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Original article

Short-run and long-run effects of climate change on agricultural output in Eastern African countries

Tasfaye Fayisa[1]*, Bartłomiej Rokicki[2]

[1]University of Warsaw, Faculty of Economic Sciences, Doctoral School of Social Sciences, Dluga 44/50, 00-241, Warsaw, Poland
[2]University of Warsaw, Faculty of Economic Sciences, Dluga 44/50, 00-241, Warsaw, Poland
E–mail address (corresponding author): t.fayisa@student.uw.edu.pl
ORCID iD: Tasfaye Fayisa: https://orcid.org/0000-0002-5158-2739; Bartłomiej Rokicki: https://orcid.org/0000-0002-8392-0536

ABSTRACT

Global warming poses a significant socio-economic threat, with uneven effects across regions and sectors. This study examines whether climate variables have a long-run relationship with agricultural output, evaluates whether their impacts change over time, and whether their impacts vary by crop type in East Africa, using the fixed effects, the Dynamic Fixed Effects (DFE) and Pooled Mean Group (PMG) models. The study revealed that the included climate variables exhibit long-term effects on agricultural output. However, there are notable differences in the impacts of climate variables on agricultural production, influenced by temporal and methodological contexts. Aggregate analysis generally shows limited short-run significance, with temperature having negative and significant effects under the DFE model during 1980–2021. In contrast, the long-run findings reveal a positive effect of rainfall under both DFE and PMG models. A 1% increase in annual rainfall increases agricultural output by 0.76% and 0.27%, respectively, although this effect turns negative in the latter case over the more recent period. The effect of temperature is insignificant except under the FE model. Crop-specific results highlight rainfall as a generally positive factor, while temperature impacts vary, with the short run negatively affecting most crops with elastic effects. The long-term relationship between climate variables and agricultural output, together with the significant effect of irrigation, underscores the need for sustained investment in irrigation infrastructure and broader climate-smart agricultural practices that consider crop-specific responses. Overall, the study emphasizes the importance of climate-resilient agricultural investments and water management policies.

KEY WORDS: climate change; Eastern Africa; agriculture; fixed effects; Pooled Mean Group

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1. Introduction

Agriculture is the dominant sector of the economy in the majority of the least developed countries (e.g., MAJED & AHMAD, 2006; BARRIOR ET AL., 2008; FAO, 2021). It contributes to employment (e.g., UNCTAD, 2018), food security (e.g., FAO, 2021; IPCC, 2023), and foreign exchange earnings (e.g., KANZA ET AL., 2015). Almost all Africans rely on agriculture as a primary source of livelihood, with small-scale farmers responsible for the bulk of agricultural production (e.g., WARD ET AL., 2014). Over the last decade, Eastern Africa has experienced strong economic performance relying precisely on agriculture (e.g., EASTERN AFRICA ECONOMIC OUTLOOK, 2019). Nevertheless, the region remains a net importer of agricultural output (e.g., FAYISA, 2021) and is, therefore, highly sensitive to climate change (e.g., NIANG ET AL., 2014; NOSIPHO & MPANDELI, 2021).

There is a widespread scientific consensus that the global average temperature is likely to rise (e.g., AUFFHAMMER ET AL., 2018; IPCC, 2023). In particular, temperatures in Africa are projected to increase faster than the global average (e.g., IPCC, 2022). For instance, in Ethiopia's highlands, the temperature is expected to increase by 2–4 degrees Celsius (°C). In Kenya and Tanzania, temperatures are projected to increase by 2–3 °C by the end of the century (e.g., Verburg et al., 2010). A warmer world will experience more intense rainfall and more frequent droughts, floods, heatwaves, and other extreme weather events (IPCC, 2022). High temperatures will also increase vapo-transpiration rates, which are particularly high in Sub-Saharan Africa (SSA), partly because high temperatures increase the water-holding capacity of the air (e.g., Barrios et al., 2008).

Currently, precipitation in Eastern Africa exhibits considerable temporal and spatial variability, influenced by various physical processes (e.g., Hession & Moore, 2011; Bahaga et al., 2014; IPCC, 2021). Rainfall has decreased across the region over recent decades, particularly during land preparation and the summer season (e.g., Smith et al., 2014; Lyon & DeWitt, 2012). However, rainfall in Eastern Africa is projected to increase during a short growing season period (October to December) (e.g., Verburg et al., 2010; USAID, 2017). Ironically, this is a time when the majority of crops complete their maturation period and, therefore, require less rainfall during the harvesting season. High inter-seasonal rainfall variability may explain the low production of rain-fed agricultural systems, especially in marginal agricultural areas (e.g., James & Washington, 2013). Furthermore, a devastating problem is the recent decline in monsoonal precipitation across much of the Greater Horn of Africa, resulting from changing sea-level pressure (e.g., Williams et al., 2012).

All these trends reduce the extent of arable land suitable for staple food production (e.g., USAID, 2017). Consequently, climate change is expected to reduce cereal crop yields in Eastern Africa by shortening the growing season (e.g., Adhikari et al., 2015), amplifying water stress, and increasing the incidence of diseases, pests, and weed outbreaks (e.g., Niang et al., 2014). Changes in mean temperature and precipitation affect soil moisture, water availability, and the incidence and distribution of plant and animal pests (e.g., Seo & Mendelsohn, 2007; Schauberger et al., 2017). These changes directly influence crop growth and development (Barrios et al., 2008; Ozdemir, 2021), the quality and quantity of animal feed, and the physiological performance and growth of animals (e.g., Seo & Mendelsohn, 2007). As a result, climate change can be regarded as a negative technical change that affects agricultural production (e.g., Thornton et al., 2009).

Still, even though the overall impact of climate change on agriculture in general is expected to be negative, it is likely to be heterogeneous across particular regions (e.g., Auffhammer et al., 2013; Ceballos-Sierra & Dall'Erba, 2021; IPCC, 2021) and for specific crops (e.g., Adhikari et al., 2015; Ochieng, 2016; IPCC, 2022a). While temperate-producing regions may benefit from higher temperatures, most tropical regions are expected to suffer severe production losses (e.g., FAO, 2021a). Moreover, the effect of increasing temperature depends on the types of crops and agro-ecological zones (e.g., Thornton et al., 2009). For example, in Tanzania, the impacts on maize, the main food crop, are strongly negative, while the impacts on coffee and cotton, important cash crops, are positive (e.g., Craparo et al., 2015). In tea-producing regions, a small temperature increase and the resulting changes in precipitation, soil moisture, and water irrigation could render large areas of land that currently support tea cultivation useless (e.g., USAID, 2017). Climate change is also likely to have an impact on livestock farming. Here, higher temperatures may be advantageous for small farms that keep goats and sheep, as they are heat-tolerant. However, they are likely to be disastrous for large farms that are more dependent on species such as cattle, which are not heat-tolerant (e.g., Seo & Mendelsohn, 2007).

Existing empirical studies demonstrate that the yields of major crops in Eastern Africa have already been negatively affected by average temperature increase and changes in precipitation regimes (e.g., Nhemachena & Mano, 2007; Deressa & Hassan, 2009; Seo & Mendelsohn, 2007; Maddison et al., 2007; Onyeneke et al., 2025). However, most of the aforementioned studies rely on cross-sectional data. In contrast, the majority of studies that utilize panel data (e.g., Kahsay & Hansen, 2016) are limited to estimating the effects of climate change on overall agricultural output. As a result, little is known about the differences between the short-run and long-run effects of climate change on agricultural productivity. Auffhammer (2018) argues that when weather variables are included linearly on the right-hand side of a regression without adaptation factors, the resulting estimate is typically interpreted as a short-term response. Conversely, when long-term historical weather averages and adaptation strategies are incorporated, the estimate reflects a long-term response. A notable strength of the PMG method, however, is its ability to estimate both short-term and long-term effects simultaneously. Furthermore, recent studies show that the effects of climate change vary even within countries (e.g., Kolstad & Moore, 2020), depending on the methods used (e.g., Carter et al., 2018; Auffhammer, 2018; Azdagaz et al., 2025), and are influenced by the types of climate variables considered (e.g., Auffhammer et al., 2013; Carter et al., 2018).

This study fills an existing gap in the literature by examining both the short-run and long-run effects of climate change on agricultural production in Eastern African countries, including Burundi, Ethiopia, Kenya, Rwanda, Tanzania, Zimbabwe, Uganda, Madagascar, Mozambique, Somalia, and Zambia. These nations share comparable crop production seasons, primarily influenced by the movement of the Inter-Tropical Convergence Zone (ITCZ). Furthermore, this study assesses the heterogeneity of climate change effects across different crops. In general, we assess the following hypotheses:

Hypothesis 1: In Eastern Africa, climatic variables have a long-run effect on agricultural output due to shared crop production seasons influenced by the movement of the Inter-Tropical Convergence Zone. However, the short-run and long-run effects of climatic variables on output differ.

Hypothesis 2: The effect of climate factors on agricultural output shifts over time, reflecting possible temporal changes.

Hypothesis 3: Climate factors affect particular crops differently. Higher temperature positively influences tropical crops like coffee and highland crops like potatoes, but reduces the productivity of lowland crops like beans and sorghum. Rainfall generally boosts production.

The remainder of this article is organized as follows. Section 2 reviews the prior literature on the effects of climate change on agricultural output. Section 3 discusses the research methodology and data sources and provides some preliminary data analysis. Section 4 presents the results of the empirical analyses. Finally, Section 5 offers some concluding remarks.

2. Climate change and agriculture – a review of existing literature

2.1. Crops and biophysical variables

An early study by Mendelsohn et al. (1994) hypothesizes that climate variables, particularly changes in temperature and rainfall, directly alter the crop production function. These changes influence key biophysical processes essential for crop growth, such as photosynthesis, respiration, water use, and nutrient uptake (FAO, 2015). Temperature plays a central role in regulating physiological processes. Optimal temperature ranges vary across crop types, with most crops showing reduced photosynthetic efficiency and growth when temperatures exceed their threshold (Hatfield et al., 2011). Elevated temperatures can accelerate phenological development, leading to shorter growing periods and reduced biomass accumulation (Lobell et al., 2013). Furthermore, they can also cause heat stress, impairing pollen viability and grain filling, particularly in crops like wheat and rice (Prasad et al., 2011). Higher temperatures increase evapotranspiration, the combined water loss from soil and plant surfaces. This can exacerbate water deficits, particularly in arid and semi-arid regions, reducing soil moisture content (Hatfield & Prueger, 2015). The rise in evapotranspiration heightens irrigation requirements to maintain optimal soil moisture levels for crop growth. Moreover, prolonged heatwaves can dry out topsoil and disrupt the root-zone water balance, leading to drought stress and lower yields (IPCC, 2022).

Rainfall, on the other hand, is the primary determinant of water availability, directly affecting crop hydration and soil moisture (FAO, 2015). Inadequate rainfall leads to drought stress, reducing photosynthesis, cell expansion, and nutrient transport (Fischer et al., 2002). Conversely, excessive rainfall can cause waterlogging, oxygen deficiency in the root zone, and increased susceptibility to pests and diseases (Jackson & Drew, 1984). Rainfall variability is especially critical in rainfed agriculture, where water availability closely aligns with crop yield potential (Rosenzweig & Parry, 1994). Moreover, irrigation mitigates the effects of irregular rainfall and maintains consistent soil moisture levels. However, irrigation efficiency is closely tied to soil type, crop water requirements, and local climatic conditions. Drip and precision irrigation systems, for example, reduce water loss through evaporation and deep percolation, thereby enhancing water-use efficiency and sustaining crop growth in water-scarce regions (Jägermeyr et al., 2015).

2.2. Economic theory and empirical studies

There are three main methodological approaches used in studying the effects of climate change on agricultural production: the production function approach (Deschenes & Greenstone, 2007), the Ricardian model (e.g., Mendelsohn et al., 1994), and the macroeconomic modelling based on the Input-Output or Computable General Equilibrium models (e.g., Horridge et al., 2005). Each methodological framework has distinctive features, as well as its own strengths and weaknesses.

Macro-economic models employ supply and demand equations within a partial or general equilibrium framework to estimate the economic effects of climate change under different scenarios. This analysis may use input-output modelling (e.g. Eamen et al., 2020), computable general equilibrium models (e.g., Horridge et al., 2005; Ochuodho et al., 2016) or integrated assessment models (e.g., Holman et al., 2005; Antle et al., 2004; Zhao et al., 2020). These models can be multifaceted and often include inter-sectoral and international linkages, such as those through trade (e.g., Dall'Erba et al., 2021; Xie et al., 2020), but also require extensive data and numerous simplifying assumptions (Ward et al., 2014). As a result, the majority of the existing studies rely either on the production function approach or the Ricardian model. While the former relates agricultural output to all inputs, including climate variables like precipitation and temperature (Barrios et al., 2008), the latter essentially focuses on estimating the response of land values to climatic changes (Mendelsohn et al., 1994).

When employing a cross-sectional production function approach, crop growth simulation models and econometric models that specifically target a single type of crop are built upon the assumption that farmers do not alter their selection of inputs and crops in response to evolving climate conditions (Mendelsohn et al., 1994; Dall'Erba et al., 2021). In this case, the model may overestimate the effects of climate change on agricultural output whenever there is an adaptation by farmers to climate change. To address this bias in cross-sectional analysis based on the production function, Mendelsohn et al. (1994) and Mendelsohn & Nordhaus (1999) introduced the Ricardian model that is based on the value of land. The Ricardian model links environmental variables, such as temperature and rainfall, to land value through the farmer's profit maximization process, also considering socio-economic variables and soil characteristics. For a profit-maximizing farmer facing a perfectly competitive land market, the land rent from agricultural production must equal the net revenue from agricultural production. As a result, the land value represents the present value of the stream of land rents (Mendelsohn et al., 1994).

There are numerous studies using the Ricardian model to examine how climate variables affect farmland value or rent, rather than studying the yields of specific crops under different climate scenarios. For instance, Mendelsohn et al. (1994) applied the Ricardian approach and showed that climate exerts complex, nonlinear effects on the agricultural sector within the US economy that vary by season. Their findings indicate that crops are adversely affected by higher temperatures during winter and summer, while they benefit from warmer fall temperatures and increased rainfall during winter and spring. Gbetibouo & Hassan (2005) employed the Ricardian model to assess the impact of climate change on agricultural rents in 300 districts of South Africa. They found that a rise in temperature improves net revenue from crop production, whereas a reduction in rainfall decreases it. Similarly, Nhemachena and Mano (2007) found that both temperature and precipitation have a significant impact on net farm revenue in Zimbabwe. However, net revenues are negatively affected by increases in temperature and decreases in precipitation. Deressa & Hassan (2009) drew similar conclusions in their study on Ethiopia. Finally, Maddison et al. (2007) analyzed data from eleven African countries and found that, even assuming perfect adaptation, regional climate change will result in significant production losses by 2050, including 19.9% for Burkina Faso and 30.5% for Niger. In contrast, countries such as Ethiopia and South Africa are projected to suffer relatively minor productivity losses of 1% and 3%, respectively.

The Ricardian model is a useful method for predicting the economic effects of climate change. However, it has limitations, as it cannot provide effects for specific crops or types of livestock. Furthermore, its reliability has been questioned due to challenges related to weak causal identification, omitted variables, and the potential endogeneity of land-use decisions, which can confound the identification of marginal effects (e.g., Lippert et al., 2009; Carter et al., 2018; DePaula, 2020). For example, Schlenker et al. (2005) revisited the analysis conducted by Mendelsohn et al. (1994) and highlighted irrigation as a significant factor influencing farm profitability, which can affect the accuracy of the Ricardian model's predictions.

In contrast to the Ricardian model, the production function approach is a tool that relates agricultural output to all inputs, including climate variables such as precipitation and temperature (e.g., MENDELSOHN & WANG, 2017). The framework can be expanded (DESCHÊNES & GREENSTONE, 2007) to leverage seemingly random annual variations in weather, allowing for a more nuanced analysis of the impact of climate change on agricultural production. By using a panel approach, this method non-parametrically controls for unobservable, time-invariant regional factors, thereby addressing the omitted-variable issue more effectively than the Ricardian approach (CARTER ET AL., 2018; AUFFHAMMER, 2018; KOLSTAD & MOORE, 2020).

Theoretically, climate change can influence agricultural output in various ways. An early study (e.g., MENDELSOHN ET AL., 1994) proposes that climate change alters the production function of crops. First, changes in temperature and precipitation affect soil moisture (e.g., FAO, 2015; AUFFHAMMER ET AL., 2013), which can be mitigated by irrigation, but only if water supplies are available (SCHLENKER ET AL., 2005). Second, temperature directly affects crop yields (e.g., IPCC, 2023; AUFFHAMMER, 2018; CARTER ET AL., 2018; KOLSTAD & MOORE, 2019) and can damage crops that are already near their tolerance limits under current conditions. Third, elevated concentrations of carbon dioxide can stimulate the growth of certain crops (e.g., BHARGAVA & MITRA, 2021), highlighting the complex and multifaceted nature of climate change impacts on agriculture.

Initially, the production function was applied to cross-sectional data (e.g., WARD ET AL., 2014). For example, MENDELSOHN & WANG (2017) demonstrate that climate and soil factors play a significant role in the cultivation of rice, maize, and wheat in China. However, this method may overestimate the effects of climate change on agricultural output because it does not account for farmers' adaptations (e.g., NHEMACHENA & MANO, 2007). To address this limitation, time-series or panel data can be combined with the production function to account for farmers' adaptation strategies and reduce potential estimation biases. The availability of data over time makes this approach appealing, as it allows for a more nuanced analysis of the relationships between climate, agriculture, and adaptation. Furthermore, using panel data addresses certain limitations of the Ricardian approach, particularly the issue of causality that the Ricardian model overlooks (e.g., AUFFHAMMER, 2018; CARTER ET AL., 2018). AUFFHAMMER (2018) and KOLSTAD & MOORE (2020) note that when weather variables are included linearly on the right-hand side of a regression without adaptation variables, the estimated coefficient typically reflect a short-run response. In contrast, using long-run averages of historical weather data, it represents a long-run response. However, short-term weather responses may not accurately represent long-term climate change impacts, since farmers adapt differently to permanent climate shifts compared to temporary weather variations. If adaptation plays a significant role, using short-term weather effects as a model for long-term climate effects could be misleading (KOLSTAD & MOORE, 2020). In contrast, one of the primary advantages of the Autoregressive Distributed Lag (ARDL) method is its ability to simultaneously estimate both short- and long-term effects, effectively addressing this issue (PESARAN ET AL., 1999). For instance, OCHIENG ET AL. (2016) provided evidence indicating that climate change exerts varying effects on distinct crop varieties within the agricultural landscape of Kenya. For example, higher average temperatures negatively influenced maize production, while having a positive impact on tea production. Conversely, an increase in rainfall had a detrimental effect on tea yields, while improving maize production. Moreover, the study highlighted that temperature exerts a more substantial influence on crop production compared to rainfall. BARRIOS ET AL. (2008) applied a cross-country panel data approach to compare the impacts of changes in annual rainfall and temperature on agricultural production in Sub-Saharan Africa (SSA) with the rest of the non-SSA developing countries. Their results showed that climate change is a major determinant of agricultural production in SSA, whereas it does not have a significant impact on non-SSA countries. However, other studies argue that both rainfall and temperature have a significant impact on the agricultural sector of non-sub-Saharan economies as well (e.g., EXENBERGER ET AL., 2014; BEN ZAIED & BEN CHEIKH, 2015; ZHAI ET AL., 2017; MENDELSOHN & WANG, 2017; VAN PASSEL ET AL., 2017; OZDEMIR, 2021; AUFFHAMMER, 2018; CARTER ET AL., 2018; KOLSTAD & MOORE, 2019; AZDAGAZ ET AL., 2025; ONYENEKE ET AL., 2025). For example, ZHAI ET AL. (2017) found that precipitation during the wheat growth period decreases wheat yield per unit area in Henan Province, China. While precipitation has a significantly positive impact on wheat yield, they found no notable short- or long-run effects of temperature on wheat yield per unit area. Similarly, OZDEMIR (2021) confirmed the presence of a long-run relationship between agricultural productivity and climate change variables in Asia for the period 1980–2016. BEN ZAIED & BEN CHEIKH (2015) analyzed the impacts of climate change on cereal and date production in Tunisia, both in the short and long term. They revealed that while the short-term effects are small, the long-term impacts are significant. In contrast, CARTER ET AL. (2018) argued that research on climate change in many developing countries remains limited, while KOLSTAD & MOORE (2020) emphasized that the effects of climate change can vary significantly even within a single country. Finally, ONOFRI ET AL. (2019) employed a two-step approach to predict the effect of climate change on the Veneto region in Italy. First, they estimated the impact of climate-induced changes on agricultural productivity using a production function. Then, they projected the future performance of the agricultural sector under various IPCC scenarios, taking into account potential shifts in land and labour usage. Their findings showed that land productivity is highly sensitive to climate-induced alterations in land use, leading to both positive and negative effects on agricultural yields. Table A8 in the Appendix summarizes the existing empirical literature on the impact of climate change on agriculture.

In general, both production function models and Ricardian models utilize statistical methods to analyze the effects of environmental factors on observed outcomes (e.g., WARD ET AL., 2014). The Ricardian model focuses on how climate variables influence farmland value or rent, rather than assessing the yields of specific crops under different climate scenarios. While this approach is useful for predicting the economic effects of climate change, it does not provide estimates for specific crops or types of livestock (e.g., AUFFHAMMER, 2018; CARTER ET AL., 2018). Moreover, the Ricardian model relies on cross-sectional data and often fails to account for other variables that influence agricultural output, which can lead to concerns about omitted variable bias, such as the role of irrigation (e.g., SCHLENKER ET AL., 2005; OCHIENG ET AL., 2016; AUFFHAMMER, 2018). This issue is particularly problematic when using time-invariant regressors (e.g., LIPPERT ET AL., 2009; CARTER ET AL., 2018; DEPAULA, 2020). In contrast, the production function approach, which is based on panel data, incorporates a wider range of variables and their interactions within a systematic framework, allowing for a more comprehensive analysis of the factors affecting production. By explicitly accounting for these factors, the production function approach can reduce omitted variable bias and potentially produce more ACCURATE ESTIMATES (e.g., DESCHÊNES & GREENSTONE, 2007; CARTER ET AL., 2018; AUFFHAMMER, 2018; KOLSTAD & MOORE, 2020).

This article applies the production function approach to examine the effects of climate change on agricultural output in Eastern African countries between 1980 and 2021. We rely on the production function approach because it allows for the incorporation of various inputs, including climate variables, into a functional form, thus minimizing potential omitted variable bias. However, unlike the majority of the existing studies, we apply the Pooled Mean Group (PMG) of Autoregressive Distributed Lag (ARDL) to distinguish between both the short-run and long-run effects. The ARDL method is particularly useful for this purpose, as it can estimate short- and long-run effects simultaneously and identify whether variables have significant long-run relationships. Our objectives are threefold. First, we examine whether annual rainfall, temperature, and other inputs have a long-term effect on aggregated agricultural output in Eastern African countries. Second, we analyze whether climate variables, such as temperature and rainfall, significantly influence crop production in the short-term or in the long-term. Third, we investigate whether there are significant differences in the impact of climate change across the major crops in these countries.

3. Methodology and data

3.1. Empirical approach

Our study explores the short-run and long-run connections between climate change and agricultural production in Eastern Africa. To investigate the effects of climate change on agricultural values in Eastern Africa over the 1980–2021 period, the following model can be specified (e.g., BARRIOS ET AL., 2008; KAHSAY & HANSEN, 2016):

$$Y_{it} = f(R_{it}, T_{it}, O_{it}) \qquad (1)$$

where Y_{it} is the Gross Production Value, R_{it} and T_{it} are mean annual rainfall measured in mm and mean annual temperature measured in °C, respectively; O_{it} refers to other inputs of agricultural production; i stands for selected Eastern African countries, and t stands for years. Other input variables include agricultural labour force, fixed capital, agricultural land, irrigated land area, and soil nutrients (manure[1] of all animals applied to the soil). A detailed description of all variables is provided in Section 3.2.

[1]Manure is a waste material produced by domestic livestock, which can be managed for agricultural purposes.

To alleviate the multicollinearity problem, all the variables are transformed into natural logarithms. Equation (1) can be rewritten as:

$$lnY_{it} = \beta_0 + \beta_1 lnCO2_{it} + \beta_2 lnR_{it} + \beta_3 lnT_{it} + \beta_h ln\mathrm{O}_{\mathrm{it}} + e_{it} \qquad (2)$$

Typically, the above equation could be estimated using the fixed effects estimator (e.g., BALTAGI, 2008). However, while such estimates may be used as a benchmark, they do not allow distinguishing between the short-run and the long-run effects of climate change. One technique commonly employed to investigate these relationships is the autoregressive distributed lag (ARDL) co-integration method. Initially introduced by CHAREMZA & DEADMAN (1997) and subsequently extended by PESARAN & SMITH (1995) and PESARAN ET AL. (1999), the ARDL approach offers several advantages over other co-integration methods (e.g., ENGLE & GRANGER, 1987; JOHANSEN, 1991; MCCOSKEY & KAO, 1998). The ARDL method can be applied regardless of whether the underlying variables are stationary, integrated of order one, or mutually co-integrated. Additionally, it can accommodate small sample sizes and address simultaneity biases in the relationship between these variables. Finally, the ARDL method helps determine the appropriate number of lags for the empirical model (PESARAN ET AL., 1999).

Equation (2) can be converted into a dynamic ARDL panel model after adding lagged variables. The dynamic panel model in an error correction model based on the panel ARDL (p, q) approach, with p as the lag of the dependent variable and q as the lag of the independent variables, will be formulated as (PESARAN & SMITH, 1995; PESARAN ET AL., 1999):

$$lnY_{it} = \sum_{j=1}^{p} \lambda_{ij} lnY_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} ln\, X_{i,t-j} + e_{it} \qquad (3)$$

where λ_{ij} are coefficients of the lagged dependent variable, δ_{ij} are coefficients of explanatory variables, p and q are optimal lag order, and e_{it} is the error term. The re-parameterized ARDL panel error correction model in a dynamic form is specified as:

$$\Delta y_{it} = \pi i\left(y_{i,t-1} - \theta'_i X_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}{}^{*} \Delta\, y_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}{}^{*} \Delta\, X_{i,t-1} + e_{it} \qquad (4)$$

where $\pi\mathrm{i} = -(1-\sum_{\mathrm{j=1}}^{\mathrm{p-1}} \lambda_{\mathrm{ij}})$, $\theta_{\mathrm{i}} = \frac{\sum_{\mathrm{j=0}}^{\mathrm{q}} \delta_{\mathrm{ij}}}{1-\sum_{\mathrm{k}} \lambda_{\mathrm{ik}}}$, $\lambda_{\mathrm{ij}}{}^{*} = -\sum_{\mathrm{m=j+1}}^{\mathrm{p}} \lambda_{\mathrm{im}}$ $\mathrm{j} = 1,2, \ldots, \mathrm{p}-1$ and $\delta_{\mathrm{ij}}{}^{*} = -\sum_{\mathrm{m=j+1}}^{\mathrm{p}} \delta_{\mathrm{im}}$ $\mathrm{j} = 1,2, \ldots, \mathrm{q}-1$

The parameter πi is the error-correcting speed of the adjustment term. If πi = 0, then there is no evidence for a long-run relationship among variables. Under the hypothesis that the variables converge to a long-run equilibrium, it is virtually assumed to be significantly negative. Of particular importance is the vector θ_i, which contains the long-run relationships among agricultural value and independent variables. Parameters λ_{ij} and δ_{ij} are the short-run dynamic coefficients.

There are three different methods to estimate the above model: the mean group (MG) estimator developed by PESARAN & SMITH (1995), the pooled mean group (PMG) estimator developed by PESARAN ET AL. (1999), and the dynamic fixed effects (DFE) estimator. The PMG estimator allows for between-group heterogeneity of coefficients only in the short-run, whereas the MG estimator allows for heterogeneity in both the short-run and the long-run. In contrast, the DFE estimator assumes homogeneity of coefficients in both the short-run and the long-run. The MG approach estimates separate equations for each group without accounting for the possibility that some parameters may be consistent across groups. In contrast, the pooled mean group (PMG) estimator combines pooling and averaging, permitting the intercepts, short-run coefficients, and error variances to vary across groups while imposing a uniform constraint on long-run coefficients. This approach is useful when a common factor, such as technology, influences all groups similarly (PESARAN ET AL., 1999).

3.2. Variable description and data sources

Our analysis utilizes data from the World Bank Development Indicators (WDI), the Food and Agriculture Organization (FAO), the World Bank Climate Knowledge (WBCK), and the African Development Bank (ADB). For climate variables, we specifically rely on the World Bank Climate Knowledge, which is a standard climate data source (e.g., OZDEMIR, 2021) that provides historical meteorological data. The dependent variable is the Gross Production Value of agricultural production (GPV), expressed in constant US dollars. In addition to the overall value of agricultural production, we also use the production data for individual crops, including banana, bean, coffee, maize, millet, potato, rice, cotton, sorghum, sugarcane, tea, and wheat. The agricultural land variable refers to the share of land area that is arable, under permanent crops, and under permanent pastures. The irrigation area variable includes any area that is prepared for completely controlled irrigation using surface, sprinkler, or targeted irrigation techniques, as well as locations that use partially controlled irrigation techniques, such as spate irrigation, fitted wetlands, equipped flood recessions, and equipped inland valley bottoms. We also use manure from all animals applied to soil as an agricultural input for soil nutrients. Gross Fixed Capital Formation, expressed in constant US dollars, serves as a proxy for capital[2]. Labour is measured as the total economically active population in agriculture, as defined by the FAO. The data considered for this study spans 41 years (1980–2021) and includes the latest available information. Our study focuses on 11 Eastern African countries: Burundi, Ethiopia, Kenya, Rwanda, Tanzania, Zimbabwe, Uganda, Madagascar, Mozambique, Somalia, and Zambia. These countries have similar crop production seasons, primarily driven by the migration of the Inter-Tropical Convergence Zone (ITCZ) (BAHAGA ET AL., 2015). We exclude the remaining Eastern African countries from our analysis due to a lack of data. Table 1 provides the sources for each variable.

Table 1. Variable description (Source: own elaboration)

Abbreviation	Description	Source
GPVA	Gross Production Value in constant 2014-2016 of Int. $	FAOSTAT
LD	Agricultural land in hectares	WDI
LB	Agricultural labor force in persons	ADB
IR	Irrigated land area in hectare	FAOSTAT
RF	Mean annual precipitations in mm	WBCK
AT	Mean annual temperature in degrees Celsius	WBCK
CA	Capital in US$, 2015 prices	FAOSTAT
SN	Soil Nutrient (manure applied to soil) in tons	FAOSTAT

4. Empirical results

Before estimating the empirical model, a series of tests are performed to ensure the reliability of the data. The first test is the cross-sectional dependence test proposed by PESARAN (2015), based on the systematic residual correlation across different units in the panel. Additionally, the panel unit root test and a slope homogeneity test were carried out to assess the stationarity of the variables and the homogeneity of coefficients, respectively. Although the ARDL method is suitable for variables exhibiting a combination of I(0) and I(1) integration, the unit root tests are still necessary to confirm that the variables do not possess I(2) integration, which could lead to spurious results.

The test outcomes indicate that the variables are not cross-sectionally dependent, stationary, with a combination of I(0) and I(1) integration. Similarly, the slope homogeneity test, which is a robust version that considers serial correlation and heteroskedasticity based on the PESARAN & YAMAGATA (2008) framework and developed by BLOMQUIST & WESTERLUND (2013), reveals that the slope coefficients are homogeneous. The results of both the panel unit root tests and the slope homogeneity test are presented in the Appendix (Tables A1 and A2, respectively) while for cross-sectionally dependent it is presented in Table A4.

To assess the existence of a long-run relationship among the variables, we employ both the PEDRONI (2004) test and the KAO (1999) test. The Pedroni tests are known for their increased explanatory power, particularly as the time dimension of the dataset becomes larger. In contrast, the Kao tests are more effective in panels with small sample cross-section unit co-integration tests. The results, presented in Table A2, indicate that the variables exhibit co-integration.

4.1. Descriptive analysis

In Eastern Africa, the mean annual temperature and rainfall have increased from 1980 to 2021 (Figures A1 and A2 in the Appendix). The mean annual temperature in Eastern Africa ranges from the lowest value of 18.72°C, registered in 1989 in Rwanda, to the highest of 27.49°C, recorded in 2010 in Somalia (Table 2). It has changed from 22.48°C in 1980 to 23.11°C in 2021, increasing by 0.63°C on average (see also Fig. A1 in the Appendix). This value falls within the range reported by many studies (e.g., CAMBERLIN, 2018). This change is statistically significant at the 1% level. In fact, for the majority of countries, the minimum annual temperature was recorded in 1989. Moreover, the change in mean

[2]Since data on agricultural tractors (mostly used *as a proxy for capital*) are unavailable after 2009, Gross Fixed Capital Formation in agriculture from FAOSTAT is used as a proxy for capital, as it captures total investments in fixed assets (excluding land) used repeatedly in production.

annual temperature follows a similar pattern across countries, suggesting that the East African Community (EAC) countries have common causes of temperature change (e.g., BAHAGA ET AL., 2015). Both the mean annual and annual maximum temperatures appear to be relatively stable, with standard deviations of 2.02°C and 1.93°C, respectively, in comparison to rainfall.

Table 2. Minimum and maximum values of climate variables (Source: own elaboration)

Countries	Temperature		Rainfall	
	Min.	Max.	Min.	Max.
Burundi	20.06	21.12	961	1492
Ethiopia	22.12	23.62	629	928
Kenya	24.27	25.56	480	1002
Rwanda	18.72	19.84	850	1382
Tanzania	22.15	23.23	792	1198
Zimbabwe	20.43	22.73	430	875
Uganda	22.42	24.13	1053	1425
Madagascar	21.89	23.09	1133	1855
Mozambique	23.29	24.92	684	1225
Somalia	26.60	27.49	187	363
Zambia	21.37	23.23	771	1097

Rainfall in Eastern Africa exhibits considerable variability across years (Fig. 1). For example, rainfall in Mozambique, Uganda, and Zimbabwe fluctuates, while in Tanzania, it declines gradually over time. In the northern part of Eastern Africa, including Somalia, Ethiopia, and Kenya (with some fluctuation), rainfall is relatively stable, but with lower amounts (Fig. 2). The mean annual rainfall in the East African Community (EAC) increased from 896.7 mm in 1980 to 1083.8 mm in 2021, although numerous studies have concluded that no particular trends are apparent at the country level (e.g., CAMBERLIN, 2018). Therefore, whether rainfall has increased or not remains a topic of debate. Altogether, the EAC receives less than 1000 mm per year on average, with a mean annual rainfall of 954.35 mm. Burundi, Rwanda, Tanzania, Uganda, Madagascar, Mozambique, and Zambia receive annual rainfall greater than this average, whereas Ethiopia, Kenya, Zimbabwe, and Somalia receive less than the average (see Table 2). Consequently, the northern part of Eastern Africa is characterized by lower rainfall and higher temperatures, while the southern part is characterized by lower temperatures and relatively higher rainfall. Figure 2 depicts deviations of temperature and rainfall from respective long-run values. While rainfall shows variations, there is a clear increase in temperature in the last two decades. As shown in Figure 3, only a few Eastern African countries have exhibited strong agricultural production. Notable progress is particularly evident in Ethiopia, Kenya, and Tanzania, while the rest have experienced relatively low growth. However, when viewed collectively, the region demonstrates significant overall agricultural growth. In Ethiopia, for example, the expansion of agricultural land, coupled with improved input utilization, has played a crucial role in enhancing productivity (BACHEWE ET AL., 2018).

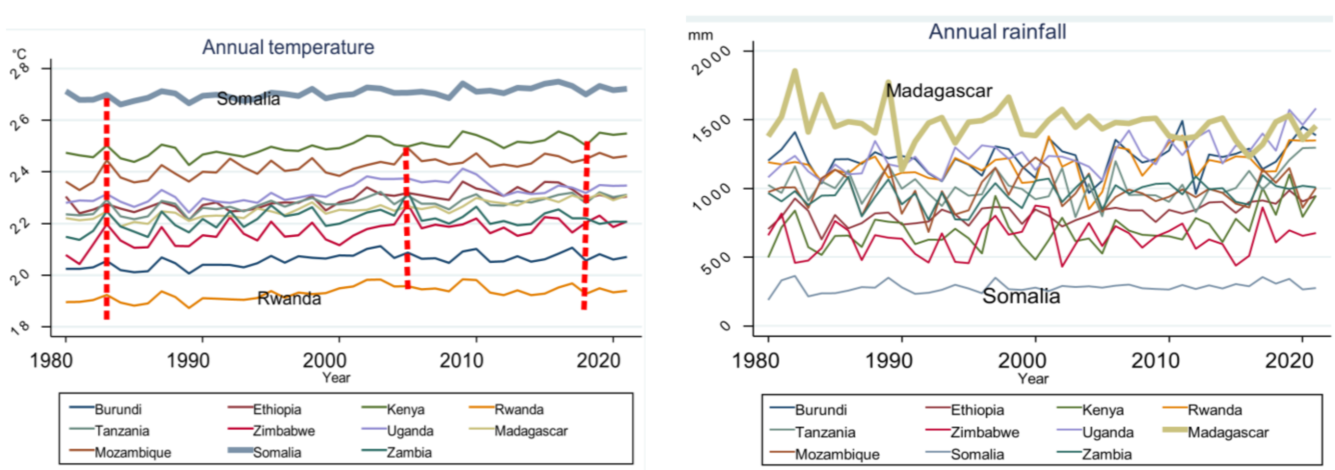

Fig. 1. Trends of climate variables (Source: own elaboration)

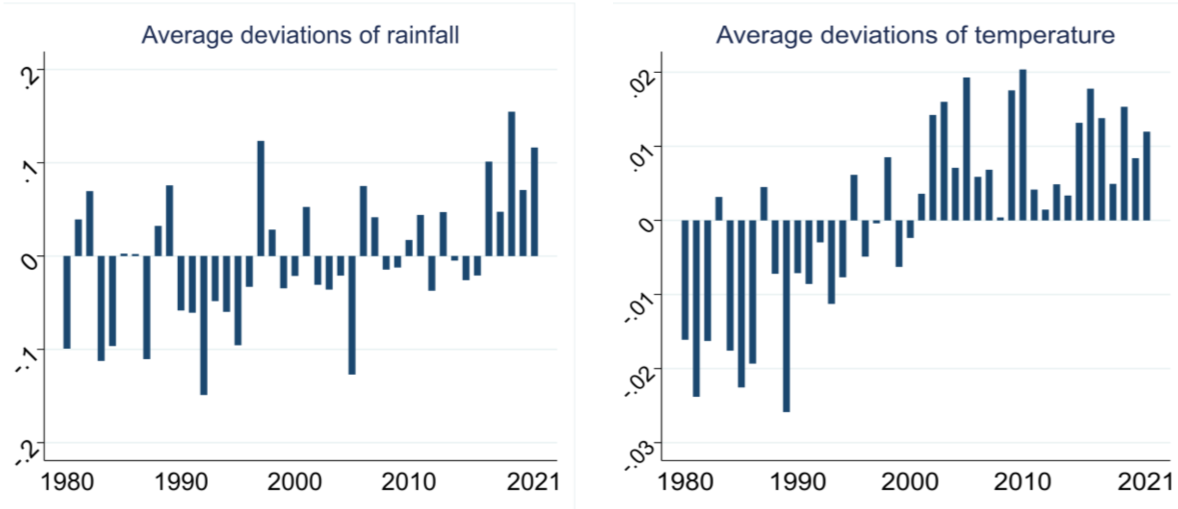

Fig. 2. Average deviations of temperature and rainfall from their respective long-run values (Source: own elaboration)

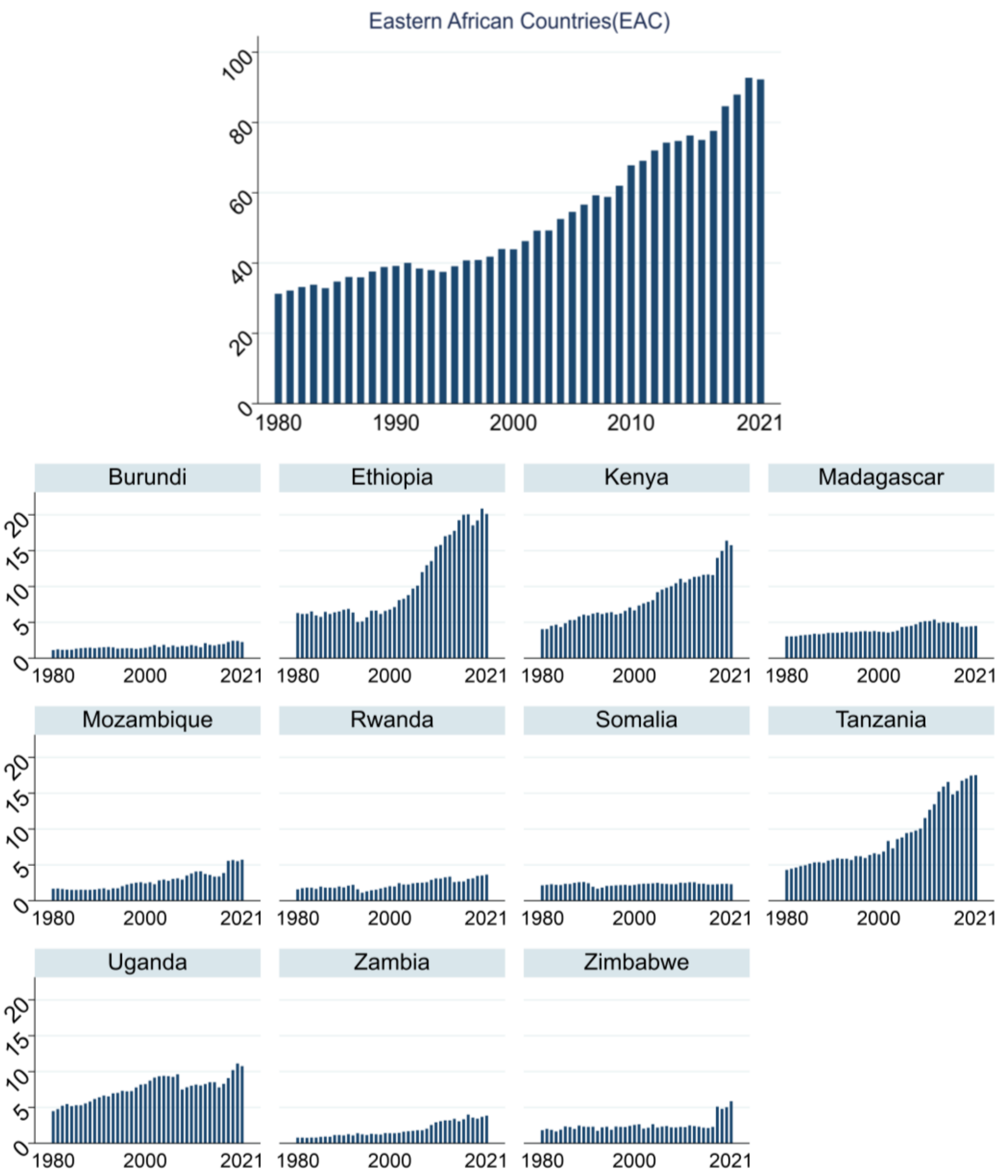

Fig. 3. Value of agricultural production in billions of $ (Source: own elaboration)

4.2. Estimation results and discussion

Our benchmark results are based on the fixed effects (FE) estimator, which helps address time-invariant, unobservable factors. The FE results in the first column of Table 3 show that capital, irrigation, and temperature have a significant and positive impact on the value of agricultural production during the 1980–2021 period. Specifically, a 1% increase in irrigated land raises agricultural value by 0.3%, a 1% increase in capital increases it by 0.2%, and a 1% rise in annual temperature (in °C) boosts agricultural value by 0.7%. Note that the coefficients for land and rainfall, while positive, are not statistically significant. The lack of statistical significance also applies to the labour force, although here the coefficient is surprisingly negative. In this sense, our results differ from those reported by Kahsay & Hansen (2016), who found that land and labour were positively correlated with agricultural production in Eastern Africa over the 1980–2006 period.

The results for the panel ARDL obtained from the dynamic fixed effects (DFE) and the Pooled Mean Group (PMG) estimators are presented in columns 2–5 of Table 3. We use the Hausman test to differentiate between the Pooled Mean Group (PMG) estimator proposed by Pesaran et al. (1999) and the Dynamic Fixed Effects (DFE) estimator. The Hausman test compares particular estimators to assess the homogeneity restriction on long-run coefficients. As Pesaran et al. (1999) illustrate, the PMG estimator combines the long-run estimators to be uniform across all panels, whereas the DFE estimator calculates uniform coefficients for both the short-run and the long-run. Efficient and consistent estimates are obtained by the PMG estimator when the homogeneity restrictions are valid under the null hypothesis. Given the calculated Hausman statistic of 10.92 with a p-value of 0.207, we rely on the more efficient PMG estimator compared to the DFE.

Table 3. Estimation results for the 1980-2021 period (Source: own elaboration)

	FE	DFE		PMG	
		Short run	Long run	Short run	Long run
Land	0.091 (0.158)	0.509*** (0.121)	-0.399 (0.542)	0.292 (0.475)	1.034*** (0.197)
Labor force	-0.089 (0.63)	-0.004 (0.093)	0.207 (0.206)	-0.075 (0.164)	0.198*** (0.075)
Capital	0.155*** (0.023)	0.027 (0.019)	0.184*** (0.069)	0.030* (0.017)	0.051* (0.028)
Irrigation	0.339*** (0.035)	0.036 (0.072)	0.381*** (0.114)	0.075 (0.099)	0.520*** (0.057)
Soil nutrients	0.002 (0.155)	0.035 (0.024)	-0.036 (0.059)	0.120 (0.096)	0.045** (0.020)
Rainfall	0.108 (0.074)	0.026 (0.034)	0.760** (0.322)	0.040 (0.035)	0.272*** (0.113)
Temperature	0.707*** (0.231)	-0.631** (0.259)	0.983 (1.213)	-0.130 (0.394)	0.599 (1.137)
Error correction		-0.147*** (0.027)		-0.231*** (0.073)	
Number of observations	462	451	451	451	451
CD test		47.479***		47.485***	
Hausman test P-value		10.92 0.207			
R^2	0.96				

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form. Short-run variables are presented in first-difference (Δ), while long-run variables are in the level form.

The short-run results of both DFE and PMG estimates indicate the lack of statistical significance of the majority of explanatory variables. The most significant exception is the temperature in the DFE model. Here, a 1% rise in annual temperature reduces agricultural value by 0.6%. However, the values of the error correction coefficients of DFE and PMG models indicate that there exist long-run effects of the explanatory variables on the value of agricultural production. This significance reinforces the assertion that these variables, when jointly examined, exhibit a long-run relationship with agricultural value, as previously evaluated through co-integration testing. According to PESARAN ET AL. (1999), long-run equilibrium relationships between variables can exist across groups due to shared factors that influence all groups similarly. In the context of environmental sciences, studies such as BAHAGA ET AL. (2015) highlight that production seasons in Eastern African countries are largely driven by the migration of the Intertropical Convergence Zone (ITCZ). The rates of adjustment under the DFE and PMG models are reported to be 14.7% and 23.1%, respectively. However, as noted by PESARAN ET AL. (1999), DFE estimators tend to exhibit a relatively slower speed of convergence compared to PMG estimators.

Regarding the DFE estimates, in the long-run, the majority of explanatory variables have a significant and positive impact on agricultural production. Capital, irrigation, and rainfall are found to significantly affect agricultural output. A 1% increase in capital is associated with a 0.18% increase in agricultural value, with strong statistical significance at the 1% level. Similarly, a 1% increase in irrigated land area leads to a 0.38% increase in agricultural production, while a 1% increase in rainfall raises it by 0.76%, both of which are statistically significant. The long-run PMG estimates show that the majority of explanatory variables significantly and positively influence agricultural output. These variables include land, labour, irrigation, soil nutrients, and rainfall. Specifically, a 1% increase in agricultural land area raises agricultural output by 1.03%, while a 1% rise in the labour force boosts production by 0.19%. Similarly, a 1% increase in irrigated land area enhances output by 0.52%, a 1% rise in soil nutrients increases it by 0.04%, and a 1% increase in rainfall raises production by 0.27% in Eastern African countries. The only exception is the average temperature coefficient, which lacks statistical significance. However, this may be due to the fact that our dataset covers a relatively long period. In fact, we have previously shown that the rise in average temperatures has been observed from 2000 onwards.

In order to examine whether the impact of climate-related variables has changed over the last two decades, we repeated the analysis for the period 2000–2021. The results, presented in Table 4, show that, on average, the findings are similar to those covering the 1980–2021 period. In the case of the FE estimates, irrigation and soil nutrients are highly significant, at the 1% and 5% levels, respectively, in influencing agricultural output, while rainfall and temperature are significant only at the 10% level. Specifically, a 1% increase in irrigated land area raises agricultural output by 0.7%, and a 1% rise in soil nutrients increases output by 0.1%. Additionally, a 1% increase in rainfall boosts agricultural output by 0.2%, whereas a 1% rise in temperature increases it by 0.5%.

The short-run DFE and PMG estimation results presented in Table 4 show that the majority of explanatory variables remain statistically insignificant. Nevertheless, the negative and significant error correction coefficient validates the existence of a long-run effect. Surprisingly, the long-run DFE estimates lack statistical significance. In contrast, the PMG specification yields different results. Specifically, a 1% increase in land area raises agricultural output by 1.4%, and a 1% increase in irrigated land boosts agricultural output by 0.4%. Additionally, a 1% rise in soil nutrients increases output by 0.3%. However, a 1% increase in rainfall leads to a 0.4% decrease in agricultural output, suggesting that the previously observed positive correlation between annual rainfall and agricultural value does not hold over time. Notably, annual temperature does not exhibit a significant adverse effect on agricultural output. The pattern of long-run significance and short-run insignificance is consistent with prior studies, such as ABBAS (2022) and AZDAGAZ ET AL. (2025), which both found that temperature and climate change significantly affect agriculture in the long-run but not in the short run in Pakistan and developing countries respectively.

A comparison of the long-run results between the 1980–2021 and 2000–2021 periods reveals that the effect of temperature remains consistent across both FE and PMG models, whereas the effect of rainfall varies. Under the FE model, temperature has a positive and significant impact in both periods. In contrast, under the PMG model, the effect of temperature is positive but insignificant in both periods.

In the case of rainfall, the impact shifts from being insignificant in the earlier period (1980–2021) to positive and significant in the later period (2000–2021) under the FE model. However, under the PMG model, the effect of rainfall changes from positive in the earlier period to negative in the later period, indicating a notable difference in the relationship between rainfall and agricultural output over time. In this sense, our results differ from the ones by

Ozdemir (2022) who found a significant impact of rainfall and a negative impact of temperature on agricultural productivity in Asian countries over the 1980–2016 period. On the other hand, our findings are partially consistent with those of Pickson & Boateng (2022), who found that rainfall plays a decisive role in Africa's food security, while temperature has no robust long-run effect when analyzed using the PMG approach.

Table 4. Estimation results for the 2000-2021 period (Source: own elaboration)

	FE	DFE		PMG	
		Short run	Long run	Short run	Long run
Land	-0.292 (0.423)	0.489 (0.570)	2.301 (1.943)	-2.945 (2.800)	1.395** (0.560)
Labor force	-0.781*** (0.147)	-0.550 (0.489)	0.285 (0.422)	-0.125 (0.939)	-0.158 (0.129)
Capital	-0.000 (0.034)	0.003 (0.031)	0.064 (0.125)	0.043 (0.044)	0.064*** (0.021)
Irrigation	0.693*** (0.094)	-0.024 (0.286)	0.162 (0.392)	-3.128 (2.463)	0.359*** (0.119)
Soil nutrients	0.102** (0.046)	0.060 (0.064)	-0.129 (0.203)	-0.063 (0.133)	0.334*** (0.050)
Rainfall	0.178* (0.096)	0.029 (0.056)	0.542 (0.482)	0.114 (0.036)	-0.435*** (0.145)
Temperature	0.490* (0.266)	-0.202 (0.346)	0.714 (1.327)	-0.407 (0.571)	0.527 (0.500)
Error correction		-0.162*** (0.045)		-0.328*** (0.112)	
Number of observations	242		231	231	231
CD test		33.985***		33.966***	
Hausman test P-value		11.46 0.1197			
R^2	0.97				

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form. Short-run variables are presented in first-difference (Δ), while long-run variables are in the level form.

Aggregate results for the entire agricultural sector may not be very informative given significant differences between different crops. Therefore, below we provide the results of analyses focusing on individual crops where the production is measured in metric tons. In order to save space we compare only FE and PMG estimates. The FE estimation results presented in Table A6 in the Appendix confirm the existence of different effects across crops over the 1980–2021 period. Specifically, agricultural land area has a significant and positive impact on the output of bananas, coffee, millet, potatoes, rice, sorghum, and sugarcane, with elastic coefficients indicating a proportional relationship between land area and output. In contrast, maize and cotton exhibit significant positive effects, but with inelastic coefficients, suggesting that a 1% increase in land area leads to a less-than-proportional increase in output, all at the 1% significance level. Notably, agricultural land area does not have a significant impact on the production of beans, wheat, or tea. Capital, on the other hand, has a significant and positive effect on the production of all crops except bananas. Soil nutrients also influence the production of almost all crops, with only a few exceptions. Rainfall generally has a positive influence on crop production, although only maize, millet, cotton, sorghum, and tea show significant positive effects. The impact of temperature is more nuanced, with millet, sorghum, and tea production being significantly, negatively affected, while coffee, cotton, and sugarcane production are significantly, and positively influenced by it.

Similar to the findings for aggregated data, the PMG model estimation results for specific crops also show that the coefficient of the error correction term falls within the range of (-1, 0) and is statistically significant for all crops analyzed, confirming that the included variables have long-term effects on crops, consistent with those observed in the aggregated analysis. However, the influence of climate factors on various crop types varies not only among crops but also between short-run and long-run perspectives. In the long-run, an increase in rainfall has a significant and positive impact on the production of several crops (see Table 5), particularly coffee, maize, cotton, sorghum, and tea. Specifically, a 1% increase in rainfall (mm) boosts production by 0.4% for coffee, 0.8% for maize, 0.3% for cotton, 0.4% for sorghum, and 3.7% for tea. While rainfall also has a positive influence on crops like millet, potato, rice, sugarcane, and wheat, the effect is not statistically significant for these crops. The beneficial impact of rainfall on agricultural output aligns with recent studies, such as AFFOH ET AL. (2022), which reported that the PMG estimator indicates a significant positive relationship between rainfall and food availability in Sub-Saharan Africa.

The results from Table 5 also indicate that the effect of annual temperature in the long-run is mixed. Temperature negatively affects bananas, beans, maize, rice, sugarcane, and tea, but only bananas and beans show significant reductions, with a 1% rise in temperature (1°C) decreasing their production by 8.9% and 3.8%, respectively. The adverse effect of temperature on agricultural output is consistent with recent research, such as the study by AFFOH ET AL. (2022), which found that the PMG estimator shows temperature negatively affects food availability and accessibility in Sub-Saharan Africa.

In contrast, a 1% increase in temperature has a positive effect on coffee, potatoes, cotton, and wheat, increasing their production by 0.5%, 4.1%, 3.6%, and 5.9%, respectively. This positive impact of temperature on coffee production can be attributed to the fact that Arabica coffee thrives at higher elevations, particularly in countries like Kenya, Ethiopia, Rwanda, and Zambia, where rising temperatures may improve its maturation process (ADHIKARI ET AL., 2015). Similarly, wheat, which is commonly cultivated in the highlands of Eastern Africa, benefits from average temperatures, as it is a cool-season crop, as highlighted in research by LIU ET AL. (2008).

Regarding other explanatory variables, land area generally has a positive and significant effect on crop production, with the exception of sorghum, where the effect is positive but not significant, and tea, where the effect is significant but negative. The labour force has a mixed impact on crop production, positively and significantly increasing the production of bananas, maize, rice, and sugarcane by 0.3%, 0.4%, 1.5%, and 0.1%, respectively. However, it has a negative and significant effect on coffee and cotton production, resulting in reductions of 0.2% and 0.2%, respectively. In contrast, capital has a positive and significant effect on most crops, including maize (0.1%), cotton (0.1%), sugarcane (0.2%), tea (1.6%), and wheat (0.2%). Additionally, irrigated land area has a significant impact on crop production, boosting the output of bananas (0.7%), maize (0.2%), cotton (0.4%), sorghum (0.2%), and sugarcane (0.24%), although it has a negative effect on bean production.

The short-run analysis results (Table A4 in the Appendix) reveal that annual temperature has a negative impact on various crops, including coffee, maize, millet, potato, rice, cotton, sorghum, sugarcane, tea, and wheat. Although the effect is not statistically significant for all crops, it is significant for maize, rice, sugarcane, tea, and wheat. Specifically, a 1% increase in annual temperature (°C) leads to a reduction in production of 2.1% for maize, 2.6% for rice, 2.8% for sorghum, 2.7% for tea, and 3.8% for wheat. Notably, the negative effect is elastic (greater than one) and significant for these crops. As these crops are crucial food sources for many Eastern African countries (ERENSTEIN ET AL., 2022; ADHIKARI ET AL., 2015), the negative impact of temperature is a concern. This finding aligns with the recent study by ONYENEKE ET AL. (2025), which, using a panel auto-regressive distributed lag model, reported that increases in the annual maximum number of consecutive dry days and higher temperatures significantly reduced the food, livestock, and crop production indices in Africa.

In contrast, annual rainfall has a positive impact on nearly all crops in the short run, although its effect is statistically insignificant. Among other variables, agricultural land area has a significant and positive effect on most crops, while the labour force positively affects nearly all crops, albeit with an insignificant effect. Similarly, capital has a positive effect on most crops, although it is statistically significant for only a few.

Table A7 in the Appendix presents the FE estimation results for individual crops within the 2000–2021 period. The results show that rainfall has a positive impact on nearly all crops, although it is statistically significant only for maize, millet, sorghum, and tea production. In contrast, temperature has a negative effect on most crops, but exhibits significant negative effects only on maize, millet, rice, cotton, and tea. Notably, temperature has a positive and significant influence on bean and coffee production. A comparison with the 1980–2021 period reveals that the positive impact of rainfall on maize, millet, sorghum, and tea remains consistent, as does the temperature effect on coffee, millet, and tea.

Table 5. Long-run PMG estimation results (1980-2021)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	0.969*** (0.053)	2.953*** (0.338)	1.026*** (0.018)	0.988*** (0.111)	1.088*** (0.034)	0.372** (0.156)	1.435*** (0.425)	0.1087*** (0.050)	0.268 (0.390)	1.388*** (0.364)	-3.129* (1.719)	1.891*** (0.478)
Labor	0.325** (0.138)	-0.003 (0.153)	-0.245** (0.123)	0.382*** (0.128)	0.132 (0.092)	-0.236 (0.216)	1.471*** (0.286)	-0.258*** (0.072)	0.148 (0.152)	0.116*** (0.140)	-0.129 (0.738)	0.014 (0.157)
Capital	-0.052 (0.046)	-0.009 (0.057)	0.018 (0.021)	0.116** (0.054)	-0.033 (0.025)	0.039 (0.063)	0.028 (0.076)	0.042* (0.022)	0.005 (0.064)	0.180*** (0.045)	1.603*** (0.399)	0.171*** (0.082)
Irrigation	0.687*** (0.109)	-0.903*** (0.127)	0.004 (0.033)	0.254*** (0.054)	0.002 (0.078)	0.147 (0.107)	0.013 (0.150)	0.439*** (0.076)	0.249* (0.149)	0.246*** (0.048)	-0.617 (0.505)	
Soil nutrients	-0.039 (0.061)	0.165** (0.068)	0.032 (0.019)	0.305*** (0.107)	-0.012 (0.034)	0.126 (0.094)	0.239 (0.192)	-0.001 (0.053)	0.193*** (0.044)	0.107 (0.1008)	0.636** (0.288)	-0.353*** (0.107)
Rainfall	-0.334* (0.185)	-0.059 (0.231)	0.417*** (0.139)	0.767*** (0.252)	0.239 (0.147)	0.326 (0.216)	0.107 (0.266)	0.306*** (0.089)	0.417** (0.191)	0.334 (0.245)	3.725*** (1.241)	0.426 (0.336)
Temperature	-8.877*** (2.369)	-3.817* (2.055)	0.531*** (0.124)	-0.430 (0.449)	2.141 (0.963)	4.080*** (0.785)	-0.128 (1.050)	3.561** (1.519)	2.005 (2.047)	-0.064 (0.317)	-13.929 (11.391)	5.871*** (1.880)
Observations	447	369	410	451	369	410	410	410	451	451	410	451
Log likelihood	547.63	123.24	304.90	195.18	142.81	310.47	17.34	116.26	47.47	241.72	20.329	10.37

Notes: Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

Table 6. Long-run PMG estimation results (2000-2021)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	1.016*** (0.028)	2.780*** (0.510)	0.803*** (0.029)	0.306*** (0.085)	1.076*** (0.0228)	0.571*** (0.118)	1.093** (0.540)	0.509*** (0.071)	0.807*** (0.773)	2.243*** (0.385)	-2.309*** (1.977)	0.791*** (0.130)
Labor	-0.025 (0.035)	-0.039 (0.254)	0.362*** (0.071)	0.836 (0.287)	-0.079 (0.061)	-0.224** (0.113)	2.773*** (0.279)	0.311 (0.268)	-0.889** (0.406)	1.702*** (0.357)	1.378*** (0.918)	-0.119 (0.087)
Capital	0.017** (0.008)	-0.081 (0.072)	0.095*** (0.008)	0.313*** (0.056)	-0.062*** (0.021)	0.060 (0.049)	0.023 (0.060)	1.006*** (0.153)	0.280** (0.129)	0.395*** (0.072)	1.504*** (0.353)	0.280*** (0.022)
Irrigation	-0.411* (0.146)	-0.643** (0.273)	-0.199 (0.126)	0.595*** (0.175)	0.055 (0.162)	0.266 (0.342)	0.157 (0.289)	-1.315*** (0.372)	-0.302 (0.389)	3.042*** (0.726)	-3.906*** (0.735)	
Soil nutrients	0.031 (0.060)	0.290 (0.123)	-0.360*** (0.049)	-0.455*** (0.166)	0.009 (0.019)	-0.089 (0.066)	0.335* (0.182)	-0.756*** (0.073)	-0.526*** (0.164)	-0.037 (0.140)	-0.719 (0.482)	0.106 (0.080)
Rainfall	-0.005 (0.045)	0.335 (0.208)	-0.069 (0.069)	0.115 (0.193)	0.017 (0.033)	-0.068 (0.142)	0.009 (0.154)	-0.994** (0.408)	-0.823** (0.391)	0.367 (0.225)	4.418*** (0.800)	0.137 (0.129)
Temperature	1.695*** (0.453)	-3.124*** (2.553)	2.276*** (0.648)	2.272 (1.641)	0.810** (0.340)	3.919*** (0.739)	-2.381 (1.761)	-2.338* (1.407)	-6.320*** (2.278)	0.288 (0.331)	6.437 (7.274)	0.456 (0.636)
Observations	238	198	220	242	198	220	220	220	242	242	220	242
Log likelihood	405.08	137.54	275.02	170.54	191.27	187.75	43.18	163.88	75.29	243.68	44.58	109.79

Notes: Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

The PMG estimation results for individual crops within the 2000–2021 period (Table 6) indicate that the long-run effect of an increase in annual temperature varies across crops. Specifically, a 1% rise in temperature (1°C) significantly reduces the production of beans, cotton, and sorghum by 3.1%, 2.3%, and 6.3%, respectively. In contrast, a 1% increase in temperature has a positive influence on the production of bananas, coffee, millet, and potatoes, boosting their outputs by 1.7%, 2.3%, 0.81%, and 3.9%, respectively. The effect of rainfall is also mixed, but it is statistically significant for only a few crops. In the short-run (–), annual temperature has a negative impact on most crops, including maize, wheat, tea, coffee, millet, potato, and sorghum. However, only in the case of maize the temperature coefficient is statistically significant.

It is essential to note that Kenya, Tanzania, and Uganda, as leading bean producers, are disproportionately affected by the negative impacts of annual temperature changes, making them highly vulnerable to the effects of climate change on this crop. Similarly, Ethiopia and Tanzania, major sorghum producers, experience significant effects from climate change on this front. Furthermore, Tanzania and Zimbabwe, key cotton-producing nations, face climate-induced challenges that affect their cotton yields. A comparison of the long-run results between 1980–2021 and 2000–2021 reveals that only the production of beans, coffee, and potatoes is significantly and consistently affected by temperature. Notably, bean production is negatively affected in both periods, whereas coffee and potato production are positively influenced. This finding is consistent with earlier research, such as the study by AHMED ET al. (2021), which found that higher altitudes are associated with enhanced sensory qualities in coffee. In contrast, the effect of temperature on bananas shifts from negative in the earlier period to positive in the latter, while the effect on cotton changes from positive to negative. Additionally, millet and sorghum are negatively affected only during the more recent period (2000–2021).

Finally, as a robustness check, we included interaction terms between soil nutrients and manure application with rainfall, and between temperature and irrigation, for both aggregated and crop-specific analyses across the two periods. The results, presented in Tables 7–10, indicate that agricultural output maintains a long-run relationship with the included variables, as evidenced by the negative and significant coefficients of the error correction term. The interaction between soil nutrients and rainfall is positive across all models but statistically significant only under the long-run DFE specification, suggesting that adequate rainfall enhances the availability and uptake of soil nutrients, thereby supporting higher crop productivity. In contrast, the interaction between temperature and rainfall is insignificant in all cases, suggesting a limited effect on agricultural output. At the crop level, the interaction between soil nutrients and rainfall remains positive for nearly all crops, though it is significant only in the long-run estimates for beans, coffee, tea, and wheat during the 1980–2021 period. The interaction between temperature and irrigation shows mixed effects – positive and significant for tea and millet, but negative and significant for beans and cotton.

Table 7. Estimation results for the 1980-2000 period with interaction between adaptation (Source: own elaboration)

	FE	DFE		PMG	
		Short run	Long run	Short run	Long run
Land	0.091 (0.514)	0.776*** (0.227)	-0.405 (0.540)	0.275 (0.460)	1.037*** (0.194)
Labor force	-0.081 (0.130)	-0.018 (0.094)	0.230 (0.219)	-0.087 (0.169)	0.191** (0.075)
Capital	0.155** (0.058)	0.021 (0.019)	0.185*** (0.069)	0.029 (0.018)	0.051* (0.028)
Irrigation	0.834 (1.106)	0.155 (0.540)	1.208 (3.181)	-1.306 (0.880)	-2.063 (3.507)
Soil nutrients	0.0001 (0.046)	0.008 (0.043)	-0.764** (0.354)	0.137 (0.091)	-3.046 (3.403)
Rainfall	0.099* (0.052)			0.061 (0.047)	-2.815 (3.404)
Temperature	0.729** (0.315)	-0.523 (0.374)	0.949 (1.268)	-1.307 (0.880)	-1.538 (3.319)
Rainfall * Soil Nutrient		0.026 (0.035)	0.727*** (0.342)	-0.022 (0.018)	3.092 (3.402)
Temperature* irrigation	-0.493 (1.095)	-0.144 (0.532)	-0.821 (3.156)	1.307 (0.880)	2.575 (3.503)

	FE	DFE Short run	DFE Long run	PMG Short run	PMG Long run
Error correction		-0.148*** (0.027)		-0.233*** (0.074)	
Number of observations	462			451	451
CD test		47.484 ***		47.486***	
Hausman test P-value		16.39 0.4371			
R^2	0.25				

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form. Short-run variables are presented in first-difference (Δ), while long-run variables are in the level form. The state omitted rainfall due to collinearity with the new variable Rainfall * Soil Nutrient

Table 8. Estimation results for the 2000-2021 period with interaction between adaptation (Source: own elaboration)

	FE	DFE		PMG	
		Short run	Long run	Short run	Long run
Land	-0.274 (0.941)	0.571 (0.573)	2.431 (2.014)	-3.235 (3.122)	1.961*** (0.582)
Labor force	-0.771*** (0.315)	-0.561 (0.502)	0.296 (0.439)	0.130 (0.887)	-0.076 (0.119)
Capital	-0.0003 (0.048)	0.0004 (0.032)	0.061 (0.128)	0.025 (0.051)	0.059*** (0.020)
Irrigation	-1.137 (1.551)	-0.907 (0.826)	0.154 (5.243)	-0.554 (0.475)	0.605 (0.067)
Soil nutrients	0.120 (0.107)	0.030 (0.084)	-0.700 (0.568)	-0.172 (0.146)	0.770*** (0.129)
Rainfall	0.199** (0.064)				
Temperature	0.457 (0.371)	-0.523 (0.422)	0.998 (1.385)	0.178 (0.604)	0.616 (0.095)
Rainfall * Soil Nutrient		0.037 (0.057)	0.568 (0.501)	0.113*** (0.039)	-0.397 (0.144)
Temperature* irrigation	1.816 (1.583)	0.876 (0.780)	-0.002 (5.214)	0.549 (0.738)	-0.603 (0.004)
Error correction		-0.159*** (0.046)		-0.305*** (0.114)	
Number of observations	242			451	242
CD test		34.785***		34.784***	
Hausman test P-value		146.33 0.1189			
R^2	0.73				

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form. Short-run variables are presented in first-difference (Δ), while long-run variables are in the level form. The state omitted rainfall due to collinearity with the new variable Rainfall * Soil Nutrient

5. Conclusions

Agricultural vulnerability to climate change is closely tied to the atmospheric concentration of temperature fluctuations and rainfall patterns. Climate change poses a significant threat to agricultural production, with its impact contingent on a range of factors, including crop varieties, geographical locations, adaptation measures, technological advancements in production, and the dynamic nature of climatic parameters. It is essential to recognize the existence of both short-term and long-term dimensions within the context of climate change's influence on agriculture. This study contributes to the existing knowledge base by examining the effects of climate change on agricultural output in Eastern African countries using the fixed effects (FE) model and the Autoregressive Distributed Lag (ARDL) model, which effectively addresses various challenges, including the simultaneous estimation of short-term and long-term effects. In general, the study confirms the presence of both short-term and long-term effects between climate variables and agricultural production, both at the aggregate level and the individual crop level.

Table 9. Long-run estimation results for individual crops with interaction between adaptation (1980-2021)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	0.829***	2.953***	1.025***	0.973***	1.087***	0.166	1.166***	1.081***	0.840***	1.028***	0.971***	1.014***
	(0.049)	(0.338)	(0.018)	(0.076)	(0.034)	(0.169)	(0.093)	(0.050)	(0.054)	(0.056)	(0.062)	(0.023)
Labor	0.294**	-0.003	-0.270**	0.555***	0.132	-0.192	-0.389*	-0.270***	0.030	0.255	0.068	-0.346***
	(0.107)	(0.153)	(0.126)	(0.146)	(0.091)	(0.187)	(0.251)	(0.072)	(0.107)	(0.187)	(0.182)	(0.091)
Capital	0.173***	-0.009	0.017	0.205***	-0.034	0.018	0.162**	0.045**	-0.0008	-0.006	-0.019	0.194***
	(0.040)	(0.057)	(0.021)	(0.039)	(0.025)	(0.065)	(0.065)	(0.022)	(0.034)	(0.068)	(0.024)	(0.030)
Irrigation	-0.402	-0.903***	0.423	-0.755***	-2.198**	0.609	-2.115		0.336		-4.704***	0.354
	(1.912)	(0.127)	(0.805)	(1.675)	(0.993)	(2.405)	(3.105)		(0.149)		(1.383)	()1.531
Soil nutrients	-0.518	-2.177*	-1.789***	0.076	-0.248		-0.016	1.724**		2.640	-0.225	-0.261*
	(0.706)	(0.850)	(0.495)	(0.865)	(0.153)		(0.345)	(0.747)		(33.516)	(0.208)	(0.141)
Rainfall	-0.543	-2.403***	-1.384***	0.811		0.144		2.024***	-0.153**	0.194		
	(0.665)	(0.826)	(0.430)	(0.786)		(0.264)		(0.771)	(0.141)	(0.205)		
Temperature	-0.884	-2.914	0.497***	-0.309		4.644***	0.375	7.922***	-0.680	-2.897	-0.151	0.421
	(0.951)	(2.103)	(0.124)	(0.456)		(0.658)	(0.673)	(1.562)	(0.621)	(33.510)	(0.193)	(0.903)
Rainfall* Soil Nutrients	0.432	2.343***	1.821***	-0.073	0.236	0.166	-0.306	-1.721**	0.031	0.003	0.361*	0.252***
	(0.702)	(0.844)	(0.494)	(0.862)	(0.146)	(0.110)	(0.330)	(0.750)	(0.039)	(0.043)	(0.207)	(0.140)
Temperature* Irrigation	0.604	-0.903***	-0.409	0.523	2.193**	-0.413	2.272	-3.848***	-0.283	-2.897	4.695***	-0.047
	(1.884)	(0.127)	(0.789)	(1.666)	(0.960)	(2.381)	(3.064)	(0.077)	(1.376)	(33.510)	(1.361)	(1.542)
Error correction	-0.254***	-0.374***	-0.370***	-0.409***	-0.561***	-0.165***	-0.321***	-0.378***	-0.579***	-0.197***	-0.166***	-0.391***
	(0.097)	(0.088)	(0.109)	(0.083)	(0.141)	(0.076)	(0.083)	(0.132)	(0.089)	(0.047)	(0.054)	(0.096)
Observations	447	369	410	451	369	410	410	410	451	451	410	451
Log likelihood	548.08	115.24	307.79	188.51	119.12	317.6	124.38	116.20	41.0	421.53	20.329	372.31

Notes: Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

Table 10. Long-run estimation results for individual crops with interaction between adaptation (2000-2021)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	1.015*** (0.029)	1.769*** (0.987)	0.802*** (0.030)	0.313*** (0.082)	1.077*** (0.022)	0.087 (0.188)	1.565*** (0.071)	1.014*** (0.023)	1.196*** (0.081)	0.630*** (0.219)	0.596*** (0.070)	0.571*** (0.042)
Labor	-0.023 (0.035)	0.146 (0.306)	0.359*** (0.071)	-0.751*** (0.281)	-0.079 (0.061)	0.319 (0.340)	-1.489*** (0.351)	-0.346*** (0.091)	0.503** (0.252)	-0.967*** (0.332)	0.600*** (0.094)	-0.157** (0.069)
Capital	0.019** (0.009)	-0.099 (0.099)	0.095*** (0.008)	0.319*** (0.057)	0.062*** (0.021)	0.040 (0.095)	0.015 (0.065)	0.194** (0.030)	0.177*** (0.059)	0.239 (0.037)	-0.088*** (0.018)	0.237*** (0.034)
Irrigation	-1.095 (1.335)		-3.524*** (0.805)		-5.233 (5.996)	1.147*** (0.056)	9.568*** (3.041)	0.354 (1.531)	1.640 (3.375)	0.441*** (0.092)	-3.165*** (0.426)	1.981* (1.200)
Soil nutrients	-0.075 (0.280)		-0.298*** (0.092)	-1.135 (0.946)		0.079 (0.262)		-0.261*** (0.141)			0.546 (0.462)	
Rainfall	-0.129 (0.257)	-1.334*** (0.270)		-0.557 (0.891)	0.008 (0.033)				-0.159 (0.213)	-0.051 (0.212)	0.174 (0.477)	0.136 (0.100)
Temperature	1.094 (1.211)	-7.817*** (2.950)	-1.049 (0.710)	2.110 (1.744)	-4.469*** (0.379)	5.183*** (0.640)	0.320 (0.270)	0.421 (0.903)	-4.757*** (2.415)	5.172 (4.726)	-0.061** (0.028)	2.281** (1.128)
Rainfall* Soil Nutrients	0.102 (0.259)	-0.007 (0.156)	-0.061 (0.081)	0.643 (0.936)	0.008 (0.019)	-0.035 (0.286)	-0.357*** (0.130)	0.252* (0.140)	-0.433*** (0.107)	0.037 (0.172)	-0.465 (0.451)	-0.136*** (0.050)
Temperature* Irrigation	0.678 (1.292)	-0.958*** (0.289)	3.327*** (0.127)	0.553*** (0.175)	5.288*** (0.162)	-8.662*** (3.109)	-5.618** (2.715)	-0.047 (1.524)	-3.194 (3.473)	5.379 (5.403)	1.142*** (1.142)	-1.572*** (1.185)
Error correction	-0.265*** (0.135)	-0.407*** (0.094)	-0.679*** (0.173)	-0.417*** (0.128)	-7.712*** (0.202)	-0.238*** (0.078)	-0.401** (0.171)	-0.391*** (0.096)	-0.513*** (0.139)	-0.141 (0.106)	-0.401*** (0.172)	-0.638*** (0.152)
Observations	238	198	220	451	198	220	220	410	242	242	220	242
Log likelihood	410.38	139.91	286.02	188.51	200.61	195.52	108.65	372.31	212.36	375.81	182.95	316.50

Notes: Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

The study reveals that, regardless of whether the analysis is conducted at the aggregate level, crop level, or over longer or more recent periods, the included variables exhibit long-term effects on agricultural output. However, there are notable differences in the impact of climate variables, particularly temperature and rainfall, on agricultural production at the aggregate level, which are influenced by the temporal and methodological context. In the short run, climate variables generally have limited significance, with temperature showing negative and significant effects under DFE over the period 1980–2021. In the FE model, temperature has a positive and significant effect in both the 1980–2021 and 2000–2021 periods. In contrast, long-run analysis highlights a positive and significant impact of rainfall on aggregate agricultural production under DFE and PMG under of the period 1980–2021. Rainfall, however, demonstrates a more dynamic impact, shifting from being insignificant during 1980–2021 to positive and significant in the later period under the FE model. Conversely, under the PMG estimates, rainfall exhibits an opposite trend, transitioning from a positive effect in the earlier period to a negative one in the later period. This finding is consistent with recent research, such as the study by Azdagaz et al. (2025) which found that the PMG estimator reveals homogeneous long-run relationships of climate change with agricultural productivity despite heterogeneous short-term dynamics in developing countries.

In the case of specific crops, an increase in rainfall has a positive influence on production, with crops such as maize, millet, cotton, sorghum, and tea exhibiting significant positive responses over the period 1980-2021. The PMG estimates corroborate this trend, particularly highlighting the beneficial long-run effects of higher rainfall on coffee, maize, cotton, sorghum, and tea. In contrast, the effects of temperature are more mixed and crop-specific. While higher temperature has a positive impact on coffee, cotton, and sugarcane over 1980–2021, it negatively affects millet, sorghum, and tea production. However, between 2000 and 2021, an increase in temperature has a positive influence on other crops, including bananas, coffee, millet, and potatoes, while reducing the production of beans, cotton, and sorghum. These effects are particularly pronounced in countries such as Kenya, Tanzania, and Uganda, which are leading bean producers, as well as in Ethiopia and Tanzania, which are major sorghum producers, and in Tanzania and Zimbabwe, which are significant cotton producers.

A comparison of the periods 1980–2021 and 2000–2021 reveals consistent long-run temperature effects in the aggregate analysis, but considerable variability in rainfall impacts. At the individual crop level, the analysis indicates that beans consistently face negative temperature impacts, while coffee and potatoes benefit from positive effects across both periods. Notably, bananas experience a shift from negative effects in the earlier period to positive effects in the later one, whereas the impact on cotton reverses from positive to negative. Additionally, millet and sorghum are adversely affected only during the more recent period. These findings emphasize the importance of developing crop- and region-specific adaptive strategies to address the varied effects of climate variables, thereby ensuring resilience in agricultural production amidst changing climatic conditions.

Given the significant long-run influence of climate change and irrigation on agricultural production, policymakers should prioritize investments in irrigation infrastructures and climate-resilient agricultural practices and technologies – such as those outlined in the Kenya Climate-Smart Agriculture Strategy 2017–2026 (2017). These efforts should consider the varying effects of climate variables on different types of crops to advance the goals of the Comprehensive Africa Agriculture Development Programme (CAADP), the African Union's initiative to enhance food security, increase agricultural investment, and promote agriculture-led growth under Agenda 2063. Based on the consistent positive influence of rainfall on agricultural value in the long-run, policymakers should emphasize not only water management policies and smart agriculture to ensure sustainable access to water resources but also how to use available water resources given huge potential water resources (both surface and groundwater) in Uganda, Ethiopia, Kenya, and Tanzania. Further research is necessary to understand the underlying mechanisms of the varying effects of climate variables on different types of crops, including the physiological and agronomic responses of various crop species to changing temperature and rainfall patterns. Additionally, statistical data on agricultural production at the sub-national level is needed to provide more detailed analysis for individual countries, enabling the development of targeted and effective climate change mitigation strategies.

Data availability statement

The datasets utilized in this study can be accessed through the World Bank Group Climate Change Portal, the FAOSTAT database, the African Development Bank, and the World Development Indicators. Additionally, all data can be obtained from the corresponding author upon reasonable request.

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Appendix

Table A1. Stationarity test

Variable	LLC test		IPS test	
	no trend	trend	no trend	trend
Gross Production Value of agriculture	0.8937	-0.9978	2.9963	-3.0238***
Agricultural land	-1.7133 **	-0.0088	2.3494	0.3589
Agricultural labor force	-2.1863**	-1.1492	2.1619	0.1298
Irrigated land area	-3.2044***	-1.6521**	-3.8566***	-1.1359
Annual rainfall	-8.0463***	-8.4424***	-11.0980***	-12.3002***
Annual temperature	-3.9738***	-6.3998***	-4.8001***	-9.6761***
Soil Nutrient	-1.0172	-2.0234 **	1.2567	-1.7464**
Capital	2.2601	-2.5502***	2.2601	-2.5502***
Banana production	-0.9675	-2.4595***	-1.3962*	-3.5320***
Beans production	-0.8495	-1.4404*	-2.4477***	-5.3371***
Coffee production	0.0814	-2.1667**	-2.9121***	-5.3321***
Maize production	-1.8084**	-2.4151**	-4.2052***	-6.5667***
Millet production	-1.8098**	-2.0199**	-6.2339***	-7.5875***
Potato production	4.6411	3.4591	2.9660	-1.8739*
Rice production	1.6562	-1.8942*	-1.4606*	-4.4849***
Cotton production	-3.6304***	-3.1526***	-4.7290***	-6.9491 ***
Sorghum production	-2.7376***	-3.0639***	-8.2788***	-9.3570***
Sugarcane production	-1.8472*	-2.0852*	-3.3401***	-5.2063***
Tea production	1.0950	1.9157	0.7140	-1.8936*
Wheat production	0.3207	0.0610*	-2.8677**	-6.6070***
First difference				
Gross Production Value of agriculture	-10.9166***	-8.6379***	-12.7217***	-12.8448***
Agricultural land	-7.9814***	-7.1271	-10.1963***	-10.8649***
Agricultural labor force	-5.8842***	-4.6912***	-8.7264***	-9.2373**
Irrigated land area	-6.2278***	-5.7010***	-8.6944***	-9.1216***
Annual rainfall	-21.2926***	-17.6094***	-15.8598***	-15.8536***
Annual temperature	-20.4048***	-16.9054***	-14.8866***	-14.9311***
Soil Nutrient	-9.3525***	-7.3547***	-11.7441***	-11.9607***
Capital	-9.5850***	-7.7166***	-9.5850***	-7.7166***
Population density	-1.1990	-2.3265**	-3.2620***	-4.1825***
Banana production	-11.5681***	-10.4264***	-12.2938***	-12.6326***
Beans production	-10.9077***	-9.6379***	-12.4558***	-12.5193***
Coffee production	-9.9350	-8.4102	-12.7802	-12.9784
Maize production	-14.5340***	-12.2946***	-13.1656***	-13.1674
Millet production	-13.9992***	-11.8214***	-13.2141***	-13.2372***
Potato production	-4.4119***	-5.9505***	-10.5567***	-11.8589***
Rice production	-10.1503***	-9.2324***	-12.4666***	-12.7849***
Cotton production	-11.1903***	-8.8734***	-12.9945***	-13.0272***
Sorghum production	-10.7008***	-8.6978***	-14.8455***	-14.8660***
Sugarcane production	-8.4717***	-6.9340***	-12.1432***	-12.2455***
Tea production	-7.3184***	-6.9576***	-11.5753***	-12.0241***
Wheat production	-10.1885***	-8.3310***	-14.0864***	-14.2005***

Note: (1): Standard errors in parentheses (2) ***, **, and * show 1%, 5%, and 10% of significance level, respectively

Table A2. Cointegration Test

Pedroni test			
H_0: No cointegration	Statistics		
Modified Phillips–Perron t	1.9348**	Time trend:	Not included
Phillips–Perron t	-1.7415**	AR parameter:	Panel specific
Augmented Dickey–Fuller t	-1.6097*	Kernel:	Bartlett
Number of panels	11	Lags:	3.00 (Newey–West)
Number of periods	41	Augmented lags:	1
Cointegrating vector:	Panel specific		
Panel means:	included		
Kao test			
H_0: No cointegration	Statistics		
Modified Dickey–Fuller t	-2.5851***	Time trend:	not included
Dickey–Fuller t	-1.7693**	AR parameter :	Same
Augmented Dickey–Fuller	-0.5719	Number of panels :	11
Unadjusted modified Dickey–Fuller t	-4.3520***	Lags:	2.18(Neway-West)
Un adjusted Dickey-Fuller t	-2.4816***	Augmented lags:	1
Number of periods	40		
Cointegrating vector:	Same		
Panel means:	included		

Note: *** , and * show rejection of no cointegration at 1%, 5%, and 10% of significant level

Table A3. Testing for slope heterogeneity

Testing for slope heterogeneity
(Blomquist, Westerlund. 2013. Economic Letters)
H0: slope coefficients are homogenous

	Delta	p-value
	1.305	0.192
adj.	1.643	0.100

HAC Kernel: bartlett
with average bandwith 3
Variables partialled out: constant

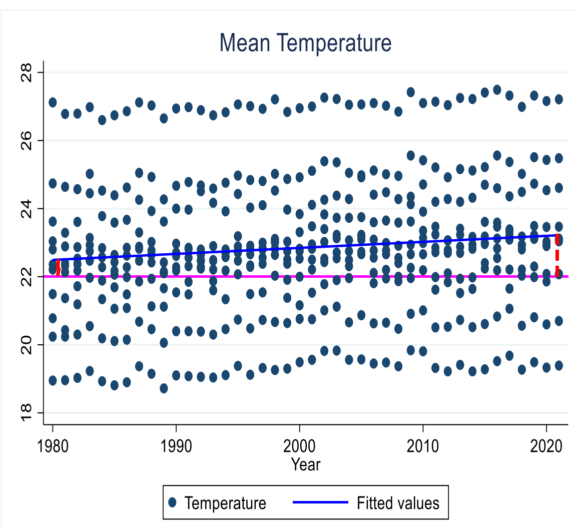

Fig. A1. Mean temperature over time

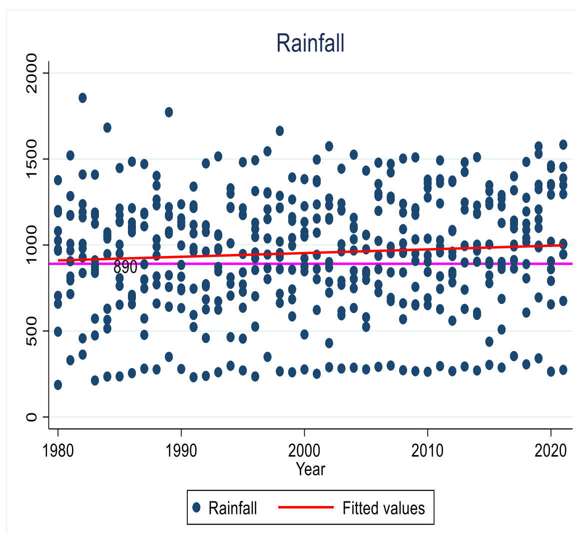

Fig. A2: Mean rainfall over time

Table A4. Results of PMG estimation (Short-run, 1980-2021) (Source: own elaboration)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Error correction	-0.127*** (0.079)	-0.374*** (0.088)	-0.377*** (0.111)	-0.359*** (0.088)	-0.544*** (0.147)	-0.180** (0.072)	-0.380*** (0.112)	-0.384*** (0.129)	-0.433*** (0.083)	-0.208*** (0.059)	-0.115*** (0.035)	-0.314*** (0.092)
Land	0.568*** (0.148)	0.035 (0.972)	0.487*** (0.138)	0.407*** (0.060)	0.269 (0.173)	0.703*** (0.164)	-0.739 (0.641)	0.397*** (0.147)	0.667 (1.106)	0.938* (0.502)	1.292* (0.707)	0.536 (0.505)
Labor	0.465 (0.296)	0.456 (1.193)	0.797* (0.465)	0.458 (0.611)	0.968 (0.792)	0.510 (0.440)	0.550 (0.514)	0.123 (0.470)	-0.149 (0.875)	0.321 (0.580)	-0.924 (0.685)	0.678 (0.653)
Capital	-0.032 (0.046)	0.171* (0.102)	0.090 (0.067)	0.182*** (0.060)	0.147** (0.074)	0.127 (0.120)	0.078 (0.101)	-0.045 (0.113)	0.090 (0.178)	0.017 (0.042)	0.172 (0.145)	0.048 (0.052)
Irrigation	-0.226 (0.206)	-0.690 (0.810)	0.331 (0.302)	-0.101 (0.326)	-0.608 (0.369)	0.215 (0.319)	0.260 (0.410)	-0.152 (0.299)	-0.205 (0.395)	-0.269 (0.485)	0.215 (0.213)	
Soil nutrients	0.109 (0.179)	-0.204 (0.199)	0.143 (0.110)	0.136 (0.362)	-0.350 (0.483)	-0.012 (0.071)	-0.096 (0.312)	0.125 (0.230)	-0.246 (0.382)	0.021 (0.203)	-0.038 (0.129)	0.464 (0.601)
Rainfall	0.127 (0.081)	-0.145 (0.135)	-0.167** (0.072)	0.154 (0.123)	0.172 (0.125)	-0.025 (0.053)	0.175 (0.167)	0.043 (0.093)	0.210 (0.178)	0.123 (0.197)	-0.73 (0.215)	0.076 (0.113)
Temperature	1.370** (0.595)	1.328 (0.827)	-0.862 (0.749)	-2.103** (0.884)	-1.111 (1.634)	-0.595 (0.691)	-2.591*** (0.792)	-1.363 (0.863)	-2.270* (1.244)	-0.076 (0.074)	-2.662* (1.465)	-3.772** (1.337)
Constant	2.757 (1.807)	-4.820*** (1.145)	-0.996*** (0.266)	-1.444*** (0.339)	-5.818*** (1.574)	-1.718** (0.744)	-15.505*** (4.773)	-6.551 (2.306)	-3.021*** (0.679)	-0.531 (1.041)	4.126*** (1.295)	-10.973 (3.224)
Num. of obs.	447	369	410	431	369	410	410	410	451	451	410	451
Log likelihood	547.63	115.24	304.90	195.18	157.41	310.47	17.34	116.26	24.95	241.72	20.32	10.37

Note: (1): Standard errors in parentheses (2) ***, **, and * show 1%, 5%, and 10% of significance level, respectively; all variables are expressed in logarithmic form. AS short-run, variables are presented in first-difference (Δ).

Table A5. Results of PMG estimation (Short-run, 2000-2021) (Source: own elaboration)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Error correction	-0.280* (0.143)	-0.535*** (0.094)	-0.684*** (0.172)	-0.421** (0.126)	-0.709*** (0.203)	-0.380** (0.109)	-0.478** (0.173)	-0.369*** (0.157)	-0.512*** (0.109)	-0.306*** (0.082)	-0.227*** (0.100)	-0.585*** (0.153)
Land	0.175 (0.172)	0.654 (0.922)	0.191 (0.191)	0.350** (0.153)	-0.098 (0.220)	0.441*** (0.165)	-1.719 (1.195)	0.501*** (0.163)	0.244 (1.021)	1.676 (1.148)	-0.572 (1.107)	-0.771 (0.932)
Labor	-3.099 (2.128)	-2.428 (2.106)	1.724 (2.125)	-3.977* (2.368)	-1.472 (2.910)	-2.559* (1.059)	-2.805 (3.422)	-1.296 (1.618)	-1.596 (4.098)	4.650 (3.448)	0.363 (2.647)	-1.435 (2.493)
Capital	-0.074 (0.154)	0.038 (0.182)	-0.030 (0.096)	0.142 (0.077)	0.175 (0.186)	0.198 (0.191)	0.079 (0.247)	-0.003 (0.125)	-0.464 (0.284)	-0.058 (0.124)	0.537 (0.424)	-0.136 (0.180)
Irrigation	-1.750 (1.092)	-1.218 (1.195)	-0.732 (1.387)	-2.396 (2.587)	-1.918 (2.917)	0.671 (0.631)	6.482** (3.215)	-1.080 (1.615)	-1.209 (2.927)	1.883 (1.560)	-2.038 (9.331)	
Soil nutrient	0.465 (0.568)	-0.073 (0.466)	0.649** (0.283)	0.262 (0.242)	-0.545 (0.702)	-0.023 (0.229)	0.357 (0.453)	0.467 (0.388)	-0.650 (0.717)	-0.039 (0.318)	0.474 (0.293)	0.846 (0.602)
Rainfall	0.161 (0.114)	-0.231** (0.101)	-0.039 (0.080)	0.115 (0.142)	0.169* (0.127)	0.061 (0.101)	0.326 (0.311)	0.047 (0.158)	0.506*** (0.154)	-0.034 (0.059)	-0.629 (0.429)	0.122 (0.235)
Temperature	2.099** (0.822)	0.802 (1.280)	-0.911 (0.997)	-2.396** (1.106)	-0.139 (1.441)	-1.034 (1.897)	0.138 (2.924)	0.013 (2.203)	-2.072 (1.592)	3.030* (1.642)	-2.603 (2.908)	-0.429 (2.664)
Constant	0.469 (0.161)	-10.447*** (1.902)	-1.391*** (0.408)	5.373*** (1.677)	-3.344*** (0.975)	-1.419 (0.471)	-25.051** (9.567)	9.431 (3.772)	25.209*** (5.513)	-11.786*** (3.094)	0.063 (0.740)	-5.808*** (1.506)
Num. of obs.	238	198	220	242	198	220	220	220	242	242	220	242
Log likelihood	405.92	137.54	275.02	170.54	191.27	187.75	43.18	163.88	75.29	243.68	44.58	109.79

Note: (1): Standard errors in parentheses (2) ***, **, and * show 1%, 5%, and 10% of significance level, respectively; all variables are expressed in logarithmic form. AS short-run, variables are presented in first-difference (Δ).

Table A6. FE estimation results (1980-2021) (Source: own elaboration)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	1.077*** (0.031)	-0.041 (0.359)	1.117*** (0.029)	0.825*** (0.075)	1.048*** (0.049)	1.234*** (0.057)	1.040*** (0.396)	0.854*** (0.057)	0.806*** (0.262)	1.220*** (0.363)	-0.819* (0.423)	0.444 (0.386)
Labor	-0.093 (0.129)	-0.021 (0.190)	0.463*** (0.161)	0.132 (0.134)	-0.075 (0.202)	0.230 (0.147)	0.694*** (0.264)	-0.731*** (0.195)	0.526*** (0.162)	0.118 (0.235)	-0.337 (0.280)	1.313*** (0.309)
Capital	0.049 (0.025)	0.389*** (0.068)	0.231*** (0.047)	0.214*** (0.039)	0.132*** (0.045)	0.111** (0.043)	0.157** (0.080)	0.327*** (0.054)	0.128** (0.059)	0.155* (0.016)	0.396*** (0.093)	0.425*** (0.087)
Irrigation	0.238*** (0.040)	0.004 (0.099)	-0.440*** (0.069)	-2.396 (2.587)	0.028 (0.080)	0.022 (0.067)	0.305*** (0.105)	0.051 (0.090)	1.209 (2.927)	-0.514*** (0.107)	-0.352*** (0.105)	
Soil nutrients	-0.148*** (0.009)	0.186*** (0.029)	0.089*** (0.013)	0.035*** (0.013)	0.046*** (0.016)	0.031*** (0.011)	0.709*** (0.103)	-0.042** (0.017)	0.107*** (0.019)	-0.025 (0.024)	0.273*** (0.021)	0.014 (0.026)
Rainfall	0.037 (0.095)	-0.123 (0.321)	-0.200 (0.178)	0.485*** (0.159)	0.490** (0.208)	0.128 (0.167)	0.175 (0.265)	1.735*** (0.491)	0.691*** (0.194)	-0.147 (0.243)	0.923** (0.358)	-0.001 (0.321)
Temperature	-0.457* (0.273)	1.155 (3.706)	0.923** (0.362)	-0.474 (0.461)	-4.860*** (0.509)	0.660 (0.911)	-0.445 (0.667)	0.328* (0.192)	-0.870*** (0.762)	1.229** (0.600)	-3.673*** (0.627)	1.441 (0.924)
Observations	458	378	420	462	378	420	420	420	462	462	420	462
R^2	0.99	0.92	0.97	0.96	0.96	0.96	0.96	0.93	0.96	0.89	0.92	0.92

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

Table A7. FE estimation results (2000-2021) (Source: own elaboration)

	Banana	Bean	Coffee	Maize	Millet	Potato	Rice	Cotton	Sorghum	Sugarcane	Tea	Wheat
Land	0.759*** (0.060)	3.519*** (0.562)	0.864**** (0.061)	0.746*** (0.091)	0.861*** (0.074)	1.170*** (0.080)	1.220** (0.526)	0.837*** (0.074)	0.765 (0.464)	1.610*** (0.454)	0.909 (0.643)	2.472*** (0.577)
Labor	-0.516* (0.268)	-0.099 (0.308)	0.609** (0.301)	-0.093 (0.308)	-0.484** (0.348)	1.346*** (0.257)	-1.149** (0.439)	0.736* (0.402)	1.384*** (0.406)	0.466* (0.267)	0.621 (0.645)	0.048 (0.437)
Capital	-0.0005 (0.037)	0.167* (0.097)	0.497*** (0.079)	0.200*** (0.075)	0.001 (0.070)	0.138*** (0.052)	-0.048 (0.125)	0.132** (0.066)	0.024 (0.085)	0.166*** (0.057)	0.473*** (0.130)	0.444*** (0.110)
Irrigation	0.700*** (0.155)	-0.705** (0.0276)	-0.511*** (0.168)	-0.100 (0.172)	0.820*** (0.182)	0.152 (0.152)	0.883** (0.353)	0.075 (0.171)	1.401*** (0.236)	-1.429*** (0.264)	-0.309 (0.304)	
Soil nutrient	-0.117*** (0.075)	-0.050*** (0.106)	0.195* (0.105)	0.417*** (0.083)	-0.146* (0.084)	0.578*** (0.099)	0.686*** (0.160)	-0.198** (0.076)	0.458*** (0.097)	-0.066 (0.107)	-0.060*** (0.171)	-0.245 (0.163)
Rainfall	0.003 (0.125)	0.220 (0.261)	-0.254 (0.268)	0.545*** (0.186)	0.449** (0.348)	0.176 (0.208)	0.297 (0.292)	0.088 (0.259)	0.795*** (0.246)	0.030 (0.189)	0.858* (0.501)	-0.079 (0.377)
Temperature	-0.203 (0.207)	6.95** (3.085)	1.00*** (0.310)	-0.306 (0.364)	-5.137*** (0.478)	1.376 (0.971)	-1.150* (0.610)	-1.958*** (0.442)	0.158 (0.645)	0.262 (0.262)	-2.696*** (0.681)	-0.277 (0.764)
Constant	8.55** (3.60)	-52.398*** (13.470)	-17.168*** (6.228)	-10.543** (4.643)	15.846*** (5.486)	-39.844*** (3.770)	-10.852 (9.846)	8.740** (3.571)	-9.389** (4.513)	-5.945*** (5.496)	-13.675 (16.533)	-27.415*** (11.573)
Observations	238	198	220	242	198	220	220	220	242	242	220	242
R^2	0.99	0.97	0.98	0.97	0.97	0.97	0.97	0.96	0.97	0.97	0.95	0.96

Notes: FE estimator includes both country and year dummies. Standard errors in parentheses. ***, **, and * show 1%, 5%, and 10% of significance level, respectively. All variables are expressed in logarithmic form.

Table A8. Summary of empirical literature findings (Source: own elaboration)

	Author	Region	Period and methodology	Finding
1	Barrios et al. (2008)	40 SSA and non-SS LDC	1960-1997, panel data	• Climate change significantly affects agricultural production in Sub-Saharan Africa (SSA). The impact on non-SSA countries is not significant.

2	Ben Zaied & Ben Cheikh (2015)	Tunisia	1979–2011, panel cointegration tests	• An increase in temperature negatively influences output in the long-run. At the same time, a rise in rainfall positively affects production.
3	DePaula (2020)	Brazil	2006 survey, Ricardian model	• Temperature increases are more harmful to farms in warm climates. Decreased annual precipitation is more damaging to farms in dry climates. Climate change effects vary significantly across farms.
4	Deressa & Hassan (2009)	Ethiopia	2003/2004, Ricardian model	• Slight temperature rise in winter and summer decreases revenue per hectare, while in spring and fall boosts revenue. Increased summer and fall precipitation slightly reduces the revenue. Overall, a rise in annual precipitation marginally reduces revenue per hectare.
5	Exenberger et al., 2014	127 Countries	1961-2002, common correlated effect	• Climate change does not have a significant impact on agricultural production in high-income countries. However, there are notable adverse effects in middle and low-income countries.
6	Gbetibouo & Hassan (2005)	South Africa	1996, Ricardian model	• On average, the rise in temperature improves net revenue while the impact of increased rainfall is negative (the result varies across agro-ecological zones).
7	Kahsay and Hansen (2016)	Eastern Africa	1980-2006; panel fixed effects	• Higher mean temperature and precipitation during the primary season have a positive and significant impact on output. Variability in precipitation within the growing season negatively influences the output.
8	Maddison et al.(2007)	Africa	2003 survey, Ricardian model	• Climate change is expected to have different impacts on particular African countries. By 2050, Burkina Faso may face a 19.9% production loss and Niger up to 30.5%. Conversely, Ethiopia and South Africa are predicted to suffer minimal impacts, with productivity reductions of just 1.3% and 3%, respectively.
9	Mendelsohn et al. (1994)	US	1982 U.S. agricultural census, Ricardian model	• Crops suffer in hot winters and summers but thrive in warm falls and benefit from more rain in winters and spring.
10	Mendelsohn and Wang (2017)	China	2009 data, Ricardian model	• Wheat productivity remains unaffected by seasonal temperature variations. In contrast, rice production benefits from higher temperatures in the spring and lower temperatures in the fall, as well as lower precipitation during the spring, summer, and autumn months, and increased precipitation during the winter. Maize production, on the other hand, is enhanced by higher temperatures in the spring and autumn, and lower temperatures in the summer and winter, whereas seasonal precipitation patterns have no significant impact on maize yields
11	Nhemachena & Mano (2007)	Zimbabwe	2002/03 and 2003/04, Ricardian model	• Temperature and precipitation significantly influence farm revenue in Zimbabwe. Dry-land farming exhibits higher revenue sensitivity to these factors than irrigated farming.
12	Ochieng et al (2016)	Kenya	2004, 2007 and 2010, augmented production function approach	• Temperature adversely affects maize revenues but has a positive impact on tea ones. Rainfall negatively affects tea production. Tea depends on stable temperatures and consistent rainfall.
13	Ozdemir (2021)	11 Asian countries	1980–2016; ARDL, MG , DFE and PMG	• There exists a long-run connection between agricultural productivity and climate related variables. However, the impacts of CO_2, rainfall and rainfall differ between short-run and long-run.
14	Van Passel et al. (2017)	Europe	2007 survey, Ricardian model	• Warmer marginal temperatures harm Southern European countries but benefit Northern European ones. Changes in temperature and precipitation yield varying impacts across different seasons.
15	Seo & Mendelsohn (2007).	Africa	2003 data, Ricardian model	• Livestock net revenues of large farms in Africa decline as temperatures increase. Small farms are not temperature-sensitive due to the substitution of livestock that is temperature-tolerant. • Increases in precipitation would reduce livestock net revenue per farm for both small and large farms.
16	Zhai et al. (2017)	China	1970-2014; ARDL	• Long-run precipitation during the wheat growth period leads to a decrease in the wheat yields. • No significant short-run or long-run impact of temperature, weak overall impacts of climate change.