Economic Consequences of Climate Risk: Evidence from High-Risk Asian Economies

Muhammad Saeed Hashmi
Ex. Director of Agriculture, Economics & Marketing, Punjab.

Dr. Allah Ditta
(Corresponding Author) Associate Professor in Economics, Govt. Graduate College Township, Lahore.
Higher Education Department Govt. of the Punjab.
Email: allah.ditta@gctownship.edu.pk

Ahmed Gulzar
PSD Expert, REMIT, Adam Smith International (ASI).
Email: ahmedgulzar2011@gmail.com

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Abstract

The present study investigates the economic consequences of climate risk by analyzing how exposure to high climate vulnerability influences macroeconomic performance in Asian economies. By incorporating climate change shocks into a neo-classical growth framework, this study develops a climate–economy growth model and employs the Pooled Mean Group–Autoregressive Distributed Lag (PMG–ARDL) estimation technique over the period 1971–2024 for high-risk Asian economies. The empirical analysis examines both aggregate and sectoral impacts of rising temperatures and climate variability on GDP growth, with special focus on manufacturing, logistics, and services sectors. The results reveal that high exposure to climate risk significantly reduces economic growth, with temperature-induced productivity losses observed to be larger in economies characterized by limited adaptation capacity and high dependence on climate-sensitive sectors. Specifically, a 1°C increase in population-weighted mean surface temperature leads to an estimated 5.2% decline in GDP growth with 2.6% deceleration in high-risk economies, exceeding regional averages by 1.4 percentage points. Further, sectoral analysis indicates that manufacturing, logistics, and services experience the highest reductions in output growth, amplifying regional disparities and income inequality. Projections based on IPCC's Shared Socio-economic Pathways (SSPs) suggest that under the high-emission scenario (SSP8.5), potential GDP losses could reach up to 63% of current levels by 2100 if no substantial mitigation or adaptation measures are implemented. Conversely, limiting temperature rise to SSP4.5 and SSP2.6 could optimize these losses to below 1% by the end of the century. The study concludes that urgent regional cooperation and targeted adaptive policies are required to strengthen

economic resilience, reduce vulnerability, and sustain long-term growth trajectories in high-risk Asian economies.
Keywords: Economic Consequences, Climate Risk, Asian Economics, Economic Growth.

Introduction

Since the late twentieth century, the relationship between climate change and macroeconomic performance has become one of the most critical areas of inquiry among economists and policymakers. The understanding that climate variability and global warming directly affect production, investment, and productivity has led to the development of integrated climate–economy models that embed environmental variables into traditional growth frameworks (Nordhaus, 1992).Empirical research has demonstrated that persistent increases in global mean temperature and greater climate volatility exert significant negative effects on both output levels and economic growth rates, particularly in developing economies with limited adaptive capacity (Burke, 2015).These findings confirm that climate change is not merely an environmental issue but a fundamental macroeconomic challenge shaping the long-term sustainability of national and regional growth.

Rising mean surface temperatures influence economic performance through several interconnected mechanisms. Heat stress reduces labor productivity and labor supply, particularly in climate-exposed industries such as agriculture, construction, and manufacturing, while higher average temperatures increase energy demand and operational costs (Heal, 2016).Climate extremessuch as floods, storms, and droughtscause physical damage to infrastructure and capital, accelerate depreciation rates, and disrupt investment in key sectors (Moore, 2015). In addition, irregular rainfall and precipitation anomalies have pronounced impacts on agricultural yields, energy production, and logistics systems, leading to volatility in output and price stability. Consequently, economies facing greater climate exposure must divert increasing portions of public and private resources toward adaptation, infrastructure maintenance, and post-disaster recovery, thereby reducing productive investment and long-run growth potential (Dasgupta P. , 2021)(IMF, 2023).

These effects are particularly acute in Asia, which is home to many of the world's fastest-growing yet most climate-vulnerable economies. The region's rapid industrialization, dense urban populations, and heavy dependence on climate-sensitive sectors have created a unique macroeconomic vulnerability to climate shocks ((ADB), 2022)(IPCC, 2021).Countries such as Bangladesh, Pakistan, India, Vietnam, and the Philippines face some of the highest projected economic damages from rising temperatures and extreme weather events (Kaushik, 2024).In addition, water stress, heatwaves, and sea-level rise pose severe threats to infrastructure, manufacturing zones, and urban logistics, further amplifying long-term economic losses. The combination of high exposure and limited adaptive capacity means that climate change has the potential to deepen regional inequality and slow Asia's structural transformation.

This paper examines how exposure to climate risk affects the macroeconomic performance of Asian countries from 1971 to 2024. Using the Pooled Mean Group-Autoregressive Distributed Lag (PMG-ARDL) estimation approach, the study quantifies the long-run and short-run effects of rising temperature and climate variability on GDP growth and sectoral output. The modified Solow–Swan growth framework employed here incorporates climate risk as a determinant of both labor and capital accumulation. In this model, labor supply and productivity are adversely affected by temperature increases, while capital accumulation slows because of higher depreciation rates caused by climate-induced infrastructure damage. Over time, these mechanisms reduce steady-state growth, requiring higher investment just to maintain existing output levels, and widening the gap between resilient and vulnerable economies ((Nordhaus W. &., 2017)(Dasgupta P. , 2021).Empirical evidence indicates that a one-degree Celsius increase in population-weighted mean surface temperature leads to an average 5.2% decline in GDP growth and a 2.6% deceleration in output growth across high-risk Asian economies. The losses are most severe in lower-middle-income and water-stressed countries, while upper-middle-income economies also experience significant but comparatively smaller declines. Agriculture results suggest heterogeneous impacts: agriculture experiences an average output reduction of 6.5% per degree of temperature rise, manufacturing 5.8%, logistics 4.9%, and services 3.7%. Precipitation variability has less consistent effects overall but shows strong regional significance in agriculture and urban infrastructure, where extreme rainfall or drought conditions distort production and supply networks. These findings align with earlier research that identifies temperature as a key driver of productivity decline and macroeconomic volatility in emerging economies (Mendelsohn, 2016); (Burke, Global non-linear effect of temperature on economic production, 2015).

Long-term projections using the Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathways (SSPs) suggest that under a high-emission trajectory (SSP8.5), cumulative GDP losses in high-risk Asian economies could reach approximately 63% of current levels by 2100. In contrast, under moderate mitigation (SSP4.5) and low-emission (SSP2.6) scenarios, potential losses decline to below 1%, and under the stringent SSP1.9 pathway—consistent with the Paris Agreement—these economies could realize net economic gains through avoided damage and improved adaptive efficiency(IPCC, 2021). These results highlight that effective mitigation and adaptation strategies, such as investment in renewable energy, green infrastructure, and climate-resilient urban planning, can substantially reduce macroeconomic vulnerability.The analysis presented in this paper offers an empirical and theoretical contribution to the growing body of literature on the economic consequences of climate change in developing regions. By focusing on high-risk Asian economies, it highlights the heterogeneity of climate impacts across income groups and sectors, providing crucial insights into the mechanisms through which temperature and precipitation shocks translate into macroeconomic instability. The findings underscore the urgent need for regionally coordinated policy responses, enhanced adaptive capacity, and greater access to climate finance to ensure that Asian economies can sustain growth in the face of escalating climate challenges. Building resilience through diversification, institutional reform, and innovation will be critical in minimizing long-term economic losses and achieving sustainable growth across one of the world's most climate-exposed regions.

DESCRIPTIVE ANALYSES

Over the past five decades, high-risk Asian economies have experienced rapid economic transformation alongside intensifying climate hazards. The frequency and intensity of extreme weather eventssuch as heat waves, flash floods, droughts, cyclones, and coastal inundationhave increased significantly, resulting in persistent economic losses, destruction of infrastructure, and reduced labor productivity. According to the World Bank (2023),

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climate-related disasters in South and Southeast Asia caused an average annual GDP loss of around 2.3% during the past three decades, with total economic damage exceeding US$1.2 trillion by 2021. As illustrated in **Figure I** and II, the real GDP of the high-risk Asian region has expanded consistently since 1971, accompanied by a cumulative 0.65°C rise in population-weighted mean surface temperature. This pattern suggests that carbon-intensive industrial and urban growth has contributed directly to regional warming and climate vulnerabilityposing a severe long-term threat to sustainable development.

Figure I: Average GDP of High-Risk Asian Economies (Constant $2015)

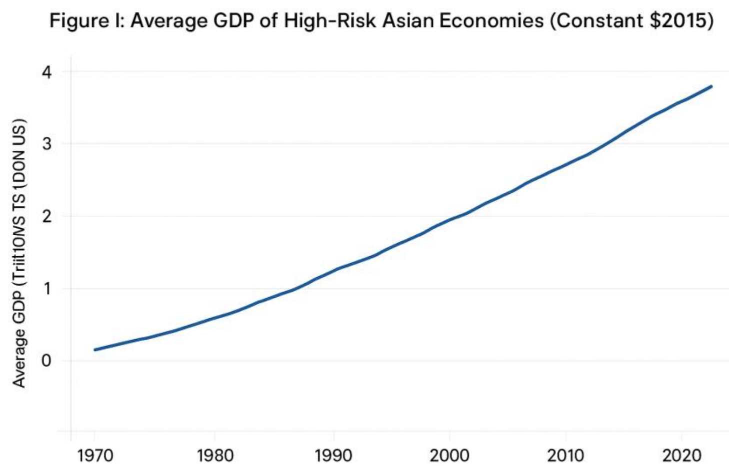
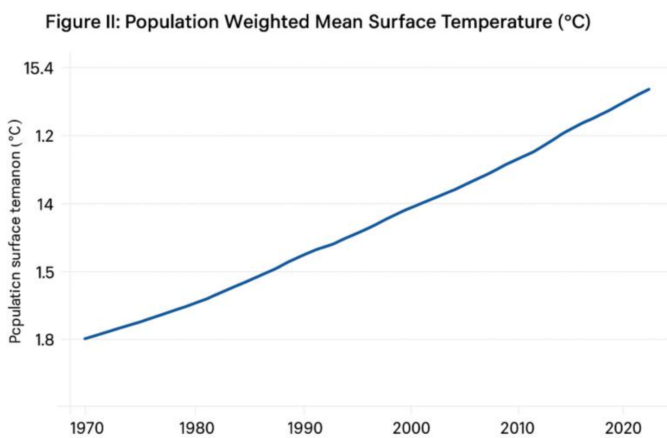


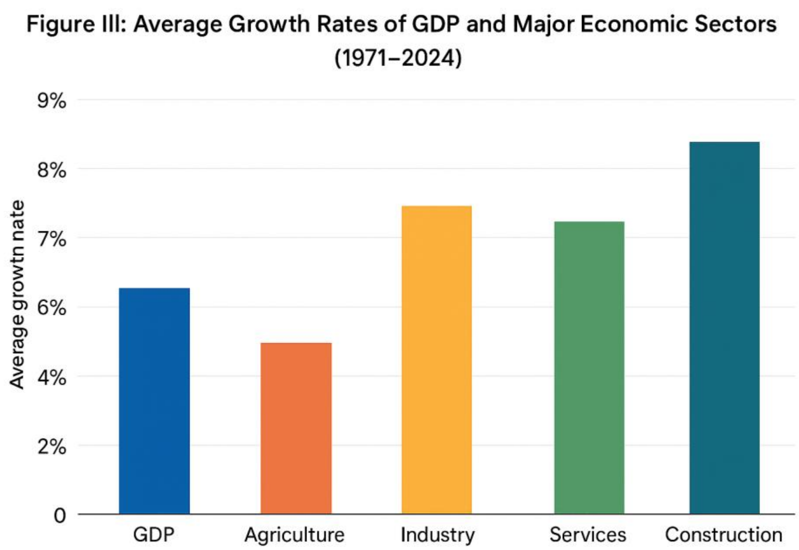
Figure II: Population Weighted Mean Surface Temperature



(°C)

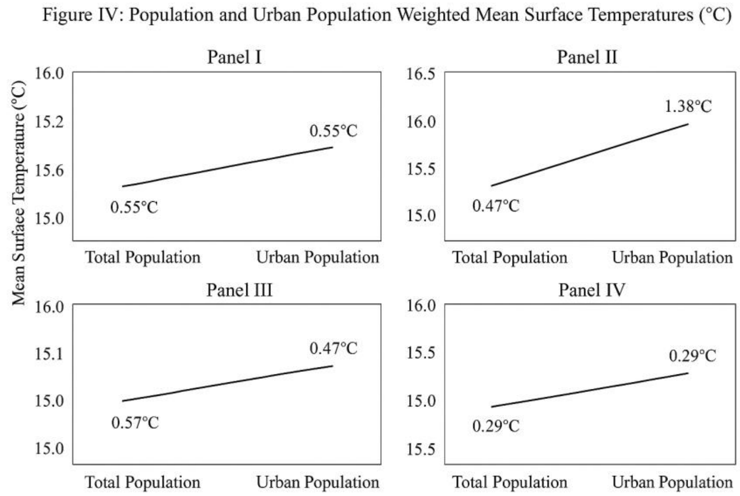
The comparative summary of GDP and sectoral growth rates for all four regional panels from 1971–2024 is presented in **Figure III**. Among these, Panel III (high climate risk and water-stressed economies)including countries such as India, Pakistan, and Bangladeshrecorded the highest average GDP growth rate of 5.12%, followed by Panel II (upper-middle-income risk economies) at 4.67%, Panel IV (low-income and small island states) at 4.41%, and Panel I (regional average group) at 4.26%. At the sectoral level, the manufacturing sector showed the strongest performance in most panels, with an average growth rate of 8.74% in Panel III, followed by transport and logistics (7.33%), construction (6.58%), services (6.05%), and agriculture (3.02%) respectively. This pattern confirms that industrialization and trade expansion drove much of Asia's growth over the study period. However, this growth occurred alongside rising emissions intensity and regional disparities.

Figure III: Average Growth Rates of GDP and Major Economic Sectors (1971–2024)



As illustrated in **Figure IV**, the urban population-weighted mean temperature remains higher than the overall population-weighted mean temperature in all four panels, confirming that urban centers contribute disproportionately to regional carbon emissions. The temperature gap between urban and total population averages is the highest in Panel II (1.38°C), followed by Panel I (0.55°C), Panel III (0.47°C), and Panel IV (0.29°C) respectively. These differences imply two major insights: (i) urbanization-driven economic activitiesparticularly in transport, logistics, and manufacturingare the dominant contributors to rising temperatures in upper- and middle-income regions; and (ii) in highly climate-exposed, low-income regions (Panel IV), rural and urban areas experience similar temperature effects due to their shared geographical exposure. Consequently, the urban–rural temperature convergence in Panels III and IV reflects widespread exposure to heat stress, which has undermined agricultural productivity and deepened income inequality between rural and industrialized areas.

Figure IV: Population and Urban Population Weighted Mean Surface Temperature



Further, **Figure V** shows the average deviation of total and urban population-weighted mean temperatures from their baseline (1961). The greatest deviations occur in Panel IV, at 0.34°C (total) and 0.27°C (urban), followed by Panel III (0.25°C, 0.19°C), Panel II (0.18°C, 0.15°C), and Panel I (0.12°C, 0.10°C) respectively. These figures highlight the persistent use of carbon-intensive energy technologies across all panels, particularly in energy, transport, and construction sectors. It can be concluded that while GDP growth has been robust, it has simultaneously been unsustainable and climate-vulnerable, with the highest risk concentrated among Panel III and IV economies.

Figure V: Average Deviation of Surface Temperatures from 1961 Norm (°C)

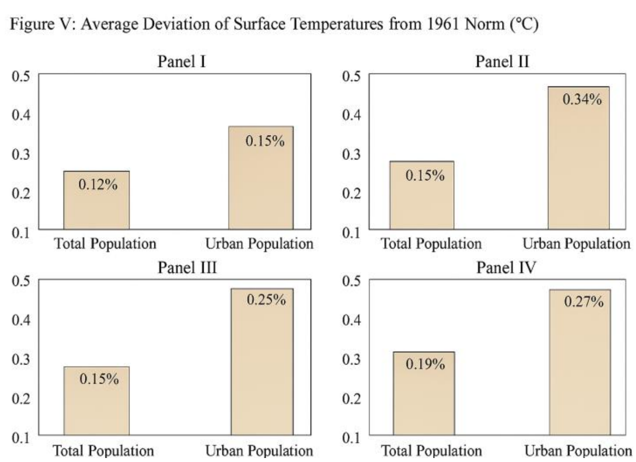
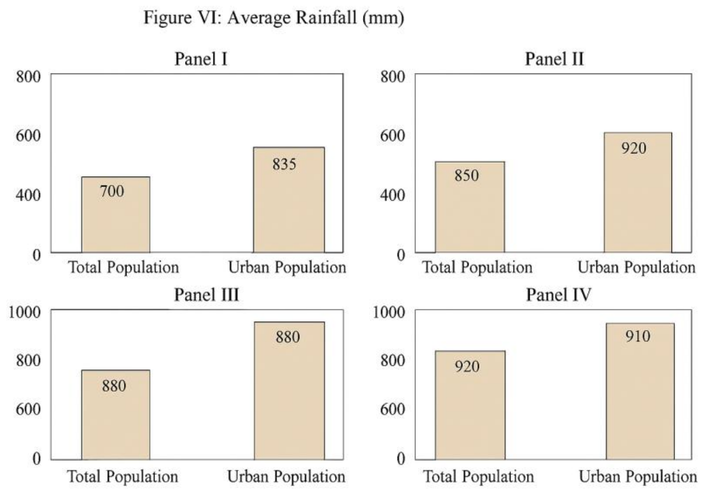


Figure VI demonstrates that the highest average rainfall occurs in high-risk tropical regions (Panel III) and small island states (Panel IV), often accompanied by high inter-annual variability. Excess rainfall and flooding events in these regions frequently damaged agricultural output and public infrastructure, while reduced rainfall in arid subregions led to severe droughts. Fig VII reveals that deviations of rainfall from their long-term norm (1961–2021) are also most pronounced in Panel IV (–9.4%), followed by Panel III (–7.6%), Panel II (–4.8%), and Panel I (–3.9%). This volatility in precipitation patterns has undermined food security, disrupted logistics, and increased adaptation costs.

Figure VI: Average Rainfall (mm)



Literature Review

The relationship between climate variables and macroeconomic output has been examined through two major empirical approaches. The first approach, emphasized in the growth and development literature, explores how variations in average temperature affect the level and growth rate of output across economies (Gallup, 1999)(Sachs, 1997)(Nordhaus W. D., Geography and macroeconomics, 2006). The second approach relies on micro-level evidence, aggregating the effects of different climate variables to estimate their overall economic impact. This is typically incorporated into Integrated Assessment Models (IAMs), which underpin climate and environmental policy frameworks concerning carbon dioxide and other greenhouse gas emissions.

Within the first approach, several methodologies have been proposed to measure mean temperature as a control variable in climate-macroeconomic models. Conventionally, a country's annual mean surface air temperature is calculated as the average of local monthly temperatures. However, this measure often lacks representativeness in economic analyses, as population density and productive land use vary geographically. Hence, researchers argue for population-weighted or cropping-area-weighted mean temperatures to capture the true impact of climate change on labor productivity and economic growth (Billie, 1998)(Dell, 2014)(Nathaniel, 1983)(Robert, 1980).

The empirical literature remains divided on whether climate variables influence the level of GDP or its growth rate. Growth effects compound over time, while level effects do not. The choice of dependent variable—GDP level versus GDP growth—significantly affects projections of future climate-related economic losses ((Burke M. H., 2015) (Dell, Temperature shocks and economic growth: Evidence from the last half century, 2012) (Deryugina, 2014). For instance, temperature effects on GDP growth rates provide insights into long-term changes in output levels (Burke M. D., 2018).

Early empirical research employed cross-sectional regression analyses to study the climate-growth nexus. While these studies provided important short-run insights, they suffered from omitted variable bias due to the exclusion of institutional and policy variables affecting output growth. To overcome this limitation, recent literature has shifted toward panel data techniques, such as fixed-effects models, to control for unobserved country-specific characteristics. These models estimate the impact of temperature shocks on labor productivity and output growth while accounting for time-invariant heterogeneity (Dell, What do we learn from the weather?, 2014)(Kolstad, 2019)

Fixed-effects models have been widely used to assess the influence of temperature and precipitation on economic growth, energy demand, labor productivity, human capital, and crop yields. However, these models may still fail to capture short-term, weather-related fluctuations. To address this, a new strand of "hybrid" panel approaches has emerged, exploiting multiple dimensions of variation to estimate climate damages more precisely (Auffhammer, 2018)(Kolstad, 2019)(Burke M. H., 2015).For example, using a long-difference method to analyze adaptation effects over time.

Recent regional studiesparticularly in Sub-Saharan Africa and Southeast Asiahave applied Pooled Mean Group Autoregressive Distributed Lag (PMG-ARDL) models to estimate the long-run effects of climate variability on output at both aggregated and sectoral levels (Dell et al., 2012). These studies consistently show that increases in temperature are associated with declines in output growth, especially in economies with limited adaptive capacity and high exposure to climate risk.

Despite growing empirical evidence, the structural relationship between climate variables and economic performance remains unsettled. (Dell, Temperature shocks and economic growth: Evidence from the last half century, 2012)identified a linear relationship between temperature shocks and output changes, whereas proposed a nonlinear (quadratic) model. According to the latter, temperature increases can enhance growth in cold regions but hinder it in hotter ones, implying an optimal mean temperature around 13°C for maximizing GDP growth. This nonlinear pattern underscores the asymmetric and region-specific nature of climate impacts across the global economy.

Theoretical Framework

In this study, to examine the macroeconomic impact of climate risk on output growth and its rate of change at both aggregated and sectoral levels in the Asian region, we construct four distinct country panels based on exposure to climate and water stress risks.

Panel I consists of forty-five Asian economies included based on data availability. Panel II comprises eighteen high climate-risk Asian economies, identified according to their Global Climate Risk Index (CRI) scores and rankings published in the Global Climate Risk Index 2021 (average for 2000–2019) by German watch e.g., where lower CRI scores indicate higher vulnerability to extreme weather events in terms of economic losses and fatalities. Panel III includes six Asian economies that are classified as both high climate-risk and water-stressed, based on baseline water stress indicators ranging from medium-high to extreme. Finally,

Panel IV represents the most vulnerable group, consisting of three lower-middle-income economies that are simultaneously exposed to high climate-risk and significant water stress.
The analytical foundation is based on the **augmented Solow Growth Model**, where output is determined by capital, labor, and productivity (technology):

$$Y = AK^{\alpha}L^{1-\alpha}; 0 < \alpha < 1$$

were
Y= Output
K= Physical Capital
L= Labor
A= Total Factor Productivity (TFP)
α=Capital's share in output
and (1 – α) = Labor's share in output
The Solow growth accounting equation becomes:

$$\frac{\Delta Y}{Y} = \frac{\Delta A}{A} + \alpha\frac{\Delta K}{K} + (1-\alpha)\frac{\Delta L}{L}$$

By differentiating with respect to time, we obtain the **growth acceleration equation**, consistent with Hausmann et al. (2005):

$$\frac{\Delta}{\Delta t}(\frac{\Delta Y}{Y}) = \frac{\Delta}{\Delta t}(\frac{\Delta A}{A} + \alpha\frac{\Delta K}{K} + (1-\alpha)\frac{\Delta L}{L})$$

Here,
$\frac{\Delta}{\Delta t}\left(\frac{\Delta Y}{Y}\right) > 0$ indicates acceleration (increasing growth momentum)
while $\frac{\Delta}{\Delta t}(\frac{\Delta Y}{Y}) < 0$indicates deceleration (slowing growth momentum).
The desired output level $Y^*$is achieved within time Tdepending on whether the growth rate is accelerating or decelerating due to climate effects.
In this study, we assume that labor productivity and the rate of capital formation are influenced not only by economic and technological factors but also by climate change variables, primarily temperature (T_{it})and precipitation (P_{it}).
These variables affect both the short-run growth rate and long-run output dynamics through their impact on labor productivity, capital depreciation, and destruction of physical and natural capital (Dell, Temperature shocks and economic growth: Evidence from the last half century, 2012)(Burke M. H., Global non-linear effect of temperature on economic production, 2015).
In the classical Solow model, labor grows at an exogenous rate n. However, due to adverse climate effects—such as extreme heat and floods—labor supply and productivity may decline. Hence, we modify the labor growth rate as:

$$L(t) = L(0)e^{(n-\phi)t}$$

where ϕrepresents the proportionate reduction in labor growth due to climate stress ($\phi > 0$) (Cai, 2018)(Dasgupta S. L., Exposure of developing countries to sea-level rise and storm surges., 2021)(Somanathan, 2021).
To capture the effect of climate change on capital accumulation, the standard Solow–Swan

capital accumulation equation is modified as follows:

$$\Delta k_t = (1-\gamma)sf(k_t) - (\delta + (n-\phi) + g + c)k_t - D$$

S= saving rate
f (kt) = output per unit of effective labor
δ = Depreciation rate
n= Population growth
g= Technical growth
Y= Rate of disinvestment due to climate uncertainty
C= Additional depreciation due to extreme weather
D= direct destruction of capital stock caused by climate disaster

Here, the first term $(1-\gamma)sf(k_t)$denotes the effective investment, adjusted for disinvestment caused by climate risk. The second term $(\delta + (n-\phi) + g + c)k_t$captures effective depreciation, and the last term Drepresents direct economic losses.

At steady state ($\Delta k_t = 0$):

$$k_c^* = \frac{(1-\gamma)sf(k_t)}{(\delta + (n-\phi) + g + c)} - D$$

Since $k_c^* < k^*$under the same parameters (s, δ, n, g), it follows that climate change lowers the steady-state capital stock and output. To restore the original equilibrium, a higher saving rate or adaptation investment is required, implying increased inequality among regions with different adaptive capacities.

Following (Dell, Temperature shocks and economic growth: Evidence from the last half century., 2012)(Burke M. H., Global non-linear effect of temperature on economic production., 2015)and (Hsiang, 2010), the impact of temperature and precipitation on GDP growth is modeled as:

$$Y_{itp} = \alpha_0 + \alpha_1 PWMT_{itp} + \alpha_2 RF_{itp} + \epsilon_{itp}$$

$$Y_{itp} = \beta_0 + \beta_1 PWMT_{itp} + \beta_2 (PWMT_{itp})^2 + \beta_3 RF_{itp} + \epsilon_{itp}$$

$$PWMDT_{itp} = (PWMT_{itp} - PWMT_{i,1960})$$
$$RD_{itp} = (RF_{itp} - RF_{i,1960})$$

These difference variables represent climate momentum, that is, the cumulative deviation of temperature and rainfall from their historical baselines. A positive deviation indicates warming or intensified rainfall relative to the long-run norm.Furthermore, to assess the role of urbanization in amplifying temperature effects, the urban population-weighted mean temperature (UPWMT) is incorporated as an alternative explanatory variable. Urban areas, being carbon-intensive hubs, contribute disproportionately to emissions and local temperature rise, which in turn affects productivity and output dynamics.

- $\frac{\partial Y}{\partial T} < 0$: Higher temperatures reduce GDP growth, particularly in already hot regions.
- $\frac{\partial Y}{\partial P} < 0$or > 0: The effect of precipitation varies; moderate rainfall supports agriculture, but extreme rainfall causes floods and damages output.

- $\frac{\partial Y}{\partial (T^2)} < 0$: The quadratic term captures the **nonlinear (inverted-U)** relationship between temperature and economic growth, implying an optimal temperature range (Burke M. H., Global non-linear effect of temperature on economic production, 2015).

To project the nonlinear relationship between future temperature increases and output, the elasticity of GDP to temperature is expressed as:

$$\Phi = [\mu(b_1 - d_{it}) \cdot d_{it}] \cdot t_k$$

where
b_1= Estimated coefficient of temperature from historical regression,
d_{it}= Difference in estimated temperature coefficients between historical (1971–2021) and projected (2022–2100) periods,
μ= Scaling factor, normalized to assume total GDP impact across SSP1.9–SSP8.5 pathways equals 100%.
This formulation allows computation of country-wise nonlinear temperature–output elasticities, reflecting how each economy's GDP responds to climate changes under various future scenarios.

DATA AND ECONOMETRIC METHODOLOGY

This study employs a balanced panel data set covering Asian economies over the period 1960–2021 (historical sample) and 2022–2100 (projected sample), to empirically analyze the macroeconomic impact of climate risk—primarily temperature and precipitation—on output growth and its rate of change. The data used in this research are entirely secondary, collected from reputable international databases including:

- The World Bank's World Development Indicators (WDI),
- The United Nations Statistics Division (UNdata), and
- The World Bank's Climate Knowledge Portal.

The variables, their definitions, units of measurement, frequency, and data sources are presented in **Table 1 below.**

Table1: Details of Variables Used in the Study

Variables	Abbreviation	Unit of Measures	Frequency	Data source/ Method of calculation
Dependent Variable				
Growth rate of Gross Domestic Product	GGDPU	US$(Constant 2015)	Annual	UNdata; growth rate of calculated by growth
Acceleration Rate of GDP Growth	DGGDPU	______	Annual	Calculated by author as rate of change of GDP growth
Growth Rate of Agriculture,	GA	US$(Constant 2015)	Annual	UN data

Hunty, Forestry, and Fishing output				
Growth rate of Manufacturing Output	GM	US$(Constant 2015)	Annual	UN data
Growth Rate of Construction Services	GC	US$(Constant 2015)	Annual	UN data
Growth Rate of Transport, Storage, and Communication Services	GTS	US$(Constant 2015)	Annual	UN data
Growth Rate of Wholesale, Retail Trade, Restaurants, and Hotels	GWRT	US$(Constant 2015)	Annual	UN data
Independent Variable				
Precipitation (Rainfall)	RF	Millimeters (mm)	Annual	WDI Climate Change Portal
Precipitation (Rainfall)	RD	—	Annual	Calculated by author
Population-Weighted Mean Temperature	PWMT	°C	Annual	Calculated by author using population and temperature data from WDI
Population-Weighted Mean Temperature Difference	PWMDT	—	Annual	Calculated by author
Urban Population-Weighted Mean Temperature	UPWMDT	°C	Annual	Calculated by author using urban population and temperature data
Urban Population-Weighted Mean Temperature Difference		—	Annual	Calculated by author

The preliminary analysis of the dataset reveals that both temperature and rainfall variables exhibit an upward trend over time, suggesting the presence of non-stationarity in their time-series properties. Since the number of time periods ($T > 20$) for each cross-sectional unit exceeds the number of cross-sectional units (N), the dataset behaves as a time-series dominant panel, as indicated by Pedroni (2008). In such a configuration, the application of Ordinary Least Squares (OLS) estimation may lead to spurious regression results, because OLS assumes that the data are independently and identically distributed in dynamic panel settings where time dependence and country-specific heterogeneity exist. Consequently, a more suitable econometric technique is required to capture both short-run dynamics and long-run equilibrium relationships among the variables.
To address this issue, the study employs the Pooled Mean Group – Autoregressive Distributed Lag (PMG-ARDL) approach developed by (Pesaran M. H., 1999). This method is particularly appropriate because it can accommodate variables that are integrated into mixed orders, specifically $I(0)$and $I(1)$, without requiring pre-difference. Moreover, the PMG-ARDL model allows for heterogeneity in short-run coefficients across countries while maintaining homogeneity in long-run parameters, thereby balancing flexibility with comparability in cross-country analysis.
Before estimating the PMG-ARDL model, it is essential to test for cross-sectional dependence (CD) among the sample economies. Cross-sectional dependence occurs when unobserved shocks or external disturbances—such as global climate events or regional economic crisis affect multiple countries simultaneously. Ignoring CD can result in biased estimates, size distortions, and spurious cointegration. Therefore, the study applies to the CD test, which is computed as:

$$\boldsymbol{CD = \sqrt{\frac{TN(N-1)}{2}}\,\bar{P}_N}$$

where $\bar{P}_N$represents the average pairwise correlation of residuals across cross-sectional units. A significant CD statistic indicates the presence of interdependence among countries, which must be accounted for in subsequent modeling stages. The results of this diagnostic procedure guide the selection of robust econometric techniques that accurately capture both the temporal and spatial dimensions of the relationship between climate variables and macroeconomic performance in high-risk Asian economies.
After confirming the absence of cross-sectional dependence, the next step involved testing for stationarity of the variables to determine their order of integration. Establishing whether the series are stationary or non-stationary is crucial before applying long-run estimation techniques such as the PMG-ARDL model. To this end, two widely recognized panel unit root tests were employed the Levin, Lin, and Chu test, both of which are designed to handle panel datasets but differ in their underlying assumptions.
The LLC test assumes a common unit root process across all cross-sectional units, meaning that all countries in the panel share a homogeneous autoregressive parameter. The test is based on the following regression equation:

$$\Delta y_{it} = \phi y_{i,t-1} + \vartheta_i' \gamma_i + \sum_{j=1}^{p} \theta_{ij} \Delta y_{i,t-j} + u_{it}$$

where y_{it} denotes the variable of interest for country i at time t, p represents the optimal lag length ensuring white-noise residuals, and u_{it} is the error term. The null hypothesis of the LLC test ($\phi = 0$) implies that the variable is non-stationary, whereas the alternative hypothesis ($\phi < 0$) suggests stationarity. By controlling serial correlation through additional lags of the dependent variable, this test provides a robust assessment of unit root behavior under the assumption of homogeneity in persistence across countries.In contrast, the IPS test allows for heterogeneity in unit root processes across cross-sectional units, acknowledging that different countries may experience distinct degrees of persistence in their time-series dynamics. The IPS regression model is expressed as:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \vartheta_i' \gamma_i + \varepsilon_{it}$$

Here, ϕ_i is country-specific, permitting variation in the autoregressive parameter across panels, while ε_{it} represents the error term assumed to be independently and normally distributed with heterogeneous variances. The IPS test combines the individual Augmented Dickey-Fuller (ADF) statistics for each cross-section into an average t-bar statistic to evaluate the overall null hypothesis of non-stationarity. Rejection of the null hypothesis in either test indicates that the corresponding variable is stationary.Together, the LLC and IPS tests provide complementary insights: the LLC test ensures consistency under homogeneity assumptions, while the IPS test captures cross-country heterogeneity, offering a comprehensive understanding of the stochastic properties of the panel variables prior to long-run modeling.
Long-run relationships among variables were tested using **Pedroni's (2000, 2004, 2008)** heterogeneous panel co-integration approach, estimated as:

$$y_{it} = \beta_i + \gamma_{1i} x_{1it} + \gamma_{2i} x_{2it} + \cdots + \gamma_{mi} x_{mit} + \varepsilon_{it}$$

$$\Delta y_{it} = \sum_{m=1}^{M} \gamma_{mi} \Delta x_{mit} + \eta_{it}$$

$$e_{it} = \delta_i e_{i,t-1} + \mu_{it}$$

where
$i = 1,2, \dots, N$ represents countries,
$t = 1,2, \dots, T$ represents time periods,
and $m = 1,2, \dots, M$ represents the number of regressors.
The residual-based statistics of Pedroni test determine whether the variables are co-integrated across heterogeneous panels.
After confirming integration and co-integration properties, the **PMG-ARDL (p, q)** model was estimated as:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}' Z_{i,t-j} + \mu_i + \varepsilon_{it}$$

where:

- y_{it} = dependent variable (e.g., GDP growth rate),

- Z_{it}= vector of explanatory variables (e.g., temperature, rainfall),
- $\lambda_{ij}$and δ_{ij}= short-run dynamic coefficients,
- μ_i= country-specific fixed effect.

If variables are I(1) and co-integrated, the above model can be rewritten in **error-correction form** as:

$$\Delta y_{it} = \phi_i(y_{i,t-1} - \theta_i' Z_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*\prime} \Delta Z_{i,t-j} + \mu_i + \varepsilon_{it}$$

where
ϕ_i= speed of adjustment towards long-run equilibrium,
θ_i= long-run elasticity vector,
$\lambda_{ij}^*$and δ_{ij}^*= short-run dynamic coefficients.

A statistically significant and negative $\phi_i$confirms the presence of long-run equilibrium between output and climate variables.

To determine the net increase in temperature between historical (1971–2021) and projected (2022–2100) periods under various Shared Socioeconomic Pathways (SSPs), including SSP1.9, SSP2.6, SSP4.5, SSP7.0, and SSP8.5, the population-weighted mean surface temperature series for each country was regressed against time:

$$C_{it} = \alpha_0 + \alpha_1 t_k$$
$$C_{it}^m = \alpha_0 + \alpha_1 t_k$$

where
C_{it}= historical population-weighted mean surface temperature of country *i*,
C_{it}^m= projected temperature under scenario *m*,
α_1= rate of temperature change over time (°C per year).

The coefficients (α_1) were estimated using Ordinary Least Squares (OLS) for each country and SSP scenario separately. This provides the empirical basis for the climate momentum variable, capturing the intensity of temperature rise across different regions and pathways.

Robustness of Methodology and Data

The robustness of this study's methodology and data was ensured through reliable data sources, appropriate econometric techniques, and multiple diagnostic tests. Data were obtained from credible international databases, including the World Bank's World Development Indicators (WDI), UNdata, and the World Bank Climate Knowledge Portal, covering 1971–2024 for high-risk Asian economies. To account for demographic and spatial heterogeneity, population-weighted and urban population-weighted mean temperature series were constructed, ensuring a more accurate representation of climate exposure (Dell, What do we learn from the weather? The new climate–economy literature, 2014)

Methodologically, the study applied the Pooled Mean Group Autoregressive Distributed Lag (PMG-ARDL) approach proposed by (Pesaran, 1999), which is robust to mixed orders of integration and allows for heterogeneous short-run adjustments and homogeneous long-run relationships across countries. Prior to estimation, diagnostic procedures were conducted to ensure model validity. These included (Pesaran M. H., 2015)Cross-Sectional Dependence (CD) Test to check for interdependence among countriespanel unit root tests to confirm stationarity, and cointegration tests to verify the existence of long-run equilibrium relationships among variables.

To improve reliability, multiple climate indicators, such as average temperature, rainfall, and their deviations from baseline values, were incorporated alongside sectoral output measures to mitigate omitted variable bias (Burke M. H., Global non-linear effect of temperature on economic production, 2015). Sensitivity analyses were also performed across different Shared Socioeconomic Pathways (SSPs) scenarios to test result stability under alternative emission trajectories (Change, 2021). Collectively, the combination of rigorous econometric methods, credible data sources, and extensive robustness checks ensures the validity, reliability, and policy relevance of the study's findings for assessing climate risk in Asian economies.

RESULTS AND DISCUSSION

The empirical results of the study, based on PMG-ARDL estimation for 1971–2024, provide strong evidence that climate risk has become a major structural constraint on long-run economic performance across Asian economies. Across all four panels, population-weighted mean temperature emerges as a consistently negative and statistically significant determinant of GDP growth, growth momentum, and sectoral output. The magnitude of the temperature effect increases progressively from the Asia-wide sample (Panel I) to high-risk countries (Panel II), to high-risk and water-stressed countries (Panel III), and reaches its highest level in lower-middle-income, high-risk, water-stressed Asian economies (Panel IV). **As shown in Table:2,** This gradient confirms that countries with higher vulnerability, weaker resilience, and limited adaptive capacity suffer disproportionately greater economic losses from rising temperatures. In all panels, the negative effect of temperature on GDP growth reflects heat-induced reductions in labor productivity, rising cooling and energy costs, supply-side disruptions, and capital depreciation resulting from more frequent extreme weather events.

Table:2 Classification of Asian economies by climate and water stress vulnerability.

Panel	Description	Characteristics
Panel I	All Asian Economies	Baseline continental analysis
Panel II	High Climate-Risk Economies	High CRI exposure
Panel III	High-Risk & Water-Stressed Economies	Dual vulnerability: heat + water scarcity
Panel IV	Lower-Middle Income, High-Risk, Water-Stressed Economies	Highest structural vulnerability

A critical insight from the results is the dominant role of urban temperature exposure. Urban population-weighted temperature explains between 70% and 90% of the total adverse effect of temperature on GDP growth across most panels, highlighting the severity of heat amplification in dense urban centers. While urban economies act as engines of growth through manufacturing, logistics, and services, they simultaneously generate heat island effects and carbon-intensive emissions that elevate surface temperatures. These rising urban temperatures significantly weaken long-run productivity, increase operational costs, and ultimately dampen growth momentum. The results indicate a structural trade-off: carbon-intensive urban development has delivered rapid short-term growth but is now reducing long-term economic potential by intensifying climate stress. In Panels III and IV, the squared term of urban temperature becomes strongly significant, indicating nonlinear effects—once heat thresholds are crossed, economic losses accelerate more rapidly.

Rainfall plays a secondary yet important role in shaping macroeconomic outcomes. In the aggregate sample, rainfall has an insignificant long-run effect on GDP growth, but the variable becomes significant for water-stressed countries (Panel III), where economies rely heavily on stable monsoon cycles for agriculture, hydro-energy, and rural livelihoods. Rainfall deviations—captured through the RD variable—have more consistent negative effects, reflecting the disruptive impacts of abnormal precipitation patterns. Heavy rainfall causes floods, destroys crops, and damages infrastructure, while rainfall deficits deepen water scarcity, reduce agricultural yields, and hinder industrial production. Importantly, when rainfall is incorporated into the model, the adverse effect of temperature on GDP growth increases further across all panels, confirming that temperature and rainfall interact and jointly exacerbate climate damage.

As described in Table:3 Weather severity—measured as deviations of temperature from long-run norms—has strong and statistically significant negative effects in all panels. A deviation of just 1°C from historical averages leads to declines of 4–5.5% in GDP growth, demonstrating the destabilizing effect of abnormal climate conditions on economic production systems. Extreme temperature deviations disrupt agricultural cycles, reduce worker efficiency, increase energy requirements, and impair infrastructure functionality. When weather severity is doubled in the model, the magnitude of GDP losses increases more than proportionally, especially in Panels III and IV, where economic structures are highly sensitive to climate extremes. Urban weather severity exhibits even more pronounced effects, contributing up to 80% of total weather-related losses in some panels. This underscores that economic activities are most concentrated in urban regions, particularly manufacturing, logistics, and services, are also the most exposed to climate volatility.

Table:3 Key Climate and Economic Indicators across Panels

Indicator	Panel I	Panel II	Panel III	Panel IV
Avg GDP Growth (%)	4.26	4.67	5.12	4.41
PWMT Rise (°C)	0.55	1.38	0.47	0.29
Rainfall Deviation (%)	–3.9	–4.8	–7.6	–9.4

Sectoral analysis reveals substantial heterogeneity in climate impacts across different components of the economy. The agriculture sector is highly vulnerable to both temperature increases and rainfall deviations, with even modest climatic shocks resulting in sizable output losses. In Panels I and II, a 1°C rise in population-weighted temperature reduces agriculture production by approximately 1–1.5%, while rainfall deviations have a positive effect due to the sector's dependence on precipitation. Manufacturing emerges as the most climate-sensitive sector overall. Across all panels, manufacturing output declines sharply with increases in temperature, with the largest losses observed in high-risk and water-stressed economies where industrial workers are exposed to extreme heat and energy systems face high cooling demand. These findings are consistent with global evidence that heat stress erodes labor productivity, increases machinery downtime, and raises operational costs.

The logistics sector, transport, storage, and communications, is also significantly affected by climate variables. Temperature increases reduce sectoral output by 5–8% across panels, indicating that heat disrupts mobility, increases road and rail maintenance requirements, and places stress on communication networks. Urban temperature effects are particularly strong due to congestion, pollution, and infrastructure vulnerability. The services sector displays similar sensitivity, particularly in retail, tourism, and hospitality industries that rely heavily on urban activity and consumer mobility. In Panels I and III, services output declines by approximately 4–6% per 1°C increase in temperature, while urban temperature deviations produce even larger negative impacts.

Long-run projections based on Shared Socioeconomic Pathways (SSPs) demonstrate the magnitude of future economic risks. Under the worst-case high-emissions scenario (SSP8.5), Asia as a whole is projected to lose 58% of its current GDP by 2100. High-risk countries are expected to lose 63%, high-risk water-stressed countries 67%, and the most vulnerable lower-middle-income climate-exposed economies up to 74% of current GDP. These results illustrate a trajectory of deepening structural losses if warming continues unchecked. However, the projections also show that these losses can be substantially reduced under moderate emission pathways (SSP7.0 and SSP4.5) and fully reversed under strong mitigation scenarios (SSP2.6 and SSP1.9). Under SSP2.6, most Asian countries exhibit positive GDP gains by 2050 due to the benefits of efficiency improvements, technological transitions, and reduced climate damages. Under SSP1.9, regional GDP could increase by more than 40% by 2100, demonstrating the economic value of rapid decarbonization.

Conclusion:

This study concludes that climate risk has become a major structural constraint on long-term economic growth in high-risk Asian economies. Rising temperatures, rainfall variability, and extreme weather events have significantly reduced GDP growth and sectoral productivity, especially in agriculture, manufacturing, logistics, and services. Empirical findings from the PMG–ARDL estimation confirm that temperature increases are consistently and negatively associated with output, with the magnitude of losses growing across vulnerability levelsfrom general Asian economies to highly climate- and water-stressed lower-middle-income countries.

Urbanization has emerged as a critical driver of heat intensity, as urban population-weighted mean temperatures explain up to 90% of the adverse climate–growth relationship. While industrial and service sectors have fueled rapid economic expansion, they have also amplified local warming and energy demands, leading to reduced labor efficiency, higher operational costs, and greater infrastructure degradation.Rainfall variability further aggravates climate damages, with both excess rainfall (causing floods) and deficits (causing droughts) disrupting agriculture, energy supply, and logistics. The compounding effects of temperature rise and precipitation volatility have deepened regional inequality, intensified food insecurity, and constrained adaptive capacity in developing economies.Projections under IPCC's Shared Socioeconomic Pathways (SSPs) reveal that without substantial mitigation, GDP losses could reach **63–74% of current levels by 2100** under high-emission scenarios (SSP8.5). However, these losses can be drastically reduced—and even reversed—under strong mitigation pathways (SSP2.6 or SSP1.9), highlighting the immense economic value of decarbonization and adaptation investment.

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