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Predicting the adoption of multiple climate-smart agriculture technologies in Tambacounda and Kolda, Senegal

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Uptake of farming technologies by smallholder farmers is necessary to speed up the transition to climate-smart agriculture so as to address the potential impacts of climate change on agricultural production, food security, and reduction of greenhouse gas emission. Using survey data from 341 households, this study analyzes the factors that determine the probability and level of adoption of multiple climate-smart agriculture technologies. The technologies assessed were improved crop varieties, minimum tillage, timely planting, fertilizer and manure use, agroforestry, and diversified farming (crop and animal production). A multivariate probit model was applied for the simultaneous multiple adoption decisions and to evaluate the determinants of adoption, allowing for the examination of synergies and trade-offs between the technologies. The adoption of various climate-smart agriculture technologies and practices was interrelated. Several factors, including the gender of the household head, age, literacy level of the household head, land size, farmers' group membership, access to extension services, access to weather information, and trust in weather information were found to affect the probability and level of climate-smart agriculture adoption. The study, therefore, calls for agricultural policy reforms so that most of the issues related to the uptake of climate-smart agriculture technologies can be effectively addressed. In addition, strategies that focus on building household resources as a pathway for improved adoption of new technologies are recommended.

Key words: Climate-smart agriculture, multiple adoption decisions, multivariate probit model.

INTRODUCTION

The agriculture sector supports the livelihoods of over 1.5 billion people worldwide and is critical in the fight against extreme poverty and hunger especially in developing nations (World Bank, 2009). However, changes in rainfall

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amounts, temperature, seasonal patterns, and the emergency of pests and diseases attributed to climate change have caused fluctuation in production and a decline in productivity (Mburu et al., 2014). The effects of climate change on West African agriculture have a huge impact on approximately 71 to 95% of farmers (Ou et al., 2018). Efforts to address the effects of climate change on agriculture, particularly among smallholder farmers, have sought to enhance innovation and access to technologies. As a result, effective practices for coping with the impacts of climate change and variability have been promoted (Beddington et al., 2011). Adoption of Climate-Smart Agriculture (CSA) technologies is one of the new ways suggested. Climate-smart agriculture is widely promoted as a solution to food insecurity, combating greenhouse gas (GHG) emissions, and improving food system resilience to climate change, especially amongst smallholder farming communities (Winowiecki et al., 2015; FAO, 2011). Previous research by Gwambene (2011), Nyanga et al. (2011), and Phillipo et al. (2015), revealed that farmers understand their environment and develop practices to alleviate the impact of climate change. Furthermore, a study by Lobell et al. (2008) indicated that farmers use technologies that are deemed viable and capable of increasing production and food security. Some of the CSA technologies used by smallholder farmers are popular and are applied for a long time, while others are applied for a short time (Taneja et al., 2019). According to Phillipo et al. (2015) crop rotation is a common method applied for a long time and is acknowledged for enhancing smallholder farmers' food security and revenue. In addition, minimum tillage, fertilizer and water management, diverse crop establishment techniques, and compost integration can boost crop yields, nutrient and water efficiency, and minimize GHG emissions from agricultural activities (Branca et al., 2011; Sapkota et al., 2015). Similarly, ICT-based agro-advisories, the use of improved seeds, rainwater harvesting, and crop/livestock insurance can also help farmers mitigate the impact of climate change and variability (Altieri and Nicholls, 2017). The many CSA choices, in general, blend innovation, traditional practices, services, and innovations that are applicable for a specific place in order to adapt to climate change and variability (FAO, 2013). Although smallholder farmers have evolved the ability to adapt to environmental change and climate unpredictability over time, climate change is exceeding their responsiveness.

According to Nyanga et al. (2011) smallholder farmers' abilities to manage agricultural difficulties and CSA adoption choices differ. In most cases, farmers operating under low-input smallholder farming systems in the least developed countries consider and prioritize technologies that provide immediate advantages in terms of increased productivity, food security improvements, and adaptability and are less prone to embrace practices that increase carbon sequestration and reduce emissions (Campbell et

al., 2014). As a result, trade-offs between adaptation and mitigation aims may be necessary. It is therefore critical to consider farmers' perceptions, the complexity of agricultural systems, and their ability and willingness to adapt for sustainability when enhancing their adaptive capacity (Coulibaly et al., 2015). This usually necessitates an assessment of the social, cultural, socioeconomic, and technical components at the household level, as well as the biophysical conditions of a certain region, as well as the characteristics of technological advances (Zerssa et al., 2021; Deressa et al., 2011; Below et al., 2012).

In this study, adoption of climate-smart crop technologies was limited to timely planting, use of improved crop varieties, diversified farming (crop and animal production), agroforestry, fertilizer and/or manure application, and minimum tillage. This study examines (i) the level of adoption of six technologies often considered as CSA across the regions, (ii) factors that determine the adoption or non-adoption of multiple CSA technologies, and (iii) complementarities and substitutability between technologies using socioeconomic data and climate information from the study areas.

MATERIALS AND METHODS

Study site

The research was carried out in two regions of Senegal: Tambacounda and Kolda (Figure 1). The major economic activity in both regions is agriculture with millet, sorghum, maize, and groundnuts being the major crops grown. The mean temperature range of both regions is between 25 and 40°C, while the annual rainfall ranges from 700 to 1000 mm, most of which is received between July and October (ANSD, 2015a, b; Bakel 2011). The study area was chosen because it is a major agricultural zone in Senegal and is also a representative of many similar climate-vulnerable locations in West Africa.

Data collection methods

Both quantitative and qualitative research designs were used in this study. Stratification was accomplished through the use of pre-existing administrative areas. For this study, the two administrative regions were divided into seven strata. Random sampling was used in each stratum to select respondents. A total of 341 farming households were surveyed; Tambacounda (N = 170) and Kolda (N = 171). Respondents in each region were selected randomly with the help of local leaders and departmental agricultural offices with a focus on households that had smallholder farmers. Then, using proportionate sampling, each rural commune was represented proportionally depending on the number of smallholder farmers that lived there.

Data collection was conducted by the researcher and seven other field research assistants who were trained before the data collection process. Quantitative data were gathered through a questionnaire administered by an interviewer that included both closed and open-ended questions. The questionnaire contained structured and short-response questions and was divided into two sections. The first section focused on participant demographic data while the second section consisted of questions on the adoption of
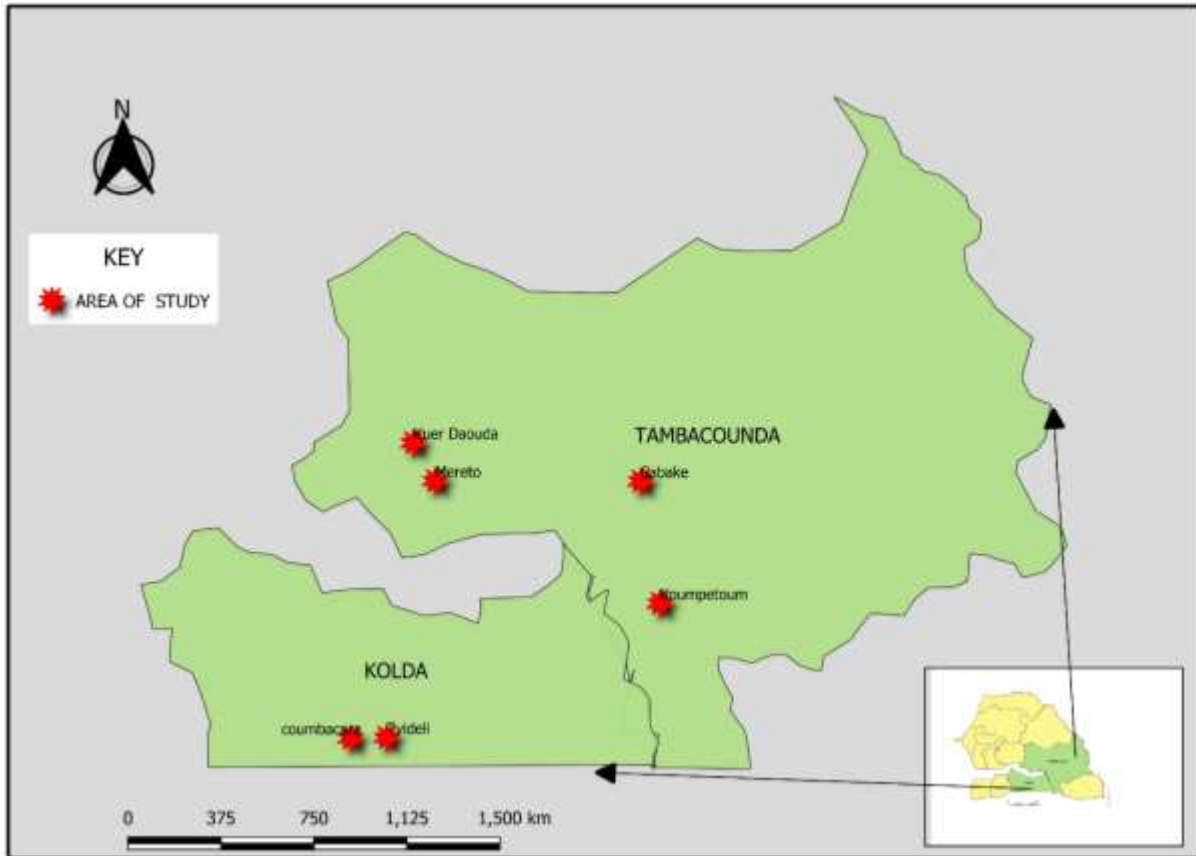
Figure 1. Map of the study area.
Source: Survey data 2020

CSA technologies. Qualitative data was collected through key informant interview guides. The questions were translated into the local languages for respondents who could not understand French.

Econometric framework and estimation strategy

Stata 16 software was used for data analysis. To capture farmers' decision-making process for the adoption of single or multiple technologies, a multivariate probit (MVP) model was applied. The MVP model was further utilized to study the interdependence of diverse technologies by examining their correlations, as well as to establish the determining factors for CSA technology adoption. This is because a farmer could use a combination of CSA technologies, and the preference to use one technology may be determined by decisions to use other technologies (Kassie et al., 2013; Ndiritu et al., 2012). This makes adoption decisions inherently multivariate. Using univariate approaches (univariate multinomial logit and probit models) in this situation could lead to biased estimates or omission of critical information because of the assumed independence of error terms of the different CSA technologies (Greene and Hensher, 2003). Therefore, the multivariate probit model aids in the identification of potential complementarities (positive association) and substitutability (negative association) across CSA technologies. Household characteristics, household economic characteristics, information sources, input access, experience in farming, and access to and trust in weather information were all factors that could impact farmers' decisions to adopt CSA technologies (Table 1).

To characterize the MVP model, a series of binary variables CSA_i were used, where each technology was given a distinctive index i which took the values (1, 2, ……6) representing the CSA technologies, and X denoted a set of determining variables. Therefore, random variables (CSA_i) represented the CSA technology chosen by any farming household. The assumption was that an individual farmer might select a combination of technologies, which were further assumed to be influenced by a set of household characteristics, household resources, social and institutional synergies, and other elements (X). Therefore, the MVP model was characterized by a set of binary dependent variables (CSA_{jpn}) meaning that,

$$CSA_{jpn}^* = \beta n' X_{jpn} + \varepsilon_{jpn} n = 1, \tag{1}$$

$$CSA_{jpn} = \begin{cases} 1 \ if \ CSA_{jpn}^* > 0 \\ 0 \ otherwise \end{cases} \tag{2}$$

In this case, CSA_{jpn}^* is the latent variable while β_n' is the corresponding vector of parameters to be assessed. Equation 2 presumes that a rational farmer has a latent variable, CSA_{jpn}^*, that captures the unobserved preferences linked with the nth choice of CSA technology. This latent variable was presumed to be a linear combination of household social characteristics, household economic characteristics, information sources, input access, experience in farming, and access to and trust in weather information (X_{jpn}) that are observed to be determining the

Table 1. Description of variables used in the study.

Variable	Description of variables	Mean	Std. Dev.
Dependent variable			
Improved crop varieties	Dummy = 1 if Improved seeds are used and 0 if otherwise	0.51	0.50
Minimum tillage	Dummy = 1 if Minimum tillage is practiced and 0 if otherwise	0.53	0.50
Timely planting	Dummy = 1 if Timely planting is practiced and 0 if otherwise	0.78	0.41
Fertilizer /manure	Dummy = 1 if fertilizer and/or manure are used and 0 if otherwise	0.89	0.32
Agroforestry	Dummy = 1 if Agroforestry is practiced and 0 if otherwise	0.48	0.50
Diversified framing	Dummy = 1 if a diversified farming system is practiced and 0 if otherwise	0.72	0.52
Explanatory variable			
Household (HH) characteristics			
Household head is male	Dummy = 1 if the gender of the household head is male, 0 otherwise	0.70	0.46
Age of male HH head	Age of male -headed households in years	43.62	14.98
Literate HH head	Dummy = 1 if literate and 0 if otherwise	0.65	0.48
Marital status	Dummy = 1 if married 0 if otherwise	0.92	0.27
Household size (#)	Total household members	12.25	6.34
Economic characteristics			
Agricultural land (ha)	Total amount of agricultural land in hectares	5.02	5.62
Income levels	Dummy = 1 if has medium or high income 0 if otherwise	0.14	0.35
Sources of information and inputs access			
Framers group membership	Dummy = 1 if member of a farmers' group 0 if otherwise	0.30	0.46
Extension services	Dummy = 1 if has access to extension services 0 if otherwise	0.48	0.50
Input Access	Dummy = 1 if has access to Agricultural inputs 0 if otherwise	0.84	0.37
Farming experience, access to weather information, trust in weather forecast and peer influence			
Crop farming experience	Experience in crop farming in years	4.52	0.87
Weather information	Dummy = 1 if has access to weather information 0 if otherwise	0.76	0.43
Trust in weather forecast	Dummy = 1 if has trust in weather information 0 if otherwise	0.77	0.42
Peer influence	Dummy = 1 if influenced by peers to adopt CSA 0 if otherwise	0.94	0.25

Source: Survey data 2020

simultaneous selection of technologies, as well as the unobserved elements that are captured by the stochastic error term ε_{jpn}. Owing to the nature of the latent variable, the estimations in this study were based on observable binary discrete variables CSA_{jpn}, which indicate the adoption or non-adoptio of a particular technology by the farming household.

In the multivariate probit model where a choice of adopting multiple CSA technologies is possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where ($\mu y1$, $\mu y2$, $\mu y3$, $\mu y4$....) MVN ~ (0, Ω) and the symmetric covariance matrix Ω is given by:

$$\Omega = \begin{Bmatrix} 1 & \rho_{y1y3} & \rho_{y1y3} & \rho_{y1y4} \\ \rho_{y2y1} & 1 & \rho_{y2y3} & \rho_{y2y4} \\ \rho_{y3y1} & \rho_{y3y2} & 1 & \rho_{y3y4} \\ \rho_{y4y1} & \rho_{y4y2} & \rho_{y4y3} & 1 \end{Bmatrix}$$

(3)

where ρ indicates the pair-wise correlation coefficient of the error terms corresponding to any two CSA technologies. If these correlations in the off-diagonal elements in the covariance matrix become non-zero, it justifies the application of a multivariate probit instead of a univariate probit for each CSA technology.

Description of data and variables

Table 1 shows the definitions and descriptive statistics for all of the variables utilized in the analysis. Technologies and practices are classified as dependent variables while determinants (factors defining adoption) are categorized as explanatory variables. For this study, six technologies were investigated. Their levels of adoption, complementarities, substitutability, and factors influencing adoption were all examined. We hypothesize that adoption decisions for these CSA technologies are interconnected. If the error terms of several decision equations are significantly correlated, then this hypothesis holds. These six technologies were chosen depending on preexisting beliefs that they could each achieve one or even more CSA goals, as well as their relevance to

Table 2. Pair-wise correlation coefficients across CSA technologies for MVP regression equations.

CSA technologies	Minimum tillage	Timely planting	Fertilizer/manure	Agroforestry	Diversification
Improved crop varieties	-0.406 (0.514)	0.046* (0.687)	1.832*** (0.413)	0.258 (0.436)	0.498** (0.212)
Minimum tillage		1.773*** (0.407)	0.547 (0.643)	0.318 (0.458)	-0.354* (0.188)
Timely planting			0.230 (0.719)	0.102 (0.401)	0.358* (0.193)
Fertilizer				-0.138 (0.360)	0.526*** (0.194)
Agroforestry					0.609*** (0.135)

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0: $\chi2(10)$ = 10.2196, Prob > $\chi2$ = 0.0042. *, **, and *** refer to significant at 90, 95 and 99% confidence level; standard errors are reported in parentheses.
Source: Survey data 2020

the farming systems in the study area. In responses to yes or no questions, respondents indicated whether they had adopted a practice.

RESULTS

Adoption of multiple CSA adoption

The results show that smallholder farmers in Tambacounda and Kolda have adopted several CSA technologies simultaneously, suggesting a correlation between decisions they have made about their CSAs preferences. Pair-wise correlation coefficients across the residuals of the multivariate probit model are used to assess this hypothesis. Eight pair-wise correlation coefficients across the residuals of the multivariate probit model were statistically significant (at P<0.01, 0.05, and 0.1), among the 15 pairs of CSA technologies (Table 2). There is a correlation between error terms in multiple decision equations, according to the results. Based on the likelihood ratio test, the null hypothesis of zero covariance of the error terms across equations is rejected ($\chi2(10)$ = 10.2196; Prob > $\chi2$ = 0.0042). Minimum tillage and diversification were shown to be significantly and inversely correlated (Coef. = -0.354*) (Table 2), indicating that farmers regard these CSA technologies to be substitutes or incompatible. For other CSA pairings such as improved crop varieties and timely planting (Coef. = 0.046*), improved crop varieties and fertilizer and/or use (Coef. =1.832***), improved crop varieties and diversification (Coef. = 0.498**), minimum tillage and timely planting (Coef. = 1.773***), timely planting and diversification (Coef. = 0.358*), fertilizer and/or manure use and diversification (Coef. = 0.526***), agroforestry and diversification (Coef. = 0.609***), farmers primarily see them as complements, as evidenced by their strong and favorable association.

Multiple CSA adoption determinants

The results of the multivariate probit model generated using the maximum likelihood method are shown in Table 3. The Wald test (Wald $\chi2(84)$ = 249.32; Prob > $\chi2$ = 0.000) rejects the null hypothesis that all regression coefficients in each equation are jointly equal to zero, indicating that the model fits the data well. This demonstrates the model's relevance in accounting for unobserved correlations between preferences to implement a combination of CSA technologies. The findings reveal that depending on the CSA technology, the effects of the explanatory variables on the likelihood of adoption differ significantly.

The results show that among the household characteristics, male-headed households were more inclined to adopt timely planting (Coef. = 0.363*). In addition, older household heads were more inclined to use improved crop varieties (Coef. = 0.009*), use fertilizers and/or manure (Coef. = 0.023***), had a diversified farming system (Coef. = 0.011*), and practiced agroforestry (Coef. = 0.011**). Households belonging to a literate head were more likely to use improved crop varieties (Coef. = 0.298*) and had a diversified farming system (Coef. = 0.346**) but were less likely to adopt minimum tillage practices (Coef. = -0.493***). Concerning household resources, the larger the agricultural land, the more the likelihood of adopting fertilizer and/or manure use (Coef. = 0.149***), while reducing the probability of adopting agroforestry (Coef. = -0.031**). For information sources, farmers belonging to village groups and cooperatives had a higher probability of adopting minimum tillage (Coef. = 0.281*) and use improved crop varieties (Coef. = 0.331*). Additionally, farmers with access to extension services were more inclined to use improved crop varieties (Coef. = 0.459***), use fertilizers and/or manure (Coef. = 0.237***), and had a more diversified farming system (Coef. = 0.406**) but were less inclined to adopt minimum tillage (Coef. = -0.728***) and agroforestry (Coef. = -0.316**). Farmers with access to inputs were less inclined to adopt minimum tillage (Coef. = -0.494*). Farmers with access to weather information had a higher probability of using improved crop varieties (Coef. = 0.834***), fertilizers and/or manure (Coef. = 0.755***), adopt minimum tillage (Coef. = 0.601***), timely planting (Coef. = 0.870***), had diversified farming

Table 3. Estimates of the multivariate probit model of explanatory variables and adoption of CSA technologies.

Variable	Improved crop varieties	Minimum tillage	Timely planting	Fertilizer/Manure	Agroforestry	Diversification
Household characteristics						
Gender (1=Male)	0.123 (0.178)	-0.062 (0.178)	0.363* (0.189)	-0.253 (0.242)	-0.058 (0.170)	0.106 (0.183)
Age (Years)	0.009* (0.005)	-0.001 (0.005)	-0.001 (0.006)	0.023*** (0.008)	0.011** (0.005)	0.011* (0.006)
Education (1=Educated)	0.298* (0.156)	-0.493*** (0.156)	-0.059 (0.174)	0.139 (0.207)	0.048 (0.150)	0.346** (0.162)
Marital status (1=Married)	-0.212 (0.289)	0.319 (0.299)	-0.084 (0.313)	-0.702* (0.389)	-0.374 (0.275)	-0.200 (0.305)
Household size (#)	-0.011 (0.012)	0.006 (0.012)	-0.004 (0.013)	-0.012 (0.016)	0.014 (0.012)	-0.000 (0.012)
Economic characteristics						
Agricultural land (ha)	-0.014 (0.014)	-0.017 (0.014)	-0.022 (0.016)	0.149*** (0.048)	-0.031** (0.014)	0.018 (0.018)
Income levels (1=Medium and high)	-0.083 (0.214)	0.030 (0.204)	0.089 (0.243)	0.074 (0.317)	-0.123 (0.205)	-0.128 (0.227)
Sources of information and inputs access						
Framers group membership (1=Member)	0.331* (0.170)	0.281* (0.166)	-0.195 (0.182)	0.301 (0.251)	0.107 (0.162)	-0.221 (0.179)
Extension services (1= Has Access)	0.495*** (0.159)	-0.728*** (0.163)	0.087 (0.182)	0.237*** (0.235)	-0.316** (0.157)	0.406** (0.179)
Input Access (1= Has access)	0.186 (0.215)	-0.494** (0.228)	-0.202 (0.238)	0.266 (0.257)	0.022 (0.204)	0.106 (0.213)
Farming experience, access to weather information, trust in weather forecast and peer influence						
Crop farming experience (Years)	0.027 (0.083)	-0.027 (0.085)	0.055 (0.096)	0.075 (0.120)	-0.075 (0.082)	-0.024 (0.093)
Weather information access (1=Access)	0.834*** (0.189)	0.601*** (0.190)	0.870*** (0.191)	0.755*** (0.223)	0.429** (0.182)	1.002*** (0.182)
Trust in weather forecast (1= Has trust)	0.147 (0.178)	-0.085 (0.173)	0.400** (0.187)	-0.129 (0.262)	-0.197 (0.168)	0.052 (0.185)
Peer influence to adopt CSA (1= presence of influence)	-0.010 (0.289)	-0.350 (0.283)	-0.485 0.374)	-0.035 (0.398)	-0.284 (0.278)	0.454 (0.286)
Constant	-1.583** (0.634)	0.994 (0.629)	0.352 (0.723)	-0.459 (0.877)	0.339 (0.597)	-1.361** (0.656)
Observations	341	341	341	341	341	341

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61= rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho54 = rho64 = rho65 = 0: Log likelihood = -985.2079; Wald χ^2(84) = 249.32; Prob > χ^2 = 0.000. *, **, and *** refer to significant at 90, 95 and 99% confidence level; standard errors are reported in parentheses.
Source: Survey data 2020

systems (Coef. = 1.002***), and engage in agroforestry (Coef. = 0.429**). On the other hand, those farmers that had trust in the weather forecasts received were more likely to adopt timely planting (Coef. = 0.400**).

DISCUSSION

The study findings show that farmers adopted several CSA technologies simultaneously, this indicates an association among the multiple CSA technologies. Other studies of similar design by Aryal et al. (2018) and Kurgat et al. (2020) have also produced similar results. The study findings emphasize the need of appreciating the potential interconnection in multiple technology adoption decisions while establishing the elements that drive technology adoption.

The study indicates that male household heads are more inclined to adopt timely planting. According to Mutoko et al. (2015) males as household heads are the *de facto* owners of production resources making them the major decision-makers on how the various factors of production are to be allocated especially when it comes to technology acquisition, therefore the power they have is a major determinant or barrier to the adoption of CSA technologies. Additionally, heads of households who are older were more inclined to utilize improved crop varieties and fertilizers, adopt a diversified farming system as well as practice agroforestry. The age of the

household is considered a strong determinant in adoption. Older people usually have adequate access to physical assets (agricultural lands), capital resources (borrowed funds), human and social resources (farm experience, technical know-how, loyalty, trust), and technological resources (access to technologies). These factors have an impact on the adoption of CSA technologies (Akrofi-Atitiant et al., 2018). According to Mwongera et al. (2017) older household heads practices diversification because they have the resources to meet the labour requirement for management of various agricultural enterprises e.g. weeding and harvesting especially when some crops mature faster than others. Additionally, studies by Hassan et al. (2016), Tamirat (2020), and Zerssa et al. (2021), indicate that older farmers have a high concern about how to deal with insufficient food for their households and the effects of the changing climate especially in third world countries, therefore, engaging in diversified farming and agroforestry allows them to combine the production of diverse products and services inorder to meet a wider range of needs. This is supported by Kassie (2016) and Amare et al. (2019) whose studies indicate that adopters of agroforestry had a 17% increase in yields and a 7% increase in revenue compared to non-adopters. This means that agroforestry presents opportunities for food security because some tree species can withstand stressful climates and can produce fruits because of the ability through their deep root systems, to absorb moisture from subsurface water sources. The various fruits produced become a source of additional food and revenue for households of smallholder farmers (Tamirat, 2020; Hassan et al., 2016). Mwongera et al. (2017) argue that agroforestry usually requires specific knowledge regarding methods of combining different plants, their compatibility, and effects on each other; such knowledge is normally available with older people because of the vast experience they have acquired over time. Furthermore, older farmers are more likely to be members of cooperatives and farming organizations; through these organizations, farmers are linked to training on land management practices (use of organic matter), can easily access agricultural inputs (improved crop varieties, fertilizers, and tree seedlings), and are linked to markets for their agricultural products (Shames et al., 2016).

The results further indicate that households belonging to an educated head are more prone to utilize improved crop varieties and have a diversified farming system but are less inclined to adopt minimum tillage practices. The level of education and the number of school years have continually determined the desire to adopt CSA technologies or become a barrier among smallholder farmers. Studies show that heads of households with at least a primary education level have opportunities to obtain additional revenue from off-farm employment which increases their ability to purchase inputs and hire

extra labour to incorporate farming techniques like farm diversification (Aryal et al., 2018; Branca and Perelli, 2020; Bagagnan and Barry, 2017; Peterson, 2014). According to Marenya et al. (2017) and Etim and Udoh (2019) farmers with more school years are more inclined to utilize complex practices due to their ability to obtain, synthesize and utilize information and experiment with novel innovations. Therefore, the education level of the household head may have an impact on the decision to adopt new technologies meaning that the more illiterate household heads have fewer chances of adopting CSA technologies.

The results also show that respondents with larger agricultural land had a higher probability of utilizing fertilizer and/or manure, while the odds of adopting agroforestry were low. Adoption of organic manure use might be credited to the fact that the area of study is immensely engaged in livestock keeping while fertilizer use could be attributed to the presence of government subsidies in Senegal. The government involvement was brought about by the world food crisis of 2007-2008 that affected the Senegalese economy immensely, the government thereafter decided to improve the agricultural production efficiency through the provision of fertilizer subsidies up to 50% with a focus on farmers that have an average plot size above the 2.5 ha (Seck, 2016). A study in Nigeria by Etim and Udoh (2019) indicated that the farm size has a positive and considerable impact on the decision to use fertilizer efficiently. The study further showed that the probability of choosing efficient fertilizer use rose by 3.08% when the farm area was increased by 1 ha. However, Donovan (2004) suggests that subsiding and utilization of fertilizers can compel farmers to abandon land-use practices like minimum tillage and low-input agroforestry, which are more sustainable and profitable. A study in Ethiopia by Zerssa et al. (2021), indicated that the less likelihood of adoption of agroforestry could be as a result of rising fuelwood demand, unsecured land tenure, and labor shortage to carry out the laborious and expensive de-stamping task. Other reasons may include difficulty in accessing the seeds, insufficient knowledge of the tree types to use, the inability of the trees to provide quick tangible benefits to the farmers since they may take a long time to mature. This is because farmers are usually constrained financially, therefore most of them will need to see quick results from a particular technique (Mohammed, 2016; Mwongera et al., 2017). Consequently, agroforestry tends to be less preferred than other CSA technologies.

Farmers belonging to farmers' groups and village cooperatives were more inclined to adopt minimum tillage and use improved crop varieties. Additionally, farmers with access to extension services were more inclined to utilize improved crop varieties, have a more diversified farming system, use fertilizers and/or manure but were not likely to adopt agroforestry and minimum tillage. Farmer groups and extensionists serve as channels of

information for CSA adoption. Agricultural support from various entities including the government is usually extended to organized farmer groups through the field officers or government extension workers. According to Jasmine and Wright (2020) and Seck (2016) the government of Senegal through its agricultural enhancement campaign provides subsidies (75% on improved seed, 50% on fertilizer, and rudimentary tools e.g., seeders, hoes, plows, and carts) to farmers' cooperatives through the extension workers at the departmental level. This means that such benefits can easily be accessed by farmers who are members of organized farmer groups. In Nigeria, a study by Etim and Udoh (2019) indicated that farmers associated with agricultural cooperatives were more inclined (8.18%), to choose improved high-yielding varieties. This is because such farmers accessed vastly different ideas, information, and training which eventually change their attitude toward innovation positively. The same study further indicated that one additional extension visit increased the likelihood of utilizing enhanced high-yielding cultivars by 17.20% while the overall probability of choosing to adopt any CSA technology due to extension contact increased by 28.10%. Therefore, successful agricultural technology adoption necessitates an appreciation of the need to adopt, knowledge of available options, the ability to analyze those options, and the ability to select and implement the most appropriate solutions from the available options.

Farmers with access to weather information were more inclined to utilize improved crop varieties, use fertilizers and/or manure, adopt minimum tillage, and timely planting, have diversified farming systems, and engage in agroforestry. On the other hand, those farmers that had trust in the weather forecast received were more likely to adopt timely planting. A report by FAO (2015) indicated that access to weather forecasts by farmers facilitates long-term decisions for example a choice to cultivate a certain type of crop, investing in technologies like water management systems, buying agricultural machinery, and increasing agricultural land. Furthermore, access to weather information aids farmers in the management of their daily activities (e.g., planting and fertilizer or manure application) plus other critical considerations like crop variety selection, input utilization intensity, crop diversity, field selection, and off-farm operations. Weather information is also important when making strategies for diversifying incomes, managing risks, and limiting climate change's negative effects. DeLonge et al. (2016) assert that the most underlying factor that has highly affected the adoption of CSA technologies lies in the acceptability of weather information, or what most scholars call trust. This is supported by a study conducted by Kniveton et al. (2014) in Tanzania which indicated that following the explanation of scientific weather forecasts and the opportunity to test their reliability over two seasons, the participating farmers' groups relied heavily on them to

guide their agricultural activities. By the end of the second season, it was evident that farmers had developed trust in scientific weather forecasts. The study also indicated that farmers had an increment greater than 15% in their maize production in a single season which was attributed to the trust they had in the weather forecasts. This is because they considered the weather forecasts relevant to their production process and were, therefore, able to use them to choose the best feasible option like the use of Crop varieties that mature early, employed agricultural approaches that have the ability to with-stand short rain periods, use of contour bunds and channeling rainfall into cultivated areas.

Conclusion

This study was conducted to examine the adoption of multiple CSA technologies and the drivers of adoption of six CSA technologies in two regions in Senegal to better understand the mechanisms and barriers that can prevent the widespread acceptance of new agricultural technologies. Eight pair-wise correlation coefficients across the residuals of the multivariate probit model were statistically significant, out of the 15 pairings of CSA technologies. Several patterns emerge when considering adoption determinants across the six technologies. First, 10 of the 14 variables examined significantly facilitate or hinder adoption. Secondly, only access to weather information significantly influenced adoption for all the six technologies.

Thirdly, access to extension services significantly influenced the adoption of five out of the six practices while the age of the household head and literacy level of the household head significantly influenced the adoption of four and three out of the six technologies, respectively. The other 6 of the 9 significant factors influenced only one or two technologies. The study underscores that the policies and programmatic efforts that affect the adoption of one CSA technology may also influence the adoption of others because trade-offs and complements exist between these technologies. This suggests a need to focus on agricultural policies and programs that can accelerate the dissemination and adoption of multiple CSA technologies to help safeguard agricultural production and food security. Additionally, local factors must be considered and solutions must be designed in conjunction with the communities where programs and policies are implemented. Therefore, for CSA to have the desired impact, (i) mitigation of GHGs, (ii) increased productivity, and (iii) resilience of agricultural systems of the agricultural sector, it must be applied across a multitude of geographical, social, economic, and political contexts. It is therefore essential to understand obstacles and enablers of CSA adoption in order to design and formulate meaningful interventions. As a result, CSAs will be widely disseminated, agricultural production and food

security will be improved and environment conservation will be attained.

Recommendation

There is a need for government collaboration with the private sector, including farmers, private traders, and agricultural research centers, to scale-out CSA technologies. Furthermore, CSA training for farmers, government extension personnel working with local communities, and the utilization of efficient communication techniques to disseminate and promote knowledge on CSA use are crucial in the fight against the global challenge of climate change. Policymakers at all levels must recognize that CSA adoption is influenced by a variety of factors, including institutional support, farmer capabilities, resource endowment, and knowledge and skills. The incorporation of these factors at the local level during the planning phases of agricultural activities and programmes can address complexity issues appropriately thus enabling climate change adaptation and food security. Although the Senegalese government is applauded for its efforts in providing fertilizer subsidies to the agricultural community there is a need to promote balanced use and site-specific nutrient management so as to increase nitrogen use efficiency in order to substantially reduce emissions from agriculture.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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