# EFFECT OF ADOPTION OF CLIMATE-SMART AGRICULTURAL (CSA) PRACTICES ON THE PRODUCTIVITY OF CASSAVA FARMERS IN ODUKPANI LOCAL GOVERNMENT AREA, CROSS RIVER STATE, NIGERIA

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***Abstract***
This study examined the effect of Adoption of Climate-Smart Agriculture (CSA) practices on the productivity of cassava farmers in Odukpani Local Government Area, Cross River State, Nigeria. Using a multi-stage sampling technique, 120 cassava farmers were surveyed with a structured questionnaire. Descriptive statistics, a CSA adoption index, logistic regression, and multiple regression models were used for analysis. Commonly adopted CSA practices included improved cassava varieties, crop rotation and cover cropping, while soil, water and pest management showed moderate adoption. Logistic regression indicated that CSA awareness/exposure ($B = 4.558$; $Exp(B) \approx 95$; $p < 0.001$) and farm income significantly influenced adoption ($p = 0.050$), while education had a positive but marginal effect ($Exp(B) = 1.12$; $p = 0.079$). The double-log regression model indicated that CSA adoption significantly increased cassava yield ($\beta = 0.283$, $p = 0.004$), with farm size also showing a strong positive effect ($\beta = 1.103$, $p < 0.001$). The study concludes that CSA adoption enhances cassava productivity and resilience but is constrained by limited access to information, finance, and extension services. It recommends strengthening extension services, farmer training, improving credit and input access, and promoting inclusive CSA policies to enhance adoption and sustainable agricultural productivity in the Study Area.

**Keywords**: Climate Smart Agriculture (CSA), Adoption, Cassava, Productivity, Farmers, Odukpani

## Introduction

Climate change continues to pose a serious threat to agricultural production systems globally, with its effects being particularly pronounced in developing countries such as Nigeria. Rising temperatures, erratic rainfall patterns, prolonged dry spells, and increasing incidence of extreme weather events have disrupted farming activities and heightened production risks for smallholder farmers who depend largely on rain-fed agriculture (IPCC, 2021). These challenges have intensified concerns over food security, rural livelihoods, and the sustainability of staple crop production systems. Cassava (Manihot esculenta) remains one of Nigeria's most important food crops due to its adaptability, widespread cultivation, and significance for household food security and income generation. It serves both subsistence and commercial purposes and plays a vital role in rural economies, particularly in southern Nigeria, including Cross River State (Kehinde & Subuola, 2015; Nwankwo *et al.*, 2021). However, despite its relative resilience, cassava production has increasingly been affected by climateinduced stresses such as irregular rainfall, declining soil fertility, erosion, and prolonged dry periods, resulting in low yields and reduced farm income (Adejuwon & Odekunle, 2006; Akpenpuun & Busari, 2013).

In response to these challenges, Climate-Smart Agriculture (CSA) has emerged as a key strategy for promoting sustainable agricultural production under changing climatic conditions. CSA seeks to enhance productivity, build resilience to climate shocks, and encourage sustainable resource use through practices such as improved crop varieties, soil and water conservation, crop rotation, diversification, and efficient input management (FAO, 2010; FAO, 2013; FAO, 2021). For cassava farmers, the adoption of CSA practices offers a practical pathway to stabilizing yields and improving income in the face of climate variability. Nevertheless, the uptake of CSA practices among smallholder farmers remains uneven, largely due to socio-economic and institutional constraints. Factors such as age, education, farm size, income level, access to extension services, credit availability, and exposure to climate-related information significantly influence farmers' adoption decisions. These factors shape how farmers perceive the usefulness and feasibility of CSA practices within their production systems (Adebayo & Sola, 2022).

This study is conceptually grounded in the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory. The TAM explains adoption behavior based on perceived usefulness and ease of use of innovations (Davis, 1989), while the DOI theory highlights the role of information dissemination, social interaction, and peer influence in the adoption process (Rogers, 2003). These frameworks provide the basis for examining how farmers' socio-economic characteristics and institutional factors influence CSA adoption decisions. Empirical evidence from Nigeria and other parts of sub-Saharan Africa indicates that climate variability negatively affects agricultural productivity, while the adoption of CSA-related practices can significantly improve crop yields and farmers' adaptive capacity (Ogundele and Jegede, 2011; Tiamiyu *et al.*, 2017; Ayanlade *et al*., 2017; Oyawole *et al*., 2019 and Sa'adu *et al*., 2024; Asfaw *et al*., 2016; Arslan *et al*., 2021; Ogunbameru *et al*., 2022). However, most existing studies focus on general crop production or farmers' perceptions of climate change, with limited attention given to the direct productivity effects of CSA adoption among cassava farmers, particularly at localized levels.

In Odukpani Local Government Area of Cross River State, empirical evidence linking CSA adoption to cassava productivity remains sparse. Moreover, little is known about the intensity of CSA adoption and the extent to which socio-economic factors influence both adoption decisions and productivity outcomes among cassava farmers in the area. This gap limits the effectiveness of policy interventions aimed at promoting climate-resilient cassava production. Against this backdrop, this study assesses the effect of Climate-Smart Agriculture practices adoption on the productivity of cassava farmers in Odukpani Local Government Area of Cross River State, Nigeria. Specifically, the study identifies CSA practices adopted by cassava farmers, examines the socio-economic determinants of CSA adoption using appropriate econometric models, and evaluates the effect of CSA adoption on cassava productivity. By providing location-specific empirical evidence, the study contributes to policy-relevant knowledge on promoting sustainable and climate-resilient cassava production systems

## Methodology

### Study area

The study was conducted in Odukpani LGA of Cross River State, Nigeria a place characterized by smallholder farming systems, and a tropical climate. Odukpani has the potential of producing rice, sugar cane, fruits, vegetables, maize, cassava, etc. to mention a few (Edem *et al.*, 2017). It is bounded to the North by Akamkpa Local Government Area and Abia State, west by Akwa Ibom State, East by Akpabuyo and South by Calabar Municipality Local Government. It covers an area of 2,624.66sq.km comprising thirteen (13) council wards namely: Adiabo Efut, Akamkpa, Creek Town 1, Creek Town 11, Ekori/Anaku, Eniong, Eki, Obomitiat/Mbiabo/Ediong, Odot, Odukpani Central, Onim/Ankiong, Ikoneto, Ito/Idere/Ukwa., forty (40) clans and over five hundred (500) villages. It lies between latitude $5^0$4'52.46" N and longitude $8^0$20'59.7" E and has an elevation of approximately 413ft. The estimated population of the area is about 270,000 persons according to the National Population Commission (NPC, 2024). The area experiences a bimodal rainfall pattern ranging from 2,000 mm to 4,300 mm annually, with average daily temperatures between 22°C and 25°C (NIMET, 2022). The terrain is generally undulating with deep, poorly drained soils typical of the rainforest zone.

### Sampling Method

A multi-stage sampling technique was employed for the study. In the first stage, four (4) wards Adiabo Efut, Creek Town I, Creek Town II, and Odukpani Central were purposively selected for their prominence in cassava production. In the second stage, a sampling frame of active cassava farmers was not formally available at the ward level. Consequently, snowball sampling was adopted to identify practicing sole cassava farmers within each selected ward through referrals from community leaders and the initial respondents. This approach was considered appropriate given the informal and fragmented nature of smallholder farmer records in the study area.

A total of thirty (30) cassava farmers were selected from each ward, yielding an overall sample size of 120 respondents. Although snowball sampling may introduce potential sampling bias, as initial participants might refer farmers with similar characteristics. This limitation was minimized through diverse entry points across wards.

### Method of Data Collection

Primary data were collected using a well-structured and pretested questionnaire. The questionnaire was pilot-tested among 10 cassava farmers outside the main study area to ensure clarity, reliability, and content validity. The content validity was achieved by the experts in the field of agricultural economics and extension services having a review on the draft questionnaire, and their inputs ensured that the questions were relevant, clear and adequately covered the study area. The reliability of the instrument was assessed using internal consistency measures, and the questionnaire items yielded acceptable reliability coefficients, indicating consistency in responses. All these feedbacks guided necessary modifications before final administration. In addition, key informant interviews were conducted with extension officers and community leaders to supplement survey data.

**Definition of Variables and Model Specification**

The logistic regression model was used to identify the socio-economic factors influencing the rate of adoption of CSA practices among cassava farmers. The model is given as:

$\ln\left(\frac{p}{(1-p)}\right) = \beta_0 + \beta_1 X_{1CSA} + \beta_2 X_{2AGE} + \beta_3 X_{3SEX} + \beta_4 X_{4EDULEVEL} + \beta_5 X_{5HHSIZE} + \beta_6 X_{6INCOME} + \beta_7 X_{7FARMSIZE} + \beta_8 X_{8INPUTCOST} + \mu_i$

Where:

P = probability of adoption

Y: Adoption of CSA (1 = adopter, 0 = non-adopter, Dependent variables)

Independent variables

$X_1$ = CSA adoption index (continuous 0–1)

$X_2$ = Age (years)

$X_3$ = Sex (male = 1, female = 0)

$X_4$ = Education level (years of schooling)

$X_5$ = Household size (number of members)

$X_6$ = Income (₦, annual)

$X_7$ = Farm size (hectares)

$X_8$ = Input cost (₦)

$\beta_0$ = intercept

$\beta_1, \beta_2, \ldots, \beta_8$ = coefficients

$\mu_i$ = error term

For productivity analysis, four functional forms (linear, exponential, semi-log, and double-log) were tested. The double-log model was selected as the lead equation because it gave the best fit, and is given as

$\ln Y = \beta_0 + \beta_1 \ln_{(CSA)} + \beta_2 \ln_{(FarmSize)} + \beta_3 \ln_{(InputCost)} + \beta_4 \ln_{(Age)} + \beta_5 \ln_{(EduLevel)} + \beta_{6(Sex)} + \varepsilon_i$

Where:

Y = Cassava yield (kg/ha): productivity measure (dependant variable)

Independent variables

$X_1$ = CSA adoption index (continuous 0–1)

$X_2$ = Farm size (hectares)

$X_3$ = Input cost (₦)

$X_4$ = Age (years)

$X_5$ = Education level (years of schooling)

$X_6$ = Sex (male = 1, female = 0)

$\varepsilon_i$ = error term

$\beta_0$ = intercept

$\beta_1, \beta_2, \ldots, \beta_6$ = regression coefficients

The coefficients are interpreted as elasticities, indicating percentage changes in yield for a 1% change in each independent variable.

**Data Analysis**

Descriptive statistic which involves the use of frequencies distributions and percentages, was used to address objective 1, CSA Adoption Index (AI) which is to quantify the level of CSA practices adoption among farmers. Where a composite index was created by assigning values to different CSA practices based on their adoption status (1 for adopted, 0 for not adopted), the adoption index varies from 0–1 depending on the farmer's degree of adoption of the practices.

The level of CSA adoption among cassava farmers was quantified using a CSA Adoption Index. This index was calculated by summing the number of CSA practices adopted by each farmer and dividing it by the total number of practices considered. The index values ranged from 0 to 1, depending on the farmer's degree of adoption of the practices. They were classified into three categories, that is, low adoption = 0.01–0.33, medium adoption = 0.34–0.66 and high adoption = 0.67–1.0, as adopted from Ibrahim *et al*. (2024). The calculated values were presented on a bar chart which was used to address objective 2. While Logit regression was used to address objective 3. Lastly, Multiple Linear Regression Analysis was used to addressed objective 4.

## Results and discussion

### Climate-Smart Agriculture (CSA) Practices Available and in Use in the study area

This section focuses on identifying the Climate-Smart Agriculture (CSA) practices that are available and currently being used by cassava farmers in Odukpani LGA as it is presented in table 1. Understanding these practices provides a foundation for assessing adoption levels and determining opportunities for further improvements in sustainable farming methods. A total of 407 responses were recorded across the various CSA practices. Because respondents could select more than one practice, totals exceeded 120 farmers (table 1). This reflects the integrated nature of CSA adoption, where farmers often combine several sustainable practices simultaneously.

Improved cassava seed varieties are widely adopted, with 85 farmers (70.8%) using them. This practice underscores farmers' awareness of productivity enhancements through superior crop genetics, this aligns with research by Akinyemi *et al.* (2022) who noted that the use of improved cassava varieties led to yield increases of up to 30% in south-eastern Nigeria. The use of cover crops, which is important for soil protection and improvement, is also adopted by 85 farmers (70.8%), as stated in research by Lipper *et al*. (2014) the introduction of cover crops can play a vital role in soil protection. Crop rotation, a key component of sustainable soil management, is practiced by 90 farmers (75%) which is in line with the studies by Ojo & Fagbenie (2020) who have emphasized that effective crop rotation can significantly improve soil fertility and reduce the incidence of pests and diseases. This demonstrates a strong effort by farmers to maintain soil health, reduce pest and disease incidence, and enhance long-term yields. The high rates of adoption of improved seed varieties (70.8%), use of cover crops (70.8%), and crop rotation (75%) suggest that farmers are both aware of and benefit from these practices. The use of improved varieties likely leads to higher yields and disease resistance, while crop rotation provides soil health benefits, leading to enhanced sustainability.

Soil management practices are implemented by 45 farmers (37.5%), which reflects a moderate level of attention to soil health, this could be linked to the challenges of accessing suitable soil amendments or lack of adequate training, as noted by researchers, such as Eze *et al.* (2021). Water management techniques, crucial for efficient water use, are employed by 50 farmers (41.7%), and Pest management practices, crucial for crop protection, are utilized by 52 farmers (43.3%). Despite the recognized benefits, the adoption of soil management practices (37.5%), water management (41.7%), and pest management (43.3%) is lower, indicating potential barriers to implementation. Farmers are faced with challenges such as lack of knowledge, access to necessary inputs, and high initial costs. Farmers are adopting multiple practices which indicates a holistic approach to CSA. However, the differences in the adoption rates suggest that some practices might be more easily implemented due to factors such as accessibility to information, the availability of resources, and the perceived benefits.

Table 1: Distribution of Respondents by CSA Practices available or in used in the study area

| CSA Practices available and in use in the study area | Number of Farmers who adopted the practice (n) | Percentage of Farmers who adopted the practice (%) |
|---|---|---|
| Improved Seed Varieties | 85 | 70.8 |
| Crop Rotation | 90 | 75 |
| Soil Management | 45 | 37.5 |
| Water Management | 50 | 41.7 |
| Cover Crops | 85 | 70.8 |
| Pest Management | 52 | 43.3 |
| Total | 407* | 339.1* |

* Multiple response

**Level of CSA Practices Adoption**

This section addresses the level of Climate-Smart Agriculture (CSA) practices adoption among cassava farmers in Odukpani LGA. The degree of CSA adoption is crucial for understanding the extent to which farmers are integrating sustainable practices into their farming operations and the potential impact on their productivity.

The distribution of CSA adoption scores in figure 1. reveals a spectrum of engagement with CSA practices among cassava farmers. A key insight is that a small proportion of farmers (2 farmers) did not adopt any of the CSA practices considered, while a more significant proportion adopted some level of CSA practices. The spread of the adoption index values suggests varying levels of integration of CSA techniques. The 2 farmers with an index of 0 highlight the challenges faced by these farmers, potentially due to factors like limited access to information, resources, and training. As noted by Adebayo and Sola (2022), these limitations often restrict farmers' ability to implement new practices. A substantial group of farmers (21 + 41 + 23 = 85 farmers) demonstrated medium levels of adoption (0.33 to 0.66), indicating that they have integrated some but not all CSA practices. This shows a degree of awareness about the benefits of these practices but also possible constraints to full adoption. For instance, it could mean that they are aware of practices that work but might not have access to others due to cost. About (19 + 8 = 27 farmers) demonstrated high levels of adoption (0.83 to 1.00). Indicating that these farmers are likely to be experiencing the benefits of a more integrated CSA approach. Only 6 farmers demonstrated low adoption level. This distribution indicates that although a good portion of the farmers practice CSA, a significant proportion still require increased assistance or incentives and interventions aimed at increasing adoption levels through focused education, training, and support. The level of CSA practices adoption among cassava farmers in Odukpani LGA exhibits a varied distribution, with a majority demonstrating medium levels of adoption and a few demonstrating very high levels of adoption. This highlights both successes and areas for improvement in promoting sustainable farming methods.

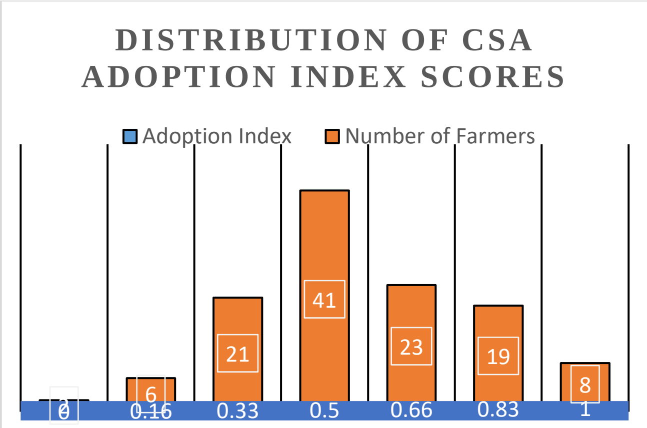


Figure 1. Bar chart showing CSA Adoption Index scores

**Socio-economic Factors Influencing the Rate of Adoption of Climate-Smart Agriculture (CSA) Practices**

The logistic regression model revealed that CSA awareness and exposure (B = 4.558, $p < 0.001$) and farm income (B = 0.214, p = 0.050) significantly influenced the rate of adoption. The odds ratio (ExpB = 95.35) indicates that farmers exposed to CSA were about 95 times more likely to adopt it than those without exposure. Education had a positive but marginal effect (B = 0.135, p = 0.079), while age was negative (B = -0.063, p = 0.076), suggesting that younger farmers were more likely to adopt CSA practices. Gender had a positive coefficient but was statistically insignificant, indicating that male-headed households were more likely to adopt CSA practices than female-headed households, which aligns with a priori expectations, given men's relatively greater access to productive resources, extension services, and decision-making power in the study area. Household size, input cost, and farm size were also insignificant but exhibited signs consistent with theoretical expectations.

The model was statistically significant ($\chi^2$ = 89.964, $p < 0.001$) with Nagelkerke $R^2$ = 0.814, indicating that 81.4% of the variation in adoption was explained by the model. These findings align with studies by Asfaw *et al*. (2016) and Nnadi and Akwiwu (2018) showing that education, income, and information access enhance CSA adoption. Arslan *et al*. (2021) similarly reported that access to information, youth involvement, and financial capacity positively influence CSA adoption.

Table 2: Logit Regression Results Revealing the Socio- economic Factors Influencing the Adoption of Climate-Smart Agriculture (CSA) Practices in the study area

| Variable | Coefficient | SE | Z | Sign | Exp(B) |
|---|---|---|---|---|---|
| $X_{1CSA}$ | 4.558*** | 1.078 | 4.228 | .000 | 95.346 |
| $X_{2Age}$ | -.063* | .071 | -0.887 | .076 | .939 |
| $X_{3Sex}$ | -.258 | .957 | -0.269 | .787 | .773 |
| $X_{4Edulevel}$ | .135* | .110 | 1.227 | .079 | 1.116 |
| $X_{5HHSize}$ | .642 | .446 | 1.439 | .150 | 1.901 |
| $X_{6Income}$ | .214** | .011 | 19.455 | .050 | 1.000 |
| $X_{7Farmsize}$ | .091 | 2.459 | .037 | .971 | 1.095 |
| $X_{8Inputcost}$ | .000 | .000 | .000 | .831 | 1.000 |
| Constant | -10.847 | 3.119 | -3.477 | .001 | .000 |

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%. Number of Observations = 120; LR $Chi^2$ = (89.964); Prob > $Chi^2$ = 0.0001; Pseudo$R^2$ = 0.246; Log likelihood = 35.474; Nagelkerke $R^2$ = .814

**Effects of CSA Adoption on the Productivity of Cassava Farmers**

The multiple regression estimates (linear, exponential, double-log, and semi-log models) in table 3 evaluated the effect of CSA adoption on cassava productivity. Across all model specifications, CSA adoption and farm size consistently showed positive and statistically significant effects on yield. Among the four functional forms tested, the double-log model gave the best fit ($R^2$ = 0.857; Adjusted $R^2$ = 0.849; F = 102.093, $p < 0.001$), explaining 85% of the variation in cassava yield. The estimated equation is:

$$\ln Y = 1.622 + 0.283\ln(CSA) + 1.103\ln(Farm\ Size) + 0.020\ln(Input\ Cost) + 0.282\ln(Age) - 0.027\ln(Edu\ Level) - 0.177(Sex)$$

CSA adoption ($\beta = 0.283$, $p = 0.004$) had a positive and significant impact, implying that a 1% increase in CSA adoption raises cassava yield by 0.28%. Farm size ($\beta = 1.103$, $p < 0.001$) was also positive and significant. Age ($\beta = 0.282$, $p = 0.079$) was positive and significant implying that a 1% increase in farmers' age is associated with about a 0.28% increase in cassava productivity, though the effect is only marginally significant. This suggests that farming experience may enhance productivity, but its influence is relatively weak compared to CSA adoption and farm size. Input cost ($\beta = 0.020$, $p = 0.813$) was positive but not significant, while education and gender were negative and insignificant. The high explanatory power confirms that CSA adoption and farm size are the primary determinants of cassava yield in the area. These results align with Makate *et al*. (2019), FAO (2018), and Ogunniyi *et al.* (2022), who observed that CSA improves productivity and resilience among smallholder farmers. Similarly, Nwajiuba *et al.* (2020) found that Nigerian farmers adopting improved cassava varieties and soil management practices achieved higher yields than non-adopters.

Table 3: The multiple regression estimates (linear, exponential, double-log, and semi-log models) showing the Effects of CSA Adoption on Cassava Productivity

| Variable | Linear | Exponential | Double-log+ | Semi-log |
|---|---|---|---|---|
| Constant | -2.843 (1.050) | .293 (.268) | 1.622 (1.238) | -33.677 (19.075) |
| $X_{1CSA}$ | .4470 (.183) | .114 (.047) | .283 (.096)*** | 1.484 (1.474) |
| $X_{2Farmsize}$ | 24.226 (.881) | 1.860 (.225) | 1.103 (.063)*** | 8.867 (.973) |
| $X_{3Inputcost}$ | -9.336E-7 (.000) | -2.426E-7 (.000) | .020 (.083) | 4.365 (1.274) |
| $X_{4Age}$ | .022 (.023) | .010 (.006) | .282 (.159)* | -1.557 (2.454) |
| $X_{5Edulevel}$ | -.020 (.050) | -.003 (.013) | -.027 (.094) | 2.070 (1.448) |
| $X_{6Sex}$ | -.603 (.447) | -.123 (.114) | -.177 (.075) | -.705 (1.158) |
| $R^2$ | .952 | .648 | .857 | .720 |
| Adj $R^2$ | .949 | .629 | .849 | .704 |
| F-Statistic | 370.481 | 34.652 | 102.093 | 43.799 |
| Std.err of the estim. | 2.30374 | .58831 | .36842 | 5.67721 |

Note: + represent Lead equation, values in parenthesis are standard errors; *** Significant at 1%, and * Significant at 10%.

## Conclusion

The study concludes that the adoption of Climate-Smart Agriculture (CSA) practices has a significant positive effect on cassava productivity in Odukpani LGA. Empirical results from the regression analysis indicate that CSA adoption and farm size are the primary determinants of cassava yield in the study area. While the study did not estimate the yield effects of individual CSA practices separately, the findings suggest that farmers who adopted CSA practices generally achieved higher productivity and improved capacity to cope with climate-related challenges. However, the overall adoption of CSA practices remains moderate, largely constrained by limited access to information, financial resources, and technical support. Socio-economic factors such as income, education, and CSA awareness were found to play critical roles in influencing adoption decisions.

## Recommendations

Based on the empirical findings of the study, the following recommendations are proposed to enhance the adoption of Climate-Smart Agriculture (CSA) practices and improve cassava productivity in the study area:

1. Strengthen Farmer Awareness and Training: Since CSA awareness and exposure were found to significantly influence adoption, government agencies, NGOs, and agricultural extension services should intensify farmer education through targeted campaigns, field demonstrations, and farmer field schools focused on CSA practices.
2. Improve Access to Credit and Farm Income Support: Given the significant role of farm income in influencing CSA adoption, financial institutions and development programs should design farmer-friendly credit schemes and income-enhancing interventions to enable farmers to invest in CSA-related inputs and technologies.
3. Enhance Agricultural Extension Services: The importance of information access highlighted in the study underscores the need to deploy more trained extension officers in rural communities to

provide technical guidance on climate adaptation, farm management, and sustainable land-use practices.

4. Integrate CSA into Local Agricultural Development Policies: Policymakers should mainstream CSA into state and local agricultural development programs to ensure sustained institutional support for adoption, particularly among smallholder farmers who face resource constraints.

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