Adoption of Drought-Tolerant Maize Varieties and Interrelated Climate Smart Agricultural Practices in Nigeria

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Abstract

Background: In Sub-Saharan Africa, drought is one of the prevailing climatic conditions that has led to the modification of improved seeds to be resilient enough to improve yield and increase farm households' welfare. However, like most climate-smart agricultural practices, the adoption of drought-tolerant maize varieties is low. This study examines the simultaneous adoption decisions of drought tolerant maize varieties and other climate-smart agricultural practices such as intercropping, row-planting, inorganic fertiliser, manure, and residue incorporation using nationally representative survey data from 1,370 rural households in Nigeria. Multivariate Tobit and ordered probit models are applied to assess the complementarity and or substitutability effect among CSAPs, the predictors of the joint adoption, and the adoption intensity of CSAPs.

Results: The results show a significant positive correlation between DTMVs & inorganic fertilisers, DTMVs and intercropping, and DTMVs and manure. However, the strongest adoption complementarity is found between DTMVs and manure. The probability and the extent of adoption of CSAPs are commonly determined by household wealth, access to loans, access to training in improved production practices, and membership in input supply and farm cooperatives.

Conclusion: The study suggests that the adoption of DTMVs has varying degrees of relations with other CSAPs informing the need for policies aimed at increasing its adoption to consider existing CSAPs among maize farm households.

Keywords: Simultaneous equation, drought, drought-tolerant maize varieties, multivariate Tobit, ordered Probit, and climate-smart agriculture

JEL classification: C30, Q16

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1. Introduction

In Sub-Saharan Africa (SSA), extreme climatic events continue to undermine productivity and impact rural farm households agricultural income and per-capita food production (Katengeza et al. 2019). Climatic variations such as erratic rainfall and prolonged dry spells have led to famine , and to date, climate change is notably a growing and continuous threat to smallholders' household welfare and food security (Baro and Deubel 2006). Drought is a prominent climate risk facing maize farm communities in SSA because maize crops require significant moisture to survive and hence are susceptible to drought conditions. (Baro and Deubel 2006) x. Policies to mitigate climate impact have led to the incorporation of climate-smart agricultural practices (CSAPs) into a rural agricultural intervention to sustainably increase food security, improve welfare, and build resilience to climate change (Lipper and Zilberman 2017). The Drought Tolerant Maize Varieties (DTMVs), are revolutionary components of climate-smart agricultural practices (CSAPs), resilient to drought, high yielding, provitamin A fortified, quality protein-fortified, and also Striga tolerant (DT Maize Bulletin, 2016). The adoption of DTMVs for example has been found to impact yield (Abdoulaye et al. 2018), reduce the incidence of poverty and reduced the downside risk (Wossen et al. 2017a) and impact is more beneficial for poorer households (Olagunju et al. 2020).

In this study, our hypothesis is driven by the susceptibility of multiple idiosyncratic and covariant risks in the SSA agricultural production that compels farm households to adopt multiple climate Smart Agricultural Practices (CSAPs) to counter impending production risks. DTMVs are although a component of CSAPs (Bedeke et al. 2019), we hypothesis that tackling problems of low DTMVs adoption may require understanding its interrelation with other combinatory technologies or practices evident among maize farm households. To illustrate, while DTMVs are adopted as a drought-risk mitigating strategy, farm households may adopt other agricultural yield protecting and yield-enhancing technologies to curb other impending risks such as soil and water conservation practices (use of organic matter, incorporation of crop residues, mulching and crop rotation) and chemical fertilisers. A typical farm household is, however, subjected to making rational choices among multiple agricultural innovations in diversified risk-driven multiple cropping systems, which may be constrained or driven by his or her observable and inherent characteristics. It suffices to say that decision to adopt DTMVs may be constrained or driven by i) other CSAPs which are likely to be complementary or substitutes and ii) prevailing household-level attributes driving or constraining joint adoption of DTMVs and other CSAPs. Thus, the objectives of these study are: (1) to determine the CSAPs that are complements and substitutes of DTMVs (2) to estimate predictors driving or constraining the adoption of DTMVs and other CSAPs, and (3) to assess factors of adoption intensity of CSAPs.

First, this study contributes to the growing literature on the jointness of multiple technology adoption across SSA (Abdulai et al. 2011; Teklewold et al. 2013; Kassie, Teklewold et al. 2015; Wainaina et al. 2016; Bedeke et al. 2019) however, with a different methodological approach. In past studies (Abdulai et al. 2011; Teklewold et al. 2013; Kassie et al. 2015; Wainaina et al. 2016; Bedeke et al. 2019), the use of bivariate or multivariate probit analysis is quite common and the factors of joint adoption cannot be estimated directly. The available means in this approach is through the interpretation of the significance or non-significance of correlation of errors between one adoption technology equation and the other. The correlation of errors can be quite conflicting with the correlation of endogenous variables and as such misleading. It, however, does not interpret the direct effects among variables. We, however, argue that adoption decisions cannot be represented adequately by a binary qualitative variable and may be censored (Rahman and Akter 2014). As such, this study adopts a simultaneous equation approach using the multivariate Tobit model that uses all observations, both those at the limit, usually zero (for example, non-users), and those above the limit (for example, users), in estimation. The multivariate Tobit approach further measures the intensity of participation rates for different choices (Rahman and Awerije 2015). Also, the assessment of factors of joint adoption in Nigeria in recent studies (Morse and McNamara 2003; Onyeneke et al. 2018; Jellason, Conway and Baines 2020; Oladimeji et al. 2020) was limited to samples from states or region, this study establishes joint adoption using a national data on maize producing households and as such captures regional differences on the effect of adoption.

Nigeria presents an important case study to address the objectives of this study. Maize (Zea mays L.) is an important cereal crop grown, especially in the Savanna zone of Nigeria due to the presence of high radiation which is favourable for its growth (Bello et al. 2014). In Nigeria, maize constitutes the main source of calories and a source of livelihood for the rural farming community (Liverpool-Tasie et al. 2017). Nigeria is the second-highest producer of maize in Africa after South Africa with an annual production of over 10 million tonnes (FAOSTAT, 2018). Although Nigeria has the largest harvested land area in the continent, its maize yield per hectare is still far behind the other major maize-producing nations such as South Africa, Kenya, Ethiopia, and Malawi. In an estimate of average yield per hectare for 25 years (1993 – 2018), Nigeria has the lowest yield per hectare (1572kg/ha) compared to the above-mentioned major maize producing countries (FAOSTAT, 2018).

The next section of this paper presents the literature review of heterogeneous factors of adoption in the context of DTMVs and CSAPs. The third section presents the econometric framework used for simultaneous adoption and its intensity. The fourth section explains the data source and describes summary statistics. The fifth section highlights the results and discussions, while the last section offers concluding remarks and policy implications.

2. Literature review

The concept of climate-smart agriculture was driven by the need to change conventional agricultural practices which impact biodiversity decline and meet the growing demand for food need(CGGI, 2021). CSAPs are a set of mitigation and adaption practices developed to simultaneously contribute to 1) sustainably increasing agricultural productivity and incomes; 2) building resilience to the impacts of climate change; and 3) contributing to climate change mitigation where possible (FAO CSA Sourcebook, 2017). CSAPs are broadly defined by their ability to meet these defined goals and can range from soil/water-conserving measures, agroforestry, sustainable soil fertility management, improved crop varieties, precision breeding etc. (Khatri-Chhetri et al. 2016; Nyasimi et al. 2017). The adoption of CSAPs in single or combinatory options delivers sustainable benefits in several case studies. For example, Oyetunde-Usman et al. (2021) found that the adoption of organic fertilizer in Nigeria significantly impacts the welfare of farm households. Also, the adoption of improved crop varieties, for example, improved chickpeas (Verkaart et al. 2017) and improved wheat varieties (Shiferaw et al. 2014) respectively impact farm household income and food security in Ethiopia. The combination of CSAPs to combat multiple risks and deliver on sustainable development goals has equally been found effective in impacting farm households' income and welfare. For example, cropping diversification, conservation tillage and modern seed adoption impact maize farm income and the impact are highest when CSAPs are jointly adopted (Teklewold, et al. 2013).

The relevance and importance of CSAPs are glaring, however, constraints to adoption in existing case studies impact diffusion across CSAPs differently (Teklewold, et al. 2013; Kassie, et al. 2015; Muriithi et al. 2018). Of fact, prevailing multiple climate risks and unpredictable changes in weather and climate patterns are realities of farm households and achieving climate-smart agriculture goals necessitate farm households' ability to adapt and adopt combinatory practices necessary to combat prevailing climate risks. In past studies, the decision to jointly adopt varies heterogeneously with farm households' attributes (Abdulai et al. 2011; Teklewold et al. 2013; Muriithi et al. 2018; Bedeke et al. 2019). Below, we explore some heterogeneous findings in broad literature on adoption factors in joint adoption scenarios.

The gender of farm households has been established in various contexts to heterogeneously impact adoption across choices of CSAPs. To highlight specific case studies, in Ndiritu et al. (2014), while gender differences exist in the adoption of minimum tillage and animal manure adoptions, no significant difference was found in the adoption of soil and water conservation measures, improved seed varieties, chemical fertilisers, maize-legume intercropping, and maize-legume rotation. Similarly, gender roles can vary with heterogenous impact across joint adoption of CSAPs, for example, female plot managers were less likely to adopt yield-enhancing (Inorganic fertiliser and or improved seed variety) and soil-restoring strategies (fungicide, herbicide/pesticide) however no differences in yield protecting strategies (e.g manure, compost, planting pits, etc) (Theriault et al. 2017). Gender differences in adoption especially for women have been linked to rigors in access to farm resources, institutional access, market and financial resources (Doss and Morris 2000; Kilic and Goldstein 2013; Ragasa et al. 2013; Achandi et al. 2018; Quaye et al. 2019). Also, farm household's educational status can indicate the level of understanding of technical information and the ability to easily grasp complex adoption practices. In Wainaina et al. 2016, well-educated farmers were more likely to adopt technical CSAPs such as improved seeds and fertilisers indicating that exposure to education in this case helps farmers to process and utilise information relevant to the adoption of improved seeds and fertilisers. Labour availability is equally an important determining factors in joint adoption literature and may play a role in adoption of technology or practices.. In joint adoption studies, labour effect on adoption is more aligned with CSAPs that are labour intensive, for examples in Ndiritu et al. (2014), larger farm households were more likely to invest in the adoption of sustainable land practice compared to farm households with lesser household size.

Institutional roles such as access to extension services and credit services are key supply side of policy instruments in developing countries can also impact adoption and agricultural productivity (Wossen, et al. 2017). Access to extension services has equally driven sole and joint adoption of CSAPs, in Makate et al. (2019), farm households that had access to extension services were more likely to adopt both single and joint CSAPs. Also, in Bedeke et al. (2019), extension access was significant in driving the adoption of all CSAPs. Conversely, the effect of access to extension services can be heterogeneous across CSAPs, while it was positive and significant in driving adoption of minimum tillage, chemical fertiliser, manure, and maize-legume intercropping, it was positive but did not significantly drive adoption of maize-legume rotation and improved seed (Ndiritu et al. 2014). Also, membership in financial institutions or platforms that provide credit support aid to mitigate a wide range of risks as perceived by farm-households (Abebaw and Haile, 2013b; Wossen et al. 2017; Ahmed and Mesfin 2017). Further to this, financial institutions, apart from relaxing liquidity constraints by providing credit, also provide market access and serves as a resource pool for buyers and sellers of inputs and produces, thereby reducing market risk (Meike 2007; Wossen et al. 2017; Ma and Abdulai 2017). The effect of credit access in Bedeke et al. (2019), positively and significantly influenced the adoption of DTMVs, mineral fertiliser, and soil-water conservation practices, In a similar study, credit-constrained farm households were less likely to adopt improved seeds, soil, and water conservation practices, minimum tillage, and maize-legume rotations (Ndiritu et al. 2014).

In developing countries, land represents the key asset in households' agriculture and it is central to development policies (Goldstein and Udry 2014). Most importantly, it is a productive resource for agricultural development and poverty reduction measures (Khonje et al. 2015).

However, evidence in past empirical studies has revealed that variation exists in the choices of adoption of agricultural innovations based on farm households' land attributes. Depending on the definition of tenure security in various studies, Wainaina et al. (2016) and Bedeke et al. (2019) found tenure security significant for use of soil and water conservation practices in Kenya and Ethiopia respectively. Other land attributes such as farm size can affect the adoption of CSAPs differently, for example, in Bedeke et al. (2019), households with large farm sizes had a higher probability of adopting drought-resistant maize varieties and mineral fertiliser in Ethiopia but less likely to adopt maize-legume copping. In addition to this finding, farm size was significant in the adoption of crop diversification, minimum tillage, and soil and water conservation in Malawi, it was positive for crop diversification and manure use in Tanzania (Kassie et al. 2015). Besides land tenure system and farm size, certain attributes of land contribute to adoption decisions, this can include quality of land (Beyene and Kassie 2015; Arslan et al. 2014); location of land in Highland or low lands (Ghimire et al. 2015), land terrains such as steep and gentle slope (Wainaina et al. 2016; Bedeke et al. 2019) and farm distance (Abebaw and Haile 2013b; Kassie et al. 2015). Having explored some background to variations in farm household attributes' effects on joint adoption decisions, it is expected that farm household attributes heterogeneously affect adoption decisions of CSAPs in this study.

3. Data, Description of Variables and Analytical Framework

3.1 Data

This study adopted nationally representative farm household survey data collected by the International Institute of Tropical Agriculture (IITA) between November 2014 and February 2015 from 18 major maize-producing States in Nigeria. The process of data collection was through a multi-stage sampling technique. The first stage involved dividing the 36 states in Nigeria into five subgroups based on the total land areas allocated to maize production. From the five subgroups, 18 states were randomly selected. Within the 18 States, Enumeration Areas

(EAs) were generated from Local Government Areas in each State (LGAs). Based on this, five maize farm households were randomly selected per Eas per LGAs for interviews. A total of 1,370 agricultural households were used in the analysis. The data comprehensively covered farm households' information on adoption of CSAPs, this includes DTMVs, inorganic fertilisers, intercropping, row-planting, incorporation of crop residues, and manure. Whether farm households adopt CSAPs or not is represented as binary for each CSAPs (see Table 1 below). The data also include explanatory variables such as households' socioeconomic variables, plot attributes, institutional variables, household cost of assets, total livestock units perception of risk and regional variables. Socioeconomic variables include gender of household head, age (measured in years), household size, years of education, years of farming experience and number of years resident in the village. Data also include farm households' wealth indicators (households' asset and total livestock units (TLU)). Plot attributes include farm size measured as total operated land areas in hectares, land tenure status (farmers ownership and rent status), and farm households' cost of hired labour. Institutional and social networks variables include data on farmers membership of input supply and cooperatives, access to advice and access to loan. Data on technological factors include farmers awareness of improved maize variables, training on improved maize production practices and wilingness to take risks. Data also covered geo-political location of farm households (North-West, North East , North Central, South West, South East and South -South).

Table 1: Description of Variables

Variables	Description of variables
CSAPs	
DTMVs	= 1 if adopted; 0 otherwise
Inorganic Fertiliser	= 1 if adopted; 0 otherwise
Intercropping	= 1 if adopted; 0 otherwise
Row Planting	= 1 if adopted; 0 otherwise
Incorporate crop residues on plot	= 1 if adopted; 0 otherwise
Manure	= 1 if adopted; 0 otherwise
Explanatory Variables	
Gender (1=male; 0=female)	=1 if household head is male; 0 otherwise
Age (years)	in years

Education (years)	in years
Number of years resident in the village	Number of years resident in the village
Own Land (yes = 1; no = 0)	=1 if household head owns a land; 0 otherwise
Land rent yes = 1; no = 0)	=1 if household head rent a land; 0 otherwise
Farm Size (ha)	Total operated farm area in hectares.
Farming experience (years)	Household head farming experience in years
Household Size	Household size (number)
Received Loan (yes = 1; no = 0)	=1 if household received loan in the past agricultural season; 0 otherwise
Member of input supply and farm cooperatives (yes = 1; no = 0)	= 1 if household head is a member of input supply groups; 0 otherwise
Received advice on improved varieties	= 1 if the household head received advice on improved maize varieties.
Total Cost of Household Asset ('000 NGN)	Total household production and non-production assets.
Total Livestock Unit (TLU)	Total Livestock Unit
Cost of Hired Labour (000 NGN)	The total cost of hired labour in the past agricultural season.
Awareness and access to improved maize varieties (yes = 1; no = 0)	= 1 if the household head was aware and had access to improved maize varieties; 0 otherwise.
Training in Improved production practices (yes = 1; no = 0)	=1 if household received training on improved production practices in the past agricultural season; 0 otherwise.
Willingness to take risk (yes = 1; no = 0)	=1 if the household has the willingness to take a risk on the adoption of agricultural technology; 0 otherwise.
North West (yes = 1; no = 0)	= 1 if farm household is in North-West region; 0 otherwise
North Central (yes = 1; no = 0)	= 1 if farm household is in North-Central region; 0 otherwise.
North East (yes = 1; no = 0)	= 1 if farm household is in North East region; 0 otherwise
South-South (yes = 1; no = 0)	= 1 if farm household is in South-South region; 0 otherwise.
South-East (yes = 1; no = 0)	= 1 if farm household is in South East region; 0 otherwise.
South-West (yes = 1; no = 0)	= 1 if farm household is in South West region; 0 otherwise.

3.2 The economic and econometric framework of simultaneous adoption fo CSAPs

3.2.1 The economic framework

In Nigeria, maize farm households choose to allocate land areas for DTMVs to adopt a combination of one or all of the other CSAPs with the motive of curbing impending climate challenges, increasing productivity and maximising profits. Let Y_D, Y_F, Y_I, Y_R, Y_W and Y_M

denote the outcomes of CSAPs which include DTMVs, inorganic fertiliser, intercropping, row planting, incorporation of crop residues, and manure respectively. These technologies are likely constrained by groups of identified attributes which include socioeconomic, farm, topographical, institutional and regional factors.

Following similar studies (Abdulai, Owusu and Goetz 2011; Ndiritu et al. 2014; Shiferaw et al. 2014), we apply a multivariate Probit model (MVP) for modelling farmers' joint adoption decisions of CSAPs Y_D, Y_F, Y_I, Y_R, Y_W and Y_M . The MVP assumes possible occurrence of adoption of multiple CSAPs and resolves issues of unobservable factors by allowing for correlation across error terms of latent equations which represent unobserved factors affecting farm households' decisions to adopt (Belderbos et al. 2004). Such correlations allow for positive correlation (complementarity) and negative correlation (substitutability) between the various agricultural technologies (Ndiritu et al. 2014; Bedeke et al. 2019).

3.2.2 The econometric framework

The MVP equation with latent dependent variables is defined as linear function of a set of observed maize farmhousehold i vector of explanatory variables X_{ij} and distributed errors ε_{ij}

$$Y^*{}_{ij} = X_{ij}\beta_j + \varepsilon_{ij} \quad \text{j=1} \qquad (1)$$

where $Y^*{}_{ij}$ denotes the latent variable, which can be represented by the level of expected benefit that would be derived from adoption of jth type of CSAPs. This latent variable is assumed to be a linear combination of observed household charcateristics X_{ij} and β_j is the estimate of parameter vector. The unobserved household characteristics is captured by teh error term ε_{ij} . The observable dichotomous choice variables is defined as follows:

$$Y_{ij} \begin{cases} 1 & if\ Y^*{}_{ij} > 0 \\ 0 & otherwise \end{cases} \qquad (2)$$

This indicate whether or not a farm household adopt CSAPs. The error term ε_{ij} are distributed multivariate normal, each with the mean 0 and a variabce-covariance matrix π is illustrated as follows:

$$\pi = \left\{ \begin{matrix} 1 & \delta DF & \delta DI & \delta DR & \delta DW & \delta DM \\ \delta FD & 1 & \delta FI & \delta FR & \delta FW & \delta FM \\ \delta RD & \delta RF & 1 & \delta RI & \delta RW & \delta RM \\ \delta ID & \delta IF & \delta IR & 1 & \delta IW & \delta IM \\ \delta WD & \delta WF & \delta WR & \delta WI & 1 & \delta WM \\ \delta MD & \delta MF & \delta MR & \delta MI & \delta MW & 1 \end{matrix} \right\} \quad (3)$$

The off-diagonal elements in the covariance matrix represent the unobserved correlation between the error components of the different types of agricultural technologies. This model considers the elimination of households' invariant unobserved characteristics heterogeneity which has been taken care of in the MVP model. The adaptation of the MVP model is evident in past studies (Abdulai, Owusu and Goetz 2011; Ndiritu et al. 2014) that considered the interdependence of adoption choices.

However, the MVP model is a non-censored approach and since adoption is binary, consisting of farm-households that adopt and do not adopt suggesting censored data, the Tobit model is suitable because it uses all observations, both those at the limit, usually zero (for example, non-adopters), and those above the limit (for example, adopters), in estimation. This way we can capture the latent level of intensity of potential households who decide not to choose a particular CSAP. We postulate an outcome function for adopting CSAPs as follows:

$$Y^*{}_i = U' X_i + \varepsilon_i \quad (4)$$

where X_i is the vector of regressors, U' is the vector of parameters to be estimated and ε_i is the error term.

To empirically investigate factors of joint adoption of DTMVs and other identified CSAPs, a simultaneous equation model is required. The equations below, illustrate maize farm households' decision to adopt CSAPs in various combinations. This implies that there is existing potential interdependence across the disturbances of each respective equation. The Multivariate Tobit (MVT) model, a form of a simultaneous equation, is employed to synchronously account for potential interdependence and censored issues, illustrated as follows:

$$
\begin{aligned}
Y^{*}{}_{Di} &= U'\,X_{Di} + \varepsilon_{Di} \\
Y_{Di} &= Max\,(Y^{*}{}_{Di}, 0) \\
Y^{*}{}_{Fi} &= U'\,X_{Fi} + \varepsilon_{Fi} \\
Y_{Fi} &= Max\,(Y^{*}{}_{Fi}, 0) \\
Y^{*}{}_{Ii} &= U'\,X_{Ii} + \varepsilon_{Ii} \\
Y_{Ii} &= Max\,(Y^{*}{}_{Ii}, 0) \\
Y^{*}{}_{Ri} &= U'\,X_{Ri} + \varepsilon_{Ri} \\
Y_{Ri} &= Max\,(Y^{*}{}_{Ri}, 0) \\
Y^{*}{}_{Wi} &= U'\,X_{Wi} + \varepsilon_{Wi} \\
Y_{Wi} &= Max\,(Y^{*}{}_{Wi}, 0) \\
Y^{*}{}_{Mi} &= U'\,X_{Mi} + \varepsilon_{Mi} \\
Y_{Mi} &= Max\,(Y^{*}{}_{Mi}, 0)
\end{aligned}
\qquad (5)
$$

$$\varepsilon_{Di}\varepsilon_{Fi}, \varepsilon_{Ii}, \varepsilon_{Ri}, \varepsilon_{Wi}, \varepsilon_{Mi} \approx N(0, V)$$

Where $Y^{*}{}_{Di}$, $Y^{*}{}_{Fi}$, $Y^{*}{}_{Ii}$, $Y^{*}{}_{Ri}$, $Y^{*}{}_{Wi}$ and $Y^{*}{}_{Mi}$ represents maximised outcome for DTMVs, Inorganic fertiliser, intercropping, incorporation of residues, row planting, and manure. X, consists of a predetermined variable. The error terms $\varepsilon_{Di}, \varepsilon_{Fi}, \varepsilon_{Ii}, \varepsilon_{Ri}, \varepsilon_{Wi}, \varepsilon_{Mi}$ follows a multivariate normal distribution as specified below:

$$
0 = \begin{Bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix}, \mathrm{V} = \begin{Bmatrix}
r_D^2 & r_F^D & r_I^D & r_R^D & r_W^D & r_M^D \\
r_D^I & r_F^2 & r_I^I & r_R^I & r_W^I & r_M^I \\
r_D^R & r_F^R & r_I^2 & r_R^R & r_W^R & r_M^R \\
r_D^W & r_F^W & r_I^W & r_R^2 & r_W^W & r_M^W \\
r_D^F & r_F^F & r_I^F & r_R^F & r_W^2 & r_M^F \\
r_D^M & r_F^M & r_I^M & r_R^M & r_W^M & r_M^2
\end{Bmatrix} \qquad (6)
$$

V, is the variance-covariance matrix of the error terms; r_D^2, r_F^2, r_I^2, r_R^2, r_W^2 and r_M^2 are the standard deviation of error terms, while the rest is the cross-equation correlation between CSAPs. Similar to the MVP model, the MVT allows for the correlation of errors and individual univariate terms (Rahman and Akter 2014).

Following Barslund (2009), the estimation procedures use simulation using Halton draws to generate the distribution of multidimensional normal integrals in the likelihood function(Train. 2000). The approach involves calculating a likelihood contribution for each replication. The simulated likelihood function is the average of the values derived from all replications. However, in a broad independent multi-equation setting that allows for the correlation of errors, the computation can be tasking, and estimating likelihoods can be complicated. We estimate the 'mvtobit' through the conditional mixed process (cmp) approach developed by Roodman (2011). The 'cmp' uses an appropriate estimation approach which allows for any possible linkage among their error processes and their discrete outcome variables.

3.2.2 The economic and econometric framework of factors driving the intensity of adoption of CSAPs.

From the MVT model above, we conceptualise, a farm household only chooses to adopt one or more CSAPs only if the net benefit is greater than non-adoption and they derive higher utility. We assess the extent of adoption by the number of CSAPs adopted by maize farm households. The poisson count distribution model is usually the starting point in count models, however, a Poisson distribution contradicts the assumption of the interdependence of agricultural technology, which renders it inappropriate (Wollni et al. 2010). The Poisson regression model assumes an equal probability of adoption of each alternatives CSAPs which is not reflective of the interdependence assumption of this study, because the probability of adopting a CSAP might be different from the probability of adopting another, the dependent variable is therefore treated as an ordinal variable that follows categories of ordered outcomes, for example, households that adopt zero, one, two, three, four, five, and six mixes of CSAPs. Similar categorical approaches can be found in (Teklewold, Kassie and Shiferaw 2013; Shee et al. 2019). Given the ordered nature of CSAPs, the ordered logit or probit can be used in the estimation process, however, we apply the ordered probit approach since it is widely used

(Davidson and Mackinnon, 2003). Following Wooldridge (2010), let the ordinal dependent variable y takes the values {0, 1, 2,….J) for some known integer J. The variable y can be derived , conditional on the regressors X, from a latent continuous variable y^* which in this case is an underlying unobserved measure of households' adoption of CSAPs in numbers and it is specified as follows:

$$y_i^* = X_i'\beta + u_i \quad (7)$$

Where u_i is normally distributed with mean zero and variance one, β is the vector of the unknown parameter to be estimated and X is a matrix of independent variables. For a Jth farm household where normalization is that the regressors X do not include an intercept, we assumed that $\sigma_1 < \sigma < \ldots < \sigma_j$ to be unknown threshold points and define these thresholds such that

$$\begin{aligned} y &= 0 \; if \; y^* \leq \sigma_1 \\ y &= 1 \;\; if \;\; \sigma_1 < y^* \leq \sigma_2 \\ &\vdots \qquad\qquad (8) \\ y &= 1 \;\; if \;\; \sigma_1 < y^* \leq \sigma_2 \\ y &= J \;\; if \;\; y^* > \sigma_J \end{aligned}$$

In our study, y takes on six values 1 ('maize farm households adopt one CSAPs'), 2 (maize farm households adopt two CSAPs'), 3 (maize farm households adopt three CSAPs'), 4 (maize farm households adopt four CSAPs'), 5 (maize farm households adopt five CSAPs'), and 6 (maize farm households adopts all the six CSAPs').

Following a standard ordered probability model where the error term is assumed to be normally distributed, each response probability can be illustrated as follows:

$$P(y = 0|X = \Psi\,(\sigma_1 - X_i'\beta)$$

$$P(y = 1|X = \Psi(\sigma_2 - X_i'\beta) - \Psi(\sigma_1 - X_i'\beta) \quad (9)$$

$$P(y = J|X = 1 - \Psi\,(\sigma_J - X_i'\beta)$$

Where Ψ(.) represents the standard normal cumulative distribution. This is a generalized version of the binary probit model in which parameters σ and β can be estimated by maximizing the following log-likelihood function:

$$(y = J|X = 1 - \Psi(\sigma_J - X_i'\beta))$$
$$L_i(\sigma,\ \beta) - [y_i\ = 0] \log\ [\Psi(\ \sigma_1 -\ X_i'\beta)]\ +\ [y_i\ =\ 1]\ \ + \cdots$$
$$+ [\ y_i\ =\ J] log\big[1 - \Psi(\ \sigma_j -\ X_i'\beta)\big] \tag{10}$$

The marginal effect of an increase in X on the probability of selecting alternative J can be written as:

$$\frac{\partial P_{il}}{\partial X_{il}} = \ \big[\Psi(\sigma_{j-1} -\ X'\beta) - \Psi(\sigma_j -\ X'\beta)\ \big]\beta \tag{11}$$

Where $\Psi(.)$ is the standard normal density function.

5. Results and Discussions

5.1 The Summary Statistics of Variables

The summary statistics of dependent variables identified among maize farm households are illustrated in Table 2. DTMVs are the least adopted (23%) among maize farm households while inorganic fertiliser and row-planting are the most adopted; 92% and 84% respectively, revealing that maize farm households are highly conversant with these practices. Also, 37%, 48%, and 53% of households adopt manure, residue incorporation, and intercropping respectively.

Gender is one of the foremost factors in adoption decisions with varying implications depending on the type of gender variable and CSAPs (Doss and Morris 2000; Theriault et al. 2017; Muriithi et al. 2018). This study considers male and female household heads that are plot managers, and they constitute 88% and 12% of the sample respectively (Table 2). Also, several studies have found differing preferences between older and younger farmers based on their experience of climate events or knowledge of the use of CSAPs, which makes age quite significant in the adoption decision. From the study sample, the mean age of household heads is approximately 47 years suggesting that household heads are still relatively in their active farming years. Besides, educational status can predict farmers' adoption decisions; however, in literature, it has various implications on the adoption (Wainaina et al. 2016). In this study, sample farm households have 7.62 years of education suggesting that most maize farm households have primary-level education and can understand the use of CSAPs. Household size can be a proxy for family labour availability for farm activities, for example, larger households are more likely to invest in the adoption of labour-intensive practices such as conservative practices (Ndiritu et al. 2014). The household size in this study is large (6.93) and it is expected that this may affect single or multiple choices of conservative practices. On average maize farm households' years of farming experience is 27.98, suggesting that households are likely to be familiar with agricultural innovations and adoption impact. This study also captures maize farm households' years of residents in the farm community which may likely suggest an understanding of the weather pattern of the village over the years and may impact their adoption choices. This study also includes wealth indicators such as total livestock unit (TLU) and total household asset cost (farm and non-farm assets).

Farm and topographical factors

We consider popular indicators of farm variables which are farm size, land ownership, and rental. From Table 2, 84% of maize farm households' own land. Land ownership in this context refers to the individual long-term rights to the land area which makes them tenure secured. We also capture the land rent variable of which only 8% of maize farm households were on land rent contracts. The average farm size among the sampled household is 11.01 ha.

3.1.3 Institutional and social network factors

Institutional roles such as credit institutions play significant roles in adoption decisions. This is because access to credit enables poorer households to adopt new technology by providing credit. Access to credit has been found significant in driving the adoption of climate-resilient technologies in the literature (Bedeke et al. 2019). We capture farm households that received a loan in the past agricultural season as a proxy for access to credit. Table 1 shows while 49% of farm households received a loan, 51% were liquidity constrained. Extension services as an institution in driving adoption have been established in several adoption case studies (Emmanuel et al. 2016; Wossen, et al. 2017b; Nakano et al. 2018). We consider proxies that are components of extension services, this includes *training in improved production practices* and *advice on improved maize varieties*. However, the data shows a low extension presence among agricultural households; only 9% and 29% of households received training in improved production practices and advice on improved maize varieties, respectively. Social networks are a means to access and exchange information such as technical information, price, and credit information (di Falco and Bulte 2011) and may influence households' decision choices and combinations of choices. About 62% of households are members of input supply and farm cooperatives group.

3.1.4 Technology and regional factors:

We further include attributes of agricultural technology in terms of risk, awareness, and access. The indicator of households' awareness and access to improve maize varieties can suggest availability and ease of access which can impact the fast adoption of CSA and its complements. However, only 14% of sampled maize farm households were aware and had access to improve maize varieties. Also, the majority (73%) of maize farm household has the willingness to adopt agricultural technology suggesting the high probability of adopting the majority of CSA components. Regional variables from Table 1 indicates that the majority of maize farm households are in North-West (35%), North Central (27%), and South West (24%) regions, with only 4%, 5%, and 5% in South-East, South-South, and North East respectively

Table 2: Summary Statistics of Maize Farm Households in Sample Study.

Variables	**Percentage**	Mean	Std. Dev
Dependent variables			
DTMVs	23%		

Inorganic Fertiliser	92%		
Intercropping	53%		
Row Planting	84%		
Incorporate crop residues on plot	48%		
Manure	37%		
Categories of number of CSAPs in ordered probit model			
Explanatory Variables			
Gender (1=male; 0=female)	88%		
Age (years)		47.45	13.97
Education (years)		7.62	6.63
Number of years resident in the village		40.74	17.6
Own Land (yes = 1; no = 0)	84%		0.37
Land rent yes = 1; no = 0)	8%		0.28
Farm Size (ha)		11.01	173.26
Farming experience (years)		27.88	14.93
Household Size		6.93	2.99
Received Loan (yes = 1; no = 0)	49%		
Member of input supply and farm cooperatives (yes = 1; no = 0)	62%		
Received advice on improved varieties	29%		
Total Cost of Household Asset ('000 NGN)		1052	3944
Total Livestock Unit (TLU)		2.33	15.51
Cost of Hired Labour (000 NGN)		62.51	95.75
Awareness and access to improved maize varieties (yes = 1; no = 0)	14%		
Training in Improved production practices (yes = 1; no = 0)	9%		
Willingness to take risk (yes = 1; no = 0)	73%		
North West (yes = 1; no = 0)	35%		
North Central (yes = 1; no = 0)	27%		
North East (yes = 1; no = 0)	5%		
South-South (yes = 1; no = 0)	5%		
South-East (yes = 1; no = 0)	4%		
South-West (yes = 1; no = 0)	24%		

5.1 Joint and marginal probabilities of adoption

The joint and marginal probability distributions of adoption of the six CSAPs for maize farm households are presented in the appendix (Table S1). The result shows zero adoption probability for DTMVs, both when adopted as a single technology and when combined individually with one other CSAPs. Joint adoption however increased in combination with two other CSAPs; in this case, adoption probability is 73% with inorganic fertilisers and row planting only. Inorganic fertilisers have the highest probability of adoption, 2.31% when adopted as a sole technology, in combination with row-planting, adoption probability is 9.70%. Adoption probability however decreases in combination with more CSAPs. Adoption probability is respectively 9.36% in combination with inorganic fertilisers, row-planting and intercropping and 7.67% in combination with Inorganic fertilisers, intercropping, row planting, and incorporate crop residues. While the joint probability of adopting all CSAPs is 2.74%, the probability of adopting none of the CSAPs is 0.24%. This suggests that a very low number of maize farm households are less likely to adopt any of the CSAPs. Similar study (Teklewold, Kassie and Shiferaw 2013) found variation across joint and marginal probability distribution of sustainable agricultural practices.

The unconditional and conditional adoption probabilities presented in Table S2 (see appendix) further indicate possible interdependence between six CSAPs. In most cases, the interdependence status shows a varying degree of substitutability effects across CSAPs. The unconditional adoption probability of DTMVs is 45% and significant at $p < 0.01$. However, adoption decisions for DTMVs significantly decrease by 97%, 66%, and 36% for adopting row planting only, incorporating crop residues only, and manure only. Similarly, conditioned on adopting DTMVs and inorganic fertilisers, the adoption decisions for row-planting, residue incorporation, and manure significantly decreased by 97%, 67%, and 36% respectively. The complementary effects of DTMVs on other CSAPs can also be seen in some instances. For example, the adoption decision for DTMVs and inorganic fertiliser is positive, but significant for DTMVs conditioned on the adoption of the other four CSAPs. In the case where farm households adopt the other five CSAPs, the decision to adopt DTMVs significantly increased by 17%.

In the exception of DTMVs, the unconditional effect of adopting manure compared to other CSAPs is more likely, however, significantly decreases the likelihood of adopting row-planting and residue incorporations when conditionally adopted with DTMVs. This shows that to an extent, manure can substitute row-planting and residue incorporation. Across most conditional situations, row-planting reflects the highest significant substitutability effects, signifying that farm households are less likely to adopt the row-planting where other CSAPs are adopted. Similarly, conditional on farm households adopting row planting only, the adoption effect is significantly highly negative for DTMVs, incorporation of crop residues and manure at -97%, -102%, and -98% respectively. This shows existing high substitutability effects among CSAPs. While it is important to assess the interrelations of CSAPs, the distributional analysis across outcome variables shows that the adoption of CSAPs is associated with maize output. This is presented in Figures 1-6. The cumulative density functions for maize output are more dominant on the right side for adopters and on the left side for non-adopters, suggesting that maize output with CSAPs holds first-order stochastic dominance over non-CSAPs adopters, however, differs for incorporation of residues CSAP. The stochastic dominance of the outcome for adopters is an important economic incentive for adopting CSAPs.

This is further confirmed by the Kolmogorov Smirnov Statistics test for cumulative distribution functions (CDF) which shows a significant difference in the vertical distances between adopters and non-adopters of CSAPs except for residue incorporation which was not significant (Table 3).

Table 3. Kolmogorov-Smirnov statistics test for the cumulative log of maize output distribution

CSA types	Distribution
DTMVs	0.245(0.000) ***
Intercropping	0.115(0.000)***
Row Planting	0.076(0.068)*
Inorganic Fertiliser	0.174(0.003)***
Incorporate crop residues	0.034(0.579)
Manure	0.156(0.000)***

Note: p-values in parentheses. *significant at 10%, ***significant at 1%

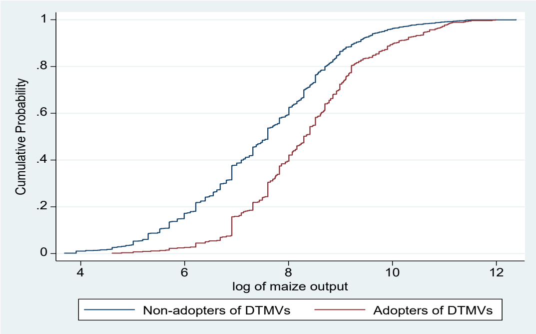

Figure 1: Impact of DTMVs on the log of maize output

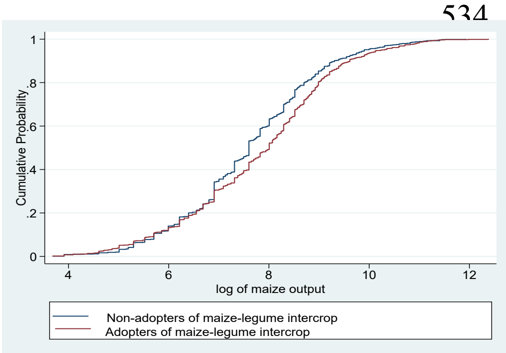

Figure 2: Impact of intercropping on the log of maize output

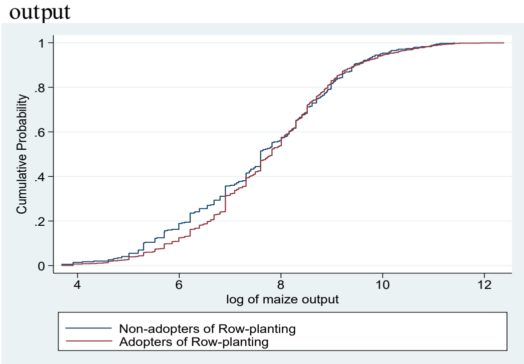

Figure 3: Impact of row planting on the log of maize output

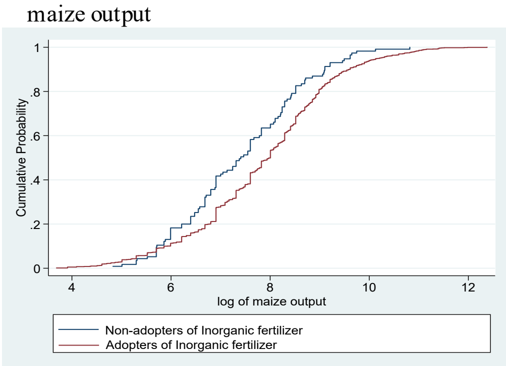

Figure 4: Impact of Inorganic fertilizers on the log of maize output

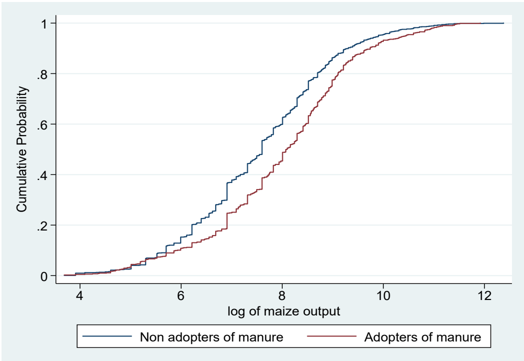

Figure 5: Impact of manure the log of maize output

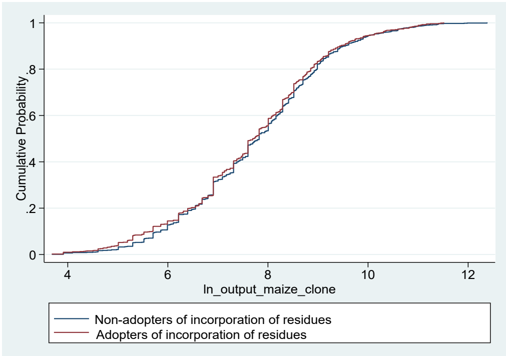

Figure 6: Impact of incorporation of residues on the log of maize output

5.2 Multivariate Tobit estimation of factors of adoption of climate-smart agriculture

Complementarity and Substitutability Effect in DTMVs and other CSAPs

Binary correlation estimations between CSAPs derived from the MVT estimations are presented in Table 4. This study finds that while some CSAPs are complements, some are substitutes. To further explain, the propensity of adopting DTMVs significantly increases with manure at 4.8% ($p<0.1$). Consequently, maize farm households are likely to adopt DTMVs with manure, a low-cost CSAP. Studies such as Ndiritu et al. (2014), Murithii et al. (2018), and Bedeke et al. (2019) found a positive relationship between low-cost sustainable practices and improved seed adoption. Also, adopting DTMVs increases fertiliser use, however not significant in this context. The existing positive correlation of DTMVs with fertiliser may be due to the popular promotion of improved seeds with fertilisers in most interventions. A similar finding is established in Muriithi et al. (2018).

Contrary to findings in Wainaina et al. (2016), manure is positively correlated with residue incorporation at a 6.4% probability. This implies that, to an extent, both CSAPs complement one another in a way that their usage is common, for example in a crop-livestock system, manure from animals is used on farmlands and crop residues can also be incorporated back into the land or used as livestock fodder. this is typical of most farm households. Similarly, the complementarity attribute is evident in the positive correlation of row planting and manure at 5.8% probability, implying that farm intercropping maize-legumes or maize-fodders crops are usually accompanied by the row planting initiative.

Conversely, negatively correlated pairs connote the possible substitutability of CSAPs. From the result, intercropping techniques and residue incorporation are negatively correlated at $p<0.05$ confidence level signifying their substitutability effect (0.143). This further implies that maize farm households, to a large extent either adopt more of intercropping and less of residue incorporation or vice versa or substitute one for the other. Intercropping and residue incorporation techniques are soil conservation practices that have a similar agronomic impact such as soil fertility improvement and protection and are a low-cost substitute for one another. The results are almost similar to estimations derived from the multivariate probit estimation illustrated in the appendix (Table S3). It shows similar significant complementary effects between intercropping and row planting; row planting and manure; incorporation of residues and manure. The result from the *MVT* shows a similar negative correlation and substitutability effect at a 10.3% probability for intercropping and incorporation of residues. Similarly, DTMVs and manure show a positive correlation, however not significant.

Table 4. Complement and Substitutes of CSAPs among maize farm households (from multivariate Tobit estimation)

CSAPs	Coefficient	Standard Error.
DTMVs and Inorganic fertiliser (atanhrho 12)	0.016	0.030
DTMVs and Intercropping (atanhrho 13)	0.041	0.027
DTMVs and Row planting (atanhrho 14)	-0.027	0.027
DTMVs and Incorporation of Residue. (atanhrho 15)	-0.002	0.027
DTMVs and Manure (atanhrho 16)	0.048*	0.027
Inroganic fertiliser & Intercropping (atanhrho 23)	-0.042	0.031
Inorganic Fertiliser & Row planting (atanhrho 24)	-0.022	0.031
Inorganic Fertiliser and Incorporation of Residue. (atanhrho 25)	0.008	0.031
Inorganic fertiliser and Manure (atanhrho 26)	0.005	0.029
Intercropping & Row planting (atanhrho 34)	0.063**	0.027
Intercropping and Incorporation of Residue. (atanhrho 35)	-0.072***	0.027
Intercropping and Manure (atanhrho 36)	0.016	0.027
Row planting and Incorporation of Residue. (atanhrho 45)	0.042	0.027
Row planting and Manure (atanhrho 46)	0.058**	0.027
Incorporation of Residue and Manure. (atanhrho 56)	0.064**	0.027

Note: *significant at 10%; **significant at 5%; ***significant at 1% . 1= DTMVs; 2=inorganic fertiliser; 3=Intercropping; 4 = Row planting ; 5 = Incorporation of crop residues ; 6= Manure

5.3 Adoption decision results

In this section, we limited discussion on determinants of adoption of CSAPs to the MVT estimations as illustrated in Table 5[1]. The likelihood ratio $(\chi^2\ (138 = 1740; p < 0.01)$ suggests the rejection of the null hypothesis of independent error terms of the overall model and across CSAPs, implying that multiple adoptions of CSAPs are not mutually independent and supports the use of the simultaneous Tobit model. The result relating to gender suggests that of all the CSAPs, female household heads that are plot managers are significantly more likely to adopt intercropping. Past research shows evidence of popular intercropping of maize, especially with legumes such as groundnut, cowpea, and soybean (Adewopo 2019) and in various contexts from time past are quite profitable (Baker 1978; Onuk et al. 2015). This may also suggest that female-headed households opt for low-cost agronomic practices such as intercropping.

[1] We have also estimated MVP, which is presented in the appendix (Table S4)

Also, the result shows that younger farmers are significantly ($p<0.05$) more likely to adopt inorganic fertiliser at 0.2% probability. This may be because younger farmers are more versatile and flexible with the adoption of agricultural technology. This is akin to the findings in Nigussie et al. (2017). Less-educated maize farm households will more likely opt for the incorporation of residues on the plot and use of manure than any other CSAPs. This may be related to non-technicality in the adoption of both CSAPs compared to other CSAPs such as intercropping and inorganic fertiliser use. The number of years of residence may suggest farm households' versatility with the plot terrain, soil type, and seasonal weather events. In this context, an increasing number of years in the village significantly increases the adoption of inorganic fertiliser and incorporation of crop residue at $p<0.05$. Older residents probably become stereotypical with popular CSAPs practices.

The years of farming experience solely influenced the increasing adoption of intercropping, suggesting that maize farm households' understanding of climate impact improved their knowledge of intercropping techniques as a continuous production practice to enhance yield and improve soil fertility. Also, maize farming communities are concentrated in the Northern region and intercropping is a popular technique in solving problems of soil infertility and weed infestation for example in the case of maize -legumes intercropping and also, in the case of Striga infestation, intercropping with weed resistant crops is quite common. This approach is similar to push-pull technology in Kenya; a cropping system in which maize or other cereals are intercropped with a perennial fodder that repels stem borer pests and stimulates abortive germination of Striga weed (Muriithi et al. 2018).

Log of cost of hired labour, although positive for most CSAPs was only significant for the adoption of DTMVs suggesting that farm households spent more on labour needs for the adoption of DTMVs. In the same vein, household size which can be a proxy of labour availability also positively influenced the adoption of DTMVs. A possible explanation is that labour requirements in the adoption of DTMVs may be indirectly influenced by other CSAPs that highly demand labour, for example, in this same study, household size was significant in the adoption of manure which requires collection and transport, and it is labour intensive.

In terms of plot variables, this study found that the adoption of manure increases for both maize farm households that owned and rented land. This is contrary to findings in some studies that the adoption of long-term investments CSAPs such as manure is more popular among tenure-secured farm households (Jansen et al. 2006; Abdulai and Huffman 2015; Kassie et al. 2015). A similar finding is evident in Wainaina et al. (2016) where plot ownership negatively influenced the adoption of zero tillage, a long-term investment sustainable land practice. This suggests that the adoption of CSAPs that are a long-term investment and increase productivity, in the long run, are not solely driven by tenure security status, but probably by immediate productivity potentials. Considering the farm size attribute, the adoption of manure increases with an increase in farm size, this is consistent with the result found in Kassie et al. (2015) for Tanzania. In the same study, contrary evidence exists in the case of Kenya and Ethiopia.

Wealth indicators such as a log of household asset positively influenced the adoption of inorganic fertiliser, row planting, and incorporation of crop residues, however negatively influenced the adoption of intercropping. Apparently, wealthy households are likely to jointly adopt a mix of CSAPs due to the ability to afford and access requires resources, including costly CSAPs such as inorganic fertiliser. Proxies of wealth in similar studies have positively influenced the adoption of CSAPs, for example in (Kassie et al. 2015) asset value influenced the adoption of crop diversification and manure. Also, in Teklewold et al. (2013), the value of major household and farm equipment positively influenced the adoption of improved seed, inorganic fertiliser, and conservation tillage. In a similar vein that confirms the importance of funds in the adoption of CSAPs, access to loans increased the adoption of DTMVs and manure suggesting that maize farm households that are liquidity constrained are less likely to adopt costly CSAPs such as DTMVs and manure that demands high labour needs. This finding is consistent with Bedeke et al. (2019) where access to loans influenced the adoption DTMVs, mineral fertilisers and soil & water conservation practices. Also, in a similar study in Nigeria, access to credit influenced the increased adoption of manure but negatively impacts intercropping (Oladimeji et al. 2020).

In terms of institutional variables, awareness and access to improved maize varieties as a proxy of household access to information is associated with a higher probability of adoption of DTMVs among maize farm households. This further revealed that awareness and access to improved maize varieties are endogenous to adoption and are unsurprising. In addition, the adoption of inorganic fertiliser and manure increases among farm households that received training in improved production practices. Also, membership in input supply and farm cooperatives significantly increased the adoption of intercropping and manure but reduced the adoption of residue incorporation. This may suggest that membership in a group promotes different types of CSAPs and intercropping and manure use may have been highly promoted or indirectly supported through other programmes or interventions in the group. In similar studies, social capital indicators such as group membership have been found to influence the adoption of sustainable land practices (Teklewold, Kassie, and Shiferaw 2013; Bedeke et al. 2019).

On the other hand, this study includes a variable that assesses the willingness to take a risk on the adoption of improved maize varieties to determine if risk status can be transferred to other CSAPs. The result is however heterogeneous across CSAPs, while it significantly increases with the adoption of DTMVs and manure, it decreases with intercropping. This result is intuitive and suggests that farm households' ability to take a risk differs within the components of CSAPs. Using the South-West region as the base/reference, indicators of regional effects revealed heterogeneity in the adoption of CSAPs. While the adoption of DTMVs, inorganic fertiliser, and manure is prominent in the North West region, the North Central region is more likely to adopt inorganic fertiliser and manure only. A high probability of adoption of inorganic fertiliser and manure is akin to North West and North East region and as such should be more promoted with DTMVs to increase the adoption of DTMVs. Decreasing the potential of adoption of DTMVs, intercropping row planting is evident in the North East region, except for manure. The North-East region agricultural community may have been affected by consistent crisis problems and obviously, the low adoption of CSAPs is evident in this region.

In the South East region, the adoption of DTMVs, residue incorporation, and manure is on the increase and implies that the promotion of DTMVs should jointly consider promoting sustainable land practices such as residue incorporation and manure. On the other hand, in the South East and the South-South regions, the result further reveals decreasing adoption of inorganic fertiliser and row planting. The explanation for this may be the high infiltration rate and erosion of fertiliser on plot land, this is because the Southern region’s weather condition is highly humid with high rainfall index. Less adoption of row-planting may suggest that manure and residue incorporation as alternatives sto oil protection and yield enhancement strategies in South East. At the same time, the increasing probability of adopting intercropping in the South-South implies that DTMVs should be promoted with intercropping in the region in other to increase adoption.

Table 5. Multivariate Tobit Estimation of Factors of Adoption of Climate-Smart Agricultural Practices.

Variables	DTMVs	Inorganic fertiliser	Intercropping	Row-planting	Incorporate crop residue	Manure
Gender (1=male; 0=female)	-0.033	-0.009	-0.103*	0.059	-0.029	-0.001
	(0.041)	(0.037)	(0.062)	(0.044)	(0.063)	(0.050)
Age (years)	0.001	-0.002**	-0.001	0.000	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Education (years)	-0.000	0.001	0.002	0.000	-0.008***	-0.004**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Household Size	0.008***	-0.004*	0.008*	0.001	0.003	0.015***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)
Number of years resident in village	-0.001	0.002**	-0.001	0.001	0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Farming experience (years)	-0.000	0.001	0.003**	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Own Land (yes = 1; no = 0)	-0.007	0.026	-0.032	0.010	0.071	0.071**
	(0.029)	(0.025)	(0.044)	(0.032)	(0.045)	(0.036)
Land rent (yes = 1; no = 0)	-0.034	-0.035	-0.039	0.022	-0.003	0.071*
	(0.032)	(0.027)	(0.049)	(0.035)	(0.049)	(0.040)
Farm Size (ha)	-0.001	0.000	-0.001	0.001	-0.001	0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Total Cost of Household Asset (log)	0.006	0.012***	-0.018**	0.024***	0.023***	-0.013*
	(0.005)	(0.005)	(0.008)	(0.006)	(0.008)	(0.007)
Log of Cost of Hired Labour (000 NGN)	0.015**	0.004	0.006	-0.004	0.014	0.002
	(0.007)	(0.006)	(0.012)	(0.008)	(0.012)	(0.009)
Total Livestock Unit (TLU)	0.001	-0.000	0.000	0.000	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Received Loan (yes = 1; no = 0)	0.057***	0.014	-0.032	-0.038*	0.011	0.054**
	(0.018)	(0.015)	(0.027)	(0.019)	(0.027)	(0.022)
Training in Improved production practices (yes = 1; no = 0)	-0.001	0.077***	0.029	0.024	0.000	0.069*
	(0.031)	(0.025)	(0.047)	(0.033)	(0.048)	(0.038)

Member of input supply and farm cooperatives (yes = 1; no = 0)	0.019	-0.004	0.123***	0.031	-0.117***	0.047*
	(0.020)	(0.017)	(0.031)	(0.022)	(0.031)	(0.025)
Received advice on improved varieties (yes = 1; no = 0)	0.012	-0.034**	0.007	-0.012	0.003	0.031
	(0.020)	(0.016)	(0.030)	(0.021)	(0.030)	(0.024)
Awareness and access to improved maize varieties (yes = 1; no = 0)	0.577***	0.023	0.003	0.031	0.046	0.045
	(0.026)	(0.021)	(0.040)	(0.028)	(0.040)	(0.032)
Willingness to take risk (yes = 1; no = 0)	0.080***	0.012	-0.080**	0.034	0.040	-0.136***
	(0.022)	(0.018)	(0.033)	(0.023)	(0.033)	(0.027)
North West (yes = 1; no = 0)	0.242***	0.122***	0.060	-0.056*	-0.188***	0.543***
	(0.028)	(0.025)	(0.043)	(0.030)	(0.043)	(0.034)
South-South (yes = 1; no = 0)	0.093	-0.192*	0.184**	-0.624***	-0.045	-0.084
	(0.057)	(0.099)	(0.086)	(0.062)	(0.088)	(0.070)
South-East (yes = 1; no = 0)	0.262***	-0.290***	0.110	-0.321***	0.231**	0.543***
	(0.065)	(0.057)	(0.098)	(0.069)	(0.099)	(0.080)
North Central (yes = 1; no = 0)	-0.028	0.041*	-0.092**	0.022	-0.035	0.249***
	(0.026)	(0.023)	(0.039)	(0.028)	(0.039)	(0.031)
North East (yes = 1; no = 0)	-0.097**	-0.002	-0.244***	-0.079*	-0.151***	0.087*
	(0.038)	(0.033)	(0.057)	(0.041)	(0.058)	(0.047)
Constant	-0.292***	0.668***	0.782***	0.518***	0.111	0.174
	(0.107)	(0.091)	(0.163)	(0.116)	(0.165)	(0.131)
lnsig_1	-1.146***					
	(0.019)					
lnsig_2	-1.454***					
	(0.021)					
lnsig_3	-0.734***					
	(0.019)					
lnsig_4	-1.084***					
	(0.019)					
lnsig_5	-0.731***					
	(0.019)					

lnsig_6	-0.944***
	(0.019)
Number of observations	1370
LR chi2(138)	1740.62***
Log-likelihood=	-3279.20
Prob > chi2	0.000

Note: Standard errors are in parentheses. *significant at 10%; **significant at 5%; ***significant at 1%

5.4 Ordered probit estimates of CSAPs adoption

Tables 6 and 7 show the estimates and marginal effects, respectively of the ordered probit model. The Chi-squared statistics of the model are statistically significant$(\chi^2(552.45), p = 0.000)$ at p<0.01 and loglikelihood of 1947.53 indicating that the hypothesis test of all slope coefficients equals zero is rejected. Results show that the number of CSAPs adopted increases with households' wealth indicator variables which are the log of total household assets and total livestock unit, suggesting that poorer maize farm households are less likely to adopt more CSAPs. This can be linked to the limited fund to procure required inputs or access resources for adoption. This is akin to the finding in Teklewold et al. (2013). From the result of marginal effect illustrated in Table 7, across the number of CSAPs, wealthier households significantly adopted from four counts of CSAPs, while poorer households are more likely to adopt less than four CSAPs practices including zero adoption. In a similar vein, access to loans increases maize farm households' propensity to adopt more CSAPs, suggesting that farm households that are liquidity constrained found it difficult to adopt more CSAPs. The marginal effect shows increasing adoption of four CSAPs.

From indicators of institutional presence, the probability of adopting more CSAPs increases among farm households that had awareness and access to improved maize varieties and also received training in improved production practices. The coefficients of these variables significantly influenced the adoption count of CSAPs at 74% and 25% respectively. The explanation for this is that institutional presences in the dissemination of CSAPs application in production practices and regular advice for farmers play significant roles in their willingness to adopt and combine various CSAPs. Also, both variables are endogenous to the adoption of CSAPs and their huge impact is not surprising. In both variables, the marginal effect of adoption increases for more than three CSAPs and decreases for less than four CSAPs

Social capital and network indicators such as membership in input supply and farm cooperatives influenced the increased adoption of the count of CSAPs at 16.5% significant at

$p<0.05$. Across the count of CSAPs, the marginal effect shows that it increases adoption from four CSAPs and decreases adoption for less than four CSAPs. This is indicative of promotions of CSAPs and other indirect resource supports within the group that may be influencing a higher count of CSAPs.

Coefficients of Household size positively and significantly influenced the adoption of the increasing count of CSAPs. The marginal effects for household size show increasing adoption of more than two CSAPs. A similar result is evident in the coefficient of cost of hired labour, this reveals that farm households that incurred more on hired labour were more likely to adopt more than three CSAPs.

Disparities in the count of CSAPs adoption are evident in the coefficient estimates of regions in this study. Increasing adoption of the count of CSAPs is evident in the North West, North Central, and South East region. This may be because these regions, especially North West and North Central have the largest share of land areas for maize production. In these regions, the marginal effect shows that maize farm households adopt more than three counts of CSAPs. Conversely, the South-South and the North East region adopt less than three counts of CSAPs.

Table 6. Estimates of factors of adoption of CSAPs: Ordered Probit

Number of CSAPs	Coef.	Std. Err.
Gender	-0.043	0.117
Age (years)	-0.005	0.004
Education (years)	-0.009	0.005
Household size	0.023**	0.011
Total House Asset (log)	0.039**	0.017
Farming experience (years)	0.003	0.003
Land ownership (yes = 1, no = 0)	0.118	0.096
Land rent (yes = 1, no = 0)	0.026	0.106
Farm size (ha)	0.001	0.001
Cost of hired labour (log)	0.074***	0.024
Trained in improved production practices (yes = 1, no = 0)	0.249**	0.108
Willingness to take risk (yes = 1, no = 0)	-0.110	0.077
Total Livestock Unit (TLU)	0.003***	0.001
Received loan (yes = 1, no = 0)	0.142***	0.058
Member of input supply and farm cooperatives	0.165**	0.066

Received advice on improved varieties (yes = 1, no = 0)	0.016	0.064
Awareness and access to improved varieties (yes = 1, no = 0)	0.748***	0.094
North West (yes = 1, no = 0)	1.087***	0.098
South South (yes = 1, no = 0)	-0.914***	0.151
South East (yes = 1, no = 0)	0.826***	0.275
North Central (yes = 1, no = 0)	0.341***	0.086
North East (yes = 1, no = 0)	-0.327***	0.107
/cut1	-0.756	0.356
/cut2	0.377	0.337
/cut3	1.435	0.339
/cut4	2.376	0.342
/cut5	3.399	0.344
/cut6	4.641	0.348
Wald χ^2 (23)	552.45***	
Prob > χ^2	0.000	
Log likelihood	1947.528	
Number of observation	1370	

**significant at 5%; ***significant at 1%

Table 8 and Figure 7 illustrate the predictive margins of adopting each category of the number of CSAPs adopted. From the result, the predictive marginal effect of adoption peaks at category three of CSAPs adoption at 0.295 probability. Suggesting that the majority of maize farm households are only likely to adopt three CSAPs within an agricultural season. As the number of CSAPs increases, adoption decreases, this is evident in categories 4, 5, and 6 with probabilities of 0.256, 0.119, and 0.018 respectively. This result implies that across multiple CSAPs to tackle climate risks and increase productivity, a higher percentage of households can marginally adopt less than four mixes of CSAPs. Beyond these categories, the decision to adopt a combination of more practices decreases significantly. It suffices to say that while promoting new interventions in an agricultural locality, certain households may have reached the thresholds of adoption and may find it difficult in adopting new interventions based on the limitation of resources. As such, promoting new interventions may require considering observable and unobservable constraints that can limit adoption.

Table 7: Average Marginal Effect of Number of CSAPs Adopted Among Maize Farm Households.

	Prob (Y=0/X)	Prob (Y=0/1)	Prob (Y=0/2)	Prob (Y=0/3)	Prob (Y=0/4)	Prob (Y=0/5)	Prob (Y=0/6)
Gender	0.001	0.005	0.007	0.001	-0.006	-0.006	-0.002
	(0.003)	(0.013)	(0.018)	(0.002)	(0.016)	(0.016)	0.004
Age (years)	0.000	0.000	0.001	0.000	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Education (years)	0.000	0.001	0.001	0.000	-0.001	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Household size	-0.001*	-0.002**	-0.004**	0.000*	0.003**	0.003**	0.001**
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)
Total House Asset (log)	-0.001	-0.004**	-0.006**	-0.001*	0.005**	0.005**	0.001**
	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)	(0.002)	(0.001)
Farming experience (years)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Land ownership (yes = 1, no = 0)	-0.003	-0.013	-0.019	-0.003	0.016	0.017	0.004
	(0.002)	(0.010)	(0.015)	(0.002)	(0.013)	(0.013)	(0.004)
Land rent (yes = 1, no = 0)	-0.001	-0.003	-0.004	-0.001	0.003	0.004	0.001
	(0.002)	(0.011)	(0.017)	(0.002)	(0.014)	(0.015)	(0.004)
Farm size (ha)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cost of hired labour (log)	-0.002**	-0.008***	-0.012***	-0.002**	0.010***	0.010***	0.003***
	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)
Trained in improved production practices (yes = 1, no = 0)	-0.006**	-0.027**	-0.039**	-0.005*	0.033**	0.035**	0.009**
	(0.003)	(0.012)	(0.017)	(0.003)	(0.015)	(0.015)	(0.004)
Willingness to take risk (yes = 1, no = 0)	0.003	0.012	0.017	0.002	-0.015	-0.015	-0.004
	(0.002)	(0.008)	(0.012)	(0.002)	(0.010)	(0.011)	(0.003)
Total Livestock Unit (TLU)	-0.000***	-0.000***	-0.000***	-0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Received loan (yes = 1, no = 0)	-0.003**	-0.015**	-0.023**	-0.003**	0.019**	0.020**	0.005**
	(0.002)	(0.006)	(0.009)	(0.002)	(0.008)	(0.008)	(0.002)

Member of input supply group (yes = 1, no = 0)	-0.004** (0.002)	-0.018** (0.007)	-0.026** (0.010)	-0.004** (0.002)	0.022** (0.009)	0.023** (0.009)	0.006** (0.002)
Received advice on improved varieties (yes = 1, no = 0)	0.000 (0.001)	-0.002 (0.007)	-0.003 (0.010)	0.000 (0.001)	0.002 (0.009)	0.002 (0.009)	0.001 (0.002)
Awareness and access to improved varieties (yes = 1, no = 0)	-0.017*** (0.005)	-0.080*** (0.012)	-0.118*** (0.015)	-0.016*** (0.005)	0.100*** (0.013)	0.105*** (0.013)	0.027*** (0.006)
North West (yes = 1, no = 0)	-0.025*** (0.006)	-0.117*** (0.013)	-0.172*** (0.016)	-0.023*** (0.007)	0.145*** (0.012)	0.153*** (0.016)	0.039*** (0.007)
North Central (yes = 1, no = 0)	-0.008*** (0.003)	-0.037*** (0.010)	-0.054*** (0.014)	-0.007** (0.003)	0.046*** (0.011)	0.048*** (0.012)	0.012*** (0.004)
North East (yes = 1, no = 0)	0.008** (0.003)	0.035*** (0.012)	0.052*** (0.017)	0.007*** (0.003)	-0.044** (0.014)	-0.046*** (0.015)	-0.012*** (0.004)
South South (yes = 1, no = 0)	0.021*** (0.006)	0.098*** (0.017)	0.144*** (0.026)	0.020*** (0.007)	-0.122*** (0.022)	-0.128*** (0.023)	-0.033*** (0.007)
South East (yes = 1, no = 0)	-0.019** (0.008)	-0.089*** (0.029)	-0.131*** (0.044)	-0.018** (0.008)	0.110*** (0.036)	0.116*** (0.040)	0.030*** (0.011)

Standard error in parenthesis. *significant at 10%; **significant at 5%; ***significant at 1%

Table 8. Estimates of Predictive Marginal Effect of Number of CSAPs Adopted

Number of CSAPs	Margin	Std. Err.
0	0.010***	0.003
1	0.076***	0.007
2	0.225***	0.011
3	0.295***	0.012
4	0.256***	0.011
5	0.119***	0.008
6	0.018***	0.003

***significant at 1%

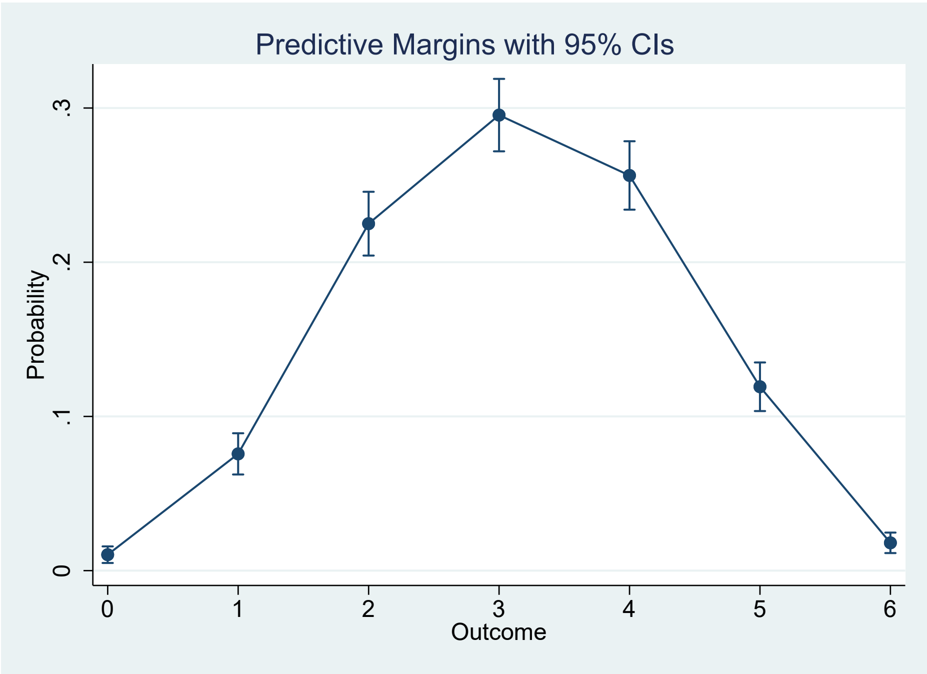

Figure 7. Graph of the predictive marginal effect of the number of CSAPs adopted.

6. Conclusions and policy implications

Understanding the determinants of joint adoption of CSAPs is important in formulating and disseminating strategies at the local, regional and national levels in Nigeria. This is significantly important for tackling poor productivity and the welfare of agricultural farm households. Based on the assumption of the interdependence of multiple CSAPs that may be limiting or fostering the promotion of DTMVs this study examined a sample of 1,370 agricultural households from nationally representative data from maize farm households in Nigeria. Using a multivariate Tobit model our result confirmed complementarity and substitutability between CSAPs, reflecting the existing interdependence of CSAPs adoption. In line with the previous study (Teklewold, Kassie and Shiferaw 2013), correlation effects between and across CSAPs remain relevant to policies and strategies in promoting the adoption of CSAPs. Promoting CSAPs in isolation may not be adequate as changes in the use of one technology or practice may affect the increase or decrease in the use of another or other groups or combinations of CSAPs. Results further shows that manure is a significant complement of DTMVs as a climate adaptation strategy. Also, the interdependence of manure with other CSAPs in the study is also evident, this includes complements such as row planting and residue incorporation. Our findings imply that in increasing the adoption of DTMVs, policy focus should consider designing and implementing promotions of DTMVs through incorporating an existing mix of other CSAPs in training and awareness programme.

This study also adopted ordered probit estimation to assess the adoption and intensity of the use of CSAPs. Household wealth, access to loan, social capital, and institutional presence significantly promotes both joint adoption and intensity of adoption. Each of these relationships can be leveraged for better CSAPs packages through policy and development focus on providing financial risks protection mechanisms that are flexible and easily accessible to aid the adoption of DTMVs and other CSAPs packages. The significance of membership in farm input supply and cooperatives in driving adoption and intensity of adoption furthershows the continued relevance of social capital platforms in the adoption of CSAPs as they provide platforms for the flow of information,risk, and cost-sharing, and access to finance and agricultural inputs. This suggests the need for agricultural policy and development programmes to consider strengthening existing social membership or group platforms by engaging these platforms in the implementation and dissemination of CSAPs. Also, extension presence is crucial in dissemination and training as the result reveals that farm households that were aware had access, and were trained, adopted more CSAPs. In particular, the significant role of labour proxied by the cost of hired labour and household size suggests that CSAPs demand high labour use and may be limiting the adoption of packages of CSAPs. As such, policy intervention to increase access to loans for farm households can effectively ease the ability to pay hired labour. The predictive margin results from adopting each category of CSAPs further show that the probability of adopting CSAPs decreases as the number of CSAPs increases. This further informs existing resource constraints in adopting more CSAPs and this may limit the adoption of new technology like DTMVs. It is however important for policies and interventions to leverage factors promoting the intensity of the use of CSAPs as this provides a means of reducing farm households' exposure to production risks.

While this study concludes with useful insights into the determinants of adoption and intensity of adoption of CSAPs, our findings are limited to the identified households' attributes considered. As such, interpretations should be carefully made as determinants of adoption are heterogeneous and depends on the CSAPs considered. There is limited focus on the identified CSAPs, and this also limits the evidence of factors of adoption of other CSAPs. Also, the adoption of innovation on farmlands is a long-term decision that can vary over ,time and using a cross-section (which applies to this study) does not adequately explain such a phenomenon. Despite these limitations, this study makes a significant contribution to the literature on the determinants of the adoption of DTMVs and other CSAPs which are highly important in Nigeria.

Declaration:
The authors declare that they have no conflict of interest**.**

Abbreviations

CSAPs	Climate Smart Agricultural Practices
DTMVs	Drought Tolerant Maize Varieties
CDF	Cumulative Distribution Function

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Authors' contributions

Author Z O-U conceptualised the study and did the first write-up, Author A.S contributed to the methodology, re,view and overall supervision of the research.

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