

# “Impact of surface temperature change on food production: Evidence from PLFC and MMQR models”


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# IMPACT OF SURFACE TEMPERATURE CHANGE ON FOOD PRODUCTION: EVIDENCE FROM PLFC AND MMQR MODELS

## Abstract

The analysis of the mechanisms through which temperature variations affect food production has become a paramount concern for sustainable development and policy formulation, as global food security faces unprecedented challenges from accelerating climate change. Temperature anomalies are threatening agricultural systems that sustain billions of people worldwide. Using panel data from 40 countries from 1980 to 2021, this study investigates the influence of annual surface temperature fluctuations on food production. The Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) model is estimated to analyze this correlation in the mixed evidence on the integration levels of the variables. The results corroborate the cointegration among the variables. Temperature change has a significant negative effect on food production in both the short and long run. Food production is positively influenced by economic growth and renewable energy consumption. The study also considers potential nonlinearity by utilizing the Partially Linear Functional Coefficient (PLFC) and the Method of Moments Quantile Regression (MMQR) model. The PLFC estimates imply that economies with lower GDP levels are more adversely influenced by temperature change, emphasizing the crucial role of economic growth in mitigating climate change. Significant negative effects of temperature change are also corroborated by the MMQR estimates in all quantiles, with the largest effects obtained at the higher quantiles. The variation in the impact of renewable energy consumption over quantiles implies that energy policies should be modified according to the developmental phases of countries. The empirical findings have significant implications for formulating sustainable agricultural policies and climate adaptation strategies.

## Keywords

temperature anomalies, food production index,  
renewable energy consumption, nonlinear panel data

## JEL Classification

C23, Q54, O13

## INTRODUCTION

Environmental issues are the major drivers of agricultural production, making this sector highly vulnerable to climate crises. Agricultural products are specifically vulnerable to rising temperatures, which can alter growing seasons, disrupt plant growth, exacerbate heat stress, and lead to output variability and decreased crop quality. Raising temperatures also affect resource availability, such as water, while increasing the prevalence of diseases and pests (Chandio et al., 2022b). Climate change additionally confounds crop management by increasing weed and insect populations, raising production costs, and ultimately negatively affecting agricultural yields. Additionally, such temperatures lead to higher evapotranspiration rates, and when combined with reduced moisture levels, adversely affect agricultural growth and economic development (Pickson et al., 2020).

Agricultural output's dependence on climatic conditions underscores its relationship with climate patterns. Temperature variations significantly influence crop growth, development, and yield. Climate extremes, including prolonged droughts, erratic rainfall, and heat waves, present substantial challenges to food production (Pickson et al., 2024). The increasing severity of climate events, such as rising temperatures, altered rainfall patterns, water scarcity, land degradation, and rising sea levels, worsens the challenges. These factors may result in the decline of agricultural systems, ultimately jeopardizing food security in all aspects (Warsame et al., 2022; Bouznit & Aïssaoui, 2024).

Due to insufficient agricultural output to satisfy the needs of an expanding global population, the enhancement of food production has emerged as a critical priority. However, obtaining comprehensive data on climatic factors remains challenging, with surface temperature often serving as the primary meteorological indicator for evaluating the extent of climate change impacting agricultural output (Li, 2023). While CO<sub>2</sub> (carbon emissions) and GHG (greenhouse gas emissions), along with average temperature, serve as climatic variables, land temperature changes have been specifically designed to track warming trends at both national and global levels. This metric is essential for assessing potential risks to food security and agricultural systems (FAO, 2024). Many studies have explored the relationship between climate change and food production. These studies primarily utilized emissions and various forms of crop production as key variables (Ahsan et al., 2020; Attiaoui & Boufateh, 2019). Several studies used the food production index to assess food security (Bouznit & Aïssaoui, 2024; Kibria et al., 2023). While some studies have explored the connection between food production and annual surface temperature changes, they have often focused on specific crops, such as wheat or soybean, instead of using a comprehensive food production index (Demirhan, 2020; Ahumada & Cornejo, 2021). However, to the best of our knowledge, no study has investigated the relationship between overall food production and annual surface temperature changes, which highlights the need for further research in this area.

## 1. LITERATURE REVIEW

As attention has increasingly turned to global warming, academics have begun investigating the relationship between food production and environmental degradation. The studies primarily concentrate on particular crops, including wheat, corn, rice, cereal, sugarcane, and soybean, as well as distinct ecological variables, such as CO<sub>2</sub> levels, average temperature, and GHG emissions, often examining specific cases in developing countries.

Focusing on Tunisia, Zaied and Cheikh (2015) observed that higher annual temperatures reduce cereal production. In the case of Pakistan, Qureshi et al. (2016) found that higher GHG emissions reduced cotton production, although CO<sub>2</sub> levels had an insignificant impact. Furthermore, they reported that a rise in energy demand led to increased cotton production. In the case of wheat production, the results show that both CO<sub>2</sub> levels and energy demand increase wheat production, whereas GHG emissions decrease it. Attiaoui and Boufateh (2019) determined that an increase in temperature results in a significant decline in cereal production

in Tunisia. Silva et al. (2019) reported that temperature reduces sugarcane production in Brazil. Simionescu et al. (2019) reported a positive connection between the previous year's GHG emissions and cereal production in European Union countries. Chandio et al. (2020) revealed that CO<sub>2</sub> emissions had no significant effect on agricultural production in Pakistan. Focusing on China, Pickson et al. (2020) found significant negative long-term effects of CO<sub>2</sub> emissions, average temperature, and temperature variability on cereal production. Conversely, energy consumption and cultivated area have significant positive long-term effects.

Focusing on Turkiye, Chandio et al. (2021a) concluded that both higher CO<sub>2</sub> emissions and higher temperatures significantly reduced wheat production, whereas higher precipitation increased it. Regarding rice production, temperature had a positive effect, whereas CO<sub>2</sub> emissions decreased it. The cultivated area has increased both rice and wheat production. In Nepal, Chandio et al. (2021b) showed that a 1% decrease in CO<sub>2</sub> emissions was associated with a 0.13% decrease in rice

production, whereas a 1% increase in average temperature was associated with a 0.72% increase in rice production. Kumar et al. (2021) identified a long-term link between India's rice production and climate change. The empirical findings indicate that carbon and ecological footprints have adverse and significant impacts on long-term rice production. Using a nonlinear Granger causality test, Koondhar et al. (2021) found causality runs from energy consumption to cereal food production in Pakistan. Specifically, cereal food production Granger-causes energy consumption and agricultural carbon emissions in both the long and short run.

Focusing on Punjab, Pakistan, Abbas et al. (2022) demonstrated that wheat cultivated area, total irrigated area, total unirrigated area, and total sown area significantly increased wheat production in the long term. Chandio et al. (2022a) found that CO<sub>2</sub> emissions and temperature reduced maize production, whereas higher precipitation and greater cultivated area increased it. This study identified a bidirectional causal relationship between cultivated land and maize production. Chandio et al. (2022c) found that a greater cultivated area and energy consumption increased cereal production in Bangladesh, whereas higher CO<sub>2</sub> levels significantly decreased it, as did higher temperatures in the short term. From their analysis of 30 Chinese provinces, Pickson et al. (2022) concluded that higher average temperatures reduce rice production in the long run. In contrast, a larger cultivated area increases it in the long term. In contrast, the higher average temperature and greater cultivated area both had positive short-term impacts on rice production. For Somalia, Warsame et al. (2022) reported that higher average temperatures significantly reduced sorghum production in the long term, whereas greater cultivated areas increased sorghum production. In Malaysia, Xiang and Solaymani (2022) found that higher temperatures and CO<sub>2</sub> levels reduced cereal production, whereas cultivated cereal land per hectare and energy consumption increased it, both in the short and long run. Focusing on Japan, Li (2023) discovered an inverted U-shaped association between temperature and rice production, whereas precipitation and wind speed had negative effects, and sunshine duration had a positive impact.

Other studies have adopted a broader perspective by focusing on groups of countries based on panel data analysis. For example, Kumar et al. (2021) demonstrated that higher temperatures reduced cereal production for eleven low-middle-income countries, whereas carbon emissions and greater cultivated areas increased it. For major rice-producing countries in Asia, Chandio et al. (2022b) revealed that both CO<sub>2</sub> emissions and temperature significantly reduce the production of rice. Focusing on nine East African countries, Abdi et al. (2023) found that CO<sub>2</sub> emissions have a significant positive long-term effect on cereal production, whereas cultivated areas are positively associated with short- and long-term cereal production. However, higher average temperatures reduce cereal production in both the short and long run. For six South Asian countries, Chandio et al. (2023) found that temperature and CO<sub>2</sub> emissions reduce crop production, while cultivated areas and income levels have positive long-term effects. The causal relationships among all the variables are significant. For six South Asian countries, Kibria et al. (2023) reported that land usage and the food production index increased cereal production. In contrast, increased agricultural CO<sub>2</sub> emissions reduced production in the long term. Pickson et al. (2024) discovered that expanding cultivated areas results in higher cereal production in African nations. Pickson et al. (2023) found a significant impact of temperature on food production in Asian countries.

Instead of focusing on particular food types, other studies have taken a broader perspective on food production through the food production index. This index encompasses a variety of nutrient-rich edible crops (The World Bank, n.d.), enabling researchers to analyze different nutritious food crops in the context of food production trends, thereby enhancing the understanding of the factors influencing global food production. Mahrous (2019) investigated the relationship between the food production index and climate change in six East African countries, revealing that an expansion in cultivation area enhances food security, whereas elevated temperatures negatively impact it. Ceasay and Ndiaye (2022) illustrate that the effects of economic growth can be either positive or negative,

contingent upon the time lag involved. Fusco (2022) examined 19 African countries and found that increased temperatures negatively impacted the food production index. The findings also underscore the importance of economic development in that higher GDP (gross domestic product) per capita and a larger cultivated area are associated with a higher food production index. Additionally, CO<sub>2</sub> emissions reduce maize production. For Algeria, Bouznit and Aïssaoui (2024) reported that higher temperatures reduce the food production index, and CO<sub>2</sub> emissions have no long-term effect. Finally, Fagbemi et al. (2023) revealed that rising CO<sub>2</sub> emissions reduce food production in Sub-Saharan African countries, whereas enhanced economic performance increases the food production index.

Few studies have examined the relationship between climate anomalies and food production. Demirhan (2020) found significant long-term correlations between climate anomalies, wheat production, and temperature with an adjustment rate of 55%. Specifically, increasing temperatures significantly reduce global wheat production in the long run, but rising CO<sub>2</sub> emissions increase it. These findings also suggest a causal relationship in which CO<sub>2</sub> emissions contribute to wheat production. Focusing on Argentina, Ahumada and Cornejo (2021) find that temperature anomalies decrease soybean yields, whereas carbon emissions increase them. In addition, global temperature anomalies and CO<sub>2</sub> emissions were cointegrated with soybean yields.

The literature review demonstrated the lack of consensus regarding the relationship between climate change and crop production. Majority of the studies have focused on individual countries and have employed narrow climate crisis indicators. While some studies examine country groups, they tend to focus on specific regions despite the global impact of climate change on various food types and countries.

Considering this research gap, the present study aims to analyze the climate change and food production nexus for 40 countries between 1980 and 2021. Recognizing that economic growth, energy consumption, land, and urbanization are key determinants of food production, this study ex-

plores energy consumption more deeply by distinguishing between renewable and fossil sources. Furthermore, the study employed nonlinear methodologies, specifically the MMQR and PLFC models, to investigate the possible nonlinear effect of annual surface temperature change on food production.

In line with this objective, this study tests the following questions: Does annual surface temperature change significantly impact food production? Is there a nonlinear relationship between annual surface temperature change and food production? How do renewable and fossil energy consumption, economic growth, and urbanization influence food production?

## 2. METHOD

This paper employs annual data from 40 countries from 1980 to 2021 to examine the connection between annual surface temperature change, economic development, renewable and fossil energy consumption, and food production. The food production index represents the weighted average of edible and nutrient-rich food crops. To obtain per capita values, it was divided by the population of each country. The surface temperature change, measured as the annual mean surface temperature change, was retrieved from the International Monetary Fund (IMF) database. At the same time, all other variables were obtained from the London Stock Exchange Group (LSEG) database. Table 1 displays the variables, their abbreviations, and their sources. The model estimated in this study can be written as follows:

$$\begin{aligned} \ln food_{it} = & \beta_0 + \beta_1 temp_{it} + \beta_2 \ln gdp_{it} \\ & + \beta_3 \ln ren_{it} + \beta_4 \ln fos_{it} + \beta_5 \ln agrland_{it} \\ & + \beta_6 \ln urb_{it} + \varepsilon_{it}. \end{aligned} \quad (1)$$

All variables are converted into natural logarithms, except for the annual surface temperature change. This variable has negative values, as it is calculated as the deviation from the normal surface temperature, and a logarithmic transformation is not applicable. Detailed information on the variables is presented in Table 1.

**Table 1.** Definitions of variables

Variables	Abbreviation	Sources
Food production per capita	food <sub>it</sub>	LSEG (n.d.)
Annual surface temperature change	temp <sub>it</sub>	IMF (n.d.)
GDP per capita (constant 2010 US\$)	gdp <sub>it</sub>	LSEG (n.d.)
Renewable energy consumption per capita (terawatt hour)	ren <sub>it</sub>	LSEG (n.d.)
Fossil energy consumption per capita (terawatt hour)	fos <sub>it</sub>	LSEG (n.d.)
Agricultural land (% of land area)	agrland <sub>it</sub>	LSEG (n.d.)
Urbanization (urban population, % of total)	urb <sub>it</sub>	LSEG (n.d.)

The descriptive statistics for the variables are presented in Table 2. The findings on the nonnormal distribution of the variables validate the use of nonlinear methodologies, such as MMQR and PLFC. Skewness statistics demonstrate asymmetry in the variables, with renewable energy consumption exhibiting significant right-skewness and urbanization revealing left-skewness. Kurtosis statistics reveal leptokurtic distributions characterized by heavy tails. More importantly, the Jarque-Bera test statistics reject the null hypothesis of normality for all variables, with values ranging from 14.81 to 23,690.39. These distributional characteristics highlight substantial deviations from the assumptions of normality and linearity inherent in conventional regression techniques, thereby necessitating the robust quantile-based approach of MMQR and the nonlinear functional framework of PLFC to capture heterogeneous and nonlinear effects across the conditional distribution of food production.

### 2.1. Cross-sectional dependence and unit root tests

In the initial stage of the analysis, suitable panel time series analyses are employed to assess cross-sectional dependence and variable heterogene-

ity. To this end, the following Breusch and Pagan (1980) Lagrange Multiplier (LM) test statistic is utilized to evaluate cross-sectional dependence.

$$CD_{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \tag{2}$$

As the LM test may produce unreliable results with large sample sizes, Pesaran (2004) introduced a cross-sectional dependence (CD) test for scenarios where both  $N$  and  $T$  approach infinity. The CD statistic, which tests the null hypothesis of zero dependence across panel units, is calculated using the following formula:

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

Here,  $N$  indicates the number of cross-sections and  $T$  represents the time dimension. The null hypothesis of the test suggests no cross-sectional dependence. The  $\hat{\rho}_{ij}^2$  test statistic is derived from the pairwise correlation coefficients of the residuals obtained by ordinary least squares regressions. Additionally, based on the test statistic of Swamy (1970), the Pesaran and Yamagata (2007) method is employed to investigate the homogeneity of slope coefficients. This involves calculating ( $\tilde{\Delta}$ )

**Table 2.** Descriptive statistics (levels)

Statistics	food <sub>it</sub>	temp <sub>it</sub>	gdp <sub>it</sub>	ren <sub>it</sub>	fos <sub>it</sub>	agrland <sub>it</sub>	urb <sub>it</sub>
Mean	0.0056	0.7787	20,505.0210	6,425.5604	24,210.9530	39.8959	66.9183
Median	0.0020	0.7370	12,412.1665	1,935.8935	23,097.7100	42.2200	72.5650
Maximum	0.0259	3.3170	90,589.1953	93,578.2188	78,919.5391	80.8900	92.5700
Minimum	0.0000	-1.6520	388.8230	3.7580	1503.5439	2.4500	19.3600
Std. dev.	0.0067	0.6506	19,533.6635	13,259.9388	17,283.4165	20.8273	17.2540
Skewness	1.3479	0.1983	1.0284	3.8639	0.8218	-0.1481	-0.8109
Kurtosis	3.5193	3.2330	3.4550	19.6947	3.3009	2.0224	2.7276
Jarque-Bera	527.5539	14.8072	310.6171	23,690.3877	195.4593	73.0411	189.2972
Probability	0.0000	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1680	1680	1680	1680	1680	1680	1680

and  $(\tilde{\Delta}_{adj})$  statistics. The  $\tilde{\Delta}$  and  $\tilde{\Delta}_{adj}$  test statistics are computed as follows:

$$\tilde{\Delta} = \sqrt{N} \left( \frac{N^{-1} \tilde{S} - k}{\sqrt{2k}} \right), \tag{4}$$

$$\tilde{\Delta}_{adj} = \sqrt{N} \left( \frac{N^{-1} \tilde{S} - E(\tilde{Z}_{iT})}{\sqrt{Var(\tilde{Z}_{iT})}} \right). \tag{5}$$

The cross-sectional CIPS panel unit root test is used to examine the unit root properties of the variables by considering the dependence of the cross sections. The following model is estimated for the CADF test:

$$\begin{aligned} \Delta Z_{it} &= \alpha_i + \rho_i Z_{i,t-1} + \beta_i \bar{Z}_{t-1} \\ &+ \sum_{j=0}^k \gamma_{ij} \Delta \bar{Z}_{i,t-1} + \sum_{j=0}^k \delta_{ij} Z_{i,t-1} + \varepsilon_{it}. \end{aligned} \tag{6}$$

The final step is to compute the CIPS statistics based on the mean value of the CADF:

$$CIPS = \frac{1}{N} \sum_{i=1}^N t_i(N, T). \tag{7}$$

## 2.2. Cross-section augmented autoregressive distributed lag (CS-ARDL) model

CS-ARDL extends Pesaran’s (2006) CCE (Common Correlated Effects) approach. Even though the CCE method is robust to cross-sectional dependence and slope heterogeneity, it is unsuitable for panels with lagged dependent variables or weakly exogenous variables as regressors. CS-ARDL addresses this limitation by accommodating these regressors. This model enables the estimation of the dependent variable for each cross-sectional unit by using unob-

served common factors, the current and lagged values of weakly exogenous regressors, and the lagged values of cross-sectional units with idiosyncratic error, which is serially uncorrelated (Chudik & Pesaran, 2013). In this study, the estimated CS-ARDL model is formulated as follows:

The number of cross-sections is represented by  $j$ , whereas  $t$  signifies the time span in the analysis. The explained variable of the model is the log-first difference of the food production index, denoted by  $\Delta \ln food_{i,t}$ .  $X_{i,t}$  contains the explanatory variables assumed to have a long-run effect, and  $\Delta \bar{X}_t$  is the mean of the short-run explanatory factors. The long- and short-term average values of the explained variables are represented by  $\Delta \ln food_{i,t-1}$  and  $\Delta \ln food_{i,t}$ , respectively. The long- and short-term averages of the explanatory variables are represented as  $\Delta \bar{X}_{t-1}$  and  $\Delta \bar{X}_{1',t-j}$ , respectively.  $\gamma_{ij}$  and  $\delta_{ij}$  are the short-run parameters for the dependent and independent factors, respectively. The parameters of the independent factors were represented as  $\beta_s$ . The short-run averages of the independent and dependent variables are represented by  $\mu_{2,i}$  and  $\mu_{1,i}$ , respectively. In this setting, the presence of cointegration is tested through the statistical significance of the error correction term denoted by  $\varphi_i$ .

## 2.3. PLFC model

The CS-ARDL model implicitly presumes that surface temperature has a linear impact on food production. In this context, the PLFC model can be employed to examine the potential nonlinearities between food production and annual surface temperature changes. In contrast to linear methodologies, the PLFC model is able to handle heterogeneity among cross-sectional units; hence, it may provide a more robust estimation of the nonlinear effects of annual surface temperature changes on food production. Following Zhang and Zhou (2021), the PLFC model is formulated as follows:

$$\begin{aligned} \Delta \ln food_{i,t} &= \omega_i + \varphi_i \left( \ln food_{i,t-1} - \beta_i X_{i,t-1} - \theta_{1,i} \overline{\ln food_{i,t-1}} - \theta_{2,i} \bar{X}_{t-1} \right) \\ &+ \sum_{j=1}^{p-1} \gamma_{ij} \Delta \ln food_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta X_{i,t-j} + \mu_{1,i} \overline{\Delta \ln food_t} + \mu_{2,i} \Delta \bar{X}_t + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

$$\ln food_{it} = h(\ln gdp_{it}) temp_{it} + X'_{it} \beta + \gamma_i + u_{it} \quad (9)$$

where  $h(\ln gdp_{it})$  signifies the functional coefficient that quantifies the marginal effect of temperature change ( $temp_{it}$ ) on food production. Building on the work of Liu et al. (2022), this analysis posits that the  $h(\ln gdp_{it})$  is influenced by the  $\ln gdp_{it}$ , facilitating an examination of the nonlinear effects of temperature change on food production.  $X_{it}$  signifies the independent variables, except for the temperature change. Specifically,  $X_{it}$  is defined as  $X'_{it} = [\ln gdp_{it \ln} \ ren_{it \ ln} \ fos_{it \ ln} \ nagrland_{it \ ln} \ nurb_{it}]$ . It is presumed that  $X_{it}$  has a linear influence on food production.  $\gamma_i$  and  $u_{it}$  represent unobserved heterogeneity and disturbance terms, respectively.

In the above equation, the unknown functional coefficient  $G(\ln gdp_{it})$ , representing the nonlinear component, and modeled as a linear combination of sieve basis functions, is initially estimated. The sieve approach is selected due to its computational simplicity enabling the approximation of functional coefficients in terms of basis functions (Du et al., 2020). The basis function of degree  $L$  is denoted by  $h_L(\cdot) = [h_1(\cdot), h_2(\cdot), \dots, h_L(\cdot)]'$ . These can be approximated as follows:  $h_k(\cdot) \approx h_L(\cdot) c_k$  for  $k = 1, 2, 3, \dots, p_d$ , where the coefficient of the sieve basis functions  $h_{it} = h(\ln gdp_{it})$  is signified by  $c_k$ . The model in Equation (9) can then be reformulated as follows:

$$\ln food_{it} = h_{it} temp_{it} + X'_{it} \beta + \gamma_i + v_{it} \quad (10)$$

The error term  $v_{it}$  has two components,  $v_{it} = u_{it} + \varepsilon_{it}$  and  $\varepsilon_{it}$ , which is represented as the sieve approximation error. Following Baltagi and Li (2002), the two-stage least squares (2SLS) approach is used for the estimation of the PFLC model in (10), utilizing the sieve approach to simulate the nonparametric components<sup>1</sup>.

## 2.4. MMQR

In addition to PLFC, this study used MMQR to examine the influence of annual surface temperature changes on food production. The MMQR has several advantages over other methodolo-

gies. First, in contrast to single-point estimators, MMQR can measure the effects of explanatory variables based on the conditional distribution of the dependent variable. As a quantile estimator, it is robust to outlying observations. Second, quantile regression allows for a broader range of distributional properties of the error terms, in contrast to approaches based on the normality of the error terms (Galvao, 2011; Machado & Silva, 2019). The MMQR form of our model is as follows:

$$\ln food_{it} = \alpha_i + X'_{it} \beta + (\delta_i + Z'_{it} \gamma) U_{it}, \quad (11)$$

where  $X'_{it}$  is the matrix of the explanatory factors  $X'_{it} = [anom_{it} \ \ln gdp_{it \ ln} \ ren_{it \ ln} \ fos_{it \ ln} \ nagrland_{it \ ln} \ nurb_{it}]$ ;  $\beta$  is the parameter vector of the regressors;  $\alpha_i$  indicates the fixed effect;  $\delta_i$  signifies the quantile fixed effect for each cross-section;  $Z_{it}$  is the vector including differentiable transformations of the regressors satisfying the condition of  $P\{\delta_i + Z'_{it} \gamma > 0\} = 1$ . The latent random variable, denoted as  $U_{it}$ , symbolizes an unobserved component that is assumed to be uncorrelated with the regressors.

The parameters of the previous equation were estimated based on the moment conditions. This approach follows the methodology devised by Machado and Silva (2019). In terms of conditional quantiles, the model is specified as follows:<sup>2</sup>

$$Q_{\ln food_{it}}(\tau | X_{it}) = (\alpha_i + \delta_i q(\tau)) + X'_{it} \beta + Z'_{it} \gamma q(\tau). \quad (12)$$

## 3. RESULTS AND DISCUSSION

### 3.1. Cross-sectional dependence and unit root tests

Before testing the unit root, the CD test devised by Pesaran (2004) is applied to investigate the existence of cross-sectional dependence (see Table 3). The results reveal that the null hypothesis of cross-sectional independence is strongly rejected at the 1% level. In this case, a shock in one country potentially affects the entire sample. The homogeneity test devised by Pesaran and Yamagata (2007) is

1 The details of the estimation can be obtained from Du et al. (2020).

2 In this study, the model outlined above was estimated using the one-step GMM estimator introduced by Hansen (1982). For additional details concerning the estimation procedures of the model, refer to Machado and Silva (2019).

conducted to assess the homogeneity of the slope coefficients. The results indicate the presence of heterogeneity within the sample.

After checking for heterogeneity and cross-sectional dependency, a CIPS unit root test is conducted to identify the integration level of the variables. As Table 4 shows, both the annual surface temperature change and agricultural land area variables are  $I(0)$ . The others are stationary at first differences. Hence, the variables exhibit a mixed order of integration.

**Table 3.** Cross-section dependence and homogeneity test results

a. Cross-sectional Dependence Tests	Statistic	p-value
LM	1258	0.000***
LM adj*	32.21	0.000***
LM CD*	3.103	0.001***
b. Slope Homogeneity Test	$\Delta$	$\Delta_{adj}$
Test statistic	45.808	50.912
p-value	0.000***	0.000***

Note: \*\*\*, \*\*, \* denote significant at 1%, 5%, and 10% level.

### 3.2. CS-ARDL results

As previously explained, the preliminary results reveal cross-sectional dependence, heterogeneity, and different orders of integration in the dataset. Accordingly, the CS-ARDL methodology is employed to estimate the long-run coefficients. Table 5, which shows the CS-ARDL estimation results, indicates that the error correction term (ECT) is negative and statistically significant, supporting the cointegration relationship among the variables. The high and significant value of the error-correction term implies a rapid adjustment of short-term disparities towards the long-term equilibrium path.

The parameter estimates shown in Table 5 imply that the annual surface temperature change ( $temp_{it}$ ) has a negative and statistically significant

impact on food production in both the short and long run. In other words, as temperatures deviate from their normal levels, food production decreases, with important implications for population nutrition. This suggests that climate change substantially jeopardizes the sustainability of the agricultural sector and food security (Silva et al., 2019; Mahrous, 2019; Fagbemi et al., 2023).

In contrast to the change in surface temperature,  $lngdp_{it}$  has a positive and significant impact on food production in both the short and long term. This finding suggests that economic growth could enhance resources, investments, and technological advancements in agriculture (Fusco, 2022; Fagbemi et al., 2023; Chandio et al., 2023). The CS-ARDL findings indicate that an increase in renewable energy positively and significantly impacts food production. Greater adoption of renewable energy may benefit the agricultural sector (Chandio et al., 2022a). Thus, adopting renewable energy may enhance energy efficiency, enabling the reallocation of resources to boost agricultural productivity.

**Table 5.** CS-ARDL results. Dependent variable:  $lnfood_{it}$

Variables	Short-run Results	Long-run Results
$temp_{it}$	-0.017*** (0.005)	-0.012*** (0.004)
$lngdp_{it}$	0.446*** (0.102)	0.347*** (0.086)
$lnren_{it}$	0.045*** (0.015)	0.030*** (0.011)
$lnfos_{it}$	-0.096 (0.857)	-0.079 (0.062)
$lnnagrland_{it}$	0.116 (0.227)	0.115 (0.135)
$lnnurb_{it}$	1.604 (2.306)	0.803 (1.673)
ECT	-1.342*** (0.038)	- -
$R^2$	0.49	

Note: \*\*\*, \*\*, \* denote significant at 1%, 5%, and 10% level.

**Table 4.** CIPS unit-root test results

Form of the Variable	$\Delta lnfood_{it}$	$temp_{it}$	$lngdp_{it}$	$lnren_{it}$	$lnfos_{it}$	$lnnagrland_{it}$	$lnnurb_{it}$
Level	-2.546	-3.642***	-1.75	-2.679	-2.634	-2.818***	-2.628
First difference	-4.612***	-	-3.128***	-3.818***	-3.495***	-	-1.861
Conclusion	$I(1)$	$I(0)$	$I(1)$	$I(1)$	$I(1)$	$I(0)$	$I(1)$

Note: \*\*\*, \*\*, \* denote significant at 1%, 5%, and 10% level.

### 3.3. PLFC results

Following the CS-ARDL analysis, the PLFC model formulated in Equation (10) is estimated to analyze the evolution of the nonlinear connection between surface temperature change and food production driven by the natural log of GDP per capita.

Figure 1 illustrates the results for the model’s nonlinear component, whereas Table 6 reports the parameter estimates of the linear component, including the control variables. Figure 1, which shows the marginal effect of the annual surface temperature change on food production, indicates that the natural log of GDP per capita is substantially affected by this relationship. That is, the estimated functional coefficient  $h(\text{Ingdp}_{it})$  for the annual surface temperature change varies significantly across different values of GDP, which shows that the relationship is nonlinear. More specifically, the functional coefficient is negative at lower GDP levels, signifying that the annual surface temperature change has a more detrimental impact on food production in nations with lower GDP. Conversely, the negative effects of annual surface temperature change decrease as GDP increases, indicating that economic development may alleviate the negative impacts of annual surface temperature change on food production. This evidence highlights the crucial role of economic development in strengthening resistance to climate change.

**Table 6.** PLFC model linear component:  $\text{Infood}_{it}$  dependent variable

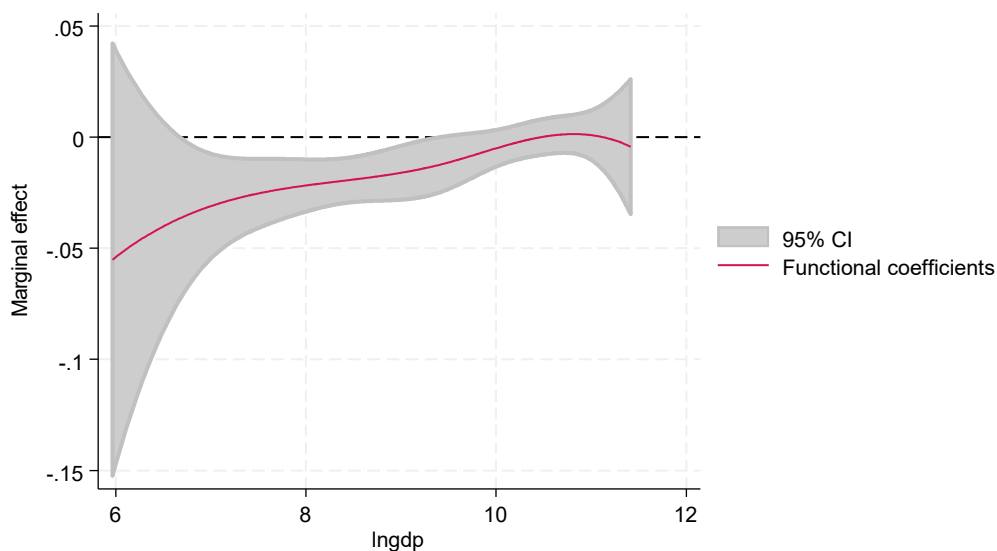
Variables	Coefficient	Std. Err.	Z-stat.	p-value
$\text{Ingdp}_{it}$	0.310	0.042	7.460	0.000
$\text{Inren}_{it}$	0.028	0.007	4.050	0.000
$\text{Infos}_{it}$	-0.045	0.031	-1.470	0.143
$\text{Innagrland}_{it}$	0.071	0.067	1.060	0.289
$\text{Innurb}_{it}$	0.087	0.148	0.590	0.558

The linear component of the PLFC model yields estimates that are consistent with those derived from the CS-ARDL model in terms of both sign and significance. It is worth noting that both GDP per capita ( $\text{Ingdp}_{it}$ ) and renewable energy ( $\text{Inren}_{it}$ ) have significant and positive effects on food production. Conversely, the parameter estimates for the remaining variables indicate that neither fossil energy consumption ( $\text{Infos}_{it}$ ), agricultural land ( $\text{Innagrland}_{it}$ ), nor urbanization ( $\text{Innurb}_{it}$ ) has any statistically significant impact on food production.

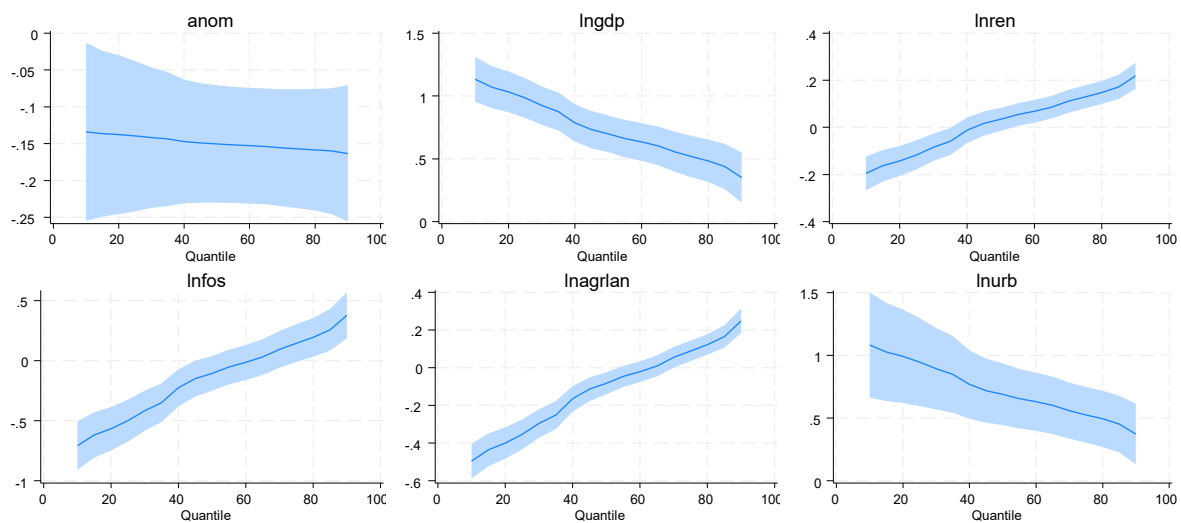
### 3.4. MMQR results

The MMQR results are reported in Table 7. The quantile parameter estimates are also presented in Figure 2 with their 95% confidence bands to analyze the significance of annual surface temperature change and the control variables across different food production quantiles.

In line with the PLFC results, the MMQR revealed a clear adverse impact of the annual sur-



**Figure 1.** Functional coefficients of surface temperature change



**Figure 2.** MMQR plot of the parameters

face temperature change on per capita food production across all quantiles. Compared to the other parameters, the coefficient for annual surface temperature change ( $temp_{it}$ ) follows a relatively stable pattern, which is statistically significant at the one percent. This implies that annual surface temperature change has a negative effect on food production. It is also worth noting that the adverse impact is more pronounced at higher quantiles of food production, which could suggest that countries with higher food production levels are more affected by annual surface temperature change.

Economic development, represented by GDP per capita ( $lngdp_{it}$ ), has a positive and statistically significant effect on food production in all quantiles. However, this impact is more pronounced at lower food production quantiles, highlighting the importance of economic resources in improving food production capabilities, likely through enhanced access to technology, inputs, and infrastructure.

While CS-ARDL estimates show that renewable energy use positively affects food production, MMQR estimates indicate that this impact varies significantly across quantiles. The impact of renewable energy is mostly significant, except for the 40% and 50% quantiles, and negative at lower quantiles, signifying that the greater use of renewable energy does not enhance food production in countries with lower food production

levels. However, at higher quantiles, the effect becomes positive, indicating that renewable energy benefits food production more in countries with higher output levels.

The parameter estimates of the remaining variables are significantly different from those of the CS-ARDL model. While the model indicates that neither fossil energy consumption, agricultural land use, nor urbanization have significant effects on food production in the short or long term, the MMQR parameter estimates are significant for all three variables. Concerning the effect of renewable energy consumption on food production, both sign and significance vary across quantiles. The effect is positive and significant at lower quantiles, implying that increasing the use of renewable energy increases food production in countries with lower production levels. However, at higher quantiles, the effect is negative, suggesting that in countries with higher food production, renewable energy is unable to meet the energy needs of intensive agricultural practices. This difference in the evolution of the effects of renewable energy consumption indicates that energy policies should be diversified to address the needs of different countries. Regarding fossil energy consumption, the results showed a negative and significant impact on food production in most quantiles. The negative impact is more pronounced for the lower and middle quantiles, suggesting that reliance on fossil fuels depresses food production due to environmental damage and inefficiencies.

**Table 7.** MMQR results. Dependent variable:  $\text{Infood}_{it}$ 

Variable	Location and scale parameters		Quantiles								
	Location	Scale	10%	20%	30%	40%	50%	60%	70%	80%	90%
$\text{temp}_{it}$	-0.148	-0.009	-0.134	-0.138	-0.142	-0.147	-0.150	-0.153	-0.156	-0.158	-0.163
Standard Error	0.042	0.023	0.062	0.055	0.049	0.043	0.041	0.040	0.041	0.042	0.047
z	-3.550	-0.400	-2.180	-2.510	-2.920	-3.440	-3.690	-3.810	-3.840	-3.760	-3.460
p-value	0.000	0.686	0.030	0.012	0.004	0.001	0.000	0.000	0.000	0.000	0.001
$\text{Ingdp}_{it}$	0.751	-0.253	1.132	1.032	0.923	0.786	0.699	0.634	0.554	0.483	0.351
Standard Error	0.074	0.039	0.091	0.083	0.078	0.075	0.075	0.077	0.081	0.086	0.101
z	10.140	-6.540	12.380	12.430	11.840	10.420	9.370	8.270	6.810	5.610	3.460
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
$\text{Inren}_{it}$	0.007	0.134	-0.195	-0.142	-0.084	-0.012	0.034	0.069	0.111	0.148	0.218
Standard Error	0.025	0.013	0.036	0.032	0.030	0.027	0.025	0.024	0.025	0.025	0.028
z	0.270	10.390	-5.370	-4.390	-2.820	-0.420	1.370	2.810	4.460	5.980	7.750
p-value	0.789	0.000	0.000	0.000	0.005	0.671	0.172	0.005	0.000	0.000	0.000
$\text{Infos}_{it}$	-0.176	0.352	-0.707	-0.567	-0.416	-0.225	-0.105	-0.014	0.096	0.195	0.379
Standard Error	0.074	0.043	0.103	0.092	0.085	0.078	0.074	0.074	0.078	0.082	0.098
z	-2.380	8.250	-6.840	-6.150	-4.900	-2.870	-1.420	-0.190	1.230	2.370	3.870
p-value	0.018	0.000	0.000	0.000	0.000	0.004	0.156	0.850	0.218	0.018	0.000
$\text{Innagrland}_{it}$	-0.132	0.241	-0.496	-0.400	-0.296	-0.165	-0.083	-0.021	0.055	0.122	0.248
Standard Error	0.030	0.017	0.047	0.042	0.038	0.035	0.029	0.028	0.028	0.028	0.033
z	-4.390	14.400	-10.550	-9.500	-7.760	-4.770	-2.820	-0.740	1.930	4.440	7.470
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.457	0.054	0.000	0.000
$\text{Innur}_{it}$	0.736	-0.230	1.082	0.991	0.892	0.768	0.689	0.630	0.558	0.494	0.373
Standard Error	0.132	0.076	0.214	0.190	0.166	0.139	0.125	0.118	0.114	0.114	0.123
z	5.590	-3.030	5.060	5.220	5.390	5.530	5.510	5.330	4.890	4.320	3.030
p-value	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002

Food production is adversely affected by agricultural land use across most quantiles; highly significant negative coefficients are observed for lower and middle quantiles. The negative impact of agricultural land use can be attributed to the major problems related to land quality and management

policies. It is also observed that urbanization has a positive and significant effect on food production across all quantiles, underlining the advantages of urbanization, such as improved infrastructure and greater market access, which may stimulate further increase in agricultural production.

## CONCLUSION

Global food security is threatened by climate change, due to the fact that rising temperatures have fundamentally altered agricultural systems throughout the world. In this study, advanced econometric techniques have been employed to capture both linear and nonlinear relationships between annual surface temperature changes and food production across 40 countries between 1980 and 2021.

The results indicate that temperature changes negatively impact food production in both the short and long term. This is consistent with the finding that economic growth can increase agricultural productivity by increasing access to technology, inputs, and infrastructure (Fusco, 2022; Chandio et al., 2023; Fagbemi et al., 2023). Renewable energy has a varying effect on food production, with increases being observed in countries with higher levels of output. It aligns with the idea that renewable energy can reduce agricultural costs and improve efficiency (Chandio et al., 2022). MMQR estimates indicate that fossil energy negatively impacts food production, especially in the lower and middle quantiles. This is consistent with studies that have highlighted the damaging effects of fossil

fuels on the environment in agriculture (Koonthar et al., 2021). Research has also demonstrated that expanding agricultural land without considering land quality and management practices may harm food production (Abbas et al., 2022). In addition, MMQR results indicate that urbanization positively impacts food production across all quantiles. As a result of improving infrastructure and market access, urban development can improve agricultural productivity.

Our empirical findings highlight critical policy implications. The substantial adverse impact of annual surface temperature fluctuations on food production underscores the urgent need for climate adaptation strategies in agriculture. Policymakers should prioritize investments in research and development of climate-resilient crop varieties and sustainable farming practices. Strengthening weather forecasting and early warning systems can assist farmers in mitigating the adverse effects of climate change. The positive correlation between economic development and food production emphasizes the importance of growth-oriented policies. Governments should focus on creating an enabling environment for agricultural investment, including infrastructure development, access to credit, and market integration. Promoting economic growth in developing nations can reduce climate vulnerability. The varying effects of renewable energy consumption on food production indicate the need for tailored energy policies. Renewable energy can enhance agricultural productivity in low-production regions, while high-production regions may require strategies to integrate renewable and alternative energy sources. The negative impact of fossil fuel usage on agricultural productivity necessitates a shift toward sustainable energy alternatives. Policymakers should support the development of cleaner energy technologies in agriculture, focusing on energy efficiency and reducing carbon footprints to achieve sustainable food production. Additionally, urbanization's positive effects on food production suggest the need for urban development policies that align with agricultural objectives. Strengthening rural-urban linkages improves market access and reduces post-harvest losses. Incorporating urban agriculture into planning frameworks can further enhance food security. Finally, the adverse effects of agricultural land expansion highlight the importance of improved land management over mere area expansion. Investments in soil health, sustainable practices, and land restoration can boost productivity. Policymakers must integrate these considerations into strategies aimed at enhancing agricultural productivity and climate resilience.

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Validation: Bekhzod Kuziboev.

Visualization: Samariddin Makhmudov, Nasiba Ashurova.

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Writing – review & editing: Abdurrahman Nazif Çatık, Coşkun Akdeniz, Esra Ballı, Bekhzod Kuziboev, Samariddin Makhmudov, Nasiba Ashurova.

## REFERENCES

1. Abbas, S., Kousar, S., & Khan, M. S. (2022). The role of climate change in food security; Empirical evidence over Punjab regions, Pakistan. *Environmental Science and Pollution Research*, 29, 53718-53736. <https://doi.org/10.1007/s11356-022-19315-7>
2. Abdi, A. H., Warsame, A. A., & Sheik-Ali, I. A. (2023). Modelling the impacts of climate change on cereal crop production in East Africa: Evidence from heterogeneous panel cointegration analysis. *Environmental Science and Pollution Research*, 30, 35246-35257. <https://doi.org/10.1007/s11356-022-24773-0>
3. Ahsan, F., Chandio, A. A., & Fang, W. (2020). Climate change impacts on cereal crops production in Pakistan: Evidence from cointegration analysis. *International Journal of Climate Change Strategies and Management*, 12(2), 257-269. <https://doi.org/10.1108/IJCCSM-04-2019-0020>
4. Ahumada, H., & Cornejo, M. (2021). Are soybean yields getting a free ride from climate change? Evidence from Argentine time series data. *Econometrics*, 9(2). <https://doi.org/10.3390/econometrics9020024>
5. Attiaoui, I., & Boufateh, T. (2019). Impacts of climate change on cereal farming in Tunisia: A panel ARDL-PMG approach. *Environmental Science and Pollution Research*, 26, 13334-13345. <https://doi.org/10.1007/s11356-019-04867-y>
6. Baltagi, B. H., & Li, D. (2002). Series estimation of partially linear panel data models with fixed effects. *Annals of Economics and Finance*, 3(1), 103-116. Retrieved from <http://aeconf.com/articles/may2002/ae030106.pdf>
7. Bouznit, M., & Aïssaoui, R. (2024). The impacts of climate change factors and innovative capabilities on food production in Algeria: Evidence from ARDL model. *Environment, Development and Sustainability*, 26, 23889-23908. <https://doi.org/10.1007/s10668-023-03627-w>
8. Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1), 239-253. <https://doi.org/10.2307/2297111>
9. Ceesay, E. K., & Ndiaye, M. B. O. (2022). Climate change, food security and economic growth nexus in the Gambia: Evidence from an econometrics analysis. *Research in Globalization*, 5, Article 100089. <https://doi.org/10.1016/j.res-glo.2022.100089>
10. Chandio, A. A., Akram, W., Bashir, U., Ahmad, F., Adeel, S., & Jiang, Y. (2022a). Sustainable maize production and climatic change in Nepal: Robust role of climatic and non-climatic factors in the long-run and short-run. *Environment, Development and Sustainability*, 25, 1614-1644. <https://doi.org/10.1007/s10668-022-02111-1>
11. Chandio, A. A., Gokmenoglu, K. K., & Ahmad, F. (2021a). Addressing the long- and short-run effects of climate change on major food crops production in Turkey. *Environmental Science and Pollution Research*, 28, 51657-51673. <https://doi.org/10.1007/s11356-021-14358-8>
12. Chandio, A. A., Gokmenoglu, K. K., Ahmad, M., & Jiang, Y. (2022b). Towards sustainable rice production in Asia: The role of climatic factors. *Earth Systems and Environment*, 6, 1-14. <https://doi.org/10.1007/s41748-021-00210-z>
13. Chandio, A. A., Jiang, Y., Ahmad, F., Adhikari, S., & Ain, Q. U. (2021b). Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. *Technology in Society*, 66, Article 101607. <https://doi.org/10.1016/j.tech-soc.2021.101607>
14. Chandio, A. A., Jiang, Y., Amin, A., Ahmad, M., Akram, W., & Ahmad, F. (2023). Climate change and food security of South Asia: Fresh evidence from a policy perspective using novel empirical analysis. *Journal of Environmental Planning and Management*, 66(1), 169-190. <https://doi.org/10.1080/09640568.2021.1980378>
15. Chandio, A. A., Jiang, Y., Fatima, T., Ahmad, F., Ahmad, M., & Li, J. (2022c). Assessing the impacts of climate change on cereal production in Bangladesh: Evidence from ARDL modeling approach. *International Journal of Climate Change Strategies and Management*, 14(2), 125-147. <https://doi.org/10.1108/IJCCSM-10-2020-0111>
16. Chandio, A. A., Jiang, Y., Rauf, A., Ahmad, F., Amin, W., & Shehzad, K. (2020). Assessment of formal credit and climate change impact on agricultural production in Pakistan: A time series ARDL modeling approach. *Sustainability*, 12(13), Article 5241. <https://doi.org/10.3390/su12135241>
17. Chudik, A., & Pesaran, M. H. (2013). *Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors* (Working Paper No. 146). Federal Reserve Bank of Dallas. Retrieved from <https://www.dallasfed.org~/media/documents/research/international/wpapers/2013/0146.pdf>
18. Demirhan, H. (2020). Impact of increasing temperature anomalies and carbon dioxide emissions on wheat production. *Science of the Total Environment*, 741, Article 139616. <https://doi.org/10.1016/j.scitotenv.2020.139616>
19. Du, K., Zhang, Y., & Zhou, Q. (2020). Fitting partially linear functional-coefficient panel-data models with Stata. *The Stata Journal*, 20(4), 976-998. <https://doi.org/10.1177/1536867X20976339>
20. Fagbemi, F., Oke, D. F., & Fajingbesi, A. (2023). Climate-resilient development: An approach to sustainable food production in sub-Saharan Africa. *Future Foods*, 7, Article 100216. <https://doi.org/10.1016/j.fufo.2023.100216>
21. FAO. (2024). *Temperature change statistics 1961–2023 Global, regional and country trend*. Retrieved from <https://openknowl->

- [edge.fao.org/server/api/core/bitstreams/81fba107-c36f-479c-af74-6b288239541f/content](https://edge.fao.org/server/api/core/bitstreams/81fba107-c36f-479c-af74-6b288239541f/content)
22. Fusco, G. (2022). Climate change and food security in the Northern and Eastern African regions: A panel data analysis. *Sustainability*, 14, Article 12664. <https://doi.org/10.3390/su141912664>
  23. Galvao, Jr A. F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*, 164(1), 142-157. <https://doi.org/10.1016/j.jeconom.2011.02.016>
  24. Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029-1054. <https://doi.org/10.2307/1912775>
  25. IMF. (n.d.). *Climate Change Indicators Dashboard*. Retrieved from <https://climatedata.imf.org/pages/climatechange-data>
  26. Kibria, Md. G., Aspy, N. N., Ullah, E., Dewan, Md. F., Hasan, Md. A., Hossain, Md. A., Haseeb, M., & Hossain, Md. E. (2023). Quantifying the effect of agricultural greenhouse gas emissions, food production index, and land use on cereal production in South Asia. *Journal of Cleaner Production*, 432, Article 139764. <https://doi.org/10.1016/j.jclepro.2023.139764>
  27. Koondhar, M. A., Udemba, E. N., Cheng, Y., Khan, Z. A., Koondhar, M. A., Batool, M., & Kong, R. (2021). Asymmetric causality among carbon emission from agriculture, energy consumption, fertilizer, and cereal food production – A nonlinear analysis for Pakistan. *Sustainable Energy Technologies and Assessments*, 45, Article 101099. <https://doi.org/10.1016/j.seta.2021.101099>
  28. Kumar, P., Sahu, N. C., Kumar, S., & Ansari, M. A. (2021). Impact of climate change on cereal production: Evidence from lower-middle-income countries. *Environmental Science and Pollution Research*, 28, 51597-51611. <https://doi.org/10.1007/s11356-021-14373-9>
  29. Li, C. (2023). Climate change impacts on rice production in Japan: A Cobb-Douglas and panel data analysis. *Ecological Indicators*, 147, Article 110008. <https://doi.org/10.1016/j.ecolind.2023.110008>
  30. Liu, J., Caporin, M., Zheng, Y., & Yu, S. (2022). The effect of renewable energy development on China's energy intensity: Evidence from partially linear functional-coefficient panel data analyses. *Journal of Cleaner Production*, 350, Article 131505. <https://doi.org/10.1016/j.jclepro.2022.131505>
  31. LSEG. (n.d.). *Datastream Macroeconomics Analysis*. Retrieved from <https://www.lseg.com/en/data-analytics/products/datastream-macroeconomic-analysis>
  32. Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, 213(1), 145-173. <https://doi.org/10.1016/j.jeconom.2019.04.009>
  33. Mahrous, W. (2019). Climate change and food security in EAC region: A panel data analysis. *Review of Economics and Political Science*, 4(4), 270-284. <https://doi.org/10.1108/REPS-12-2018-0039>
  34. Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (IZA DP Working Paper No. 1220). Institute for the Study of Labor. Retrieved from <https://docs.iza.org/dp1240.pdf>
  35. Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 967-1012. <https://doi.org/10.1111/j.1468-0262.2006.00692.x>
  36. Pesaran, M. H., & Yamagata, T. (2007). Testing slope homogeneity in large panels. *Econometrics*, 142(1), 50-93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
  37. Pickson, R. B., Boateng, E., Gui, P., & Chen, A. (2024). The impacts of climatic conditions on cereal production: Implications for food security in Africa. *Environment, Development and Sustainability*, 26, 18333-18360. <https://doi.org/10.1007/s10668-023-03391-x>
  38. Pickson, R. B., Gui, P., Chen, A., & Boateng, E. (2023). Climate change and food security nexus in Asia: A regional comparison. *Ecological Informatics*, 76, Article 102038. <https://doi.org/10.1016/j.ecoinf.2023.102038>
  39. Pickson, R. B., He, G., & Boateng, E. (2022). Impacts of climate change on rice production: Evidence from 30 Chinese provinces. *Environment, Development and Sustainability*, 24, 3907-3925. <https://doi.org/10.1007/s10668-021-01594-8>
  40. Pickson, R. B., He, G., Ntiemoah, E. B., & Li, C. (2020). Cereal production in the presence of climate change in China. *Environmental Science and Pollution Research*, 27, 45802-45813. <https://doi.org/10.1007/s11356-020-10430-x>
  41. Qureshi, M. I., Awan, U., Arshad, Z., Rasli, A. Md., Zaman, K., & Khan, F. (2016). Dynamic linkages among energy consumption, air pollution, greenhouse gas emissions and agricultural production in Pakistan: Sustainable agriculture key to policy success. *Natural Hazards*, 84, 367-381. <https://doi.org/10.1007/s11069-016-2423-9>
  42. Silva, W. K. de M., Freitas, G. P. de, Coelho, L. M. J., Pinto, P. A. L. de A., & Abrahão, R. (2019). Effects of climate change on sugarcane production in the state of Paraíba (Brazil): A panel data approach (1990–2015). *Climatic Change*, 154, 195-209. <https://doi.org/10.1007/s10584-019-02424-7>
  43. Simionescu, M., Bilan, Y., Gedeck, S., & Streimikiene, D. (2019). The effects of greenhouse gas emissions on cereal production in the European Union. *Sustainability*, 11(12), Article 3433. <https://doi.org/10.3390/su11123433>
  44. Swamy, P. A. V. B. (1970). Efficient inference in a random coefficient regression model. *Econometrica*, 38(2), 311-323. <https://doi.org/10.2307/1913012>
  45. The World Bank. (n.d.). *World Development Indicators*. Retrieved from <https://databank.worldbank.org/source/world-development-indicators>
  46. Warsame, A. A., Sheik-Ali, I. A., Jama, O. M., Hassan, A. A., & Barre, G. M. (2022). Assessing the effects of climate change and

- political instability on sorghum production: Empirical evidence from Somalia. *Journal of Cleaner Production*, 360, Article 131893. <https://doi.org/10.1016/j.jclepro.2022.131893>
47. Xiang, X., & Solaymani, S. (2022). Change in cereal production caused by climate change in Malaysia. *Ecological Informatics*, 70, Article 101741. <https://doi.org/10.1016/j.ecoinf.2022.101741>
48. Zaied, Y. B., & Cheikh, N. B. (2015). Long-run versus short-run analysis of climate change impacts on agricultural crops. *Environmental Modeling & Assessment*, 20, 259-271. <https://doi.org/10.1007/s10666-014-9432-4>
49. Zhang, Y., & Zhou, Q. (2021). Partially linear functional-coefficient dynamic panel data models: Sieve estimation and specification testing. *Econometric Reviews*, 40(10), 983-1006. <https://doi.org/10.1080/07474938.2021.1889175>