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SOCIOLOGY | RESEARCH ARTICLE

Effect of adoption of alternative conservation agricultural practices on smallholder farmers' production output in South-West Nigeria

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Abstract: Sustainable agricultural practices, such as conservation agriculture (CA), remain an important crux of conservation efforts to boost food crop production output due to productivity decline. Using cross-sectional survey data from 350 smallholder farmers, this study investigated the likelihood of adoption of CA practices in South-West Nigeria based on a number of factors as well as factors predicted to effect farmers' output when these practices were adopted. Cross-tabulation technique was applied to profile the farmers' features, while heckman selectivity model was used to estimate the effect of CA adoption on farmers' production output from CA plots and to sequentially address potential selectivity problem in a bid to disentangle the effect of adoption and other confounders which vary across individual farmers. Findings revealed that exposure time period, land acquisition, CA farm size cultivated, total farm size, access to extension services and social capital components are significant predictors of adoption. Likewise, human capital (years of formal education and farming experience), marital status, access to extension service and frequency of extension visit significantly predict farmers' production output. Most importantly, the estimated selection bias control

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PUBLIC INTEREST STATEMENT

Agriculture as livelihood means in many global south countries, particularly in Nigeria, serves as source of income, employment and food supply to all. However, the sustainability of Nigeria agri-food system is threatened due to human-induced activities and climate change extreme events. This calls for urgent need to adopt sustainable agricultural production systems capable of dealing with environmental impact threatening the food and nutrition security of Nigeria. Meanwhile, majority of the vulnerable individuals in the agri-food system are the smallholder farmers. Therefore, this study will be of public interest as it attempts to establish that investment in sustainable agriculture such as conservation agricultural practices and farmers' full adoption of such practices in South-West Nigeria can potentially raise agricultural productivity in addressing the spate of food insecurity, agrarian poverty, and depletion of natural resource due to environmental degradation and climate related events. This represents a vital component of the global responses to the current food insecurity challenges in Nigeria.

parameter was significantly different from zero, which is an indication that there was a significant effect of CA adoption on farmers' production output from CA plot.

Subjects: Environment & Agriculture; Sustainable Development; Development Policy; Rural Development

Keywords: adoption; conservation agriculture; smallholder; heckman selectivity model; Nigeria

1. Introduction and background information

The Nigerian agricultural system is characterized by a peasant production system owing to customary land tenure system, low productivity arising from poor response to technology adoption, as well as rain-fed and rudimentary crop husbandry methods (Aina, 2011). Rural farmers are known to use several traditional farming techniques such as simple agronomic practices, age-long soil amendments management practices as well as the obsolete mechanical methods of soil management. Nonetheless, the application of these techniques has sustained the pace of production, at least on a subsistence level, but not without its associated consequences such as land degradation and productivity decline after certain limit or threshold (Babalola & Olayemi, 2013). Therefore, more sustainable agricultural practices such as conservation agriculture (CA) remain an important crux of conservation efforts to boost food crop production and improve soil quality in a bid to reduce food and nutrition insecurity issue threatening humans' right to food in sub-Saharan Africa (SSA) and Nigeria in particular.

The right to an improved living standard, especially "the Right to Food", is recognized by United Nations' 1948 Universal Declaration of Human Rights. Nonetheless, Food and Agricultural Organization (FAO) (2015) reported consistent deprivation of this basic human right by many people in SSA even with the acclaimed progress achieved in fighting food and nutrition insecurity. For instance, in SSA, about 236.5 million people are malnourished now; this represents more than 23.2% of the population in this region (FAO, 2018). In the light of these statistics, it is pertinent to invest in agricultural sector through incentive-based agricultural innovation programmes because of the resource-poor state of the farmers. This can potentially facilitate adoption of more sustainable methods: one is CA among smallholder farmers towards increased production yield and sufficient food availability for human sustenance so as to progressively achieve "the right to food" (Husmann et al., 2015).

According to Brown, Nuberg, and Llewellyn (2018), sustainable intensification through CA farming practices has been put forward in other scientific works as a way and strategy to boosting smallholder productivity, particularly in SSA. CA is a package of three inter-twined principles of minimum soil disturbance, sequential rotation of different crops and crop biomass mulching to simultaneously improve soil fertility, conserve ground water and ultimately increase productivity output. CA has been strongly embraced by many African governments and development experts (Giller, Witter, Corbeels, & Tittonell, 2009). However, literature has shown that there is limited utilization of CA in SSA relative to what is obtainable in many developed countries (e.g. Andersson & D'Souza, 2014; Giller et al., 2009; Kassam, Friedrich, Derpsch, & Kienzle, 2015; Ngwira, Johnsen, Aune, Mekuria, & Thierfelder, 2014). The underutilization of CA is attributed to land-less situation and customary land tenure barriers as well as poor information delivery about CA, which, by extension, reflects poor/negative judgement and evaluation of CA by farmers, thus resulting in the observed limited trust, interest and low rate of adoption (Brown, Nuberg, & Llewellyn, 2017).

Oni (2009) had earlier reiterated that adoption of soil conservation practices in Nigeria and other SSA countries may improve farmers' profitability through high yield, reduce drudgery and improve soil quality as well as the attendant degrading ecosystem. However, despite the enormous benefits, scaling up the adoption of these technologies in many SSA countries and Nigeria in particular has remained untapped and not well documented. Exceptions of this are Kenya, South Africa, Mozambique, Zambia, Malawi, Zimbabwe, Lesotho and Ethiopia, which are presently at the forefront in terms of CA practices and its documentation in Africa, as shown in Tables 1 and 2 (Kassam et al. 2015).

Table 1. Cropland under CA by continent (2013 update)

Continent	Cropland under CA (M ha)	Percentage of global CA area	Percentage of cropland
South America	66.4	42.3	60.0
North America	54.0	34.4	24.0
Australia and New Zealand	17.9	11.4	35.9
Asia	10.3	6.6	3.0
Russia and Ukraine	5.2	3.3	3.3
Europe	2.0	1.3	2.8
Africa	1.2	0.8	0.9
World total	157.0	100.0	10.9

Source: Kassam et al. (2015).

Table 2. CA adoption in Sub-Saharan Africa (2008/2009 and 2013 updates)

Country	CA cultivated area (ha) 2008/2009 update	CA cultivated area (ha) 2013 update
South Africa	368,000	368,000
Zimbabwe	15,000	332,000
Zambia	40,000	200,000
Mozambique	9,000	152,000
Malawi	–	65,000
Kenya	33,100	33,100
Ghana	–	30,000
Tanzania	–	25,000
Sudan	10,000	10,000
Madagascar	–	6,000
Lesotho	130	2,000
Namibia	–	340
Total	475, 230	1, 223, 440

Source: Kassam et al. (2015).

Several dynamics such as agronomic, socio-economic and cultural factors drive the CA adoption process; the interplay of these factors majorly determines the extent of its success (Corbeels et al., 2010). The important aspect of adoption process centres on farmers' production objectives, constraints and risk attitudes as well as the expected benefits and upfront costs associated with CA. According to Corbeels et al. (2010), farmers in SSA often place higher priority on immediate associated spending and expected future gains by weighing the options to make adoption choice decision. In the light of this, it thus becomes imperative to pay proper attention to this topical issue as it concerns food and nutrition security by promoting policies to aid the uptake, adoption and scaling up of agricultural technologies such as CA in Nigeria.

2. Materials and methods

2.1. The study area

This research work was carried out in South-West Nigeria. The study area consists of six states, namely Ekiti, Lagos, Ogun, Ondo, Osun and Oyo States. However, for the purpose of this research work, Oyo, Osun and Ondo States were used. The choice of these states was premised on the fact that adoption (full and/or partial) of improved agricultural technologies (such as improved maize seeds, improved rice varieties,

and vitamin-A-fortified cassava varieties) had earlier been mentioned and reported in these states/regions of South-West Nigeria (Nguezet, Diagne, Okoruwa, & Ojehomon, 2011; see also Oparinde, Banerji, Birol, & Ilona, 2014; Obisesan, 2015; Awotide, Karimov, & Diagne, 2016). Moreover, majority of the rural households in these states are into farming and farming related activities.

An overview of the study area is shown in Figure 1 (COPINE, 2018).

2.2. Sampling technique and data collection

Multistage sampling technique was used to select the representative size of 350 smallholder farmers from whom responses were elicited using a carefully prepared questionnaire extract based on the guidelines provided in “Qualitative expert Assessment Tools for assessing the adoption of CA in Africa (QAToCA)” taking into consideration the “regional factor caution (Corbeels et al., 2010)”. Hence, smallholder farmers represent the entity under study (i.e. the unit of analysis).

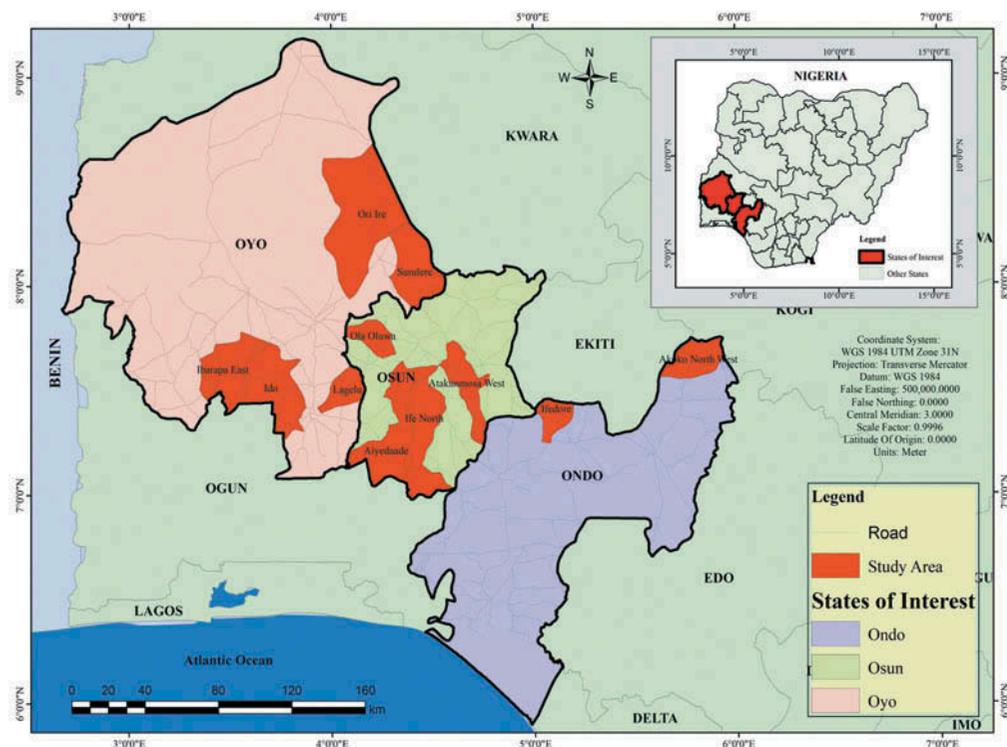
These states are stratified into agro-ecological zones that are predetermined by the Ministry of Agriculture, Natural Resources and Rural Development in each of the states. Thus, Oyo, Osun and Ondo States are stratified into four, three and two Agricultural Development Programme (ADP) zones, respectively, based on rurality. Thus, simple random sampling technique was used in the second stage to select 50% of the ADP zones in each of the three states/provinces to arrive at two ADPs from Oyo State, two ADPs from Osun State and one ADP from Ondo State.

Then, the second stage made use of simple random sampling technique to select one-third of the local government areas (LGAs)/blocks from each of the ADPs selected in across the chosen states. The third stage also involved simple random sampling to choose three villages/cells from each of the LGAs/blocks selected in the second stage, while the fourth stage involved the use of proportionate to size sampling technique to select 350 registered smallholder farmers used as sample size for this study.

The proportionality factor applied for a bias free selection of the 350 respondents (sample size) is as follows:

Figure 1. Map of South-West Nigeria showing the States and LGAs of Interest.

Source: Cooperative Information Network (COPINE), Nigeria, 2018



$$N_i = n_i / N * 350 \quad (1)$$

where

N_i is the number of respondents/instruments selected in each of the i th state ($i = 1, 2$ and 3),

n_i is the population of all registered farmers in i th states selected,

N is the total population of all registered farmers in all the three states selected and

350 is the total number of respondents sampled across the selected states.

2.3. Data analytical techniques

The study applied descriptive statistics analytical tools (frequency counts, percentages, mean, and standard deviation) to describe farmers' personal attributes and farm-based factor such as size of farmland as well as farmers' full adoption status (simultaneous use of the practices of minimum soil disturbance, sequential rotation of different crops and crop biomass mulching) and pattern in the study area. Similarly, heckman selectivity model was used to estimate the effect of CA adoption on farmers' production output. Importantly, Wald test of non-linear hypotheses with adjusted p -values was carried out using Holm, Sidak and Bonferroni correction methods; this became necessary as additional tests of independence equations of heckman model to ascertain the reliability and consistency of the model estimates.

2.3.1. Introduction and application of the models

Following the utility maximization technique that is in line with Lubungu, Chapoto, and Tembo (2012), all things being equal, individual is assumed to be rational by selecting the alternative that yields maximum utility. Thus, the satisfaction and benefits derived from adoption has a motivating effect on individuals with respect to adoption of alternative CA practices, especially when the utility derived is greater than what would have been derived from the choice of non-adoption.

The total utility is then expressed as a function of farmers' crop production output and other exogenous factors as provided in the literatures:

$$U_{ij} = \alpha(Y_{ij}) + \varphi x_{ij} + \varepsilon_{ij} \quad (2)$$

where

Y_{ij} is the farmers' crop production output, x_{ij} is the vector of observed factors that affect total utility and

Φ is the standard normal cumulative distribution function (CDF), ε_{ij} is the random component capturing the unobserved factors, i denotes an individual and j mirrors the choice decision of CA adoption.

Here, farmers are assumed to be adopters if and only if they adopt all the three full basic packages/principles of CA simultaneously, while a farmer is regarded as non-adopter if the farmer adopts none or anything short of all the three full basic packages/principles of CA. In this case, this suggests that a non-adopter in the real sense of it may not necessarily be a non-adopter of CA (i.e. "true zero" principle) but operating on partial adoption scale.

However, partial adoption is the adoption of one or more CA technologies/practices rather than the "full" package, while adoption of full package of CA by farmers is the simultaneous application of all three principles of CA on any given plot (D'Souza & Mishra, 2018; Lalani, Dorward, & Holloway, 2017)

Therefore, the issue of “true zero” (non-adoption) needs to be accounted for in the model: a necessary and sufficient justification for the choice and use of heckman selectivity model to correct this potential overt and hidden bias. In doing this, and to control for unobservable heterogeneity, serious attention must be given to the choice decision of non-adoption as represented by “zero” which may arise from three basic reasons as highlighted by Humphreys (2013). First, decision associated with “zero” (non-adoption) may be as a result of genuine or optimal decision of the respondent. “This type of outcome presupposes a ‘corner solution’ to a constrained utility maximization problem”. Second, it may be as a result of non-response outcomes or missing values because a respondent decides not to respond to the question or that there is time constraint “too short survey time frame” to include the actual behaviour. Finally, it may represent a decision which the respondent has no control over for some reasons; that is, the respondent has no choice about the outcome. All these suggest that some individuals who are observed as non-adopters could actually be adopters under some conditions as it pertains to the first reason. Humphreys (2013) further gave a supportive instance that: “the price/cost associated with a bundle of good (in this case, CA adoption) may be high enough to generate a corner solution to the agents’ utility maximization problem, but at a lower price/cost, an individual might choose to adopt”. On the other hand, with respect to the second and third reasons, non-adopters will always be observed not adopting, no matter what happens; these do not involve any choice.

All things being equal, individual compares the satisfaction associated with each choice, so is the level of production output before the choice decision on adoption is made i.e. adoption or non-adoption of alternative CA practices. But the “difference in utilities is however not observed and only the decision that the individual takes is observed which is always estimated using heckman model” (Lubungu et al., 2012).

2.3.2. *Mathematical/model representation of the heckman selectivity model*

The challenges associated with impacts or intervention evaluation (for instance, adoption of agricultural technologies) is selection bias. Estimation of such impacts with ordinary least-squares (OLS) technique in the presence of self-selection bias will likely generate spurious and inconsistent estimates (Heckman, 1979; Humphreys, 2013). In this case, differences in production output between adopters and non-adopters cannot be attributed to adoption of alternative CA practices using OLS in as much as selection bias exists; therefore, the caveat necessary to correct the possible selection bias must be observed. Heckman (1979)’s selectivity model has been widely applied in behavioural choice models to solve this issue; this is also supported by Greene (2003).

The heckman model corrects for the sample selection bias that may arise from unobservable factors through estimation of two equations in stages: the first stage is the *selection equation* estimation through probit model; this is used to model CA adoption and the second stage involves the empirical estimation of *outcome equation* through OLS model, which is used to model production output. Hence, “heckman model is apt for such estimation because it addresses endogeneity problems”.

Indeed, Sinyolo, Mudhara, and Wale (2014), Ngwira et al. (2014) and Awotide et al. (2016) also buttressed the need to address this issue and provided supportive guidelines towards the estimation procedures.

Following these guidelines, CA adoption equation (i.e. selection equation) is modelled as follows:

$$CAD_i^* = \mathbf{y}z_i + u_i, \quad (3)$$

$$CAD_i = 1 \text{ if } CAD_i^* > 0, \text{ and } 0, \text{ otherwise} \quad (4)$$

where

CAD_i^* is the latent endogenous variable, such that $CAD_i = 1$ when $CAD_i^* > 0$,

z_i is a vector of explanatory variables that influence farmer's adoption decision,

γ is the estimated coefficients and u_i is the statistical noise.

This model can be explicitly specified as follows:

$Y = CAD = 1, CA \text{ adoption}, 0, \text{ otherwise}$; $X_1 = \text{gender (male} = 1, 0, \text{ otherwise)}$; $X_2 = \text{age (years)}$;

$X_3 = \text{years of formal education (years)}$; $X_4 = \text{years of experience in CA practices (years)}$;

$X_5 = \text{land acquisition (inheritance} = 1, 0, \text{ otherwise)}$; $X_6 = \text{CA farm size (plot/ha-continuous)}$;

$X_7 = \text{total farm size (plot/ha-continuous)}$; $X_8 = \text{access to credit facilities (yes} = 1, 0, \text{ otherwise)}$;

$X_9 = \text{access to extension service (yes} = 1, 0, \text{ otherwise)}$; $X_{10} = \text{frequency of extension visit (actual number-continuous)}$; $X_{11} = \text{farmers risks attitude or behaviour (index-continuous)}$; $X_{12} = \text{social capital-trust (continuous)}$; $X_{13} = \text{density of social groups membership (actual number-continuous)}$; $X_{14} = \text{diversity of social group members (heterogeneity-index)}$; $X_{15} = \text{participation in decision making (decision making-index)}$; $X_{16} = \text{social capital-benefits (index-continuous)}$;

$X_{17} = \text{CA-perceived benefits (index-continuous)}$.

It is worthy mentioning that “the selection (adoption)” equation normally generates a “selection variable” which is called “inverse mills ratio (IMR)”, and more importantly, this and the predicted errors are both captured in the second-stage equation (OLS model) during the estimation process; hence, the estimates become unbiased and consistent. Also, “the inverse mill's ratio (IMR) or inverse of the mill's ratio, denoted by (λ) refers to the ratio of the probability density function over the cumulative distribution function of a distribution which measures the covariance between the two errors in the selection and outcome equations” (Greene, 2003); equally, the use of the IMR is more driven by the property of the truncated normal distribution. Thus, the selection parameter (IMR) is usually used as an indicator to ascertain if there is significant sample selection bias or not in the model (Ngwira et al., 2014; Sinyolo et al., 2014).

Similarly, the second-stage procedure of the heckman selectivity model estimation is specified as follows:

$$L_n Y_i = \alpha + \beta x_i + \beta_\lambda \lambda_i + \eta_i \quad (5)$$

where

$L_n Y_i$ is the natural log of production output of i th farmer, x_i is the vector of farmers' and farm-based characteristics, λ_i is the IMR, η_i is the sample selection-corrected error term, and β and δ are parameters to be estimated.

The IMR (λ) is given by

$$\lambda_i = \frac{\phi(\rho + \alpha x_i)}{\Phi(\rho + \alpha x_i)}$$

where

ϕ and Φ are, respectively, the standard normal density function and standard normal distribution functions. Recall that the estimated IMR (λ_i) in the first stage equation provides OLS selection equation in the second stage with corrected estimates as pointed out by (Greene, 2003). In line

with this submission, “the null hypothesis for sample selection bias is that $\beta_\lambda = 0$, that is, the IMR collapses to zero; hence, there is no sample selection bias” (Ngwira et al., 2014).

Therefore, if the λ_i value is not significant statistically, then sample selection bias is not an issue in the model, which further suggests that a single equation of OLS estimation would yield efficient estimates; according to Ngwira et al. (2014), although this situation does not completely rule out sample selection bias in the model, “it simply suggests that the available sample selection bias is not significant enough to render OLS estimates inefficient”. Conversely, if λ_i is statistically significant, the null hypothesis for sample selection bias is not accepted (rejected) ($\beta_\lambda \neq 0$) (this suggests that there is a strong evidence of significant sample selection bias) (Ngwira et al., 2014). If there is a revelation of a “statistically significant λ_i ” in the outcome (production output) equation model, it does suggest that “important difference exists” between the farmers that adopt CA practices and those that did not adopt.

However, there is an argument on the submission of Ngwira et al. (2014) and Sinyolo et al. (2014). This has to do with the significance of IMR (λ_i) as a measure of sample selection bias. Kennedy (2006) had earlier pointed out that selection bias is not always well construed by most researchers. Therefore, in line with Kennedy’s submission, Certo, Busenbark, Woo and Semadeni (2016) emphatically stated that the use of significance status (significant or not significant) of IMR (λ_i) may be misleading and provide professionally unacceptable conclusion about the sample selection bias in heckman selectivity model. These authors further cautioned against using insignificant λ_i as a valid indicator of selection bias absence, noting that such insignificance may stem from small sample frame and/or weak exclusion restrictions.

Similarly, the ability to detect a significant λ_i hinges on the strength of exclusion restrictions (variables used) as well as the correlation between the covariate and lambda (λ_i); these are touted to influence the degree to which the covariates and lambda (λ_i) are statistically significant in the model. Suffice to say that the use of stronger exclusion restrictions, according to Certo et al. (2016), influences the statistical significance of both the covariates and lambda (λ_i); in turn, the strength of the exclusion restrictions can be determined through the use of the correlation (ρ) between the covariates and the lambda; hence, λ_i does not necessarily suggest sample selection bias; rather much focus should be placed on the correlation factor (ρ) in addition to lambda factor (λ_i). Correlation factor-rho (ρ) ranges from -1 to $+1$. The closer ρ is to $+1$ or -1 , the more closely the two variables are related; and if ρ is close to 0 , it means there is no relationship between the variables. In other words, ρ varies in degree; it could suggest a strong relationship if is very close to unity, or a weak or no relationship if it is close to zero (Cuddeback, Wilson, Orme, & Combs-Orme, 2004).

Certo et al. (2016) also noted that endogeneity (which could either be a sample-induced or traditional endogeneity) problem may result from sample selection bias; it could also be caused by simultaneous causality and/or error in measurement (Semadeni, Withers, & Certo, 2014). All these suggest a correlation between the covariates, and the error terms in the heckman equations, which is denoted by rho (ρ); then, it is good to stress that lambda (λ_i) is a product of sigma (σ) and rho (ρ) while σ is the standard deviation of the residuals in the second-stage equation.

Importantly, Certo et al. (2016) did emphasize that heckman (i.e. full information maximum likelihood, FIML) model accounts for only sample-induced endogeneity, and caution was given against any attempt to conflate endogeneity because of sample selection bias, with endogeneity resulting from other sources.

Therefore, taking into consideration all the aforementioned arguments, the variables included in the outcome model are explicitly expressed as follows:

$L_n Y_i$ = natural log of production output (continuous)

X_1 = gender (male = 1, 0, otherwise); X_2 = age (years); X_3 = years of formal education (years);

X_4 = marital status (married = 1, 0, otherwise); X_5 = total years of experience in farming (years);

X_6 = CA farm size (plot/ha-continuous); X_7 = total farm size (plot/ha-continuous); X_8 = access to credit facilities (yes = 1, 0, otherwise); X_9 = access to extension service (yes = 1, 0, otherwise);

X_{10} = frequency of extension visit (actual number-continuous).

Furtherance to the earlier explanations on getting a consistent parameters, another important caveat to guarantee a reliable estimates of the outcome equation as emphasized by Heckman and Vytlacil (2005) is premised on the inclusion of “at least one regressor (with a non-zero coefficient) in the selection equation which does not influence the outcome (production output) directly” (Blundell & Costa-Dias, 2000 as cited in Sinyolo et al., 2014).

This suggests that inclusion of variable/variables, which directly affect(s) selection equation (adoption of CA), but having no direct influence on the outcome equation (production output), is pertinent, which is also required for model identification purpose; these variables are referred to as exclusion restrictions (Certo et al., 2016). Likewise, including the same number of variables in the selection and outcome equations may result in serious co-linearity and of course produces an imprecise estimates; this is also stressed by Sartori (2003) who though has a slightly divergent opinion about this submission.

Conclusively, smallholder farmers are usually termed resource poor farmers and it will be expected that those who adopt CA practices would better of due to their exposure and adoption choice (Sinyolo et al., 2014). Based on this submission, the production output differences between adopters and non-adopters cannot be emphatically attributed to adoption of CA practices with the use of OLS estimation strategy as long as selection bias exists; hence, the justification for using heckman selectivity model estimation to correct this bias and eliminate potential confounders to the barest minima.

2.4. Results and discussion

The summary statistics of the selected socio-economic characteristics of the farmers are presented in Table 3, which shows the mean values of the farmers’ and farm-based features as well as their social capital endowments.

2.5. Adoption pattern of full basic CA techniques (pooled)

The adoption pattern of the earlier discussed three recommended full basic CA techniques in South-West Nigeria is presented in Table 4. The distribution revealed that majority (82.57%) of the smallholder farmers did not adopt the three basic CA techniques (i.e. minimum soil disturbance, the use of crop biomass for permanent cover of soil and sequential rotation practice for different unrelated crops) as outlined by FAO (2011). Conversely, there exist very few (17.43%) risk-averse farmers who indeed adopted all the three basic CA principles highlighted above.

By implication, this result suggests that the diffusion of CA as an agricultural innovation is still partial and very limited in Nigeria and many SSA countries; this could have a serious and devastating consequence on the sustainability of food production and by extension, attainment of food and nutrition security as enshrined in the Sustainable Development Goal 2. Perhaps, this finding could be attributed to information gap about the potential benefits of CA adoption and/or the reluctance of farmers to adopt the CA in full because of its long-term associated benefits, which is in line with those of D’Souza and Mishra (2018).

2.6. Adoption pattern of full basic CA techniques (by states/regions)

The adoption pattern of the three recommended full basic CA techniques as disaggregated by states in the study area (South-West Nigeria) presented in Table 5 revealed that majority (44.26%) of the smallholder farmers who did adopt the three basic CA techniques are domiciled in Oyo

Table 3. Summary description of farmers & farm features and social capital components

Variables	Mean	Std. dev.	Min.	Max.
Age (years)	52.13	8.34	24	63
Years of formal education (years)	6.88	5.11	0	18
Family (household) size (actual)	6.28	1.64	3	9
Total years of farming experience (years)	20.95	10.66	5	40
Years of experience in CA practices (years)	12.97	8.41	2	25
Basic CA principles adopted (actual)	1.60	0.96	0	3
Total CA principles adopted (actual)	4.33	1.58	1	9
Output (kg ha^{-1})	346.37	531.55	15.23	2667.99
Farm size for CA (ha)	2.60	1.18	1	7
Total available farm size (ha)	4.92	2.43	2	10
Transaction cost (N)	57,518.31	26,266.83	16,000	125,500
Frequency of extension visit (actual)	1.92	1.13	0	3
Risk preference index level (actual-continuous)	3.43	2.19	0	9
Density of social groups membership (actual)	3.82	1.08	2	6
Attendance in group meetings (%)	61.38	15.71	0	96.67
Diversity of social group members (%)	23.40	12.06	3.33	80
Involvement in decision-making (%)	53.16	12.50	22.22	77.78
Cash contribution (N)	2791.6	2626.06	450	22,400
In-kind contribution to groups (man-day)	14.29	16.28	0	66
*Aggregate social capital (%)	41.82	18.65	10.37	86.67

Source: Data Analysis (2018).

Table 4. Distribution of respondents by adoption decision (pooled)

Full CA adoption decision	Frequency	Percentage
Non-adopters	289	82.57
Adopters	61	17.43
Total	350	100.0

Source: Data Analysis (2018).

Table 5. Distribution of respondents by adoption decision by state/region

State/region	Full CA adoption decision by state/region		Total
	Non-adopters	Adopters	
Oyo	58	15 (24.59)	73
Osun	127	19 (31.15)	146
Ondo	104	27 (44.26)	131
Total	289	61	350

Source: Data Analysis (2018).

state/region, while about one-third (31.15%) of the adopters are found in Osun state. Conversely, only one-quarter (24.59%) of the total adopters are domiciled in Ondo state.

The implication of this finding is that Oyo state has the largest proportion of CA adopters in the study area of South-West Nigeria. The reason for this observation could be attributed to the presence of a research institute known as International Institute of Tropical Agriculture (IITA) in the region

which is very proactive in rural development research and transfer of innovative techniques in agriculture across the agrarian settlements in Nigeria (for instance, Manyong, Dixon, Makinde, Bokanga, and Whyte 2000; Sanni et al., 2009). Further intensification of efforts by this research institute and other allied research establishments in South-West Nigeria can induce positive CA adoption behaviour among smallholder farmers towards increased agricultural yields.

2.7. Econometrics results

2.7.1. Heckman selectivity model

This study analysed the relationship between adoption CA adoption and smallholder farmers' production output using FIML of heckman selectivity model to control for potential selection bias problems. Table 6 shows that the fitted model is good as indicated by the overall Wald χ^2 which is highly significant at $p < 0.01$; this finding is consistent with that of Ngwira et al. (2014) and Baiyegunhi, Hassan, and Ortmann (2018).

Table 6. Effect of CA adoption and production output: heckman estimates

Variable	Outcome equation (log of production output)	Selection equation (CA adoption)
Gender	- 0.1618 (-1.21)	- 0.0324 (-0.17)
Age	- 0.0023 (-0.29)	1.0099 (0.92)
Years of formal education	- 0.0290 (-2.21)**	- 0.0096 (-0.54)
Marital status	- 0.2353 (-1.85)***	-
Total years of farming experience	- 0.0207 (-3.48)*	-
Years of CA farming experience	-	- 0.0230 (-2.29)**
Land acquisition	-	- 0.4033 (-1.86)***
Farm size cultivated under CA	- 0.0585 (-0.92)	0.1710 (1.88)***
Total farm size available	0.0001 (-0.00)	- 0.0885 (-2.20)**
Credit access	0.0145 (0.10)	0.0970 (0.47)
Access to extension	3.2621 (11.54)*	0.7013 (1.81)***
Frequency of extension visit	- 1.2079 (-17.90)*	- 0.1855 (-1.61)
Farmers' risk preference	-	- 0.2695 (-0.64)
Social capital-trust	-	- 0.6672 (-2.33)**
Density-social groups membership	-	0.0227 (0.26)
Diversity of social group members	-	1.7576 (1.70)***
Involvement in decision-making	-	0.4709 (0.58)
Benefits index of social capital	-	1.3885 (1.94)***
Benefits index of CA	-	0.3799 (0.49)
Constant	5.1060 (8.28)*	- 0.4699 (-0.39)
/athro	- 0.5165 (-1.82)***	0.0914
/lnsigma	0.0627 (1.11)	
rho (ρ)	- 0.4750	0.1132
sigma (σ)	1.0647	
lambda/inverse mills ratio (λ)	- 0.5058 (1.99)**	
LR test of indep. equations ($\rho = 0$): $\chi^2(1)$	2.20 (0.1379)	
Wald $\chi^2(10)$	417.15***	
Number of observation	350	

* $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$ level, respectively. Values in parentheses are z-values.

Source: Data Analysis (2018)

Similarly, the IMR (λ), which is a selection bias control parameter, was found to be significantly different from zero ($p < 0.05$) in the second stage of the heckman selectivity model, suggesting that there was a significant sample selection bias, but the bias was accounted for by this control parameter (Bascle, 2008; Quigley & Hambrick, 2012). This finding is also consistent with that of Awotide et al. (2016) and Baiyegunhi et al. (2018). Broadly speaking, the significance of IMR parameter also suggests correlation of the error terms in both the selection and outcome equations. Consequently, there are *unobserved dynamics* that make CA adoption more likely to be associated with a higher productivity output, and a further indication of sample-selection bias. Hence, this justifies the use of heckman selectivity model.

Following Satori (2003), Heckman and Vytlačil (2005) and Certo et al. (2016), selection of strong exclusion restrictions is paramount in estimating heckman model. This study observed this condition by using farmers' risk preference and social capital-trust which serve as exclusion restrictions in the heckman model estimation; these exclusion restrictions are predictive of selection equation (i.e. CA adoption) but not correlated with the outcome equation (i.e. production output).

The interesting thing about these exclusion restrictions variables chosen and used is that they also represent indirect proxies for social capital. Table 6 indicates that the estimated correlation parameter (ρ) is negative and weak as expected because the estimation observed a very strong exclusion restrictions caveat required for the heckman selectivity model.

The results from the first stage (selection equation) of the heckman selectivity model revealed that factors, such as exposure time period proxied by years of CA farming experience ($p < 0.05$), mode of land acquisition ($p < 0.1$), farm size cultivated under CA farming systems ($p < 0.1$), total available farm size ($p < 0.05$), access to extension agents ($p < 0.1$), social capital-trust ($p < 0.05$), diversity of members in social groups ($p < 0.1$) and benefits index of social capital ($p < 0.1$), are statistically significant predictors with respect to adoption of full CA principles.

This finding is in agreement with that of Cheteni, Mushunje, and Taruvunga (2014) and Ngwira et al. (2014) who also reported that, years of farming experience, farm size cultivated as well as the social capital are important predictors of CA adoption. It is equally important to further stress that social capital components in the fitted model have significant effect on CA adoption. This further permits to strongly reject the null hypothesis and accept the alternative hypothesis that there is a significant effect of social capital on CA adoption in the study area.

Consequently, from the findings, exposure time period proxied by years of CA farming experience was indicated to have an inverse relationship with CA adoption, suggesting that the probability of CA adoption is lower among smallholder farmers with high exposure time period; this is inconsistent with expectations and, by implications, the chances of alternative CA adoption decline by about 2.3%, *ceteris paribus*. As expected, mode of land acquisition was negatively related with CA adoption, suggesting that, all else equal, there is a decrease in probability of CA adoption by farmers who acquired their farmland holding through inheritance.

This finding supports the earlier submission that land fragmentation because of land inheritance from one generation to another discourages adoption of improved agricultural practices such as CA because of limited availability of farmland. The reason for this submission is that land acquisition through inheritance is the prevalent mode of land acquisition in the study area and was used as a basis of comparison with other modes of land acquisition. Similarly, the negative association of total available size of farmland with CA adoption could be because of limited capability status of farmers to expand and maximize their farming operations with available farmland even when there is opportunity to do so.

In the same vein, social-capital factor (trust) has a U-shaped relationship with CA adoption; a plausible explanation for this result is that CA adoption will likely decrease first due to trust issue

on the technology as currently seen, but most likely to increase with time and through socialization process when substantial trust is built once the CA technique becomes more viable, visible and attractive to most farmers; thus, the level of social capital-trust declines the probability of CA adoption by approximately 67% in the study area at the moment. This is evident from the direction of movement of the social capital-trust variable in the heckman estimates. This obviously explains the reason behind farmers' apathy to embrace improved agricultural technologies-CA (Hunecke, Engler, Jara-Rojas & Poortvliet, 2017).

Conversely, the findings also revealed a direct relationship between farm size cultivated under CA and CA adoption. This suggests that, as expected, increase in farm acreage under CA system will induce a rise in the probability of CA adoption by 17.1%. In a similar manner and in line with *a-priori* expectations, extension service delivery also has a direct effect on CA adoption. Evidently, it is within the mandate of extension agents to diffuse beneficial information on improved agricultural technologies and demonstrate such technologies among the targeted audience, usually the smallholder farmers.

All things being equal, the chance of CA adoption in the study area is increased by approximately 70.1% with increased and improved extension service delivery by government. Although frequency of extension visit in the study area is not encouraging, because the study found somewhat low contact (twice per month) of the extension personnel with farmers as shown in Table 3. Meanwhile, a consistent contact of farmers with extension agents cannot be detached from a successful adoption process.

Similarly, social capital components (diversity of social group members and social capital benefits) as expected, did have a direct relationship with CA adoption in the study area. The implication of these findings is that, the likelihood of CA adoption is increased by factors of 1.76 and 1.39 with increase in diversity among members of social groups and enjoying maximum benefits, respectively. These findings are in line with *a-priori* expectations and earlier submission where it was posited that enjoying high continuum of benefits especially in terms of social and environmental benefits would likely foster wider acceptance of CA practices and induce positive adoption behaviour in farmers (for instance, Silici, Ndabe, Friedrich, & Kassam, 2011). In sum, the above expositions have revealed the important dynamics that significantly predict farmers' decision to adopt alternative CA practice in the study area.

The second stage (outcome equation) of the heckman selectivity model assessed the factors driving production output with reference to CA adoption in the study area; it also estimated the presence of possible endogeneity between CA adoption and production output as indicated in the early part of this discussion. Thus, findings as indicated in Table 4a revealed that, of the fitted variables, years of formal education ($p < 0.05$), marital status ($p < 0.1$), years of farming experience ($p < 0.01$), access to extension service ($p < 0.01$), and frequency of visits by the extension agents ($p < 0.01$) significantly predict production output, among other factors in the study area.

This finding is partly in tandem with Awotide et al. (2016). Thus, years of formal education had a negative effect on production output, suggesting that increase in the level of educational attainment is inconsequential to production output. There is a mixed feeling about this result; first, all things being equal, education is expected to expose individuals to beneficial information especially as it concerns improved agricultural techniques such as CA which if adopted is likely to boost production output. Second, education may also induce migration, especially among the youths category in search of white-collar jobs; this is expected to impact negatively on the volume of production output.

Similarly, there is an inverse relationship between farmers' marital status and production output; this non-linear relationship is inconsistent with *a-priori* expectations. By implication, it suggests that increase in the number of married individuals negatively impacts on the production output.

On the contrary, married individuals with children are expected to access family labour. Therefore, a positive impact on crop production output from CA is assumed; hence, a positive impact on production output is expected. However, this not the case and the reason could be a possible migration of children/youths (who serves as family labour) away from the rural areas in search of perceived better paid jobs.

Importantly, this can best be described by the models according to Lewis (1954), as well as Fei and Ranis (1961) which established that “migration is a response to the high demand of labour by an industrial sector, which assures workers, greater levels of productivity, and, for investors, positive profits superior to the opportunities found in the traditional agricultural sector”. Similarly, Harris and Todaro (1970) provided a supportive instance that rural–urban migration in less developed countries is premised on the difference between the “expected wage from migration (urban wage) and the agricultural wage”. Consequently, this scenario provides incentives and an easy gateway for migration to the cities or urban areas by the youths. Based on these models, rural areas suffer from limited labour productivity.

Inverse impact on production output was observed for years of farming experience. This result is also with mixed feelings because years of farming experience is expected to play a positive role during farming operations as farmers with many years of experience should be better off than farmers with less years, but the reverse is the case here. The possible reason for this is simply lack of production efficiency and the inability to maximize production output because of limited resources in terms of productive inputs and other multifaceted constraining factors (Mango, Siziba, & Makate, 2017).

In the same vein, there is a negative relationship between frequency of extension visit and production output. This is not unexpected going by the previous result observed. The average frequency of extension visit in the study area is approximately twice every month. This is very low especially with the rising call for adequate extension delivery system among farmers. Adequate extension delivery system is very important for diffusion and adoption of improved agricultural practices such CA among the smallholder farmers in sub-Saharan Africa.

On the other hand, access to extension service was found to have a direct relationship with production output, as expected. Access to timely and adequate extension delivery service apparently will boost efforts on the fight against land degradation, as important farming techniques such as CA can easily and successfully be transferred and diffused through constant interactions of extension agents and the smallholder farmers. This result indicated a direct relationship of farmers’ access to extension service with production output while an inverse relationship was observed for frequency of extension visit with production output.

A plausible explanation for this is that access to extension service by farmers has a positive effect on production output as expected while the negative relationship attached to frequency of extension contact and production output could be because of low frequency of visit by extension personnel in the study area, as previously explained.

2.8. Wald tests of non-linear hypotheses

The likelihood-ratio test of independence equations in the heckman selectivity model as discussed in Table 4a, indicating a chi-square of 2.20 with estimated *p*-value of 0.1379, does satisfy the null hypothesis of “representation invariance”; this is indeed a necessary but not enough sufficient condition that must be satisfied to ascertain the existence of invariance in the representation. Consequent on this, there is a need for post-estimation test of non-linear hypotheses. According to Baum (2010), Wald test of non-linear hypotheses with adjusted *p*-values was carried out using Holm, Sidak, and Bonferroni correction methods. As indicated in Table 7, the tests’ verdicts overwhelmingly reject (at 99% confidence level) the joint hypothesis that the model excluding the covariates is correctly specified relative to the full model. More importantly, it also revealed strong evidence

Table 7. Tests of non-linear hypotheses

Equation	χ^2	Df	p-value (holm)	p-value (sidak)	p-value (bonferroni)
(1)	3.41	1	0.0646 #	0.1817 #	0.1939 #
(2)	27.76	1	0.0000 #	0.0000 #	0.0000 #
(3)	30.05	1	0.0000 #	0.0000 #	0.0000 #
All	64.61	3	0.0000	0.0000	0.0000

Holm/Sidak/Bonferroni-adjusted p-values.

Source: Data Analysis (2018).

against the proportionality of the specified variables' coefficients in the model; similarly, all the coefficients seem to contribute to the highly significant test result on the overall. By implication, it suggests that the differences in the residual variances of the smallholder farmers' characteristics can be ruled out as the explanation for the observed characteristics differences among the adopters and non-adopters of CA, which further explain the production output differences among these farmers. Hence, independence assumption is satisfied.

3. Conclusion and policy recommendations

The estimates from heckman selectivity model did indicate that exposure time period, mode of land acquisition, farm size cultivated under CA farming systems, total available farm size, access to extension agents, social capital-trust, diversity of members in social groups and benefits index of social capital are statistically significant predictors with respect to the *selection equation* that is the CA adoption model. However, years of formal education, marital status, years of farming experience, access to extension service and frequency of visits by the extension agents significantly predict the *outcome equation* that is the production output. Importantly, the estimated IMR (λ), which is a selection bias control parameter, was found to be significantly different from zero in the second stage of the heckman model. This is an indication that there was a significant sample selection bias, but the bias was accounted for by this control. A further indication that there was a significant impact of CA adoption on farmers' predicted production output.

Thus, it can be concluded that a proper action is needed to relax the land endowment constraints being faced by smallholder farmers to fully adopt CA systems; especially with the existing customary land tenure system, in as much as farm families cannot be denied their traditional land rights entitlements, government's involvement in functional land rental market will be beneficial to CA adoption as this will assist farmers to benefit from farm size economies, while at the same time serves as an income generation avenue for the families whose farm-lands are left fallow without being put to use. There is need for strengthening and improving the extension delivery system associated with diffusion of information about CA practices in Nigeria through continuing and ongoing supports of extension services using farmer-led extension approach facilitated by public extension agencies and NGOs saddled with outsourced extension services.

Similarly, as indicated in Table 6, years of formal education by farmers is significantly important. Therefore, efforts towards human capital development needs to be put in place because the fastest way to defeat poverty and capacity build people is by educating them; education has a multiplier effect and it is indeed a gift that keeps on giving. Meanwhile, this can be done by repositioning the Universal Basic Educational system of the country, making it a genuine and compulsory free education for people even if it is at the basic/elementary level. Likewise, there is a need for extensive campaign on the scaling up of CA adoption because adoption is still limited in Nigeria owing to farmers' risk averse behaviour; when the fear of unknown attached to CA farming practices is allayed, increase in farm size dedicated to CA can also be achieved.

Conclusively, proper awareness is needed on the climate smart importance of CA systems, so that the farmers can be exposed to CA technologies because exposure time period significantly drives positive adoption behaviour in farmers. Importantly, social capital-trust represents a solid foundation upon which social networks can be built. In the light of this, a high level of trust among peers, which can be obtained through a lengthy process of repeated positive interactions, is regarded as a safety net for individuals to reduce risk especially when it was also established that most of the farmers are risk averse. Consequently, policy to promote formal and/or informal social networks is essential because information acquired through individual's social networks (which is regarded as a strong tie) is very vital in fostering positive adoption behaviour in farmers.

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Ethical Considerations

This research observed the following ethical considerations: anonymity, informed consent, privacy, confidentiality as well as professionalism in the study area.

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