Impacts of farmers' participation in social capital networks on climate change adaptation strategies adoption in Nigeria

Ayodeji Ogunleye a,*, Ayodeji Kehinde a, Ashok Mishra b, Abiodun Ogundele c

a Obafemi Awolowo University (OAU), Ile-Ife, Osun State, Nigeria
b Morrison School of Agribusiness, Arizona State University, Tempe, AZ, USA
c University of Free State, South Africa

ARTICLE INFO

Keywords:
Climate change
Adoption
Adaptation strategies
Participation
Social capital

ABSTRACT

Most studies on climate change adaptation strategies adoption have focused on economic factors with little or no attention to the impact of collective actions and social capital networks. This paper investigates how farmers' participation in social capital networks influenced climate change adaptation strategies adoption in Nigeria. This study was carried out in the South-western Nigeria. Data were analysed using descriptive statistics, binary probit regression, multinomial logit regression, endogenous switching regression and multinomial endogenous switching regression models. The results suggest that significant differences exist in the years of membership in the social capital networks, access to weather information and market between farm managers who adopted climate change adaptation strategies and those who did not. Plot managers who adopted climate change adaptation strategies are found to have obtained much mean yield and farm revenue than their counterparts. The results further show that participation in the social capital networks does not only significantly influence plot manager's decision to adopt but also influences the choice of climate change adaptation strategies adopted by farmers. The study concludes that a farmer who chooses to participate in social capital networks has a higher level of adopting climate change adaptation strategies than what a random farmer would have had in Nigeria. We recommend that policies aimed at increasing the adoption of climate change adaptation strategies among farmers should be channelled through locally organised farmers-based social capital networks.

1. Introduction

Recently, there has been a growing interest in the effects of climate change on agricultural productivity, and the various means of combating the scourge of climate alteration on agricultural production, food security and poverty. Climate change often leads to varying degrees of land degradation, severe erosion, desertification and deforestation (Alexandratos and Bruinsma, 2012). Although climate change has a negative effect on agriculture, crop yield and food security, the trend may continue if urgent adaptation measures are not put in place (IPCC, 2007, 2014). However, farmers who are conscious of the potential consequences of changes in climate would definitely adopt different adaptation strategies to address its negative effects on crop production (Niles et al., 2013; Gordon et al., 2013; Rosenzweig et al., 2013). There are studies on the adaptation strategies that farmers have adopted to lessen the effect of climate variation on food production especially in sub-Saharan Africa (Di Falco and Bulte, 2009; World Bank, 2010; Rosenzweig et al., 2014; FAO, 2016). Studies from developing countries have shown that capacity to adapt is influenced by many factors such as perceptions about climate change, access to appropriate technology, institutions, and their level of information, among others (Brulle et al., 2012; Alam et al., 2016).

The determinants of farmers’ decision between the time they perceive a change in climate and when they begin adaptive processes have been studied in Africa and Nigeria (Apata et al., 2009; Mulenga et al., 2017; Collins-Sowah et al., 2019). According to the aforementioned studies, other determinants of farming households’ capability to adopt climate change adaptation strategies include household resources and other socio-economic characteristics. Although adoption of climate change adaptation strategies has been hypothesised to reduce the adverse effects of climate change on crop productivity, rural farming households which are usually characterised with poor resources and uncertainties often find it difficult (if not impossible) to acquire and adopt appropriate adaptation techniques (Lobell et al., 2008; Wood et al., 2014). For an effective...
adaptation, all resources (economic, environmental and social) have to be utilized (Yiran, 2016). One important approach commonly employed by resource-poor farmers to acquire such management practices and adaptation measures is through the formation of networks that provide self-protection and risk-sharing (Jan, 2016). These networks create social capital which is defined as a shared asset in the form of customs, ideas, opinions, belief, social systems, communal relations and institutions, among others which facilitate cooperation for mutual benefits. Social capital is an essential feature that helps communities to solve collective action problems such as responding to both micro and macro climate threats (Aldrich, 2010; Prasad et al., 2014; Kehinde et al., 2021).

Social capital helps the farmers to pool their scarce economic resources together in order to help themselves in their farming operations (Okumadewa et al., 2005; Di Falco and Bulte, 2011; Wossena et al., 2015; Kehinde et al., 2021). Several studies suggest a positive correlation between social capital, technology adoption, crop productivity, food security and income (Kehinde and Adeyemo et al., 2020) but there is a shortage of information on the impact of farmers’ participation in social capital networks on the adoption of climate change adaptation strategies particularly in Nigeria where over 70% of the population engages in agricultural production at a subsistence level (Collins-Sowah et al., 2019; Muhaimin et al., 2020). Few attempts have been made to evaluate the level of the use of climate change adaptation strategies among farmers (Ibidapo et al., 2018; Oluwole and Shuaib, 2016). They posit that changes in climate pattern such as; increased intensity and frequency of extreme temperature have negative impact on food production, the environment as well as the population that depend on it for food security. These studies recommend access to capital (social and financial), subsidy, provision of infrastructural facilities, and reintegration of climate information into Nigeria national policies as means of promoting the use of climate change adaptation strategies in Nigeria.

Most adoption studies on climate change adaptation strategies have focused on the economic incentives while paying little or no attention to the impact of collective actions (through information sharing, diffusion of ideas and access to informal financial resources) that could result from the social networks that individual farmer belong to (Chinvanno et al., 2008). Studies have shown that social capital could have a statistically positive and significant impact on the adoption of agricultural innovation (Isham, 2006; Krishna, 2001). This underscores the importance of social capital as a factor that could have a significant impact on the adoption of climate change adaptation strategies among farmers. On the contrary, however, studies have indicated that social capital has the tendency to slow down adoption rates by encouraging a sharing obligation on the beneficiaries (Di Falco and Bulte, 2009). Therefore, there is a need for an empirical study to determine the impact of social capital on the adoption of climate change adaptation strategies. The main contribution of this article knowledge is to explore how participation in social capital networks influences the choice of climate change adaptation strategies among farmers. To the best of our knowledge, this study is about the first study to explore the causal relationships between participation in social capital networks and adoption of climate change adaptation strategies using a cross-sectional survey that accounts for rich data both on climate change and farmers’ participation in social capital networks. This will be done using endogenous switching regression model (ESRM). This model (unlike other impact models) has two major advantages: (i) it explicitly accounts for selection bias, and (ii) endogeneity. The ESRM model simultaneously accounts for both selection bias and endogeneity problems (Maddala, 1983).

The rest of the study is organized as follows. In section 2 we briefly discuss the review of literature relating to social capital and technology adoption in Nigeria. We discuss the various strategies that are available to farmers in order to protect them against shocks of climate change. In section 3 we present our methodology, data and outline our empirical strategy. Section 4 presents the main results and discusses the drivers of climate change adaptations in Nigeria, particularly on the role of social capital formation. Section 5 concludes.

2. Concept of social capital network and adoption of climate change adaptation strategies

Generally, social capital networks (SCNs) is defined as a network of collective asset in the form of shared norms, values, beliefs, trust, networks, social relations, and institutions that facilitate cooperation and collective action for mutual benefits. It is described as “networks” with shared norms, values and understandings that facilitate co-operation within or among groups. It is the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. Thus, social capital comprises both the network and the assets that could be mobilized through that network (Putnam 1995; Nahapiet and Ghoshal 1998). Africa has recorded extensive research works on the structure and pattern of adoption among rural farming households (Abdulai and Huffman 2014) and the impacts of the adoption of innovation on farming households (Bidzakiz et al., 2018; Kassie et al., 2008). The correlation between household participation in social networks, innovation platforms, contract farming and adoption of innovations have also received attention in Africa over the past decades (Kehinde et al., 2021; Ogunleye et al., 2020; Kehinde and Adeyemo, 2020; Olurotimi et al., 2018; Wossena et al., 2015; Demeke, 2010). Few studies have also examined the interactions between household’s participation in social networks and the associated impacts on the adoption of innovation (Wossena et al., 2015; Bidzakiz et al., 2018; Demeke, 2010; Bolwig et al., 2009; Bandiera and Rasul, 2006). They suggest that adoption is an individual action that often time goes beyond economic incentives and reasons (Abdulai and Huffman, 2014). Consequently, it is important to view adoption decision as a combination of economics incentives to adopt and individual ability to implement adoption practices successfully (Wossena et al., 2017). Most studies in some parts of Africa have examined the determinant of farmer’s choice of climate change adaptation techniques (Thomas et al., 2018; Desera et al., 2009). These studies identified the use of climate change adaptation techniques such as planting of crop varieties, tree planting, soil conservation, early and late planting and irrigation, among others.

This study simultaneously applies the three theories to develop a conceptual framework for the research problem. Conceptually, Lugandu (2013) states that the decision of adopting climate change adaptation strategies depends on farmers’ perceptions of climate change adaptation strategies compared to other farm technologies. There are several reasons farmers may adopt new technology. Some farmers may be rational in their behaviour; hence, their perceptions might be influenced by the information available to them, their socioeconomic situation and farm enterprises (Kangalawe et al., 2016). Adoption is the extent to which farmers put into practice a new technology, given adequate information about the technology and the potential benefits (FAO, 2018) (see Figure 1).

2.1. Description and construction of social capital indexes

Principal component analysis (PCA) is an appropriate methodology because it maximizes the variance rather than minimizes the least square distance. PCA is capable of providing the original set of variables into a smaller set of uncorrelated variables containing most of the information. PCA is capable of providing the original set of variables into a smaller set of uncorrelated variables containing most of the information.

Social capital index is calculated by dividing each SC value by the highest SC value. Therefore, SCINDEX ranges from 0 to 1. The description and calculation of the different indexes used in this study are detailed below.

(a) Cash contribution index (N)

This is achieved by taking records of payment of membership dues and other contributions. The summation of total cash contributed to the various social capital networks, which the farmer belonged is calculated.
The actual contribution for each farmer was rescaled by dividing the amount by the maximum fee in the data, and multiplying the resultant fraction by 100.

(b) Decision-making index

It has been argued that social capital networks which follow a democratic pattern of decision-making, giving men and women equal rights, are more effective than others (Balogun et al., 2011). The questionnaire asked members of the social capital networks to evaluate their level of contribution to decision-making subjectively (whether they were ‘very active’, ‘active’, ‘passive’, or not participating in the groups’ decision making). These responses were scaled from 4 to 0 respectively and averaged across the three most important social capital networks for each farmer. The responses were averaged and multiplied by 100 for each farmer.

(c) Heterogeneity index

The questionnaire identified three most important social capital networks for each farmer and for those groups, a number of supplementary questions were asked including the internal homogeneity of the group. The internal homogeneity of the group was rated according to twelve criteria (Balogun et al., 2011), viz, neighbourhood, kin group, same occupation, same economic status, same religion, same political affiliation, sex, same age group, same level of education, cultural practices, belief and trust. For each of these responses, a “yes” was coded 2 while a “no” was coded 1 (Lawal et al., 2009). A maximum score of 24 for each association represents the highest amount of heterogeneity. The scale for each farmer was averaged by dividing the total score by the maximum score 72 to obtain the index. The resulting index was multiplied by 100. A zero-value represented complete homogeneity and 100 correspond to the highest heterogeneity.

(d) Membership density index

This was measured by the number of active memberships in existing social capital networks. A complete inventory of all social capital networks was made; each farmer was given the inventory and asked to identify the group they belonged to. In other words, the proportion of membership of social capital networks by individual was found and rescaled to 100.

(e) Meeting attendance index

This index was measured by finding the number of times, members of social capital networks were meeting over a period of time. The summation of attendance of farmers at the meetings in relation to the total number of meetings scheduled were determined and rescaled to 100.

(e) Aggregate social capital index

To create aggregate social capital indexes and relate them to individual within this framework, we chose the individual social capital indexes and determined the relative weights to form a single or aggregate index (Adepoju and Oni, 2012). This is the multiplicative social capital index. The index was calculated using the products of density of membership, heterogeneity index and decision-making index of household in their various social groups. The expected sign is positive.

3. Methodology

3.1. The study area and data collection procedure

This study was carried out in the south-western Nigeria (SWN). It comprises six states which are Ekiti, Oyo, Ogun, Ondo, Lagos and Osun. The SWN has a population of 27,581,992 and the influence of climate change on crop production and food security in the region is very high compared to other geopolitical zones in the country. The data for this study is premised on a farm household survey conducted between January and March 2020. We followed a multistage sampling procedure and the first stage was a simple random sampling of three states (Osun, Ogun and Ekiti States) from south-western Nigeria. The second stage involved a simple random selection of two Local Government Areas (LGAs) from each of the three senatorial districts in each selected state to make a total of eighteen LGAs. This was necessary for equal representation of the social capital networks. At the third stage, we obtained the list of registered organisations at the Ministry of Commerce in each State and using proportionate random sampling, we selected between one and three functional social capital networks (SCNs) in each LGA which makes a total of 30 SCNs. The final stage of sampling involved the random selection of farm plot managers from ten (10) farm households in each of the selected social capital networks. This was done with the assistance of agricultural extension officers who are periodically in contact with the
farm households. In all, a total of 300 farmers were interviewed for this study.

3.2. Empirical methodology

The study adopted four estimation procedures to achieve its objectives. First, we employed the Probit model to estimate the probability that a farming household will adopt climate change adaptation strategies. Secondly, we applied the multinomial logit regression model to analyze the determinants of the choice of climate change adaptation strategies adopted by the farming household. Thirdly, we employed endogenous switching regression and multinomial endogenous switching regression models to estimate the impact of household’s participation in social capital networks on the adoption of climate change adaptation strategies. Sections 3.2.1, 3.2.2, 3.2.3 and 3.2.4 discuss the estimation techniques of probit model, multinomial logit regression, endogenous switching regression and multinomial endogenous switching regression models respectively.

Previous studies attempted to discuss the various adaptation strategies practiced by farmers. This includes conservation agriculture, changing planting dates, changing crop varieties, crop diversification, soil conservation, mulching, irrigation, non-agricultural activities, livestock production, and migration, among others (Di Falco and Bulte, 2009; Bryan et al., 2009; Mabe et al., 2014). In our questionnaire, we asked the question “Did you adopt any of the following CCA strategies in the last farming season?” The variable was in binary format and one is assigned to a maize producer who had adopted any of the CCA strategy (s) in one of the plots; otherwise, that farmer is assigned a zero value. Likewise, the concept of tenure status is derived from the land tenure system, which refers to a set of rules on how access is granted to rights to use, control, and transfer land as well as associated responsibilities and restraints. In this paper, we asked the farmers “if they perceived their right to their farmland is secure or not”. The variable “tenure status” was in binary format and one is assigned to a maize producer who perceived that his right to the farmland is secure in one of the plots; otherwise, that farmer is assigned a zero value.

### 3.2.1. Probit model

Probit model estimates the distinct decision (selection model) to adopt a technology, and then predicted values of the dependent variable from the probit model are generated. The selection equation representing whether farmers adopt or not can be specified as in Eq. (1):

\[
A_i = \beta X_i + \epsilon_i
\]  

(1)

Where, \(A_i\) is defined as adoption status (1, if adopted and 0, if otherwise), \(X_i\) represents the farmer’s characteristics (socioeconomic, institutional and social capital factors), \(\epsilon_i\) represents the error terms, and \(\beta\) defines the parameters to be estimated respectively. The second stage estimates intensity of adoption \((Y_i)\) through an OLS estimator.

\[
Y_i \text{ is observed if } A_i > 0 \text{ as indicated in Eq. (1), the equation for the second stage is specified as in Eq. (2)}
\]

\[
E(Y_i | A_i = 1, Z_i) = \alpha Z_i + E(\mu_i | A_i = 1) = \alpha Z_i + E(\mu_i / \epsilon_i > \beta X_i)
\]  

(2)

In Eq. (2), \(\alpha\) is a set of coefficient estimates of the explanatory variables \((Z_i)\), and \(\mu_i\) is the error term. Let \(p\) denote the correlations between the error terms of Eqs. (1) and (2). If the error terms have a bivariate normal distribution, according to Greene (2012), the expected value of conditional on \(p\) is given as in Eq. (3)

\[
E(\mu / \epsilon > \beta X_i) = \phi(\beta X_i) \sigma_\mu / \phi(\beta X_i)
\]  

(3)

Where \(\sigma_\mu\) are the error variances of the probit and OLS estimations, respectively. In estimating the selection equation with the probit model, \(\sigma_i\) is assumed to be equal to 1 (Greene 2012). The terms in the bracket at the right-hand side of Eq. (3) is the correction factor called the Inverse Mill Ration (IMR). It is given by the ratio of the normal density function to that of the cumulative function. Inserting the IMR \((\lambda_i)\) into Eq. (2) controls for any selectivity bias and the outcome equation then becomes in Eq. (4)

\[
E(Y_i | A_i = 1, Z_i) = \alpha Z_i + p \sigma_\mu \lambda_i
\]  

(4)

### Table 1. Summary of the descriptive statistics.

| Variables                        | Pooled Sample | Adopter (n = 152) | Non-adopters (n = 148) | t-value |
|----------------------------------|---------------|-------------------|------------------------|---------|
| Output of maize produced (kg)    | 2996.20       | 3020.18           | 2972.50                | 2213.00 | 0.14 |
| Variable cost of maize production (₦) | 2293.31       | 2265.084          | 2321.73                | 1488.20 | –0.31 |
| Total farm revenue (₦)           | 324,857.55    | 341213.27         | 309326.47              | 244252.91 | 0.99 |
| Demographic factors             |               |                   |                        |         |
| Marital status (married = 1)     | 1.00          | 1.00              | 1.00                   | 0.00    | 0.99 |
| Educational attainment (years)   | 9.10          | 8.81              | 9.40                   | 4.14    | –1.18 |
| Household size (count)           | 7.60          | 7.73              | 7.47                   | 3.89    | 0.41 |
| Farm-specific factors            |               |                   |                        |         |
| Age of the farmers (years)       | 47.36         | 47.24             | 47.48                  | 14.00   | –0.15 |
| Farm size (hectares)             | 1.44          | 1.46              | 1.41                   | 1.99    | 0.38 |
| Farming experience (years)       | 22.52         | 22.24             | 22.83                  | 13.53   | –0.37 |
| Institutional factors            |               |                   |                        |         |
| Access extension services (yes = 1) | 0.61          | 0.59              | 0.63                   | 0.48    | –0.64 |
| Access agricultural credit (yes = 1) | 0.52          | 0.55              | 0.50                   | 0.50    | 1.03 |
| Years of membership in SCNs (years) | 9.60          | 10.41             | 8.77                   | 9.45    | 1.53 |
| Access to weather info (yes = 1) | 0.58          | 0.84              | 0.52                   | 0.50    | 2.15 |
| Awareness of CC                  | 0.82          | 0.64              | 0.78                   | 0.40    | 0.85 |
| Distance to nearest market (km)  | 5.18          | 5.84              | 4.73                   | 3.92    | 1.48 |
| Social capital factors           |               |                   |                        |         |
| Aggregate social capital index   | 54.54         | 57.25             | 51.91                  | 15.30   | 2.94 |

Note: SD denotes standard deviation, b and c denote significance level at 5% and 10% respectively.
A. Ogunleye et al. Heliyon 7 (2021) e08624

Table 2a. Factors influencing adoption of climate change adaptation among plot managers.

| Determinants                                      | Probability of Adoption of CC | Marginal Effects |
|---------------------------------------------------|-------------------------------|------------------|
|                                                   | Coefficient | p-values | Coefficient | p-values |
| **Socioeconomic factors**                         |              |          |             |          |
| Age                                               | 0.000053    | 0.747    | 0.0009053   | 0.618    |
| Gender (male or female)                           | 0.1086425   | 0.617    | 0.0425989   | 0.623    |
| Marital status                                    | -0.1171644  | 0.603    | -0.057027   | 0.521    |
| Household size                                    | 0.0008906   | 0.958    | -0.009318   | 0.884    |
| Farm size                                         | 0.0448499   | 0.509    | 0.0217511   | 0.423    |
| Total variable cost                               | -0.000543   | 0.266    | -0.000217   | 0.266    |
| Farm revenue                                      | -2.8%e-07   | 0.071b   | -1.15e-07   | 0.07b    |
| **Institutional factors**                         |              |          |             |          |
| Access to extension                               | -0.1397904  | 0.364    | -0.0557638  | 0.364    |
| Access to weather information                     | 0.3230859   | 0.036b   | 0.1288823   | 0.036b   |
| Distance to nearest market                        | -0.0152471  | 0.395    | -0.0060822  | 0.395    |
| Tenure status (secured – 1, 0 otherwise)          | 0.2200426   | 0.197    | 0.0877772   | 0.197    |
| Aggregate Social Capital                          | 0.0137291   | 0.005a   | 0.0054767   | 0.005a   |
| Years of Membership in a Social capital network   | 0.0166653   | 0.044b   | 0.006648    | 0.044b   |
| Constant                                          | 0.98921     | 0.898    |              |          |
| Probability (LR stat)                             | 27.86        |          |              |          |
| S.D dependent variables                           | 0.0149b     |          |              |          |
| McFadden R-squared                                | 0.0570      |          |              |          |

Note: a, b and c represent significance level at 1%, 5% and 10% respectively.

3.2.2. Multinomial logit regression model

The Multinomial Logit model is used for the study, following Hassan and Nhemachena (2008), Otitoju (2013), and Mabe et al. (2014) estimate approach, because it can evaluate unordered qualitative data and is easier to compute than its alternative, the Multinomial Probit model. Multivariate choice models are distinguished by their capacity to evaluate the links between each adaptation option and a shared set of descriptive variables at the same time (Hassan and Nhemachena, 2008). With no requirement for multivariate integration, the model gives a handy closed form for underlying choice probabilities, making it straightforward to compute decision scenarios with numerous options. Farmers’ decisions about which climate change adaptation method to choose are influenced by the utility of each option. As a result, the analytical framework for determining the causes of farmers’ adaptation strategies is based on the utility maximization theory. Certain socioeconomic variables, farm characteristics, and changes in climatic factors are used to categorize this decision (Deressa et al., 2008). A farmer chooses an adaptation approach based on the weighted projected benefits, and only if he or she believes that the utility or net benefit of doing so outweighs the disadvantages of not doing so. The utility linked with such judgments can’t be seen directly. Farmers’ adaption strategies are being observed in the meantime. Farmers’ decisions are random, and hence their adaption tactics are based on random utility maximization. Assume that $U_j$ is the expected utility that a farmer will gain from using adaptation strategy $j$ whereas $U_k$ is the expected utility for not choosing adaptation strategy $j$ but rather $k$. The linear random utility model of adapting to climate change by choosing the $j$th adaptation strategy ($U_j$) can be expressed as a function of explanatory variables $X_i$ as shown in Eq. (5).

$$U_j = x_j\beta_j + \mu_j$$ (5)

Also, the random utility model for the $i$th farmer who does not practice $j$th adaptation strategy but rather $k$th adaptation strategy is specified as in Eq. (6):

$$U_k = x_k\beta_k + \mu_k$$ (6)

Where: $x_i$ is a vector of explanatory variables such as socioeconomic factors, farm characteristics, and social capital indexes. These are vectors of parameters for choosing $j$th and $k$th adaptation strategy respectively. Also, $\mu_j$ and $\mu_k$ are error terms for choosing the $j$th and $k$th adaptation strategy respectively. The error terms in the above equations are assumed to be normally independently and identically distributed (Gujarati and Porter, 2006). The utility, $U_k$, of choosing a particular adaptation strategy is a stochastic linear function of farm, farmers and technology specific attributes ($X_i$). In this Multinomial logit, the probability of choosing a given adaptation strategy, $j$, is equal to the probability that the utility of that particular adaptation strategy is greater than or equal to the utilities of all other adaptation strategies in the model as specified in Eqs. (7) and (8).

$$Prob(choice_j) = \frac{exp(\beta_jX)}{\sum_j exp(\beta_jX)}$$ (7)

$$P(y = j|x) = \frac{\exp(x_j\beta_j) + \sum_{n=1}^{J} \exp(x_j\beta_j)}{\sum_{n=1}^{J} \exp(x_j\beta_j)n}$$ (8)

where, $J$ denotes a random variable taking on the values $\{1, 2, …, J\}$ for a positive integer $J$ and $x$ denote a set of conditioning variables. $X$ is a $1 \times K$ vector with first element unity and $\beta_j$ is a $K \times 1$ vector with $j = 2, …, J$. In this case, $y$ denotes the adaptation strategies while $x$ denotes specific household and institutional characteristics of the farmers. The inherent question is how changes in the household and institutional characteristics affect the response probabilities $P(y = j|x), j = 1, 2, …, J$. Since the probabilities must sum to unity, $P(y = j|x)$ is determined once the probabilities for $j = 1, 2, …, J$ are known. In order for the parameter estimates of the MNL model in Eq. (8) to be unbiased and consistent, the Independence of Irrelevant Alternatives (IIA) is assumed to hold (Deressa et al., 2008). The IIA assumption requires that the probability of choosing
a particular adaptation strategy must be independent of the probability of choosing another adaptation strategy (that is, $P_j/P_k$ is independent of the remaining probabilities). Following the commonly used adaptation strategies identified in the research conducted by Deressa et al. (2008), Bryan et al. (2011), Mabe (2011), Mabe et al. (2014) and the preliminary survey by the researchers, the adaptation strategies that are considered in this study are changing crop varieties, changing planting dates, planting of trees, destocking, increase farm size, application of fertilizer, farming on fallowed land, diversification and mulching.

### 3.2.3. Endogenous switching regression model

The study assumed that the social capital network is endogenous to climate change adaptation strategies. The source of endogeneity is self-selection into social capital networks. The problem of endogeneity arises from the postulation that social capital networks membership is voluntary. To address this, the endogenous switching regression model (ESRM), an approach that explicitly accounts for the source of endogeneity is used. To address this, the endogenous switching regression model (ESRM), an approach that explicitly accounts for the source of endogeneity is used. Consider the following model as presented by Maddala (1983), which describes the behaviour of an agent (in our case the farmer or plot manager) with two regression equations defining two regimes, and a certain function $\gamma$ that determines which regime the agent faces (selection equation):

Let the latent variable $I_i^*$ be expressed as in Eq. (9):

$$I_i^* = \gamma Z_i + U_i \leq 0$$

Eq. (10) is defined for those groups of individuals who are without access to social capital because their excess demand equation valued either zero or negative.

$$I_i^* = 0 \text{ if } \gamma Z_i + U_i \leq 0$$

The above Eq. (11) applies for those groups of individuals whose participation in social capital networks assumed a negative value. This implies that farmers under this group face a constraint in terms of access to social capital. Following the above arguments from Eqs. (14) and (15), a continues adoption equation for both constrained and unconstrained regimes can be explicitly represented as in Eqs. (12) and (13)

**Regime 1:**

$$Y_{ii} = \beta_1 X_{ii} + \epsilon_1$$

**Regime 2:**

$$Y_{i2} = \beta_2 X_{i2} + \epsilon_2$$

In the above model $Y_{i}$ represents the dependent variable, i.e., the land area under climate change adaptation strategies treatment (hectare). Eqs. (12) and (13) present the adoption equation for social capital unconstrained and constrained farmers respectively. These adoption equations are formed based on the screening procedure under the selection equation. While $X_{ii}$ and $X_{i2}$ are vectors of weakly exogenous variables, $\beta_1$, $\beta_2$ and $\gamma$ are vectors of population parameters that need to be estimated in the model using the survey data. Our model relies on the assumption that the error terms, i.e., $U_i$, $\epsilon_1$ and $\epsilon_2$, possess a tri-variate normal distribution, with mean vector zero and covariance represented by the following matrix sketch.

$$\begin{pmatrix}
\delta_{\epsilon_1} & \delta_{\epsilon_1 \epsilon_2} & \delta_{\epsilon_1 \gamma} \\
\delta_{\epsilon_2} & \delta_{\epsilon_2} & \delta_{\epsilon_2 \gamma} \\
\delta_{\gamma} & \delta_{\gamma \epsilon_2} & \delta_{\gamma \gamma}
\end{pmatrix}$$

On the above covariance matrix, $\delta_{\epsilon_2}$ characterizes the variance of the error term in the selection equation. $\epsilon_1$ and $\epsilon_2$ have a covariance of $\delta_{\epsilon_1 \epsilon_2}$, and $\epsilon_1$ and $\gamma$ have a covariance of $\delta_{\epsilon_1 \gamma}$. The model assumes that $Y_{i1}$ and $Y_{i2}$ cannot observe simultaneously. This implies their corresponding error terms don't have a defined covariance. The model further assumes that $\delta_{\epsilon_2} = 1$, i.e., $\gamma$ can only be estimable up to a scalar factor.

Based on our argument on the distribution of disturbance terms, the logarithmic likelihood function can be formulated following the procedure by Lokshin and Sajaia, (2004) who placed their derivation on Maddala (1983) as shown in Eq. (14).

$$\ln L = \sum_{i=1}^{n} \left[ I_i W_i \ln(f(\gamma_{i1})) + \ln(f(\gamma_{i2})/\delta_1) + (1 - I_i) W_i \ln(1 - F(\gamma_{i2})) + \ln(f(\gamma_{i2})/\delta_2) \right]$$

Where $F$ is a cumulative normal distribution function, $f$ is a normal density distribution function, $W_i$ is an optional weight for observation $i$, and, $\eta_j$ is defined as, $\eta_j = \frac{\sigma_{\epsilon_j}^2}{\sqrt{1 - \rho_{\gamma j}^2}}$, where $j = 1, 2$, $\rho_1 = \sigma_{\epsilon_1}^2/\sigma_{\epsilon_1} \sigma_{\gamma}$ is the correlation coefficient between $\epsilon_1$ and $\gamma$, and $\rho_2 = \sigma_{\epsilon_2}^2/\sigma_{\epsilon_2} \sigma_{\gamma}$ is defined as a correlation between $\epsilon_2$ and $\gamma$.

**Note that:** In line with the standard statistical arguments, $\rho_2$ and $\rho_2$ must lie between -1 and 1, and $\delta_1$ and $\delta_2$ must be always positive.

The estimates of parameters in the endogenous switching regression can be obtained by using the full information maximum likelihood estimation by using the move stay command in Stata. The robust and meaningful standard errors and correlation coefficients are obtained simultaneously in the FIML estimation procedure (Maddala, 1983; Lokshin and Sajaia, 2004).

Given the aforementioned conditional expectations, the average impact of social capital formation on level of adoption can be computed as the difference between the expected level of adoption of climate change adaptation strategies by the farmers who participated in social capital networks and that of farmers who did not.

### 3.2.4. Multinomial endogenous switching regression model

Furthermore, to estimate the impact of participating in social capital networks on the adoption of climate change adaptation strategies in the study area, we accounted for sample selection using selectivity corrected multinomial logit model (Bourguignon et al., 2007; Khanal et al., 2018). The parameter estimates from this approach are consistent and efficient, even when the assumption of the independence of irrelevant alternatives is not fulfilled (Bourguignon et al., 2007; Khanal et al., 2018). The estimation is performed simultaneously in two steps. In the first step, we estimated factors influencing participation in social networks using the multinomial logit selection model, while accounting for interactions between them. In the second stage, we estimated the impact of each social capital dimension on climate change adaptation strategies using least-squares regressions with selectivity correction terms as expressed in Eq. (15).

$$Y_{ii} = \beta_1 X_{ii} + \epsilon_i$$

where $Y$ represents climate change adaptation strategies (land area under climate change adaptation treatment); $X$ represents the vector of observed exogenous variables—such as demographic, socioeconomic, and household-level characteristics—and $\epsilon$ represents error term. The utility of the decision to participate in social network to the farmer is not observable, but the decision is observable. Following Khanal et al. (2018), Kassie et al. (2015) and Bourguignon et al. (2007), a farmer's decision in social networks can be expressed as in Eq. (16)
Social capital network participants with some dimensions of participation in social capital networks (actual):

\[ E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) = \delta Z_{ji} + \sigma_{ji} \hat{\lambda}_{ji} \]  

(20)

Social capital network non-participants with some dimensions of participation in social capital networks (actual) are expressed as shown in Eq. (21):

\[ E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) = \delta Z_{ji} + \sigma_{ji} \hat{\lambda}_{ji} \]  

(21)

Social capital network participants had they decided not to participate in any dimension of social capital networks (counterfactual) is expressed as shown in Eq. (22):

\[ E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) = \delta Z_{ji} + \sigma_{ji} \hat{\lambda}_{ji} \]  

(22)

Social capital network non-participants had they decided not to participate in any dimension of social capital networks (counterfactual) is expressed as shown in Eq. (23):

\[ E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) = \delta Z_{ji} + \sigma_{ji} \hat{\lambda}_{ji} \]  

(23)

Eqs. (20) and (21) represent actual expected adoption of climate change adaptation strategies (land area under treatment) actually observed in the sample for social capital networks participants and nonparticipants, respectively, and Eqs. (22) and (23) represent their respective counterfactuals. Using conditional expectations from Eqs. (20), (21), (22), and (23), the average participation impact of social capital networks (influence on adoption of climate change adaptation strategies) on participants (ATT) (Eq. (24)) can be defined as the difference between Eqs. (20) and (22):

\[ ATT = E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) - E(R_i | I = J, Z_{ji}, \hat{\lambda}_{ji}) \]  

(24)

4. Results and discussions

4.1. Summary statistics of variables

The study collected a wide range of data on farmers and farm-specific characteristics, institutional variables, output, and input, including climate change adaptation strategies, social capital networks, among others. The summary statistics in Table 1 present the information for the full sample and disaggregated data based on whether or not the plot manager adopted climate change adaptation strategies in the models. The last column in Table 1 is the t-statistic that indicates whether the differences in mean characteristics between plot managers that adopted and those who did not adopt climate change adaptations strategies are statistically significant or not.

Although the differences in means are not statistically significant for the mean output of maize and total farm revenue, the plot managers who practised climate change adaptation strategies obtained higher mean yield values of (3020.18 kg) and total farm revenue (₦341,213.30) than their counterparts (maize output = 2972.50 kg and total farm revenue = ₦309,326.47) who did not adopt despite the fact that the mean variable cost of the plot managers who practised climate change adaptation strategies is lower than those who did not. The lower variable the cost could be attributed to a reduction in transaction cost, risk hedging and higher prices for commodities plot manager belonging to a group, cooperative or other social networks. Previous studies (Alam et al., 2012; Alam, 2017; Collins-Sowah et al., 2019) have shown that plot managers who adopted land enhancing technologies tend to have a higher output than their counterpart who did not. The mean maize output for the sampled population was 2966.20 kg. Studies argued that limited access to supply-driven variables such as access to extension services, production information, inputs and output market and agricultural credit are capable of undermining farmers’ productivity. Findings from this study
The factors that determine the practice of climate change adaptation strategies by a plot manager are analysed using a Probit regression model. The model, as presented in Table 2a, examines the contributions of the socioeconomic factors, institutional factors and social capital indexes to the plot manager's choice to adopt climate change adaptation or otherwise. The results show that, apart from the socioeconomic characteristics (farm revenue) and institutional factor (access to weather information), participation in the social capital networks influences the plot manager's decision to practice climate change adaptation strategies (Tesfahunegn et al., 2016). The marginal effects analysis (column 4) also indicates that a unit increase in the plot manager's aggregate social capital increases the chances of adoption of climate change adaptation strategies by 0.5 per cent. A detailed analysis of the social capital indexes (Table 2b) further reveals that the Cash contribution index (p < 0.05) and Decision-making index (p < 0.01) significantly contributes to the plot manager's choice to adopt climate adaptation. This study corroborated the findings of (Alam et al., 2016, 2017a, 2017b; Wossena et al., 2015). The length of years that the plot manager has spent within the social capital network(s) also influences the decision to adopt climate adaptation strategies or not. The marginal effect also indicates that the probability that a plot manager will adopt climate adaptation strategies will increase by 0.6 per cent with the additional year spent within the social capital network (s). This is probably due to the fact that social capital networks provide information on farmers who have adapted successfully which in turn will stimulate other farmers to adopt strategies while providing appropriate support in terms of credit and technical expertise. This according to Alam et al. (2017a, 2017b) is crucial to promoting farmers adaptation decision.

### Table 2b. A detailed analysis of the social capital indexes on adoption of climate change adaptation among plot managers.

| Determinants                  | Coefficient | p-values | Marginal Effects | Coefficient | p-values |
|------------------------------|-------------|----------|------------------|-------------|----------|
| Socioeconomic factors        |             |          |                  |             |          |
| Age                          | 0.001588    | 0.729    | 0.00057          | 0.728       |
| Gender                       | 0.142944    | 0.517    | 0.05130          | 0.516       |
| Marital status               | −0.095332   | 0.677    | −0.03421         | 0.676       |
| Household size               | 0.003357    | 0.841    | 0.001205         | 0.841       |
| Farm size                    | 0.682841    | 0.325    | 0.024507         | 0.323       |
| Farm revenue                 | −3.54e-07   | 0.039*** | −1.27e-07        | 0.035***    |
| Social capital factors       |             |          |                  |             |          |
| Cash index                   | 0.023012    | 0.649**  | 0.008259         | 0.045**     |
| Meeting attendance index     | 0.002854    | 0.620    | 0.001024         | 0.620       |
| Decision making index        | −0.016840   | 0.005*** | −0.006044        | 0.003***    |
| Heterogeneity index          | −0.004169   | 0.647    | −0.001946        | 0.647       |
| Membership index             | 0.005094    | 0.347    | 0.001828         | 0.620       |
| No of years spent in social networks | 0.016990 | 0.040** | 0.006998       | 0.037***    |
| Tenure status                | 0.211569    | 0.225    | 0.075933         | 0.222       |
| Access to credit             | 0.173596    | 0.275    | 0.06220          | 0.272       |
| Access to extension          | −0.213812   | 0.190    | −0.076738        | 0.187       |
| Access to weather information | 0.367409    | 0.020*** | 0.131864         | 0.017***    |
| Distance to nearest market   | −0.003774   | 0.839    | −0.001355        | 0.839       |
| Tenure status                | 0.211569    | 0.225    | 0.075933         | 0.222       |

***, ** and * denote significance level at 1%, 5% and 10% respectively.
4.3. Adoption of climate change adaptation strategies

Investigating farmers’ adaptation to changes in climate, Table 3 reports that farmers in the area of study have adopted one climate change adaptation strategy or the other depending on their knowledge and perception about climate change (Abid et al., 2020). For instance, about 10 conventional approaches are used by farming households in the study area. The climate change adaptation strategies adopted include changing planting dates, changing crop varieties, crop diversification, fertilization, soil conservation, mulching, migration and irrigation. Other adaptation strategies are irrigation and non-farm business. However, the adoptions of climate change adaptation strategies vary strategically according to farmers’ needs and capabilities. A value of 1 is assigned to each climate change strategy adopted and 0, if otherwise. It is worthy of note that these strategies, however, are mostly adopted in combination with other strategies. Table 3 reveals that changing planting date is the most common strategy (179). Changing crop varieties is the second most common strategy (159), and crop diversification (135) comes third. Non-farm business is also a common adaptation practice among the respondents. The implication is that farmers are gradually moving away from farming to non-farm business.

4.4. Social capital networks as determinants of farmer’s choice of climate change adaptation strategies

The estimation of the multinomial logistic regression model is used to elicit the influence of farmer’s participation in social capital networks on the choice of a particular adaptation strategy to minimize the adverse effects of climate change on their farm production. To address the possibility of interactions of adaptation decisions by farmers, we carried out the multinomial logit regression models for each of the adaptation strategies. The results of other factors influencing the type of climate change adaptation strategies adopted by farmers are also presented in Table 4b. The results confirm the submissions of the previous studies on the determinants of farmers’ choice of adaptation strategies to climate change (Mabe et al., 2012, 2014; Bryan et al., 2011; Deresa et al., 2009). The results of the maximum likelihood-multinomial logit (quadratic hill climbing) estimates on how social capital networks influence plot manager’s choices of climate change adaptation strategies are obtainable in Table 4a below. The result of the maximum binary-logit in Table 4a indicate that meeting attendance and heterogeneity indexes significantly influence the choice of change in planting date as a climate change adaptation strategy among plot managers. The marginal effect is that a unit increase in the meeting attendance and heterogeneity indexes will increase the choice of adopting change in planting date as climate change adaptation strategies by 0.6 and 1 per cent respectively. This implies that the plot managers who attend more meetings and those who belong to social capital networks with heterogeneous component have a higher chance of adopting change in planting date as a strategy to alleviate the effect of climate change. This is probably due to the fact that heterogeneity and meeting attendants facilitate the flow of information about the success of such strategies among adopters (Lambrecht et al., 2014; Donkor et al., 2016; Bismungu and Kabunga, 2016). Out of all the social capital indexes included in change in crop varieties model, only the decision-making index shows a significant influence on the plot manager’s choice to adopt change in crop varieties as climate change adaptation strategy. The direction of its relation with the choice of change in crop varieties by way of climate change adaptation strategy is negative. This is contrary to our a priori expectation. This however, confirmed the positions of some studies which posit that participation in social and group activities can be costly in terms of commitments of time and resources (Roodmen and Morduch, 2014). This implied that the longer it takes a plot manager to make a decision, the lesser the chance that they will adopt change in crop varieties by way of climate change adaptation strategy (Chanlee-Wright, 2010).
### Table 4b. Maximum likelihood-binary logit models indicating the influence of social capital in the choice of climate change adaptation strategies.

| Determinants                          | Adoption of Adaptation Strategies (Marginal Effects) | Socioeconomic factors | Institutional factors |
|---------------------------------------|------------------------------------------------------|-----------------------|-----------------------|
|                                       | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|                                       | Changing planting date | Changing crop varieties | Crop diversification | Soil conservation | Livestock production | Non-farming business | Migration | Irrigation | Fertilization | At least five strategies |
| Age                                   | 0.0036305 (0.054)** | 0.002853 (0.137) | −0.0025519 (0.215) | 0.01964 (0.169) | 0.000162 (0.172) | −0.000894 (0.377) | −0.00039 (0.813) | −0.000129 (0.928) | 0.0098204 (0.662) | 0.000158 (0.984) |
| Gender                                | −0.0387856 (0.677) | −0.071347 (0.451) | 0.10197 (0.315) | −0.039125 (0.518) | −0.008759 (0.769) | 0.01688 (0.733) | −0.04817 (0.543) | 0.1277 (0.098)** | −0.0016929 (0.982) | −0.192587 (0.615) |
| Marital status                        | −0.3152687 (0.003)** | −0.290171 (0.003)** | −0.184214 (0.069)** | −0.038578 (0.530) | −0.022336 (0.481) | 0.074629 (0.213) | 0.11096 (0.236) | −0.047896 (0.481) | −0.0190082 (0.800) | 0.582646 (0.132) |
| Household's size                      | −0.0079463 (0.268) | 0.004204 (0.571) | −0.0136218 (0.090)** | −0.002137 (0.648) | 0.004852 (0.053)** | 0.005509 (0.116) | −0.00019 (0.978) | 0.011687 (0.020)** | 0.0025114 (0.662) | −0.001591 (0.958) |
| Farm size                             | 0.0012621 (0.964) | 0.077394 (0.012)** | 0.124987 (0.000)** | 0.0064659 (0.714) | 0.01473 (0.084)** | −0.00289 (0.834) | 0.05088 (0.035)** | 0.01663 (0.395) | 0.0022204 (0.916) | 0.456229 (0.001)* |
| Years of farming experience           | −0.0005482 (0.666) | 0.000313 (0.478) | −0.0014753 (0.571) | −0.004154 (0.008)* | −0.001827 (0.012)** | −0.000421 (0.737) | −0.00051 (0.709) | −0.000529 (0.739) | −0.001437 (0.756) | −0.001617 (0.119) |
| Farm revenue                          | 5.63e-07 (0.043)** | 5.18e-08 (0.478) | −7.84e-07 (0.040)** | 1.29e-07 (0.474) | −2.68e-08 (0.731) | 1.47e-07 (0.210) | −6.57e-08 (0.803) | 2.64e-08 (0.886) | 6.04e-07 (0.010)** | −6.54e-07 (0.569) |
| Total variable cost (TVC)              | −0.0000316 (0.117) | −1.84e-06 (0.930) | −0.000127 (0.549) | 8.51e-06 (0.520) | 3.20e-06 (0.638) | 7.79e-06 (0.469) | 6.05e-08 (0.723) | −6.99e-06 (0.634) | −0.0000216 (0.221) | 0.000037 (0.656) |
| Gross margin (GM)                     | −6.25e-07 (0.031)** | −6.38e-08 (0.821) | 8.05e-07 (0.037)** | 1.70e-08 (0.928) | 3.76e-08 (0.647) | −1.39e-07 (0.256) | 1.91e-08 (0.992) | −1.81e-09 (0.922) | −5.16e-07 (0.027)** | −6.5e-07 (0.569) |
| Membership of microlend group         | −0.0005482 (0.326) | 0.209936 (0.003)* | −0.1202699 (0.087)** | −0.0268524 (0.548) | 0.034541 (0.142) | −0.024149 (0.496) | −0.01304 (0.827) | 0.101886 (0.042)** | 0.1497332 (0.006)* | 0.013901 (0.828) |
| Access to extension                   | 0.1043766 (0.106) | 0.025352 (0.705) | 0.0499595 (0.556) | −0.006413 (0.885) | 0.019587 (0.402) | −0.006959 (0.836) | 0.09743 (0.103) | 0.027906 (0.571) | −0.036919 (0.482) | 0.148556 (0.020)** |
| Access to weather information         | 0.1365215 (0.033)** | 0.291913 (0.000)* | 0.1040713 (0.125) | 0.0380033 (0.399) | 0.043359 (0.070)** | 0.06788 (0.066)** | 0.03084 (0.597) | 0.036424 (0.455) | 0.1301999 (0.014) | 0.105135 (0.091)** |
| Distance to nearest market            | 0.0022902 (0.763) | 0.022265 (0.017)** | 0.017864 (0.026)** | 0.0052573 (0.291) | 0.000374 (0.533) | 0.003778 (0.292) | 0.02621 (0.001)* | −0.007329 (0.255) | −0.0031786 (0.603) | 0.019419 (0.015)** |
| Tenure status                         | −0.0677642 (0.333) | −0.101833 (0.165) | −0.0219596 (0.771) | −0.0233241 (0.629) | 0.022778 (0.309) | 0.037633 (0.291) | 0.03185 (0.619) | 0.025927 (0.604) | 0.0382525 (0.494) | −0.008047 (0.902) |

Values in parenthesis are p-values, *, ** and *** denote significance level at 1%, 5% and 10% respectively.
The result in Table 4a shows that social capital indexes (cash contribution, decision making and membership indexes) significantly influence the plot manager's decision to adopt soil conservation as a climate change adaptation strategy in the study area. Decision making and cash contribution indexes present a negative relationship with plot manager choice of soil conservation as a strategy to alleviate the adverse effect of climate change. This suggests that those plot managers who give more of their resources (time and cash) to social capital networks do not often have enough to adopt soil conservation as a climate change strategy. This is partly because farmers are usually characterised with limited resources that will not be available for farm work once it is committed to another use. The membership index is positively significant to the probability of farm manager adopting soil conservation as a means to alleviate the adverse effect of climate change. Farmers who are members of more social networks could have access to information and training. This tends to help the farmers to have access to more productive resources in terms of cash and farmland. Therefore, practising soil conservation techniques would be a lot easier for them. The marginal effect showed that a unit increase in the number of social networks that a plot

The result in Table 4a shows that social capital indexes (cash contribution, decision making and membership indexes) significantly influence the plot manager's decision to adopt soil conservation as a climate change adaptation strategy in the study area. Decision making and cash contribution indexes present a negative relationship with plot manager choice of soil conservation as a strategy to alleviate the adverse effect of climate change. This suggests that those plot managers who give more of their resources (time and cash) to social capital networks do not often have enough to adopt soil conservation as a climate change strategy.

This is partly because farmers are usually characterised with limited resources that will not be available for farm work once it is committed to another use. The membership index is positively significant to the probability of farm manager adopting soil conservation as a means to alleviate the adverse effect of climate change. Farmers who are members of more social networks could have access to information and training. This tends to help the farmers to have access to more productive resources in terms of cash and farmland. Therefore, practising soil conservation techniques would be a lot easier for them. The marginal effect showed that a unit increase in the number of social networks that a plot

### Table 5. Full information maximum likelihood estimates of the switching regression model for adoption of climate change adaptation strategies.

| Variables           | SCNs Participation | Level of Adoption of CC Adaptation Strategies | Farmers Participating in SCNs | Farmers Not Participating in SCNs |
|---------------------|--------------------|----------------------------------------------|-------------------------------|-----------------------------------|
|                     | Coef.              | Std. Err.                                   | Coef.                         | Std. Err.                         |
| Age                 | 0.01337*a          | 0.00512                                     | 0.161658                      | 0.10117                           |
| Age²                | 0.00005            | 0.00006                                     | −0.00154                      | 0.00119                           |
| Gender              | −0.16496           | 0.24476                                     | 2.34727                       | 5.01743                           |
| M-Status            | −0.04051           | 0.24436                                     | −12.2161*b                   | 5.29204                           |
| H-Size              | 0.03968*a          | 0.01737                                     | −0.07266                      | 0.37881                           |
| Farm size           | 0.04745            | 0.08207                                     | 4.4371*                       | 1.51554                           |
| Farming_Exp         | 0.00013            | 0.00107                                     | −0.01348                      | 0.01447                           |
| Credit access       | −0.10830           | 0.17322                                     | 3.9831                        | 3.8371                            |
| Total credit        | 9.90e-08           | 3.31e-07                                    | 6.94e-06                      | 6.75e-06                           |
| Extension access    | 0.64458*b          | 0.16607                                     | −3.6277                       | 3.7209                            |
| Distance_Mkt        | −0.00194           | 0.01879                                     | 2.0259*b                     | 0.48614                           |
| Weather info        | −0.30604*a         | 0.17253                                     | 11.6609*                      | 3.6262                            |
| Tenure status       | 0.03836            | 0.17905                                     | 2.54699                       | 3.9309                            |
| Cash_index          | 0.10298            | 0.18155                                     | −0.2551                       | 0.23813                           |
| Hetero_index        | 0.24613            | 0.21094                                     | −0.35504                      | 0.37402                           |
| Decision_index      | 0.27679*b          | 0.13779                                     | −0.25432                      | 0.23815                           |
| Member_index        | 0.21217*b          | 0.12371                                     | −0.12178                      | 0.18531                           |
| Meeting_index       | −0.0295            | 0.12998                                     | 0.12371                       | −0.17939                          |
| Assets              | 1.26e-06*a         | 4.49e-07                                    | −2.37e-06                     | 5.35e-06                           |
| Constant            | 0.18399            | 0.87451                                     | 20.6585                       | 18.1027                           |
| /ln1                | 3.3245*a           | 0.059974                                    |                               |                                   |
| /ln2                | 2.9648*a           | 0.40086                                     |                               |                                   |
| /r1                 | 1.76221*a          | 0.33160                                     |                               |                                   |
| /r2                 | 0.56887            | 1.12577                                     |                               |                                   |
| sigma_1             | 27.7852            | 1.66639                                     |                               |                                   |
| sigma_2             | 19.3915            | 7.77323                                     |                               |                                   |
| rho_1               | 0.94275            | 0.03688                                     |                               |                                   |
| rho_2               | 0.51453            | 0.82774                                     |                               |                                   |

**Note:** a, b and c represent significance level at 1%, 5% and 10% respectively.

### Table 6. Average expected land area under climate change adaptation strategies treatment (hectare) with social capital network participation options.

| Variables                                | Actual outcome (Climate Change Adaptation Strategies if farmers participate in social capital networks) | Counter outcome (Climate Change Adaptation Strategies if farmers do not participate in social capital networks) | Average Treatment Effects for Treated (ATT) |
|------------------------------------------|-------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|-------------------------------------------|
|                                          | Land size under treatment (Hectare)                                                                  | Percentage Change (%)                                                                                     |                                           |
| Cash contribution                        | 16.45 (5.71)                                                                                         | 13.81 (4.03)                                                                                            | 2.64 (1.34)                               |
| Heterogeneity                            | 18.57 (13.77)                                                                                        | 15.76 (11.20)                                                                                            | 2.81*** (1.74)                            |
| Decision making                          | 16.39 (13.37)                                                                                        | 15.67 (9.71)                                                                                            | 0.72** (0.49)                             |
| Membership                               | 9.380 (2.00)                                                                                         | 5.21 (3.28)                                                                                            | 4.17 (1.94)                               |
| Meeting attendance                       | 18.85 (15.00)                                                                                        | 12.69 (10.42)                                                                                            | 2.16*** (0.63)                            |

**Note:** *, ** and *** denote significance level at 1%, 5% and 10% respectively.
manager belongs to will increase the choice of adopting soil conservation by 0.5 percent. This result corroborates the findings of Yiran (2016); Jan (2016); Wossena et al. (2015) and Putnam (1995).

The result of the binary logit regression indicates that the choice to adopt livestock production to cushion the effect of climate change among plot managers is significantly influenced by the social capital index (Meeting attendance index). The result shows a negative relationship between the number of meetings attended by the plot manager and his adoption of livestock production as a hedge against adverse effects of climate change. This is not unexpected as most crop farmers tend to join social networks that address their common interest. It is highly unlikely that social capital networks that focus on crop-related activities will encourage members to pay less attention to their common interest even with the adverse effects of climate change. Such association would rather opt for strategies that will help their members to remain in business in order to keep the network viable.

Social capital index (heterogeneity index) statistically influences the plot manager's decision to adopt a non-farm business as a strategy to avert the adverse effect of climate change. The result indicates that the decision of the plot manager to adopt a non-farm business as climate change strategy increase by 0.4 percent with a unit increase in the diversity of the social capital networks they belonged. This implies that the plot manager who belongs to a social capital network with the diverse, cultural and socioeconomic background are most likely going to diversify into non-farm business as a coping strategy against the negative impact of climate change. Our analysis reveals that heterogeneity index of the social capital networks to which the plot manager belongs significantly influences the choice to adopt migration as climate change adaptation strategy. The result indicates that a unit increase in the level of diversity in the social capital networks within which a plot manager operates will lead to 0.01 per cent decision to adopt migration a means to tackle the adverse effect of climate change. The meeting attendance and decision-making indexes of the plot manager are the two significant indexes which determine the decision of farmers to adopt at least five adaptation strategies. Additionally, plot managers who attended more meetings and participate in the decision-making processes have a higher likelihood of adopting a minimum of five adaptation strategies to mitigate the negative effects of climate change on their agricultural output and production than plot managers who do otherwise.

4.5. Effects of participation in social capital networks on adoption of climate change adaptation strategies

In this model, the assumption is that farmers' participation in social capital networks is endogenous to the adoption of climate change adaptation strategies. Some unobservable characteristics that influence plot manager's participation in social capital networks could also influence their adoption of climate change adaptation strategies. These selectivity effects have been corrected with the use of simultaneous ML estimation. As indicated by the descriptive and adoption analysis above there is a significant difference in several relevant variables and adoption level between the plot managers who participate in social capital networks and those who do not. These differences could be due to several observable and unobservable factors apart from participation in social capital networks. The estimation results for the model with respect to land area under climate change adaptation strategies treatment (hectare) as the outcome variable are presented in Table 5.

The second column in Table 5 reports the estimates of the determinants of the decision to participate in social capital networks. Age, household's size, assets, access to extension and access to weather information are the significant variables determining plot manager's participation in social capital networks. Generally, age tends to be negatively related to individual participation in social capital networks because participation seems to decline with an increase in age (Wabele, 2012). Studies have shown that there is a positive relationship between household's size, extension services, assets base, and participation in social capital networks (Omonona et al., 2008; Balogun et al., 2011; Lam and Bui, 2014). However, weather information shows a negative relationship with the plot manager's participation in the social capital network. This is contrary to our prior expectation because we expected that participation in social capital networks will facilitate access to different kinds of information including weather information. One of the possible explanations for this could be because weather information and other specialized information are often not available within the social networks; rather individuals access such information from specialized information channels such as radio, television and other weather-related agencies. The model estimates variables against participation in social capital networks and level of adoption of climate change adaptation strategies. The results are presented in the fourth and sixth columns of Table 5. Farm size, access to weather information, distance to the market and social capital indexes (such as the decision-making index and membership index) show a positive significant relationship with the level of adoption of climate change adaptation strategies among plot managers. This implies that participation in social capital network could increase the level of adoption of climate change adaptation strategies to between 21 to 28 percent. These results are in consonance with the findings of Wossen and Berger (2015) and Collinson-Sowah et al. (2019) who posit that membership of credit and saving associations facilitate and complement the adoption of land management strategies and productivity-enhancing technologies by accessing informal financial resources that may relax the farmers' cash constraints. This is particularly important because such networks often provide insurance with the mechanism for members in case of accidents, such as fire, loss of livestock, harvest failure, and during times of illness. In this model, all variables except for access to weather information and farming experience show an insignificant relationship with the level of adoption of climate change adaptation strategies among farmers who do not participate in social capital networks. The result further emphasizes the impact of the plot manager's participation in social capital networks on the level of adoption of climate change adaptation strategies in the study area. The correlation coefficients of rho_1 and rho_2 are positive. Since rho_1 is positive and significantly different from zero, the model suggests that a plot manager who chooses to participate in the social capital network adopts climate change adaptation strategies more than a random plot manager from the study area.

4.6. Average expected land area under climate change adaptation strategies with social capital network participation options

We also estimated the impact of participation in social capital networks dimensions such as cash contribution, heterogeneity, decision-making, membership index and meeting attendance, on the adoption of climate change adaptation strategies using a multinomial endogenous switching regression model. We estimated the ATT (see Table 6). Table 6 suggests a significant positive impact of participation in social capital network with any of the dimensions (cash contribution, heterogeneity, decision-making, membership index and meeting attendance). We compare the expected adoption of climate change adaptation strategies (land area under treatment) under the actual case that the farmers participate in all the social capital networks dimensions and the counterfactual case that they do not. Column 2 shows the counterfactual cases which show that there is a significantly lower adoption of climate change adaptation strategies. This shows that farmers who participate in social capital networks would have a lower adoption if they do not participate. Column 3 presents the ATT, calculated as the difference between column 1 and column 2. We estimate this to control the effects of several covariates and the selection bias stemming from both observed and unobserved variables on the adoption of climate change adaptation strategies. Participation in social capital networks options is associated with significant gains in the adoption of climate change adaptation strategies of
about 5%–80%. Interestingly, the highest adoption of climate change adaptation strategies (4.17 ha, an 80% increase) is obtained from participation in numerous social capital networks.

5. Conclusions and recommendations

Climate change has negatively impacted every aspect of human endeavours especially food security. Its impact continually leads to decrease crop yields in the developing countries if adequate adaptive strategies are not put in place. However, one of the barriers to the adoption of such climate change adaptation strategies is lack of resources. One important approach commonly employed by resource-poor farmers to acquire such climate change management practices is through the formation and participation in social capital networks. Social capital network in the form of membership of farmer-based organizations such as cooperatives creates an environment where farmers can access and learn new technologies. Other benefits of such networks include a reduction in transaction cost, risk hedging and higher prices for commodities. In this paper, we investigate the impact of social capital on the adoption of climate change adaptation strategies by investigating the determinants of the choice of climate change adaptation strategies by farmers, and analysing the impact of social capital on the adoption of climate change adaptation strategies in Nigeria.

The findings from this study show that the plot managers who adopted climate change adaptation strategies obtained higher mean values and total farm revenue than their counterparts who did not adopt despite the fact that the mean variable cost of the plot managers who adopted climate change adaptation strategies are lower than those who did not adopt. We find that, apart from the socioeconomic characteristics and institutional factors, participation in the social capital networks significantly influence plot manager’s decision to adopt climate change adaptation strategies. The lengths of years that the plot manager has spent within the social capital network(s) also, influence the decision to adopt climate adaptation strategies or not. Findings from this study further suggest that participation in social capital networks also affects the choice of climate change adaptation strategies among the plot managers.

The empirical results show a positive and significant relationship between participation in social capital networks and the adoption of climate change adaptation strategies. The findings suggest that a plot manager who chooses to participate in the social capital network has a higher level of adopting climate change adaptation strategies than a random plot manager from the study area. This is the nutshell implies that social capital has a positive impact on the adoption of climate change adaptation strategies in the study area. These results can be used to formulate policies aimed at increasing the adoption of climate change adaptation strategies among farmers using locally organised farmers-based social capital networks. However, in this paper, we are not able to decompose by gender, the impact of social capital on the adoption of climate change adaptation strategies. Hence, future research should not only also focus on the effects of social capital on the adoption of climate change adaptation strategies and outcomes but should also account for the effect of social capital along the gender line.

Declarations

Author contribution statement

Ayojede Ogunleye: Conceived and designed the experiments.
Ayojede Kehinde: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Ashok Mishra: Conceived and designed the experiments; Performed the experiments.
Abiodun Ogundele: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Funding statement

This work was supported by the Federal government of Nigeria through TETFund Institutional Based Research (IBR).

Data availability statement

Data will be made available upon request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

References

Abdulai, A., Huffman, W., 2014. The adoption and impact of soil and water conservation technology: an endogenous switching regression application. Land Econ. 90, 26–43.
Abid, M., Ali, A., Rabut, D.B., Raza, M., 2020. Ex-ante and Ex-post coping strategies for climatic shocks and adaptation determinants in rural Malawi. Clim. Risk Manag. (27), 100050.
Adepoju, A.A., Oni, O.A., 2012. Investigating endogeneity effects of social capital on household welfare in Nigeria: A control function approach. Q. J. Int. Agric. 51 (1), 73–96.
Alam, M.M., Siwar, C., Mollah, R.I., Talib, B., Toriman, M.E.B., 2012. Paddy farmers’ adaptation practices to climate vulnerability in Malaysia. Mitig. Adapt. Strategies Glob. Change 17, 415–423.
Alam, M.M., Alam, K., Shabbaz, M., 2016. Influence of institutional access and social capital on adaptation choices: empirical evidence from vulnerable rural households in Bangladesh. Ecol. Econ. 130, 243–251.
Alam, M.M., Alam, K., Mushtaq, S., 2017a. Climate change perceptions and local adaptation strategies of hazard-prone rural households in Bangladesh. Clim. Risk Manag. 17, 52–63.
Alam, M.M., Alam, K., Shabbaz, M., Clarke, M.L., 2017b. Drivers of vulnerability to climatic change in riparian and river-bank households in Bangladesh: implications for policy, livelihoods and social development. Ecol. Indic. 72, 23–32.
Alam, M.M., 2017. Livelihood cycle and vulnerability of rural households to climate change and hazards in Bangladesh. Environ. Manag. 59 (5), 777–791.
Aldrich, Daniel P., 2010. Fixing Recovery: Social Capital in Post-Crisis Resilience. Department of Political Science Faculty Publications. Paper 3. Available at http://docs.lib.purdue.edu/pspubs/3.
Alexandratos, N., Bruinsma, J., 2012. World Agriculture towards 2030/2050. ESA Working Paper. Number 12-03.
Aptata, T.G., Samuel, K.D., Adeola, A.O., 2009. Analysis of Climate Change Perception and Adaptation Among Arable Food Crop Farmers in South-Western Nigeria. Paper presented at the International Association of Agricultural Economists’ 2009 Conference, Beijing, China, pp. 16–22. August 2009.
Balogun, O.L., Yusuf, S.A., Monozonza, B.T., Okorowa, V.O., 2011. ‘Social capital and microcredit effects on poverty among rural households in the southwest states’, Nigeria. ARPN J. Agric. Biol. Sci. 6 (3), 5–10.
Bandiera, O., Rasul, I., 2006. Social networks and technology adoption in northern Mozambique. Econ. J. 116, 869–902.
Bidzaklin, J.K., Fialor, S.C., Awunyo-Vitor, D., Yahaya, I., 2018. Impact of irrigation ecology on rice production efficiency in Ghana. Adv. Agric. 2018, Article ID 5287138, 10. https://doi.org/10.1155/2018/5287138.
Bismungu, Emmanuel, Kabunga, Nasul, 2016. A Latent Class Analysis of agricultural technology adoption behavior in Uganda: Implications for Optimal Targeting, No 249347, 2016 Fifth International Conference, September 23-26, 2016, Addis Ababa, Ethiopia, African Association of Agricultural Economists (AAAE). https://EconPapers.repec.org/RePEc:ags:aaae16:249347.
Bolwig, S., Gibbon, G., Jones, S., 2009. The economics of smallholder organic contract farming in tropical Africa. World Dev. 37, 1094–1104.
Bourguignon, F., Fournier, M., Gurgand, M., 2007. Selection bias corrections based on the multinomial logit model. Monte Carlo comparisons. J. Econ. Surveys 21 (1), 174–205.
Brulle, R., Carmichael, J., Jenkins, J., 2012. Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the U.S., 2002–2010. Clim. Change 114, 169–188.
Bryan, E., Deserra, T.T., Ghoshbis, G.A., Ringer, C., 2009. Adoption to climate change in Ethiopia and South Africa: options and constraints. Environ. Sci. Pol. 12 (4), 413–426.
Bryan, E., Ringer, C., Okoba, B., Roncolli, C., Silvestri, S., Herrero, M., 2011. Adapting Agriculture to Climate Change in Kenya: Household and Community Strategies and Determinants. Kenya. Chamlee-Wright, 2010. Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. Clim. Change 117, 943–950.
Wood, S.A., Jina, A.S., Jain, M., Kristjanson, P., DeFries, R.S., 2014. Smallholder farmer cropping decisions related to climate variability across multiple regions. Global Environ. Change 25, 163–172.

World Bank, 2010. World Development Report 2010. Development and Climate Change, Washington, DC.

Wosena, T., Bergera, T., Falcoc, S.D., 2015. Social capital, risk preference and adoption of improved farmland management practices in Ethiopia. Agric. Econ. 46, 81–97.

Yiran, G.A.B., 2016. Mapping Social Capital for Adoption to Climate Variability in Savanah Ecosystem of Ghana. Springer International Publishing, Switzerland.