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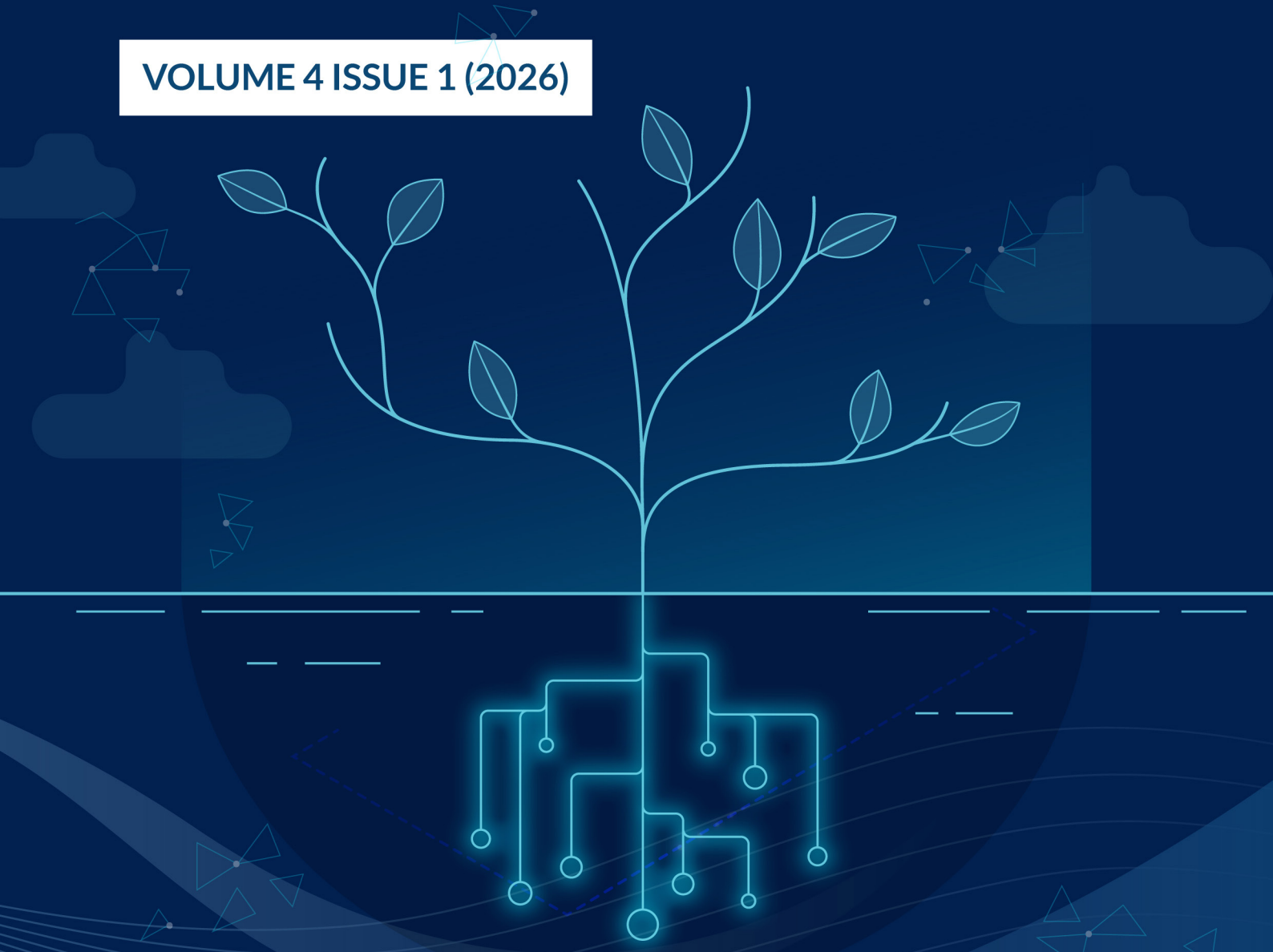

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Factors Influencing the Adoption of Climate-Smart Agricultural Practices in Maryland, USA

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ABSTRACT

The rapidly growing population and changing climate underscore the urgent need for identifying and adopting sustainable agricultural practices to ensure the food security of the growing population while also mitigating the adverse effects of climate change on agricultural production and productivity. Climate-smart agriculture (CSA) is a feasible solution that ensures improved agrarian productivity, enhances crop resilience, and reduces greenhouse gas (GHG) emissions. Despite these benefits, the adoption of CSA practices by small-scale producers remains low. Literature focusing on the factors that influence the adoption of CSA practices, particularly in the context of the United States, is limited. This study examined the demographic, socioeconomic, institutional, and knowledge and skills-related factors influencing the adoption of CSA practices among Maryland farmers. Three Ordinary Least Square (OLS) Regression models were employed using survey data collected from 37 Maryland farmers (n = 37) in 2025. The results revealed that race, farm type (i.e., nature of farming operation based on farm sales), farm scale, and understanding of how to adopt CSA practices were significantly associated with the number of adopted CSA practices. Farmers who sold some of their surplus produce, practiced commercial farming, and had a good understanding of how to implement CSA practices adopted significantly more CSA practices than their counterparts. In contrast, white farmers and small-scale farmers adopted fewer CSA practices. These study findings underscore the importance of considering these factors while designing programs and policies to improve the adoption of climate-smart agricultural practices.

INTRODUCTION

The world population is expected to reach 10.3 billion in the mid-2080s (United Nations, 2024). Given the limited land resources, there will be significant pressure to feed the growing population (McCarthy *et al.*, 2018). At the same time, a rapidly changing climate has seriously challenged agricultural production and productivity, resulting in global food insecurity (Lipper *et al.*, 2014). Increasing temperatures and fluctuating rainfall patterns due to climate change negatively impact crop productivity, leading to lower production for a growing global population (Mahato, 2014). Since climate is a chief determinant of agricultural productivity, climate variability causes a decline in yearly crop production even in high-yield and high-technology agricultural areas. Meeting food demand for the rapidly growing population is already a daunting challenge, but the condition further worsens with the changing climate. Furthermore, the reduction of arable land around the globe due to rapid urbanization makes the issue of food security more pressing than ever (Guitart *et al.*, 2012). Over 13% of U.S. households were food insecure in 2023, facing difficulty in providing sufficient food to their family members at some point during that year (Rabbitt *et al.*, 2024).

While agriculture is one of the sectors most vulnerable to climate change, it is also one of the chief contributors to major greenhouse gas (GHG) emissions such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), which constitute about 12% of the total emissions (Pu *et al.*, 2022; Raihan & Tuspekova, 2022; Wu *et al.*, 2022). According to Crippa *et al.* (2021), approximately 3.5 petagrams (PgC; 1 PgC = 10^{15} gram of carbon) of carbon are emitted annually from agricultural activities. The global GHG emissions from agri-food systems increased by 16% over three decades between 1990 and 2019 (FAO, 2021). GHG emissions from agriculture are primarily a result of soil management (e.g., tillage, cultivation, fertilization, irrigation, and drainage), rice cultivation, residue burning, enteric fermentation, and livestock manure management (Lal, 2004; Shakoor *et al.*, 2021).

The main challenge global agriculture currently faces is increasing sustainable food production while also controlling and reducing the emissions of major GHGs. Such a challenge underscores the need for adopting sustainable agricultural practices to increase productivity, mitigate greenhouse gas emissions, and increase resilience against a changing climate. One such promising practice that promotes sustainable production and minimizes the adverse effects of a changing climate is climate-smart agriculture (CSA), which was introduced by the Food and Agriculture Organization (FAO, 2013). Compared to conventional farming methods, climate-smart

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agriculture (CSA) integrates a set of practices, including conservation tillage, agroforestry, cover crops, optimized nitrogen fertilization, improved water management, use of improved varieties, mulching, and crop rotation, which support productivity, adaptation, and mitigation. The combination of these practices within climate-smart agriculture reduces vulnerability to climate change and improves the resilience of agriculture at the farm level. Numerous studies have shown that CSA practices enhance soil health, improve crop productivity, and mitigate GHG emissions through carbon sequestration (Eagle *et al.*, 2012; Khatri-Chhetri *et al.*, 2016; Miralles-Wilhelm, 2021; Smith *et al.*, 2013).

Given the three-fold benefits increased productivity, enhanced adaptation, and mitigation potential climate-smart agricultural (CSA) practices offer significant opportunities for sustainable agricultural production, highlighting the need for their widespread adoption. However, the adoption of climate-smart agricultural practices remains low and varies greatly across the world (Cary & Frey, 2020). Understanding the factors that influence the adoption of these practices is therefore crucial for developing effective policies to promote their broader implementation. Despite growing research interests, most studies on the determinants of adopting climate-agricultural practices have focused on developing countries, while research in the United States is limited (Chen *et al.*, 2024). Notably, the majority of farms in the United States are small-scale and family-owned, accounting for approximately 89% of all farms, operating in 45% of the nation's farmland, and contributing approximately 18% of the nation's agricultural production (USDA, 2022). These small farms are disproportionately vulnerable to climate risks compared to large-scale farms due to limited resources, financial constraints, and limited access to information and educational opportunities. These vulnerabilities underscore the importance of adopting CSA practices, which can help small-scale farmers increase farm productivity, improve crop resilience, and reduce greenhouse gas emissions.

Although prior studies have shown that CSA adoption is influenced by farmers' demographic, socioeconomic, and farming characteristics, as well as institutional factors and information availability (Maguza-Tembo *et al.*, 2017; Murage *et al.*, 2015; Tey *et al.*, 2014), the effect and direction of these determining factors may not be consistent across geographic and socioeconomic contexts.

Therefore, the objective of this study is to assess the demographic, socioeconomic, institutional, and knowledge- and skills-related factors that influence the adoption of climate-smart agricultural practices among farmers in Maryland. By identifying the determining factors of CSA adoption in Maryland, the study aims to support the ongoing campaign, particularly by the University of Maryland Eastern Shore Extension, to promote the widespread adoption of CSA practices at the community level.

LITERATURE REVIEW

Climate-Smart Agriculture

Climate-smart agricultural (CSA) practice is an integrated approach aimed at improving the resilience of agri-food systems by responding to the existing climate change effectively. Expanding CSA can play a crucial role in achieving food security and sustainable agri-food production through adaptation to climate change and reduced emissions. The three main objectives of CSA are:

(i) Sustainably enhancing agricultural productivity and profitability,

(ii) Increasing resilience to climate change and minimizing susceptibility to climate-related threats, and

(iii) Mitigating greenhouse gas emissions (Palombi & Sessa, 2013).

What distinguishes CSA from other approaches is that it acknowledges agriculture as a contributor to global GHG emissions, while also recognizing the agricultural sector's vulnerability to climate variability. Moreover, CSA emphasizes the huge potential of agriculture in mitigating climate change by reducing GHG emissions and sequestering carbon in soils and plant biomass. It integrates management approaches essential for sustainable resource implementation and focuses on developing resilient agri-food systems, with the goal of achieving global food security amidst climate change and variability (Lipper *et al.*, 2014). Examples of CSA practices include enhanced cropping systems (e.g., use of improved varieties, crop diversification, crop rotation, incorporation of legumes, etc.), integrated soil and nutrient management (e.g., use of farm yard manure, green manure, compost, etc.), conservation agriculture (e.g., minimum tillage or zero tillage), improved water management (e.g., water harvesting, improved water-use efficiency, etc.), and integrated pest and disease management. These practices can mitigate the adverse effects of climate change and variability while enhancing crop productivity and economic returns (Khatri-Chhetri *et al.*, 2016).

Factors Affecting the Adoption of Climate-Smart Agricultural Practices

Several studies have investigated the factors influencing the adoption of climate-smart agricultural practices. These include demographic, economic, and institutional factors.

Demographic Factors

Prior research has emphasized that demographic factors heavily influence farmers' decision-making and, consequently, their adoption of CSA practices. These demographic factors include age, gender, education, and farming experience.

Farmers' age has been found to be negatively associated with CSA adoption in many studies, as older farmers tend to avoid risks and are hesitant to adopt new practices (Djido *et al.*, 2021; Khan *et al.*, 2020; Sattar *et*

al., 2023; Tran *et al.*, 2020). In terms of gender, studies have found mixed results. Several studies reported that female farmers were less likely to adopt climate-smart agricultural practices than male farmers (Abdur Rashid Sarker *et al.*, 2013; Mutombo & Musarandega, 2023; Tran *et al.*, 2020). The difference in adoption of climate-smart agricultural practices between genders could be attributed to differences in access to resources and information. However, some studies indicated that female farmers were more likely to adopt certain CSA practices, such as the use of improved varieties and animal manure (Bernier *et al.*, 2015; Musafiri *et al.*, 2022; Trinh *et al.*, 2018). Education has been found to be positively and significantly associated with CSA adoption (Gwambene *et al.*, 2015; Ma *et al.*, 2017; Saptutyningsih *et al.*, 2020). Educated farmers are more likely to understand the benefits of climate-smart agricultural practices for mitigating the negative impacts of climate change. Additionally, while some studies have reported a positive association between the farming experience and the adoption of CSA practices (Ainembabazi & Mugisha, 2014; Sardar *et al.*, 2021), surprisingly, a study by Machete *et al.* (2024) revealed that the farming experience is negatively associated with CSA adoption. This inverse relationship may be attributed to experienced farmers being more reluctant to adopt newer technologies.

Economic Factors

Some climate-smart agricultural (CSA) practices are cost-intensive. For instance, agroforestry requires a high initial investment and has a very long recovery period (Waaswa *et al.*, 2022). Such substantial upfront costs and extended production cycles associated with some CSA practices can negatively impact the adoption of these practices (Abdul-Salam *et al.*, 2022). Low-income households were less likely to adopt CSA practices (Zeleke *et al.*, 2022), whereas the adoption of CSA practices increased with increasing farm income (Ashraf *et al.*, 2014; Jianjun *et al.*, 2015). Financial resources is the primary reason behind such low adoption among low-income households. In addition to financial requirements, most CSA practices often demand very high labor inputs, such as weeding and digging holes, which can further hinder adoption (Waaswa *et al.*, 2022). Labor shortage has been found to be a significant barrier to CSA adoption (Murray *et al.*, 2016). Farm size is another important factor that determines farmers' decisions to adopt climate-smart agricultural practices. Farmers with large farm sizes tend to adopt CSA practices more than those with small farm sizes due to better access to resources and greater flexibility for experimentation (Sardar *et al.*, 2019).

Institutional Factors

Institutional factors, including access to extension services, credit facilities, and training opportunities, have been found to influence farmers' decisions to adopt climate-smart agricultural practices. Extension services can promote the adoption of climate-smart agricultural practices by providing knowledge about CSA practices, organizing training to enhance farmers' skills, and providing farmers with essential supplementary production inputs. Therefore, access to extension services is positively associated with the adoption of CSA practices among farmers (Asfaw *et al.*, 2016; Bryan *et al.*, 2013). Similarly, the availability of agricultural training is also positively correlated with CSA adoption (Chicas *et al.*, 2023; Martey *et al.*, 2021). As discussed earlier, since some CSA practices require high investment, access to credit for farmers plays a pivotal role in CSA adoption. For example, a study in Pakistan concluded that access to bank credit significantly increased the probability of CSA adoption among farmers (Chamberlin & Ricker-Gilbert, 2016).

MATERIALS AND METHODS

Sampling Procedure and Data Collection

A survey questionnaire was developed to collect the data from respondents across Maryland. The survey instrument included questions to collect information about the respondents' demographic and socioeconomic characteristics, perceptions of climate-smart agricultural practices, willingness to adopt climate-smart agricultural practices, and details about currently implemented CSA practices. The questionnaire primarily consisted of closed-ended questions, including Likert-scale, multiple-choice, and binary response items, along with a few open-ended questions.

Prior to data collection, the survey received approval from the University of Maryland Eastern Shore Institutional Review Board. The survey was then administered to potential respondents whose contact and email information were obtained from a database maintained by the University of Maryland Eastern Shore (UMES) Extension. The database included contact information of farmers, ranchers, agricultural professionals, educators, agricultural entrepreneurs, agritourism operators, and agriculture students. A convenience sampling approach was used for data collection, as the participants were selected from an existing Extension database.

The online survey was designed using Microsoft Forms and was sent out in three waves to 424 people via email in January 2025. A follow-up email was sent two weeks after the first email. The responses were collected through mid-March 2025. A total of 47 responses were received online. An additional seven responses were obtained through in-person interviews, bringing a total of 54 responses, with a response rate of 12.7%. Out of 54 responses, one case was excluded due to duplication, and two other cases were removed due to incomplete data. Additionally, 14 responses from the respondents who did not identify as farmers currently engaged in farming were excluded from the study. Therefore, the final sample size included responses from 37 farmers (n = 37). It was deemed appropriate to include only farmers in the study, as they were the ones currently in a position to implement such practices and respond to the survey question of interest.

Measurement of Variables

Dependent Variable

The number of climate-smart agricultural practices currently implemented by a farmer was used as the dependent variable. The survey included a total of 12 climate-smart agricultural practices categorized into five smart groups carbon-smart, water-smart, energy-smart, nitrogen-smart, and weather-smart, which are presented in Table 1. Respondents were asked, "Do you currently implement this practice?" for each of the 12 climate-smart agricultural practices. The responses were recorded as 1 if the participant answered "yes," and 0 if they responded otherwise. The total number of climate-smart practices (out of 12) that a farmer reported implementing, irrespective of their types, was used as a continuous dependent variable in the regression analysis.

Independent/Explanatory Variables

Table 1: Climate-smart agricultural practices included in the study and their categories

Smart categories	Climate-smart agricultural practices
Climate-smart	Conservation tillage
	Crop rotation
	Mixed cropping/Intercropping
	Organic manuring
	Agroforestry
Water-smart	Cover cropping
	Mulching
	Rainwater harvesting
Energy-smart	Composting
Weather-smart	Use of weather information via smartphone/internet for informed decisions
Nitrogen-smart	Use of legume crops
	Site-specific fertilizer application

Source. Mthethwa et al. (2022)

The measurements of the independent variables, used to predict the number of adopted climate-smart agricultural practices, are described below.

The explanatory variables were grouped into four categories socio-demographic characteristics, farm characteristics, institutional factors, and knowledge and skills-related factors. Socio-demographic characteristics included gender, race, and education level of the respondents. Gender was binary coded male (coded as 1) and female (coded as 0), with the female being the reference group for the analysis. For race, farmers selected from multiple options including White, Black or African American, American or Alaska Native, Asian, Native Hawaiian or Pacific Islander, two or more races, some other race, Hispanic or Latino, Non-Hispanic or Latino. For the analysis, White was coded as 1, and all other races were coded as 0. The information on farmers' education level was collected by asking respondents to select from options including no formal education, less than a high school degree or equivalent, a high school degree, some college degree, some associate degree, undergraduate, and graduate. The responses were dichotomized by recoding graduate and undergraduate as 1 and others as 0.

Farm characteristics included farming experience, total farm size (in acres), type of farm, and scale of farm. Farming experience was measured as a categorical variable with three options to choose from: 1–5 years, 6-10 years, and over 10 years. For regression analysis, experience over 10 years was coded as 1, while the other two categories were grouped and coded as 0 (reference group). The total farm size, defined as the total farm area owned by the farmer, was natural log-transformed prior to including it in the analysis. Farm type was categorized based on the nature of the operation. Participants were asked whether they produced just enough to meet their household needs, sold surplus production, or operated a commercial farm. These responses were binary-coded, and "farming just enough to meet household needs" was used as a reference group. Regarding farm scale, the respondents were asked whether they were identified as small-scale farmers. Those reporting "yes" were coded as 1 and compared to others who did not identify as small-scale farmers (coded as 0).

Under institutional factors, farmers were asked whether they had access to Extension services. The responses were recorded on a 5-point Likert scale (strongly agree with a weight of 5 and strongly disagree with a weight of 1). "Strongly agree" and "agree" were grouped and coded as 1, and the others neutral, disagree, and strongly disagree were coded as 0.

Similarly, under the knowledge and skill factors, farmers were asked, "Do you have a good understanding of how to adopt climate-smart agricultural practices?" The responses were collected on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). "Strongly agree" and "agree" were collectively coded as 1 and compared to "neutral," "disagree," and "strongly disagree," which were coded as 0.

Data Analysis

Prior to analysis, the data was first explored for missing values. The dataset had a few missing values in some responses, primarily in variables related to socio-demographic characteristics, such as income, race, age, gender, education, and number of family members. In addition to non-responses, some respondents also selected the "prefer not to respond" option for those variables. Due to the small number of such responses, it was not feasible to treat them as a separate category for analysis. Thus, these responses were also treated as otherwise values. Multivariate imputation by chained equations (MICE) was employed using the mice package in R for missing value imputation. Predictive mean matching (pmm) and logistic regression models within the mice package were used to impute missing continuous and categorical variables in the dataset, respectively, with

a total of five iterations (Blazek *et al.*, 2021). Secondly, descriptive statistics of the variables used in the study were calculated. Thirdly, bivariate and multivariate associations between dependent variable and independent variables was examined.

Model Specification

Three Ordinary Least Squares (OLS) regression models were estimated to examine the factors influencing the number of adopted climate-smart agricultural practices. This included model 1 (bivariate model), model 2 (full model), and model 3 (reduced model). Model 1 (bivariate model) explored the individual (main) effect of each explanatory variable on the dependent variable without adjusting for other variables. Model 2 (full model) included all explanatory variables simultaneously to estimate the effect of independent variables on the dependent variable while adjusting for other confounders. Model 3 (reduced model) is a subset derived from the full model, using a step-wise regression, where non-significant variables were sequentially removed based on the magnitude of p-values and their effect sizes. The Variance Inflation Factor (VIF) values were calculated to identify possible collinearity issues. A VIF value of less than 10 was deemed acceptable, with no concern of collinearity (Neter *et al.*, 1983). Additionally, F-statistic and adjusted R^2 values were used to test the model fit and statistical significance of the parameter estimates.

According to Wooldridge (2016), the general multiple linear regression model can be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + u \quad \ldots(1)$$

Where, Y = dependent/predicted variable; β_0 = intercept; $\beta_1 + \beta_2 + \beta_3 + \ldots + \beta_k$ = parameters associated with predictor variables; $X_1 + X_2 + X_3 + \ldots + X_k$ = independent/predictor variables; u = residuals (error term).

Then, the estimated OLS equation for the full model (model 2) to predict the number of adopted climate-smart agricultural practices can be written as:

$$\widehat{ncsa} = \beta_0 + \beta_1 \cdot male + \beta_2 \cdot \text{white} + \beta_3 \cdot \text{unidegree} + \beta_4 \cdot \text{farmexp} + \beta_5 \cdot \text{logarea} + \beta_6 \cdot \text{surplussale} + \beta_7 \cdot \text{commercial} + \beta_8 \cdot \text{smallscale} + \beta_9 \cdot \text{extension} + \beta_{10} \cdot \text{understand} \quad \ldots(2)$$

Where:

$\widehat{ncsa}$ = predicted value of the dependent variable (number of adopted climate-smart practices)

β_0 = intercept

$\beta_1 + \beta_2 + \beta_3 + \ldots + \beta_{10}$ = regression coefficients

male = dummy variable for gender (male = 1, female = 0)

white = dummy variable for race (white = 1, otherwise = 0)

unidegree = dummy variable for farmers with a university degree (yes = 1, otherwise = 0)

farmexp = dummy variable for farmers with over 10 years of farming experience (yes = 1, otherwise = 0)

logarea = total farm area (acres, logged)

surplussale = dummy variable for farmers selling surplus produce (yes = 1, otherwise = 0)

commercial = dummy variable for farmers practicing commercial farming (yes = 1, otherwise = 0)

smallscale = dummy variable for farmers identifying as a small-scale farmer (yes = 1, otherwise = 0)

extension = dummy variable for farmers with access to Extension services (agree = 1, otherwise = 0)

understand = dummy variable for farmers with a good understanding of how to implement climate-smart agricultural practices (agree = 1, otherwise = 0)

Similarly, the estimated OLS equation for the reduced model (model 3) can be written as:

$$\widehat{ncsa} = \beta_0 + \beta_1 \cdot \text{white} + \beta_2 \cdot \text{surplussale} + \beta_3 \cdot \text{commercial} + \beta_4 \cdot \text{smallscale} + \beta_5 \cdot \text{understand} \quad \ldots(3)$$

RESULTS AND DISCUSSION

Descriptive Results

The descriptive results of the variables used in the regression analysis are presented in Table 2.

Dependent Variable

Of the total 12 CSA practices presented to the respondents, on average, a farmer practiced over six CSA practices (Mean = 6.05, SD = 3.61), with a minimum of 0 to a maximum of 12 practices.

Independent Variables

The socio-demographic characteristics included gender, race, and education variables. Among the 37 farmers surveyed, 35% were male, and 65% were female. Of the total, 62.2% were White farmers, and the remaining 37.8% were non-White farmers (Black or African American, 21.6%; Asian, 10.8%; Hispanic or Latino, 5.4%). Regarding education levels, 64.8% reported having earned a university degree (graduate degree, 40.5%; undergraduate degree, 24.3%). The remaining 35.2% had not completed a university degree (associate degree, 2.7%; some college degree, 24.3%; high school degree/GED certificate, 8.1%).

Farm characteristics included farming experience, farm size, farm type, and farm scale. Among the 37 respondents, 32.4% reported having over 10 years of farming experience, while 67.6% had less than 10 years of experience (1-5 years, 59.5%; 6-10 years, 8.1%). The average farm size was 89.76 acres, with a standard deviation of 188.13 acres, ranging from a minimum of 0.2 acres to a maximum of 780 acres. Due to this large variation and highly skewed distribution, the farm size was natural log-transformed prior to including it in the analysis. Regarding farm type, 19% stated that they practiced farming to produce just enough to meet household consumption, 54% reported selling their surplus produce, and 27% reported engaging in commercial farming. In terms of the scale of farming, over 62% of the respondents identified themselves as small-scale farmers.

The institutional factors group consisted of a single variable, which reported farmers' access to Extension services. Among the farmers, 73% agreed (strongly agree, 37.8%; agree, 35.1%) that they had access to Extension services, while 27% responded otherwise (neutral, 10.8%;

disagree, 8.1%; strongly disagree, 8.1%).

The knowledge and skills category also had a single variable, which measured farmers' perceived understanding of how to implement CSA practices. Of the total, 51.3% agreed (strongly agreed, 10.8%; agree, 40.5%) that they had a good understanding. In contrast, 48.7% reported otherwise (neutral, 27%; disagree, 16.2%; strongly disagree, 5.4%).

Table 2: Descriptive statistics of the variables used in the regression analysis (n = 37)

Variables	Descriptive Statistics			
	Mean	SD	Minimum	Maximum
A. **Dependent variable**				
Number of adopted CSA practices	6.05	3.61	0.00	12.00
B. Independent variables				
Socio-demographic characteristics				
a. Male (yes = 1)	0.35	0.48	0.00	1.00
b. White (yes = 1)	0.62	0.49	0.00	1.00
c. University degree (yes = 1)	0.65	0.48	0.00	1.00
Farm characteristics				
d. Farming experience: Over 10 years (yes = 1)	0.32	0.47	0.00	1.00
e. Total farm size (acres)	89.76	188.13	0.20	780.00
• Total farm size (acres, logged)	2.71	1.90	0.17	6.66
f. Farm type: Nature of operation				
• Grow just enough to meet household needs (Ref.)	0.19	0.40	0.00	1.00
• Sell surplus produce (yes = 1)	0.54	0.51	0.00	1.00
• Commercial farming (yes = 1)	0.27	0.45	0.00	1.00
g. Farm scale				
• Small-scale farmer (yes = 1)	0.62	0.49	0.00	1.00
Institutional factors				
h. Has access to Extension services (agree = 1)	0.73	0.45	0.00	1.00
Knowledge and skills				
i. Has a good understanding of how to implement CSA practices (yes = 1)	0.51	0.51	0.00	1.00

Factors Influencing the Adoption of CSA Practices

Table 3 presents bivariate and multivariate associations between the number of adopted climate-smart practices and the explanatory variables using the Ordinary Least Squares (OLS) regression to assess the factors influencing the adoption of climate-smart agricultural (CSA) practices among farmers. The unadjusted results (model 1) and adjusted results (model 2 and model 3) are reported using unstandardized β coefficients along with standard errors. The Variance Inflation Factor (VIF) for the regression model was calculated to check for multicollinearity. The VIF values for all predictor variables were below 3 (1.265 – 2.910), indicating that the issue of multicollinearity was not a concern for the regression analysis.

The unadjusted results from the bivariate model suggested that farm scale and understanding of how to implement climate-smart agricultural practices had significant associations with the number of adopted CSA practices. It was revealed that small-scale farmers were found to adopt fewer climate-smart agricultural practices compared to those who did not identify themselves as small-scale farmers (β = -2.786, $p < 0.05$, bivariate model). Similarly, farmers with a good understanding of how to implement climate-smart agricultural (CSA) practices adopted more of these practices (β = 2.594, $p < 0.05$, bivariate model). Farmers' socio-demographic characteristics, such as gender, race, and university degree, were not significantly associated with the number of adopted CSA practices. Additionally, other variables, including farming experience, farm size (logged), and farm type, were also not significantly associated with the number of adopted climate-smart agricultural practices in the bivariate model. While access to Extension services was positively associated with the number of adopted CSA practices, the relationship was not statistically significant.

The adjusted models (model 2 and model 3) account for other confounding variables in predicting the number of adopted CSA practices. The overall fit of the full model (model 2) was statistically significant (F-statistic = 2.510, $p < 0.05$), with an adjusted R-squared value of 0.296, indicating that 29.6% of the variance in the number of adopted CSA practices was explained by the variables in the model. Similarly, the reduced model, i.e., model 3, with key predictors from model 2, also provided a statistically significant fit (F-statistic = 4.613, $p < 0.01$). Notably, model 3 produced a stronger F-statistic and a higher adjusted R-squared value (Adjusted R^2 = 0.334),

suggesting a better model fit.

The full model (model 2) assessed the combined effects of the ten predictor variables used in model 1. Model 2 revealed a strong and significant negative association between farm scale and the number of adopted CSA practices, indicating that small-scale farmers adopted fewer CSA practices (β = -3.435, $p < 0.01$, model 2) as compared to those who did not identify as small-scale farmers. Both the magnitude and statistical significance improved in model 2 compared to model 1. The positive association between farmers' understanding of implementing climate-smart agricultural (CSA) practices and the number of adopted CSA practices persisted in model 2; however, it was only marginally significant (β = 2.945, $p < 0.1$, model 2). Interestingly, race (White farmers), which was not significant in model 1 became statistically significant in model 2, particularly after controlling for the effects of farm type. The results revealed that White farmers adopted fewer CSA practices as compared to non-White farmers (β = -2.969, $p < 0.05$, model 2). Similarly, farm types, which were not significant in the bivariate model (model 1), showed significant positive associations with the number of adopted CSA practices in model 2. Farmers who sold their surplus produce or engaged in commercial farming tended to adopt more CSA practices than those who practiced farming just enough to meet household consumption (sell surplus produce: β = 4.219, $p < 0.05$; commercial farming: β = 4.140, $p < 0.05$, model 2). The results suggest the presence of a confounding effect between race and farm type; wherein true effects were masked in model 1 and only became apparent after adjusting for the effects of both variables in model 2.

The reduced model (model 3) was constructed using only the predictor variables that showed statistically significant associations with the dependent variable in model 2. This included four predictors: race, scale of farming, farm type, and understanding of how to implement CSA practices. The statistically significant associations between these predictor variables and the number of adopted CSA practices persisted in model 3. White farmers adopted significantly fewer CSA practices than non-White farmers (β = -2.428, $p < 0.05$, model 3). Among farm types, both farmers who sold surplus produce (β = 3.263, $p < 0.05$, model 3) and those engaged in commercial farming (β = 4.036, $p < 0.05$, model 3) adopted significantly more CSA practices compared to those who practiced farming just enough to meet household consumption needs. Farmers with a good understanding of how to implement CSA practices adopted more CSA practices than those without such understanding (β = 2.261, $p < 0.05$, model 3). The significance of this association strengthened in Model 3 compared to Model 2. Another variable that showed improvement in both the magnitude of effect and significance strength is the scale of farming. Small-scale

Table 3: Ordinary least square (OLS) regression estimates for factors determining adoption of climate-smart agricultural practices (n = 37)

Variables	Model 1: Bivariate Model (Unadjusted Results)	Model 2: Fully Adjusted Results	Model 3: Reduced Model (Partially Adjusted Results)
	Unstandardized β(S.E.)	Unstandardized β (S.E.)	Unstandardized β(S.E.)
Socio-demographic characteristics			
a. Male (yes=1)	0.865 (1.251)	1.657 (1.188)	-
b. White (yes=1)	-0.488 (1.237)	-2.969* (1.401)	-2.428* (1.169)
c. University degree (yes=1)	-0.510 (1.256)	0.434 (1.172)	-
Farm characteristics			
d. Farming experience: Over 10 years (yes=1)	1.770 (1.249)	-0.649 (1.722)	-
e. Total farm size (acres, logged)	0.344 (0.316)	0.405 (0.381)	-
f. Farm type: Nature of operation			
• Grow just enough to meet household needs (Ref.)	-	-	-
• Sell surplus produce (yes=1)	0.100 (1.206)	4.219* (1.703)	3.263* (1.428)
• Commercial farming (yes=1)	1.296 (1.336)	4.140* (1.846)	4.036* (1.636)
g. Farm scale			
• Small-scale farmer (yes=1)	-2.786* (1.146)	-3.435** (1.176)	-3.875*** (1.099)
Institutional factors			
h. Has access to Extension services (agree=1)	1.170 (1.339)	0.159 (1.310)	-
Knowledge and skills			
i. Has a good understanding of how to implement CSA practices (agree=1)	2.594* (1.120)	2.945^{+} (1.464)	2.261* (0.980)

Intercept		3.253 (2.268)	5.957*** (1.378)
F-statistic		2.510*	4.613**
Residual degrees of freedom		26	31
Adjusted R^2		0.296	0.334

*Note. *** p<0.001; ** p<0.01; * p<0.05; + p<0.10; S.E. = Standard Error*

farmers adopted fewer CSA practices than those who did not identify as small-scale farmers (β = -3.875, p < 0.001, model 3).

Discussion

A notable but surprising finding from the study was that White farmers reported adopting fewer CSA practices than non-White farmers (β = -2.969, p < 0.05, full model; β = -2.428, p < 0.05, reduced model). This result is surprising, given that minority farmers are typically more likely to face greater barriers, including limited access to resources, information, and institutional support. One possible explanation for such a finding could be the impact of targeted outreach and support programs aimed at promoting sustainable agricultural practices among minority farmers. Alternatively, non-random sampling may have resulted in selection bias, which contributed to such results, where more motivated and well-informed non-White farmers were overrepresented. While further investigation is required to confirm this result, the finding highlights the importance of tailoring the CSA outreach and support programs to ensure the participation of farmers from all races.

The nature of farm operations was another significant factor in CSA adoption. Farmers who sold their surplus production or engaged in commercial farming adopted significantly more CSA practices than those farmers who grew just enough to meet their household needs (*sell surplus produce:* β = 4.219, p < 0.05, full model; β = 3.263, p < 0.05, reduced model; *commercial farming:* β = 4.140, p < 0.05, full model; β = 4.036, p < 0.05, reduced model). This is likely because farmers engaged in commercial farming and those who sell surplus produce are more likely to understand the benefits of adopting CSA practices, such as improved yields, higher incomes, and greater crop adaptability. This finding is consistent with prior studies, which indicated that the adoption of CSA practices increased with increasing farm income (Ashraf *et al.*, 2014; Jianjun *et al.*, 2015).

Interestingly, both the farm type and race were not statistically significant in the bivariate model but became statistically significant in the full and reduced model when added simultaneously. To test the confounding effect, a stepwise regression approach was used where race was added to the model, and the farm type was then added subsequently, which resulted in statistically significant results indicating that the effect of race was masked by the nature of the operation and vice versa when analyzed in isolation. This finding underscores the importance of evaluating the effect of race and farm type in combination to predict the adoption of CSA practices.

Small-scale farmers adopted significantly fewer CSA practices than farmers who did not identify as small-scale farmers (β = -3.435, p < 0.01, full model; (β = -3.875, p < 0.001, reduced model). This aligns with the findings from several studies (Gelaw, 2017; Kpadonou *et al.*, 2017; Sardar *et al.*, 2019) that reported that access to higher financial and institutional resources enables large-scale farmers to be flexible with the number of CSA practices they adopt. Small-scale farmers face a significant barrier in the adoption of CSA practices due to the cost and labor-intensive nature of practices, such as agroforestry and cover cropping, especially due to financial constraints and labor shortage (Gelaw, 2017; Murray *et al.*, 2016; Waaswa *et al.*, 2022).

Another key finding of the study was that farmers' understanding of how to implement CSA practices was a significant positive predictor of their adoption. Farmers who reported having a good understanding of implementing CSA practices adopted significantly more CSA practices than those who did not have such an understanding (β = 2.945, p < 0.1, full model; (β = 2.261, p < 0.05, reduced model). This finding aligns with the results of Luu (2020) and Machete *et al.* (2024), who reported that knowledge and skills of CSA practices positively influenced the adoption decision of farmers. Moreover, farmers' perception of their capabilities to implement CSA practices influences their behavioral intentions and, subsequently, the adoption of these practices (Atta-Aidoo *et al.*, 2022).

Surprisingly, variables such as gender, education, farming experience, farm size, and access to extension services were not significantly associated with the number of adopted CSA practices, in contrast with the findings of some studies (Asfaw *et al.*, 2016; Gwambene *et al.*, 2015; Machete *et al.*, 2024; Masud *et al.*, 2017; Mutombo & Musarandega, 2023; Sardar *et al.*, 2021).

CONCLUSION

In this study, we explored the factors influencing the adoption of climate-smart agricultural (CSA) practices among farmers in Maryland. We found that farmers' race, nature of farm operation, scale of farming, and understanding of CSA practices significantly influenced the number of climate-smart agricultural practices adopted by the farmers. White farmers adopted fewer CSA practices than non-White farmers. In contrast, farmers who sold surplus production or those engaged in commercial farming adopted more CSA practices than others who cultivated only enough to consume in their household. Smaller farmers adopted fewer CSA practices, likely due to limited financial resource availability. Farmers who agreed they understood how to apply CSA practices

adopted more than those who disagreed.

These findings highlight the need for developing inclusive and tailored outreach programs for farmers of different races, farm types, and farming scales. Similarly, the findings underscore that hands-on training, on-farm demonstrations, and workshops are essential to increase the adoption of CSA practices. However, this study has a few limitations. Some of the important limitations are the small sample size, non-probability sampling technique, and geographic limitation to Maryland, which may limit the generalizability to broader farming populations. Thus, the results from this study should be considered more carefully. Future studies should use probability sampling techniques and include larger samples across broader regions to generate more robust and conclusive evidence.

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