Climate and Development

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tcld20

Impact assessment of sustainable agricultural practices on smallholder households food security: evidence from Burkina Faso

Sita Kone & Ayşe Uzmay

To cite this article: Sita Kone & Ayşe Uzmay (28 May 2024): Impact assessment of sustainable agricultural practices on smallholder households food security: evidence from Burkina Faso, Climate and Development, DOI: 10.1080/17565529.2024.2357183

To link to this article: https://doi.org/10.1080/17565529.2024.2357183

CLIMATE AND DEVELOPMENT
https://doi.org/10.1080/17565529.2024.2357183

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

Impact assessment of sustainable agricultural practices on smallholder households food security: evidence from Burkina Faso

Sita Kone and Ayşe Uzmay

Department of Agricultural Economics, Faculty of Agriculture, Ege University, Bornova, Izmir, Turkey

ABSTRACT
This study investigates the factors affecting smallholder farmers' decisions to adopt Sustainable Agricultural Practices (SAPs) and the impacts of single and multiple SAPs adoption on household food security in the Hauts-Bassins region of Burkina Faso. Data were collected through an individual face-to-face survey with 384 farmers. The study used both the multinomial endogenous switching regression and the average treatment effect model complemented with the multivalued inverse probability weighted regression model for the analyses. Results showed that age, education, cooperative membership, farm size, and access to climate and technology information are some socio-economic determinants of farmers' decisions to adopt SAPs. Several factors can affect the adoption of SAPs and the impact of adopted SAPs on household welfare. Therefore, adopting single or joint SAPs can't lead to a positive impact on crop yield, income, and further food security, unless implemented in suitable conditions. Also, the adoption of SAPs may enable food diversification and availability but not cover all aspects of food security. Thus, future studies can deeply explore the impact of SAPs on the different dimensions of food security. Our findings advocate for policies that target reducing constraints faced by farmers in successfully implementing SAPs.

ARTICLE HISTORY
Received 9 May 2023
Accepted 14 May 2024

KEYWORDS
Climate change; adaptation; agricultural practices; food security; multinomial endogenous switching regression

JEL
I30; O30; Q16; Q18; Q54

1. Introduction

The agricultural sector occupies an important place in Sub-Saharan Africa (SSA) countries. It contributes to 35% of GDP, employs 65% of the population, and over 80% of the rural population of SSA countries derives their livelihoods from small-scale agriculture, which supports over 60% of the region's population (IRRI, 2021; OECD et FAO, 2016; World Bank, 2016). Despite its vast agricultural potential and its many efforts, the region still has a long way to go to achieve zero hunger, as it still faces major food security problems affecting millions of its citizens (Affoh et al., 2022). Rapid population growth, political instability and conflict, economic disparities, and especially climate change consequences induced by droughts and floods, temperature, and precipitation variability have collectively contributed to cops' productivity decreasing and further food insecurity in many SSA countries (FAO, 2018; Jaleta et al., 2018; Manda et al., 2016). Burkina Faso, a landlocked country in West Africa, is no exception to these challenges. Climate change is an unprecedented challenge that affects the sustainability of food and agricultural systems and threatens the livelihoods of millions of farmers across the globe (FAO, 2018) including Burkina Faso. According to FAO estimations in 2018, among the 828 million people under food insecurity worldwide, Africa accounts for 1/3 of the hunger. The prevalence of undernourishment in the continent is projected to increase from 19.1% in 2019 to 25.7% by 2030 (Camara et al., 2022).

Burkina Faso, with a predominantly agrarian economy depending on rain-fed agriculture, is particularly highly susceptible to climate change impacts, leading to reducing agricultural crop yields, food shortages, and exacerbating food insecurity (Alvar-Beltrán et al., 2020; Maré et al., 2022). The smallholder farmers of the country who are mostly operating with limited resources and traditional farming methods, are particularly susceptible to the challenges posed by a changing climate and economic uncertainties. Nevertheless, the nation's food security is intricately linked to the success and sustainability of its agricultural practices. Integrating improved agricultural technologies such as the use of biochar becomes essential for enhancing agricultural production, and further population welfare such as household income, and food security (Koné et Galiegue, 2023). In this dynamic landscape, where agriculture remains the backbone of the economy and the cornerstone of the population's livelihoods, the analysis of the intersection of implemented effective agricultural practices and household food security is crucial in taking action and developing adequate solutions.

Among the possible solutions, the adoption of sustainable agricultural practices (SAPs) offers a promising pathway towards not only enhancing agricultural productivity but also ensuring the long-term food security and well-being of households (Kassie et al., 2015). Thus, to address the impacts of climate change on agriculture, there has been increasing promotion of sustainable agricultural practices including soil and water conservation techniques, and new crop seed varieties tolerant to climate variability consequences. These strategies have been encouraged and

CONTACT Sita Kone sitakon33@yahoo.fr Department of Agricultural Economics, Faculty of Agriculture, Ege University, 35100, Bornova, Izmir, Turkey
Supplemental data for this article can be accessed online at https://doi.org/10.1080/17565529.2024.2357183.

supported by development projects and various research evidence (e.g. Geffersa et al., 2022; Koné & Galiegue, 2023; Lu et al., 2021b; Teklewold et al., 2013) and Ng'ombe et al., 2017). These practices aim to increase sustainable agriculture productivity by addressing soil degradation, and poverty, and increasing yields, as well as building the resilience of farmers to adapt to climate change and variability (Koné et Galiegue, 2023). Improved agricultural innovations are considered crucial in ensuring a profitable, successful, and sustainable agricultural sector in the context of climate change (FAO, 2018) and in achieving the Sustainable Development Goals (SDGs).

In the light of literature searches, outside of Burkina Faso, previous studies elsewhere in Africa that explore the link between sustainable coping strategies and well-being (including food security, income, poverty, and productivity) were largely found. For example, in Ethiopia, Di Falco et al. (2011) analyzed the potential impact of climate change adaptation practices on wheat production and household food security. Similarly, the study by Demeke et al. (2011), again in the case of Ethiopia investigated the effects of rainfall shocks on food security and rural household vulnerability. On the other hand, in Malawi, Pangapanga et al. (2012) examined the impacts of drought and flood adaptations on household agricultural production and food security. In their studies, Shiferaw et al. (2014) evaluated the impact of farmers' adoption of improved wheat varieties on food security, while Ahmad et al. (2016) assessed the impact of a combination of adaptation strategies on household food security in Pakistan. In their investigations, Jaleta et al. (2018) and Manda et al. (2018) explored the impact of improved maize variety adoption on household food security in Ethiopia and Zambia respectively using the endogeneity switching regression models. Lu et al. (2021a) used the same approach to analyze the effects of improved rice variety adoption on food security in northern Ghana and identified positive effects on household dietary diversity score and subjective food security.

However, it can be noted that many gaps exist in the literature research. Some of these studies focused only on food supply or agricultural production yield and did not consider many aspects of food security. In addition, the majority of these studies mainly investigated the adoption by farmers of a single SAP, such as improved maize or rice, or cowpea varieties (e.g. Geffersa et al., 2022; Kassie et al., 2018; Khonje et al., 2015; Lu et al., 2021a; Manda et al., 2018; Manda et al., 2019; Ojo et al., 2021), agroforestry, and other packages of practices (Aldulai & Huffman, 2014; Arslan et al., 2015; Zeng et al., 2017). Nevertheless, it is known that farmers seldom use only one farming practice or technology, instead, a combination of complementary technologies is implemented sequentially over time as shown in our survey results. Furthermore, farmers are confronted with several agricultural practices that can be jointly adopted as supplements, alternatives, or add-ons to maximize production and profit while dealing with such overlapping concerns as weed management, soil fertility, and harvest productivity (Teklewold et al., 2013). Thus, ignoring this interrelationship between adoption and impact assessment research can distort the results of the analyses. So, it must therefore be taken into account in the assessment of the adoption and impact of climate change sustainable agricultural technologies for adaption to climate change.

On the other hand, rigorous empirical evidence is yet limited in Burkina Faso regarding the adoption and impacts of the implementation of multiple agricultural technologies for climate change adaptation on farmers' welfare. Previous studies in Burkina Faso have focused instead on assessing the determinants of the adoption of these new agricultural technologies and the factors affecting the intensification of sustainable agricultural practices (Alvar-Beltrán et al., 2020; Ayantunde et al., 2020; Kaboré et al., 2019; Maré et al., 2022; Nana & Thiombiano, 2018; Sanfo et al., 2017; Zampaligré & Fuchs, 2019). To fill these mentioned gaps, our study examines the factors affecting smallholder farmers' adoption of single and multiple SAPs (soil and water conservation and improved seed varieties cultivation) and the impacts of adopting the combination of SAPs on household food security in Burkina Faso by using primary data collected with the farmers in the three provinces of the Hauts-Bassins region of the country.

This paper makes a more significant contribution to the emergent empirical research based on the analysis of the adoption and welfare impacts of climate adaptation agricultural technologies in the following three areas: First, not only do we analyze the potential factors determinants of the adoption of agricultural practices, but we also analyze and compare the effects of the adoption of a single agricultural technology and several agricultural technologies adoption on the smallholders household food security. Food security is represented here by the food security index and the subjective food security. The use of the food security variable as a proxy indicator for welfare is particularly important in the context of Burkina Faso, where food insecurity is increasing largely due to a critical subsistence agricultural system unable to feed the population itself. To the best of our knowledge, no studies have explored the impact of sustainable agricultural practices on food security in Burkina Faso. This paper will make an outstanding and first-ever unique contribution to the development of the literature by providing empirical evidence from Burkina Faso. Second, we applied multinomial endogenous switching regressions (MESR) to our most recently collected data to control both selection bias and endogeneity in observed and unobserved factors. We also extend the analysis to average treatment effect (ATE) and multivalued inverse probability weighted regression (MIPWR) (Linden et al., 2016; Lu et al., 2021b; and Manda et al., 2021). Third, investigating the role of multiple agricultural technologies on welfare is of critical importance to policymakers in Burkina Faso as well as in Africa where climate change is an increasing threat to food security and increased adoption of climate-smart agriculture innovated technologies are essential to improve agricultural productivity, food security, income, and farmers' living standards. Thus, in this way, the results of the research will help formulate some specific policies aimed at improving the adoption of SAPs and strengthening agricultural systems and the food security of farm households in the face of changing climate.

The structure of the rest of this research paper is as follows: after the introduction in Section 1 including the background, research gaps, and the study importance; Section 2 describes the methodology adopted, detailing the construction of the food security index, the theoretical framework, and the empirical model. Section 3 introduces the data used and presents the descriptive statistics. Followed by the empirical results and discussion in Section 4. Finally, the last Section 5 concludes the paper by highlighting the key findings and evidence-based policy considerations related to the results.

2. Methodology

2.1. Food security index construction

The food security concept has largely changed, developed, and diversified over time. In general, the term food security is used to refer to whether people can access an acceptable amount and quality of food. The most widely accepted definition is that of the 1996 World Food Summit (WFS), which has defined the term as follows: "Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life" (FAO, 1996). This definition includes four important aspects of people's food consumption: availability, access, utilization, and stability. That being said, food security is a concept that is very complex, and not directly measurable. Therefore, in this study, we try to capture food security by using several selected indicators that reflect its multiple dimensions. The choice of indicators was guided by the literature about food security, mainly based on the studies of Alene and Manyong (2006), Smith et Subandoro (2007), Qureshi (2007), Demeke et al. (2011), Abafita & Kim (2014), Ahmad et al. (2016).

Unlike Demeke et al. (2011) who captured only three dimensions, we could capture all four dimensions of food security mentioned above. Following Qureshi (2007), Ahmad et al. (2016); Abafita & Kim (2014); and Demeke et al. (2011), we identify a range of food security parameters, such as farm size, production of major food crops (millet, maize, rice, sorghum), diversification of food consumed from food crops (vegetables, meat, cereals, legumes, and fruits, eggs …), food storage time and ability, food consumption expenditure, farm assets owned (ox, sheep, goat, machine …), and facility of access (to water and toilet access facility). For further justification of these dimensions, the farmland size ownership, the production of principal food crops, food consumption expenditure, and physical assets of farm households are two important components of food security including food access and availability (Ahmad et al., 2016). Being able to store food over a long period indicates the stability of the food supply at the household level. It also illustrates the household's capability to cope with any unanticipated food emergency situation (Demeke et al., 2011; Haddad et al., 1994). The diversity of foods consumed is indicative of the diversity of food that also reflects the nutritive status of the quantity of food being consumed by households (Demeke et al., 2011). The toilet and water supply type implies the level of sanitation and health status of the household which is linked to the health status of its members (Ahmad et al., 2016; Abafita & Kim, 2014).

We developed a global food security index (FSI) using nine main indicators that encompass all dimensions of food security (including food accessibility, availability, utilization, and stability). Unlike previous studies by Demeke et al. (2011) and Abafita & Kim (2014) that used five and six indicators, respectively, our FSI is more complete. We used principal component factor analysis (PCA) to construct the index, which is a method also employed by the World Food Program and other authors such as Qureshi (2007), Ahmad et al. (2016), and Demeke et al. (2011). The PCA method transforms the selected food security variables into smaller, uncorrelated indices that capture most of the information from the original indicators (Dunteman, 1994). In mathematical terms, PCA creates linear weighted combinations of the initial variables from an initial set of n correlated variables (X1, X2, X3, … , Xn) as given in the following equation. Please refer to Table S1 in the supplementary material for a detailed description of the nine main indicators used to construct our FSI.

$$\mathrm{PC_m} = \mathrm{a_{m1}X_1} + \mathrm{a_{m2}X_2} + \mathrm{a_{m3}X_3} + \ldots \mathrm{a_{mn}X_n} \qquad (1)$$

Where *amn* represents the weight for the *mth* principal component and the *nth* variable. The components are ordered so that the first component explains the largest amount of variance in the data subject to the constraint of the sum of the squared weights ($a_{m1}^2 + a_{m2}^2 + a_{m3}^2 + \ldots + a_{mn}^2$) is equal to one. Each subsequent component explains an additional but less proportion of variation of the variables. The higher the degree of correlation among the original variables, the fewer components are required to capture common information. Once the first component is identified, we can derive the food security index for each household as follows:

$$\mathrm{FSI_j} = \sum \frac{\mathrm{F_i(X_{ji} - X_i\ )}}{\mathrm{S_i}} \qquad (2)$$

Where *FSIj* is the Food Security Index that follows a normal distribution with a mean of 0 and a standard deviation of 1. Due to missing values, this condition may not be respected after computation. *Fi* is the weight for the *i*th variable in the PCA model. Xji is the *j*th household's value for the *i*th variable, and *Xi* and *Si* are the mean and standard deviations of the *i*th variable.

2.2. Theoretical framework

In economic theory, households are assumed to maximize their utility function under certain constraints such as budget, information, access to credit, and availability of technology and other inputs. Considering adoption through optimization by rational agents, we assume that farm households adopt a particular technology if and only if adoption is indeed a choice that can be made, and at the same time adoption is expected to be profitable, or otherwise advantageous. According to Di Falco et al. (2011), Khonje et al. (2018), Ng'ombe et al. (2017), Adjin et al. (2020), Asfaw et al. (2019), Ojo et al. (2021), Kassie et al. (2015), Liang et al. (2021), Lu et al. (2021a), Manda et al. (2019), a farmer will decide to practice a given adaptation strategy or combination of agricultural practices if the utility of these strategies is greater than that of alternative strategies or non-adoption. However, the utility gained from adopting an agricultural technology is not observed. What can be observed instead is only the farmers' choice of technology. To obtain an accurate estimate of the impact of technology adoption it is crucial to randomly assign exposure to the technology so that the effect of observable and unobservable characteristics between the adopter and non-adopter groups is the same (Shiferaw et al., 2014). In that case, we can assume a random utility model that states conditional probability choice given farmers' choices for modelling purposes. Farmers may self-select to adopt these adaptation strategies based on their individual and unobservable characteristics, which can lead to selection bias problems in the regression models (Khonje et al., 2018). The issue of selection bias remains a significant challenge in impact evaluation studies based on non-randomized experimental data. To address observable selection bias concerns, in this study, the impact of farmers' adoption of two Sustainable Agricultural Practices (soil and water conservation and improved seed varieties usage) on food security is modelled on the food security index as an outcome variable by using a multinomial endogenous switching regression model (MESR). We prioritize using the MESR model because of its potential to address impact evaluation estimation challenges like endogeneity problems, sample selection bias, and inadequate counterfactuals. The model also allows the evaluation of alternative single and combinations of strategies adoption of and other covariates in the productivity functions (Kassie et al., 2018; Mansur et al., 2008).

Using MESR involves three main stages. Firstly, a multinomial logit selection (MNLS) model is conducted to determine the factors influencing farmers' adoption of specific packages of SAP technologies, accounting for unobserved heterogeneity. Secondly, using a set of exogenous variables, an ordinary least squares (OLS) model is used to assess the impact of SAP technology adoption on the outcome variables (FSI and SFS). Finally, the authors calculate the average treatment effects to capture both the actual and the counterfactual effects.

2.3. Empirical model

2.3.1. Multinomial logit selection (MNLS) model

The decisions to implement an adaptation strategy may be modelled in a framework of a random utility. Therefore, in the first stage, the condition for a farmer i to choose any technology package, j, over any alternative package, m, is that Uij > Uim m ≠ j, or equivalently ΔUim = Uij − Uim > 0 m ≠ j. The probable profit, Uij*, that the farmer obtains from the selection of the package j is a latent determined through the observed household, farm, location-specific characteristics (Xi), and unobserved factors (εij):

$$U^*_{ij} = X_i\beta_j + \varepsilon_{ij} \tag{3}$$

Where Xi represents observable exogenous factors (household, and farm characteristics), βj denotes unknown parameters, and εij is a random error. Let (I) be an indicator that denotes the farmer's choice of package, so that the following expression is derived:

$$I = \begin{cases} 1 \;\; if \;\; U^*_{i1} > \max\limits_{m\neq j}(U^*_{im}) \;\; or \;\; \eta_{i1} < 0 \\ \vdots \qquad \vdots \qquad\qquad \vdots \qquad \forall\, m \neq j \\ J \;\; if \;\; U^*_{ij} > \max\limits_{m\neq j}(U^*_{im}) \;\; or \;\; \eta_{ij} < 0 \end{cases} \tag{4}$$

Where $\eta_{i1} = \max\limits_{m\neq j}(U^*_{im} - U^*_{ik}) < 0$ (Bourguignon et al., 2007). The expression (4) indicates that the ith farmer selects a combination of technologies expecting the maximum benefit if the expected profit from that combination is greater than any other combination of technologies. This can be represented as m≠ j, that is, $\eta_{i1} = \max\limits_{m\neq j}(U^*_{im} - U^*_{ik}) > 0$ as proposed by Bourguignon et al. (2007). Assuming that ε are independently and identically Gumbel distributed, the probability of a farmer i with characteristics X selecting package j can be expressed using a multinomial logit selection model (MNLS), as explained by McFadden (1973):

$$P_{ij} = P_r\left(\eta_{ij}\langle 0|X_i\right) = \frac{\exp(X_i\beta_j)}{\sum_{m=1}^{j}\exp(X_i\beta_m)} \tag{5}$$

The parameters and variables in Equation (5) are as defined above. The parameters of the latent variable model are estimated by maximum likelihood. We estimated MNLS in the first stage of the MESR model in Equation (5) and the results are detailed in the results section.

2.3.2. Multinomial endogenous switching regressions (MESR)

In the second stage of the MESR, the relationship between the outcome variables (FSI and SFS) and a set of exogenous variables Z (HC, PC, SC, FC)[1] is estimated according to the chosen package of SAPs. In our SAP specification, the base category (as a reference category combination), non-adoption of SAPs (i.e. SWC_0 ISV_0), is denoted as j = 1. In the remaining packages (j = 2, 3, 4), at least one SAPs is used. That is, Soil and water conservation (SWC_1ISV_0), j = 2; Improve Seed Varieties (SWC_0ISV_1), *j* = 3; and both SWCs and ISV (SWC $_1ISV_1$), *j* = 4 (see Table 2). The welfare outcome equation for each possible regime j package is given as follows:

$$\begin{cases} \text{Regime 1: } Y_{i1} = Z_{i1}\alpha_1 + \mu_{i1} \quad \text{if } I = 1 \\ \vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \\ \text{Regime J: } Y_{ij} = Z_{ij}\alpha_j + \mu_{ij} \quad \text{if } I = j \end{cases} \tag{6}$$

Where Yij's are the outcome variables of the ith farmer in the regime j and error term (μ's) whose E(uij| X, Z) = 0 and Var (uij|X, Z) = σj^2. It is assumed that Yij is identified if, and only if, the combination j is adopted, that happens when:

$$U^*_{ij} > \max_{m\neq j}(U^*_{im}) \;\; or \;\; \eta_{ij} < 0$$

"If the error terms ε's and μ's are not independent, OLS estimations for Equation (6) will be biased. Consistent maximum likelihood estimates αj require the addition of the selection correction terms of the selection in Equation (6). The Dubin and McFadden (1973) model assumes the following linearity hypothesis" (Lu et al., 2021a):

$$E(\mu_{ij}|\varepsilon_{i1}\ldots\varepsilon_{ij}) = \sigma_j \sum_{m\neq j}^{J} r_j(\varepsilon_{im} - E(\varepsilon_{im}))$$

With $\sum\limits_{m=1}^{J} r_j = 0$ (it is assumed that the sum of the correlation between ε and μ equals zero). Using this assumption, the equation of the MESR in Equation (6) can be specified as:

$$\begin{cases} \text{Regime 1: } Y_{i1} = Z_{i1}\alpha_1 + \sigma_1\hat{\lambda}_1 + \omega_{i1} & \text{if } I = 1 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots & \\ \text{Regime J: } Y_{ij} = Z_{ij}\alpha_j + \sigma_j\hat{\lambda}_j + \omega_{ij} & \text{if } I = j \end{cases} \quad (7)$$

Where σj is the covariance between ε's and μ's. λj is the selection bias correction term which is estimated from computed probabilities from Equation (7) as follows:

$$\lambda = \sum_{m \neq j}^{J} \rho_j \left[\frac{\hat{P}_{im} ln \hat{P}_{im}}{1 - \hat{P}_{im}} + ln(\hat{P}_{ij}) \right]$$

Where ρ, is the correlation coefficient of ε's, and μ's and ω's are error terms with a possible value of zero (0). In the MESR choice setting, there are (J − 1) selection correction terms, one for each alternative package (Teklewold et al., 2013). The standard errors in Equation (7) were bootstrapped using 50 replicates to address the possible heteroscedasticity from the derived regressor (λj).

In order to identify the impact of adoption on food security output variables using the MNLS model, it is crucial to include at least one selection instrument in the X input variables, in addition to those generated by the nonlinearity of the adoption selection model for Equation (7) (Di Falco, 2014; Kassie et al., 2015). Although it can be difficult sometimes to find the right instruments in empirical research, instrumental variables have been suggested in the literature to generate robust estimations. Chamberlain and Griliches (1975) have stated that a system of equations does not necessarily need instrumental variables to be identified, but many authors still recommend their use. To be consistent with other studies, such as Liang et al. (2021), Ng'ombe et al. (2017), and Khonje et al. (2018), we use the following selection instruments for identification purposes: education level (education), farm size, pesticide/herbicide (pesticides) use, access to climate information (climate information), and access to agricultural technology and adaptation information (adaptation information). These instruments are excluded from Equation (8) but included in the MNLS model. We believe that these IV variables are correlated with SAPs adoption (Adoption 1/0) but are unlikely to directly influence the outcome food security (FSI and SFS) variable or should be correlated with unobserved errors in the equations (7). We establish the eligibility of these instruments by performing a simple falsification test developed by Di Falco et al. (2011) and a correlation analysis, which has been widely used in many impact assessment studies, such as those of Khonje et al. (2018), Ng'ombe et al. (2017), and Lu et al. (2021a). All independent variables are likely to affect the decision to adopt a farming practice, and the dependent variable, which is food security, so likely to be an instrument. However, the conditions of the falsification test to validate the instrument's reliability are that IV should not impact the outcome variables of non-adopters but should impact the decision of adoption.

To validate our instruments, in our regression analysis, we utilized the probit model for the first equation and the linear regression model for the other two equations, as recommended by Di Falco et al. (2011). Our findings indicate that the selected instrumental variables are statistically significant in determining the decision to adapt to climate change (Model 1, $\chi2 = 68.02$; $p = 0.0000$). However, these variables do not significantly impact the food security outcomes of non-adopters (Model 2 and 3, F-stat = 1.37, $p = 0.23$ and F-stat = 6.00, $p = 0.0000$). Please refer to Table S2 in the supplementary material for more details. We conducted the second stage of the MESR model in Equation (7) and we present our results in the results section.

2.3.3. Estimation of the counterfactual and treatment effects

The MESR framework can be used to evaluate the average treatment on the treated (ATT) by comparing the expected outcomes of adopters and non-adopters. However, estimating the counterfactual outcome, which is the outcome measuring that adopters could have achieved if they had not adopted the agricultural practice packages, is a challenge in impact evaluations that use observational data. To address this, various researchers including Di Falco et al. (2011), Teklewold et al. (2013), Ng'ombe et al. (2017), and Khonje et al. (2018) have proposed methods to calculate the ATT in the actual and counterfactual scenarios as follows:

Adopters with adoption (sample actual adoption observed)

$$\begin{cases} (a)\ E(Y_{i2} | I = 2) = Z_i\alpha_2 + \sigma_2\lambda_2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ (b)\ E\ (Y_{ij} | I = J) = Z_i\alpha_j + \sigma_j\lambda_j \end{cases} \quad (8)$$

Adopters had they not adopted (counterfactual)

$$\begin{cases} (a)\ E(Y_{i1} | I = 2) = Z_i\alpha_1 + \sigma_1\lambda_1 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ (b)\ E\ (Y_{ij} | I = J) = Z_i\alpha_j + \sigma_j\lambda_j \end{cases} \quad (9)$$

The predicted values in the counterfactual analysis are used to derive unbiased estimates of the ATT. The ATT is defined as the difference between equations (8a) and (9a) or equations (8b) and (9b). For example, the difference between equations (8a) and (9a) is given by:

$$\begin{aligned} ATT &= (8a) - (9a) = E[Yi2|I = 2] - E[Yi1|I = 2] \\ &= Zi\ (a2 - a1) + \lambda(\sigma_2 - \sigma_1) \end{aligned} \quad (10)$$

The first term on the right side of Equation (10) represents the expected change in adopters' average outcome, if adopters' characteristics performed the same as non-adopters, i.e. if adopters had the same attributes as non-adopters. The second term (λj) is the selection term capturing all potential effects of the difference in unobserved variables.

Similarly, the expected change in the food security status of a non-adopting if it had adopted an agricultural technique, i.e. the average effect on untreated (ATU) is given by (Jaleta et al., 2018):

$$\begin{aligned} ATU &= E[Yi1|I = 0] - E[Yi2|I = 0] \\ &= Zi(a1 - a2) + \lambda(\sigma_1 - \sigma_2) \end{aligned} \quad (11)$$

Literally, households that adopted the new agricultural technologies may have better food security status than non-adopting households, regardless of whether these households use the agricultural practices, because of non-observable variables that may potentially impact the household dietary status (Jaleta et al., 2018).

Furthermore, following Linden et al. (2016); Lu et al. (2021b), and Manda et al. (2021), on the sidelines, we supplement our MESR with the multivalued inverse probability weighted regression (MIPWR) model as a robustness check. The MIPWR model is known to be doubly robust and controls for selection bias associated with the identified confounders. Most importantly, the MIPWR model uses the estimated inverse of the probability of treatment weights to generate missing data-corrected regression estimations that are then used to construct a robust ATT estimation (Lu et al., 2021b).

3. Data and descriptive statistics

This study was conducted in the Hauts-Bassins region in western Burkina Faso where agriculture, the most important activity, is still extensive and highly dependent on rainfall and is dearly affected by climate change consequences (Ayanlade et al., 2017). Structured questionnaires were used to collect the data in June and July 2021 through survey interviews with 384 farmers randomly selected from 16 villages in the three provinces: Houet, Kénédougou, and Tuy provinces. The sample size was determined using the proportional sample size formula developed by Newbold (1995). The variables were selected based on a review of various theoretical and empirical published literature related to climate change adoption and impact assessment of adopted strategies (e.g. Khonje et al., 2018; Lu et al., 2021a; Manda et al., 2019; Ng'ombe et al., 2017; Setsoafia et al., 2022; Teklewold et al., 2013). In this research, the question databank included socio-demographic and economic characteristics of households and questions on climate change perception adaptation strategies, and food security. Based on past studies we have identified several explanatory variables that are supposed to influence adoption and, consequently, our outcome variables. The factors considered here include five principal categories: 1. (HC) Human capital, 2. (PC) Physical capital, 3.(SC) Social capital, 4. (FC) Financial capital and 5. (AS) adaptation strategies.

One of our outcome variables is the food security index (FSI) (explained above) and the second one is subjective food security (SFS) (farmer self-evaluation 1/0). Descriptive statistics of the set of key variables (the explanatory, explained, treatment, and instrumental variables) used in the analysis, including the purpose of these sets of variables, their characteristics, and the descriptive statistics by SAP packages (See supplementary material Table S3) are presented in more detail below (Table 1).

This study focused on the SWC practices that are widely used in Africa and Burkina Faso, such as the use of stone/rock bunds, manure pits, digues/ big embankments, and diguettes/small embankment, as well as the use of improved crop varieties (ISV). These techniques have been identified as adaptation strategies to climate change, and if well implemented, they can increase agricultural productivity while preserving the soil, and the environment, and reducing greenhouse gas emissions. These technologies are particularly relevant in the context of climate change issues in Burkina Faso, where rainfall is limited, soils are degraded, and poor in nutrients, leading to low productivity. Therefore, promoting these practices is

Table 1. Definitions and descriptive statistics of variables.

Variables	Description	Mean	SD
Dependent variables (Y = food security)			
FSI	Food security index derived	0.000	0.630
SFS	Subjective food security status (1 = food secure; 0 = food insecure)	0.518	–
Treatment variable			
Adoption	Adoption of SAP (1 = yes, 0 = no)	0.872	–
Explanatory variables (X)			
Human Capital (HC)			
Gender	Gender of household head (1 = male, 0 = female)	0.813	–
Age	Age of household head (years)	43.583	12.194
Marital status	Marital status (1 = married, 0 = no)	0.979	–
Household size	Household size	10.068	6.077
Active	Number of active family members	5.716	4.473
Formation	Participation in an agricultural training (1 = yes, 0 = no)	0.581	–
Farm experience	Number of years in farming	34.759	10.397
Number of labours	Number of employees hired on the farm	11.134	17.38
Physique Capital (PC)			
Number of lands	Land ownership/Number of plots (number)	1.742	1.039
Number of oxen	Number of oxen owned	5.438	10.801
Number of goats	Number of goats owned	4.182	6.127
Number of sheep	Number of sheep owned	4.255	8.480
Number of machines	Number of machines owned	0.302	0.465
Number of plows	Number of plows owned	1.185	0.999
Number of charettes	Number of charrettes owned	0.641	0.570
Social Capital (SC)			
Member of cooperative	Farmers' cooperative membership (1 = yes, 0 = no)	0.495	–
Communication	Communicate with other farmers (1 = yes,0 = no)	0.997	–
Assistance	Received assistance from extension agents (1 = yes; 0 = no)	0.237	–
Source TV	Access to TV as an information source (1 = yes; 0 = no)	0.289	–
Source radio	Access to radio as a source of information (1 = yes; 0 = no)	0.760	–
Source cooperative	Access to information from farmer cooperatives (1 = yes; 0 = no)	0.250	–
Financial capital (FC)			
Credit	Access to credit (1 = yes; 0 = no)	0.479	–
Off-farm	Off-farm activity (1 = yes; 0 = no)	0.008	–
Transfer	Remittance received (1 = yes; 0 = no)	0.083	–
Adaptation strategies (AS)			
SWC	Soil and water conservation use (1 = yes, 0 = no)	0.489	–
ISV	Improved seed varieties usage (1 = yes; 0 = no)	0.760	–
Organic manure	Organic manure usage (1 = yes, 0 = no)	0.935	–
Chemical fertilizer	Chemical fertilizer usage (1 = yes, 0 = no)	0.961	–
Instrumental Variable (IV)			
Education	Formal education level (1 = yes, 0 = no)	0.271	–
Farm size	Farmland size (hectare)	8.179	7.248
Pesticides	Pesticides/herbicides use (1 = yes, 0 = no)	0.987	–
Climate information	Access to climate information (1 = yes, 0 = no)	0.352	–
Adaptation information	Access to information on improved technologies (1 = yes, 0 = no)	0.430	–

Table 2. Adoption combinations of multiple agricultural technologies.

Technology(j) choice	Binary combinations	Soil and Water Conservation (SWC)		Improved Seed Variety (ISV)		Frequency (%)
		SWC_1	SWC_0	ISV_1	IMV_0	
1	SWC_0 ISV_0		√		√	12.76
2	SWC_1 ISV_0	√			√	11.20
3	SWC_0 ISV_1		√	√		38.28
4	SWC_1 ISV_1	√		√		37.76

Notes: SWC_0 ISV_0 -nonadopters; SWC_1 ISV_0 -adopted SWC only; SWC_0 ISV_1 -adopted ISV only; SWC_1 ISV_1-adopted both SWC and ISV simultaneously. 1 = adoption; 0 = non-adoption

crucial for ensuring sustainable agriculture and food security in the country and the region.

The data collected shows that SWC was used by 49% of farmers and ISV was used by 76% of farmers. We expect that these adaptation strategies positively influence farm household food security. Agricultural practices, such as SAPs, are presented as "packages" with several components (Khonje et al., 2018). These components may complement each other in combination or be independently operationalized, thus an adopter can be defined as a farmer who uses one, all, or some of the SAPs (Abdulai, 2016). This study defines SAPs adoption in line with Khonje et al. (2018), i.e. farmers who have adopted one or more adaptive practices are defined as SAPs adopters. Otherwise, they are considered as non-SAPs adopters. Considering the joint adoption of the multiple agricultural technologies (or SAPs) selected in our study (SWC and ISV), we came up with four (4) possible combinations of agricultural practices (Table 2). Overall, only 12.76% of farm households had not adopted any of these practices. As shown in the table, only 11.20% practiced the single SWC (SWC_1 ISV_0) and 38.28% adopted only ISV (SWC_0 ISV_1). However, 37.76% of farm households adopted both SWC and ISV (SWC_1 ISV_1).

4. Empirical results and discussion

4.1. Determinants of combination SAPs adoption

The estimates of the MNLS model that allow us to identify factors that influence the adoption of SAPs are presented in Table S4 (supplementary material). The basic category is the non-adoption of SAPs (SWC_0 ISV_0). The results show that the model used for the estimations is adequate, has strong explanatory power, and consequently fits the data reasonably. The Wald test of the null hypothesis to check whether all regression coefficients are jointly equal to zero is rejected [$\chi2(81) = 1305.46$; $p = 0.000$]. The model is statistically significant at 1% and the variables introduced into the model are significant overall. The R^2 indicates that 34.05% of the variation in the dependent variable is explained by the independent variables, although this variable in the multinomial logit model varies with the number of independent variables in the model. The instruments (education, farm size, pesticides, climate information, and adaptation information) used to identify the MESR are also jointly significant at 1%. However, the coefficients estimated in the multinomial logit model are not directly interpretable. Instead, they are used to provide an orientation on the nature of the relationship between the dependent variable and the explanatory variables. Thus, the economic interpretation of the parameters to better identify their influence on the probability of adopting agricultural technologies is possible from the interpretation of the marginal effects of the different variables introduced in the model. Nguyen-Van et al. (2017) state that the marginal effects have a good fit and significance concerning the impact intensities on the individual probabilistic models. The marginal effects are obtained by deriving the probabilities regarding the explanatory variables (dy/dx). However, the signs of the marginal effects are not necessarily the same as those of the coefficients estimated in the multinomial logistic model. Table 3 briefly explains some variables' effects from the determination of the marginal effects, and the interpretations are made according to ceteris paribus. The results show that the estimated coefficients differ significantly between the alternative agricultural technology packages.

The gender of the head of the household appears to be weakly significant and negative in the analysis of the marginal effects of the combined use of the two technology packages SWC_1ISV_1. With more males than females in our sample, we can conclude that a male-headed household is more likely to practice several combinations of agricultural techniques. Also, men are more involved than women in these adaptation activities (especially for the application of SWCs that require muscle forces) and have more access to land than women. For example, Ng'ombe et al. (2017) confirmed that male-headed households are more likely to adopt a combination of technologies than female-headed households because men are in a better position to attend extension meetings in traditional societies, allowing them to respond more favourably to the adoption of new agricultural technologies than women. Teklewold et al. (2013), Nana & Thiombiano (2018); and Setsoafia et al. (2022) instead found a positive relationship. Other studies (e.g. Maré et al., 2022) found a non-significant of the gender variable as a determinant of adoption. This shows that adoption is not necessarily determined by gender but by the means available, the knowledge, and a real commitment.

Logically, the variable age of the household head is assumed to increase the probability of SAPs adoption. This is because older farmers have long years of farming experience to notice changes in their environment and adopt adaptation strategies (Alemayehu & Bewket, 2017). Despite these expectations, our variable age is weakly positive for the single adoption of ISV (SWC_0ISV_1) adoption alone and negative and statistically significant for the single adoption of SWC (SWC_1ISV_0). This shows that as the age of the farmer advances, the probability of ISV implementation increases by 0.090, but they do not have the necessary force for SWC application (decreasing by 0.079). Otherwise, we can say that younger farmers are more inclined to adoption of SWC. For example, Fontes (2020) finds in his study that SWC technologies are effective in reducing soil erosion and increasing yields but are labour-intensive (need a real labour force). Issahaku & Abdulai (2020) and Ng'ombe et al. (2017) also found similar results to our study. Previous studies have also reported that the age of household heads affected the choice of climate change adaptation strategies (Alemayehu & Bewket 2017; Opiyo et al., 2016).

Table 3. Multinomial logit model marginal effects for the various combinations of agricultural technologies.

	SWC_0 ISV_0		SWC_1ISV_0		SWC_0ISV_1		SWC_1ISV_1	
Variables	dy/dx	SE	dy/dx	SE	dy/dx	SE	dy/dx	SE
Gender	0.050	0.066	0.014	0.044	0.047	0.070	−0.111*	0.046
Age	−0.019	0.031	−0.079**	0.038	0.090*	0.047	0.007	0.041
Age squared	0.219	0.393	0.956**	0.443	−1.003*	0.549	−0.172	0.461
Household size	−0.021	0.018	0.007	0.022	0.013	0.023	0.000	0.019
Household size squared	0.170	0.120	−0.115	0.141	−0.143	0.151	0.088	0.131
Active	0.008	0.019	−0.000	0.023	0.024	0.026	−0.031	0.022
Active squared	−0.059	0.103	0.043	0.134	−0.110	0.139	0.126	0.127
Farm experience	−0.027	0.035	0.064*	0.039	−0.054	0.047	0.017	0.043
Farm experience squared	0.374	0.393	−0.671*	0.407	0.470	0.503	−0.173	0.452
Formation	0.051	0.035	−0.032	0.037	−0.167***	0.049	0.148***	0.045
Member of cooperative	−0.100***	0.037	−0.019	0.032	0.096*	0.052	0.023	0.044
Off-farm	0.395***	0.094	−0.602***	0.134	1.214***	0.193	−1.007***	0.179
Farm size squared	0.154**	0.072	−0.003	0.038	0.034	0.076	−0.185***	0.049
Number of oxen	0.002**	0.001	0.000	0.002	−0.003*	0.002	0.001	0.002
Number of machines	0.038	0.036	0.014	0.039	−0.007	0.050	−0.046	0.042
Assistance	−0.066	0.045	−0.026	0.040	0.143**	0.058	−0.051	0.049
Credit	−0.040	0.034	−0.029	0.038	−0.044	0.047	0.113***	0.043
Organic manure	0.076	0.070	0.066	0.091	−0.213***	0.083	0.071	0.097
Chemical fertilizer	0.078	0.076	−0.165	0.132	−0.003	0.159	0.089	0.274
Source TV	−0.034	0.041	0.026	0.037	0.042	0.055	−0.034	0.050
Source radio	0.002	0.037	−0.002	0.043	0.010	0.053	−0.011	0.052
Source cooperative	0.006	0.051	−0.025	0.035	−0.031	0.058	0.050	0.047
Education	0.096***	0.035	−0.101**	0.047	0.023	0.053	−0.018	0.050
Farm size	−0.026**	0.012	0.003	0.006	−0.007	0.014	0.030***	0.008
Pesticides	−0.499***	0.144	−0.567***	0.180	−0.857***	0.239	1.922***	0.331
Climate information	−0.112***	0.036	−0.023	0.034	0.065	0.045	0.070*	0.039
Adaptation information	−0.153**	0.067	0.116***	0.035	−0.165**	0.068	0.202***	0.036

Note: dy/dx and SE represent marginal effect and standard errors respectively; ***, **, and * are statistically significant at 1%, 5%, and 10% levels; SWC_0 ISV_0 is the reference category of non-adoption of agricultural technologies. Sq = square

On the other hand, the study finds that, as the number of years of experience increases, farmers are more likely to adopt a combination of SWC_1ISV_0. Specifically, an additional year of experience increases the probability of SWC adoption alone by 0.064. This result is consistent with previous research indicating that agricultural experience is a critical determinant of technology adoption (Grazhdani, 2013; Ojo & Baiyegunhi 2020; Zakaria et al., 2020). Zakaria et al. (2020) report that an additional year of farmer experience in rice cultivation leads to a 2.4 percent increase in the adoption intensity of smart farming practices in Ghana. Similarly, Ojo & Baiyegunhi (2020) suggest that increasing rice farmers' experience will increase their net farm income in Southwestern Nigeria. On the other hand, Baiyegunhi et al. (2018) argue that farming is a vocation, and farmers gain knowledge and skills as they spend more years in it. With longer years in farming, farmers become more knowledgeable and better equipped to evaluate the benefits of adopting new agricultural innovations.

Membership in a farmer cooperative can increase the likelihood of adopting SWC_0ISV_1 and improve a producer's ability to adapt to climate change. Multiple studies, including those of Setsoafia et al. (2022), Liang et al. (2021), Ojo & Baiyegunhi (2020), and Manda et al. (2020) have found consistent results in support of these results. For instance, Manda et al. (2020) found that membership in farmer cooperatives can accelerate the adoption of improved maize crops from 1.6 to 4.3 years. Access to agricultural technical training by an additional individual can increase the probability of joint application SWC_1-ISV_1 by 0.148, according to various studies such as Kaboré et al. (2019), Lu et al. (2021a), Zakaria et al. (2020), and Midingoyi et al. (2019). Additionally, it can reduce the likelihood of adopting SWC_0ISV_1 by 0.167. The marginal effect determined by Zakaria et al. (2020) suggests that farmers in Ghana who received training on agronomic practices were 49.8% more likely to adopt smart farming practices compared to those who did not receive similar training. Moreover, Midingoyi et al. (2019) demonstrated that insufficient technical training reduces the likelihood of adopting innovative practices. Lastly, technical assistance provided by agricultural agents can increase the probability of ISV adoption by 0.143 according to our findings.

The variable education has a negative and statistically significant influence on the household head's decision to adopt SWC_1-ISV_0. Koç and Uzmay (2022) found that education level is one of the determinants of adoption in the Thrace/Turkey region. The study by Lu et al. (2021b) also finds that the years of schooling variable exerts a negative and statistically significant influence on the head of household's adoption decision. This contradicts the findings of Gebremariam and Tesfaye (2018), who indicated that better-educated households should be more aware of the benefits of new technologies. The practice of an off-farm activity by a farmer reduced the probability of joint adoption of SWC_1-ISV_1 and SWC_0ISV_1 by 0.602 and 1.007 respectively. While this variable increases the probability of adoption of ISV alone by 1.214. In their study on Ghana and Pakistan, Setsoafia et al. (2022) and Kousar and Abdulai (2016) found that participation in non-farm jobs increases farmers' adoption of soil conservation measures. A farmer's use of organic manure results in a decrease in ISV application by 0.213. This can be explained by the fact that organic manure is an effective stimulant that boosts plant production. Therefore, if the farmer has applied organic manure, it reduces the application of ISVs which are sometimes difficult to acquire. The use of traditional seeds combined with organic manure seems to be effective at this level.

The likelihood of joint adoption of selected SAPs (SWC_1-ISV_1) is strongly supported by access to credit, pesticide use, and access to adaptation information. However, findings from previous literature are divergent regarding the impact of credit access on the adoption of agricultural practices. While Nana & Thiombiano (2018) found no significant influence, Abid et al. (2015) and Kaboré et al. (2019) reported a positive impact. Ng'ombe et al. (2017) found both negative and positive effects of credit access on the likelihood of adopting different practices, suggesting that the impact of credit access depends on the combination of technologies and what it promises to generate.

Our findings show that the farm size has a significant and positive impact on the likelihood of adopting both SAPs, with an increase in farm size leading to a 0.030 increase in the probability of adopting both technology packages (SWC_1-ISV_1). This finding is consistent with Koç and Uzmay's (2022) study, which also identified farm size as a determinant of adaptation. However, Lu et al. (2021b) found that an increase in farm size by one hectare is associated with a decrease in the probability of adopting a combination of farming practices, suggesting that farmers may not be able to afford the cost of such technologies. This finding is also supported by Yigezu et al. (2018). Access to climate information is another important factor that positively affects the joint adoption of agricultural technology packages (SWC_1ISV_1), as climate information is expected to increase the probability of adopting adaptation strategies (Tazeze et al., 2012). An additional individual's access to climate information increases the probability of adopting agricultural technologies (SWC and ISV jointly adoption) by 0.070. This is because having access to climate information allows farmers to understand the severity of the situation and motivates them to adopt agricultural technologies (Nana & Thiombiano, 2018). Regarding the choice of adaptation options, Alemayehu & Bewket (2017) claimed that significant determinants include the agro-ecological zone, access to markets, farmer-to-farmer extension, farm size, access to climate change information, amount of rainfall, and education level of household heads.

In summary, several diverse factors in different studies influence the likelihood of adopting agricultural practices either alone or jointly. However, their effects on the decision to adopt farming practices differ and depend on farm agro-environmental and socio-economic characteristics and on how the farming practices are combined and applied (Maré et al., 2022; Ng'ombe et al., 2017).

4.2. Impacts of adopting SAPs on household food security

Estimated results from the second stage of our regressions are represented in Table S5 and Table S6 in the Supplemental materials. Because the main purpose of the MESR model estimates in this second stage is to calculate selectivity correction terms rather than fully explain the determinants of the adoption of SAPs adoption, we briefly explained the results of the tables. We present the determinants of FSI and SFS by SAP combination choice in the tables. The selectivity correction terms, denoted m1, m2, m3, and m4, capture the selectivity effects resulting from unobserved factors. The estimated variances are all bootstrapped with 50 replicates to cope with heteroscedasticity as suggested by Bourguignon et al. (2007).

The results show that the selectivity correction terms are significant in the FSI equations only for the joint adoption of the two agricultural technology packages (SWC_1ISV_1). Similarly, the results show that the selectivity correction terms are significant in the SFS equations only for the adoption of the improved seed variety agricultural technology package (SWC_0ISV_1). These results indicate the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates (Issahaku & Abdulai, 2020). Thus, accounting for selectivity effects is essential to obtaining consistent estimates in the MESR model. However, it is also worth mentioning the fact that the selection term is negative in most cases, this suggests that farmers with lower-than-average food security probability are more likely to adopt the agricultural practices when possible (Shiferaw et al., 2014).

Regarding the effects of other variables, the results of the tables further demonstrate that organic manure and chemical fertilizer use significantly influence household food security among adopters of improved seeds only (SWC_0ISV_1) and joint adopters of agricultural technologies (SWC_1ISV_1). This indicates that the application of these products (organic manure) could be a complementary input in the effective application of these practices (SAPs) and result in high yields as well as further ensuring the level of food security. Age of the household head (which can be considered as a proxy of the number of years of experience), household size, farm size, number of years of experience, number of oxen owned, membership in a farmer cooperative, having off-farm activities are also factors that positively influence the level of food security among farmers adopting improved seeds only (SWC_0ISV_1) and joint adopters of agricultural technologies (SWC_1ISV_1). In their study, Issahaku & Abdulai (2020) found in their research that off-farm labour participation has a positive and significant influence on crop income, which implies a possible income effect of off-farm labour participation on crop production and thus on food security.

Most of the significant variables are significant for the adoption of ISV only and the joint adoption of both ISV and SWC technology packages. From this, it can be concluded that the joint application of agricultural technologies increases the level of food security. Manda et al. (2016) found that a combination of SAPs increased maize yields in Zambia. The combination of multiple SAP can allow farmers to benefit from agronomic effects related to complementarities between these techniques. For example, multiple adoptions of SAPs enable more efficient use of soil nutrients and water in production. The adoption of a multiple SAP is potentially necessary to overcome the constraints of water stress, continued land degradation, and low soil fertility in Sub-Saharan African countries like Burkina Faso (CIMMYT and ACIAR, 2014). Maré et al. (2022) argue that intensification of sustainable agriculture through the adoption of multiple sustainable agricultural practices may therefore be a key solution to overcoming declining per capita production and food insecurity in Sub-Saharan Africa.

Table 4. MESR-based average treatment effects of adoption of SAPs on FSI and SFS.

Outcome variables	Combinations	Adopting (j = 2, 3, 4) (1)	Non-adopting (j = 1) (2)	UATE (1)-(2)
FSI	SWC_1 ISV_0	0 .325 (0.08)	0 .354 (0.03)	−0.028 (0.09)
	SWC_0 ISV_1	−0.047 (0.02)	0.354 (0.03)	−0.402*** (0.04)
	SWC_1 ISV_1	0.103 (0.04)	0.354 (0.03)	−0.251***(0.05)
SFS	SWC_1 ISV_0	0.456 (0.07)	0.477(0.02)	−0.021 (0.08)
	SWC_0 ISV_1	0.542 (0.01)	0.477(0.02)	0.064** (0.03)
	SWC_1 ISV_1	0.374 (0.03)	0.477(0.02)	−0.103** (0.04)
ATT				
FSI	SWC_1 ISV_0	0.680 (0.16)	0.135 (0.04)	0.544***(0.17)
	SWC_0 ISV_1	0.084 (0.03)	0.135 (0.04)	−0.050 (0.05)
	SWC_1 ISV_1	0.234 (0.10)	0.135 (0.04)	0.099 (0.10)
SFS	SWC_1 ISV_0	0.336 (0.15)	0.477 (0.04)	−0.141 (0.16)
	SWC_0 ISV_1	0.503 (0.01)	0.477 (0.04)	0.025 (0.05)
	SWC_1 ISV_1	0.299 (0.07)	0.477 (0.04)	−0.178**(0.08)

Notes: *j* represents the adoption combination of technologies defined. Standard errors are in parenthesis; ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels. UATE = Unconditional average treatment effect ATT = Average treatment effects on treated

4.3. Average treatment effects

The predicted outcomes from the second stage of the MESR regression are used to estimate the effects of strategies adoption under conditional (effects of adopters if they had not adopted) and unconditional (effects of adopters and non-adopters with no condition) mean effects. The unconditional mean effects of adoption on the outcome variables derived from the actual and counterfactual distributions are presented in Table 4.

4.3.1. UATE results

The results of UATE show that most of the combinations of agricultural practices, on average, adopters, as well as non-adopters, have positive effects on food security (table 4 columns 3 and 4 for UATE). However, contrary to our expectations, the effects on food security of our SAPs adopters were inferior to the effects of non-adopters for both FSI and SFS estimations except in the adoption of single ISV use where the impact is positive and significant (Table 4 Column 5 for UATE). This means that, for the SFS output, ISV adoption alone increases the level of food security of adopters than of non-adopters. This demonstrates the heterogeneity of unconditional mean effects by outcome variable. However, the positive results of ISV on food security outcomes are consistent with the results of Shiferaw et al. (2014). These authors argue that the adoption of improved wheat varieties in isolation leads to higher food security and per capita food consumption. Similarly, Jaleta et al. (2018) found that the adoption of improved maize varieties has a positive impact on per capita food consumption and increases the likelihood of smallholders being in food surplus. Lu et al. (2021b) also found that the adoption of improved rice varieties improves household food security levels in Ghana. These studies confirm the role of climate change-adaptable improved crops/seeds in enhancing farm household food security.

In general, the non-effectiveness of other results as expected can be interpreted according to many aspects including productivity and other factors as follows. The adoption of SAPs is facing many challenges sometimes and is not always successful with positive outcomes. The application can increase productivity and even farmers' income but can't necessarily lead to a better level of food security than those who did not adopt. The effects and success story of SAPs adoption on productivity and welfare depend on the ways they are implemented, the socio-economic conditions, precipitation and temperature variability, soil type, off-farm activity, and knowledge among other factors. For example, when interviewing farmers, some of them said that when they sowed their seeds, before germination, the flood destroyed some of them. Sowing times also change, posing many problems. For instance, they said that when farmers think the farming season is about to start and they sow the seeds, the rain doesn't fall at the right time and, because of the lack of water, the seeds can die. This results in a loss of yield, even for improved seed varieties, which sometimes fail to germinate. In addition, farmers do not make widespread use of SWC applications, as they do not have sufficient equipment, knowledge, and extension agents to help them achieve better results. When we interviewed farmers, most SWC techniques were not successful. Other possible reasons for the non-effectiveness of SAPs adoption could be the inappropriate use of seeds, such as poor combinations with chemical fertilizers, the lack of the quantity of fertilizer needed, or the use of ineffective seeds that were not sown at the optimal time. Some seed varieties require a lot of fertilizer and water in the soil, which requires the use of irrigation equipment to improve production. To discuss further farmers are facing other impacts on the crops such as bird attacks, new pests, and diseases these last times. However, other aspects are that farmers have no irrigation system, face a lack of precipitation, and struggle to obtain appropriate fertilizer to accompany with their crops' production. Our results are in accordance with some other studies that showed that the application of SAPs doesn't always have positive results. For example, the results of Setsoafia et al. (2022) support the findings of this study, as their analysis showed that the combination of improved seed varieties and fertilizer use leads to a reduction in farmers' incomes and thus in the level of food security. However, these results are only indicative of the effects of SAPs adoption and could be misleading due to selection bias from observed and unobserved factors (Khonje et al., 2018; Lu et al., 2021b).

4.3.2. ATT results

Furthermore, a clearer picture of the impacts of agricultural technology adoption is one that takes into account both observed and unobserved factors. Thus, Table 4 presents also the average treatment effects (ATT) based on the MESR of SAPs adoption on food security (FSI and SFS outcomes) under actual/observable conditions (Adoption conditions) and counterfactual conditions (Adoption condition if they had not adopted). The average outcomes of the treaties (Adopters) over the treaties (ATT), if they had not been adopted, are shown as conditional average effects. Our results show that all positive outcomes for adopters (table 4 column 3 for ATT) and positive and negative outcomes for adopters if they had not adopted (table 4 column 4 for ATT). This confirms our UATE results mentioned above with positive outcomes impact on food security for adopters. However, the effect of ATT if they have not been adopted is only positively significant for the adoption of the SWC_1 ISV_0 package, meaning that the effects of adoption are superior to non-adoption, thus it is better to adopt SWC than no adoption. Also, the effects of joint adoption of SWC_1 ISV_1 are positive for FSI. The signs of the estimates in the UATE are consistent with the signs of our estimations in the ATT hence the robustness of our results. Like the UATE results, we can observe that the adoption of all agricultural technology packages does not positively and significantly impact food security. Our ATT estimation results show differentiated results for the impacts of single and joint adoption of SAP technologies on food security.

The results of joint adoption (SWC_1ISV_1) are positively related to the FSI scores (i.e. increase the level of food security according to our FSI outcome variable). However, several other previous studies following our results (e.g. Kassie et al., 2018; Khonje et al., 2018; Lu et al., 2021b; Manda et al., 2016; Ng'ombe et al., 2017; Oduniyi & Chagwiza, 2021; Teklewold et al., 2013) highlighting that adoption of multiple SAP has greater impacts on farmer welfare measures than adoption of only one or two SAP. The results indicate that the joint adoption of multiple agricultural technologies had greater impacts on farmers' welfare. For example, Khonje et al. (2018) find that joint adoption increases crop yields and household income and decreases poverty more than individual component adoption. Teklewold et al. (2013) showed that multiple SAP adoption significantly increases household income in Ethiopia. Oduniyi and Chagwiza (2021) found that the adoption of sustainable land management practices increases food security among smallholder farmers in South Africa. Results from Ahmad et al. (2016) suggest that households that adapted to climate change in Pakistan were statistically significantly more food secure than those that did not. The combination of sustainable agricultural practices increased household yields and incomes in Zambia (Manda et al., 2016). These studies conclude that non-adopting farmers would have benefited if they applied an adaptation strategy. Therefore, efforts to achieve a high level of sustainable agriculture in response to climate change must focus on proposing adaptation of multiple agricultural technologies and practices.

The SFS results show that the joint adoption of technology packages is negatively significant with SFS scores. A possible reason for the divergence of these results could be the inappropriate use and combination of these agricultural technologies by smallholder farmers, linked to constraints such as poor rainfall and flooding, lack of knowledge, means, and labour. As a result, they do not achieve the potential production and income necessary to ensure the desired level of food security. Another possible explanation may be because of that feeling of self-food-secured situation that leads those farmers to not make any effort to adopt new improved agricultural technologies. The adoption of SWC and ISV may require more labour and this may not be an incentive for households that feel themselves food secure regarding the technology already used on their farm. For example, Koné et Galiegue (2023) suggested that a combination of improved seed varieties, and SWC with the application of biochar (climate-friendly soil amendment) is a perfect match to get effective yield results. Similar results to our results were found by Setsoafia et al. (2022) in the case of Ghana. According to their results, the adoption of three sustainable agricultural technologies is more beneficial and positively impacts the level of food security than the adoption of one or two techniques. It can be concluded that the effectiveness of agricultural technologies depends on the type of combination of agricultural technologies adopted. Joint adoption does not have a significant impact on crop income in the transition zone in Ghana (Issahaku & Abdulai, 2020). The finding of Ma and Wang (2020) also demonstrates that the adoption of SAPs significantly decreases farm income in China.

To sum up, the results in Table 4 show that single and joint adoption have a positive effect and positively impact the food security of farm households of adopters. These results confirm the effectiveness of adoption, even though it can't sometimes reach the level of desirable impact which is higher than the impact of non-adoption. Otherwise, the adoption of SAPs can have positive effects, but the effectiveness on food security is not evident to be more than those who did not adopt. Also, many factors and challenges can affect the real effect of SAPs adoption on adopters' welfare such as productivity and food security. However, the results are consistent with previous studies on the effects of SAPs adoption such as those by Nana & Thiombiano (2018), Kaboré et al. (2019), Maré et al. (2022), Ayantunde et al. (2020), and Alvar-Beltrán et al. (2020). Additionally, studies by Fontes (2020) and Issahaku & Abdulai (2020) have shown that SWC technologies can increase the resilience of the agricultural sector to climate change and reduce the probability of crop failure or income loss, while the single adoption of ISV has the opposite effect on food security.

The average treatment effects on non-adopters (ATU) were also estimated (see Table S7 in supplementary material). The results indicate significant and positive results for the adoption of SWC_1 ISV_0 and SWC_1 ISV_1 packages. That concludes that non-adopters would have reached a good level of food security if they had adopted SWC and ISV (for our outcome variable FSI). Again, it can be said that farmers who adopt SAP improve their welfare.

Overall, the results highlight the importance of individual and joint adoption of improved seeds and water and soil conservation practices among farmers to manage ex-ante production risk and food insecurity risk, especially under conditions of climate uncertainty. However, the heterogeneity effect is negative in most cases (Table S8 in supplementary material), i.e. the effect is significantly smaller for farm households that did adapt compared to those that did not. The results do not support the idea that farmers who adopt climate-smart practices to avoid crop failure end up being food insecure. Nevertheless, farm households that have adapted are still better off adapting than not adapting. And when adopted correctly, SAPs implementation would have a positive impact on household welfare. The results further demonstrate the importance of the adoption and application of climate-smart practices individually and some complementarity between crop choice and soil and water conservation practices. This finding would not have been possible if we had examined these climate-smart practices individually without considering the joint adoption effect that was not considered in some studies.

4.4. Robustness checks

Following Lu et al. (2021b), as a robustness check for causal effects of the MESR model, we applied the multivalued inverse probability weighted regression (MIPWR) model. It can be affirmed that the adoption of all combinations of agricultural technologies considered in this study significantly improves the level of food security for our SFS outcome variables. The overall main message from the results (see Table S9 in supplementary material) is that, on average, agricultural technologies adopted in combination result in increased food security. Also, it is important to note that the MIPWR-based ATT shown are quantitatively superior to those of the MESR. As in Gormley and Matsa (2014), Lu et al. (2021b), and Manda et al. (2021) this is because the matching-based estimators simply account for observed heterogeneity, thus exposing the results to unobserved heterogeneity. However, Zhou and Xie (2014) also showed that propensity score-related methods and causal inference methods for marginal treatment effects could produce different estimations because of the way their estimations are derived. This is also a potential explanation for our results. However, according to Lu et al. (2021b), the two results are generally consistent, giving robust confidence in our MESR model specifications.

5. Conclusion and implications

Sustainable agricultural practices (SAPs) have been promoted by stakeholders, government, and different institutions to tackle climate change consequences on agriculture and reduce agricultural contribution du climate change as well. This study uses farm-level survey data collected from 384 farmers in the Haut-Bassins region in Burkina Faso to examine the determinants of smallholder farmers' decisions to adopt a combination of SAPs (improved seeds and soil and water conservation) and the impacts of SAPs adoption on food security in the region. Food security is captured by the subjective food security and food security index. For the analysis, this study used both the multinomial endogenous switching regression and the average treatment effect model (to account for selectivity bias due to observable and unobservable factors) complemented with the multivalued inverse probability weighted regression model for robustness check.

The results showed that farmers' decisions to adopt a different combination of SAPs are influenced by several socioeconomic and demographic factors of the households. Gender, age, farm experience, level of education, agricultural cooperative membership, use of pesticides/herbicides, farm size, asset and livestock owned, access to agriculture technical training and assistance from agriculture extension agents, access to credit, off-farm activity practice, access to climate information, and access to information on agricultural technologies are the significant determinants of farmers' decisions to adopt different category of SAPs. Several factors affect the effect of the adoption of SAPs depending on the combinations in which they are adopted and other related factors socioeconomic and climatic factors. The study also recorded differentiated findings regarding the impacts of adopting only one or multiple SAPs on smallholder household food security. Globally, adopting single or joint SAPs has positive impacts on food security if implemented correctly than the non-adoption. However, generally, the success of adoption and SAPs impact on welfare are limited by different constraints such as education, knowledge, materials, and labour force to rightly apply the techniques, access to extension services, organic and inorganic fertilizer, rainfall shocks, and flood and farming seasons variability. Leading to non-high level impact that can be considered as more than for non-adopters.

Based on these results, some relevant policy implications are raised. The results suggest that reducing constraints and promoting SAPs for wider adoption could generate significant benefits for smallholder households in terms of increasing crop productivity, as well as reducing food insecurity. Overall, the results suggest that efforts to increase household welfare should focus on promoting the adoption of SAPs through investments in farmer education, knowledge, and capacity building in sustainable agricultural practices, provision of quality extension services, and input supply. Investing in modern, sustainable agricultural technologies is not only an investment in the objective of addressing climate change, but also the objective of achieving food security, increasing household incomes, alleviating rural poverty, increasing shared prosperity and economic growth, and achieving sustainable development goals. Otherwise, an investment process should be completed by monitoring and evaluation exercises in order to know what is effective or not and to take better action for future consideration.

This study is based on cross-sectional data and for a single region of Burkina Faso. In addition, the crops grown by farmers are not differentiated. Therefore, our estimations may not have fully captured the adoption dynamics and long-term effects of SAPs on specific crop yields and food security. Future research should therefore investigate the adoption dynamics and welfare impacts of SAPs based on nationally representative panel datasets, especially of the consumption of important crops in Burkina Faso. Also, we recommended future studies to explore the impact of SAPs on the different dimensions of food security.

Note

1. 1.(HC) Human capital (age, gender, education level, active labour force, etc.), 2.(PC) Physical capital (such as size of land, ownership of livestock, machines), 3.(SC) Social capital (such as membership in a cooperative …), 4.(FC) Financial capital (access to credit, farm, and non-farm income, etc.)

Acknowledgements

The authors are grateful to the regional directorate of the Ministry of Agriculture of the Hauts-Bassins region for facilitating the data collection. We are also very grateful to the anonymous reviewers and editors for their time and relevant comments that helped us to improve the paper and meet the publication standards.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data is available from the corresponding author upon the reasonable request not made public because of privacy considerations.

Notes on contributors

Dr. Sita Kone is a Research Economist with a Doctorate degree in Agricultural Economics/ Agricultural Policy and Extension from EGE University/Turkey. Her main research areas are climate change and sustainable adaptation strategies in agriculture, climate-smart agricultural technologies, adoption of new technologies in agriculture, sustainable agri-food systems, food security, impact evaluation, rural development, gender, and population welfare.

Prof. Dr. Ayşe Uzmay is a Professor at the Department of Agricultural Economics/Faculty of Agriculture at EGE University/Turkey under whose supervision I completed my doctorate degree.

References

Abafita, J., & Kim, K. R. (2014). Determinants of household food security in rural Ethiopia: An empirical analysis. *Journal of Rural Development/ Nongchon-Gyeongje*, *37*(2), 129–157.

Abdulai, A., & Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, *90*(1), 26–43. https://doi.org/10.3368/le.90.1.26

Abdulai, A. N. (2016). Impact of conservation agriculture technology on household welfare in Zambia. *Agricultural Economics. (United Kingdom)*, *47*(6), 729–741. https://doi.org/10.1111/agec.12269

Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. J. E. S. D. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab province, Pakistan. *Earth System Dynamics*, *6*(1), 225–243. https://doi.org/10.5194/esd-6-225-2015

Adjin, K. C., Goundan, A., Henning, C. H. C. A., & Sarr, S. (2020). Estimating the impact of agricultural cooperatives in Senegal: Propensity score matching and endogenous switching regression analysis, Working Papers of Agricultural Policy, No. WP2020-10, Kiel University, Department of Agricultural Economics, Chair of Agricultural Policy, Kiel, https://nbn-resolving.de/urn:nbn:de:gbv:8:3-2021-00299-3

Affoh, R., Zheng, H., Dangui, K., & Dissani, B. M. (2022). The impact of climate variability and change on food security in Sub-Saharan Africa: Perspective from panel data analysis. *Sustainability*, *14*(2), 759. https://doi.org/10.3390/su14020759

Ahmad, M., Mustafa, G., & Iqbal, M. (2016). Impact of farm households' adaptations to climate change on food security: Evidence from different agro-ecologies of Pakistan, Online at https://mpra.ub.uni-muenchen.de/72865/ MPRA Paper No. 72865, posted 08 Aug 2016 13:54 UTC.

Alemayehu, A., & Bewket, W. (2017). Determinants of smallholder farmers' choice of coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Environmental Development*, *24*, 77–85. https://doi.org/10.1016/j.envdev.2017.06.006

Alene, A., & Manyong, V. M. (2006). Endogenous technology adoption and household food security: The case of improved cowpea varieties in northern Nigeria. *Quarterly Journal of International Agriculture*, *45*(3), 211–230.

Alvar-Beltrán, J., Dao, A., Marta, A. D., Heureux, A., Sanou, J., & Orlandini, S. (2020). Farmers' Perceptions of Climate Change and Agricultural Adaptation in Burkina Faso, Atmosphere 2020, 11, 0827; www.mdpi.com/journal/atmosphere doi:10.3390/atmos11080827

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., & Kokwe, M. (2015). Climate-smart agriculture? Assessing the adaptation implications in Zambia. *Journal of Agricultural Economics*, *66*(3), 753–780. https://doi.org/10.1111/1477-9552.12107

Asfaw, S., Scognamillo, A., Caprera, G. D., Sitko, N., & Ignaciuk, A. (2019). Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, *117*, 278–295. https://doi.org/10.1016/j.worlddev.2019.01.017

Ayanlade, A., Radeny, M., & Morton, J. F. (2017). Comparing smallholder farmers' perception of climate change with meteorological data: A case study from southwestern Nigeria. *Weather and Climate Extremes*, *15*, 24–33. https://doi.org/10.1016/j.wace.2016.12.001

Ayantunde, A. A., Oluwatosin, B. O., Yameogo, V., & van Wijk, M. (2020). Perceived benefits, constraints, and determinants of sustainable intensification of mixed crop and livestock systems in the Sahelian zone of Burkina Faso. *International Journal of Agricultural Sustainability*, *18*(1), 84–98. https://doi.org/10.1080/14735903.2019.1698494

Baiyegunhi, L. J. S., Hassan, M. B., Danso-Abeeam, G., & Ortmann, G. F. (2018). *Diffusion and adoption of integrated striga management (ISM) technologies among smallholder maize farmers in Rural Northern Nigeria*. Technology in Society.

Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys*, *21*(1), 174–205. https://doi.org/10.1111/j.1467-6419.2007.00503.x

Camara, O., Bindraban, P., et Adzawla, W. (2022). Agricultural Transformation, Developments, and Strategies in Africa. https://ifdc.org/2022/08/04/agricultural-transformation-developments-and-strategies-in-africa/

Chamberlain, G., & Griliches, Z. (1975). Unobservables with a variance-components structure: Ability, schooling, and the economic success of brothers. *International Economic Review*, *16*(2), 422–449. https://doi.org/10.2307/2525824

CIMMYT and ACIAR. (2014). Sustainable agricultural intensification through multi-technology adoption: A regional overview from East and Southern Africa. CIMMYT; Policy Brief No. 4.

Demeke, A. B., Keil, A., & Zeller, M. (2011). Using panel data to estimate the effect of rainfall shocks on smallholder's food security and vulnerability in rural Ethiopia. *Climatic Change*, *108*(1–2), 185–206. https://doi.org/10.1007/s10584-010-9994-3

Di Falco, S. (2014). Adaptation to climate change in Sub-Saharan agriculture: Assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics*, *41*(3), 405–430. https://doi.org/10.1093/erae/jbu014

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), 825–842. https://doi.org/10.1093/ajae/aar006

Dunteman, G. H. (1994). Principal component analysis. In M. S. Lewis-Beck (Ed.), *Factor analysis and related techniques. International handbooks of quantitative applications in the social sciences, vol. 5* (pp. 157–245). Sage Publications.

Fontes, F. P. (2020). Soil and water conservation technology adoption and labour allocation: Evidence from Ethiopia. *World Development*, *127*, 104754. Security: Risks and Responses, 98p. https://doi.org/10.1016/j.worlddev.2019.104754

Food and Agriculture Organization. (2018). FAO's work on agricultural innovation: Sowing the seeds of transformation to achieve the SDGs. http://www.fao.org/3/CA2460EN/ca2460en.pdf

Food and Agriculture Organizations (FAO). (1996). Rome Declaration on World Food Security. World Food Summit. 13-17 Nov. 1996, Rome/ Italy.

Gebremariam, G., & Tesfaye, W. (2018). The heterogeneous effect of shocks on agricultural innovations adoption: Microeconometric evidence from rural Ethiopia. *Food Policy*, *74*, 154–161. https://doi.org/10.1016/j.foodpol.2017.12.010

Geffersa, A. G., Agbola, F. W., & Mahmood, A. (2022). Improved maize adoption and impacts on farm household welfare: Evidence from rural Ethiopia. *Australian Journal of Agricultural and Resource Economics*, *66*(4), 860–886. https://doi.org/10.1111/1467-8489.12489

Gormley, T. A., & Matsa, D. A. (2014). Common errors: How to (and not to) control for unobserved heterogeneity. *The Review of Financial Studies*, *27*(2), 617–661. https://doi.org/10.1093/rfs/hht047

Grazhdani, D. (2013). An analysis of factors affecting the adoption of resource-conserving agricultural technologies in Al-Prespa park. *Natura Montenegrina, Podgorica*, *2*(12), 431–444.

Haddad, L., Kennedy, E., & Sullivan, J. (1994). Choice of indicators for food security and nutrition monitoring. *Food Policy*, *19*(3), 329–343. https://doi.org/10.1016/0306-9192(94)90079-5

IRRI. (2021). The potential for rice sector development in Sub-Saharan Africa and opportunities for women and youth. OpEd for International Women's Day 2021 https://www.irri.org/news-and-events/news/potential-rice-sector-development-sub-saharan-africa-and-opportunities-women

Issahaku, G., & Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of Agricultural and Resource Economics*, *64*(2), 396–420. https://doi.org/10.1111/1467-8489.12357

Jaleta, M., Kassie, M., Marenya, P., Yirga, C., & Erenstein, O. (2018). Impact of improved maize adoption on household food security of maize producing smallholder farmers in Ethiopia. *Food Security*, *10*(1), 81–93. https://doi.org/10.1007/s12571-017-0759-y

Kaboré, P. N., Barbier, B., Ouoba, P., Kiema, A., Some, L., & Ouedraogo, A. (2019). Perceptions du changement climatique, impacts environnementaux et stratégies endogènes d'adaptation par les producteurs du Centre-nord du du Burkina Faso. *VertigO*, *19*(1), 19.

Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of Agricultural Economics*, *69*(1), 76–95. https://doi.org/10.1111/1477-9552.12221

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2015). Production risk and food security under alternative technology choices in Malawi: Application of multinomial endogenous switching regression. *Journal of Agricultural Economics*, *66*(3), 640–659. https://doi.org/10.1111/1477-9552.12099

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development*, *66*, 695–706. https://doi.org/10.1016/j.worlddev.2014.09.008

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., & Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: Evidence from eastern Zambia. *Agricultural Economics (United Kingdom)*, *49*(5), 599–609. https://doi.org/10.1111/agec.12445

Koç, G., & Uzmay, A. (2022). Determinants of dairy farmers' likelihood of climate change adaptation in the Thrace Region of Turkey. *Environment, Development and Sustainability*, *24*(8), 9907–9928.

Koné, S., & Galiegue, X. (2023). Potential development of biochar in Africa as an adaptation strategy to climate change impact on agriculture. *Environmental Management*, *72*(6), 1189–1203.

Kousar, R., & Abdulai, A. (2016). Off-farm work, land tenancy contracts, and investment in soil conservation measures in rural Pakistan. *Australian Journal of Agricultural and Resource Economics*, *60*(2), 307–325. https://doi.org/10.1111/1467-8489.12125

Liang, Z., Zhang, L., Li, W., Zhang, J., & Frewer, L. J. (2021). Adoption of combinations of adaptive and mitigatory climate-smart agricultural practices and its impacts on rice yield and income: Empirical evidence from Hubei, China. *Climate Risk Management*, *32*, 100314. https://doi.org/10.1016/j.crm.2021.100314

Linden, A., Uysal, S. D., Ryan, A., & Adams, J. L. (2016). Estimating causal effects for multivalued treatments: A comparison of approaches. *Statistics in Medicine*, *35*(4), 534–552. https://doi.org/10.1002/sim.6768

Lu, W., Addai, K. N., & Ng'ombe, J. N. (2021a). Impact of improved rice varieties on household food security in Northern Ghana: A doubly robust analysis. *Journal of International Development*, *33*(2), 342–359. https://doi.org/10.1002/jid.3525

Lu, W., Addai, K. N., & Ng'ombe, J. N. (2021b). Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana. *Agrekon*, *60*(4), 370–387. https://doi.org/10.1080/03031853.2021.1992290

Ma, W., & Wang, X. (2020). Internet use, sustainable agricultural practices and rural incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics*, *64*(4), 1087–1112. https://doi.org/10.1111/1467-8489.12390

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics*, *67*(1), 130–153. https://doi.org/10.1111/1477-9552.12127

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Kamara, A. Y., Olufajo, O., Boukar, O., & Manyong, V. M. (2020). Adoption and ex-post impacts of improved cowpea varieties on productivity and net returns in Nigeria. *Journal of Agricultural Economics*, *71*(1), 165–183. https://doi.org/10.1111/1477-9552.12331

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Wossen, T., Chikoye, D., & Manyong, V. (2019). The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development*, *122*, 261–271. https://doi.org/10.1016/j.worlddev.2019.05.027

Manda, J., Azzarri, C., Feleke, S., Kotu, B., Claessens, L., & Bekunda, M. (2021). Welfare impacts of smallholder farmers' participation in multiple output markets: Empirical evidence from Tanzania. *PloS One*, *16*(5), e0250848. https://doi.org/10.1371/journal.pone.0250848

Manda, J., Gardebroek, C., Kuntashula, E., & Alene, A. D. (2018). Impact of improved maize varieties on food security in Eastern Zambia: A doubly robust analysis. *Review of Development Economics*, *22*(4), 1709–1728. https://doi.org/10.1111/rode.12516

Mansur, E. T., Mendelsohn, R., & Morrison, W. (2008). Climate change adaptation: A study of fuel choice and consumption in the US energy sector. *Journal of Environmental Economics and Management*, *55*(2), 175–193. https://doi.org/10.1016/j.jeem.2007.10.001

Maré, T. F., Zahonogo, P., & Savadogo, K. (2022). Factors affecting sustainable agricultural intensification in Burkina Faso. *International Journal of Agricultural Sustainability*, *20*(6), 1225–1236. https://doi.org/10.1080/14735903.2022.2070341

McFadden, D. (1973). Conditional logit analysis of qualitative choice be. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). Academic Press.

Midingoyi, S. K., Kassie, M., Muriithi, B., Diiro, G., & Ekesi, S. (2019). Do farmers and the environment benefit from adopting integrated pest management practices? Evidence from Kenya. *Journal of Agricultural Economics*, *70*(2), 452–470. https://doi.org/10.1111/1477-9552.12306

Nana, T. J., & Thiombiano, T. (2018). Adoption of adaptation strategies for climate change: Case of Burkina Faso farmers. *Journal of Agriculture and Environmental Sciences June 2018*, *7*(1), 53–65. ISSN: 2334-2404 (Print), 2334-2412 (Online) Copyright © The Author(s). All Rights Reserved. Published by American Research Institute for Policy Development DOI: 10.15640/jaes.v7n1a6 URL: https://doi.org/10.15640/jaes.v7n1a6.

Newbold, P. (1995). *Statistics for business and economics*. Prentice-Hall International.

Ng'ombe, J. N., Kalinda, T. H., & Tembo, G. (2017). Does the adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. *Agrekon*, *56*(2), 205–221. https://doi.org/10.1080/03031853.2017.1312467

Nguyen-Van, P., Poiraud, C., & To-The, N. (2017). Modeling farmers' decisions on tea varieties in Vietnam: A multinomial logit analysis. *Agricultural Economics (United Kingdom)*, *48*(3), 291–299. https://doi.org/10.1111/agec.12334

Oduniyi, O. S., & Chagwiza, C. (2021). Impact of adoption of sustainable land management practices on food security of smallholder farmers in mpumalanga province of South Africa. *GeoJournal*, https://doi.org/10.1007/s10708-021-10497-0

OECD and FAO. (2016). *OECD-FAO Agricultural outlook 2016–2025*. OECD Publishing. https://doi.org/10.1787/agr_outlook-2016-en.

Ojo, T. O., & Baiyegunhi, L. J. S. (2020). Determinants of climate change adaptation strategies and its impact on the net farm income of rice farmers in south-west Nigeria. *Land Use Policy*, *95*, 103946.

Ojo, T. O., Ogundeji, A. A., & Belle, J. A. (2021). Climate change perception and impact of on-farm demonstration on the intensity of adoption of adaptation strategies among smallholder farmers in South Africa. *Technological Forecasting and Social Change*, *172*, 121031. https://doi.org/10.1016/j.techfore.2021.121031

Opiyo, F., Wasonga, O. V., Nyangito, M. M., Mureithi, S. M., Obando, J., & Munang, R. (2016). Determinants of perceptions of climate change and adaptation among Turkana pastoralists in northwestern Kenya. *Climate and Development*, *8*(2), 179–189. https://doi.org/10.1080/17565529.2015.1034231

Pangapanga, P. I., Jumbe, C. B., Kanyanda, S., & Thangalimodzi, L. (2012). Unravelling strategic choices towards droughts and floods' adaptation in Southern Malawi. *International Journal of Disaster Risk Reduction*, *2*, 57–66. https://doi.org/10.1016/j.ijdrr.2012.08.002

Qureshi, A. (2007). *An index measuring food security: Identifying the components and determinants and testing usefulness*. Heller School for Social Policy and Management, Brandeis University.

Sanfo, S., Barbier, B., Dabiré, I. W., Vlek, P. L., Fonta, W. M., Ibrahim, B., & Barry, B. (2017). Rainfall variability adaptation strategies: An ex-ante assessment of supplemental irrigation from farm ponds in southern Burkina Faso. *Agricultural Systems*, *152*, 80–89. https://doi.org/10.1016/j.agsy.2016.12.011

Setsoafia, E. D., Ma, W., & Renwick, A. (2022). Effects of sustainable agricultural practices on farm income and food security in northern Ghana. *Agricultural and Food Economics*, *10*(1), 1–15. https://doi.org/10.1186/s40100-022-00216-9

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, *44*, 272–284. https://doi.org/10.1016/j.foodpol.2013.09.012

Smith, L. C., & Subandoro, A. (2007). *Measuring food security using household expenditure surveys, food security in practice technical guide series*. IFPRI.

Tazeze, A., Haji, J., & Ketema, M. (2012). Climate change adaptation strategies of smallholder farmers. The case of Babilie District, East Harerghe zone of Oromia Regional State of Ethiopia. *Journal of Economics and Sustainable Development*, *3*(14), 1–12.

Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, *93*, 85–93. https://doi.org/10.1016/j.ecolecon.2013.05.002

World Bank. (2016). *CPIA Africa - Assessing Africa's policies and institutions: 2015 CPIA results for Africa*. World Bank Group.

Yigezu, Y. A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., & Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

Zakaria, A., Alhassan, S. I., Kuwornu, J. K., Azumah, S. B., & Derkyi, M. A. (2020). Factors influencing the adoption of climate-smart agricultural technologies among rice farmers in northern Ghana. *Earth Systems and Environment*, *4*(1), 257–271. https://doi.org/10.1007/s41748-020-00146-w

Zampaligré, N., & Fuchs, L. E. (2019). Determinants of adoption of multiple climate-smart adaptation practices in Sudano-Sahelian pastoral and agro-pastoral production systems. *Sustainability*, *11*(18), 4831. https://doi.org/10.3390/su11184831

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2017). Agricultural technology adoption and child nutrition enhancement: Improved maize varieties in rural Ethiopia. *Agricultural Economics*, *48*(5), 573–586. https://doi.org/10.1111/agec.12358

Zhou, X., & Xie, Y. (2014). Propensity score–based methods versus MTE-based methods in causal inference: Identification, estimation, and application. *Sociological Methods & Research*, *45*(1), 3–40. https://doi.org/10.1177/0049124114555199