



Research article

Adoption of soil and water conservation technology and its effect on the productivity of smallholder rice farmers in Southwest Nigeria

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ABSTRACT

This study estimated the effect of the adoption of soil and water conservation (SWC) on the productivity of 360 smallholder rice farmers in Southwest Nigeria. An endogenous switching regression model (ESRM) was employed to estimate the productivities of adopter and non-adopters of SWC. A doubly robust inverse-probability-weighted regression adjustment (IPWRA) was used as a credible remedy for potentially biased estimates of average treatment on the treated (ATT) and potential outcome mean (POM) of the endogenous treatment model. Significant variables, such as farmers' locations, gender, marital status, annual temperature, annual precipitation, log of fertiliser and membership in farm-based organisation (FBO), were factors influencing the adoption of SWC among smallholder rice farmers. Factors such as age, marital status, rice experience, farm size, formal education, access to extension and labour in man-days significantly influenced the rice productivity of smallholder farmers who adopted SWC technology, while location, marital status, rice experience, farm size, formal education, access to extension and labour in man-days were the determinants of rice productivity among smallholder farmers who did not adopt SWC technology. The result from the inverse-probability-weighted regression adjustment estimation indicates that the adoption of SWC technology to mitigate the adverse effects of climate change improves the productivity of rice in the study area. To ensure effective dissemination and the adoption of new conservation technologies, government and stakeholders in rice production could take the lead in promotion and dissemination in the initial stages and, in the process, create an enabling environment for the effective participation of other stakeholders in rice production.

1. Introduction

The degree of soil degradation in Sub-Saharan Africa (SSA) has been reported to be heavily linked to the inadequate adoption of proper soil management strategies, and to climatic conditions, among other factors (Sanginga and Woomer, 2009). Climate change poses a significant threat to the rate of soil erosion through various means, such as the drivers of rainfall, temperature and atmospheric concentrations of CO₂, which influence crop production and runoff, and which in turn affect erosion rates (Nearing et al., 2004; Izaurralde et al., 2011; Walthall et al., 2013). The intensity of CO₂ and frequency of rainfall are generally expected to have a positive relationship with crop production; however, the effect of rainfall and temperature from an intense storm and heat events could cause damage to crop seedlings in the early stages of growth (Bassu et al.,

2014). As a result of climate change, farmers may change planting and harvest dates, as well as the type of cultivars or crops produced due to changes in rainfall, temperature and soil moisture patterns (Pfeifer and Habeck, 2002; Southworth et al., 2002; Walthall et al., 2013).

Maintaining food security is of high importance to livelihood and this can be achieved through sustainable, high-yield crop production, particularly during a time of climate change. The application of soil management practices is necessary for the long-term sustainability of high crop yields, which promote soil function, soil quality, and soil health (Garbrecht et al., 2015). The effects of soil erosion on soil productivity occur gradually via the depletion from the soil of nutrients, fine soil particles, and water-holding capacity. The degradation of soil aggregate stability also increases the risks of crusting and increased runoff, which cause exposure of the soil. The exposure of the soil cover results in poor

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soil fertility owing to erosion (Hjelm and Dasori, 2012). Soil conservation practices (SWC) have proven effective in decreasing soil erosion and maintaining soil productivity (Garbrecht et al., 2015).

In Nigeria, agriculture is vastly reliant on rainfall, and a larger percentage of the sector is constituted by smallholder farmers who produce using local farming methods at a subsistence level. Moreover, the sub-standard state of infrastructure that aids agricultural production, in terms of hard physical amenities and soft service systems, is a major challenge to the performance of the sector (Obadih et al., 2016). These threats, together with the effects of climate change, are limitations to the growth of the agricultural sector in Nigeria. The projected climate change, which is predicted to elevate the magnitude and severity of climate-related risks, will have effects on the productivity of crops such as wheat, rice and sorghum (Elliott et al., 2014) and, of course, on food security as a whole.

Rice is one of the most important food crops, being a staple food for about half of the world's population (Lin et al., 2019). Rice production must be increased by about 60% to meet dietary needs by the year 2025 if it is to match the explosive increase in world population (Chiambo et al., 2019; Tripathi et al., 2019). Given the sensitivity of rice to climate change, particularly changes related to temperature increases (Darzi-Naftchali and Karandish, 2019) and extended drought periods (Yoshida et al., 2019), adapting to the future global demand for rice seems a difficult task. In addition, changes in the length of the growing period due to temperature increases will affect not only rice yield, but also will shift farming systems away from rice towards more suitable crops with adequate temperature optima (Korres et al., 2017).

Rice productivity is generally low in SSA countries, where most farmers are smallholders, and it is even lower for female farmers compared to their male counterparts. Studies have persistently identified a gap in agricultural productivity of 20%–30%, to the disadvantage of women, as an important barrier for the development of the agricultural sector in this region. The extent of the effect of climate change such as soil degradation on rice production depends on the adaptability of each location. The adoption of soil and water conservation (SWC) technology can greatly reduce the magnitude of effects on rice production under conditions of climate change.

Although several soil conservation technologies have been developed and promoted in the past decades, the rate of adoption of many recommended measures is still minimal, particularly in Nigeria (Rezvanfar et al., 2009; Amadu et al., 2020; Lasway et al., 2020). Therefore, it is no longer beneficial to neglect the effect of the depletion of soil and water resources that results in declining crop productivity, diminishing income and loss of resources. While previous studies (such as those by Ozor and Ebe, 2012; Asfaw and Neka, 2017; Olawuyi and Mushunje, 2019) have explored the determinants of SWC adoption, there are limited existing studies that have explored how the adoption of SWC technology could contribute to improved rice productivity in Nigeria. Thus, there is a strong need for the identification of the factors influencing the decisions of farmers to adopt SWC technology in Nigeria. Widespread adoption of appropriate technologies, in relation to site-specific biophysical factors and the socioeconomic and human dimensions issues, is crucial to advancing the sustainable use of soil and water resources, alleviating poverty and achieving food security in Southwest Nigeria. In the light of this, the study investigated factors influencing the adoption of SWC technology and also analysed the effect of SWC technology adoption on the rice yield using a full-information maximum likelihood endogenous switching regression. To the best of our knowledge, the robust estimation technique employed in this study (inverse-probability-weighted regression adjustment – IPWRA) provides deeper insight into the role played by the adoption of SWC technology in rice farm productivity compared to the techniques in previous studies (Bhatt et al., 2016; Asfaw and Neka, 2017). The findings of this study will inform smallholder farmers, development practitioners and poli-

cymakers of the benefits associated with the adoption of SWC technology in rice production.

2. Conceptual framework

In this section, the conceptual framework and empirical specification are presented to guide the analysis.

2.1. Adoption of soil and water conservation and its effect on rice productivity

The decision to adopt a new technology, as depicted in Figure 1, may be undertaken on the basis of an assessment of the relative productivity and risks associated with adoption, among others. The way farmers perceive such risk and utility will differ, depending on their own cognitive capacities, which in turn are influenced by a set of socio-demographic features. Age, for example, can positively or negatively affect the adoption of conservation measures (Bekele and Drake, 2003). Age, associated with long years of experience in agriculture, could positively influence the decision to adopt. Relatively older farmers are also likely to have an advantage of more flexibility in access to credit, and are likely more aware of the environmental benefits of conservation practices (Baumgart-Getz et al., 2012). Education is often argued to be a variable that influences rates of adoption (Alcon et al., 2011)."

The lessons from the literature related to the adoption of new agricultural technology gives insight on the causes of minimal adoption of SWC technology, for example inadequate credit access, insufficient information available to farmers barriers, risk aversion and environmental and institutional factors, and costs and benefits associated to the adoption (Abdulai and Huffman, 2014; Ojo and Baiyegunhi, 2020a; Thinda et al., 2020). While the empirical literature on the adoption and implementation of technology in SSA appears enormous, there remains limited studies that have explored the effect of SWC technologies on farmers' rice productivity (Kassie et al., 2015).

2.2. Endogenous switching regression model (ESRM) of the effect of the adoption of soil and water conservation on farmers' productivity

This study followed the approach of Abdulai and Huffman (2014) and Ojo et al. (2019) to quantify the causal impact of the binary treatment of technology by using the propensity score matching (PSM) or endogenous switching regression (ESR) model. This approach allows to test whether the household has positively benefited from the technology. Nevertheless, the application of PSM estimation is for balancing the observed distribution of covariates across the groups of adopters and non-adopters. Therefore, "the probit or logit estimates obtained in the estimation is not suitable to be considered as determinants of adoption. Also, the PSM approach is the unconfoundedness assumption, in other word, the conditional independence assumption, which indicates that, the control of the observable factors results into a random adoption of the technology and become uncorrelated with the outcome variable. According to Smith and Todd (2005), and Abdulai and Huffman (2014), there may be systematic differences between adopters' and non-adopters' outcomes even after conditioning, due to unmeasured selection characteristics. In this light, the study examined the determinants of adoption, as well as the effects of the adoption of SWC on rice productivity, using ESR model to account for selection bias in our estimation of the effect of adoption on farm outcome.

Following Aravindakshan et al. (2018) and Khanal et al. (2018), an ESRM was employed for this study. The approaches model was used to estimate the effect of SWC on the productivity of rice farmers, using SWC as a dummy variable, which poses the potential of yielding biased and inconsistent estimates because adoption is potentially endogenous (Di Falco et al., 2011). This model consists of two parts: endogeneity due to

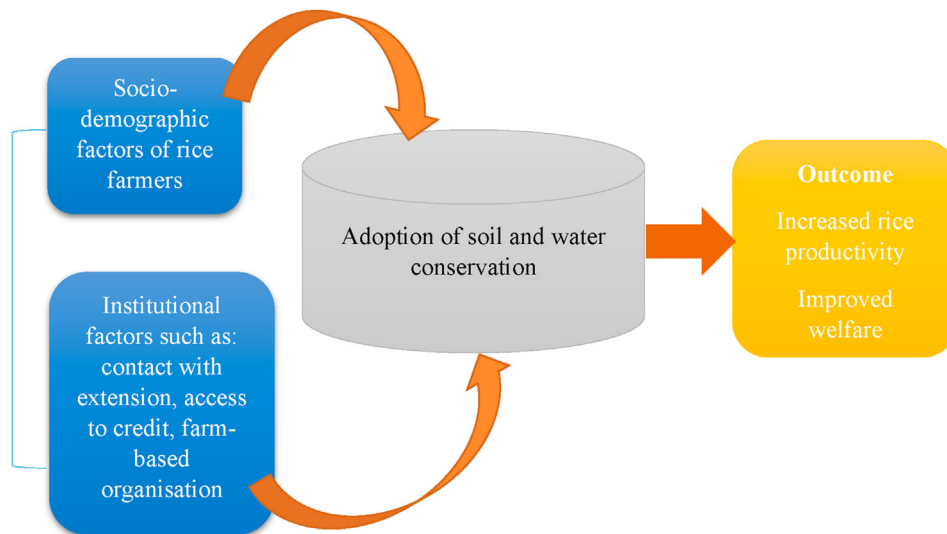


Figure 1. Conceptual framework of SWC adoption and its effect on rice productivity.

self-selection using a probit selection model¹ was corrected for in the first part of the model, in which farmers were separated into adopters and non-adopters of SWC. Following Abdulai and Huffman (2014), an SWC technology is normally adopted by a farmer if the net benefits derived by adopting it are higher than the benefits derived by not adopting it: ($M_{Y1} \geq M_{Y2}$), where M_{Y1} is the net benefit that farmer i derives from adopting SWC and M_{Y2} is the net benefit of not adopting it. The net benefits derived by adopting SWC technology were unknown to the researcher. However, the characteristics of farmers were observed during the survey period, with Y_i^* representing the net benefits derived from adopting SWC that were not observed but could be expressed as a function of the observed attributes.

$$Y_i^* = \beta Z_i + \varepsilon_i \tag{1}$$

$Y_i = 1$ if $Y_i^* > 0$ and 0 if otherwise,

where Y_i^* represents a variable that was not observed (or latent) for adopting SWC technology, while Y is the observable counterpart (equal to 1 if the farmer adopted it, and 0 if otherwise).

In the second stage, the outcome equations of the effect of the SWC on rice productivity were estimated using a production function, expressed in Eq. (2) as:

$$M = f(Y, \beta, Z) + \varepsilon, \tag{2}$$

where M denote the log form of rice yield in kilogrammes; Y is the adoption of an SWC technology; β is a vector of parameters to be estimated; and Z is a set of covariates used in the model, as expressed in Eqs. (3a) and (3b).

$$\text{Regime 1 (adopters): } M_{1i} = \lambda_1 H_i + v_{1i} \tag{3a}$$

$$\text{Regime 2 (non - adopters): } M_{2i} = \lambda_2 H_i + v_{2i}, \tag{3b}$$

where M_{1i} and M_{2i} are the logs of the rice yields in regimes 1 and 2, respectively; H_i is a vector of covariates that hypothetically are the determinants of rice productivity; and v_{1i} and v_{2i} are the stochastic error terms. The stochastic error terms were assumed to have a trivariate

normal distribution, with a zero mean and non-singular covariance matrix, as expressed in Eq. (4):

$$\text{cov}(\varepsilon_i v_1 v_2) \begin{vmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_2^2 & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & \sigma^2 \end{vmatrix}, \tag{4}$$

where $\sigma_1^2 = \text{var}(v_1)$; $\sigma_2^2 = \text{var}(v_2)$; $\sigma^2 = \text{var}(\varepsilon_1)$; $\sigma_{12} = \text{cov}(v_1 v_2)$; $\sigma_{1\varepsilon} = \text{cov}(v_1, \varepsilon_i)$; $\sigma_{2\varepsilon} = \text{cov}(v_2, \varepsilon_i)$; σ^2 represents the variance of the error term in the selection equation, while σ_{12}, σ_{22} indicates the variance of the stochastic error term in the generated equation.

According to Maddala (1983), when latent characteristics are related to selection bias, the structure of the error might arise because the error term, ε_i of the selection Eq. (2) is correlated with the error terms, v_{1i} and v_{2i} , of the generated Eqs. (3a) and (3b), with the expected values of v_{1i} and v_{2i} being conditional on the sample selection being non-zero.

$$E(v_{1i} | Y_i = 1) = E(v_{1i} | \varepsilon_i > -Z_i \beta) = \sigma_{1\varepsilon} \frac{\theta(Z_i \beta / \sigma)}{\varphi(Z_i \beta / \sigma)} \equiv \beta_{1\varepsilon} \gamma_1 \tag{5a}$$

$$E(v_{2i} | Y_i = 0) = E(v_{2i} | \varepsilon_i \leq -Z_i \beta) = \sigma_{2\varepsilon} \frac{-\theta(Z_i \beta / \sigma)}{1 - \varphi(Z_i \beta / \sigma)} \equiv \beta_{2\varepsilon} \gamma_2, \tag{5b}$$

where θ and φ are the PDF and CDF of the standard normal distribution, respectively. The ratio of θ and φ was evaluated with βZ_i , as represented by γ_1 and γ_2 in Eqs. (5a) and (5b). This ratio is the inverse mills ratio (IMR), which indicates the selection bias terms. The IMR shows the correlation between the adoption of SWC technology and the rice productivity of smallholder farmers. Previous studies used the two-stage endogenous switching model (Fuglie and Bosch, 1995; Baiyegunhi et al., 2010). A probit model of the selection equation was estimated in the first stage, and the IMRs γ_1 and γ_2 were predicted as indicated in Eqs. (5a) and (5b). The second stage involved adding the derived IMRs to Eqs. (3a) and (3b), respectively, with the following sets of equations being formed:

$$M_{1i} = \lambda_1 H_i + \beta_{1\varepsilon} \gamma_1 + \varphi_1 Y_{1i} + \psi_1 \tag{6a}$$

$$M_{2i} = \lambda_2 H_i + \beta_{2\varepsilon} \gamma_2 + \varphi_2 Y_{2i} + \psi_2 \tag{6b}$$

The coefficient of the variables γ_1 and γ_2 gave parameter estimates of the covariance terms $\beta_{1\varepsilon}$ and $\beta_{2\varepsilon}$ of Eqs. (6a) and (6b), respectively. Through estimating variables γ_1 and γ_2 , the standard errors of the two-stage estimates could not be calculated using the residuals ψ_1 and ψ_2 . Heteroskedastic errors are always confounded with methods in which

¹ For this study, the decision of rice farmers to adopt SWC in response to the impact of climate change was a dummy variable, taking the value 1 as an adopter and 0 as a non-adopter.

IMRs are manually inserted from probit equations into the generated equations. A full information maximum likelihood (FIML), as proposed by Lokshin and Sajaia (2004), represents an efficient method for analysing endogenous switching regression models. The FIML simultaneously fits the selection equation and the generated equations (equation (1) and Eqs. (3a) and (3b), respectively) to yield consistent standard errors. In turn, this makes γ_1 and γ_2 in Eqs. (6a) and (6b), respectively, homoscedastic. The log likelihood function of the FIML for the switching regression model employed in this study follows that proposed by Lok-

$$P(x) = \Pr(A_i = 1 / x) = F\{h(x)\} = E(A_i / x), \tag{9}$$

where x represents a vector of observed characteristics and $F\{\}$ is a cumulative distribution function. Following Austin (2016), the inverse weights for the treated group are equal to 1, while those for the control group as depicted in Eq. (10) can be defined as $\frac{\hat{p}(x)}{1-\hat{p}(x)}$ and the propensity score weight can be expressed as

$$\ln Y_i = \sum_{i=1}^N \left\| Y_i t_i \left[\ln F \left(\frac{Z_i \beta + \sigma_{1\epsilon} (M_{1i} - H_{1i} \lambda / \phi_1)}{\sqrt{1 - \alpha_{1i}^2}} \right) + \ln \left(f \left(M_{1i} - H_{1i} \lambda / \phi_1 \right) \right) + (1 - Y_i) t_i \left[\ln \left(1 - F \left(Z_i \beta + \sigma_{2\epsilon} (M_{2i} - H_{2i} \lambda / \phi_2) \right) \right) + \ln \left(f \left(M_{2i} - H_{2i} \lambda / \phi_2 \right) \right) \right] \right\| \tag{7}$$

shin and Sajaia (2004), as expressed in Eq. (7):

According to Fuglie and Bosch (1995), the signs of the correlation coefficients $\alpha_{1\epsilon}$ and $\alpha_{2\epsilon}$ have economic meanings. If $\alpha_{1\epsilon}$ and $\alpha_{2\epsilon}$ have alternate signs, rice farmers adopted the SWC technology based on their comparative advantages. For example, the adopters of the SWC would have above-average rice yields, while those who did not adopt would have below-average rice yields. However, if the coefficient has the same sign, adopters would have above-average rice yields whether they adopted or not, but would be better off if they adopted. Relatively, non-adopters would have below-average rice yields in either case, but would be better off if they chose not to adopt. As suggested by Kassie et al. (2015), Khanal et al. (2018) and Ojo and Baiyegunhi (2020a), the current study shows how an ESR model determines counterfactual effects and the effects of adoption. The counterfactual effect is the rice yield produced of the SWC technology adopters that would have been derived if the characteristics of the rice yield had been the same as the characteristics of the rice yield of non-adopters, and vice versa. The change in the yield of rice farmers as a result of adopting SWC technology was estimated as the difference between Eqs. (3a) and (3b), which were represented as the average treatment effects on the treated (ATT) in Eq. (8), is expressed as:

$$ATT = E(M_{1i} - M_{2i} | Y_i = 1) = H_1(\lambda_1 - \lambda_2) + (\sigma_{1\epsilon} - \sigma_{2\epsilon})\gamma_1. \tag{8}$$

In Eq. (3), $E(M_{1i} | Y_i = 1) = \lambda_1 H_1 - \sigma_{1\epsilon} \gamma_1$ represents the expected outcome for the adopters, had they adopted, while $E(M_{2i} | Y_i = 1) = \lambda_2 H_1 - \sigma_{2\epsilon} \gamma_1$ represents the expected rice yield for farming households that adopted had they chosen not to adopt an SWC technology."

2.3. Inverse-probability-weighted regression adjustment – IPWRA

IPWRA serves as a credible remedy for potentially biased estimates (ATT) that might emanate from propensity score models in the presence of misspecification (Vansteelandt et al., 2007; Wooldridge, 2007). As posited by Wooldridge (2003), the IPWRA estimates would be consistent even if the treatment/outcome was miss-specified, but not if both were. The IPWRA therefore can ensure consistent results, as it allows for the treatment and the outcome model to account for misspecification due to its double-robust property.²

Rosenbaum and Rubin (1983) first described propensity score-weighting methods, with the probability of receiving treatment, as shown in Eq. (9), being expressed as:

$$w_i = A_i + (1 - A_i) \frac{\hat{p}(x)}{1 - \hat{p}(x)}, \tag{10}$$

where \hat{p} are the estimated propensity scores.

For the regression adjustment (RA) model in Eq. (11), the ATT can be expressed as

$$ATT_{RA} = n_Q^{-1} \sum A_i [r_Q(x, \delta_Q) - r_N(x, \delta_N)], \tag{11}$$

where n_Q is the adoption of SWC technology sub-sample, r_Q is the regression model for adopters of SWC technology (Q), and r_N is the regression model for non-adopters of SWC technology (N) regressed on observed characteristics x_i and parameter estimates $\delta_i = (\alpha_i, \beta_i)$. The regression adjustment averages the predicted outcomes to determine the effects.

IPWRA, a doubly-robust estimator that combines RA in Eq. (11) and IPW in Eq. (10) is then expressed in Eq. (12) as

$$ATT_{IPWRA} = n_Q^{-1} \sum_{i=1}^n A_i \left[r_Q^* \left(x, \delta_Q^* \right) - r_N \left(x, \delta_N^* \right) \right], \tag{12}$$

where $\delta_Q^* = (\alpha_Q^*, \beta_Q^*)$ is determined from a weighted regression process in Eq. (13):

$$\min_{\alpha_Q^*, \beta_Q^*} \sum_{i=1}^n A_i \left(Y_i - \alpha_Q^* - X \beta_Q^* \right) / \hat{p}(X, \hat{\gamma}) \tag{13}$$

and is estimated from the weighted regression process in Eq. (14):

$$\min_{\alpha_N^*, \beta_N^*} \sum_{i=1}^n (1 - A_i) \left(Y_i - \alpha_N^* - X \beta_N^* \right)^2 / (1 - \hat{p})(X, \hat{\gamma}). \tag{14}$$

As posited by Wooldridge (2010), ATTs obtained from IPWRA and RA are similar, except that differently weighted estimates are used for the regression parameters.

3. Research methods

3.1. Study area

The data used for this study was obtained in the southwestern region of Nigeria, which include 6 geo-political states, namely; Ogun, Oyo, Lagos, Osun, Ondo and Ekiti state. The selected study areas are between longitude 2°31' and 6°00'E and latitude 6°21' and 8°37'N, covering around 77 818 km². As shown in Figure 2, the selected study areas shared boundaries with two eastern states (Edo and Delta), two northern states

² The mathematical equations of estimating IPWRA can be found in Imbens and Wooldridge (2009).

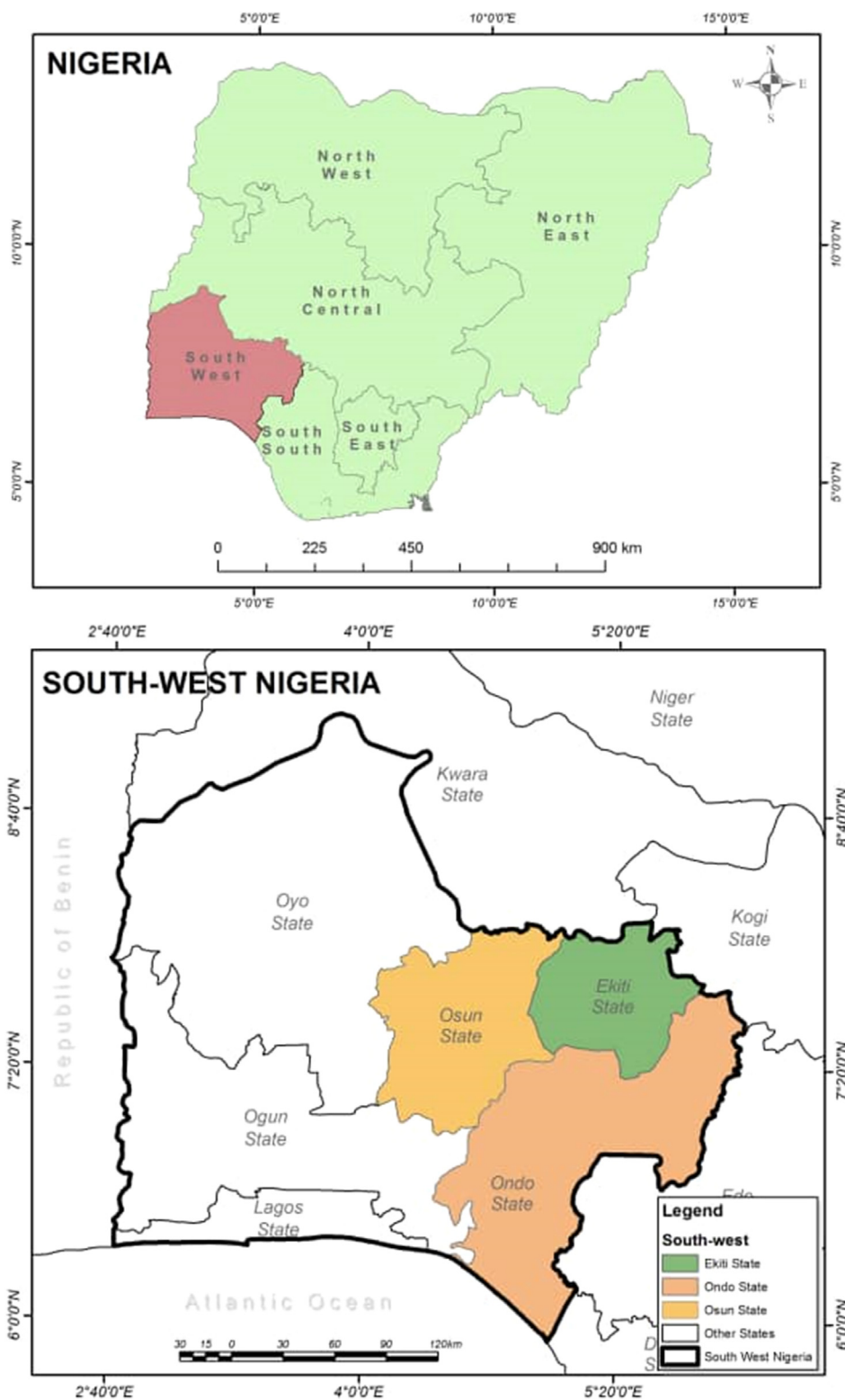


Figure 2. Maps of Africa and Nigeria showing the study area. Source: Adapted from Ojo and Baiyegunhi (2020b).

(Kwara and Kogi), and the Gulf of Guinea in the south. The Southwest Nigeria is characterized as a tropical climate, with significant variations in mean temperatures (21 °C and 34 °C) and annual precipitation (150 and 3000 mm) of the states. . The raining season is associated with the monsoon wind originating from the Atlantic Ocean, while the dry season is associated with the north-eastern trade wind from the Sahara desert.

The vegetation in the selected study areas is made of swamp and thick forest as well as lowland forests which spreads across to Ogun State and Ondo State. In the northern boundary, the areas is composed of forests towards the southern Guinea (Agboola, 1979). According to Ayanlade et al. (2017), agricultural production encounters various issues in the Southwest region of Nigeria, in terms of recurrent damages of crops

Table 1. Definitions and summary statistics of variables used in the model.

Variable	Description of variables	Mean	S.D.	Min	Max	(Skewness)	(Kurtosis)
Dependent variables							
Log of rice yield	Log of rice yield	7.406	.091	7.244	7.507	0.000	0.001
SWC	1 if HH chooses soil and water conservation, 0 if otherwise	.672	.47	0	1	0.000	
Explanatory variables							
Location_Ekiti State	1 if HH is from Ekiti, 0 if otherwise	.375	.485	0	1	0.000	
Location_Ondo State	1 if HH is from Ondo, 0 if otherwise	.383	.487	0	1	0.000	
Location_Osun State	1 if HH is from Osun, 0 if otherwise	.35	.478	0	1	0.000	
Age	Age of HH head (years)	47.283	7.671	30	61	0.197	0.000
Gender	1 if HH head is male, 0 if female	.558	.497	0	1	0.067	
Marital status	1 if HH head is married, 0 if other/single/widowed	.803	.398	0	1	0.000	0.200
Household size	Number in HH	4.658	1.243	2	8	0.295	0.899
Farming experience	Years of farming	15.733	5.088	8	25	0.000	0.000
Farm size	HH size	7.375	3.043	2	13	0.613	0.000
Years of formal education	Years of education of HH head	6.447	5.704	0	18	0.202	0.000
Membership	1 if HH belongs to a farmer association	.536	.499	0	1	0.255	
Access to ext. contacts	1 if HH has access to extension, 0 if otherwise	.533	.5	0	1	0.293	
Access to climate info	1 if HH has access to climate change information, 0 if otherwise	.364	.482	0	1	0.000	
Annual_Temp	Mean of annual temperature	27.659	.047	27.22	27.77	0.000	0.000
Annul_ppt	Mean of annual precipitation	111.055	16.09	88.31	122.8	0.000	
Ln_Herbicides	Log of quantity of herbicides applied per ha in litres	2.482	.293	1.946	4.808	0.000	0.000
Ln_Fertilizer	Log of quantity of fertiliser applied per ha in litres	5.771	.21	5.521	6.215	0.000	0.014
Ln_Labour	Log of hired and family labour in man-days	79.917	24.544	42	105	0.004	0.000

owing to unstable weather conditions and also pests' outbreak. The harsh weather variability such as droughts and floods have had detrimental impact on agricultural productivity, farmers' income and food security over the past decades, in this region. These weather issues caused by climate change, are mostly pronounced at the drier areas occupied by mostly the emerging farmers (Idowu et al., 2011).

For the selection of respondents in the study area, this study employed a multistage sampling approach. The first stage involved a typical-case purposive selection of three states (Ekiti, Ondo and Osun) located in the same agroecological area. In the second stage, four local government areas (LGAs) were selected from each state, based on the predominance of smallholder rice farmers in these areas, using typical-case purposive sampling. In the third stage, five villages were randomly selected from each of the four LGAs. Following Tesfahunegn et al. (2016), the sample size for the study was determined using the sample determination formula at a 95% confidence level and 5% margin of error, as described by Cochran (1977). Within this framework, six smallholder rice farmers were selected from each of the five villages, giving 360 respondents who were interviewed for the study. In line with the climate variables, monthly averages of precipitation and temperatures from 1970 to 2014 were obtained from the Nigeria Meteorological Agency at Oshodi in Lagos, Nigeria, and the International Institute for Tropical Agriculture in Ibadan, Nigeria.

4. Results and discussion

4.1. The descriptive statistics of the smallholder rice farmers

This section presents the descriptive statistics of the smallholder rice farmers, as shown in Table 1. Based on the results from the survey, 67% of smallholder rice farmers adopted SWC technology as a mechanism to cope with the changes in climatic conditions. For the average age and years of education of the households' heads, results shows that respondents had 47 years and 6 years, respectively. "The results further shows that around 80% of the respondents were married, and possess around 15 years of farming experience in rice production. About 53% are

frequently contacted of the extension officers. The result of the statistics shows that around 57% of the smallholder rice farmers were financially supported through a reliable access to credit, which is contributes significantly to their determination in choosing adaptation strategies. Conversely, there was noticeable deviation in the statistical result in terms of access to information. For instance, as low as about 36% of rice farmers who adopted SWC technology had direct access to climate change information. .

4.2. Full information maximum likelihood (FIML) estimates of the endogenous switching regression model (ESRM) – determinants of SWC technology adoption among smallholder rice farmers

This section presents the results from the empirical analysis shown in Table 2. This study used an ESRM as the impact model because it was able to control for all possible biases that could confound the results. As shown in the results in Table 2, the correlation coefficients rho_1 and rho_2 in the ESRM were both positive and statistically significant for the correlation between the adopters and non-adopters vis-à-vis rice productivity. This shows that self-selection occurred among the adopters and non-adopters of SWC technology. The first part of this section focuses on the discussion of the significant variables that influence the adoption of SWC practices. The variables that are statistically significant and influence the decision to adopt the SWC include Location_Ekiti, gender, marital status, annual temperature, annual precipitation, log of fertiliser, labour in man-days and membership in farm-based organisation (FBO). As discussed earlier, the ESR method estimated two separate but related outcomes for each group (adopters and non-adopters), combining them to form a selection equation. The results for each group (adopters and non-adopters) are discussed in the second part of this section. Lastly, the treatment effects of the adoption of the SWC are discussed.

Location variables are hypothesised to increase farmers' probability to adopt SWC technology, especially if the location of the farm is the place where a particular crop produced serves as the main source of income for the farmers. For this study, we found that the estimated coefficient of farmers' location in Ekiti (Location_Ekiti) was positive and statistically

Table 2. Full information maximum likelihood (FIML) estimates of the endogenous switching regression model (ESRM).

Variables	Adoption of SWC			Rice yield (tonnes/ha)			Rice yield (tonnes/ha)		
				Adopters			Non-adopters		
	Coef.	Std. err.	P-value	Coef.	Std. err.	P-value	Coef.	Std. err.	P-value
Location_Ekiti	0.601	0.224	0.007***	-0.006	0.005	0.188	-0.012	0.007	0.074*
Location-Osun	0.227	0.257	0.376	-0.009	0.006	0.160	-0.026	0.008	0.001***
Gender	0.313	0.187	0.094*	0.005	0.004	0.245	0.004	0.006	0.521
Age	0.013	0.013	0.289	-0.001	0.000	0.025**	-0.001	0.000	0.190
Marital status	-0.606	0.294	0.039**	-0.157	0.006	0.000***	-0.172	0.009	0.000***
Household size	0.103	0.077	0.180	0.002	0.002	0.339	0.001	0.002	0.666
Rice experience	-0.020	0.024	0.417	0.003	0.000	0.000***	0.004	0.001	0.000***
Farm size	0.019	0.034	0.575	0.003	0.001	0.000***	0.004	0.001	0.000***
Formal education	-0.015	0.020	0.453	-0.003	0.000	0.000***	-0.002	0.001	0.001***
Access to extension	-0.341	0.487	0.484	-0.015	0.007	0.031**	0.030	0.012	0.011**
Access to information	-0.073	0.199	0.716	0.007	0.004	0.106	0.007	0.006	0.241
Annual temperature	5.123	2.621	0.051*	-0.016	0.039	0.684	0.019	0.086	0.828
Annual precipitation	0.122	0.056	0.030**	-0.000	0.000	0.112	-0.000	0.000	0.389
Log of herbicides	-0.529	0.371	0.154	0.004	0.006	0.515	0.024	0.017	0.171
Log of fertiliser	0.788	0.444	0.076*	-0.001	0.009	0.928	0.016	0.014	0.253
Labour in man-days	0.005	0.005	0.273	0.003	0.000	0.000***	0.003	0.000	0.000***
Constant	-161.047	74.657	0.031**	7.756	1.111	0.000***	6.608	2.396	0.006***
FBO	5.345	1.973	0.007***						
/lns1	-3.500	0.064	0.000***						
/lns2	-3.543	0.077	0.000***						
/r1	-0.781	0.359	0.030**						
/r2	0.326	0.321	0.310						
sigma_1	0.030	0.002							
sigma_2	0.029	0.002							
rho_1	-0.653	0.206							
rho_2	0.315	0.289							
LR test of indep.	0.0360								
Prob > chi2	0.000								
Loglikelihood	647.043								
Wald Chi ² (16)	2044.07								

***, ** and * represent significance at the level of 1%, 5% and 10%, respectively.

significant, suggesting that the location of farmers contributes to decisions on the adoption of SWC technology. The reason for this could be ascribed to the fact that there are limited off-farm activities for farmers in Ekiti, hence, rice farming serves as the main source of income generation for the farmers. The farmers in these locations therefore are likely to adopt SWC practices to increase rice output with the aim to increase profits. The result implies that the location differential influences farmers' decisions to adopt SWC technology in rice farming. Thus, the results show that farmers in Ekiti are more likely to adopt the SWC method, perhaps due to its tendency to increase the yield of and revenue from rice production. The findings of this study are in line with those of [Donkor et al. \(2019\)](#), who found that farmers' locations play a role in decision making related to the adoption of a practice or technology.

The variable gender is statistically significant and shows a positive coefficient in the adoption of SWC technology. This indicates that male farmers are more likely to adopt SWC practices. The findings of this study are in line with those of [Asfaw and Neka \(2017\)](#), who found that male farmers have a higher probability of being involved in SWC practices compared to female farmers because, in most cases, designing and maintaining SWC structures require hard labour."

The estimate of marital status is negative and statistically significant, indicating that single farmers have a higher likelihood of adopting SWC practices compared to farmers who are married. The reason is that single farmers have few responsibilities and channel their financial resources to SWC practices, which is contrary to the case for married farmers. Moreover, the results suggest that married farmers are less likely to adopt

SWC, as marriage could result in a large family size, which consequently would put pressure on the financial resources available to hire employees for SWC practices. This is consistent with the study of [Bakhsh et al. \(2012\)](#), who found that family size has a significant negative effect on the adoption of water conservation practices.

The estimate for annual temperature is positive and statistically significant. This result indicates that a high annual temperature could increase the probability that smallholder rice farmers adopt SWC technology, which could help to lower elevated evaporation from the soil. High temperature cause increased evaporation, which often results in more demand for irrigation water for rice produced under irrigation conditions. High temperatures caused by climate change have been reported by [Gedefaw et al. \(2018\)](#) to have a negative effect on crop production through a reduction in crop productivity. Therefore, the adoption of SWC practices is more frequent when temperatures are extremely high, as they affect rice productivity and farmers' incomes.

The coefficient of annual precipitation is positively signed and statistically significant in influencing the adoption of SWC among smallholder rice farmers. Similar to the annual temperature, the results show that the annual precipitation contributes significantly to farmers' decisions to adopt SWC practices. The decision to adopt SWC practices could be positively influenced when there is lower or unstable precipitation, as this could lead to soil moisture that is too low for rice production. This is in consonance with the study of [Maggio and Asfaw \(2020\)](#), who find a positive relationship between annual precipitation and the adoption of SWC practices in Malawi.

Table 3. Treatment effects of the adoption of soil and water conservation techniques on rice productivity – Inverse-probability-weighted regression adjustment.

Treatment effects	Coefficient	Std. err.
Average treatment on the treated (ATT)	0.1276*	0.0749
Potential-outcome mean (POM)	1.367***	0.0723

Note: The bootstrap replications were changed from 100 to 1 000, but no significant change occurred, hence 500 replications were used to bootstrap the standard errors.

The variable log of fertiliser shows a positive and statistically significant association with smallholder farmers' probability to adopt SWC technology. This implies that farmers are more likely to adopt SWC technology with the aim of reducing the cost of fertilisers. The results of this study correlate with those of Yesuf (2004), who found that the adoption of SWC resulted in a reduction in fertiliser application. Also, the potential of SWC technology to increase soil fertility through a reduction in erosion could be considered by smallholder rice farmers as a reason to reduce fertiliser applications (Nyangena and Köhlin, 2009).

The findings of this study show that FBO, which can be categorised as an institutional factor, is statistically significant and positively influences farmers' probability to adopt SWC practices. This result indicates that rice farmers who belong to a farmers' association have a higher probability of adopting SWC practices compared to their counterparts. Becoming a member of an organisation creates linkages between farmers and others, such as scientists, extension agents and other landholders. Farmers' associations are increasingly becoming common in Africa, including in Nigeria. They have become an essential network for governments and non-governmental organisations to provide a different form of support, such as finance and farm inputs (e.g. fertiliser and technical assistance to farmers, especially rural farmers). Findings from this study align with those of Ogada et al. (2014) and Ojo et al. (2019) who found that membership of farmers' associations promoted agricultural technology adoption in Kenya.

4.3. Effect of SWC technology adoption on rice productivity of smallholder rice farmers

The second stage estimated rice yields for adopters and non-adopters of SWC technology using ESR, and "the results are presented in the same Table 2. One of the covariance terms (Rho_1) for yield equations is statistically significant, which signifies that the application of ESR in the empirical estimation is suitable.

The variable, Location_Ondo State, was used as a base outcome for location variables. The dummies are to account for regional differences due to agroclimatic conditions among the three regions, which are expected to have an effect on farmers' decisions to adopt SWC. The two location variables (Location_Ekiti and Location_Osun) are signed negatively and are statistically significant in relation to the rice yields of non-adopters of SWC technology. This implies that smallholders rice farmers who are non-adopters of SWC technology and are located in Ekiti and Osun may experience a decrease in rice yields. The decreases in rice yields in the locations could be ascribed to soil erosion issues – a major problem confronting agricultural production (Junge et al., 2009; Thinda et al., 2020), particularly in Osun State. Similarly, cultivable soils in the Ekiti production area are mostly degraded as a result of deforestation and economic activities (Amusa et al., 2015), thus highlighting the deficits in rice productivity for the non-adopters in these areas.

The age of smallholder rice farmers has a significant negative effect on the rice productivity of adopters of SWC technology. This result indicates that, as farmers get older, they are less likely to invest more in SWC technologies, which may have negative effects on rice productivity. Elderly farmers become tired over time and pay little attention to their farmlands. In contrast to the old farmers, younger farmers are more

willing to invest in SWC practices. The odds ratio shows that an increase in the age of smallholder farmers by one year will result in a decrease in the rice productivity of adopters of SWC practices by a factor of 0.001. These findings are consistent with Bekele and Drake (2003), Bayard et al. (2006) and Tiwari et al. (2008), who found that the age of households reduced rice productivity of adopters of improved technology.

The results of the study show a significant negative effect of marital status on the rice yields of adopters and non-adopters. This indicates that marital status is an important variable in explaining the variations in rice productivity of the adopters and non-adopters of SWC technology. The negative sign suggests that, irrespective of a household's marital status, the decision to adopt or not to adopt SWC technology may not translate into increased rice productivity. This is consistent with the study of Ojo and Baiyegunhi (2020b), who found a negative and significant association between households' marital status and the net income of adopters and non-adopters of climate change adaptation strategies."

The results show that experience in rice farming has a significant positive effect on the rice yields of adopters and non-adopters. This signifies that the longer the farming experience of rice farmers, the higher the rice yield. As expected, an increase in farming experience in rice production could allow farmers to properly apply SWC practices to improve rice productivity. Farming experience in rice farming has been found to be statistically significant and to have positive effects on rice productivity (Ashoori et al., 2016; Danso-Abbeam et al., 2020). For the non-adopters, the results show that experience in rice farming in the absence of SWC practices would in turn help rice farmers improve rice productivity "(Ojo and Baiyegunhi, 2020b).

The findings of this study show that farm size contributes significantly, with positive effects on the rice yields of adopters, which indicates that as farm size increases, the rice yield of adopters increases. Larger farm size often allows or the extensive production of rice crops and consequently results in higher yields. This is similar to the findings of Nkegbe et al. (2011), Bakhsh et al. (2012) and Jara-Rojas et al. (2013). Farmers with larger farm sizes are more likely to adopt SWC measures and produce higher yields because they have the financial resources to invest. The results further show that the farm size variable has a positive influence on the rice yield of non-adopters. The results demonstrate that, as non-adopters increase the size of the farm, they are more likely to increase their rice yields. Since non-adopters do not apply SWC practices, they tend to extend their farm size to cover places with sufficient soil nutrients, where rice could grow and generate higher yields.

Formal education shows a statistically significant negative effect on rice yields for both adopters and non-adopters. The negative association observed in the result of rice yield is a result of farmers' ability to make critical decisions regarding adopting SWC innovations after obtaining several years of schooling, which eventually reflects in the rice productivity. An increase in farmers' formal education would result in a decrease in rice productivity for adopters and non-adopters of SWC practices. The results of this study confirm the existing literature Shuaibu and Nchake (2021) which highlights that farmers' levels of academic education have negative effects on farmers' adoption and productivity.

The coefficient of farmers' access to extension is negatively signed and statistically significant in influencing the rice productivity of adopters of SWC practices. This finding is consistent with previous studies, for instance Darkwah et al. (2019), who found a negative and significant relationship between farmers' access to extension and the adoption of SWC practices. The negative sign in the coefficient of farmers' access to extension services could be ascribed to ineffective and inaccurate information disseminated to the rice farmers, perhaps when applying for SWC technology (Bamire et al., 2002; Ojo et al., 2019), which could result in a reduction in rice yield productivity. For the non-adopters, the results show that access to extension is positively signed with rice productivity. Farmers who are non-adopters of SWC technology are more open to making use of extension services, which serve as an alternative to enhance rice productivity.

The empirical findings have shown that labour in man-days is one of the major factors influencing rice productivity for both adopters and non-adopters of SWC practices. This implies that a unit increase in labour in terms of man-days will result in an increase in rice yields. Labour remains key for rice production, from the land preparation stage to harvesting, and thus can be considered an important factor for improving rice productivity for both adopters and non-adopters of SWC practices. For instance, highly intensive labour is required to apply fertiliser to the rice crops, highlighting the positive relationship between labour and rice productivity. This is consistent with the findings of [Di Falco et al. \(2011\)](#), who found that labour is significantly associated with fertiliser application and an increase in yields for adopters and non-adopters.

The ex-post estimates of the causal effects of the adoption of SWC on the rice productivity of smallholder farmers from the IPWRA are presented in [Table 3](#).

The results of the inverse-probability-weighted regression adjustment estimation indicate that the adoption of SWC technology to mitigate the adverse effects of climate change improves the productivity of rice in the study area. [Table 3](#) shows that the ATT and POM are approximately 12% and 136%, respectively. Thus, the potential effect of SWC on rice productivity has a substantial influence on rice productivity per hectare. Thus, the adoption of SWC among smallholder rice farmers improves productivity and translates into spill-over effects on rice farmers' welfare. The positive effect of the adoption of SWC technology on rice productivity agrees with the study of [Ojo and Baiyegunhi \(2020a\)](#) in Nigeria. These findings are also consistent with the studies of [Abdulai and Huffman \(2014\)](#) and [Asfaw and Workineh \(2019\)](#), with views that the adoption of new agricultural technologies such as SWC can improve productivity and household farm income. Generally, the empirical results presented in this study support the notion that the adoption of SWC in relation to rice productivity can play a positive role by serving as a panacea for improved income, and that increased SWC adoption tends to improve the economic performance of farm households."

5. Conclusion and policy recommendations

This study has established the importance of adopting SWC technology by estimating the effect of the adoption of SWC technology and analysed how the decision to adopt influences the rice productivity of smallholder farmers in Southwest Nigeria. An ESRM was employed to estimate the productivities of adopters and non-adopters of SWC. A doubly-robust inverse probability weighted regression adjustment was used as a credible remedy for potentially biased estimates of ATT, ATET and POM of the endogenous treatment model. The study found that variables such as farmers' location, gender, marital status, annual temperature, annual precipitation, log of fertiliser and membership in FBO significantly influenced the decisions of smallholder rice farmers to adopt SWC technology. The resultant effect of factors such as age, marital status, rice experience, farm size, formal education, access to extension, and labour in man-days translates into increased rice productivity for smallholder farmers who adopted SWC technology. For non-adopters, factors such as location of farmer, marital status, rice experience, farm size, formal education, access to extension and labour in man-days were found to influence the determinants of rice productivity among smallholder farmers. The result of the inverse-probability-weighted regression adjustment estimation indicates that the adoption of SWC technology to mitigate the adverse effects of climate change improves the productivity of rice in the study area.

The findings of this study have policy implications for the adoption of SWC technology and increasing farm productivity. In particular, the study suggests that effective policy measures to promote the adoption of new technologies, such as SWC, should include the improvement of farmers' education, and access to credit, climate change information and social networks. To ensure effective dissemination and adoption of new conservation technologies, government and stakeholders in rice production could take the lead in promotion and dissemination at the initial

stages and, in the process, could create an enabling environment for the effective participation of other stakeholders in rice production. However, while SWC might be effective in improving rice productivity, this option might be costly to implement and might not be consistent with other societal and environmental objectives. Therefore, in addition to assessing the effect of SWC on rice productivity, future studies should also evaluate the effect of SWC on the environment and society.

Declarations

Author contribution statement

Temitope O. Ojo: Conceived and designed the experiments; Wrote the paper.

Lloyd J.S. Baiyegunhi; Abiodun A. Ogundeji: Contributed reagents, materials, analysis tools or data.

Adetoso A. Adetoro: Conceived and designed the experiments; Analyzed and interpreted the data.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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