Impact of Climate Change on Agricultural Productivity in the East African Community

Dahir Mohamed Ali[1](✉) and Giuseppe Borruso[2]

[1] Faculty of Economics, Accounting, Statistics and Management Science, Somali National University, Gaheyr Afgoye Street, Mogadishu, Somalia
dahireco@snu.edu.so

[2] DEAMS - Department of Economics, Business, Mathematics and Statistics "Bruno de Finetti", University of Trieste, Via A. Valerio 4/1, 34127 Trieste, Italy
giuseppe.borruso@deams.units.it

Abstract. This study explores the influence of climate change on agricultural productivity in the East African Community (EAC), a region heavily dependent on agriculture for food security and economic stability. The study employs a mixed-methods strategy to analyse the impact of crucial climate factors such as carbon dioxide (CO2) levels, rainfall, higher temperature, and sun radiation on cereal yields across EAC member states over the last three decades. Applying dynamic panel data techniques, this study Implemented first-order differencing to remove unobserved effects and employ the Generalized Method of Moments (GMM) estimation for robust analysis. Based on 192 observations from six countries, the fixed-effects model reveals that CO2 concentration positively affects cereal yields, with a rise of nearly 2000.87 units per unit increase in CO2 ($p = 0.002$). Conversely, maximum temperature and solar radiation negatively affect production, declining it by 37.42 and 467.72 units, respectively ($p = 0.062$ and $p = 0.007$). This research discovers compelling evidence of homoskedasticity ($Chi2(6) = 1755.38$, $p < 0.001$) and no serial correlation ($F(1, 5) = 6.570$, $p = 0.0504$). To address potential endogeneity, the study implemented GMM estimation using lagged response Variables as instruments. The Arellano-Bond test shows no significant second-order autocorrelation ($z = -0.87$, $p = 0.384$), validating my approach. The two-step GMM results expose that all variables are essential, highlighting the complex interactions between climate variables and agricultural productivity.

Keywords: Climate change · agricultural productivity · cereal yields · dynamic Panel Data · Generalized Method of Moments · East African Community

1 Introduction

Climate change is one of the world's leading challenges, and its impact on global agricultural productivity cannot be ignored, particularly in vulnerable states such as East Africa. The East African Community (EAC) consists of six countries: Kenya, Uganda,

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2026
O. Gervasi et al. (Eds.): ICCSA 2025 Workshops, LNCS 15890, pp. 371–386, 2026.
https://doi.org/10.1007/978-3-031-97606-3_25

Tanzania, Rwanda, Burundi, and Somalia. The EAC mainly relies on agriculture for economic stability and food security. The region's economy is strongly linked to agriculture, which constitutes a substantial part of the Gross domestic product and offers careers for numerous populations, operating as the social core of economic growth. The EAC climate change master plan offers a framework for partner nations to enforce climate change and migration industries through the East African Community Protocol on Environment and Global Accords [1]. A significant relationship links agricultural productivity in the East African Community (EAC) and the region's agro-environmental landscapes, with temperature crucial in influencing crop growth or failure. In lowland regions with high temperatures and inconsistent rainfall, heat-tolerant crops like maize, sorghum, and cassava dominate [2]. As climate conditions shift, characterised by higher temperatures, changing precipitation, and the escalation in frequency and severity of extreme weather events, the implications for agricultural output in the EAC worsen progressively. [3] approved a 2.3 billion program to improve food security in Eastern and Southern Africa. The agricultural sector is the backbone of the EAC economy, significantly enhancing job opportunities and overall economic development [4].

However, it is increasingly becoming more fragile due to the effects of climate change, which is altering essential environmental elements like temperature, rainfall patterns, and the regulars of extreme weather events [5]; these shifts present influential obstacles to agriculture output, particularly for staple produce such as maize, wheat, and beans, which are positively exposed on climatic interpretations. Although some research has explored the global implications of climate change agriculture [6], little emphasis has been placed on the region-specific threats to the agriculture of the East African Community.

2 Literature review

The East African community's agriculture industry is grappling with many difficulties. Climate change remains a global issue in the current century. This literature review explores the established framework and observed data considering the impact of climate change on agriculture output. The Arllano-Bond method, developed by [7], has effectively examined mixed variable data agronomic investigation. This model has been considerably applied to explore the impacts of climate adaption on farming productivity as it considers both temporal dynamics and unnoticed heterogeneity [8]. Similarly, [9] and [10] employed this method to examine the impact of climate finance and climate change on food security and economic results, respectively. [11] explore Somalia's farming landscape, observing that while precipitation can boost long-term crop yields, it adversely impacts short-term production due to increasing temperatures.. [12] examine how variations in temperature and rainfall affect crop yield, revealing the underlying mechanisms.

They advocate for funding irrigation systems and developing heat-tolerant crops as essential adaptation measures. Additionally, [13] emphasizes the critical role of the EAC in enhancing food security by sharing agricultural knowledge and Technology, particularly in rice farming. The agricultural and agri-food sector is the primary employer in East Africa and is a significant revenue source. [14] fills this void by investigating

how fluctuations in temperature and rainfall affect agricultural production in East Africa by considering both intermediate and extended effects as well as regional disparities.

2.1 Empirical Evidence

Recent innovations in panel dynamic modelling, including advancement in GMM estimation techniques and integration of higher-precision climate change, improved its utilization in agricultural studies. For instance, [16] indicates that combining remote sensing data with the Arllano-Bond model provides a comprehensive study of how to achieve healthy crops and vegetation adapt to climate Variation. He emphasized the importance of innovative methods to enhance agricultural productivity and sustained capacity in East Africa. Likewise, [17] examined the impact of technological innovation and improved crop Varieties that contribute to overcoming obstacles like low productivity and regional climate shift. In addition, according to [18], the role of climate-smart agricultural extension services in Uganda is to assist farmers with adapting climate variability and improving sustainability.

Recent study by [19], has observed substantial changes in temperature and precipitation patterns in the East African Community. Data from the [20] revealed a marked Rise in temperature irregularity and seasonal precipitation changes, impacting crop production seasons and water availability. For example, [21] found inconsistent temperatures and variable precipitation during the maize growing season led to substantial yield decreases. Similarly, a study by [22] discovered that factors influencing rainfall patterns lead to decreased productivity and a higher rate of harvest loss in small-scale farming systems. [23] Personal Communication with the agricultural development officer, Uganda. The DAO contributed to food shortages due to insufficient early rains, delayed heavy rains, Locust swarms, and Escalating prices due to Sudanese refugees. [24] Uganda's diverse agroecological zones have contributed to the development of various farming technologies. [25] Their study focused on two nations in Eastern Kenya. [26] Tanzania has seven agroecological areas, with arid and semi-arid zones more at risk from climate change. In spite of these challenges,

[27] defines climate change as long-term temperature and rainfall changes. It is particularly alarming for East Africa, where [28] predicted that at the global warning level of 4.6 °C, many East African cities are expected to show an increase to 2000-fold increase in exposure to extreme heat (days $>$ 40.6 °C) in contrast to covering the time from 1985 to 2005, including Blantyre-Limbe, Lusaka, and Kampala. [29] implemented advanced forecasting methods for wheat yields in the context of climate change, which projected a 27 per cent decrease in yield in North-West Victoria and a 14 per cent drop across Victoria by 2036–2065 in line with the IPCC's "Hotter & Drier" scenario. In contrast, findings from [30] highlight the importance of climate-resilient farming practices, such as incorporating drought-resistant crop varieties and enhancing irrigation methods. Complementing this, [31] investigated food security issues in East Africa, forecasting decreased crop yields in Sudan and potential increases in the Oromia region of Ethiopia due to climate change.

3 Descriptive Analysis

3.1 Country- Level Trends in Agricultural land use (% of Land Area) of EAC

Agricultural land use and productivity in the East African Community (EAC) have experienced significant changes over the years due to the interplay between socio-economic factors and climate change. According to [32] the Average temperature was 0.61 °C higher than the 1991–2020 mean and 1.28 °C higher than the 1961–1990 average. The African continent cautioned at the rate of + 0.3 °C/decade between 1991 and 2023, a slightly faster rate than the worldwide average.

The bar chart below compares longitude, latitude, and the maximum temperature together with latitude and longitude for the EAC nations; Somalia exhibits the highest maximum temperature due to its closeness to the equator, while other countries, like Rwanda and Burundi, have comparatively maximum temperatures, and both Kenya and Tanzania show moderate highest temperatures. South Sudan faced high temperatures, like Somalia, primarily due to its low elevations and conditions (Fig. 1).

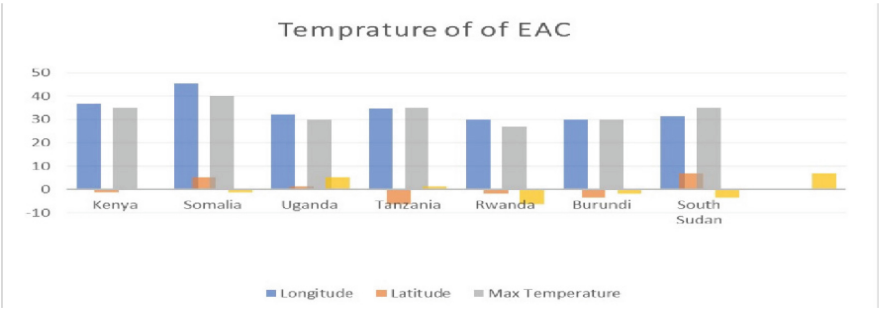

Fig. 1. Higher Temperature effect on Agricultural productivity

Figure 2 illustrates that the East African Community (EAC) comprises six member states: Burundi, Kenya, Rwanda, South Sudan, Tanzania, and Uganda. Situated across the tropical and subtropical zones, this varied terrain renders the region especially susceptible to the consequences of climate change, such as increasing temperature, irregular precipitation patterns and extreme weather occurrences.

Figure 2 demonstrates the agricultural land patterns in the East African Community nations from the past three decades (1990 to 2020), emphasizing the different socio-economic, political, and environmental pathways. In Kenya, agricultural land varied between 1990 and 2000, with phases of decline and recovery, likely because of changing policies or external pressures. From 2000 onwards, there was consistent growth, peaking between 2005 and 2010 and reaching stability with gradual expansion until 2020, stimulated by economic progress, population growth and land planning policies. Somalia displayed a gradual increase in agricultural land until 205, followed by a steep rise and decline between 2005 and 2010 due to political upheaval and conflict; after 2010, the trend stabilized, with slight upward growth by 2020, indicating recovery actions and progress in governance. Burundi saw a substantial decrease from around 80 in 1990



Fig. 2. Map location in EAC

to under 70 by 2005, probably because of land degradation, reforestation projects, and socio-economic issues (Fig. 3).

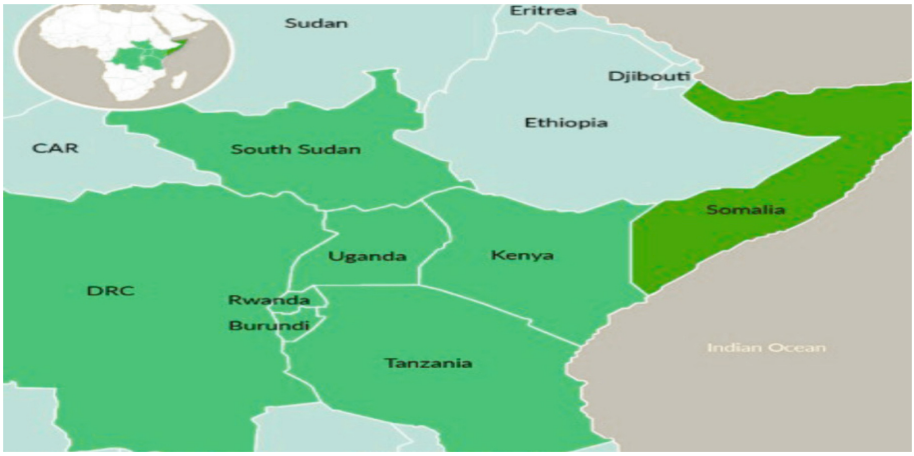

Fig. 3. Map of eight Countries currently part of the EAC regional Bloc

The East African Community countries consist of eight states: Burundi, DRC, Kenya, Rwanda, South Sudan, Tanzania, and Somalia. They have considerable areas of farmland, though their utilization varies greatly. States like Burundi and Rwanda have a higher percentage of agricultural land (more than 80%) and regular utilization of most of it due to dense populations and high-input farming. On the other hand, Somalia, South Sudan, and DRC have extensive regions classified as agricultural, but much remains underused because of political instability, inadequate infrastructure, and limited investment. Kenya, Uganda, and Tanzania fall in between, with significant agricultural areas ranging between 45% and 72% but only limited use. Uganda, for instance, Cultivates only roughly 21% of its arable land (Fig. 4).

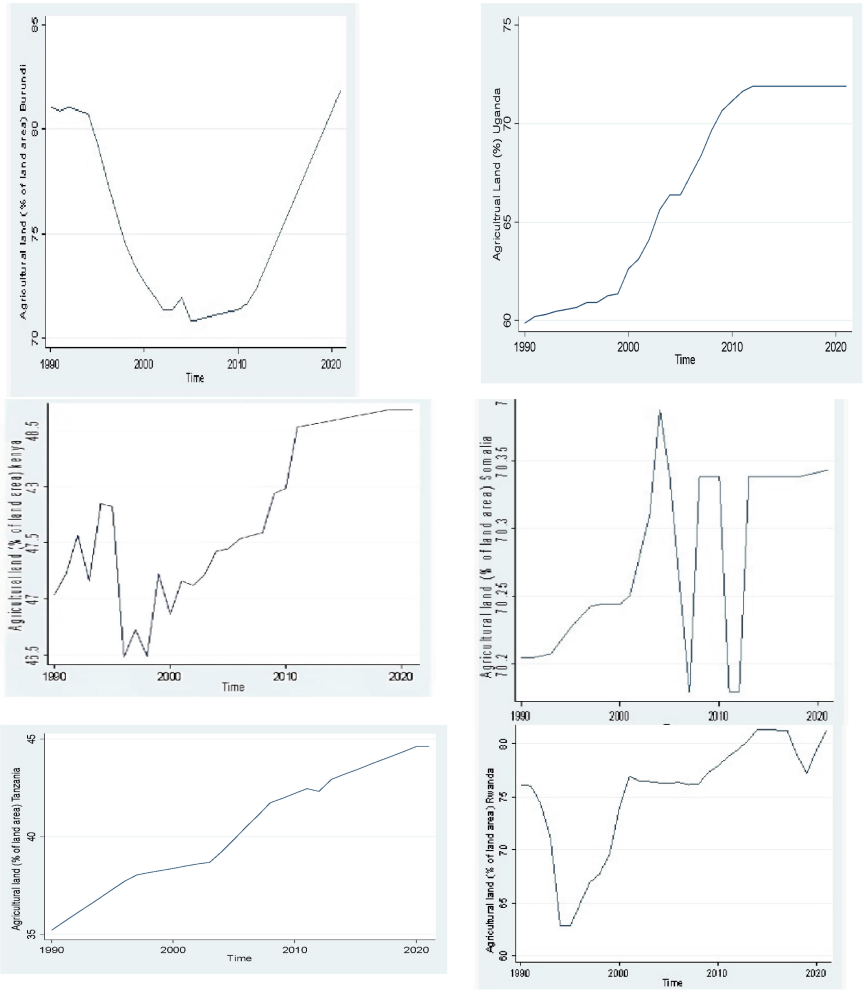

Fig. 4. Line chart showing Agricultural land trends for six EAC from 1990 to 2021

4 Materials and method

4.1 Data collection and Analysis

This study collected data from NASA and the World Bank from 1990 to 2020. Data gathered from NASA Power offered essential climate variables such as Maximum temperature, Precipitation, and Solar radiation, which are crucial for assessing the effect of weather conditions on agriculture. Agricultural output data, including Cereal yields and CO2, are sourced from the World Bank. In the description part of the study, the GIS tool drew a map and investigated spatial trends, while statistical analysis was carried out using STATA. [33] challenged traditional econometric frameworks for their inadequacies in policy assessments, stemming from insufficient addressing of fluid linkages

and causal interconnections. For the statistical analysis, this research is 1st differencing Generalized method of moments (GMM) estimator developed by [7]. On this, [34] criticized traditional econometric models for their insufficiencies in policy assessments arising from poor handling of dynamic relations and causal interactions.

Model Specification

Dynamic panel data Where: CY_{t-1} = cereal productivity of the state i at time t-1

The equation represents the linkage between cereal output (the dependent variable) and several independent variables, including rainfall, CO2 levels, solar radiation, and maximum temperature.

First Order Differencing to Eliminate Unobserved μ Effect

$$\begin{aligned}\Delta CY_{it} = CY_{it} - CY_{i(ti1)} \;=\; & \beta_1 \Delta CY_{i(t-1)} \\ & + \beta_2 \Delta Tmax_{it} + \beta_3 \Delta PSA_{it} \\ & + \beta_4 \Delta Solar\ Ra_{it} + \beta_5 \Delta CO2_{it} + \epsilon_{it}\end{aligned} \quad . \tag{2}$$

Specify Instruments. Employing $CY_{i(t-2)}$ and other lagged variables t-2 or previous as instruments for $\Delta CY_{i(t-1)}$. Utilizing $Tmax_{t(t-1)}$, $PSA_{i(t-1)}$, $SolarRadation_{i(t-1)}$, $CO2_{i(t-1)}$ as instrument for the consistent first differencing.

Moment Conditions

The condition can be expressed as:

$$\mathrm{E}\left[\Delta_{it} \backslash CY_{i(t-2)}, Tmax_{t(t-1)}, PSA_{i(t-1)}, SolarRa_{i(t-1)}, CO2_{i(t-1)}\right] = 0 \tag{3}$$

GMM Estimation

$$\begin{aligned}Q(\beta) = & \left(\frac{1}{T}\sum_{T=2}^{T} \Delta CY_{it} - \beta_1 \Delta CY_{i(t-1)} - \beta_2 \Delta Tmax_{it} - \beta_3 \Delta PSA_{it} - \beta_4 \Delta Solar\ Ra_{it} - \beta_5 \Delta CO2_{it}\right)' \\ & W \left(\frac{1}{T}\sum_{T=2}^{T} \Delta CY_{it} - \beta_1 \Delta CY_{i(t-1)} - \beta_2 \Delta Tmax_{it} - \beta_3 \Delta PSA_{it} - \beta_4 \Delta Solar\ Ra_{it} - \beta_5 \Delta CO2_{it}\right)\end{aligned} \quad . \tag{4}$$

5 Results

Result contained in Table 1 shows that based on 192 observations across six countries in east African community, the fixed-effects regression analysis reveals that CO2 concentration positively impacts cereal output, with a significant increase of approximately 2000.87 units per unit rise in CO2 ($p = 0.002$). Conversely, two-meter maximum temperature and solar radiation negatively affect output, decreasing it by about 37.42 and 467.72 units, respectively, with both effects being statistically significant ($p = 0.062$ and $p = 0.007$). Precipitation showed no significant impact ($p = 0.217$).

The results in Table 2 show that the random effect of the (GLS) regression analysis of 192 observations from six countries shows that climate factors and cereal productivity are linked meaningfully. Carbon dioxide concentration positivity affects cereal output, with a coefficient of 2473.7 ($P < 0.001$) pointing to higher CO2 levels increasing output. Precipitation also has a positive effect, with a coefficient of 0.37990 ($P < 0.001$),

Table 1. Fixed-effects(within) regression

	Number of obs =					192
Group country	Number of groups =					6
R-sq:	Obs per group:					
within =0.139	min =					32
between =0.10	avg =					32
overall = 0.115	max =					32
	F (4,182) =					7.35
Corr (u_i, Xb) = -0.0548	Prob > F =					0.0000
Cereal Y	Coef.	Std. Err.	t	P>t	[95%	interval
T Max	-37.4234	19.923	1.8 76.7	0.06	-	1.8868
PSA	-0.1004	0.081	1.2 .260	0.21	-	0.059
C02	2000.8	629.9	3.1 757.8		0.002	3243.9
Solar Radi	-467.72	171.0	2.7 805	0.007	-	-130.3
_cons	4989	1223.4	4.08	0.00	257	7403
Sigma_u	412.8424					
Sigma_e	313.36255					
Rho	0.6344628	(Fraction of variance due to u_i)				

Source: our elaborations from NASA Data and World bank Data

while a two-meter maximum temperature is linked to a rise of approximately 93.89 units ($P < 0.001$), indicating potential regional adaptations. Conversely, solar radiation negatively affects productivity (coefficient: -259.0, $P = 0.005$). The model shows that country-specific factors account for around 48.29% of the total variability, with a substantial between-group R-squared of 94.66%. The result underscores the intricate relationships between climatic variables and the productivity of agriculture in the East African Community (EAC).

The result contained in Table 3 shows that the fixed effect estimate for higher temperature (T Max) is -37.423, while the random effect estimate is 93.88, a difference of -131.31. The fixed effect coefficient for participation (PSA) is -0.10041, while the random effect coefficient is -0.48035. The fixed effect estimate for carbon dioxide is 2000.8, which is -472.88 different from the random effect estimate of 2473.7, and the fixed effect estimate for solar radiation is -467.72, which is different from the random effect estimate of -259.04 by 208.67. The Hausman test statistic is $\chi^2\ (4) = 97.08$ with a corresponding P-value of 0.0000. Shows that the subject-specific effects are correlated with the predictors, violating the random effects assumption. Thus, the fixed effects model offers more consistent and robust estimates for investigating the effect of the climate factors on cereal output in the East African Community members.

Table 2. Random-effects GLS regression

		Number of Obs =			192	
Group country		Number of groups =			6	
R-sq:		Obs per group:				
within = 0.0325		min =			32	
between = 0.946		avg =			32	
overall = 0.4829		max =			32	
		Wald chi2(4) =			174.62	
Corr (u_i, X) = 0 (assumed)		Prob > chi2 =			0.0000	
Cereal Y	**Coef.**	**Std. Err.**	**z**	**P>t**	**[95% Conf.**	**Interval**
TMax	93.888	16.630	5.65 61.29	0.000	126.482	
PSA	0.37993	0.0655	5.80 0.2515	7.4	0.000 0.000	0.50833
C02	2473.7	333.70	1819 2.79	0.005	-	3127.79
Solar Rad	-259.0	92.999	441.3 1.17	0.241	-	-76.766
_cons	-863.59	36.7	7 230.7			580.311
Sigma_u		0				
Sigma_e		313.36255				
Rho	0	(fraction of variance due to u_i)				

Source: our elaborations from NASA Data and World bank Data

Table 4 illustrates that the adjusted Wald test for groupwise heteroskedasticity in the fixed-effects regression model strongly rejects the null hypothesis (H0) that the error variances are the same across groups. A test statistic of X2 (6) = 559.98 and a p-value of 0.0000 indicates significant evidence of heteroskedasticity. Using robust standard errors may be necessary to address this issue in the model estimation.

The results in Table 5 indicate that the Wooldridge test for autocorrelation in panel data assesses the null hypothesis (H0), which posits the lack of first-order autocorrelation. The results indicate an F-statistic of F (1,5) = 10.142 with a p-value of 0.0244. Given that the p-value is below the statistically significant threshold of 0.05, we reject H0, signifying the existence of first-order autocorrelation in the panel dataset.

Table 3. Hausman Fix Random

Coefficients -	(b) Fix	(B) random	b-B) Difference	Sqrt (diag(V b-V_B)) S.E.
T Max	37.423	93.88	-131.31	10.971
PSA	- .10041	0.3799	-.48035	.0.04785
C02	2000.8	2473.7	-472.88	534.34
SolarRa	-467.72	-259.04	-208.6	143.50

b = consistent under Ho and Ha; obtained from xtreg
Test: Ho: difference in coefficients not systematic
Test: Ho: difference in coefficients not systematic
97.08

Prob>chi2 = 0.0000

(V_b-V_B is not positive definite)

Source; Authors Used STATA For this Analysis

Table 4. Hausman Fix Random

H0: sigma(i)^2 = sigma^2 for all	I
chi2 (6) =	559.98
Prob>chi2 =	0.0000

Source; Authors Used STATA For this Analysis

Table 5. Wooldridge' test for autocorrelation In Panel data

H0: no first-order autocorrelation
F (1, 5) = 10.142
Prob > F = 0.0244

Source: Authors Used STATA For this Analysis

The result in Table 6 shows that the higher temperature of the coefficient is 93.88 ($p < 0.001$), suggesting that for every 1 unit increase in high temperature, cereal output increases by approximately 93.88 units. The precipitation value of the coefficient is 0.3799 ($p < 0.001$), indicating that a 1-unit increase in rainfall is associated with an increase of about 0.38 units in cereal output. The coefficient for carbon dioxide is 2473.7 (p-value is less than 0.001), showing that for every additional unit of CO2, grain yield rises by around 2473.7 units. This shows a robust, helpful connection. The solar radiation coefficient is −259.0 ($p = 0.006$), reflecting that an increase in solar radiation relates to a decline of around 259 units in the production of cereals.

Table 6. Linear Regression Results

. reg CY TMax PSA C02 SolarRa,						
		Robust				
Linear regression			Number of obs =			192
			F(4, 187) =			58.98
			Prob > F =			0
			R-squared =			0.4829
			Root MSE =			375.42
Robust						
Cereal Y	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
T Max	93.88	14.71	6.38	0	64.85275	122.92
PSA	0.3799	.0757	5.01	0	0.230441	0.5294
C02	2473	266.2	9.29	0	1948.47	2999.0
SolarRa	-259.0	93.67	2.77	0.006	443.83	-74.25
_cons	-863.	672.0	-1.2	0.2	2189.2	462.09

Table 7 demonstrates that high temperature strongly correlates positively with Cereal productivity (0.7191, the P value is less than 0.0001), showing that cereal yield also tends to rise with increasing the maximum temperature. High temperature is positively associated with Cereal productivity and has a moderate correlation with PT (0.3940, P-Value less than 0.0001) and Carbon dioxide (0.3564, P-value is less than 0.0001), indicating that higher temperatures are related to increases in precipitation and Carbon dioxide levels. Rainfall positively correlated with Cereal yield (0.3623, $p < 0.0001$), implying increased precipitation is associated with higher cereal production. However, there is a slight inverse relationship with radiation (−0.1208, P- value equals 0.0952), demonstrating that solar Radiation may decrease as precipitation rises, although this association is not statistically significant. CO2 has a positive correlation with cereal output Y (0.3366, $p < 0.0001$) and T2mMax (0.3564, $p < 0.0001$), showing that higher CO2 levels are associated with increased cereal productivity.

Table 7. Correlation Matrix Summary

	e	Cereal Y	T2mMax	PPT	CO2	Solar Rada
Cereal Y	0.7191* 0.0000	1.0000				
T Max	−0.0000 1.0000	0.3940* 0.0000	1.0000			
PSA	−0.0000 1.0000	0.3623* 0.0000	−0.1208* 0.0952	1.0000		
CO2	0.0000 1.0000	0.3366* 0.0000	0.3564* 0.0000	−0.3517* 0.0000	1.0000	
Solar Rada	0.0000 1.0000	−0.2616* 0.0002	0.1660* 0.0214	−0.6804* 0.0214	0.3909* 0.0000	1.0000

Source: Authors Used STATA For this Analysis

Table 8 show that Coefficient of the error(e) and Lagged Cereal output (L. Cerealy) is 0.522 with a p-value of 0.0000, indicating a strong positive correlation between the error term and lagged cereal output.

Table 8. Coefficient of error and lagged

	e L.Cere ~ y
e	1.0000
L.Cereal Y	0.5221* 1.0000
	0.0000

Source: Authors Used STATA For this Analysis

Table 9 presents the results of dynamic panel-data analyses using a single-step difference Generalized Method of Moments (GMM) approach, focusing on the variable "Cerealy" across six countries with a total of 174 observations. The Wald chi-squared statistic is 31.34, with a p-value of 0.003, indicating that the model is statistically significant. This suggests that the regressors collectively have a significant impact. The coefficient for lagged "Cerealy (L1) is significant at 0.7628 (P value is less than 0.001), emphasizing strong persistence in the Variable. "T2mMax" has a significant negative effect on "Cereal" (−36.41, P value is less than 0.001), suggesting that rises in temperature correlate with decreases in "Cerealy." The other Variable integrates lagged terms for "T2mMax", PPT," CO2″, and "Solar radiation," which illustrates mixed significance and shows complex associations. Notably, the lagged impact of "Solar radiation" is essential and positive (L1: 297.69, P value = 0.042), while the second-order lag(L2) is significantly negative (−377.7, P value less than 0.001), indicating intricate dynamics over time. The Arellano-Bond tests demonstrate first-order autocorrelation (AR) (1) where Z

$= -2.25$, P value $= 0.024$) but no second-order autocorrelation AR (2), where $z = -0.97$, P value $= 0{,}188$), confirms the validity of the model's instruments.

Table 9. Dynamic panel-data estimation, one-step difference GMM

	Group Variable: country		**Number of obs _ =**		**174**	
	Time variable : year		Number of Groups =		6	
	Number of instruments =		Obs per group: min =		29	
163						
	Wald ch12 (13) = 31.34		avg =		29.00	
	Pro > chi2 = 0.003		max=		29	
Cerealy	**Coef.**	**Robust Std. Err.**	**Z**	**P>|z|**	**[95% Conf. interval**	
L1-	.762766	.16021	4.76	0.000	.4487594	1.07677
T max						
-- _	-36.409	8.6779	-4.20	0.000	-53-417	-1940
L1-	-29.16	16.731	-1.74	0.081	-61.961	3.623
L2-	13.823	9.57743	1.44	0.149	-4.9480	32.59
PSA						
-- _	-06292	-07011	-0.90	0.369	-2003591	0745
Ll.	-04979	0527	-0.94	0.345	-15309	0534
L2.	04189	071995	0.58	0.561	-.0992168	.1830
CO2						
-- _	69.705	2371.26	0.03	0.977	-4577-89	4717.
Ll.	-1689	4092.45	-0.41	0.680	-9710.714	6331.
L2.	2671.4	2324.22	1.15	0.250	-1883.965	7226.
SolarRa_						
	-250-2	156.280	-1.60	0.10	-556.527	56.08
	297.6886	146.246	2.04	0.04	11.0500	584.32
Ll.						
L2.	-3.77.793	86.55858	-4.36	0.00	-547.4454	-208.1

Instruments for first differencing equations standard
D. (TMax PSA CO2 SolarRa)
GMM-type (missing = 0, separation instruments for each period unless collapsed)
L (2/31) _ L. Cereal y
Arellano-Bond test for AR (1) in first differencing: z = -2.25 pr > z = 0.024
Arellano-Bond test for AR (2) in first differencing: z = -0.97 pr > z = 0.332
Sargan test of overid_ restrictions: chi2(150) = 165.13 Prob > chi2 = 0.188
(Not roubust, but not weakened by many instruments)
Hansen test of overid. restrictions: chi2(150) = 0.00 Prob > chi2 = 1.000
(Robust, but weakened by many instruments.)

6 Recommendations and Conclusions

The outcomes of this research emphasize the need for strategic policy recommendations to reduce the adverse consequences of climate change on agriculture in the East African community. Development of Climate-adaptive crop types: The East African Community nations should invest in developing and transferring climate-resilient crop types. These crops should be heat-resistant, drought-tolerant, and adaptive to fluctuating temperatures and sunlight conditions. Research and development in this part should be prioritized, and seed pots and distribution channels should be set to ensure farmers can access these enhanced sorts. Establishment of integrated water management systems: Promotion of Climate-Smart Agriculture: Policymakers should encourage adopting climate-smart agricultural practices, like agroforestry, protection tillage, and mulching. This research offers significant data regarding the effects of climate changes on the agricultural productivity of the EAC. The results underscore the importance of understanding the intricate interactions between climatic conditions and agricultural practices. While CO2 enhances yields in the short term, increasing temperatures and solar radiation pose significant threats to the region's food security.

Author Contributions. Dahir Mohamed Ali and Giuseppe Borruso contributed equally to the following aspects of the manuscript: Formulation, Verification, Supervision, and Writing—Original Draft preparation. Dahir Mohamed Ali was responsible for data collection, formal analysis, and research analysis using Stata software and visualization. Giuseppe Borruso handled mapping, Resources, and Review & editing which significantly enhanced the study's methodology framework. Further investigation is ongoing.

Conflict of Interest. Their authors declare no conflict of interest.

References

1. E. EAC, 'Climate Change Policy Framework'. Accessed 4 Feb 2025. https://www.eac.int/environment/climate-change/eac-climate-change-policy-framework
2. FAO, 'The State of Food and Agriculture 2020'. Accessed 6 Apr. 2025. https://www.fao.org/interactive/state-of-food-agriculture/2020/en/
3. W. World Bank, 'World Bank Approves $2.3 Billion Program to Address Escalating Food Insecurity in Eastern and Southern Africa', World Bank. Accessed 4 Fe. 2025. https://www.worldbank.org/en/news/press-release/2022/06/21/world-bank-approves-2-3-billion-program-to-address-escalating-food-insecurity-in-eastern-and-southern-africa
4. World Bank, 'Africa: Development news, research, data | World Bank'. Accessed 4 Feb 2025. https://www.worldbank.org/en/region/afr
5. NASA, 'Climate Change - NASA Science'. Accessed 04 Feb 2025. https://science.nasa.gov/climate-change/
6. Schmidhuber, J., Tubiello, F.N.: Global food security under climate change. Proc. Natl. Acad. Sci. U.S.A. **104**(50), 19703–19708 (2007). https://doi.org/10.1073/pnas.0701976104
7. Arellano, M., Bond, S.: Some tests of specification for panel data: monte carlo evidence and an application to employment equations. Rev. Econ. Stud. **58**(2), 277 (1991). https://doi.org/10.2307/2297968

8. Blundell, R., Bond, S.: Initial conditions and moment restrictions in dynamic panel data models (1997)
9. Doku, I., Phiri, A.: Climate finance and hunger among non-annex-1 parties: a lens on Sub-Saharan Africa. Int. J. Sustain. Econ. **14**(4), 380–398 (2022). https://doi.org/10.1504/IJSE.2022.125972
10. Geda, A., et al.: Unraveling the climate-macro conundrum: the macroeconomic impact of climate change in Eastern Africa, August 2023, Accessed 04 Feb 2025. https://hdl.handle.net/10568/135660
11. Warsame, A.A., Sheik-Ali, I.A., Ali, A.O., Sarkodie, S.A.: Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. Environ. Sci. Pollut. Res. Int. **28**(16), 19838–19850 (2021). https://doi.org/10.1007/s11356-020-11739-3
12. 'Climate Change Impacts in Agriculture', SciSpace - Paper. Accessed 04 Feb 2025. https://typeset.io/papers/climate-change-impacts-in-agriculture-5e82q77q4t
13. 'Towards planet and people-positive agriculture in East Africa | FAO'. Accessed 04 Feb 2025. https://www.fao.org/family-farming/detail/en/c/1639928/
14. Mubenga, T.: Full article: climate variability impacts on agricultural output in East Africa. Accessed 04 Feb 2025. https://www.tandfonline.com/doi/full/10.1080/23322039.2023.2181281
15. Smith, K.: The anti-competitive effects of common institutional ownership in health insurance markets, 09 Mar 2022, Social Science Research Network, Rochester, p. 4053176, NY. https://doi.org/10.2139/ssrn.4053176
16. Warinda, E., Nyariki, D.M., Wambua, S., Muasya, R.M., Hanjra, M.A.: Sustainable development in East Africa: impact evaluation of regional agricultural development projects in Burundi, Kenya, Rwanda, Tanzania, and Uganda. Nat. Res. Forum **44**(1), 3–39 (2020). https://doi.org/10.1111/1477-8947.12191
17. Turyasingura, B., Chavula, P.: Climate-smart agricultural extension service innovation approaches in Uganda: review paper. IJFSA **6**(1), 35–43 (2022). https://doi.org/10.26855/ijfsa.2022.03.006
18. Kogan, F.: Remote Sensing Land Surface Changes: The 1981–2020 Intensive Global Warming. Springer Nature (2023)
19. A. D. Bank, 'Annual Report 2021', African Development Bank Group. Accessed: 24 Aug 2024. https://www.afdb.org/en/documents/annual-report-2021
20. Yasin, M., et al.: Climate change impact uncertainty assessment and adaptations for sustainable maize production using multi-crop and climate models. Environ. Sci. Pollut. Res. **29**(13), 18967–18988 (2022). https://doi.org/10.1007/s11356-021-17050-z
21. Adesina, O.S., Loboguerrero, A.M.: Enhancing food security through climate-smart agriculture and sustainable policy in Nigeria. In: Leal Filho, W., Luetz, J., Ayal, D. (eds.), Handbook of Climate Change Management: Research, Leadership, Transformation, Springer, Cham, pp. 1–17 (2020). https://doi.org/10.1007/978-3-030-22759-3_338-1
22. TIM ALLEN, 'Social upheaval and the struggle for community: a study of the Ugandan Madi - ProQuest'. Accessed 06 Apr 2025. https://www.proquest.com/openview/00e76f2403c1d4353a3bd2aaf516a5d7/1?cbl=2026366&diss=y&pq-origsite=gscholar
23. Peter, E., et al.: Drivers of land use change and household determinants of sustainability in smallholder farming systems of Eastern Uganda | Population and Environment. Accessed 06 Apr 2025. https://doi.org/10.1007/s11111-010-0104-2
24. Mburu, S.W., Koskey, G., Kimiti, J.M., Ombori, O., Maingi, J.M., Njeru, E.M.: Agrobiodiversity conservation enhances food security in subsistence-based farming systems of Eastern Kenya. Agric. Food Secur. **5**(1), 19 (2016). https://doi.org/10.1186/s40066-016-0068-2
25. Mkonda, M.Y.: Agricultural sustainability and food security in Agroecological Zones of Tanzania. In: Lichtfouse, E. (ed.) Sustainable Agriculture Reviews, vol. 52, Springer, Cham, pp. 309–334 (2021). https://doi.org/10.1007/978-3-030-73245-5_9

26. Masson-Delmotte, V.P., et al.: IPCC, 2021: summary for policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Jan 2021, Accessed 04 Feb 04 2025. https://doi.org/10.1017/9781009157896.001
27. 'Projections of Human Exposure to Dangerous Heat in African Cities Under Multiple Socioeconomic and Climate Scenarios - Rohat - 2019 - Earth's Future - Wiley Online Library'. Accessed 04 Feb 2025. https://doi.org/10.1029/2018EF001020
28. Bailey, N., Hochman, Z., Mao, Y., Silvapulle, M., Silvapulle, P.: Impact of climate change on agriculture in Australia: an interactive fixed effects model approach. Appl. Econ. 1–14 (2024). https://doi.org/10.1080/00036846.2024.2387361
29. 'Can we avert the looming food crisis of climate change?', ScienceDaily. Accessed 04 Feb 2025. https://www.sciencedaily.com/releases/2024/11/241126134816.htm
30. Choi, Y.-W., Eltahir, E.A.B.: Near-term climate change impacts on food crops productivity in East Africa. Theoret. Appl. Climatol. **152**(1), 843–860 (2023). https://doi.org/10.1007/s00704-023-04408-1
31. World Meteorological Organization, State of the Climate in Africa 2023. Erscheinungsort nicht ermittelbar: United Nations (2024)
32. Sims, C.: Are forecasting models usable for policy analysis? Quart. Rev. **10**(Win), 2–16 (1986)
33. Sims, C.A.: Are forecasting models usable for policy analysis? Quart. Rev. **10**(Win), 2–16 (1986)