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Navigating paths to food security in East Africa: strengthening rural development amid climate shocks, political instability, and rising food prices

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As the most food-insecure region in Africa, East Africa faces persistent challenges in ensuring adequate food supply, as climatic fluctuations, political instability, and economic hardships continue to undermine its ability to meet the dietary needs of its growing population. While previous research has predominantly examined climate change and political instability as primary drivers of food insecurity, the influence of rural development on food security outcomes remains insufficiently explored. Hence, this study investigates the relationship between rural development and food security while incorporating climatic and socio-economic factors using panel data from 12 countries between 2001 and 2020. Employing heterogeneous panel cointegration techniques, the findings derived from PCSE and FGLS estimators reveal that rainfall substantially improves food availability and utilization while diminishing food accessibility and stability. In contrast, higher temperatures negatively affect all four dimensions of food security. Moreover, population growth exerts a significant negative influence on food availability and stability, while food imports enhance food availability but simultaneously reduce accessibility and utilization. Furthermore, political stability is crucial in strengthening food availability and stability, whereas rural development significantly boosts food availability, accessibility, and utilization. Nevertheless, the Dumitrescu–Hurlin panel tests indicate bidirectional predictive linkages between population growth and food security, and a unidirectional linkage from temperature to food security. These findings propose targeted recommendations for East African authorities to strengthen food security policies and resilience.

KEYWORDS

rural development, food security, climate change, political stability, food inflation, food imports

1 Introduction

The battle against hunger has emerged as a resounding global call for immediate and decisive action. As the world's population continues to grow, meeting the dietary needs of billions presents an ever-pressing challenge. In 2021, an alarming 828 million people worldwide faced hunger, and projections suggest these numbers will rise if immediate action is not taken (FAO, IFAD, UNICEF, WFP and WHO, 2022). Food security, defined as a condition where all individuals have consistent access to nutritious, affordable, and safe food aligned with their dietary preferences, is crucial for human health, social stability, and economic development. Ensuring food security guarantees fundamental human rights, such as access to clean water and proper nutrition, while fostering productivity and economic progress (Abdi et al., 2024a, 2024b; Conceição et al., 2016). However, the four pillars of food security—accessibility, availability, stability, and utilization—are increasingly threatened by climate change, political instability, food price inflation, and underdeveloped rural areas. Weak governance in food-insecure regions further limits the capacity to mitigate and adapt to food security challenges, while strong institutional frameworks are critical for policy implementation and resilience-building (Connolly-Boutin and Smit, 2016; Yiadom et al., 2023).

Climate change poses a dual threat to global food security. On the one hand, it directly affects agricultural productivity through erratic rainfall, rising temperatures, water scarcity, altered soil conditions, pest outbreaks, and shifting crop growth timings (Chandio et al., 2023; Mubenga-Tshitaka et al., 2023). The Intergovernmental Panel on Climate Change [IPCC] reports that Earth's average temperature has increased by 1.1 °C since the industrial era, with projections exceeding 1.5 °C within the next two decades (IPCC, 2021). These changes result in more frequent droughts and floods, land degradation, and declining agricultural yields (Adhikari et al., 2015). Climate change has already caused a 10% reduction in global agricultural yields between 2000 and 2019 (FAO, 2023). Regions such as tropical and subtropical areas, including East Africa, are particularly vulnerable due to their dependence on rain-fed agriculture and limited adaptation capacities (Kumar et al., 2021; Ntiamoah et al., 2022). On the other hand, climate change exacerbates food insecurity indirectly by fueling conflicts over dwindling natural resources such as land and water (Abdi et al., 2023a, 2023b). Competition for these resources often intensifies communal disputes, particularly between farmers and pastoralists migrating in search of better opportunities (Delgado et al., 2023; Warsame et al., 2023; Yiadom et al., 2023).

Conflicts and political instability further aggravate food insecurity, particularly in regions like East Africa. Recurring conflicts disrupt food production, displacement rates increase, and access to food supplies becomes severely limited (World Food Programme, 2024). According to the Global Report on Food Crises (2023), conflicts pushed over 117 million people into acute food insecurity globally. Moreover, conflicts influence food prices (Hussein et al., 2021). The Russia-Ukraine geopolitical crisis, for instance, disrupted wheat exports—both countries account for 25% of global wheat shipments—leading to sharp increases in food prices and reduced purchasing power (FAO, 2022; Karume et al., 2024). Consequently, food inflation rates exceeded 5% in low-income countries, deepening inequalities and worsening poverty (Abdi et al., 2024a, 2024b; World Bank, 2022). On the other hand, rural development plays a pivotal role in alleviating food insecurity by enhancing agricultural productivity and building resilience to climate and political shocks. Globally, 9.1% of the population experienced hunger in 2023, up from 7.5% in 2019, with rural communities bearing the brunt of this burden (FAO, 2024). Rural areas, home to 80% of the poorest populations, are characterized by limited access to infrastructure, education, and healthcare, which exacerbates food insecurity (Abdi et al., 2024a, 2024b; IFAD, 2021). Improved rural infrastructure, such as road networks and irrigation systems, facilitates access to markets, reduces post-harvest losses, and enables the adoption of climate-smart agricultural practices (Ali Warsame and Hassan Abdi, 2023; Chandio et al., 2022). However, rural development remains inadequate in many regions, leaving rural communities particularly vulnerable to hunger and poverty.

East Africa, a region marked by high climate vulnerability and persistent conflicts, faces immense challenges in addressing its food security crisis. With a population growth rate of 5.8%, it accounts for 44% of Africa's food-insecure population, making it the most vulnerable on the continent (FAO, 2021). Rain-fed agriculture, which contributes 43% to the region's GDP and sustains 80% of its population, is highly susceptible to climate-induced shocks such as droughts, floods, and locust infestations (Adhikari et al., 2015; Mubenga-Tshitaka et al., 2023). Climatic disruptions, including erratic weather patterns, water shortages, and pest outbreaks, have severely impacted crop yields, with projections showing declines of up to 72% for wheat, 45% for maize and rice, and substantial losses in other staple crops (Adhikari et al., 2015). Locust infestations alone have devastated 5,000 hectares of pastureland in Djibouti (World Bank, 2020). The region's dependence on food imports further exacerbates its vulnerability. Countries like Ethiopia (39%), Djibouti (55%), Somalia (91%), and Eritrea (100%) relied heavily on Russian and Ukrainian wheat in 2021, making them susceptible to supply chain disruptions and price surges caused by geopolitical tensions (FAO, 2022; Karume et al., 2024). Such challenges disproportionately affect low-income households, which exacerbates food insecurity and deepening socio-economic disparities. As illustrated in Figure 1, rural development funding in Eastern Africa presents steady growth from 2000 to 2013. However, subsequent fluctuations demonstrate ongoing underinvestment, which hinders the region's ability to strengthen agricultural resilience and infrastructure. Additionally, East Africa's high fertility rate, averaging four to six children per woman, places further pressure on limited domestic production, which perpetuates cycles of poverty and malnutrition (World Bank, 2022).

The adverse effects of climate change on food security have been extensively studied, particularly in vulnerable regions like SSA, where socioeconomic, political, and adaptive capacity limitations exacerbate food insecurity (Connolly-Boutin and Smit, 2016). Climate change has been linked to reduced agricultural productivity, as evidenced by Mubenga-Tshitaka et al. (2023), who found that rising temperatures negatively impacted East Africa's agricultural yields in the long-term, while precipitation influenced productivity primarily in the short-term. Fagbemi et al. (2023) conceptualized that the change in climatic patterns had exacerbated the ever-increasing hunger in SSA countries. Similarly, Abdi et al. (2023a, 2023b) observed that increasing temperatures were negatively correlated with cereal production in East Africa, whereas precipitation enhanced yields. However, the impact of climate change on food security varies depending on the crops grown. For instance, Abdi et al. (2024a, 2024b) found that rising temperatures reduced the production of sorghum, rice, banana, and beans but increased sugarcane yields, while Adhikari et al. (2015) identified wheat, maize, rice, and soybeans as highly vulnerable to climatic shifts, with sweet potato, potato, and cassava being more resilient. Furthermore, extreme weather events such as droughts and floods significantly exacerbate food insecurity across Africa (Yiadom et al., 2023). They also affirmed the role of institutional quality in lessening these effects. Delgado et al. (2023) highlighted how climate-induced food insecurity has deepened inequality and social divides across the continent. In addition to these challenges, Misra (2014) reported the depletion of natural resources in SSA due to climate change and

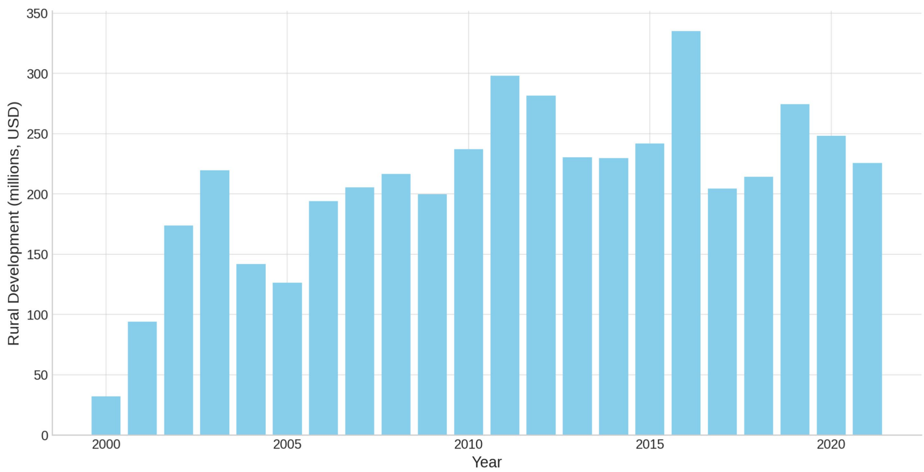

FIGURE 1
Annual rural development funding in Eastern Africa (2000–2021).

advocated for sustainable measures such as Soil Aquifer Treatment (SAT) and artificial groundwater recharge to address the growing crisis.

Changes in food prices significantly influence both the quantity and quality of food people can access, particularly in developing countries where a substantial share of household income is spent on food (Chandio et al., 2023). Rising food prices often reduce food security by forcing families to stretch their budgets, which makes it harder to afford adequate and nutritious meals (Zhou and Wan, 2017; Chavas, 2017). Recent global crises, such as the COVID-19 pandemic and the Russian invasion of Ukraine, have further exacerbated food insecurity in low- and middle-income countries, with higher global food prices driving up the cost of staple foods, especially in nations reliant on imports (Zereyesus et al., 2023; Okou et al., 2022). However, countries with stronger local food production tend to experience less inflation in staple food prices, which marks the importance of agricultural self-sufficiency (Okou et al., 2022). Inflation also plays a critical role in shaping food availability, as it disrupts prices and limits farmers' access to inputs, leading to lower crop yields (Mumuni and Joseph Aleer, 2023). Although inflation has less impact on other dimensions of food security, lower inflation levels have been associated with reduced undernourishment, as stable prices enable households to purchase sufficient food (Candelise et al., 2021). Furthermore, Abdi et al. (2024a, 2024b) found that the effects of higher food prices on food security in 32 SSA countries were mixed, with both positive and negative outcomes depending on local contexts.

Political stability is paramount in shaping food security outcomes, as effective governance is deeply intertwined with food systems. The literature asserts that stable political institutions enhance food availability, accessibility, and utilization through supportive policies and efficient implementation. Zhou and Wan (2017) found that good governance boosts agricultural productivity and food distribution, thereby improving food security. Similarly, Smith and Haddad (2015) observed that stable governments are better equipped to sustain nutrition programs, combat food deficiencies, and promote healthier diets. In Somalia, Maxwell (2013) documented how political instability between 2011 and 2012 disrupted food systems, which exacerbated vulnerabilities and worsened food insecurity. On a broader scale, Soffiantini (2020) revealed that political unrest in Arab countries hindered food production and distribution, which led to widespread shortages and nutritional deficits. Abdullah et al. (2020), using a dynamic panel model of 124 countries from 1984 to 2018, found that political stability, democratic accountability, and good governance are positively associated with improved food and nutrition security. Conversely, they observed that conflict, corruption, and military involvement in politics undermine food security. Deaton and Lipka (2015) further demonstrated that political stability attracts investment in agricultural infrastructure and social safety nets while fostering policies that address food security challenges.

Many studies have proposed that rural development delivers an integral solution to the challenges posed by climate change, political instability, and food inflation by enhancing food security through improved infrastructure and technological advancements (Abdi et al., 2025). Physical infrastructure, such as roads and storage facilities, boosts agricultural performance and ensures food availability. Upgraded rural road networks reduce food system costs, which makes goods more affordable and accessible (Edeme et al., 2020; Pivoto et al., 2018). Fedderke and Bogetić (2009) reiterated that physical infrastructure significantly enhances labor productivity, which fosters sustainable growth and agricultural resilience. In Nigeria, Adepoju and Salman (2013) found that road access, soil quality, and extension services positively affect farmers' productivity, while Boakye (2019) noted that inadequate storage facilities in Ghana result in more than half of cultivated crops failing to reach consumers, which stresses the necessity for improved warehousing. Similarly, in India, Lokesha and Mahesha (2017) demonstrated that improved rural roads facilitate crop diversification and profitability. Beyond physical infrastructure, access to electricity and ICT amplifies the impact of rural development by enhancing market connectivity and providing critical agricultural information (Abdi et al., 2025). Ezeoha et al. (2020) found that mobile phone and internet access improve food security by increasing market linkages, while Candelise et al. (2021) showed that access to electricity enhances food availability and nutrition in 54 developing countries.

East Africa's food security crisis is shaped by the interconnected challenges of climate change, political instability, and economic pressures, yet the potential of rural development as a transformative solution remains underexplored. The region's reliance on non-irrigated agriculture makes it particularly vulnerable to extreme weather events and erratic rainfall patterns that significantly reduce crop yields (Abdi et al., 2023a, 2023b; Adhikari et al., 2015; FAO, 2021). Political instability further exacerbates these issues, with governance failures and conflicts disrupting food systems and preventing the implementation of sustainable agricultural policies (Maxwell, 2013; Soffiantini, 2020). Additionally, the sharp rise in global food prices, driven by crises such as the Russia-Ukraine conflict, has strained household affordability, particularly in import-dependent nations that source their food externally (FAO, 2022). While substantial research has examined the links between climate change, conflicts, and food security (Adhikari et al., 2015; Delgado et al., 2023), rural development—through improved infrastructure, access to technology, and market connectivity—suggests an exhaustive pathway to lessen these vulnerabilities. This study aspires to bridge the gap by investigating how rural development, alongside climatic and socio-economic factors, influences food security in East Africa. Utilizing empirical data from 2000 to 2021, the analysis strives to present actionable insights into creating a resilient and sustainable food system for the region. To find reliable and region-specific outcomes, this study employs robust econometric methodologies, including panel-corrected standard errors (PCSE), feasible generalized least squares (FGLS), and the Dumitrescu and Hurlin panel causality test, to address limitations in prior research by accounting for heterogeneity and cross-sectional dependencies across East African countries.

This study makes a significant contribution to the existing body of knowledge on food security in East Africa by addressing critical research gaps and employing innovative methodologies. Initially, while much of the existing literature focuses on isolated factors such as climate change, political instability, or food price inflation, this study adopts an integrated approach to examine their combined effects alongside rural development. By integrating diverse variables—including climate change, governance quality, and rural infrastructure—this research proposes pioneering insights into the varied determinants of the region's food security landscape. Subsequently, while previous studies primarily illustrate the challenges faced by food security, including climate change, political instability, and economic pressures, they often overlook the role of rural development as a climate resilience strategy. This study addresses this gap by demonstrating how investments in rural development, such as improved infrastructure, electricity access, and ICT, can mitigate the adverse effects of climate change, enhance agricultural productivity, and stabilize food systems. By positioning rural development as a solution rather than just scrutinizing the obstacles, the research shifts the narrative toward actionable strategies for resilience and sustainability. Rather than treating food security as a singular dependent variable, this study investigates its core components—availability, access, utilization, and stability—to uncover how climate change, political stability, and rural development influence these factors. By disaggregating food security, the research provides a profound understanding of the specific mechanisms through which environmental and economic variables impact different dimensions of food security. Finally, the study equips policymakers with evidence-based recommendations to foster rural development, promote climate-smart agriculture, and build resilient food systems in East Africa and beyond.

2 Materials and methodology

2.1 Data sources and food security measurement framework

This study investigates the relationship between rural development and food security in East Africa, incorporating climatic and socio-economic factors. The analysis utilizes a balanced panel dataset spanning 12 East African countries—Democratic Republic of Congo, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Rwanda, Somalia, Tanzania, Uganda, Zambia, and Zimbabwe—covering the period from 2001 to 2020. These countries were selected based on their exposure to climatic volatility, institutional fragility, and macroeconomic shocks, which heighten their vulnerability to food insecurity. The dependent variable is food security, operationalized through a composite index that captures four core dimensions: availability, accessibility, stability, and utilization. These dimensions are represented by heterogeneous indicators—such as average dietary energy supply adequacy, GDP per capita, prevalence of undernourishment, food production variability, child malnutrition rates, and access to water and sanitation. To consolidate these variables into a single index, the study employs Principal Component Analysis (PCA), a data-reduction technique widely used in development economics and public health research to handle multidimensional constructs (Greco et al., 2019; Jolliffe, 2002). PCA transforms correlated indicators into uncorrelated principal components by capturing the maximum variance within the data. While PCA assumes linear relationships and enforces orthogonality, these assumptions serve the analytical purpose of simplifying interpretation and mitigating multicollinearity (Abdi and Williams, 2010).

Prior to extraction, all variables were standardized to address differences in units and scales to ensure that no single dimension dominates the composite measure due to measurement units. Justification for component retention follows a robust criterion, combining the Kaiser rule (eigenvalues >1), scree plot analysis, and cumulative variance thresholds—as recommended by Hair et al. (2019)—to ensure meaningful representation and minimize information loss. Though PCA's limitations—such as its linearity assumption and orthogonality constraint—are acknowledged, the method remains a practical and theoretically grounded tool for summarizing complex constructs like food security. This is further supported by applications in similar contexts, such as Headey and Ecker (2013), who developed a PCA-based food security index for SSA, and Zezza et al. (2017), who used PCA to analyze household food security. More recently, Hamadjoda Lefe et al. (2024) applied PCA to construct a food security index for 40 SSA countries. On the other hand, the independent variables include climatic factors—mean annual rainfall and average temperature (from the Climate Change Knowledge Portal)—and socio-economic indicators such as rural development, food imports, food price levels, population growth, and political stability. Data were sourced from authoritative databases, including the Food and

TABLE 1 Variables description and data sources.

Variable	Code	Indicator	Source
Food security indices			
Food security	FS		
Availability	ADESA	Average dietary energy supply adequacy (percent) (3-year average)	FAO
Accessibility	GDPPC	Gross domestic product per capita, PPP, (constant 2017 international $)	FAO
	PU	Prevalence of undernourishment (percent) (3-year average)	
	NPU	Number of people undernourished (million) (3-year average)	
Stability	FPV	Per capita food production variability (constant 2014–2016 thousand int.$ per capita)	FAO
	PFSV	Per capita food supply variability (kcal/cap/day)	
Utilization	CHW	Percentage of children under 5 years affected by wasting (percent)	FAO
	CHS	Percentage of children under 5 years of age who are stunted (modelled estimates) (percent)	
	CHO	Percentage of children under 5 years of age who are overweight (modelled estimates) (percent)	
	WAT	Percentage of population using at least basic drinking water services (percent)	
	SAN	Percentage of population using safely managed sanitation services (Percent)	
Climatic indicators			
Mean rainfall	RF	Average annual rainfall (mm)	CCKP
Mean temperature	TEM	Average annual temperature in (°C)	CCKP
Macroeconomic variables			
Food prices	FPI	Food price inflation (value %)	FAO
Population growth	PG	Population growth (annual %)	WDI
Food imports	FM	Imported food excluding fish (value, millions USD)	FAO
Rural development	RD	Development Flows to Agriculture (Disbursement millions USD)	FAO
Political stability	PS	Political Stability and Absence of Violence/Terrorism: Estimate	WGI

Agriculture Organization (FAO), World Development Indicators (WDI), and the Worldwide Governance Indicators (WGI). Table 1 provides a detailed overview of the variables utilized in the analysis and their corresponding data sources. Equations 1–4 present the mathematical formulation of the PCA-based index across the four food security dimensions. This relationship is represented as:

$$FS_{it} = \theta_1 AVAIL_{it} + \theta_2 ACC_{it} + \theta_3 STAB_{it} + \theta_4 UTIL_{it} \quad (1)$$

where FS_{it} represents the food security index for country i at time t. The availability dimension, $AVAIL$, captures the adequacy of dietary energy supply, while accessibility, ACC, accounts for economic access to food. Stability, $STAB$, represents the resilience of food supply chains, and utilization, $UTIL$, assesses the nutritional and health-based quality of food. The coefficients θ_1, θ_2, θ_3, and θ_4 define the relative importance of each dimension in contributing to overall food security.

Specifically, this study delineates food availability via the average dietary energy supply adequacy (ADESA). Moreover, food accessibility is formulated as a function of economic and nutritional access indicators, given by:

$$Accessibility_{it} = \omega_1 GDPPC_{it} + \omega_2 PU_{it} + \omega_3 NPU_{it} \quad (2)$$

where $GDPPC$ denotes gross domestic product per capita, which reflects the economic capability of individuals to afford food. PU represents the prevalence of undernourishment, which indicates the proportion of the population consuming inadequate calories. NPU denotes the number of people undernourished by offering a numerical measure of food deprivation. The coefficients ω_1, ω_2, and ω_3 capture the respective influences of these factors on food accessibility. Moreover, food stability is modeled to account for fluctuations in food production and supply, expressed as:

$$Stability_{it} = \delta_1 FPV_{it} + \delta_2 FSV_{it} \quad (3)$$

where FPV represents per capita food production variability, which measures inconsistencies in agricultural output and FSV denotes per capita food supply variability, which reflects fluctuations in food availability due to external shocks. The coefficients δ_1 and δ_2 determine the extent to which these variables influence food stability. Food utilization is captured through multiple nutritional and hygiene-related factors, expressed as:

$$Utilization_{i,t} = \gamma_1 CHW_{it} + \gamma_2 CHS_{it} + \gamma_3 CHO_{it} + \gamma_4 WAT_{it} + \gamma_5 SAN_{it} \quad (4)$$

where CHW represents the percentage of children under five affected by wasting, an indicator of acute malnutrition, while CHS reflects the percentage of children under five affected by stunting, measuring chronic malnutrition. CHO accounts for the percentage of children under five affected by overweight, which highlights imbalances in nutritional intake. Additionally, WAT represents access to basic drinking water services, ensuring safe hydration, and *SAN* refers to safely managed sanitation services. The coefficients γ_1, γ_2, γ_3, γ_4, and γ_5 measure the relative impact of these variables on food utilization.

2.2 Econometric model framework

Building on the conceptual foundations outlined by Abdi et al. (2024a, 2024b), Fagbemi et al. (2023), and Hamadjoda Lefe et al. (2024), this study models the functional relationship between climate change and food security in East African countries. The initial framework can be expressed in Equation (5) as follows:

$$FS = f\left(RF, TEM, W\right) \tag{5}$$

In this formulation, *RF* signifies average annual rainfall, *TEM* represents mean annual temperature, and *W* encompasses a set of control variables that potentially influence food security outcomes in the region. To address the broader research objectives, the model is extended to include key macroeconomic and institutional determinants. The extended model takes the following form (see Equation (6)):

$$FS = f\left(RF, TEM, FPI, PG, FM, RD, PS\right) \tag{6}$$

where *FPI* denotes food price inflation, *PG* indicates population growth, *FM* represents food imports, *RD* captures rural development, and *PS* accounts for political stability. This broader formulation allows for a more comprehensive assessment of both climatic and non-climatic determinants of food security in East Africa. To operationalize the empirical analysis, three model specifications are developed. The first model examines the effects of climate change on food security, while also controlling for selected economic influences. This is specified in Equation (7):

$$FS_{it} = \alpha_0 + \varphi_1 RF_{it} + \varphi_2 TEM_{it} + \varphi_3 FPI_{it} + \varphi_4 PG_{it} + \varphi_5 FM_{it} + \varepsilon_{it} \tag{7}$$

where α_0 is the intercept, φ_1 through φ_5 are the coefficients of the explanatory variables, and ε_{it} is the error term capturing unobserved factors. The second model introduces rural development to evaluate its direct contribution to food security, modifying the baseline model as show in Equation (8):

$$\begin{aligned} FS_{it} = \alpha_0 + \varphi_1 RF_{it} + \varphi_2 TEM_{it} + \varphi_3 FPI_{it} + \\ \varphi_4 PG_{it} + \varphi_5 FM_{it} + \varphi_6 RD_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

The final and most comprehensive model integrates all climatic, economic, and institutional dimensions, as shown in Equation (9).

$$\begin{aligned} FS_{it} = \alpha_0 + \varphi_1 RF_{it} + \varphi_2 TEM_{it} + \varphi_3 FPI_{it} + \\ \varphi_4 PG_{it} + \varphi_5 FM_{it} + \varphi_6 RD_{it} + \varphi_7 PS_{it} + \varepsilon_{it} \end{aligned} \tag{9}$$

Based on theoretical expectations, *RF*, *FM*, *RD*, and *PS* are expected to positively influence food security. In contrast, *TEM* and *FPI* are anticipated to exert negative effects due to their adverse impacts on food production and affordability. The expected effect of *PG* is ambiguous, as it can increase food demand and pressure agricultural systems, yet potentially improve accessibility through labor supply expansion and market dynamics. The panel dataset covers 12 East African countries $\left(i = 1,2,\ldots,N\right)$ over the period 2001 to 2020 $\left(t = 2001, 2002, \ldots, T\right)$.

2.3 Empirical technique

2.3.1 Cross-sectional dependence

A critical challenge in panel data analysis, with profound implications for estimation precision and inference validity, is the presence of interdependencies among individual units (Sarafidis and Wansbeek, 2012). These interdependencies often emerge from shared economic networks, spatial proximity, and deep-rooted cultural ties, making cross-sectional dependence (CSD) a probable concern in the East African context (Abdi et al., 2023a, 2023b). Economic integration through trade fosters financial interlinkages, geographical contiguity amplifies spillover effects, and cultural affiliations enhance social and economic interconnectedness. Ignoring CSD risks producing biased and unreliable estimates, which ultimately weakens the robustness of empirical findings (Sarkodie and Owusu, 2020). To address this, a preliminary diagnostic step involves testing for CSD among the panels under investigation. A widely employed technique for this purpose is the Lagrange Multiplier (LM) test, initially formulated by Breusch and Pagan (1980), along with its scaled variant proposed by Pesaran (2004). These tests assess the null hypothesis of cross-sectional independence—implying no contemporaneous correlation in the error terms across cross-sectional units—against the alternative hypothesis of significant interdependence.

2.3.2 Slope heterogeneity test

The second critical issue in panel data analysis is the determination of the homogeneity of slope coefficients. If the assumption of homogeneity is made without empirical validation, it can result in the omission of country-specific idiosyncrasies (Bedir and Yilmaz, 2016). Swamy (1970) introduced a test for slope homogeneity that assesses the dispersion of individual slope estimates from an appropriate pooled estimator. Pesaran and Yamagata (2008) argue that both the F-test and Swamy's test require panel data models with a relatively small cross-sectional dimension (N) compared to the time dimension (T). To circumvent this limitation, they proposed a standardized version of Swamy's test, referred to as the $\tilde{\Delta}$ test, for assessing slope homogeneity in large panels. The $\tilde{\Delta}$ test is asymptotically valid as (N, T) → ∞, without any constraints on the relative rates of increase of N and T under the assumption of normally distributed error terms. Pesaran and Yamagata (2008) subsequently derived the following standardized dispersion statistic (see Equation 10):

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2K}}\right) \tag{10}$$

where k signifies the number of regressors, and $\tilde{S}$ represents Swamy's statistic. Under the null hypothesis, with the assumption that

(N, T) → ∞ and the error terms are normally distributed, the $\tilde{\Delta}$ test adheres to an asymptotic standard normal distribution. To refine the small sample properties of the $\tilde{\Delta}$ test, assuming normally distributed errors, one can employ the following bias-adjusted mean and variance (see Equation 11):

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E\left(\tilde{Z}_{iT}\right)}{\sqrt{Var\left(\tilde{Z}_{iT}\right)}}\right) \tag{11}$$

In this context, $E\left(\tilde{Z}_{iT}\right) = k$, and $Var\left(\tilde{Z}_{iT}\right) = 2k\left(T-k-1\right)/\left(T+1\right)$

2.3.3 Second-generation unit root test

Once cross-sectional dependence has been identified, the next crucial step is to examine the stationarity of variables and determine their order of integration. Traditional first-generation unit root tests operate under the assumption that panel units are independent across sections; however, this assumption is often violated when cross-sectional dependence exists (Breitung and Das, 2008). Neglecting this dependence can lead to misleading inferences and spurious regression results. To overcome this limitation, Pesaran (2007) introduced second-generation panel unit root tests, such as the cross-sectional augmented Dickey-Fuller (CADF) test and its extended variant, the cross-sectional augmented IPS (CIPS) test. These advanced techniques explicitly account for interdependencies among panel units and mitigate the influence of unobserved common factors. While both tests follow a similar methodological framework, the CIPS test offers an enhanced approach by incorporating cross-sectional averages. Fundamentally, these tests evaluate whether the data support the alternative hypothesis of stationarity or whether the null hypothesis of a unit root persists. The CIPS procedure builds upon the CADF model, aggregating the CADF statistics across cross-sections to compute the final CIPS statistic. The CADF test statistic is formally expressed as shown in Equation (12):

$$\Delta Y_{i,t} = \alpha_i + \beta_i Y_{i,t-1} + \gamma_i \overline{Y}_{t-1} + \delta_i \Delta \overline{Y}_{i,t} + \varepsilon_{it} \tag{12}$$

where $\overline{Y}_{t-1}$ and $\Delta\overline{Y}_{i,t}$ denote the cross-sectional averages of the lagged values and the first differences of the individual series, respectively. The computation of the cross-sectional mean follows Equation (13).

$$\overline{Y}_{t-1} = \frac{1}{N}\sum_{i=1}^{N}\Delta\overline{Y}_{i,t} \tag{13}$$

The CADF statistic is obtained by averaging the individual CADF statistics $CADF_i$ as illustrated in Equation (14):

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{14}$$

where $CADF_i$ represents the t-statistics derived from the CADF regression outlined in Equation (12).

2.3.4 Panel cointegration test

Before proceeding with the main analysis, it is essential to determine whether a long-run equilibrium relationship exists among the variables. This is accomplished through panel cointegration tests, specifically those developed by Pedroni (1999, 2004) and Kao (1999). Pedroni test is notable for handling differences between panels by including specific fixed effects and time trends in the cointegration regression. This approach allows the autoregressive (AR) coefficient to vary from one panel to another. Here's a look at how the Pedroni panel cointegration method is typically set up. The general structure of the Pedroni panel cointegration equation is presented in Equation (15) :

$$Y_{it} = \rho_i + \omega_{1i} X_{it} + \omega_{2i} X_{2it} + \ldots\ldots \omega_{pi} X_{pit} + \varepsilon_{it} \tag{15}$$

In this setup, ρ_i and ω_i represent the intercepts and slope coefficients, which can differ between cross-sections. The assumption is that Y, X, and p all have the same integration order of I(1). According to the null hypothesis, which suggests that there is no cointegration, the residuals ε_i would be integrated at I(1). If the p-value is significant at the 1%, 5%, or 10% levels, we would reject the null hypothesis and conclude that a cointegration relationship is present.

2.3.5 Panel model approach

FGLS, introduced by Parks (1967), was the first method used to examine the relationships among the study variables. This static panel technique is especially suited for long-term analysis. When dealing with non-spherical errors and an unknown covariance matrix, FGLS helps estimate the coefficients of a multiple linear regression model and their covariance matrices. The FGLS process involves creating an inverse matrix of the estimated variance–covariance matrix (EVCM) of the errors, which transforms the regression equation. FGLS is appropriate for panels with T greater than N (Biswas et al., 2022). Below is the basic setup for the FGLS models, as specified in Equations (16) and (17), respectively:

$$\hat{\beta} = \left(X'\hat{\Omega}^{-1}X\right)^{-1} X'\hat{\Omega}^{-1}y \tag{16}$$

$$Var\left(\hat{\beta}\right) = \left(X'\hat{\Omega}^{-1}X\right)^{-1} \tag{17}$$

In this context, $\hat{\Omega}$ takes into account implicit assumptions about varying error variances (heteroscedasticity), serial correlation, and dependencies between different cross-sectional units. On the other hand, OLS is applicable when $\grave{U}_{NT}$ is assumed to have constant error variances (homoscedasticity), no time-based correlations, and no cross-sectional dependencies. The second method used to analyze the relationship between the variables is the PCSE technique, proposed by Beck and Katz (1995). Like FGLS, PCSE is well-suited for long-term analysis in static panel data. Panel data often present challenges such as autocorrelation, group-wise heteroscedasticity, and CSD. The PCSE method effectively addresses these issues (Doku et al., 2019; Sandow et al., 2021). Additionally, Nickell (1981) demonstrated that PCSE can reduce bias in dynamic models with fixed effects, particularly when there is slope heterogeneity. This technique is especially useful when the dataset contains more N than T (Biswas et al., 2022; Hoechle, 2007). The PCSE estimator is computed using the following formulas, as shown in Equations (18) and (19), respectively:

$$\hat{\beta}=\left(\tilde{X}'\tilde{X}\right)^{-1}\tilde{X}'\tilde{y} \tag{18}$$

$$Var(\widehat{\beta})=\left(\tilde{X}'\tilde{X}\right)^{-1}\left(\tilde{X}'\tilde{\Sigma}\tilde{X}\right)\left(\tilde{X}'\tilde{X}\right)^{-1} \tag{19}$$

In this setup, $\tilde{X}$ and $\tilde{y}$ are the Prais-transformed versions of the explanatory and dependent variables. We use $\tilde{\Sigma}$ to represent our estimate of Σ. The equation $\Omega_{NT}=\Sigma\otimes\pi$ means that Ω_{NT} is formed by taking the Kronecker product of Σ and π.

2.3.6 Dumitrescu-Hurlin granger causality

To investigate causality among the variables, this study utilizes the Dumitrescu–Hurlin causality test proposed by Dumitrescu and Hurlin (2012). This test is designed to uncover how variables influence each other by showcasing their effectiveness in diverse panel structures. It is particularly versatile and applicable whether N exceeds or falls short of T (Abdi et al., 2024a, 2024b). The method is adept at identifying causation within specific segments of the panel (Lopez and Weber, 2017), which is crucial for developing well-informed policy recommendations. Given that it accommodates CSD, the Dumitrescu–Hurlin test is classified as a second-generation test (Çeştepe et al., 2024). In this causality analysis, we outline the null and alternative hypotheses as follows:

$$H_0:\beta_i=0,\forall_i=1,2,\ldots,N$$

$$H_1:\begin{cases}\beta_i=0,\forall_i=1,2,\ldots,N_1\\ \beta_i=0,\forall_1=N_{1+1},\ldots,N\end{cases}$$

In this procedure, we compare the null hypothesis with the alternative hypothesis. To do this, the test uses two statistics, Wald statistics (W) and the standardized statistics (Z). The formulas for these test statistics are given in Equations (20) and (21)

$$\bar{W}=\frac{1}{N}\sum_{i=1}^{N}W_i \tag{20}$$

$$\bar{Z}=\sqrt{\frac{N}{2K}}\left(\bar{W}-K\right) \tag{21}$$

3 Empirical investigation and analytical discussion

3.1 Descriptive and preliminary analysis

Figure 2 illustrates the development flows to agriculture across Eastern African countries by asserting significant disparities in funding allocation over time. Kenya and Ethiopia emerged as the largest recipients, with Kenya recording the

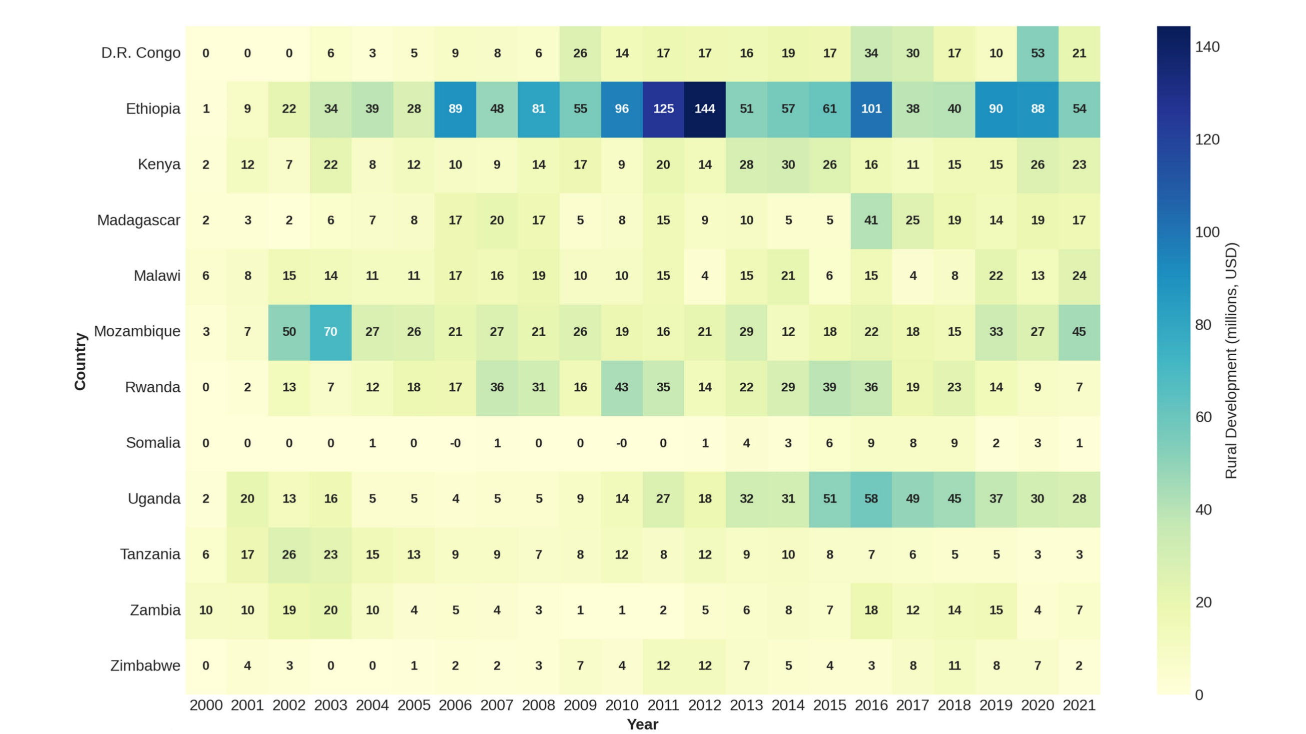

FIGURE 2
Development flows to agriculture across Eastern African countries.

TABLE 2 Descriptive summary of variables.

	FS	RF	TEM	FPI	PG	FM	PS	RD
Mean	0.000	1006.725	23.816	15.136	2.766	0.661	−0.883	18.234
Maximum	2.879	1601.820	30.440	685.400	3.927	2.955	0.661	144.402
Minimum	−2.847	249.270	19.010	−13.110	0.524	0.043	−3.313	−0.038
Std. Dev.	1.270	347.877	2.622	57.534	0.585	0.574	0.908	20.719
Skewness	−0.120	−0.321	0.822	10.366	−1.552	1.467	−0.532	2.842
Kurtosis	2.647	2.611	3.757	113.318	6.560	4.798	2.620	13.452
Jarque-Bera	1.823	5.635	32.760	125998.200	223.148	118.362	12.747	1415.583
Probability	0.402	0.060	0.000	0.000	0.000	0.000	0.002	0.000
Observation	240	240	240	240	240	240	240	240

TABLE 3 Analysis of pair-wise correlations.

Variables	FS	RF	TEM	FPI	PG	FM	PS	RD
FS	1.000							
RF	0.134**	1.000						
TEM	−0.479***	−0.042	1.000					
FIN	−0.038	0.020	0.078	1.000				
PG	−0.341***	0.171***	0.392***	−0.023	1.000			
FM	0.037	−0.249***	0.304***	−0.020	0.005	1.000		
PS	0.501***	0.326***	−0.662***	−0.076	−0.054	−0.330***	1.000	
RD	−0.003	0.102	−0.065	−0.034	0.058	0.343***	−0.029	1.000

***, **, * denote significance levels at 1, 5% and 10%, respectively.

highest peak (144 million) in 2012. This reflects strong external support and policy prioritization of agriculture. Ethiopia also experienced multiple years of high inflows, particularly between 2012 and 2014, which suggests sustained donor interest that has facilitated improvements in agricultural productivity and food availability. In contrast, countries like Somalia, Zambia, and Zimbabwe receive consistently lower agricultural development flows, potentially due to weak institutional mechanisms or socio-political challenges, which exacerbate food insecurity by limiting agricultural output and market access. Mozambique, Uganda, and Rwanda exhibit moderate but steady increases in agrarian funding. Though challenges remain in sustaining rural livelihoods, this indicates gradual improvements in food security. D.R. Congo demonstrates fluctuating inflows, which stresses the variability of donor commitments and its continued vulnerability to food insecurity. The regional differences in Figure 2 suggest that countries with stable agricultural policies and more muscular governance structures tend to attract higher funding. At the same time, fragile economies struggle with limited inflows that further deepen food insecurity.

3.1.1 Summary statistics and correlation analysis

Table 2 presents a detailed statistical summary of the variability of central tendencies and distributional characteristics of the study variables. Rural development exhibits the highest mean value (18.234), which indicates its prominence in the dataset. However, political stability records the lowest mean (−0.883), which reflects the persistent challenges associated with governance and institutional stability. The data further reveal substantial variability in food imports, which exhibit the highest maximum value (685.400) and the second-largest standard deviation (57.534). In contrast, food security and population growth demonstrate the least dispersion with standard deviations of 0.574 and 0.585, respectively, indicating relative stability in these variables over time. The distributional properties reveal key data patterns. Food security, rainfall, population growth, and political stability are left-skewed, while average temperature, food prices, imports, and rural development are right-skewed. Food inflation, imports, and rural development trends have critical food security implications. High import variability and right-skewed food prices indicate unstable external reliance, worsening food insecurity when domestic production falls short. Meanwhile, uneven rural development suggests that while some areas receive significant investment, many lag behind, restricting agricultural capacity and resilience to inflation. Furthermore, the Jarque-Bera test results confirm that all variables except food security deviate from normality, as evidenced by probability values below the 0.05 threshold.

To assess the strength of relationships among the variables, this study conducted a correlation coefficient analysis, as presented in Table 3. The results reveal both positive and negative correlations among the variables. Positive correlations indicate that increases in certain factors enhance food security. Specifically, rainfall, food imports, and political stability positively correlate with food security, which suggests their contributions to improved outcomes in East Africa. Conversely, negative correlations stress variables that hinder food security. Higher temperatures, rising food prices, and population

TABLE 4 Results of cross-sectional dependence analysis.

H_0: No cross-section dependence		
Variable	Breusch-Pagan LM	Pesaran scaled LM
FS	299.226	20.3
	[0.000]	[0.000]
RF	203.807	11.995
	[0.000]	[0.000]
TEM	316.631	21.815
	[0.000]	[0.000]
FPI	120.882	4.777
	[0.000]	[0.000]
PG	458.288	34.144
	[0.000]	[0.000]
FM	723.117	57.195
	[0.000]	[0.000]
PS	220.447	13.443
	[0.000]	[0.000]
RD	168.819	8.949
	[0.000]	[0.000]

TABLE 5 Heterogeneity analysis results.

H_0: slope coefficients		
	Statistic	p-Value
$\tilde{\Delta}$	3.334	0.001
$\tilde{\Delta}$ Adjusted	4.714	0.000

TABLE 6 Findings of second-generation unit root tests.

Variables	CIPS		CADF	
	Level	1st difference	Level	1st difference
FS	−1.642	−3.128***	−1.846	−2.531***
RF	−4.245***	−5.448***	−3.071***	−4.26***
TEM	−2.704***	−5.681***	−1.918	−3.773***
FPI	−3.274***	−4.696***	−2.187*	−3.316***
PG	−0.989	−2.381**	−1.549	−2.771***
FM	−2.876***	−4.630***	−2.260**	−2.920***
RD	−2.600***	−4.526***	−2.415**	−3.023***
PS	−2.022	−4.623***	−1.549	−2.749***

***, **, * denote significance levels at 1, 5% and 10%, respectively.

TABLE 7 Results of Pedroni and Kao cointegration tests.

	Statistic	p-Value
Pedroni cointegration test		
Modified Phillips–Perron t	5.492	0.000
Phillips–Perron t	2.288	0.011
Augmented Dickey–Fuller t	2.650	0.004
Kao cointegration test		
Modified Dickey–Fuller t	−1.754	0.040
Dickey–Fuller t	−1.404	0.080
Augmented Dickey–Fuller t	−2.170	0.015
Unadjusted modified Dickey–Fuller t	−1.308	0.095
Unadjusted Dickey–Fuller t	−1.183	0.118

growth are linked to lower food security, which suggests the challenges these factors impose on the region. Notably, rural development exhibits a weak negative correlation with food security, implying that, in this dataset, increases in rural development are marginally associated with declines in food security across the region.

3.1.2 Evaluation of cross-sectional dependence and heterogeneity

It is essential to assess the presence of CSD before proceeding with panel estimation techniques. Table 4 presents the results of two widely used CSD tests—the Breusch-Pagan LM test and the Pesaran scaled LM test. These tests were employed to examine whether the residuals across countries in the panel are correlated, which would indicate the influence of unobserved common factors or regional spillover effects. The findings from both the Breusch-Pagan LM and the Pesaran scaled LM tests consistently reject the null hypothesis of cross-sectional independence at the 1% significance level for all variables. This suggests a statistically significant presence of cross-sectional dependence in the panel dataset, implying that shocks or changes in one country may affect others within the region. Additionally, the heterogeneity of the slope coefficients was evaluated using the Pesaran and Yamagata (2008) test. The results, presented in Table 5, indicate that the null hypothesis is rejected at the 1% significance level, as indicated by the significance of both $\tilde{\Delta}$ and $\tilde{\Delta}$ Adjusted. This confirms the presence of heterogeneity in the slope coefficients across the cross-sectional units, which implies that the relationships between variables vary significantly among countries in the dataset.

3.1.3 Panel unit root and cointegration tests

To address the limitations associated with cross-sectional dependence in first-generation unit root tests and to ensure accurate inference regarding the stationarity properties of the variables, this study employed second-generation panel unit root tests—namely, the CIPS and CADF tests. The results, presented in Table 6, indicate a mixed order of integration across the variables. According to the CIPS test, rainfall, temperature, food imports, food prices, and rural development are stationary at level [I(0)], thereby rejecting the null hypothesis of a unit root. Conversely, food security, population growth, and political stability become stationary only after first differencing, indicating integration at order one [I(1)]. The CADF test results corroborate these findings, showing that rainfall, food imports, and rural development are stationary at level, while food security, temperature, food prices, population growth, and political stability are stationary at first difference.

The cointegration among the variables was assessed using the Pedroni and Kao cointegration tests. The results, presented in Table 7, indicate a strong cointegration relationship among the variables. The Pedroni test results, including Modified Phillips-Perron, Phillips-Perron, and Augmented Dickey-Fuller, reject the null hypothesis of no cointegration at the 1% significance level, which confirms that the variables share a long-run relationship and move together over time. Similarly, the Kao test supports the presence of cointegration through the Modified Dickey-Fuller and Augmented Dickey-Fuller statistics. However, the *p*-values for the Dickey-Fuller, Unadjusted Modified Dickey-Fuller, and Unadjusted Dickey-Fuller t-statistics exceed the 5% significance level, which indicates that these tests fail to reject the null hypothesis.

3.2 Empirical analysis—PCSE and FGLS techniques

Given the presence of mixed integration orders and confirmed cointegration among the variables, conventional long-run estimators such as FMOLS, DOLS, or ARDL-PMG were considered. However, these approaches produced inconsistent and unstable estimates, likely due to sample size constraints or convergence difficulties inherent in the data. As an alternative, this study adopts the PCSE and FGLS estimators applied to first-differenced data, which enable robust short-run analysis while controlling for cross-sectional dependence and heteroskedasticity. The findings indicate that rainfall exhibits a significant positive impact on food security using the PCSE and FGLS estimators. Specifically, increased rainfall favourably correlates with food security, which reinforces its vital role in East Africa's rain-fed agricultural systems. This finding aligns with Adhikari et al. (2015), who affirm the importance of adequate rainfall in boosting agricultural productivity, and Abdi et al. (2024a, 2024b), who report a similar positive effect in Somalia. Similarly, Randell et al. (2022) and Hamadjoda Lefe et al. (2024) also report a positive relationship between rainfall and food security in SSA. These assert the importance of sustainable water management in addressing precipitation variability. However, the region's rainfall variability remains a challenge, as frequent dry spells lead to crop failures while excessive precipitation accelerates soil erosion, both of which undermine food security. Given East Africa's dependence on agriculture, ensuring water availability through efficient irrigation systems and climate adaptation strategies is essential to mitigating these risks and sustaining food production.

As anticipated, higher temperatures negatively influence food security due to their detrimental effects on crops throughout the plant life cycle. Elevated temperatures impair photosynthesis, disrupt fertilization processes, and limit nutrient and water uptake, ultimately reducing both the quantity and quality of crop yields. These findings align with Parthasarathi et al. (2022), who highlight the adverse physiological effects of rising temperatures on crop growth. Similarly, Abdi et al. (2023a, 2023b), Mubenga-Tshitaka et al. (2023), and Yiadom et al. (2023) emphasize the negative impact of higher temperatures on agricultural performance in East Africa, which reinforces the paramount role of temperature regulation in sustaining food production. However, the implications of rising temperatures extend beyond reduced yields. Increased heat stress accelerates soil moisture loss, intensifies pest infestations, and shortens growing seasons, further exacerbating food insecurity. In East Africa, where many farming systems rely on rain-fed agriculture, these effects pose significant challenges for smallholder farmers who lack access to irrigation and climate-adaptive technologies. Given these risks, targeted climate adaptation strategies—such as heat-resistant crop varieties, improved irrigation infrastructure, and agroecological practices—are essential for mitigating the adverse effects of temperature increases and ensuring food security in East Africa.

Across both models, the coefficient of food prices ranges from −0.00123 to 0.000242, indicating an insignificant relationship with food security. This suggests that while food prices may have both positive and negative effects, their overall impact remains statistically weak in the East African context. Unlike Abdi et al. (2024a, 2024b), who found significant mixed effects of food prices on food security in SSA, our findings suggest that food price fluctuations alone may not be a primary driver of food security outcomes in the region. While prior studies, such as Headey and Hirvonen (2022), argue that higher food prices can incentivize agricultural production and increase demand for unskilled labour, these effects may not be strong enough to translate into measurable improvements in food security. Similarly, although Gustafson (2013) highlights the adverse impact of rising food prices on household purchasing power, our findings suggest that other factors, such as income levels, market access, and government interventions, may mitigate the direct influence of food prices on food security. The insignificant results indicate the complexity of food security dynamics in East Africa, where multiple structural factors likely dominate over food price fluctuations alone.

In addition to climatic factors, several non-climatic factors significantly influence food security in East Africa. The findings from both PCSE and FGLS estimators reveal a consistently negative effect of population growth across all estimated models. Rapid population growth intensifies food demand, placing immense pressure on agricultural systems and often leading to the overexploitation of arable land (Muyanga and Jayne, 2014). Furthermore, urbanization exacerbates CO_2 emissions, contributing to climate change and the depletion of natural resources, which further threatens agricultural productivity and food availability (Abdi et al., 2024a, 2024b). These findings align with empirical studies such as Miladinov (2023), who demonstrated a positive relationship between population growth—both rural and urban—and undernourishment, which demonstrates the growing strain on food supply systems. Similarly, Hall et al. (2017) projected that rapid population growth would be a key driver of food insecurity and undernourishment in Africa. In East Africa, where much of the population relies on subsistence farming, the connection between rapid demographic expansion and limited agricultural resources displays the urgency of approaches to sustainable food production, land management, and infrastructure development to mitigate food insecurity risks.

Food imports play a vital role in enhancing food security by increasing the availability of diverse, high-quality food options. The findings from both estimators confirm that food imports significantly and positively contribute to alleviating food insecurity, aligning with Arias et al. (2024), who affirm their role in supplementing domestic food production. Similarly, Smith and Glauber (2020) exhibit how food imports mitigate domestic production shortfalls, ensuring a stable food supply, particularly in regions vulnerable to climate-induced agricultural disruptions. In East Africa, where erratic weather patterns often constrain local agricultural productivity, food imports serve as a crucial buffer against production deficits and seasonal shortages. However, the broader implications of food imports on food security remain a subject of debate. While imports improve food availability, their long-term effects on food system resilience raise concerns, especially in light of disruptions from the COVID-19 pandemic and the Russia-Ukraine war. COVID-19 exposed vulnerabilities in global supply chains, while the Russia-Ukraine conflict disrupted grain markets, driving up food prices and worsening food insecurity in import-dependent regions like East Africa. Subramaniam et al. (2024) argue that heavy dependence on food imports may undermine local agricultural development, discourage domestic investment in food production, and create vulnerabilities in times of global supply chain disruptions. Additionally, fluctuations in global food prices can impact affordability, making food access unpredictable for lower-income populations.

Strikingly, political stability favorably influences food security across all model specifications, which affirms the importance of stable governance in ensuring food availability and accessibility. These findings align with Yiadom et al. (2023), who emphasize that institutional quality fosters political stability, which in turn alleviates key drivers of food insecurity. Stable governance creates an enabling environment for investment in agriculture, improves policy implementation, and enhances food supply chain efficiency. Similarly, Subramaniam et al. (2022) and Cassimon et al. (2022) support the critical role of strong institutions in formulating policies that address food supply challenges, improve the availability and accessibility of nutritious food, and reduce undernourishment—particularly in developing economies. In East Africa, where food security is often undermined by political instability, governance reforms aimed at strengthening institutional frameworks, reducing conflict, and ensuring policy continuity are essential for building resilient food systems and promoting long-term food security outcomes. Moreover, our findings indicate that while rural development contributes to food security by improving agricultural productivity and market access, its effect remains statistically insignificant across both PCSE and FGLS estimators. This suggests that rural development alone may not be a direct or immediate driver of food security in East Africa. Unlike Ghanem (2015), who highlighted the positive role of rural development in supporting smallholders and enhancing food security, our results imply that additional factors, such as infrastructure investment, financial inclusion, and access to technology, may be necessary for rural development to have a measurable impact (see Table 8).

3.2.1 Robust findings from food security index components

The estimation results, reported in Tables 9, 10, indicate the effects of climatic variables on the four dimensions of food security across East African countries. In particular, rainfall exhibits a two-sided effect: it improves food availability and utilization but tends to undermine accessibility and stability. This pattern suggests that while higher rainfall supports agricultural yields and enhances nutritional outcomes, it can simultaneously destabilize food markets and infrastructure, especially in areas prone to flooding or seasonal variability. These findings resonate with those of Randell et al. (2022) and Hamadjoda Lefe et al. (2024), who reinforce the role of sustainable water management—particularly irrigation and water governance—in enhancing food availability across SSA. However, unlike these studies, which primarily focus on the productive benefits of rainfall, our results demonstrate additional perspective that rainfall variability can also compromise food access and supply consistency, thereby broadening the understanding of rainfall's role in shaping food security outcomes.

TABLE 8 Results from the PCSE and FGLS.

Variables	PCSE			FGLS		
	[1]	[2]	[3]	[4]	[5]	[6]
RF	0.000748***	0.000346**	0.00013	0.000732***	0.000510***	0.000201
	(4.557)	(2.001)	(0.751)	(5.519)	(3.945)	(1.287)
TEM	−0.224***	−0.0755**	−0.138***	−0.237***	−0.115***	−0.159***
	(−10.55)	(−2.456)	(−3.551)	(−12.16)	(−4.379)	(−4.306)
FIN	−0.000139	0.0000817	0.000237	−0.000335	−0.000315	0.000242
	(−0.213)	(0.127)	(0.521)	(−0.530)	(−0.516)	(0.539)
PG	−0.426***	−0.594***	−0.271**	−0.341***	−0.466***	−0.254**
	(−4.774)	(−7.018)	(−2.477)	(−4.412)	(−7.141)	(−2.499)
FM	0.507***	0.561***	0.503***	0.619***	0.629***	0.507***
	(4.165)	(5.520)	(5.715)	(8.893)	(10.010)	(6.401)
PS		0.610***	0.409***		0.557***	0.395***
		(6.181)	(4.522)		(7.429)	(4.738)
RD			0.000365			0.000963
			(0.180)			(0.498)
Constant	5.425***	3.261***	3.785***	5.507***	3.598***	4.143***
	(12.080)	(6.376)	(4.331)	(13.580)	(7.604)	(4.953)
Observations	240	240	240	240	240	240
Countries	12	12	12	12	12	12

z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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TABLE 9 Robust results from the PCSE estimator.

Variables	Food availability	Food accessibility	Food stability	Food utilization
	[1]	[2]	[3]	[4]
RF	0.000846***	−0.000299**	−0.000302	0.000266*
	(5.218)	(−2.006)	(−0.212)	(1.861)
TEM	−0.0205	0.0645***	−0.283	0.0357
	(−0.674)	(2.722)	(−0.910)	(1.105)
FPI	0.000274	−0.000559	−0.00741	0.000
	(0.637)	(−1.020)	(−0.996)	(0.159)
PG	−0.116	0.436***	−2.769***	0.200*
	(−1.434)	(6.968)	(−3.550)	(1.878)
FM	0.612***	−0.296***	0.491	−0.566***
	(5.214)	(−2.970)	(0.647)	(−6.441)
PS	0.238***	−0.517***	2.470***	0.0839
	(2.576)	(−7.482)	(3.133)	(0.980)
RD	0.0217***	0.00810**	−0.0752***	0.000161
	(5.357)	(2.284)	(−3.740)	(0.0939)
Constant	−0.638	−2.843***	29.89***	−1.241*
	(−1.311)	(−6.902)	(5.078)	(−1.736)
Observations	240	240	240	240
Countries	12	12	12	12

***, **, * denote significance levels at 1%, 5% and 10%, respectively.

TABLE 10 Robust results from the FGLS estimator.

Variables	Food availability	Food accessibility	Food stability	Food utilization
	[1]	[2]	[3]	[4]
RF	0.000963***	−0.000364***	0.000505	0.000350**
	(6.847)	(−3.290)	(0.395)	(2.431)
TEM	0.0289	0.0885***	−0.317	0.168***
	(1.059)	(5.078)	(−1.160)	(5.276)
FPI	0.00002	0.000178	−0.00799	−0.0001
	(0.0595)	(0.422)	(−1.079)	(−0.0602)
PG	−0.260***	0.395***	−2.151***	0.134
	(−3.898)	(8.533)	(−3.275)	(1.462)
FM	0.361***	−0.408***	1.082*	−1.369***
	(4.255)	(−6.226)	(1.742)	(−18.700)
PS	0.224***	−0.474***	1.693**	0.358***
	(2.686)	(−9.978)	(2.550)	(4.240)
RD	0.0151***	0.00581**	−0.0912***	0.0171***
	(4.676)	(2.313)	(−4.981)	(5.317)
Constant	−1.491***	−3.045***	26.41***	−3.803***
	(−3.352)	(−8.851)	(4.966)	(−6.207)
Observations	240	240	240	240
Countries	12	12	12	12

***, **, * denote significance levels at 1, 5% and 10%, respectively.

Temperature fluctuations exhibit a differentiated relationship with the dimensions of food security in East Africa, producing negative effects on food availability and stability, while showing positive associations with accessibility and utilization. The declines in availability and stability likely stem from the physiological stress that elevated temperatures impose on crop growth, leading to reduced yields and increased volatility in production. In contrast, the positive correlations with accessibility and utilization may reflect localized agroecological dynamics, where higher temperatures—within certain thresholds—extend growing seasons or improve productivity in warmer zones. This divergence underscores the non-linear and spatially contingent nature of temperature impacts, whereby the same climatic driver can simultaneously constrain output while enabling adaptive shifts in cultivation or food consumption patterns. These results are consistent with Parthasarathi et al. (2022), who document the inhibitory effects of rising temperatures on plant development, particularly in thermally sensitive regions, thereby supporting our findings on the adverse production-related consequences of warming.

The PCSE results, corroborated by the FGLS estimator, suggest that food prices are negatively associated with food accessibility and stability, but positively linked to availability and utilization. However, none of these relationships reach statistical significance. This outcome implies that, within the East African context, the influence of food prices on food security remains limited. One likely explanation is the predominance of subsistence agriculture, where smallholder farmers are not tightly integrated into formal markets and thus respond weakly to price signals. Furthermore, the prevalence of informal trade networks and government interventions—such as price controls and subsidies—may dilute the direct transmission of price fluctuations to households, especially in rural areas. The combination of positive and negative directional effects points to a more layered interaction between prices and food security, where incentives for production may coexist with affordability challenges. These findings partially align with those of Agyei et al. (2021), who reported that COVID-19-related price shocks adversely affected food availability in selected African countries. Yet, unlike their study, our results do not indicate statistically significant effects, which suggests a more muted or context-specific relationship between food prices and food security outcomes in East Africa.

Population growth presents a differentiated relationship with the various dimensions of food security in East Africa. While it appears to support food accessibility and utilization, it exerts a significant negative effect on availability and stability, as evidenced by the results from both PCSE and FGLS estimators. These outcomes suggest that rising population density places considerable strain on agricultural systems and natural resources, leading to diminished per capita food availability and greater exposure to fluctuations in supply. At the same time, the positive associations with accessibility and utilization may reflect improvements in market integration, labor force participation, and dietary diversity that often accompany demographic expansion, particularly in more urbanized settings. This duality speaks to the multifaceted nature of demographic change, where increased population can both challenge production capacity and simultaneously foster conditions that improve food access and use. Our findings intersect with those of Miladinov (2023), who identified a linkage between population growth and undernourishment; however, whereas that study emphasizes nutritional deficits, our analysis takes a broader approach, which provide a disaggregated view of how population dynamics shape food systems along both supply and demand channels.

The results indicate a multifaceted relationship between food imports and the dimensions of food security in East Africa. Food imports are found to significantly enhance food availability, suggesting that external sourcing plays a key role in supplementing domestic production and mitigating supply shortfalls. The effect on food stability is positive but statistically insignificant, implying that while imports may contribute to a more consistent supply, their stabilizing impact is not uniform across the region. In contrast, food accessibility and utilization are negatively and significantly affected by food imports, which may reflect affordability challenges linked to the cost structures of imported goods. Tariffs, transportation expenses, and currency-related trade costs can elevate retail prices, thereby restricting access for low-income households and limiting dietary diversity and quality. These findings are broadly consistent with Arias et al. (2024) and Smith and Glauber (2020), who argue that food imports can serve as a short-term solution to supply gaps but may also introduce market distortions and reinforce socioeconomic disparities in food access.

The results reveal the considerable role of political stability in shaping food security outcomes across East Africa. Political stability is positively and significantly associated with food availability and stability. This implies that a secure governance environment contributes to stronger agricultural performance and more reliable food supply systems. In a region where political unrest has frequently disrupted farming activities, market operations, and transport infrastructure, a more stable context appears to support sustained agricultural investment and the efficient functioning of food distribution networks. While political stability also proposes a positive relationship with food utilization, the association is not statistically significant. This suggests that improvements in governance may not be sufficient on their own to influence food quality and dietary practices, which often depend on complementary factors such as education, income, and public health infrastructure. In contrast, a significant negative effect is observed between political stability and food accessibility. This result may reflect persistent structural inequalities—such as rural–urban divides, economic exclusion, or post-conflict recovery gaps—that limit equitable access to food despite improvements in the broader political landscape. These findings are consistent with the observations of Yiadom et al. (2023), Subramaniam et al. (2022), and Cassimon et al. (2022), who document similar patterns in the uneven effects of governance on different dimensions of food security.

Rural development shows a significant positive association with food availability, accessibility, and utilization. This asserts its central role in supporting agricultural productivity, improving market integration, and promoting more favorable food consumption patterns in East Africa. These findings imply that investments in rural infrastructure, transportation networks, and local market systems enhance both the supply and accessibility of food, particularly for communities dependent on smallholder and subsistence farming. The observed positive effect on utilization may also be attributed to improved access to diverse and nutritious food options as rural livelihoods and local economies expand. However, the analysis also reveals a significant negative correlation between rural development and food stability. This result suggests that while rural expansion supports short-term gains in production and access, it may simultaneously introduce new risks—such as market volatility, land pressure, or resource degradation—that undermine the long-term consistency of food systems. This contrasts with Ghanem (2015), who emphasized the uniformly beneficial effects of rural development on

TABLE 11 Outcomes from Dumitrescu–Hurlin causality analysis.

Null Hypothesis: ≠	W-Stat.	Zbar-Stat.	Decision
RF ≠ FS	1.14	−0.006	No causality
FS ≠ RF	1.783	1.226	
TEM ≠ FS	2.461**	2.526	Unidirectional
FS ≠ TEM	1.322	0.343	
FPI ≠ FS	1.338	0.374	No causality
FS ≠ FPI	1.709	1.085	
PG ≠ FS	2.429**	2.465	Bidirectional
FS ≠ PG	5.476***	8.306	
FM ≠ FS	1.613	0.901	Unidirectional
FS ≠ FM	4.341***	6.131	
PS ≠ FS	1.16	0.032	Unidirectional
FS ≠ PS	2.803***	3.183	
RD ≠ FS	1.632	0.938	No causality
FS ≠ RD	1.964	1.575	

The symbol ≠denotes the null hypothesis of no homogeneous causality across panel units—that is, the independent variable does not Granger-cause the dependent variable uniformly across all countries.
***, **, * denote significance levels at 1%, 5% and 10%, respectively.

food security, without addressing potential trade-offs between growth and stability.

3.2.2 Analysis of panel causality tests

To probe short-run predictive linkages, we apply the Dumitrescu and Hurlin (2012) panel Granger non-causality test, which accommodates slope heterogeneity across countries. The test evaluates whether lagged values of one variable improve forecasts of another; it speaks to temporal precedence, not structural causality, and in its canonical form assumes cross-sectional independence. As reported in Table 11, we fail to reject the null of no Granger-causality for the pairs rainfall–food security, food prices–food security, and food security–rural development, consistent with complex, potentially non-linear pathways not captured by a linear lag structure. In the short-run, shocks to rainfall or prices do not systematically improve forecasts of food security at the panel level, which suggests that policy responses premised on immediate pass-throughs may be unreliable. By contrast, we find bidirectional Granger-causality between population growth and food security. This indicates mutual predictive content (demographic pressures forecast subsequent food outcomes, and past food conditions forecast population dynamics). Moreover, we detect unidirectional Granger-causality from temperature to food security and from food security to food imports and food security to political stability. This implying that past temperature shocks help forecast food security, while past food security helps forecast subsequent import volumes and political stability.

The study's estimates are interpreted as conditional associations rather than causal effects. Several endogeneity channels may bias inference: reverse causality, where food security can reshape rural development priorities and political stability; omitted common shocks such as climate anomalies, commodity cycles, and donor timing that co-move with regressors and outcomes; simultaneity in policy responses; and measurement error in institutional and development indicators. To mitigate these risks, we include country and year fixed effects and estimate the main specifications with PCSE and FGLS, using first differences where appropriate, to accommodate heteroskedasticity, serial correlation, and contemporaneous correlation across panels. In addition, we adopt the Dumitrescu–Hurlin panel Granger non-causality test to assess temporal precedence under heterogeneity; it does not provide structural identification and, in its canonical form, assumes cross-sectional independence. Accordingly, the reported linkages should be read as precedence patterns rather than causal effects, and residual endogeneity from unobserved common shocks, simultaneity, or measurement error may remain despite these safeguards.

4 Conclusion and policy implications

East Africa's struggle for food security encapsulates the region's broader challenges, including climatic volatility, political instability, and economic fragility. Ensuring food security not only mitigates malnutrition and lowers mortality rates but also fosters social cohesion and underpins long-term sustainable development. However, persistent climatic shocks—such as droughts, erratic rainfall, and rising temperatures—continue to undermine agricultural productivity by reducing crop yields, depleting natural resources, and heightening susceptibility to extreme weather events. These challenges are exacerbated by weak institutional frameworks, inadequate infrastructure, exposure to global price fluctuations, and constrained financial resources, all of which limit the effectiveness of mitigation efforts. The humanitarian cost of food insecurity remains dire; as of May 2023, hunger-related deaths in Somalia, Kenya, Ethiopia, and South Sudan alone ranged between 1,126 and 3,095 per day, equating to an hourly rate of 47 to 129 deaths (Oxfam, 2023). Without urgent and coordinated intervention, the region faces an escalating crisis marked by further loss of life, deepening human suffering, and the continued erosion of fundamental human rights.

Using PCSE and FGLS estimators, this study analyzed the influence of rural development, climatic variability, political stability, and food inflation on the four dimensions of food security in East Africa, based on panel data spanning from 2001 to 2020. The results reveal that rainfall significantly improves food availability and utilization but adversely affects accessibility and stability, likely due to disruptions caused by irregular or excessive precipitation. Rising temperatures are negatively associated with food availability and stability, which reflects the impact of heat stress on agricultural production and supply volatility. Population growth places a substantial strain on food availability and stability while showing a positive association with accessibility and utilization—potentially linked to shifts in labor dynamics and urban market development. Food imports contribute positively to food availability but negatively to accessibility and utilization. Political stability supports food availability and stability yet shows a negative association with accessibility, possibly reflecting uneven governance benefits across regions or population groups. Rural development positively and significantly affects availability, accessibility, and utilization, consistent with improvements in infrastructure and market access, but is negatively associated with food stability, which may reflect exposure to market volatility or transitional effects of rural transformation. In addition, the Dumitrescu–Hurlin panel Granger

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analysis shows no panel-wide evidence of Granger-causality between food security and precipitation, food price inflation, or rural development. By contrast, we find bidirectional Granger-causality between population growth and food security, and unidirectional Granger-causality running from food security to political stability and to food imports.

Drawing from the preceding findings, targeted policy actions in East Africa should reflect the multidimensional and context-specific nature of food security, addressing its four key dimensions. Strengthening irrigation systems, water harvesting infrastructure, and flood control mechanisms is critical for improving availability and ensuring the stability of food supply amid rainfall variability. Likewise, investment in heat-resilient crop varieties, agroecological practices, and localized climate advisory services can reduce climate-induced production risks and contribute to both stable supply chains and consistent access. Responding to population pressures will require a dual approach that promotes sustainable agricultural intensification and rural employment generation, thereby enhancing availability while supporting accessibility and utilization through improved livelihoods and dietary options. The region's reliance on food imports underscores the need to strengthen regional integration under the AfCFTA, streamline trade logistics, and expand domestic food processing capacity—actions that can support availability while improving the affordability and nutritional quality of food, thus influencing both accessibility and utilization. Governance reforms are equally important: improving market efficiency, transparency in distribution, and rural service delivery is essential to ensuring that political stability translates into equitable food access and more stable food systems. Rural development strategies should be coupled with risk mitigation investments—including storage infrastructure, market regulation, and climate-resilient land planning—to protect stability while enhancing the other three dimensions. Moreover, the identified causal links between food insecurity, political stability, and food import dynamics point to the importance of integrated food security planning and early warning systems. A coordinated, forward-looking policy agenda rooted in these dimensions will be essential for strengthening climate resilience across East Africa's food systems.

A key limitation is measurement: the composite food security index constructed with PCA integrates availability, accessibility, stability, and utilization into a single score, which can conceal trade-offs and distinct movements among the pillars. Although the panel approach accounts for CSD and slope heterogeneity across countries, country-specific estimations are absent, and important national differences in governance quality, agricultural investment, and infrastructure may therefore be blurred. Substantively, estimates are interpreted as conditional associations rather than causal effects. The Dumitrescu–Hurlin panel test is used to assess temporal precedence under heterogeneity, not structural causality, and in its canonical form assumes cross-sectional independence. Despite country and year fixed effects and the use of PCSE and FGLS to address heteroskedasticity, serial correlation, and contemporaneous correlation, residual endogeneity may persist through reverse causality, omitted common shocks, simultaneity in policy responses, and measurement error. The limited time dimension of the dataset further restricts fully disaggregated country-level regressions.

To preserve multidimensional detail, future research should pursue complementary approaches that retain pillar specificity, including dashboard frameworks, multi-criteria decision analysis (MCDA), and fuzzy-logic aggregation. Longitudinal techniques such as time-varying PCA and dynamic factor models can better capture how components evolve and interact under climatic and institutional shocks. Besides, we recommend that future studies with longer time series and finer-resolution data conduct country-level analyses to deliver country-specific policy guidance. To strengthen identification, researchers should deploy event-study and modern staggered difference-in-differences around exogenous reforms or eligibility thresholds with transparent pre-trend checks; develop instrumental-variable strategies with clearly defined relevance and exclusion, for example using donor allocation rules or administrative discontinuities; and employ factor-absorbing panel estimators such as common correlated effects (CCE) or interactive fixed effects to partial out latent common shocks. Methodologically, testing for state dependence and non-linearity—through threshold or quantile Granger causality and interactions with baseline aridity, market access, and price levels—together with subnational or higher-frequency data and microdata linkages, would reveal heterogeneous pathways and help triangulate results across complementary designs.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://databank.worldbank.org/source/world-development-indicators and https://www.fao.org/faostat/en/#data/RA.

Author contributions

AA: Validation, Data curation, Writing – review & editing, Supervision, Conceptualization, Methodology, Project administration, Investigation, Writing – original draft, Software, Resources, Visualization, Formal analysis. AM: Writing – review & editing, Methodology, Writing – original draft. SS: Writing – original draft.

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