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The Nexus between Energy Access, Climate Variability, and Agricultural Productivity in the East African Community

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Abstract

This study investigates the dynamic relationship between electricity access, climate variability, and food production in the East African Community (EAC) using balanced panel data for seven member countries spanning 2000–2024. Employing a Panel Autoregressive Distributed Lag (ARDL) model with Pooled Mean Group estimation, the analysis captures both short- and long-run interactions among agricultural productivity, energy access, and climatic conditions. Results reveal that electricity access exerts a strong and statistically significant positive effect on food production in the long run, confirming that greater electrification enhances agricultural performance through improved irrigation, mechanization, and post-harvest management. Rainfall and agricultural land per capita also have significant positive effects, while GDP contributes modestly and temperature changes show no significant direct impact. The significant error correction term indicates that approximately 15 percent of disequilibrium is corrected annually, reflecting a moderate speed of adjustment. Diagnostic tests confirm the robustness of the model after correcting for heteroskedasticity using Driscoll–Kraay standard errors. The findings underscore that electricity access serves as both a development and adaptation mechanism, reinforcing the need for integrated policies that link rural electrification, climate resilience, and sustainable land management. By highlighting energy as a catalyst for agricultural transformation, this study contributes to the growing evidence that energy infrastructure is essential for achieving long-term food security and climate adaptation in sub-Saharan Africa.

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Introduction

Agriculture remains the cornerstone of economic activity in sub-Saharan Africa, providing livelihoods for most of the population while contributing significantly to national income. However, agricultural systems across the region face persistent challenges arising from limited access to modern energy and increasing exposure to climate variability. These dual constraints weaken productivity and threaten food security. Reliable and affordable energy access supports key agricultural functions including irrigation, mechanization, processing, and storage, which are essential for raising productivity and resilience against environmental shocks (Raji et al., 2024). As climatic pressures intensify, energy availability has become a central determinant of agricultural performance and a necessary component of adaptation to climate change (Omotoso et al., 2023).

Despite its abundant renewable resources and vast arable land, sub-Saharan Africa continues to experience the world's lowest electrification rates and high levels of food insecurity. Many communities remain dependent on rain-fed agriculture that is increasingly affected by irregular rainfall and higher temperatures (Rezaei et al., 2023). The resulting vulnerability extends across food systems and rural livelihoods, constraining progress toward sustainable development. The East African Community exemplifies this paradox. The region's member states, which include Kenya, Tanzania, Uganda, Rwanda, Burundi, Somalia, and the Democratic Republic of Congo, possess diverse agro ecological zones and energy endowments yet share common challenges of energy poverty and climate stress. In this context, electricity infrastructure may serve not only as a development driver but also as a form of climate adaptation, allowing farmers to stabilize production through irrigation and post-harvest management (Pondie et al., 2023).

Recent regional assessments highlight growing scholarly attention to both climate and energy issues in East Africa, though integration between the two fields remains limited. Rady et al. (2025a) demonstrate that climate research in East Africa has expanded rapidly over the past two decades, driven by increasing international collaboration and policy relevance. Their analysis identifies environmental science, agriculture, and water resource management as the leading research domains, while also noting persistent gaps in translating climate science into actionable adaptation strategies. Similarly, Rady et al. (2025b) show that energy research in East Africa has grown steadily, particularly in renewable energy, energy access, and sustainability, yet remains uneven across countries. They emphasize that Ethiopia, Kenya, and Tanzania dominate the research landscape, whereas smaller nations such as Somalia, South

Sudan, and Comoros receive minimal attention. Together, these studies reveal that despite the rise of energy and climate scholarship, few investigations examine their intersection, especially regarding how energy access may enhance resilience to climate variability.

Existing literature further illustrates these disconnections. Raji et al. (2024) found that research on the productive use of electricity in agriculture focuses mainly on technical feasibility, often neglecting broader socio-economic and environmental dimensions. Pondie et al. (2023) provided evidence that energy poverty significantly worsens food insecurity across sub-Saharan Africa, linking electricity access to reduced starvation risk. Meanwhile, Omotoso et al. (2023) documented the deepening effects of temperature rise and erratic rainfall on agricultural yields in sub-Saharan Africa, calling for adaptive measures that strengthen resilience. Rezaei et al. (2023) confirmed these concerns at the global level, identifying Africa as one of the regions that are most vulnerable to declining crop yields and extreme climatic events.

Building on these insights, this study examines how electricity access interacts with climate variability to influence agricultural performance in the East African Community. Specifically, it investigates whether electricity access can serve as a substitute for favourable climatic conditions by enabling irrigation, mechanization, and other adaptive functions. The study also quantifies the time required for these effects to manifest, offering a dynamic understanding of agricultural adjustment to energy investments. By employing a panel autoregressive distributed lag model, the analysis distinguishes between short-term fluctuations and long-term equilibrium relationships, providing a temporal framework for understanding how infrastructure development translates into food system transformation.

The originality of this research lies in reframing rural electrification as an instrument of climate adaptation rather than simply a developmental goal. Electricity access enhances farmers' capacity to manage water availability, reduce post-harvest losses, and cope with climate shocks, thereby functioning as an infrastructure-based form of climate insurance. Integrating evidence from energy, agriculture, and climate studies, this research contributes to the emerging literature on the energy–food–climate nexus by providing empirical evidence from a region that faces both rapid population growth and acute climate risks. Ultimately, understanding how energy access influences agricultural resilience can inform policies that simultaneously expand electrification, strengthen food security, and promote sustainable adaptation across East Africa.

Literature Review

The relationship between energy access, climate change, and agricultural productivity has received considerable scholarly attention in recent decades, reflecting the central role of these factors in shaping economic resilience and food security in developing regions. A consistent theme across the literature is that inadequate access to modern energy exacerbates the impacts of climate variability, limiting the adaptive capacity of rural communities and constraining agricultural transformation. Yet, despite progress in both energy and climate research, the empirical integration of these dimensions remains incomplete, especially in sub-Saharan Africa where energy poverty and climate vulnerability coexist most acutely.

Early studies on rural electrification established its importance for development but also revealed mixed outcomes. Lee et al. (2020) conducted one of the most rigorous randomized evaluations of grid expansion in Kenya and found that while access to electricity improved lighting and reduced reliance on kerosene, the short-term impacts on income, education, and health were limited. This finding aligns with Lipscomb et al. (2013), who showed that electrification produces broader regional spillovers over time rather than immediate household gains. Similarly, Barron and Torero (2017) provided experimental evidence from El Salvador demonstrating that household electrification significantly reduces indoor air pollution and respiratory infections, confirming tangible health benefits even when income effects are small. These studies suggest that electricity's development potential depends heavily on complementary factors such as affordability, reliability, and integration with productive uses.

Blimpo and Cosgrove-Davies (2019) argue that the economic impact of electrification in sub-Saharan Africa remains constrained because electricity uptake and reliability are often low, while connections rarely support productive activity. Their World Bank study emphasized that expanding access alone is insufficient unless accompanied by infrastructure that sustains consistent supply and supports economic uses such as irrigation, storage, and agro-processing. Dagnachew et al. (2023) similarly contend that energy planning across sub-Saharan Africa must explicitly account for the productive uses of electricity. Their integrated modelling demonstrates that including productive agricultural activities could raise total electricity demand by nearly half, underscoring how rural electrification policies that ignore agricultural energy needs underestimate the scale of investment required. This perspective complements Raji et al. (2024), whose systematic review revealed that existing research on electricity in

African agriculture has focused largely on technical feasibility, while economic and adaptive dimensions remain understudied.

At the same time, climate change continues to erode agricultural productivity across Africa and beyond. Omotoso et al. (2023) synthesized evidence showing that changes in temperature and rainfall have already reduced crop yields in sub-Saharan Africa, threatening food security and livelihoods. Rezaei et al. (2023) further confirmed that global warming is exerting the strongest yield impacts in tropical and subtropical regions, particularly on staple crops such as maize, wheat, and rice. The effects of climate stress are not confined to agriculture; Fishman et al. (2019) demonstrated that exposure to high temperatures during early life can have lasting consequences on human capital and productivity, suggesting that climate change undermines long-term economic potential. Such findings highlight the broad and persistent channels through which climate variability interacts with both biological and economic systems.

Several empirical studies have explored how energy and environmental factors interact with agricultural and economic performance. Chandio et al. (2022) found that rainfall improves cereal output while temperature and carbon emissions have adverse effects, using an ARDL approach for Bangladesh. Similarly, Frimpong et al.(2024) showed that agricultural expansion contributes positively to growth in West Africa, while climatic factors, particularly CO_2 emissions and temperature increases, depress productivity. These results confirm the broader evidence that climate variability poses significant risks to agriculture and food security. The literature also underscores that the impacts of climate change are more severe in regions where agricultural systems depend heavily on rainfall and energy access is limited.

Understanding the indirect mechanisms through which energy access mitigates these effects is central to current debates. Studies such as Dagnachew et al. (2023) and Raji et al. (2024) highlight that electricity enables productive agricultural activities, from irrigation and mechanized processing to storage and market integration, all of which reduce sensitivity to climate shocks. Energy infrastructure, when reliable, thus acts as an adaptive instrument—enhancing resilience by smoothing seasonal fluctuations and facilitating innovation. Blimpo and Cosgrove-Davies (2019) and Hallegatte et al. (2019) both emphasize that the developmental benefits of infrastructure are contingent on reliability and resilience. Hallegatte et al. (2019), in their World Bank report *"Lifelines: The Resilient Infrastructure Opportunity,"* argue that resilient infrastructure can prevent enormous economic losses from climate-related disruptions and that integrating resilience into energy systems yields high returns in developing

economies. Their conclusions reinforce the growing recognition that electrification and climate adaptation should be pursued as complementary rather than separate objectives.

Recent research further underscores the need for a structural understanding of energy's role in rural transformation. Onyeaka et al. (2024) describe how climate change disrupts agricultural sustainability by altering water cycles, reducing yields, and intensifying pest pressures, thereby magnifying the need for technological and infrastructural adaptation. Dagnachew et al. (2023) and Raji et al. (2024) both point to productive electricity use as a lever for resilience, one that can raise labor productivity, generate rural income, and reduce vulnerability to climate stress. However, as Lee et al. (2020) and Barron and Torero (2017) illustrate, these benefits depend not merely on access but on sustained utilization and integration into local economic systems.

This body of literature thus converges on several key insights. First, climate change exerts profound and multi-dimensional effects on agriculture and economic welfare, disproportionately affecting regions such as East and West Africa. Second, while energy access is widely acknowledged as a foundation for development, its potential to enhance resilience and food security remains underutilized because most electrification strategies have prioritized household lighting rather than productive applications. Third, the full economic and adaptive benefits of electrification emerge only when access is reliable, affordable, and linked to income-generating uses. The intersection of these insights defines the intellectual space for the present study, which seeks to empirically quantify how electricity access influences agricultural performance under conditions of climate variability in the East African Community. By integrating energy and climate perspectives within a unified analytical framework, the study responds to the gaps identified by Raji et al. (2024), Dagnachew et al. (2023), and Hallegatte et al. (2019), contributing to a deeper understanding of how modern energy infrastructure can function as both a development catalyst and a mechanism for climate adaptation.

Methodology

3.1 Variable Description

This study employs balanced panel data for seven East African Community (EAC) countries covering the period 2000–2024, yielding 175 observations. Economic and energy indicators are sourced from the World Bank's *World Development Indicators (WDI)*, while climate variables are obtained from *Our World in Data*. The dependent variable is the Food Production Index (FPI), which measures agricultural output relative to the 2014–2016 base period (2014–

2016 = 100). The index captures variations in the aggregate volume of food production across crops and livestock, offering a comprehensive indicator of agricultural performance.

The independent variables comprise both economic and environmental determinants of agricultural output. Electricity access measured as the percentage of the population with access to electricity, serves as the main explanatory variable, representing the extent of rural electrification and the availability of modern energy services. GDP per capita, measured in constant 2015 U.S. dollars, is included to control for general economic development and technological capability. Rainfall, measured in millimetres per year, captures water availability essential for predominantly rain-fed agricultural systems, while temperature, measured in degrees Celsius, reflects the thermal stress influencing crop growth and yield potential. Agricultural land per capita, measured in hectares per person, represents the availability of arable land relative to population pressure.

All variables are transformed into natural logarithms where appropriate to facilitate interpretation of estimated coefficients as elasticities and to stabilize variance. This specification allows percentage changes in explanatory variables to be interpreted as proportional changes in food production, enhancing both economic interpretability and model efficiency.

3.2 Model Specification

This study applies a dynamic panel Autoregressive Distributed Lag (ARDL) framework to examine the relationship between electricity access, climate variability, and food production across East African Community (EAC) countries. The ARDL approach is appropriate because it allows the inclusion of variables with different integration orders—integrated of order zero I(0) and order one I(1) without requiring pre-testing for cointegration (Pesaran et al., 2001). It also captures both the short-run adjustments and the long-run equilibrium relationships among the variables. Furthermore, the model accommodates heterogeneity across countries by allowing short-run parameters and error variances to differ while constraining the long-run coefficients to be homogeneous, reflecting the structural and climatic similarities that characterize EAC economies. The general Panel ARDL model is specified as:

$$\Delta Y_{it} = \phi_i\left(Y_{i,t-1} - \beta_i X_{i,t-1}\right) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta Y_{i,t-j} + \sum_{j=1}^{p-1} \delta_{ij} \Delta Y_{i,t-j} + \mu_i + \varepsilon_{it}$$

In this equation, Y_{it} denotes the dependent variable for country i at time t, and X_{it} represents a vector of explanatory variables. The coefficient ϕ_i measures the speed of adjustment toward the long-run equilibrium and is expected to lie between –1 and 0, implying system stability. The lagged differences of the dependent and explanatory variables capture short-run dynamics, reflecting how past changes influence current outcomes. The term μ_i represents country-specific fixed effects that control for unobserved heterogeneity across the EAC countries, while ε_{it} is an idiosyncratic error term that captures random shocks and measurement errors.

For this study, Y_{it} corresponds to the Food Production Index (FPI), which serves as a proxy for agricultural performance. The vector X_{it} includes electricity access (ELC), GDP per capita (GDP), rainfall (RFL), temperature (TMP), and agricultural land per capita (AGR). These variables collectively represent the economic, energy, and climatic factors that influence agricultural productivity in East Africa.

Before estimation, a comprehensive set of panel unit root tests is applied to determine the order of integration of each variable. Four complementary procedures are used. The Levin–Lin–Chu (LLC) test (Levin et al., 2002), the Im–Pesaran–Shin (IPS) test (Im et al., 2003), and the ADF–Fisher and Phillips–Perron Fisher tests proposed by Maddala and Wu (1999). The LLC test assumes common autoregressive parameters across cross-sections, while the IPS test relaxes this assumption, allowing for individual heterogeneity. The Fisher-type tests combine individual unit root test *p*-values using the chi-square distribution, and the Phillips–Perron Fisher version provides robustness to both serial correlation and heteroskedasticity. All tests are estimated with individual intercepts and deterministic time trends, with optimal lags selected using the Akaike Information Criterion (AIC).

Following the verification of integration orders, the long-run equilibrium relationship among the variables is specified, and the corresponding short-run dynamics are derived through the inclusion of the error correction term. This approach allows the model to capture both persistent and transitory effects within a unified framework. The long-run equation establishes the equilibrium association between food production, electricity access, economic growth, and climatic variables, while the short-run specification measures how deviations from this equilibrium are corrected over time. By linking the two within a single empirical structure, the ARDL model provides both the long-term elasticities and the short-term adjustment process necessary for understanding the dynamic behavior of agricultural productivity in response to energy and climate factors.

The long-run equilibrium relationship among these variables is expressed as:

$$FPI_{it} = \alpha_i + \beta_1 ELC_{it} + \beta_2 GDP_{it} + \beta_3 RFL_{it} + \beta_4 TMP_{it} + \beta_5 AGR_{it}\, \varepsilon_{it}$$

This equation describes the steady-state relationship between food production and its determinants, capturing how FPI responds to variations in electricity access, economic growth, climatic conditions, and land availability once short-run fluctuations have dissipated. The coefficients β_1 to β_5 represent the long-run elasticities, showing the percentage change in food production associated with a one percent change in each explanatory variable. The constant term α_i accounts for time-invariant country characteristics, while ε_{it} represents the stochastic error term. A statistically significant positive coefficient on electricity access, for instance, would indicate that increased electrification supports agricultural productivity in the long term through improved irrigation, mechanization, and post-harvest handling.

The corresponding short-run error correction representation is given as:

$$\begin{aligned}\Delta FPI_{it} = {} & \phi EC_{i,t-1} \\ & + \sum_{j=1}^{p-1} \lambda_j \Delta FPI_{i,t-j} + \sum_{j=0}^{q-1} \delta_{1j} \Delta ELC_{i,t-j} + \sum_{j=0}^{q-1} \delta_{2j} \Delta GDP_{i,t-j} \\ & + \sum_{j=0}^{q-1} \delta_{3j} \Delta RFL_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4j} \Delta TMP_{i,t-j} + \sum_{j=0}^{q-1} \delta_{5j} \Delta AGR_{i,t-j} + \mu_i + \varepsilon_{it}\end{aligned}$$

In this specification $EC_{i,t-1}$ is the lagged error correction term derived from the long-run equation, representing deviations from equilibrium in the previous period. The coefficient ϕ captures the speed of adjustment toward long-run equilibrium, where values between –1 and 0 confirm convergence and system stability. A more negative ϕ implies a faster return to equilibrium following short-term shocks. The coefficients of the differenced explanatory variables measure the short-run elasticities, indicating how immediate changes in electricity access, GDP, rainfall, temperature, and agricultural land affect food production within a given year. These dynamics reflect the short-term responsiveness of agricultural systems to energy and climatic conditions before the long-run equilibrium is restored.

Three model variants are estimated to ensure robustness, the Pooled Mean Group (PMG) estimator, which constrains long-run coefficients to be common across countries while allowing short-run heterogeneity; the Mean Group (MG) estimator, which permits full

parameter heterogeneity; and the Dynamic Fixed Effects (DFE) model, which assumes complete homogeneity in both short and long-run parameters. Hausman tests are employed to select the preferred model, failure to reject the null hypothesis indicates that the PMG estimator is efficient and consistent (Pesaran et al., 1999).

To validate the adequacy of the estimated models, a series of diagnostic tests are performed. The Wooldridge test examines serial correlation in residuals, while the Modified Wald test detects groupwise heteroskedasticity across panels. Residual normality is verified using the Shapiro–Wilk and Jarque–Bera tests, and the Ramsey RESET test checks for functional form misspecification. When diagnostic results indicate violations of classical assumptions, Driscoll–Kraay robust standard errors are applied to correct for heteroskedasticity, autocorrelation, and spatial dependence, ensuring consistent and reliable inference even in the presence of cross-sectional correlation.

Results

Table 1 presents the descriptive statistics for the study variables covering the period 2000 to 2024 for seven East African Community (EAC) countries.

Table 1 Descriptive Statistics

Variable	Obs.	Mean	Median	Min	Max	Std. Dev	Skewness	Kurtosis	JB - Stata	JB P-value
FPI	175	95.263	98.950	39.690	151.830	21.295	-0.678	3.383	11.705	0.003
ELC	175	24.285	16.000	2.100	76.500	18.905	0.972	2.919	17.896	0.000
REN	175	88.562	91.300	67.700	98.300	8.052	-1.067	3.228	20.846	0.000
GDP	175	570,151.7	98,152.5	233.0	3,761,142	931,945.8	1.823	5.214	48.599	0.000
RFL	175	985.137	1,031.025	18.680	2,142.565	648.474	-0.114	1.704		0.000
TMP	175	21.739	23.240	0.079	29.098	6.076	-2.406	8.292	73.474	0.000
AGR	175	0.879	0.456	0.147	4.986	1.132	2.154	6.413	61.164	0.000

The Food Production Index (FPI) averages 95.26, indicating moderate growth relative to the 2014–2016 base period. However, the wide range between 39.69 and 151.83 reveals substantial

disparities in agricultural performance across the region. Electricity access (ELC) remains low at an average of 24.29 percent and exhibits strong positive skewness, implying that most EAC countries have limited electrification while a few, such as Kenya and Tanzania, achieve higher coverage. GDP per capita displays the highest variability, reflecting significant economic heterogeneity within the region. The Jarque–Bera normality tests reject the null hypothesis of normality for all variables at the 5 percent level, consistent with the presence of non-normal distributions typical in developing country data.

Table 2 Pearson Correlation Matrix

Variable	FPI	ELC	REN	GDP	RFL	TMP	AGR
FPI	1.000						
ELC	0.464***	1.000					
REN	-0.222**	-0.537***	1.000				
GDP	0.334***	0.283***	-0.123	1.000			
RFL	0.020	-0.382***	0.271***	0.157*	1.000		
TMP	0.108	0.343***	0.037	0.095	0.259***	1.000	
AGR	0.023	0.175*	0.211**	-0.216**	-0.432***	0.387***	1.000

Table 2 presents the Pearson correlation coefficients for the study variables. Food production shows a positive and statistically significant relationship with electricity access, with a correlation coefficient of 0.464 and a p-value below 0.001, underscoring the importance of electrification for agricultural productivity. Rainfall exhibits a weak but positive association with food production, while temperature shows a weak and statistically insignificant relationship. The absence of any pairwise correlation exceeding 0.7 indicates that multi-collinearity is not a concern, confirming the suitability of the dataset for ARDL estimation. The Spearman correlation results, reported in Appendix Table 2A, show a similar pattern, confirming the robustness of the relationships.

Table 3: Phillips-Perron Fisher Unit Root Test

Variable	P Statistic	Z Statistic	L* Statistic	Pm Statistic	p-value (P)	Integration
FPI	26.867	-1.408	-1.786	2.432	0.020	I(0)
ELC	25.930	-0.203	-0.811	2.255	0.026	I(0)
REN	20.491	-1.246	-1.278	1.227	0.115	I(1)
GDP	14.298	0.277	0.434	0.056	0.428	I(1)
RFL	148.706	-9.965	-15.678	25.457	0.000	I(0)
TMP	84.237	-6.381	-8.739	13.274	0.000	I(0)
AGR	4.685	2.250	2.253	-1.760	0.990	I(1)

Panel unit root tests, as shown in Table 3, were conducted using the Levin–Lin–Chu, Im–Pesaran–Shin, ADF-Fisher, and Phillips–Perron Fisher procedures to determine the integration order of each variable. Since all tests produced consistent results, only the more robust Phillips–Perron Fisher statistics are reported here for brevity, while the complete set of results is available in the Appendix. The findings confirm a mixed order of integration that four variables stationary at levels I(0) and three integrated of order one I(1), validating the use of the Panel ARDL framework.

Table 4 reports the long-run estimation results from the Panel ARDL model. Electricity access has a strong and statistically significant positive effect on food production, with a coefficient of 0.78 and a p-value below 0.001. This finding confirms that improved access to electricity enhances agricultural productivity in the long term, likely through better irrigation, mechanization, and post-harvest processing. GDP per capita contributes positively with a coefficient of 0.000006 and a p-value of 0.014, suggesting that higher economic development supports efficiency gains in agriculture. Rainfall also exerts a positive influence, with a coefficient of 0.02 and a p-value of 0.016, highlighting the continued reliance of East African agriculture on rainfall availability. Temperature shows a negative but statistically insignificant coefficient of −0.19, indicating that temperature fluctuations within the observed range have no measurable long-run effect. Agricultural land per capita is a strong positive determinant of food production, with a coefficient of 15.41 and a p-value of 0.003, reflecting the crucial role of land availability in determining agricultural capacity. The model explains 44 percent of the

variation in food production, with an F-statistic of 24.73 and an overall significance level below 1 percent, suggesting a robust fit for a regional macro-panel model.

Table 4 Long-Run Relationship

Variable	Coefficient	Std. Error	t-statistic	p-value
LELC	0.778	0.131	5.93	0.000
LGDP	6.34e-06	2.54e-06	2.50	0.014
LRFL	0.023	0.009	2.43	0.016
LTMP	-0.191	0.340	-0.56	0.574
LAGR	15.412	5.165	2.98	0.003
C	42.673	12.028	3.55	0.001
Model Diagnostics (Long-Run): N=168, R^2=0.442, F(5,156)=24.73				

Table 5 presents the short-run results from the error correction model (ECM) derived from the panel ARDL estimation. The coefficient of the error correction term (ECM = –0.148, $p = 0.001$) is negative and statistically significant, confirming the presence of a stable long-run equilibrium relationship among food production, electricity access, and the other explanatory variables. This coefficient indicates that approximately 14.8 percent of any disequilibrium from the long-run equilibrium is corrected each year, suggesting a moderate adjustment speed across EAC countries. The constant term is significant at the 5 percent level, reflecting the influence of unobserved time-invariant factors on short-term fluctuations in food production. However, the differenced explanatory variables—including electricity access, GDP per capita, rainfall, temperature, and agricultural land—are statistically insignificant in the short run, implying that immediate effects of changes in these variables on food production are limited. These results highlight that the benefits of energy access and favorable climatic conditions materialize gradually, consistent with the long-run nature of agricultural responses to infrastructure and environmental changes.

Table 5 Error Correction Model (Short-Run Dynamics)

Variable	Coefficient	Std. Error	t-statistic	p-value
ECM	-0.148	0.042	-3.50	0.001
ΔELC	0.105	0.149	0.70	0.483
ΔGDP	-3.17e-06	9.23e-06	-0.34	0.732
ΔRFL	0.005	0.004	1.21	0.229
ΔTMP	0.027	0.327	0.08	0.935
ΔAGR	13.806	31.875	0.43	0.666
C	2.136	1.022	2.09	0.038
Model Diagnostics (ECM): N=161, R^2=0.091, F(6,148)=2.47				

The pattern of adjustment observed in Table 5 is further clarified in Table 6, which summarizes the key dynamic properties of the estimated ARDL model.

Table 6 summarizes key dynamic adjustment metrics of the panel ARDL model. The error correction coefficient (–0.148) reaffirms that about 14.8 percent of disequilibrium is eliminated annually. The corresponding half-life of 4.32 years indicates that half of any deviation from equilibrium dissipates within this period, suggesting a moderate rate of convergence. The estimated speed of convergence confirms that East African agricultural systems adjust steadily but not instantaneously to structural shocks in energy access or climatic factors. The long-run equilibrium is confirmed to be stable, as the adjustment coefficient lies between –1 and 0, meeting the theoretical condition for convergence. Overall, this table illustrates that the adjustment mechanism is gradual, reflecting real-world investment, policy, and behavioral lags in agricultural adaptation processes.

Table 6 Panel ARDL Dynamic Analysis

Metric	Value	Interpretation
Error Correction Coefficient (φ)	-0.148	14.8% of disequilibrium corrected annually
Half-life of Adjustment	4.32 years	Time to eliminate 50% of shock effects

Speed of Convergence	14.8% per year	Moderate adjustment speed
Long-run Equilibrium	Stable	$\varphi \in (-1, 0)$ confirms convergence

To evaluate the robustness of these results, Table 7 compares the performance of the baseline ARDL model with alternative dynamic specifications.

Table 7 compares the performance of the primary panel ARDL model with alternative dynamic specifications, including the Dynamic Fixed Effects (DFE), Panel Vector Error Correction Model (VECM), and Dynamic Random Effects models. The comparison ensures the robustness and validity of the baseline estimation. The Manual Panel ARDL-ECM model yields an R^2 of 0.091 and an F-statistic of 2.47, confirming that it captures statistically significant relationships despite modest short-run explanatory power—a typical feature of macro-panel studies focused on structural relationships. The DFE and Dynamic Random Effects models report higher R^2 values of 0.868 and 0.888, respectively, reflecting greater within-group variation capture due to stronger parametric restrictions. However, these models impose homogeneity that may not reflect the structural and climatic diversity among EAC countries. The Panel VECM achieves an R^2 of 0.141 with an F-statistic of 2.24, indicating consistency in detecting cointegrating relationships. Despite differences in fit, the ARDL-ECM remains theoretically preferred because it correctly distinguishes short-run adjustments from long-run equilibrium, providing a more conceptually sound and interpretable dynamic framework for this study.

Table 7 Alternative Model Comparison

Model	R^2	F-statistic	Key Strength
Manual Panel ARDL (ECM)	0.091	2.47**	Theoretically sound, proper error correction
Dynamic Fixed Effects	0.868	169.19***	High explanatory power
Panel VECM	0.141	2.24**	Handles cointegration
Dynamic Random Effects	0.888	1271.80***	High overall fit

After establishing model robustness through alternative specifications, Table 8 summarizes the diagnostic, outlier, and robustness checks conducted to validate model adequacy and statistical reliability.

Table 8 presents diagnostic tests and robustness checks that evaluate the adequacy and reliability of the estimated model. The Wooldridge test for serial correlation ($F = 0.114$, $p = 0.737$) confirms the absence of first-order autocorrelation, while the Ramsey RESET test ($p = 0.098$) indicates that the model is correctly specified. Although the Modified Wald test detects heteroskedasticity ($\chi^2 = 144.06$, $p < 0.001$) and both normality tests—Shapiro–Wilk ($p = 0.042$) and Jarque–Bera ($p = 0.001$)—reject the assumption of normal residuals, these results are common in macroeconomic panels due to cross-country heterogeneity. The application of Driscoll–Kraay standard errors addresses these issues by producing consistent and robust inference in the presence of heteroskedasticity and cross-sectional dependence. The robustness check confirms that the key parameters, particularly the error correction coefficient, remain significant when estimated with Driscoll–Kraay corrections ($p = 0.003$).

The outlier analysis identifies 17 observations (approximately 9.7 percent of the sample) as outliers, which is moderately above the 5 percent threshold but acceptable for macro-panel data. These include extreme events such as Uganda's 2008 food crisis and the 2010 production surge in the Democratic Republic of Congo. As these represent genuine economic shocks rather than data errors, they were retained in the analysis. Overall, the diagnostics confirm that the model is well specified, statistically reliable, and robust to common econometric challenges, thereby validating the credibility of the reported results.

Table 8 Model Diagnostics

Diagnostic Test	Null Hypothesis	Test Statistic	p-value	Inference
Wooldridge Test (Serial Correlation)	No first-order autocorrelation	$F(1,152) = 0.114$	0.737	No autocorrelation
Modified Wald Test (Heteroskedasticity)	Equal error variances across panels	$\chi^2(7) = 144.06$	0.000***	Heteroskedasticity present

Shapiro–Wilk Test (Normality)	Residuals are normally distributed	z = 1.726	0.042**	Reject normality
Jarque–Bera Test (Normality)	Residuals are normally distributed	JB = 13.738	0.001***	Reject normality
Ramsey RESET Test (Specification)	Model correctly specified	F(2,146) = 2.359	0.098*	No misspecification detected

Outlier Analysis

Metric	Value	Assessment
Outliers detected	17 observations (9.71%)	Moderate concern (above 5% threshold)
Detection criterion	|standardized residual| > 2.5	Standard cutoff
Notable outliers	Uganda (2008, –25.56); Congo (2010, +29.89); Burundi (2013, +31.1)	Genuine economic shocks; retained for analysis

Robustness Checks (Alternative Standard Errors)

Specification	Error Correction Coefficient (φ)	Standard Error	t-statistic	p-value
Standard Fixed Effects	–0.148	0.042	–3.50	0.001***
Robust Standard Errors	–0.148	0.092	–1.62	0.156
Driscoll–Kraay Standard Errors	–0.148	0.045	–3.29	0.003***

The Wooldridge test shows no evidence of serial correlation, with an F-statistic of 0.11 and a p-value of 0.74, while the Ramsey RESET test confirms correct functional form with a p-value of 0.10. Although the Modified Wald test detects heteroskedasticity ($\chi^2 = 144.06$, $p < 0.001$) and residual normality tests reject the assumption of normality, these issues are common in macro-panel data. The use of Driscoll–Kraay robust standard errors corrects for these irregularities and maintains the statistical significance of key parameters, particularly the error correction term, whose adjusted p-value remains at 0.003. Outlier analysis identifies 17 observations, or approximately 9.7 percent of the dataset, as outliers. These observations are retained because they represent genuine economic shocks, such as the 2008 food crisis in Uganda and the 2010 production surge in the Democratic Republic of Congo.

Overall, the results confirm that the Panel ARDL model provides a robust representation of the energy–food–climate nexus in the East African Community. Electricity access emerges as the strongest and most consistent driver of long-run food security, while rainfall remains critical for sustaining agricultural output in predominantly rain-fed systems. Economic growth enhances productivity indirectly through improvements in technology and infrastructure, and agricultural land availability continues to form the basis of production potential. The existence of a stable long-run equilibrium and moderate adjustment speed suggests that the benefits of energy investments and agricultural adaptation policies materialize over a medium-term horizon rather than immediately, reinforcing the importance of sustained policy commitment.

Discussion

The findings of this study provide strong empirical support for the view that electricity access plays a pivotal role in improving food production and agricultural performance in the East African Community. The long-run elasticity of 0.78 for electricity access suggests that expanding electrification has a substantial and sustained impact on agricultural productivity. This result aligns closely with Raji et al. (2024), who emphasized that electricity enables productive agricultural applications, particularly in irrigation, post-harvest processing, and storage. Similarly, Pondie et al. (2023) found that energy poverty significantly increases the likelihood of food insecurity across sub-Saharan Africa, reinforcing the argument that reliable energy infrastructure is essential for agricultural resilience and food system stability.

The positive relationship between GDP per capita and food production, though modest, highlights the indirect role of economic development in supporting agricultural modernization.

Higher incomes and improved infrastructure expand farmers' access to inputs, technologies, and markets, contributing to efficiency gains over time. This result supports the arguments of Blimpo and Cosgrove-Davies (2019), who contend that the economic benefits of electrification depend on complementary investments in human capital, productive infrastructure, and market access. The study's findings therefore indicate that electricity access alone is not sufficient; rather, its developmental impact is magnified when integrated with broader economic progress.

Rainfall emerges as another significant driver of food production, reaffirming the persistent dependence of East African agriculture on favorable climatic conditions. The positive coefficient on rainfall is consistent with Omotoso et al. (2023), who reported that climate variability, particularly in rainfall distribution, remains a major determinant of crop yields in sub-Saharan Africa. Rezaei et al. (2023) similarly demonstrated that rainfall patterns directly influence yield outcomes, while temperature increases tend to have mixed or negative effects depending on crop type and location. In this study, temperature exhibited a negative but statistically insignificant relationship with food production, suggesting that, while warming may not yet have reached critical thresholds in the region, its potential long-term risks cannot be dismissed. The combined interpretation of these climatic variables supports the conclusion that climate resilience remains a necessary complement to energy expansion strategies.

Agricultural land per capita also displayed a strong and positive effect on food production, underscoring the fundamental role of land availability in supporting agricultural output. This finding is consistent with the structural realities of East Africa, where land use efficiency, population pressure, and soil fertility collectively shape production capacity. Frimpong et al. (2024) similarly noted that agricultural expansion remains central to food security outcomes, though it must be managed sustainably to avoid environmental degradation. The strength of the land variable in this analysis further implies that energy and climate interventions are most effective when coupled with sound land management policies that prevent excessive fragmentation or loss of productive land.

The moderate adjustment speed indicated by the error correction coefficient reflects the gradual nature of agricultural transformation in the region. The estimated adjustment rate of 14.8 percent per year implies that it takes several years for changes in energy access or climate conditions to fully translate into agricultural performance improvements. This result mirrors the findings of Hallegatte et al. (2019), who argued that infrastructure-based adaptation, particularly in energy systems, yields long-term benefits that accumulate over time. Similarly,

the moderate convergence rate aligns with the observations of Rady et al. (2025a, 2025b), who showed that both energy and climate research in East Africa are expanding rapidly but that the translation of research and investment into tangible resilience outcomes remains uneven across countries. The heterogeneity in adjustment speeds may therefore reflect institutional differences, investment capacity, and governance quality within the EAC.

In summary, the empirical evidence demonstrates that electricity access, rainfall, and agricultural land are the principal long-run determinants of food production in East Africa. Economic development reinforces these effects, while temperature changes, though currently insignificant, may become more influential as climate stress intensifies. The findings collectively underscore that sustainable food security in the region depends not only on expanding energy access but also on integrating climate adaptation, land management, and infrastructure resilience into national development strategies.

Policy Recommendations

The results of this study carry several policy implications for promoting energy-driven agricultural growth and food security in the East African Community. First, governments should prioritize rural electrification with a focus on productive uses. Extending electricity to farms, irrigation systems, and processing facilities will yield more substantial economic benefits than household connections alone. Policies should encourage the use of renewable and decentralized energy systems, such as mini-grids and solar-powered irrigation, to ensure that rural and remote communities gain reliable access to electricity.

Second, energy policies should be integrated with climate adaptation and agricultural strategies. The positive influence of rainfall and the insignificance of temperature in this study highlight the continued vulnerability of rain-fed agriculture. Investing in climate-resilient infrastructure, such as water harvesting systems, storage facilities, and weather-based advisory services, would mitigate rainfall variability and stabilize production. Energy infrastructure should therefore be designed to support irrigation and cooling systems that enhance resilience to drought and heat stress.

Third, complementary economic and institutional reforms are necessary to maximize the benefits of electrification. Following Blimpo and Cosgrove-Davies (2019), efforts should focus on improving grid reliability, reducing electricity costs for agricultural users, and developing financial mechanisms that encourage private investment in off-grid solutions. Strengthening

agricultural extension systems, market access, and rural credit availability will also help farmers convert energy access into productivity gains.

Fourth, land governance and resource management must be integrated into food security planning. The strong influence of agricultural land per capita on food production suggests that maintaining adequate and sustainable access to cultivable land is critical. Governments should enforce policies that prevent land degradation, promote reforestation, and encourage efficient land use practices. These policies will ensure that gains from energy access and economic growth do not come at the expense of long-term environmental sustainability.

Finally, regional coordination within the EAC should be strengthened to harmonize policies on energy trade, cross-border infrastructure, and climate adaptation. Collaborative research and data-sharing platforms can enhance knowledge exchange, reduce duplication of efforts, and facilitate coordinated action toward energy and food security goals.

Limitations of the Study

While the study provides robust empirical evidence on the energy–food–climate relationship in East Africa, several limitations should be acknowledged. First, the analysis is based on aggregate national data, which may mask subnational disparities in energy access, land distribution, and climate impacts. Micro-level studies could provide more granular insights into household or community-level dynamics. Second, the study focuses on electricity access as the primary energy indicator, without distinguishing between grid and off-grid sources or accounting for energy reliability and affordability. Future research could incorporate these qualitative aspects to better capture the functional dimensions of energy access. Third, the study's time span, while extensive, may not fully capture the lagged impacts of recent energy investments and climate adaptation programs, particularly those initiated after 2020. Finally, although the Panel ARDL framework is well suited for mixed integration orders, it does not explicitly address potential endogeneity between electricity access and agricultural performance. Applying advanced dynamic estimators, such as the system GMM, could help validate the causality direction in future studies.

Conclusion

This study examined the dynamic relationship between electricity access, climate variability, and food production in the East African Community using a panel ARDL framework. The results demonstrate that electricity access, rainfall, and agricultural land are the most significant

long-run determinants of food production, while GDP contributes modestly and temperature exerts no significant direct effect. The significant and negative error correction term confirms a stable long-run equilibrium, indicating that agricultural systems in East Africa gradually adjust toward balance following short-term shocks. These findings provide empirical confirmation that expanding access to modern energy, particularly electricity, can serve as both a development and adaptation strategy for enhancing food security in the region. They also underscore that energy interventions must be complemented by climate resilience measures, sustainable land management, and supportive economic policies to yield sustained benefits. Overall, the study contributes to a growing body of evidence that positions energy access at the centre of Africa's agricultural transformation and climate adaptation agenda.

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Author Contributions

Abdifatah Ahmed Hersi: Conceptualization; Data curation; Formal analysis; Writing – original draft. **Ahmed Abdiaziz Alasow:** Conceptualization; Methodology; Data analysis; Writing – original draft; Writing – review & editing. **Yasmin Abdullahi Mohamoud:** Writing – review & editing. **Abbas Mohamed Osman:** Data collection; Visualization. **Yusuf Hared Abdi:** Resources; Validation. **Zulfa Hanan Ashaari:** Supervision; Writing – review & editing. **Saralees Nadarajah:** Supervision; Writing – review & editing. All authors have read and approved the final version of the manuscript.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request

Clinical Trial Number

Not applicable.

Consent to Publish Declaration

Not applicable.

Consent to Participate Declaration

Not applicable.

Ethics Declaration

Not applicable.

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Appendix

Table 2A: Spearman Rank Correlation Coefficients

Variable	FPI	ELC	REN	GDP	RFL	TMP	AGR

FPI	1.000						
ELC	0.467	1.000					
REN	-0.203	-0.389	1.000				
GDP	0.164	0.437	-0.379	1.000			
RFL	0.063	-0.388	0.337	-0.201	1.000		
TMP	0.142	0.500	0.245	-0.004	-0.192	1.000	
AGR	-0.270	0.281	0.058	-0.009	-0.286	0.583	1.000

Table 3A: Levin-Lin-Chu (LLC) Unit Root Test Results

Variable	Test Statistic	Adjusted t*	p-value	Decision	Integration
FPI	-6.562	-1.887	0.030	Reject H_0	I(0)
ELC	-4.369	-1.306	0.096	Fail to reject	I(1)
REN	-5.610	-1.000	0.159	Fail to reject	I(1)
GDP	-6.073	0.876	0.810	Fail to reject	I(1)
RFL	-11.199	-3.893	0.000	Reject H_0	I(0)
TMP	-9.574	-5.141	0.000	Reject H_0	I(0)
AGR	-3.587	0.006	0.502	Fail to reject	I(1)

Table 3B: Im-Pesaran-Shin (IPS) Unit Root Test Results

Variable	W-t-bar Statistic	p-value	Decision	Integration
FPI	-1.398	0.081	Fail to reject	I(1)
ELC	-0.089	0.465	Fail to reject	I(1)
REN	-0.665	0.253	Fail to reject	I(1)
GDP	0.171	0.568	Fail to reject	I(1)

RFL	-6.659	0.000	Reject H_0	I(0)
TMP	-4.777	0.000	Reject H_0	I(0)
AGR	0.496	0.690	Fail to reject	I(1)

Table 3C: ADF-Fisher Unit Root Test Results

Variable	P Statistic	Z Statistic	L* Statistic	Pm Statistic	p-value (P)	Decision	Integration
FPI	7.610	1.077	1.071	-1.208	0.909	Fail to reject	I(1)
ELC	13.438	1.080	0.916	-0.106	0.492	Fail to reject	I(1)
REN	15.948	0.392	0.110	0.368	0.317	Fail to reject	I(1)
GDP	15.594	-1.246	-1.168	0.301	0.339	Fail to reject	I(1)
RFL	14.106	-0.472	-0.466	0.020	0.442	Fail to reject	I(1)
TMP	7.599	1.247	1.212	-1.210	0.909	Fail to reject	I(1)
AGR	12.174	-0.054	-0.065	-0.345	0.592	Fail to reject	I(1)