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Agricultural development and food production in East Africa: The role of water availability, environmental degradation, and institutional quality

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A R T I C L E I N F O

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A B S T R A C T

Food production remains a fundamental concern across East African economies where agriculture sustains livelihoods, supports rural employment, and supplies the majority of domestically consumed food. Despite its vital significance, agricultural production in the region continues to face constraints associated with limited investment, water scarcity, environmental pressures, and institutional conditions. Accordingly, this study examines the determinants of food production across 15 East African countries over the period 2002–2022. As major factors influencing food production, the analysis focuses on agricultural development, water availability, environmental degradation, and institutional quality. A heterogeneous panel framework is employed to examine long- and short-run dynamics. Diagnostic tests indicate cross-sectional dependence and slope heterogeneity. The analysis applies the panel autoregressive distributed lag (ARDL) model using the pooled mean group (PMG) and mean group (MG) estimators, with FMOLS and DOLS used for robustness checks. The findings indicate that agricultural development and water availability exhibit strong positive associations with food production across the region. Agricultural employment and cultivated land also contribute positively to food production within East African agricultural systems. Environmental degradation does not display a statistically significant effect on food production in the estimated models. Nevertheless, institutional quality reveals a negative long-run relationship but a positive short-run association with food production. The robustness checks confirm the stability of the estimated relationships across alternative estimation techniques. Consequently, the findings indicate the need to strengthen agricultural investment, expand irrigation and water management, integrate environmental considerations into agricultural planning, and enhance institutional coordination in agricultural governance across East Africa.

1. Introduction

Agriculture remains a foundational pillar of economic growth and food security, especially in places where considerable portions of the population rely on farming for revenue, employment, and subsistence. In many developing economies, agricultural production sustains rural livelihoods while also contributing substantially to national output and social stability [1,2]. Despite its dominant role in employment and economic activity, agricultural production maintained fundamental weaknesses in recent decades in sub-Saharan Africa (SSA) [3]. Food security conditions across the continent are vulnerable, with 282 million Africans undernourished in 2022 [4]. Much of the agricultural output growth has occurred through the expansion of cultivated land rather than productivity improvements. Limited technology adoption, inadequate infrastructure, and limited productive inputs explain this trend. In East Africa, where smallholder farmers dominate farming, technological diffusion is uneven, and climate-sensitive production conditions are crucial [5]. Under these conditions, rainfall variability, environmental pressures, and market fluctuations can translate directly into changes in agricultural output. Therefore, food production in the region is not

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determined by a single factor but rather by the combined influence of institutional arrangements, economic structures, and environmental conditions [6]. Environmental degradation, market conditions, and governance structures impact agricultural performance and the ability of food systems to maintain stable production levels across the region.

As the global population expands and consumption patterns change, ensuring sufficient food production is harder to sustain. Rising demand places substantial pressure on agricultural systems to increase output while operating under tightening natural resource constraints [7,8]. In many regions, per capita availability of water, land, and energy has declined as population growth accelerates, which makes it challenging to produce a sufficient and nutritious food supply [7,8]. As 70% of global freshwater withdrawals go to agriculture, the sustainability of long-term food production under growing resource scarcity is debated [7]. In addition, reduced water availability and land productivity have raised concerns about agricultural systems' ability to meet future food demand, especially in resource-constrained regions [9]. Recent global shocks have further intensified these pressures. For instance, the Russia–Ukraine conflict disrupted global energy markets and raised production costs through higher fertilizer, irrigation, and transportation prices across agriculture [10]. Accordingly, improved agricultural productivity increasingly depends on structural transformation in production systems, including technological progress, improved farming practices, and modernization of agricultural activities [2,11]. At the farm level, production decisions are influenced by livelihood risks like environmental shocks, financial constraints, and institutional limitations that limit farmers' investment and adoption of better practices [12]. Thus, increasing food production requires extending cultivated area and improving agricultural productivity via technology, input usage, and resource management.

In economies that depend on rainfall and irrigation, water availability constitutes a fundamental input in agricultural production. Due to the strong connection between water supplies and agricultural output, agriculture accounts for the majority of worldwide water withdrawals [13,14]. Crop production relies on stable water availability, since over 70% of worldwide freshwater withdrawals are utilized in agricultural activities [13]. In SSA, agricultural systems are largely rain-fed, which exposes food production to fluctuations in rainfall and seasonal water availability [5]. Only about 6% of Africa's cultivated land is irrigated, compared to 37% in Asia and 14% in Latin America. The continent's irrigation development remains limited [15]. Therefore, rainfall variability and water shortages translate directly into changes in crop yields and food availability, particularly in smallholder farming systems [16]. In addition, irrigation water boosts crop yield and stabilizes agricultural output in various production situations [17–19]. Improvements in irrigation systems and water management practices can raise agricultural productivity by ensuring a more reliable water supply during critical stages of crop growth [17,18,20]. At the same time, growing population pressures, climate variability, and competition for water across domestic and industrial uses continue to intensify constraints on freshwater resources [7,9].

Environmental conditions encompass another important role in agricultural development and food availability. Agricultural output depends on ecosystem services such as soil fertility, biodiversity, water regulation, and climatic stability that support crop growth and productive agricultural landscapes. Degradation of these resources weakens agricultural performance by reducing soil quality, disrupting ecological balances, and limiting processes that sustain crop productivity [21]. Pressures, including deforestation, land degradation, and biodiversity loss, gradually erode the ecological base on which agricultural systems depend [22]. Environmental pressures may also affect productivity through changes in temperature, rainfall patterns, and atmospheric composition that influence plant growth and production conditions [6, 23]. Climate variability and environmental degradation, therefore, remain major sources of agricultural vulnerability in developing regions where production systems rely heavily on natural conditions [16,24]. On the other hand, institutional situations affect agricultural productivity through policy, resource management, and the environment. Weak institutional frameworks may restrict agricultural investment and land and water management required for productivity [6]. Institutional environments also affect governments' ability to coordinate agricultural programs, manage environmental resources, and support farmers through extension services and input distribution. However, governance indicators may not immediately enhance food production due to fundamental agricultural and ecological conditions [24,25].

Despite the importance of agriculture for economic stability and food availability, many East African countries continue to face persistent challenges in maintaining stable agricultural productivity and food production. Agricultural systems in the region remain highly dependent on climate-sensitive production conditions, particularly rainfall variability, which increases the exposure of food production to environmental shocks and water-related constraints [5,16]. Rain-fed farming dominates much of the agricultural landscape, while irrigation development remains limited. Across Africa, only about 6 percent of cultivated land is equipped for irrigation, compared with substantially higher shares in Asia and Latin America [15]. Consequently, variability in precipitation and recurrent drought episodes translate directly into fluctuations in crop yields and agricultural output across East African economies [26]. Structural pressures further intensify these challenges. Rapid population growth continues to increase demand for food while placing greater pressure on land and freshwater resources required for agricultural production [7,8]. These production constraints occur alongside persistent food security challenges across the continent. Recent assessments indicate that about 868 million people in Africa experience moderate or severe food insecurity, including 342 million facing severe food insecurity [4]. These factors indicate that East African agricultural systems are subject to climate unpredictability, resource limits, and structural constraints that impact food production.

Although their effects vary by region, the literature documents that agricultural development and water availability are frequently identified as significant drivers of food production. Several studies confirm that agricultural inputs and development policies boost production. Chandio et al. [27] and Ali and Bayale [28] indicated that public agricultural investment significantly increases crop production and improves rural welfare, while financial development through credit and monetary expansion also supports agricultural output by enabling investment in modern inputs and technologies. Further evidence suggests that fertilizer use, irrigation water, cultivated land, and credit access positively influence agricultural productivity [17,18,20]. Recent research asserted the impact of technology and digitalization on improving agricultural production. Li et al. [29] and Chandio et al. [30] reported that technological progress, mechanization, and digital technologies enhance agricultural efficiency and food production, while digital connectivity improves information access and market integration for farmers [31]. Recent developments in intelligent agricultural systems further indicate that AI-based crop monitoring technologies, automated orchard management systems, and deep-learning yield prediction models can improve production efficiency, disease detection, and agricultural decision-making processes within modern farming systems [32,33]. At the same time, irrigation water availability remains essential for crop production in many agricultural systems [17–19], while rainfall variability and water scarcity can severely restrict food production, especially in rain-fed farming systems [5]. Studies widely recognized that agriculture is the largest consumer of freshwater resources and that water scarcity limits food production [13,14]. Global assessments displayed that declining water availability and rising population pressure will worsen food production challenges [7,8].

The literature on environmental degradation and institutional quality reveals heterogeneous regional effects on food production. Several studies demonstrate that environmental degradation constrains agricultural productivity by weakening ecosystem services and altering climatic conditions essential for crop growth. Tan et al. [21], for instance, found that biodiversity loss significantly reduces agricultural, cereal, and vegetable production in European countries, while Ali Warsame and Hassan Abdi [22] reported that deforestation reduces crop production in Somalia. Other studies, however, show mixed relationships between environmental pollution and agricultural productivity. Ramzan et al. [23] identified a positive long-run association between CO_2 emissions and agricultural productivity in Pakistan, which they attributed to short-run photosynthetic gains, whereas Jadoon et al. [19] found that CO_2 emissions have a negative but statistically insignificant effect on crop productivity once key production inputs are considered. Institutional quality has also been examined as a factor influencing food production and food security outcomes. In SSA, Abdi et al. [6] found that institutional quality is negatively associated with food security. However, other studies reported limited direct effects of governance on food production. Oyelami et al. [24] identified that institutional quality does not significantly affect food security once climate and structural conditions are considered, while Mohamed et al. [25] reported that institutional quality has a minimal direct effect on food production in Somalia. Tran et al. [34] also found a negative relationship between institutional quality and agricultural value added in Asian countries.

This study contributes to the literature on agricultural production by addressing several empirical and conceptual limitations in existing research. First, much of the literature examining agricultural systems focuses primarily on food security indicators rather than food production outcomes [6,32,34]. While food security encompasses availability and access dimensions, production remains the fundamental supply-side factor determining food system stability. Limited empirical evidence exists on the structural drivers of food production, particularly in developing agricultural economies. By focusing on food production dynamics, this study directly assesses the productive capacity of agricultural systems. Second, previous studies often examined agricultural performance determinants in dispersed analytical models, focusing separately on inputs, environmental conditions, water resources, or institutional arrangements [13,21,30]. However, agricultural production systems operate through the simultaneous interaction of development conditions, natural resource availability, environmental pressures, and governance structures. Empirical analyses that concurrently investigate these dimensions are limited. Through the incorporation of environmental degradation, water availability, agricultural development, and institutional quality into a single empirical model, this study delivers a more thorough evaluation of the structural forces influencing food production.

Third, existing empirical evidence remains geographically concentrated, with many studies focusing on single-country cases or regions such as China, Pakistan, Europe, or the Gulf Cooperation Council [23,27,35]. Comparatively fewer studies investigate the structural determinants of food production in East African economies, despite the region's strong dependence on rain-fed agriculture and high exposure to environmental variability. Thus, analyzing these connections among East African nations offers fresh empirical support for a region where agricultural systems continue to be extremely vulnerable to resource limitations, water availability, and climate. Finally, methodological limitations persist in the literature, as many studies assume homogeneous relationships across countries or rely on single estimation approaches. Such assumptions may obscure cross-country differences in agricultural structures and environmental conditions. To address this limitation, this study applies heterogeneous panel estimators, including the pooled mean group (PMG) and mean group (MG) techniques, which allow long-run relationships to be examined while accommodating country-specific short-run dynamics. In addition, fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) estimators are employed to validate the robustness of long-run relationships. Fig. 1 illustrates the conceptual framework of the determinants of food production considered in this study.

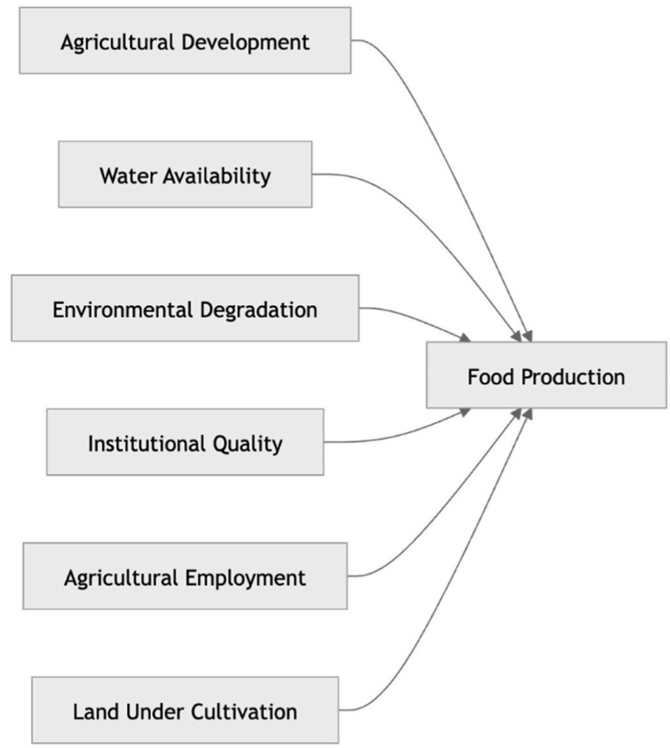

Fig. 1. Conceptual framework of the determinants of food production in East Africa.

2. Methodology

2.1. Data, sampling, and variables

This study employs annual panel data to examine the determinants of food production across East African economies. The analysis covers the period 2002–2022 and includes 15 countries: Burundi, Comoros, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Rwanda, Somalia, Sudan, Tanzania, Uganda, Zambia, and Zimbabwe. These countries were selected because agriculture remains a central component of economic activity and rural livelihoods across the region. Moreover, the selected countries exhibit similar structural characteristics, including high dependence on rain-fed agriculture, exposure to climate variability, and persistent food security challenges, which make the region appropriate for comparative panel analysis. The country selection was also guided by the availability of consistent and balanced panel data for the study variables over the period 2002–2022. Agricultural production systems in East Africa are strongly influenced by natural resource availability, labour conditions, and institutional arrangements [6,25]. In addition, the region has experienced persistent pressures associated with climate variability, environmental stress, and structural constraints in agricultural systems. Hence, food production serves as the dependent variable in this study. It is measured using the food production index obtained from the World Development Indicators (WDI), where the base period 2014–2016 equals 100. The index captures aggregate food output relative to the reference period and has been widely applied in studies examining food production and food security [25,36]. Agricultural development represents the first explanatory variable. It is measured using development flows to agriculture from all donors, expressed in millions of US dollars, and obtained from the Food and Agriculture Organization (FAO) database. This variable represents external financial support directed toward the agricultural sector, including investments in agricultural infrastructure, productivity programmes, and institutional support [27,28].

Water availability constitutes another key determinant of agricultural production [18]. It is measured as annual freshwater withdrawals for agriculture expressed as a percentage of total freshwater withdrawals, obtained from the WDI. Water resources remain a fundamental input in agricultural systems, particularly in regions where crop cultivation depends on rainfall and irrigation [17,20]. Moreover, environmental degradation is proxied by per capita carbon dioxide (CO_2) emissions generated from fossil fuel combustion and industrial activities. The data are sourced from Our World in Data (OWID). Carbon emissions are frequently used in empirical studies as a proxy for environmental pressure affecting agricultural systems through climate variability, ecological stress, and temperature-related changes in production conditions [22,23]. Nevertheless, per capita CO_2 emissions may not fully capture localized forms of environmental degradation that directly affect agricultural systems in East Africa, including soil erosion, deforestation, land degradation, and biodiversity loss. The indicator is primarily employed due to the availability of consistent cross-country panel data for the sampled countries and study period. Consequently, the environmental degradation variable should be interpreted as a broad measure of environmental pressure rather than a direct indicator of farm-level ecological deterioration. Institutional quality is measured using the regulatory quality estimates obtained from the Worldwide Governance Indicators (WGI) database. The regulatory quality estimate reveals the ability of governments to formulate and implement sound policies that support private sector development and economic activity [6,32].

Additionally, the study considers agricultural employment and cultivated land area as control variables. Agricultural employment is measured as employment in agriculture expressed as a percentage of total employment, obtained from the WDI, based on modeled estimates from the International Labour Organization (ILO). This variable indicates the share of the labour force engaged in agricultural activities and captures the role of labour availability in agricultural production systems. The importance of agricultural labour for food production and agricultural output has been documented in previous studies [26,37]. Finally, land under cultivation is measured as land under cereal production in hectares, obtained from the WDI. This variable reflects the scale of arable land devoted to cereal cultivation and captures the contribution of land resources to agricultural production capacity. Similar land-based indicators have been used in studies examining crop production and food output, where cultivated area is found to remain an important determinant of agricultural performance [17,38]. Table 1 presents the description, measurement, and data sources of the variables employed in the study.

2.2. Econometric model specification

To examine the determinants of food production across East African economies, this study follows the empirical modeling approaches widely adopted in recent agricultural and food production literature [23,25–27,39]. The econometric specification captures the influence of agricultural development, water availability, environmental degradation, institutional quality, agricultural employment, and cultivated land on food production. These variables denote structural, environmental, and institutional factors that influence agricultural performance and food production capacity. Two model specifications are estimated. Model 1 excludes water availability, while Model 2 incorporates water availability in order to examine whether water conditions alter the estimated relationship between agricultural development and food production. The baseline empirical model is specified as follows:

$$FP_{it} = \alpha_0 + \beta_1 AGDEV_{it} + \beta_2 ED_{it} + \beta_3 RQ_{it} + \beta_4 AE_{it} + \beta_5 LUC_{it} + \varepsilon_{it} \tag{1a}$$

The extended specification that incorporates water availability is written as:

$$FP_{it} = \alpha_0 + \beta_1 AGDEV_{it} + \beta_2 WA_{it} + \beta_3 ED_{it} + \beta_4 RQ_{it} + \beta_5 AE_{it} + \beta_6 LUC_{it} + \varepsilon_{it} \tag{1b}$$

where *FP* denotes food production, *AGDEV* represents agricultural development, *WA* captures water availability, *ED* indicates environmental degradation, *RQ* refers to regulatory quality, *AE* represents agricultural employment, and *LUC* denotes land under cultivation. The term α_0 denotes the intercept, $\beta_1 - \beta_6$ represent the coefficients of the explanatory variables, and ε_{it} denotes the stochastic error term. The subscripts *i* and *t* represent the country and time dimensions of the panel dataset respectively. To reduce heterogeneity across the variables and allow coefficient estimates to be interpreted as elasticities, the variables are transformed into their natural logarithmic forms. Logarithmic transformation also mitigates potential scale differences among variables and improves the stability of the estimated parameters. Following this transformation, the empirical specification becomes:

$$lnFP_{it} = \alpha_0 + \beta_1 lnAGDEV_{it} + \beta_2 lnED_{it} + \beta_3 RQ_{it} + \beta_4 lnAE_{it} + \beta_5 lnLUC_{it} + \varepsilon_{it} \tag{2a}$$

$$lnFP_{it} = \alpha_0 + \beta_1 lnAGDEV_{it} + \beta_2 lnWA_{it} + \beta_3 lnED_{it} + \beta_4 RQ_{it} + \beta_5 lnAE_{it} + \beta_6 lnLUC_{it} + \varepsilon_{it} \tag{2b}$$

In this specification, the coefficients associated with the logarithmically transformed variables represent long-run elasticities of food production with respect to the corresponding determinants. Agricultural development, water availability, agricultural employment, and land under cultivation are expected to exert positive effects on food production because they strengthen agricultural production capacity. Conversely, environmental degradation is expected to exert a negative influence due to its adverse effects on climatic conditions and agricultural productivity. Institutional quality may influence food production through regulatory frameworks, policy implementation, and market conditions. The empirical model is estimated using a panel dataset consisting of 15 East African countries observed over the period 2002–2022, where $i = 1, 2, \ldots, 15$ and $t = 1, 2, \ldots, 21$. The panel framework allows the analysis to capture both cross-country heterogeneity and temporal dynamics in the determinants of food production across the region. To provide a clearer presentation of the methodological framework, Fig. 2 summarizes the empirical strategy and sequential econometric estimation procedures employed in the study.

2.3. The empirical model

Before estimating the empirical model, it is necessary to determine whether the cross-sectional units are independent or influenced by common shocks [40]. In regional panels such as East Africa, countries often share similar climatic conditions, environmental shocks, and

Table 1
Description, measurement, and data sources of the study variables.

Variable	Code	Measurement	Source
Food Production	FP	Food production index (2014–2016 = 100)	WDI
Agricultural Development	ADEV	Development flows to agriculture (million US$)	FAO
Water Availability	WA	Agricultural freshwater withdrawals (% of total freshwater withdrawals)	WDI
Environmental Degradation	ED	CO_2 emissions per capita	OWID
Institutional Quality	RQ	Regulatory quality: estimate	WGI
Agricultural Employment	AE	Employment in agriculture (% of total employment)	WDI
Land Under Cultivation	LUC	Land under cereal production (hectares)	WDI

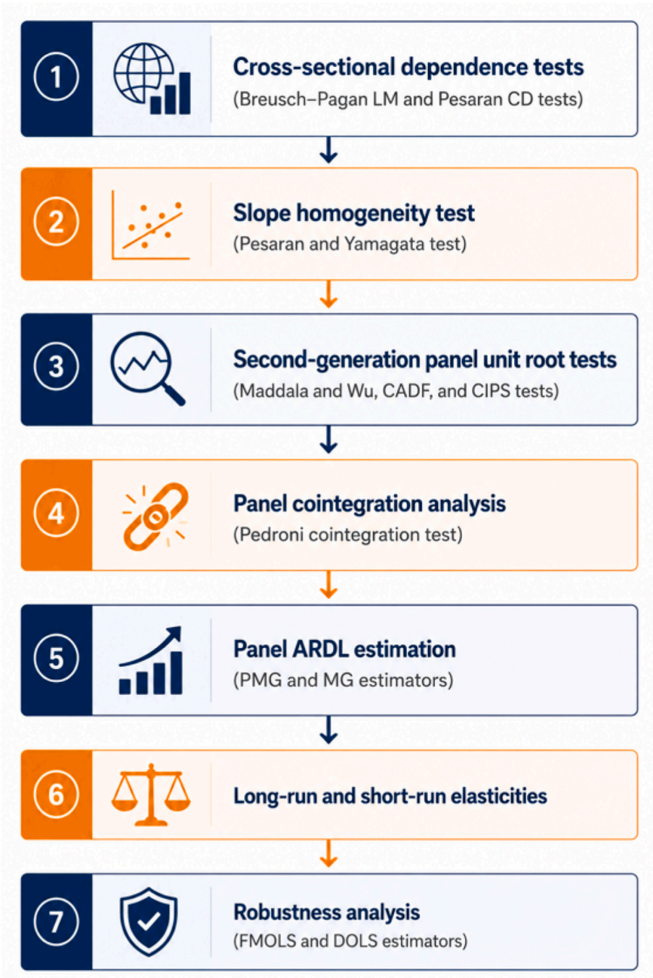

Fig. 2. Empirical strategy and econometric procedure of the study.

economic linkages [41]. These factors may generate correlations across countries, particularly in agricultural systems that depend on common rainfall patterns, regional food markets, and environmental conditions. Ignoring such cross-sectional interactions may lead to biased estimates and unreliable statistical inference. To examine whether cross-sectional dependence exists in the panel dataset, this study applies the Pesaran [42] CD test. The test evaluates the null hypothesis of cross-sectional independence against the alternative hypothesis that cross-sectional units are correlated. The CD statistic is expressed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij} \tag{3}$$

where N denotes the number of cross-sectional units, T represents the time dimension, and $\widehat{\rho}_{ij}$ denotes the pairwise correlation coefficient between the residuals of countries i and j. Under the null hypothesis, the test statistic follows a standard normal distribution.

Following the examination of cross-sectional dependence, it is important to assess whether the slope coefficients are homogeneous across the countries included in the panel. In cross-country analyses, assuming identical coefficients may overlook structural differences in economic conditions, agricultural systems, and institutional environments. Such variations are particularly relevant in East Africa, where countries differ in agricultural resources, policy frameworks, and production structures. To examine slope heterogeneity, this study employs the Pesaran and Yamagata [43] slope homogeneity test. The test evaluates the null hypothesis that slope coefficients are identical across cross-sectional units against the alternative hypothesis that they differ among countries. The test statistic is defined as:

$$\widetilde{\Delta} = \sqrt{N}\left(\frac{\widetilde{S} - K}{\sqrt{2K}}\right) \tag{4}$$

where N represents the number of cross-sectional units, K denotes the number of explanatory variables, and $\widetilde{S}$ refers to the adjusted Swamy test statistic. Under the null hypothesis of slope homogeneity, the statistic follows a standard normal distribution. For panels with relatively small samples, the adjusted statistic proposed by Pesaran and Yamagata [43] is also applied:

$$\widetilde{\Delta}_{adj} = \sqrt{N}\left(\frac{\widetilde{S} - E(\widetilde{Z}_{iT})}{\sqrt{\mathrm{Var}(\widetilde{Z}_{iT})}}\right) \tag{5}$$

Testing slope heterogeneity helps determine whether the estimated relationships vary across countries and provides guidance for selecting appropriate estimation techniques in subsequent stages of the analysis.

Testing the stationarity of the variables is a necessary step before estimating long-run relationships in panel data models. Traditional first-generation panel unit root tests assume cross-sectional independence among panel units. When cross-sectional dependence exists, these tests may produce biased results. For this reason, second-generation panel unit root procedures that account for cross-sectional interactions are more appropriate. Therefore, this study employs the Cross-sectional Augmented Dickey–Fuller (CADF) and the Cross-sectional Im, Pesaran, and Shin (CIPS) tests developed by Pesaran [44]. These tests incorporate cross-sectional averages of the variables into the regression equation, which allows for the analysis to control for unobserved common factors that may affect all countries in the panel. The null hypothesis states that all variables contain a unit root, while the alternative suggests that at least some of the series are stationary. The CADF regression is expressed as:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \overline{y}_{t-1} + \delta_i \Delta\overline{y}_t + \sum_{k=1}^{p} \phi_{ik} \Delta y_{i,t-k} + \varepsilon_{it} \tag{6}$$

Based on the CADF statistics obtained for each cross-sectional unit, the CIPS statistic is calculated as the average of the individual CADF values:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i \tag{7}$$

After determining the order of integration of the variables, the next step is to examine whether a long-run equilibrium relationship exists among them. Cointegration analysis determines whether the variables move together over time despite short-run fluctuations. To test for cointegration, this study employs the Pedroni [44,45] panel cointegration test. This method allows for heterogeneity across cross-sectional units by permitting country-specific intercepts and slope coefficients. Such flexibility is important in cross-country panels where economic structures and agricultural conditions differ across countries. The Pedroni cointegration model can be expressed as:

$$Y_{it} = \alpha_i + \beta_{1i} X_{1it} + \beta_{2i} X_{2it} + \cdots + \beta_{ki} X_{kit} + \varepsilon_{it} \tag{8}$$

where Y_{it} represents the dependent variable and X_{kit} denotes the explanatory variables. Under the null hypothesis, no cointegration exists among the variables, while the alternative hypothesis indicates a long-run relationship.

After confirming cointegration among the variables, the next step is to estimate the long-run relationships and short-run dynamics. For this purpose, the study employs the panel autoregressive distributed lag (ARDL) framework proposed by Pesaran et al. [46]. This approach is suitable when variables are integrated at different orders, such as a mixture of I(0) and I(1), and allows the estimation of both long-run equilibrium relationships and short-run adjustments. Within this framework, two estimators are commonly used: the mean group (MG) estimator developed by Pesaran and Smith [47] and the pooled mean group (PMG) estimator proposed by Pesaran et al. [46]. The MG estimator allows both long-run and short-run coefficients to vary across countries. In contrast, the PMG estimator assumes common long-run coefficients while allowing short-run dynamics and intercepts to differ across countries. To determine the preferred estimator, the study applies the Hausman [48] test, which evaluates whether the long-run homogeneity restriction imposed by the PMG estimator is appropriate. The panel ARDL model can be expressed in its error correction form as follows:

$$\Delta lnFP_{it} = \alpha_0 + \beta_1 lnFP_{it-1} + \beta_2 ln\, AGDEV_{it-1} + \beta_3 lnED_{it-1} + \beta_4 RQ_{it-1} + \beta_5 lnAE_{it-1} + \beta_6 lnLUC_{it-1} + \sum_{i=1}^{p} \delta_1 \Delta lnFP_{it-k} + \sum_{i=1}^{q} \delta_2 \Delta ln\, AGDEV_{it-k} + \sum_{i=1}^{q} \delta_3 \Delta lnED_{it-k} + \sum_{i=1}^{q} \delta_4 \Delta RQ_{it-k} + \sum_{i=1}^{q} \delta_5 \Delta lnAE_{it-k} + \sum_{i=1}^{q} \delta_6 \Delta lnLUC_{it-k} + \mu_i + \varepsilon_t \tag{9a}$$

$$\Delta lnFP_{it} = \alpha_0 + \beta_1 lnFP_{it-1} + \beta_2 ln\, AGDEV_{it-1} + \beta_3 lnWA_{it-1} + \beta_4 lnED_{it-1} + \beta_5 RQ_{it-1} + \beta_6 lnAE_{it-1} + \beta_7 lnLUC_{it-1} + \sum_{i=1}^{p} \delta_1 \Delta lnFP_{it-k} + \sum_{i=1}^{q} \delta_2 \Delta ln\, AGDEV_{it-k} + \sum_{i=1}^{q} \delta_3 \Delta lnWA_{it-k} + \sum_{i=1}^{q} \delta_4 \Delta lnED_{it-k} + \sum_{i=1}^{q} \delta_5 \Delta RQ_{it-k} + \sum_{i=1}^{q} \delta_6 \Delta lnAE_{it-k} + \sum_{i=1}^{q} \delta_7 \Delta lnLUC_{it-k} + \mu_i + \varepsilon_t \tag{9b}$$

where α_0 denotes the intercept, β represents long-run coefficients, and δ represents short-run parameters. The operator Δ denotes the first difference, while p and q indicate the lag orders of the dependent and explanatory variables. The term μ_i captures country-specific effects, and ε_t denotes the disturbance term.

3. Empirical results

3.1. Pre-estimation diagnostic tests

Table 2 reports the descriptive statistics of the variables employed in the analysis, including the mean, standard deviation, minimum and maximum values, and distributional properties. The summary statistics reveal notable variation across the variables included in the panel dataset. Land under cereal production exhibits the largest mean and dispersion among the variables, with an average value of 2,426,732 ha and a standard deviation of 2,969,217. This pattern indicates substantial cross-country variation in cultivated land across East African economies, where agricultural production structures differ widely in scale and land availability. Food production records an average value of 96.25 with a standard deviation of 20.64, which indicates moderate variation in aggregate food production levels across the sample countries. Institutional quality, measured through regulatory quality, reveals the lowest average value at −0.96, with a range extending from −2.548 to 0.186. These values indicate generally weak regulatory environments across several countries in the region. The distributional properties also indicate that agricultural development, water availability, environmental degradation, and cultivated land display positive skewness. In contrast, food production, agricultural employment, and regulatory quality exhibit negative skewness. The Jarque–Bera statistics reported in Table 2 reject the null hypothesis of normality at the 1 percent significance level for all variables.

Table 3 presents the pairwise correlation matrix among the variables to assess the association between the variables prior to model estimation. Correlation coefficients range between −1 and 1, where values closer to zero indicate weaker associations among variables. The results indicate that most explanatory variables exhibit positive correlations with food production. Agricultural development exhibits the strongest association with food production, with a correlation coefficient of 0.826, which suggests that higher development flows to the agricultural sector are linked with increased food production across East African economies. Environmental degradation also displays a positive correlation with food production (0.212), although the magnitude of the relationship is relatively modest. By contrast, agricultural employment is negatively correlated with food production (−0.256). This pattern might be an indication of fundamental changes in the distribution of labor in agricultural systems, where increases in productivity do not always translate into increased labor participation. Water availability and cultivated land display weak correlations with food production.

Before proceeding with panel estimations, it is necessary to examine whether cross-sectional dependence exists among the variables. In panels consisting of interconnected economies such as those in East Africa, countries often experience common shocks related to climate variability, agricultural markets, and regional economic conditions. When such dependence is present, conventional first-generation panel tests that assume cross-sectional independence may produce biased results. To evaluate this issue, the analysis applies the Breusch–Pagan [49] LM test together with the Pesaran [50] CD test. The results presented in Table 4 indicate that the null hypothesis of cross-sectional independence is rejected for most variables at conventional significance levels. These outcomes suggest that the variables exhibit cross-country interdependence, which implies that developments in one country may be associated with changes in others within the regional panel. In addition to cross-sectional dependence, the study examines whether slope coefficients are homogeneous across countries. This is assessed using the Pesaran and Yamagata [43] slope homogeneity test. The delta and adjusted delta statistics reported in Table 4 reject the null hypothesis of homogeneous slope coefficients for both Model I and Model II. These findings indicate that the estimated relationships vary across countries due to structural differences in agricultural systems, environmental conditions, and institutional frameworks within the region.

Table 2
Descriptive analysis.

	FP	AGDEV	WA	ED	RQ	AE	LUC
Mean	96.265	26.228	78.212	0.205	−0.960	63.195	2426732
Maximum	161.670	212.201	99.555	0.984	0.186	91.254	12424860
Minimum	35.750	0.000	33.190	0.022	−2.548	26.282	4654
Std. Dev.	20.638	31.204	17.449	0.190	0.658	16.371	2969217
Skewness	−0.437	2.659	−0.862	1.817	−0.677	−0.584	1.868
Kurtosis	3.896	12.680	2.791	6.125	2.423	2.409	5.474
Jarque-Bera	19.799	1540.244	38.087	290.047	27.361	21.639	253.547
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	303	303	303	303	303	303	303

Table 3
Correlation matrix.

	lnFP	lnADEV	lnWA	lnED	RQ	lnAE	lnLUC
lnFP	1.000						
lnADEV	0.826***	1.000					
lnWA	0.016	0.010	1.000				
lnED	0.212***	0.186***	−0.051	1.000			
RQ	0.004	0.007	−0.423***	−0.111**	1.000		
lnAE	−0.256***	−0.217***	−0.042	−0.272***	0.336***	1.000	
lnLUC	0.045	0.041	0.453***	0.139**	0.222***	0.190***	1.000

Table 4
Cross-sectional dependence test and homogeneity test.

H_0: No cross-section dependence		
Variable	Breusch-Pagan LM	Pesaran CD
lnFP	2205.000	46.957
	[0.000]	[0.000]
lnADEV	2205.000	46.957
	[0.000]	[0.000]
lnWA	637.170	−2.168
	[0.000]	[0.030]
lnED	1078.262	15.452
	[0.000]	[0.000]
RQ	579.945	−0.635
	[0.000]	[0.526]
lnAE	1763.656	41.762
	[0.000]	[0.000]
lnLUC	558.029	9.652
	[0.000]	[0.000]
H_0: coefficient slopes are homogeneous		
Model I	Delta	p-value
	11.671	0.000
Adjusted	14.294	0.000
Model II		
	10.274	0.000
Adjusted	13.058	0.000

3.2. Panel unit root test results

Following the confirmation of cross-sectional dependence and slope heterogeneity, second-generation panel unit root tests were employed to determine the order of integration of the variables. Specifically, the Maddala and Wu [51], CIPS, and CADF tests were utilized. The results reported in Table 5 indicate some variation across the three testing procedures. While several variables, including water availability, environmental degradation, regulatory quality, agricultural employment, and land under cultivation, exhibit evidence of stationarity at levels under at least one of the applied tests, food production and agricultural development appear non-stationary in most level specifications. However, all variables become stationary after first differencing according to the three unit root procedures. Given the presence of cross-sectional dependence and following the recommendation of Pesaran (2007), greater weight is assigned to the CIPS and CADF tests because these procedures explicitly account for cross-sectional interactions among panel units. Based on the combined evidence, the variables are integrated of order zero and one, with none exhibiting integration beyond the first difference. The presence of a mixture of I(0) and I(1) variables therefore justifies the application of the panel ARDL framework, which is specifically designed to accommodate such integration properties while estimating both long-run and short-run relationships.

3.3. Panel cointegration analysis

After establishing that the variables have mixed orders of integration, the next step is to examine whether a long-run equilibrium relationship exists among them. For this purpose, the study applies the Pedroni panel cointegration test, which allows for heterogeneity across cross-sectional units. The results presented in Table 6 provide evidence of cointegration for both Model I and Model II. The modified Phillips–Perron, Phillips–Perron, and Augmented Dickey–Fuller statistics reject the null hypothesis of no cointegration at conventional significance levels. These outcomes indicate that food production and its explanatory variables move together over time and maintain a stable long-run relationship across the panel countries. The confirmation of cointegration implies that long-run equilibrium relationships exist between food production and the explanatory variables. Consequently, the analysis proceeds to estimate the long-run coefficients using the panel ARDL technique.

Table 6
Panel cointegration tests.

Test	Model I	
	Statistic	p-value
Modified Phillips–Perron t	3.738	0.000
Phillips–Perron t	−1.290	0.099
Augmented Dickey–Fuller t	−1.917	0.028
	Model II	
Modified Phillips–Perron t	4.565	0.000
Phillips–Perron t	−1.913	0.028
Augmented Dickey–Fuller t	−1.696	0.045

Table 5
Panel unit root tests.

Variables	Level			1st Difference		
	Maddala and Wu [51]	CIPS	CADF	Maddala and Wu	CIPS	CADF
lnFP	5.862	2.610	2.610	58.862***	2.610	2.610
lnADEV	15.179	2.610	2.610	137.362***	2.610	2.610
lnWA	131.389***	−2.304**	−0.368	75.793***	−2.072	−0.625
lnED	39.069	−2.310**	−2.361***	92.479***	−4.266***	−2.284**
RQ	23.870	−2.277**	−1.712	124.930***	−4.238***	−2.636***
lnAE	17.142	−2.517***	−2.423***	101.314***	−3.094***	−1.916
lnLUC	39.068	−3.481***	−2.263**	273.590***	−5.323***	−2.581***

Notes: Maddala and Wu reports Fisher-type χ^2 statistics, whereas CIPS and CADF report Z[t-bar] statistics. The null hypothesis states that the series contains a unit root. Rejection of the null hypothesis indicates stationarity. ***, **, and * indicate p-values at the 1%, 5%, and 10% significance levels, respectively.

3.4. Long-run and short-run elasticities

This study examines the long-run and short-run relationships between agricultural development, water availability, environmental degradation, institutional quality, and food production in 15 East African economies. Two model specifications were estimated to assess the contributions of agricultural development and water availability to food production dynamics. Model I excludes water availability, while Model II includes this variable to determine whether water conditions modify the estimated relationships among the remaining determinants. Primarily, this study relies on the outcomes of the PMG estimator, as it allows for heterogeneous short-run adjustments across countries while maintaining a common long-run relationship. The panel ARDL specification selected according to the Akaike Information Criterion (AIC) was therefore estimated to examine the dynamics of food production in East Africa.

The PMG long-run estimates presented in Table 7 indicate that agricultural development has a positive and statistically significant association with food production in both model specifications. The magnitude of the coefficients indicates that a one percent increase in agricultural development increases food production by approximately 0.322 percent in Model I and 0.481 percent in Model II. This result indicates that improvements in agricultural systems contribute to higher food output across East African economies. When water availability is introduced in Model II, it exhibits a positive and statistically significant relationship with food production. The estimated coefficient exhibits that a one percent increase in water availability increases food production by approximately 11.75 percent. This result presents the significance of reliable water resources for agricultural production in a region where rainfall variability and recurrent droughts frequently constrain farming activities.

Environmental degradation does not exhibit a statistically significant relationship with food production in either model specification. The estimated coefficients remain statistically insignificant, which indicates that environmental degradation does not exert a measurable direct effect on food production within the estimated framework. Institutional quality, however, shows a negative and statistically significant association with food production in the long-run. The coefficients indicate that a one percent increase in institutional quality reduces food production by approximately 0.388 percent in Model I and 0.601 percent in Model II. This result indicates that improvements in governance indicators are not necessarily accompanied by immediate increases in agricultural production within the region.

In addition, agricultural employment exhibits a positive and statistically significant relationship with food production in the long-run. The estimated elasticities indicate that a one percent increase in agricultural employment increases food production by approximately 2.199 percent in Model I and 3.283 percent in Model II. This finding indicates that labour availability continues to play an important role in agricultural production in East African economies. Similarly, cultivated land exhibits a positive and statistically significant association with food production in the long-run. The estimated coefficients indicate that expanding land under cultivation increases food production by approximately 0.435 percent in Model I and 0.528 percent in Model II. These results suggest that land expansion remains an important mechanism through which agricultural production increases in the region.

The short-run estimates reveal that agricultural development maintains a positive and statistically significant relationship with food production across both model specifications. The estimated coefficients indicate that a one percent increase in agricultural development increases food production by approximately 0.011 percent in Model I and 0.018 percent in Model II. In contrast, water availability, agricultural employment, cultivated land, and environmental degradation do not show statistically significant short-run relationships with food production. Strikingly, institutional quality reveals a positive and statistically significant short-run relationship with food production, which suggests that short-term improvements in governance conditions may coincide with temporary increases in agricultural output. The error correction term (ECT) is negative and statistically significant in both models, which indicates the existence of a long-run equilibrium relationship among the variables. The adjustment coefficients indicate that deviations from long-run equilibrium are corrected at an annual rate of approximately 7.5 percent in Model I and 5.4 percent in Model II. This adjustment process indicates that short-run fluctuations in food production gradually return toward the long-run equilibrium path.

Table 7
PMG and MG estimations.

Variables	PMG		MG	
	Model I	Model II	Model I	Model II
Long-run elasticities				
lnADEV	0.322***	0.481***	0.148***	0.212**
	(3.420)	(2.650)	(3.650)	(2.220)
lnWA		11.754*		5.004
		(1.780)		(1.040)
lnAE	2.199**	3.283**	−1.825***	−1.376***
	(2.470)	(2.110)	(−3.910)	(−2.710)
lnLUC	0.435***	0.528***	0.095	0.380
	(3.720)	(2.880)	(0.650)	(1.370)
lnED	0.021	−0.081	−0.150	−0.202
	(0.230)	(−0.560)	(−1.460)	(−1.420)
RQ	−0.388***	−0.601**	0.082	0.148
	(−2.710)	(−2.380)	(0.670)	(0.920)
Short-run elasticities				
ECT	−0.075***	−0.054***	−0.520***	−0.522***
	(−3.490)	(−3.070)	(−9.980)	(−9.820)
ΔlnADEV	0.011*	0.018**	−0.007	−0.012*
	(1.830)	(2.410)	(−1.170)	(−1.820)
ΔlnWA		7.538		−7.219
		(1.00)		(−1.100)
ΔlnAE	0.316	0.139	1.314***	1.323***
	(0.820)	(0.330)	(2.760)	(3.040)
ΔlnLUC	−0.008	−0.005	−0.006	0.002
	(−0.260)	(−0.160)	(−0.110)	(0.040)
ΔlnED	0.005	0.024	0.023	0.024
	(0.150)	(0.770)	(0.540)	(0.530)
ΔRQ	0.053***	0.045**	0.048	0.043
	(2.600)	(2.010)	(1.060)	(0.910)
Constant	−0.872***	−3.778	5.486***	0.356
	(−3.380)	(−3.130)	(2.850)	(0.070)
Observations	300	300	300	300
Countries	15	15	15	15

3.5. Robustness of the long-run findings

The FMOLS and DOLS estimations further support the long-run relationships obtained from the PMG approach. These estimators correct for endogeneity and serial correlation in cointegrated panels. Consistency across them, therefore, provides additional evidence on the stability of the estimated relationships. As reported in Table 8, the principal determinants of food production display comparable coefficient magnitudes under both FMOLS and DOLS specifications. Agricultural development maintains relatively large and precisely estimated coefficients in both models. The pattern indicates that its contribution to food production remains stable across estimation methods. Moreover, cultivated land presents small but consistently positive coefficients across all specifications. Expansion of land under cultivation remains associated with higher levels of food production in the region. The robustness results also confirm two additional patterns identified in the baseline estimation. Environmental degradation remains statistically insignificant under both FMOLS and DOLS. The absence of statistical significance suggests that its direct association with aggregate food production is weak within the empirical framework. Institutional

Table 8
FMOLS and DOLS estimations.

Variable	FMOLS	DOLS	FMOLS	DOLS
	Model I		Model II	
lnADEV	0.413***	0.371***	0.287***	0.031***
	(10.959)	(11.569)	(6.202)	(2.739)
lnWA			0.384***	10.912
			(3.845)	(0.715)
lnAE	0.603***	0.631***	0.244***	−1.987***
	(12.341)	(13.075)	(3.626)	(−14.089)
lnLUC	0.044***	0.046***	0.066***	0.093**
	(3.615)	(3.767)	(2.686)	(2.472)
lnED	−0.013	−0.008	−0.032	−0.044
	(−0.491)	(−0.303)	(−1.037)	(−0.986)
RQ	−0.148***	−0.155***	0.011	−0.089***
	(−4.789)	(−4.854)	(0.230)	(−2.712)

quality continues to display a negative relationship with food production in most specifications. However, the magnitude of this effect becomes smaller in certain estimations. The agricultural employment coefficient identifies some variation across estimators, although statistically insignificant.

4. Discussion of findings

The findings display the significance of agricultural development in influencing food production in East African economies. Improvements in agricultural systems strengthen the capacity of the sector to generate higher output over time. In East Africa, farming systems are predominantly smallholder-based, and production is highly dependent on rainfall. Under these conditions, progress in agricultural development can translate directly into higher levels of food production. Agricultural systems in many parts of the region continue to operate with limited mechanization. Access to improved inputs remains constrained and extension services are often weak. Therefore, targeted improvements in agricultural support systems can generate substantial productivity gains. These improvements include wider access to improved seeds, greater fertilizer availability, expansion of irrigation infrastructure, and strengthened agricultural extension programmes. Strengthening agricultural development also improves the ability of farming systems to respond to climate variability and land constraints. Related evidence from developing agricultural economies further indicates that commercialization, access to agricultural finance, and farmer-centered training programmes contribute to improvements in productivity and rural welfare outcomes. Studies conducted in Ghana, for example, observed that credit access and commercialization enhance production efficiency among smallholder farmers, while climate-smart agricultural training strengthens technology adoption and adaptive farming capacity [52]. It also helps the sector respond to the rising demand for food associated with rapid population growth across East African countries. Existing empirical evidence largely supports this relationship. Studies have reported that stronger agricultural sectors are associated with improved food availability and food security outcomes [53]. Research on climate smart agricultural practices also reports positive effects on agricultural productivity and food security [53–55]. Evidence on agroforestry systems is also consistent with these findings [56–58].

In East African economies, the availability of water also becomes a significant determinant of food production. Reliable access to water is closely linked with the stability and productivity of agricultural systems in the region. In many parts of East Africa, agricultural production remains heavily dependent on rainfall. Irrigation infrastructure is still limited, and rainfall variability is high. These conditions make agricultural output particularly sensitive to fluctuations in water supply. Thus, improvements in water availability support crop growth and allow farmers to maintain production during dry periods. Additionally, stable water access reduces the risk of crop failure during prolonged drought episodes, which frequently affect several countries in the region. This relationship is especially important in semi-arid and drought-prone areas where water constraints often limit agricultural productivity [41]. Evidence from previous research supports this pattern. Studies on water scarcity indicate that declining water availability is associated with reductions in food production [59]. Research on improved irrigation management also shows that better water management practices can increase agricultural yields while improving resource efficiency [60]. At the same time, excessive rainfall can damage crops and disrupt growing conditions [61]. Both insufficient and excessive water supply therefore influence agricultural outcomes. These observations reinforce the significance of reliable and consistent water availability for maintaining agricultural output throughout East Africa.

Environmental degradation does not appear to exert a statistically discernible influence on food production in the estimated models. This outcome may indicate the indirect mechanisms by which environmental pressures influence agricultural systems in East Africa. Agricultural production in the region often responds more immediately to factors such as rainfall variability, water availability, and agricultural inputs. The effects of environmental degradation may operate gradually and may not be captured in aggregate food production within the observed period. Moreover, the use of per capita CO_2 emissions as a proxy for environmental degradation may not sufficiently capture localized ecological pressures such as soil erosion, deforestation, biodiversity loss, and land degradation that directly influence agricultural productivity in East African farming systems. In addition, many farming systems in East Africa rely on extensive cultivation practices and traditional crop varieties that are adapted to harsh environmental conditions. Such characteristics may partly buffer short-term production against environmental deterioration, even though long-term ecological consequences remain important. Previous studies provide mixed evidence regarding the production effects of environmental degradation. Research examining biodiversity loss, deforestation, and pollution has reported negative effects on agricultural productivity [21]. Other studies similarly show that climate-related environmental pressures such as rising temperatures and carbon emissions can reduce crop yields [61,62]. At the same time, some research indicates that rising atmospheric CO_2 concentrations may improve crop productivity under certain conditions through enhanced photosynthesis and improved water-use efficiency [63–65]. These contradictory results suggest that environmental degradation affects agricultural production depending on the type of environmental pressure, regional climate, and agricultural system characteristics.

institutional quality exhibits differing associations with food production across the short- and long-run estimations, suggesting that governance conditions interact with agricultural production through broader structural and institutional processes within East African economies. The short-run relationship suggests that improvements in governance conditions may initially support agricultural activities. Measures such as better coordination of agricultural programmes, improved distribution of inputs, and stronger administrative oversight can facilitate production in the near term. In many East African countries, government initiatives related to extension services, input subsidies, and emergency support during climatic shocks often depend on institutional coordination. Therefore, strengthening these administrative functions can contribute to short run improvements in agricultural output. The growing expansion of digital financial systems across East Africa also appears to support agricultural entrepreneurship and market participation by improving access to savings mechanisms and credit facilities among rural households [66]. However, the negative long-run relationship may reflect the structural adjustments that accompany institutional reforms in the region. However, the negative long-run relationship appears to reflect broader structural and institutional adjustment dynamics within the agricultural sector. The regulatory quality indicator primarily captures overall governance conditions rather than specific agricultural policy mechanisms or sectoral regulatory arrangements. Under such conditions, improvements in institutional environments do not always correspond with immediate increases in agricultural production, particularly in economies where agricultural systems remain constrained by limited infrastructure, weak market integration, low technological diffusion, and persistent production bottlenecks. Empirical evidence provides mixed insights. Some studies report that stronger governance structures contribute to improved food availability and agricultural performance [66–69]. Other studies report weaker or insignificant relationships between governance indicators and food production outcomes in developing regions [24]. Evidence from SSA indicates that governance weaknesses is negatively associated with persistent food security [6].

Agricultural employment and cultivated land both reveal positive relationships with food production in the long-run. Expansion of agricultural employment increases the labour available for land preparation, cultivation, harvesting, and post-harvest activities. In many East African economies, agriculture remains labour intensive and dominated by smallholder farming. A larger agricultural workforce strengthens the capacity of farming systems to sustain production. Empirical evidence also reports that agricultural employment supports agricultural output and value chain development [70–72]. However, labor mobility to non-farm sectors may reduce agricultural labor availability. Previous studies indicate that labor migration may increase household food access through remittances but decrease agricultural production due to labor shortages [73,74]. Moreover, the expansion of land under cultivation increases the productive capacity of agricultural systems. Land availability remains a key factor in East African agriculture, where production growth often depends on expanding cultivated areas [41]. Previous studies similarly stated the centrality of land for agricultural output. At the same time, agricultural output depends on land quality. Soil erosion, desertification, and unsustainable land management practices have been shown to reduce crop yields by degrading soil conditions [75,76]. Evidence from Nigeria further presents that land degradation lowers agricultural productivity and contributes to food insecurity [77]. In addition, urbanization and industrial expansion can reduce the availability of arable land for agriculture [77,78].

5. Conclusion and policy suggestions

Food production remains a central concern for East African economies, where agriculture continues to sustain rural livelihoods and provide the primary source of food supply for a rapidly growing population. Climate variability, limited irrigation infrastructure, environmental pressures, and institutional constraints influence agricultural systems across the region, which makes it important to examine structural factors associated with food production across countries. Against this background, this study examined the determinants of food production across 15 East African countries over the period 2002–2022 by focusing on agricultural development, water availability, environmental degradation, institutional quality, agricultural employment, and land under cultivation. The empirical analysis employed heterogeneous panel approaches in the panel ARDL approach to capture long-run linkages and short-run changes. Diagnostic procedures confirmed the presence of cross-sectional interdependence and slope heterogeneity among the panel countries, while second-generation unit root tests and panel cointegration analysis supported the existence of a stable long-run relationship linking food production with its explanatory variables.

The empirical evidence indicates that variations in food production across the region are closely associated with agricultural development and the availability of water resources, both of which remain central elements of agricultural activity in economies where farming systems depend heavily on natural resource conditions. Labour participation in agriculture and the extent of cultivated land also appear closely connected with agricultural output across the sample countries. However, environmental degradation does not exhibit a direct measurable association with food production in the estimated models. Institutional quality presents contrasting dynamics across the long- and short-run, which indicates that governance conditions may influence agricultural outcomes through gradual structural mechanisms rather than through immediate changes in aggregate production levels. The robustness checks based on alternative long-run estimators support the stability of these relationships and confirm the consistency of the empirical results across different estimation approaches.

The empirical findings of this study suggest several policy directions that are relevant for improving food production across East African economies. First, strengthening investment in agricultural development remains essential, particularly through increased support for agricultural infrastructure, improved technologies, and research systems that enhance farm productivity. Recent advancements in agricultural technologies further demonstrate the potential contribution of intelligent crop monitoring systems, AI-based yield prediction models, and automated farm management technologies in improving agricultural efficiency and long-term production sustainability within developing agricultural systems [33].Second, expanding irrigation systems and improving water resource management should receive greater attention, since reliable access to water is central in stabilizing agricultural output in a region where farming remains largely rain-fed. Third, policies aimed at improving agricultural labour productivity are important, including farmer training, extension services, and the diffusion of improved cultivation practices that allow labour to generate higher output. Fourth, maintaining and protecting cultivated land should remain a priority through sustainable land management practices, soil conservation programs, and policies that limit the conversion of agricultural land to non-agricultural uses. Fifth, environmental management should be incorporated into agricultural planning in order to address the longer-term effects of environmental degradation on agricultural systems, particularly through the promotion of climate-resilient farming practices and ecosystem restoration initiatives. Finally, strengthening institutional coordination in agricultural governance is necessary to improve policy implementation, resource allocation, and market functioning within the agricultural sector. Improved coordination among institutions responsible for agriculture, water resources, and rural development can contribute to more effective agricultural policies and more stable food production outcomes across the region.

Despite the robustness of the empirical framework, certain limitations remain relevant to the interpretation of the findings. Environmental degradation was measured using per capita CO_2 emissions, which may not sufficiently capture localized ecological pressures directly linked to agricultural production, particularly soil erosion, deforestation, biodiversity decline, and land degradation. In addition, the reliance on aggregated national-level panel data limits the ability to account for subnational differences in climatic conditions, agricultural systems, and resource availability across the sampled economies. The empirical specification also did not explicitly incorporate several climate-related factors, including rainfall variability, drought severity, and temperature extremes, despite their relevance to agricultural performance within East Africa. Likewise, institutional quality was proxied through regulatory quality, which may not comprehensively reflect wider governance dimensions associated with agricultural production, such as political stability, government effectiveness, and corruption control. These considerations indicate that agricultural production dynamics across the region are influenced by a broader set of ecological, climatic, and institutional conditions than those captured within the present framework. Future research could therefore benefit from employing more disaggregated environmental, institutional, and climate-related indicators to provide deeper insight into agricultural systems across East Africa.

CRediT authorship contribution statement

Abdikafi Hassan Abdi: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Visualization, Writing – original draft. **Abdisalan Aden**

Mohamed: Data curation, Formal analysis, Investigation, Resources, Validation, Writing – original draft. **Amina Omar Mohamud:** Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Omar Mohamed Omar:** Writing – original draft.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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