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Original Research Article

Climate Change and Production of Cereal Crops in East Africa: Role of Temperature, Precipitation, Ecological and Carbon Footprint

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Abstract: This study was conducted to examine the impact of changes in annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested on cereal crop production in East Africa. The study was conducted in a panel cointegration framework using annual time series from 1980 to 2018 for five East African countries i.e., Ethiopia, Kenya, Rwanda, Tanzania, and Uganda. Unit root tests were performed using LLC, IPS, ADF-Fisher, and PP-Fisher tests, while panel co-integration tests were performed using Pedroni residual, Kao residual, and Johansen Fisher panel co-integration tests. Long-run coefficients were estimated using the Pooled Mean Group/Autoregressive Distributed Lag, Panel Fully-modified OLS, and Panel Dynamic OLS models. Empirical findings from the three models revealed that increases in annual mean temperature have adverse effects on cereal crop production, while increases in annual mean precipitation, carbon footprint, ecological footprint, and area harvested have positive effects on cereal crop production in East Africa. Based on these findings, it can be suggested that prioritization of climate change adaptation strategies in the region such as the development of drought and heat-resistant crop varieties, changing in planting dates, and investment in irrigation technologies to boost cereal crops productivity could play a role in minimizing the adverse effects of changes in climate factors.

Keywords: Cereal crop production, Climate change, East Africa, Panel cointegration, Panel Dynamic OLS, Panel Fully-modified OLS, Pooled Mean Group/Autoregressive Distributed Lag model.

INTRODUCTION

Agriculture plays a significant role in the economies and livelihoods of communities in Sub-Saharan Africa (SSA). The sector employs between 70% and 80% of the population in SSA, contributes around 30% of the gross domestic product (GDP) on average, and no less than 40% of exports (Calzadilla, Zhu, Rehdanz, Tol, & Ringler, 2013). In the East African region, the sector contributes 22.4%, 23.8%, 24.1%, 25.9%, and 37.6% to GDP in Kenya, Uganda, Rwanda, Tanzania, and Ethiopia, respectively according to the World Bank (WB). The sector also employs 54%, 62%, 65%, 67%, and 72% of the population in Kenya, Rwanda, Tanzania, Ethiopia, and Uganda, respectively (WB, 2022). However, factors such as specific agro-ecological features, subsistence farming practices with the majority of farms less than 2 hectares, limited access to extension services, low investment levels, high levels of dependence on natural weather conditions, limited markets and supporting institutions have limited development of the region's agricultural sector (Calzadilla *et al.*, 2013; Kahsay & Hansen, 2016; Zizinga *et al.*, 2022).

SSA relies majorly on rain-fed agricultural production with more than 95% of total cropland under rain-fed farming (Adhikari, Nejadhashemi, & Woznicki, 2015; Calzadilla *et al.*, 2013; Kahsay & Hansen, 2016). This makes the sector highly vulnerable to changes in climatic conditions especially variations in seasonal rainfall. For instance, crop failures have been witnessed in the East African region as a result of the higher prevalence of droughts and floods over the last 40 years (Kahsay & Hansen, 2016). Such losses are further aggravated by the limited capacity to adapt to climate changes by the majority of farmers due to the high poverty levels (Calzadilla *et al.*, 2013), poor policy

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framework, and low levels of institutional development (Kahsay & Hansen, 2016). In addition to variations in rainfall amounts and patterns, climate change affects the productivity of the agricultural sector through changes in temperature, carbon dioxide (CO_2) fertilization, and surface water runoff (Calzadilla *et al*., 2013), inadequate soil moisture, and shortening of the crop growing seasons (Zizinga *et al*., 2022). Considering the major role of cereals in the diets and livelihoods of the population, a change in climatic conditions has impacts on the food security and livelihoods of the communities (Calzadilla *et al.*, 2013; Zizinga *et al*., 2022).

This study examines the impact of changes in temperature, precipitation, carbon, and ecological footprint on the production of cereal crops in East Africa. Precipitation influences the availability of freshwater and the level of soil moisture, which are important factors for crop growth. On the other hand, temperature and soil moisture determine the length of the growing season and control the development and water requirements of crops (Calzadilla *et al.*, 2013). In cereals, higher temperatures shorten their life cycle and duration of the reproductive phase causing a reduction in grain yield (Calzadilla *et al*., 2013; Hatfield *et al*., 2011). According to recent research, temperature increases of 1.7–5.4°C and annual rainfall reductions of 5–20% have been projected across the East African region by the end of the 21st century (Zizinga *et al*., 2022). This is likely to affect agricultural production in the region, for instance, a 7-10% reduction in annual yields of maize has been projected in Uganda for the next 3 decades (Zizinga *et al*., 2022). Plant growth is enhanced and water use efficiency is improved under higher atmospheric concentrations of CO_2 (Calzadilla *et al*., 2013).

Among studies examining the role of climatic factors on crop production, Lobell and Field (2007) investigated the impact of temperature and precipitation trends on the yields of the six most widely grown crops in the world i.e., wheat, rice, maize, soybeans, barley, and sorghum using data from 1961 to 2002. The study results revealed a negative impact of increased temperatures on the global yields of all crops. Specifically, a 1ºC rise in temperatures led to a 5.4%, 0.6%, 8.3%, 1.3%, 8.9%, and 8.4% reduction in the global yields of wheat, rice, maize, soybeans, barley, and sorghum, respectively. Similarly, Zhao *et al.*, (2017) investigated the impacts of temperature on yields of wheat, rice, maize, and soybean by compiling extensive published results from global grid-based and local point-based models, statistical regressions, and field-warming experiments. The authors concluded that results from the different methods consistently showed negative temperature impacts on crop yield on the global scale i.e., each 1ºC increase in global mean temperature would, on average, reduce global yields of wheat, rice, maize, and soybean by 6.0%, 3.2%, 7.4%, and 3.1%, respectively.

Of all crops grown in East Africa, cereal crops are dominant. These include majorly maize, millet, sorghum, rice, and wheat, maize being the most widely cultivated crop as can be noted in Table 1, and 77% of its total production is consumed as food (Adhikari *et al*., 2015). Table 1 below presents the production and area harvested of these crops in Ethiopia, Rwanda, Kenya, Tanzania, and Uganda in 2020 according to the Food and Agriculture Organization (FAO).

Table 1: Production of major cereals in East African countries in 2020

		Ethiopia	**Rwanda**	**Kenya**	**Tanzania**	**Uganda**
Maize	Production (Tons)	10022286	448633	3789000	6711000	2750000
	Area harvested (Ha)	2363507	294439	2188911	4200000	991056
Millet	Production (Tons)	1218582	5067	153000	325000	209671
	Area harvested (Ha)	480511	10637	118411	270000	150638
Sorghum	Production (Tons)	5058043	170489	315000	750000	251634
	Area harvested (Ha)	1789720	169419	219657	700000	305721
Rice	Production (Tons)	189649	116504	180890	4528000	200000
	Area harvested (Ha)	62551	29584	28276	1586952	68452
Wheat	Production (Tons)	5478709	12811	404700	77000	25000
	Area harvested (Ha)	1829051	12309	132231	60000	16209

Source: FAO (2022)

LITERATURE REVIEW

Among studies conducted in the East African region, Kabubo-Mariara and Karanja (2007) utilized the Ricardian approach and reported that increases in temperatures reduced crop productivity in Kenya, which in turn reduced net revenues from agriculture. Increases in precipitation on the other hand led to increased crop productivity, which in turn increased net revenues from agriculture. Tumwine, Lokina, and Matovu (2019) employed the same approach to examine the effect of climate change on agricultural crop returns in Uganda. Among the key findings of this study, a 1% increase in temperature and rainfall led to a 2.02% and 0.025% reduction in maize farm returns, respectively. Kahsay and Hansen (2016) estimated the production function for agricultural output in Eastern Africa by incorporating climate variables disaggregated into growing and non-growing seasons. Results revealed a substantial negative effect of within growing season variance of precipitation. The authors reported a reduction in agricultural output by around 1.2% and 4.5%.

Ochieng, Kirimi, and Mathenge (2016) utilized a household fixed effects estimator to estimate the effect of climate variability and change on revenue from maize alongside tea in Kenya. Results revealed a negative effect of temperature on maize revenues, and a positive effect of precipitation. While reviewing the impacts of climate change on crops in SSA, Adhikari *et al*., (2015), reported a 72% projected decrease in wheat yields by the end of the current century as a result of increases in temperatures and variability of rainfall. Maize and rice yields could reduce up to 45%, while millet and sorghum being more resilient to climate change, their yields could reduce by less than 20%. Finally, Abera, Crespo, Seid, and Mequanent (2018) also reported a negative impact of rainfall variability and increasing temperatures on maize yields in Ethiopia.

In African countries outside the East African region, Blignaut, Ueckermann, and Aronson (2009) employed a panel data econometric model to estimate how sensitive South Africa's agriculture was to changes in rainfall. Results of the study revealed that each 1% decline in rainfall was likely to lead to a 1.1% decline in the production of maize and a 0.5% decline in wheat production. In Tunisia, Ben Zaied and Ben Cheikh (2015) reported that increased annual temperature had a negative effect on cereals production, while annual rainfall had a positive effect.

In Nigeria, Adedeji, Tiku, Waziri-Ugwu, and Sanusi (2017) used descriptive and regression analysis to examine the effect of climate change on rice production in Adamawa State from 1990-2015. Results of the study revealed that a 1% increase in rainfall increased rice production by 22.2%, while a 1% increase in temperatures decreased rice production by 3.7%. Gbenga, Ibrahim, and Ayodele (2021) reported that a 1% increase in rainfall led to a 1% increase in rice production, while a 1% increase in temperature led to a 2.7% decrease in rice production. In this study, the Fully Modified Least Squares (FMOLS) regression model was utilized on data from 1970 to 2016. Contrary to Adedeji *et al*., (2017)'s and Gbenga *et al.*, (2021)'s findings, Emenekwe, Onyeneke, and Nwajiuba (2022) reported a positive long-run impact of temperature and a negative long-run impact of precipitation on rice production. A 1% increase in temperature increased rice production by 4.2% in the short run, while a 1% increase in precipitation decreased rice production by 1.3% in the short run, and between 1 and 1.3% in the long run. Emenekwe *et al*., (2022)'s findings further revealed a positive impact of ecological footprint, and a negative impact of carbon footprint on rice production. In this study, the authors employed the novel dynamic autoregressive distributed lag (DYNARDL) simulation approaches on data from 1971 to 2018.

Ntiamoah, Li, Appiah-Otoo, Twumasi, and Yeboah (2022) also utilized the same approach as Emenekwe *et al*., (2022) in Ghana on maize and soybean data from 1990 to 2020. Results revealed that a 1% increase in precipitation led to a 1.297% and 0.885% increase in maize production in the short and long run, respectively. While a 1% increase in precipitation led to a 0.969% and 0.351% increase in soybean production in the short and long run, respectively. The authors further reported a statistically significant positive effect of CO_2 emissions on maize yield in both the short run and long run i.e., a 1% increase in CO_2 emissions increased maize production by 0.599% and 0.611% in the short run and long run, respectively. In this study, the authors utilized the dynamic simulated autoregressive distributed lag (ARDL) model for the period 1990 to 2020. The impact of climate change on the production of crops has also been widely researched in several countries outside the African continent. For example Pakistan (Shujaat Abbas, 2022; Sohail Abbas, Kousar, Shirazi, Yaseen, & Latif, 2022; Gul, Chandio, Siyal, Rehman, & Xiumin, 2022), Türkiye (Chandio, Gokmenoglu, & Ahmad, 2021; Chandio, Ozturk, Akram, Ahmad, & Mirani, 2020; Doğan & Kan, 2019), Nepal (Chandio, Jiang, Ahmad, Adhikari, & Ain, 2021), and India (Baig *et al*., 2022; Bhardwaj, Kumar, Kumar, Dagar, & Kumar, 2022; Kumar, Sahu, Ansari, & Kumar, 2021).

In the literature, the impact of temperature and precipitation changes on the production of crops is inconclusive and varies across countries. The majority of the studies reveal that temperature increases lead to reductions in the production of crops while increases in precipitation lead to increases in the production of crops. However, studies such as Chandio, Jiang, *et al*., (2021) and Emenekwe *et al.*, (2022) reveal a positive impact of temperature on rice production. On the other hand, Kumar *et al.*, (2021), Baig *et al*., (2022), Bhardwaj *et al*., (2022), and Emenekwe *et al*., (2022) reveal a negative impact of rainfall on the production of crops under study. Contradictions are also reported on the impact of CO_2 emissions on crop production. While Chandio *et al*., (2020), Chandio, Gokmenoglu, *et al*., (2021), and Emenekwe *et al*., (2022) report a negative impact of CO_2 emissions on the production of crops under study, Ahsan, Chandio, and Fang (2020) and Kumar *et al*., (2021) report a positive impact. This lack of consensus in the empirical literature could imply that the impact of temperature and precipitation on the production of crops varies across countries, agro ecological zones, and individual crops, making it necessary to conduct empirical analyses for individual countries or regions.

Considering the dearth of literature on the subject in the East African region, this study addresses this research gap by empirically examining the impact of temperature, precipitation, carbon footprint, and ecological footprint on cereal crop production in the region. The inclusion of temperature and precipitation changes in this study's model is because high temperatures and inadequate precipitation have been reported to be the two major climate factors affecting the yield of major crops especially cereals across the world (Liaqat *et al*., 2022). Similar to Kumar *et al*., (2021) and Emenekwe *et al*., (2022)'s studies, this study also includes carbon footprint and ecological footprint as proxies for climate change. According to the Global Footprint Network (GFN), carbon footprint "*measures CO_2 emissions associated with fossil fuel use*". While ecological footprint refers to the "*measure of how much biologically productive land and water is required by individuals, populations, or activities to produce all the consumed resources and absorb the generated wastes, utilizing the available technology and resource management systems*"(GFN, 2022). Including ecological footprint as a proxy for climate change is important because it captures the total environmental emissions (Kumar *et al*., 2021). Secondly, ecological footprint incorporates the effects of human activities on nature in terms of water pollution, soil degradation, built-up-land, fishing grounds, grazing land, forest and cropland, components which negatively affect the agriculture sector (Emenekwe *et al*., 2022; GFN, 2022; Kumar *et al*., 2021). Therefore, it is considered a superior indicator of climate change and the quality of the environment, and a reliable indicator of the earth's potential to support economic growth (Emenekwe *et al*., 2022; Kumar *et al*., 2021).

This paper is organized as follows: Section 1 was an introduction to the subject and provided an overview of the available literature on the subject. Section 2 describes the data and econometric methodology; section 3 presents the empirical results and discussion while section 4 provides the conclusion of the study.

MATERIAL AND METHODS

Data

In this study, annual panel time series data covering the period from 1980 to 2018 are used for five East African countries, namely, Ethiopia, Kenya, Rwanda, Tanzania, and Uganda. The variables used in this study are, the production of cereals used as the dependent variable, annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested used as the exogenous variables. The variables, their acronyms, units of measurement, and sources are presented in Table 2. For the empirical analysis, all variables were transformed into their natural logarithm to mitigate fluctuations of individual variables thus increasing the likelihood of stationarity after first differencing and overcoming heteroscedasticity (Keho, 2021; Kumar *et al*., 2021). Secondly, to allow the first differences of the variables to be interpreted as growth rates and coefficients in terms of elasticity (Keho, 2021).

Table 2: Variables used

Variables	Acronym	Units of measurement	Data source
Cereal crop production	CP	Tons	Food and Agriculture Organization statistics website (FAOSTAT)
Annual Mean Temperature	AMT	Degrees Celsius (°C)	The World Bank, Climate Change Knowledge Portal
Annual Mean Precipitation	AMP	Millimeters (mm)	The World Bank, Climate Change Knowledge Portal
Carbon Footprint	CF	Global hectares (gha)	Global Footprint Network Database
Ecological Footprint	EF	Global hectares (gha)	Global Footprint Network Database
Area of cereal crops Harvested	AH	Hectares (Ha)	FAOSTAT

Model specification

The panel co-integration is applied to explore the long-run association of cereal crop production with annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested for the five East African countries. The econometric model is specified as, cereal crop production expressed as a function of climate change factors and area harvested, as shown below:

CP = f(AMT, AMP, CF, EF, AH) ……………….. (1)

Equation 1 can further be specified as:

$LnCP_t = \alpha + \beta_1 LnAMT_t + \beta_2 LnAMP_t + \beta_3 LnCF_t + \beta_4 LnEF_t + \beta_5 LnAH_t + \varepsilon_t$ ……………….. (2)

Where LnCP, LnAMT, LnAMP, LnCF, LnEF, and LnAH are the natural logarithms of cereal crop production, annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested, respectively. α is the intercept, β_1, β_2, β_3, β_4, and β_5 are coefficients of their respective variables, and ε_t is the error term.

This study utilizes panel data because of its wide range of benefits, i.e., it contains more information and greater variability of data (Da Silva, Cerqueira, & Ogbe, 2018), it eliminates collinearity among the variables and contains more degrees of freedom, which improves the econometric estimations (Shafique, Azam, Rafiq, & Luo, 2021). Therefore, equation (2) can be rewritten in a panel data form as follows:

$LnCP_{i,t} = \alpha + \beta_1 LnAMT_{i,t} + \beta_2 LnAMP_{i,t} + \beta_3 LnCF_{i,t} + \beta_4 LnEF_{i,t} + \beta_5 LnAH_{i,t} + \varepsilon_{i,t}$ ……………….. (3)

Where the subscript i = 1, 2,…,5, represents the index of each country, and t = 1980, …, 2018 represents the year.

Econometric methodology

This study examines the influence of climate change on the production of cereal crops in East Africa. To investigate the causal relationship, this study presents a model using cereal crop production as the dependent variable, and annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested are used as the explanatory variables. This is achieved in 4 steps: (i) All variables are checked for stationarity using Levin, Lin & Chu (LLC), Im, Pesaran and Shin (IPS), Augmented Dickey-Fuller (ADF) Fisher, and Phillips–Perron (PP) Fisher panel unit root tests. (ii) Panel co-integration tests are conducted using Pedroni residual, Kao residual, and Johansen Fisher panel co-integration tests to determine the presence of the long-run relationship among the series. (iii) Pooled Mean Group/ Autoregressive-Distributed Lag (PMG/ARDL) model is estimated to determine the long and short-run coefficients of the explanatory variables. (iv) Finally, Panel Fully-modified OLS (FMOLS) and Panel Dynamic OLS (DOLS) are employed to examine the robustness of the results of the PMG/ARDL model.

Stationarity tests

Stationarity tests were performed using LLC, IPS, ADF Fisher, and PP Fisher panel unit root tests to investigate the order of integration of the variables. The LLC test, with the null hypothesis of the presence of a unit root in the series, assumes that there is a common unit root process so that ρ_i is identical across cross-sections (Erdal & Erdal, 2020; Streimikiene & Kasperowicz, 2016). Following Streimikiene and Kasperowicz (2016), the LLC test considers the following basic ADF specification.

$\Delta Y_{it} = \alpha Y_{it-1} + \sum_{j=1}^{pi} \beta_{ij} \Delta Y_{it-j} + X_{it}^{'}\delta + \varepsilon_{it}$ ………….. (4)

Where a common $\alpha = \rho - 1$ is assumed, but the lag order for the difference terms ρ_i is allowed to vary across cross-sections. The null hypothesis H_0 is $\alpha=1$ (there is a unit root) and the alternative hypothesis H_1 is $\alpha<0$ (there is no unit root).

The IPS test begins by specifying a separate ADF regression for each cross-section on equation 4. The null hypothesis may be written as H_0: $\alpha_i=0$, for all i, while the alternative hypothesis may be represented by:

$H_1: \begin{cases} \alpha_i<0 \text{ for } i=1,2,\ldots\ldots,N_1 \\ \alpha_i=0 \text{ for } i=N+1, N+2, \ldots,N \end{cases}$ ……………….. (5)

Where i may be interpreted as a fraction of the individual processes which is not zero and is stationary (Streimikiene & Kasperowicz, 2016). The ADF-Fisher and PP-Fisher tests are characterized by combining individual unit root tests to derive a panel-specific outcome. These tests allow for individual unit root processes so that ρ_i may vary across cross-sections. Their null hypothesis is that the series contains a unit root, while the alternative hypothesis states that some cross sections do not contain a unit root (Streimikiene & Kasperowicz, 2016).

Panel co-integration tests

Panel co-integration tests were performed using the Pedroni residual co-integration, the Kao residual co-integration, and the Johansen Fisher panel co-integration tests to examine the existence of a long-run relationship among the variables. In the Pedroni residual co-integration test, the null hypothesis of no co-integration is tested using two types of co-integration tests i.e., panel tests and group tests. The panel tests based on the within-dimension method includes four statistics i.e., panel v-statistic, panel rho-statistic, panel PP-statistic and panel ADF-statistic. The group tests based on the between-dimension method include three statistics, i.e., group rho-statistic, group PP-statistic, and group ADF-statistic.

PMG/ARDL model

After establishing the panel co-integration, the PMG/ARDL model was estimated to determine the long and short-run coefficients of the explanatory variables. In comparison with other co-integration approaches, the ARDL approach has several advantages. First, this approach can be applied regardless of whether the variables are integrated of order one [I(1)], order zero [I(0)], or a mix of both. However, this approach can not be applied when the variables are integrated of order 2 [I(2)] (Keho, 2021). Second, this approach is appropriate for even small samples. Third, this approach allows that the variables may have different optimal lags. Fourth, this technique generally provides unbiased estimates of the long-run model and valid t-statistics even when some of the regressors are endogenous, thus adequately addressing autocorrelation and endogeneity problems. Finally, this approach employs a single reduced-form equation which makes its implementation and interpretation simple (Ahmed, Zhang, & Cary, 2021; Rahman & Kashem, 2017). The ARDL model used in this study was expressed as equation 6:

$\Delta LnCP_{i,t} = \alpha + \sum_{j=1}^{q} \theta_{i,j} \Delta LnCP_{i,t-j} + \sum_{j=1}^{q} \beta_{i,j} \Delta LnAMT_{i,t-j} + \sum_{j=1}^{q} \omega_{i,j} \Delta LnAMP_{i,t-j} + \sum_{j=1}^{q} \varphi_{i,j} \Delta LnCF_{i,t-j} + \sum_{j=1}^{q} \delta_{i,j} \Delta LnEF_{i,t-j} + \sum_{j=1}^{q} \psi_{i,j} \Delta LnAH_{i,t-j} + \lambda_1 LnCP_{i,t-1} +$

$\lambda_2 LnAMT_{i,t-1} + \lambda_3 LnAMP_{i,t-1} + \lambda_4 LnCF_{i,t-1} + \lambda_5 LnEF_{i,t-1} + \lambda_6 LnAH_{i,t-1} + \varepsilon_{i,t}$ ……………….. (6)

Where Δ represents the first difference, α is the term of the constant, θ, β, ω, φ, δ, and ψ are the short-run coefficients, λ represents long-run coefficients, $\varepsilon_{i,t}$ is the error term, q represents the lag length used for the variables. In this study, the appropriate values for the optimum lags q were determined using the Akaike information criteria (AIC). The null hypothesis of no co-integration can be expressed as H_0: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = 0$, while the alternative hypothesis expressing the existence of co-integration can be expressed as H_1: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq 0$.

After estimating the long-run coefficients, short-run coefficients are estimated using the regular error correction mechanism (ECM) as depicted in Equation 7.

$$\Delta LnCP_{i,t} = \alpha + \sum_{j=1}^{q} \theta_{i,j} \Delta LnCP_{i,t-j} + \sum_{j=1}^{q} \beta_{i,j} \Delta LnAMT_{i,t-j} + \sum_{j=1}^{q} \omega_{i,j} \Delta LnAMP_{i,t-j} + \sum_{j=1}^{q} \varphi_{i,j} \Delta LnCF_{i,t-j} + \sum_{j=1}^{q} \delta_{i,j} \Delta LnEF_{i,t-j} + \sum_{j=1}^{q} \psi_{i,j} \Delta LnAH_{i,t-j} + \lambda_1 ECT_{i,t-1} + \varepsilon_{i,t} \text{ ……………….. (7)}$$

Where λ_1 is the coefficient of the error correction term (ECT). A negative and statistically significant ECT ensures convergence of the dynamics to the long-run equilibrium (Abuhabel & Olanrewaju, 2020). This implies that in the presence of external shock resulting in the disequilibrium of the system, the model can still converge with time to its normal state with a relatively average speed of adjustment of λ_1% percent per time.

Robustness tests

The study further employs the Panel Fully-modified OLS (FMOLS) and Panel Dynamic OLS (DOLS) to examine the robustness of the results of the Panel ARDL model. Some of the advantages of DOLS and FMOLS models over OLS models are that these methods give better estimates than the Ordinary Least Squares (OLS) in a heterogeneous panel with nonstationary series (Bildirici, 2014). Secondly, estimates from OLS may show serial correlation and heteroscedasticity in the presence of a strong finite sample bias because the excluded dynamics are captured by the residual, thus rendering regular table inference invalid even asymptotically (Affoh, Zheng, Dangui, & Dissani, 2022). However, DOLS and FMOLS eliminate endogeneity, serial correlation, and errors in the long-run coefficients (Affoh *et al.*, 2022; Kumar *et al.*, 2021). DOLS and FMOLS yield consistent standard errors and t-statistics in the presence of endogenous regressors (Bildirici, 2014). In the literature, several authors have employed these models i.e., Affoh *et al.*, (2022); Bildirici (2014); Doğan and Kan (2019); Erdal and Erdal (2020); Khan *et al.*, (2019); Ozturk, Aslan, and Kalyoncu (2010); Streimikiene and Kasperowicz (2016) among others. These articles can be consulted for further details on the application of the panel FMOLS and DOLS models.

Results and Discussion

This study was conducted using a total of six variables (cereal crop production, annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested), in five East African countries (Ethiopia, Kenya, Rwanda, Tanzania, and Uganda) from 1980 to 2018. Table 3 presents a summary of the statistics of the variables used in their original and logarithmic transformations. According to the original values of the variables, the mean cereal crop production was 4.61 million tons, the mean temperature was 22.64°C, the mean precipitation was 978.82mm, the mean carbon footprint was 2.82 million gha, the mean ecological footprint was 39.04 million gha, while the mean area of cereal crops harvested was 3.01 million ha. The maximum cereal crop production was 28.76 million tons recorded in Ethiopia, while the minimum was 0.13 million tons recorded in Rwanda. The maximum temperature was 25.56°C recorded in Kenya, while the minimum was 18.52°C recorded in Rwanda. The maximum precipitation was 1439.14 mm recorded in Uganda, while the minimum precipitation was 498.41 mm recorded in Kenya. The maximum carbon footprint was 12.92 million gha recorded in Kenya, while the minimum was 0.16 million gha recorded in Rwanda. The maximum ecological footprint was 111 million gha recorded in Ethiopia, while the minimum was 4.38 million gha recorded in Rwanda. The maximum area of cereal crops harvested was 11.33 million ha recorded in Ethiopia, while the minimum was 0.12 million ha recorded in Rwanda.

It can be noted that Kenya has the highest CO_2 emissions, the highest temperatures, and the lowest precipitation in the region during the sample period. Rwanda has the lowest CO_2 emissions and the lowest temperatures in the region during the sample period, while Uganda receives the highest amount of precipitation. Ethiopia has the highest cereal crop production, which could be attributed to the fact that Ethiopia also has the largest area of cereal crops harvested, while Rwanda has the lowest production and lowest area of cereal crops harvested. From the logarithmic series, it can be noted that the standard deviations of all variables are smaller than their mean values, which suggests that the values of the variable are clustered around the mean (Ntiamoah *et al.*, 2022). The skewness values of all variables are negative which indicates that their distributions have fat left tails (Kuhe, 2019). The kurtosis values of all variables are less than 3 suggesting that the series are platykurtic i.e., their tails are lighter than the normal distribution (Kallner, 2018). The implication of non-normality of the series is further supported by the Jarque-Bera test statistic, which points out that the null hypothesis of normal distribution for all variables is rejected ($p<0.05$).

Table 3: Summary statistics

Original Series						
	CP	AMT	AMP	CF	EF	AH
Mean	4614097.00	22.64	978.82	2823066.00	39041537.00	3010923.00
Median	3270391.00	23.00	956.10	1548388.00	36181902.00	1903025.00
Maximum	28763752.00	25.56	1439.14	12919112.00	111000000.00	11327016.00
Minimum	130073.00	18.52	498.41	161670.90	4382723.00	124965.00
Std. Dev.	5251824.00	1.96	225.18	2836715.00	23890969.00	2824867.00
Skewness	2.5912	-0.8538	0.0149	1.4513	0.6380	1.3221
Kurtosis	10.5549	2.7065	2.0510	4.6458	3.5063	3.9900
Jarque-Bera	681.9556	24.3929	7.3249	90.4583	15.3097	64.7743
Probability	0.0000	0.0000	0.0257	0.0000	0.0005	0.0000
Observations	195	195	195	195	195	195
Logarithmic Series						
	LnCP	LnAMT	LnAMP	LnCF	LnEF	LnAH
Mean	14.7605	3.1158	6.8585	14.2964	17.2080	14.4021
Median	15.0004	3.1355	6.8629	14.2527	17.4041	14.4590
Maximum	17.1746	3.2410	7.2718	16.3742	18.5292	16.2427
Minimum	11.7759	2.9189	6.2114	11.9933	15.2932	11.7358
Std. Dev.	1.2131	0.0903	0.2408	1.1465	0.8533	1.1384
Skewness	-0.5802	-0.9755	-0.3978	-0.2260	-0.9669	-0.4900
Kurtosis	2.8305	2.8004	2.4175	2.0876	2.8208	2.4251
Jarque-Bera	11.1741	31.2535	7.8997	8.4233	30.6424	10.4874
Probability	0.0037	0.0000	0.0193	0.0148	0.0000	0.0053
Observations	195	195	195	195	195	195

Stationarity tests

Panel unit root tests i.e., LLC, IPS, ADF-Fisher, and PP- Fisher tests were used to identify the order of integration of each variable used in the study and their results are presented in Table 4. Results of all tests revealed that the null hypothesis that the series contains a unit root at level is rejected at the 95% confidence interval for cereal crop production, annual mean temperature, annual mean precipitation, and area harvested. This implies that these variables are integrated of order 0 [I(0)].

The tests give differing results for carbon footprint. Results of the LLC test reveal that the null hypothesis of the presence of a unit root in the carbon footprint series is rejected at the 95% confidence interval implying that the series is I(0). However, all other tests reveal that the null hypothesis cannot be rejected implying that the series is not I(0). Upon taking the first difference, results revealed rejection of the null hypothesis at the 99% confidence interval, which implies that the series are I(1). Unlike carbon footprint which had differing results, the results of all tests reveal that the null hypothesis of the presence of a unit root in the ecological footprint series at levels cannot be rejected. This implies that the series is not stationary at levels. However, after applying the first difference, the tests revealed a rejection of the null hypothesis at the 99% confidence interval, implying that the series is I(1).

Table 4: Stationarity test results

Variable Statistic (Prob)	**Levin, Lin & Chu**	**Im, Pesaran and Shin W-stat**	**ADF - Fisher Chi-square**	**PP - Fisher Chi-square**
LnCP	-3.1001 (0.0010)	-3.0945 (0.0010)	31.7969 (0.0004)	43.6719 (0.0000)
LnAMT	-6.8553 (0.0000)	-6.4065 (0.0000)	56.7269 (0.0000)	51.3128 (0.0000)
LnAMP	-10.6363 (0.0000)	-10.8551 (0.0000)	107.224 (0.0000)	110.148 (0.0000)
LnCF	-2.1559 (0.0155)	-0.5423 (0.2938)	10.3871 (0.4072)	11.0792 (0.3514)
ΔLnCF	-10.2571 (0.0000)	-10.2999 (0.0000)	101.835 (0.0000)	114.958 (0.0000)
LnEF	-0.4178 (0.3381)	1.0875 (0.8616)	5.2099 (0.8767)	5.2962 (0.8705)
ΔLnEF	-13.1716 (0.0000)	-12.5716 (0.0000)	128.745 (0.0000)	145.204 (0.0000)
LnAH	-3.1619 (0.0008)	-2.5625 (0.0052)	24.0992 (0.0073)	20.5400 (0.0245)

Panel co-integration tests

Panel co-integration tests were performed using the Pedroni residual, Kao residual, and Johansen Fisher panel co-integration tests, and the results are presented in Table 5. Under the Pedroni tests, six statistics significantly reject the null hypothesis of no co-integration among the variables at the 5% level of significance. Only the panel v-statistic accepts the null hypothesis of no co-integration. However, since the majority of the test statistics reject the null hypothesis of no co-integration at the 5% significance level, it can be concluded that the series are co-integrated. The existence of co-integration among the variables is further supported by the Kao residual, and Johansen Fisher panel co-integration tests, whose results reject the null hypothesis of no co-integration at the 5% significance level. These results confirm the existence of co-integration relationships between cereal crop production, annual mean temperature, annual mean precipitation, carbon footprint, ecological footprint, and area harvested. Therefore, it can be stated that there is a long-run relationship between these variables for the selected sample.

Table 5: Panel co-integration analysis

Pedroni residual co-integration test				
Common AR coefs. (within-dimension)				
		Statistic		Prob.
Panel v-Statistic		0.7523		0.2259
Panel rho-Statistic		-2.0077		0.0223
Panel PP-Statistic		-4.8498		0.0000
Panel ADF-Statistic		-4.6897		0.0000
Individual AR coefs. (between-dimension)				
		Statistic		Prob.
Group rho-Statistic		-2.0755		0.0190
Group PP-Statistic		-6.8710		0.0000
Group ADF-Statistic		-6.7287		0.0000
Kao Residual Cointegration Test				
		t-Statistic		Prob.
ADF		-2.1533		0.0156
Residual variance		0.0212		
HAC variance		0.0092		
Johansen Fisher Panel Cointegration Test				
Hypothesized No. of CE(s)	Fisher Stat. (from trace test)	Prob.	Fisher Stat. (from max-eigen test)	Prob.
None	85.41	0.0000	46.74	0.0000
At most 1	51.09	0.0000	29.28	0.0011
At most 2	29.70	0.0010	17.12	0.0717
At most 3	19.13	0.0386	14.84	0.1381
At most 4	11.41	0.3263	12.77	0.2368
At most 5	4.267	0.9345	4.267	0.9345

PMG/ARDL model

After confirming the existence of co-integration among the variables, the long and short-run coefficients are estimated using the PMG/ARDL (1, 1, 1, 1, 1, 1) model, and the results are presented in Table 6. This model was selected based on the AIC with 1 as the optimal lag length. The ECT is negative and statistically significant at the 95% confidence interval. This provides additional evidence of the presence of a long-run relationship among the variables in the model. This coefficient further signifies the speed of adjustment toward the long-run equilibrium (Rahman & Kashem, 2017).

Examining the estimated long-run coefficients reveals that annual mean temperature is negatively related to cereal crop production. However, its coefficient is not statistically significant. On the other hand, annual mean precipitation positively and significantly affects the production of cereal crops in East Africa at the 1% level of significance. The estimated coefficient suggests that the production of cereal crops increased by about 0.7966%, with a 1% rise in precipitation. This is expected because an increase in precipitation lengthens the grain filling period and reduces water loss through transpiration (Özdoğan, 2011), thereby increasing yields of cereals. This result is in line with findings from Kabubo-Mariara and Karanja (2007), Ben Zaied and Ben Cheikh (2015), Chandio *et al.*, (2020), and Gul *et al.*, (2022) who reported a positive relationship between precipitation and cereal crop production in Kenya, Tunisia, Turkey, and Pakistan, respectively. According to the available literature, a positive relationship has also been reported between precipitation and the production of cereals such as maize (Ntiamoah *et al.*, 2022; Ochieng *et al.*, 2016), rice (Sohail Abbas *et al.*, 2022; Gbenga *et al.*, 2021), and wheat (Chandio, Gokmenoglu, *et al.*, 2021; Doğan & Kan, 2019).

Carbon footprint positively and significantly affects the production of cereals in East Africa at the 1% level of significance. The estimated coefficient suggests that the production of cereal crops increased by about 0.1595%, with a 1% increase in carbon footprint. This could be attributed to both carbon dioxide's role in photosynthesis and its regulatory role that increases the water use efficiency by plants (Kumar *et al*., 2021; Özdoğan, 2011). This finding corroborates well with Ahsan *et al*., (2020)'s findings where the authors reported a positive relationship between CO_2 emissions and the production of cereals in Pakistan. A positive relationship has also been reported between CO_2 emissions and cereals such as maize (Ntiamoah *et al*., 2022) and rice (Kumar *et al*., 2021).

Ecological footprint also positively and significantly affects the production of cereals in East Africa at the 1% level of significance. The estimated coefficient suggests that the production of cereal crops increased by about 0.7075%, with a 1% increase in ecological footprint. This is supported by the fact that utilization of natural resources such as land, cropland, and water facilities in a sustainable manner reduces the adverse effects of temperature increases, drought, floods, and emission of greenhouse gases thus creating space for ecological balance, which eventually lead to positive impacts on the production of crops (Kumar *et al*., 2021). In the literature, there are only two studies that included ecological footprint as a proxy for climate change i.e., Kumar *et al*., (2021) and Emenekwe *et al*., (2022), and similar to this study's findings, they all reported a positive effect of ecological footprint on rice production.

The non-climatic factor area harvested had a positive and statistically significant effect on the production of cereal crops at the 99% confidence level. Its coefficient reveals that the production of cereal crops increased by about 0.2796%, with a 1% increase in the area harvested. This finding corroborates with Ahsan *et al*., (2020) and Kumar *et al*., (2021)'s studies, where the authors reported a positive effect of area harvested on the production of cereal crops in Pakistan and India, respectively.

Examining the short-run coefficients reveals that annual mean temperature and carbon footprint positively affect the production of cereal crops in the short run, however, their coefficients are not statistically significant. Annual mean precipitation negatively and significantly affects the production of cereal crops in the short run at the 10% level of significance. Its coefficient suggests that the production of cereal crops decreased by about 0.1806% with a 1% increase in annual mean precipitation. Ecological footprint positively and significantly influences the production of cereal crops at a 10% level of significance. Its coefficient reveals that the production of cereal crops increased by about 0.4987%, with a 1% increase in ecological footprint. Similarly, the area harvested positively and significantly influences the production of cereal crops in the short run at the 1% level of significance. Its coefficient implies that a 1% increase in the area harvested leads to a 0.3667% increase in the production of cereal crops in the short run.

Table 6: PMG/ARDL long-run and short-run results PMG-ARDL (1, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run Equation				
LnAMT	-0.7851	1.3396	-0.5861	0.5587
LnAMP	0.7966	0.2180	3.6539	0.0004
LnCF	0.1595	0.0503	3.1749	0.0018
LnEF	0.7075	0.1571	4.5029	0.0000
LnAH	0.2796	0.0925	3.0226	0.0029
Short Run Equation				
ECT(-1)	-0.4870	0.2109	-2.3095	0.0222
D(LnAMT)	0.0823	0.9216	0.0894	0.9289
D(LnAMP)	-0.1806	0.0926	-1.9496	0.0530
D(LnCF)	0.0377	0.0962	0.3916	0.6959
D(LnEF)	0.4987	0.2887	1.7273	0.0861
D(LnAH)	0.3667	0.1381	2.6566	0.0087
C	-3.2962	1.4144	-2.3305	0.0211

Robustness tests

Finally, the panel FMOLS and DOLS models were employed to test for the robustness of the estimated panel ARDL model, and the results are presented in Table 7. These models were performed with pooled weighted estimation method. The panel DOLS coefficients were estimated using one lag and zero lead in the change of the regressors. The panel FMOLS and DOLS estimators produce similar results with the panel ARDL in terms of the signs of coefficients i.e., annual mean temperature negatively influenced the production of cereal crops, while annual mean precipitation, carbon footprint, ecological footprint, and the area harvested contribute positively to the production of cereals in East Africa. However, the results are different in terms of statistical significance and the magnitudes of the estimated coefficients.

All coefficients are highly significant in the FMOLS model, at a 99% confidence interval. Unlike in the panel ARDL and panel DOLS models, the results of the panel FMOLS revealed a negative and statistically significant relationship between annual mean temperature and the production of cereals, moreover at the 99% confidence interval. The coefficient suggests that the production of cereal crops decreased by about 1.5145%, with a 1% increase in annual mean temperature. This result is similar to findings by Ben Zaied and Ben Cheikh (2015), Chandio *et al.*, (2020), and Gul *et al*., (2022) where the authors reported a negative and statistically significant relationship between temperature and the production of cereal crops in Tunisia, Pakistan, and Turkey, respectively. Meanwhile, the other coefficients suggest that the production of cereal crops increased by about 0.3198%, 0.1841%, 0.4053%, and 0.6810% with a 1% increase in annual mean precipitation, carbon footprint, ecological footprint, and area harvested, respectively.

Results of the panel DOLS model revealed a negative but statistically insignificant relationship between annual mean temperature and the production of cereal crops similar to the panel ARDL model results. Annual mean precipitation and ecological footprint are positive and statistically significant at the 90% confidence interval. While carbon footprint and area harvested are positive and statistically significant at the 99% confidence interval. The coefficients suggest that the production of cereal crops increased by about 0.6062%, 0.1683%, 0.4945%, and 0.5416% with a 1% increase in annual mean precipitation, carbon footprint, ecological footprint, and area harvested, respectively.

Table 7: Robustness tests

Panel FMOLS				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LnAMT	-1.5145	0.0781	-19.3810	0.0000
LnAMP	0.3198	0.1007	3.1756	0.0018
LnCF	0.1841	0.0236	7.7973	0.0000
LnEF	0.4053	0.0353	11.4681	0.0000
LnAH	0.6810	0.0435	15.6705	0.0000
R-squared	0.9828			
Adjusted R-squared	0.9820			
Panel DOLS				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LnAMT	-0.5016	1.6392	-0.3060	0.7601
LnAMP	0.6062	0.3404	1.7808	0.0772
LnCF	0.1683	0.0601	2.7978	0.0059
LnEF	0.4945	0.2560	1.9314	0.0555
LnAH	0.5416	0.1496	3.6214	0.0004
R-squared	0.9863			
Adjusted R-squared	0.9803			

CONCLUSION

The production of cereal crops plays a significant role in the economies and livelihoods of the East African population. However, the high level of reliance on rain-fed agriculture makes the agricultural sector highly vulnerable to changes in climatic factors. To develop effective adaptation strategies to minimize the impact of changes in climatic factors on agricultural production, policymakers need to understand the impacts of these changes on individual crops and individual countries or agro ecological regions. In this paper, the panel ARDL, panel FMOLS, and panel DOLS models are employed to investigate the nexus between the production of cereal crops and changes in climatic factors such as temperature, precipitation, carbon footprint, ecological footprint, and a non-climatic factor, area harvested in East Africa based on annual time series from 1980 to 2018.

Empirical findings from the three models revealed that annual mean temperature negatively influenced cereal crop production, while annual mean precipitation, carbon footprint, ecological footprint, and area harvested contribute positively to the production of cereal crops in East Africa. However, while all other variables were statistically significant in the three models, statistical significance of annual mean temperature was only revealed in the panel FMOLS model with a 1% increase in annual mean temperature leading to a 1.5145% reduction in the production of cereal crops. Long-run estimates of the panel ARDL model revealed that the production of cereal crops increased by 0.7966%, 0.1595%, 0.7075%, and 0.2796% with a 1% increase in annual mean precipitation, carbon footprint, ecological footprint, and area harvested, respectively. The panel FMOLS estimates revealed that the production of cereal crops increased by 0.3198%, 0.1841%, 0.4053%, and 0.6810% with a 1% increase in annual mean precipitation, carbon footprint, ecological footprint, and the area harvested, respectively. Finally, the panel DOLS model estimates revealed that the production of cereal crops increased by 0.6062%, 0.1683%, 0.4945%, and 0.5416% with a 1% increase in annual mean precipitation, carbon footprint, ecological footprint, and the area harvested, respectively. These findings suggest prioritization of climate change adaptation strategies in the region such as the development of drought and heat-resistant crop varieties, changing in planting dates, and investment in irrigation technologies to boost cereal crops productivity.

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