32nd International Conference of Agricultural Economists
2-7 August 2024 I New Delhi I India

Impact of Agroforestry on Household Food Security: A Micro-Perspective from Southern Rwanda

Jules Ngango[1*], Edouard Musabanganji[2], Aristide Maniriho[1], Ferdinand Nkikabahizi[1], Anitha Mukamuhire[1], and John N. Ng'ombe[3]

[1]Department of Economics, School of Economics, College of Business and Economics, University of Rwanda, Rwanda.

[2]Department of Applied Statistics, School of Economics, College of Business and Economics, University of Rwanda, Rwanda.

[3]Department of Agribusiness, Applied Economics and Agriscience Education, North Carolina A&T State University, United States of America.

Corresponding author: Email: ngajules2@gmail.com

Abstract

This study utilizes an endogenous switching regression model, complemented with coarsened exact matching, to ascertain the effects of adopting agroforestry on household food security. Our analysis employs data from a sample of 615 farms in Southern Rwanda. The findings indicate that the main determinants of agroforestry adoption include secure land tenure, membership in cooperatives, access to credit, household size, and farmers' awareness of agroforestry practices. Findings highlight the substantial contributions of agroforestry to food security, with adopters experiencing 19.81 percentage points higher food consumption scores compared to non-adopters. Moreover, the results reveal potential benefits for non-adopters through agroforestry adoption, thereby suggesting that even individuals who do not currently engage in agroforestry could enhance their food security by considering adoption. These insights emphasize the long-term potential of promoting agroforestry for current and prospective adopters. Policies reinforcing land security, supporting cooperatives, providing accessible credit, and promoting farmer sensitization are crucial for encouraging agroforestry adoption and improving food security. By identifying key determinants and quantifying impacts, this study offers targeted guidance for interventions that leverage agroforestry as a sustainable solution to enhance household food security

JEL Codes: Agroforestry, endogenous switching regression model, food security, Rwanda

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1. Introduction

In 2020, the Food and Agriculture Organization (FAO) issued a report revealing that one-third of the global population grappled with hunger, and strikingly, over one-third of those suffering from undernourishment were situated in Africa (Shembe et al., 2023). This disconcerting revelation underscores the profound challenges associated with attaining and sustaining food security on a global scale. Moreover, the quest for food security is intricately woven into the complex fabric of poverty and various socioeconomic factors. Among these factors are the constraints imposed by limited arable land, the mounting pressure of population growth, and the critical variable of agricultural productivity (Johnson et al., 2023; Kehinde et al., 2021; Murugani and Thamaga-Chitja, 2019; Mutisya et al., 2015; Yazew et al., 2023). These components collectively contribute to the puzzle of food security, something that requires comprehensive and strategic solutions to ensure the well-being of communities worldwide.

Amidst these formidable challenges, delving into the intricate dynamics of food security becomes not just a necessity but a paramount concern. The issue at hand is intricately interwoven with global imperatives such as poverty alleviation, sustainable development, and the delicate equilibrium between meeting the needs of a burgeoning population and the finite resources available. Within this global context, Africa emerges as a focal point of concern, grappling with the fastest population growth on the planet. Projections indicate that Africa's population, standing at 1.1 billion in 2015, is anticipated to burgeon to 2.5 billion by the year 2050, signifying profound implications for food security (Kazungu and Kumburu, 2023).

In response to this imminent challenge, African nations, in collaboration with international donors and development partners, have initiated numerous programs. These include the Comprehensive Africa Agriculture Development Programme (CAADP), the Science, Technology, and Innovations Strategy for Africa 2024, and the African Union's pivotal 2014 Malabo Declaration (Kazungu and Kumburu, 2023). These initiatives collectively aim to revolutionize agricultural practices and fortify efforts toward ensuring food security across the continent. However, the path toward food security in Africa is fraught with multifaceted challenges. Issues such as soil fertility loss, unpredictable food price fluctuations, and restricted access to essential resources act as formidable barriers, hindering the achievement of stable agricultural production and robust food security on the continent (Kazungu and Kumburu, 2023; Mutungi et al., 2023; Radeny et al., 2022).

In the context of securing food for Africa's rising population, strategic investments in agricultural transformation have assumed critical importance. Within this landscape, agroforestry has emerged as a promising and multifaceted solution, as underscored by research studies (Coulibaly et al., 2017; Duffy et al., 2021; Jacobi, 2016; Kalanzi et al., 2021; Kiptot et al., 2014; Magcale-Macandog et al., 2010; Pandit et al., 2019). Agroforestry encompasses land-use systems and technologies that intentionally integrate woody perennials, such as trees, shrubs, palms, bamboos, etc., within the same land management units as agricultural crops and/or animals. This integration occurs through various spatial arrangements or temporal sequences (Sarvade and Singh, 2014). Within agroforestry systems, there exist both ecological and economic interactions among the diverse components (Lundgren and Raintree, 1982). With its potential to enhance ecosystem services, improve health outcomes, and positively impact livelihoods, agroforestry aligns seamlessly with the United Nations' Sustainable Development Goals (SDGs), particularly those focused on eradicating poverty, ensuring zero hunger, and promoting the sustainable use of terrestrial ecosystems (Duffy et al., 2021).

Given the foregoing, this research delves into agroforestry's role in bolstering household food security within the context of Rwanda. Leveraging the Food Consumption Score (FCS) as an indicator of food security, the study’s goal is to determine the impact of adoption of agroforestry among rural farms on food security whereby food security is measured using FCS. We use data from rural farmers from Southern Rwanda. Since its introduction in 1996, the FCS, devised by the World Food Programme (WFP), has become a widely accepted and utilized metric for assessing the access dimension of food security (Marivoet et al., 2019). Its widespread adoption is attributed to its effectiveness in monitoring and evaluating food security in various countries and serving as a pivotal tool for designing and implementing interventions by the agency on a global scale (WFP, 2008; Marivoet et al., 2019).

This study makes the following contributions to existing. First, understanding the role of agroforestry is crucial for addressing food insecurity challenges in Rwanda and Sub-Saharan Africa as a whole. Agroforestry, with its ability to improve ecosystem services, enhance health outcomes, and positively influence livelihoods, aligns seamlessly with key United Nations'

Sustainable Development Goals (SDGs), including no poverty, zero hunger, and the sustainable use of terrestrial ecosystems. By elucidating the specific contributions of agroforestry in the local context of the Southern province in Rwanda, the study provides region-specific insights even for broader SSA where hunger and food insecurity dominate other challenges. This localized perspective is essential for crafting tailored interventions that consider unique regional considerations, ultimately contributing to the broader discourse on sustainable and context-specific strategies for achieving food security. Therefore, the study's contribution is pivotal in informing policymakers and researchers about the potential importance of agroforestry as a viable solution to address food insecurity challenges, offering a pathway toward more resilient and sustainable food systems in Rwanda and beyond.

Second, this study's other contribution lies in the way we determine the impacts of agroforestry. Given that the adoption of agroforestry is not a random process (Coulibaly et al., 2017), farmers often self-select into practicing agroforestry based on unobservable characteristics, such as inherent abilities, farming expertise, conscientiousness, and risk perception, among others. These factors may be correlated with both the decision to adopt agroforestry and the outcomes related to food security, introducing endogeneity that, if unaddressed, can lead to biased results (McElreath, 2021; Wooldridge, 2010). Recognizing the potential selectivity bias inherent in the adoption of agroforestry, this article utilizes an endogenous switching regression model (Maddala, 1998) to effectively control for selectivity bias arising from both observable and unobservable confounders. To ensure the robustness of our findings, we further validate the causal effects of agroforestry on food security through coarsened exact matching, a reliable matching econometric estimator. This approach ensures a comprehensive analysis of the impact of agroforestry adoption on food security, providing valuable insights for policymakers and researchers.

2. Conceptual framework

The conceptual framework employed in this study draws upon a review of the relevant literature surrounding agroforestry and household food security (Ngango et al., 2023; Coulibaly et al., 2017; Waldron et al., 2017; Kuntashula and Mungatana, 2013; Duffy et al., 2021; Dagar et al., 2020; Ndoli et al., 2021; Kuyah et al., 2020; Kiptot et al., 2014). Figure 1 presents the conceptual framework, offering a visual representation of the comprehensive understanding of the key variables influencing the impact of agroforestry on household food security. The framework categorizes these variables into socio-demographic, economic, and institutional factors, providing a structured approach to the assessment.

[Figure 1 here]

Within this framework, numerous independent variables have been identified as pivotal factors influencing the adoption of agroforestry. These variables encompass diverse aspects, including age, gender, marital status, education, household size, land tenure, cooperative membership, farming experience, farmland size, market orientation, credit access, distance to the market, household head's main activity, and farmers' sensitization about agroforestry. These factors collectively contribute to shaping the landscape of agroforestry adoption.

Figure 1 does not only delineate the variables influencing agroforestry adoption but also highlights the hypothesized relationships between agroforestry adoption and households' food security. As mentioned before, recognizing the multifaceted nature of food security, the study utilizes the FCS – an important indicator of food security as its outcome variable. More specifically, the FCS is employed as a key measure in this study, providing a nuanced understanding of households' food security outcomes in the context of agroforestry adoption. The utilization of FCS enhances the study's ability to capture the intricate dynamics of food security, offering a robust foundation for analysis and interpretation.

3. Materials and Methods

3.1. Study location

This study was conducted in the Huye, Gisagara, and Nyaruguru districts of the southern province of Rwanda, situated within an agro-ecological zone characterized by a fragmented, hilly terrain featuring steep slopes and deep-water valleys (Csorba et al., 2019). The region experiences an annual rainfall ranging from 1300mm to 1450mm, coupled with a mean annual temperature of 20°C (Mukuralinda et al., 2010). The rainfall is distributed across two cropping seasons: Season A, spanning from September to January, and Season B, occurring from February to May (Mukuralinda et al., 2010).

Specifically, Huye, Gisagara, and Nyaruguru districts are predominantly rural areas where residents heavily rely on subsistence agriculture as a primary source of livelihood. The challenging topography and climatic conditions in this agro-ecological zone significantly influence agricultural practices and livelihood strategies adopted by the local population (Ngango et al., 2023). Understanding the contextual backdrop of these districts is essential for interpreting the study's findings within the specific socio-economic and environmental context of this region.

3.2. Survey design and data collection

The target population for this research project consists of farmers who have adopted agroforestry practices (i.e., those that had planted one or more agroforestry trees which include *Alnus acuminata, Persea americana, Calliandra calothyrsus, Erythrina abyssinica, Gliricidia sepium, Grevillea robusta, Leucaena leucocephala, Mangifera indica, Markhamia lutea,* and *Acacia polyacantha*) and those who have not yet adopted agroforestry (i.e., still practicing conventional farming) in Rwanda. However, due to the limited resources to conduct a nationwide survey, data for this research project came from a household survey conducted in the Huye, Gisagara, and Nyaruguru districts of the southern province of Rwanda. A multi-stage sampling technique was used to select respondents. In the first stage, three districts (i.e., Huye, Gisagara, and Nyaruguru) were purposively selected because they are among the regions of Rwanda with a dominance of productive agroforestry practices. The second stage involved the selection of villages in each district. This was done with the help of sector agronomists and social economic development officers (SEDOs) at the cell level, to identify potential villages with high dominance of agroforestry practices. Approximately 24 villages were selected in each district giving a total of 72 villages.

The third stage involved a random selection of household farmers (including both adopters and non-adopters of agroforestry) in each village. About 8 households were randomly selected from each village, giving a total sample size of 615 households. Prior to conducting the formal survey, the questionnaire was pre-tested to a few numbers of households in the study area, to inspect the adequacy of the survey instrument. Before the survey, enumerators and the field supervisor who speak the local language (*Kinyarwanda*) were trained to understand the questionnaire. They were also trained to conduct the data collection using a digitalized questionnaire in Kobo Tool Box with tablets. The enumerators and a field supervisor were instructed to adhere to all ethical protocols and codes of conduct related to surveys and interviews that involved humans as research subjects. The University of Rwanda, Directorate of Research and Innovation’s Research and Ethics Screening Committee reviewed and approved the Ethical Research on October 31, 2022.

3.3. Model specification

3.3.1. Endogenous Switching Regression Model

The evaluation of the impact of agroforestry adoption on outcome variables presents a complex challenge when using a traditional mathematical model with a single outcome variable and explanatory variables. As highlighted by Kim et al. (2000), estimating such a model can result in inconsistent estimators due to the voluntary nature of agroforestry adoption, leading to a self-selectivity bias. This bias arises from the likelihood that certain households, characterized by higher education levels or increased income, may be more inclined to adopt agroforestry compared to others, introducing subgroup heterogeneity. The issue becomes further complicated as unobserved characteristics are distributed unevenly between households with adoption and those without, creating a potential correlation with exogenous factors and introducing endogeneity, thereby violating the Gauss-Markov theorem and yielding biased estimators (Greene, 2012).

To address these challenges, we use the Endogenous Switching Regression Model (ESRM), a common simultaneous equations model. This approach entails estimating the adoption equation and outcome equations separately for households that adopted agroforestry and those that did not. According to utility maximization theory, households decide to adopt agroforestry based on the expected utility they anticipate. In this context, the decision to adopt is not solely determined by the household head's assessment of expected utility; rather, it is influenced by various socio-demographic and economic aspects of the household. This modeling strategy allows for a nuanced exploration of the decision-making process behind agroforestry adoption, acknowledging the multifaceted factors that contribute to this choice within rural households. Then, the decision whether or not to adopt for the household i can be formalized using the following specifications:

$$U_i^* = \phi X_i + \xi_i;\ with\ U_i = 1\ if U_i^* > 0\ and\ \ U_i = 0\ otherwise \tag{1}$$

where, U_i^* is the latent variable, which is not observable, X_i is the vector of household characteristics affecting the adoption of agroforestry, ϕ the vector parameters to be estimated, and ξ_i the error term. U is a dummy variable with $U_i = 1$ for adopters, and $U_i = 0$ otherwise.

In terms of outcome variables, the literature has shown that in practice, adopters of agroforestry have a different impact compared to those without adoption. Adoption may affect the outcome variable whose specification, for adopters (Equation 2) and non-adopters (Equation 3)

$$Y_{1i} = \psi_1 H_i + \varepsilon_{1i} \text{ if } U_i = 1 \quad (2)$$

$$Y_{0i} = \psi_0 H_i + \varepsilon_{0i} \text{ if } U_i = 0. \quad (3)$$

Here, Y_{1i} and Y_{0i} are the outcome variables for adopters and non-adopters, respectively, H_i is the vectors of household characteristics, ψ the vector of parameters to be estimated, i stands for households, and ε_{1i} and ε_{0i} the error terms.

For adopters and non-adopters, the outcome equation which is corrected for endogenous adoption is given as:

$$Y_{1i} = \psi_1 H_i + \sigma_{1\xi}\lambda_{1i} + \eta_{1i}, \text{ if } U_i = 1 \quad (4)$$

$$Y_{0i} = \psi_0 H_i + \sigma_{0\xi}\lambda_{0i} + \eta_{0i} \text{ if } U_i = 0 \quad (5)$$

where λ_{1i} and λ_{0i} are Inverse Mills Ratios (IMRs) which denote the selectivity terms and provide the correlation between adoption of agroforestry and the outcome variable.

Using the probit model of the selection equation to correct the selection bias in the second stage estimate, ψ and σ are the parameters to be estimated, while η is an independently and identical distributed error term with mean zero and constant variance. The full model is estimated using full information likelihood estimation. Following the two outcome equations, i.e., 4 and 5, the actual and counterfactual food security outcomes are

$$[Y_1|X,\ U_i = 1] = \psi_1 H_{1i} + \sigma_{1\xi}\lambda_{1i} \text{ (adopters)} \quad (6)$$

$$[Y_0|X,\ U_i = 0] = \psi_0 H_{0i} + \sigma_{0\xi}\lambda_{0i} \text{ (non-adopters)} \quad (7)$$

$$[Y_0|X,\ U_i = 1] = \psi_0 H_{1i} + \sigma_{0\xi}\lambda_{1i} \text{ (adopters had they been non-adopters)} \quad (8)$$

$$[Y_1|X,\ U_i = 0] = \psi_1 H_{0i} + \sigma_{0\xi}\lambda_{0i} \text{ (non-adopters had they been adopters)} \quad (9)$$

Equations (6) and (7) denote the actual expectations observed in the sample, while the Equations (8) and (9) indicate the counterfactual results. We compute the average effect of the treatment (adopters) on the treated (ATT) by taking the difference between Equations (6) and (8) which is defined as:

$$ATT = (\text{Error! Reference source not found.}) - (\text{Error! Reference source not found.}) = [Y_1|X,\ U_i = 1] - [Y_0|X,\ U_i = 1] = (\psi_1 - \psi_0)H_{1i} + \lambda_1(\sigma_{1\xi} - \sigma_{0\xi}) \quad (10)$$

The average treatment effect on the untreated (ATU) is computed by subtracting Equation (7) from Equation (9).

3.3.2. Coarsened Exact Matching

For robustness check of the results from the ESRM, we employ the coarsened exact matching (CEM) approach. The CEM was developed by Iacus et al. (2011) and serves as a valuable method for comparing the observed outcomes of adopters and non-adopters of agroforestry with similar characteristics. Addressing the fundamental issue highlighted by Stuart & Rubin (2008), which revolves around differences in the characteristics of individuals in the treatment and control groups influencing bias in estimators, various matching techniques have been developed to construct a valid control group.

Propensity Score Matching (PSM) is a commonly used matching technique, particularly in quasi-experimental designs involving a large list of observable characteristics (Rosenbaum & Rubin, 1983). However, concerns about PSM, including criticisms of approximating an experimental design with lower standards and increasing imbalance, inefficiency, model dependency, and bias, have led researchers to seek alternative methods (King & Nielsen, 2019).

The CEM method has gained popularity as another matching approach, chosen in this study for its distinctive advantages. Unlike PSM, CEM focuses on reducing covariate imbalances between adopters and non-adopters of agroforestry ex-ante, before the matching process, minimizing model dependence (Nilsson & Wixe, 2022). The algorithm ensures that adjusting the imbalance on one variable does not affect the balance of other covariates, minimizing errors in estimating treatment effects and achieving exact matches between treated and control groups (Nilsson, 2019).

The CEM algorithm involves coarsening each control variable for matching, sorting, and matching the coarsened data using an exact matching algorithm, and discarding unmatched units. Subsequently, the coarsened data is removed, retaining un-coarsened values of the matched data to ensure inclusion of at least one treated and one control unit. This meticulous process ensures a robust and precise matching of adopters and non-adopters, enhancing the reliability of the study's findings.

According to Abokyi et al. (2020), the success of the matching is measured by the multivariate imbalance measures $\mathcal{L}_1$; that is, the distances in covariate values between the treated and control before and after the matching are compared with a reduction indicating success. Specifically, the $\mathcal{L}_1$ statistic is a measure of the overall imbalance based on the multivariate distribution of all the pre-treatment covariates and their interactions specified as follows

$$\mathcal{L}_1(f,g) = \frac{1}{2} \sum_{\ell_1 \dots \ell_k \in H(X)} \left| f_{\ell_1 \dots \ell_k} - g_{\ell_1 \dots \ell_k} \right| \quad (11)$$

where $f_{\ell_1 \dots \ell_k}$ and $g_{\ell_1 \dots \ell_k}$ denote the relative frequency distributions for the treated and control groups, respectively. $\mathcal{L}_1$ ranges from 0 to 1, with the value of 0 implying perfect balance between the treated and the control groups and the value of 1 implying the total imbalance. $H(X)$ is the set of values generated by coarsening from the set of continuous variables X, with binary and categorical variables retaining their original values (Abokyi et al., 2020).

It is important to observe that for the pre-matching, the $H(X)$ is just the original value of X. The measure in Equation (11) can also be quantified for each variable j separately, i.e., univariate imbalance measure (I_1), for assessment of variable-specific imbalance as:

$$I_1^j = \overline{X}^j_{m_T,w} - \overline{X}^j_{m_C,w} \quad j = 1,2,\dots k \quad (12)$$

where m_T and m_C are the means of the matched treated and matched control groups, respectively, and w is the weight assigned to each unit during the CEM matching.

According to Equation (112), the I_i is the difference in the means of variable j for the group of treated (m_T) and control group (m_C) matched, weighted by the matching weights assigned to each group. As mentioned before, following literature, we use age, gender, marital status, education, household size, land tenure, cooperative membership, farming experience, farmland size, market orientation, credit access, distance to the market, household head’s main activity, and sensitization as the matching variables because these variables influence the adoption of agroforestry.

3.4. Computation of Food Consumption Score

Food Consumption Score (FCS) is a common indicator to measure food security which is recommended by the World Food Programme (WFP) (Muhammed Mustafa et al., 2023). FCS measures both the types of food groups consumed and the frequency of consumption of these food groups (Aweke et al., 2021). The FCS is a composite score that was built following the Consolidated Approach to Reporting Indicators of Food Security (CARI) guidelines produced by the WFP in 2015 (World Food Programme, 2015). The CARI is a quantitative methodology that has considered a household as its unit of analysis and is founded on a single household-level survey dataset. By combining food security variables systematically and transparently, this approach classifies households into four descriptive groups: food secure, marginally food secure, moderately food insecure, and severely food insecure. Along this study, we have considered two groups, food secure (including food secure and marginally food secure, if FCS>35), and food insecure (accounting for moderately food insecure and severely food insecure, if FCS≤35) (Maniriho et al., 2022). The approach is appropriate for assessments at the national and local levels as well as in more specific areas. FCS measures the current adequacy of households' food consumption. Data on food items, their weights, and the days that household members consumed them over the course of the previous seven days were used to compute the FCS (Maniriho et al., 2022; World Food Programme, 2016). Table 1 provides the information on food groups and their weights in food consumption score.

[Table 1 here]

In practice, the FCS is decoded into food consumption group (FCG), where the 2-point scale indicator scores (food secure=1; and food insecure =0) were considered. Following World Food Programme (2016), the FCS is computed as per Equation 3.

$$\boxed{FCS_i = \sum_{i=1}^{9} c_i D_i,} \tag{3}$$

where c_i is the weight of a food item i and D_i the number of days that household members have eaten the food item i during the past 7 days.

3.5. Descriptive Statistics

Table 2 presents the description and summary statistics of key variables, revealing that the average FCS is 33.469. Household food security status was determined by classifying sampled households into two groups: food secure (FCS > 35) and food insecure (FCS ≤ 35), based on the benchmark score of 35. Notably, approximately 41% of households are classified as food secure (Table 2). As previously indicated, adoption of agroforestry practices was equal to 1 if a respondent responded Yes to the question whether they had planted one or more of the following agroforestry trees: *Alnus acuminata, Persea americana, Calliandra calothyrsus, Erythrina abyssinica, Gliricidia sepium, Grevillea robusta, Leucaena leucocephala, Mangifera indica, Markhamia lutea, and Acacia polyacantha*) and zero otherwise. Table 2 indicates that 40.7% of farmers in the sample adopted agroforestry as their farming system while the rest did not.

[Table 2 here]

Table 2 reveals that the average age of farmers is around 47 years, indicating a predominantly middle and productive age group. Additionally, approximately 37.1% of households are male-headed, and the average level of formal education is around three years of primary education.

Table 3 presents the mean differences in observed characteristics between adopters and non-adopters for the unmatched sample. Statistical *t*-tests indicate significant differences in most variables such as age, marital status, household size, land tenure, cooperative membership, farming experience, market orientation, credit access, distance to the market, and sensitization between adopters and non-adopters of agroforestry. For example, we find that 43.6% of adopters and 39.7% of non-adopters are food secure on average, with no statistically significant mean difference. These differences emphasize the need for more in-depth analysis to understand the nuanced dynamics of agroforestry adoption and its potential impact on household food security.

[Table 3 here]

4. Results and Discussion

The results from the full information maximum likelihood estimation of the endogenous switching regression model (ESRM) are presented in Table 4. Column 1 presents variable names while column 2 presents linear model results of FCS estimated by Ordinary Least Squares (OLS). Columns 3 – 5 respectively present the ESRM results. To ensure identification of the ESRM, we imposed an exclusion restriction using a valid instrumental variable (IV). An appropriate IV should significantly influence a farmer's decision to adopt agroforestry while not significantly explaining food security. In our study, we considered agroforestry sensitization as a plausible IV. This IV is deemed relevant since being sensitized about agroforestry is expected to influence a farmer's decision to practice agroforestry without directly affecting food availability or security.

To validate our choice of the IV, we conducted a falsification test following Di Falco et al. (2011) and Kiwanuka-Lubinda et al. (2021). The falsification test involves ensuring that the selected IV influences the practice of agroforestry but not the outcome variable among non-adopters. The Wald test of the selected IV, conducted from a probit model of agroforestry on sensitization, indicated a significant influence of sensitization on agroforestry ($\boxed{\chi_1^2 = 50.09, p - value < 0.000)}$. Further, the F-test results of whether the sensitization affects FCS among agroforestry non-adopters from a linear regression of FCS on the IVs, demonstrated that sensitization does not affect FCS $\boxed{(F(1{,}363) = 2.05, p - value = 0.153).}$ This falsification test supports the robustness and validity of our instrumental variable selection and the usual exclusion restriction was imposed in the estimation of the ESRM where sensitization was excluded from the outcome models but included in the selection equation. The full ESRM was estimated using full information maximum likelihood estimation in Stata software (StataCorp, 2023).

We now delve into the nutritional implications of adopting agroforestry. To assess the impact of agroforestry on the FCS, we initially employ a straightforward approach by estimating a linear model of FCS with a dummy variable indicating agroforestry adoption (Table 4, column (2)). However, this analysis suggests no discernible difference in FCS between farm households that adopt agroforestry and those that do not (indicated by a non-statistically significant, negative coefficient for the agroforestry dummy variable). This method assumes exogenous determination of agroforestry adoption, potentially leading to biased and inconsistent estimates.

Recognizing the potential endogeneity of agroforestry adoption, OLS estimates may not adequately capture structural differences in the FCS function between adopters and non-adopters (Di Falco et al., 2011). In contrast, the estimates in the last three columns of Table 4 (3) consider endogenous switching in the food consumption score function.

Notably, the estimated coefficients of the correlation term (ρ) for adopters from the ESRM are significantly different from zero (bottom row). This rejection of the hypothesis of an absence of sample selectivity bias supports the appropriateness of employing the ESRM to account for potential endogeneity in agroforestry adoption. Furthermore, variations in the coefficients of the FCS equation between adopters and non-adopters (under ESRM) underscore the presence of heterogeneity within the sample.

The results derived from the selection equation (Equation (1)) presented in column 3 of Table 4 (under ESRM) shed light on the pivotal role of specific variables in influencing the probability of adopting agroforestry practices. Notably, factors such as land tenure, cooperative membership, credit access, household size, and farmers' sensitization about agroforestry emerge as significant determinants of agroforestry adoption. Specifically, the positive and statistically significant impact of land tenure underscores that households owning farmland are more inclined to embrace agroforestry practices compared to those leasing land for agricultural purposes. This aligns with existing literature positing that secure land tenure provides the incentive and assurance necessary for long-term agricultural and land-related investments (Lawin and Tamini, 2019; Ngango and Hong, 2021; Benjamin et al. 2021). Landowners may have a longer-term perspective on their investment and, as a result, may be more willing to invest in practices like agroforestry that might take time to yield returns. According to Cyamweshi et al. (2023), agroforestry practices have the potential of enhancing the soil fertility, soil moisture, and overall land productivity which may influence landowners to uptake agroforestry for the sustainable land productivity improvement.

Farmers' participation in cooperatives emerges as a robust influencer of agroforestry adoption. Past studies, including Ma and Abdulai (2016) and Addai et al. (2021), have consistently demonstrated that cooperative engagement promotes the uptake of agricultural technologies among its members. Likewise, access to credit proves to be a crucial factor, with a positive and statistically significant influence on the likelihood of adopting agroforestry practices. This suggests that farmers equipped with credit access are more predisposed to embracing agroforestry. The negative coefficient on household size implies that with more household members to feed, larger families need to prioritize maximizing food production from their land in the short-term. They may have less flexibility to allot land specifically for trees and shrubs as in agroforestry.

The positive and statistically significant coefficient associated with farmers' sensitization about agroforestry reinforces the idea that mobilized and informed farmers are more prone to adopting these practices on their own farms. This finding aligns with expectations, as education and advisory services enhance farmers' knowledge and awareness of the benefits associated with agroforestry (Kuntashula and Mungatana, 2013; Ngango et al., 2023). This is plausible because the Rwanda's agricultural extension strategy via public institutions and partners provides more reliable information and advisory services on agroforestry (Ngango et al., 2023).

[Table 4 here]

The results in columns 4 and 5 are estimations of Equations (4-5) where the outcome variable is FCS. The findings reveal a noteworthy trend among agroforestry non-adopters, demonstrating that older household heads may not be able to be associated with a noteworthy decrease in FCS, with other variables held constant. This pattern may be attributed to the idea that older household heads may be retired or have declining earning potential, resulting in less household income available for food purchases.

Contrary to our expectations, agroforestry non-adopters exhibit a counterintuitive association between the quantity of agricultural produce sold to the market (measured in kilograms) and a reduction in the food consumption score. While it is generally anticipated that selling more farm produce would contribute to increased income for these households and therefore the FCS, our results suggest a different scenario. It is plausible that, in the case of non-adopters, an elevated volume of sold agricultural output may ironically diminish the available quantity for domestic consumption. This unexpected outcome potentially explains the observed decrease in FCS among non-adopters, underscoring the complex dynamics influencing food security in this group. Among agroforestry adopters, we find that those that own land are positively associated with increased FCS. Land tenure security is expected to incentivize long-term investments such as planting agroforestry trees (Kuntashula and Mungatana, 2013; Ngango et al., 2023). This finding is therefore plausible because, with secure land rights, farmers are more inclined to make investments like agroforestry that provide longer-term returns, knowing they will reap the benefits. This could boost productivity and therefore FCS.

Our findings demonstrate a significant association between marital status, credit access, and cooperative membership with an elevated FCS among farmers. This implies that individuals who are married, have access to credit, and are members of cooperatives tend to experience higher levels of food security and a more diverse and nutritious diet compared to their counterparts among non-adopters of agroforestry. With regard to marital status, marriage often facilitates resource pooling and shared responsibilities within a household (Kiwanuka-Lubinda et al., 2022). This collaborative effort may contribute to a more stable and secure food environment, positively impacting the FCS. For access to credit, credit allows non-adopters to invest in agricultural activities, purchase inputs, and navigate financial challenges. This financial support likely enhances their capacity to secure an adequate and diverse range of food, leading to an increase in FCS among both adopters and non-adopters of agroforestry.

The positive influence of cooperative membership (which also exists among agroforestry adopters) could be because cooperative membership implies participation in collective efforts, sharing of knowledge, and potentially gaining access to resources that contribute to improved agricultural practices (Addai et al., 2021). This collaboration may lead to increased productivity and, consequently, higher FCS among both agroforestry adopters and non-adopters. Among agroforestry adopters, while a longer distance to market would be expected to be a disadvantage among farmers as it would reduce their chances to access a wider market of foods, we find that increased distance to the market is associated with reduced FCS among agroforestry adopters. A plausible reason could be that the farmers further from markets may need to rely more on producing their own food rather than purchasing, encouraging them to maximize productivity of their land through agroforestry practices. This has the potential to increase food availability from their own farms (Mergos, 2022).

Turning to the impacts of agroforestry on FCS, Table 5 illustrates the expected FCS estimates derived from the ESRM, comparing actual conditions (cells (a) and (b)) to counterfactual scenarios (cases (c) and (d)). For farm households that adopted agroforestry, the expected FCS is approximately 33.256 units, while for those that did not adopt agroforestry, it stands at about 33.626 units. A straightforward comparison might lead to the misconception that, on average, agroforestry adopters had a marginally lower FCS, approximately 0.37 units (equivalent to 1.1%) less than non-adopters.

In the final column of Table 5, we present the treatment effects of agroforestry adoption on food security. The Average Treatment on the Treated (ATT) is 31.683 units, signifying that agroforestry adopters would experience a reduction of approximately 31.7 units (equivalent to a substantial 19.81 percentage points) in their FCS if they had not adopted agroforestry. Conversely, the Average Treatment Effect on the Untreated (ATU) is 4.489 units, indicating that non-adopters could potentially witness an increase of about 4.5 units (or 0.13 percentage points) in their FCS if they were to adopt agroforestry. These findings underscore the significant enhancement of food security among farm households through the adoption of agroforestry. Moreover, the positive effects extend even to non-adopters but decide to adopt in the future.

[Table 5 here]

As mentioned before, we used the coarsened exact matching (CEM) approach to determine the impacts of agroforestry on FCS, as a robustness check. Table A1 in the appendix presents estimates of the imbalance measure based on raw data and CEM. The results reveal a substantial reduction in the global imbalance measure statistic (L1) for each individual explanatory variable after applying CEM, indicating the method's success in mitigating the imbalance of control variables. The CEM technique facilitates the matching of adopters and non-adopters, aiming to assess the treatment's impact by aligning the percentage of adopters, even though not all individuals in both groups may find a match. This can occur when some adopters share a Bin signature with non-adopters (Iacus et al., 2011).

Based on Table A1, variables such as land size, age, and distance to the market are highlighted to exhibit various forms of imbalance in the raw data, while market orientation is balanced in terms of the average but not in terms of the quantiles of the two distributions. Notably, achieving balance in means between adopters and non-adopters does not guarantee balance in the remaining parts of the distribution. The critical consideration lies in the global imbalance measure (L1), where a high L1 value indicates an imbalance between the adopter and non-adopter groups. A significant reduction is observed in the L1 values before and after coarsening for each individual variable, affirming the consistency and effectiveness of the CEM approach we employed. The matched observations were 58 observations comprising 31 adopters and 27 non-adopters of agroforestry (Table S2 in the Appendix).

Table 6 displays the results of the Coarsened Exact Matching (CEM), with a particular focus on the agroforestry coefficient, representing the impact of agroforestry adoption on the FCS. Notably, the coefficient is positive and significantly different from zero at 5% significance level, indicating a favorable influence of agroforestry on food security. To be more precise, farmers that adopted agroforestry exhibited a higher FCS by approximately 8.7 units compared to their counterparts who did not adopt this technology. It is worth noting that while these positive impacts align with those obtained from the ESRM, they appear slightly diminished in magnitude. This discrepancy could be attributed to potential unobserved confounders that matching estimators are not free from, highlighting the nuanced nature of assessing the impact of agroforestry on FCS. However, the positive impacts observed indicate robust effects of agroforestry on household food security among rural farmers in a developing country context.

[Table 6 here]

Our results corroborate the results of previous related research that revealed a positive correlation between agroforestry adoption and the dietary diversity of households (Coulibaly et al., 2017; Ghosh-Jerath et al., 2021). Also, they align with Duffy et al. (2021) who noted that agroforestry appears to be a potentially valuable intervention that may boost ecosystem services and, with meticulous planning and execution, have a favorable impact on rural livelihoods, food access, and health. Similarly, a number of research have revealed a strong positive relationship between agroforestry and food security (Jacobi, 2016; Kalanzi et al., 2021; Pandit et al., 2019). Different scholars attributed this positive effect to the increased cultivation of nutrient-dense crops and the incorporation of tree-based foods into diets (Coulibaly et al., 2017) as well as the adoption of trees that are talented to increase soil nutrients for food crops (Dollinger & Jose, 2018; Ekise et al., 2013; Pardon et al., 2017).

5. Conclusion and Policy Implications

This study determines the effect of agroforestry adoption on household food security. Leveraging data gathered from 615 rural farms in southern Rwanda, we employed a simultaneous equations model with endogenous switching. This model addresses the challenge of both observed and unobservable factors influencing both food security and the decision to adopt agroforestry, providing a comprehensive understanding of the interplay between these variables.

Our study's findings reveal several insights with important policy implications. First, we identify some key determinants influencing agroforestry adoption, encompassing factors such as land tenure, cooperative membership, credit access, household size, and farmers' sensitization about agroforestry. The positive correlation between secure land tenure, active participation in cooperatives, and access to credit with agroforestry adoption emphasizes the pivotal role of policies in reinforcing land security, supporting cooperative endeavors, and providing accessible credit facilities. This underscores the need for targeted interventions that encourage the adoption of sustainable soil management practices, particularly agroforestry. Therefore, prioritizing initiatives such as advisory services, sensitization campaigns, and cooperative strengthening becomes essential, considering the food security benefits.

Second, our findings underscore the substantial contribution of agroforestry to food security. Agroforestry adopters experience significant enhancements in food security, as evidenced by higher food consumption scores. This implies that the adoption of agroforestry practices translates into tangible benefits for household food security a result consistent with Coulibaly et al. (2017), Ghosh-Jerath et al. (2021) and Jacobi (2016). Third, this study reveals the potential benefits for non-adopters through agroforestry adoption. Even those currently not engaging in agroforestry practices could significantly improve their food security by considering adoption. This insight underscores the long-term potential of promoting agroforestry not only for current adopters but also for those contemplating adoption.

In summary, our research provides valuable insights for policymakers grappling with the challenge of enhancing household food security in the context of a developing country. By emphasizing the multifaceted benefits of agroforestry adoption and identifying key determinants, this study offers a nuanced foundation for designing targeted interventions that can effectively promote sustainable practices and improve household food security.

References

Abokyi, E., Strijker, D., Asiedu, K. F., & Daams, M. N. (2020). The impact of output price support on smallholder farmers' income: evidence from maize farmers in Ghana. *Heliyon*, *6*(9), e05013. https://doi.org/10.1016/j.heliyon.2020.e05013

Addai, K. N., Temoso, O., & Ng'ombe, J. N. (2021). Participation in farmer organizations and adoption of farming technologies among rice farmers in Ghana. *International Journal of Social Economics*, 49(4), 529-545.

Aweke, C. S., Hassen, J. Y., Wordofa, M. G., Moges, D. K., Endris, G. S., & Rorisa, D. T. (2021). Impact assessment of agricultural technologies on household food consumption and dietary diversity in eastern Ethiopia. *Journal of Agriculture and Food Research*, *4*, 100141. https://doi.org/10.1016/j.jafr.2021.100141

Benjamin, E. O., Ola, O., Sauer, J., & Buchenrieder, G. (2021). Interaction between agroforestry and women's land tenure security in sub-Saharan Africa: A matrilocal perspective. *Forest Policy and Economics*, *133*, 102617. https://doi.org/10.1016/j.forpol.2021.102617

Bidzakin, J. K., Fialor, S. C., Awunyo-Vitor, D., & Yahaya, I. (2019). Impact of contract farming on rice farm performance: Endogenous switching regression. *Cogent Economics & Finance*, *7*(1), 1618229. https://doi.org/10.1080/23322039.2019.1618229

Binam, J. N., Place, F., Djalal, A. A., & Kalinganire, A. (2017). Effects of local institutions on the adoption of agroforestry innovations: evidence of farmer managed natural regeneration and its implications for rural livelihoods in the Sahel. *Agricultural and Food Economics*, *5*(1), 2. https://doi.org/10.1186/s40100-017-0072-2

Brouwers, J., Sanogo, D., Fayama, T., Dabire, D., Bastide, B., Seghieri, J., Ingram, V., & Van den Berg, J. (2023). Premières expériences pour ancrer les Plateformes d'Innovation agroforestière dans leur contexte institutionnel local. *Biotechnology, Agronomy, Society and Enviroment*, *27*(Special issue). https://doi.org/10.25518/1780-4507.20340

Coulibaly, J. Y., Chiputwa, B., Nakelse, T., & Kundhlande, G. (2017). Adoption of agroforestry and the impact on household food security among farmers in Malawi. *Agricultural Systems*, *155*, 52–69. https://doi.org/10.1016/j.agsy.2017.03.017

Csorba, A., Szegi, T., Fodor, H., Bukombe, B., Uwiragiye, Y., Naramabuye, F. X., & Michéli, E. (2019). Characterization of rice agriculture in the Southern Province of Rwanda by means of microwave remote sensing. *Physics and Chemistry of the Earth, Parts A/B/C*, *112*, 58–65. https://doi.org/10.1016/j.pce.2019.02.002

Cyamweshi, R. A., Kuyah, S., Mukuralinda, A., Ngango, J., Mbaraka, S. R., Manirere, J. D., &

Muthuri, W. C. (2023). Farming with Trees for Soil Fertility, Moisture Retention and Crop Productivity Improvement: Perceptions from Farmers in Rwanda. *Small-Scale Forestry*, *22*, 649–667. https://doi.org/10.1007/s11842-023-09547-x

De Cock, N., D'Haese, M., Vink, N., van Rooyen, C. J., Staelens, L., Schönfeldt, H. C., & D'Haese, L. (2013). Food security in rural areas of Limpopo province, South Africa. *Food Security*, *5*(2), 269–282. https://doi.org/10.1007/s12571-013-0247-y

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.

Dlamini, C. S. (2020). *Socio-Economic and Policy Issues in Relation to the Adoption of Agroforestry in Africa BT - Agroforestry for Degraded Landscapes: Recent Advances and Emerging Challenges - Vol.1* (J. C. Dagar, S. R. Gupta, & D. Teketay (eds.); pp. 283–304). Springer Singapore. https://doi.org/10.1007/978-981-15-4136-0_10

Dollinger, J., & Jose, S. (2018). Agroforestry for soil health. *Agroforestry Systems*, *92*(2), 213–219. https://doi.org/10.1007/s10457-018-0223-9

Duffy, C., Toth, G. G., Hagan, R. P. O., McKeown, P. C., Rahman, S. A., Widyaningsih, Y., Sunderland, T. C. H., & Spillane, C. (2021). Agroforestry contributions to smallholder farmer food security in Indonesia. *Agroforestry Systems*, *95*(6), 1109–1124. https://doi.org/10.1007/s10457-021-00632-8

Ekise, I. E., Nahayo, A., Mirukiro, J. D. D., & Nsengiyumva, B. (2013). Analysis of the Impact of Agricultural Input Subsidies Voucher Programme on the Livelihoods of Small Scale Maize Producers in Kirehe District, Eastern Rwanda. *New York Science Journal*, *6*(9), 32–44.

Ghosh-Jerath, S., Kapoor, R., Singh, A., Nilima, Downs, S., Goldberg, G., & Fanzo, J. (2021). Agroforestry diversity, indigenous food consumption and nutritional outcomes in Sauria Paharia tribal women of Jharkhand, India. *Maternal & Child Nutrition*, *17*(1), e13052. https://doi.org/10.1111/mcn.13052

Greene, W. H. (2012). *Econometric Analysis* (7th ed.). Prentice Hall.

Honarvar, M. R., Gholami, M., Abdollahi, Z., Ghotbabadi, F. S., Lashkarboluki, F., Najafzadeh, M., Mansouri, M., Veghari, G., & Behnampour, N. (2023). Household food insecurity and associated factors in the Northeast of Iran: a cross-sectional study. *BMC Nutrition*, *9*(1), 5. https://doi.org/10.1186/s40795-022-00665-x

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361. https://doi.org/10.1198/jasa.2011.tm09599

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Jacobi, J. (2016). Agroforestry in Bolivia: opportunities and challenges in the context of food security and food sovereignty. *Environmental Conservation*, *43*(4), 307–316. https://doi.org/10.1017/S0376892916000138

Johnson, E., Thow, A. M., & Nisbett, N. (2023). Opportunities to strengthen trade policy for food and nutrition security: an analysis of two agricultural trade policy decisions. *Food Security*, *15*(4), 1109–1125. https://doi.org/10.1007/s12571-023-01377-1

Kalanzi, F., Kyazze, F. B., Isubikalu, P., Kiyingi, I., Orikiriza, L. J. B., Okia, C., & Guuroh, R. T. (2021). Influence of Socio-Technological Factors on Smallholder Farmers' Choices of Agroforestry Technologies in the Eastern Highlands of Uganda. *Small-Scale Forestry*, *20*(4), 605–626. https://doi.org/10.1007/s11842-021-09483-8

Kazungu, I., & Kumburu, N. P. (2023). Agripreneurship as a panacea for food security in Tanzania: A systematic review. *Heliyon*, *9*(2), e13305. https://doi.org/10.1016/j.heliyon.2023.e13305

Kehinde, A. D., Adeyemo, R., & Ogundeji, A. A. (2021). Does social capital improve farm productivity and food security? Evidence from cocoa-based farming households in Southwestern Nigeria. *Heliyon*, *7*(3), e06592. https://doi.org/10.1016/j.heliyon.2021.e06592

Kim, S.-Y., Nayga, R. M., & Capps, O. (2000). The Effect of Food Label Use on Nutrient Intakes: An Endogenous Switching Regression Analysis. *Journal of Agricultural and Resource Economics*, *25*(1), 215–231. http://www.jstor.org/stable/40987057

King, G., & Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, *27*(4), 435–454. https://doi.org/10.1017/pan.2019.11

Kiptot, E., Franzel, S., & Degrande, A. (2014). Gender, agroforestry and food security in Africa. *Current Opinion in Environmental Sustainability*, *6*, 104–109.

Kiwanuka-Lubinda, R. N., Ng'ombe, J. N., & Machethe, C. (2021). Impacts of interlocked contractual arrangements on dairy farmers' welfare in Zambia: a robust Bayesian instrumental variable analysis. *Agrekon*, 60(1), 10-30.

Kuntashula, E., & Mungatana, E. (2013). Estimating the causal effect of improved fallows on farmer welfare using robust identification strategies in Chongwe, Zambia. *Agroforestry systems*, 87, 1229-1246.

Lawin, K. G., & Tamini, L. D. (2019). Tenure security and farm efficiency analysis correcting for biases from observed and unobserved variables: Evidence from Benin. *Journal of agricultural economics*, 70(1), 116-134.

Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, 58, 94-102.

Magcale-Macandog, D. B., Rañola, F. M., Rañola, R. F., Ani, P. A. B., & Vidal, N. B. (2010). Enhancing the food security of upland farming households through agroforestry in Claveria, Misamis Oriental, Philippines. *Agroforestry Systems*, *79*(3), 327–342. https://doi.org/10.1007/s10457-009-9267-1

Maniriho, A., Musabanganji, E., & Lebailly, P. (2022). Food security status and coping strategies among small-scale crop farmers in Volcanic Highlands in Rwanda. *Journal of Central European Agriculture*, *23*(1), 165–178. https://doi.org/10.5513/JCEA01/23.1.3276

Marivoet, W., Becquey, E., & Van Campenhout, B. (2019). How well does the Food Consumption Score capture diet quantity, quality and adequacy across regions in the Democratic Republic of the Congo (DRC)?. *Food Security*, 11, 1029-1049.

McElreath, R. (2018). *Statistical rethinking: A Bayesian course with examples in R and Stan*.

Chapman and Hall/CRC.
Mergos, G. (2022). Population and Food System Sustainability. In International Handbook of Population Policies (pp. 131-155). Cham: Springer International Publishing.
Muhammed Mustafa, N., Fetene Asfaw, F., Adem Endris, E., & Bojago, E. (2023). Evaluating the impact of productive safety net program on rural household food security achievement: Endogenous switching regression modeling approach. *Journal of Agriculture and Food Research*, *14*, 100674. https://doi.org/10.1016/j.jafr.2023.100674
Mukuralinda, A., Tenywa, J. S., Verchot, L., Obua, J., Nabahungu, N. L., & Chianu, J. N. (2010). Phosphorus uptake and maize response to organic and inorganic fertilizer inputs in Rubona, Southern Province of Rwanda. *Agroforestry Systems*, *80*(2), 211–221. https://doi.org/10.1007/s10457-010-9324-9
Murugani, V. G., & Thamaga-Chitja, J. M. (2019). How does women's empowerment in agriculture affect household food security and dietary diversity? The case of rural irrigation schemes in Limpopo Province, South Africa. *Agrekon*, *58*(3), 308–323. https://doi.org/10.1080/03031853.2019.1610976
Mutisya, M., Kandala, N., Ngware, M. W., & Kabiru, C. W. (2015). Household food (in)security and nutritional status of urban poor children aged 6 to 23 months in Kenya. *BMC Public Health*, *15*(1), 1052. https://doi.org/10.1186/s12889-015-2403-0
Mutungi, C., Manda, J., Feleke, S., Abass, A., Bekunda, M., Hoschle-Zeledon, I., & Fischer, G. (2023). Adoption and impacts of improved post-harvest technologies on food security and welfare of maize-farming households in Tanzania: a comparative assessment. *Food Security*, *15*(4), 1007–1023. https://doi.org/10.1007/s12571-023-01365-5
Nilsson, P. (2019). The Role of Land Use Consolidation in Improving Crop Yields among Farm Households in Rwanda The Role of Land Use Consolidation in Improving Crop Yields among Farm Households in Rwanda. *The Journal of Development Studies*, *55*(8), 1726–1740. https://doi.org/10.1080/00220388.2018.1520217
Nilsson, P., & Wixe, S. (2022). Assessing long-term effects of CAP investment support on indicators of farm performance. *European Review of Agricultural Economics*, *49*(4), 760–795. https://doi.org/10.1093/erae/jbab038
Ngango, J., Musabanganji, E., Maniriho, A., Nkikabahizi, F., & Mukamuhire, A. (2023). Examining the adoption of agroforestry in Southern Rwanda: a double hurdle approach. *Forest Science and Technology*, 19(4), 260-267.
Ngango, J., & Hong, S. (2021). Impacts of land tenure security on yield and technical efficiency of maize farmers in Rwanda. *Land Use Policy*, 107, 105488.
Pandit, B. H., Nuberg, I., Shrestha, K. K., Cedamon, E., Amatya, S. M., Dhakal, B., & Neupane, R. P. (2019). Impacts of market-oriented agroforestry on farm income and food security: insights from Kavre and Lamjung districts of Nepal. *Agroforestry Systems*, *93*(4), 1593–1604. https://doi.org/10.1007/s10457-018-0273-z
Pardon, P., Reubens, B., Reheul, D., Mertens, J., De Frenne, P., Coussement, T., Janssens, P., & Verheyen, K. (2017). Trees increase soil organic carbon and nutrient availability in temperate agroforestry systems. *Agriculture, Ecosystems & Environment*, *247*, 98–111.

https://doi.org/10.1016/j.agee.2017.06.018
Radeny, M., Rao, E. J. O., Ogada, M. J., Recha, J. W., & Solomon, D. (2022). Impacts of climate-smart crop varieties and livestock breeds on the food security of smallholder farmers in Kenya. *Food Security*, *14*(6), 1511–1535. https://doi.org/10.1007/s12571-022-01307-7
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41
Sarvade, S., & Singh, R. (2014). Role of agroforestry in food security. Popular Kheti, 2(2), 25-29.
Shembe, P. S., Ngobese, N. Z., Siwela, M., & Kolanisi, U. (2023). The potential repositioning of South African underutilised plants for food and nutrition security: A scoping review. *Heliyon*, *9*(6), e17232. https://doi.org/10.1016/j.heliyon.2023.e17232
StataCorp. (2023). Stata Statistical Software: Release 18. College Station, TX: StataCorp LLC.
Stuart, E. A., & Rubin, D. B. (2008). Best practices in quasi-experimental designs. *Best Practices in Quantitative Methods*, 155–176.
Warinda, E., Nyariki, D. M., Wambua, S., Muasya, R. M., & Hanjra, M. A. (2020). Sustainable development in East Africa: impact evaluation of regional agricultural development projects in Burundi, Kenya, Rwanda, Tanzania, and Uganda. *Natural Resources Forum*, *44*(1), 3–39. https://doi.org/10.1111/1477-8947.12191
Wiesmann, D., Bassett, L., Benson, T., & Hoddinott, J. (2009). Validation of the world food programme s food consumption score and alternative indicators of household food security. Intl Food Policy Res Inst.
Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.
World Food Programme. (2015). *Consolidated Approach to Reporting Indicators of Food Security (CARI). United Nations World Food Programme, Food security analysis (VAM). Second Edition*.
World Food Programme. (2016). *Technical Guidance for the Joint Approach to Nutrition and Food Security Assessment (JANFSA). First Edition*.
Yazew, T., Daba, A., Hordofa, L., Garedew, G., Negash, A., Merga, G., & Bakala, T. (2023). Covid-19 related factors to food security and dietary diversity among urban households in western Oromia, Ethiopia. *Heliyon*, *9*(3), e14476. https://doi.org/10.1016/j.heliyon.2023.e14476

Table 1. Food groups and their weights in food consumption score

Category	Food groups and examples	Weights
1	Cereals: Rice, maize, sorghum, alike Tubers: Cassava, potato, yam, and alike	2
2	Pulses: beans, peas, cowpea, soy, peanuts, and alike	3
3	Vegetables: carrot, pumpkin, spinach, broccoli, amaranth and/or other dark green leaves, cassava leaves, onions, tomatoes, cucumber, radish, green beans, green peas, lettuces, and alike	1
4	Fruits: mango, papaya, avocado, banana, apple, lemon, orange, and alike	1
5	Meat and fish: goat, beef, chicken, liver meat, kidneys, heat and/or other organs, fish (including tuna canned, snail, and other sea food), and alike	4
6	Milk: fresh milk / sour, yogurt, cheese, other dairy products	4
7	Sugar: sugar, honey, jam, cakes, sweets, cookies, juice and other sugary drinks	.5
8	Oil: vegetable oil, palm oil, butter, shea butter, margarine, other fats and oils.	.5
9	Spices and condiments: tea, coffee, salt, pili-pili, garlic, spices, yeast, lanwin, tomato paste, and alike	0

Source: World Food Programme (2016) and Maniriho et al. (2022).

Table 2. Description of variables and summary statistics

Variable	Description	Sample mean	Std. Dev.
Outcome variable			
FCS	Food consumption score (FCS) – continuous variable	33.469	16.310
Food secure	Dummy variable for food security status, taking the value of 1 if the household is food secure (i.e., FCS>35) and 0 otherwise	0.413	0.493
Treatment variable			
Agroforestry Adoption	Farmer adopting agroforestry (1 = yes; 0 = otherwise)	0.407	0.492
Independent variables			
Age	Age of household head (years)	47.533	13.836
Gender	1 if the household head is male, 0 otherwise	0.371	0.483
Marital Status	1 if the household head is married, 0 otherwise	0.706	0.456
Education	1 if the farmer has a formal education, 0 for non-formal education	0.315	0.465
Household size	Total household size (number of persons)	4.755	2.130
Land tenure	1 if a farmer owns the land, 0 otherwise	0.572	0.495
Cooperative membership	1 if a farmer is a member of an agricultural cooperative, 0 otherwise	0.228	0.420
Farming experience	Number of years in farming	23.741	13.089
Land size	Size of the land under cultivation (m^2)	2270.511	7568.023
Market orientation	Amount of harvest (in Kg) sold to the market	49.057	128.534
Credit access	1 if the farmer has access to credit, 0 otherwise	0.260	0.439

Distance to market	Time (in minutes) taken to reach preferred selling point	37.457	37.407
Main Activity	1 if the primary job of household head is agriculture, 0 otherwise	0.941	0.235
Sensitization	1 if the farmer was sensitized about agroforestry, 0 otherwise	0.834	0.372

Table 3. Mean difference in outcome variables and other key variables between adopters and non-adopters of agroforestry

Variable	Adopters (N = 250)	Non-adopters (N = 365)	Mean difference	*t*-values
FCS	33.242	33.625	-0.383	-0.286
Food secure	0.436	0.397	0.039	0.957
Age	49.288	46.331	2.956***	2.615
Gender	0.344	0.389	-0.045	-1.135
Marital Status	0.636	0.753	-0.117***	-3.158
Education	0.332	0.304	0.027	0.730
Household size	4.576	4.876	-0.299*	-1.712
Land tenure	0.820	0.402	0.417***	11.269
Cooperative membership	0.284	0.189	0.094***	2.771
Farming experience	26.000	22.184	3.815***	3.581
Market orientation	74.540	31.742	42.797***	4.098
Credit access	0.296	0.235	0.060*	1.677
Distance to market	31.651	41.428	-9.779***	-3.202
Main Activity	0.932	0.948	-0.016	-0.826
Sensitization	0.968	0.742	-0.225***	-7.724

Notes: ***, **, * denote the statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. Parameters estimates of agroforestry adoption and food consumption score equations

(1)	(2)	(3)	(4)	(5)
Model	**Linear model**	**Endogenous switching regression**		
Variable name		Agroforestry (1/0)	Adopters	Non-adopters
Agroforestry (=1 if yes, 0 o/w)	-0.717			
	(1.461)			
Age	-3.487**	0.014	-0.469	-6.504***
	(1.710)	(0.150)	(3.029)	(2.219)
Gender	-2.657*	0.005	-2.935	-1.640
	(1.462)	(0.128)	(2.610)	(1.839)
Marital status	1.719	-0.198	-4.236	5.106**
	(1.664)	(0.143)	(2.804)	(2.233)
Education	0.887	-0.119	-3.460	2.410
	(1.441)	(0.124)	(2.540)	(1.836)
Household size	0.605*	-0.050*	0.122	0.360
	(0.348)	(0.030)	(0.566)	(0.511)
Land tenure	-0.148	1.244***	17.26***	0.330
	(1.478)	(0.127)	(3.169)	(2.230)
Cooperative membership	3.406**	0.334**	6.821**	4.515**
	(1.586)	(0.133)	(2.672)	(2.163)
Log of farm size	0.893**	-0.027	1.891**	-0.280
	(0.415)	(0.037)	(0.736)	(0.533)
Market orientation	-3.646***	-0.051	-1.512	-4.211**
	(1.337)	(0.116)	(2.301)	(1.746)
Credit access	3.010*	0.384***	7.780***	3.561*
	(1.548)	(0.133)	(2.700)	(2.043)
Distance to market	1.937	0.176	7.722***	0.540

	(1.416)	(0.126)	(2.707)	(1.715)
Main activity	-3.024	0.0134	-7.821	1.447
	(2.837)	(0.255)	(4.937)	(3.735)
Sensitization		1.167***		
		(0.185)		
Constant	28.18***	-1.750***	-2.538	31.86***
	(4.563)	(0.443)	(8.777)	(5.657)
Sigma			20.341	15.309***
			1.352	0.616
Rho			1.453***	0.221
			(0.200)	(0.165)
Observations	612	612	612	612

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Number of obs = 612; Wald chi2(12) = 55.36; Prob > chi2 = 0.0000. LR test of indep. eqns.: chi2(2) = 20.55; Prob > chi2 = 0.000.

Table 5: Average Expected Food Consumption Score and Treatment Effects

	Decision stage		
Sub-samples	To adopt agroforestry	Not to adopt agroforestry	Treatment effects
Farm households that adopted	(a) 33.256	(c) 1.573	ATT = 31.683***
Farm households that did not adopt	(d) 38.115	(b) 33.626	ATU = 4.489***

Notes: *** denotes statistical significance at the 1% level.

Table 6: Coarsened Exact Matching Regression Results of Food Consumption Score

(1)	(2)
Variable name	Parameter estimates
Agroforestry (=1 if yes, 0 o/w)	8.688**
	(3.874)
Age	-3.609
	(7.033)
Gender	-4.539
	(4.966)
Marital status	-6.123
	(5.718)
Education	-6.697
	(4.805)
Household size	5.257**
	(2.048)
Land tenure	10.90
	(6.491)
Cooperative membership	10.01*
	(5.896)
Log of farm size	2.141
	(1.613)
Market orientation	-8.028**
	(3.952)
Credit access	-9.761
	(10.51)
Distance to market	-6.099

	(7.207)
Constant	0.493
	(14.27)
R-squared	0.429
Observations	58

Notes: *,** denote statistical significance at the 10 and 5% levels.

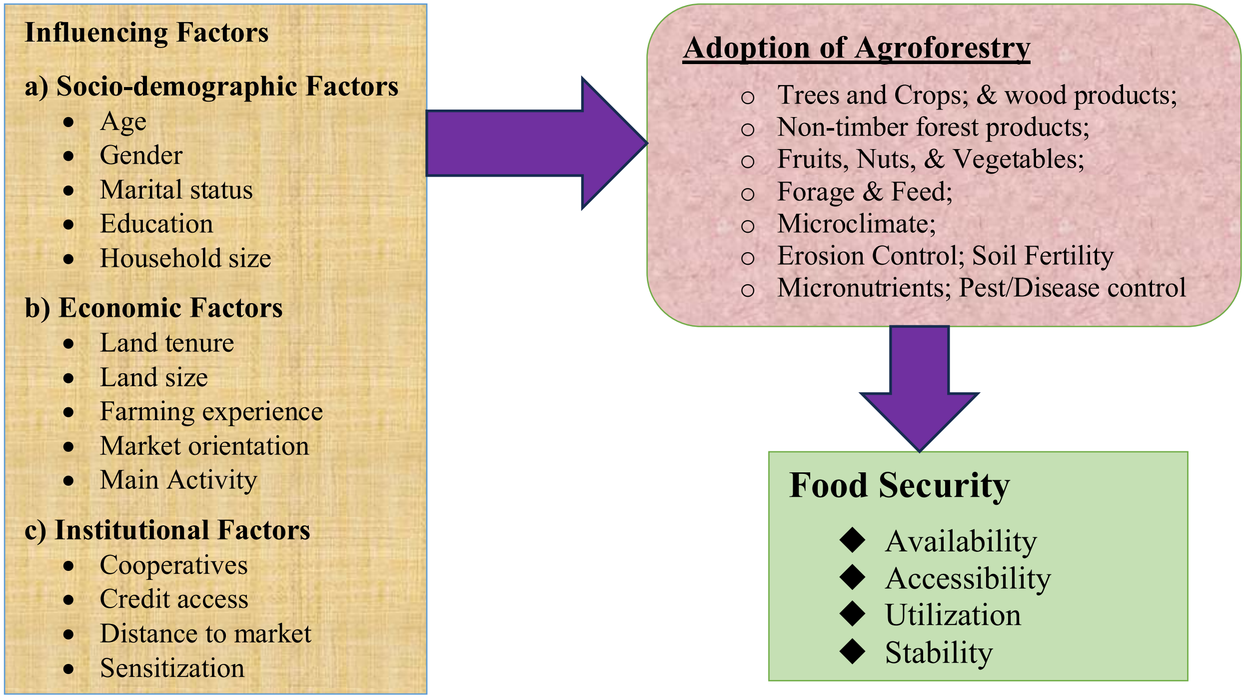

Fig. 1. Conceptual framework of agroforestry adoption and impact on households' food security developed for the study.