3095$   |                |           |         |
|                     |                              | $E(y^*) = 0.4999$ |                |           |         |

Significance levels \* significant at 10%, \*\* Significant at 5%, \*\*\* Significant at 1%.

The decomposition analysis suggest that the amount of labor has a negligible influence on the adoption decision and intensity. A unit increase in available labor at mean decreases the probability of adoption by a minuscule 0.1% and the amount of land allocated to fertilizer trees and shrubs by 0.001 hectare. Some studies (e.g., Wafuke (2012) [27]) have found that land-tenure security was one of the main determinants of the decision to adopt different aspects of agroforestry technologies. Decomposition of the Tobit model further shows that land ownership increases the probability of adopting fertilizer trees and shrubs by 43% with an expected increase in landholding size allocated to fertilizer tree species by the farmers that have already adopted of about 0.3 hectares. The length of the period of farmer exposure to fertilizer trees and shrubs significantly influenced their decision to adopt but its relative importance was lower than for land amount, education and ownership status. Specifically, a one-year increase in the period that non-adopters were exposed to fertilizer trees and shrubs at mean increases the probability of adoption by 6.2% and the amount of land allocated to fertilizer trees and shrubs by 0.04 hectare (Table 6).

#### 4. Conclusions

Our findings have shown that farmers identified soil-fertility enhancement, provision of shade for crops during high solar radiation and moisture stress, source of food and prevention of soil erosion as the primary roles of fertilizer trees and shrubs on their farms. The primary roles of fertilizer trees and shrubs as perceived by local farmers include mitigating the effects of adverse impacts of climate change in the forms of high solar radiation during critical crop-growth periods, insufficient moisture levels due to erratic rainfall and increased intensity of prolonged dry spells. Given the high levels of soil erosion and degradation, farmers also perceive the enhancement of soil fertility and controlling soil erosion as equally important. Although there was only one fertilizer tree that also provided food, *Cajanus cajan*, provision of food was another positive attribute of fertilizer trees and shrubs that farmers and key informants highlighted and may need further consideration in the future as a potential entry point to promote fertilizer-tree adoption in the study area and elsewhere with similar agroecological conditions. *C. cajan* was relatively commonly grown in the area and most of the interviewed farmers used the (pigeon pea) grain as a protein food.

Furthermore, findings show that farmers valued the functions of fertilizer trees and shrubs that enhanced resilience of smallholder farming systems to the adverse impacts of climate change, on top of improving food production, availability and security. These functions included protection of farmland against high levels of soil erosion and enhancement of soil moisture during dry periods. Therefore, policy makers, extension workers and project/program implementers can use the aforementioned functions and the commonly promoted fertilizer-tree species as entry points for promoting the adoption and retention of fertilizer-tree technologies. These actions and the fertilizer trees/shrubs, can positively contribute to attainment of sustainable agricultural intensification, especially for smallholder farmers who are vulnerable to the adverse impacts of climate change, are food insecure and live in areas where soils are degraded.

This paper has identified several household socio-demographic characteristics, resource endowments and extension-service exposure as main factors that influenced farmers' decisions to adopt fertilizer trees and shrubs. The analysis suggests that education level, land-tenure security, labor and amount of land influence the adoption and expansion of land for fertilizer trees and shrubs. In particular, completion of primary school or attainment of a secondary school education by the household head, ownership status and the amount of land owned/farmed by the household and the length of farmer-exposure time to fertilizer trees and shrubs are positively associated with the fertilizer-tree adoption decision. The amount of labor available in the form of family size was counterintuitively negatively associated with the decision to adopt fertilizer trees and shrubs and statistically insignificant. The generally low education levels in rural Malawi and small landholding sizes also help to explain why adoption of these technologies have been low in Salima and other parts of Malawi and should serve to temper expectations. These findings illustrate the general significance of household characteristics and quality extensions services in the adoption of fertilizer-tree technologies.

These findings have several implications for scaling up the adoption of fertilizer trees and shrubs in Malawi. First, they show that many farmers already recognize the value of fertilizer trees and shrubs to enhance food security, climate smart agriculture and the resilience of smallholder farmers to climate change and socioeconomic shocks. These values include providing food to households and enhancing food security, soil protection and fertility improvement and shade to crops and conserving moisture and mitigating impacts of extreme heat. Existing farmer-based knowledge, including on the benefits of particular species and the mechanisms for enhancing food provision and climate-resilience capabilities further highlight the appropriateness of fertilizer-tree and shrubs interventions for smallholder farmers with limited resources to purchase inorganic fertilizer or sufficiently adapt to the adverse impacts of climate change. More importantly, the findings show that education, land size and tenure security and significant exposure time to fertilizer-tree technologies should be considered during program and project planning to enhance chances of adoption and scale-up of such interventions. For instance, project/program planners and implementers can use these findings to more effectively target specific

households as a means to “seed” the adoption of fertilizer-tree technologies and provide exposure to late adopters to learn from and ensure broader adoption and sustainability of these technologies among smallholder farmers. Finally, the promotion of these trees needs to consider longer project and program implementation periods essential for success, along with vibrant extension service to enhance adoption.

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