What Impact Does the Uptake of Climate-Smart Agricultural Practices have on Rural Household Income? Evidence from Nigeria

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Abstract. Recent studies have verified the importance of adopting CSA practices to reduce greenhouse gases (GHGs), combat climate change, and boost food security and farmers welfare. However, there have been few studies that have examined the causal impact of CSA practices on household income. This paper assesses the impact of adoption of CSA practices on farming households' income in Northern Nigeria. Our sample consists of cross-sectional data of 480 (160 adopters and 320 non-adopters of CSA) rural farming households selected using randomize control trial (RCT) from three Northern States in Nigeria. This study employed propensity score matching (PSM) to establish the causal effect of adoption of CSA on households' income while inverse probability-weighted regression adjustment (IPWRA) was used to controlled for selection bias that may arise from both observed and unobserved factors. We found that, age, education, farm size, access to extension, membership of association, and access to climatic information are positive and statistically significant influencing adoption of CSA practices among farming households. The empirical findings revealed that adoption significantly impacts the farming households' income across the two estimators used. This highlights the importance of promoting adoption of CSA practices among rural farming households. Our findings emphasize that enlightenment campaign on CSA practices, access to extension and climate information, education of farming households, the size of farmland cultivated and group formation should be promoted in order to scale up its adoption and increase households' income.

Keywords: Adoption, Climate-Smart Agriculture, Matching technique, Household income, Rural, Practices.

1. Introduction

Africa's growth and development hinge heavily on agriculture, but climate change might disrupt indigenous markets, dragging economic expansion, and accelerate risk for agricultural investment. The proof for climate change is now relatively strong and satisfying [1]. Agriculture depends largely on the

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climate. Because weather varies, so do the relative productivity of the seasons, which supports variation in the world's food markets and decides where farming is located. Global hunger is anticipated to rise by 20% by 2050 due to the likely negative effects of climate change on farm productivity and farmers' livelihood [2-4]. Farming households in evolving nations and communities that have insufficient capacity for climate adaption are most at threat. Rich nations aren't vulnerable to the effects of climate change. Smallholder farmers are particularly susceptible to the effects of climate change in developing countries [5]. Numerous rural farmers would lose their livelihoods if climate change were left unaddressed due to its effects on agriculture [6]. Climate change laterally lowers agricultural productions, which reduces farmer earnings. African farmers are particularly vulnerable to the effects of climate change and variability due to a number of factors, including a lack of land for farming activities, low adaptive capacity of farmers, and current climate-related stressors, similar as drought, floods, high temperature, and rainfall variability. Due to this, smallholder farmers' and their households' agricultural production is persistently poor, and the food system has not experienced a meaningful transition that would reduce household vulnerability and ameliorate food security and livelihood [7].
Rapid action is demanded to address the growing climate disaster on two crucial fronts (1) slashing greenhouse gas emissions; and (2) removing carbon dioxide from the atmosphere and storing it safely for the long term [8]. Adoption of innovative farming approaches that are resilient to climatic variability has been encouraged over the times, especially among smallholder farmers who make up the majority of farmers and are the most vulnerable, in order to sustain agriculture and farm productivity in light of these challenges. Climate smart agriculture (CSA) practices are one of them. Adopting climate-smart agricultural (CSA) practices including using organic manure, acquiring crop insurance, and using irrigation approaches could help reduce the impact of climate change on agriculture. One of the many advantages of using climate-smart agriculture (CSA) practices is that they can help farmers quadruple their income. In order to help farmers, acclimatize to climate change, climate smart farming is a collection of micro-level soil and water conservation strategies including planting and agroforestry. Many recent studies have demonstrated the present efficacy and, in some cases, the desire of farmers in locations like Ethiopia, Peru, and Malawi to embrace CSA practices [9-11].
According to Cramer [12], CSAs can help agricultural systems adapt to climate change by reducing greenhouse gas emissions. Researchers in sub-Saharan African countries have assessed the causes of the low capacity of smallholder farmers to adapt to climate change [9, 13], as well as how climate stressors affect public food security, household welfare, and development goals [14]. Still, there have been limited studies that have examined the effects of climate change on household income in the region. For instance, there's inadequate evidence proving whether or not smallholder farmers in Africa south of the Sahara adopting CSA increases their profit [15]. To give policymakers and development professionals with pertinent data, further study is still needed on the relationship between CSA practices, farm productivity, and household income. As a result, the impact of climate smart agricultural (CSA) practices on rural farming household income in Northern Nigeria was examined in this paper. We also examine the rate of CSA practice adoption as well as the variables affecting CSA adoption among rural agriculture households. This study adds to the limited body of literature on the influence of CSA practices adoption in the context of climate change adaption and its impact on the outcome variable (household income). It's expected that the implementation of CSA approaches will sustainably boost agricultural output and earnings from crops, livestock, and fish without having a negative impact on the environment [16].

2. Literature Review

A significant source of greenhouse gases (GHGs) that affect climate change and the greenhouse effect is agriculture. Still, the effects of climate change on agricultural production are far- reaching and could pose a future danger to food security. A series of practices known as climate smart agriculture (CSA) aim to reduce greenhouse gas emissions while improving resource effectiveness on farms. An

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increasing body of literature has stressed the significance of CSA implementation on a global scale [17-19]. Many studies have tried, at the household level, to interpret, using a variety of approaches, the factors that impact the adoption of CSA conditioning as well as their effects on household life. Wekesa et al. [20] used factor analysis to discover that gender, farm size, and the value of productive assets all had an impact on the adoption of CSA practices in Kenya, with the impact of adoption being higher in households that enforced further CSA approaches. Also, it has been discovered that some of the factors impacting the choice of CSA techniques employed include proximity to the market and local extension center, weather fluctuation, education, and labour [21]. In Southern Africa, [22] discovered that multiple innovation adoption is driven by household land size, access to financing, income, and information. In a different study, [23] examined the effects of multi-season cropping systems and discovered that, in comparison to single- season cropping systems, multi-season cropping systems produce larger yields, generate greater crop proceeds, and are less susceptible to rainfall variability. Amadu et al. [9] reported that the implementation of CSA approaches resulted in a 53% improvement in maize yield in Malawi using an endogenous switching regression model and control function methodology. According to [24], using CSA measures that are both adaptive and mitigating raises rice yield and net income. However, [25]'s investigation of the effects of CSA practices on livelihood outcomes using matching approaches and simultaneous equations showed that the adoption of several stress-tolerant crops increases household income, which in turn promotes the accumulation of household assets. Makate et al. [22] discovered that the simultaneous adoption of conservation agriculture, stress- adapted legume varieties, and drought-tolerant maize has larger benefits on production and income than when each is taken into account independently in the southern African region. Also, [26] used Propensity Score Matching and a semi-parametric local instrumental variable version of the generalized Roy model to estimate the effects of row planting as a climate wise agriculture practice on the welfare of rural households in Ethiopia. They discovered that the use of row planting technology significantly and favourably affects crop yields per hectare and per capita consumption.

3. Methodology

3.1. Study Area

The study was conducted in Northern region of Nigeria. Our study covered Bauchi State in Northeast, Benue State in Northcentral, and Kebbi State in Northwest. These areas were randomly chosen from each of the three zone in the region. Bauchi State consists of twenty Local Government Areas (LGAs). The State occupies a total land area of 49,119 km^2 (18,965 sq mi) representing about 5.3% of Nigeria's total land mass and is located on the coordinates 11° east. 10°30′N 10°00′E. The state is bordered by seven states, Kano and Jigawa to the north, Taraba and Plateau to the south, Gombe and Yobe to the east and Kaduna to the west. Benue State lies within the lower river Benue trough in the middle belt region of Nigeria. Its geographic coordinates are longitude 7° 47' and 10° 0' East. Latitude 6° 25' and 8° 8' North; and shares boundaries with five other states namely: Nasarawa State to the north, Taraba State to the east, Cross-River State to the south, Enugu State to the south-west and Kogi State to the west. Benue State consists of twenty-three (23) Local Government Areas and its referred to as the nation's food basket because over 75% of the state engage in farming. While Kebbi state lies on the coordinates 11°30′N 4°00′E, it has a total of 21 Local Government areas. Agriculture remains the main occupation of the people especially in rural areas, Crops produced are mainly grains; animal rearing and fishing are also common. However, all the selected states are predominantly agrarians and rich in agricultural produce which include Yam, Rice, Beans, Sweet-potato, Maize, Soybean, Sorghum, Millet, Sesame, tomato, vegetables etc.

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3.2. Data and Sampling Technique

Our study used a cross-sectional survey data from rural farming households and selected through a multi-stage random sampling method. The first stage involved a purposive selection of one state from each of the three regions in Northern Nigeria who are predominantly agrarian state. They include Bauchi (Northeast), Benue (Northcentral), and Kebbi (Northwest). At stage two; 25% of local government areas (LGAs) were randomly selected from 20 LGAs in Bauchi state, 23 LGAs from Benue State, and 21 LGAS from Kebbi State making a total of approximately 16 LGAs (i.e., 5 from Bauchi, 6 from Benue, and 5 from Kebbi states). The list of rural farming households was retrieved from Agriculture Department of respective LGAs selected. In stage three; 2 rural farming households from each of the sampled LGAs were randomly selected, making 32 rural farming households for the study. Since we are interested in evaluating the causal effect, we adopted a randomized controlled experiment by allocating farming households in to "CSA adopters" (treatment group) and "non-adopters" (control group) at the fourth stage. And lastly, a random selection of 5 CSA adopters and 10 non-adopters from each of the selected farming households giving a total of 480 respondents (160-adopters and 320 non-adopters) were sampled for the study. We collected data using a structured questionnaire that was deployed on electronic Android Tablet software (surveybe). The survey questionnaire was sectionalized according to the study's objectives. From the respondents, data on socioeconomic characteristics, production and agronomic/climate smart agriculture techniques, factors influencing CSA adoption, decision to adopt CSA practices, and institutional characteristics were gathered. Respondents were required to sign a consent form before answering the enumerators' questions. If they were uncomfortable at any point during the survey, all participants were encouraged to end the survey. We applied Propensity Score Matching (PSM) and Inverse Probability-weighted Regression Adjustment (IPWRA) to our data to ascertain the causal impact of CSA adoption on rural farming household income. By aggregating the conditional probability of CSA adoption given pre-treatment characteristics, PSM does this by pairing rural farming households that embraced CSA practices with one or more non-adopters with equivalent observable attributes. The IPWRA estimator was used to correct the selection bias and misspecification that plagued the PSM because IPWRA combines regression and propensity score approaches to create some robustness against misspecification in the PSM model [27-29].

3.3. Empirical Estimation Methods

We begin our estimation with logit regression model to identify the determinants for adoption CSA practices for a pooled sample of farming households. Regression model is, in fact, one of the most commonly employed statistical techniques in practice. Assuming a linear relationship exists between a dependent variable Y and an independent variable X, the linear model is mathematically expressed as follows:

$$Y = \alpha F + \beta X + \varepsilon \quad (1)$$

From equation (1), dependent variable Y represent the natural log of farming household income (measure in Naira), F indicates dummy (1=adoption, 0=otherwise); X represent a vector of control variables; α and β are parameters to be estimated (*i.e.,* α indicates the value of Y when all vales of the explanatory variables are zero and β parameter indicates the average change in Y that is associated with a unit change in X, whilst controlling for the other explanatory variables in the model); and ε is the statistical error term; that is, it is a random variable that accounts for the failure of the model to fit the data exactly. The vector X includes the covariates such as age, marital status, education, household size, farming experience, farm size, labour, farm yield, access to extension services and credit, access to varietal information, and land tenure system.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, i = 1,2, \ldots\ldots, n \quad (2)$$

The relationship between causal and effect (causality) is an important issue in economics and other related fields. One important and commonly employed measure of causality is the average treatment

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effect (ATE) for a binary policy or treatment on a scalar outcome, which is the mean outcome difference between the treatment and control groups. Economic evaluations in many observational studies often require identification and estimation of ATEs, which is challenging because randomized experiments cannot always be implemented. Using the Average Treatment Effect (ATE) on the treated populations, we looked at how the adoption of CSA techniques affected household income in our study. The counterfactual impact of policies and programs is extensively studied in the literature using the ATET estimate approach [30-35]. This method entails evaluating the average difference between rural households that implemented CSA practices ($In = 1$) and those that did not ($In = 0$) in terms of the outcome variable (income). This suggests that the causal effect of the households' choice to adopt CSA practices is equal to the variation in potential outcomes between the treated (adopters) group, Y_1, and the control (non-adopters) group, Y_0. In practice, a model (Probit or Logit for binary treatment) is estimated in which enrollment in a treatment or program is explained by a number of pre-treatment variables. Predictions from this estimation are then used to construct the propensity score, which ranges from 0 to 1. The Propensity Score Matching (PSM) methodology is the most widely used method that does not rely on the assumptions of distributional form or covariate exogeneity. PSM is frequently used in literature [36-39]. PSM can be implemented using a variety of methods, such as Nearest Neighbor (NN), Caliper or Radius, Stratification or Interval, Kernel-based Matching (KBM), and Local Linear Matching [40]. In our investigation, the Nearest Neighbor Matching (NNM) and Kernel-based matching (KBM) are however employed.

Regarding the application of the PSM, there are two key assumptions. The first one is known as the *unconfoundedness assumption* or *conditional independence assumption* [41]. Consequently, any systematic difference in outcomes between the treatment and comparison groups with the same values for characteristic X can be attributed to the treatment if the treatment satisfies the requirement of being exogenous. The second presumption, known as *common support or overlap*, guarantees that individual or groups who have similar values for characteristic X have a positive likelihood of both adopting and not adopting CSA activities [42]. It is possible to compare similar units thanks to the overlap condition. The average treatment effect on the treated (ATT), one of the most important evaluation parameters that primarily emphasizes the effects on those desired treatment observations (CSA adopters), is thus evaluated after matching. The difference between the expected outcome values with and without treatment for the household that has adopted CSA practices is known as the ATT [43]. It is written as:

$$\tau_{ATT} = E\left(\frac{\tau}{Y_i} = 1\right) = E\left[\frac{In_i(1)}{Y_i} = 1\right] - E\left[\frac{In_i(0)}{Y_i} = 1\right] \quad (3)$$

where $In_i(1)$ = the potential outcomes when the *ith* household that adopted CSA practices; $In_i(0)$ = the potential outcomes of the *ith* household when they do not adopt CSA practices; Y_i represents CSA adoption; 1= adopted and 0 = otherwise. The mean difference between the observable characteristics and control is written as:

$$E\left[\frac{In_i(1)}{Y_i} = 1\right] - E\left[\frac{In_i(0)}{Y_i} = 0\right] = \tau_{ATT} + \varepsilon \quad (4)$$

where ε is the selection bias,

$$\varepsilon = E\left[\frac{In_i(1)}{Y_i} = 1\right] - E\left[\frac{In_i(0)}{Y_i} = 0\right] \quad (5)$$

The true parameter τ_{ATT} is only identified if the treatment and control outcome is the same in the absence of adoption of CSA practices. It is specified as follows:

$$E\left[\frac{In_i(1)}{Y_i} = 1\right] - E\left[\frac{In_i(0)}{Y_i} = 0\right] \quad (6)$$

There are several methods available to verify covariate balancing throughout the matching process. When comparing means, a two-sample t-test can be used to determine whether or not there are significant variations in covariate means between the treated and comparison groups [41]. As a general rule, there shouldn't be any noticeable mean differences after matching. In order to verify balancing, Sianesi [44] suggests comparing Pseudo-R^2 before and after matching. The Pseudo-R^2 shows how well the covariates account for the likelihood of being included in the treatment. After matching, the Pseudo-R^2 must be very low to show that the matching procedure was successful. Furthermore, matching should not be rejected until the Likelihood Ratio (LR) test on the joint significance of all covariates in the (Logit) model is rejected [43]. The estimated results may be biased if the propensity score model is misspecified, which is another obvious difficulty with the implementation of PSM [45, 27]. We used the Inverse Probability Weighted Regression Adjustment (IPWRA) method, a PSM version, to solve the problem envisioned in the PSM approach. The IPWRA method offers a reliable remedy for the possibly biased estimations (ATET) that may result from the occurrence of misspecification in the propensity score models [27]. We can consistently estimate the treatment effect parameters using the IPWRA approach as long as we correctly define only one of the two models (either the outcome or treatment). This property, termed as a "doubly robust property," is achieved by this model by combining regression and propensity score approaches [27]. Because each rural farming household is only observed in the potential outcome, the IPWRA estimators use probability weights to produce outcome regression parameters that take the missing data problem into account. The treatment-level means of the anticipated outcomes are then computed using the adjusted outcome regression parameters. The estimations of the treatment effects are derived from the contrasts between these means. We estimated the propensity score model in accordance with Wooldridge [27] to get the propensity score $p(x_i, \hat{\delta})$, and then we used the regression model, whereby we weighted by the inverse probability. In this study, we used inverse probability-weighted least squares to estimate (β_i, φ_i) using a linear outcome function, which may be written as follows:

$$\min_{\beta_0 \varphi_0} \sum_{i=1}^{k} (\gamma_i - \beta_0 - \varphi_0 x_i) / p(x_i, \hat{\delta}) \; if Y_i = 0 \quad (7)$$

$$\min_{\beta_1 \varphi_1} \sum_{i=1}^{k} (\gamma_i - \beta_1 - \varphi_1 x_i) / p(x_i, \hat{\delta}) \; if Y_i = 1 \quad (8)$$

where the propensity score $p(x_i, \hat{\delta})$ is the estimated conditional probability of treatment given the household's observable characteristics; β_1, β_0, φ_0, and φ_1 are the parameters to be estimated for the adopters and non-adopters of CSA practices, and r_i is the potential outcome variable. The ATET is then estimated as the average difference between Equation (7) and Equation (8) as follows:

$$ATET_{ipwra} = K_Y^{-1} \sum_{i=1}^{K_T} [(\widehat{\beta_\iota} - \widehat{\varphi_1 x_\iota}) - (\widehat{\beta_0} - \widehat{\varphi_0 x_\iota})] \quad (9)$$

where $(\widehat{\beta_\iota}, \widehat{\beta_0})$ are the estimated inverse probability-weighted parameters for $Y = 0$ and $Y = 1$, respectively; K_L is the number of treated households in the sample. Differences between matched treatment and control cases are determined for the outcome variable in the final PSM step (log of net farming household income). The average treatment effect, which measures the difference in household income between CSA adopters and non-adopters, is the sum of these changes.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 show the descriptive statistics of the important variables of interest including outcome variable and other covariates based on the adoption status of farming households. Our data also presents the difference in means (of outcome and all covariates) between CSA adopters and non-adopters. The mean difference is are statistically significant for our outcome (income) indicator. For instance, the mean household income for CSA adopters was ₦830,500.00 while only ₦480,056.25 of farming households who did not adopt CSA practices. The difference in the mean household income between the two groups is statistically significant at 1%. On average, households who adopted CSA practices earn more income, better farm output and resilient with adaptive capacity to changing climate and tend have improved livelihood than those who did not adopt CSA practices. Similar to our results, Amadu et al. [9] reported that the implementation of CSA methods resulted in a 53% improvement in maize yield in Malawi, and Liang et al. [24], opined that using CSA measures that are both adaptive and mitigating raises rice yield and net income. As shown in Table 1, the mean age of the respondents in the whole sample was 50.14years. While comparing the respondents age between CSA adopters (55.74years) and non-adopters (47.34years), we found significant difference between the two categories at 1%. Both CSA adopters and non-adopters are older and active with adequate farming experience in agriculture. This supports the recent studies by Varma [46], that experience in terms of age is found to positively affect adoption of a System of Rice Intensification (SRI) in India. Results show that most of the farming household heads are male (90.0%) and married. Also, most of the respondents are relatively literate with junior secondary education, with an average of 8.04years of schooling. This could imply that there is transition to higher education among the rural farming households, and that's why most them had completed basic education. Table 1 show that the average household size is about 17.49 members for the full sample. In comparison household size between CSA adopters (18.54 members) and non-adopters (16.97 members), we observed a statistically 1% significant difference between the two groups. The large number of household size as reported both CSA adopters and non-adopters would provide labour for implementation of CSA practices especially for the farming households that rely heavily on family labour. Also, the mean total farm size of farming households for the whole sample was 4.76ha. However, a significant difference existed between the size of farm operated by CSA adopters (5.89ha) and non-adopters (4.19ha) at 1% level. The average farming experience for the full sample was 25.66years. On comparing the farming experience between CSA adopters (27.56years) and non-adopters (24.71years), there is significant difference between the two groups at 10%. Only 24% of the rural farming households have access to extension services for the whole sample. While comparing access to extension services between CSA adopters (43%) and non-adopters (15%), we also observe a significant difference between the two categories. Our finding implies that farming household with access to extension services, would have a better information on climate change and its related adaptation and mitigation measures. Similar to our findings, [22] found a positive association between access to information and adoption of multiple CSA innovations in Southern Africa. Results in Table 1 further show that the mean differences are statistically significant between CSA adopters (38%) and non-adopters (16%) in access to credit facilities. This implies that rural farming who have access to credit have better chance to adopt and implement CSA practices than those who did not. Also, about 69% and 58% of CSA adopters and non-adopters, respectively, belongs to one farmers' association or other. A significant difference exists between the two groups in term of membership of farmers' association at 1%. This suggests that being a member of a farmers' association can influence the adoption of CSA.

Table 1. Descriptive statistics by treatment.

Variables	**Adopters (n=160)**		**Non-adopters (n=320)**		**Mean Difference (1-2)**	***t*-value**	***p*-value**	**Full sample (N=480)**	
	Mean (1)	**S.D.**	**Mean (2)**	**S.D.**				**Mean**	**S.D.**
Outcome variable									
Household income (Naira)	830,500.00	297,143.211	480,056.25	66,093.242	350,443.750	20.143	0.000***	596,870.83	244,061.297
Other covariates									
Age of farmer (years)	55.74	12.945	47.34	14.538	8.400	6.184	0.001***	50.14	14.563
Sex (1=male, 0=otherw	0.90	0.301	0.96	0.190	-0.063	-2.770	0.000***	0.94	0.235

Variables	**Adopters (n=160)**		**Non-adopters (n=320)**		**Mean Difference (1-2)**	***t*-value**	***p*-value**	**Full sample (N=480)**	
	Mean (1)	**S.D.**	**Mean (2)**	**S.D.**				**Mean**	**S.D.**
ise)									
Marital status (1=married, 0=otherwise)	1.11	0.309	1.28	0.452	-0.178	-4.488	0.000***	1.23	0.418
Education (Years of schooling)	10.14	2.753	6.99	3.811	0.038	0.432	0.007***	8.04	3.793
Household size (number)	18.54	12.588	16.97	6.914	1.578	1.772	0.000***	17.49	9.219
Farm size (hectare)	5.89	2.505	4.19	2.045	1.694	7.920	0.001***	4.76	2.347
Farming experience (years)	27.56	10.105	24.71	11.243	2.850	2.706	0.165*	25.66	10.949
Access to extension (1=yes, 0=otherwise)	0.43	0.497	0.15	0.358	0.281	7.098	0.000***	0.24	0.43
Access to credit (1=yes, 0=otherwise)	0.38	0.486	0.16	0.364	0.219	5.533	0.000***	0.23	0.421
Membership of farmers' union (1=yes, 0=otherwise)	0.69	0.465	0.58	0.494	0.103	2.199	0.000***	0.62	0.486
Access to climate information (1=yes, 0=otherwise)	0.76	0.427	0.43	0.496	0.334	7.288	0.000***	0.54	0.499
Participation in social activities (1=yes, 0=otherwise)	0.96	0.191	0.68	0.468	0.284	7.384	0.000***	0.77	0.419
Number of years'	47.98	18.549	42.45	16.379	5.525	3.331	0.160*	44.29	17.311

Variables	Adopters (n=160)		Non-adopters (n=320)		Mean Difference (1-2)	t-value	p-value	Full sample (N=480)	
	Mean (1)	S.D.	Mean (2)	S.D.				Mean	S.D.
resident in the village									

The t-test was carried out to test for difference in outcome and other covariates between CSA adopters and non-adopters;
*, **, ***Significant at 10, 5 and 1%, respectively.
Source: Field survey (2022)

4.2. Factors Influencing Adoption of CSA Practices Among Rural Farming Households

Table 2 presents the results of logistic model that determines the factors influencing the probability of CSA adoption among rural farming households. We estimated the average marginal effect after logistics regression of adoption of CSA. The average marginal effects indicate the change in the likelihood of adoption of CSA given a unit change in the explanatory variable. One possible explanation of using marginal effect is that, it seems to be more robust than the coefficient at describing the size of a probability model. Our justification follows [47], that the sign and size of the marginal effect show the direction and strength of the possible influence of covariates on farmers' decisions to adopt or not.

Table 2. Logistic estimates of the factors influencing adoption of CSA.

Variable	Logistic regression		Marginal effects	
	Coefficient	Std. error	dy/dx	Std. error
Age of farmer (years)	0.029**	0.012	0.008**	0.003
Sex (1=male, 0=otherwise)	-1.328	0.324	-0.474	0.118
Marital status (1=married, 0=otherwise)	-0.211	0.345	-0.057	0.092
Education (Years of schooling)	0.303***	0.038	0.081***	0.009
Household size (number)	-0.014	0.012	-0.004	0.003
Farm size (hectare)	0.148**	0.059	0.039**	0.016
Farming experience (years)	-0.004	0.011	-0.001	0.003
Access to extension (1=yes, 0=otherwise)	0.684***	0.189	0.209***	0.065
Access to credit (1=yes, 0=otherwise)	0.044	0.217	0.012	0.059
Membership of farmers' union (1=yes, 0=otherwise)	0.454**	0.21	0.127**	0.061
Access to climatic information (1=yes, 0=otherwise)	0.719***	0.183	0.187***	0.046
Participation in social activities (1=yes, 0=otherwise)	1.531	0.268	0.274	0.033
Number of years' resident in the village	2.50E+04	0.006	6.87E+05	0.002
Constant	0.463	0.019	0.038	0.005
Log likelihood = -163.17843; Pseudo R^2 = 0.4659; LR chi^2 (13) = 284.7; Prob>chi^2 = 0.000; Observation = 480				

*, ** and *** represent, respectively, statistical significance at the 0.1, 0.05, and 0.01 level.
Source: Author's computation (2022).

Results in Table 2 show that six factors were found to significantly influence the adoption of CSA among rural farming households in the study area. These explanatory factors are age, education, farm size, access to extension, membership of association, and access to climate information. Age size is positively associated with the probability of CSA adoption. The age is expected to signify experience and sound judgment. A possible explanation for this is that older farming household heads with longer farming experience are more likely to adopt CSA than the younger ones. That is, year increase in the age of the farming household heads increased the probability of adopting CSA practices by 0.029 unit. This is consistent with the finding of Yirga et al. [48] on the adoption and diffusion of sustainable intensification practices for maize-legume production in Ethiopia. The level education of farming household heads is positively associated with the probability of CSA adoption in the study area. One possible explanation to this is that a literate farming household recognized the benefits of adoption to influence their farm productivity and income level. This is consistent with the findings of [49] found that adoption was significantly affected by educational status, farming experience, farm income, membership of an agricultural association or group, farmland size, contact with agricultural extension, and exposure to media South Africa. Size of farm land cultivated is positively associated with the probability of CSA adoption. The probability of adopting CSA practices among rural farming households increased by 14.8% for every unit increase in the farm size. This implies that farming households with large farm size are more like to adopt CSA practices than those with small farm size. Also, in corroboration of our findings, [22] found that size of land owned by a farmer is positively associated with adoption of multiple Climate Smart Agricultural (CSA) innovations in Southern Africa, and [50] observed positive relationship between farm size and adoption of improved agricultural technology in Ethiopia. Access to extension services was positively related to the decision of the farming household to adopt CSA practices. Our finding implies that farming household with access to extension services, would have a better information on climate change and its related adaptation and mitigation measures. Similar to our findings, [22] found a positive association between access to information and adoption of multiple CSA innovations in Southern Africa. Membership of farmers' association positively associated with the CSA adoption in the study area. A possible explanation of this is that farming households who are members of farmers association or cooperative have better chance of adopting CSA practices than non-members, this is because members share variety of information during their meetings including agricultural technologies. Access to climate information increases the probability of a farming household adopting CSA practices thus, implying that access to weather forecast and information provide farmers with the adaptive capacity and build resilience against the changing climate. This is consistent with findings documented by [22], that access to information is found to be positively associated with adoption of multiple CSA innovations in Southern Africa.

4.3. Estimation of the Impact of CSA Practices on Outcome Variable (Household Income)

We estimated the causal effect of adoption of CSA practices on farming household income using the Propensity Score Matching (PSM). Our estimation of Propensity Score Matching (PSM) was carried out using the Nearest Neighbour Matching (NNM) and Kernel-based Matching (KBM). Before we carried out the PSM analysis, various diagnostic tests were conducted to guarantee that the matching procedure was consistent and reliable. And to ascertain that the covariates included in the model did not differ, the common support condition was evaluated after obtaining the propensity score.

Table 3. Distribution of sampled farming households by estimated propensity score.

Sample	Observation	Mean	Standard Deviation	Minimum	Maximum
Total	480	0.336	0.472	0.039	0.944
Treatment	162	0.634	0.413	0.031	0.989
Control	320	0.285	0.651	0.026	0.833

Source: Author's computation (2022)

Results in Table 3 show that propensity scores of CSA adopters range from 0.039 to 0.944 while among non-adopters, the propensity scores range from 0.026 to 0.833. The probability of total farming households sampled was 0.336 which implies that the entire sample population had 33.6% chance of adopting CSA practices with respect to the outcome variable (household income). The common support region lies between 0.026 and 0.833. In this case, farming households whose estimated propensity scores lies below 0.026 and above 0.833 are excluded for the matching exercise. The propensity scores of CSA adopters (treated) and non-adopters (untreated) further showed that 98.8% of the farming households' profiles were matched while 1.2% of the profiles were discarded from the analysis (Table 4) suggesting the fitness of the model. However, if the number is too large, there may be concerns about whether the estimated effect on the remaining samples can be viewed as representative. Accordingly, the proportion of individuals lost in this case is negligible and therefore there is no violation of the assumption of common support. Figure 1 presents the common support graph that show comparable characteristics between the treatment (CSA adopters) and control (non-adopters) groups before and after matching. The common support condition was imposed and the balancing property was satisfied in the estimated regression model. The density distribution of the propensity scores shows a good overlap between CSA adopters and non-adopters (Figure 1). This support the assertion of [42], that the importance of the common support graph is to improve the quality of the match by ensuring that matches are formed only when the distribution of the density of the propensity scores overlaps adopter and non-adopter observations.

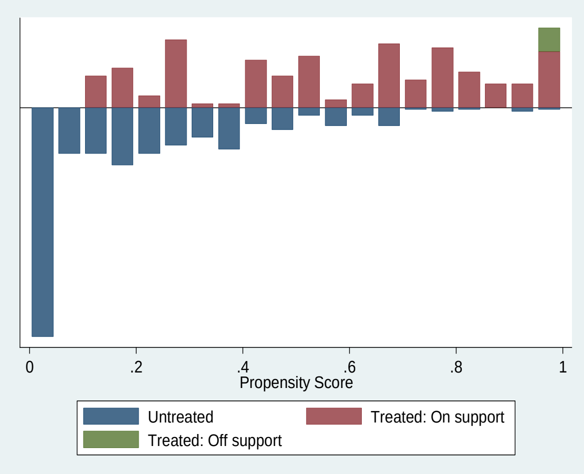

Figure 1. Propensity score distribution and common support region between treated and control cases with outcome variable (income). Source: Author's computation (2022).

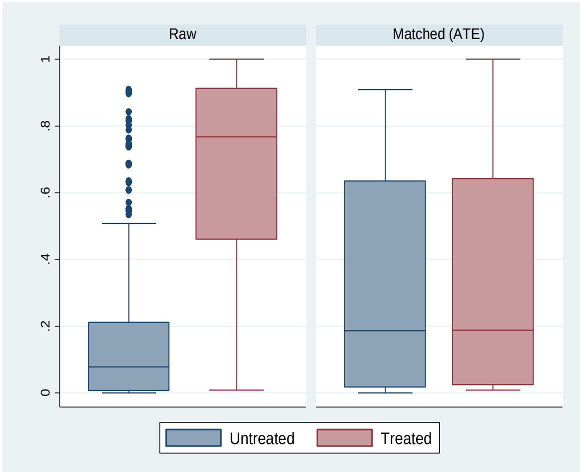

Figure 2. Propensity score distribution and balancing box plot between treated and control cases using Kernel-based matching for outcome variable (income). Source: Author's computation (2022)

Table 4. Distribution of propensity score matching outcome.

Treatment assignment	Off support	On support	Total
Untreated	0	320	320
Treated	6	154	160
Total	6	474	480

Source: Author's computation (2022)

Our selection of matching procedure was based on three independent criteria; standardize mean biased a t-test [41] and joint significance of covariates and pseudo R^2 [44]. Our estimation results suggest that all the matching methods produce similar results but kernel matching was the best algorithm (Figure 2). Kernel matching estimator with a bandwidth of 0.01 satisfied the selection criterion and so was used alongside nearest neighbour matching to estimate average treatment effect (ATE), average treatment effect on the treated (ATET) and average treatment effect on the untreated (ATU) which can be seen in Table 7. In addition, we further carried out covariates balancing test for the matching procedure to ensure both treatment (adopters) and control (non-adopters) of CSA practices are similar under the same characteristics and the quality of common support condition (Figure 1). Table 5 present the results of the covariates balancing property test. Our findings that show that none of the covariates is significant after matching, implying that our matching quality is satisfactory for all covariates used in the model. Therefore, both adopters and non-adopters of CSA practices exhibited similar characteristics of their covariates.

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Table 5. Test of equality of means of variables before and after matching

Variable	Unmatched Sample			Matched Sample			% Reduction Bias
	Adopters (Mean)	Non-adopters (Mean)	Diff: *p*-value	Adopters (Mean)	Non-adopters (Mean)	Diff: *p*-value	
Age of farmer (years)	55.74	47.34	0.000***	53.45	52.82	0.710	92.5
Sex (1=male, 0=otherwise)	0.90	0.96	0.006***	0.89	0.82	0.319	69.9
Marital status (1=married, 0=otherwise)	1.11	1.28	0.000***	1.12	1.07	0.214	70.00
Education (Years of schooling)	10.14	6.99	0.000***	9.50	9.96	0.131	85.4
Household size (number)	18.54	16.97	0.077**	16.87	17.5	0.532	60.3
Farm size (hectare)	5.89	4.19	0.000**	5.40	5.33	0.814	95.5
Farming experience (years)	27.56	24.71	0.007***	26.57	25.44	0.369	60.4
Access to extension (1=yes, 0=otherwise)	0.43	0.15	0.000***	0.35	0.34	0.897	97.3
Access to credit (1=yes, 0=otherwise)	0.38	0.16	0.000***	0.37	0.23	0.221	53.7
Membership of farmers' union (1=yes, 0=otherwise)	0.69	0.58	0.028**	0.72	0.55	0.205	62.8
Access to climate information (1=yes, 0=otherwise)	0.76	0.43	0.000***	0.76	0.63	0.302	63.5
Participation in social activities (1=yes, 0=otherwise)	0.96	0.68	0.000***	0.95	0.84	0.342	59.7
Number of years' resident in the village	47.98	42.45	0.001***	48.78	45.86	0.415	67.1

Source: Author’s computation (2022). Note: *, ** and *** represent, respectively, statistical significance at the 0.1, 0.05, and 0.01 level.

Results in Table 6 shows the overall covariates' balanced test before and after matching. Table 6 show a significant reduction in value of the Pseudo-R^2 from 0.792 (79.2%) before matching to 0.089 (8.9%) after matching. According [43] the low pseudo-R^2 after matching implies no systematic differences in the distribution of covariates between treated and untreated. Thus, our findings indicate that the matching procedure was able to identify a control group with similar observable characteristics as the treatment group. The likelihood ratio test *p*-values show that the joint significant was accepted for both the unmatched and matched samples (*p*-value = 0.000). Also, the standardized mean bias for overall covariates reduced from 59.0% before matching to 16.3% after matching. Our findings show that matching reduces bias by 81.6%. Therefore, the high reduction in total bias, the insignificant *p*-values of the likelihood ratio test for the matched samples, as well as reduced Pseudo-R^2, and a significant reduction in the mean standardized bias are indicative of successful balancing of the distribution of

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covariates between the adopters and non-adopters of CSA, hence we fail to reject the hypothesis that both groups have the same distribution in covariates after matching.

Table 6. Overall propensity score matching quality test.

Sample	Pseudo R^2	LR χ^2	p>(χ^2)	Mean Standard bias	Bias	Total % Bias reduction
Before matching	0.792	483.72	0.000***	59.0	192.0	
After matching	0.089	25.14	0.597	16.3	35.3	81.6

Source: Author's computation (2022). Note: ***significance level at 1%.

4.4. Impact of Adoption of CSA Practices on Outcome (Household Income) Variable

The estimates of the mean average treatment effect on the treated (ATT) for PSM using the two matching estimators (NNM and KBM) are presented in Table 7. Our PSM estimates show that adoption of CSA practices has a significant impact on farming households' income. Specifically, the PSM estimates showed that CSA adopters had increased income than the non-adopters. Both NNB and KBM algorithms show a positive and highly significant average treatment effect on the treated (ATT). The ATT for CSA adopters increased households' income by ₦505,299.50 using the NNM algorithm and by ₦384,521.50 in the Kernel-based matching (KBM) algorithm. The implication of these results is that adoption of CSA practices has tendency to increase household income by ₦505,299.50 and ₦384,521.50, respectively. Our result is consistent with earlier findings of [50] in eastern Ethiopia, who indicated improved income as result of adoption of improved agricultural technology; [51] in Tanzania, who indicated the positive income effect of adopting fertilizer micro-dosing and tied-ridge technologies; and, [52] and [53] in Ethiopia, who documented a positive income effect of adopting Sustainable Agricultural Practices, and improved seeds and fertilizer, respectively. The ATE for the entire sample population, that is, when picking any farming household at random, was ₦267,711.60 for the NNM algorithm and ₦217,041.90 for the KBM algorithm.

Table 7. Impact of CSA on farming households' income.

Matching method	Sample	Adopters	Non-adopters	Difference	Standard Error	T-stat
Nearest Neighbour Matching (NNM)	Unmatched	830,500.00	480,056.25	350,443.75	17,397.48	20.14***
	ATT	830,500.00	325,200.50	505,299.50	27,490.42	11.83**
	ATU	757,175.57	449,122.14	308,053.43		
	ATE			267,711.60		
Kernel-based Matching (KBM)	Unmatched	830,500.00	480,056.25	350,443.75	17,397.48	20.14***
	ATT	781,990.63	397,469.13	384,521.50	24,314.31	5.30**
	ATU	698,894.70	421,549.10	248,345.70		
	ATE			217,041.90		

Source: Authors, 2020. Note: *** and **imply significance at 1% and 5%, respectively.

Results in Table 8 represent the average treatment effect on the treated (ATT) using Inverse Probability-weighted Regression Adjustment (IPWRA) estimate. This is to address the PSM model misspecification. Our estimation shows a positive and strong significant relationship with the outcome (household income) variable. Table 8 show that adoption of CSA practices had increased farming household income by ₦477,481.20. A piece of vital evidence from the impact estimate (ATT) is the difference between PSM and IPWRA estimates. The PSM estimates roughly doubled the estimate from IPWRA. The increase in the PSM estimates might be due to its inability to control for unobserved factors associated with adoption of CSA practices, thus, over-estimating the impact and proving that failure to control for the unobservable bias could lead to erroneous policy recommendations.

Table 8. Results of average impact of adoption of CSA on farming households' income using IPWRA.

Sample	Coefficient	Robust Standard error
ATT	477,481.20***	5,921.04
ATE	353,018.80***	25,104.83

Source: Authors, 2020. Note: *** imply significance at 1% level.
IPWRA= Inverse Probability-weighted Regression Adjustment.

Conclusion

We draw our conclusion based on the findings of this study. We investigated the impact of adoption of CSA practices on farming household income using a randomize control design. We begin our estimations first, by adopting logistics regression model to determine factors influencing adoption of CSA practices among rural farming households; second, we employed Nearest to Neighbour Matching (NNM) and Kernel-based Matching (KBM) algorithms using Propensity Score Matching (PSM) estimation procedure to evaluate the causal effect of adoption of CSA on household income; and third, we used Inverse Probability-weighted Regression Adjustment (IPWRA) to correct the selection bias and misspecification that plagued the PSM. Our findings show that, age, education, farm size, access to extension, membership of association, and access to climatic information are positive and statistically significant influencing adoption of CSA practices among farming households. The empirical findings showed that the impact of adoption of CSA vary significantly across the two estimators (NNM and KNM), confirming that there is significant heterogeneity in our two matching algorithms of causal effect of adoption CSA on household income. Therefore, it is recommended that scaling up the adoption of CSA among farming household would ensure increased household income for farmers thereby, call for farm expansion. Enlightenment campaign on CSA practices, access to extension and climate information, education of farming households, group formation and the proportion of farmland cultivated should be promoted in order to increase the adoption of CSA and increase households' income.

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