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Climate Change and Crop Productivity: Implications for Food Security in Global North and South

ABSTRACT

A special predicament in global climate-agriculture nexus is the existence of asymmetricity in empirical relationships, which the existing literature fails to capture these threshold effects. The present study addresses this gap by investigating the non-linear relationship between climate variability and crop productivity with a particular focus on global disparities between the Global South and Global North. Using panel data from 1980 to 2022, the analysis employs a panel quantile regression framework to understand the relationship across different levels of global crop productivity. The results reveal significant non-linear responses of crop production to climate variables, where moderate increases in temperature and precipitation enhance yields up to a threshold, beyond which productivity declines. Global South demonstrates higher vulnerability to rising temperatures due to limited adaptive capacity and dependence on rain-fed agriculture, while Global North exhibits greater sensitivity to excessive rainfall, although its advanced technologies and management practices help mitigate losses. These findings emphasize that climate impacts are context-specific, shaped by regional agronomic practices, technological adoption, and resource availability.

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Author's contribution in the article: 1- Conceived and designed the analysis, 2- Reviewed and compiled the literature, 3- Collected the data, 4- Contributed data or analysis tools, 5- Performed the analysis, 6- Wrote the paper, 7- Financial support for the conduct of the study, 8-Other

1. INTRODUCTION

Agriculture remains a cornerstone of global economic stability and food security, contributing about 4% to global GDP and employing over 26% of the world's workforce (World Bank, 2023). Beyond its economic role, agricultural productivity underpins rural livelihoods, trade balances, and the capacity to feed a global population projected to reach 9.7 billion by 2050 (United Nations, 2022; World Bank, 2025). Within this framework, crop production systems form interdependent components of a complex network that supplies food, fiber, and raw materials essential for human survival and economic growth.

Food insecurity is a crucial global challenge and despite advances in technology and trade, nearly 733 million people or 1 in 11 globally goes hungry every day, with the majority concentrated in climate-vulnerable regions. Moreover, over 2.8 billion inhabitants, 34% of the world population, could not afford a healthy diet, with the problem concentrated in the Global South that is around 71.5%. According to FAO (2023), about 82% of people lacked affordability in Sub-Saharan Africa, and around 70% in Southern Asia as compared to only 14% in high-income countries. Under these circumstances, climatic variability exacerbates the crisis by reducing crop yields, destabilizing food supplies, and driving up food prices, disproportionately affecting low-income and agrarian economies (IPCC, 2022) and directly widening the gap between food supply and demand (Wheeler & Von Braun, 2013).

Owing to the rise in global temperatures and volatility in precipitation patterns, the climate-agriculture nexus has gained unprecedented attention (Vermeulen et al., 2012). The literature advocates that favorable weather conditions lead to surpluses whereas the opposite conditions lead to shortfalls of food supply (Tanveer & Kalim, 2025; Tanveer et al., 2025). This alarming condition is very crucial for global agriculture system, where nearly 80% of the area is rain-fed (FAO, 2021), leaving it highly sensitive and vulnerable to erratic climatic variations.

In this regard, the existing research demonstrates that agriculture production is not directly proportional to climate change such as temperature and rainfall and its variation depends on level of climatic conditions (Lobell et al., 2011; Schlenker & Roberts, 2009; Zhao et al., 2017). Several researchers identified polynomial inverted U-shaped relationships, where initially rising temperature and precipitation boost agriculture productivity until a threshold is reached, after which further rise become harmful (Lobell et al., 2011; Schlenker & Roberts, 2009; Tanveer & Kalim, 2025; Zhao et al., 2017; Zambrano-Medina et al., 2024). This non-linearity has multiple implications for smart agricultural, climate adaptation and mitigation policies, and global food security (Seneviratne et al., 2021).

Despite growing recognition of the impacts of climate change on crop production, significant gaps remain in understanding optimal climate conditions for crop productivity on a global scale, particularly for global north and south, where the Global South refers to developing countries, mostly in the southern half of the world, that generally have lower incomes and face various economic challenges. The Global North, by contrast, are the developed, wealthier countries, often found in the northern hemisphere that are characterized by high incomes, advanced technology, and stable economies (Kowalski, 2020). The study tries to estimate the impacts of climatic variables, average annual temperature and annual precipitation, on crop production index globally as well as on global south and north regions.

The current study contributes to literature in multiple ways. First, existing research is region specific and crop specific studies which have estimated the complex relationship in climate change and crop production and comprehensive global analyses remain limited. Second, to identify how global warming is differently affecting poor and rich regions, the current study separates the analysis for global south and north for the whole crop system. Third, while much of the prevailing literature relies on projections and forecasts of the potential impacts of global warming on the food system, the present study employs actual observed data to provide empirical estimates of climate effects. Finally, by applying a panel quantile regression framework, the study is able to capture the distributional impacts of climate variability on crop productivity specifically across productivity quantiles like how climatic variations influence both low-productivity and high-productivity regions in the Global South and Global North. Besides, the key novelty of the study is the estimation of global threshold levels for temperature and precipitation across quantiles of global crop productivity and compares them with global south and north.

2. LITERATURE REVIEW

The relationship between climate change and crop productivity has been extensively investigated over the past decades, with empirical evidence showing that temperature and precipitation shifts play crucial roles in shaping agricultural performance. At the global level, crop productivity responds non-linearly to climate variables, with moderate changes sometimes enhancing yields, but extremes often exert adverse effects. The direction and magnitude of these impacts vary significantly between regions, largely due to differences in agro-ecological conditions, adaptation capacities, and resource endowments.

Temperature has been identified one of the most important climatic determinants of crop productivity. Lobell and Field (2007) found that global warming trends since 1981 have had a negative effect on major cereal crops, with wheat and maize particularly sensitive to higher growing-season temperatures. Similarly, Schlenker and Roberts (2009), using county-level data for the United States, reported that crop yields exhibit strong yield declines beyond certain temperature thresholds, suggesting limited adaptation capacity within existing agricultural systems. In the context of developing countries, Zhang et al. (2017) observed that tropical and subtropical crops are more tolerant of higher average temperatures than temperate crops but are more vulnerable to extreme heat events.

In addition to temperature, precipitation patterns also play a crucial role and have important implications for crop production. It also has non-linear impacts on crop production as Tao et al. (2008) estimated that moderate increases in precipitation boosted yields, but excessive rainfall caused waterlogging, nutrient leaching, and pest outbreaks. On the other hand, shortage in rainfall limited soil moisture availability, reduced photosynthesis, and hindered plant growth (Rosenzweig et al., 2014). Moreover, Tanveer and Kalim (2025) identified quantile-wise threshold levels for both temperature and precipitation for global agricultural system.

Taking together, the simultaneous effects of them are more challenging because of the influence on evapotranspiration, soil moisture balance, and plant physiology. Warming-induced yield losses are often amplified under drought conditions, particularly in water-limited areas (Lobell et al., 2011). Similarly, Zhao et al. (2017) used a global meta-analysis to show that simultaneous increases in temperature and precipitation variability can lead to substantial reductions in yields of staple crops, especially in low-income countries with limited adaptive technologies.

Beyond crop-level impacts, regional disparities further complicate the phenomenon. Climate change has different impacts on different regions (FAO, 2021; Tanveer & Kalim, 2025) and several cross-country analyses strengthen this proposition like Nelson et al. (2014) estimated that climate change could reduce global agricultural productivity by up to 17% by 2050, with losses disproportionately larger in developing countries. Similarly, Moore and Lobell (2015) reported that although the North has a relatively high potential for adaptation owing to availability of sources, it is still not enough to fully offset the impacts of global warming. Nevertheless, adaptation in the South is limited due to low financial resources, weak extension services, and poor access to modern farming technologies.

The literature has portrayed significant evidence that how crop production responses to the climatic variations worldwide. Nevertheless, a key dilemma in global climate-agriculture nexus is the existence of asymmetricity in empirical relationships, which the existing literature fails to capture these threshold effects. The present study has estimated temperature and rainfall threshold levels for global south and north which is the key novelty of the analysis. Moreover, authors have contributed to the literature in multiple ways such as providing global analysis based on observed data beyond region- and crop-specific research, comparing Global South and North difference and employing median based model to estimate distributional effects of climate variability across different levels of crop productivity.

3. DATA AND METHODOLOGY

The basic economic theory illustrates that agricultural production is determined by land, labor, capital, and ecological factors (Zambrano-Medina et al., 2024) where climate variables like temperature and precipitation affect productivity through multiple channels. Therefore, the basic functional form of the model is given as:

$$Crop\ productivity = f(input\ variables, climatic\ variables, technology) \tag{1}$$

Where input variables include land, labour and capital, climate variables contain temperature and precipitation whereas technology is presented as patents. These variables have multiple effects on crop yield. These effects include volatility in photosynthesis and respiration of plants (Lobell & Gourdji, 2012) as well as variation in insects' infestations, weedicides, pesticides, herbicides, moisture Stress and soil erosion (Malhi et al., 2021; Rosenzweig et al., 2014; Tao et al., 2008). Their influences generate the possibility of non-linear relationships where crops perform best within an optimal range. Below this range, growth of the plants slows; at the optimum, photosynthesis and growth peak; above it, heat stress damages plant cells and disrupts metabolism, reducing yields. These thresholds vary by crop, region, and management practice, and adaptation can extend tolerance but often with trade-offs (Hatfield & Prueger, 2015; Schlenker & Roberts, 2009). Consequently, the quadratic term for the climatic variables has been incorporated to estimate the potential polynomial relationships.

Moreover, water stress theory describes precipitation effects in a similar inverted U-shaped manner (Vandana et al., 2024) where shortage of water leads to drought stress, reduced photosynthesis, and smaller yields (Akhtar & Nazir 2013; Wu et al. 2022), while excessive rainfall causes waterlogging, nutrient leaching, and disease (Akhtar & Nazir 2013; Vandana et al., 2024). However, the optimal rainfall level varies in different types of crops, soil, and growth stage, and rainfall variability can disrupt planting and harvesting schedules (Lobell et al., 2011). Collectively, both theories elaborate that impacts of climate change crop productivity are mainly not linear; nevertheless, climatic thresholds differ across regions. This rate of change is also critical to allow adaptation, but rapid one's risk overwhelming capacity (Porter et al., 2014). In this regard, the following quadratic functional form has been developed:

$$Crop\ productivity = f(input\ variables, climatic\ variables^2,\ technology) \tag{2}$$

Equation (2) thus provides the theoretical basis for our empirical model, which is operationalized in Equation (3). For empirical analysis, the study has used a balanced panel dataset comprising 169 countries[1] over the period 1980 to 2022, ensuring broad global coverage and consistent temporal observations for all cross-sectional units. Given the macro-panel structure, where cross-country linkages and common shocks are likely, the analysis first examines cross-sectional dependence using the Breusch–

[1] List of countries used for the analysis is given in Appendix-A.

Pagan LM test, Pesaran scaled LM test, bias-corrected scaled LM test, and Pesaran CD test. The outcomes of this cross-sectional dependence test indicate the application of second-generation panel unit root tests, which explicitly account for such interdependence (Baltagi, 2021). Resultantly, the study has employed Pesaran's (2007) Cross-sectionally Augmented Dickey–Fuller (CADF) test to determine the stationarity properties of the series.

Based on the results of the panel unit test, Panel Quantile Regression (PQR) is found to be the most suitable econometric model for empirical analysis. PQR models provide heterogeneous relationships across the median based conditional distribution of the dependent variable and do not need normal distribution assumption (Baltagi, 2021). By Using PQR the present study has estimated the distributional effects of the climatic variables, temperature and rainfall, on crop productivity across all quantiles. Econometrically, Koenker (2004) and Canay (2011) provided the foundational frameworks for implementing PQR in panel settings with fixed effects.

A number of researchers used PQR to examine environmental effects of economic growth in sub-Saharan Africa (Twerefou et al., 2017) and to assess the heterogeneous impacts of growth, environmental policy, and innovation on energy consumption (Nguyen et al., 2020). Similarly, Ibrahim and Law (2014) applied PQR to investigate the relationship between social capital and CO_2 emissions. Therefore, PQR is a robust and flexible tool for capturing distributional heterogeneity, making it well-suited for analyzing the global and regional impacts of climatic variables on crop productivity in the present study. The present study has used the following models for the estimation:

$$\mathrm{CRPI}\tau_{it} = \alpha_{\tau 1} TEMP_{it} + \alpha_{\tau 2} TEMP_{it}^2 + \alpha_{\tau 3} PREC_{it} + \alpha_{\tau 4} PREC_{it}^2 + \beta_{\tau 1} CLPC_{it} + \beta_{\tau 2} CLR_{it} + \beta_{\tau 3} PTNT_{it} + \varepsilon_{\tau it} \quad (3)$$

Where in equation (3), $\mathrm{CRPI}\tau_{it}$ is the quantile-specific crop productivity index for country i at time t and $\alpha_{\tau i}$ and $\beta\tau_j$ are the quantile-specific coefficients for the explanatory variables and $\varepsilon_{\tau it}$ is the quantile-specific error term. The estimated values of $\alpha_{\tau i}$ present the existence of non-linear impacts of climatic variables on CRPI whereas estimates of $\beta\tau_j$ show how input and technology variables influence crop production. To examine regional heterogeneity, the analysis is further stratified into two subsamples: the Global South and the Global North. Separate PQR estimations are conducted for each subsample, and results are presented for the global sample, the Global South, and the Global North to facilitate comparative interpretation.

4. DATA DESCRIPTION

Table 1 summarizes the variables used in the analysis, their definitions, sources, and time coverage. The dependent variable, Crop Production Index (CRPI), from the *World Development Indicators (WDI)*, measures agricultural output relative to the 2014–2016 base period. Key climatic variables—average temperature (TEMP) in °C and precipitation (PREC) in millimeters—are obtained from the *Climate Change Knowledge Portal*. Permanent cropland (CLPC), expressed as a percentage of total land area, also comes from *WDI*, while the capital–labor ratio (CLR), an indicator of mechanization and input intensity, is sourced from the *United States Department of Agriculture (USDA)*. Patent applications (PTNT), serving as a proxy for technological innovation, are drawn from *WDI*. All variables cover the period 1980–2022, ensuring consistent cross-country and temporal comparisons.

Table 2 reports the descriptive statistics for the variables used in the study. The mean value of the Crop Production Index (CRPI) is 82.92, with a median of 86.86, suggesting a slightly left-skewed distribution. Climatic variables show substantial variation: average temperature (TEMP) ranges from –13.71°C to 34.90°C, while precipitation (PREC) spans from zero to over 4,700 mm. The dispersion is similarly pronounced for structural variables—permanent cropland (CLPC) ranges from 0% to over 50%, and capital–labor ratio (CLR) from 0.03 to 9.93—while patent applications (PTNT) exhibit extreme heterogeneity, from zero to more than 1.5 million. High skewness and kurtosis values across most variables, combined with statistically significant Jarque–Bera test results ($p < 0.01$), indicate strong departures from normality and the presence of outliers. These distributional characteristics imply that mean-based estimators, such as pooled OLS or fixed effects, may mask important heterogeneity and be sensitive to extreme values. Panel Quantile Regression (PQR), by contrast, allows the estimation of covariate effects across the entire conditional distribution of CRPI, providing a more robust and nuanced understanding of how climatic and structural factors influence crop productivity at different performance levels.

Table 1: Details and Description of the Variables used for the Analysis

Variable	Description	Source	Time
CRPI	Crop production index (2014-2016 = 100)	World Development Indicator (WDI)	1980-2022
TEMP	Average mean temperature over the aggregation period (Unit °C)	Climate Change Knowledge Portal	1980-2022
PREC	Aggregated accumulated precipitation. (Unit mm)	Climate Change Knowledge Portal	1980-2022
CLPC	Permanent cropland (% of land area)	World Development Indicator (WDI)	1980-2022
CLR	Ratio of capital input to labor input index	United Stated Department of Agriculture	1980-2022
PTNT	Residents and nonresidents patent applications (Proxy for Technological Innovations)	World Development Indicator (WDI)	1980-2022

Source: Authors' own work.

Table 2: Descriptive Statistics of the Study Variables

Statistics	CRPI	TEMP	PREC	CLPC	CLR	PTNT
Mean	82.92	18.58	906.75	3.13	0.85	9136.30
Median	86.86	22.07	686.70	1.03	0.80	53.00
Maximum	355.97	34.90	4761.13	50.51	9.93	1585663.00
Minimum	5.62	-13.71	0.00	0.00	0.03	0.00
Std. Dev.	30.81	8.58	846.92	4.85	0.56	65825.19
Skewness	0.54	-0.82	1.10	2.66	5.52	14.71
Kurtosis	5.63	2.73	3.86	12.46	61.57	281.18
Jarque-Bera	2451	834	1699	35661	10757	236939
Probability	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors' own work.

5. ANALYSIS AND RESULTS

5.1 Results of cross-sectional dependency test

Table 3 presents the results of cross-sectional dependence (CSD) tests, including the Breusch–Pagan LM, Pesaran scaled LM, bias-corrected scaled LM, and Pesaran CD statistics, for all variables used in the study. The test statistics are all highly significant ($p < 0.01$) for most variables, indicating the presence of strong cross-sectional dependence across countries in the panel dataset. This suggests that shocks or changes in one country's agricultural productivity, climate indicators, or economic factors are likely to be correlated with those in other countries, reflecting interconnected global patterns. The only exception is the Pesaran CD statistic for patents (PTNT), which is insignificant, implying weaker contemporaneous correlations for this variable.

Table 3: Results of Cross-Sectional Dependent Tests

Variables	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
CRPI	236754.28 (0.00)	1320.83 (0.00)	1318.81 (0.00)	255.18 (0.00)
TEMP	137683.46 (0.00)	732.87 (0.00)	730.85 (0.00)	250.60 (0.00)
PREC	30428.45 (0.00)	96.34 (0.00)	94.32 (0.00)	19.91 (0.00)
$TEMP^2$	135537.20 (0.00)	720.13 (0.00)	718.12 (0.00)	238.46 (0.00)
$PREC^2$	27801.86 (0.00)	80.75 (0.00)	78.74 (0.00)	19.47 (0.00)
CLR	276967.98 (0.00)	1559.48 (0.00)	1557.47 (0.00)	221.47 (0.00)
CLPC	26998.37 (0.00)	100.79 (0.00)	97.31 (0.00)	11.98 (0.00)
PTNT	25620.24 (0.00)	198.71 (0.00)	196.37 (0.00)	-1.88 (0.06)

Source: Author's own work, Note: Probability values are given in parenthesis.

5.2 Results of panel unit root test

Table 4 reports the outcomes of Pesaran's CADF panel unit root test for the study variables, indicating their stationarity properties. The results show that all variables—crop production index (CRPI), temperature, temperature square, precipitation, precipitation square, capital–labor ratio (CLR), permanent cropland (CLPC), and patents (PTNT)—are stationary at level, as evidenced by their statistically significant p-values ($p < 0.05$). The negative t-statistics and large negative Z-statistics confirm rejection of the null hypothesis of non-stationarity for each variable. This implies that the series do not require differencing and can be used directly in the model without transformation, supporting the validity of further econometric analysis.

Table 4: Outcomes of Pesaran's CADF Panel Unit Root Test for the Study Variables

Variable	T-Statistic	Z Statistic	P-value	Conclusion
CRPI	-2.33	-7.63	0.000	Stationary at Level
TEMP	-3.19	-19.46	0.000	Stationary at Level
PREC	-3.28	-20.8	0.000	Stationary at Level
$TEMP^2$	-4.06	-31.47	0.000	Stationary at Level
$PREC^2$	-4.02	-30.94	0.000	Stationary at Level
CLR	-2.46	-1.82	0.035	Stationary at Level
CLPC	-3.61	-25.24	0.000	Stationary at Level
PTNT	-2.16	-5.3	0.000	Stationary at Level

Source: Author's own work

5.3 Results of panel quantile regression model

The panel quantile regression results, given in Table 5, for the global analysis reveal a consistent and statistically significant inverted-U relationship between temperature and crop productivity across all quantiles. At lower productivity quantiles, a 1°C increase in mean temperature is associated with a 1.58-point rise in the crop production index, while at higher quantiles the effect increases to 2.49 points. This shows that temperature has stronger marginal positive effects in relatively high-productivity regions. However, this effect is non-linear and inverted U-shaped confirming by the negative and significant coefficients of the temperature-squared term across all quantiles.

Temperature thresholds, reported in Table 6, range from 12.91°C for lowest productive quantile to 24.36°C for the highest productive quantile. This implies that moderate warming boosts yields, but beyond these points, additional heat reduces productivity. High-productivity regions are more than twice as resilient to temperature increases compared to lower-productivity regions, likely due to climate-resilient technologies and heat-tolerant crop varieties.

Table 5: Results of Panel Quantile Regression Model for Overall World and Global South and North Regions

		Outcomes of Econometric Model for the Whole Globe/World			
Variables	**Q20**	**Q40**	**Q50**	**Q60**	**Q80**
TEMP	1.580***	1.901***	1.836***	1.975***	2.487***
	(0.208)	(0.193)	(0.180)	(0.148)	(0.190)
$TEMP^2$	-0.061***	-0.058***	-0.051***	-0.048***	-0.051***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.007)
PREC	0.019***	0.024***	0.026***	0.027***	0.022***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
$PREC^2$	($-6.8x6^{-10}$)***	($-9.3x6^{-10}$)***	($-9.6x6^{-10}$)***	($-9.6x6^{-10}$)***	($-7.9\ x6^{-10}$)***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLR	16.251***	29.044***	34.554***	37.52***	42.487***
	(2.300)	(2.386)	(2.713)	(2.664)	(2.245)
CLPC	1.595***	1.236***	0.966***	0.643***	0.167
	(0.165)	(0.115)	(0.128)	(0.127)	(0.157)
PTNT	4.884***	4.710***	4.778***	4.971***	6.008***
	(0.153)	(0.183)	(0.169)	(0.176)	(0.176)
		Outcomes of Econometric Model for Global South Region			
Variables	**Q20**	**Q40**	**Q50**	**Q60**	**Q80**
TEMP	0.182	0.452	1.060***	1.751***	2.575***
	(0.282)	(0.313)	(0.272)	(0.335)	(0.377)
$TEMP^2$	0.017	0.013	0.001	-0.020	-0.040***
	(0.010)	(0.010)	(0.008)	(0.009)	(0.012)
PREC	-0.004	0.003	0.006**	0.004**	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
$PREC^2$	($7.9\ x7^{-10}$)	($-1.7\ x6^{-10}$)**	$-2.6\ x6^{-10}$)***	($-2\ x6^{-10}$)***	($-2.5\ x6^{-10}$)***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLR	28.565***	45.159***	50.701***	55.872***	56.820***
	(1.461)	(2.317)	(2.385)	(2.581)	(2.877)
CLPC	0.843***	0.553***	0.421***	0.295***	0.017
	(0.186)	(0.138)	(0.137)	(0.110)	(0.128)
PTNT	3.349***	2.948***	2.033***	1.676***	2.408***
	(0.288)	(0.259)	(0.255)	(0.218)	(0.195)
		Outcomes of Econometric Model for Global North Region			
Variables	**Q20**	**Q40**	**Q50**	**Q60**	**Q80**
TEMP	2.167***	2.205***	2.286***	2.147***	0.331
	(0.242)	(0.244)	(0.245)	(0.235)	(0.510)
$TEMP^2$	-0.070***	-0.075***	-0.077***	-0.069***	0.044
	(0.012)	(0.013)	(0.014)	(0.015)	(0.033)
PREC	0.057***	0.059***	0.058***	0.052***	0.063
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
$PREC^2$	($-2.8\ x5^{-10}$)***	($-3.2\ x5^{-10}$)***	($-3.2\ x6^{-10}$)***	($-2.8\ x5^{-10}$)***	($-3.4\ x6^{-10}$)***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CLR	2.842***	11.692***	17.791***	24.402***	32.867***
	(0.386)	(2.474)	(4.497)	(3.679)	(3.613)
CLPC	1.787***	1.469***	1.613***	1.496***	1.912***
	(0.197)	(0.197)	(0.251)	(0.247)	(0.380)
PTNT	4.651***	5.385***	5.449***	5.786***	6.787***
	(0.203)	(0.230)	(0.290)	(0.252)	(0.315)

*Source: Author's own work. Note: Standard errors are given in parentheses and ***, **, and * represent 1%, 5%, and 10% level of significance, respectively*

Precipitation, the second climatic variable, also exhibits an inverted-U polynomial pattern. Positive precipitation coefficients and negative, significant square terms indicate yield benefits up to 1,313–1,400 mm annually, after which excess rainfall becomes harmful. Agronomically, crops require adequate heat and water for growth, but extreme heat can cause heat stress, reduce photosynthesis, and increase water loss, while excessive rainfall can cause flooding, waterlogging, and soil erosion. These results align with Lobell et al. (2011), who found global yields peaking with moderate warming; Schlenker and Roberts (2009), who reported U-shaped temperature effects in U.S. crops; and Zhang et al. (2017), who emphasized mechanization's role in resilience. Moreover, these results are also well matched with Tanveer and Kalim (2025) where researchers estimated similar outcomes for agricultural total factor productivity.

Among control variables, the capital–labour ratio has a strong, increasing positive effect, from 16.25 at the lower quantile to 42.48 at upper quantile, suggesting that investments in human and physical capital significantly boost productivity. Additionally, high-productivity regions demonstrate deeper and larger marginal returns on such investments. By contrast, cropland expansion has stronger positive effects at lower productivity quantiles (1.59 at Q20) than at higher quantiles, reflecting lower-productivity regions' reliance on land and labour, while high-productivity regions achieve greater output from existing land. Technological innovation, measured by patents, has robust positive effects across all quantiles, increasing from 4.88 at lower quantile to 6.01 at upper quantile, showing that innovation is most effective where complementary factors already exist.

In the Global South, temperature effects are weaker and statistically insignificant at lower quantiles, becoming positive and significant only from middle quantile onward (1.06 at Q50 and 2.58 at Q80). The estimated coefficients of temperature-squared term are insignificant except for the upper quantile, denoting that heat damage emerges only at the highest productivity levels. The lack of significant impacts in lower quantiles suggests that many countries with subsistence or low yield crops already operate in challenging climates, where small changes in temperature or precipitation have little marginal effect. Moreover, it would be possible that Global South regions' economies may not yet be at the point where average temperatures consistently reduce yields, though vulnerability rises in high-performing areas.

Mixed effects of precipitation are found in the South regions with insignificant coefficients for lower quantiles and positive but small from mid-quantiles onward and with negative and significant estimated coefficients for precipitation-squared terms at these higher levels which indicate an inverted U-shape. Thresholds appear only in mid- to high-quantiles, at 1,085–1,114 mm relatively lower than of global precipitation thresholds and higher than global north, suggesting that moderate rainfall is beneficial but excess water is harmful in more developed cropping areas.

The capital–labour ratio has large positive effects across all quantiles, underlining the productivity gains from mechanization in capital-scarce contexts. Cropland's impact drops sharply from 0.84 at lower quantiles to near zero at higher ones, showing that land expansion matters more in early productivity stages. Technological innovation has positive but smaller coefficients than in the North, possibly due to slower adoption or weaker institutional support for technological diffusion.

These patterns reflect the South's greater tolerance for higher temperatures, owing to crop adaptation and agronomic practices, but also its reliance on capital deepening rather than land expansion for yield growth. Similar patterns were reported by Seo and Mendelsohn (2008) for African farms adapting to warming, Gollin et al. (2014) on mechanization in developing countries, and Fuglie and Toole (2014) on technology adoption gaps.

For the Global North, the temperature–productivity relationship is strong and positive up to the upper-middle quantiles (about 2.15–2.29 points per °C), showing that lower- to upper-middle-productivity regions benefit from warming. Yet this relationship is non-linear, with negative, significant temperature-squared coefficients confirming the inverted-U. Thresholds are lower than the global average, at 14–15°C, and do not significantly vary across quantiles, highlighting temperate agriculture's greater warming sensitivity. At the highest quantile, temperature effects become insignificant, suggesting that top-performing regions may be near or beyond their optimal thermal range.

Table 6: Quantile-Wise Threshold Levels of Temperature and Precipitation[2]

Quantile	Temperature's Thresholds			Precipitation's Thresholds		
	World	Global South	Global North	World	Global South	Global North
Q20	12.91	Not Significant	15.43	1374.03	Not Significant	1011.05
Q40	16.38	Not Significant	14.69	1313.12	Not Significant	930.92
Q50	17.85	Not Significant	14.84	1366.67	1094.88	921.26
Q60	20.38	Not Significant	15.45	1379.76	1085.17	924.56
Q80	24.36	Not Significant	Not Significant	1399.84	1113.97	912.35

Source: Authors' work based on empirical analysis. Note: (only statistically significant values are included)

Precipitation effects are consistently positive and larger than in the South (0.052–0.059), but thresholds are also lower (912–1,011 mm), implying that excess rainfall causes harm sooner, possibly due to soil saturation and higher disease pressure in cooler climates. Given efficient irrigation systems, additional rainfall beyond the norm may reduce yields in these developed regions. The capital–labour ratio has a positive effect that rises with productivity, though magnitudes are smaller than in the South due to already high mechanization levels.

Cropland consistently has a strong positive impact, suggesting stable land productivity and intensive management. Moreover, technological innovation effects are large and rise with quantiles, reinforcing that advanced solutions like precision agriculture and genetic improvements are especially valuable in high-yield contexts. Overall, the North's lower climate thresholds reflect narrower crop temperature ranges and less historical heat exposure, while precipitation sensitivity is linked to cooler soils' reduced drainage capacity. These findings are consistent with Schlenker et al. (2011) on Northern agriculture's climate sensitivity, Tack et al., (2015) on precipitation extremes in U.S. wheat, and Fuglie and Toole (2014) on innovation's central role in sustaining productivity.

It can be concluded that both the Global South and Global North show that temperature, precipitation, and technological innovations significantly influence crop productivity, but the direction and magnitude of these effects differ (Farah et al., 2025; Fuglie et al., 2024; Gray, 2021). In the South, moderate increases in temperature are less harmful due to crop adaptation and heat-resilient farming practices (Ruane and Rosenzweig, 2019), while in the North, even slight warming tends to reduce yields because crops are more suited to cooler climates (Gray, 2021). Similarly, precipitation benefits productivity in both regions (He et al., 2025), but the South shows greater sensitivity to rainfall variability, reflecting its higher dependence on rain-fed agriculture (Tefera et al., 2025). Technological innovation boosts productivity across both regions (Fuglie et al., 2024), yet in the South it complements capital-intensive farming to offset climate pressures (Daum, 2023), whereas in the North it primarily enhances efficiency within stable climatic conditions (Coninck et al., 2022). These patterns highlight that while the two regions share

[2] Figure Appendix-B1 and Appendix-B2 give graphs of quantile-wise threshold levels of temperature and precipitation, respectively.

common drivers of productivity, their responses are shaped by distinct climatic, structural, and technological contexts (Raitzer & Drouard, 2024).

6. CONCLUSION AND POLICY IMPLICATIONS

Food insecurity is a crucial global problem where more than 2 billion people lack access to a healthy diet. Climatic conditions are further exacerbating this challenge by affecting crop productivity worldwide, with unfavorable weather disproportionately harming the already poor and vulnerable segments of the population. A special predicament in the global climate–agriculture nexus is the existence of asymmetric and non-linear empirical relationships, which much of the existing literature fails to capture.

The present study addresses this gap by investigating the non-linear relationship between climate variability and crop productivity, with particular attention to disparities between the Global South and the Global North. The findings reveal that moderate temperature increases can enhance productivity in certain regions, especially in the Global South, where crops and farming practices are better adapted to warmer conditions. However, excessive heat beyond a threshold exerts significant negative impacts across the globe, and these thresholds are relatively narrow in the Global North, where temperature variability disrupts traditional growing cycles.

Rainfall patterns similarly show a non-linear relationship with crop productivity across the globe, where moderate increases support growth, while heavy rainfall led to declines crop production index. In this regard, it can be concluded that the Global South is more vulnerable to rising temperatures, reflecting lower adaptive capacity and dependence on rain-fed agriculture owing to limited resources, whereas the Global North shows higher sensitivity to excessive rainfall, where productivity declines sharply beyond critical thresholds yet their higher mechanization, innovation, and advanced crop management allow them to mitigate adverse effects more effectively. These results emphasize that climate impacts are context-specific, shaped by regional agronomic practices, technological adoption, and resource availability.

Therefore, policymakers should prioritize investment in climate-resilient crop varieties, improved irrigation systems, and water conservation technologies in global south regions. This can be done by strengthening adaptive capacity through farmer training, crop diversification, and affordable access to climate-smart practices is crucial. On the other hand, in global north, it is recommended to focus on enhancing drainage infrastructure, soil management practices, and flood-resilient cropping systems. To achieve this, advanced climate monitoring and early-warning systems can help farmers adjust planting and harvesting decisions to rainfall extremes.

The study has certain limitations due to the use of aggregate data for crop production and climatic variables. Future research can be extended by incorporating seasonal temperature data aligned with specific crops, as well as additional climatic indicators such as droughts and extreme weather events. Furthermore, including factors like soil quality, pest outbreaks, and input use would provide a deeper understanding of climate–productivity dynamics. Longitudinal analyses tracking changes in farming practices over time could also offer valuable insights into how adaptation evolves, and which strategies are most effective in mitigating climate-induced productivity losses.

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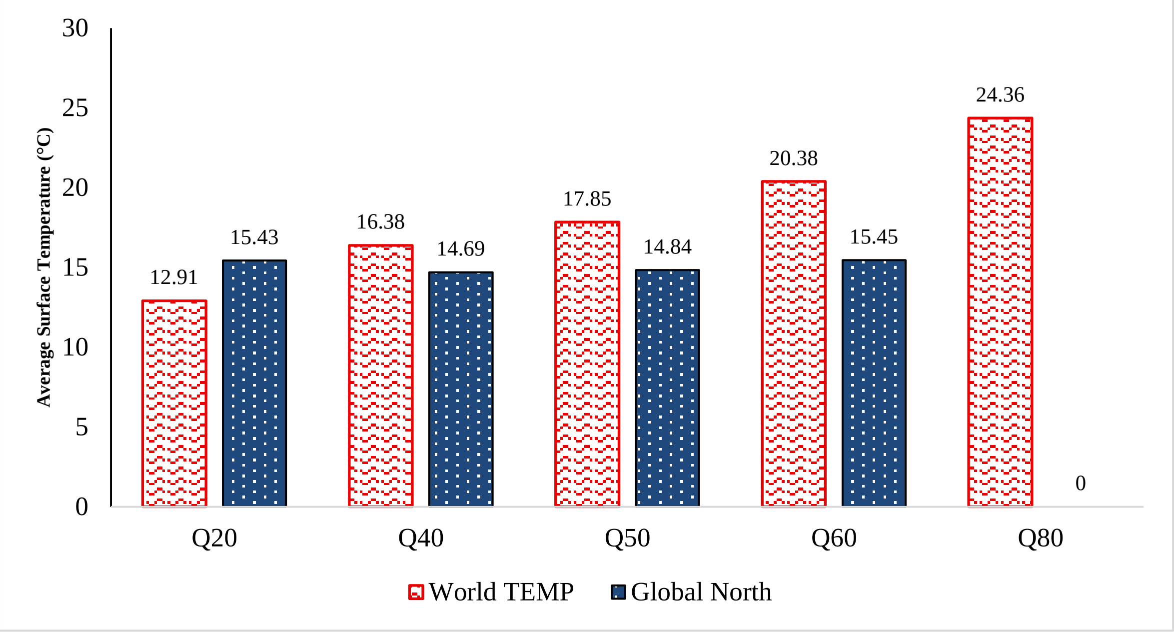
Appendix-A: List of Countries Used for the Analysis

Sr. No.	Country
1	Afghanistan
2	Albania
3	Algeria
4	Angola
5	Argentina
6	Armenia
7	Australia
8	Austria
9	Azerbaijan
10	Bahrain
11	Bangladesh
12	Belarus
13	Belgium
14	Belize
15	Benin
16	Bhutan
17	Bolivia
18	Botswana
19	Brazil
20	Brunei Darussalam
21	Bulgaria
22	Burkina Faso
23	Burundi
24	Cabo Verde
25	Cambodia
26	Cameroon
27	Canada
28	Central African Republic
29	Chad
30	Chile
31	China
32	Colombia
33	Comoros
34	Congo DR
35	Congo Republic
36	Costa Rica
37	Croatia
38	Cuba
39	Cyprus
40	Czechia
41	Denmark
42	Djibouti
43	Dominican Republic
44	Ecuador
45	Egypt
46	El Salvador
47	Equatorial Guinea
48	Eritrea
49	Estonia
50	Eswatini
51	Ethiopia
52	Fiji
53	Finland
54	France
55	Gabon
56	Gambia
57	Georgia
58	Germany
59	Ghana
60	Greece
61	Guatemala
62	Guinea
63	Guinea-Bissau
64	Guyana
65	Haiti
66	Honduras
67	Hungary
68	Iceland
69	India
70	Indonesia
71	Iran
72	Iraq
73	Ireland
74	Israel
75	Italy
76	Jamaica
77	Japan
78	Jordan
79	Kazakhstan
80	Kenya
81	Korea DPR
82	Korea Republic
83	Kuwait
84	Kyrgyzstan
85	Laos
86	Latvia
87	Lebanon
88	Lesotho
89	Liberia
90	Libya
91	Lithuania
92	Luxembourg
93	Madagascar
94	Malawi
95	Malaysia
96	Mali
97	Malta
98	Mauritania
99	Mauritius
100	Mexico
101	Micronesia
102	Moldova
103	Mongolia
104	Montenegro
105	Morocco
106	Mozambique
107	Myanmar
108	Namibia
109	Nepal
110	Netherlands
111	New Caledonia
112	New Zealand
113	Nicaragua
114	Niger
115	Nigeria
116	North Macedonia
117	Norway
118	Oman
119	Pakistan
120	Panama
121	Papua New Guinea
122	Paraguay
123	Peru
124	Philippines
125	Poland
126	Portugal
127	Qatar
128	Romania
129	Russian Federation
130	Rwanda
131	Saudi Arabia
132	Senegal
133	Serbia
134	Sierra Leone
135	Slovakia
136	Slovenia
137	Solomon Islands
138	Somalia
139	South Africa
140	Spain
141	Sri Lanka
142	Sudan
143	Suriname
144	Sweden
145	Switzerland
146	Syria
147	Tajikistan
148	Tanzania
149	Thailand
150	Timor-Leste
151	Togo
152	Trinidad and Tobago
153	Tunisia
154	Turkiye
155	Turkmenistan
156	Uganda
157	Ukraine
158	United Arab Emirates
159	United Kingdom
160	United States
161	Uruguay
162	Uzbekistan
163	Vanuatu
164	Venezuela
165	Vietnam
166	West Bank and Gaza
167	Yemen
168	Zambia
169	Zimbabwe

Appendix B1: Quantile-Wise Comparison of Threshold Levels of Temperature



Appendix B2: Quantile-Wise Comparison of Threshold Levels of Precipitation