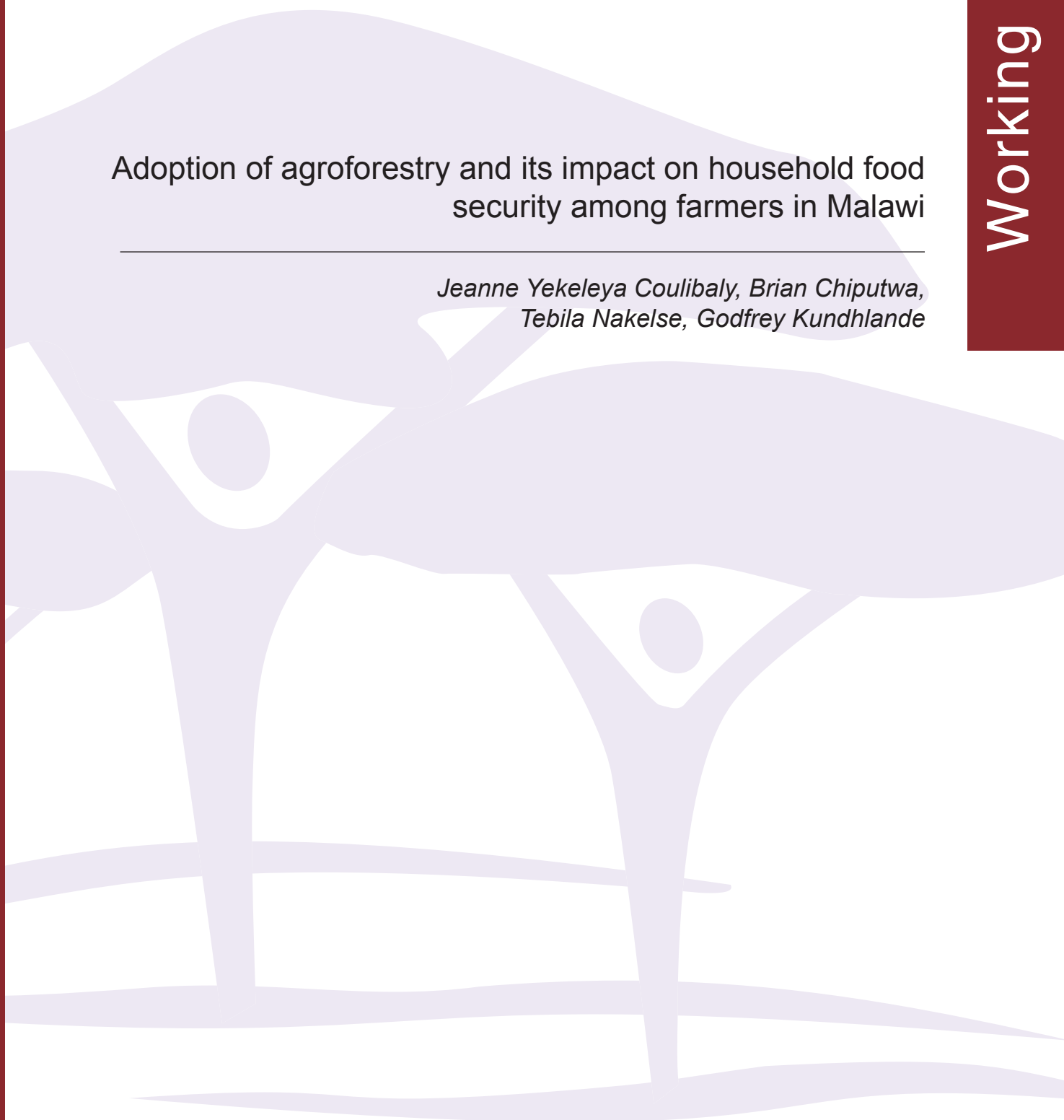


## Adoption of agroforestry and its impact on household food security among farmers in Malawi

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*Jeanne Yekeleya Coulibaly, Brian Chiputwa,  
Tebila Nakelse, Godfrey Kundhlande*



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**Abstract**

Malawi is often described as a country that faces increasing soil deterioration exacerbated by climate change, which affects crop productivity and food security. Research and development efforts to improve food security through restoration of soil fertility have included promotion of nitrogen fixing trees or fertilizer trees in food farming systems. This working paper provides evidence of the causal impact of the adoption of fertilizer trees on food security on smallholder farmers in Malawi. The impact assessment methodology used an Endogenous Switching Regression model that accounts for selection bias. The main drivers of the decision to adopt fertilizer trees include households' perception of land degradation, training on agroforestry and farm assets. Results of the impact assessment model show evidence that fertilizer trees improve food security for adopters in maize-based mixed farming systems through increased in average value of food production and maize productivity. Policies that address barriers to adoption of fertilizer trees and scale up adoption of these technologies will be beneficial to restore soil fertility in degraded land and improve food security of smallholder farmers.

**Keywords:** fertilizer trees, soil fertility, food security, Endogenous switching regression, maize based farming system

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## **Acronyms**

FAO	Food and Agriculture Organization of the United Nations
IFAD	International Fund for Agricultural Development
AFSP	Agroforestry for Food Security Programme
IPCC	Intergovernmental Panel for Climate Change
MAFE	Malawi Agroforestry Extension Project
ICRAF	International Center for Research in Agroforestry (World Agroforestry Center)
CBO	Community Based Organization
PSM	Propensity Score Matching
ESR	Endogenous Switching Regression

## 1. Introduction

In the last few decades, there have been considerable efforts by the international community to develop strategies that reduce global poverty and hunger. Despite the modest success in reducing food insecurity, there are still around 795 million people worldwide who remain undernourished, the majority of whom are in sub-Saharan Africa (FAO, IFAD, & WFP, 2014). In many of these impoverished communities, agriculture still remains as one of the most important sectors in driving economic growth and reducing poverty. However, one of the main constraints faced by smallholder farmers is low agricultural productivity. In fact, sub-Saharan Africa is the only region in the world where food insecurity is driven by insufficient food production. This is in contrast with other regions in the world where aggregate food production has increased through higher yields and food insecurity results more from poor distribution and lack of consumer purchasing power (Sanchez, 2002).

In Malawi, like the rest of the developing world, food productivity is threatened by soil degradation, population pressure, low-use of improved inputs, particularly inorganic fertilizer and poor agricultural practices. Soil erosion and declining soil fertility (in terms of nitrogen (N), phosphorus (P) and potassium (K)) are the key productivity constraints for farmers in Malawi (Akinnifesi et al. 2007). Farmers continuously cultivate the staple crop maize, with little or no rotations with leguminous crops that fix nitrogen into the soil contributing to a steady decline in fertility (Manfongoya et al. 2006, Sileshi et al. 2010). Furthermore, the country's population growth rate of 2.8% (National Statistics Office, 2012) creates pressure on the natural resource base leading to greater land degradation which further contributes to low productivity (Bojo, 1996). While the use of inorganic fertilizer may contribute to improving soil fertility, the high cost limits farmers' uptake (FAO, 2011).

The Intergovernmental Panel on Climate Change (IPCC) predicts increased climate uncertainties in Malawi with higher temperatures and possibly higher rainfall. These extreme weather events will affect poor farmers in developing countries like Malawi more due to lack mitigation strategies (IPCC, 2014). In addition to these average changes, seasonal and spatial variations in rainfall patterns are expected to occur, manifesting in terms of increased incidences of droughts and floods. Empirical studies have demonstrated that the adverse effects of climate change lead to decreases in yields and are one of the greatest causes of crop failure in small scale farming in Malawi (Makoka, 2008; Coulibaly et al., 2015a).

In the face of growing population, higher food demand and fixed agricultural land, sustainable intensification is widely viewed as an important strategy to respond to the challenges of low yields, environmental degradation and adaptation to climate change (Antle and Diagana, 2003). Adoption of agroforestry technologies (incorporation of trees in farming systems) is increasingly being promoted as a promising solution that provides mitigation and adaptation benefits by



sequestering carbon, improving food security and building resilience to negative impacts of climate change and variability. Nitrogen fixing tree species and shrubs (fertilizer trees) intercropped with field crops can provide considerable amount of organic matter, fix nitrogen (N) into the soil and help to increase productivity. For example, in maize based systems, Akinnifesi et al (2010) demonstrate that maize yield increases by 583% depending on fertilizer tree species used.

While there are a number of field trials that prove the productivity gains of using fertilizer trees, a lot of these have been limited to testing the yield response rate of crops such as maize to different tree-species. Beyond these biophysical relations between fertilizer tree adoption and yield, one aspect that has received little attention is if there is empirical evidence that proves if fertilizer trees actually increase household food security. A few studies have employed a cost benefit analysis and an econometric approach to assess the impact of soil fertility replenishment technologies on yield and production risks (for example, Ajayi, 2007) and household welfare (for example, Place et al., 2005). The methodologies used were important in demonstrating the economic and welfare gains provided by the soil fertility technologies. However, they failed to attribute the increased outcome to the targeted agroforestry technology since they did not control for farmers' self-selection on the adoption decision and a number of other actors that could also affect the welfare benefits. So far, little is known on the causal impact of fertilizer trees on household food security. We contribute to this lean literature by analysing the effects of fertilizer trees on household food security using empirical data from maize farmers in Malawi. We use a treatment effect model that explicitly controls for non-random selection bias to quantitatively assess the causal impacts of fertilizer tree adoption on food security.

The remaining part of this paper is organized as follows: Section 2 presents background information on dissemination of fertilizer trees in Malawi; Section 3 describes the methods used to assess the economic impact of technology adoption; Section 4 presents the data used for the analysis and the results of the descriptive statistics; Section 5 discusses the findings of the econometric model on adoption and impact assessment; and Section 6 lays out concluding remarks and suggests some policy implications.

## **2. Overview of Agroforestry Production for Food Security in Malawi**

The benefits of nitrogen fixing trees and shrubs such as *Faidherbia albida* (Msangu), *Cajanus cajan* (pigeon peas) and other leguminous crops have been known to government extension officers and farmers in Malawi. However, their use by farmers for soil fertility management and in improving food production has been limited. The early efforts to promote widespread use of fertilizer trees in agricultural systems in Malawi were through ADDFOOD project implemented by the Ministry of Agriculture with financial support from the European Union, and the Malawi

Agroforestry Extension Project (MAFE)<sup>1</sup> in the early 1990s. These initiatives were the first to promote extensive diffusion of fertilizer trees including systematically dispersed planting of *Faidherbia albida*, alley cropping, undersowing and intercropping with exotic species such as *Acacia angustissima*, *Calliandra calothyrsus*, *Leucana spp* and *Gliricidia sepium* and *sesbania sesban*.

Building on the results of nearly two decades of on-station and on-farm adaptive research on sustainable, farmer-friendly and economically viable agroforestry practices, the World Agroforestry Centre (ICRAF) launched the Malawi Agroforestry Food Security Programme (AFSP) in 2007 with the financial support of the Irish Government through Irish Aid. This four-year program was implemented jointly with government departments (Extension Services, Agricultural Research Services, Land Resource Conservation) and a local research and training institution (Bunda College of Agriculture) from 2007 to 2011. The goal of AFSP was to provide agroforestry options to smallholder farmers in Malawi to enable them to increase food security through improvements in soil fertility, and increase nutrition security and income diversification through fruit production. The programme also aimed to increase the supply of timber for fuelwood and other uses and thereby reduce pressure on natural forests and woodlands (ICRAF, 2011). Fertilizer tree technologies are based on planting fast growing and nitrogen fixing leguminous trees and shrubs that produce large quantities of biomass that easily decompose and release nitrogen for crop growth (Kwesiga and Coe, 1994). Other fertilizer trees such as *Faidherbia albida* can be planted in crop fields in appropriate agro-ecological zones but take longer before benefits are seen. They do, however, provide nitrogen rich leaf litter and protection against extreme temperatures for several decades (60+ years) before the need for replanting.

Fertilizer trees contribute to food security through increased crop productivity. Cropping systems that combine cereals, fertilizer trees and small doses of inorganic fertilizer have been shown to produce greater food crop yields than those that do not (Akinnifesi et al., 2007). Improved food productivity and crop diversification represent a buffer mechanism against harvest failure due to climate and other environmental hazards. Using data from long term field trials, Sileshi et al. (2012) show that crop yields under agroforestry systems are more stable over time compared to crop yields from non-agroforestry fields. This is due to increased soil water in fields under agroforestry (Chirwa et al., 2007), reduced evaporation losses and protection of crops from excessive heat on fields that have increased tree cover. In addition to providing large amounts of nitrogen, foliage of fertilizer trees help increase soil carbon when incorporated in the soil (Beedy et al, 2010) and increase soil water holding capacity. The increased soil water enables crop growth during dry spells. *Faidherbia* trees reduce moisture loss through evaporation and protect

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<sup>1</sup> The Malawi Agroforestry Extension Project (MAFE) was established in 1992 and was implemented through a cooperative grant between USAID and Washington State University under the Department of Land Resources Conservation in the Ministry of Agriculture and Irrigation. The project was operational for a 10 year period between 1992-2002.

crops growing under the canopy from heat stress. Syampugani et al. (2010) stress that a mix of different trees and crop varieties in a field, increases resilience to erratic weather changes and decreases the probability of pest and diseases.



Maize intercropped with Tephrosia in Lilongwe, Malawi. Photo by Olu Ajayi

The first phase of the AFSP programme (AFSP I) was implemented in 11 of the 28 districts of Malawi. These districts were selected as they represent eight agro-systems and the country's cultural diversity. Farmers in each district were given their choice of fertilizer trees species to the extent supply and logistics allowed (Beedy et al. 2012). The most commonly adopted species were *Tephrosia candida* and *Sesbania sesban* (93%) and smaller amounts of *Gliricidia sepium* and *Faidherbia albida* (ICRAF, 2011). The first two species are fast growing nitrogen-fixing shrubs

planted usually in relay intercropping with maize. These legumes are planted two to four weeks after sowing maize and are left to grow in the off-season after the maize has been harvested (Phiri et al. 1999, Akinnifesi, 2010). Farmers clear-cut the legumes and incorporate the biomass/ foliage into the soil as they prepare land for the next season. Further detailed description of the technologies can be found in Phiri et al. (1999) and Akinnifesi et al. (2010).

In order to reach large numbers of farmers with agroforestry tree seeds and seedlings, as well as encourage them to incorporate these in their production system, ICRAF partnered with extension workers from the government, NGOs, community based organizations and lead farmers. The network of government extension agents is not well developed in all villages covered by the project. In areas with underrepresentation of extension agents, the project had to rely on community-based organizations (CBOs) and lead farmers to reach more farmers. This introduced a possibility of selection bias in the programme evaluation as farmer members of the CBO or lead farmers may be more inclined to distribute the agroforestry species primarily to their members or to their friends. Participation of farmers was voluntary at the village level. This leads to a second source of selection bias as most participating farmers or those who expected to benefit from the technology, for example through increased soil fertility, might be disproportionately represented among those who signed up for the programme. The project was designed to target the most vulnerable and poor populations. A third source of selection bias is introduced as adopters of the technology may appear to be poorest farmers in the community or with fewer assets than non-adopters which may result in an overestimation of the project impact. In order to address the project impact in a rigorous way, it is necessary to use an evaluation methodology that takes into account all these potential sources of selection bias.

### 3. Methods

#### 3.1 Conceptual framework

There are several evaluation approaches that can be used to assess the impact of adoption of fertilizer trees practices. The choice of the appropriate evaluation method depends on how the selection process to receive treatment (in this case fertilizer tree adoption) was conducted (Blundell and Costa Dias, 2000). In the AFSP I, the selection of beneficiaries and non-beneficiaries was not randomized as we have highlighted in the previous section. This implies that the population of farmers in the different regions of Malawi was not equally and randomly exposed to the new technology under assessment. As a result, the treatment and control groups may have different characteristics. Rosenbaum and Rubin (1983, 1985) point out that when adopters and non-adopters have similar characteristics their outcomes can be directly compared. However, such comparison is invalid when they have different characteristics. Hence comparing these two groups using simple difference in yields means between adopters and non-adopters alone is not sufficient to establish causal effects.

Given the likely differences in households' characteristics in the present study, we used a quasi-experimental design to evaluate the impact of adoption of fertilizer trees on food security.

The average treatment effect ( $\alpha$ ) defined by Rosenbaum and Rubin (1983) in a counterfactual framework can be written as:

$$\alpha = E(Y_1^i - Y_0^i) \quad (1)$$

Where  $Y_1^i$  is yield for household  $i$  with the treatment and  $Y_0^i$  is yield for household  $i$  without treatment. A fundamental problem in estimating this equation is that we cannot observe both  $Y_1^i$  and  $Y_0^i$  simultaneously. At a given time  $t$ , a household is either an adopter or non-adopter of agroforestry practices. A household cannot be in both states at the same time. So, what we observe at a given time is:

$$Y_i = D_i(Y_1^i) + (1 - D_i)(Y_0^i) \text{ with } D_i = 0,1 \quad (2)$$

The average treatment effect for household with a probability  $P$  of participating in the program can be specified as:

$$\alpha = [PE(Y_1|D = 1) - E(Y_0|D = 1) + (1 - P)E(Y_1|D = 0) - E(Y_0|D = 0)] \quad (3)$$

The above equation implies that the effect of adoption on the entire sample is a weighted average of the effect of adoption on the adopters (treated households) and the non-adopters (control households). The issue that arises with this equation is that the counterfactual  $E(Y_0|D = 1)$  and  $E(Y_1|D = 0)$  is not observed leading to a problem of missing data. Also, the decision of household to adopt fertilizer trees is explained by observed and unobserved characteristics resulting in a problem of self-selection. For a non-randomized design, several econometric approaches can be used to address the problem of selection bias including propensity matching

score and instrumental IV methods. Propensity Score Matching (PSM) accounts for bias due to observable characteristics (Heckman and Vytlačil, 2007). This assumption can sometimes be difficult to justify since unobservable factors such as skills and motivation can also influence the decision to adopt a technology. This may result in inconsistent estimates if this is not accounted for in the estimation. To overcome this problem, IV instrumental variable approaches and endogenous treatment effect models, which account for the endogeneity of the adoption decision, are used.

Instrumental variable estimation techniques are built on finding valid instruments that are correlated with the decision to adopt but uncorrelated with the unobserved factors that affect the outcome. A main constraint in using this approach is finding valid instruments for the adoption variable. Such methods of addressing selection bias, assume also that there is only an intercept shift with respect to the outcome variable and not a slope shift in the outcome variable (Alene and Manyong, 2007, Shiferaw et al. 2014). To overcome this issue, the endogenous switching regression (ESR) that relaxes the above assumption is applied. This model estimates two separate outcome equations, respectively for adopters and non-adopters, conditional on a selection equation.

### ***3.2 Modeling food security impacts of fertilizer tree adoption***

To analyze the impact of fertilizer tree adoption on food security, we use a two-stage endogenous switching regression model that accounts for bias due to unobservable variables. Our model follows closely the empirical applications of other studies that analyzed adoption impacts, while controlling for selection bias due to both observable and unobservable characteristics, of improved technologies such as improved varieties of wheat (Shiferaw et al. 2014); pigeon pea (Asfaw et al, 2012); pineapple (Kleeman and Abdulai, 2013); tissue culture banana (Kabunga et al. 2014) and improved fallows (Kantashula and Mungatana, 2013).

In the first stage, we performed a probit estimation.

A farm household  $i$  chooses to adopt agroforestry technologies if they generate perceived net benefit. This is specified as follows:

$$A_i^* = W_i\gamma + \mu_i \quad \text{with } A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where  $A_i^*$  is the latent variable that captures the expected benefit from adopting fertilizer trees. A farm household  $i$  chooses to adopt the technology if the expected benefit is positive.  $A_i$  represents the binary variable adoption or non-adoption of fertilizer trees. It is the treatment variable and is equal to 1 if the household adopts fertilizer trees and 0 otherwise.

$W_i$  represents a vector of variables that affect the probability of adopting fertilizer trees. Several types of control variables are introduced in the model based on the literature in the first stage of determining the probability of adopting fertilizer trees technologies. First, the traditional household socio-demographic characteristics including age, gender, education level of the household head, household size, farm asset, and farm size, affect the probability of adopting

fertilizer trees. We consider also the farm agro-ecological conditions proxied by household perception of land degradation as a main challenge in their farm over the past years. Households who perceive the soil fertility status of their fields as being good may be less impacted by climate shocks and less likely to adopt the technologies. Quantity of inorganic fertilizer applied on food crops may influence soil fertility and the probability to adopt the nitrogen fixing trees. Access to extension services, particularly training in agroforestry management provide technical information to farmers and build their skills and as a matter of fact facilitate adoption of agroforestry. Distance to extension services and market for farm inputs were included and capture barriers faced by farm households in deciding to adopt fertilizer trees.

Climatic variables incorporated in the model are households' experience with flood or high rainfall and drought or erratic rainfall over the past five years before the survey, as well as household perception of rainfall and temperature changes over the past 20 years. Other studies (Di Falco et al. 2011a, Di Falco et al. 2011b) also incorporated proxies of climate change in the form of long-term trends in temperature and rainfall. This was done by spatially interpolating these climatic variables and by using the geographic coordinates of each household to impute specific rainfall and temperature values for each respondent. However, as the geographical coordinates were only collected at the village level, the lack of adequate spatial variation in the climatic variables precluded us from using these household specific proxies. Nevertheless, using households' actual experience with climate stress reflects the impact of climate shocks on their farms and will bring good insights into how households use agroforestry technologies to cope with climate variability.

In the second stage, the differential impact of covariates on the food security of the group of adopters and non-adopters is modeled simultaneously through an endogenous switching regime model. The outcome equation is specified for each regime as:

$$\text{Regime 1: } y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \quad \text{if } A_i = 1 \quad (5)$$

$$\text{Regime 2: } y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \quad \text{if } A_i = 0 \quad (6)$$

Where  $y_i$  is the outcome, food security variable. We use several outcome variables as indicators of food security. The most common approaches used to measure food security rely on per capita food consumption which is based on food expenditures. The food insecurity indicators frequently used include food consumption, anthropometric indicators or health data (Kabunga, 2014).

However, these measurements are data intensive, often times suffer from recall bias and are relatively costly to implement (de Haen et al. 2011, Shiferaw, 2014). In this study, we focused on the availability dimension of food security. We used one of the recommended FAO indicators of availability, which is the average value of food production. In the analysis, we will use the average value of food productivity which corresponds to the average value of food production per acre of land cultivated for food crops. In addition to this indicator, we used maize productivity, as it is a major staple crop in Malawi's agricultural system. Food availability will also be determined by the productivity of this crop.

$X$  represents a vector of covariates and  $\beta$  are parameters to be estimated. Residuals  $\varepsilon$  from equation (2) and  $\mu$  in equation (1) are assumed to be jointly normally distributed with a mean of zero and a covariance matrix specified as:

$$cov(\mu, \varepsilon_1, \varepsilon_2) = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1\mu} \\ \sigma_{21} & \sigma_2^2 & \sigma_{2\mu} \\ \sigma_{\mu 1} & \sigma_{\mu 2} & \sigma^2 \end{pmatrix} \quad (7)$$

Where  $\sigma_1^2 = var(\varepsilon_1)$ ,  $\sigma_2^2 = var(\varepsilon_2)$ ,  $\sigma^2 = var(\mu)$ ,  $\sigma_{12} = covar(\varepsilon_1\varepsilon_2)$ ,  $\sigma_{1\mu} = covar(\varepsilon_1\mu)$

$\sigma_{2\mu} = covar(\varepsilon_2\mu)$ . The variance of  $\mu$  is set to zero since the  $\gamma$  coefficients in the selection equation are only estimable up to a scale factor (Maddala 1983, Greene 2011). Besides  $\sigma_{12}=0$  since  $y_{1i}$  and  $y_{2i}$  are never observed at the same time.

Given the selection bias due to some unobservable factors, the error terms in the selection equation (adoption of fertilizer trees) and outcome regression (food security) are correlated. Therefore  $\sigma_{2\mu}$  and  $\sigma_{1\mu}$  are non-zero and estimates of the covariance terms provide a test for endogeneity. If these terms are statistically significant, it will indicate that there is sample selectivity bias due to unobservable factors. We will also confirm the sensitivity of our estimates to the presence of unobserved selection bias by performing a Rosenbaum test applied to the propensity matching approach and following the procedure developed by Rosenbaum (2002).

The expected value of  $\varepsilon_1$  and  $\varepsilon_2$  conditional on the sample selection can be expressed as:

$$E(\varepsilon_{i1} | A_i = 1) = \sigma_{1\mu} \frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)} \quad (8)$$

$$= \sigma_{1\mu} \lambda_{i1}$$

$$E(\varepsilon_{i2} | A_i = 0) = \sigma_{2\mu} \frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)} \quad (9)$$

$$= \sigma_{2\mu} \lambda_{i2}$$

Where  $\phi()$  and  $\Phi(.)$  are the probability and cumulative distribution functions of the standard normal distribution function, respectively.  $\lambda_{i1}$  and  $\lambda_{i2}$  are the Inverse Mills Ratio (IMR) computed from the selection equation and included in the outcome regression to correct for the selection bias. We used the full information maximum likelihood approach that jointly estimates parameters in the selection and the outcome regression, in order to have more efficient parameters.

Equations (5) and (6) can then be specified as:

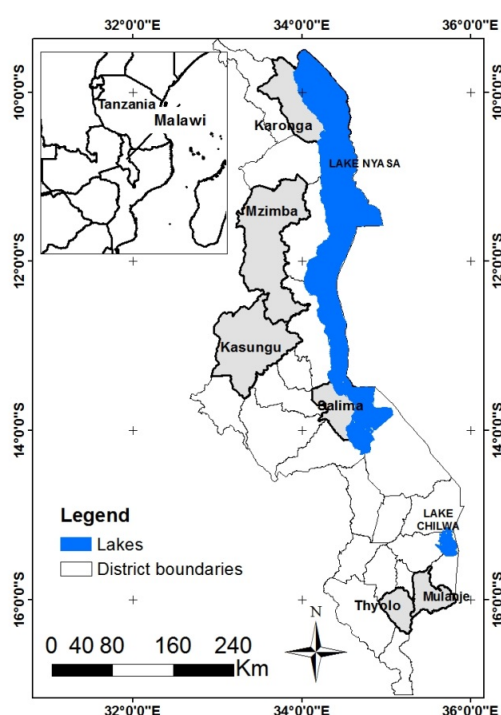
$$y_{i1} = X_i\beta_1 + \sigma_{1\mu}\lambda_{i1} + \xi_{i1} \quad \text{if } A_i = 1 \quad (10)$$

$$y_{i2} = X_i\beta_2 + \sigma_{2\mu}\lambda_{i2} + \xi_{i2} \quad \text{if } A_i = 0 \quad (11)$$

The ESR is identified by construction through non-linearities of  $\lambda_{i1}$  and  $\lambda_{i2}$  (Lokshin and Sajaia, 2004). However, it is also recommended to use a selection instrument in addition to these non-linearities in order to improve the model identification. In our study, we used variables related to source of information and knowledge following several other studies (Di Falco et al. 2011, Shiferaw et al. 2014). Participation in agroforestry training was therefore included as a selection instrument. Agroforestry training provides farmers with knowledge on agroforestry management, which can influence their decision to adopt fertilizer trees but do not have a direct effect on the outcome, the food security variable. We tested the validity of this instrument by running a regression against the dependent variable in the first and the second stages. Good instruments are expected to influence the decision to adopt fertilizer trees but not the outcome variable. The standard errors in equation (10) and (11) are bootstrapped to produce more efficient estimates.

## 4. Data and descriptive statistics

### 4.1 Farm household survey



Source: Coulibaly et al., 2015b

This study builds on data collected from the north, central and south regions of Malawi using a stratified multi-stage sampling design. To ensure representativeness, districts were first stratified by geographical location. In each of the three regions, two districts with significant levels of adoption of agroforestry practices were selected based on monitoring reports. In total, six (6) districts were selected: Karonga and Mzimba in the north, Salima and Kasungu in the central, and Thyolo and Mulanje in the south. In each of these districts, two (2) Extension Planning Areas (EPAs) were randomly drawn and thirty (30) households also randomly chosen to ensure equal probability of representation in the sample. In each of the EPAs, households were selected randomly based on criteria provided by extension agents. The control group was also randomly selected in the same village among farmers who did not use any agroforestry practices. The districts are inhabited by different ethnic groups of different socio-cultural backgrounds, which may have an influence on adoption decisions of agroforestry practices. In total, 338 households were selected to participate in the survey. Figure 1 shows the location of these districts.

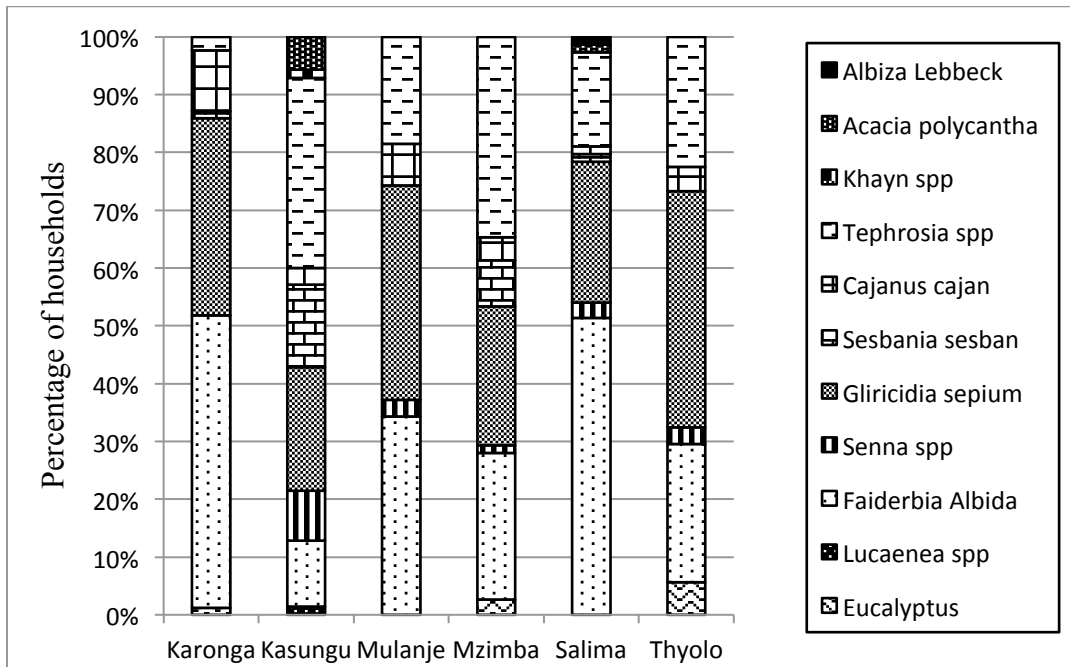
The survey was conducted between July and August 2014, which is a post-harvest period. This made it easy for farmers to recall harvest information in the season prior to the survey. Farmers



had enough time to answer questions because they were not busy in the fields. The structured questionnaire enquired on household socio-economic characteristics, asset ownership, crop and agroforestry production, food consumption and sales, adoption of agroforestry practices, climate shocks, households' perception of climate change, food gap, and respondents' perception of agroforestry. The questionnaire was pre-tested and administered by a team of well-trained and experienced enumerators with a minimum qualification of a first university degree and fluency in the local languages of the sampled districts.

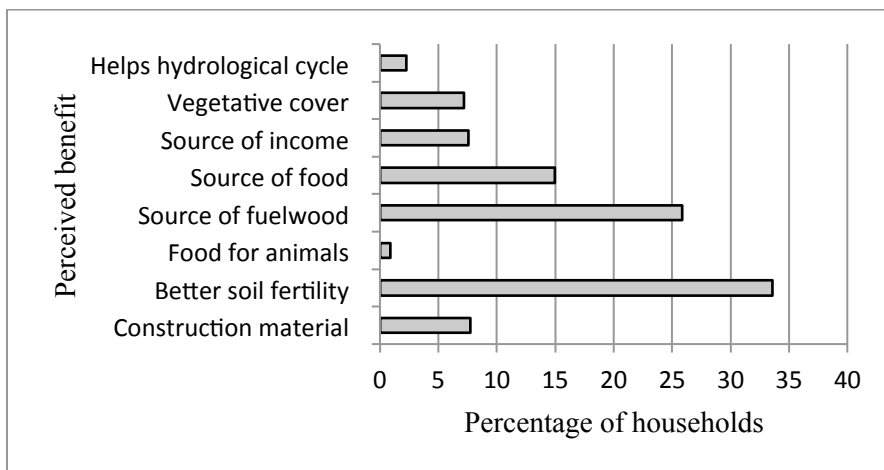
40% of the sampled households are classified as adopters of fertilizer trees implying they were growing one or more fertilizer tree species. Figure 2 presents the different fertilizer tree species adopted by farmers by district (please see also annex for illustration). Farmers in the sampled districts grew a total of 13 different tree species. The most widely adopted species in these districts are *Faidherbia albida*, *Tephrosia spp* and *Gliricidia sepium*. We define adopters as farmers who use any fertilizer tree species or combination of species among those shown in figure 1, while non-adopters include farmers who did not use any of these species. Maize is the main food crop grown by all households surveyed. Other commonly grown food crops include groundnuts, beans, vegetables and rice.

Figure 2. Fertilizer tree species adopted across districts



During the survey, sampled farmers were asked to indicate their perceived importance of adopting agroforestry practices such as fertilizer trees. Farmers' subjective responses, which are reported in figure 3, show that improved soil fertility is perceived as the main benefit derived from practicing agroforestry. In addition to enhancing soil fertility, agroforestry is also perceived to increase supply of food for both home consumption (fruits and vegetables) and livestock (fodder), and to increase energy supply sources through fuel-wood for home consumption and/or for sale.

Figure 3. Farmers' perception on the importance of agroforestry technologies



## *4.2 Descriptive statistics*

Table 1 shows the summary statistics of sampled farmers. There are only a few significant differences between adopters of fertilizer trees and non-adopters in terms of household and farm characters as well as perceptions and shocks. Farmers that adopted fertilizer trees are better-educated, mostly engaged in non-farming activities, received training in agroforestry and have higher asset ownership. Adopters also perceive their land to have been degraded over time compared to non-adopters. All other covariates are statistically non-significant.

Considering the food security outcomes shown in the top half of table 1, adopters of fertilizer trees appear to be more food secure as they reported significantly higher maize yields and value of food crops compared to non-adopters. This is also illustrated and is visualized in figures 4 and 5, which show the cumulative distribution functions (CDFs) of maize yield and value of food production, respectively. A Kolmogorov–Smirnov test confirms that the CDFs of fertilizer tree adopters stochastically dominates that of non-adopters for maize yield ( $p < 0.01$ ) and value of maize yield ( $p < 0.1$ ).

While these descriptive statistics suggest that observed differences between adopters and non-adopters are minimal, there still might be systematic differences that are unobserved. Therefore, without estimating treatment effects, that at least controls for unobserved heterogeneity between farmers, we cannot be certain whether the observed differences in maize yield and value of food crops are causal effects of adoption of fertilizer trees or the result of other confounding factors. We analyzed treatment effects, using endogenous switching regression in the next section.

Table 1: General differences between fertilizer tree adopters and non-adopters

	Non-adopters N=203	Adopters N=135
<b>Outcome variables</b>		
Maize yield (kg/acre)	478.749 (384.30)	597.665* (459.77)
Value of food crops MWK/acre <sup>#</sup>	45172.920 (43833.33)	59567.560** (54250.99)
<b>Household characteristics</b>		
Household size	2.768 (1.54)	3.059 (1.47)
Male headed household (dummy)	0.704 (0.46)	0.689 (0.46)
Age of the household head (years)	48.621 (15.56)	46.785 (13.48)
Age of the household head squared (years)	2604.916 (1599.58)	2369.244 (1352.86)
Secondary education for household (dummy)	0.330 (0.47)	0.459* (0.50)
Household head main occupation is farming (dummy)	0.892 (0.31)	0.770** (0.42)
<b>Farm characteristics</b>		
Farm size (acres)	3.920 (3.37)	4.088 (3.12)
Total livestock unit	1.165 (1.97)	1.290 (1.83)
Farm asset index	-0.253 (1.13)	0.360*** (1.92)
Distance to output market (km)	7.741 (7.03)	6.964 (9.98)
Distance to government extension (km)	8.233 (7.55)	8.761 (7.31)
Quantity of fertilizer applied to maize (kg)	4.375 (1.65)	4.517 (1.52)
Household received agroforestry training (dummy)	0.483 (0.50)	0.652** (0.48)
<b>Household perceptions and shocks</b>		
Rainfall has decreased in the last 20 years	0.601 (0.49)	0.674 (0.47)
Temperature has increased in the past 20 years	0.384 (0.49)	0.430 (0.50)
Experienced drought in the past 5 years (dummy)	0.788 (0.41)	0.800 (0.40)
Experienced floods in the past 5 years (dummy)	0.118 (0.32)	0.104 (0.31)
Land degraded over time (dummy)	0.650 (0.48)	0.770* (0.42)

Notes: Mean values are shown with standard deviations in parenthesis; \*, \*\*, \*\*\* denotes significance level at 10%, 5% and 1%, respectively.

<sup>#</sup> MWK: Malawian Kwacha

Figure 4. Cumulative distribution of maize yield by fertilizer tree adoption

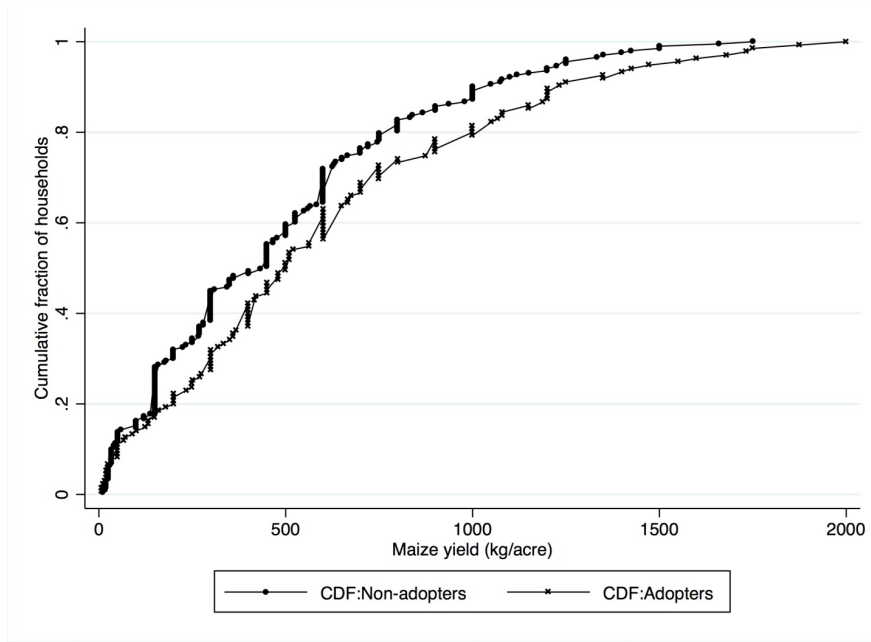
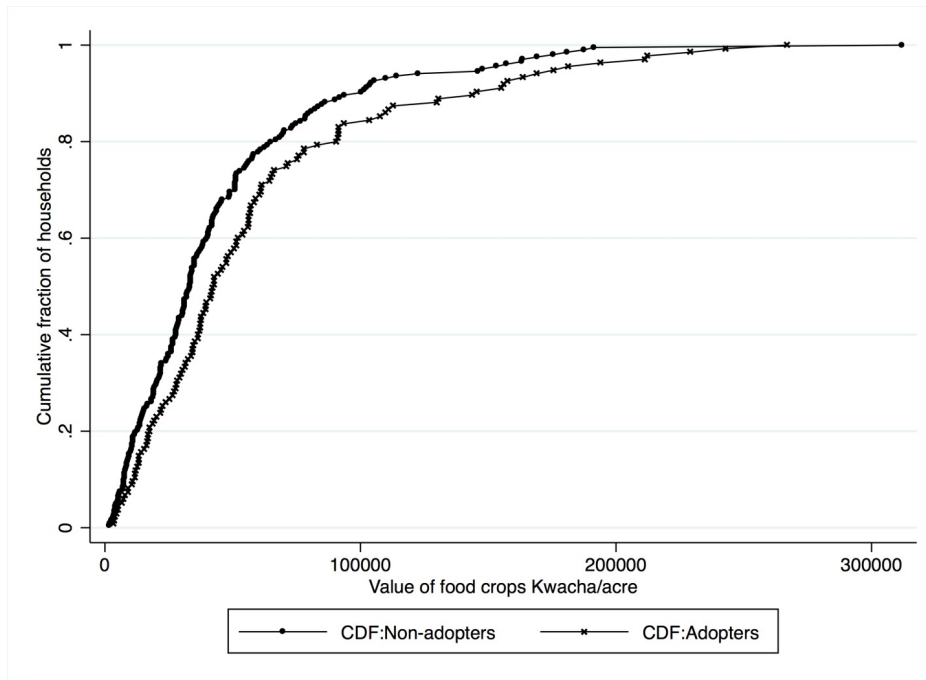


Figure 5. Cumulative distribution of value of maize by fertilizer tree adoption



## 5. Econometric results

### 5.1 Determinants of adoption of fertilizer trees

We start by analyzing the factors that influence households to adopt fertilizer trees presented in table 2. The results are from the selection equation that is estimated jointly with the value of food produced. The results reveal that the main factors that significantly influence the tree fertilizer adoption decision are farming as an occupation, farm asset, agroforestry training, use of inorganic fertilizer, distance from extension agent office and perception of long-term change in temperatures and perception of land degradation (table 2).

Agro-pastoralists and farmers who are primarily engaged in off-farm business are more likely to adopt to adopt fertilizer trees. In fact, agro-pastoralists or farmers selling fuelwood may have a greater incentive to use fertilizer trees because these trees not only enrich soil fertility and enhance crop productivity but also provide fodder for livestock and wood energy. Another likely explanation is that since farming is not their main occupation, they do not purchase inorganic fertilizer and prefer to substitute it by fertilizer trees.

Ownership of farming related assets is positively and statistically significantly associated with adoption of fertilizer trees. Farm equipment can be considered as proxy of wealth and are necessary assets to foster adoption of technologies on farm. Farmers with more resources are less risk averse, have more access to information (Franzel, 1999) and are more eager to test technologies that have the potential to increase agricultural productivity and income.



Maize intercropped with Sesbania in Eastern Province, Zambia. Photo by Olu Ajayi

Agroforestry training exerts a positive effect on adoption of fertilizer trees. Agroforestry, including fertilizer trees, are more complex technologies as compared to annual crops and are considered as knowledge intensive technologies. Training in agroforestry therefore builds capacities of farmers to appropriately manage their fertilizer trees. This is consistent with a study by Franzel et al (2001) who highlighted that farmers' ability to adopt and manage agroforestry is enhanced with access to required information and skills.

Use of inorganic fertilizer positively influences the adoption of fertilizer trees. Research has shown that there is often a positive interaction and complementarity between the supply of mineral fertilizer and organic fertilizer (Akinnifesi et al., 2007). This is also emphasized in the theory of Integrated Soil Fertility Management (ISFM) that states inorganic fertilizer and organic

matter have complementary interactions and are both necessary for sustainable improvement in soil health and crop productivity (Buresh et al., 1997, Vanlauwe et al., 2002). Farmers who are aware of potential benefits of agroforestry may be more willing to boost further their crop productivity by using both inorganic fertilizer and fertilizer trees.

Distance to the extension office is negatively and significantly correlated with adoption of fertilizer trees. This is unpredicted, as one would expect that proximity to extension agents would increase the likelihood of receiving frequent technical advice and therefore higher probability of adoption new technologies. This negative relationship may be due to programme implementation where adopters may have been deliberately selected in remote areas. It may also indicate that fertilizer trees have been widely disseminated and reached even remote villages. Another explanation may lie in the way farmers' training was conducted in the programme. Extension agents first trained some lead farmers who in turn other farmers residing in the village. So the variable distance to extension office may actually capture the lead farmers villages' distance from the extension office.

Farm households that perceive a long-term change in temperatures are more likely to adopt fertilizer trees. A number of studies have shown increasing interest of smallholder farmers in the contribution of agroforestry in climate change mitigation and adaptation (Akinnifesi et al., 2010, Thorlakson and Neufeldt, 2012). Fertilizer trees provide numerous benefits including fuelwood, income generation, soil fertility enhancement and environmental services. These technologies can therefore reduce smallholders' vulnerability to climate change and enhance their resilience to current and future climate shocks.

Farmers' perception of land degradation is positively associated with adoption of fertilizer trees. Farmers are more likely to invest time, labour and capital in the management of fertilizer trees, soil fertility enhancing technologies, if they perceive soil fertility as a major problem on their farms. This finding corroborates several other studies that found that farmers' perception with soil problem is positively correlated with adoption of soil conservation practices (Gould et al. 1989, Traore et al. 1998).

Table 2: Determinants of fertilizer tree adoption

	Probit estimates	Standard error
<b><i>Household characteristics</i></b>		
Male headed household (dummy)	-0.229	-0.173
Age of the household head (years)	0.161	0.034
Age of the household head squared (years)	-0.000	-0.000
Secondary education for household (dummy)	0.234	0.172
Household size	0.033	0.061
Household head main occupation is farming (dummy)	-0.694***	-0.197
<b><i>Farm characteristics</i></b>		
Farm size (acres)	-0.024	-0.024
Total livestock unit	-0.049	-0.036
Farm asset index	0.215***	0.052
Distance to output market (km)	-0.012	-0.014
Distance to government extension (km)	0.024**	0.011
Quantity of fertilizer applied to maize (kg)	0.074*	0.044
Household received agroforestry training (dummy)	0.514***	0.114
<b><i>Household perceptions and shocks</i></b>		
Rainfall has decreased in the last 20 years	0.263*	0.154
Temperature has increased in the past 20 years	0.078	0.150
Experienced drought in the past 5 years (dummy)	-0.210	-0.246
Experienced floods in the past 5 years (dummy)	-0.195	-0.299
Land degraded over time (dummy)	0.340**	0.148
Constant	-0.795	-0.845
Observations	338	
Log likelihood	-625.363	

Notes: Coefficient estimates with standard errors are shown; \*, \*\*, \*\*\* denotes significance level at 10%, 5% and 1%, respectively.

## ***5.2 Impact of adoption of fertilizer tree on food security***

The findings of the full information maximum likelihood estimates of the endogenous switching regression model are presented in table 3. Results of the correlation coefficients (r1 and r2) provide an indication of the selection bias. Correlation coefficient (r1) of the adopters is positive and significant indicating that there is self-selection among adopters. Such finding highlights the existence of observed and unobserved factors influence the decision to adopt fertilizer trees. In fact, as shown in figure 3 above, the perceived benefits of agroforestry technologies could trigger



farmers' decisions to adopt fertilizer trees. Farm households who choose to adopt fertilizer trees would have had higher than average values of food productivity in comparison to a random household in the sample. The non-significance of covariance estimates for the non-adopters indicate that in the absence of adoption of fertilizer trees, there will be no evident difference in the average value of food productivity between non-adopters and a random household caused by unobserved factors. Moreover, the significant value for the Wald test for independence of the equations is statistically significant suggesting inter-dependence between selection equation and outcome equations for adopters and non-adopters, providing further evidence of endogeneity.

Test results confirmed the validity of our instrument because it has a significant effect on the decision to adopt fertilizer trees but do not influence the outcome variable, here value of food productivity<sup>2</sup>.

The estimation results of the second stage show that some variables such as distance to crop market, perception of increase in temperature and livestock numbers, affect the value of food productivity of both adopters and non-adopters. The coefficient on the perception of temperature increase variable suggests that even if farmers are more likely to claim to have witnessed an increase in temperature, and adopt fertilizer trees. This may not necessarily translate in an increase in the average value of food productivity. This may be an indication that farmers face some barriers in implementing climate change adaptation strategies. Such perceptions of climate change may not necessarily lead to greater food security if these barriers are not lifted.

Other estimates encompassing age, farm size, gender, use of chemical fertilizer influence the food productivity of these two groups differently. The coefficient for farm size is negative suggesting that among adopters, small-scale farmers have higher productivity than larger scale farmers. This result at first sight may appear counterintuitive but may imply that farmers with small areas of land are more technically efficient than farmers with larger farms. This inverse relationship between farm size and agricultural productivity has also been found in several studies. For example, Ansoms et al. (2008) confirms a strong inverse relationship between farm size and land productivity in rural Rwanda, justified partly by less alternative options for smallholders farmers' labour forces. Harris and Orr (2014) also stress that smallholders are often limited in keeping the same return achieved from a small area of land on a larger scale.

Age is a main determinant of the value for food productivity among adopters. The value for food productivity increases with age as it can be considered as a proxy for farm experience. Older farmers have more experience with fertilizer tree management and are thus able to produce than

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<sup>2</sup> Training in agroforestry is correlated with decision to adopt fertilizer trees ( $\rho=0.480$ ,  $se=0.132$ ) but uncorrelated with food productivity ( $\rho=-0.019$ ,  $se=0.126$ ).

their younger counterparts. However beyond a certain age, they become less productive due to the life cycle effect.

Putting in an additional kilogram of chemical fertilizer per unit of land increases the average value of food productivity among adopters. The use of inorganic fertilizer among fertilizer tree adopters exerts a significant effect on food crop productivity and thereby on the average value of food productivity. This result is in line with some authors' findings that there is a higher increase in crop productivity when inorganic fertilizer is coupled with fertilizer trees in farm management (Place et al. 2002, Beedy et al., 2010).

Gender is the main factor that determines the productivity among non-adopters only. Male-headed households are more likely to have greater average value of food productivity than female-headed households. This is because female household heads are often divorcees or widows with less assets and resources to use in managing their farms.

Table 3. Full information maximum likelihood parameter estimates for value of maize produced

	Fertilizer tree non-adopters		Fertilizer tree adopters	
	Non-adopters	Standard error	Adopters	Standard error
<b><i>Household characteristics</i></b>				
Male headed household (dummy)	0.432 <sup>***</sup>	0.127	0.153	0.198
Age of the household head (years)	0.004	0.028	0.117 <sup>***</sup>	0.038
Age of the household head squared (years)	-0.000	0.000	-0.001 <sup>**</sup>	0.000
Secondary education for household (dummy)	0.069	0.144	-0.092	0.177
Household size	0.002	0.031	0.008	0.055
Household head main occupation is farming (dummy)	-0.272	0.190	-0.061	0.233
<b><i>Farm characteristics</i></b>				
Farm size (acres)	-0.032	0.027	-0.054 <sup>**</sup>	0.027
Total livestock unit	0.127 <sup>***</sup>	0.030	-0.058 <sup>*</sup>	0.033
Farm asset index	-0.055	0.075	0.087	0.058
Distance to output market (km)	-0.022 <sup>**</sup>	0.009	-0.022 <sup>***</sup>	0.008
Distance to government extension (km)	0.006	0.010	0.004	0.013
Quantity of fertilizer applied to maize (kg)	0.007	0.048	0.126 <sup>**</sup>	0.050
<b><i>Household perceptions and shocks</i></b>				
Rainfall has decreased in the last 20 years	-0.195	0.137	-0.029	0.204
Temperature has increased in the past 20 years	-0.472 <sup>***</sup>	0.152	-0.505 <sup>***</sup>	0.176
Experienced drought in the past 5 years (dummy)	0.011	0.177	-0.110	0.255
Experienced floods in the past 5 years (dummy)	0.102	0.187	-0.320	0.249
Land degraded over time (dummy)	-0.029	0.141	0.039	0.233
Constant	10.35 <sup>***</sup>	0.710	7.312 <sup>***</sup>	1.171
lnS0	-0.102	0.090		
lnS1			-0.032	0.124
r0	-0.376	0.324		
r1			0.797 <sup>***</sup>	0.304
Observations	338			
Log likelihood	-625.363			
Wald test of independent equations $\chi^2(2) = 7.21$				

Notes: Coefficient estimates are shown with standard errors; \*, \*\*, \*\*\* denotes significance level at 10%, 5% and 1%, respectively.

The estimates of the treatment effect of impact of adoption of fertilizer trees on the average value of food productivity and maize productivity are reported in table 4. The Average Treatment effect on the Treated (ATT) measures the difference between the average productivity of adopters and what they would have had if they had not adopted fertilizer trees. The Average Treatment Effect on the Untreated (ATU) on the other hand assesses the difference between average productivity of non-adopters and their counterfactuals. These estimates account for selection bias unlike the mean differences reported in table 1.



Maize intercropped with Gliricidia in Lilongwe, Malawi. Photo by Olu Ajayi

Result of the ATT reveals that adopters of fertilizer trees have a greater average value of food crop productivity of 11,585 kwacha<sup>3</sup> per acre than their counterfactuals. In the same vein, adoption of fertilizer trees generates greater maize productivity by 106 kg per acre of maize compared to the counterfactual situation. These results mean that the adoption of fertilizer trees increases the average value of food productivity by an average of 35% and the maize productivity by an average of 32%. These results provide evidence that fertilizer trees have an impact on food security in maize based food system as also attested by Akinnifesi et al. (2007, 2010).

Without controlling for selection bias, the effect would have been an increase of 112% and 85% respectively in the average value of food and maize productivity attributed to the use of fertilizer trees. This corresponds to the percentage change between actual productivity of adopters and non-adopters.

For the case of non-adopters, we have a decrease in their productivity if they have to adopt fertilizer trees. This later result is significant for the average value of food productivity but not significant for the maize productivity. Significance of this later result highlights a heterogeneous effect in the adoption of fertilizer trees between adopters and non-adopters. It implies that non-adopters are better off in allocating their resources to other uses than to agroforestry. These findings, as indicated in the paragraphs above point to the fact that adopters and non-adopters have different assets and endowment which shape their production function and responses to agro-forestry technologies.

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<sup>3</sup> approximately US dollar 2.23 as per March 2016 exchange rates

The heterogeneity effects is positive for maize yield and the average value of food productivity, indicating that the impact of adopting fertilizer tree on the outcomes is higher for the farm households that actually did adopt compared to those that did not adopt.

Table 4: Average treatment effect of fertilizer tree adoption on food security

	Decision stage		Average Treatment effect
	To adopt	Not to adopt	
<b><i>Maize yield (kg/acre)</i></b>			
Farm households that adopted	435.455 (2.500)	329.642 (1.689)	105.803*** (3.047)
Farm households that did not adopt	182.205 (6.581)	235.390 (44.072)	-53.184*** (44.503)
Heterogeneity effects	253.240 (5.803)	94.252 (44.204)	158.987*** (44.427)
<b><i>Value of food crops (MWK/acre)</i></b>			
Farm households that adopted	44671.318 (496.890)	33085.930 (405.430)	11585.390*** (352.390)
Farm households that did not adopt	16555.760 (1186.274)	21054.920 (1855.391)	-4499.157*** (2172.791)
Heterogeneity effects	28115.550 (1198.880)	12031.010 (1773.822)	16084.550*** (2140.114)

Notes: Coefficient estimates are shown with bootstrapped standard errors in parenthesis; \*, \*\*, \*\*\* denotes significance level at 10%, 5% and 1%, respectively.

## 6. Conclusion

Adoption of fertilizer trees provides an opportunity to improve soil fertility, food productivity and therefore contribute to food security. Yet, there is still little empirical research that documents the impact of fertilizer trees on food security on smallholder households. This paper analyzed the causal impact of adoption of fertilizer trees on food security. We used data from a recent field survey on rural farm households across the main agro-ecological zones of Malawi. An endogenous switching regression model was used in the analyses to account for selection bias due to observable and unobservable variables that influence the decision to adopt fertilizer trees and the food security outcome. We estimated the impact on the average value of food productivity and maize productivity on both adopters and non-adopters of fertilizer trees.

The results of the adoption point out some important issues. First, adoption of fertilizer trees is dictated by the perceived effectiveness of this technology in restoring fertility on degraded land. Fertilizer trees therefore represent a viable option to improve soil fertility in a country where farmers face constraints in using optimal quantities of inorganic fertilizer. Second, fertilizer trees like any other agroforestry technology is knowledge intensive since adopters of this technology were found to be those who had access to training on agroforestry management. Third, having a farm asset base is fundamental to facilitate adoption. These findings have important implications for the design of policy actions to address impediments to adoption of fertilizer trees and in targeting the right types of households with higher likelihood to adopt agroforestry technologies. Hence public policies to enhance adoption of fertilizer trees should emphasize on building knowledge base of farmers through training, and facilitating access to credit or farm capital.

From the impact assessment model, the findings reveal that food productivity functions of adopters and non-adopters are driven by different factors. We were able to show that adoption of fertilizer trees improved food security of farmers who opted for this technology in maize-based mixed farming systems. However, results of the impact on non-adopters are more mitigated. Such results highlight the fact that adoption of fertilizer trees has heterogeneous effect on food productivity for adopters and non-adopters.

The results presented in this study are average effects of the impact of fertilizer tree technologies. However, since farmers are not homogeneous groups of individuals with similar biophysical and socio-economic characteristics, an innovative research approach will be to look at the differentiated effect of the fertilizer tree technologies across different biophysical and socio-economic endowments such as soil fertility, altitude, slope, farm size, and land ownership. Such research analysis can be conducted with large sample size and comprehensive data on the biophysical and socio-economic characteristics and is left for future investigation.

Although this study demonstrated significant and positive food security as a result of adoption of fertilizer trees, this impact could have been more impressive with a farming system that allows trees to grow for more than a year before being cut (for example, more use of *Gliricidia sepium* and *Faidherbia albida* by farmers). Indeed, most of the farming systems surveyed in this study are fast growing intercropped leguminous shrubs species that were renewed annually in the field. Normally, the larger the fertilizer tree and the greater the volume of biomass produced (nitrogen rich leaf foliage), the higher the soil fertility benefit. Nonetheless, in spite of the short-term management option analyzed, this study contributes to filling the evidence gaps regarding the causal impact of fertilizer trees on food security, and their contribution to biodiversity of the system and to the local economies.

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The World Agroforestry Centre is an autonomous, non-profit research organization whose vision is a rural transformation in the developing world as smallholder households increase their use of trees in agricultural landscapes to improve food security, nutrition, income, health, shelter, social cohesion, energy resources and environmental sustainability. The Centre generates science-based knowledge about the diverse roles that trees play in agricultural landscapes, and uses its research to advance policies and practices, and their implementation that benefit the poor and the environment. It aims to ensure that all this is achieved by enhancing the quality of its science work, increasing operational efficiency, building and maintaining strong partnerships, accelerating the use and impact of its research, and promoting greater cohesion, interdependence and alignment within the organization.



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