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Climate-Smart Agriculture as an Adaptation Measure to Climate Change in Togo: Determinants of Choices and Its Impact on Rural Households' Food Security

Raïfatou Affoh [1], Haixia Zheng [1,2,*], Xuebiao Zhang [1,2,*], Xiangyang Wang [3], Kokou Dangui [4] and Liwen Zhang [1]

[1] Agricultural Information Institute, Chinese Academy of Agricultural Sciences, Beijing 100081, China; raifatouaffoh@yahoo.fr (R.A.); liwen.zhang91@outlook.com (L.Z.)
[2] Key Laboratory of Agricultural Big Data, Ministry of Agriculture and Rural Affairs, Beijing 100081, China
[3] Chinese Academy of Fiscal Sciences, Beijing 100142, China; wangxiangyang@caas.cn
[4] College of Economics and Management, Northwest A&F University, Yangling, Xianyang 712100, China; kokoudangui@gmail.com
* Correspondence: zhenghaixia@caas.cn (H.Z.); zhangxuebiao@caas.cn (X.Z.)

Abstract: Climate-smart agriculture is one of the most important actions for agricultural climate change adaptation, especially in Togo, a sub-Saharan African country with a fragile ecology and where agriculture is profoundly impacted by climate change. Using a multinomial endogenous switching regression (MESR) and a multinomial endogenous treatment effect (METE) approach, we conducted empirical research to identify the factors influencing the adoption decisions of climate-smart agricultural practices (CSAPs) and their impact on household food security among smallholder farmers in Togo. The findings of this study revealed that the adoption of CSAPs by farmers is influenced by a range of factors, such as age, marital status, the household head's gender, engagement in off-farm activities, level of education, farm size, agroecological zone, regional location, land ownership, distance between homestead and farm, access to credit, the presence of agricultural associations and cooperatives, and access to extension agents. On the one hand, the MESR analysis demonstrated a positive correlation between the number of adopted CSAPs and households' food consumption score. Similarly, greater adoption of CSAPs resulted in a significant reduction in the food insecurity experience scale. On the other hand, the METE model portrayed an increase in acceptable food consumption when households adopted up to three CSAPs. Likewise, it significantly alleviated severe food insecurity. Further results based on the propensity score matching technique showed that the adoption of a crop rotation system, utilization of improved varieties of seeds, plant protection products, inorganic fertilizer, organic fertilizer, and irrigation improved adopters' food consumption scores while reducing their level of food insecurity.

Keywords: climate change; adaptation; climate-smart agricultural practices; food security; Togo

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1. Introduction

Global population growth, urbanization, climate change, and environmental pressures have significantly impacted the ability of agricultural systems to utilize resources and produce food sustainably. By 2050, the world's population is expected to reach 9.7 billion [1]. Hence, there is increasing global agreement that improving the efficiency, resilience, inclusiveness, and sustainability of agri-food systems is necessary for achieving the 2030 Agenda for Sustainable Development [2].

Compared to 2019, before the global pandemic, about 281.6 million persons, or 21.5% of the population, experience severe food insecurity, mostly in 59 countries experiencing food crises in 2023 [3]. Today, the percentage of the population that experienced severe acute food insecurity in 2023 was 2.7%, somewhat less than in 2022. Nonetheless, since 2022, the number of impacted individuals has climbed by 24 million, making this the

fifth year in a row of increases [4]. Agri-food systems fail to prevent approximately 10% of the global population from experiencing hunger [2]. Africa saw a rise in the prevalence of undernourishment (PoU) from 19.4% in 2021 to 19.7% in 2022, primarily due to rises in Northern and Southern Africa. Africa now has 11 million more hungry individuals than it did in 2021, and since the pandemic began, more than 57 million more people are hungry [5]. The COVID-19 pandemic has drawn attention to the weaknesses in our societies' social structures and agri-food systems, exacerbating global hunger and acute food insecurity. According to FAO et al. [6], since the pandemic began, an additional 112 million individuals worldwide lack access to a healthy diet, bringing the total number of people unable to afford a healthy diet to nearly 3.1 billion. Ending hunger, food insecurity, and all forms of malnutrition are faced with increasing difficulties. Despite various advancements made worldwide, patterns in child undernutrition, such as stunting and wasting, deficiencies in vital micronutrients, and childhood overweight and obesity continue to be very concerning. Additionally, the worrying trends in adult obesity and maternal anemia persist. The prolonged violence in Ukraine is disrupting supply chains and driving up the cost of food, fertilizer, and oil. In the first half of 2022, this led to further increases in food prices.

Extreme climate events going on more recurrently and severely, particularly in low-income nations are one of the triggering causes for shortage in food supply [6]. Agriculture, the primary source of food, is seriously impacted by climate change and variability. Climate factors substantially impact the increase in agricultural productivity [7,8], which is a key determinant of food security.

The case studies in sub-Saharan Africa (SSA) and China confirm that climate change has a significant negative impact on agricultural production, especially reflected in the small scale of agricultural production in SSA, China and many other developing countries [9–12]. Furthermore, smallholders' livelihoods are severely impacted by the severity of climate change, making it crucial for governments to take supportive actions to aid smallholders in their adaptation efforts [13].

Like many developing nations, Togo's economy is highly agriculture-dependent. The agricultural sector contributed 31% to the total GDP in 2021 and employed 70% of the Togolese population [14]. The frequency of severe food insecurity in Togo over the previous five years has been relatively high (33.25%) [15]. Food insecurity affects approximately 21% of the rural population. Among children under 5, 23.8% suffer from chronic malnutrition and 5.7% from emaciation [14]. According to the latest Harmonized Framework (CH) study, 5946 people are severely food-insecure and need urgent food assistance to save lives, protect livelihoods, and reduce mortality in Togo. In addition, 534,221 people cannot cover certain essential non-food expenses without compromising their livelihoods [16]. The country's food and nutritional insecurity are exacerbated by climate variability. Togo is confronted with a much-accentuated climatic variability on a spatio-temporal scale. In 2020, temperatures experienced a maximum increase of 1.2 °C, equivalent to a 20% increase compared to 2012. Precipitation has decreased with amplitudes of rain ranging from 15 mm to 98 mm [15]. This led to climatic risks that influenced all development sectors and are manifested by floods, drought, high temperatures, shifts in the seasons, violent winds, poor distribution of rain, and soil and coastal erosions. Future projections of climate variability based on rigorous IPCC methods predict that if the country remains in the stabilization of emissions (RCP6.0) compared to 2020, temperatures will increase with an amplitude of 0.6 °C to 0.7 °C in 2025 and 2.15 °C to 2.75 °C in 2100. Precipitation will vary from −0.08% to +0.35% (2025) and from −0.3% to +1.26% (2100) [17].

Significant efforts will be needed to progress the three main goals of increased agricultural yields, carbon sequestration, and agricultural resilience to harsh weather shocks in order to balance global food supply with demand in the face of climate change [18]. Achieving these three policy goals will depend largely on climate-smart agriculture (CSA), an adaptable approach designed to help rural development and food security in agricultural systems under climate change [19,20]. CSA is fundamental to ongoing efforts to promote the Sustainable Development Goals (SDGs) of the United Nations (UN), including

eradicating hunger and combating climate change, especially in low- and middle-income countries [19,21]. Climate-smart agriculture is crucial for Africa's future economic success because the continent's agricultural sector is vulnerable to climate change [22]. The consequences of climate change on agriculture may be mitigated when CSA technology and practices are employed. Since the introduction of CSA, the agricultural sector has significantly reduced its greenhouse gas emissions [20,23]. However, the lack of financial resources is the primary cause of the poor adoption rate of CSA procedures and technology, particularly for small-scale and marginalized farmers [24–26].

Notwithstanding the many benefits of CSAPs the government's and development partners' coordinated efforts to persuade farmers to invest in them, there is still a shortage of data regarding the incentives for farmers, the factors that either hinder or accelerate their adoption, and the impact of CSAPs on the status of food security in Togo. This study contributes to the empirical literature in three ways. First, it identifies the factors influencing Togolese rural farmers' decisions when selecting the most suitable CSA techniques and combinations for their production systems. Second, it assesses the impacts of adopting a single CSAP versus a combination of practices on food security, using the household food consumption score (HFCS) and food insecurity experience scale (HFIES) as proxies. Finally, it provides micro-level evidence by linking farmers' utilization of CSAPs with household food security status.

2. Materials and Methods

2.1. Study Area

This study was undertaken in Togo, a country located between 6° N and 11° N latitude and 0° E and 2° E longitude and with a surface area of 56,600 km^2. Togo has five main administrative regions (Figure 1). The study region is divided into five agroecological zones, based on natural resources and agricultural production circumstances. Out of the five agroecological zones in Togo (tropical savannahs, northern mountainous, Savannahs of Guinean woodland, semi-deciduous moist forests, and coastal highlands (Figure 2), this study was undertaken in the first four. The soil in these regions and agroecological zones is more fertile for maize, paddy rice, sorghum, millet, cassava, and yam production, which are the staple foods in Togo. Worryingly, research conducted in 2005 by Balme et al. has demonstrated that there may be a 60-day delay before the rainy season officially begins, occasionally with dry intervals in between. It has been recorded that floods destroyed 6902 hectares (9000 tons) of crops (corn, rice, millet, sorghum, yam, etc.) in 2020 [27]. An average annual deficit of more than XOF 25 billion was estimated based on average yield losses, areas sown, and agricultural produce prices on a nationwide scale [27]. Similarly, crop yields are negatively impacted by rising temperatures, especially for maize, the most widely grown and consumed cereal in Togo. With the lowest average maize yield of all of Togo's economic zones and a persistently deficient food balance, the maritime region is the one most negatively impacted by climate variability [28].

Most Togolese farmers rely on rain-fed agriculture, and household labor is the basic unit of agricultural production. With 16.1% of its population suffering from undernourishment in 2021, Togo is ranked 89th out of 116 countries, according to the Global Hunger Index. During the 2022–2023 period, cereal production (maize, paddy rice, sorghum, millet, and fonio) was estimated at 1,439,851 tons, an increase of 2.1% compared to the previous season (1,403,574 tons), with a surplus cereal balance [29]. The average maize and rice yields were, respectively, 1167.8 kg/ha and 1149.5 kg/ha in 2022 and 2021 compared to 5878 and 4764 kg/ha globally [30], equivalent to 21% and 35% of the international average, respectively [31].

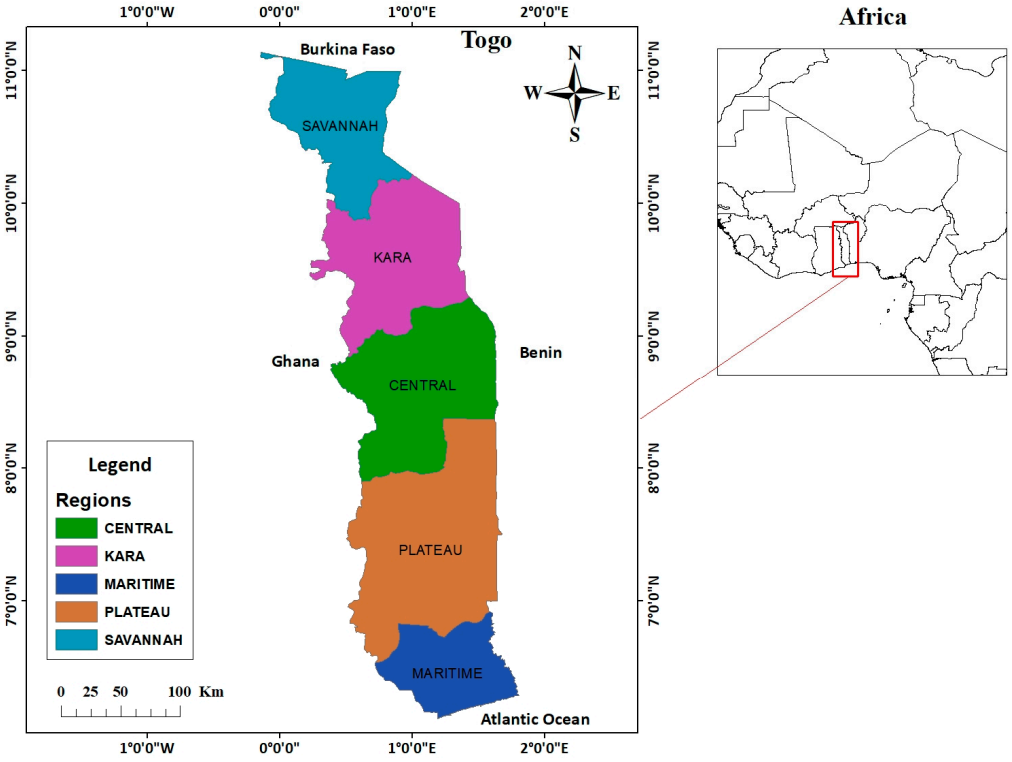


Figure 1. Study area map. Source: Authors' conception.

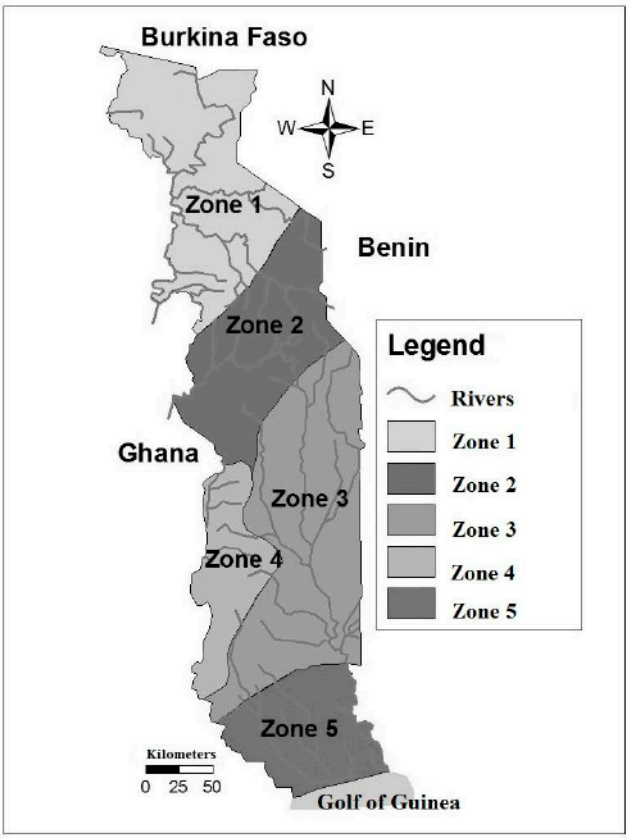


Figure 2. Agroecological zones in Togo.

2.2. Theoretical Framework

There are multiple frameworks explaining the determinants of household food security. However, our study is framed around the hypotheses that

➢ Climate change affects rural household food security by affecting agricultural yield and farm income (Figure 3);

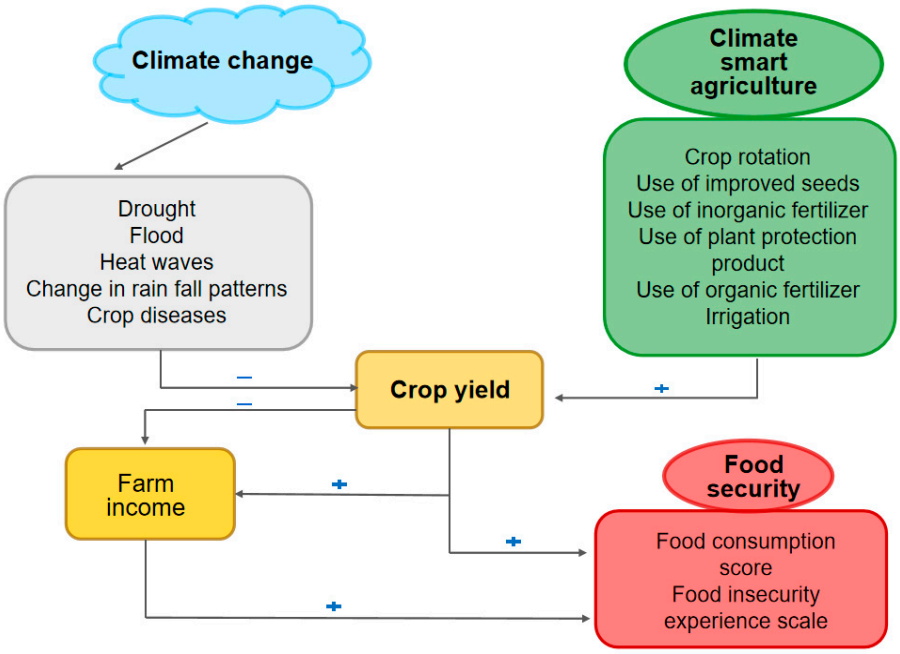


Figure 3. Conceptual framework. Source: Authors' conception.

➢ When farmers adopt CSAPs, their farm productivity tremendously improves, increasing their income. Because of yield improvement, farmers will have more physical access to food from their production. The increase in income will enable them to afford other nutritious components of a well-balanced meal, thus attaining food security.

Numerous CSAPs have been adopted by farmers in Togo: changing crop varieties, integrating crops and livestock, conserving soil and water, using monocropping systems, intercropping systems, crop rotation systems, using organic or inorganic fertilizers, planting early maturing crops, adjusting sowing times, planting trees, and irrigation practices [31]. These strategies vary depending on the agroecological zone. For instance, managing soil fertility, adjusting planting dates, and using short-cycle, high-yielding cereal varieties suggested by the National Plan for Adaptation to Change (PNACC) are all part of the adaptation process in the marine region [32]. Manure recovery, hilling, ridging, lowland management, and chemical fertilizer application are examples of soil fertility management techniques. Applying soil fertility management techniques improves soil moisture content, boosts agricultural yields, and supplies crops with nutrients [33]. In reaction to early or late rainfall, farmers adjust the timing of their plantings. Better crop varieties—particularly those with a short cycle—are more resilient to water stress, resulting in higher yields even during dry seasons [34].

CSAPs, such as crop rotation systems, improved seeds, plant protection products, fertilizers, and irrigation systems, are the important subject of the current study.

2.3. Methods and Data

Following the previous studies, the determinants of choice and the effect of CSA practices on small-scale farmers' food security are modeled using multinomial endogenous switching regressions (MESRs) [35–39] and multinomial endogenous treatment effects (METEs) [36,40]. The latter is used to check for the former's robustness. However, if

selection bias resulting from both observed and unobserved heterogeneousness is ignored, these methods would produce unreliable estimates. Endogenous self-selection of farmers is possible, and decisions are likely to be impacted by unseen factors but may have a correlation with outcome variables [41].

Selection bias makes it extremely challenging to adopt and carry out impact assessment studies based on non-randomized experimental data [36] when observable selection bias arises. Many impact evaluation studies [9,42–47] have used propensity score matching (PSM). The PSM technique, however, is unable to address selection bias due to undetected factors [48,49]. In contrast to PSM, the MESR and METE models employ a selection correction method by estimating an inverse Mills ratio using the theories of truncated normal distribution and latent factor structure, respectively, to rectify this bias [50]. The endogenous switching regression (ESR) is performed in two stages. In the initial stage, a multinomial logistic selection (MNLS) model is used to estimate the farmer's selection of various techniques while accounting for unobserved variability. The estimated probabilities used in the MNLS model are used to calculate the inverse Mills ratios (IMRs). In the second stage, OLS is used to evaluate each combination of different CSAPs, and IMRs are introduced as extra factors to account for selection bias caused by time-varying unobserved heterogeneity. ESR has also been applied to other empirical studies' effect evaluations [36–39,51].

Nonetheless, we also used the propensity score matching (PSM) technique to assess the influence of single-CSAP adoption on food security after estimating the marginal effect using binary logistic regression in this study.

2.3.1. Stage One: Multinomial Adoption Selection Model

At this stage, we used a multinomial logistic model to assess the determinants of the CSAP combination choice. It is hypothesized that farmers would increase their level of food security Y_i by comparing the benefit provided by M alternative CSAPs. The constraint for farmer i to choose any plan j over other alternatives M is that $Y_{ij} > Y_{iM}$ $M \neq j$, where j offers greater anticipated food security than any alternative option. Y_{ij}^*, the latent variable, represents the expected degree of food security, combining unobserved factors described as follows with observed household and land characteristics:

$$Y_{ij}^* = X_i\beta_j + \varepsilon_{ij} \quad (1)$$

X_i captures the observed exogenous variables (household and farm features), whereas the error term ε_{ij} depicts unobserved features. The covariate vector X_i will not exhibit any correlation with the unique unobserved stochastic component ε_{ij}, that is, the following:

$E(\varepsilon_{ij}/X_i) = 0$ assuming that ij can stand alone and identically Gumbel-distributed in accordance with the theory of independent, irrelevant alternatives. The selection model (1) leads to a multinomial logistic model [52] where the probability of choosing strategy j (p_{ij}) is

$$p_{ij} = p(\varepsilon_{ij} < 0/X_{ij}) = \frac{\exp(X_i\beta_j)}{\sum_{N=1}^{j}\exp(X_i\beta_M)} \quad (2)$$

2.3.2. Stage Two: Multinomial Endogenous Switching Regression Model and Multinomial En-Dogenous Treatment Effect

Multinomial Endogenous Switching Regression Model

The present study employs multinomial endogenous switching regression (MESR) in conjunction with the selection bias correction model proposed by Bourguignon et al. [49] to examine the effects of individual response practices on food security. Farmers are part of a

total of M regimes, with the reference category being regime j = 1 (non-responsive). For each potential regime, the following equation represents the food security status:

$$\begin{array}{l} \text{Regime 1 } Q_{i1} = z_i\alpha_1 + \mu_{i1} \quad if\ i\ =\ 1 \\ \text{Regime } j\ Q_{ij} = z_i\alpha_j + \mu_{ij} \quad if\ i\ =\ j \end{array} \tag{3}$$

From the above equation, Q_{ij}'s represents the food security status of the i^{th} farmer in regime j, and the error terms μ_{ij}'s are distributed with $E(\mu_{ij}/x,\ z)$ and Var$(\mu_{ij}/x,\ z) = \sigma_j^2$. Q_{ij} is observed if, and only if, CSAP j is used, which happens when $Y_{ij}^* > {}^{max}_{M\neq 1}\ (Y_{im})$. If the error terms in (2) and (3) are not independent, OLS estimates for Equation (3) are biased. Consistent estimations of α_j must include the selection correction terms of the choices in Equation (2). MESR works on the linear hypothesis below:

$E(\varepsilon_{ij}/\varepsilon_{i1}\ldots..\varepsilon_{ij} = \sigma_j\sum_{m\neq j}^{j} r_j(\varepsilon_{im} - E(\varepsilon_{im}))$. The association between the error terms in (2) and (3) is zero.

Using the above assumption, Equation (3) can be expressed as follows:

$$\begin{array}{l} \text{Regime 1 : } Q_{i1} = z_i\alpha_1 + \sigma_1\lambda_1 + \omega_{i1} \quad if\ i\ =\ 1 \\ \text{Regime } j\text{ : } Q_{ij} = z_i\alpha_j + \sigma_j\lambda_j + \omega_{ij} \quad if\ i\ =\ 1 \end{array} \tag{4}$$

σ_j is the covariance between $\varepsilon's$ and $\mu's$ while λ_j, the inverse Mills ratio, is calculated using the estimated probabilities in Equation (4) as follows:

$$\lambda_j = \sum_{m\neq j}^{j} \rho_j \left[\frac{p_{im}\ In(p_{im})}{1 - p_{im}} + In(p_{ij})\right] \tag{5}$$

where r stands for the correlation coefficient of e's and m's while ω_{ij} are error terms with an expected value of zero. There were $j - 1$ selection correction terms in the previously stated multinomial choice situation, one for each CSAP's alternative. In order to account for the heteroskedasticity resulting from the produced regressors denoted by λ_j, the standard errors in Equation (4) were bootstrapped.

Average Treatment Effects Estimate

To investigate average treatment effects (ATT), a contrary-to-fact analysis was performed by contrasting the anticipated outcomes of adopters with and without adopting a certain CSAP. The ATT for the actual and theoretical cases was calculated following previous studies' methods [38,39]:

Food security status with adoption/usage

$$E(Q_{i2}|i = 2) = z_i\alpha_2 + \sigma_2\lambda_2 \tag{6a}$$

$$E(Q_{ij}|i = j) = z_i\alpha_j + \sigma_j\lambda_j \tag{6b}$$

Food security status without adoption (counterfactual)

$$E(Q_{i1}|i = 2) = z_i\alpha_1 + \sigma_1\lambda_2 \tag{7a}$$

$$E(Q_{i1}|i = j) = z_i\alpha_1 + \sigma_1\lambda_j \tag{7b}$$

The ATT is the difference between (6a) and (7a)

$$ATT = E(Q_{i2}|i = 2) - E(Q_{i1}|i = 2) = z_i(\alpha_{\ 2}\alpha_1) + \lambda_2(\sigma_2 - \sigma_1) \tag{8}$$

The equation on the right-hand side would designate the projected variation in adopters' mean food security status, if adopters' characteristics have similar returns as non-adopters, for instance, if adopters have the same attributes as non-adopters while λ_j stands for the selection term that includes all possible effects of difference in unobserved variables.

Multinomial Endogenous Treatment Effect (METE)

We ran multinomial endogenous treatment effects (METE) model to confirm the MESR results. Rather than using multinomial endogenous switching regression (MESR), which only takes into account continuous results, METE was chosen because it can be expanded to predict binary results. Similar to the MESR paradigm, METE is modeled in two stages concurrently. A farmer selects one of the four CSAP combinations in the first step. The first stage is estimated as a mixed multinomial logistic (MMNL) model. In the second stage of multinomial endogenous treatment effects (METE), we measure the effects of adopting any CSAP package on food security as a binary outcome. The projected result equation for individuals is adapted from [53] (Equation (9)):

$J = 1, \ldots 4$ is formulated as:

$$E\left(FCS_{\theta it} = 1/d_{jit}, z_{it}, \xi_{it} \right) = z\prime_{it}\beta + \sum_{j=1}^{j} \gamma_j d_{ijt} + \sum_{j}^{j} \lambda_j \xi_{ijt} \quad (9a)$$

$$E\left(FIES_{\theta it} = 1/d_{jit}, z_{it}, \xi_{it} \right) = z\prime_{it}\beta + \sum_{j=1}^{j} \gamma_j d_{ijt} + \sum_{j}^{j} \lambda_j \xi_{ijt} \quad (9b)$$

where $FCS_{\theta it}$ and $FIES_{\theta it}$ represent food consumption and food insecurity status, respectively, for household i at time t measured by γ_{jit} as food consumption status or food insecurity level; $FCS_{\theta it} = 1$ if γ_{jit} is lower than the food consumption status and $FIES_{\theta it} = 1$ if γ_{jit} is lower than food insecurity levels; d_{jit} indicates binary variables used for reported treatment choice; and γ_j represents treatment effects relative to non-adopters, and its value measures the effects of adopting CSA practices on food security. z_{it} is a set of external variables with the related parameter vector β. Assuming that the decision to implement CSA practices is external leads to contradictory estimations of γ_j if the decision is internal.

$E\left(FIES_{\theta it} \middle| FCS_{\theta it} = 1/d_{jit}, z_{it}, \overline{z}_i, \xi_{it} \right)$ depends on each of the hidden components ξ_{ijt}; for example, factors that influence the choice of treatment but are not visible for observation may have an impact on the result.

2.3.3. Propensity Score Matching (PSM)

We used the PSM approach to evaluate the determinants of every CSA practice adoption. PSM is a three-analytic-step approach [54]; the first step is a binary logistic estimation, followed by the treatment effects. The final step is the post-matching analysis. For simplicity reasons, only the first two stages are used in our study. The PSM estimator studies how a household's level of food security would have changed if the CSAP-adopting households had decided not to adopt the corresponding CSA technology.

Equation (10) below represents the average treatment effect on the treated (ATT) adapted from [55]:

$$\mathrm{ATT} = \mathrm{E}[\mathrm{Y}_i(1) - \mathrm{Y}_i(0) | \mathrm{I} = 1] \quad (10)$$

where $\mathrm{Y}_i(1)$ and $\mathrm{Y}_i(0)$ are outcomes for farmers' households who applied CSAPs and the control group of households; I = 1 designates households who adopted CSAPs, and I = 0 refers to households who did not use CSAPs. However, because our data is cross-sectional, we cannot observe adopters' food security outcomes if they had not used CSAPs. We can only observe $E[\mathrm{Y}_i(1) | = 1]$. Simply comparing the results of food security for households with and without adoption will introduce an estimation bias caused by self-selection bias, which is presented in Equation (11):

$$E[\mathrm{Y}_i(1) - \mathrm{Y}_i(0) | I = 1] = ATT + E[\mathrm{Y}_i(0) | I = 1 - \mathrm{Y}_i(0) | I = 0] \quad (11)$$

PSM limits the comparison of results to households with similar visual attributes to address the possible bias, eliminating the bias that might otherwise emerge if the two sets were purposefully different [56]. In order to lessen the bias caused by observable factors, PSM provides analogous alternative households for the adopters and pairs households according to identifiable characteristics. A further assumption made by PSM is that, after households have been paired on visible features, there will not be a consistent difference in

the unobserved features of adopters and non-adopters [57]. If the overlap is attained and the conditional independence assumption is valid, the ATT can be calculated as follows (Equation (12)):

$$ATT = E[Y_i(1)|I = 1,\ p(x)] - E[Y_i(0)|I = 0,\ p(x)] \quad (12)$$

2.4. Data Source

With funding from the World Bank, the Togo Harmonized Survey on Household Living Conditions 2018–2019 (EHCVM 2018/19) provided the most recent and countrywide cross-sectional data collection for this study. Since the dataset was based on a nameless public use dataset that contained no personally identifying information about the study sample, it was exempt from particular permission requirements, and our request to utilize the data was approved.

We selected the EHCVM 2018/19 dataset for this study because it is the most recent dataset to be released and offers comprehensive information on household welfare and activities like agriculture. We used agricultural households' data which include information on the adoption of CSAPs and the degree of food security.

The Togolese National Institute of Statistics, Economical Studies, and Demography (INSEED) oversaw the administration of EHCVM 2018–19. The West Africa Economic Monetary Union (WAEMU) Household Survey Harmonization Project (P153702), a collaborative effort between the World Bank and the WAEMU Commission, aims to produce household survey data in member countries: Benin, Burkina Faso, Chad, Côte d'Ivoire, Guinea Bissau, Mali, Niger, Senegal, and Togo. The Togo EHCVM 2018/19 is the first edition of this nationwide sample household survey.

With the exception of Lomé Commune, where all respondents are from rural areas, the survey included both urban and rural areas in all regions (Figure 4). The investigation's team determined the sample size and repartition and then used a two-stage sampling process. In the first stage, 540 enumeration areas (EAs) were chosen from the sample setting. In each enumeration region, 12 randomly chosen families were included in the second stage. There are 6171 households in this study overall, 2270 of which are in urban areas and 3901 of which are in rural areas. The survey design then split each enumeration area into two equal groups at random. The first group in wave one and the second group in wave two were questioned by the survey team. Ultimately, the survey teams conducted interviews with 2931 families (1034 in urban areas and 1897 in rural areas in wave 1) for a variety of reasons, including availability and quality monitoring. The team conducted interviews with 3240 households in wave 2 (1236 in urban areas and 2004 in rural areas).

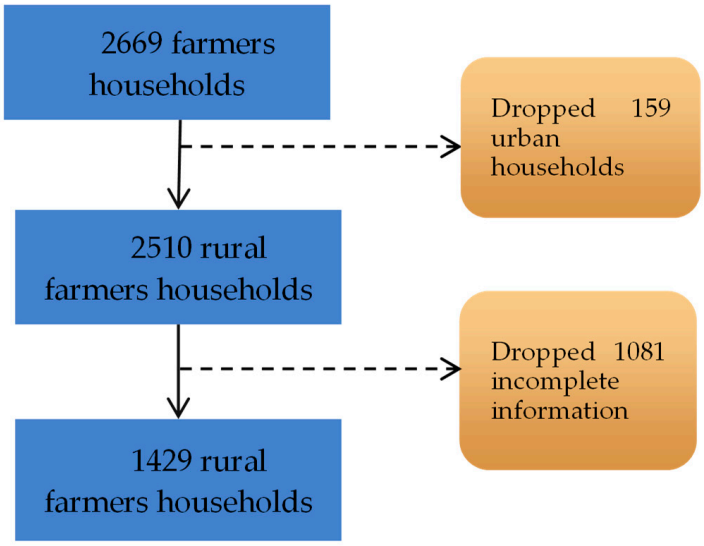


Figure 4. Participant flow chart. Source: Authors' conception.

For each visit, there were two surveys. Every family in the sample received the family questionnaires. In order to gather data on the socio-economic variables of the enumeration areas where the sample households dwell, the community was given the community questionnaire. Out of 6171 households interviewed, we were interested in the households with agriculture as their first source of income, this being 2669 households in total. We further eliminated the urban households from the sample and households with incomplete information. This study considered a final sample size of 1429 households (Figure 4).

3. Results and Discussion

3.1. Descriptive Statistics Analysis

The outcome, treatment, and explanatory variables' summary statistics for the current study are shown in Table 1.

Table 1. Descriptive statistics.

Variable	Obs	Measurement	Mean	Std. Dev.
Outcome variables				
Household food consumption score (HFCS)	1429	1 = poor; 2 = borderline; 3 = acceptable	1.27	1.70
Household food insecurity experience scale (HFIES)	1429	1 = food-secure; 2 = moderately food-insecure; 3 = severely food-insecure	2.03	2.59
Treatment variables				
Crop rotation system	1429	Dummy = 1 if yes 0 = No	0.75	0.43
Improved seeds	1429	Dummy = 1 if yes 0 = No	0.09	0.28
Plant protection products	1429	Dummy = 1 if yes 0 = No	0.33	0.47
Inorganic fertilizer	1429	Dummy = 1 if yes 0 = No	0.37	0.48
Organic fertilizer	1429	Dummy = 1 if yes 0 = No	0.04	0.20
Irrigation system	1429	Dummy = 1 if yes 0 = No	0.01	0.07
CSA practice combinations	1429	0 = practices; 1 = 1 practice; 2 = 2 practices; 3 = 3 practices; 4 = 4 practices	1.54	0.94
Explanatory variables				
Age of household head (HH) (years)	1429	Continuous	45.99	14.51
Gender of HH	1429	Dummy = 1 if male 0 = female	0.86	0.35
Marital status of HH	1429	Dummy = 1 if yes 0 = No	0.80	0.40
Household size	1429	Discrete	5.50	2.89
Level of education of HH	1429	1 = university; 2 = high school; 3 = secondary school; 4 = primary school; 0 = non educated	0.69	0.81
Participation in off-farm activities	1429	Dummy = 1 if yes 0 = No	0.18	0.38
Agroecological zone	1429	1 = northern plain zone; 2 = northern mountains zone; 3 = central plain zone; 4 = southern plain zone	2.76	1.07
Maritime region	1429	Dummy = 1 if yes 0 = No	0.29	0.45
Plateau region	1429	Dummy = 1 if yes 0 = No	0.21	0.40
Central region	1429	Dummy = 1 if yes 0 = No	0.16	0.37
Kara region	1429	Dummy = 1 if yes 0 = No	0.23	0.42
Savannah region	1429	Dummy = 1 if yes 0 = No	0.12	0.32
Farm size (meter square)	1429	Continuous	14.23	202.45
Land ownership	1429	Dummy = 1 if yes 0 = No	0.62	0.49
Time to farm (minutes)	1429	Continuous	44.74	50.48
Soil fertility	1429	1 = poor; 2 = medium; 3 = fertile	2.04	0.67
Member of farmer group	1429	Dummy = 1 if yes 0 = No	0.89	0.31
Access to credit	1429	Dummy = 1 if yes 0 = No	0.05	0.21
Access to extension agents	1429	Dummy = 1 if yes 0 = No	0.52	0.50

Source: Authors' conception.

3.1.1. Outcome Variables

To gauge the level of farmers household's food security, we used the household food consumption score (HFCS) and the household food insecurity experience scale (HFIES). The World Food Program (WFP) created HFCS, which is frequently used as a stand-in for food access [58]. Food access, dietary diversity, and the nutritional content of ingested food groups are the three factors that make up the HFCS-weighted score. The weighting of

each food group is multiplied by the frequency of foods ingested throughout a seven-day period to determine the HFCS. Food groups were weighted by the WFP based on their respective nutrient densities [59]. Appendix A, Table A1 presents a list of the different food components that were utilized to calculate the HFCS. This indicator has been validated for the quantity component of food security (i.e., caloric sufficiency) and helps classify and track households' food security over time. Since respondents are asked to recollect their seven-day eating history, the HFCS gathers data on the typical household diet. The HFCS can be applied in various contexts, such as population-level targeting program monitoring and evaluation.

With a few minor variations in the constituents of the different food clusters, HFIES and HFCS are analogous. While HFCS considers food items consumed within seven days, the FIES considers those consumed within the last 12 months. The Gallop World Poll (GWP) began gathering data on food security in 2014 by employing FIES, the FAO-Voice of the Hungry tool. Eight questions make up the FIES, and the answers are as easy as "Yes" or "No" (Appendix A, Table A2). The question of whether respondents had ever encountered varying degrees of food insecurity (FI) intensity was posed to them during the preceding year.

These concerns range from "being worried about not having enough food to eat" to "going hungry for a whole day" because of insufficient funds or other resources. These FIES questions are scored overall, with a range of 0 to 8; then, the responses are combined. Based on the global standard, the scores were divided into three groups for these analyses: (1) food-secure (0–3), (2) moderately FI (4–6), and (3) severely FI (7, 8) [60]. Food security can be measured using the FIES: to evaluate food insecurity prevalence in the population (both for national and SDG monitoring purposes); identify vulnerable groups; direct and track the effectiveness of food security policies and programs; and pinpoint the causes and impacts of food insecurity [61].

3.1.2. Treatment Variables

According to the CSAPs' adoption in our case study, we chose six treatment variables: crop rotation system, improved seeds, using plant protection products, using organic fertilizer and inorganic fertilizer, and irrigation system.

For simplicity reasons, we grouped the households into seven categories: non-adopters, adopters of 1 practice, adopters of 2 practices, adopters of 3 practices, and adopters of 4–6 practices. Since no household adopted 4–6 practices, we dropped the category. Table 2 presents different CSAP combinations used in our study. Of the farmers, 10.36% were non-adopters. The largest share of farmers (44.72%) adopted one CSAP; 43.39% of farmers were found to have adopted two CSAPs; and only a few adopted three CSAPs (2.6%) (Figure 5).

Table 2. Categories of CSA practice adoption.

CSA Adopters' Categories	Possible Combinations	Frequency	Percentage
Non-adopters	$C_0S_0P_0F_0O_0I_0$	148	10.36
1 Practice	$C_1S_0P_0F_0O_0I_0/C_0S_1P_0F_0O_0I_0/C_0S_0P_1F_0O_0I_0/C_0S_0P_0F_1O_0I_0/C_0S_0P_0F_0O_1I_0/C_0S_0P_0F_0O_0I_1$ (6 kinds)	639	44.72
2 Practices	$C_1S_1P_0F_0O_0I_0/C_0S_1P_1F_0O_0I_0/C_0S_0P_1F_1O_0I_0/C_0S_0P_0F_1O_1I_0/C_0S_0P_0F_0O_1I_1/C_1S_0P_1F_0O_0I_0$ (15 kinds)	620	43.39
3 Practices	$C_1S_1P_1F_0O_0I_0/C_0S_1P_1F_1O_0I_0/C_0S_0P_1F_1O_1I_0/C_1S_1P_0F_0O_0I_1/C_1S_0P_1F_1O_0I_0/C_1S_0P_0F_1O_1I_0$ (20 kinds)	22	1.54
Total		1429	100

Source: Authors' conception.

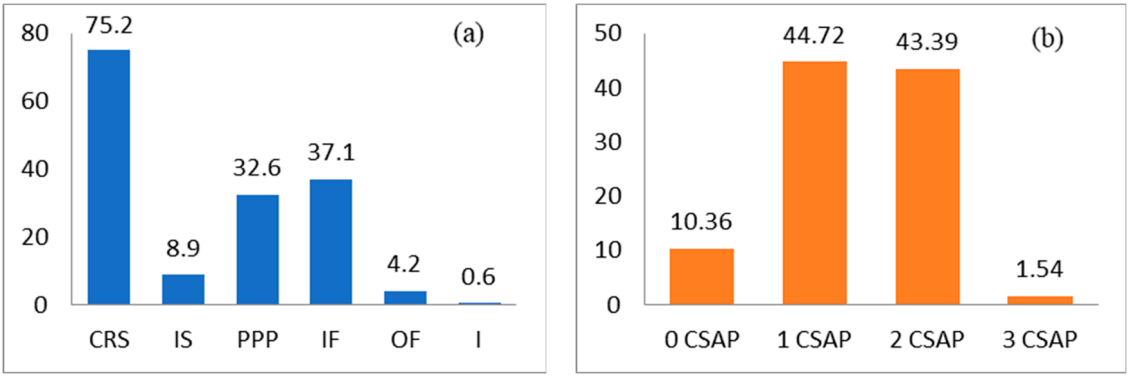


Figure 5. Single CSAP (**a**) and CSAP combinations (**b**) adopted by Togolese rural household farmers. Note: CRS (crop rotation system); IS (improved seed); PPP (plant protection product); IF (inorganic fertilizer); OF (organic fertilizer); I (irrigation). Source: Authors' conception.

3.1.3. Explanatory Variables

In the process of choosing the befitting independent variables, we scrupulously inspected the existent recent literature related to CSA technology adoption, farm income, welfare, and food security [36–39,42,51,62–65]. We then included socio-demographic variables (age, gender, marital status, household size, and education); socio-economic factors (participation in off-farm activities and access to credit); farm characteristics (agroecological zone, region, soil fertility, farm size, land ownership, and time to farm); and third-party influence (member of farmer group and access to extension agent).

3.2. Factors Influencing Specific CSA Practices and Combination Choice

3.2.1. Marginal Effect of Multinomial Logistic Regression

Table 3 displays the marginal effect of the four exclusive combinations of CSAPs. The level of education of the household head (HH), farm size, agroecological zone, access to extension agents, and gender of the HH influence the adoption of CSAP. Household size, participation in off-farm activities, farm size, being in the northern plain agroecological zone, land ownership, and access to an extension agent negatively affects the probability of adopting one CSAP. The time to farm is more likely to positively influence the adoption of one CSAP.

Table 3. Marginal effect of adoption of multiple CSAPs.

Variables	Non-Adopters	Adopters		
		1 Practice	2 Practices	3 Practices
	d*y*/d*x*	d*y*/d*x*	d*y*/d*x*	d*y*/d*x*
Household size	0.001 (0.003)	−0.009 * (0.005)	0.011 ** (0.005)	−0.003 (0.002)
Age of HH	0.00 ** (0.001)	0.001 (0.001)	−0.002 ** (0.001)	0.000 (0.001)
Gender of HH	−0.051 * (0.027)	0.039 (0.047)	0.013 (0.046)	−0.001 (0.011)
Marital status of HH	0.032 (0.025)	−0.057 (0.040)	0.016 (0.039)	0.009 (0.010)
Level of education of HH	−0.028 *** (0.011)	−0.002 (0.018)	0.027 (0.017)	0.003 (0.005)
Participation in off-farm employment	−0.011 (0.020)	−0.099 *** (0.034)	0.095 *** (0.033)	0.014 ** (0.007)
Soil fertility	0.005 (0.012)	0.018 (0.020)	−0.023 (0.019)	0.000 (0.005)

Table 3. *Cont.*

Variables	Non-Adopters	Adopters		
		1 Practice	2 Practices	3 Practices
	d*y*/d*x*	d*y*/d*x*	d*y*/d*x*	d*y*/d*x*
Farm size	−0.009 ** (0.003)	−0.023 *** (0.006)	0.031 *** (0.006)	0.001 (0.001)
Time to farm	0.000 (0.000)	0.001 *** (0.000)	−0.001 ** (0.000)	0.000 * (0.000)
Agroecological zone	−0.054 *** (0.009)	−0.045 *** (0.013)	0.112 *** (0.012)	−0.013 *** (0.004)
Land ownership	−0.021 (0.016)	−0.045 * (0.026)	0.057 ** (0.025)	0.008 (0.019)
Access to credit	0.056 (1.835)	0.069 (5.497)	0.062 (4.251)	−0.188 (11.581)
Member of farmer group	0.015 (0.030)	0.022 (0.053)	−0.045 (0.051)	−0.008 (0.015)
Access to extension agents	−0.028 * (0.016)	−0.050 * (0.026)	0.067 *** (0.025)	0.011 (0.007)

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Source: Authors' conception.

A household is more likely to engage in two CSAPs if it has more family members, participate in off-farm activities, owns a larger farmland, lives in the northern plain agroecological zone, and has access to an extension agent. Households participating in non-farm activities have lesser time to spend on the farm; hence, they will prefer to invest more in CSAPs, which have proven to increase yields with less labor work. Similarly, the income earned from these activities will enable him to invest more in CSAPs, thereby increasing the crop yield and farm income.

Farm size has a beneficial influence on multiple CSAP adoption. For instance, farmers with larger farms could use larger combinations, contrary to their counterparts with a small piece of land. The availability of land gives farmers the chance to test out these technologies, which in turn affects how the big packages are used. This outcome is in line with Belay et al. [64] and Wekesa et al. [39], who claimed that larger farms allow farmers to benefit from economies of scale and offer a way to diversify their output. The conclusion is credible since farmers who own more land could produce more and, as a result, have more money to spend on modern agricultural tools [35]. The farmers with land ownership prefer to adopt CSAPs. The results support those of Aryal et al. [66], who found that landholding farmers are comparatively rich, more inclined to change their agricultural practices, and consequently have more resources to engage in more climate adaptation strategies.

Agricultural extension is also a great influential factor in CSAP adoption. Our study found that farmers with access to extension agents easily adopted two CSAPs. Extension agents promote new technology and act as go-betweens for improved seed varieties and plant protection products. Similar results were reported by other researchers [35,42,51,67].

Furthermore, the likelihood of adopting two CSAPs is less as the household head grows older. This result is corroborated by Ali and Erenstein's [68] findings according to which old age had a negative association with adopting climate change adaptation measures, arguing that due to the labor-intensive nature of agriculture, farmers must be robust, risk-takers, and healthy. Elderly farmers might not be knowledgeable of the latest trends in agriculture. Moreover, older people tend to stick to farming methods previously used in the community, finding it hard to let go of older ancestral practices [67,69–71]. However, Wekesa et al. [39] found the opposite result. The adoption of two CSAPs is negatively related to the distance from homestead to farm. This finding is substantiated by Abegunde et al. [72] who argued that longer distances can lessen farmers' motivation to try out new or suggested technologies or approaches; hence, it is anticipated that the distance between the farm and the homestead will negatively correlate with the level of

CSA adoption. Additionally, farmland that is far from the farmers' home will cost more to deliver inputs to and be more challenging to supervise.

The results further show that farmers who engage in off-farm activities are more likely to adopt three CSAPs. Conversely, being in the northern plain agroecological zone negatively influences the adoption of many CSAPs and will most likely discourage the household from adopting more CSAPs. The reason could be because the northern plain is among the poorest areas of Togo, and farmers have no capacity to invest in crop production and adopt more CSAPs.

3.2.2. Marginal Effect of Binary Logistic Regression

The results in Table 4 show that factors influencing the choice of a single CSAP vary significantly across practice choices. Adopting a crop rotation strategy is inversely correlated with the HH age. On the contrary, a household with a university education, living in the northern plain zone, being a member of a farmer group, and having access to extension agents lead to a high chance of adopting a crop rotation system. Crop rotation is a strategy of growing crops in a sequential manner on the same plot of land with the intention of maintaining the land's fertility without minimizing farmers' profits from their crops [73]. With land degradation phenomenon, it is becoming imperative to protect the soil by using such a cropping technique. The results above imply that agricultural policy makers are more conscious about this danger and are making great effort using educational, farmer training, and counselling means to help slow down the pace of land degradation. This result agrees with previous conclusions, according to which having access to extension services increases the likelihood of adopting a crop rotation strategy [74].

Table 4. The influencing factors of a single-CSAP choice.

Variables	Crop Rotation System	Improved Seeds	Plant Protection Products	Inorganic Fertilizer	Organic Fertilizer	Irrigation
Household size	0.006 (0.004)	−0.002 (0.003)	0.002 (0.004)	0.002 (0.004)	−0.006 (0.003)	−0.002 (0)
Age of HH	−0.002 ** (0.001)	−0.000 (0.000)	−0.003 *** (0.001)	−0.001 (0.001)	0.000 (0.000)	0.000 (0)
Marital status of HH head	−0.026 (0.033)	0.069 ** (0.030)	−0.067 * (0.037)	0.095 ** (0.039)	−0.007 (0.021)	0.010 (0)
Gender of HH	−0.000 (0.039)	−0.031 (0.030)	0.073 * (0.044)	−0.037 (0.045)	0.051 * (0.028)	0.001 (0)
Level of education of HH	0.022 * (0.014)	0.008 (0.010)	0.679 *** (0.017)	0.001 (0.017)	0.015 (0.010)	−0.003 (0)
Participation in off-farm employment	0.024 (0.028)	−0.013 (0.022)	0.075 ** (0.031)	0.033 (0.032)	0.031 * (0.016)	0.023 *** (0)
Soil fertility	−0.020 (0.016)	−0.004 (0.011)	0.052 *** (0.018)	−0.073 *** (0.018)	0.003 (0.011)	0.009 (0)
Farm size	−0.005 (0.005)	0.014 *** (0.039)	0.047 *** (0.007)	0.035 *** (0.006)	0.004 (0.004)	−0.002 (0)
Time to farm	0.000 (0.000)	−0.000 ** (0.000)	−0.000 (0.000)	−0.001 *** (0.000)	−0.000 (0.000)	0.000 (0)
Agroecological zone	0.149 *** (0.044)	0.088 *** (0.029)	0.147 *** (0.044)	0.034 *** (0.047)	−0.055 (0.041)	−0.132 (0)
Land ownership	0.027 (0.022)	0.020 (0.016)	0.051 ** (0.025)	0.052 ** (0.025)	0.021 (0.016)	0.007 (0)
Access to credit	−0.024 (0.063)	0.042 (0.044)	0.039 (0.071)	−0.077 (0.071)	−0.023 (0.047)	0 (0)
Member of farmer group	0.071 * (0.041)	0.029 (0.035)	−0.013 (0.050)	−0.105 ** (0.049)	−0.026 (0.025)	0 (0)
Access to extension agents	0.069 *** (0.023)	0.035 ** (0.016)	−0.062 ** (0.025)	0.014 (0.026)	−0.008 (0.016)	−0.013 (0)

Table 4. *Cont.*

Variables	Crop Rotation System	Improved Seeds	Plant Protection Products	Inorganic Fertilizer	Organic Fertilizer	Irrigation
Maritime region	−0.032 (0.138)	−0.264 *** (0.089)	−0.499 *** (0.138)	−0.029 (0.145)	0 (0)	0 (0)
Plateau region	0.147 (0.105)	−0.222 *** (0.079)	−0.395 *** (0.116)	−0.152 (0.119)	0.038 (0.095)	0.254 (0)
Central region	0.049 (0.061)	−0.276 *** (0.064)	−0.296 *** (0.070)	−0.381 *** (0.074)	0.051 (0.050)	0 (0)
Kara region	0.032 (0.055)	−0.149 *** (0.040)	−0.130 ** (0.055)	−0.168 *** (0.063)	0.049 (0.046)	0.116 (0)

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Source: Authors' conception.

Furthermore, using improved seed varieties is on the one hand positively correlated with the household head being married, cultivating extensive farmland, living in the northern plain zone, and having access to extension agents. On the other hand, living in the Maritime, Plateau, Central, and Kara regions has a negative effect on improved seeds varieties usage. These findings corroborate the results from Eliya et al. who found that farm size and having access to extension agents [75], in addition to off-farm income and membership of associations [76], are appealing factors to adopting improved varieties of seeds. Likewise, Mutanyagwa et al. [77] also concluded that the agroecological zone and farm size increased the likelihood of adopting this aforementioned strategy.

Likewise, using plant protection products such as herbicides, pesticides, and fungicides is positively correlated with the household head's gender and level of education, participation in off-farm employment, soil fertility, farm size, agroecological zone, and land ownership, but negatively correlated with the age and marital status of the household head, extension agents, and living in Maritime, Plateau, Central, and Kara regions. Pesticides are a great means to protect crops against external attacks, hence increasing the yield. With a proper knowledge of its benefits, a farmer owning large, cultivated land can easily invest in them if he has enough financial resources from his off-farm income. Moreover, agroecological zones also have a role to play. This result is substantiated with previous conclusions [78,79] where it was discovered that farm size is a determinant factor in producers' choice to use pesticide in rice farming. Nonetheless, ref. [80] came to a contradictory conclusion by finding a negative association between farm size and pesticide use.

Moreover, married households owning bigger farmlands, living in the northern plain zone, and with an access to extension services, have a higher probability of using inorganic fertilizers. However, this probability is negatively influenced by poor soil fertility, time from homestead to the farm, farm group membership, and living in the Central and Kara regions. Regarding the farm size, a similar result was found by Aryal et al. [81].

Adopting organic fertilizer is strongly correlated with the household head's gender. Participation in off-farm activities not only increase the likelihood of using organic fertilizer but is also a solid motive for using irrigation systems. Female household heads are more likely to utilize organic fertilizer than their male counterparts. This result aligns with previous findings [82]. However, Foudi and Erdlenbruch [83] found a contradictory result. Additionally, when a household has other sources of income, it is more capacitated to acquire organic fertilizer to boost their productivity. This result is consistent with previous findings [84–86].

Based on the results above, it is obvious that CSAP adoption is negatively associated with regional factors.

3.3. Effect of CSAP Adoption on Food Security

Table 5 displays the average treatment effect of various CSAP combinations on the treated (ATT) and untreated (ATU) for multinomial endogenous switching regression (MESR) on household food security under actual and counterfactual circumstances. Table 6,

on the other hand, presents the multinomial endogenous treatment effect results. Lastly, the propensity score's average treatment effect (ATT) of single-CSAP adoption on the treated is presented in Table 7.

Table 5. MESR-based average treatment effects of the adoption of CSAPs on household food security.

Outcome Variables	Samples	To Adopt	Not to Adopt	Treatment Effect	Changes (%)
HFCS			ATT		
	1 CSAP	44.78	29.60	15.18 ***	51.28
	2 CSAPs	63.23	31.39	31.84 ***	101.43
	3 CSAPs	62.25	25.81	36.44 ***	141.03
			ATU		
	1 CSAP	42.59	27.523	15.07 ***	54.75
	2 CSAPs	58.267	27.53	30.74 ***	111.66
	3 CSAPs	97.67	27.53	70.14 ***	254.78
HFIES			ATT		
	1 CSAP	6.01	8	−1.98 ***	−24.75
	2 CSAPs	2.23	8	−5.76 ***	−72
	3 CSAPs	2.54	8	−5.45 ***	−68.13
			ATU		
	1 CSAP	6.29	8	−1.71 ***	−21.378
	2 CSAPs	3.35	8	−4.65 ***	−58.13
	3 CSAPs	1.72	8	−6.28 ***	−78.5

*** Significant at 1% level. Source: Authors' conception.

Table 6. Multinomial endogenous treatment effect estimates of CSAPs on household food security.

	Exogenous			Endogenous		
Practice Choice (j)	**Poor**	**Borderline**	**Acceptable**	**Poor**	**Borderline**	**Acceptable**
			Food consumption score			
1 CSAP	−0.10 *** (0.01)	−0.81 *** (0.02)	0.91 *** (0.02)	−0.11 *** (0.01)	−0.84 *** (0.02)	0.94 *** (0.02)
2 CSAPs	−0.09 *** (0.01)	−0.85 *** (0.02)	0.94 *** (0.02)	−0.07 *** (0.01)	−0.77 *** (0.02)	0.88 *** (0.02)
3 CSAPs	−0.12 *** (0.02)	−0.90 *** (0.05)	1.02 *** (0.04)	−0.13 *** (0.02)	−0.89 *** (0.05)	1.01 *** (0.04)
λ1				−0.03 ** (0.00)	−0.10 *** (0.01)	0.08 *** (0.01)
λ2				0.01 * (0.01)	−0.01 (0.02)	0.01 (0.01)
λ3				0.06 * (0.03)	0.01 (0.01)	−0.01 (0.01)
	Mild	Moderate	Severe	Mild	Moderate	Severe
			Food insecurity experience scale			
1 CSAP	−0.04 (0.03)	0.55 *** (0.04)	−0.51 *** (0.03)	−0.16 *** (0.03)	0.80 *** (0.04)	−0.64 *** (0.03)
2 CSAPs	0.60 *** (0.03)	0.19 *** (0.04)	−0.80 *** (0.03)	0.71 *** (0.04)	−0.01 (0.04)	−0.60 *** (0.03)
3 CSAPs	0.46 *** (0.06)	0.58 *** (0.10)	−1.04 *** (0.07)	0.45 *** (0.07)	0.59 *** (0.10)	−1.04 *** (0.07)
λ1				0.17 *** (0.03)	−0.32 *** (0.03)	0.15 *** (0.02)
λ2				−0.14 *** (0.03)	0.28 *** (0.03)	−0.28 *** (0.01)
λ3	−0.10 *** (0.01)	−0.81 *** (0.02)	0.91 *** (0.02)	0.01 (0.04)	0.01 (0.04)	0.02 (0.02)

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Source: Authors' conception.

Table 7. PSM estimate effects of the adoption of CSAPs on household food security: ATT.

Outcome Variables	CSA Practices	Average Treatment Effect on the Treated (ATT)	
		Coefficient	Standard Error
HFCS	Crop rotation system	14.34 ***	1.15
	Improved seeds	21.33 ***	1.71
	Plant protection products	17.77 ***	1.02
	Inorganic fertilizer	15.41 ***	0.86
	Organic fertilizer	2.51	−1.28
	Irrigation	24.13	10.75
HFIES	Crop rotation system	−2.4 ***	0.22
	Improved seeds	−3.38 ***	0.26
	Plant protection products	−3.26 ***	0.19
	Inorganic fertilizer	−2.91 ***	0.16
	Organic fertilizer	0.55	0.41
	Irrigation	−3.63 **	1.63

*** Significant at 1% level, ** Significant at 5% level. Source: Authors' conception.

3.3.1. Second Stage of MESR for HFCS and HFIES

Results in the first part of Table 5 show that all CSAP combinations can potentially increase the HFCS for both the adopters and non-adopters. For instance, households who have adopted a three-CSAP combination would notice a significant improvement in their food consumption score (141.03%) followed by the two-CSAP-combination adopters (101.43%) and the single-CSAP adopters (51.28%). The non-adopters would also have an approximately similar benefit had they adopted these practice combinations. Our findings are consistent with the results of [35,87], wherein they found that farmers who adopted many CSAPs are more food-secure than their counterparts who did not.

Moreover, the HFIES level decreased compared to their pairs who did not adopt CSAPs. The decrement would reach 24.75%, 72%, and 68.13% for one-, two-, and three-CSAP combinations, respectively. Overall, farmers who adopted more CSAPs saw their food consumption score (FCS) increase, while their food insecurity experience scale (FIES) considerably decreased. These results corroborate the findings of [42,65,70,88], where it was revealed that rural households with one climate coping strategy at their farms have lower food security levels than households with two or more adopted practices.

3.3.2. Second Stage of METE for HFCS and HFIES

Multinomial endogenous treatment effect results for the effect of CSAP adoption on HFCS are shown in Table 6.

For the robustness check, HFCS classification is estimated under the assumptions of exogenous (i.e., columns 1–3 of Table 6) and endogenous (i.e., columns 4–6 of Table 6) adoption decisions of CSAPs. The results under exogenous assumptions show that adopting CSAPs significantly increases food consumption probability.

Nonetheless, since the endogenous outcomes take into consideration the unobservable components, we concentrate our discussion on these. Results in Table 6 show that adopting one, two, and three CSAPs has the likelihood to increase the probability of acceptable food consumption by 94%, 88%, and 101%, respectively (Table 6, column 6).

The factor loading coefficient λ_1 is estimated to be positive in the "acceptable food consumption" equation. The significantly positive factor loading coefficients imply that the unobserved factors that increase the probability of adopting one CSAP lead to higher food consumption relative to that of the randomly chosen number of adopted CSAPs, highlighting the significant unfavorable selection of unobservable factors into the number of adopted CSAPs.

Additionally, adopting one CSAP reduces the probability of rural household severe food insecurity by 64%. Likewise, adopting two and three CSAPs will likely decrease food insecurity by up to 60% and 104%, respectively. The factor loading coefficient λ_1 is positive in the "severe food security" equation. The significantly positive factor loading coefficients highlight the negative but significant selection of unobservable factors into the number of adopted CSAPs, which shows that the unobserved factors that increase the likelihood of adopting one CSAP also cause lower food insecurity compared to that of the randomly chosen number of adopted CSAPs. However, negative factor loading coefficients imply that the unobserved factors that increase the probability of adopting two CSAPs lead to higher food insecurity relative to that of the randomly chosen number of adopted CSAPs, meaning there is a significant favorable selection of unobservable factors into the number of adopted CSAPs. The METE results are consistent with the MESR outcome; both estimates confirmed that the more CSAPs a farmer adopts, the more likely the farmer is to be food-secure.

3.4. Propensity Score Matching for HFCS and HFIES

Regarding CSAP influence, Table 7 reveals that adopting each CSAP is beneficial for improving food security. For instance, farmers who adopted a crop rotation system could improve their food consumption score by 14.34 points and reduce food insecurity by 2.4 points compared to their pairs who did not. Similarly, users of improved varieties could see their food consumption level improve by 21.33 points while their food insecurity status decreased by 3.38 points compared to non-users. Furthermore, adopting plant protection products and using inorganic fertilizer considerably improved adopters' food consumption, up to 17.77 and 15.41 points, and food insecurity could decrease by 3.26 and 2.91 points, respectively, as opposed to the farmers who did not adopt them. Finally, irrigation was likely to increase the users' food consumption level by 24.13 points and reduce food insecurity by 3.63.

Overall, the results are consistent with the MESR results (Table 5), meaning each of these CSAPs has a significantly positive and negative effect on the HFCS and HFIES, respectively. However, the effect is slightly higher when taken separately than together as a combination of practices.

Our results align with prior empirical studies, which found a positive effect of agricultural technology adoption on food security [38,39]. Similarly, a recent study in Nigeria has confirmed the first-order importance of technology adoption in crop yields and agricultural income increments [88].

This study has filled a huge gap in the existing literature; however, it has some limitations. We used a cross-sectional dataset; hence, our results may not have fully depicted the reality across regions and the long-term effects of CSAP adoption on food security. Therefore, we suggest that future studies consider a time series or panel datasets to have more accurate and real-time food insecurity results in the five administrative regions of Togo. Because of data availability constraints, this study failed to include a wide range of CSAPs and other food security indicators, such as the household dietary diversity score and food insecurity access scale used in previous studies [44,89], where the 24 h recall method was used during the interviews for data collection. Hence, future studies should include a wider number of CSAPs and food security indicators.

4. Conclusions

This study aims to determine the effect of CSAP adoption on household food security using household data from rural Togo. The findings indicate that CSAP adoption is highly effective in enhancing household food security and decreasing food insecurity. The multinomial endogenous switching regression reveals that adopting more CSAPs increases the household food consumption score, whereas it sharply reduces the food insecurity experience. On the other hand, the multinomial endogenous treatment effect model shows an increase in acceptable food consumption when the household adopts more CSAPs. Likewise, it decreases severe food insecurity. Furthermore, we also find that adopting a

single CSAP (crop rotation system, using improved varieties of seeds, plant protection products, inorganic fertilizers, organic fertilizer, and irrigation) positively and negatively affects food consumption and food insecurity, respectively.

Conclusively, our findings suggest that adopting more CSAPs has a higher and positive effect on food consumption while reducing food insecurity. One of the most sustainable ways to combat the negative effects of climate change is to adopt CSAPs. These agricultural practices would play a determinant role in crop yield increments, thereby capacitating farmers to possess enough food for both consumption and sale. They can then utilize the income made from sales to purchase additional necessary items to make a more balanced and nutrient-dense meal. However, the CSAP adoption process is often constrained by socio-demographic, socio-economic, and farm characteristic factors as highlighted in our study. Therefore, policy makers and food security advocates should promote public awareness of the benefits of using CSAPs. Additionally, there is a need to increase the ratio of extension agents to farmers to ease farmers' access to information, new agricultural technologies, and training programs. Similarly, more subsidies on inputs such as improved varieties of seeds, plant protection products, fertilizers, and irrigation equipment should be offered to facilitate their adoption. Likewise, the Togolese meteorological center should gather more accurate data on the meteorological factors to aid farmers in planning their farm activities; then, farmers may be able to attain food security and be less vulnerable to the effects of climate change.

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Appendix A

Table A1. Food groups for food consumption score (FCS) by World Food Program [58].

Food Item	Food Group	Weight
Cereals and tubers	Main staples	2
Pulses, beans, and nuts	Pulses	3
Dark green, leafy, and other vegetables	Vegetables	1
Fruits	Fruit	1
Meat, fish, seafood, poultry, and eggs	Meat/Fish	4
Milk and dairy products	Milk	4
Sugar, honey, and sugar-related products	Sugar	0.5
Oil	Oil	0.5
Spices, tea, coffee, salt, fish power, and small amounts of milk for tea	Condiments	0

Table A2. Questions for food insecurity experience scale (FIES) by the FAO-Voice of the Hungry [61].

	Questions	Assumed Severity of FI
	During the Last 12 Months, Was There Any Time When, Because of a Lack of Money or Other Resources. . .	
Q1	You were worried you would run out of food?	Mild
Q2	You were unable to eat healthy and nutritious food?	Mild
Q3	You ate only a few kinds of foods?	Mild
Q4	You had to skip a meal?	Moderate
Q5	You ate less than you thought you should?	Moderate
Q6	Your household ran out of food?	Moderate
Q7	You were hungry but did not eat?	Severe
Q8	You went without eating for a whole day?	Severe

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