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THE IMPACT OF NATURAL DISASTERS AND CLIMATE CHANGE ON AGRICULTURE: AN EMPIRICAL ANALYSIS

Muhammad Tariq Iqbal Khan [a,*], Sofia Anwar [a], Muhammad Rizwan Yaseen [a], Abdul Majeed Nadeem [a]

[a] *Department of Economics, Government College University, Faisalabad-38000, Pakistan*

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ABSTRACT

This study shows the effect of natural disasters, rainfall, temperature, economic growth, renewable energy, and contributing family workers on the agricultural development index in 101 countries of all income groups (i.e., 24 high, 29 upper-middle, 32 lower-middle, and 16 low). It develops a new agricultural development index using a standard procedure. The two-step generalized method of moments depicts revealed the adverse consequences of natural disasters on agriculture. Renewable energy showed a favorable impact on agricultural development in all panels. Contrarily, the reduction in agricultural development was reported due to an increase in temperature in all panels. Agricultural development increased due to economic growth in all panels. It is required to increase disaster resilience to minimize disaster-related losses. It is recommended to increase renewable energy use for agricultural development. Policymakers should make strategies to mitigate the adverse impacts of global warming.

* *Email: tariqiqbal88@yahoo.com*

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INTRODUCTION

Climate change is continuously shown negative effects on agricultural production (Faisal et al., 2020), which in turn disturbs food availability (Faisal et al., 2021). Thus, climate change is ranked as an important issue for human beings in the 21st century. Policymakers trying to mitigate the adverse effects of climate change on human beings. According to Intergovernmental Panel on Climate Change (IPCC), climate change is evident in changing patterns of rainfall, global warming, saltwater intrusion, increasing sea level, and higher frequency of natural disasters (Trinh et al., 2021). The SDG-13 dubbed "Climate Action" focuses on climate change mitigation through five targets requiring immediate action by countries. The first target (SDG-13.1) of "Climate Action" entails strengthening country-specific resilience and adaptive capacity towards climate-related hazards and natural disasters (Doni et al., 2020). Natural disasters are earthquakes, droughts, floods, high temperatures, epidemics, wildfire, insect infection, storms, landslides, mass movement (dry), and volcanic activity (Fang et al., 2019). The World witnessed an increase in the intensity and frequency of natural disasters (Panwar and Sen, 2019). Since 1970, the world witnessed 13,386 natural disasters, which were responsible for 3.6 million deaths, 7.7 billion affected people, and 3.3 trillion USD losses (Fang et al., 2019). Disasters show devastating effects on food security, which in turn led to greater vulnerability (FAO, 2018). The awareness of the consequences of natural disasters has been increased in the recent era to mitigate disaster-related losses (Marin and Modica, 2017).

The agriculture sector is risk-prone, especially farmers in developing economies who faced risk and uncertain conditions (Akhtar et al., 2019). Farmers work under vulnerable circumstances due to climate change (Akhtar et al., 2018). Natural disasters show significant adverse effects on agricultural production (Qianwen and Junbiao, 2007). Agriculture is the most affected sector by climate change and natural disasters (Figure 1). It destruct agricultural production due to a reduction in crop yield, non-availability of irrigation water, and potential evapotranspiration (Trinh et al., 2021). The agricultural sector faced approximately 16% of total damage, 31% of total disaster loss, and 23% of total damage and loss in the world (FAO, 2018). The damage to agricultural production poses serious threats to food security, especially in countries where the majority of smallholders depend upon agriculture for their livelihoods and subsistence (FAO, 2018). It is forecasted that losses due to natural disasters will rise due to climatic changes and the vulnerability of modern societies (Panwar and Sen, 2019). The developing nations are vulnerable to natural disasters due to less diversification and dependence on agriculture (Noy, 2009).

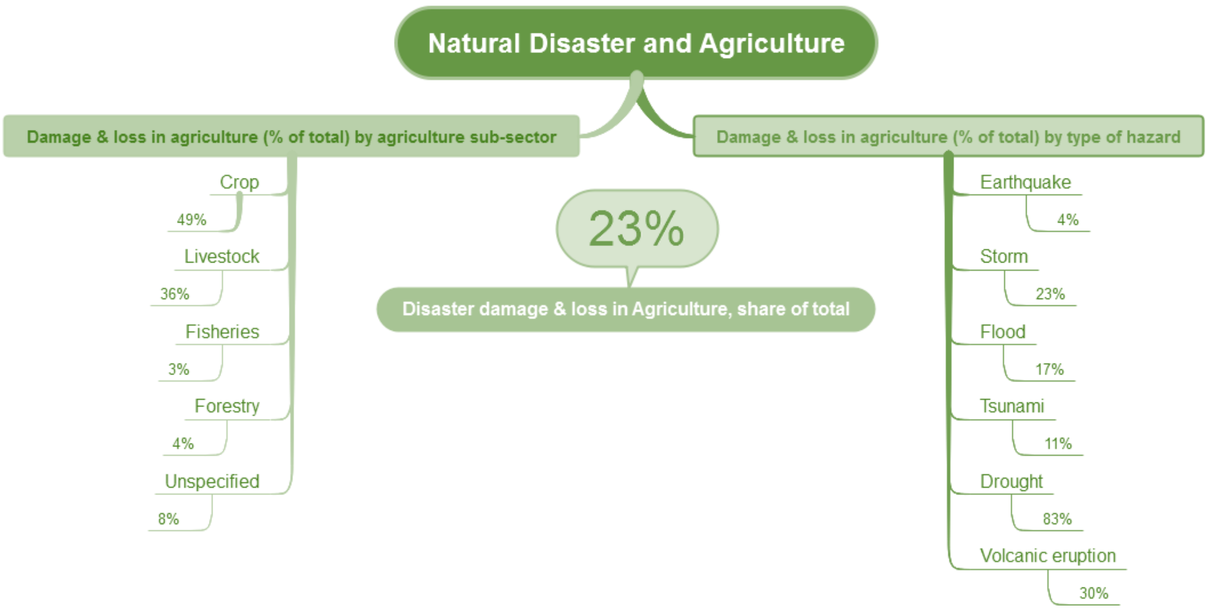

Figure 1. Natural disasters and agriculture sector losses, restructured from FAO (2018).

Floods are responsible for the reduction in farming, transportation, and urban activities, which in turn reduce productivity. Due to intense and long-lasting floods, water-borne diseases emerged, which are responsible for the loss of total factor productivity. Localized and moderate floods are linked with higher growth due to (a) floods may accelerate agricultural growth due to an increase in productivity and irrigation water, (b) floods may accelerate industrial growth through an increase in electricity generation and agricultural products, which are intermediate inputs, and (c) floods positively affect the services sector by increasing the supply of inputs for retail and commerce (Loayza et al., 2012). Earthquakes adversely affected both capital and labor and destroyed infrastructure, buildings, and factories. However, earthquakes may favorably influence the industrial growth, through (a) capital-worker ratio diminished sharply, (b) average product of capital rises, (c) output increases as the economy entered the reconstruction phase, and (d) replacement of destroyed capital with better-quality capital, which was linked with higher factor productivity, leading to higher growth (Loayza et al., 2012).

Droughts are accountable for the adverse impacts on agricultural growth due to a shortage of irrigation water. It disturbs industrial growth through (a) reducing the supply of agricultural inputs to agro-based industries, and (b) disturbing the supply of electricity, especially electricity generation from hydropower. The adverse impact of a drought is more on labor as compared to capital, which implies the increase in k beyond the steady-state capital (k*). Storms adversely affected agricultural production due to the destruction of seedlings and plants. Storms are linked with the destruction of physical capital. However, moderate storms show a favorable impact on industrial growth (Loayza et al., 2012). The UN gives the Sendai Framework for disaster risk reduction (DRR) 2015-2030, which aims to avoid new disasters and minimize the risk of existing disasters (UNDRR, 2015). This study contributes to the literature in multiple ways. First, it develops an agricultural development index using multiple indicators like agricultural land, agricultural value addition, and employment share in agriculture. Second, it assesses the impact of climate indicators (rainfall and temperature) and renewable energy on agriculture development. Third, it performed the empirical analysis for 101 countries, divided into four income groups.

The literature examined the effect of natural disasters on economic growth but its impact on agriculture remained inconclusive. Some researchers probed the effect of natural disasters (flood, drought, earthquake, and storm) on different growth indicators including agricultural growth. It has been reported that the consequences of natural disasters were higher in low and middle-income countries (Coulibaly et al., 2020). Qianwen and Junbiao (2007) reported the increase in rural poverty and reduction in sown areas due to an increase in the area affected by agricultural natural disasters in China. Israel and Briones (2012) analyzed the consequences of natural disasters on agriculture, natural resources, the environment, and food security in the Philippines. Natural disasters like floods and typhoons showed an insignificant effect on national agricultural production. However, typhoons adversely affected provincial rice production. Typhoons also adversely affected the food availability in affected regions. Klomp and Hoogezand (2018) described the consequences of natural disasters on agriculture in 76 countries. The trade balanced the trade-off between food availability and protection of the domestic agricultural sector. Natural disasters increased agricultural trade controls to protect local farmers. However, the level and pattern of protection were different across the selected countries. Natural disasters like storms and floods increased the protection of agriculture in developed countries while trade barriers were reduced during drought to minimize food scarcity in the least developed countries. The environmental disturbance deteriorated the services and agricultural sectors (Oliveira, 2019). In a recent study, Coulibaly et al. (2020) examined the impact of natural disasters and climate change on agriculture in the panel of African countries. The temperature was identified as a major climate factor that affects agricultural production. Disasters adversely affect agricultural production is irrespective of the development stage of countries. This study is a new addition to the literature (Table 1) as it explored the impact of natural disasters and control variables on agricultural development in 101 countries.

Table 1. Literature about the consequences of natural disasters on agriculture

Author(s)	Variables	Countries	Method	Duration	Results
Israel and Briones (2012)	Natural disasters, agriculture, natural resources, food security, and the environment	Philippines	Generalized Algebraic Modeling	2010	1) Floods, typhoons, and droughts showed an insignificant effect on agriculture. 2) Typhoons showed an adverse effect on food security in the affected areas.
Klomp and Hoogezand (2018)	Natural disasters, agricultural protection, real GDP, inflation rate, foreign aid, trade, EU membership, Uruguay Round, democracy, population, land, and capital endowment	76 countries	Two-step system Generalized Method of Moments	1985-2010	1) Natural disasters increased agricultural trade to favor domestic farmers. 2) Storm and floods increased agricultural protection in developed countries. 3) Trade barriers were removed during droughts in the least developed countries.
Panwar and Sen (2019)	GDP growth, agricultural and non-agricultural growth, natural disasters initial output, financial burden, trade, education, inflation, and financial depth	29 developed and 73 developing countries	Generalized Method of Moments	1981-2015	1) Natural disasters showed diversified effects on different economic sectors subject to the intensity and type of disaster. 2) Economic consequences of natural disasters were higher in developing countries.
Coulibaly et al. (2020)	Agricultural production, labor, rainfall, average temperature, droughts, floods, fertilizer, capital, and agricultural area	45 African countries	Regression with Driscoll-Kraay standard errors	1960-2016	1) Temperature is a major climate factor that affects agricultural production. 2) Droughts adversely affect agricultural production, especially in poor countries.

METHODOLOGY

This study is based on panel data of 101 countries (Appendix A), including 24 HICs, 29 UMICs, 32 LMICs, and 16 LICs. Disaster data of all countries (all income groups) were obtained from the Emergency Events Database (EM-DAT) by the Centre for research on the Epidemiology of Disasters (CRED) (CRED, 2021)a global database that shows disaster-related data for about 200 countries. The disaster-related data were also obtained from Disaster Information Management System (UNDRR, 2021). We removed those countries whose disaster data were not available at CRED. Thus, we selected only those countries which had a higher frequency of natural disasters. However, some countries were deleted due to the non-availability of data of control variables. The EM-DAT counted a disaster based on different facts like (a) report of 10 or more fatalities, (b) report of 100 affected people, (3) announcement of emergency, and (d) call for international assistance. The disasters are hydro- eteorological (droughts, storms, floods, wave surges, avalanches, and landslides); geophysical (tsunamis, volcanic eruptions, and earthquakes); and biological (insect infestations and epidemics).

Model

Based on the theoretical relationship (Figure 2), the following model is used for empirical analysis:

$$AGR_{it} = f\left(AGR_{i,t-1}, DIS_{it}, RF_{it}, TEM_{it}, GDP_{it}, REN_{it}, FAM_{it}\right) \quad (1)$$

Where AGR_{it} shows agricultural development index (0-100); $AGR_{i,t-1}$ shows a one-period lag value of agricultural development index; DIS_{it} shows total people affected due to natural disasters (per million); RF_{it} shows the rainfall (mm per 1000 sq. km.); TEM_{it} shows average daily temperature (Celsius);GDP_{it} shows GDP (constant 2010 USD/capita); REN_{it} shows renewable energy (% of total); FAM_{it} shows contributing family workers (% of total employment); t is the time (1995-2019), and i shows countries. The model was converted into a double-log form to avoid heteroscedasticity and outliers effect, as (Rahman et al., 2019):

$$nAGR_{it} = \beta_{i0} + \beta_{1i} lnAGR_{it-1} + \beta_{2i} lnDIS_{it} + \beta_{3i} lnRF_{it} + \beta_{4i} lnTEM_{it} + \beta_{5i} lnGDP_{it} + \beta_{6i} lnREN_{it} + \beta_{7i} lnFAM_{it} + \varepsilon_{it} \quad (2)$$

Where β_0 and γ_0 shows intercept of constant; the symbols β1-7 shows regression coefficients; ε shows the error term.

Justification of Variables

This study used five control variables in the disaster-agriculture framework. These variables are theoretically associated with the agriculture sector, as:

Agriculture Development Index: The agricultural development index was developed using three indicators (a) agricultural land (% of land area), (b) agriculture, forestry, and fishing, value added (% of GDP), and (c) employment in agriculture (% of total employment) (WDI, 2021).

Rainfall: The effects of climate change are evident at regional, national, and international levels. Agriculture is closely associated with climate change due to due to high vulnerability (Olayide et al., 2016). Reduction in rainfall may lead to low yields from rain-fed crop production (Kogo et al., 2021). Lack of water shows adverse impacts on plant cells while excessive water also shows adverse impacts on crops (Bhadouria et al., 2019). Therefore, rainfall can have either positive or negative effects on agriculture yield, which are region or area-specific (Li et al., 2019).

Temperature: Agricultural production faced challenges due to increases in temperature under a warming climate with intensified water cycle (Li et al., 2019). It has been predicted that the increase in average global temperature will be 0.2°C each decade. Due to global warming, it is difficult for species (human beings, plants, animals, microorganisms, and ecosystems) to adopt a new climate. In general, plants show substantial growth due to an increase in air temperatures up to a point. After that, extreme heat may slow down the process of growth and reduce moisture content, which in turn reduces agricultural productivity (Bhadouria et al., 2019).

Economic Growth: Agriculture shows a vital role in economic development. It is a multi-dimensional practice that shows positive impacts on urban and rural areas (Udemezue and Osegbue, 2018). Lewi's growth model (Lewis, 1954) stated that rapid industrial growth is fueled by the agricultural sector. Thus, industrial growth is possible through surplus labor and cheap food. So, development economists show less interest in rapid industrialization (Todaro, 1997). Agricultural development shows a leading role in the economic development process. However, the agriculture sector is inefficient in developing countries (Katircioglu, 2006).

Renewable Energy: Renewable energy usage in agricultural practices is beneficial for farmers due to multiple advantages (i.e., economic, social, and environmental) (Ben Jebli and Youssef, 2017). It can be used in multiple agricultural operations, including (i) solar energy utilization in cooling and heating of the greenhouse, drying of products, irrigation, and lighting; (b) utilization of modern biofuels (i.e., biogas and bioethanol) in agricultural practices; (c) utilization of geothermal energy in barns, greenhouse, aquaculture, drying of products, soil improvement; and heating soil; (d) utilization of wind turbines in irrigation, land drainage, watering livestock, and electricity generation; (e) utilization of hydropower in water-related practices (drinking, irrigation, flood control, and equitable water sharing) (Khan et al., 2018).

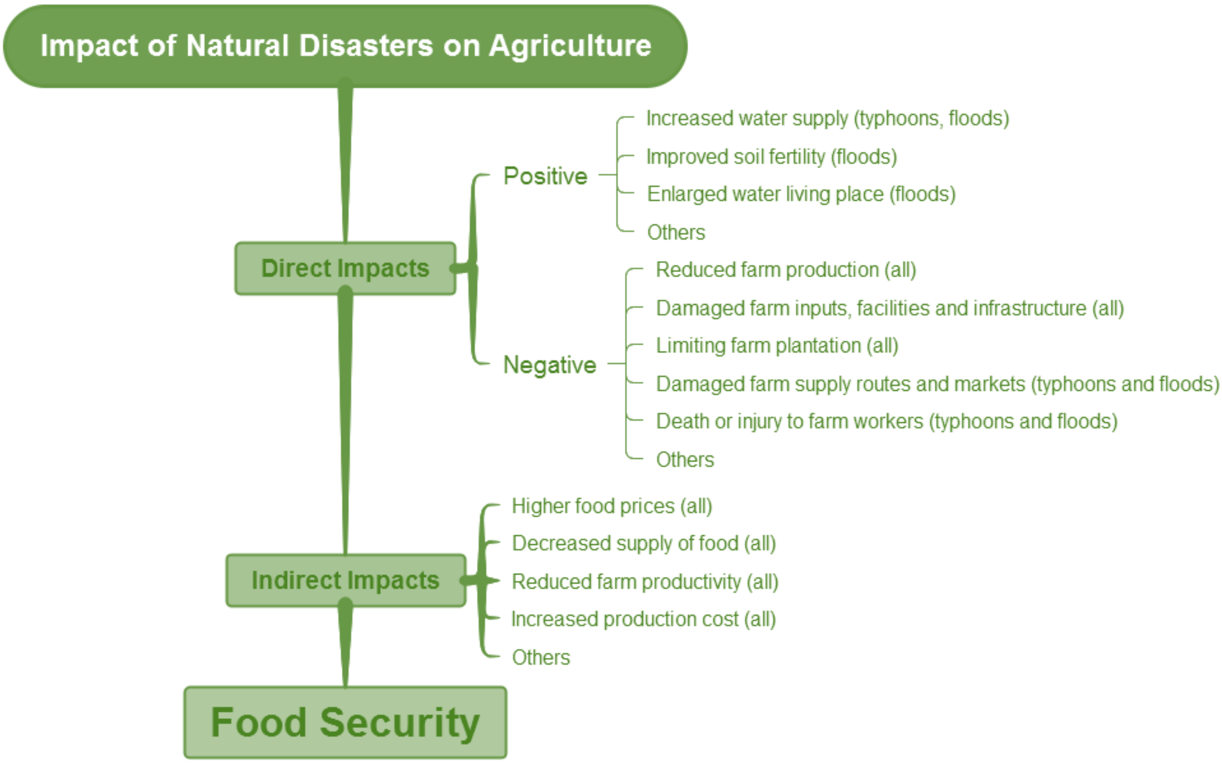

Figure 2. Impact of natural disasters on agriculture, reconstructed from (Israel and Briones, 2012).

Contributing Family Workers: Contributing family work is generally a type of unpaid labor, which may receive indirect compensation in the form of family income. Such activities are common among women, especially in households where other members engage in self-employment like farming or running a family business. The increase in the shares of contributing family workers is likely responsible for poor development, little job growth, an increase in poverty, and the establishment of a rural economy (ILO, 2015).

Index-Making procedure

this study used the index-making procedure of the IMF, which was applied on a balanced panel. The procedure involved five steps, (a) selection of indicators, (b) winsorization with cutoff values i.e. 95th and 5th percentiles, (c) normalization (0,1) with the min-max method, (d) weights obtained using PCA, and (e) construction of an additive index (0,100), as (Svirydzenka, 2016; Ali et al., 2021):

$$Index_i = \sum_{i=1}^{n} w_i I_i \tag{3}$$

Preliminary tests

This study used several diagnostic tests (cross-sectional dependence, slope heterogeneity heteroscedasticity, multicollinearity, and autocorrelation) before regression analysis for better results. Multicollinearity leads to inconsistent and insignificant estimates. The variance inflation factor (VIF) (Neter et al., 1989; Thompson et al., 2017) is used as:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{4}$$

The score of VIF is less than 5 in the absence of multicollinearity (Kalnins, 2018).

Cross-sectional dependence leads to inefficient and invalid estimations (Ali et al., 2020a). Thus, it was tested using multiple tests such as (a) Breusch and Pagan LM (Breusch and Pagan, 1980) test (Eq. 5), (b) Pesaran CD (Pesaran, 2021) test (Eq. 6), and (c) bias-adjusted LM (Pesaran et al., 2008) test (Eq. 7) (Destek and Aslan, 2017; Ali et al., 2021):

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \mathcal{X}^2_{N(N-1)/2} \tag{5}$$

$$\text{CD} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(\hat{\rho}_{ij} - 1\right) N(0,1) \tag{6}$$

$$LM_{adj} = \sqrt{\left(\frac{2}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} N(0,1) \tag{7}$$

Heteroscedasticity leads to biased estimation and wrong hypothesis interpretation (Alabi et al., 2020). The group-wise heteroskedasticity was tested with modified Wald statistic using the residuals of a fixed-effect model, expressed as (Baum, 2001):

$$W = \sum_{i=1}^{N_g} \frac{\left(\hat{\sigma}_i^2 - \hat{\sigma}^2\right)^2}{V_i} \tag{8}$$

Autocorrelation leads to biased standard errors and inefficient results. Wooldridge (2002) autocorrelation test used a few assumptions and a linear model. It is expressed as (Drukker, 2003):

$$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta_1 + \epsilon_{it} - \epsilon_{it-1} \tag{9}$$

$$\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta\epsilon_{it} \tag{10}$$

Where y_{it} shows dependent variable, X_{it} shows a ($1 \times K_1$) vector of covariates (time-varying), Δ shows the first-difference operator. The β_1 is estimated by regressing Δy_{it} on ΔX_{it}, and obtaining the residuals (ϵ_{it}) (Drukker, 2003). Due to country-related features, slope heterogeneity may exist in the panel (Khan et al., 2019). To check the slope homogeneity across countries, this study used three tests such as (a) Swamy's (1970) slope test (Eq. 11), (b) the $\tilde{\Delta}$ (Pesaran and Yamagata, 2008) test for large panels (Eq. 12), and (c) bias-adjusted $\tilde{\Delta}$ (Pesaran and Yamagata, 2008) test to improve small sample properties (Eq. 13) (Chang et al., 2013; Tong and Yu, 2018):

$$\tilde{S} = \sum_{t=1}^{N} \left(\hat{\beta}_\iota - \hat{\beta}_{WFE}\right)' \frac{X_i' M_\tau X_i}{\hat{\sigma}_i^2} \left(\hat{\beta}_\iota - \hat{\beta}_{WFE}\right) \tag{11}$$

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{12}$$

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right) \tag{13}$$

Unit root test

Non-stationarity series leads to meaningless forecasts, difficulty in model selection, and spurious results (Ali et al., 2020a). Due to cross-sectional dependence, it is suitable to use a second-generation cross-sectionally augmented IPS (CIPS) test (Pesaran, 2007). It is expressed as (Tong and Yu, 2018; Ali et al., 2021):

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \tilde{t}_i \tag{14}$$

Cointegration Test

To control spurious results, a long-run relationship between variables is required (i.e., cointegration) (Ali et al., 2020b). Two variables exhibit order (1,1) cointegration if these were non-stationary individually but their linear combination becomes stationary (Yaseen et al., 2018). However, it is better to use the second generation Westerlund cointegration test (Westerlund, 2005) due to CD, which is expressed as (Wang and Dong, 2019):

$$VR = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{E}_{it}^2 \hat{R}_i^{-1} \tag{15}$$

$$VR = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{E}_{it}^2 \left(\sum_{i=1}^{N} \hat{R}_i\right)^{-1} \tag{16}$$

Regression Analysis

Endogeneity, an econometric problem, leads to inconsistent estimates, wrong inferences, incorrect interpretations, and misleading conclusions (Ullah et al., 2018). Arellano and Bond (1998) and Blundell and Bond (1998) give the GMM model for dynamic panel data estimation, which is superior to PMG and MG based on the fact that it controls the dynamic panel bias due to the addition of lagged dependent variables. It is suitable for growth models, having larger N and smaller T. It controls the endogeneity and gives efficient and consistent results (Berk et al., 2020). The dynamic model used the lag of dependent variables as an explanatory variable, which is used as an instrument to control endogeneity. The GMM has two transformations i.e. first-order (one-step GMM) and second-order (two-step GMM) (Ullah et al., 2018). Due to limitations of one-step estimation (Roodman, 2009), Arellano and Bover (1995) recommended to used two-step GMM, which is based on 'forward orthogonal deviations' or subtraction of average of all future values of a variable (Roodman, 2009). It shows efficient and consistent results in a balanced panel (Arellano and Bover, 1995). Diagnostic tests were used to check the reliability of GMM estimation such as (a) absence of serial correlation (Roodman, 2009), (b) the Sargan test of overall validity of instruments (Ali et al., 2016), and Hansen (1982) test of over-identifying restrictions showed p-values for the null hypothesis (instrument validity).

RESULTS AND DISCUSSION

Table 2 depicts the summary of selected indicators in selected income groups from 1995 to 2019. This situation of natural disasters is worst in UMICs and LMICs. Natural disasters were accountable for human loss (death, injured, affected, and missing), which was higher in UMICs (28191.930 per million) followed by LMICs (26126.840 per million), LICs (21824.080 per million), and HICs (2401.602 per million). The disaster-related damage was less in HICs. The GDP per capita showed a significant difference in the four panels, which was 31521.010 USD in HICs and 609.835 USD in LICs. The mean rainfall was more in HICs (0.220 mm per 1000 sq. km.) and less in LMICs (0.010 mm per 1000 sq. km.). The average temperature was higher in LICs (23.201°C) followed by LMICs (21.943°C), UMICs (19.779°C), and HICs (11.948°C). The agriculture sectors showed dominance in LICs, which implies that the score of the agricultural development index decreased with the level of income. The average agricultural development index was 23.446 (HICs), 32.717 (UMICs), 54.992 (LMICs), and 76.101 (LICs). The share of renewable energy was higher in LICs (82.260%), LMICs (49.282%), UMICs (23.745%), and HICs (15.054%). It implies that the utilization of renewable energy was inversely related to the level of income. It showed the potential of renewable energy utilization in the HICs and UMICs. The share of contributing family workers in total employment was higher in LICs (25.822%) followed by LMICs (18.890), UMICs (8.525), and HICs (2.411). Several diagnostic tests were applied before regression estimation (Table 3). Results of cross-sectional dependence tests indicate the cross-dependency in each panel. Dependency is a situation in which a country is associated with the expansion or distortion in the economy of another country (Balcilar et al., 2017). The slope homogeneity tests show slope heterogeneity in all panels. Results confirmed autocorrelation and heteroskedasticity in all groups. Multicollinearity was not found in all panels because the VIF is less than 5. The CIPS unit root test (Table 4) shows that stationarity was not found at the level for some variables i.e. agricultural development index, GDP per capita, contributing family workers, and renewable energy consumption. However, stationarity was observed in all variables at the first difference. The Westerlund cointegration test (Table 5) showed the long-run cointegration between selected indicators in all panels.

Table 6 reveals the impact of natural disasters, rainfall, temperature, GDP per capita, renewable energy, and contributing family workers on the agricultural development index in the panel of HICs, UMICs, LMICs, and LICs using two-step difference GMM. The agricultural development index includes three indicators like agricultural land, agricultural value-addition, and agricultural employment. The one-period lag of the agricultural development index was positive, which implies that the previous year's agricultural development index showed a favorable effect on the current year's value of the agricultural development index. The decrease in agricultural development index was 0.003% in high, 0.007% in upper-middle, 0.005% in lower-middle, and 0.001% in low income panel for 1% increase in total people affected due to natural disasters. It is because the total affected people (per million) was also higher in UMICs and LMICs. Natural disasters were found harmful for the agriculture sector. Typhoons adversely affected the paddy rice production in the Philippines (Israel and Briones, 2012). A strong negative effect of droughts on agricultural production was also found in the literature (Dercon, 2004; Hlavinka et al., 2009; Berlemann and Wenzel, 2015). A drought was responsible for 0.02% and 0.04% reduction in agricultural production in LICs and MICs, respectively (Coulibaly et al., 2020). Education plays a key role in the agriculture sector to implement climate change mitigation policies (Faisal et al., 2021). It is required to formulate resilience strategies to mitigate the adverse impacts of natural disasters on the agriculture sector. It is also recommended to provide financial assistance to small or marginal farmers, especially in developing countries. The increase in agricultural development index was 0.002% (High), 0.175% (upper-middle), 0.151% (lower-middle), and 0.079% (low) for 1% expansion in the use of renewable energy. Renewable energy use was found favorable for agricultural development. The positive role of renewable energy was not higher in HICs due to less share of renewable energy. The use of renewable resources like wind, solar, tidal, biomass, small-scale hydro, geothermal, wave-generated power, and biofuels showed huge potential for the agriculture sector. It is required to provide financial support to farmers about the use of renewable energy technology (Chel and Kaushik, 2011). The increase in agricultural development was higher in UMICs (0.227%) followed by HICs (0.122%), LICs (0.122%), and LMICs (0.012%) for 1% rise in GDP per capita. The economic growth produced a favorable impact on agricultural activities in all panels. The increase in agricultural production was 0.417% (least developed countries), 0.387% (LICs), and 0.336% (MICs) for 1% rise in GDP per capita (Coulibaly et al., 2020). The reduction in the agricultural development index was 0.007% for 1% increase in the rainfall in HICs. However, an increase in agricultural development was observed in UMICs (0.831%) and LMICs (0.296%). A positive connection between rainfall and agricultural production was also found in Africa, showing 0.11% increase in agricultural production for 1% increase in rainfall in Africa and Sub-Saharan Africa (Coulibaly et al., 2020). It is a fact that water scarcity was responsible for the negative effect on agricultural production (Panwar and Sen, 2019). It implies the significance of rainfall for the agriculture sector and the dependency of agricultural production on climatic factors. The reduction in agricultural development index was more in 0.482% in UMICs, 0.470% in HICs, 0.446% in LICs, and 0.423% in LMICs for 1% increase in average temperature. The increase in temperature or global warming was not favorable for the agriculture sector in all panels. This result is consistent with the literature, as the reduction in agricultural production was 0.954% (Africa), and 1.787% (Sub-Saharan Africa) for 1% increase in temperature (Coulibaly et al., 2020). The increase in agricultural development index was 0.051% (HICs), 0.125% (UMICs), and 0.157% (LICs) for 1% increase in the contributing family workers.

Table 2. Descriptive analysis.

Panel	Mean	Min.	Max.	SD	Source	Mean	Min.	Max.	SD	Source
	Total affected persons (DIS) (per million)					GDP/capita (GDP) (constant 2010 USD)				
HICs	2401.602	0.000	263575.20	14064.41	CRED (2021); UNDRR (2021)	31521.010	4775.307	79406.660	16947.03	WDI (2021)
UMICs	28191.930	0.000	1051291.00	101288.20		6140.169	1077.190	15190.100	3000.841	
LMICs	26126.840	0.000	909496.00	73145.38		1714.925	242.344	4828.626	1006.989	
LICs	21824.080	0.000	535208	65952.67		609.835	183.548	1900.093	332.847	
Panel	Total rainfall (RF) (mm per 1000 sq. km.)					Average temperature (TEM) (Celsius)				
HICs	0.220	0.000	6.799	1.023	TCCKP (2021)	11.948	-7.433	27.225	6.521	TCCKP (2021)
UMICs	0.158	0.000	5.420	0.735		19.779	-6.517	27.458	7.701	
LMICs	0.010	0.000	0.125	0.021		21.943	-0.758	29.008	6.549	
LICs	0.020	0.000	0.118	0.028		23.201	2.717	28.942	5.539	
Panel	Agricultural development index (AGR) (0-100)					Renewable energy (REN) (% of total energy consumption)				
HICs	23.446	0.521	63.645	11.824	WDI (2021)	15.054	0.064	62.255	11.696	WDI (2021)
UMICs	32.717	3.711	78.144	14.632		23.745	0.438	70.759	17.857	
LMICs	54.992	16.352	87.614	14.715		49.282	0.018	94.266	28.278	
LICs	76.101	43.224	99.993	12.275		82.260	41.549	98.343	13.120	
Panel	Contributing family workers (FAM) (% of total employment)									
HICs	2.411	0.030	20.720	3.215	WDI (2021)					
UMICs	8.525	0.060	36.270	8.298						
LMICs	18.890	0.230	51.920	12.453						
LICs	25.822	5.790	51.530	11.567						

Table 3. Diagnostic tests results.

Econometric problem	Tests	HICs		UMICs		LMICs		LICs	
		Test-stat.	Prob.	Test-stat.	Prob.	Test-stat.	Prob.	Test-stat.	Prob.
Cross-sectional dependence	Breusch and Pagan LM	481.600***	0.000	652.200***	0.000	648.000***	0.000	154.8**	0.018
	Pesaran CD	2.196**	0.028	2.398**	0.017	1.964**	0.050	1.270	0.204
	Pesaran LM adj	15.700***	0.000	15.130***	0.000	6.355***	0.000	2.835***	0.005
Slope Hetrogeniety	Swamy's test	210000***	0.000	87581.6***	0.000	54838.70***	0.000	13281.1***	0.000
	$\tilde{\Delta}$ test	13.103***	0.000	16.287***	0.000	19.100***	0.000	10.863***	0.000
	$\tilde{\Delta}_{adj}$ test	15.890***	0.000	19.751***	0.000	23.162***	0.000	13.174***	0.000
Autocorrelation	Wooldridge test	98.187***	0.000	21.870***	0.000	58.890***	0.000	53.997***	0.000
Heteroskedasticity	Modified Wald test	3624.740***	0.000	75621.23***	0.000	11136.08***	0.000	140.37***	0.000
Multicollinearity	Mean VIF score	1.39		1.38		1.53		1.61	

***Significant at 1%, ** Significant at 5%.

Table 4. CIPS unit root test.

Variables		Level (Intercept & trend)				First difference (intercept)			
		HICs	UMICs	LMICs	LICs	HICs	UMICs	LMICs	LICs
lnAGR		-2.642*	-2.299	-2.058	-2.996***	-4.841***	-4.343***	-4.100***	-4.627***
lnRF		-4.640***	-4.575***	-4.411***	-3.863***	-6.024***	-6.070***	-5.947***	-5.718***
lnTEM		-4.489***	-4.421***	4.301***	-4.059***	-5.825***	-5.861***	-6.014***	-5.882***
lnGDP		-2.067	-1.925	-1.403	-2.620	-2.618***	-3.452***	-3.187***	-3.938***
lnFAM		-3.231***	-2.331	-2.210	-2.074	-5.058***	-4.529***	-3.751***	-4.029***
lnREN		-2.870***	-2.322	-2.515	-2.402	-4.549***	-4.730***	-4.676***	-4.616***
lnDIS		-5.182***	-5.043***	-4.043***	-4.785***	-5.867***	-6.070***	-6.129***	-5.891***
Critical values	*1%*	*-2.81*	*-2.81*	*-2.73*	*-2.88*	*-2.30*	*-2.30*	*-2.23*	*-2.38*
	5%	*-2.66*	*-2.66*	*-2.61*	*-2.72*	*-2.15*	*-2.15*	*-2.11*	*-2.20*
	10%	*-2.58*	*-2.58*	*-2.54*	*-2.63*	*-2.07*	*-2.07*	*-2.04*	*-2.11*

***Significant at 1%, * Significant at 10%.

The increase in contributing family workers was favorable for the agriculture sector. Contributing family work is generally a type of unpaid labor, which may receive indirect compensation in the form of family income. Such activities are common among women, especially in households where other members engage in self-employment like farming or running a family business. The increase in the shares of contributing family workers is likely responsible for poor development, little job growth, an increase in poverty, and the establishment of a rural economy (ILO, 2015).

Sustainable agriculture implies the maximization of crop productivity and economic stability while minimizing the utilization of limited natural resources and environmental damage (Chel and Kaushik, 2011). It is suggested to minimize the disaster-related loss to human beings (deaths, injured, affected, missing) through an increase in resilience. Disaster resilience is a vital aspect of natural hazard planning (Parsons et al., 2016). Resilience explains the opportunities to improve the preparedness of a society and restoration processes (Marzi et al., 2019). Disaster resilience for a community is a major objective of disaster management policies. The impact of a disaster was less for the communities having higher disaster resilience. The Sendai Framework set seven targets and four priority areas related to the strengthening of resilience like (1) understanding risk of a disaster, (2) strengthening governance to control disaster risk, (3) investing in DRR, and (4) increasing disaster readiness for the timely response, and "build back better" in recovery, reconstruction, and rehabilitation (UNDRR, 2019). The insignificant AR(2) confirmed the absence of second-order serial correlation in the first-differenced residuals. The insignificance of test statistics for the Sargan test and Hansen test confirmed the validity of instruments.

Table 5. Westerlund cointegration results.

Panel	Test	Statistics	Prob.
HICs	Variance ratio	6.394***	0.000
UMICs	Variance ratio	5.849***	0.000
LMICs	Variance ratio	4.883***	0.000
LICs	Variance ratio	5.604***	0.000

***Significant at 1%

Table 6. Impact of natural disasters on agricultural development.

Variables	HICs			UMICs			LMICs			LICs		
	Coef.	Std. Err.	Prob.	Coef.	Std. Err.	Prob.	Coef.	Std. Err.	Prob.	Coef.	Std. Err.	Prob.
lnAGR(-1)	0.994***	0.001	0.000	0.171**	0.068	0.013	0.485***	0.010	0.000	0.597***	0.106	0.000
lnRF	-0.007***	0.001	0.000	0.831***	0.198	0.000	0.296***	0.075	0.000	0.044	0.524	0.933
lnTEM	-0.470***	0.002	0.000	-0.482***	0.097	0.000	-0.423***	0.011	0.000	-0.446**	0.193	0.021
lnGDP	0.122***	0.001	0.000	0.227***	0.040	0.000	0.012**	0.006	0.036	0.122*	0.071	0.085
lnFAM	0.051***	0.001	0.000	0.125**	0.057	0.028	0.013	0.010	0.214	0.157*	0.095	0.098
lnREN	0.002***	0.001	0.000	0.175***	0.031	0.000	0.151***	0.005	0.000	0.079	0.144	0.587
lnDIS	-0.003***	0.001	0.000	-0.007***	0.001	0.000	-0.005***	0.001	0.000	-0.001**	0.001	0.029
AR(1)	-1.98** (0.047)			-2.18** (0.029)			-1.93* (0.054)			-2.17** (0.030)		
AR(2)	-1.27 (0.204)			0.78 (0.437)			1.48 (0.138)			-0.75 (0.454)		
Sargan test	19.23 (0.257)			28.16 (0.920)			10.55 (0.879)			16.66 (0.478)		
Hansen test	18.26 (0.309)			25.48 (0.964)			19.10 (0.323)			5.81 (0.994)		

****Significant at 1%,*** ** Significant at 5%, * Significant at 10%.

CONCLUSIONS AND RECOMMENDATIONS

This study shows the effect of natural disasters, rainfall, temperature, GDP per capita, renewable energy, and contributing family workers on the agricultural development index in 24 HICs, 29 UMICs, 32 LMICs, and 16 LICs from 1995 to 2019. It develops a new agricultural development index using standard procedure. The two-step GMM confirmed the adverse effects of natural disasters on agricultural development. Renewable energy showed a favorable impact on agricultural development in all panels. The reduction in agricultural development was reported due to an increase in temperature in all panels. Economic growth shows a favorable influence on agricultural development across all panels. It is recommended to increase resilience to improve preparedness and restoration processes, which in turn minimize disaster-related losses. It is recommended to increase renewable energy use for agricultural development. Policymakers should make strategies to mitigate the adverse impacts of global warming. Trees played a vital role to control the storm, high temperature, and rainfall frequency. It is recommended to increase the forest area and awareness about the plantation. Countries should adopt the Hartwick rule in the case of non-renewable natural capital like fossil fuels that is an efficient use of natural capital and investing the profits in health, education, infrastructure, and development of renewable natural capital. The governments should provide financial support to farmers for renewable energy technology. This study has some limitations. First, it did not consider technological disasters. Second, it fails to investigate the impact of natural disasters on the economy in different geographical zones. Future studies could assess the impact of natural disasters on sub-sectors of agriculture (i.e., crops, forest, livestock, and fisheries).

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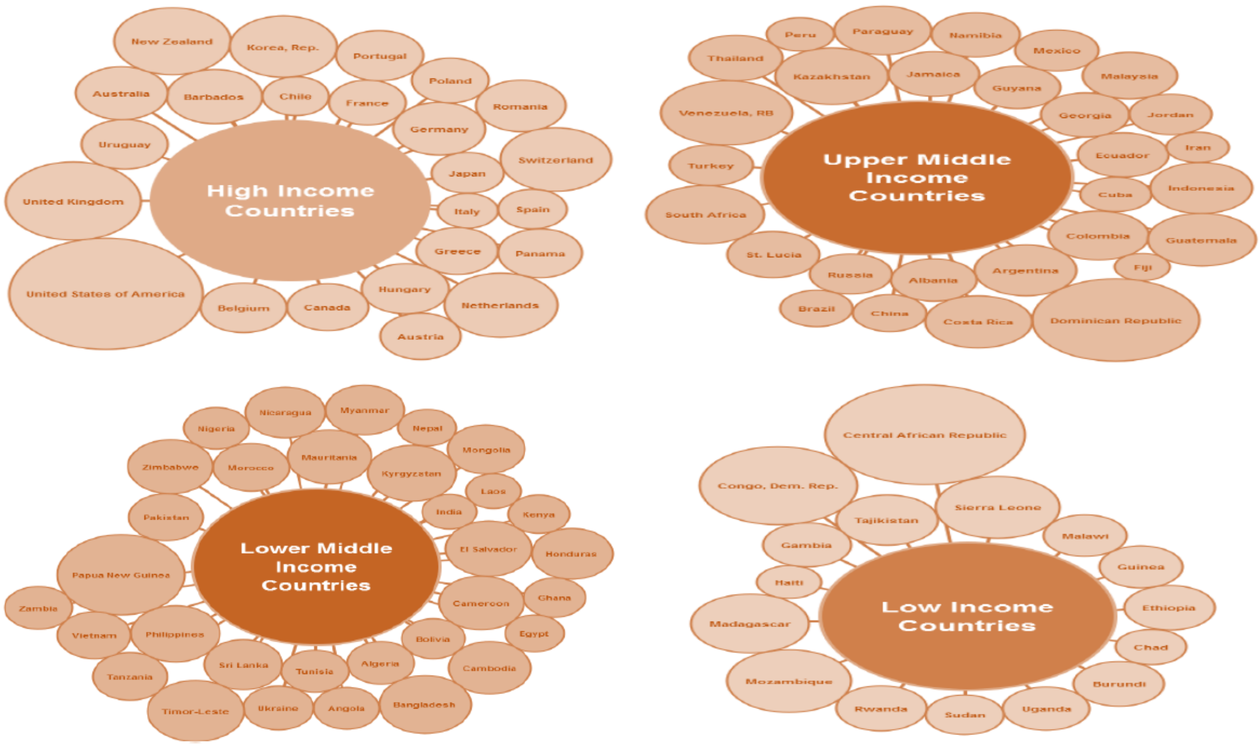

Appendix A. Selected countries