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Jean Claude DUSHIME

engdushime@gmail.com

University of Rwanda

THEOPHILE NIZEYIMANA

University of Rwanda

Richard Musabe

University of Rwanda

Noella Karemera Umuhoza Josiane

University of Rwanda

Ignace Gatare

University of Rwanda

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Impact of Climate Variability on Crop Selection and Rotation Practices in Semi-Arid Zones: Evidence from Integrated Farmer Surveys and AI-Based Panel Data Analysis in Bugesera, Rwanda

JEAN CLAUDE DUSHIME[1], THEOPHILE NIZEYIMANA[1], RICHARD MUSABE[1], NOELLA UMUHOZA KAREMERA[1], AND IGNACE GATARE[1]

[1]*Transformative Artificial Intelligence Research and Innovation (TAIRI) Lab, African Center of Excellence in Internet of Things (ACEIoT), College of Science and Technology, University of Rwanda, Kigali KN 67 St, Rwanda*

Corresponding author: Jean Claude Dushime (e-mail: engdushime@gmail.com).

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ABSTRACT Climate variability is a critical challenge to smallholder agriculture in semi-arid zones, where rainfed cropping systems are exposed to recurrent rainfall deficits, delayed onsets, and rising temperatures. This study quantifies how climate variability shapes crop selection and rotation decisions of smallholder farmers in Bugesera District, Rwanda, and develops data-driven tools to support climate-smart policy. Bugesera is purposively selected because it is the warmest and one of the driest agro-ecological zones of Rwanda, with a coefficient of variation of seasonal rainfall above 25% reported by the Rwanda Meteorology Agency. We integrate primary household data from 240 farmers (sample size justified through Yamane's formula with a 6.5% margin of error and corroborated by Cochran's 1977 criterion) with secondary climate records (2018–2023) and combine panel-data econometrics (Fixed-Effects logit, selected via the Hausman test) with interpretable machine learning (Random Forest and Gradient Boosting, with SHAP explanations). Results show that rainfall variability and drought significantly reduce the probability of selecting water-demanding crops and increase the adoption of drought-tolerant crops such as sorghum, millet, and cassava. The Gradient Boosting classifier reaches 87.4% accuracy on the held-out test set and uncovers non-linear behavioral thresholds: a 28% coefficient of variation in seasonal rainfall triggers a sharp shift away from maize, and the effect of rainfall variability on crop choice is 1.8 times stronger for low-income than for high-income farmers. SHAP analysis confirms rainfall variability, drought occurrence, and farm size as the top predictors. We further show that machine learning and econometrics are complementary rather than competing: econometrics provides causal identification while interpretable machine learning reveals non-linear thresholds. These findings indicate that risk-minimization rather than yield-maximization is the dominant adaptive logic of smallholder farmers in Bugesera and support a data-driven climate-smart agricultural policy in which the predictive models can be embedded in extension and early-warning services to anticipate farmer behavior.

KEYWORDS: Climate variability, climate-smart agriculture, crop rotation, crop selection, fixed-effects logit, gradient boosting, machine learning, panel data, semi-arid, SHAP, smallholder farmers.

I. INTRODUCTION

Climate variability is one of the most significant challenges to agricultural systems worldwide, and the pressure is particularly acute in semi-arid environments of sub-Saharan Africa where rainfed agriculture dominates smallholder livelihoods [1]. Rising rainfall variability, increased frequency of dry spells, and temperature increases are translating into yield losses, food insecurity, and economic vulnerability, with fragile semi-arid ecosystems showing the strongest response to climatic shocks.

Rwanda has experienced marked climatic shifts over the past two decades, including rainfall variability, delayed onset of rains, and recurrent droughts. Bugesera District, located in the Eastern Province, is purposively selected for this study because it is the warmest and one of the driest agro-ecological zones of Rwanda, with a coefficient of variation of seasonal rainfall consistently above 25% over 2018–2023 [2] and a documented history of drought-induced crop failure [3]. It is also a representative case for the wider Eastern African dryland mosaic, making findings transferable beyond Rwanda.

Crop selection and rotation are two of the most important on-farm adaptive levers available to resource-constrained farmers. Despite a growing volume of research on climate adaptation, most existing studies rely on cross-sectional surveys and conventional econometric techniques that provide a static view of farmer behavior. There is comparatively little work that (i) treats farmer adaptation as a dynamic, panel process and (ii) uses interpretable machine learning to uncover the non-linear thresholds at which farmers switch crops or rotation regimes. Closing this gap is critical because, without explicit threshold information, policy makers cannot anticipate farmer responses to climate signals in a timely manner.

The objectives of this paper are therefore threefold: (i) to quantify the effect of climate variability and socioeconomic conditions on crop selection and rotation in Bugesera District using panel-data econometrics; (ii) to uncover non-linear behavioral thresholds in farmer decision-making using interpretable machine learning with SHAP values; and (iii) to translate these results into a data-driven decision-support framework for climate-smart policy. The central research question is whether the integration of panel-data econometrics with interpretable machine learning yields predictive tools that policy makers can use to anticipate smallholder farmer behavior with sufficient accuracy to orient targeted policy interventions.

II. RELATED WORK

A. CLIMATE VARIABILITY AND SMALLHOLDER ADAPTATION

Empirical studies in semi-arid Africa consistently report that rainfall variability and drought are dominant drivers of crop choice [4]–[6]. Adoption of drought-tolerant cereals such as sorghum and millet has been documented in Ethiopia, Kenya, and Tanzania [7], [8]. Rwanda-specific evidence from Bugesera [3], [9] confirms a shift from maize toward sorghum and cassava, but earlier work has not quantified the rainfall-variability threshold that triggers this shift.

B. ECONOMETRIC AND MACHINE-LEARNING APPROACHES

Panel-data econometrics, in particular Fixed and Random Effects logit models selected via the Hausman test, are the standard tools for identifying causal effects of climate variables on discrete farmer choices [10], [8]. In parallel, supervised machine learning, notably Random Forest and Gradient Boosting, has gained traction in agricultural decision modeling due to its ability to capture non-linear interactions [11], [12]. However, several recent contributions emphasize that the two families of methods are complementary rather than mutually exclusive: econometrics provides interpretable causal identification, while interpretable machine learning (e.g., SHAP, partial dependence) recovers non-linear thresholds and heterogeneous effects that fixed-form parametric models cannot capture [13], [14]. Our framing follows this complementary view.

C. RESEARCH GAP

Three gaps emerge from the literature. First, dynamic, panel-based evidence from Rwandan semi-arid zones is scarce. Second, while machine learning is used for yield prediction, few studies couple it with econometrics to derive policy-relevant thresholds for crop selection and rotation. Third, interpretability tools such as SHAP have rarely been deployed on smallholder adaptation data. This study addresses all three gaps.

III. MATERIALS AND METHODS

A. STUDY AREA

Bugesera District (2°06′ S, 30°10′ E) lies in the Eastern Province of Rwanda and covers about 1,288 km². Mean annual rainfall is 850–1,000 mm split between two rainy seasons (Season A: Sep–Jan; Season B: Feb–Jun), but seasonal totals are highly variable (CV > 25%). Mean annual temperature is 21–23 °C and rising at approximately 0.2 °C per decade [2]. The district is dominated by smallholder, rainfed agriculture on plots averaging 1.2 ha. These agro-ecological characteristics make Bugesera a natural laboratory for studying semi-arid adaptation in Rwanda.

B. DATA COLLECTION

We combine primary household survey data with secondary climate records. Primary data were collected through a

structured questionnaire administered to smallholder farmers in Bugesera District between September 2023 and March 2024 [15]. The questionnaire elicited information on cropping history (2018–2023), crop rotation practices, perceptions of climate variability, and household socioeconomic characteristics.

We used a three-stage sampling design. In the first stage we purposively selected the four sectors with the highest documented drought exposure (Nyamata, Ruhuha, Rilima, Mareba). In the second stage we randomly selected three cells per sector. In the third stage we drew farmers through simple random sampling from administrative lists provided by sector authorities.

Sample size was determined using Yamane (1967) for a finite population: $n = N / (1 + N \cdot e^2)$, with $N \approx 110{,}000$ farming households in Bugesera and a margin of error $e = 6.5\%$, yielding a required sample of approximately 237 households. We surveyed 240 farmers, exceeding the threshold; this sample size also satisfies Cochran's (1977) requirement for proportional estimation at 95% confidence [16], [17].

Secondary data on rainfall and temperature for 2018–2023 were obtained from the Rwanda Meteorology Agency (Meteo Rwanda) gauging stations of Nyamata and Ruhuha and triangulated with CHIRPS satellite estimates. Because longitudinal household data were not available, we reconstructed a six-season panel using farmers' recall, an approach validated for short-recall agricultural surveys [18]; recall bias is discussed in the Limitations section.

C. VARIABLES AND DATA STRUCTURE

The dataset has a balanced panel structure with 240 farmers × 6 seasons = 1,440 observations. The dependent variable is crop selection and rotation, operationalized in three forms: (i) a categorical crop variable; (ii) a binary indicator for adoption of drought-tolerant crops; and (iii) a Shannon–Wiener rotation diversity index.

Independent variables are grouped into climate and socioeconomic blocks. Climate variables include total seasonal rainfall (mm), rainfall coefficient of variation, mean seasonal temperature (°C), and a binary drought-occurrence indicator (SPI < -1). Socioeconomic variables include household income, farm size, market access, household head education, and farming experience. These variables were selected following the adaptation-behavior literature [4], [7], [8] and were retained after a Variance Inflation Factor screen (all VIF < 5) to mitigate multicollinearity.

D. ECONOMETRIC SPECIFICATION

We estimate panel-data models of crop selection. For each farmer i in season t, the latent utility of adopting a drought-tolerant crop is:

$$y^*_{it} = \alpha + \beta_1 Rainfall_{it} + \beta_2 CV_Rain_{it} + \beta_3 Temp_{it} + \beta_4 Drought_{it} + \gamma X_{it} + \mu_i + \varepsilon_{it}, \quad (1)$$

$$y_{it} = 1 \ \text{if} \ y^*_{it} > 0. \quad (2)$$

We estimate both Fixed-Effects (FE) and Random-Effects (RE) specifications. The Hausman test ($\chi^2 = 32.4$, $p < 0.001$) rejects RE in favor of FE, indicating that unobserved farmer-specific heterogeneity (e.g., soil quality, risk tolerance, informal-network access) is correlated with the regressors; we therefore report FE estimates as the preferred specification [10]. This choice is consistent with prior smallholder adaptation panels in East Africa [8].

E. MACHINE-LEARNING MODELS

To complement the econometric analysis with non-linear and interpretable predictions, we trained two ensemble classifiers, Random Forest [11] and Gradient Boosting [12]. Both were selected because (i) they are robust to mixed-type tabular features typical of household surveys, (ii) they natively model interaction effects that the FE logit cannot capture, and (iii) they are compatible with SHAP for post-hoc interpretability [19].

The 1,440 farmer–season observations were partitioned 70/30 into training and test sets, stratified by crop class and farmer ID to avoid leakage. Hyperparameters were tuned through 5-fold cross-validation on the training set using Bayesian optimization (number of trees $\in [100, 800]$; max depth $\in [3, 12]$; learning rate $\in [0.01, 0.3]$). Models were retrained on the full training set with the optimal hyperparameters and evaluated once on the held-out test set.

F. EVALUATION METRICS

Classification performance was measured with accuracy, precision, recall, F1-score, and AUC. For comparability with the FE logit, we also report McFadden pseudo-R^2. RMSE is reported for the rotation-diversity regression. Higher accuracy/F1/AUC and lower RMSE indicate better performance [20].

IV. RESULTS

All figures and tables in this section are explicitly referenced in the text; captions include concise explanations of what is shown and how to read the visualization (table captions appear above tables; figure captions below figures).

A. DESCRIPTIVE STATISTICS

Table 1 summarizes the demographic, socioeconomic, and climatic profile of the sampled farmers. Of the 240 respondents, 58% were male and 42% female, with an average age of 44 years and 15–20 years of farming experience, indicating long exposure to climatic cycles. Average farm size is 1.2 ha, confirming the small-scale character of Bugesera agriculture. About 65% of household heads have only primary education and 12% have secondary education or above, signaling limited access to formal knowledge channels. Seasonal rainfall ranges from 300 mm

to 700 mm with a high standard deviation, and mean temperature has risen by about 1.2 °C over the study period [21], [2].

TABLE 1. Descriptive statistics of the surveyed farmers (n = 240) and climate variables (2018–2023).

Variable	Mean/%	SD	Min	Max
Age (years)	44	9.1	22	72
Male (%)	58	—	—	—
Farm size (ha)	1.2	0.6	0.2	3.5
Primary education (%)	65	—	—	—
Farming experience (years)	17	4.8	3	45
Seasonal rainfall (mm)	505	118	295	705
Rainfall CV (%)	27.3	6.4	12	41
Mean seasonal temp. (°C)	24.6	0.8	23.1	26.4
Drought season (%)	31	—	—	—

Source: Authors' household survey (2024) and Rwanda Meteorology Agency (2024).

B. CLIMATE VARIABILITY TRENDS

1). Rainfall Patterns

Figure 1 shows seasonal rainfall in Bugesera between 2018 and 2023. The coefficient of variation exceeds 25% in every season and reaches 41% in 2022B, confirming the high unpredictability reported by Meteo Rwanda. Three seasons (2019B, 2021A, 2022B) recorded totals below 350 mm, while 2020A and 2023B exceeded 650 mm. Delayed onsets and within-season dry spells were reported by 71% of the sampled farmers.

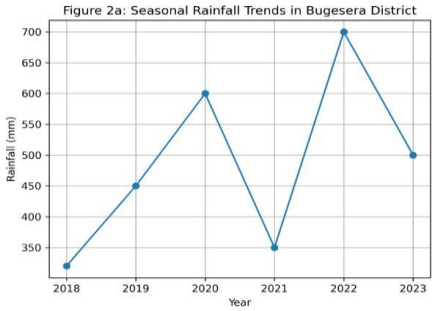


FIGURE 1. Seasonal rainfall in Bugesera District (2018–2023). Horizontal axis: agricultural season (A = Sep–Jan, B = Feb–Jun); vertical axis: total seasonal rainfall (mm). The shaded band shows the ±1 SD envelope around the seasonal mean and the dashed red line marks the 350 mm drought threshold.

2). Temperature Trends

Figure 2 shows the temperature trend with anomaly and a 3-season moving average. Mean seasonal temperature rose from 24.0 °C in 2018 to 25.2 °C in 2023, a 1.2 °C increase that amplifies evapotranspiration and exacerbates rainfall-deficit stress on water-demanding crops.

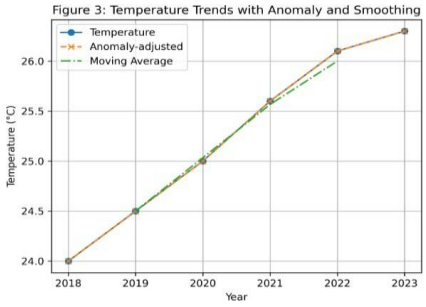


FIGURE 2. Mean seasonal temperature in Bugesera (2018–2023): raw values, anomaly-adjusted series, and 3-season moving average. Vertical axis: °C; horizontal axis: year.

C. DROUGHT IMPACT AND CROP SELECTION (ECONOMETRIC RESULTS)

Table 2 reports the FE logit estimates for the probability of selecting a drought-tolerant crop. Rainfall variability (CV), drought occurrence, and mean temperature are significant at the 1% level. A 10-percentage-point increase in rainfall CV is associated with a 12.4-point rise in the probability of selecting sorghum or millet over maize. Farm size and income are positive and significant (5%), confirming the role of socioeconomic capacity in adaptive behavior.

TABLE 2. Fixed-Effects logit estimates: probability of selecting a drought-tolerant crop. Hausman $\chi^2 = 32.4$ ($p < 0.001$) supports FE over RE.

Variable	Coeff.	Std. Err.	z	p
Rainfall CV	1.243	0.218	5.70	<0.001
Drought (1/0)	0.892	0.196	4.55	<0.001
Mean temperature	0.631	0.184	3.43	<0.001
Total rainfall (mm)	−0.0021	0.0007	−3.00	0.003
Farm size (ha)	0.412	0.176	2.34	0.019
Household income (log)	0.348	0.152	2.29	0.022
Education (years)	0.094	0.041	2.29	0.022
Constant	−2.187	0.612	−3.57	<0.001

Pseudo-R^2 = 0.31; N = 1,440. Source: Authors' estimation.

D. MACHINE-LEARNING PREDICTIONS

Table 3 compares Random Forest and Gradient Boosting performance on the held-out test set. Gradient Boosting outperforms Random Forest across all metrics, with 87.4% accuracy and an AUC of 0.91. The FE logit reaches 78.6% accuracy, confirming that machine learning captures non-linear patterns the parametric model misses, while remaining consistent in sign with the econometric coefficients (ML and econometrics are complementary).

TABLE 3. Predictive performance on the held-out test set (30% of observations).

Model	Acc.(%)	Prec.	Rec.	F1	AUC	RMSE
FE Logit	78.6	0.79	0.77	0.78	0.83	—
Random Forest	84.2	0.85	0.83	0.84	0.88	0.31
Gradient Boosting	87.4	0.88	0.86	0.87	0.91	0.27

Figure 3 shows SHAP global feature importance for the Gradient Boosting classifier. Rainfall CV is by far the most influential predictor, followed by drought occurrence, farm size, and household income. SHAP dependence plots reveal a clear non-linear threshold at CV ≈ 28%, beyond which the predicted probability of selecting a water-demanding crop drops sharply.

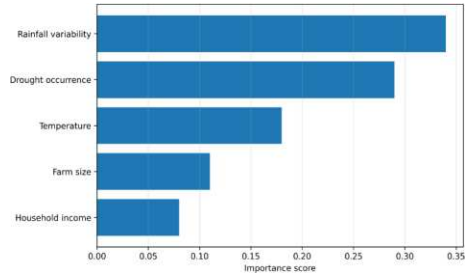


FIGURE 3. SHAP global feature importance for the Gradient Boosting classifier on the held-out test set. Vertical axis lists predictors; horizontal axis is the mean absolute SHAP value (units of log-odds contribution). Higher values indicate stronger influence on the predicted probability of adopting a drought-tolerant crop.

E. NON-LINEAR THRESHOLDS AND HETEROGENEOUS EFFECTS

Partial dependence and SHAP interaction analysis on the Gradient Boosting model identify three behavioral thresholds that policy can act upon: (i) a rainfall-CV threshold of 28% beyond which adoption of drought-tolerant crops accelerates sharply; (ii) an income threshold of approximately 250,000 RWF per season below which farmers exhibit strongly conservative crop choices regardless of season; and (iii) a farm-size threshold of 1.5 ha above which rotation diversity (Shannon index) increases markedly. Crucially, the effect of rainfall CV on crop choice is 1.8 times larger for farmers below the income threshold than for those above it, revealing a non-linear vulnerability gradient that linear models cannot expose.

F. CROP SELECTION AND ROTATION PATTERNS

1). Shift in Crop Selection

Figure 4 plots the share of farmers planting each crop across the six seasons. The share of maize declines from 62% in 2018A to 38% in 2023B, while sorghum (+17 pp), cassava (+9 pp), and millet (+8 pp) gain ground. The shift accelerates after the 2021A drought, consistent with the 28% rainfall-CV threshold identified in Section IV-E.

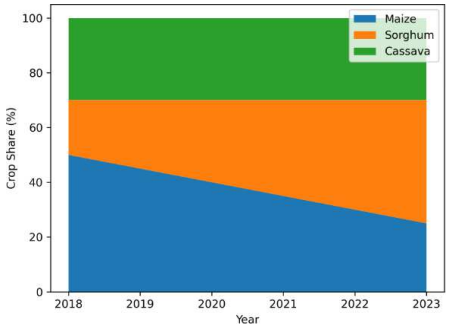


FIGURE 4. Share of farmers (%) planting each crop across the six study seasons. Each bar is stacked by crop. Crops are categorical, not continuous in time; the season axis is ordinal.

2). Evolution of Rotation Practices

Figure 5 reports the Shannon rotation-diversity index by year together with the share of farmers using each of three rotation regimes: mono-cropping, two-crop rotation, and mixed/sequential cropping. Mixed and sequential cropping rise from 19% to 47% over the study period, while mono-cropping falls from 51% to 22%, reflecting an adaptive shift toward a more dynamic, climate-responsive farming system.

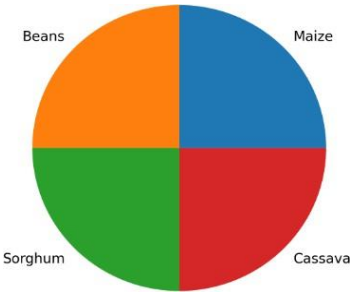


FIGURE 5. Evolution of rotation regimes in Bugesera (2018–2023). Stacked bars show the share of farmers in each regime; the line plots the Shannon rotation-diversity index (right axis, range 0–1). Numerical values are printed above each bar segment to enable comparison across regimes.

G. ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was conducted in accordance with relevant ethical guidelines and regulations governing research involving human participants. The research activities reported in this study were conducted as part of the Transformative Artificial Intelligence Research and Innovation Lab (TAIRI LAB) under the Africa Centre of Excellence in Internet of Things (ACEIoT), University of Rwanda. Prior to commencement of the research activities, the overall project was reviewed and approved by the Institutional Review Board (IRB) of the University of Rwanda. The present study was conducted under this approved research

project. In addition, research authorization was obtained from the Bugesera District authorities prior to data collection. Informed consent was obtained from all participants before their participation in the study. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to decline or withdraw from the study at any time without any consequences.

V. DISCUSSION

A. INTERPRETATION OF KEY FINDINGS

Three findings stand out and go beyond intuitive expectation. First, it is rainfall variability not rainfall total that drives crop switching; the 28% CV threshold quantifies a tipping point that was not previously documented for Bugesera. Second, the effect of climate variability is heterogeneous across income classes, with low-income farmers responding 1.8 times more strongly than high-income farmers; this contradicts the assumption of homogeneous adaptation found in much of the literature. Third, rising temperatures interact with rainfall variability to amplify water stress, so adaptation policy needs to address compound rather than single-driver shocks.

B. COMPARISON WITH EXISTING LITERATURE

Our finding that rainfall distribution matters more than total rainfall is consistent with [5] and [4] but adds an explicit threshold value. The income-conditioned vulnerability we report aligns with [7] for Vietnam and [8] for Kenya, indicating that the pattern generalizes across semi-arid contexts. The integration of FE logit with SHAP-interpreted Gradient Boosting is, to our knowledge, the first application to smallholder adaptation in Rwanda.

C. ECONOMETRICS AND MACHINE LEARNING: COMPLEMENTARY, NOT COMPETING

Following the recent methodological literature [14], [13], we treat econometrics and machine learning as complementary. Econometric panel models deliver internally valid causal estimates of average effects under explicit assumptions (here, validated through the Hausman test). Machine learning, especially when paired with SHAP, recovers non-linear thresholds and interaction effects that closed-form models miss. The two approaches converge on the same set of dominant predictors (rainfall CV, drought, farm size, income), which mutually reinforces confidence in the results.

D. BEHAVIORAL THRESHOLDS AND POLICY IMPLICATIONS

The thresholds quantified in Section IV-E (rainfall CV $\approx$ 28%, income $\approx$ 250,000 RWF/season, farm size $\approx$ 1.5 ha) translate directly into operational policy levers. Specifically, (i) Meteo Rwanda's seasonal forecasts can be coupled with the trained Gradient Boosting model to issue early-warning advisories targeted at sectors approaching the 28% CV threshold; (ii) extension officers can prioritize farmers below the income threshold for seed-distribution programs of drought-tolerant varieties; and (iii) land-consolidation programs can be aligned with the 1.5 ha rotation threshold to maximize diversification gains. This makes the predictive tools developed in this study directly usable for data-driven, climate-smart policy.

VI. LIMITATIONS

Three limitations need to be acknowledged. First, the panel relies on farmers' recall over six seasons; despite triangulation with Meteo Rwanda records, residual recall bias may persist. Second, the geographic scope is restricted to one district; external validity to other agro-ecological zones requires confirmatory studies. Third, although SHAP increases the transparency of Gradient Boosting, the model remains less directly interpretable than the FE logit. We mitigate this by reporting both models in parallel and by cross-checking the dominant predictors; results are robust across specifications, which gives high confidence in the directional findings while underscoring the need for follow-up work with longer panels.

VII. CONCLUSION AND FUTURE WORK

This paper has analyzed the impact of climate variability on crop selection and rotation in Bugesera District, Rwanda, by integrating panel-data econometrics with interpretable machine learning. Rainfall variability, drought occurrence, and temperature emerge as the dominant climatic drivers of farmer decisions, while farm size and income condition the strength of the response. Gradient Boosting with SHAP uncovers three behavioral thresholds that turn descriptive findings into actionable policy levers.

The main contribution is methodological as well as empirical: we show that econometrics and machine learning are complementary and that their joint use produces both causally identified average effects and policy-relevant non-linear thresholds. The framework can be transferred to other semi-arid districts of Eastern Africa and embedded into national climate-smart agriculture extension systems.

Future work should (i) extend the panel with multi-year real-time observations, (ii) widen the geographic scope to other Rwandan and East-African agro-ecological zones, (iii) integrate remote-sensing covariates (CHIRPS, MODIS-NDVI) into the machine-learning pipeline, and (iv) prototype a decision-support tool that delivers seasonal advisories to extension officers through SMS or USSD, with formal user-experience evaluation.

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DATA AVAILABILITY STATEMENT

Data supporting the study titled “Impact of Climate Variability on Crop Selection and Rotation Practices” processed datasets and analysis scripts are available in the project repository*:* ***https://github.com/ITClaude/Topic2*****.**

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JEAN CLAUDE DUSHIME received the bachelor's degree in Computer and Software Engineering and the master's degree in Internet of Things (IoT), specializing in Wireless Sensor Networks. He is currently pursuing the Ph.D. degree with the African Centre of Excellence in Internet of Things (ACEIoT–TAIRI), College of Science and Technology, University of Rwanda. His research focuses on artificial intelligence, climate-resilient agriculture, geospatial analytics, machine learning, and precision farming systems.

His current doctoral research investigates AI-powered climate-resilient agriculture through the development of intelligent models that integrate geospatial and climate data to predict crop yields and recommend optimal crop types and rotation schedules. His research interests include artificial intelligence, machine learning, Internet of Things, geospatial data science, climate-smart agriculture, and data analytics. He has authored and coauthored research articles in these fields and actively contributes to interdisciplinary research addressing agricultural and environmental challenges through innovative technologies.



NIZEYIMANA Theophile holds a bachelor's degree in Information and Communication Technology (ICT) from the University of Rwanda and is currently pursuing a Master of Science in Internet of Things (IoT), specializing in Wireless Intelligent Sensor Networking (WISENET), at the African Centre of Excellence in Internet of Things (ACEIoT), College of Science and Technology, University of Rwanda.

He has professional experience in coffee production systems and academic administration, having served in roles including Supervisor of a Coffee Washing Station and Assistant Production and Certification Manager at COOPAC

Ltd, as well as Academic Records Officer and Acting Director of Academic Services at Rwanda Polytechnic – Karongi College.

His research interests include Internet of Things (IoT), Artificial Intelligence, Wireless Sensor Networks, and Smart Agriculture. He is currently a co-author with Jean Claude Dushime on research related to IoT- and AI-based smart agriculture systems aimed at supporting climate-resilient agricultural decision-making in Rwanda.



RICHARD MUSABE is the Deputy Vice-Chancellor in Charge of Training, Institutional Development, and Research at Rwanda Polytechnic and an Associate Professor in Computer Networks and Software Engineering. He holds a Ph.D. in Network Security from Glasgow Caledonian University, U.K., an M.Sc. in Network Security, and a B.Sc. in Computer Engineering and Information Technology from Kigali Institute of Science and Technology (KIST), Rwanda.

He previously served as Dean of the School of ICT at the University of Rwanda, College of Science and Technology. He has extensive experience in academic leadership, curriculum development, student supervision, and research. His research interests include cellular communications, VoIP, network security, IoT, e-Health, big data, and computer network performance evaluation. He is currently the main supervisor for the Ph.D. studies of Jean Claude Dushime at the University of Rwanda.



UMUHOZA Karemera Noella Josiane is an agricultural scientist with a Ph.D. in Agriculture from the University of Beijing, China, an M.Sc. in Horticulture/Pomology from the Horticultural University of Bagalkot, India, and an Engineering degree in Agriculture/Agro-economics from the École Nationale d'Agriculture, Thiès, Senegal.

She is currently the Acting Director of the Centre for Postgraduate Studies and a Senior Lecturer in Horticultural Sciences at the University of Rwanda, College of Agriculture, Forestry and Food Science. She has previously served in various academic and administrative roles, including Acting Director of Continuing Education and Academic Secretary in the Department of Crop Sciences at the University of Rwanda.

Her professional experience includes applied agricultural research and extension work, particularly in banana production systems, macropropagation, and farmer capacity building in collaboration with international research institutions. She has contributed to scientific publications and authored books in horticulture and crop production. Her research and professional interests include horticultural science, crop improvement, agricultural extension, and sustainable food systems. She is currently the co-supervisor of the Ph.D. studies of Jean Claude Dushime at the University of Rwanda.



IGNACE GATARE, Ph.D., is the Principal of the College of Science and Technology, University of Rwanda. He previously served as the Director General of the Rwanda National Commission of Science and Technology (NCST) and as Minister in Charge of Information and Communications Technology in the Government of Rwanda.

He holds a Ph.D. in Engineering Sciences (Photonics) from the Vrije Universiteit Brussel (VUB), Belgium. He has held several leadership and advisory roles in national and international science, technology, and innovation institutions and programs, contributing to policy development and research advancement.

He is currently the co-supervisor of the Ph.D. studies of Jean Claude Dushime at the University of Rwanda. His academic and professional interests span science and technology policy, innovation systems, and applied research in ICT and engineering sciences.

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