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Impact of credit on the climate adaptation utilization among food crop farmers in Southwest, Nigeria: application of endogenous treatment Poisson regression model

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Abstract

The importance of credit in agriculture and technology adoption is well researched, but little is known about its impact on the intensity of climate adaptation strategies (CAS) utilization. To contribute to the literature on climate change, the study examines the impact of credit status on the intensity of CAS utilization with its treatment effects. Unlike previous studies that investigated CAS as binary decisions or multi-class models, the study changed the narrative by measuring the number of CAS adopted and utilized by crop farmers. Farm-level data were collected from 150 crop farmers in Southwest Nigeria using a well-designed questionnaire. Descriptive statistics and the endogenous treatment Poisson regression (ETPR) model were used for the data analysis. The results revealed that credit status positively and significantly impacts the intensity of CAS utilization. Other farm-level factors that jointly impacted CAS utilization were education, experience, age, income, extension contacts and farm size. Likewise, the credit status co-joints with climate variables, such as access to climate information, perceived rainfall and temperature, to impact the intensity of CAS utilization in the area. Based on the treatment effects estimates, an average crop farmer will utilize 1.986 times CAS more when he is not being credit constrained, while the average crop farmer in the treated group will utilize 1.757 times CAS more than it would if s/he is credit constrained. Thus, the policy should focus on revamping credit institutions that prioritize requisite adaptation strategy resources.

Keywords: Climate change, Credit, Crop farmers, Endogeneity, Impact, Treatment effects, Nigeria

Introduction

The negative impact of climate change has been established globally, especially on food crops. Its consequence is increasingly becoming worrisome to global sustainable development and human existence (Zadawa and Omran 2020; Adeagbo et al. 2021). It has been projected that global poverty under climate scenarios would escalate by 35–122

million if no mitigation and adaptation measures are adopted (FAO 2016; Shahzad and Abdulai 2020). However, several researchers affirm that no amount of mitigation of greenhouse gases (GHGs) can avert some climate change even if the best effort is exerted by the international community (Bryan et al. 2009). The situation gets worse with African countries being most vulnerable to climate change due to their total dependence on rain-fed agriculture as reported by IPCC (2007). It was on this note that many scientists advocate for urgent adaptation responses to the precarious consequence of climate change not only in Nigeria or Africa but in the world at large. However, climate adaptation has been widely researched in terms of identification, classification and assessment (Bryan et al. 2009; Deserra et al. 2009; Asrat and Simane 2018; Adeagbo et al. 2021). A lot of location-specific adaptation strategies have been reported by the researchers, especially in crop production and ascertained that no one adaptation option can combat the effect of climate change. It normally goes with the combination of several adaptation measures or options, especially among food crop farmers (Khan et al. 2020). The adoption and utilization of adaptation options attract some costs (Adeagbo et al. 2021). Therefore, to achieve sustainable development in the area of climate change adaptation, the opportunity cost of adaptation would only be economically addressed if the food crop farmers are financially capable. Due to the low adaptive capacity in terms of technological and institutional resources, the nexus between credit access and adaptation utilization will provide tangible input for proper planning of climate change adaptation.

Despite the manifold benefits of credit and the adoption of adaptation measures, studies on their impacts are still very scarce, especially in developing countries (Chen and Flatnes 2019; Midingoyi et al. 2019; Ma and Wang 2020). A better understanding of the impact of credit constraints on climate adaptation utilization would be germane for designing climate adaptation policies that could enhance productivity and economic performance. Many prior studies on climate adaptation focused on the identifications and its choice determinants using either binary or polynomial regressions (Nhemachena and Hassan 2007; Deressa et al. 2009, 2011; Nhemachena et al. 2014; Dhanya and Ramachandran 2016; Mulwa et al. 2017; Asrat and Simane 2018; Ojo and Baiyegunhi 2020; Khan et al. 2020) in which credit access was one of the independent variables. Thus, the motivation for this study is born out of the paucity of information on the impact of credit on the degree of climate adaptation utilization knowing fully that farmers employ a combination of multiple adaptation strategies in the production processes and the adaptation strategies do not come without costs as reported by Adeagbo et al. (2021).

Furthermore, the impact of credit on the degree of adaptation utilization was analysed by focusing on the number of climate adaptation strategies utilized by the food crop farmers. Only a few studies have investigated climate adaptation strategies from the point of view of count data (e.g., Shahzad and Abdulai 2020; Adeagbo et al. 2021) but both authors differently worked on the impacts of the adoption of adaptation strategies (dichotomous) and internet use (dichotomous), respectively on the intensity of adaptation adoption. Thus, this study contributes to the previous literature by analysing climate adaptation strategies from the viewpoint of the count data model but makes a difference using credit status as a selection equation.

Moreover, this study also adds to the literature on the endogenous-treatment Poisson regression (ETPR) model. This study, by taking into account the heterogeneities

(observed and unobserved), corrects for selection bias associated with credit constraints. However, previous literature identified two techniques (a propensity score matching (PSM) and an inverse-probability weighted regression adjusted estimator (IPWRA)), but the two techniques failed to cater for the selection bias due to unobservable factors (Ma and Wang 2020). Also, Adeagbo et al. (2021) used a double-hurdle count data model which accounted for selection bias but failed to estimate the treatment effects. The ETPR model not only accounts for the selection bias caused by observed and unobserved factors, but it also predicts the treatment impacts of credit constraints on the degree of climate adaptation utilization.

Review of empirical studies on climate change and the roles of credit facilities

The effects of climate change will be greatly felt in developing countries (including Nigeria) because of their low income and inadequate adaptive capacity (Georgopoulou et al. 2017). Dhanya and Ramachandran (2016) added that farmers, especially crop farmers, will find it hardest compared with other sectors of the economy. In Nigeria, there is irrefutable evidence that the climate is drastically changing due to a decrease in rainfall and an increase in temperature (0.19°C per decade in the last 30 years) in the several past decades, with about a 0.5-m increase in sea level (World Bank 2021). This has caused about 24% of Nigerians to live in climate-prone areas, and many people (between 27 and 53 million) have relocated due to the climate's extreme events (USAID 2018). Again, Climate Scorecard (2019) put Nigeria among the top ten most vulnerable countries to the impacts of climate change and the risks of many natural hazards. Due to these facts, it has been projected that climate-sensitive sectors such as agriculture and forestry could cost Nigeria an estimated loss of US\$100 to 460 billion by 2050 if climate resilience through strong mitigation or adaptation strategies is not properly and urgently addressed (World Bank 2020). As it has been reported, agriculture (farmers) would be most affected, which means that about 80% of the rural Nigerians who source their income from agriculture (World Bank Group 2021) would be greatly impacted.

Again, a sustainable adaptation to climate change needs a farm credit institution capable to produce a source of revenue. The Central Bank of Nigeria (CBN) disbursed about 2.5% of loans amassed for commercial banks to agriculture (CBN 2008). Despite this, many studies have affirmed that smallholder farmers are constrained to access credit in financial institutions, and the inadequacy in the credit supply has hindered technology transfer (adaptation strategies in this case) and production expansion (Okojie et al. 2009; Olagunju and Ajiboye 2010; Mulwa et al. 2017; Oparinde and Olutumise 2022). However, the economic importance of credit facilities to agricultural productivity and technology adoption cannot be over-emphasized. For instance, Adebayo and Adeola (2008) argue that agricultural credit does not only increase productivity but improves the standard of living by alleviating poverty among the farmers. The direct association between an adequate credit facility and increasing farming efficiency was reported by Mejeha and Ifenkwe (2007) while Oparinde and Olutumise (2022) affirmed that output increases when input levels are closer to optimal through the marginal contribution of credit. Foltz (2004) argues that households without credit constraints always have the conviction to separate consumption decisions from production decisions with optimally use of production resources. Dong et al. (2010) report that credit constraint farmers face

a decrease in productivity due to the deviation from optimally using of limited production resources. The credit availability has significantly improved farmers' income by about 23% while the credit constraints account for losses of nearly 18% of farmers' profit with a significant decrease in household consumption (Dong et al. 2010; Li et al. 2013; Tran et al. 2016).

Likewise, several studies have investigated the significant effect of credit access on the adoption of adaptation strategies. For instance, Deressa et al. (2009), Fosu-Mensah et al. (2012), Adeagbo et al. (2021) found a positive and significant relationship between credit access and adaptation strategies. Again, Chen and Flatnes (2019) argue that credit access makes farmers combat extreme climate events without relocation. Khan et al. (2020) reported that credit accessibility influences farmers' adaptation to climate change and might help them to sufficiently manage climate change without changing the crop calendar. Rafiq and Blaschke (2012) state that credit constraints expose farm households to be highly vulnerable to the impact of climate change while Olutumise et al. (2021) argue that credit accessibility can positively promote the adaptive capabilities to climate change.

Materials and methods

Location description, sampling procedure and data collection

The research was conducted in the Southwestern region of Nigeria. The region comprises three agroecological zones (humid forest, derived savanna and guinea savanna) which favour the production of food crops, and accounted for about 87.6% of the agricultural sector (PwC 2020). The climate is tropical in nature and characterized by distinct dry and wet seasons. The average temperature is between 21 and 35 °C while the average annual rainfall ranges from 150 to 3000 mm. Agriculture engages nearly 75% of the population and forms the major source of income generation. The data used for this study were collected between January and March 2022 (3 months), for the 2021 production season, from predominately crop farmers in the area. The data collection involved a multistage sampling procedure. First, the purposive sampling technique was used to select three states in the region, namely Ekiti, Ondo and Oyo. In terms of agroecological zones, Ekiti state was purely derived savanna, Ondo state combined the attributes of both derived savanna and humid forest, while Oyo state combined the attributes of both derived savanna and guinea savanna (Fig. 1). The three states are preponderant in crop production with an average nominal GDP of about \$1336.40 (Ekiti), \$3012.47 (Ondo) and \$1461.41 (Oyo) between 2013 and 2017 (NBS 2019). The second part of the procedure involved using a simple random selection technique to select two (2) Local Government Areas (LGAs) from each state, for a total of six (6) LGAs for the study. They include; Gbonyin and Ikole LGAs in Ekiti state; Akure North and Owo LGAs in Ondo state; and Ibarapa East and Saki West LGAs in Oyo state. Third, five (5) communities within each LGA were randomly selected, making a total of thirty (30) communities. Lastly, a snowball sampling technique was used to identify and select five (5) major crop farmers in the area, making a total of 150 samples. The State Extension Agent in each LGA assisted the enumerators in getting the key informants which are always the farmers' group heads in each community. It is worth noting that most of the farmers were not registered with the Government and getting the farmers sampled at a random would be

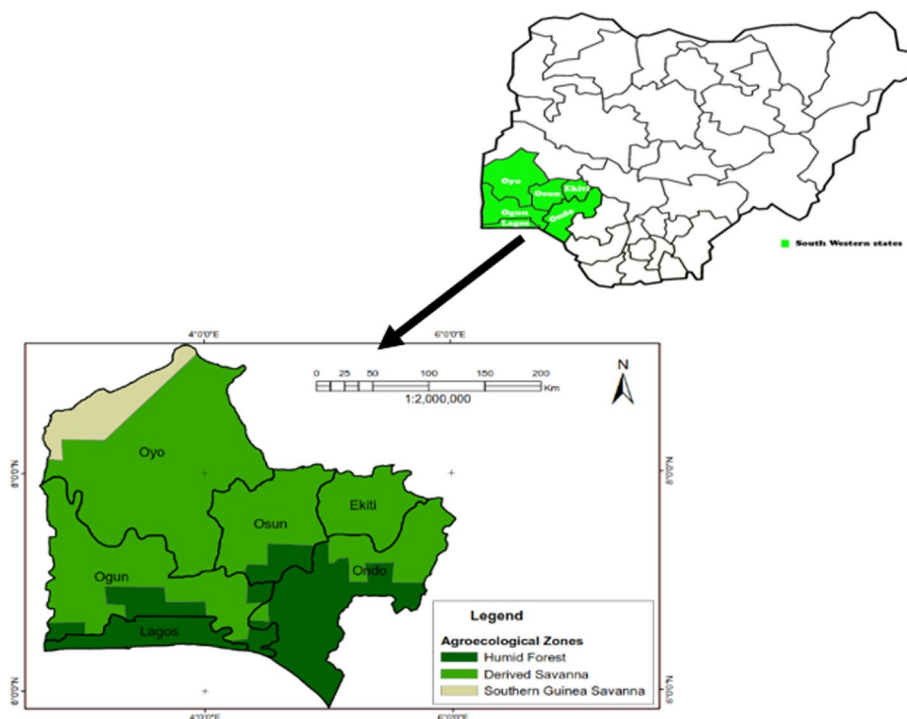


Fig. 1 Nigeria map and the Southwestern ecological zone

an effort in futility. The idea of using farmers’ groups really assisted to overcome some challenges such as incomplete information, missing copies of questionnaire and untrue data. A structured questionnaire was constructed and tested for reliability before being used in the study for accurate data collection. The test–retest method was employed to determine the instrument’s reliability, and a Cronbach’s Alpha coefficient of 0.803 was obtained.

Measurements of outcome indicators

The questionnaire was designed to accommodate questions on socioeconomic, institutional, climatic and farm-level factors. The main dependent variables in this study based on the primary objective are credit status and climate adaptation strategies (CAS). Credit status is measured as a binary variable, with zero (0) indicating that the farmer is a credit constraint (CCT) and one (1) indicating that the farmer is a non-credit constraint (NCT). To avoid untrue data, the farmers were asked questions in stages on credit acquisition as reported by Oparinde and Olutumise (2022). First, it was asked if the farmer applied for a loan/credit or not. Second, if applied, were you granted the exact amount or less. The categories that applied and received less than the amount requested were grouped as CCT, while those that did not apply for a loan at all and those that received the exact amount requested were grouped as NCT. Again, CAS utilization is measured as a count variable by focusing on the intensity or number of CAS utilized by farmers. The study posited several CAS followings the prior studies (Deressa et al. 2009; Bryan et al. 2009; Diallo et al. 2020; Adeagbo et al. 2021; Ogunleye et al. 2021) and asked the farmers to pick the CAS adopted and utilized in the last production season. Due to location specific, the study harmonized

and re-grouped to arrive at a list of 12 CAS mainly available for adoption in the area. They include: (i). change crop calendar; (ii). Crop rotation; (iii). Soil and water conservation; (iv). Irrigation system; (v). income diversification; (vi). Tree planting/Afforestation; (vii). Use of agrochemicals; (viii). Changing input mix; (ix). Crop diversification; (x). Diversifying seed varieties; (xi). Using improved seed variety; and (xii). Use of insurance. Multiple choices were allowed for the question and no adaptation was scored zero (0). Thus, values ranging from 0 to 12 were used to measure the intensity or number of CAS utilized by the crop farmers in the area.

Theory, concept and estimation strategy

The study is built on the Rational Choice Theory (RCT) to explain consumer (farmers) behaviour following Green and Shapiro (1996) and Green (2002). In RCT, the choice behaviour of an individual decision-making units is considered. It represents preferences with a utility function. RCT explains that a rational farmer maximizes utility given some constraints. That is, constraints make a choice necessary and allow trade-offs among alternatives. According to Zeng et al. (2019) and Adeagbo et al. (2021), when it comes to the adoption of innovations or new technology, farmers always make rational decisions. A rational farmer maximized profit given constraints such as capital (credit) input. Thus, for a rational farmer to adopt and utilize any technology, the expected benefits (profits) utility will be weighed by comparing the new technology with the old one (Channa et al. 2019; Adeagbo et al. 2021). The utility functions are employed to understand how crop farmers are making the preferred choices from among available alternatives (CAS) given the budget constraints (credit), which is translated into a mathematical expression in constrained optimization. Hermans (2004) and Olsen et al. (2009) reported that consumer preference describes how a consumer derives utility among alternatives which provides a better relationship between the expected costs and benefits. The RCT analyses how consumers may achieve equilibrium preferences by maximizing utilities as subject to consumer budget constraints (Green 2002).

The study develops a model for count data (number of CAS utilized by farmers) as the outcome variable H_i , which is the function of the binary variable (credit status) Q_i . The Q_i indicates the i^{th} farmer's credit status; that is, $Q_i=1$ if the farmer is a non-credit constraint (NCT) and $Q_i=0$ if the farmer is a credit constraint (CCT). The Q_i is always observed and serves as a causal shifter of the conditional distribution of H_i . Since the credit status might not be random, the Q_i is endogenous because some unobservable characteristics of the farmers influence Q_i at the same time affect the outcome variable H_i . Based on this scenario, the study employed an endogenous treatment Poisson regression (ETPR) as an econometric tool, to determine the impact of credit status on the CAS utilization being measured as count data. The ETPR model of estimation is carried out in two stages. The first stage, which is the selection equation, models the farmer's credit status. The underlying latent variable of credit status is hypothesized to affect the likelihood of utilizing CAS by crop farmers.

Let Q_i^* represents the difference between the utility of NCT and CCT, such that a farmer i will decide his/her credit status as indicated as:

$$Q_i^* = V_{NCT} - V_{CCT} > 0 \quad (1)$$

The two utilities are subjective, and they can only be described in a latent variable (selection equation) model as a function of observable components as:

$$Q_i^* = \gamma_i T_i + \omega_i R_i + \varepsilon_i \quad \text{with } Q_i = \begin{cases} 1 & \text{if } Q_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where Q_i^* represents the credit status which is determined by the observed variable Q_i . That is, $Q_i = 1$ if a farmer i is NCT and $Q_i = 0$ otherwise. γ_i and ω_i are the parameters to be estimated for exogenous (explanatory) variable T_i and instrumental variable R_i , respectively. T_i is a vector of explanatory variables that denotes household, farm-level, climate and institutional factors that might influence the latent variable Q_i^* . ε_i is a random error term. For identification purposes, variable R_i was incorporated into the model as it is expected to affect the credit status of the farmers but not the outcome variable (CAS utilization).

The impact of credit status on CAS utilization was determined in the second phase of the ETPR model. The CSA was modelled as a linear function of credit status and a vector of other independent variables, T_i . The equation can be expressed as:

$$H_i = \beta_i Q_i + \gamma_i T_i + \mu_i \quad (3)$$

where H_i is the number of CAS utilized by the farmers; Q_i denotes the credit status (CCT and NCT); β_i and γ_i means parameters to be estimated; μ_i is an error term. Thus, the γ_i measured the impact of credit status on the CAS utilization among the crop farmers. It should be noted that instrumental variable R_i was excluded from Eq. (3). This instrumental variable R_i in Eq. (2) is valid if it influences the credit status of the farmers but does not directly influence the intensity of CAS utilization (outcome variable) by the farmers. Possession of collateral was used as instrumental variable R_i following Oparinde and Olutumise (2022). Following Ma and Wang (2020), a Pearson correlation test was used to validate the instrumental variable, R_i .

Again, the ETPR model can further estimate treatment effects (Bratti and Miranda 2010; Ma and Wang 2020). Based on this, the average treatment effects (ATE) and average treatment effects on the treated (ATT) were calculated to provide a clearer understanding of how credit status impacts CAS utilization. The full sample for the CCT and NCT was used in Eq. (4) to estimate ATE, while the sample of the treated group (NCT) in a counterfactual context was calculated in Eq. (5). The equations were as follows:

$$ATE = E(H_{i1} - H_{i0}) = E\{(H_{i1} - H_{i0}|T_i)\} \quad (4)$$

$$ATT = E(H_{i1} - H_{i0}|Q_i = 1) = E\{(E(H_{i1} - H_{i0}|T_i, Q_i = 1)|Q_i = 1)\} \quad (5)$$

Results and discussion

Summary of the dependent and explanatory variables for the regression

In response to climate change’s effect, crop farmers in the study area adopted several adaptation strategies as reported in previous studies (e.g., Diallo et al. 2020; Adeagbo et al. 2021; Ogunleye et al. 2021). According to Table 1, about 91% apiece, of the respondents utilize changing cropping calendars and crop diversification as adaptation strategies

Table 1 Descriptive statistics of the number of CAS utilized by the crop farmers

| Number of CAS | Mean | SD |
|--------------------------------|------|------|
| Adopting improved seed variety | 0.60 | 0.49 |
| Changing cropping calendar | 0.91 | 0.13 |
| Changing input mix | 0.54 | 0.50 |
| Crop diversification | 0.91 | 0.14 |
| Crop rotation | 0.56 | 0.50 |
| Diversifying seed varieties | 0.14 | 0.35 |
| Income diversification | 0.31 | 0.47 |
| Irrigation system | 0.05 | 0.23 |
| Soil and water conservation | 0.79 | 0.21 |
| Tree planting/afforestation | 0.29 | 0.45 |
| Use of insurance | 0.03 | 0.18 |
| Use of agrochemicals | 0.67 | 0.46 |
| No adaptation | 0.10 | 0.25 |

Multiple choices allowed; CAS total number = 12

to climate change. Due to the unprecedented rainfall, many farmers delay planting most crops until the rain starts and stables for the season. At the same time, most farmers diversify into other crops while waiting for the rain, especially tree crops that might likely be harvesting during the periods, e.g., cocoa, cashew and palm oil. Nearly 79% of the respondent attest that they adopt soil and water conservation as an adaptation strategy. The least adopted strategies were irrigation systems (5%) and the use of insurance (3%). The probable reason might be due to the cost implication and low awareness about the benefits of the two strategies. The results are similar to the findings of studies from Nigeria (Apata 2011; Fatuase and Ajibefun 2014; Adeagbo et al. 2021; Ogunleye et al. 2021) and other sub-Saharan African countries (e.g., Bryan et al. 2009; Nhemachena and Hassan 2007; Deressa et al. 2009; 2011; Nhemachena et al. 2014; Dhanya and Ramachandran 2016; Mulwa et al. 2017; Asrat and Simane 2018; Khan et al. 2020; Diallo et al. 2020). It was observed that about 10% of the sampled farmers were not adapting to climate change. This value was far lower than the previous studies (e.g., Nhemachena and Hassan 2007; Deressa et al. 2009; Shahzad and Abdulai 2020; Ogunleye et al. 2021) on climate change adaptation. Two things might be responsible for the findings; there might have been more awareness and sensitization on climate change over time which might have influenced the adoption and utilization of climate adaptation strategies or due to the approach used in selecting the major crop farmers in each location. Whichever way it may be, the study finds out that many farmers have been adapting to climate change. The result agrees with the findings of Fadina and Barjolle (2018) and Tanimonure and Naziri (2021), who found 14.2% and 15% of non-adapters of climate adaptation strategies in South Benin and Nigeria, respectively.

In Fig. 2, it was noted that the average crop farmers utilize approximately 5 CAS in the area. The variation of climate change is mostly location specific, necessitating the adoption and utilization of multiple CAS (Shahzad and Abdulai 2020). Thus, about 22.7%, 20.7% and 18.0% of crop farmers utilize 3, 5 and 4 CAS, respectively, in the last production season. However, only a few farmers utilize 9, 8 and 2 CAS with about 1.3%, 2.7% and 4.0%, respectively. The average value of 5.05 reported by Adeagbo et al. (2021)

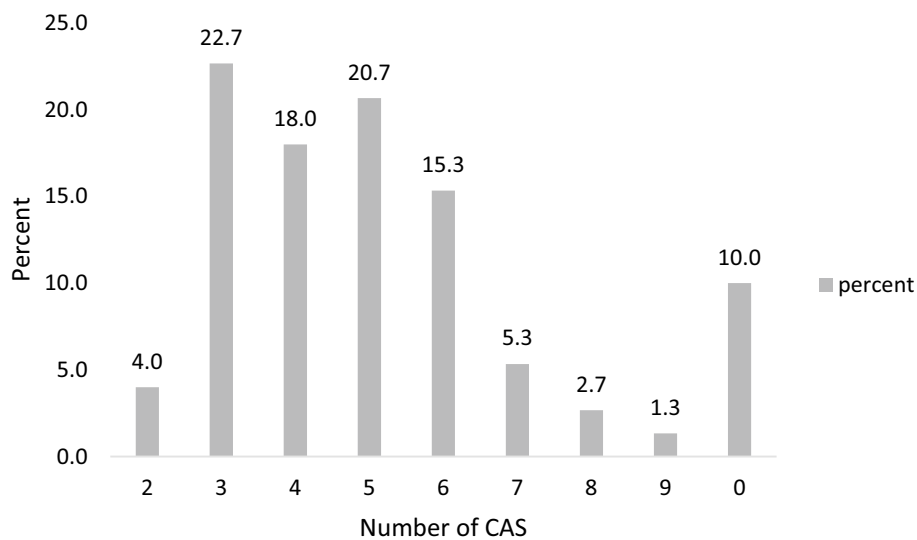


Fig. 2 Distribution by the number of CAS utilized by the crop farmers

was approximately the same as in this study. According to FAO (2013), adopting CAS is a sustainable approach to agricultural development that would guarantee food security under the climate change impacts. The study shared a similar view with several studies in the literature that reported that farmers utilize multiple CAS, such as Bryan et al. (2009), Deressa et al. (2009), Apata (2011), Shahzad and Abdulai (2020), Tanimonure and Naziri (2021), Ogunleye et al. (2021).

Table 2 reveals the descriptive statistics of all the variables used in the regression model. The study has two components in the dependent variable: the selection equation (credit status) and the numbers of CAS utilized. It showed that about 44% of the farmers are non-credit constraints while the crop farmers in the area utilized an average of 4.83 CAS. Credit availability allows farmers to adopt agricultural technologies (Pattanayak et al. 2003; Deressa et al. 2009). The dependent variables were drawn from previous studies on climate change and farmers’ credit facilities (Bryan et al. 2009; Deressa et al. 2009; Adeagbo et al. 2021; Oparinde and Olutumise 2022). The selected variables were based on the estimated model’s desirability, availability and appropriateness. The study revealed that the average years spent in school (education) was about 6 years. This shows that most farmers are literate, and it is expected to influence the utilization of CAS due to the ability to get information quickly. Norris and Batie (1987) and Maddison (2007) reported a positive and strong correlation between higher educational levels and the adoption of improved technologies, especially the adaptation to climate change. The majority (83%) of the farmers were male-headed households with an average household size of 4 persons. Several studies have ascertained that male-headed dominated crop farming (Olutumise et al. 2021; Tanimonure and Naziri 2021; Ogunleye et al. 2021) and also reported that male household had a positive association with technology adoption due to the ability to get information and undertake risks more than the female counterparts (Asfaw and Admassie 2004; Deressa et al. 2009). The famers’ age and experience gave approximately an average of 44 and 17 years, respectively. This implies that most farmers are still economically active with good years of experience. Although

Table 2 Selected variables, scale of measurements and the data summary statistics

| Variable | Description and measurement scales | Mean | SD |
|---|--|------------|------------|
| Dependent | | | |
| Credit status | Dummy: Credit constraint (CCT) = 0; Non-credit constraint (NCT) = 1 | 0.44 | 0.53 |
| CAS | Discrete (count): The number of climate adaptation strategies (CAS) utilized by the farmer in the last season (0–12) | 4.83 | 1.67 |
| Independent (T) | | | |
| Education | Continuous: Number of years spent in school (years) | 6.05 | 3.98 |
| Family size | Continuous: The number of people living and eating under the same roof | 4.31 | 2.10 |
| Gender | Dummy: Sex of the farmer: 1 = male 0 = female | 0.83 | 0.26 |
| Experience | Continuous: The number of years of engaging in crop farming (years) | 17.24 | 9.39 |
| Age | Continuous: Age of the farmer (years) | 44.37 | 11.01 |
| Farm income | Continuous: Average income from the farm produce (Naira) | 404,006.81 | 698,760.09 |
| Non-farm income | Continuous: Average income from non-farm activities (Naira) | 184,415.00 | 173,187.80 |
| Extension | Continuous: The number of times being visited by the extension agents in the last production season | 1.56 | 2.03 |
| Farm size | Continuous: Land area cultivated for crop production in hectares (Ha) | 3.98 | 6.38 |
| Market distance | Continuous: Distance from house to the nearest market (kilometers) | 4.56 | 3.49 |
| Awareness of climate change | Dummy: 1 = aware; and 0, otherwise | 0.93 | 0.26 |
| Access to climate information | Dummy: 1 = access; and 0, otherwise | 0.58 | 0.45 |
| Perceived rainfall | Dummy: 1 = increase; and 0, otherwise | 0.24 | 0.43 |
| Perceived temperature | Dummy: 1 = increase; and 0, otherwise | 0.77 | 0.40 |
| Instrumental variable (IV)—“R” in Eq. (2) | | | |
| Possession of collateral | Dummy: 1 = possessed collateral; and 0, otherwise | 0.42 | 0.63 |

1USD=415.4 Naira

some studies consider age and farming experience variables as a proxy, both have been reported to have a positive relationship with the adoption rate (Fatuase and Ajibefun 2014; Deressa et al. 2009; Fatuase 2017; Olutumise et al. 2021). Except for some studies (e.g., Shiferaw and Holden 1998; Soglo and Nonvide 2019; Diallo et al. 2020) who have reported a negative relationship between the farmers’ age and the innovative adoption rate. Income has been a pivot variable in determining the technology adoption, as documented in almost all the previous studies cited above. Thus, the average values of farm income (N404,006.81) and non-farm income (N184,415.00) are expected to influence the intensity of CAS utilization. The study uses the number of contacts by the extension agents, which is different from access to extension services commonly used in the literature. It was shown that farmers were contacted on an average of approximately two times in the last production season. The average farm size was about 3.98 ha which still categorized the crop farmers in the area as smallholders. Farm size’s effect on the adoption of technologies does not reach a consensus (Bradshaw et al. 2004; Ma and Wang

2020). Most studies (e.g., Deressa et al. 2009; Bryan et al. 2009; Diallo et al. 2020; Ma and Wang 2020) reported a positive relationship and linked large farm size with greater wealth, which is expected to increase the rate of CAS utilization. The average distance to the nearest market was 4.56 km, less than 5.18 km and 5.60 km reported by Ogunleye et al. (2021) and Tanimonure et al. (2021), respectively in Southwest Nigeria. The summary of climate factors revealed that the majority (93%) of crop farmers were aware of climate change, which is greater than the 82% and 84% reported by Adeagbo et al. (2021) and Ogunleye et al. (2021), respectively (2021). In the previous crop season, around 58% of farmers had access to climatic information. This result supports the findings of Ogunleye et al. (2021), however it is smaller than the 76% reported by Adeagbo et al. (2021). Furthermore, in the study, 24% and 77% of farmers experienced a rise in rainfall and temperature, respectively. The findings were consistent with other previous research, particularly in Africa (e.g., Deressa et al. 2009; Bryan et al. 2009; Apata 2011; Fatuase 2017; Olutumise et al. 2021; Tanimonure et al. 2021; Adeagbo et al. 2021). The instrumental variable was collateral possession, and around 42% of the farmers reported having collateral when assessing the loan. This number is lower than the 67% recorded by Oparinde and Olutumise (2022) in a study of Nigerian fish farmers.

Explanation for the mean differences between CCT and NCT crop farmers

The mean differences in the characteristics of the credit constraints (CCT) and non-credit constraints (NCT) crop farmers were reported in Table 3. The results indicated some observed characteristics that were systematically different between CCT and NCT respondents. It was revealed that NCT farmers are more experienced with larger farm sizes. The farm income and non-farm income of the NCT farmers were significantly higher than that of CCT farmers. Also, the frequency of extension contacts was

Table 3 Differences in absolute mean values of selected variables for CCT and NCT farmers

| Variable | CCT | NCT | Absolute mean difference |
|-----------------------------|------------|------------|--------------------------|
| Education | 4.89 | 4.93 | 0.04 |
| Family size | 4.29 | 4.37 | 0.08 |
| Gender | 0.93 | 0.93 | 0.00 |
| Experience | 10.20 | 13.35 | 3.15** |
| Age | 44.45 | 44.15 | 0.30 |
| Farm income | 328,300.00 | 612,175.00 | 283,875.00** |
| Non-farm income | 169,852.00 | 224,465.01 | 54,613.01* |
| Extension | 1.64 | 1.35 | 0.29* |
| Farm size | 3.83 | 4.40 | 0.57** |
| Market distance | 1.59 | 1.47 | 0.12 |
| Awareness of climate change | 0.93 | 0.93 | 0.00 |
| Climate information | 0.55 | 0.53 | 0.02 |
| Perceived rainfall | 0.22 | 0.30 | 0.08 |
| Perceived temperature | 0.85 | 0.89 | 0.04 |
| Possession of collateral | 0.38 | 0.62 | 0.24** |
| observations | 84 | 66 | 150 |

, * denote 5% and 1% significant level, respectively

observed to be higher among CCT farmers than NCT farmers. The collateral possession by the NCT was statistically different compared with the CCT farmers. There are no significant differences between NCT and CCT farmers in the variables such as education, family size, gender, and distance to the nearest market. In the case of climatic variables, no significant difference was observed between the two groups, such as awareness of climate change, access to climate information, perceived temperature and rainfall. As also noted by Ma and Wang (2020), the information on the mean differences is inadequate to draw conclusions. This is because each variable does not singly affect the farmers’ decisions, and the mean estimates do not address the confounding factors or the joint influence of the explanatory variables. Thus, this necessitates robust econometric analyses to investigate the impact of credit on the intensity of CAS utilization.

Determinants of credit impact on the rate of CAS utilization

Table 4 presents the estimates of the ETPR model in determining the impact of credit status on the rate of CAS utilization among crop farmers. The Table indicated the determinants of credit status and the determinants of CAS utilization. The value (65.54) of

Table 4 ETPR estimates—impact of credit status on CAS utilization

| Variable | Credit status | | CAS | | IRR |
|-----------------------------------|--------------------------|----------|-------------|----------|-------|
| | Coefficient | SE | Coefficient | SE | |
| Credit status | | | 0.488*** | 0.161 | 1.629 |
| Education | 0.042*** | 0.004 | 0.015** | 0.007 | 1.015 |
| Family size | −0.310*** | 0.092 | 0.185 | 0.134 | 1.203 |
| Gender | −0.022 | 0.025 | −0.017 | 0.104 | 0.983 |
| Experience | 0.056 | 0.327 | 0.035** | 0.014 | 1.036 |
| Age | −0.058*** | 0.005 | 0.063** | 0.027 | 1.065 |
| Farm income | 1.47e−06*** | 2.60e−07 | 2.82e−06** | 1.35e−06 | 1.000 |
| Non-farm income | 1.04e−06* | 5.71e−07 | 3.40e−06 | 6.63e−06 | 1.000 |
| Extension | −0.209 | 0.445 | 0.719*** | 0.104 | 2.052 |
| Farm size | 0.057** | 0.023 | 0.087*** | 0.034 | 1.091 |
| Market distance | −0.428 | 0.424 | −0.091 | 0.068 | 0.913 |
| Awareness of climate change | 0.020 | 0.025 | 0.002 | 0.005 | 1.002 |
| Climate information | 0.099*** | 0.035 | 0.270*** | 0.025 | 1.310 |
| Perceived rainfall | −0.428 | 0.424 | −0.236** | 0.112 | 0.790 |
| Perceived temperature | 0.051** | 0.023 | 0.181** | 0.074 | 1.198 |
| Possession of collateral | 0.228*** | 0.036 | | | |
| constant | −0.541 | 1.113 | 0.926*** | 0.288 | |
| Diagnostic Tests | | | | | |
| rho (ρ) | −0.921*** | 0.047 | | | |
| sigma | 0.015 | 0.021 | | | |
| /athrho | −1.594*** | 0.309 | | | |
| /Insigma | −4.206*** | 1.410 | | | |
| Wald test (ρ = 0) | Chi2(1) = 26.53*** | | | | |
| Wald chi2(15) | 65.54*** | | | | |
| Log pseudolikelihood | −353.344 | | | | |
| Matrix of correlation test for IV | 0.019 (not significance) | | | | |
| Observations | 150 | | | | |

*, **, *** denote 10%, 5% and 1% significant levels, respectively

Wald $\chi^2(15)$ was strongly significant at a 1% probability level, meaning the model has goodness of fitness. This was also reiterated by negatively signed Log pseudolikelihood and the significance of Wald test of independent equations at 1% level. The rho (ρ) value of -0.921 means the estimated correlation coefficient between the outcome error (μ_i) and treatment error (ε_i). The coefficient is statistically significant at a 1% probability level and indicates the presence of negative selection bias. Thus, there is presence of unobservable factors that positively influence the likelihood of being non-credit constraints but are negatively correlated with the rate of CAS utilization. All the estimates confirmed the appropriateness of the ETPR model in the study.

Determinants of credit status

The results showed that nine out of fifteen variables were statistically significant in explaining the credit status of the crop farmers. The coefficient of education is positive and significantly associated with credit status at a 1% level. The implication is that an increase in years spent in school will likely increase the likelihood of being non-credit constraints, *ceteris paribus*. Twumasi et al. (2020) reported that the bureaucratic bottleneck of formal credit lending affects uneducated farmers. Thus, education helps in loan management and enhances innovation adoption. The result is consistent with the findings of Bashir and Mehmood (2010) and Chandio and Jiang (2018). The negative but significant relationship between family size and credit status indicates that households with a larger number of individuals are less likely to be non-credit constraints. This is because a household head with a large family size might divert the funds to other family expenditures, thereby denying them getting the requested loan from the lenders. The age variable showed a negative but significant association with credit status, meaning that older farmers are less likely to be non-credit constraints. Omonona et al. (2010) gave a probable reason that most lenders fail to lend money to the old farmers because they fear they might not live long enough to repay the loan. This is contrary to Chandio and Jiang (2018) who reported a positive relationship in their study in Sindh, Pakistan. The farm and non-farm income variables are positive and significant with credit status at 1% and 10% levels, respectively. It implies that a money increase in any of these variables will increase the chance of being non-credit constraints, all things being equal. This is in line with the findings of Twumasi et al. (2020), who concluded that farmers generating extra income are creditworthy and always favour by the lenders. The coefficient of the farm size variable was positive and significant at 5% level in addressing the credit status of the crop farmers. It suggests that the more cultivated farmland, the more the likelihood of being non-credit constraints. Larger farm size is proxied to greater wealth (Deressa et al. 2009) and this might make the farmers to be less credit constrained. Given the positive and significant association between access to climate information and credit status, crop farmers who have access to climate information are less likely to face credit constraints. This is expected because some studies (e.g., Deressa et al. 2009; Asrat and Simane 2018; Ogunleye et al. 2021; Olutumise et al. 2021) reported that access to credit and climate information jointly influence the choice of adaptation strategies, meaning there is a positive correlation between the two variables. The perceived temperature variable is positive and statistically significant at a 1% probability level in explaining the credit status of the crop farmers. *Ceteris paribus*, the indication of the result is that crop

farmers that perceived an increase in the temperature in the past three decades might have the probability of being a non-credit constraint. It has been argued that farmers' perceptions increase adoption of adaptation strategies (Nhemachena et al. 2014), while Adeagbo et al. (2021) further stated that the degree to adopt adaptations increase with improved credit availability.

Determinants of CAS utilization

The second component of Table 4 describes the factors influencing the rate of CAS utilization. The estimates from the count data model are curvilinear, thus making the coefficients difficult to interpret. Therefore, to ease the interpretation, incidence rate ratios (IRR) are estimated following Erdogdu (2013), Zhang et al. (2019) and Ma and Wang (2020). The IRR is computed by calculating the exponential of CAS coefficient in the fourth column.

The credit status variable is the main focus of this section as the variable is positive and statistically significant at a 1% level of probability. The IRR of the NCT suggests that, on average, NCT farmers adopt 1.629 times more CAS than the CCT farmers. The result shows how vital credit is in the utilization of CAS. Its importance is reiterated as over 64% of the sampled crop farmers are observed to utilize up to 5 CAS in the last production season (Fig. 2). Credit conditions determine the asymmetry of multipliers which play crucial roles in the size and direction of the farm (McManus et al. 2020). Thus, having access to credit allows farmers to mitigate and enhance adaptation to climate change's impact (Deressa et al. 2009; McManus et al. 2020). Fahad and Wang (2018) reported a positive relationship between credit access and adaptation decisions of the farmers in Pakistan; and argued that lack of credit facility accounted for the main constraints to adaptation to climate change. The studies of Deressa et al. (2009) and Bryan et al. (2009) in Ethiopia and South Africa claimed that credit availability positively increases adaptation decisions and also eases capital inadequacy by allowing farmers to purchase required input resources such as irrigation equipment, resistant crops, agrochemicals and improved crop varieties. The studies (e.g., Apata 2011; Fatuase and Ajibefun 2014; Adeagbo et al. 2021; Ogunleye et al. 2021) carried out in Nigeria also affirm that credit access has positive and significant associations with climate adaptation decisions. Most of their findings revealed that farmers had recorded improved net revenue through increased farm-level productivity due to their credit capability to purchase improved farm inputs, especially the climate adaptation equipment and resources. Furthermore, a study conducted in rural India by Burgess et al. (2017) reported that having access to better credit markets reduces the impact of extreme temperature on mortality.

The other variables also made significant contributions to the rate of CAS utilization. For instance, the education variable was positive and statistically significant in addressing the rate of CAS utilization. The IRR's coefficient (1.015) implies that an increase in the year spent in schooling will cause about 1.015 times more utilization of CAS. This is consistent with the findings of Khan et al. (2020) and Diallo et al. (2020), who argue that education increase the adoption of adaptations in Pakistan and Mali, respectively. The variables of farmer age and farming experience were statistically significant and positively influencing CAS use. The IRR results suggested that a year increase in age and experience would result in approximately 1.065 and

1.036 times more CAS utilization, respectively. The findings are consistent with those of Deressa et al. (2009), Fatuase (2017), and Olutumise et al. (2021), who found that farmers’ age and experience considerably boost the adoption of adaptations. The farm income variable showed a positive and significant IRR, meaning the magnitude of the farm income variable was insignificant in contributing to CAS utilization. The contribution does not follow the expected theory as one expects a large magnitude of impact. The positive association is consistent with many studies in the literature (Asrat and Simane 2018; Khan et al. 2020; Ogunleye et al. 2021). The extension variable coefficient was significant and had the highest impact of IRR. It means that the more the extension agents pay the crop farmers visit, the more the farmers will utilize CAS by 2.052 times. This is expected as Adeagbo et al. (2020) argued that investment in extension services is pivotal to adopting the right climate adaptation options. The farm size variable, once again, exhibited an IRR coefficient of 1.091 and was statistically significant at the 1% level. This implies that increasing farm size will result in a 9.1% rise in the incident rate of using CAS, *ceteris paribus*. The coefficient of climate information is positive and strongly significant at the 1% level, implying that crop farmers who have access to climate information will use CAS 1.310 times more than farmers who do not. Similarly, the variable describing perceived temperature has a positive and significant IRR, indicating that crop farmers who experience a rise in temperature will use CAS 1.198 times more than those who do not. A negative but statistically significant IRR of the perceived rainfall variable means that the incident rate of crop farmers who perceived an increase in rainfall is nearly 21% less likely to utilize CAS than those who perceived otherwise. Climate change perceptions and access to climate information have been reported to increase the adoption of adaptations (Deressa et al. 2009; Apata 2011; Diallo et al. 2020; Khan et al. 2020).

Treatment effects of credit status on CAS utilization

The estimates of ATE and ATT further shed more light on credit’s impact on CAS utilization. The result is presented in Table 5. The coefficient of ATE (1.986) was statistically significant at 1% probability level. The result implies that the average crop farmer will utilize 1.986 times more of CAS when s/he is not credit constrained. In the same vein, the coefficient of ATT was 1.575, which is statistically significant at 1% probability level. This means that the average crop farmer in the treated group (non-credit constraint farmers) will utilize 1.575 times more of CAS than it would have utilized if s/he is credit constraint. Thus, the findings are plausible and confirm the crucial role of credit in adopting and utilizing CAS among farmers, especially in rural areas.

Table 5 Treatment effects of credit status on CAS utilization

| Treatment effects | Coefficient | SE | t-value |
|-------------------|-------------|-------|---------|
| ATE | 1.986*** | 0.331 | 6.00 |
| ATT | 1.575*** | 0.327 | 4.81 |

*, **, *** denote 10%, 5% and 1% significant levels, respectively

Conclusion and policy implications

Climate change and variability are wreaking havoc on the agricultural system, particularly in developing countries such as Nigeria. The indirect effects on crop production have been recorded regarding yield reductions, low food quality, food scarcity, pest infestations, disease outbreaks, land degradation and others. This has pressurized farmers to adopt and utilize several CAS to combat the adverse effects of climate change and still obtain the expected yields. Thus, the study investigates the impact of credit status on the intensity of CAS utilization among crop farmers in the Southwestern region of Nigeria. The study affirms some significant differences between NCT and CCT farmers, but the information is insufficient to conclude because other confounding factors are not accounted for. Therefore, the study employs endogenous treatment Poisson regression (ETPR) model as a robust econometric tool to provide more insight into the impact of credit on the intensity of CAS utilization. The first part of the analysis shows that education, age, incomes, farm size, access to climate information, perceived temperature increase and possession of collateral are the significant determinants of credit status in the area. The focus of this study, which is the second part, presents the impact of credit status on CAS utilization. The results reveal that credit status positively and significantly impacts the intensity of CAS utilization. The study shows that, on the average, NCT farmers adopt 1.629 times more CAS than the CCT farmers. The implication is that access to credit will promote utilization of diverse climate adaptation strategies that could abate the consequences of climate change on food crops. The significant socioeconomic factors that co-joint with credit status to impact CAS utilization are education, experience, age, income, extension contacts and farm size. With access to credit, it is expected that young, educated, and experienced farmers who have large farms and are guided by extension agents will utilize more appropriate climate adaptation strategies than their counterparts who do not have access to credit. Likewise, the credit status co-joints with significant climate variables such as access to climate information, perceived rainfall and temperature to impact the intensity of CAS utilization in the area. Farmers who have access to credit and correct climate information based on perceived weather behaviours will utilize climate adaptation strategies to combat the effects of climate change. The findings are further buttressed by the results of the average treatment effects (ATE), and the average treatment effects on the treated (ATT) estimates. Based on the estimates, an average crop farmer will utilize 1.986 times of CAS more when he is not being credit constrained, while the average crop farmer in treated group will utilize 1.757 times of CAS more than it would if he is credit constrained in the area. The study has reconfirmed the relevance of credit in promoting crop farmers' adoption and utilization of CAS. It is an indication that access to credit improves farmers' CAS vis-à-vis their net farm income. This is because it helps farmers guard against losses as a result of climate extremes. However, the smallholder farmers might find it difficult to adapt even when all the significant variables are in place without adequate credit facilities. This is because they might not be able to afford the cost of adaptation strategies. Thus, policy focus should be directed on revamping formal and informal credit institutions by expanding branches to rural areas. The provision of micro-credit that prioritize requisite adaptation strategy resources should be made available to the farmers to relax liquidity constraints. Government should build programmes that focus on input subsidies and incentives for the farmers on climate change, especially on those strategies that require substantial financial implications, such as irrigation systems,

changing input mix and improved crop varieties. In addition to agricultural credit policy, the government should empower extension systems and provide reachable information channels to guide the farmers in the appropriate adaptations. Farmers should be encouraged, through extension agents, to reinvest profits from farm and non-farm activities as a form of social capital formation. Again, because education aids in loan (credit) management and increases innovation adoption (CAS), investing in the education system can be a policy option for sourcing credit facilities that could help farmers adopt the appropriate adaptations to combat the negative effects of climate change. It is paramount for the government to create more platforms to broadcast weather information among the rural farming households, especially both formal (radio, television and social media) and informal (town criers and film shows) means.

Limitations

Instead of relying on farmers' perceptions of climate change, spatial interpolation could have been used to calculate location-specific farm-level temperature and rainfall. Furthermore, the findings of this study cannot be used to draw conclusions for Nigeria as a whole because cultural and operational practices for crop production, as well as environmental issues, differ from one geopolitical zone to the other. As a result, additional studies should be conducted to collect data on the coordinates of each of the respondents' farms and to broaden the scope of the research to include the entire country of Nigeria.

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Author contributions

The author conceptualizes the research, designs the methodology, hires enumerators with him for the field survey and writes the report. All authors read and approved the final manuscript.

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