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# Assessing the Economic Implications of Climate Variability and Adaptation Strategies among Smallholder Farmers in South-West Nigeria

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## ABSTRACT

***Agriculture in sub-Saharan Africa is highly exposed to climate variability, yet micro-level evidence linking hydroclimatic exposure, farm income, and adaptation behaviour remains limited. This study examines associations among rainfall, temperature, farm-income patterns, and the adoption of climate-smart agricultural practices among 300 smallholder farmers in Oyo, Ondo, and Ekiti States, South-West Nigeria. Cross-sectional household data for the 2024 production year were matched with location-specific meteorological records. Descriptive and bivariate analyses were used to characterise climate–income patterns, while binary logistic regression estimated correlates of adopting at least one climate-smart practice. Mean annual rainfall was highest in Ondo (1,509.84 mm) and lowest in Oyo (1,305.98 mm), while adoption rates ranged from 21% in Oyo to 33% in Ondo. Within the observed data, rainfall showed a positive descriptive gradient with farm income and a positive multivariable association with adoption ($\beta = 0.0035$ per mm, $p < 0.001$; approximately OR = 1.42 per 100 mm). Temperature showed a negative but only marginally supported association with adoption ($\beta = -0.1614$, $p = 0.064$). Farm size, education, and IHS-transformed income were not independently significant after adjustment for climatic exposure and state fixed effects. Model discrimination was modest (AUC = 0.67); the reported 73% classification accuracy should be interpreted cautiously because it is approximately equal to the majority-class baseline implied by the sample adoption prevalence. The findings support integrated attention to water management, climate information, extension support, and accessible adaptation finance, while the cross-sectional design precludes causal claims about climate impacts.***

***Keywords:*** climate variability; farm income; climate-smart agriculture; adaptation; smallholder farmers; Nigeria

## I. INTRODUCTION

Climate change is reshaping agrarian livelihoods through interacting biophysical and socio-economic pathways, including heat stress, rainfall variability, flooding, and disruptions to labour, markets, and input access that can amplify income volatility in rain-fed systems (IPCC, 2022; WMO, 2025). Across Africa, observed warming and increasing hydroclimatic extremes are intensifying risks to water availability, crop production, and food security (IPCC, 2022; WMO, 2025). These pressures intersect with persistent structural food insecurity, with recent global assessments showing that Africa remains disproportionately affected by hunger and undernourishment (FAO et al., 2024).

Smallholder farmers occupy a central yet vulnerable position within this landscape. Many operate predominantly rain-fed systems with limited access to irrigation, storage, insurance, formal credit, and timely climate information, increasing exposure to climatic shocks (IPCC, 2022; Mosha & Ngulube, 2025). Within the climate-risk framework, risk arises from the interaction of hazard, exposure, and vulnerability (IPCC, 2022). Vulnerability is shaped by access to human, physical, natural, financial, and social capital (Chambers & Conway, 1992), as well as by the capacity of social-ecological systems to absorb, reorganise, and transform under stress (Folke et al., 2010).

Adaptation encompasses behavioural, technological, and institutional responses intended to reduce climate-related harm or exploit emerging opportunities (IPCC, 2022). The climate-smart agriculture literature identifies recurring farm-level responses, including adjustments to planting dates, varietal diversification, soil and water conservation, irrigation or water harvesting, mixed cropping, and climate-informed decision-making (Adeagbo et al., 2023; Saadu et al., 2024; Izuogu et al., 2025). However, the evidence base remains uneven: many studies rely on cross-sectional indicators of any adoption, provide limited evidence on welfare effects or persistence, and treat institutional determinants such as extension access, climate information, finance, and governance as background conditions rather than jointly modelled constraints.

These limitations are especially relevant in Nigeria, where severe floods, recurrent drought and heat stress, and infrastructure constraints create substantial welfare and fiscal risks. The 2022 floods caused widespread losses across agricultural and non-agricultural sectors (UNDP, 2023), while macroeconomic assessments identify climate change as a material long-term risk to growth and public finances (IMF, 2025). Nigeria also remains highly vulnerable relative to its readiness to adapt (ND-GAIN, 2024). Although the national policy architecture has evolved, including the Climate Change Act 2021, available adaptation finance remains far below estimated needs (Federal Government of Nigeria, 2021; Stout et al., 2025; UNEP, 2025).

Despite a growing Nigerian and West African literature on climate perceptions and adaptation, fewer studies explicitly connect observed hydroclimatic exposure with both farm-income patterns and the probability of adopting climate-smart practices. Discrete-choice models provide a coherent framework for estimating adoption probabilities conditional on climatic and socio-economic covariates (Greene, 2012; Wooldridge, 2010), while descriptive climate–income analyses can reveal patterns that motivate, but do not establish, causal climate–income relationships. Community-level evidence from South-West Nigeria also underscores the importance of context-specific assessment of climate impacts and adaptation responses (Odelola et al., 2025).

Using household survey data from 300 smallholder farmers in Oyo, Ondo, and Ekiti States, matched to location-specific rainfall and temperature records for the 2024 production year, this study examines hydroclimatic patterns in farm income and estimates correlates of adopting at least one climate-smart practice. The analysis is intentionally associational: the cross-sectional design does not identify causal climate effects.

The study addresses three questions: (RQ1) How do observed rainfall and temperature conditions vary across the sampled locations, and what bivariate patterns are evident between rainfall and farm income? (RQ2) How are hydroclimatic exposures associated with the probability of adopting at least one climate-smart practice? (RQ3) Do human-capital and asset proxies, including education, farm size, and income, remain independently associated with adoption after climatic exposure and state-level heterogeneity are accounted for?

This article reports the quantitative cross-sectional component of a broader research project on the economic impacts of climate change on agricultural productivity in South-West Nigeria. The present analysis focuses on associations among matched 2024 hydroclimatic exposure, farm-income patterns, and climate-smart practice adoption among 300 sampled farmers. Historical and projected climate-trend analysis, qualitative interviews and focus-group discussions, and formal policy evaluation are outside the scope of this article.

## II. METHODS

### 1.1 Study area and sampling design

The study was conducted in Oyo, Ondo, and Ekiti States in South-West Nigeria. The states were selected to capture agro-ecological and hydroclimatic variation within a broadly comparable regional setting. Agriculture is predominantly rain-fed, with major production systems including cassava, maize, vegetables, and tree crops such as cocoa. Although the states share important institutional and market features, rainfall distribution and temperature regimes vary sufficiently to support within-region analysis of climate exposure and adaptation behaviour.

Meaningful hydroclimatic variation also occurs within states across Local Government Areas (LGAs) and rural communities. This local variation is important because farmers' production and adaptation decisions respond to conditions experienced at farm and community scales rather than to state-wide averages alone.

A cross-sectional household survey was implemented in 2025 and collected information relating to the 2024 production year from 300 smallholder farmers, with 100 respondents in each state. A multistage sampling procedure was used. Farming-dominant LGAs were identified first; rural communities were then sampled within selected LGAs; and respondents were randomly drawn from available community-level farmer lists. The analytical sample therefore represents the sampled farming communities rather than all smallholders in South-West Nigeria.

### 1.2 Data sources and variable construction

Primary data were collected using a structured questionnaire covering household characteristics, years of formal education, cultivated area in hectares, annual farm income, and the use of climate-smart agricultural practices during the 2024 reference year.

Adoption was operationalised as a binary indicator equal to one when a household reported using at least one climate-smart agricultural practice during the reference season and zero otherwise. This definition captures the extensive margin of adoption and does not measure the number, intensity, duration, or effectiveness of practices (Greene, 2012).

Daily rainfall and temperature records were obtained from Nigerian Meteorological Agency (NiMet) station archives and, where station coverage was sparse, from the historical gridded source retained in the study database. Surveyed communities were matched to the nearest available climate record, and daily observations were aggregated over the 2024 production year. Annual total rainfall ($R_i$) and mean annual temperature ($T_i$) therefore vary across sampled locations, including within states.

State fixed effects were included in the adoption model to absorb time-invariant state-level heterogeneity, while climate coefficients were identified from residual spatial variation in exposure within states. Cluster-robust standard errors were calculated at the sampling-cluster level to account for within-cluster dependence arising from the multistage design and shared local exposure.

### 1.3 Income measurement and transformation

Farm income was measured in Nigerian naira (NGN) for the 2024 agricultural year. Because some households reported zero or negative net income, the inverse hyperbolic sine (IHS) transformation was used for income in the regression model:

$$\mathrm{IHS}(Y_i) = \ln[Y_i + \sqrt{(Y_i^2 + 1)}] \quad (1)$$

The IHS transformation is defined for positive, zero, and negative values and behaves similarly to the natural logarithm for sufficiently large positive values. It reduces the leverage of extreme observations while retaining the full sample. Because interpretation depends on the scale of the underlying monetary variable, the IHS coefficient is treated here primarily as an adjusted covariate effect rather than as an exact elasticity.

### 2.4 Analytical strategy

#### 2.4.1 Climate-income relationship and Ricardian framework

To frame the climate–income relationship, the study adopts a reduced-form Ricardian specification relating farm income to rainfall, temperature, nonlinear climate terms, observed household and farm characteristics, and state fixed effects:

$$Y_i = \alpha_0 + \alpha_1 R_i + \alpha_2 R_i^2 + \alpha_3 T_i + \alpha_4 T_i^2 + \delta' X_i + \gamma_s + u_i \quad (2)$$

where $Y_i$ denotes farm income; $R_i$ and $T_i$ denote rainfall and temperature; $X_i$ is a vector of observed household and farm characteristics; $\gamma_s$ represents state fixed effects; and $u_i$ is the disturbance term. The nonlinear terms allow for potential threshold or diminishing marginal associations. In the present article, the climate–income evidence reported in Section 3 is descriptive and bivariate; the Ricardian specification is presented as the analytical framework and is not used to support unreported coefficient estimates.

#### 2.4.2 Adoption model

A binary logistic regression model was estimated to examine associations between climatic exposure and the probability of adopting at least one climate-smart practice (Greene, 2012; Wooldridge, 2010):

$$\ln[p_i/(1 - p_i)] = \beta_0 + \beta_1 R_i + \beta_2 T_i + \beta_3 S_i + \beta_4 E_i + \beta_5 \mathrm{IHS}(Y_i) + \gamma_s + \varepsilon_i \quad (3)$$

where $p_i$ is the probability that household i adopts at least one climate-smart practice; $R_i$ and $T_i$ denote annual rainfall and mean annual temperature; $S_i$ is farm size in hectares; $E_i$ is years of formal education; $\mathrm{IHS}(Y_i)$ is transformed farm income; and $\gamma_s$ represents state fixed effects. The coefficients are interpreted as conditional associations rather than causal effects.

### 2.5 Model estimation and evaluation

The logistic model was estimated by maximum likelihood using Python's statsmodels package. Statistical inference used cluster-robust standard errors at the sampling-cluster level. Model discrimination was evaluated using the area under the receiver operating characteristic curve (AUC) (Fawcett, 2006). Classification accuracy is also reported, but it is compared with the majority-class baseline because accuracy can be misleading when outcome classes are imbalanced. Predicted probabilities were generated over a rainfall–temperature grid while holding non-climate covariates at their sample means; regions of the plotted grid extending beyond the empirical support of the sample should be interpreted as extrapolations rather than observed response patterns.

## III. RESULTS

### 3.1 Descriptive hydroclimatic patterns and adoption rates

Table 1 summarises state-level hydroclimatic conditions and adoption rates. Mean annual rainfall was highest in Ondo State (1,509.84 mm), followed by Ekiti (1,393.48 mm) and Oyo (1,305.98 mm). Mean annual temperatures varied less, from 26.70 °C in Ekiti to 27.70 °C in Oyo. Adoption rates differed more clearly: Ondo recorded the highest share of farmers using at least one climate-smart practice (0.33), followed by Ekiti (0.26) and Oyo (0.21). These state averages are descriptive and should not be interpreted as causal climate effects.

The observed rainfall differences are consistent with pronounced spatial and temporal variability documented for South-West Nigeria (Awode et al., 2025; WMO, 2025). At the same time, state means can conceal substantial within-state heterogeneity, which motivates the use of respondent-location climate exposure in the multivariable model.

**Table 1. Descriptive hydroclimatic conditions and adoption rates by state**

| State | Mean rainfall (mm) | Mean temperature (°C) | Adoption rate |
|---|---|---|---|
| Oyo | 1305.98 | 27.70 | 0.21 |
| Ondo | 1509.84 | 27.48 | 0.33 |
| Ekiti | 1393.48 | 26.70 | 0.26 |

*Note. Adoption rate is the proportion of sampled farmers reporting at least one climate-smart agricultural practice during the 2024 reference year.*

### 3.2 Bivariate association between rainfall and farm income

Figure 1 displays the bivariate relationship between annual rainfall and reported farm income. Within the plotted data, state-specific fitted lines show positive rainfall-income gradients. The vertical separation among fitted lines also indicates persistent differences across states at comparable rainfall levels, potentially reflecting cropping systems, input use, infrastructure, or market access. Because rainfall co-varies with agro-ecological and institutional conditions and the data are cross-sectional, the figure is descriptive; it neither estimates a causal effect of rainfall nor validates a structural Ricardian response (Mendelsohn et al., 1994).

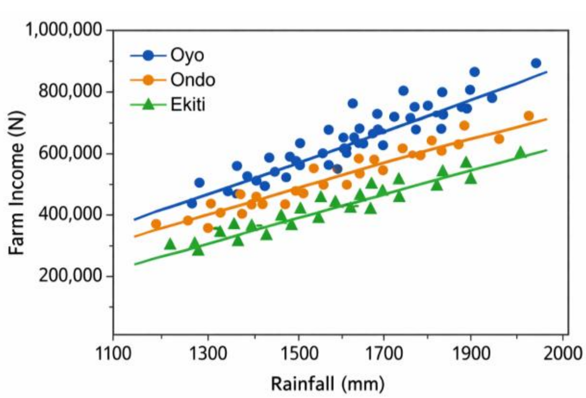


**Figure 1. Relationship between farm income and rainfall across sampled smallholder farmers in Oyo, Ondo, and Ekiti States. Each point represents a farmer; state-specific linear trend lines illustrate descriptive associations only.**

### 3.3 Multivariable correlates of climate-smart practice adoption

Table 2 reports the logistic regression estimates. Rainfall is positively associated with adoption (β = 0.0035 per mm, $p < 0.001$). The corresponding odds ratio is approximately 1.0035 per millimetre; scaled to 100 mm, the estimated odds ratio is approximately 1.42 (95% CI ≈ 1.17–1.73). Thus, within the model and observed data structure, higher rainfall exposure is associated with greater odds of adopting at least one climate-smart practice.

Temperature has a negative coefficient (β = -0.1614, p = 0.064), corresponding to an odds ratio of approximately 0.85 per 1 °C increase (95% CI ≈ 0.72–1.01). The confidence interval includes unity and the p-value exceeds 0.05; the result should therefore be described as suggestive or marginal rather than statistically significant at the conventional 5% level. Farm size, years of education, and IHS-transformed income are not statistically significant at conventional thresholds. This absence of significance does not demonstrate that the variables are unimportant; it indicates that their independent associations are imprecisely estimated in this specification.

**Table 2. Logistic regression estimates for adoption of at least one climate-smart practice**

| Variable | Coefficient | SE | p-value |
|---|---|---|---|
| Constant | -2.1958 | 2.760 | 0.426 |
| Rainfall (mm) | 0.0035*** | 0.001 | <0.001 |
| Temperature (°C) | -0.1614* | 0.087 | 0.064 |
| Farm size (ha) | 0.2899 | 0.279 | 0.299 |
| Education (years) | 0.3862 | 0.273 | 0.156 |
| Income (IHS-transformed) | -0.0686 | 0.139 | 0.621 |

*Note. The model includes state fixed effects ($\gamma_s$). SE = cluster-robust standard error at the sampling-cluster level. *** $p < 0.01$; * $p < 0.10$.*

### 3.4 Model discrimination and climate–response surface

The model yields an AUC of 0.67, indicating modest discrimination between adopters and non-adopters (Fawcett, 2006). The reported classification accuracy is 73%; however, because the overall adoption prevalence is approximately 27%, a classifier that predicts the majority class for every observation would achieve roughly 73% accuracy. The accuracy value therefore does not, by itself, demonstrate strong predictive performance.

Figure 2 shows predicted adoption probabilities across a rainfall–temperature grid while other covariates are held at their sample means. The surface is useful for visualising the fitted logistic model, but grid regions outside the empirical support of the observed data are extrapolations and should not be interpreted as directly observed response patterns.

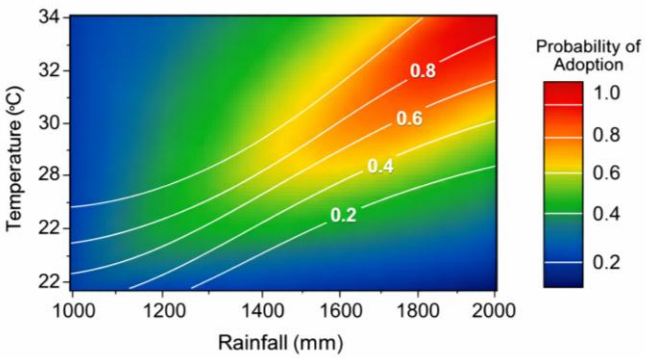


**Figure 2. Predicted probability of adopting at least one climate-smart practice as a function of rainfall and temperature, holding other covariates at their sample means. Portions of the grid outside the observed data support are extrapolations.**

## IV. DISCUSSION

### 4.1 Hydroclimatic conditions, income patterns, and adaptation

The positive rainfall-income gradients in Figure 1 are agronomically plausible in predominantly rain-fed systems, where adequate moisture can reduce within-season water stress and support crop establishment. Nevertheless, the cross-sectional bivariate pattern cannot establish that additional rainfall causes higher income. Rainfall may proxy for agro-ecological conditions, crop portfolios, market access, input use, or other spatially structured factors. The result is therefore best interpreted as an exploratory association rather than a causal climate–income effect.

The positive rainfall coefficient in the adoption model may reflect several mechanisms, but these mechanisms were not directly tested. Wetter environments may improve expected returns to selected soil, seed, and water-management practices; alternatively, rainfall exposure may be correlated with programme placement, crop systems, extension activity, or local market density. South-West Nigeria also experiences substantial rainfall variability, dry spells, and intense precipitation events (Awode et al., 2025; WMO, 2025), so adoption may represent responses to variability and excess-water risk as well as to water scarcity. Practices such as mulching, drainage, mixed cropping, and soil improvement can serve both productivity and risk-management functions.

### 4.2 Temperature stress and constrained adaptation capacity

The negative temperature coefficient is consistent with broader evidence that heat stress can reduce agricultural productivity and labour capacity, but the statistical evidence in this sample is only marginal ($p = 0.064$). Accordingly, the result should not be presented as definitive proof that higher temperature reduces adoption. A plausible interpretation is that heat-related production stress may reduce surplus income or risk-bearing capacity, particularly when adaptation requires upfront or recurrent expenditure. This interpretation is consistent with wider assessments of climate-related heat risk in African agriculture (IPCC, 2022; WMO, 2025; Sheng et al., 2025), but longitudinal data would be needed to test the mechanism directly.

### 4.3 Interpreting non-significant socioeconomic covariates

Farm size, education, and IHS-transformed income are not independently significant in the reported model. This should not be interpreted as evidence that socioeconomic resources are irrelevant to adaptation. Nigerian studies repeatedly identify extension contact, credit access, climate information, perceptions, and farmer capabilities as important correlates of climate-smart agriculture uptake or investment (Adeagbo et al., 2023; Saadu et al., 2024; Izuogu et al., 2025; Olugbenga et al., 2025). The modest AUC of 0.67 is consistent with a model that captures part, but not most, of the behavioural variation. Climatic variables may also proxy for unmeasured agro-ecological and institutional differences, which can attenuate or confound estimated socioeconomic associations.

### 4.4 Policy and investment implications

Adoption rates of 21%–33% indicate substantial scope for wider uptake of climate-smart practices in the sampled communities. The findings support a policy emphasis on enabling conditions rather than awareness alone. Nigeria-specific climate-finance assessments identify persistent financing and project-preparation constraints, while the global adaptation-finance gap remains large (Stout et al., 2025; UNEP, 2025).

The positive rainfall-adoption association highlights water-related investments as a plausible leverage point, but it does not by itself identify which intervention is most effective. Small-scale irrigation, water harvesting, drainage, erosion control, climate information, extension support, and accessible adaptation finance merit consideration as complementary measures. These statements are policy implications derived from the observed associations; they do not constitute a formal evaluation of existing agricultural or climate policies.

### 4.5 Limitations and scope

The cross-sectional design limits causal inference; reported coefficients represent associations rather than causal effects. Climate exposure was matched to respondent locations using the nearest available NiMet station or the historical gridded source retained in the study database where station coverage was limited. Measurement error may persist because of spatial gaps and the use of annual aggregates that can mask within-season extremes. The binary adoption measure captures whether any practice was used, but not adoption intensity, duration, or effectiveness.

This article reports the quantitative cross-sectional component of the broader research programme. It does not present historical and projected climate-trend analysis, qualitative key-informant interviews or focus-group discussions, or a formal evaluation of policy effectiveness. The Ricardian specification is included as an analytical framework, but no Ricardian coefficient estimates are reported; the climate–income evidence is limited to the descriptive bivariate relationship in Figure 1. These scope boundaries should be considered when interpreting and generalising the findings.

## V. CONCLUSION

This study examined associations among hydroclimatic exposure, farm-income patterns, and climate-smart agricultural adoption among 300 smallholder farmers in Oyo, Ondo, and Ekiti States. Three findings emerge from the reported evidence. First, rainfall shows a positive descriptive gradient with farm income, but the cross-sectional bivariate pattern does not establish a causal economic impact. Second, rainfall is positively associated with the odds of adopting at least one climate-smart practice in the adjusted logistic model. Third, temperature has a negative but only marginally supported association with adoption, while farm size, education, and IHS-transformed income are not independently significant in the reported specification.

The results suggest that hydroclimatic exposure may condition adaptation decisions alongside institutional and financial constraints. However, the modest AUC and the majority-class baseline underlying the reported accuracy indicate that substantial behavioural variation remains unexplained. Policy responses should therefore avoid single-factor interpretations and instead consider complementary investments in water management, climate information, extension services, and accessible finance.

The study provides a transparent quantitative contribution to the broader investigation of climate change, agricultural livelihoods, and adaptation in South-West Nigeria by separating descriptive climate–income patterns from multivariable adoption results and limiting inference to the analyses reported here.

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