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KEYWORDS	ABSTRACT
Agricultural Value Added, Employment in Agriculture, Total Damages, GDP per capita.	The study aims to identify and explain the influence of natural disasters on agricultural output in developing countries. Natural disasters have been characterized as one of the most critical challenges affecting developing economies. Many types of natural disaster events such as droughts, storms, wildfires, extreme floods and earthquakes, leading to a significantly impact on agricultural output, especially among vulnerable rural populations in developing economies. Our study uses recent twenty-first-century data for developing countries, covering the period between 2000 to 2024. The researchers employ advanced econometric techniques including the Method of Moments quantile regression (MMQR) and Bootstrap Quantile Regression (BSQR) to determine the relationship between variables. The findings reveal that natural disasters and various climate change events have adverse effects on agricultural output by damaging crops, destroying agricultural assets, rural infrastructure and causing food shortage problems in developing countries. Based on the findings, the study recommended that policymakers promote effective disaster response mechanisms, early warning systems, disaster relief funds, drought-resistant crops and crop insurance programs are essential for minimizing disaster-related losses.
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Introduction

Over the last two decades, many environmental changes have impacted the global economy and its development. Many types of disasters including droughts, storms, wildfires, extreme floods, pests, and diseases occurred during the year 2023, which has broken all existing records. This year record lifetime high temperatures inflicted severe impacts on the global community as a whole including the Food and Agriculture Organization of the United Nations (FAO, 2023b). Therefore, disasters may cause the country’s economy and development to shift back temporarily or even permanently (Weerasekara et al.2022). During the 1970s, disaster events were increasingly recorded at 100 per

year, and it was also recognized that over the past 20 years, disaster-related events were recorded at around 400 per year. Natural disasters have severe impacts on food and grain production, destroy crops, and ultimately threaten the development of the global food supply, especially in developing nations (Zheng et al. 2020).

Agricultural activities and food production systems are commonly dependent on natural resources, ecosystems, and environmental conditions, which also play an important role in protecting the availability of food for healthy diets. It is the key driver in developing employment opportunities, providing food security, and decreasing poverty in rural areas (FAO, 2023a). Agricultural productivity is severely affected by climate-induced disasters in developing countries. Between 2003 and 2013, the agricultural productivity of 67 developing nations was damaged due to large-scale disaster events occurring. These events not only cripple developing countries' economies but also destroy or damage livestock, seeds, crops, harvests, equipment, stored food and supplies (FAO, 2015). The Russian Federation and Ukraine are both high-ranking exporters of sunflower seeds, wheat, and maize. But in 2021, a war was started between these two nations, which caused an increase in global food commodity prices. The variability occurs in temperature, rainfall, and precipitation rate due to increased climate variability and extremes that inflict high levels of economic loss of agricultural output.

Climate-related disasters cause damage and losses in agriculture subsectors like fisheries, livestock, and others, which leads to severe impacts on food production, farmer's income, and trade patterns (FAO, 2021b; Holleman et al., 2020). Global crises such as epidemics, ongoing armed conflicts, and the COVID-19 pandemic are all producing bad impacts on agricultural production as well as input and output markets leading to the development of a comprehensive view of today's risk landscape (World Bank & FAO, 2018). This precipitation rate leads to too much rainfall, which also increases the risk of flooding. Moreover, the overall effects of climate change could destabilize food and energy security and lead to unstable commodity prices. Due to droughts and cold spells, La Niña is predicted to diminish agricultural yields, mainly affecting wheat and soybean crops, and heavy rainfall is expected to disrupt the extraction of key minerals in Australia, Southeast Asia and Africa (ADB, 2024; Adhikari, R. B., 2024). The impact of climate-related natural disaster shocks not only on agricultural productivity crops but also on environmental degradation and farm infrastructure (i.e., machinery and equipment, storage buildings, installations, and irrigation systems. In low-income developing economies, when disaster-related events occur such as floods, earthquakes, and droughts, then fifty percent of agriculture output decreases and consequently the GDP of these developing economies declines by ten percent (Klomp & Hoogezand, 2018).

The study is significant because it shows how natural disasters interact with agricultural output. Also, we have found that much work has been done on the impact of natural disasters on agricultural output in individual countries, but this study has analyzed the impact of natural disasters on agricultural output, specifically in a single framework of developing countries. The novelty of this study is that many previous studies have mainly depended on ARDL, OLS, and GMM, which demonstrate first-generation econometric techniques. This study incorporates advanced third-generation econometric techniques including the Method of Moments of quantile

regression (MMQR) and Bootstrap Quantile Regression (BSQR), to determine the impact of natural disasters on agricultural output. The paper is organized as: Section 2 explains the comprehensive review of literature, summarizing the findings of previous studies and identifying the research gaps that the present study addresses. Section 3 present the model specification, variable data sources and research methodology. Section 4 highlights the link between natural disasters, agricultural productivity using MMQR and BSQR econometric analysis. Section 5 summarizes the overall conclusion of the whole study along with policy implication and recommendations.

Review of Literature

A considerable review of literature has explored the linkage between natural disasters, agricultural output. The following existing studies present a comprehensive review of studies that based on theoretical and empirical perspectives.

For determined the impact of natural disasters on agriculture productivity, Tu et al. (2024) determined that natural disasters events less affected on animal husbandry than the more affected on the agriculture crops as soil erosion, land degradation, decreased arable land area, reduced agriculture productivity and slow-growing plants in Tuyen Hoa district, Quang Binh province of Vietnam. Gunadal et al. (2024) investigated the relationship between floods, crops, and livestock production. The study results revealed the negative impacts of floods on crops (sugarcane and maize) caused substantial economic losses for the farmers. Furthermore, floods badly impact livestock and farmers reported death and injuries of many animals, also incurring huge amounts of loss. Also, people are unable to fulfil basic needs and farmers have difficulty arranging income for the treatment of animals. This condition is very pathetic and challenging for farmers in India. Dinh and Ngo (2023) concluded that information technology positive impact on agriculture crops and disaster-related events produced a negative impact on agriculture productivity. Furthermore, the ICT and IT dissemination give knowledge to farmers about disaster-related events that help to resolve any threat promptly and save agriculture productivity.

Ismayilzada et al. (2023) argued that that the impact of disasters negatively affects agricultural production in the form of destroying crops and yields, reducing product quality, and ultimately leading to a food crisis. Wei et al. (2023) founded that natural disaster event flood and storms caused to destroyed the around 70% of the total supply chain networks. Hua et al. (2023) inspected that the natural disasters caused the positive impact on agriculture goods prices and returns. The quantile regression results-based findings indicated that the bullish market conditions posited the positive impact on soybean and wheat returns and under bearish market condition, not found the significant impact on returns of agriculture crops. Fernie et al. (2022) asserted that that extreme heat waves generate a very significant and negative impact on the quality of wheat grain crops and their yields. Moreover, the natural disasters events as high temperature and post-anthesis heat stress more severe effect on the physical quality parameters of wheat grains such as grain hardness, gain size and gain weight. Khan et al. (2022) revealed that natural disaster poses some positive impacts on agriculture including raising the water supply, enlarging water living space, and improving soil fertility. Also, the study showed the negative impact of disasters on agriculture

such as damage (farm infrastructure, inputs, and crops), decreased farm productivity, and damaged transportation routes that increased food prices.

Natural disasters cause destroys the agricultural crops and also declines the growth of the developing economies. The outcomes showed that the hail disaster negatively impacts the application of drip irrigation water-saving technology for cotton-producing farmers, causing farmers to adopt the technology equipment. The natural disasters have a significant negative impact on the TE of rice production. Both floods and drought have severe impact on growing the technical efficiency of agriculture production (Yu and Wei 2022; Weerasekara et al. 2022). Trinh et al. (2021) examined that effect of natural disaster event heterogeneous in different region on different crops. The central and north west region face more challenges due to disasters and climate change events especially rice production becomes decline and found to be vulnerable. Guan et al. (2021) analyzed that impact of drought higher than the impact of flood on crops, also caused the downward trend of agriculture in some region of China. Moreover, the natural disaster event as drought caused the severe impact on Northeast, Northwest and North region of China and flood more affected the Southwest, Central-south and East region of China agriculture production. Zheng et al. (2020) estimated drought negative impact on cereal crops and destroyed more than half of the crops of Silica. Furthermore, the biochemical cycle and natural disaster events caused not only destroyed the silica sink capability of the agricultural system but also decreases the decreases the soil silicon supply. Shi et al. (2020) attempted that the efficiency agriculture production stable in eastern region and inferior in western region due to climate change and natural disaster issues. The agricultural water resources more balanced at regional level but the agriculture overall production decline at national level.

Coulibaly et al. (2020) explored that negative impact of climate change and disaster-related factors on African agriculture production. But the middle-income and not least developed countries face less shock on productivity crops of agriculture by disaster-related events. Klomp and Hoogezand (2018) studied that natural disasters cause to increase trade control by adopting agriculture protection policies and ultimately raise the government revenue through imposing import tax. The disaster-related events increase agriculture protection in developed countries, but in low-income countries, these trade barriers become reduced due to extreme drought and food insecurity. Chapagain and Raizada (2017) founded that emergency sustainable agriculture kit (eSAK) framework for disasters effective areas especially in rural side for the purpose to address the needs of shelter, first aid, hunger, seeds, preservation of indigenous crop varieties, and post-disaster labor shortage which are helpful in providing relief to smallholder farmers. Hossain et al. (2016) determined disasters events destroyed the crops and caused by rise in soil salinity and vulnerability of agriculture production which leads to create the socioeconomic problems especially for women. Du et al. (2015) asserted that the two natural disaster events mainly caused the changes in the Chinese economy, drought caused the severe impact on northern side of China and flood more effect the southern part of the China. Zhang et al. (2015) floods and its related factor increasing consecutive dry days precipitation extremes, decreasing consecutive wet days mainly affected the agriculture crops production across China. Moreover, the flood and drought both caused the loss of agriculture production and the trend increases before changing the points in most part of China.

Model, Data, and Methodology

This section of the study specifies the empirically estimated models data and methodological framework that determine the impact of natural disasters on agricultural output.

Model 1: Natural Disasters and Agricultural Output

The functional form of the natural disasters and agriculture output model is given as

$$AVA = f(AL, EMP, GFCF, GDP, EPI, ND, AGRIEX)$$

The econometric form of the model is given as

$$AVA_{it} = \alpha_0 + \alpha_1 AL_{it} + \alpha_2 EMP_{it} + \alpha_3 GFCF_{it} + \alpha_4 GDP_{it} + \alpha_5 EPI_{it} + \alpha_6 ND_{it} + \alpha_7 AGRIEX_{it} + \varepsilon_{it}$$

Data: Description and Measurement

Table 1 depicts a clear picture of the data description, measurement units of the variables and corresponding sources of all the variables.

Table 1: Variables, Description, Unit of Measurement and Sources

Variables	Description	Unit of Measurement	Sources
AVA	Agriculture Value Added	(% of GDP)	WDI
AL	Arable Land	(% of land area)	
AGRIEX	Agriculture Raw Material Exports	(% of merchandise export)	
EMP	Employment in Agriculture	(% of total employment)	
GDPPC	GDP Per Capita Growth	(Annual % growth)	
GFCF	Gross Fixed Capital formation	(Annual %)	
ND	Natural Disasters	Total affected Population in Natural Disasters (persons)	EM-DAT from the Centre for Research
EPI	Environmental Performance Index		https://epi.yale.edu/

Data and Methodology

This study collects data on natural disasters (total affected population and total damages) obtained by EM-DAT from the Centre for Research on the Epidemiology of Disasters (CRED). The data on agriculture output variables were collected from the World Bank Indicators. The period for data

collection in this study is from 2000 to 2024. We collected data for 129 developing countries based on the availability of data on all relevant variables. The selection of developing countries based on the World Bank's country classification includes 25 low-income countries, 50 lower-middle-income countries and the remaining 54 are upper-middle-income countries. The advanced econometric techniques Method of Moments Quantile Regression (MM-QR) and Bootstrap Quantile Regression (BSQR) are applied in this research for determining the effect of natural disasters on agricultural output.

Results and Discussion

Summary Statistics and Correlation Analysis

This section explains the descriptive statistics and pairwise correlation analysis of the key variables. Concerning the mean of the variables, GGPPC exhibits the highest value 6399.10% and the lowest mean value of the variables is EPI 0.47. Table 2 presents the variables that exhibit right-tail skewness values such as AVA, AL, and AGRIEXP while GFCF, TD and TAP show a left-tail distribution. On the other hand, EPI, EMP, GFCF, TAP and TD have values that are close to zero. For determining Kurtosis, we examine the highest kurtosis values are GDPPC 2446.85, suggesting an extremely heavy tail and these variables possess a leptokurtic distribution. The lowest kurtosis values are EPI 2.694 and EMP 2.248 indicating a close-to-normal distribution. The Jarque-Bera test probability value confirms non-normality in all variables except TAP.

Table 2: Summary Statistics of Key Variables (2000-2024)

	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
AVA	15.43	12.47	79.04	-0.26	10.59	1.09	4.67	1019.76	0.00
EPI	0.47	0.46	1.00	0.00	0.20	0.11	2.69	19.60	0.00
GDPPC	5.97	4.318	4231.72	-50.33	80.09	48.10	2446.85	810000000	0.00
AL	14.22	10.29	64.14	0.04	13.66	1.43	4.54	1420.37	0.00
EMP	36.69	34.24	91.93	0.57	20.84	0.37	2.24	144.31	0.00
GFCF	10.87	7.38	884.50	-938.99	41.43	-0.55	215.16	5157937.00	0.00
AGRIEXP	5.76	1.70	156.506	-0.07	13.89	5.22	36.85	158205.90	0.00
TAP	10.80	10.71	19.65	0.00	2.75	-0.05	3.07	2.22	0.32
TD	11.52	11.71	18.52	0.69	2.44	-0.50	3.41	99.38	0.00

Table 3 shows the correlation analysis which shows the strength and direction (either positive and negative) of the relationship among variables. Agriculture value added (AVA) positively correlated with EPI, GDPPC, AL, EMP, GFCF, AGRIEXP and TAP. Also, a weaker correlation was found between AL with GFCF and AGRIEXP. There is a weaker negative relationship between the two variables GFCF and AGRIEXP with TAP.

Table 3: Correlation Analysis (2000-2024)

	AVA	EPI	FSI	AFS	POU	PFSV	PBDW	GDPPC	GDPPC2	AL	EMP	GFCF	AGRIEXP	TAP	TD	HCI
AVA	100															
EPI	0.17	100														
FSI	-0.40	-0.11	100													
AFS	-0.39	-0.20	0.48	100												
POU	0.50	0.20	-0.56	-0.74	100											
PFSV	-0.03	0.08	0.11	0.03	-	100										
PBDW	-0.72	-0.29	0.56	0.53	0.02	0.07	100									
GDPPC	0.15	-0.08	-0.06	-0.09	-0.71	0.06	-0.12	100								
GDPPC2	0.03	0.01	-0.06	-0.07	0.11	0.04	-0.04	0.39	100							
AL	0.00	-0.27	0.05	0.01	0.10	-0.04	0.12	0.01	-0.01	100						
EMP	0.78	0.16	-0.36	-0.49	0.06	-0.01	-0.74	0.17	0.05	0.05	100					
GFCF	0.11	0.03	-0.12	-0.09	0.61	-0.00	-0.15	0.26	0.05	-	0.12	100				
AGRIEXP	0.34	0.27	-0.20	-0.14	0.11	-	-0.25	-0.02	-0.02	0.06	0.13	0.06	100			
TAP	0.13	-0.11	-0.14	-0.17	0.14	0.03	-0.09	-0.11	0.06	-0.15	0.16	-0.03	-0.10	100		
TD	-0.25	-0.05	0.17	0.18	-	-0.02	0.29	-0.08	-0.03	0.19	-0.19	-0.10	-0.19	0.17	100	
HCI	0.00	0.01	-0.02	-0.06	0.23	0.07	-	0.01	-0.01	0.14	-0.19	-0.10	-0.19	-0.01	-0.19	100
					0.07	-	0.03			-0.01	-	-0.05	-0.04	-0.01	-0.19	100
											0.05					0

Cross-Sectional Dependence Test

Table 4 presents the Pesaran Cross-Sectional Dependence (CD) Test value. The GDP per capita and employment in agriculture displays the highest values of CD-Test that represent the highest cross-sectional dependence across countries and units.

Table 4: Cross-Sectional Dependence Test

Variables	CD-Test	P-value
AVA	66.60	0.00
EPI	12.97	0.00
GDPPC	102.88	0.00
AL	11.44	0.00
EMP	292.52	0.00
GFCF	29.57	0.00
AGRIEXP	16.93	0.00
TAP	11.89	0.00
TD	21.37	0.00

Slope Homogeneity Tests

Table 5 represents the findings of slope homogeneity and heterogeneity by employing two tests: the Delta test and the HAC Robust Adjusted Delta test. In this model, the results found that the test

statistics are significant and reject the null hypothesis in both models, which confirms that slope heterogeneity exists in these models. The results of the model based on agricultural output show slope heterogeneity.

Table 5: Slope Homogeneity Tests

Models	(Pesaran and Yamagata, 2008)				(Blomquist and Westerlund, 2013)			
	Delta Test Adjusted	p-value	Unadjusted	p-value	HAC Robust Adjusted Delta Test Adjusted	p-value	Unadjusted	p-value
1	24.82	0.00	19.20	0.00	-9.96	0.00	-7.70	0.00

Unit Root Test

In this section, we will elaborate the results of second-generation panel unit root test by considering CD test data. Some variables are stationary in both test MW and CIPS at with and without trend because of highly significant test statistics including AVA, GDPPC, GFCF, AGRIEXP, TAP and TD. Moreover, some variables are stationary in MW but give mixed results due to both significant and insignificant p-values in the CIPS name as EPI, AL and EMP at both with and without trend.

Table 6: Results of Second-Generation Panel Unit Root

Second-Generation Panel Unit Root Tests												
Maddala and Wu (1999) Panel Unit Root test (MW)							Pesaran (2007) Panel Unit Root test (CIPS)					
Variables	Without Trend			With Trend			Without Trend			With Trend		
	Lags	Zt Statistics	P-value	Lags	Zt Statistics	P-value	Lags	Zt Statistics	P-value	Lags	Zt Statistics	P-value
AVA	0	518.79	0.00	0	477.77	0.00	0	-3.22	0.00	0	-4.54	0.00
EPI	1	290.39	0.00	1	220.01	0.56	1	-1.60	0.05	1	-0.69	0.24
GDPPC	0	1725.51	0.00	0	1529.22	0.00	0	-27.52	0.00	0	-25.03	0.00
AL	0	184.34	0.00	0	170.38	0.00	1	0.64	0.74	1	3.02	0.99
EMP	0	185.09	0.00	1	137.05	0.32	1	-1.90	0.03	1	2.47	0.99
GFCF	0	1332.00	0.00	0	1218.48	0.00	0	-20.99	0.00	0	-18.79	0.00
AGRIEXP	0	344.75	0.00	0	362.91	0.00	0	-2.92	0.00	0	-6.85	0.00
TAP	0	1058.01	0.00	0	1040.02	0.00	0	-17.89	0.00	0	-18.57	0.00
TD	0	756.43	0.00	0	695.56	0.00	0	-15.85	0.00	0	-14.11	0.00

Table 7 reports that the researcher determined the long run relationship among variables and used a different panel cointegration test. In this study, we have employed three major cointegration tests such as the Westerlund test, Kao test, and Pedroni test. The panel cointegration test findings reveal that in the case of the Westerlund test, all group statistics are significant, that show the long-run relationship does exist in this model except for Gt. The results of the Kao test statistics are insignificant in all models, that confirm there is no cointegration except for two tests, such as the Unadjusted Modified Dickey-Fuller and unadjusted Dickey-Fuller. Regarding Pedroni tests, the findings are significant in all models, which show the long-run relationship between variables. So, overall, we conclude overall findings reveal cointegration among variables.

Table 7: Panel Cointegration Tests

Models	Westerlund Test	Gt	Ga		Pt	Pa
1		-1.210 (0.182)	-2.002 (0.000)		-10.432 (0.000)	-10.093 (0.000)
Models	Kao Test	Modified Dickey-Fuller	Dickey-Fuller	Augmented Dickey-Fuller	Unadjusted Modified Dickey	Unadjusted Dickey-Fuller
1		1.397 (0.081)	-0.072 (0.470)	1.609 (0.053)	-2.610 (0.009)	-2.840 (0.005)
Models	Pedroni Test	Modified Phillips-Perron	Phillips-Perron	Augmented Dickey-Fuller		
1		5.510 (0.000)		-6.014 (0.000)	-5.495 (0.000)	

MMQR and BSQR Results of Agricultural Output

In this section, we have discussed the empirical estimated model findings of natural disasters and agricultural output. This section encapsulates the results of Method of Moments-Quantile Regression and Bootstrap Quantile Regression. The results of the model are presented in this section using the 10th, 25th, 50th, 75th, and 90th quantiles.

Table 8: MM-QR Estimates of Natural Disasters and Agricultural Output

Variables	Location	Scale	(Q 0.10)	(Q 0.25)	(Q 0.50)	(Q 0.75)	(Q 0.90)
EMP	0.333*** (0.00853)	0.0505*** (0.00625)	0.257*** (0.00944)	0.293*** (0.00742)	0.325*** (0.00803)	0.367*** (0.0111)	0.416*** (0.0165)
GFCF	0.0139 (0.00988)	0.0167** (0.00724)	-0.0113 (0.0105)	0.000503 (0.00861)	0.0111 (0.00934)	0.0249* (0.0129)	0.0414** (0.0189)
GDPPC	0.0109 (0.0306)	-0.0451** (0.0224)	0.0789** (0.0325)	0.0470* (0.0266)	0.0183 (0.0289)	0.0190 (0.0401)	0.0633 (0.0585)
EPI	0.0777 (0.749)	0.841 (0.548)	-1.191 (0.794)	-0.597 (0.652)	-0.0610 (0.708)	0.634 (0.981)	1.461 (1.432)
TD	-0.407***	-0.0468	-0.336***	-0.369***	-0.399***	-0.438***	-0.484***

	(0.0623)	(0.0456)	(0.0660)	(0.0543)	(0.0589)	(0.0817)	(0.119)
TAP	0.115**	-0.113**	0.286**	0.206**	0.134**	-0.0408	-0.0703
	(0.0531)	(0.0389)	(0.0566)	(0.0463)	(0.0502)	(0.0696)	(0.102)
AGRIEXP	0.208**	0.00736	0.196**	0.202**	0.206**	0.212**	0.220**
	(0.0177)	(0.0130)	(0.0188)	(0.0155)	(0.0168)	(0.0232)	(0.0339)
Constant	5.048**	3.506**	-0.244	2.236**	4.470**	7.370**	10.82**
	(0.942)	(0.690)	(1.010)	(0.822)	(0.892)	(1.237)	(1.808)
Observations	1,719	1,719	1,719	1,719	1,719	1,719	1,719

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This study employs MMQR results on natural disasters and agricultural output for developing countries using estimated regression at five quantiles. Table 8 shows the outcomes of MMQR estimates; these results depict how agricultural output is affected by different factors EMP, GFCF, GDPPC, EPI, natural disaster variables (TD and TAP) and AGRIEXP. There is a positive and highly statistically significant relationship between employment in agriculture and agricultural output across all quantiles. The classical production theory supports this relationship, where land, labor and capital are the more important inputs in the production function. In the agriculture sector, labor is a core source of production, so an increase in labor input leads to an increase in output (Moldavan & Pimenowa, 2025; Smith, 1793). The results align with these studies (Cobb & Douglas, 1928; Debertin, 2012; Mankiw, 1980). The effect of gross fixed capital formation on agricultural output is positive and statistically significant across higher quantiles at the 75th and 90th. However, at the 10th, 25th and 50th quantiles, the relationship between gross fixed capital formation and agricultural output is positive but statistically insignificant. In this study, gross fixed capital used for agricultural capital. The investment in tangible assets in the farming sector led to an increase in capital effectiveness in the agriculture sector. Also, it may help to increase the total agricultural output of the developing countries (Venkataramana et al. 2019; Canton, 2021; Obe et al. 2024; Das et al. 2015; Solow, 1999). González-Blanco et al. (2019), Griliches (1969), Berlingieri et al. (2024) also confirm that capital formation plays a crucial role in the development of the agricultural output especially in higher middle-income developing countries.

For the third variable GDPCC, the study findings depict that GDPPC is positive relationship with agricultural output in 25th to 90th quantiles. The findings of GDPPC indicate that the coefficients are statistically significant at the lower quantiles 10th and 25th but are insignificant at the middle and higher quantiles. The findings show that economic growth raises agricultural output and is an important driver of farmers income in low-productive country. In middle and upper quantiles, coefficient results linked with an advanced agrarian system, where not only focus on economic growth but also other factors farm mechanisms, technological transformation, climatic conditions and infrastructural development dominant role in raising the output. The results are aligned with already concluded studies (Dercon & Gollin, 2014; Diao et al., 2007; Phillips & Sul, 2003). Furthermore, this study found the negative association between the environmental performance index and agriculture output at lower and middle quantiles i.e. 0.1 quantile up to 0.5 quantile. The findings also indicate a positive effect of EPI on agricultural output at the upper quantile from 0.75

to 0.90. EPI is statistically insignificant across all quantiles. farmers mostly depend on traditional methods due to a lack of knowledge about the latest technological equipment. Also, they have limited financial capacity and are not able to benefit from the latest technologies and institutions. That's why at lower and middle quantiles; countries get lower agricultural output. From the results provided by Boerger et al. (2021), FAO (2013), Riofrio & León (2022) are in favor of our findings in terms of lower and middle quantiles. The results of upper quantiles support these studies Porter & Linde (1995), Vaezi et al. (2013), Thomakos & Alexopoulos (2016). The study results elaborate the impact of natural disasters (total damages use a proxy variable) on agricultural output. The coefficient estimation indicates a highly significant results and a negative impact of total damages on agricultural output across all quantiles. Nonlinear temperature and greenhouse gases have a severe impact on agriculture (FAO, 2016; Schlenker & Roberts, 2009; World Bank, 2021).

Regarding the relationship between the total affected people by natural disaster events and agricultural output, the research indicates a positive and significant relationship for lower and middle quantiles. Moreover, TAP shows a negative and insignificant association with agricultural output at higher quantiles i.e. 75th and 90th. This finding represents that natural disaster events cause an increase in the number of total affected people and these affected people are mostly part of agricultural labor and related activities (FAO, 2018; Singh et al. 1986). The research findings support these studies (UNDRR, 2019; World Bank, 2020). The coefficient of agricultural raw material export (AGRIEXP) has a positive association with agricultural output and significant across all quantiles. The percentage of variation and influence of agricultural raw material exports on agrarian output differ in all quantiles. This estimation indicates that agricultural exports stimulate the economic activities and enhance agricultural output in developing countries. The results of our study are in line with the findings of Feder (1983), FAO (2023), Bigsten & Gebreeyesus (2009) and Van Biesebroeck (2005) Krugman et al. (2018) Nagel & Burnete (2018) Widodo (2009).

Table 9: BS-QR Estimates of Natural Disasters and Agricultural Output

Variables	(Q 0.10)	(Q 0.25)	(Q 0.50)	(Q 0.75)	(Q 0.90)
EMP	0.204*** (0.0158)	0.305*** (0.0107)	0.341*** (0.00657)	0.371*** (0.00643)	0.411*** (0.0134)
GFCF	0.00332 (0.0114)	0.00226 (0.00885)	0.0133*** (0.00380)	0.0261*** (0.00516)	0.0443*** (0.0103)
GDPPC	0.0850*** (0.0298)	0.0281 (0.0477)	0.0190 (0.0306)	-0.0244 (0.0242)	-0.0402 (0.0521)
EPI	-1.113 (0.989)	-1.307*** (0.504)	-0.512 (0.684)	0.947 (0.782)	-2.171** (0.951)
TD	-0.299*** (0.0379)	-0.280*** (0.0442)	-0.399*** (0.0720)	-0.459*** (0.0685)	-0.237* (0.132)
TAP	0.253*** (0.0607)	0.0778* (0.0425)	0.0962* (0.0511)	-0.00307 (0.0994)	-0.173 (0.138)

AGRIEXP	0.202** (0.0220)	0.176** (0.0227)	0.232** (0.0270)	0.236** (0.0360)	0.248** (0.0280)
Constant	1.224 (1.249)	2.709** (0.598)	4.433** (0.806)	7.653** (1.230)	10.47** (2.830)
Observations	1,719	1,719	1,719	1,719	1,719

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

BSQR estimates of natural disasters and agricultural output. BSQR (Bayesian Spatial Quantile Regression) is employed to address three problems simultaneously as heterogeneity, spatial dependence, and uncertainty. MMQR captures heterogeneity but ignores spatial dependence, its findings may lead to biased results. BSQR is used for checking the robustness of MMQR findings under spatial dependence. The coefficient estimation of BSQR supports the MMQR estimates of natural disasters and agricultural output.

Conclusions and Policy Recommendations

This study offers an in-depth overview of the factors influencing natural disasters in developing countries, aiming to emphasize their implications for agricultural output. The natural disasters data were gathered from the period 2000 to 2024, forming a comprehensive large panel data set of developing countries. The study employs 129 developing countries, their classification based on the World Development Indicators (WDI) database; 25 are low-income, 50 are categorized as lower-middle-income and 54 are classified as upper-middle-income. The actual data on natural disaster indicators are derived from EM-DAT from the Centre for Research on the Epidemiology of Disasters (CRED). This study incorporates the Method of Moments Quantile Regression (MM-QR) and Bootstrap Quantile Regression (BSQR). The empirically investigated results of the model of natural disasters and their influence on agricultural output in developing countries show a worse relationship between variables rather than a positive influence on agricultural output, especially in less developed countries. The results demonstrate that TD (total damages by natural disasters), TAP (total affected people by natural disasters) and EPI (environmental performance index) are negatively linked with agricultural output. Natural disaster events cause severe damage in low-income regions; these shocks not only disturb environmental quality but also damage healthy crops. The results also indicate that EMP (employment in agriculture), GFCF (gross fixed capital formation) and GDPPC (GDP per capita) and AGRIEXP (agricultural raw material export) have positive influence on agricultural output.

Based on empirical results, the study provides key insights for policymakers and researchers seeking guidance on managing natural disasters in developing countries. Government policies and programs are essential for stabilizing economic growth and strengthening agricultural output during food crises and natural disasters, especially in less developed nations.

The present study gives practical insights for policymakers and researchers based on empirical findings.

- Early warning systems and risk-sensitive land-use planning should be a core component of national development planning.
- It is suggested that policymakers promote effective disaster response mechanisms, disaster relief funds, drought-resistant crops, improved seed varieties and efficient irrigation infrastructure rather than focusing on post-disaster relief.
- There is a need for more investment in a disaster-resilient agricultural system.
- A priority would be for national governments and aid agencies to provide disaster relief packages in rural areas that can be combined into low-oxygen grain storage bags, agricultural equipment, seeds of early-maturing crops and fertilizers.
- The government provides a favorable institutional environment for the development of the crop insurance program and expanding facilities to access credit for farmers can strengthen farmers to adopt adaptive technologies and modern inputs against income shocks caused by natural disasters.
- The coordinated planning and development of certain measures would promote balanced development in agricultural water-use areas in developing countries.

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