SPATIO-TEMPORAL ANALYSIS OF CLIMATE CHANGE AND FOOD PRODUCTION: A CROSS REGIONAL COMPARISON BASED ON PANEL DATA

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CERTIFICATE OF APPROVAL

This is to certify that the research work presented in this thesis, entitled "***Spatio-Temporal Analysis of Climate Change and Food Production: A Cross Regional Comparison Based on Panel Data***" was conducted by **Ms. Amina Qureshi** under the supervision of **Dr. Muhammad Jamil, Professor, SBP Memorial Chair.**

No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the School of Economics, Quaid-i-Azam University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the field of Economics, School of Economics, Quaid-i-Azam University, Islamabad.

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I, Amina Qureshi, daughter of Shafqat Rasul Qureshi, Registration no: 03091411003, Candidate for Ph.D. Economics at School of Economics, Quaid-i-Azam University Islamabad, declare the thesis **"*Spatio-Temporal Analysis of Climate Change and Food Production: A Cross Regional Comparison Based on Panel Data*"** Submitted for the partial fulfillment of Doctorate of Philosophy (Ph.D.) degree in Economics, is my work. All the errors and omissions are lonely goes to me, and I also somberly pronounce that it will not be submitted for attaining any other degree in the future from any institution.

Amina Qureshi

Dedicated To

My parents, grandparents, and teachers who taught me to hold the pen, pronounce words, learn, unlearn and relearn…

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Amina Qureshi

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List of Abbreviations

ADB	Asian Development Bank
AIC	Akaike's Information Criterion
APEC	Asia-Pacific Economic Cooperation
AR-5	Fifth Assessment Report
AR-6	Sixth Assessment Report
CD	Cross Sectional Dependence Test
CGE	Computable General Equilibrium Model
CH4	Methane
CO_2	Carbon Dioxide
COPs	Conference of the Parties
CRU	Climate Research Unit
CV	Climate Variability
DEs	Developing Economies
EAP	East Asia Pacific
EBA	Everything but Arms
ECA	Europe And Central Asian
EF	Ecological footprint
EKC	Environmental Kuznets Curve
EMT	Ecological Modernization Theory
ETS	Emission Trading System
FDI	Foreign Direct Investment
GCMs	Global Circulation Models
GHGs	Greenhouse Gases
GIS	Geographical Information System
GNI	Gross National Income
GSP plus	Generalized system of preferences
GTAP-W	Global Trade Analysis Project-Water
HH	Household
HIC	High-Income Countries
HL	High-Low
H-O	Hecksher-Ohlin
IEA	International Energy Agency
IEs	Industrialized Economies
IGs	Industrialization Group
IPAT	Impact Population Affluence Technology
IPCC	Inter-Governmental Panel on Climate Change
LAC	Latin America and the Caribbean
LDEs	Least Developing Economies
LIC	Low-Income Countries

LM	Lagrangian Multiplier
LMDI	Logarithmic-Mean Divisia Index
LMIC	Lower Middle-Income Countries
LR	Likelihood Ratio
MENA	Middle East And North African
MNCs	Multinational Companies
N2O	Nitrous Oxide
NA	North America
NDCs	Nationally Determined Contributions
NIEs	Newly Industrialized Economies
NSSA	Non Sub Saharan African
OLS	Ordinary Least Square
PGPR	Plant Growth Promoting Rhizobacteria
PPH	Pollution Haven Hypothesis
QGIS	Quantum Geographical Information System
SA	South Asia
SAR	Spatial Autoregressive Model
SBC	Schwarz Criterion
SEM	Spatial Error Model
SLM	Spatial Lag Model
SDA	Structural Decomposition Analysis
SDGs	Sustainable Development Goals
SDM	Spatial Durbin Model
SDM-FE	Spatial Durbin Fixed Effect Model
SDM-RE	Spatial Durbin Random Effect Model
SEM	Spatial Error Model
SHE	Structural Human Ecology
SLX	Spatial Lag Model
SRES	Special Report on Emission Scenarios
SSA	Sub Saharan African
STIRPAT	Stochastic Impact by Regression on Population, Affluence and Technology
UMIC	Upper Middle-Income Countries
UN	United Nations
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
UNIDO	United Nations Industrial Development Organization
USD	United States Dollar
WB	World Bank
WMO	World Meteorological Organization

Abstract

Climate Change has already been realized and endorsed by multi-disciplinary researchers as an outcome of excessive economic activity based on fossil fuels. Experiencing consistent natural disasters, the global policy dynamics shifted more towards sustainability. However, the central questions still debatable are the disproportionate nature of the climate change impact, adaptation and mitigation measures, and possible ways to reduce the pace of changing climate that is harmful to human existence. One of the immediate global policy responses to climate change was the formation of international organizations that came up with major global agreements, i.e., the Kyoto Protocol and the Paris Agreement. The current study employs exploratory analysis to study the relationship between climatic variability and geographical location, income, and industrialization levels of countries in regimes when two important agreements took place. However, global warming is constantly increasing in the period of analysis (1991 to 2018), irrespective of geographical location, income, and industrialization levels. The results show that global warming slowed after the policy measures taken by these organizations. Among income groups, high income countries are experiencing greater climate variability (temperature) in terms of magnitude, while LIC's warming pace is more pronounced than any other group. Climate variability expressed by rainfall shows volatile behavior in all categories considered. There is no clear pattern in rainfall behavior throughout the time used in the analysis, thus, adding to the existing challenges. Climate variability behavior for the degree of industrialization shows that newly industrialized countries' pace of additional warming is relatively faster than others. Regional results show that Europe and Central Asian countries are experiencing greater temperature variability, followed by the Middle East and North African countries, North America, Sub-Saharan Africa, South Asia, East Asia Pacific, Latin America, and the Caribbean.

The study also highlights the distinction between climate, climate variability, and climate change considering their short-term and long-term changes in climatic variables. The study quantifies the spatial determinants of climate, climate variability, climate change, and carbon intensity to accelerate mitigation and adaptation measures. The study also incorporates the spillover effect of these determinants on climatic variables by using the spatial Durbin model. For climate variability and carbon intensity, we have considered panel data for 116 countries from 1991 to 2018. While for climate and climate change, we have cross-sectional data averaged for 30 years (1989 to 2018). GDP per capita, energy intensity, population, industrialization, and urbanization are significant determinants of climate variability (temperature), while energy intensity, population size, and proportion of urban population spillover affect nearby countries' climate variability. For climate variability expressed by rainfall is affected by energy intensity, trade openness has a spillover effect on nearby countries' climate variability (rainfall). Carbon intensity over the same period is influenced by the GDP per capita, trade openness, population size, and urbanization, while energy intensity has a spillover effect on the carbon intensity of nearby countries. Climate change (temperature), population density, and trade are key spatial determinants.

For impact assessment, the present study evaluates the impact of climate change on food production by considering wheat, rice, and maize production per agricultural land. Certain non-climatic (fertilizer, machinery, labor, openness) and climatic input factors (temperature, temperature variability, rainfall, and rainfall variability) are used in the analysis by the spatial Durbin model. Results vary with the type of crop considered. For wheat production per unit of land area, fertilizer usage, labor, trade openness, rainfall, and its variability are major input factors affecting wheat production. For the spillover effect, increased fertilizer use by neighboring countries has a negative significant spillover effect on the domestic country's production. Also, an increase in labor usage by neighboring countries negatively affects wheat production in the home country. Free movement and access to wheat in domestic and neighboring countries positively impact wheat production in domestic countries. An increase in rainfall variability in one region and its neighboring countries increases wheat production in the domestic country.

For rice production per agricultural land, fertilizer, agriculture labor, average annual temperature and its variability, and rainfall are major input factors affecting rice production. Increased machinery usage, rainfall, and variability have spatial repercussions on nearby countries. Maize production per agricultural land is affected by increased fertilizer usage, labor, machinery, temperature, rainfall, and their respective variability. In the case of maize, non-climatic input factors such as fertilizer, labor, machinery, and trade openness of nearby countries have a spillover effect on the domestic country's maize production.

Chapter 1

INTRODUCTION

1.1. Background of the Study

World GDP has increased multifold in the past century, led by an incentive structure that promotes production, consumption, technological innovation, and increased economic integration. Brown growth based on fossil fuels, overutilization of natural resources, and excessive production have a greater negative spillover effect on the environment, biodiversity, and our ecological systems. Climate and environmental concerns have increased considerably as natural disasters worldwide have increased. Consequently, many climate agreements and climate change conventions led by international organizations for global collaboration emerged. Paris Agreement, Sustainable Development Goals (SDGs) 2030, and the recent Conference of all Parties-26 (COP-26) identified climate risks and adaptive and mitigation measures. United Nations, in its COP-26, has urged countries to limit the net emission to zero by 2030, limit methane emissions, loss of forest, coal-driven production, and international financing of fossil fuel projects. In addition, they emphasized the need for global action and collaboration to reduce the pace of climate change.

In its subsequent reports, Inter-governmental Panel on Climate Change (IPCC) stressed that global warming beyond 1.5 degrees Celsius above the pre-industrial level would have a detrimental effect globally. Some of the intrinsic warmings naturally take place due to our ecosystem. However, literature largely agrees that past-century warming is the negative externality of industrialization led by fossil fuels. IPCC, in its AR-5, revealed that some of the world regions are experiencing warming greater than the global average while some regions, in one season, experience temperatures greater than 1.5 degrees Celsius from the preindustrial levels. The latest issue, i.e., the Sixth Assessment Report (AR-6), highlighted that manmade factors are responsible for increased Greenhouse Gases (GHG) emissions causing environmental damage. The risk associated with climate change, possible solutions, and transformations required to contain global warming below 2 degrees Celsius from pre-industrial levels by 2028 are discussed.

Besides global warming beyond the preindustrial level, climate variability and carbon dioxide (CO_2) emissions are also used to assess the pace and magnitude of climate change. However, some of the researchers conclude that variability and change are two different concepts as they affect economic activity varyingly. Climate variability is a short-run phenomenon measured by the deviation of climatic variables from their long-run mean, often known as climate anomalies. At the same time, climate change is a long-run measure to analyze thirty-year average of climate variables. Moore and Lobell (2014) used deviation of climate variables from a 30-year baseline period of 1961-90 to access climate variability. Tol (2021) used a 30-year average of climate variables as climate change. The impact of variability and change matters for policymakers as short-term fluctuations require immediate policy responses, while long-term fluctuations require a structural change to counter the negative impacts.

Economic activity directly influences the environment and vice versa. To contain, adapt and mitigate the negative impact of climate change, it is important to analyze the factors causing this change. A number of socio-economic drivers have been identified in the literature for increasing the pace of GHGs. Theoretically and empirically, Malthus studied the impact of population on natural resource degradation. While Environmental Kuznets Curve (EKC) indicates that economic growth initially increases CO_2 emissions, economic growth leads to lower environmental degradation after a certain limit as counties tend to be better off adapting to a better quality of economic growth. Literature also suggests N-shaped relation between economic growth and environmental quality (Friedl & Getzner, 2003).

Similarly, other factors responsible for climate change include industrialization, urbanization, population size, trade openness, and energy intensity (Lin et al., 2017; Rahman, 2017; Du et al., 2018; Liu & Bae, 2018; Dong et al., 2019; Ghazali & Ali, 2019). The sign and impact of these factors on climate change remain contingent on their sustainability and renewable nature. For example, when led by fossil fuels, industrialization has a detrimental effect on climate change and variability, while using renewable energy in the process of industrialization reduces the negative impact on climate change (Appiah et al., 2019). Urbanization increases the demand for energy and results in rural-urban migration. However, if urbanization is unplanned and unevenly dispersed, it adds additional pressure on the environment (Wang et al., 2020; York et al., 2003). The population is also considered one of the factors affecting climate change, as highlighted by Malthus; however, the Boserupian view considers the population as a source of innovation that reduces the negative impact on the environment. Developed and developing countries have differentiated impacts on climate change for socioeconomic factors as developing countries mostly remain unplanned, overpopulated, and poverty-ridden, while developed countries have planned urban systems that are more climate-friendly and sustainable. Energy intensity and trade openness are also examined in literature as important determinants of climate change.

Importantly, the risk and impact of climate change are disproportionately distributed among countries (IPCC). The literature also highlights that climate change's impact, adaptation, and mitigation will be subject to geographical location and income levels (Tol et al., 2004; Mendelsohn et al., 2006; Tol, 2009). Countries near the equator are more prone to the risk of high temperature as they have already achieved their upper limit of high temperature (Tol et al., 2004). Countries located towards the poles are likely to get warmer. Geographical and income levels of countries are important to gauge the risk and cost associated with climate change. Several studies concluded that climate change has a heterogeneous impact across countries. Developing and underdeveloped regions of the world are mostly located in warmer regions and close to the equatorial belt. At the same time, their economy is mostly dependent on the agriculture sector that is under serious threat of climate change. Developed regions, on the other hand, have a geographical location and income level conducive to adaptation to climate change (Nordhus, 1993; Gallup, 1999; Tol et al., 2004; Dell et al., 2008).

Climate change impact assessment on various sectors is extensively researched. Mendelsohn et al. (2006) study reveals that the relationship of climate variables with economic sectors is hill shaped, indicating a benchmark temperature level where revenues for that particular sector are maximum and beyond which it tends to decline with increasing temperatures. Climate is the agriculture sector's basic input, affecting labor (Kjellstrom et al., 2009), capital (Tsigaris & Wood, 2019), and land productivity. Major climatic factors affecting agriculture productivity include a rise in temperature, irregular or extreme rainfall, and a rise in CO_2 emission to the levels that disturb the photosynthesis process.

Food security is the prime concern for countries in post-pandemic and Russia-Ukraine war world. One of the major concerns is that the world population is increasing at a high rate compared to crop yield per hectare (Arora, 2019). With additional burden from climatic change risks, ambitious policy measures are required to achieve the global sustainable development goal of zero hunger by 2030. Climatic factors such as temperature, precipitation, and humidity directly affect crop cycle, growth, yield, and production. The impact of climate change is heterogeneously distributed across space and type of crop. Literature suggests that agriculture activity will likely shift to colder regions as temperature surges. The fertilization process will provide a beneficial effect until a certain limit of temperature rises. However, on the other hand, tropical zones are likely to incur losses. Developing and least developed economies are situated in tropical and equatorial belts. Most of them depend heavily on agriculture as a primary source of their livelihood. In addition, their high levels of poverty and minimum capacity for adaptation make them more vulnerable to climate change. In their study, Wheeler and Kay (2010) concluded that crop area would shift towards the north by 50kms for every 1 degree increase in temperature.

Literature provides ample evidence that south Asia and sub-Saharan Africa are likely vulnerable due to their limited adaption and high dependence on the agriculture sector to feed their rising population. Many studies in the literature predict a decline in cereal yields in sub-Saharan Africa (Barrios et al., 2008; Ward et al., 2014; Blanc, 2012; Ginbo, 2022) and Asia (Bandara & Cai, 2014; Chandio et al., 2022). Also, climate change impacts various crops according to their ability to retain CO_2 emissions in photosynthesis. Increased CO_2 emissions can improve yields of C3 (rice, wheat, oats, barley, cotton) plants as the photosynthesis process expedites with increased CO_2 emissions. In contrast, C4 crops (maize, sugarcane, pearl millet, sorghum) are negatively affected by CO_2 emissions (Calzadilla et al., 2010). A rise in CO_2 emissions will only be beneficial if other determinants of plant growth should be adequately available.

Global integration in trade, value chains, technology diffusion, and labor migration has increased the spillover effect of economic activities. The post-pandemic and global economic recession in most countries highlights the externality of economic decisions. Indeed, developed regions with high productivity are closely connected geographically in Europe and America, while developing regions with low to moderate productivity levels are mostly clustered around each other in Asia and Africa. Macroeconomic, trade, investment, and environmental policy measures taken in one country have more spillover effects on immediate neighboring countries rather than distant ones.

It is rightly said;

> *"Everything is related to everything else, but near things are more related than distant things"*
>
> *Tobler's (1969)*

Climate change is intrinsically a global phenomenon that cannot be limited to one country. Carbon emission emitted in one country affects its neighboring countries and the global climate system. Similarly, the factors that cause climate change have negative or positive externality on nearby countries. Spatial effects in empirical literature have been incorporated through the gravity model that incorporates spatial location and distance as a source of variation in economic activity between two countries. Countries that are in close geographical proximity to each other gain more in terms of any economic activity as compared to their distant neighbors. Also, the use of panel data has facilitated to capture of the unobserved heterogeneity between countries by fixed and random effects; however, it fails to capture the spatial dependence and spatial heterogeneity between countries. Spatial econometric methods have been devised to incorporate the spatial effects between countries. The spatial relationship is captured by the weight matrix that can be modified according to the spatial relationship between countries. For example, literature considers inverse distance, socio-economic variables, and countries with borders as a source of explaining the spatial relationship.

Considering the background of the study, firstly, we have differentiated climate change and variability, considering variability a short-run phenomenon, i.e., the deviation of climatic variables from their long-run mean. In contrast, climate change is the change in the long-run trend of climate variables. Secondly, by using historical data on climatic variables, we have analyzed climate variability under the footprint of income, geographical location, and industrialization by highlighting the role of international collaboration in global climate policy process breakthroughs. Thirdly, as drivers of climate change in one country have a spillover effect on the neighboring country, we have quantified spatial association of climate variability and change. Lastly, we have examined the impact of climate change and other related inputs and their direct and indirect impact (spillover) on the agriculture production of countries that produce wheat, maize, and rice.

1.2. Research Gap and Research Questions

1.2.1 Research Question 1:

Many studies have analyzed the relationship between climatic variables and economic activities. Initial studies have focused on calculating the damage function by assuming different future climatic scenarios. Some studies focused on how temperature changes affect sectors such as agriculture, industry, and energy labor productivity. The relationship between economic growth and environmental factors such as CO_2 emissions have been well researched. The role of geographical factors in determining the impact of climate change has also been analyzed by considering region-specific studies. Existing literature has used complex methodologies to access climate change and related sectors under study and has ignored the impact of policy measures taken in different periods. The present uses historical data on climate anomalies under different policy regimes in the global climate policy process formation by considering the transition of economies based on income levels and industrialization. The geographical location of countries is also considered with their respective climate anomalies. GIS analyzes the spatial spread of climate anomalies across different regions. We have considered the following research question in the first part of our analysis;

- Is there any spatial climate variability across regions, income groups, and levels of industrialization?
- Is there any role of international organizations in decreasing the pace of climate variability (anomalies)?

1.2.2 Research Question 2:

Existing literature has analyzed non-spatial and spatial determinants of climate change using several proxies such as carbon emissions, sulphur dioxide (Wang et al., 2016), various pollutants (Hao & Liu, 2016; Du et al., 2018), and ecological footprint (Aydın et al., 2019; Xun & Hu, 2019; Destek & Sinha, 2020; Akadiri et al., 2020; Koyuncu et al., 2021). Often in existing literature, climate change and variability are used interchangeably. Some of the studies, for example, Tol (2021), considered climate anomalies as climate variability while climate change is considered as 30 years average of climate variables. Keeping the distinction between climatic variability and climate change, we have devised the following research questions;

- What are the spatial determinants of climate?
- What are the spatial determinants of climate variability?
- What are the spatial determinants of climate change?
- What are the spatial determinants of carbon intensity?
- What are the spatial determinants of climate variability and carbon intensity across regions?

1.2.3 Research Question 3:

Literature provides ample evidence on the relationship between climate change, crop yield, and agriculture production at global and regional levels by using crop simulation models, GTAP-W, and production function approach (Isik & Devadoss, 2006; Lobell et al., 2011; Lobell & Field, 2007; Blanc, 2012; Fei et al., 2020; Ray et al., 2019). Also, the relationship of climate variables with farm values (Passel et al., 2017) and farm profits (Moore & Lobell, 2014) is discussed. Some of the studies (Donfouet et al., 2017; Zhong et al., 2019; Nicita et al., 2020; Qingshi & Akbar, 2022) have incorporated the role of the spillover effect of agriculture production on nearby regions. Most of these studies are country-specific that measures the spillover effect of climatic and other agriculture inputs on output. The role of countries producing similar crops close by is missing in the literature. There is a need to examine the direct, indirect, and feedback effects of factors responsible for the disparity in a county's agriculture production of wheat, rice, and maize nearby. We are interested in evaluating whether climatic variability, trade openness, and the use of other agricultural inputs of any country have repercussions on countries located near them. Following this, we have devised the research question as under;

- Does climate variability spatially affects wheat production across wheat-producing countries?
- Does climate variability spatially affects rice production across rice-producing countries?
- Does climate variability spatially affects maize production across maize-producing countries?
- Does climate variability spatially affects wheat, maize, and rice production across the producing regions?

1.3. Significance and Scope of the Study

Policymakers have stressed the need for sustainable and inclusive economic growth. Despite technological advancement and innovations, climate change is one of the greatest threats facing both developed and developing countries. It has been widely agreed that a global temperature increase of 1.5 degrees Celsius compared to pre-industrialization is detrimental to our natural ecosystem. Earlier, proponents of Malthus's theory highlighted the negative impact of population increase on environmental degradation. However, with the emergence of the Kuznets curve, most researchers found that the negative impact of economic activity on the environment prevails up to a certain limit. Beyond that, high income and industrialization cushion the negative impact on the environment, causing climate change. Some scholars are of the view that this relationship is N-shaped. Also, the impact of climate change on developing and developed economies is heterogeneous, while some scholars believe that the net impact depends on a country’s adaptive capacity.

Geographical location also holds a key position in determining the impact of climate change. The controversy about the relationship between climatic variables, income, industrialization levels, and geographical location still prevails. Furthermore, the role of breakthroughs such as the Kyoto Protocol and the Paris Agreement in the history of global collaboration for climate change has been ignored in the literature. The present study's first paper contributes to the existing literature by studying the historical data on climatic anomalies across income levels, industrialization, and geographic location, keeping in view the time frame of major international agreements. Importantly, the time frame chosen in the analysis is when some countries moved from lower middle income to upper middle income and experienced industrialization based on fossil fuels. Thus, to the best of our knowledge, the present study is the first to evaluate and highlight the role of international agreements in considering the transition in income levels and industrialization across countries.

In its subsequent reports, IPCC highlighted the number of anthropogenic factors responsible for the past century's warming. Moreover, the earlier carbon emissions are likely to persist in the atmosphere even if net emissions are reduced to zero. Studying the drivers causing climate change is important to effectively manage the mitigation and adaptive measures. However, the central question remains inconclusive as to what climate change is. Literature evaluating the determinants of climate change has used several proxies to study climate change; for example, the vast majority of the studies have used carbon emissions as an important measure to gauge climate change. Some studies have used sulphur dioxide (Wang et al., 2016), various pollutants (Hao & Liu, 2016; Du et al., 2018), and ecological footprint (Aydın et al., 2019; Xun & Hu, 2019; Destek & Sinha, 2020; Akadiri et al., 2020; Koyuncu et al., 2021) as measures to access climate change.

Unlike the existing studies, in the second paper, we employed climatic variables to measure climate change and variability. Importantly, one of the prime concerns is also the short-term (climate variability) and long-term (climate change) changes in climatic variables (temperature and rainfall). Short-term changes call for a different set of policy measures than long-term ones. Most studies consider climatic variability and change as synonyms, while some consider climate variability as the deviation of climatic variables from a long-run mean of 30 years and climate change as a 30-year average of climatic variables. The present study separates itself from the literature by evaluating the determinants of climatic variables (temperature and rainfall) as a proxy for climate variability and change. For comparison with the existing studies, we have also employed carbon intensity and have evaluated its determinants.

The major climate change determinants identified in the literature are economic growth, population, industrialization, trade openness, and energy intensity. Country-specific policies often have a spillover effect on neighboring countries. The free rider problem in climate-related issues fails to provide a competitive global solution. Nationally determined goals and common policies for countries often help internalize the cost and benefits of spillover effects. We have examined the direct and indirect effects of drivers responsible for climate change, variability, and carbon intensity to analyze the determinants effectively.

One of the major sectors vulnerable to climate change in agriculture. Food security in the post-pandemic and post-Russian-Ukraine war has raised concerns for developed and developing countries. Besides this transitory threat to food security, climate change is a permanent risk facing the agriculture sector. The agriculture sector, in general, and crop production, in particular, are connected to the natural environment, climate, and land conditions that show similar patterns across closely connected regions. Most agriculture regions suitable for crop production are clustered around each other. Besides agroecological conditions, globalization, increased communication, and information sharing create dependency of regions on one another, creating a spillover effect of their economic decisions not just on their own country but on countries in close proximity to them. Ulimwengu and Sanyal (2011) found that regions with low agriculture productivity surrounded by highly productive regions tend to catch up with the highly productive regions in case Africa. Keeping this in mind, the third paper in the study considers the direct, indirect, and feedback effects of factors affecting the agriculture production of wheat, rice, and maize. Contrary to the existing literature, we have considered countries that produce wheat, rice, and maize and have accounted for the spillover effect on countries that also produce the same crop. We are interested in evaluating whether countries producing the same crop can affect each other, considering climate variability and other agricultural inputs.

The study has a few limitations. In the first paper, we considered the number of countries falling in income groups and industrialization. We have not accounted for their actual income or industrialization values. We have considered temperature and rainfall as a proxy for climate variables in the study. Other variables such as humidity, sunshine, and evaporation are ignored in the analysis that can be used for future research. Most crop production studies consider data on a monthly or crop seasonal basis as crop growth patterns requirement of climate input tend to change within a season. For agriculture production and climate variables, we have analyzed the data on an annual basis as data on climate variables is readily available daily, but the data on agriculture production and other agriculture inputs is available annually.

1.4. Plan of the Thesis

Following the chapter of Introduction, the second chapter outlines the exploratory analysis of climate anomalies, considering the breakthrough in international collaboration across regions, income, and industrialization levels. In the third chapter, we quantified the spatial determinants of climate change, climate variability, and carbon intensity. In the fourth chapter, we analyzed the impact of climate variability on food production by considering a spatial econometric model for wheat, rice, and maize. Chapter 5 concludes the study with a policy recommendation

Chapter 2

THE FOOTPRINT OF SPACE, INCOME, AND LEVEL OF INDUSTRIALIZATION ON CLIMATE CHANGE

2.1. Introduction

Climate change, often termed a distant threat, has already begun to show its visible signs with the emergence of natural disasters in the past few years. The recent global outbreak of locusts in Africa, South Asia, and the Middle East has been reasoned by a longer than usual rainy season and floods in Indonesia, India, Bangladesh, Iran, and Brazil. Australian bush fires, a volcanic eruption in the Philippines, and earthquakes in Russia, Turkey, India, China, and Jamaica give glaring signals for widespread impacts and consequences.[1]

Generally, climate evolves over time, explaining some natural forces intrinsically altering the earth's climate.[2] Changes in biological factors majorly cause the pre-industrial era's climate variations. The post-industrial revolution came up with technological progress, increased urbanization, enhanced efficiency, and global integration with significant changes in global temperatures. The primary reason behind these significant changes is the excessive increase in human activities that emits carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and other greenhouse gases (GHGs).[3] As compared to pre-industrial levels (1750), in 2011, global CO_2 concentration swelled by 40 percent (278 ppm to 390.5ppm), while CH_4 and N_2O were picked up by 150 percent (722 ppb to 1803 ppb) and 20 percent (271 ppb to 324.2 ppb) respectively (IPCC AR5). Unfortunately, the pressing concern is that many of these emissions are permanent and cannot be reversed in centuries.

[1] The international disaster database, (CRED) https://www.emdat.be/

[2] Variations in solar energy, volcanic eruptions, and natural changes in greenhouse gas (GHG) concentrations

[3] Increase use of fossil fuels and change in land use activities increases carbon dioxide emissions while agriculture sector is responsible of intensifying methane and nitrous oxide content in the atmosphere.

Earth's surface temperature will continue to rise even if net CO_2 emissions are marginalized to zero.[4]

Industrial activity has played an essential role in economic growth, development, and technological innovation in developed and upper middle income. However, the present series of climate change disasters reveals that industrial innovation and progress are also coupled with negative externality that affects our ecosystem's standard working capacity. Carbon dioxide is continuously released and removed from the atmosphere by natural processes. However, excessive release of gases that absorb carbon content in the atmosphere increases the earth's temperature. Multi-disciplinary scientists have analyzed several natural and anthropogenic factors responsible for climate change. This fact has also been validated in the current health crisis COVID-19 when more than half of the world has halted production, transportation, and all kind of carbon-intensive activities. Le-Quéré et al. (2020) revealed that daily carbon emissions decreased by 17% in April 2020 compared to 2019. International Energy Agency (IEA) also ensures the reduction of 2.6 gigatons of CO_2 emissions globally in 2020.

Global collaboration to address climate change started in the late 1990s. International organizations such as United Nations Environment Programme (UNEP), United Nations Framework Convention on Climate Change (UNFCCC), and World Meteorological Organization (WMO) came into existence. Later UNEP and WMO jointly established a scientific body as Inter-governmental Panel on Climate Change (IPCC), for climate change research and awareness.

UNFCCC came up with several tools and policy measures in its Conference of the Parties (COPs) each year since 1995 (for details, see Table 1). However, the *Kyoto Protocol* and the *Paris Agreement (COP-21)* are breakthroughs in global collaboration. Developed countries were considered responsible for the past century's industrial activity and were constrained to reduce their GHGs emissions levels. The Kyoto Protocol agreement restricted developed countries from cutting their emission by 5% compared to 1990 and country-specific goals for 2008 to 2012. In 2005, the EU

[4] Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change

also introduced an Emission Trading System (ETS) to strengthen emission reduction further. Through its technical and scientific reports (AR4 & AR5), IPCC assured an increasing carbon emissions rate from emerging economies (China, India, and Russia). Later, in 2015, the Paris agreement included developed, emerging, and developing economies as part of the global climate change process. The world's top GHGs emitters agreed to move forward in decelerating the pace of worldwide temperature and keeping it between 1.5 °C to 2°C as compared to pre-industrial levels.[5]

Climate change is not confined to geographical boundaries. Carbon emission emitted from one part of the world is homogenously mixed across the atmosphere irrespective of the country emitting it, but the impact of climate and natural disasters are heterogeneous. Distributional consequences across regions hold a crucial position for policy formulation at regional and country levels. The present study measures climate change's spatial and temporal spread across regions, income groups, and industrialization levels. Existing research on distributional analysis focuses more on impacts and future climate change based on process-based simulations.[6] However, the present study uses historical climate change data to gauge climate change magnitudes across different regions, income groups, and key industrialization drivers. This paper does not explain complex models nor uses any complex methodologies in the analysis. Instead, it narrates merely factual data and graphically gives a birds-eye view of income levels, socio-economic linkages, and climate change.

It is essential to have global and regional perspectives for international policy formulation. Considering differences in an economic framework, level of industrialization, and geographical location present study provides important insights to international policymakers. IPCC formulates its policy, keeping in view the income level of countries. The present study highlights the role of other factors, such as industrialization and geographical space, in devising climate change policies.

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[5] Both Kyoto Protocol and Paris agreements includes three subgroups for countries. Annex I, Annex II and Non- annex I countries. Detail list of countries and their divisions into these sub groups can be assessed through https://unfccc.int/process/parties-non-party-stakeholders/parties-convention-and-observer-states?field_national_communications_target_id%5B515%5D=515&field_partys_partyto_target_id%5B511%5D=511

[6] climate models such as by Global Circulation Models (GCMs), regional climate models (RCMs), integrated assessment models (IAMs) and many more are being used to access climate change impacts

Table 2.1: Key Developments in Climate Change Policy Formulation

Period	Key developments
Pre-1990	1972- UN conference on the human environment
	1979- First World climate change conference
	1987- Montreal Protocol (restrict the use of chemicals that damage ozone)
	1988- IPCC was set up
1990-1996	The 1990-IPCC first assessment report was launched
	1991- First meeting of intergovernmental negotiating committee IPCC
	1992-convection on climate change adopted. Rio Summit Declaration
	1994-UNFCCC was established
	1995-COP1 takes place in berlin
1997-2004	1997- Kyoto Protocol was adopted
	2001-Marrakesh Accords
2005-2014	2005-EU's emission trading system was launched
	2007- IPCC's fourth assessment report was launched
	2009-Copenhagen Summit on Climate Change
	2010- The Cancun Agreement was adopted
2015-2019	2016- The Paris Agreement was enforced
	2018-Rules for Paris Agreement Decided
	2019-UN Climate Action Summit for world leaders in New York

Source: https://www.unfccc.int/, https://www.ipcc.ch/

The rest of the paper is structured as follows. Section 2 outlines the review of relevant literature on the distributional impact of climate change. Section 3 discusses methodology, data description, and data sources. Section 4 discusses findings by analyzing climate change across regions, income groups, and industrialization levels through graphical and spatial analysis. Section 5 concludes the study

2.2. Review of Literature

Climate change has already begun; it is a well-agreed phenomenon endorsed by multi-disciplinary literature. It is not confined to geographical boundaries; therefore, countries are more concerned about the impacts, adaption, and possible mitigation. Going deeper into the causes of climate change, the literature reveals that human-induced factors are crucial in altering climatic variables' trajectories[7]. Others strengthen this fact by recognizing global warming as a *by-product* or *externality* of

[7] IPCC (2007)

unsustainable technological and industrial progress (Stern, 2007). The world economic system incentivizes production, consumption, capital accumulation, and technological progress. The industrial revolution, accompanied by the capitalist system, led to exponentially high growth levels for the global economy. However, every economic activity directly impacts our ecological system (Li, 2009; Burke et al., 2015), while some economic activities (crops, fisheries) are now contingent on climate and weather conditions.

Climate variables, particularly temperature, nonlinearly affect economic productivity (Burke et al., 2015), labour supply (Zivin & Neidell, 2014), and agriculture yields (Mendelsohn & Dinar, 1999). Initial literature on climate change focused on GHGs damage functions and abatement costs for world regions. Nordhaus (1991), Tol et al. (2000), Fankhauser and Tol (1996), and Pearce et al. (1996) assumed different climate scenarios, damage functions, and adaptation practices to estimate future carbon emissions cost in monetary terms. Further studies analysed the impact of climate change on other sectors (agriculture, forestry, marine life, energy) have linear[8] (Arnell et al., 2013) quadratic or parabolic[9] (White et al., 1999) relationships with temperature changes. All these models that assumed different damage function forms predicted that each country would suffer from climate change relative to its income level. Experimental and cross-sectional studies on the climate sensitivity of different sectors reveal that climate change has a *hill-shaped* relationship in each industry. It means a specific optimal temperature for each industry maximizes revenues for that sector and beyond which gains tend to diminish (Mendelsohn et al., 2006).

Burke et al. (2015) examined the non-linear relationship between temperature, precipitation, and productivity, irrespective of a country's economic status. Deviations from growth trends are compared with deviations from temperature and precipitation trends. Besides this, the study identifies benchmark temperature (13°C to 16°C) that yields the highest productivity gains and beyond which productivity starts diminishing.

[8] Degree of impact is same as temperature increases
[9] Initial climate change may yield benefits until a point where benefits start diminishing with high levels of climate change

Comparative development theorists consider a strong correlation between a country's location from the equator and economic prosperity (Andersen et al., 2016). We move away from the equator, and the income per capita of countries increases. Andersen et al. (2016) study revealed a strong and negative relationship between ultra-violent radiations on economic activity. The impact of climate change differs across countries. Existing literature, for example, Schelling (1992), Mendelsohn et al. (2006), Tol (2009), and Tol et al. (2004), revealed that developing countries, because of their geographical location, on average, are already more prone to hot temperature. Besides geographical conditions, most of their economic activities are dependent on climate-sensitive natural resources. Also, their limited capacity to adapt makes them more vulnerable to additional warming. On the other hand, rich countries are relatively colder, rely on human-made resources, and have improved adaptive capacity, making them somewhat better off than developing countries.

Climate models often predict that warming will increase towards the poles (Mendelsohn et al., 2006). While Tol et al. (2004) expressed that the temperature increase will drift more towards the equator because countries near the equator have already overcome warming resistance. Additional warming will harm them more than countries far from the equator. For further distributional analysis for climate change across the world's poor and rich, Mendelsohn et al. (2006) analysed three different climate models with response functions and divided the world population based on their per capita income expected in 2100. The study predicted that the poor half of the world would be adversely affected by climate change compared to the wealthy half.[10]

Changes in temperature and precipitation affect output and hinder output growth in developing countries (Dell et al., 2008; World Bank, 2010). With no prior assumption of channels through which temperature affects economic activity, Dell et al. (2008) estimated that temperature changes have a more pronounced negative impact on developing countries economic growth than on the rich. At the same time, changes in precipitation do not affect economic growth for both groups. The study examined the

[10] For further clarification on distributional impact, it was assumed that other things being different only climate change and initial climate is similar across countries. With similar climate change cross countries, the study strengthens the existing results while in case of same initial climate damage increases with income thus reducing the gap between rich and poor nations.

impact on both the level and growth of output. Horowitz (2009) examined the relationship between temperature and income using the econometric method and explored contemporaneous and historical climate factors. Dell et al. (2012) revealed that a 1°C rise in developing countries' temperature would decrease agriculture growth by 2.6 percentage point. While 1°C increase in warming decreases economic growth falling by 1.3 percentage points.

Existing literature has used complex methodologies to assess climate change and related future predictions for rich and developing countries. Most studies focus on economic growth as an important determinant causing and threatened by this change. The present study first separates itself from existing literature by reviewing climate change under the footprint of income, geographical location, and industrialization levels by overviewing factual historical data instead of complex economic models and scenarios. Secondly, the role of international collaboration, climate adaptation, and mitigation efforts has been accessed by analysing the pre and post-era significant breakthroughs in the global climate policy process.

2.3. Methodology & Data

The present study is exploratory and uses spatial analysis to capture climatic variables' behavior given income, industrialization, and geographical location. The study uses spatial graphs using QGIS and excel software. Tobler's (1969) first law of geography states that "everything is related to everything else, but near things are more related than distant things." Location and geographical factors hold critical information that policy decisions can't ignore. Thus, a mapping tool such as a geographical information system (GIS) is used to minimize the loss of information. Many studies have used GIS for environmental (Rahman, 2015) and metrological and socio-economic variables mapping. GIS is a computer-based program that integrates spatial information and other socio-economic variables into meaningful maps. Spatial analysis tools are widely used in urban planning (Kohsaka, 2000), poverty mapping (Vista & Murayama, 2011), land use management, and tourism management (Boers & Cottrell, 2007). Before quantitative analysis, GIS tools explain the visual relationship between variables graphically. For climate variables, annual average temperature (°C) and rainfall (mm) is used. Climate variability (anomaly) is measured by the deviation of climatic variables from their long-run mean, often known as climate anomalies. WMO (2017) has also updated climate typical with changing conditions as the most recent 30 years ended with zero. The current climate standard period is 1981-2010, but 1961-1990 can be used for long-run analysis. We have used the 1961- 1990 baseline period for the current research because major international organizations were formed after the 1990s. Therefore, the base period is chosen before any policy measures are enforced to capture climate change organizations' roles effectively. Climate Research Unit (CRU) UK published various climate variables data sets under CRU TS 4.03 with high resolution (0.5°x 0.5°). It covers data for the entire world from 1901 to 2018. Several stations are being captured for a single country[11]. Overall, CRU monitors four thousand weather stations around the world.

The study utilizes seven regions: North America, Europe, Central Asian, Latin America and Caribbean, East Asia and Pacific, Middle East and North Africa, South Asia, and Sub-Saharan Africa. Each year's historical classification of countries is taken from the World Bank database to categorize income groups (For detail, see Appendix A). The study uses the United Nations Industrial Development Organization (UNIDO) bifurcation of countries into Industrialized Economies (IEs), Newly Industrialized Economies (NIEs), Developing Economies (DEs), and Least Developing Economies (LDEs). The analysis is divided into four regimes with two principal policy interventions to analyze the international organizations' role.

Figure 2.1: Major Regimes in Climate Change Policy Formulation

1990-1996	**1997-2004**	**2005-2014**	**2015-2018**
Regime 1: pre-Kyoto protocol (R1)	Regime 2: post-Kyoto protocol (R2)	Regime 3: pre-Paris agreement and Kyoto protocol enforcement (R3)	Regime 4: post-Paris agreement (R4)

2.4. Discussion on climate, climate variability, and climate change

Many international organizations use various climate definitions, variability, and change. It is important to quantify climate change and variability for effective policy formulation. World Metrological Organization (WMO) defines climate *as:*

[11] Complete list of stations considered for each country can be accessed through https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ge/

> *"the state of the average behavior of climatic variables over a period of time of 30 years or more".*

For climate change, WMO defines the statistically significant change in climatic variables' average behavior that persists for a decade or more, caused by external and internal factors. However, UNFCCC defines climate change as the changes caused by anthropogenic factors. Climate variability is measured by the deviation of climatic variables from their long-run mean, often known as climate anomalies (WMO). Climate variability defines a prerequisite for a benchmark or baseline from which change is calculated. Thus, WMO has defined climate normal as a reference to compare current climate variables. These reference periods show climate variables' average behavior for thirty continuous years. The benefit of using thirty years is to minimize extreme events' effects and get insight into climate variables' historical perspectives.

Literature suggests several indicators to access climate change. For example, Bugmann and Pfister (2000) considered the year-to-year fluctuations around the long-run mean of climate variables as climate variability. Katz and Brown (1992) depicted the long-run trend in climate variables as climate change, and Chang (2002) used the difference of seasonal mean temperature and rainfall from 20 years moving average as climate variability. Rowhani et al. (2011) measured climate variability by the coefficient of variation of seasonal temperature and precipitation. Agovino et al. (2019) used mean annual temperature and mean annual precipitation to measure climate change in analysis.

Gohar and Cashman (2016) considered the study's climate average, climate change, and climate variability assumptions. A normal climate zone lies where annual average rainfall follows normal distribution around the mean with a 5 percent variation. If average annual precipitation falls below 50 percent, it is climate change. At the same time, climate variability is a 30 percent variation of average yearly rainfall around mean rainfall. Badolo and Kinda (2014) defined climate variation as the absolute deviation of rainfall from its long-run mean. Moore and Lobell (2014) used the deviation of climate variables from a 30-year baseline period of 1961-90 to assess weather variability while the 30-year average temperature to gauge climate. Tol (2021) used multiple forms of weather anomalies, such as linear, square, and asymmetric, to assess weather variability. Tol (2021) defines weather as what we get at a point in time and defines climate as the weather we expect in the future. The climate in the study is defined as long-run temperature.

Considering the definitions outlined by international organizations and existing literature, we refer to climate as 30 year average of climatic variables in the present study. For climate anomaly, we define it as climatic variables from a long-run mean of 30 years. For climate variability, we define the square deviation of climatic variables from a long-run mean of 30 years. We assign more weight to large deviations when using a square.[12] On the other hand, climate change is defined by the change in the 30-year average temperature from the long-run mean. We will use these definitions in the subsequent chapters to evaluate the impact. The present chapter considers temperature and rainfall deviation of climate variables from the long-run mean to assess climate variability.

2.5. Theoretical Background

Malthus was the first to coin environmental degradation when he studied the relationship between population and environmental degradation. Simultaneously, development economics theorists suggest that structural transformation is vital for economies to take off and transit from one income level. When countries move from low to high income, more resources are diverted from agriculture to the manufacturing and services sector. Excessive production and a conductive capitalist system encourage profit-seeking and thus overexploit resources at the cost of the environment. Contrary to this, modernization theories such as the Environmental Kuznets curve (EKC) followed by ecological modernization theory (EMT) favored industrialization as a significant growth and innovation source that ultimately improves the environment. However, controversy still prevails on the relationship between climate change countries' income, industrialization, and geographical location. Thus, the present study uses historical data to revisit the relationship between industrial activity and climate change.

[12]Weather colder or warmer than usual will incur adaptation cost for countries.

2.6. Results

2.6.1 Climate Anomaly: A Historical Perspective across Varying Income Levels

Economic theory suggests that countries' production or income levels are driven by four production factors, i.e., capital, labor, resources, and technology. Climate change comes under the domain of help as it is the primary input for agriculture, affects labor productivity (Kjellstrom et al., 2009), and capital to net income ratio (Tsigaris & Wood, 2019). The present section highlights how climate change varies with countries' income levels across the past three decades. World Bank (WB) has classified countries according to four income groups: High-Income Countries (HIC), Upper Middle-Income Countries (UMIC), Lower Middle-Income Countries (LMIC), and Low-Income Countries (LIC). In the present section, we have analyzed the economic status of countries from 1991 to 2018. The prime reason to choose this period is that most countries have improved their economic status. Few have gone down while others have sustained. Secondly, many international organizations took aggressive steps to minimize climate change vulnerability. As our data set is divided into different time intervals, countries' income status is ranked according to each interval's year ending.[13] The number of countries within the subgroup of income level varies with time

All income groups experienced more warming than usual in periods beyond the 1990s. A constant warming trend is accompanied by a higher magnitude of warming in all income groups each additional year. Considering international agreements, most of the HICs were part of the Kyoto Protocol and the Paris agreement. Warming has increased in pre-and post-Kyoto protocol times from 1990 to 2004. However, before the Paris agreement regime (R3), additional warming slowed significantly across all income groups except UMICs (see Table 2.2). It was the time when the EU launched an emission trading scheme, IPCC reports were launched, and COPs were being held each year with conclusive policy discussions in the form of a Paris agreement. R4 magnitude of temperature anomaly for HIC increased more than any other income group, followed by increased UMICs, LMICs, and LICs. Within a short span of 4 years, an increase in warming is more pronounced in this period (See Table 2.2).

[13] For example, for interval 1990-1996 income status of countries in year 1996 is used in the analysis and vice versa for other regimes

Interestingly, if we see the percentage change of anomalies from regime 1 to R4, LICs speed of change in temperature anomaly is highest, followed by UMIC, LMIC, and HIC (See Table 2.2). The rainfall anomaly fluctuates for all income groups (See Figure 2.3). Most regimes witness less rainfall than the standard benchmark of 1961-90, except for R3. In the past few years (2015 to 2018), all income groups received less than an average period.

Literature also widely supports that high-income countries will experience warming but will be less damaging for them because of their location, resources, and adaptive capacity (Nordhaus, 1993; Gallup et al., 1999; Tol et al., 2004;[14] Dell et al., 2008). They have also examined that the economic activities of HICs do not heavily rely on climate-sensitive sectors. This fact is also validated if we look at the sectoral contribution to the GDP and sector-wise employment status of HICs. The services sector has increased its value-added in GDP in HICs from 65 to 69 percent in the past two decades, and it is the highest among all income categories. However, agriculture, manufacturing, and industry shares have declined over the same period.[15] Employment also followed the same trend; the services sector caters to more than 70 percent of HICs individuals. Socio-economic factors such as low population growth (0.4 percent),[16] small household size (less than three persons)[17], and stable low annual consumption growth (2.02 percent) as compared to other income groups provide further cushion for HICs. GNI growth rate (4.2 percent) in HICs is greater than the population growth, which shows less burden on their existing resources. HICs have not only empowered themselves economically but have built strong institutions with more adaptive capacity towards changing circumstances. One of the prime reasons for achieving economic success long ago and developing this adaptive capacity is increased reliance on cheap energy resources (fossil fuels) for massive production.

[14] climate models such as by Global Circulation Models (GCMs), regional climate models (RCMs), integrated assessment models (IAMs) and many more are being used to access climate change impacts
[15] According to World Bank, agriculture value added has declined from 2 % to 1.3% while manufacturing sectors contribution has contracted from 17.5% to 14 %. Despite this, manufacturing valued added itself has surged and is highest among all income groups as most of HICs produce complex value-added technological goods.
[16] Data for population growth, annual consumption expenditure growth and GNI growth rate is for year 2018. Source: World Bank Data Base, 2020
[17] United Nations, Department of Economic and Social Affairs, Population Division (2019)

Major UMICs, often called "Plus Five" emerging economies experienced the transition from LMICs and LICs. Development economic theorists suggest that structural transformation is vital for economies to take off and transit from one income level. When countries move from low to middle income, more resources are diverted from agriculture to the manufacturing and services sector. Unfortunately, all this has been achieved at the stake of environmental and resource degradation. UMICs and other developing economies' contributions to world GDP improved from 35.5 percent in the 1990s to 51.3 percent in 2018, while HIC decreased from 63.7 percent to 47.9 percent in the same period[18]. The prime reason for the strong and steadily increasing growth rate is the interconnectedness and global collaboration in production. Presently UMICs value-added contribution to GDP is dominated by the services sector (55.6 percent), followed by industry (32.5 percent), manufacturing (19.8 percent), and agriculture (6.1 percent). UMICs are home to 37.4 percent of the world population, with a per capita income growth of 3.2 percent (WB, 2019) annually. About 21 percent of the employed are dependent on agriculture, while the share of industry and services in the labor force is 25.7 percent and 52.6 percent, respectively.

Cereal production in UMICs is the highest (1.28 billion metric tons) and is increasing among all income groups; industry, services, and manufacturing value-added stood at USD 8.7 trillion, USD 12.6 trillion (2017), and USD 5.5 trillion in 2018, respectively. Literature suggests that the service sector will be less affected by climate change than other sectors. (Tol, 2018; OECD, 2015). UMICs make up 20 percent of world tourism receipts, with an increase of 2.97percent in 2013-2018. Several arrivals in UMIC are second-highest after HICS. As most of these countries are situated near the tropical zone with outdoor tourism activities, there is a high probability that climate change in the form of a surge in temperature and sea level will reduce their earnings and deteriorate coastal infrastructure. Socioeconomic factors are not accommodating for UMICs as 66 percent of the total population resides in urban areas, with a significant population living in urban slums. Average HH size of four members with limited access to health, education, and other social services. Besides this, GDP and consumption expenditure growth exceed HICs, i.e., 3.8 percent (2019) and 4.6 percent (2018), respectively.

[18] World bank database on GDP PPP (constant 2017 USD)

Considering LMICs, their industry and manufacturing sector are backed by the growth of foreign direct investment (FDI) in the late 1980s and the emergence of MNCs with the global value chain mechanism. Sectoral contribution of GDP in LMICs shows that agriculture holds a 15.7 percent share in GDP, with manufacturing having 14.8 percent, followed by industry at 27.4 percent, and services at 49.8 percent. The share of agriculture, the most climate-sensitive sector, holds a predominant role in LMICs. Agriculture land is 43.7 percent of the total land area (WDI, 2016), the highest among all income groups. About 39.5 percent of the population is employed by the sector, with a rural population of 60.3 percent (WDI, 2019). The trade scenario for food suggests that LMICs export food products that account for 13.7 percent (WDI, 2018) of their merchandise trade. Most food products are traded in the raw or primary form with minor value addition. It makes them more susceptible to changing climatic conditions.

Geographical location further adds to the existing challenges as most countries are water-stressed and dependent on rainwater for irrigation. Rent from natural resources has decreased considerably over the past two decades (World Bank). Nordhaus (1993), Tol (2009, 2018), Mendelsohn and Dinar (1999) also validated the above facts through macro-economic models. Around 42.4 percent of the urban population lives in urban slums. Consumption expenditure growth of HHs is highest among all income groups with five persons' average household size. High population density causes additional stress on existing natural resources threatening food and water security, shelter, conflicts, and mass migration.

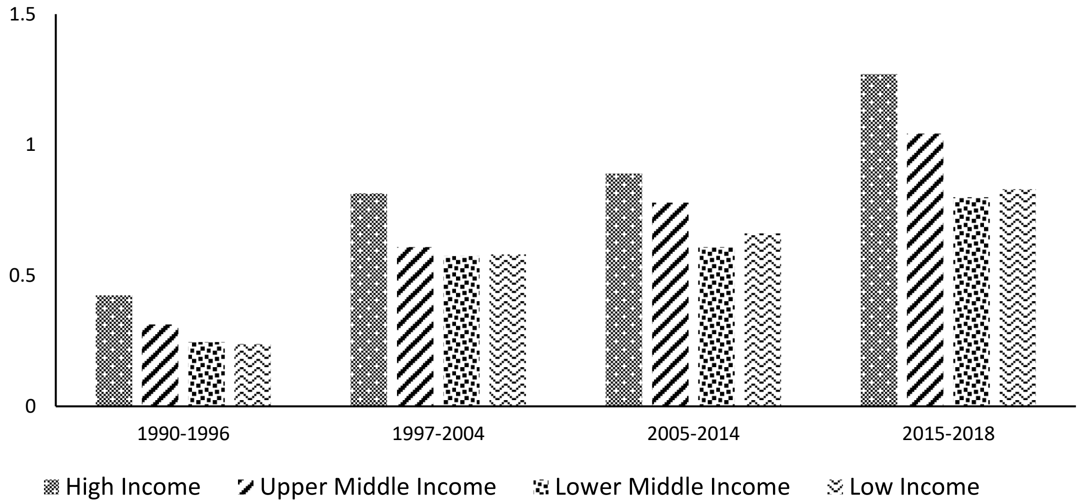
Mendelsohn et al. (2006), Dell et al. (2008), and Dell et al. (2012) are of the view that developing countries will be adversely affected by climate change as they are already hot. LIC is the agrarian economy as they have a more sectoral share in agriculture than any other income group, with a more significant fraction of the population linked with agriculture activities. In 2018, agriculture had a 24.5 percent share of GDP, followed by industry at 25.7 percent and services at 40.2 percent. Agriculture land is 39.6 percent of the total land (WDI, 2016). About 59.1 percent of the population is employed by the sector, with a rural population of 66.6 percent (WDI, 2019). Their dependence on natural resources is highest among all income groups as rent from natural resources accounts for 12.5 percent of GDP, i.e., highest among all income groups. LIC is the most vulnerable group to changes in climatic conditions. Most LICs are part of Sub-Saharan Africa near the equator and have already achieved the maximum temperature tolerance limit. Besides, warming and low rainfall will severely affect food and water security (Mendelsohn et al., 2006). LIC has a low per capita income and the highest population growth rate globally, with an average HH size of 5 members. About 60 percent of the urban population lives in urban slums with poor health and living conditions. Trade accounts for 50 percent of the GDP, based on primary agriculture products. International tourism accounts for 13.6 percent of the GDP. Any damage to natural or physical resources affects earnings from the tourism sector.

Table 2.2: Percentage Change of Temperature Anomalies across Different Income Groups (Values in Percentage)

Regions	1990-1996 R1	1997-2004 R2	2005-2014 R3	2015-2018 R4	percentage change between R1 & R4
High Income	-	91.8	9.3	42.8	199.3
Upper Middle Income	-	94.8	27.9	33.9	233.6
Lower Middle Income	-	133.7	6.1	31.2	225.4
Low Income	-	143.3	13.8	25.5	247.5

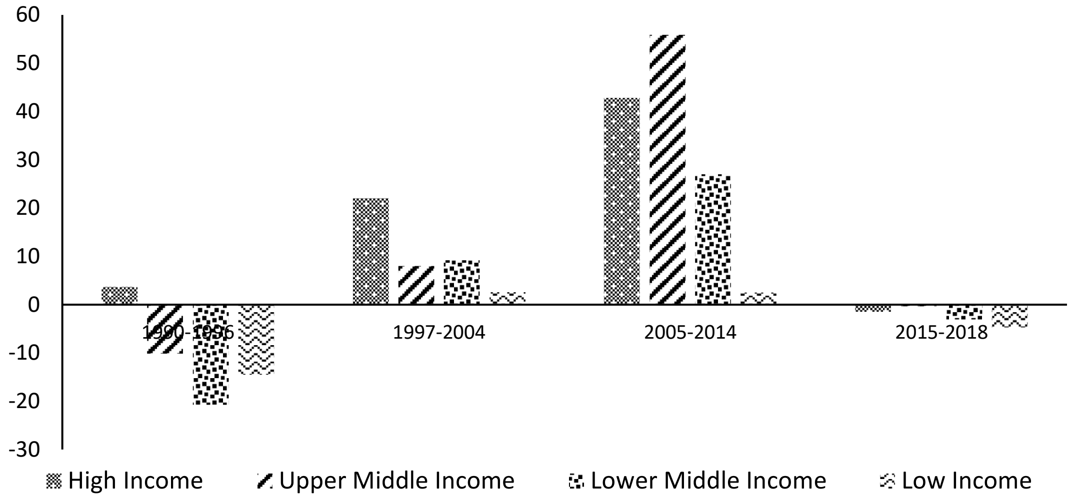
Source: Authors' calculation from Climate Research Unit Database CRU TS 4.03

Figure 2.2: Temperature Anomaly across Income Level of Countries



Source: Author's calculation from Climate Research Unit Database CRU TS 4.03

Figure 2.3: Rainfall Anomaly across Income Level of Countries



Source: Author's calculation from Climate Research Unit Database CRU TS 4.03

2.6.2. Climate Anomaly across Varying Levels of Industrialization

IPCC reported that anthropogenic factors induced significant sources of past-century warming. High GDP growth, technological advancement, massive production, and growing consumption worldwide have left far-reaching negative stimuli on the challenging environment. The present section sheds some light on the historical trends of climate variables for industrialization. The study also examines the past trend in CO_2 emissions with varying industrialization degrees, as industrialization is directly linked to carbon emission.

Countries have experienced more warming at all industrialization levels than usual in periods beyond the 1990s—the warming trend to surge in the post-Kyoto protocol period (R2) in all countries. NIEs percentage change in temperature anomaly from 1990 to 2018 increased the most, followed by an increase in DEs, LDEs, and IEs in this period. It shows that NIEs have experienced more significant temperature changes from their usual than any other industrialization group (IG).

Regarding cross IG comparison, the magnitude of temperature anomaly experienced by IEs recorded is the highest, i.e., 1.3°C, followed by an increase in NIEs, DEs, and LDEs. In 2015-2018, the rise in warming again surged, yet it was slower than warming in the post-Kyoto protocol period (See Table 2.3 & Figure 2.4). The rainfall anomaly shows a fluctuating trend for all IGs. Initially, in 1990-96, rainfall in all IGs declined from the standard period. At the same time, most regimes witness more rain than the common benchmark of 1961-90 in R3. In the past few years (2015 to 2018), DEs and LDCs received rainfall less than benchmark periods. The volatile behavior of rainfall anomaly (See Figure 2.5) creates uncertainty and serves as a twin challenge to handle in the presence of ever-increasing warming.

Table 2.3: Percentage Change of Temperature Anomalies across Levels of Industrialization (Values in Percentage)

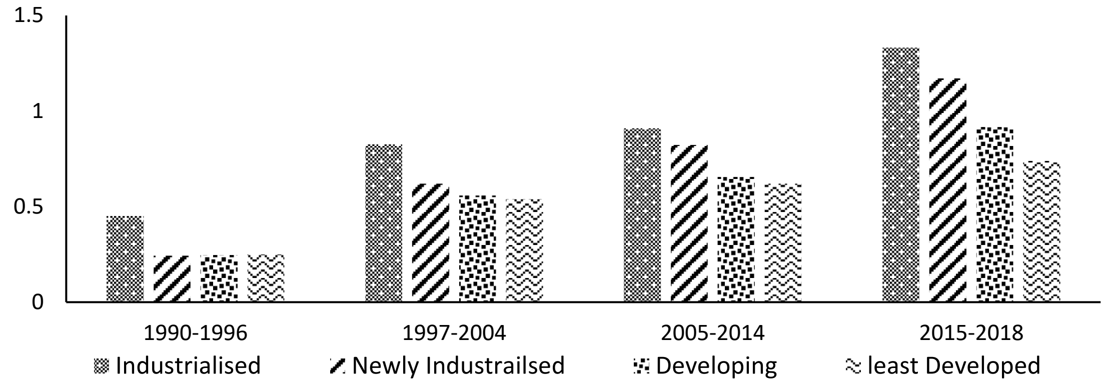
Regions	**1990-1996 R1**	**1997-2004 R2**	**2005-2014 R3**	**2015-2018 R4**	**% Change between R1 & R4**
Industrialized	-	83.5	10.1	46.3	195.5
Newly Industrialised	-	154.0	32.7	42.5	380.2
Developing	-	125.7	17.6	39.7	270.7
least Developed	-	114.9	15.0	19.1	194.4

Source: Author's calculation from Climate Research Unit Database CRU TS 4.03

Global collaboration to address climate change started with central IE member states. *Kyoto Protocol*, the first international agreement for reducing GHGs, restricted developed countries from cutting their emission by 5 percent in 1990 and country-specific goals for 2008 to 2012. Most of the IEs except the US[19]reduced GHGs emissions in this period (see Figure 2.6 and Figure 2.7). Besides this, the EU also introduced an emission trading system (ETS) to strengthen emission reduction further. After 2013, most of the HICs experienced warmer than average temperatures. Before 2006 HICs' share in global carbon emission was 47 percent, the highest among all countries. However, this share was reduced considerably after enforcing the *Kyoto Protocol* in 2006. As GHGs are irreversible, they exist in the atmosphere even if net emission is zero (AR5, 2014). Thus, despite international organizations' concerted efforts, most IEs show a warming trend even though emissions rates have significantly decreased (See Figure 2.6 and Figure 2.7). Abban et al. (2020) examined that energy consumption increases carbon emissions in HIC by 0.8 percent. However, renewable energy consumption in IEs has significantly increased (See Figure: 2.14).

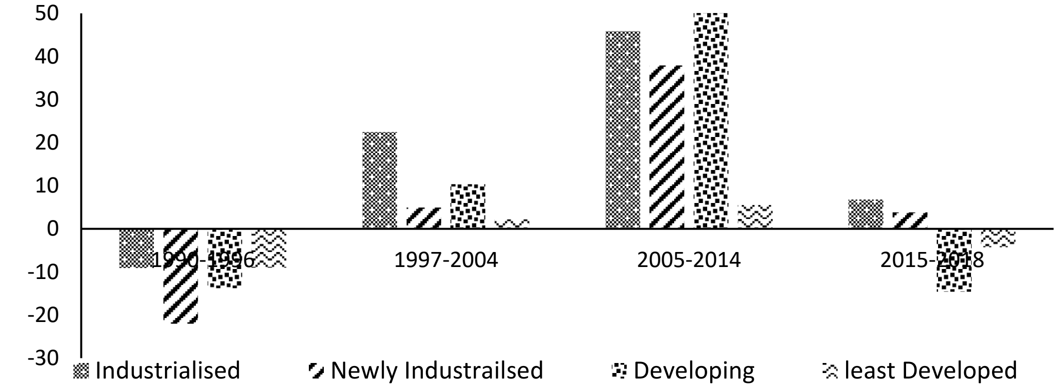
[19] US was the largest emitter of GHGs, but it was not part of the protocol at the time of its commencement

Figure 2.4: Temperature Anomaly across the Level of Industrialization



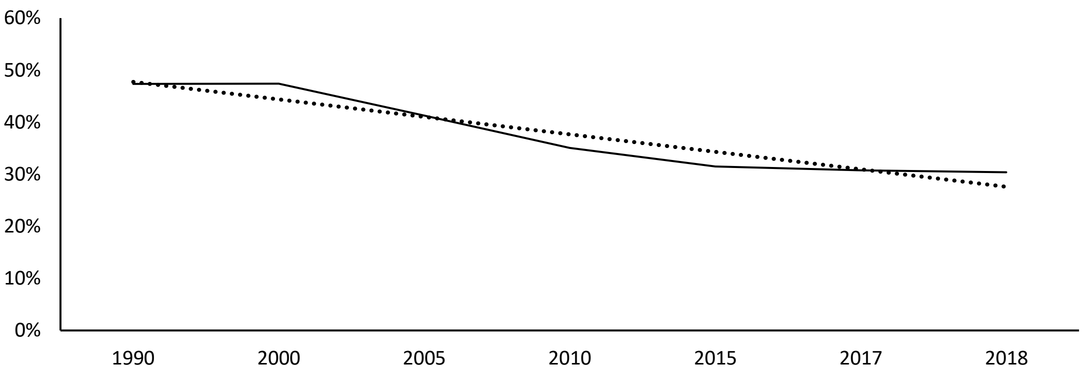
Source: Author's work based on Climate Research Unit Database CRU TS 4.03

Figure 2.5: Rainfall Anomaly across the Level of Industrialization



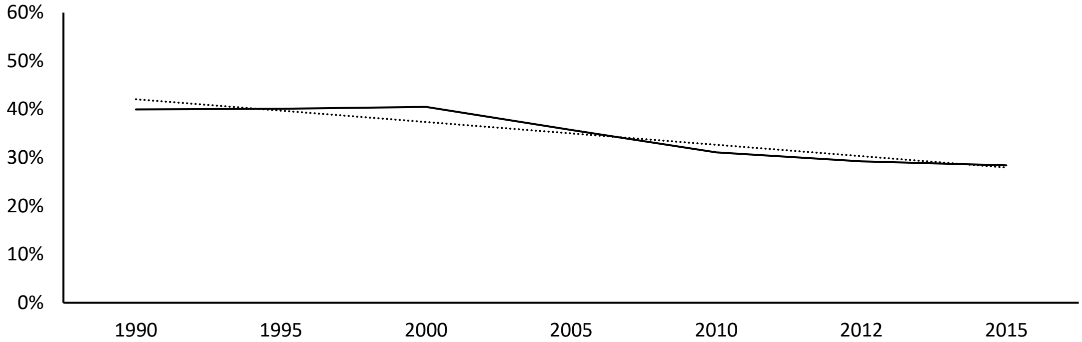
Source: Author's work based on Climate Research Unit Database CRU TS 4.03

Figure 2.6: The Percentage Share of IE's in Global Total Carbon Emissions (Mton) 1990-2018.



Source: Emissions Database for Global Atmospheric Research (EDGAR), EU

Figure 2.7: The Percentage Share of IE's in Global Total GHGs Emissions (Mton CO_2 eq) 1990-2015.



Source: Author's work based on Emissions Database for Global Atmospheric Research (EDGAR), EU

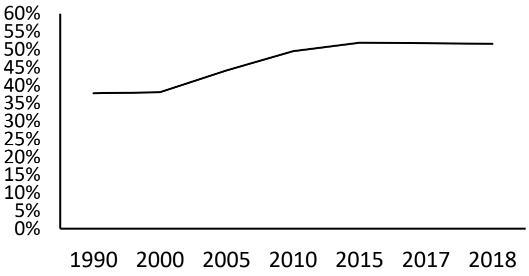
Fast-growing economies of East Asia Pacific and Latin American regions have achieved exceptionally high growth levels in the past two decades. Global collaboration in manufacturing and industry, exploitation of natural resources, cheap energy as the primary input, large market size, export, and investment-led growth has served these economies well. However, these countries were one of the small-time's most significant contributors to carbon emissions. Major NIEs that experienced a transition in their economies include China, Brazil, Mexico, Russia, Malaysia, and Venezuela. Total carbon emissions by these countries in 2018 alone comprised 37.9 percent of global carbon emissions.[20]

Initially, newly industrialized countries were not part of the *Kyoto Protocol* as IEs were considered responsible for past century industrial activity; thus, developed countries and the EU was constrained to reduce their GHGs emissions levels. NIEs entered a carbon reduction mechanism in the Paris Agreement in 2015. This agreement was a hallmark for international collaboration on climate change reduction efforts. The world's top GHGs emitters agreed to move forward in decelerating the pace of global temperature and keeping it between 1.5 °C to 2°C as compared to pre-industrial levels. In the early 1990s, NIEs contribution to global total carbon emission was around 37 percent, yet this share reached 51.6 percent in 2018, making NIEs the highest contributor among all country groups. Carbon emissions in NIEs show an increasing trend till 2010; after that, emission tends to be stable (See Figure: 2.8, Figure 2.9).

[20] China (29.7%) Brazil (1.32%), Mexico (1.31%), Russia (4.61%), Malaysia (0.68%) and Venezuela (0.32%) data is taken from https://ec.europa.eu/eurostat/data/database

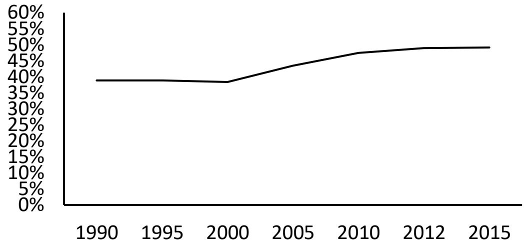
Renewable energy resources increase more rapidly in NIEs than in IEs (See Figure: 2.14).

Figure 2.8: The Percentage Share of NIEs in Global Total Carbon Emissions (Mton) 1990-2018



Source: Global atmospheric research (EDGAR),

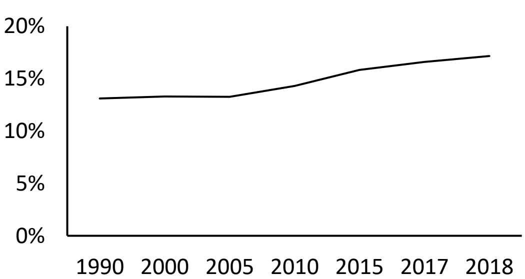
Figure 2.9: The Percentage Share of NIEs in Global Total GHGs Emissions (Mton CO_2 eq) 1990-2015.



Source: Global atmospheric research (EDGAR),

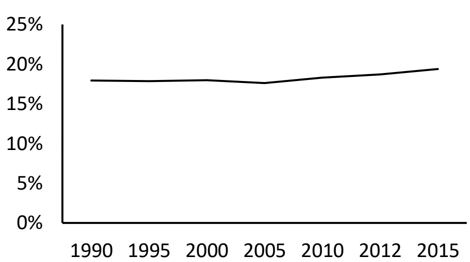
Developing economies have a large population, rising demand for energy, transportation services, and rapidly growing urban areas. Industrial growth is driven by power as the primary source of input. The percentage share of global carbon and GHG emission in DEs (See Figure 2.10 and Figure 2.11) and LEs (See Figure 2.12 and Figure 2.13) is far less than IEs and NIEs but has increased since 1990. Most of them are agriculture-based economies and are in their initial stages of development in which they use conventional cheap energy resources for production. Literature also suggests no causality between energy consumption and economic growth in low-income countries (Yasar, 2017).

Figure 2.10: The percentage share of DEs in global total carbon emissions (Mton) 1990-2018.



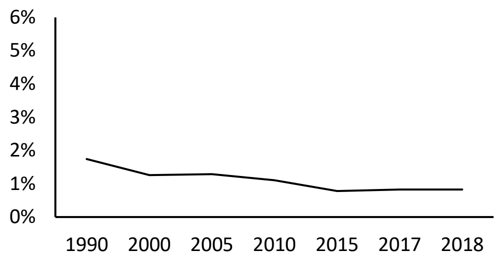
Source: Global atmospheric research (EDGAR), EU

Figure 2.11: The percentage share of DEs in global total GHGs emissions (Mton CO_2 eq) 1990-2015.



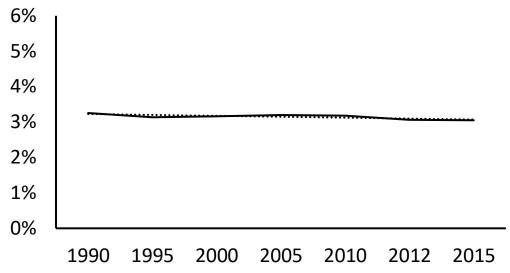
Source: Global atmospheric research (EDGAR), EU

Figure 2.12: The Percentage Share of LDEs in Global Total Carbon Emissions (Mton) 1990-2018.



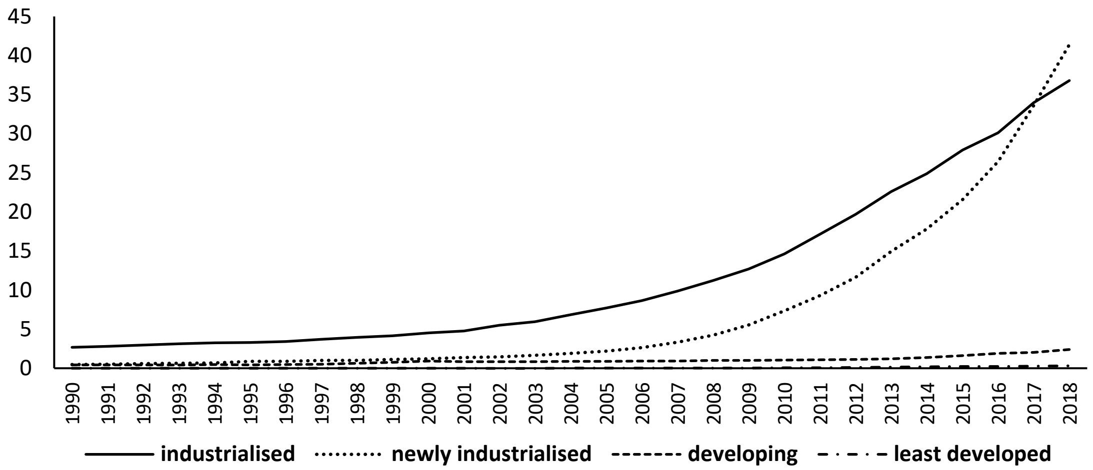
Source: Global atmospheric research (EDGAR),

Figure 2.13: The Percentage Share of LDEs in Global GHGs Emissions (Mton) 1990-2015



Source: Global atmospheric research (EDGAR),

Figure 2.14: Renewable Energy Source Calculated in (TWh) Terawatt Per Hour. Source; BP Review 2019

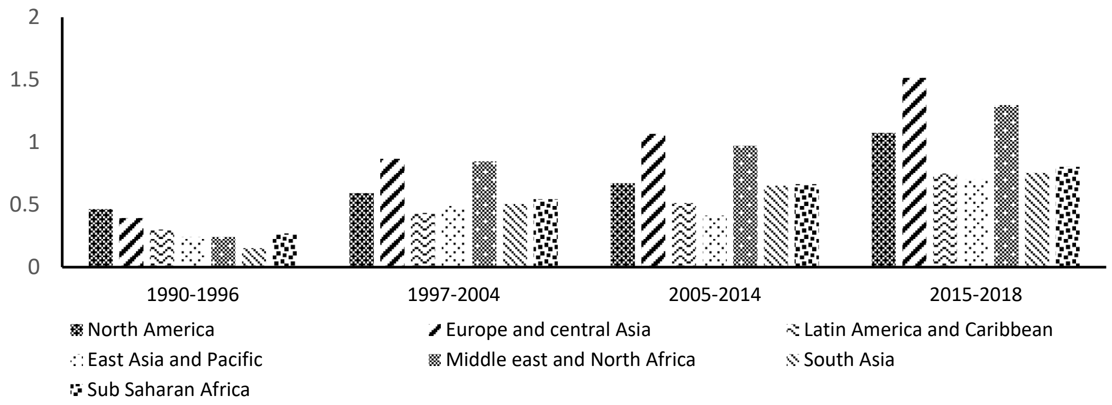


2.6.3 Measuring Climate Anomaly Dynamics across Space

The present section describes the regional disparity of climate change variables across geographical locations. For climate change analysis individual country's geographical location, population, adaption capacity, and other factors determine the scale of impact. The literature has well documented that climate change will affect low latitude countries near the equator, while those at high latitude will reap benefits. All regions of the world, irrespective of regimes considered in our analysis, have experienced more warming than the reference period.

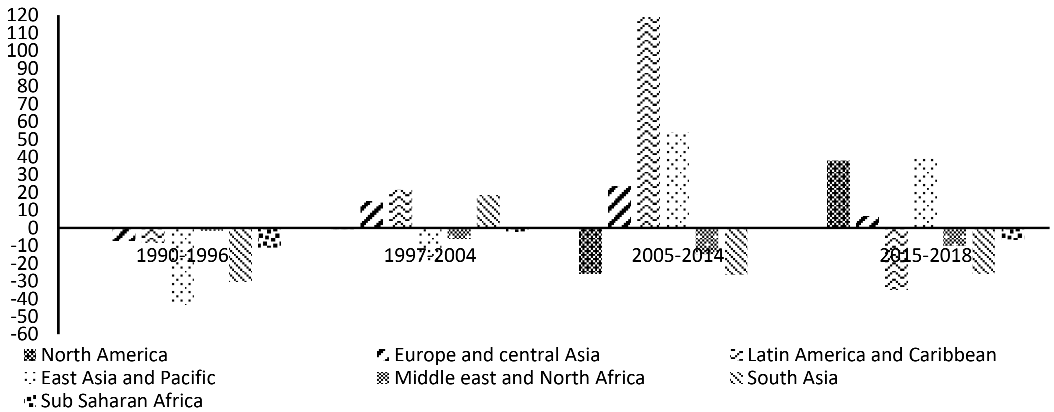
In addition, the magnitude of warming with each additional year is increasing (See Table 2.4 & Figure 2.15). Rainfall anomaly revealed fluctuating trend along reference period for all regions except the Middle East and North African (MENA), South Asia (SA), and Sub Saharan African (SSA) countries that have experienced rainfall reduction from 2005 to 2018 (See Figures 2.17e to 2.17h & Figure 2.16). Although the magnitude of change is not much, the constant direction of an anomaly in decreasing trend is an alert for an already heat-stressed equatorial belt.

Figure 2.15: Temperature Anomaly across Regions



Source: Climate Research Unit Database CRU TS 4.03

Figure 2.16: Rainfall Anomaly across Regions



Source: Climate Research Unit Database CRU TS 4.03

Unlike existing literature, North America (NA) and Europe, and Central Asian (ECA) countries' temperature anomalies are more in terms of magnitude than other regions (See Figures 2.17a and 2.17d). Considering the policy intervention regimes, most of the temperature rise is evident in Europe's post-Kyoto protocol and pre-Paris agreement period. Most European countries are part of the Kyoto Protocol and the Paris agreement as annex I countries that restrict carbon emissions with their nationally determined contributions (NDCs) and provide funds to developing countries to adapt to climate change. However, NA countries had undergone warming in the post-Paris agreement when three of the two countries in NA (Canada, US) ratified significant carbon emissions cuts when they experienced warming than usual[21]. Other regions like Latin America and the Caribbean (LAC), East Asia Pacific (EAP), SS, and SSA also experienced an increase in temperature anomaly. However, their magnitude was lower than most high-altitude countries (See Figures 2.17a to 2.17d). All these regions lie in non-annex I members that were not part of the Kyoto protocol but were members of the Paris agreement with carbon emission restrictions. One of the prime reasons for the overwhelming response from all regions to the Paris Agreement is excessive warming in all regions within two decades.

European countries such as France, Germany, and the Netherlands experienced record heat waves in 2019. Southern European countries[22] are projected to experience high temperatures, melting glaciers, and disruption in hydrological cycles. Eastern and Central Europe[23] are projected to be more sensitive to climate change because of their limited adaptive capacity and low-income levels than other European countries. Northern Europe is projected to have relatively warm temperatures favorable for the agriculture and tourism industry, particularly in some parts of Russia. Central Asian countries are landlocked and are often called the world's driest regions. These countries have a delicate ecological system susceptible to water shortages. The primary source of water supply through glacier melting (Zhang et al., 2019). Climate change in high temperatures will reduce water flow from upstream countries. Any disruption or shortage in water makes downstream central Asian countries vulnerable to rising inter-regional conflicts.

MENA is a resource-rich region for oil and natural gas. MENA[24] is adversely affected by climate change. The whole area is situated near the equatorial belt. These countries have already achieved upper tolerance limit for high temperatures; the further increase will harm this region the most. Low rainfall than usual and rising temperature lead to

[21] It is important to mention US and Canada where not part of Kyoto protocol, but they were important signatory of Paris agreement.
[22] Includes countries: Italy, Malta, Greece, Croatia, Bosnia and Herzegovina, Montenegro, Slovenia, Spain, Southern France, European Turkey and Cyprus.
[23] Central and Eastern European Countries (CEECs): Albania, Bulgaria, the Czech Republic, Hungary, Poland, Romania, the Slovak Republic, Slovenia, and the three Baltic States: Estonia, Latvia and Lithuania.
[24] Algeria, Bahrain, Djibouti, the Arab Republic, Egypt, the Islamic Republic of Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, the Syrian Arab Republic, Tunisia, the United Arab Emirates and the Republic of Yemen are included

drought and water scarcity. According to World Bank, MENA is the most water-stressed region globally, which might cost the region a loss of 6 to 14 percent of the GDP by 2050. Sand and dust storms are also frequent in the region. The current outbreak of locusts in eastern Africa and its favorable environments in other parts of the Middle East, such as Oman and the Kingdom of Saudi Arabia, is also an irregular rainfall pattern.

LAC is blessed with natural resources such as amazon forests, fertile lands, livestock, and water resources.[25] Rapidly growing population and increasing world demand have led LACs to excessive land and other resource extractions. Deforestation to improve land for agriculture, production of biofuels, and livestock grazing activities augment climate change’s negative impact. However, the magnitude of warming is less in LAC (See Figures 2.17a and 2.17d) than in other regions.

East Asian economies are the largest archipelagos with coastal mangroves and coral reefs. EAP is a densely populated region with consumption and investment-led growth structures. These economies are also production hubs for innovative value-added goods and are part of the global value chain. Massive resource utilization has threatened mangroves, forests, and other natural resources that affect the balance of the ecosystem. EAP has faced a series of floods, storms, and tropical cyclones every year. Many MNCs have moved away from these economies because of a series of natural disasters. Costal infrastructure destruction also leads to mass migration and deterioration of income from coastal tourism and fishing. The hardest-hit countries by climate extremes are in this region.

South Asia is considered vulnerable to climate change because most countries are agrarian and home to 24.8 percent of the world population. Geographical and natural resources make these countries dependent on water from rainfall and glacier melting. The Himalayas are a water source, balance rainfall dynamics, and regulate groundwater for crops. Rain is also less than their respective usual since 2005. Rising temperature is catastrophic for glacier melting. Besides this, South Asian countries have little capacity to adapt to climate change due to their weak economy and financial conditions.

[25] LAC holds 25% of world forest and fertile land area with 30 percent of water resources of the world.

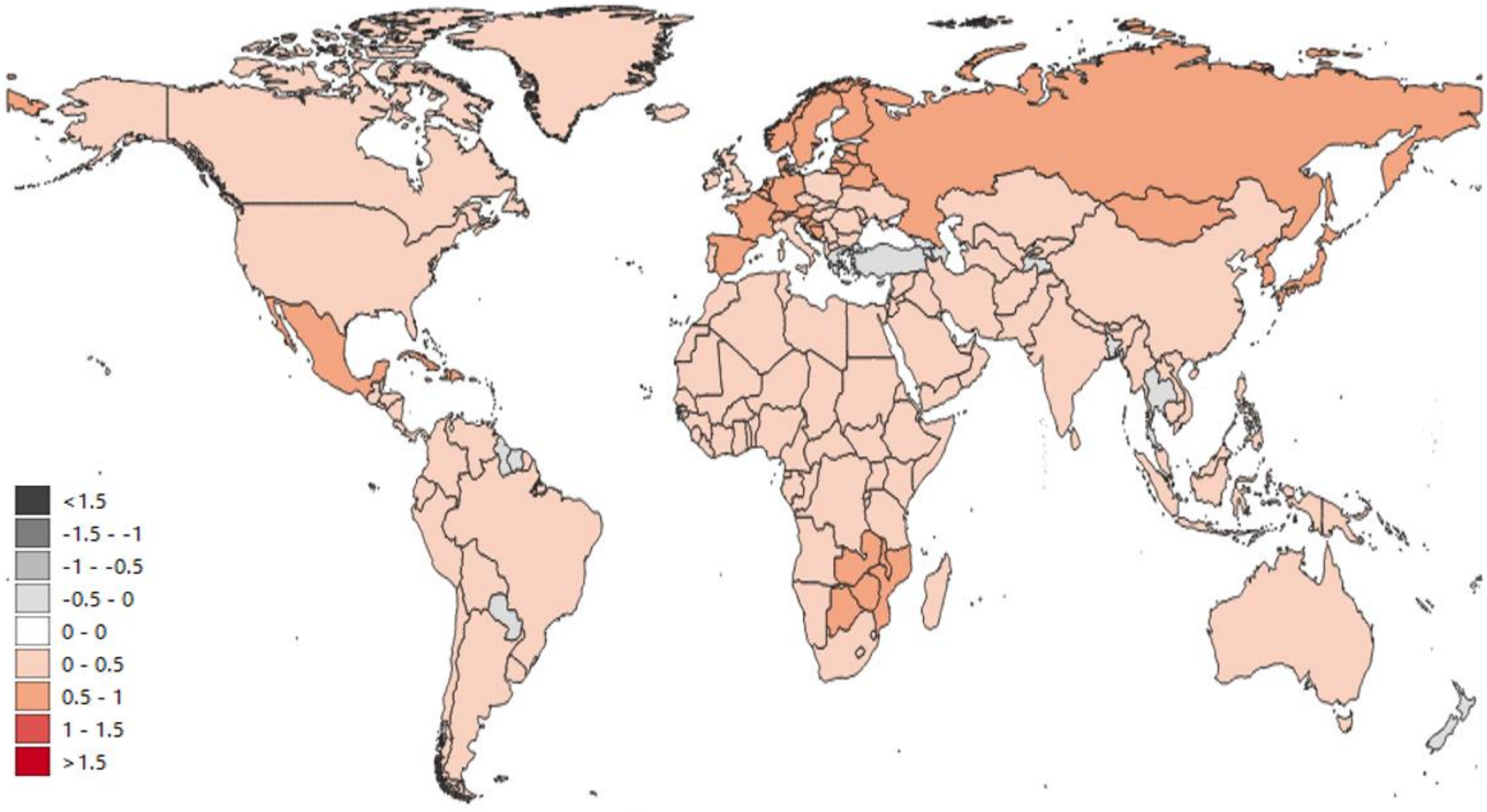
SSA is a region where most agrarian economies depend on rain-fed water. About 96 percent of crops are dependent on rainwater. The agriculture sector contributes to the GDP and employment opportunities for more than 60 percent of the population. IPCC, 2014 declared it the most vulnerable region due to its low adaptive capacity, poverty, and dependence on natural resources. Any disruption in rain-fed water leads to food insecurity in the region.

Table 2.4: Percentage Change of Temperature Anomalies across Regions (Values in Percentage)

Regions	**1990-1996 R1**	**1997-2004 R2**	**2005-2014 R3**	**2015-2018 R4**	**percentage change between R1 & R4**
North America	-	28.1	13.3	59.4	131.4
Europe and Central Asia	-	120.1	23.2	41.9	284.6
Latin America and the Caribbean	-	43.8	18.7	45.5	148.3
East Asia and the Pacific	-	103.5	-16.3	69.9	189.6
The Middle East and North Africa	-	248.1	15.1	33.4	434.4
South Asia	-	229.6	28.8	16.0	392.6
Sub Saharan Africa	-	101.5	22.3	20.6	197.1

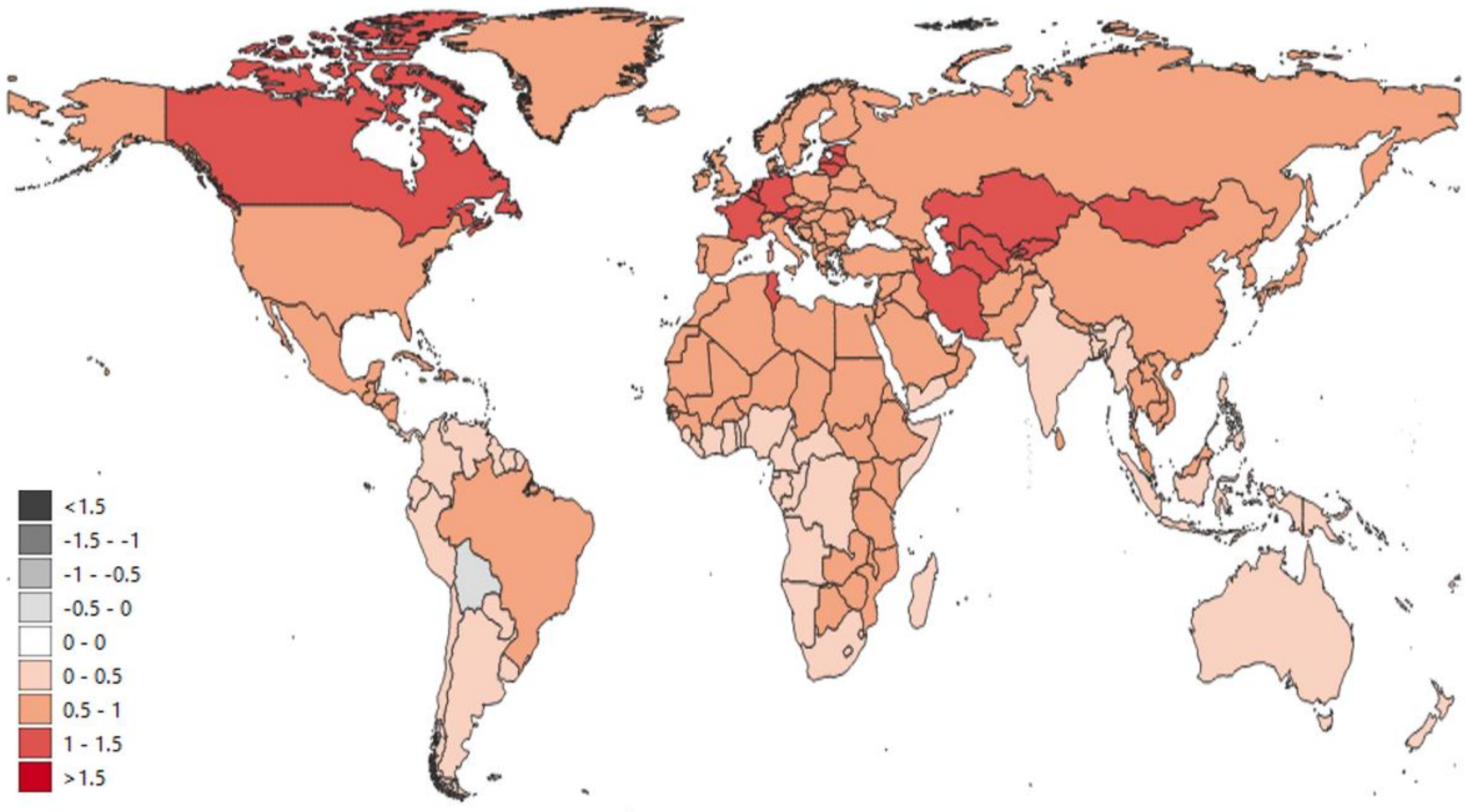
Source: Author’s calculation from Climate Research Unit Database CRU TS 4.03

Figure 2.17a: Annual Temperature Anomaly (°C) 1990-1996



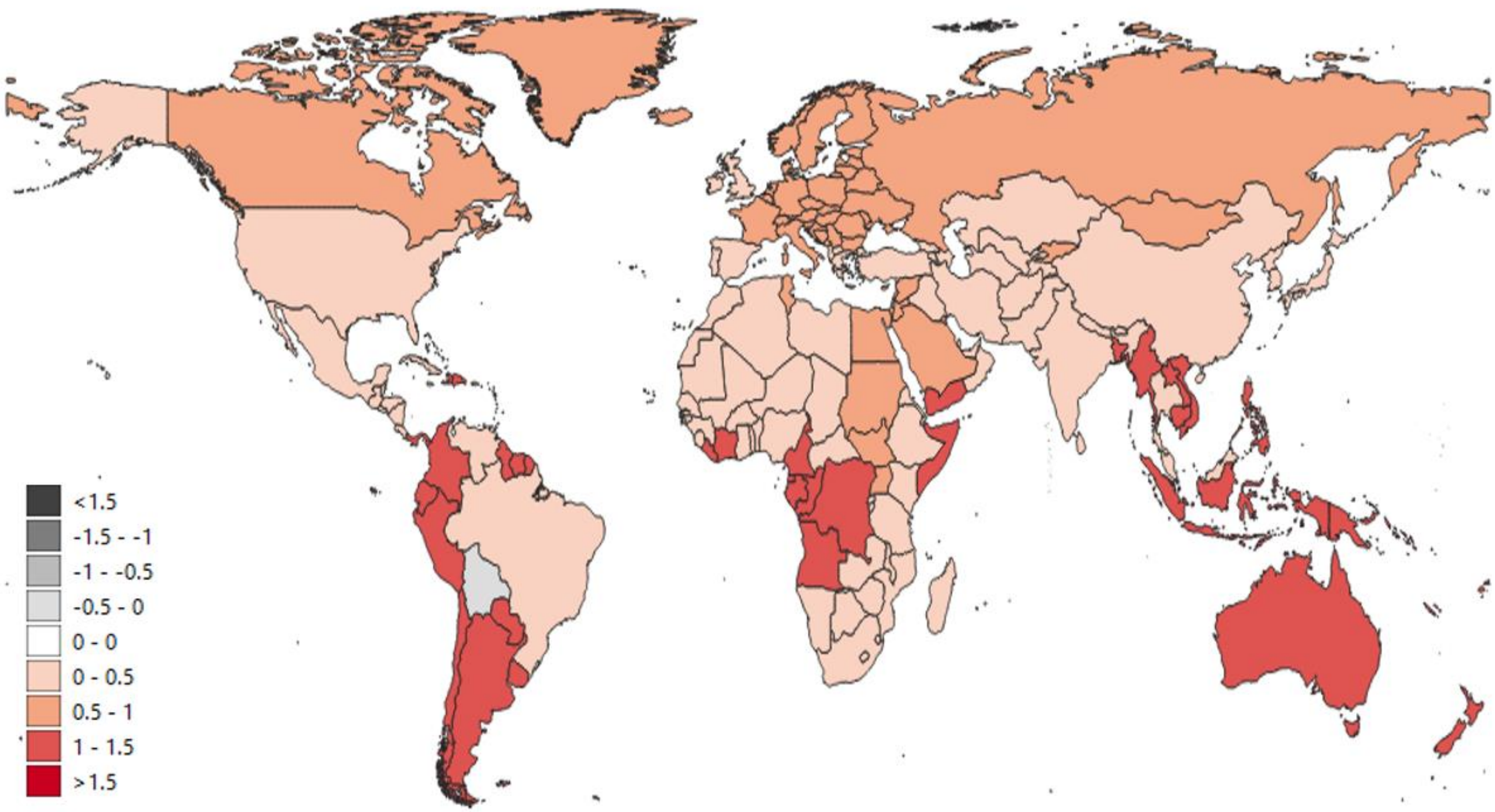
Source: Author's work from climate research unit database

Figure 2.17b: Annual Temperature Anomaly (°C) 1997-2004



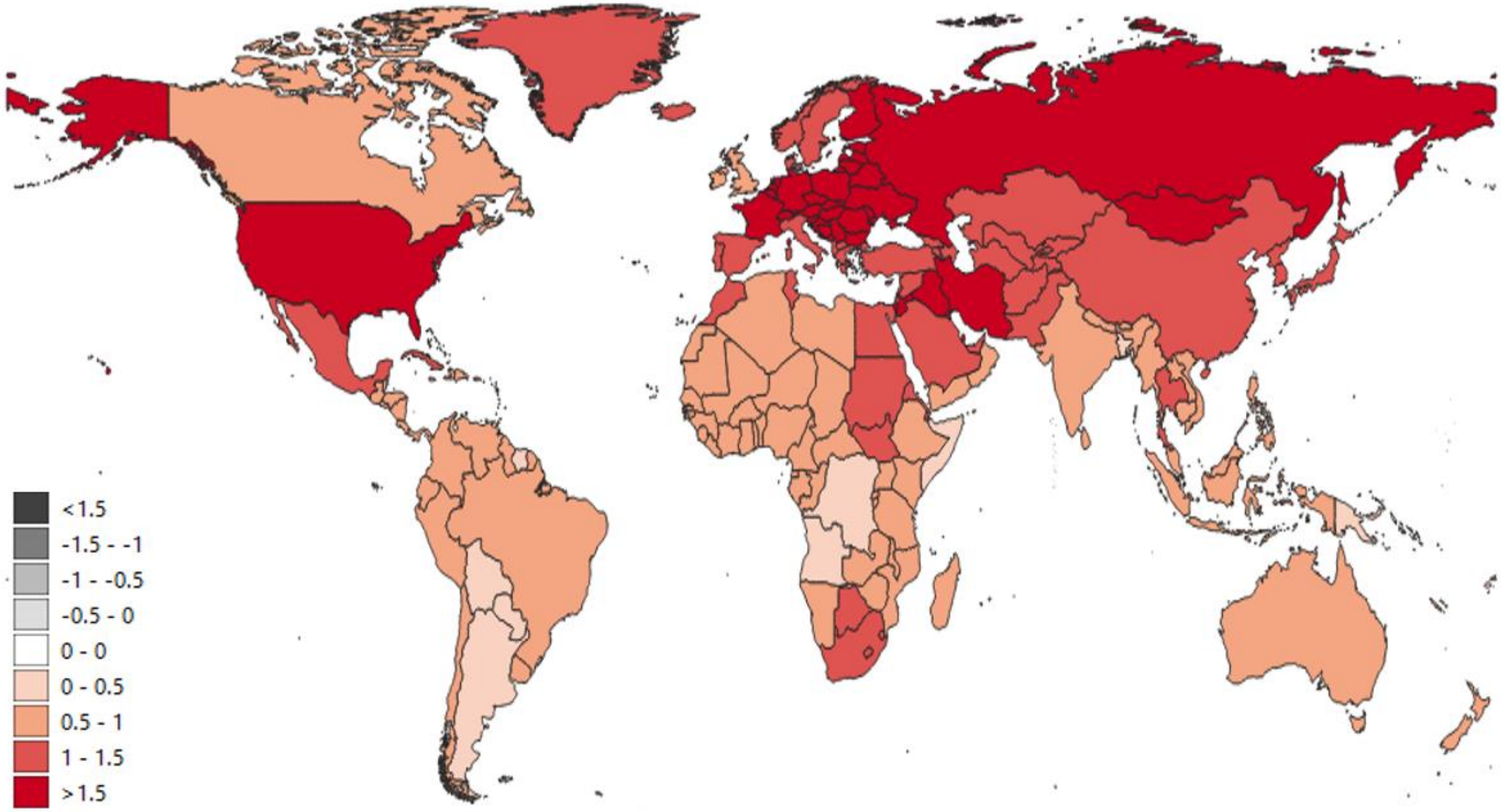
Source: Author's work from climate research unit database

Figure 2.17c: Annual Temperature Anomaly (°C) 2005-2014



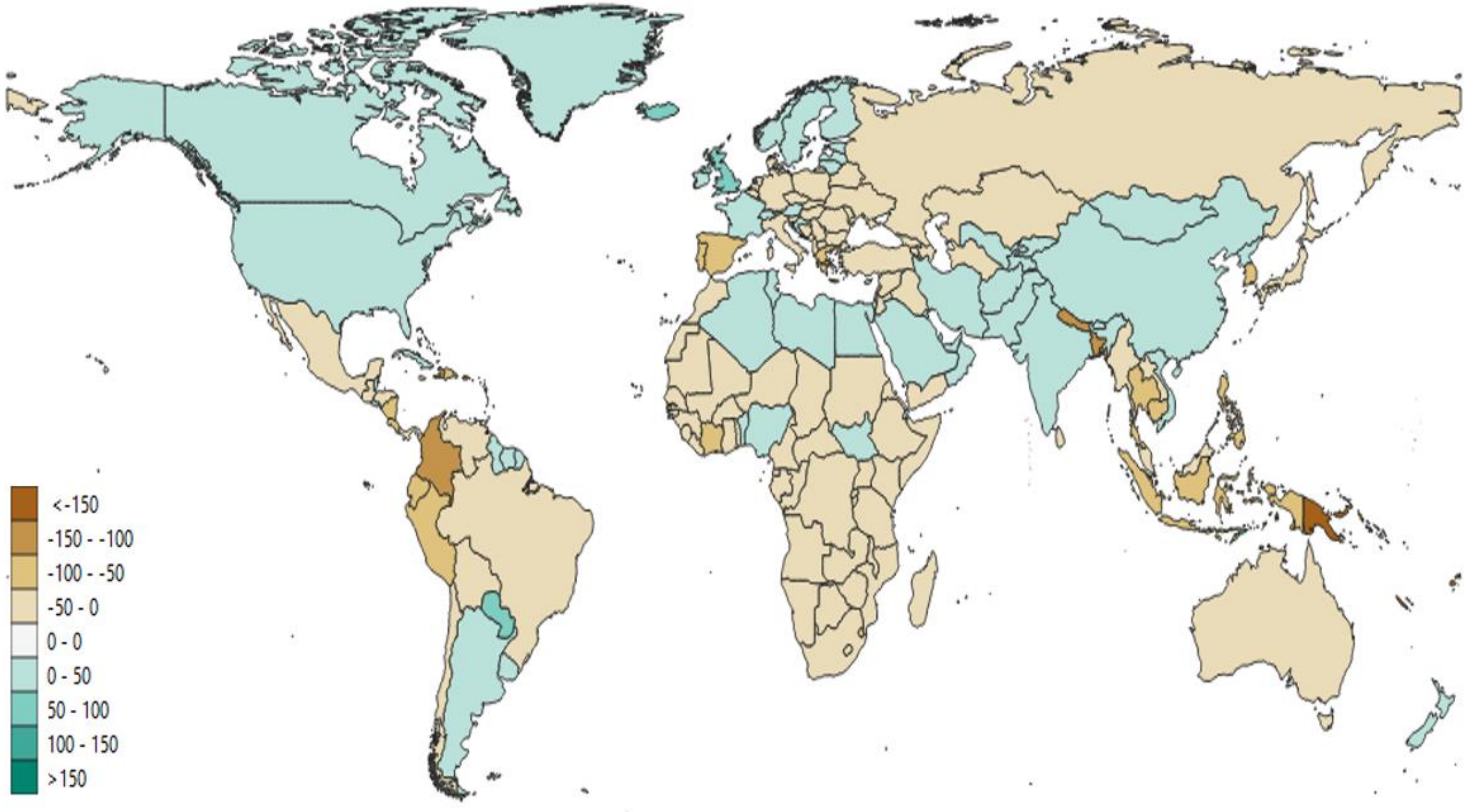
Source: Author's work from climate research unit database

Figure 2.17d: Annual Temperature Anomaly (°C) 2015-2018



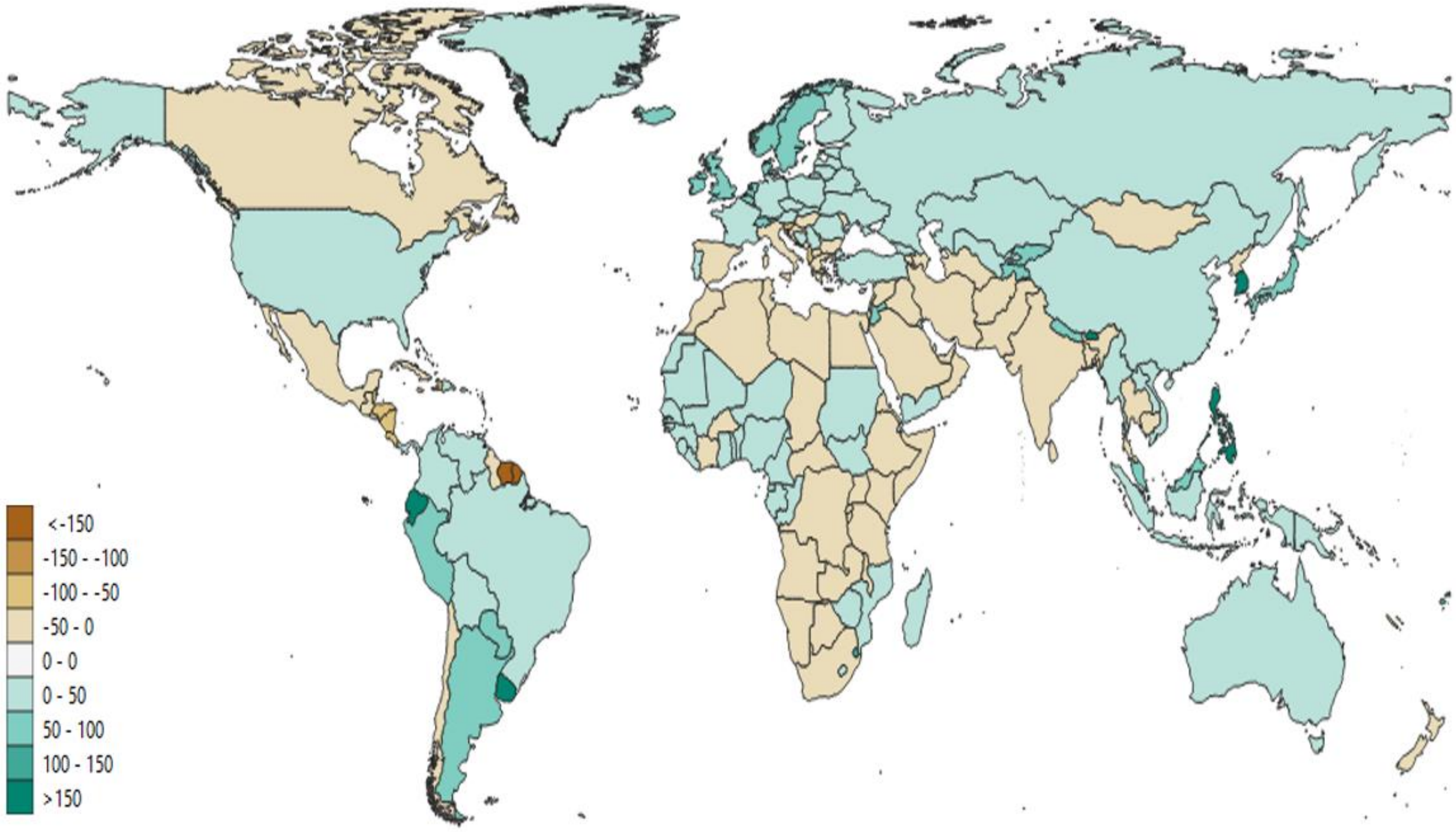
Source: Author's work from climate research unit database

Figure 2.17e: Annual Rainfall Anomaly (mm) 1990-1996



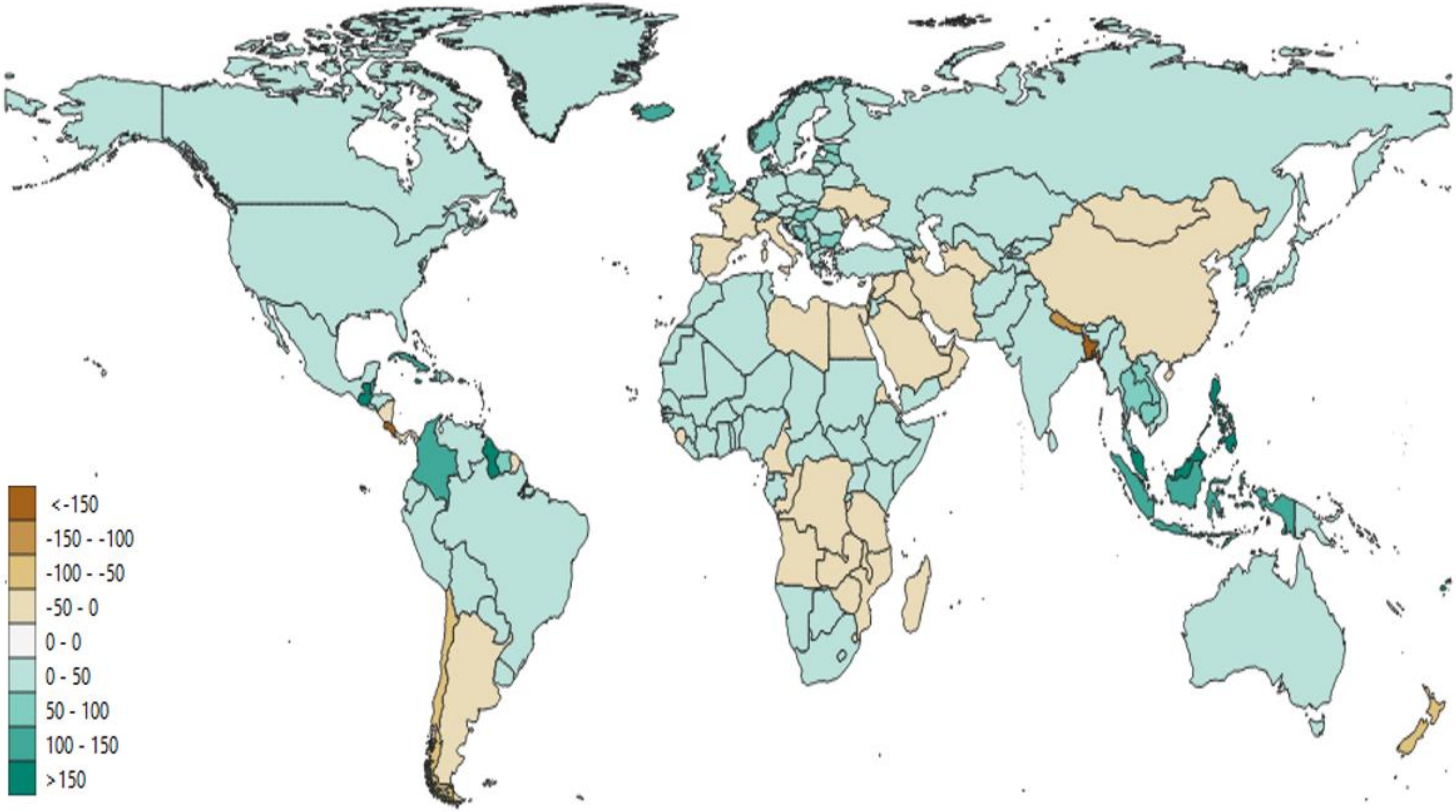
Source: Author's work from climate research unit database

Figure 2.17f: Annual Rainfall Anomaly (mm) 1997-2004



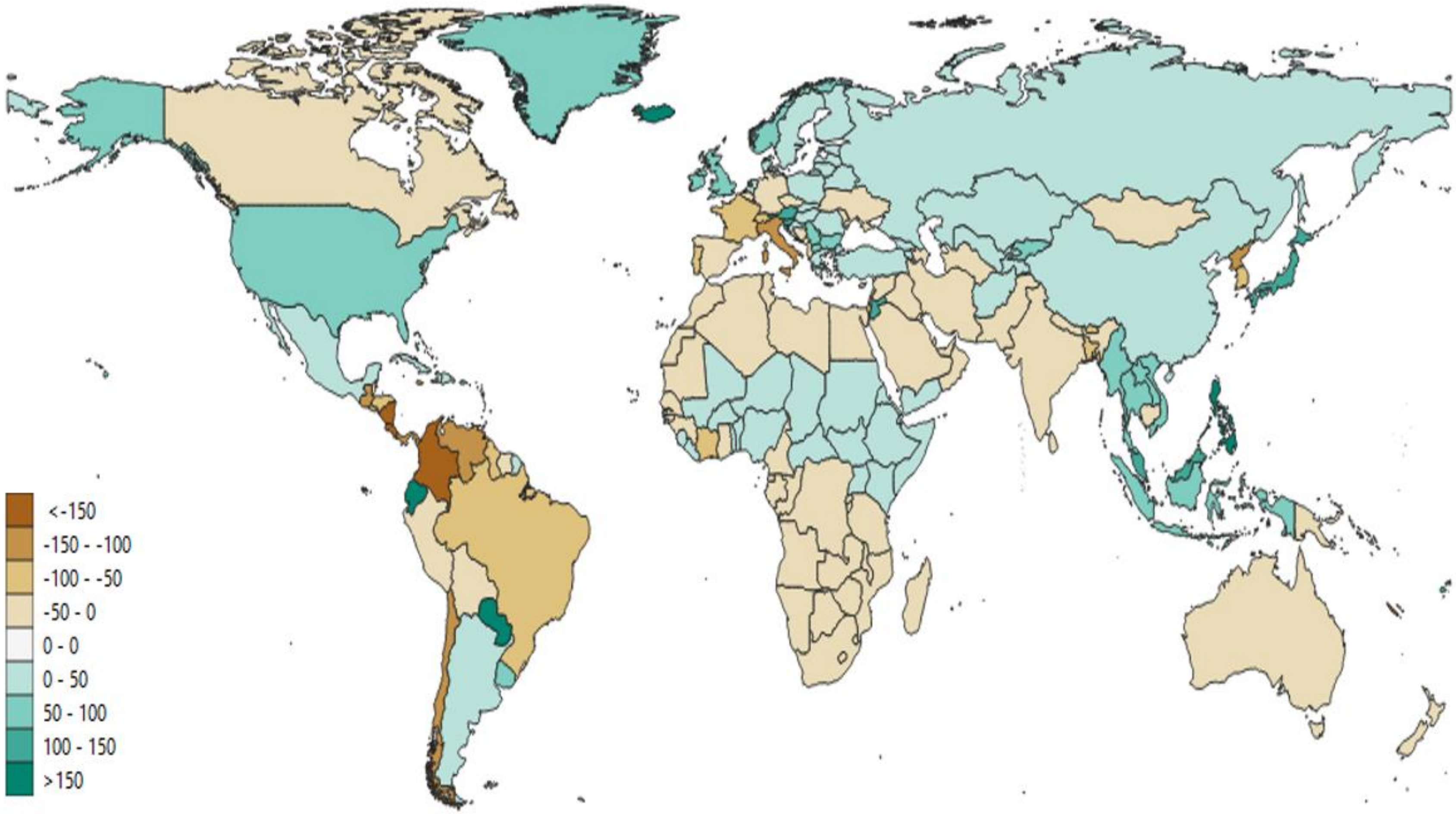
Source: Author's work from climate research unit database

Figure 2.17g: Annual Rainfall Anomaly (mm) 2005-2014



Source: Author's work from climate research unit database

Figure 2.17h: Annual Rainfall Anomaly (mm) 2015-2018



Source: Author's work from climate research unit database

2.7. Conclusion

The past century's unprecedented industrialization based on fossil fuel consumption has caused far-reaching consequences for the world. GHGs emissions are considered a key contributor to climate change. At the same time, industrial activity is the primary source of emitting it. Sustainability has held a key position in policy formulation since climate change realization. Climate adaptation and mitigation policies aim to move the global economy to a sustainable path by managing driving sources such as industrial activity. International organizations have devised policies such as carbon emission restrictions to minimize climate change vulnerabilities. The present study considers countries' industrial activity, location, and income levels to assess the dynamic of climate change. Also, the role of international organizations has been viewed by analyzing time before and after significant climate change agreements.

A constant warming trend is accompanied by a higher magnitude of warming with each additional year irrespective of income groups, level of industrialization, and region considered. It is keeping in view the four policy regimes in the analysis, all income groups, levels of automation, and areas (except North America, Europe, and Central Asia) experienced more significant warming in regime two, the period after the Kyoto protocol. In regime 3, the pre-Paris agreement and Kyoto protocol enforcement period, additional warming increased slower than in other regimes. In regime 4, the pace of warming increased, yet it was slower than warming in the post-Kyoto protocol period. Overall, two significant climate change policy measures have deaccelerated the rate of additional warming in the world.

Contrary to the magnitude of warming, the speed of change in temperature anomaly is different and is subject to income group, level of industrialization, and region considered in the analysis. Both income level and level of industrialization are positively associated with the magnitude of temperature anomaly. Higher-income levels and more industrialized countries have experienced more significant deviations from the reference period. Interestingly, the speed with which this change has been registered is different; LICs have more speed of warming as indicated by the percentage change from1991 to 2018, trailed by UMICs, LMICs, and HICs. It shows that LICs temperature is changing at a more excellent pace; they need to speed up their adaptation and mitigation process more than any other income group. Considering industrialization, the NIEs pace of additional warming is relatively faster than other IGs followed by DEs, IEs, and LDs. DEs pace of further warming is more than IEs. However, their carbon emissions are far less than IEs and NIEs. The rainfall anomaly shows a fluctuating trend in all income groups and industrialization groups, with the rise in rainfall from 2005 to 2014 followed by a decrease in rains from average from 2015 to 2018. The volatile behavior of rainfall anomaly creates uncertainty and serves as a twin challenge to handle in the presence of ever-increasing warming.

All seven world regions experienced more warming than their reference period in the past two decades. Regional disparity is observed across regions regarding the magnitude and pace of warming. Europe and Central Asia experienced the highest temperature change, followed by the Middle East and North African countries, North America, Sub-Saharan Africa, South Asia, East Asia Pacific, Latin America, and the Caribbean. The magnitude of the warming trend shows that the Middle East, North Africa, Europe, and Central Asia are getting warmer than any other region. Most of the countries in this region have experienced warming since 1990. Unlike the magnitude of warming, the speed of change in MENA countries is the highest, followed by SA, ECA, EAP, SSA, LAC, and NA. MENA countries are already situated in the equatorial belt; further temperature hikes will burden these countries' upper limits. The SA region is also vulnerable to climate change due to its dependence on rain and glacier meltwater. MENA, SA, and SSA countries have also experienced rainfall reductions from 2005 to 2018. All these regions face dual challenges of increased warming with decreased rainfall.

Distributional impacts across regions are crucial for regional and country-level policy formulation. The present study creates a sense of urgency for international cooperation in industrial, renewable energy, and climate change policies. It enables sharing goals and creating and adapting new innovative techniques to help mitigate the overall adverse effects of climate change. Innovation-driven industry policy encourages sustainable industrialization; hence research and development expenditure should be inclined towards energy-efficient and green technology projects. The cost of environmental degradation needs to internalize by applying carbon taxes stringently. An incentive structure can be built that encourages investors and entrepreneurs toward green technologies. Policies to transfer environmentally friendly technology across different levels of industrialized countries can be facilitated by applying low barriers to entry.

Quantitative income analysis is not included in the analysis as a major aim of the study was to analyze the spatial spread of a diverse set of IEs, NIEs, DEs, and LDs in their respective climate change. Therefore, future research could be extended by incorporating quantitative analysis. Further breakthroughs in industrial sectors, such as the emergence of multiple industrial revolutions (3.0 and 4.0 generation) and their impact on climate change, can be analyzed. Industrialization can mitigate the adverse effects of climate change. The level of industrialization in countries can explore more cost-effective techniques. Industrial parks have proved to be cost-effective in many ways. Further research can be extended to gauge how they can help limit the upward trajectory of consistent warming.

Chapter 3

QUANTIFYING SPATIAL DETERMINANTS OF CLIMATE CHANGE

3.1. Introduction

The prime global concern for the world as it steps into the 21st century is to maintain a balance between its excessive production and environmental degradation. Excessive production based on fossil fuels led by industrialization has disrupted the ecosystem's natural balance. Sustainability is central for effective policy formulation. UN, in its COP-26, has urged countries to limit the net emission to zero by 2030, limit methane emissions, loss of forest, coal-driven production, and international financing of fossil fuel projects. These measures were devised to keep countries on track with the global goal of keeping temperatures below 1.5 degrees Celsius.

Climate change is fundamentally a global phenomenon that cannot be limited to one country. Countries that have closely proximity share the common meteorological conditions. Carbon emission emitted in the form of fossil fuel based industrialization, vehicles emissions, and burning agriculture residue in one country affects the air quality of neighboring countries and leads to transboundary movements of emissions. In addition to this, emergence of global value chains model for global production and industrialization have made economic activities more interconnected and the spillover effect of these activities is more profound than ever before.

Climate change has been an equal concern for both developed and developing countries. Many transmission channels and drivers have been identified in the literature for climate change to minimize the expected threats and devise informed policies that can decrease the pace of climate change and improve environmental quality. High global economic growth is generally linked to industrialization, urbanization, transport infrastructure, and mechanization of industries and agriculture. In comparison, intensive industrialization and urbanization are associated with increased energy consumption that affects climate change (Waheed et al., 2019).

Economic growth has been considered the critical determinant of climate change, led by CO_2 emissions and various pollutants. Literature provides ample evidence on the relationship between environmental degradation and economic growth by EKC. Initially, economic growth increases ecological degradation, but economic growth improves environmental quality after a certain income level. Literature also examined the N inverted relationship of economic growth with environmental factors, suggesting that economic growth first increases environmental degradation, decreases, and finally increases exponentially.

Industrial structure plays a vital role in economic growth and development. Industrialization can amplify or discourage additional warming. Industrial activities increase the demand for energy within and across other sub-sectors. Better income levels also come up with increase demand for luxury items that trigger energy demand and thus increase pollution. Some researchers believe that industrialization expands and restructure industries with technological advancement that aids the reduction of CO_2 emissions.

Appiah et al. (2019) study revealed that in emerging economies, carbon stock emitted is low when considering renewable energy resources and industrialization. However, carbon stocks surge if the population, urbanization, and non-renewable energy resources are employed. Asghar et al. (2020) found a long-run positive relationship between industrial growth, energy consumption, trade, and environmental degradation for 13 Asian countries, while in the short-run unidirectional causal relationship runs from industrialization to environmental degradation.

Environment impact assessment studies related to drivers of climate change use urbanization as a proxy for measuring lifestyle and energy demand. It is also a proxy for development (Liddle & Lung, 2010). Ecological modernization theories suggest that when countries move from low to middle-income groups, economic growth becomes a primary target at the cost of environmental sustainability, but as economic growth, development, and urbanization increase, ecological issues become of significant concern.

Trade openness is also considered a key driver of climate change. Trade theories, for example, Hecksher-Ohlin (H-O), suggest that a country should produce goods with a comparative advantage in free trade. Often in the presence of trade openness, governments try to reduce their cost of production to achieve high profits by overlooking the enforcement of environmental laws and their implementation. Some researchers believe that greater integration helps improve the environment by enacting better solutions to environmental problems, as economic integration is the gateway for knowledge and technology integration. Most developed counties are equipped with capital-intensive industries, while developing countries are abundant in labor and natural resources. Exploiting more natural resources and excessive mechanization at the cost of cheap energy resources deters the natural equilibrium of the environment.

Literature shows mixed evidence on the relationship between environment and population. Proponents of the Malthusian theory believe that each person added to the population also adds to environmental damage by increasing CO_2 emissions in the atmosphere through increased water, food, energy, and resource consumption. Others follow the Boserupian view that considers the population as a source of innovation and reduces the negative environmental impact. York et al. (2003) found a proportional relationship between population and environmental impact. In contrast, Shi (2003) found varying results in the case of developed and developing countries. Some studies have also considered energy intensity an important predictor of climate change.

Since the debate on climate change realization has reached a mutual consensus, an international collaboration for climate change policy and adaptive measures has increased. An essential instrument for climate change policy is to contain factors that exacerbate the pace of climate change at global and national levels. Several factors have been outlined that affect CO_2 emissions and other pollutants; however, the impact of these factors on temperature has not been studied in literature to the best of our knowledge. WMO and IPCC have made a distinction between climate change and variability. Climate change is a long-run phenomenon considering the 30-year average temperature (rainfall), while climate variability is the average temperature (rainfall) from the 30-year average. The present study considers this difference and analyses climate variability and change predictors. As climate change is a global phenomenon and climate regulations are globally determined, countries' spillover effect on neighboring countries is under research area that needs more attention. For this, the present study considers spatial determinants of climate change and climate variability driven by temperature and rainfall change. The study also finds carbon intensity as a measure of climate change to analyze the variation in determinants using alternate dependent variables.

3.2. Review of Literature

3.2.1 Non-Spatial Determinants of Climate Change

Sustainable economic growth and policies are the prime concern for developed and developing countries. The literature explains the relationship between economic growth and environmental factors by the Environmental Kuznets Curve (EKC). The hypothesis postulates a linear relationship of economic growth with environmental factors and a non-linear relationship with its square term, indicating that economic growth initially increases environmental degradation while improving environmental quality at later stages.

Most of the studies found GDP per capita a vital determinant while studying environmental factors such as carbon emissions, Sulphur dioxide (Wang et al., 2016), various pollutants (Hao & Liu, 2016; Du et al., 2018), and ecological footprint (Aydın et al., 2019; Xun & Hu, 2019; Destek & Sinha, 2020; Akadiri et al., 2020; Koyuncu et al., 2021).

Some studies estimated the relationship between carbon emissions and growth at the country and regional levels. Some of the Asian (Rahman, 2017), and OECD countries (Martínez and Morancho, 2004) confirmed the presence of U shaped relationship between CO_2 emissions and economic growth. Literature also reveals an N-shaped relationship between environmental factors and GDP per capita. Friedl and Getzner (2003) found an N-shaped relationship between environmental factor CO_2 emission and the GDP per capita of industrialized country Austria. This indicates that emission tends to fall with a rise in income level, but after a specific time, they grow exponentially.

Du et al. (2018) studied the association between haze pollution and economic growth, energy intensity, and industrial structure for a panel of 27 capital cities from 2011 to 2015. The study found varying trends for relationships in each region. For the central part, the study found a U-shaped relationship, while for other areas, the study found an inverted N-shaped association between economic growth and CO_2 emissions. Al-Mulali and Ozturk (2015) found industrialization, urbanization, trade openness, and political stability have a long-run positive relationship with the ecological footprint for 14 MENA countries. Lin et al. (2017) studied the determinants of CO_2 emissions using the extended STIRPAT model for 53 non-high -, middle- and low-income countries and found that population, GDP per capita, and energy intensity are the key drivers of CO_2 emission in low-income countries.

In addition to the economic growth and environmental factors nexus several studies have used other socioeconomic factors to examine the complexity of the relationship. Rahman (2017) study found an adverse impact of exports, population density, and energy use on CO_2 emissions. Ghazali and Ali (2019) estimated the impact of various socioeconomic factors on CO_2 emission for a panel of 10 newly industrialized countries and found that GDP per capita, population, energy, and carbon intensity increase CO_2 emissions. For Arab countries Abdelfattah et al. (2018) examined that GDP per capita, population, and energy intensity increase CO_2 emission while institutional quality reduces the negative impact of environmental.

Some studies in the literature considered industrialization a significant determinant of climate change driven by CO_2 emissions. Li and Lin (2015) studied the impact of industrialization and urbanization on energy emission and consumption for 73 countries grouped by their development levels. Using threshold panel regression model study shows that urbanization decreases energy consumption but augments carbon dioxide emissions in low-income economies. Industrialization in the middle- and low-income countries decreases energy consumption but increases CO_2 emissions. Urbanization in middle- and high-income countries reduces the negative impact of carbon dioxide emissions.

Dong et al. (2019) examined various industrial development stages affecting CO_2 emission. At the initial and intermediate level impact of industrialization is more pronounced on CO_2 emissions; however, when industrialization matures in the presence of environmental regulations, the positive impact reduces for sub-Saharan African countries. Appiah et al. (2021) study examined the bi-direction causality between industrialization, energy use, and fossil fuel consumption. In the long run, both energy use and industrialization increase CO_2 emissions. Opoku and Boachie (2020) examined the environmental impact of the presence of industrialization and FDI for 36 African countries.

Some of the studies focused on single country analysis to analyse the relationship. Liu and Bae (2018) singled out causal linkages between China's per capita CO_2 emissions, urbanization, industrialization, economic growth, and renewable energy resources. Sarkodie and Owusu (2017) tested the causality between environmental variables and Rwanda’s GDP per capita, industrialization, and population. Mahmood et al. (2020) studied the role of industrialization and urbanization in the environmental degradation of Saudi Arabia.

Dalton et al. (2008) reveal that the aging population contributes to changes in US carbon emissions. Several indicators have been identified to gauge demographic aspects. For example, existing studies take the population size, growth, dependency ratio, and HH size. York et al. (2003) also used urbanization as component T of the STRIPAT model and found a positive relationship between urbanization and carbon emissions. Increased urbanization is conducive to economic growth, and increased consumption increases the demand for residential and transport infrastructure construction, which further adds to CO_2 emissions and gives way to climate change. Wang et al. (2020) explained the effect of urbanization and industrialization on CO_2 emissions, considering a panel of 18 Asia-Pacific Economic Cooperation (APEC) countries from 1990 to 2014. Results show that economic growth, energy intensity, industrialization, and urbanization are the prime factors enhancing environmental degradation.

Energy intensity is also considered an essential determinant of climate change. More energy consumption per unit of output increases carbon emissions, exacerbating climate change. In literature, energy intensity in the STIRPAT model is often used as a source of energy efficiency. Aydin and Turan (2020) analyzed the impact of energy intensity, economic growth, trade, and financial openness on an ecological footprint for BRICS economies. Results show that energy intensity exacerbates environmental pollution in all countries except Russia.

Economic integration with increased international trade has increased the consumption and production of goods across borders. Literature suggests two different hypotheses for emissions and trade openness nexus. *The Pollution Haven Hypothesis (PPH)* states that multinational companies' (MNCs) for-profit motives choose destinations with low production costs and fewer environmental regulations. Thus, trade openness accompanies emission increases. In comparison, *the pollution halo hypothesis* states that trade openness decreases pollution by introducing modern and efficient technology in the production process. Besides this, more wealth brings greater consciousness for environmental problems (Atici, 2012). Shahbaz et al. (2013) examined the impact of economic growth, trade, coal consumption, and financial development on CO_2 emissions per capita in South Africa. The study found that trade liberalization reduces the detrimental impact of CO_2 emissions. Essandoh et al. (2020) examined the positive relationship between CO_2 emissions and trade openness for 52 developed and developing countries. Low-income countries' emissions increase with increased FDI inflows, while trade openness for high-income countries effectively reduces their carbon emissions. Sarkodie and Strezov (2019) study showed that the top five carbon emitters are satisfied with the PPH.

3.2.2 Spatial Determinants of Climate Change

Literature provides evidence for a spatial relationship between socioeconomic variables and climate change in CO_2 emissions and various pollutants. Kang et al. (2016) estimated the EKC for China by considering the spillover effects.   EKC in the presence of spillover effect of neighboring regions. You and Lv (2018) analyzed the spillover effect of globalization on CO_2 emissions for a panel of 83 countries. Results indicate the spillover effect of a country's CO_2 emissions on its neighboring country. The study revealed a negative indirect impact of globalization, which shows that environmental quality tends to improve if the country is located near liberal economies.

Zeng and Ye (2019) studied the impact of FDI, economic growth, population, and technology on energy intensity for 30 Chinese provinces. Results show evidence of spatial spillover effect of energy intensity in local and nearby regions. FDI has a positive direct and significantly high indirect effect on energy intensity. Results revealed that FDI inflows increase energy efficiency because of the energy-saving technology brought by firms in the region. This also has a high positive spillover effect on nearby countries. Zambrano et al. (2020) estimated the spatial determinants of ecological footprint (EF) for 158 nations using the Spatial Durbin Model (SDM). Results indicate that EF is spatially correlated across space. Biocapacity, trade liberalization, and GDP per capita are spatial determinants of EF. Both biocapacity and trade openness have a positive spatial spillover effect on a domestic country's EF, while GDP per capita directly affects EF.

3.2.3 Analysis of Literature Review

Literature provide several socioeconomic drivers of climate change including GDP per capita, urbanization, population, energy intensity, trade openness, FDI, and industrialization levels. However, the relationship of these variables vary with the income levels of countries, industrial development and the geographical location.

Among the major drivers, GDP per capita is considered to be the key factor affecting climate change, indicating that the development levels and means to achieve development matters for climate change. The relationship is empirically captured by Environmental Kuznets curve that is inverted U shaped. However, in some countries the relationship is N shaped representing that emission tends to fall with a rise in income level, nevertheless after a benchmark, they grow exponentially. Other notable drivers such as level of industrialization and energy intensity also increases CO_2 emissions that reflect climate change. Industrialization also mitigates the negative impact of climate change if it aids expansion and restructuring of industries with climate-resilient technology. While contrary to it, it has also been highlighted that industrialization increases energy demand, produces industrial waste and this, in turn, affects weather patterns.

Climate change is not limited to geographical boundaries as the countries contributing limited part of the global emissions are the most vulnerable to climate change related natural disasters. Climate change mitigation and adaptation policies are globally determined therefore, it is important to consider and incorporate the spillover effects of neighboring countries to internalize the true effects of climate change and plan global policies accordingly. The spatial dimension and neighborhood effects of these drivers have been analyzed in literature to some extent. Among the indirect effects (spillover), trade openness and FDI are the key drivers that tend to show spillover effects on neighboring countries. You and Lv (2018) study finds improvement in environmental quality if nearby countries have open trade policies. Zeng and Ye (2019) estimated that GDP, population size and technology have indirect spatial spillover effects on energy consumption on any given region in case of China. FDI that aimed for energy saving technologies in a region and its neighbors reduces the energy consumption.

Limited studies have focused on the spatial effects of drivers of climate change and in addition to this, different environmental factors such as carbon emissions, Sulphur dioxide, and ecological footprint have been studied to measure the complexity of these factors with socio-economic variables. WMO and IPCC have made a distinction between climate change and variability. The present study considers this difference and examines climate variability and change predictors using temperature and rainfall as prime measures to access climate change. Region wise analysis has also been incorporated to study the regional differences in drivers and their spillover effects.

3.3. Theoretical Framework

Environmental impact assessment and critical driving forces affecting the environment have been an important concern since 200 years ago, when Malthusian theory highlighted the role of natural resources in population growth (Sherbinin et al., 2007; Dietz & Rosa, 1994). Neo-Malthusian theories considered high population growth a key driver of natural resource degradation. However, the post-World War II era was dominated by modernization theories that focused on economic growth and industrialization as key determinants aligned with our natural ecosystem. Environmental Kuznets curve (EKC), followed by ecological modernization theory (EMT) by sociologists, and reinforced the capitalist system by highlighting the positive role of economic growth, industrialization, and innovation on environmental resources[26]. Neo-Marxist economists are of the view that production negatively affects the environment. Firstly, showing the cost of excessive extraction of resources is detrimental to the natural environment. Secondly, production assets are majorly owned by wealthy elites who influence the policy process of society. They tend to devise and propagate those policies that give them high profits (York et al., 2003).

In their subsequent reports, the intergovernmental panel on climate change (IPCC henceforth) highlighted the number of anthropogenic factors responsible for the past century's warming. Several studies have analyzed economic growth as a critical factor affecting CO_2 emissions. However, controversy still exists in economic growth and environmental impact nexus. Studies following EKC have used limited explanatory variables to explain the environmental impact. However, additional factors affecting the ecosystem are analyzed using structural decomposition analysis (SDA), logarithmic-Mean Divisia Index (LMDI), Computable General Equilibrium model (CGE), and Stochastic Impact by Regression on Population, Affluence, and Technology (STIRPAT) (Zhang et al., 2014; Wang & Liu, 2017; Yang et al., 2018). Most studies have used the STIRPAT model to analyze a diversified range of factors explaining impact.

IPAT equation, the basic starting point of STIRPAT, was proposed by Ehrlich and Holdren (1971). IPAT considers impacting directly linked to population, affluence, and technology.

[26] Proponents of these theories based their argument on the notion that industrialization coupled with technological advancement has intrinsic ability to be compatible with natural resources. Moreover, with progressive society, markets provide incentive for reforms by restructuring industries with environmentally friendly solutions.

The impact depends on the population's size and its interaction with varying affluence and technology levels.

$$I = PAT \tag{3.1}$$

Where P signifies population size, A refers to affluence, and T is the technology measured as *impact per unit of economic activity*. IPAT has several limitations; firstly, it assumes a multiplicative and proportional relationship of factors affecting the environment, i.e., factors are not independent. Secondly, the model assumes similar elasticities with monotonic effects for all drivers. Thirdly, a model is based on restrictive assumptions and is a mathematical identity that limits hypothesis testing[27] (York et al., 2003; Rosa et al., 2004; Yang et al., 2018).

IPAT equation followed by *stochastic impact by regression on population, affluence, and technology* STIRPAT model, both are based on Structural Human Ecology (SHE) theory[28]. Considering all these limitations, Dietz and Rosa (1994) presented STIRPAT with a stochastic blend with a non-monotonic and non-proportional relationship of environmental factors. Besides this, the model could perform hypothesis testing (York et al., 2003). STIRPAT's theoretical base also stems from SHE and has been used extensively for recognizing socioeconomic drivers of environmental threats. The model is expressed as follows.

$$I = aP^b A^c T^d e \tag{3.2}$$

Taking natural log on both sides model takes the form.

[27] IPAT has undergone several modifications like ImPACT in which T has been segregated into two parts such as C and T. Where C shows energy consumption per economic activity and T explains impact per unit of economic activity. Both IPAT and ImPACT can't be used for statistical analysis due restrictive assumptions.

[28] Structural Human Ecology (SHE) theory is based on human interaction with environment. Duncan and Schnore 1959, formulated POET model based on SHE, showed bi-directional relationship between four factors (population, organization, environment, and technology) that considers broader aspects of human interaction with environment.

$$lnI = lna + blnP + clnA + dlnT + lne \quad (3.3)$$

Where P is the population size, A refers to affluence, T includes all drivers not included in P, and A. e is the error term, while b, c, and d are respective elasticities of drivers included. Considering the definition of T, researchers have moved on to an extended STIRPAT model that goes beyond conventional factors like population and affluence and contains elements like urbanization, energy intensity, industrial structure, primary energy structure, trade, foreign direct investment, and technology. Initially, numerous studies analyzed drivers of CO_2 emissions using the STIRPAT model. However, later, due theoretical flexibility of the STIRPAT model, researchers examined a variety of environmental concerns such as GHG emissions, deforestation, ecological footprint, energy footprint, and water footprint as the dependent variable and called STIRPAT an extended-STIRPAT model (York et al., 2003; Rosa et al., 2004; Dietz et al., 2007; Zhao et al., 2014).

Using an extended STIRPAT model, the present study uses climate change as an environmental threat and examines the underlining factors causing it. Existing literature has analyzed climate change attribution from anthropogenic drivers such as radioactive forcing, ocean heat content, volcanic forcing sulphate arsenals (Kaufmann et al., 2011; Triacaa et al., 2013; Stern & Kaufmann, 2014; Zhai et al., 2018). This gave us room to explore socio-economic drivers responsible for climate change. This study separates itself from existing studies by using two different indicators to assess the impact of climate change impact. Following (Tol, 2021), we consider square temperature anomalies a dependent variable. In the second step, we have to use the 30-year average mean of the climate variable to measure impact.

We can specify our model in the panel setting as follows;

$$lnCV_{it} = \beta_{\circ} + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \beta_4 lnTRADE_{it} + \beta_5 lnIND_{it} + \beta_6 lnPOP_{it} + \beta_7 lnURP_{it} + lne_{it} \quad (3.4a)$$

And in cross-section setting model take the form.

$$lnC_i = \beta_\circ + \beta_1 lnGDPpc_{it} + \beta_2 lnGDP_{it}^2 + \beta_3 lnPOPD_{it} + \beta_4 lnTRADE_{it} + \beta_5 lnIND_{it} + lne_{it} \quad (3.4b)$$

$$lnCC_i = \beta_\circ + \beta_1 lnGDP_{it} + \beta_2 lnGDP_{it}^2 + \beta_3 lnPOPD_{it} + \beta_4 lnTRADE_{it} + \beta_5 lnIND_{it} + lne_{it} \quad (3.4c)$$

Following Tol (2021) and Moore and Lobell (2014), climate variability CV is calculated by the square deviation of the climate variable from its 30 years (1961-90) average; C stands for the climate, which is 30 years (1989-2018) average of climate variables; CC stands for climate change which is the deviation of 30 years (1989-2018) average of climate variables from the long-run mean (1961-1990); $GDPpc$ is the gross domestic product per capita; $GDPpc^2$ indicates the square term of gross domestic product per capita; EI weighs energy intensity; $TRADE$ is the sum of exports and imports divided by GDP; IND is used for a share of industrial value added in GDP; POP is the total population; URP is the proportion of the total population living in urban areas; $POPD$ shows population density.

3.4. Methodology

3.4.1 Spatial Econometric Models

In the current globalize and integrated world, Tobler (1969) first law of geography[29] can't be ignored. Traditional panel and cross-sectional econometrics models assume no spatial autocorrelation and heterogeneity in error terms. However, classical linear regression models are not valid in spatial dependence. Geographical boundaries do not restrict climate change. Indeed, one prime example is a homogenous distribution of GHGs worldwide, irrespective of the country emitting them. Climate change in the form of change in temperature and rainfall is being experienced globally. Considering the nature of climate change variables, it is essential to consider drivers and spillover of the effects of drivers causing climate change. Following You and Lv (2018) and Zeng and Ye (2019), the present

[29] First law of geography states "*Everything is related to everything else, but near things are more related than distant things"*

study uses the extended STIRPAT model to analyze variables' spatial relationships in a spatial econometric setting.

The spatial econometrics model deals with three types of spatial interaction effects that further define spatial models, i.e., the Spatial Lag of X Model (SLX) deals with exogenous spatial relationships; the *Spatial Autoregressive (SAR)* model handles endogenous interaction effect*; Spatial Error Model (SEM)* deals with spatial interaction in the error term, *and Spatial Durbin Model (SDM)* takes both endogenous and exogenous spatial relationships.

In the presence of externality, the data generating process shows the spatial relationship of the exogenous variable of a given location with exogenous variables in its proximity, i.e., the variability in the dependent variable is explained by both exogenous variables at a given location and its neighborhood. In our case, climate variability and change depend on determinants like GDP, population, energy intensity, and industrial structure of a country and its neighboring countries.

In general SLX model can be written as:

$$CV_{it} = \mu_i + \lambda_t + \gamma \sum_{j=1}^{N} w_{ij} x_{jt} + \beta x_{it} + \varepsilon_{it} \tag{3.5a}$$

If the dependent variable of nearby location explains spatial relation, and the data generating process describes spillover effects, we use SAR. Unlike time series analysis, where the spillover effect is explained by dynamic modeling, spatial econometrics considers the spatial lag of the dependent variable. In this case, the dependent variable at a given location is associated with a spatially weighted average of the dependent variable of its neighboring locations. In our case, climate variability at one location increases the likelihood of having similar climate variability at nearby locations.

In general form, SAR can be written as.

$$CV_{it} = \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} CV_{jt} + \beta x_{it} + \varepsilon_{it} \quad (3.5b)$$
$$i = 1,2, \dots, N \quad t = 1,2, \dots, T$$

where $w_{ij}CV_{jt}$ is the spatially weighted average of the dependent variable of nearby countries, δ is the spatial autocorrelation coefficient; w_{ij} refers to the weight matrix explaining the spatial relation between two locations i and j; x_{it} shows independent variables in the model ; μ_i shows country-specific fixed effect; λ_t indicates time-specific fixed effect ; ε_{it} is the error term which is independent and identically distributed.

In our case of climate variability and CO_2 intensity, the model takes the form.

$$lnCV_{it} = \beta_\circ + \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} lnCV_{jt} + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \beta_4 \beta_6 lnTRADE_{it} + \beta_7 lnIND_{it} + \beta_8 lnPOP_{it} + \beta_9 lnURP_{it} + \varepsilon_{it} \quad (3.5c)$$
$$i = 1,2,3, \dots, N \quad t = 1,2,3, \dots, T$$

$$lnCO_{2\,it} = \beta_\circ + \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} lnCO_{2\,jt} + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \beta_4 \beta_6 lnTRADE_{it} + \beta_7 lnIND_{it} + \beta_8 lnPOP_{it} + \beta_9 lnURP_{it} + \epsilon_{it} \quad (3.5d)$$
$$i = 1,2,3, \dots, N \quad t = 1,2,3, \dots, T$$

In the case of climate change, the model in SAR becomes.

$$lnCC_i = \beta_\circ + \delta \sum_{j=1}^{N} w_{ij} lnCC_j + \beta_1 lnGDPpc_i + \beta_2 lnGDPpc^2{}_i + \beta_3 lnPOPD_i + + \beta_4 lnTRADE_i + \beta_5 lnIND_i + \omega_i \quad (3.5e)$$

If the model's omitted variables explain the spatial structure, i.e., by the error term, we move towards SEM. By introducing the spatial error lag structure in the model, SEM handles spatial autocorrelation. Errors of neighboring locations are correlated with the errors of a given location. This model is inapplicable in cases where spatially correlated error term influences given and adjacent locations (You & Lv, 2018).

In general form, this can be written as:

$$CV_{it} = \beta x_{it} + \mu_i + \eta_{it}$$
$$\eta_{it} = \rho \sum_{j=1}^{N} w_{ij}\eta_{jt} + \varepsilon_{it} \quad (3.6a)$$
$$i = 1,2,3, \dots, N, t = 1,2,3, \dots, T$$

η_{it} specifies spatially auto correlated error term dependent on the error structure of adjacent locations and normally distributed error term, ρ represents the spatial autocorrelation parameter.

In our case, the panel model takes the form.

$$lnCV_{it} = \beta_\circ + \mu_i + \lambda_t + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \beta_4\beta_6 lnTRADE_{it} + \beta_7 lnIND_{it} + \beta_8 lnPOPT_{it} + \beta_9 lnURP_{it} + \eta_{it} \quad (3.6b)$$
$$\eta_{it} = \rho \sum_{j=1}^{N} w_{ij}\eta_{jt} + \varepsilon_{it} \qquad i = 1,2,3, \dots, N;\ t = 1,2,3, \dots, T$$

$$lnCO_{2\,it} = \beta_\circ + \mu_i + \lambda_t + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \beta_4\beta_6 lnTRADE_{it} + \beta_7 lnIND_{it} + \beta_8 lnPOPT_{it} + \beta_9 lnURP_{it} + \eta_{it} \quad (3.6c)$$
$$\eta_{it} = \rho \sum_{j=1}^{N} w_{ij}\eta_{jt} + \epsilon_{it} \qquad i = 1,2,3, \dots, N;\ t = 1,2,3, \dots, T$$

In the case of climate change, the model in SEM becomes.

$$lnCC_i = \beta_\circ + \mu_i + \lambda_t + \beta_1 lnGDPpc_i + \beta_2 lnGDPpc^2{}_i + \beta_3 lnPOPD_i + + \beta_4 lnTRADE_i + \beta_5 lnIND_i + \eta_i \quad (3.6d)$$
$$\eta_i = \rho \sum_{j=1}^{N} w_{ij}\eta_j + \omega_i$$

An alternative specification to the SEM model is SDM, presented by LeSage and Pace (2009), in which spatial relation is explained by spatial exogenous and spatial autoregressive terms of the model. In this case, it is not only climate variability in one country that simulates neighboring countries' climate variability but also the determinants, like GDP, population, energy intensity, etc., of one country affected by its neighboring countries. SDM is a more generalized and unrestricted form that embeds SAR and SEM.

In general form, this can be written as.

$$CV_{it} = \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} CV_{jt} + \gamma \sum_{j=1}^{N} w_{ij} x_{jt} + \beta x_{it} + \varepsilon_{it} \quad (3.7a)$$
$$i = 1,2,3, \dots, N; \; t = 1,2,3, \dots, T$$

γ is the coefficient of spatially autocorrelated explanatory variables. In our case, the panel model takes the form.

$$\begin{aligned} lnCV_{it} = {} & \beta_\circ + \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} lnCV_{jt} + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \beta_3 lnEI_{it} + \\ & \beta_4 lnTRADE_{it} + \beta_5 lnIND_{it} + \beta_6 lnPOPT_{it} + \beta_7 lnURP_{it} + \\ & \theta_1 \sum_{j=1}^{N} w_{ij} lnGDPpc_{ijt} + \theta_2 \sum_{j=1}^{N} w_{ij} lnGDPpc_{ijt}^2 + \theta_3 \sum_{j=1}^{N} w_{ij} lnEI_{ijt} + \\ & \theta_4 \sum_{j=1}^{N} w_{ij} \beta_4 lnTRADE_{ijt} + \theta_5 \sum_{j=1}^{N} w_{ij} lnIND_{ijt} + \theta_6 \sum_{j=1}^{N} w_{ij} lnPOPT_{ijt} + \\ & \theta_7 \sum_{j=1}^{N} w_{ij} lnURP_{ijt} + \varepsilon_{it} \end{aligned} \quad (3.7b)$$

$$\begin{aligned} lnCO_{2\,it} = {} & \beta_\circ + \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} lnCO_{2\,jt} + \beta_1 lnGDPpc_{it} + \beta_2 lnGDPpc_{it}^2 + \\ & \beta_3 lnEI_{it} + \beta_4 lnTRADE_{it} + \beta_5 lnIND_{it} + \beta_6 lnPOPT_{it} + \beta_7 lnURP_{it} + \\ & \theta_1 \sum_{j=1}^{N} w_{ij} lnGDPpc_{ijt} + \theta_2 \sum_{j=1}^{N} w_{ij} lnGDPpc_{ijt}^2 + \theta_3 \sum_{j=1}^{N} w_{ij} lnEI_{ijt} + \\ & \theta_4 \sum_{j=1}^{N} w_{ij} \beta_4 lnTRADE_{ijt} + \theta_5 \sum_{j=1}^{N} w_{ij} lnIND_{ijt} + \theta_6 \sum_{j=1}^{N} w_{ij} lnPOPT_{ijt} + \\ & \theta_7 \sum_{j=1}^{N} w_{ij} lnURP_{ijt} + \epsilon_{it} \end{aligned} \quad (3.7c)$$

In the case of climate change, the model in SDM becomes.

$$\begin{aligned} lnCC_i = {} & \beta_\circ + \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} lnCC_j + \beta_1 lnGDPpc_i + \beta_2 lnGDPpc_i^2 + \beta_3 lnEI_i + \\ & \beta_4 lnPOPD_i + \beta_5 lnTRADE_i + \beta_6 lnIND_i + \theta_1 lnGDPpc_{ij} + \end{aligned}$$

$$\theta_2 \sum_{j=1}^{N} w_{ij} lnGDPpc_{ij}^2 + \theta_3 \sum_{j=1}^{N} w_{ij} lnEI_{ij} + \theta_4 \sum_{j=1}^{N} w_{ij} lnPOPD_{ij} + \theta_5 \sum_{j=1}^{N} w_{ij} lnTRADE_{ij} + \theta_6 \sum_{j=1}^{N} w_{ij} lnIND_{ij} + \omega_i \quad (3.7d)$$

3.4.2 Weight Matrix

The selection of an appropriate weight matrix is important to uncover the prior spatial structure between observations at locations i and j. For spatial structure, one needs to consider the network structure and the source of the relationship between regions i and j. The weight matrix is non-stochastic, non-zero, and exogenously defined. The analysis uses an inverse square distance weight matrix, showing that the spillover effects tend to decay as distance increases. Matrix is row standardized as per standard procedure, and the weighted average of nearby locations calculates the spatial value of variables.

3.4.3 Model Selection

The present study has employed the Elhorst and Vega (2013) method for appropriate model selection. Firstly, a non-spatial panel model is estimated, and the Hausman test is used to choose between fixed and random effects. In the next step, we have employed the LM test (LM-lag and LM-error) and their robust forms for spatial diagnostics and choosing between non-spatial and spatial lag or spatial error models. If the spatial models better fit the data than the non-spatial model, we have used Wald and LR tests to choose the most appropriate model. Two hypotheses have been tested: first is spatial Durbin model can be simplified to the SLM model (H_o= γ =0), and can spatial Durbin model can be reduced to the spatial error model (H_o= γ +$\delta\beta$).

3.5. Data Description

The present study considers macro and socio-economic variables to analyze the spatial determinants of climate change, variability, and carbon intensity. One hundred sixteen countries were considered for accessing climate variability in the analysis from 1991 to 2018. Climate variability is accessed through the difference in average annual temperature (rainfall) from its long-run mean of 30 years. Following Tol (2021), Burke et al. (2015), Moore and Lobell (2014), climate change is calculated by the average temperature (rainfall) of 30 years (1989 to 2018). For a cross-sectional analysis of climate change, we have used 114 countries. Carbon intensity is another dependent variable used to study the environmental impact. It is the carbon content per unit of energy used through coal consumption.

Explanatory variables in the analysis include GDP per capita; its square term; urbanization measured through a share of the urban population in the total population; total population; trade openness measured by the merchandise trade volume as a percentage of the GDP; energy intensity is the ratio of energy consumed per unit of output, industrialization access through value added share of industrialization as a percentage of the GDP. Population density is another proxy for the population (for detailed definitions, see appendix B).

3.6. Empirical results

3.6.1 Spatial Autocorrelation Test

We have employed global local Moran-I statistics for spatial autocorrelation of climate variability. The global Moran test is calculated as follows.

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(z_i - \bar{z})(z_j - \bar{z})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{3.8}$$

Where,

$$S^2 = \sum_{i=1}^{n} (z_i - \bar{z})^2$$

$$\bar{z} = \frac{1}{n}\sum_{i=1}^{n} (z_i - \bar{z})$$

z_i and z_j indicates the value of climate variability at locations i and j while $\bar{z}$ indicates the mean value of climate variability. The matrix explains the spatial relationship w_{ij} that is an inverse distance matrix that shows a geographical spatial relationship that represents that the spatial relationship tends to decay as distance increases between countries.

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}$$

d_{ij} represents the distance between location i and j measured by their respective latitude and longitudes. While n indicates the number of countries, i.e., 116 considered in the analysis.

Positive and statistically significant Moran I show the presence of positive spatial autocorrelation, i.e., countries with the same level of climate variability are clustered geographically. The value of the Moran I test ranges between -1 and 1. Positive values indicate the presence of spatial clustering, while negative values signify spatial dispersion. Keeping in view the limitation[30] of the global Moran's I test, we have analyzed the relationship graphically through a scatter plot. The top right quadrant shows that countries with high climate variability are surrounded by neighbors that also experience more variability, while the top left quadrant indicates that countries with low climate variability are surrounded by neighbors sharing high climate variability. The bottom left quadrant shows that countries with low climate variability are accompanied by countries experiencing low climate variability. In contrast, the bottom right quadrant countries have both dependent variables (log temperature variability and log of rainfall variability), showing the presence of spatial autocorrelation (see table 3.1).

The IV quadrant is "High-Low (HL)" clustering which shows that countries with low values enclose countries with high values. The I and III quadrants show positive spatial autocorrelation. The II and IV quadrants present negative spatial autocorrelation.

[30] As Moran-I tests the presence of overall spatial autocorrelation. Negative and positive value of index for some countries might cancel each other and value of index turns out to be zero, indicating no spatial auto correlation.

Table 3.1: Global Moran's I Climate Variability with Inverse Distance Matrix

	Temperature variability		Rainfall variability	
Year	**Moran-I**	**Z**	**Moran-I**	**Z**
1991	0.351***	24.407	0.136***	9.801
1992	0.180***	12.914	0.152***	10.9
1993	0.250***	17.595	0.147***	10.591
1994	0.183***	13.158	0.171***	12.199
1995	0.164***	12.090	0.184***	13.047
1996	0.355***	24.837	0.155***	11.106
1997	0.203***	14.713	0.158***	11.350
1998	0.143***	10.498	0.180***	12.770
1999	0.123***	9.201	0.178***	12.661
2000	0.130***	9.649	0.173***	12.341
2001	0.160***	11.685	0.183***	13.026
2002	0.079***	5.956	0.179***	12.736
2003	0.123***	9.06	0.159***	11.346
2004	0.153***	11.029	0.142***	10.225
2005	0.126***	9.351	0.190***	13.480
2006	0.051***	4.918	0.136***	9.801
2007	0.121***	9.055	0.186***	13.214
2008	0.178***	12.926	0.146***	10.491
2009	0.128***	9.321	0.143***	10.308
2010	0.235***	16.636	0.182***	12.945
2011	0.028***	2.579	0.171***	12.155
2012	0.166***	11.953	0.120***	8.723
2013	0.177***	12.720	0.175***	12.462
2014	0.221***	15.729	0.153***	10.979
2015	0.135***	9.726	0.189***	13.451
2016	0.137***	9.992	0.151***	10.855
2017	0.084***	6.351	0.202***	14.304
2018	0.259***	18.299	0.132***	9.579
Average	0.282***	19.768	0.235***	16.55

Source: Author's calculation. Note: ***, **, * indicates the significance level at 1%, 5% and 10% respectively

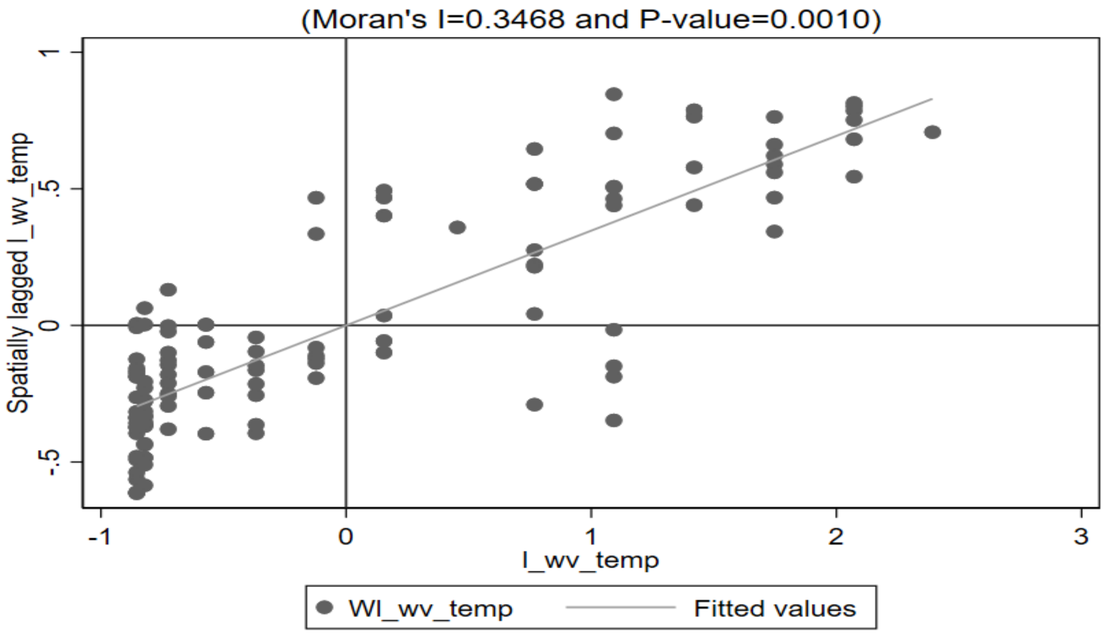
In figure 3.1, from 1991 to 2018, the Moran I scatter plot indicates that positive spatial autocorrelation exists signifying that countries experience same magnitude of temperature variability as their neighbors. As most of the countries lie in the 3rd quadrant indicating that countries experiencing low temperature variability are surrounded by neighbors also having low average temperature variability. Temporal pattern along these years, indicate post 2010, some more countries tend to experience high variability along with their neighbors. The graph also indicates that countries share common climate conditions and variability and highlights the need to study the factors causing the variability in the countries clusters

In figure 3.2, for rainfall variability, the Moran I scatter plot also shows that positive spatial autocorrelation exists signifying that countries experience same magnitude of rainfall variability as their neighbors. Unlike temperature variability, most of the countries lie in the 1st quadrant indicating that countries experiencing high rainfall variability are surrounded by neighbors also having high average rainfall variability. Temporal pattern along these decades, remains the same indicating that high rainfall variability counties are clustered around each other.

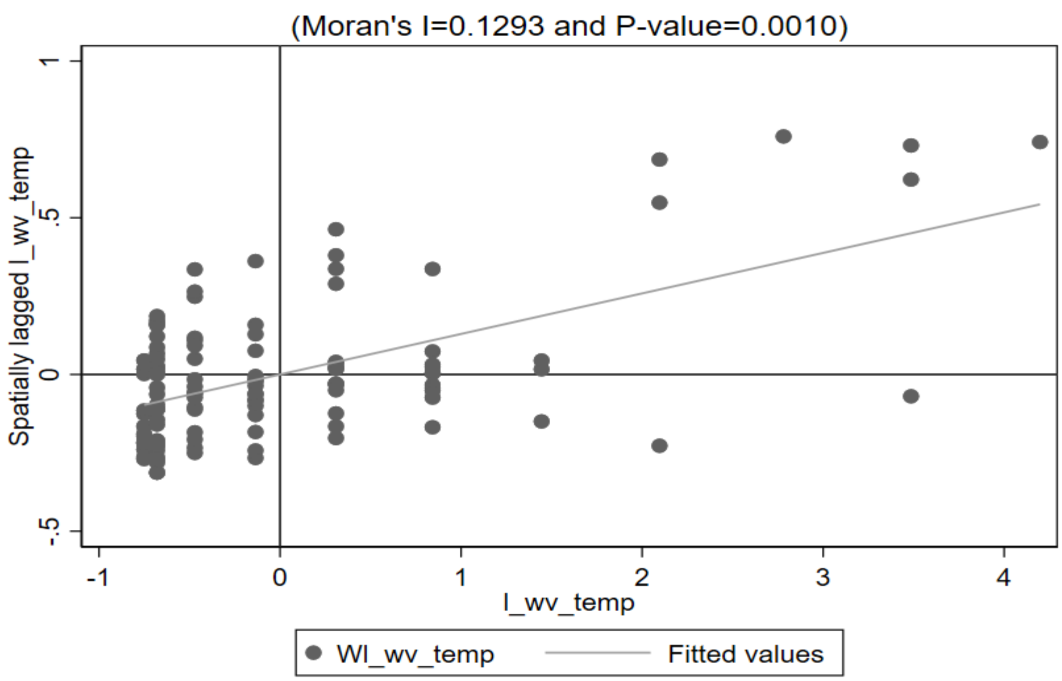
In figure 3.3, for CO_2 emissions, the Moran I scatter plot also shows that positive spatial autocorrelation exists indicating that countries having high CO_2 intensity are clustered around and vice versa. Few countries also experience negative spatial autocorrelation (high CO_2 intensity countries are surrounded by low CO_2 intensity neighbors). Most of the countries lie in the 1st quadrant indicating that high CO_2 intensity countries are surrounded by neighbors with similar high CO_2 intensity. Temporal pattern along these decades, remains the same.

Figure 3.1: Moran I Scatter Plot for the log of Temperature Variability

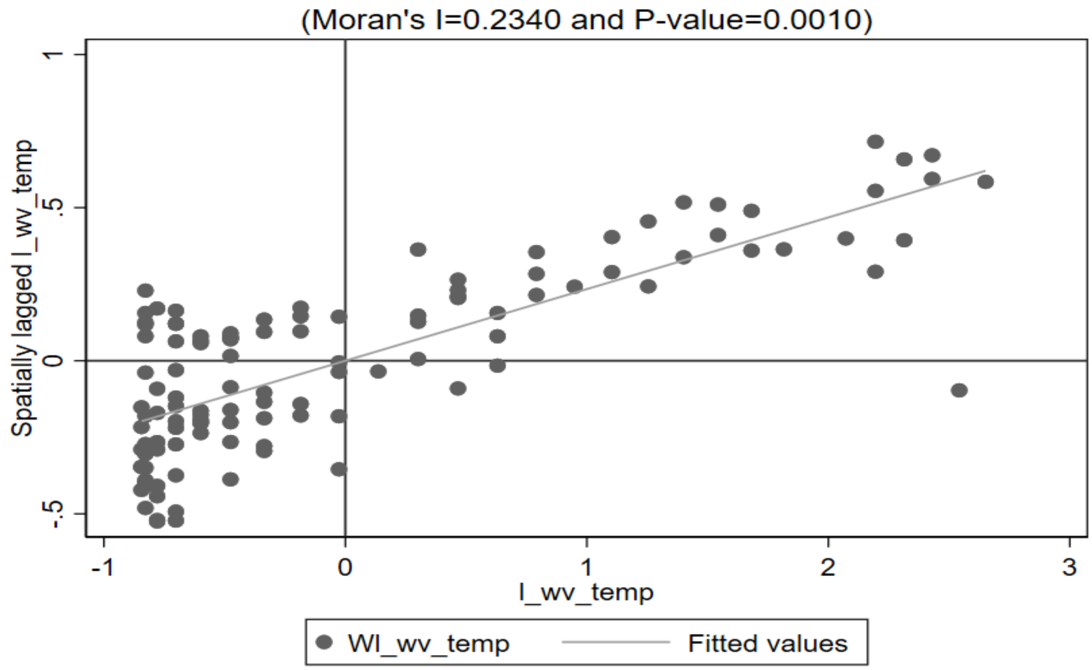
1991



2000



2010


(Moran's I=0.2340 and P-value=0.0010)
Spatially lagged l_wv_temp
1
.5
0
-.5
-1
0
1
2
3
l_wv_temp
Wl_wv_temp
Fitted values

2018

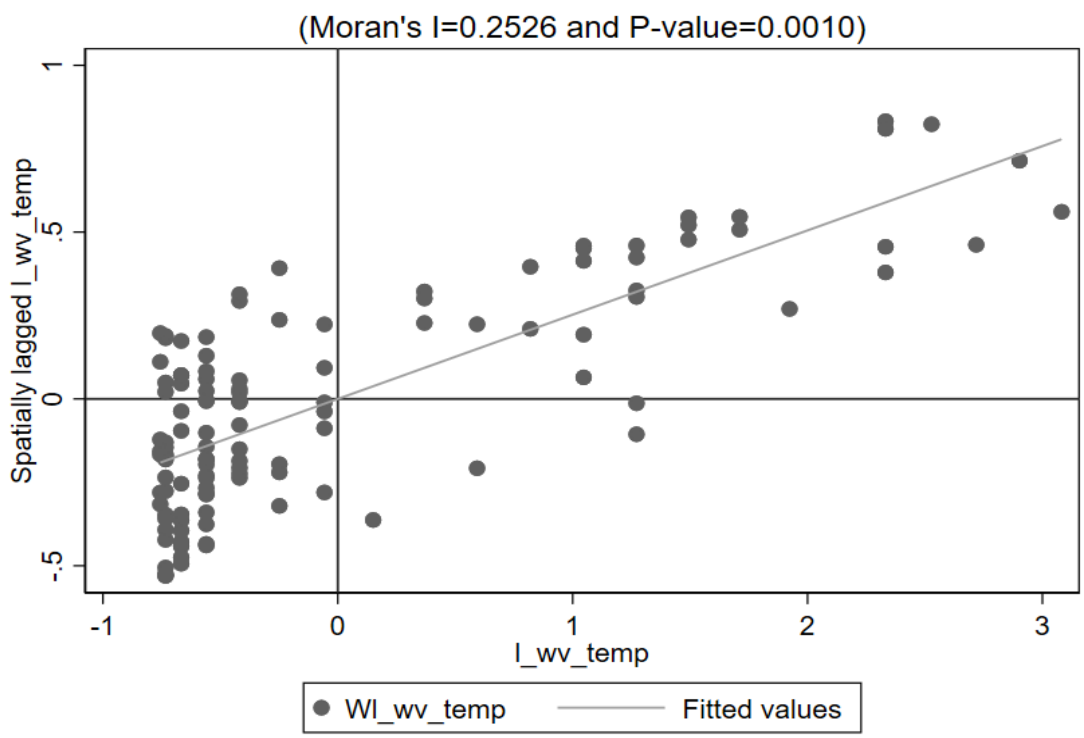
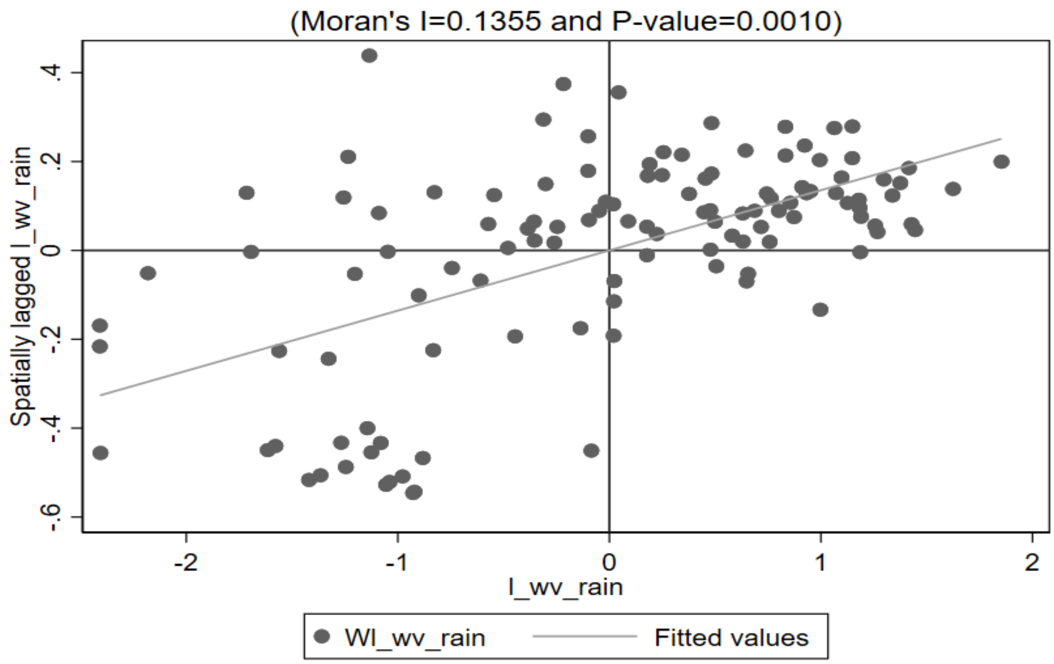
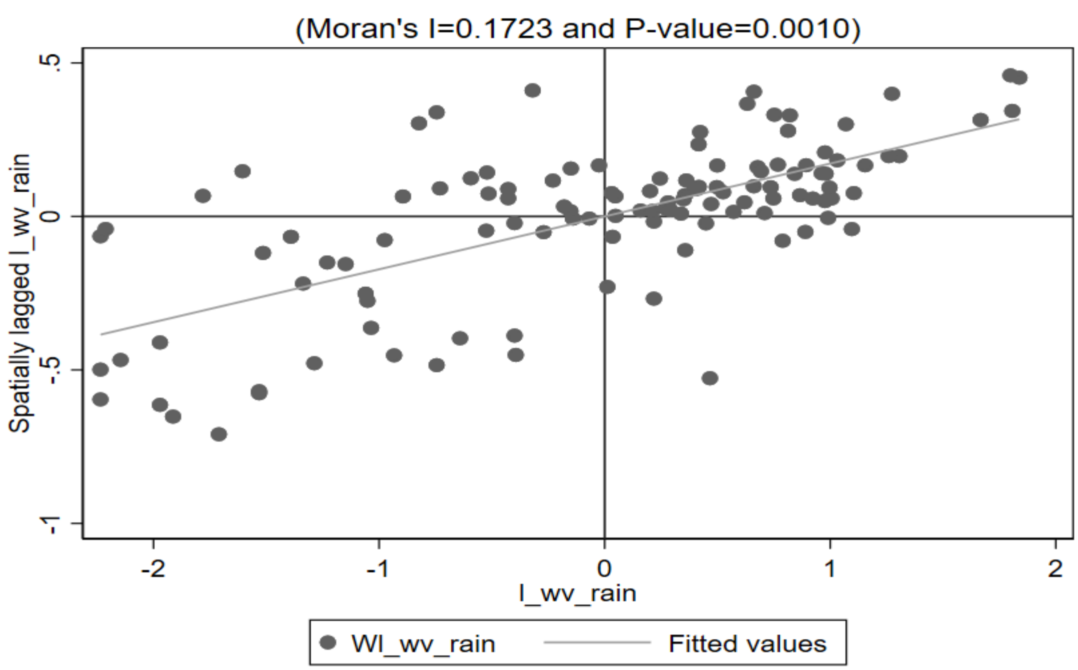

(Moran's I=0.2526 and P-value=0.0010)
Spatially lagged l_wv_temp
1
.5
0
-.5
-1
0
1
2
3
l_wv_temp
Wl_wv_temp
Fitted values

Figure 3.2. Moran-I Scatter Plot for the log of Rainfall Variability

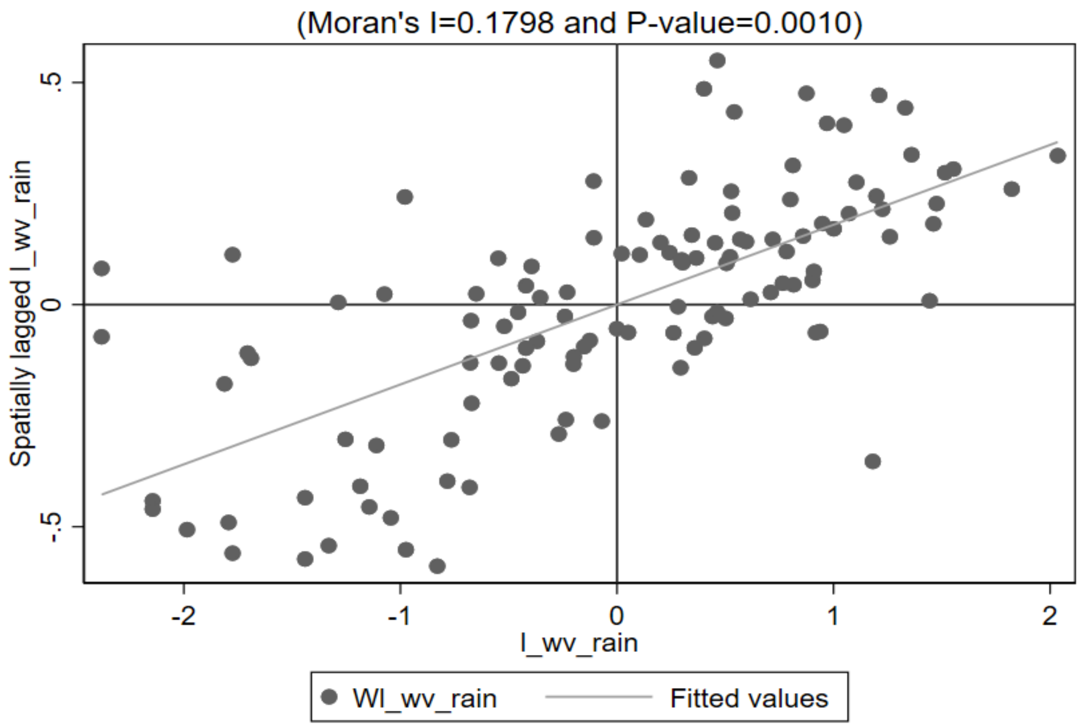
1991



2000



2010


(Moran's I=0.1798 and P-value=0.0010)
Spatially lagged l_wv_rain
.5
0
-.5
-2
-1
0
1
2
l_wv_rain
Wl_wv_rain
Fitted values

2018

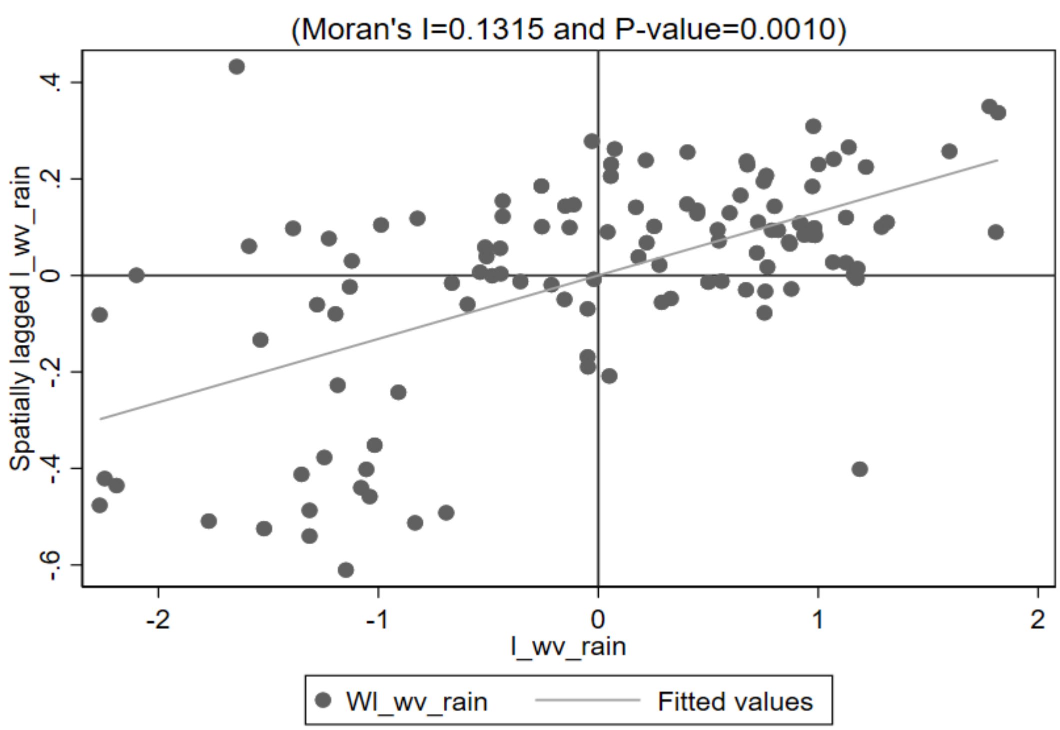
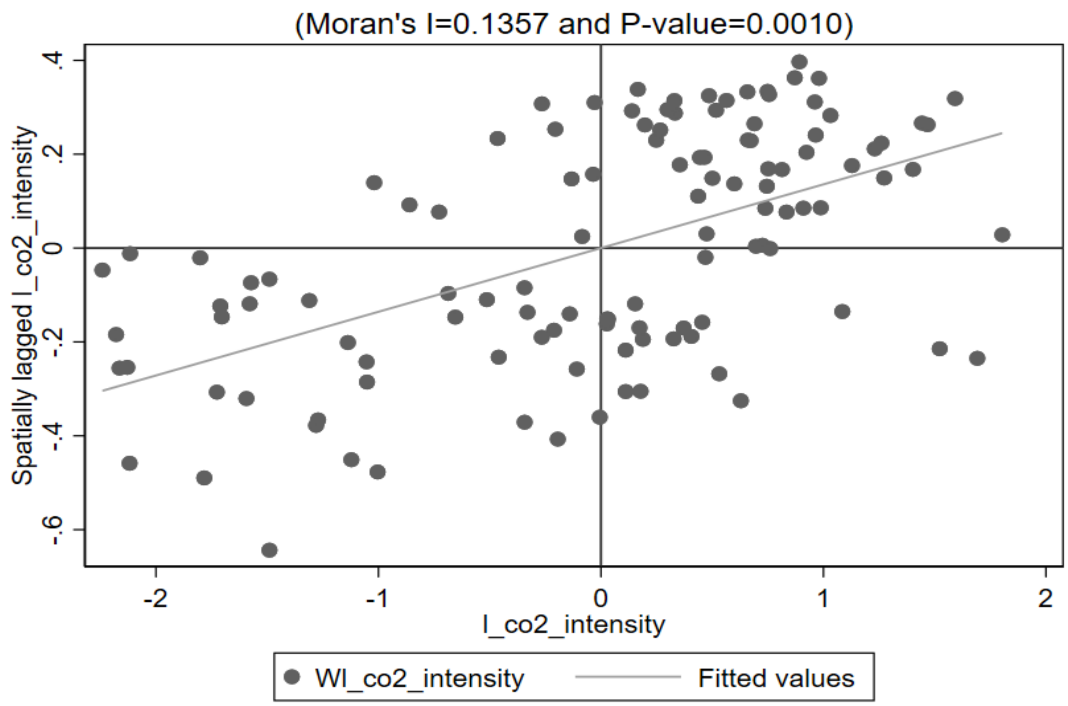
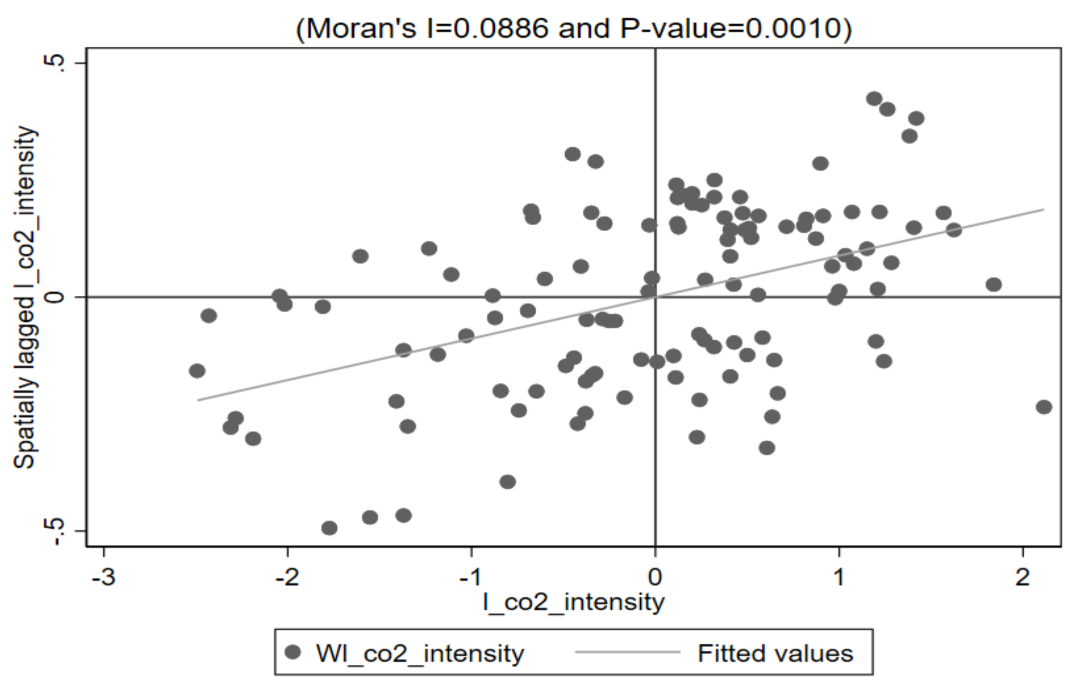

(Moran's I=0.1315 and P-value=0.0010)
Spatially lagged l_wv_rain
.4
.2
0
-.2
-.4
-.6
-2
-1
0
1
2
l_wv_rain
Wl_wv_rain
Fitted values

Figure 3.3. Moran-I Scatter Plot for the log of CO_2 Intensity

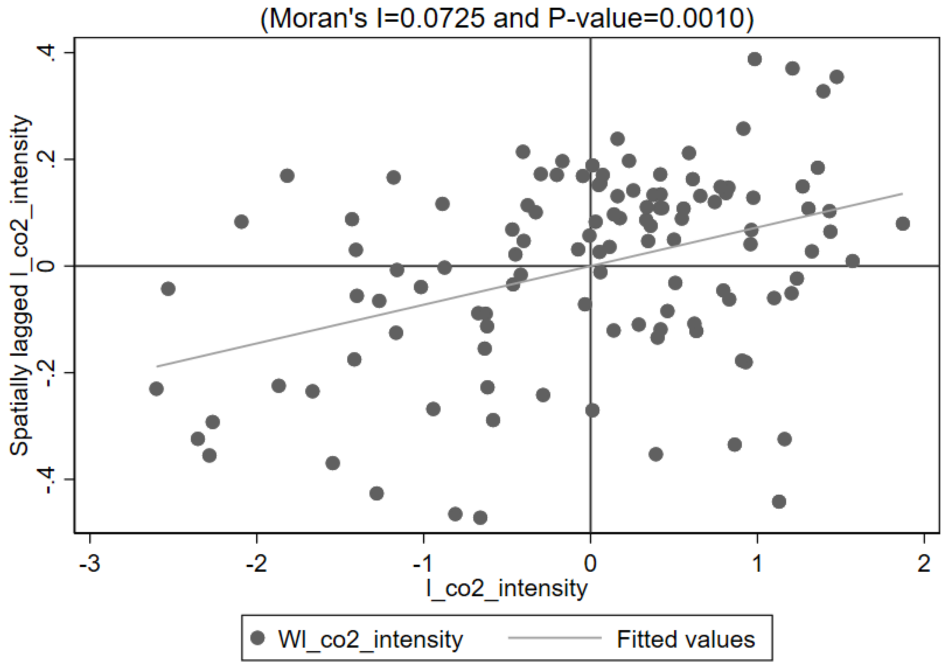
1991



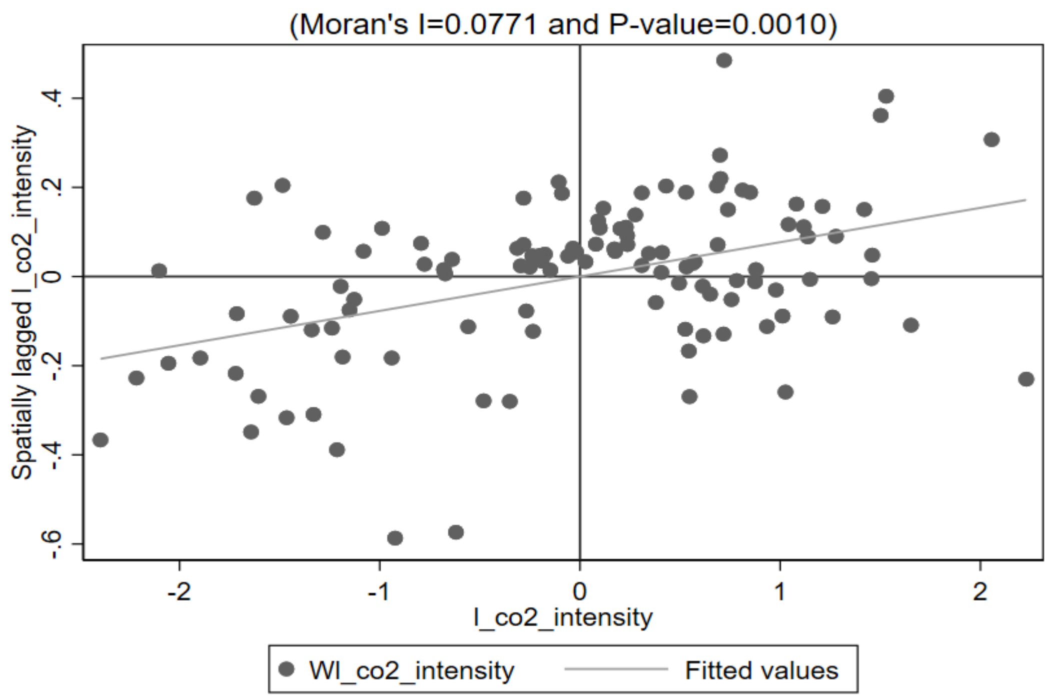
2000



2010


(Moran's I=0.0725 and P-value=0.0010)
Spatially lagged l_co2_intensity
-.4
-.2
0
.2
.4
-3
-2
-1
0
1
2
l_co2_intensity
Wl_co2_intensity
Fitted values

2018

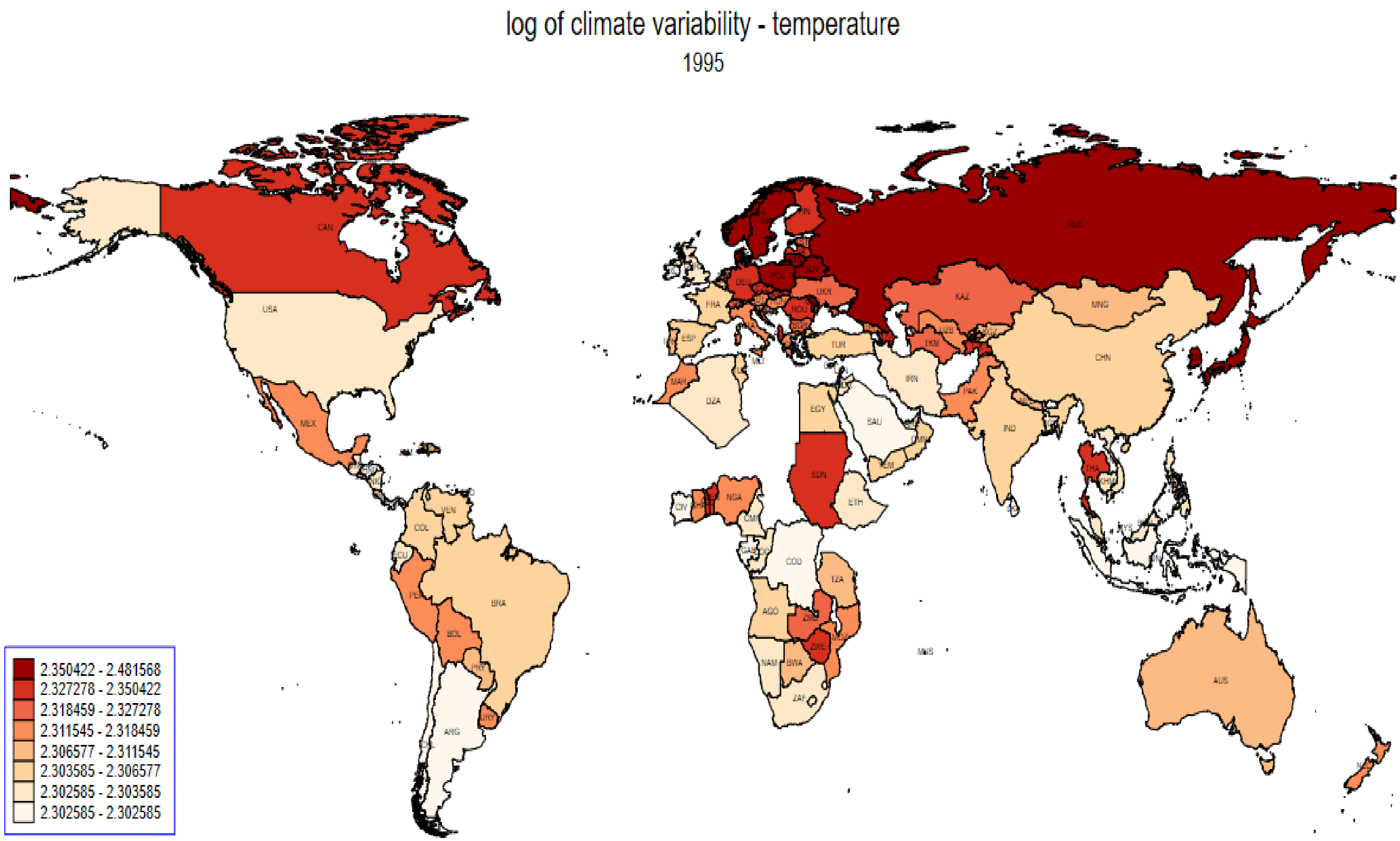

(Moran's I=0.0771 and P-value=0.0010)
Spatially lagged l_co2_intensity
-.6
-.4
-.2
0
.2
.4
-2
-1
0
1
2
l_co2_intensity
Wl_co2_intensity
Fitted values

In figure 3.4a, spatial distribution of temperature variability across the countries indicate that in the year 1995, the northern part of the world (Russia, central Asian, northern Europe and Canada) experienced more climate variability as compare to the others. The magnitude of values is the square deviation of temperature variables from long run mean. As we look into the temporal pattern temperature variability becomes more pronounced in countries located near equator (Middle East, south Asia), parts of Europe, USA and Mexico.

In figure 3.4b, indicates that in the year 1995, Latin American economies, parts of Europe and East Asian economies experienced greater rainfall variability as compare to other regions. However, the magnitude of rainfall variability increased for South Asia in 2018. East Asia and parts of Europe also experienced greater rainfall variability.

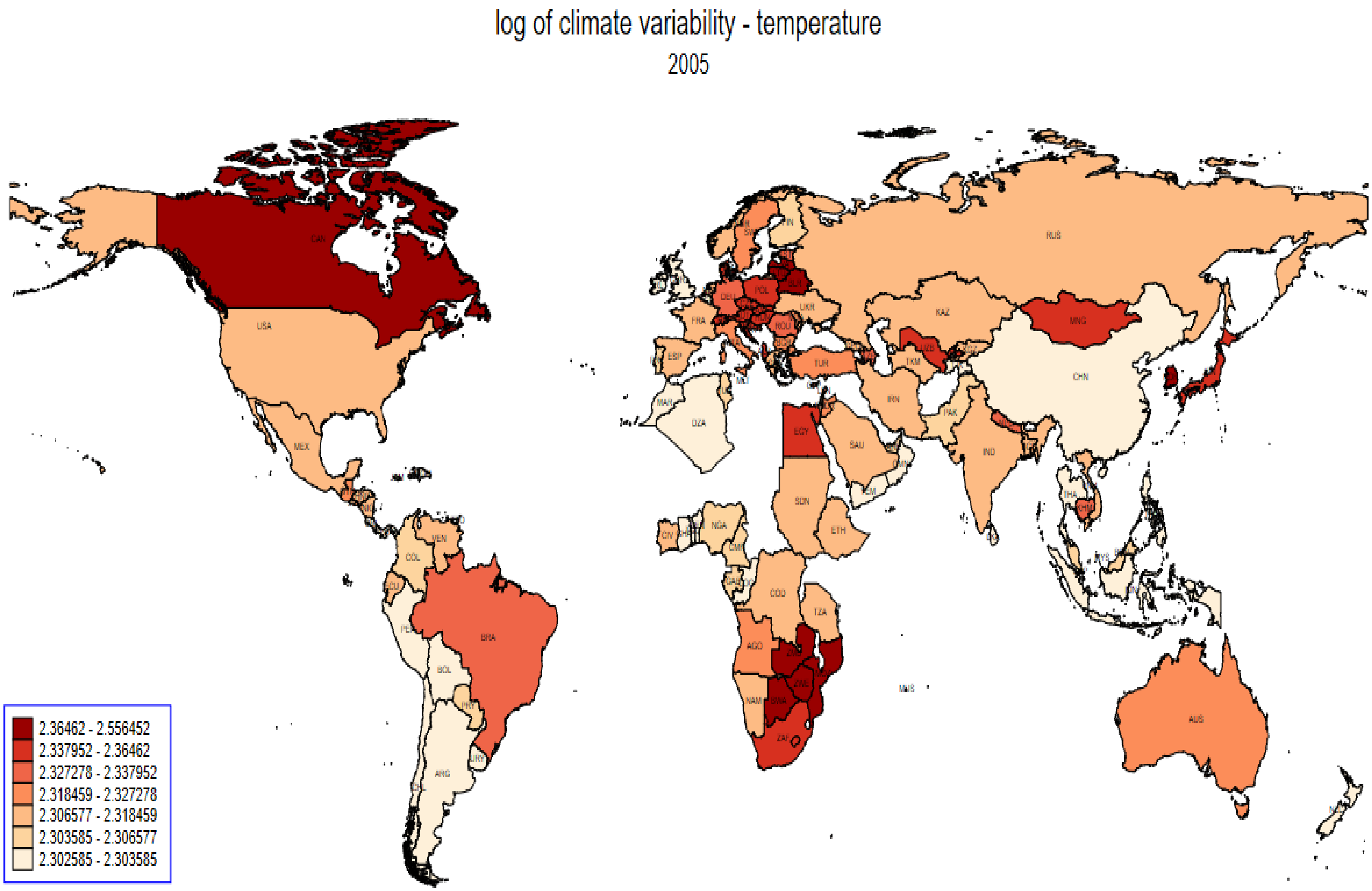
Figure 3.4c, depicts that CO_2 emission intensities of China, Australia, parts of Europe and some of the Middle East countries had high carbon intensities owing to their reliance on fossil fuel to produce electricity. In 2018, India's carbon intensity increased while some European economies CO_2 emission intensities decreased.

Figure 3.4a: Spatial Distribution of Climate Variability – Temperature (1995)



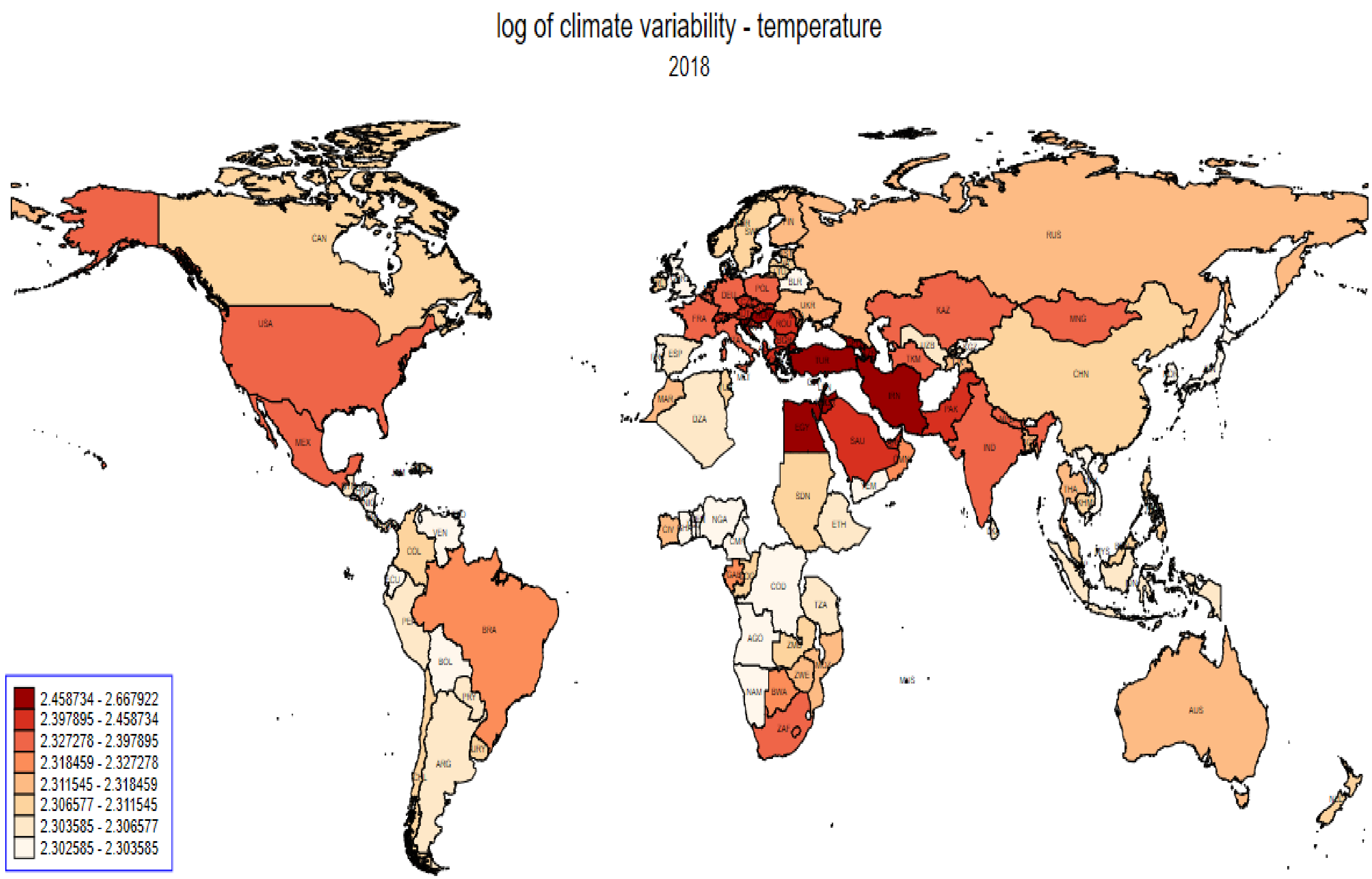
Source: Author's work from Climate Research Unit Database

Figure 3.4b: Spatial Distribution of Climate Variability – Temperature (2005)



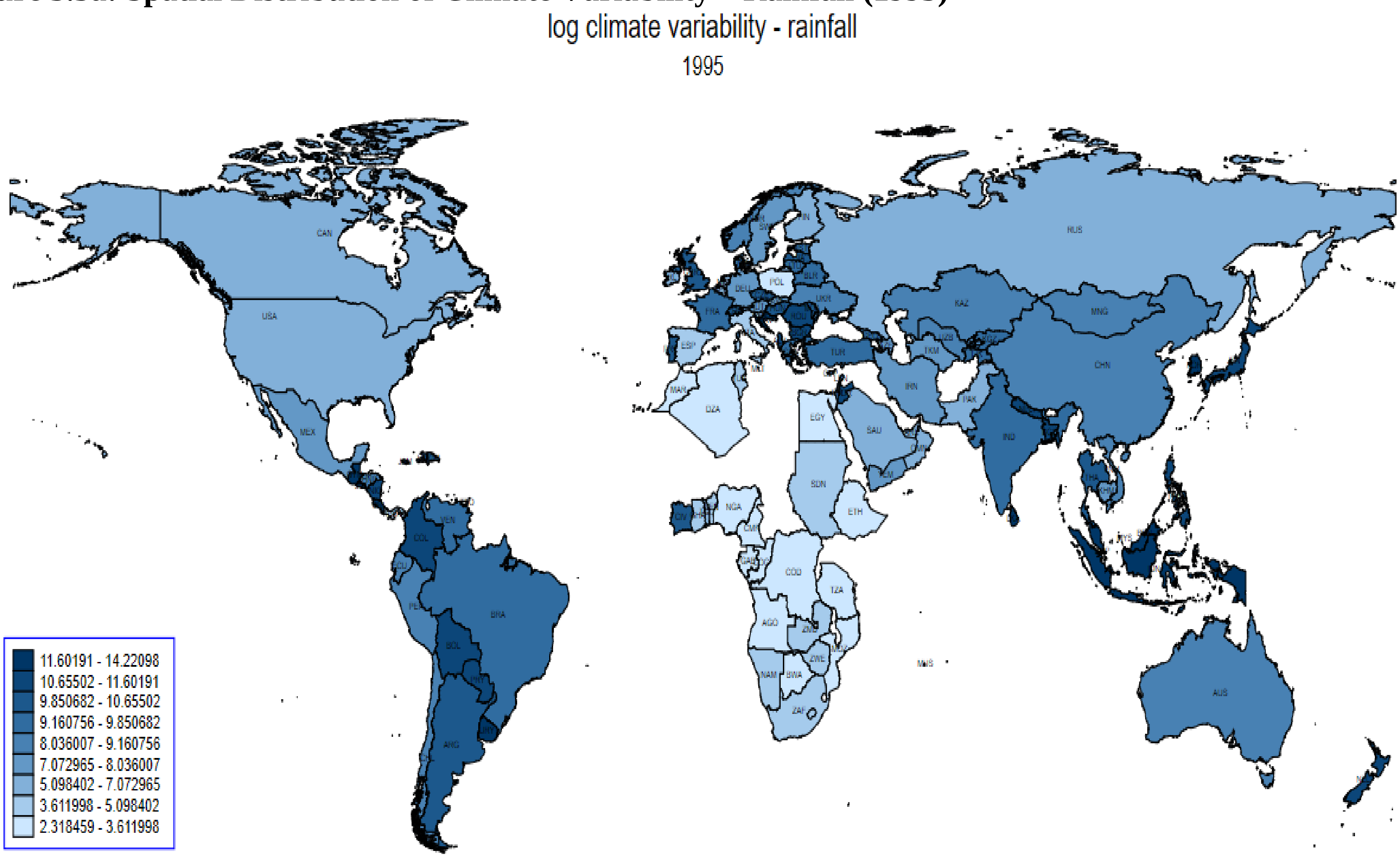
Source: Author's work from Climate Research Unit Database

Figure 3.4c: Spatial Distribution of Climate Variability – Temperature (2018)



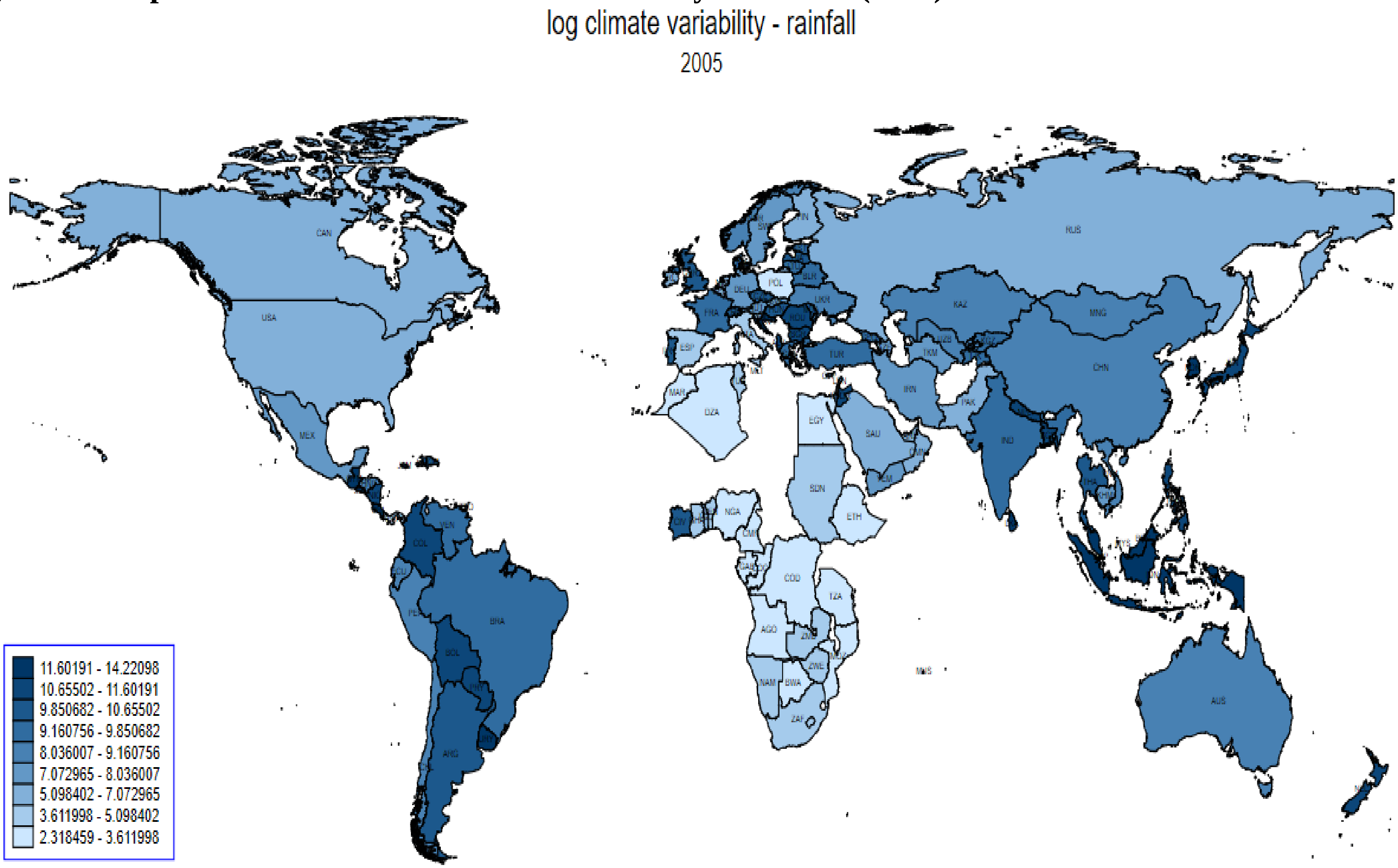
Source: Author's work from Climate Research Unit Database

Figure 3.5a: Spatial Distribution of Climate Variability – Rainfall (1995)



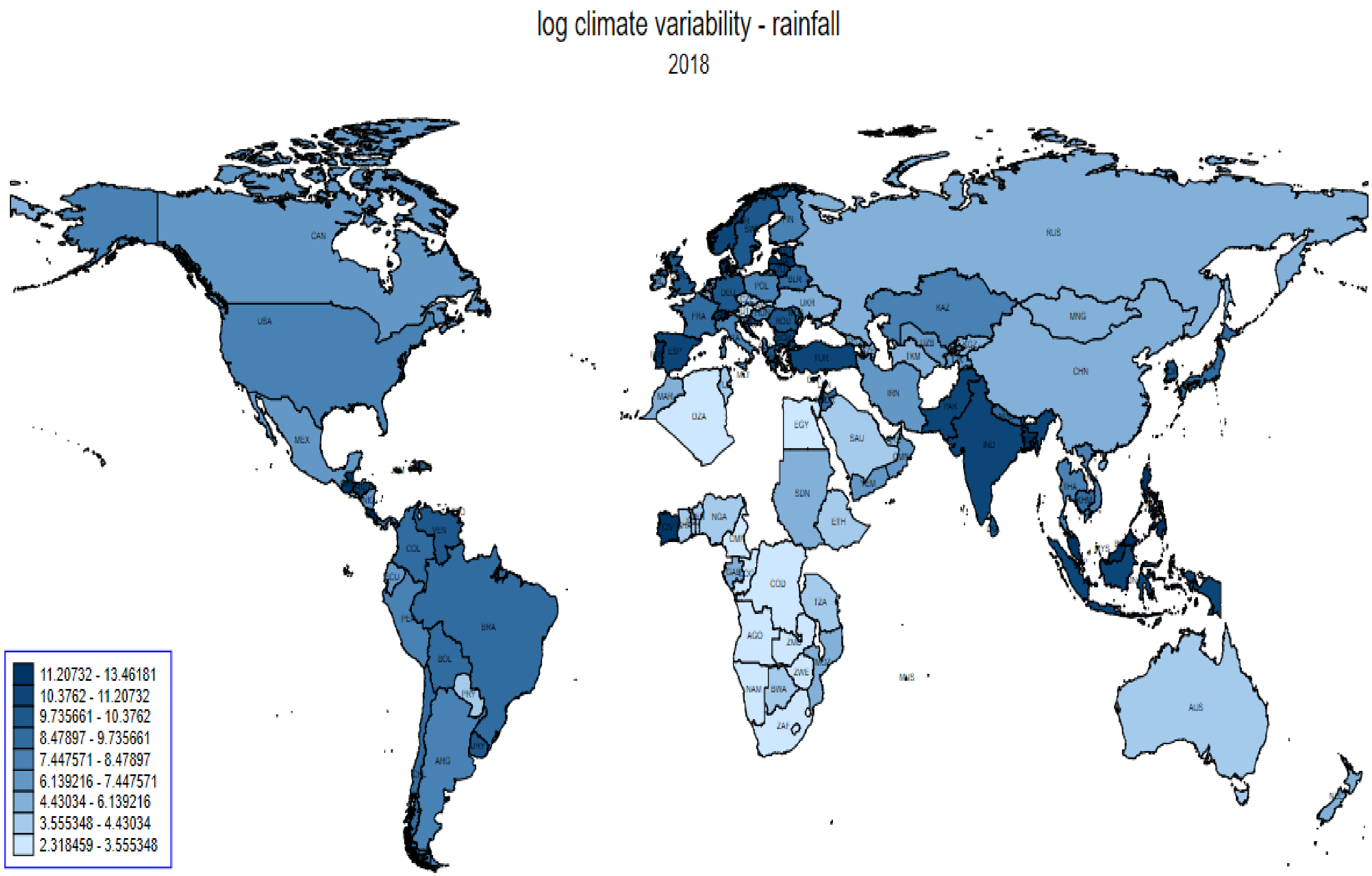
Source: Author's work from Climate Research Unit Database

Figure 3.5b: Spatial Distribution of Climate Variability – Rainfall (2005)



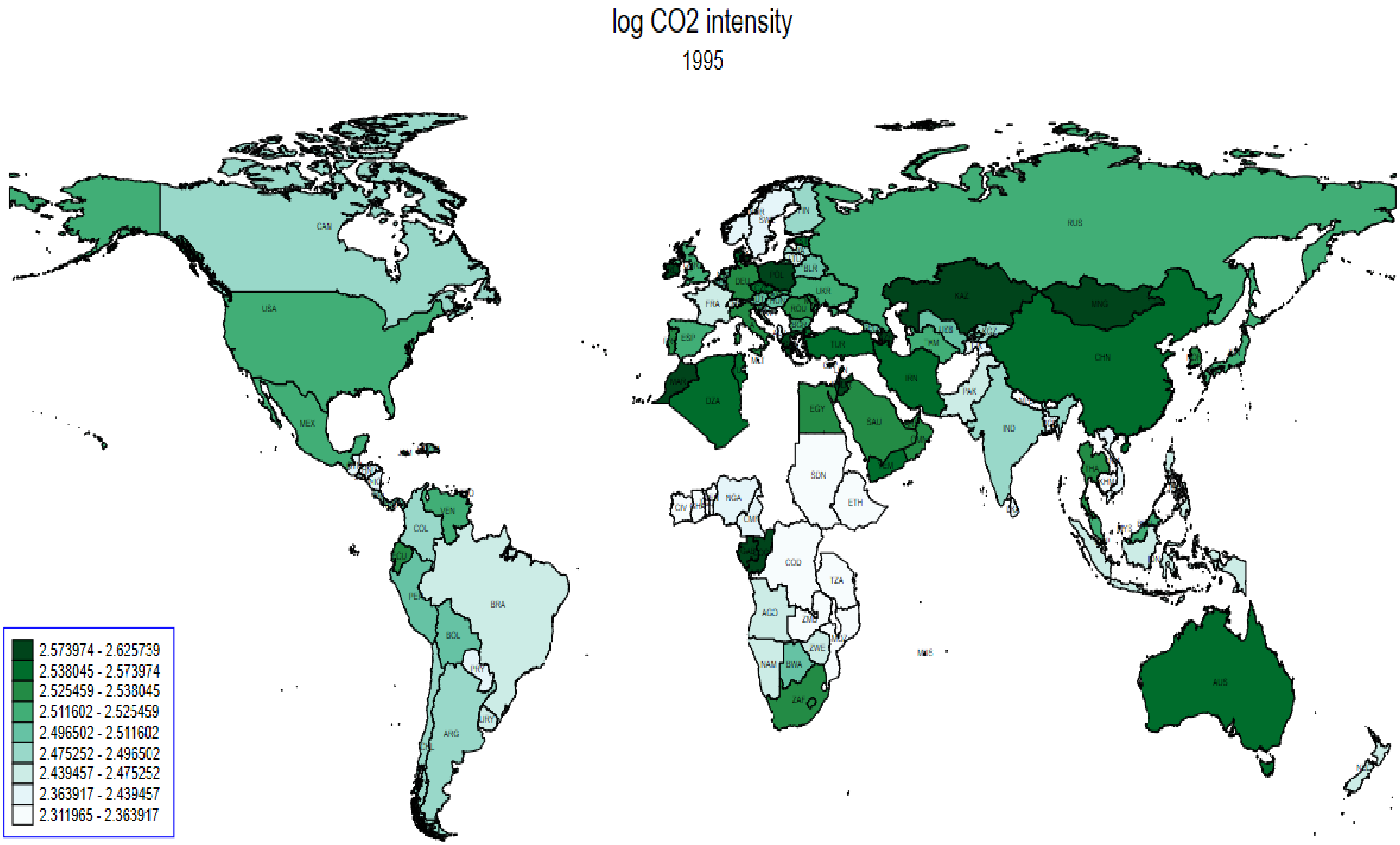
Source: Author's work from Climate Research Unit Database

Figure 3.5c: Spatial Distribution of Climate Variability – Rainfall (2018)



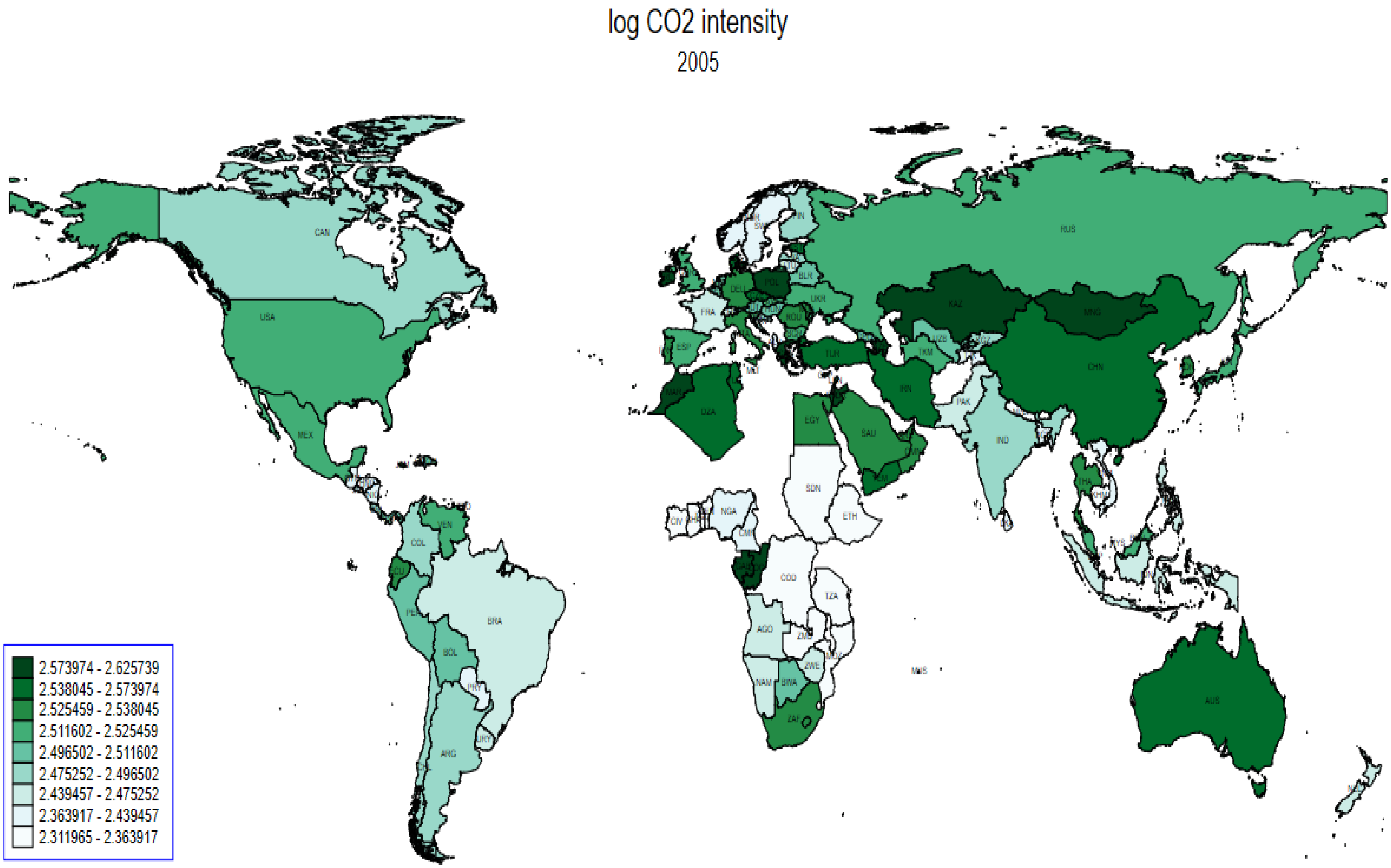
Source: Author's work from Climate Research Unit Database

Figure 3.6a: Spatial Distribution of CO_2 Intensity (1995)



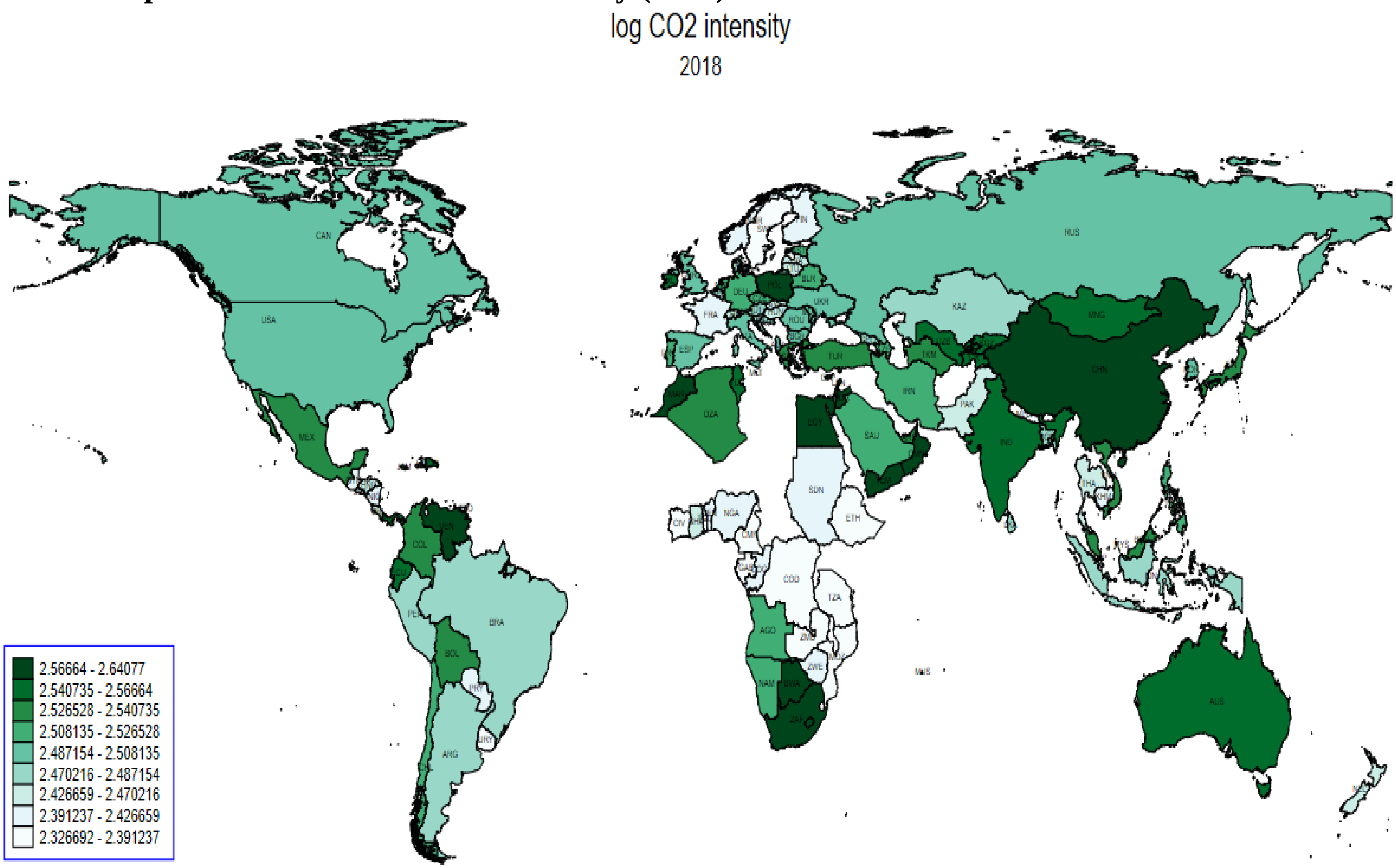
Source: Author's work from World Development Indicators, World Bank

Figure 3.6a: Spatial Distribution of CO_2 Intensity (2005)



Source: Author's work from World Development Indicators, World Bank

Figure 3.6a: Spatial Distribution of CO_2 Intensity (2018)



Source: Author's work from World Development Indicators, World Bank

3.6.2 Cross-Sectional Dependence Test

We have also tested the cross-sectional dependence of variables through the cross-sectional dependence test (CD). This test was conducted to further examine the presence of dependence across countries without considering the spatial weight matrix. All the variables included rejecting the null hypothesis of no cross-sectional dependence at 1% and 5 % significance levels.

Table 3.2: Cross-Sectional Dependence Test

Variables	CD test
CV_{temp}	60.85***
CV_{rain}	3.12**
CO_2	-2.24**
GDP_{pc}	283.50
GDP_{pc}^2	283.57
EI	156.21
$TRADE$	113.59
IND	44.16
POP	231.23
URP	217.07

Notes: Under the null hypothesis of cross-section independence, CD ~ N (0, 1). ***, **, * indicates the significance level at 1%, 5% and 10% respectively. All variables are taken in log form

3.6.3 Spatial Econometric Regression for Climate Variability

Following Elhort (2013), we first test which of the non-spatial or spatial models fits the data well. For this, we try non-spatial panel models against spatial models (spatial lag and spatial error models). The LM diagnostics test, i.e., LM lag and LM error test in case of temperature variability, rainfall variability, and carbon intensity, significantly reject the presence of no spatial lagged dependent variable and rejects the null hypothesis of no spatial auto correlated error term (see Table; 3.4). Robust LM lag and Robust LM error test have been employed to strengthen our estimates further. The robust LM test indicates that the spatial lag model is preferable in the case of temperature variability as it rejects the presence of no spatial lag-dependent variable. In contrast, both hypotheses are rejected for rainfall variability, but the robust LM error test value is higher than the LM lag. Therefore, the study concludes that SEM is best suited for rainfall variability.

For CO_2 intensity, LM robust test rejects null of no spatial auto correlated error term; therefore, the study concludes that the spatial error model fits the data. The diagnostic test reveals spatial effects in the data, as highlighted by the Moran-I test.

Estimation results of non-spatial panel models are shown in Table 3.3. Alternative model specifications, such as pooled OLS, fixed effect, and random effect models, are presented. The model specification (1) – (9) Hausman test suggests a fixed effect model. The key determinants for temperature variability are; GDP per capita, its square term, energy intensity, industrialization, trade openness, total population, and urban population. For rainfall variability, results indicate no significant determinants. For carbon intensity, GDP per capita, its square term, energy intensity, trade openness, total population, and urban population are the prime factors affecting carbon intensity in the fixed effect model setting.

Table 3.3: Estimation Results of the Non-Spatial Panel Model

Variables	Temperature variability			Rainfall variability			CO_2 intensity		
	Pooled OLS (1)	**Fixed effect (2)**	**Random effect (3)**	**Pooled OLS (1)**	**Fixed effect (2)**	**Random effect (3)**	**Pooled OLS (7)**	**Fixed effect (8)**	**Random effect (9)**
GDP_{pc}	0.0473***	0.145***	0.0884***	3.663***	0.819	1.178	0.250***	0.201***	0.202***
	(4.53)	(4.91)	(4.61)	(6.84)	(0.79)	(1.24)	(24.76)	(16.81)	(17.34)
GDP_{pc}^2	-0.00216***	-0.00727***	-0.00439***	-0.185***	-0.0229	-0.045	-0.0136***	-0.0117***	-0.0116***
	(-3.79)	(-4.42)	(-4.19)	(-6.36)	(-0.39)	(-0.86)	(-24.60)	(-17.49)	(-17.82)
EI	0.0417***	0.0898***	0.0596***	-1.616***	0.9	0.614	-0.00246	0.0136*	0.0176**
	(8.85)	(6.47)	(7.17)	(-6.70)	(1.84)	(1.46)	(-0.54)	(2.41)	(3.29)
$TRADE$	-0.001	-0.0143**	-0.00792*	0.736***	0.0373	0.0387	0.00605*	-0.0102***	-0.0106***
	(-0.39)	(-3.24)	(-2.18)	(5.6)	(0.24)	(0.26)	(2.44)	(-5.70)	(-5.98)
IND	-0.0260***	-0.0210*	-0.0218**	-2.035***	-0.39	-0.5	0.0206***	0.00239	0.00344
	(-6.09)	(-2.40)	(-3.19)	(-9.31)	(-1.26)	(-1.69)	(4.98)	(0.670	(0.98)
POP	-0.00066	0.0555***	0.000489	-0.0222	-0.383	-0.225	0.00322***	-0.00828*	-0.00567**
	(-0.88)	(6.74)	(0.32)	(-0.58)	(-1.32)	(-1.86)	(4.44)	(-2.48)	(-2.59)
URP	0.000156	-0.0780***	-0.00327	-0.619*	-0.0342	-0.189	0.0251***	0.0517***	0.0474***
	(0.030)	(-3.65)	(-0.32)	(-2.24)	(-0.05)	(-0.33)	(4.81)	(5.96)	(6.25)
intercept	2.084***	0.944***	1.859***	2.103	7.611	5.445	1.111***	1.561***	1.502***
	(43.68)	(6.08)	(20.94)	(0.86)	(1.39)	(1.19)	(24.05)	(24.8)	(25.75)

Note: t-statistics in parentheses and ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

Table 3.4: Spatial Diagnostics

	Temperature variability	Rainfall variability	Carbon intensity
Spatial error model			
Moran-I	14.97***	17.11***	7.89***
Lagrange multiplier	94.50***	125.90***	22.83***
Robust Lagrange multiplier	0.487	5.29**	3.32*
Spatial lag model			
Lagrange multiplier	119.32***	124.78***	19.54***
Robust Lagrange multiplier	25.31***	4.18**	0.04

Note: ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

As the non-spatial panel model is rejected in the presence of spatial panel models in all three cases considered, the study chooses between alternative spatial panel models that best describe the data. We first estimate the spatial Durbin fixed (SDM-FE) and random effect model (SDM-RE) for temperature variability, rainfall variability, and carbon intensity. Hausman test is employed to choose between fixed and random effect models. Results show that SDM-FE is more applicable in temperature variability, carbon intensity, and rainfall variability at 1% and 10 % significant levels, respectively (see Table 3.5a).

To test whether SDM best represents our data, we further test two hypotheses to identify if SDM can be reduced to SLM or SEM. The study employs the LR test to conclude whether SDM can be reduced to SLM in all three cases. Further Wald test is applied to test if SDM can be simplified to SEM.

In the case of temperature variability, the hypothesis that SDM can be simplified to SLM is significantly rejected at a 1 percent level of significance (LR; 42.13, p-value = 0.000), while the hypothesis that SDM can be reduced to SEM is also rejected at 1 percent (Wald; 60.70 p=0.000). Thus, in the case of temperature variability, the SDM is more applicable.

In the case of rainfall variability, the LR test (LR; 13.79; p-value 0.0550) rejects the null hypothesis that SDM can be simplified to SLM at a 10% significance level. Wald test (Wald; 13.26, p; 0.0661) also rejects the null hypothesis that SDM can be reduced to SEM. Thus, in the case of rainfall variability, we estimate SDM.

In the case of carbon intensity, LR (LR; 108.23, p-value 0.000) and Wald tests (Wald; 68.78; p-value 0.000) reject the hypothesis that SDM can be reduced to SLM or SEM. Thus, in the case of carbon intensity, we estimate SDM. In the case of climate variability, SDM-FE results are shown in Table 3.5a; energy intensity, industrialization, population, and urbanization are the vital spatial drivers of temperature variability. Energy intensity shows a positive spillover effect on neighboring countries. As energy intensity increases across nearby countries, temperature variability in the domestic country increases by 0.4 percent.

The spatial autocorrelation coefficient ρ shows positive and statistical significance at a 1 percent significance level. Thus, if a country is surrounded by neighboring countries experiencing an increased temperature variability, it positively affects its temperature variability. The country's per capita income raises temperature variability by 0.2 percent. Economic development, as measured by GDP per capita, shows a positive coefficient indicating a better standard of living comes at the cost of increased temperature variability. The negative square term of GDP per capita is in line with the inverted Environment Kuznets Curve (EKC), but its coefficient is statistically insignificant in SDM-FE but significant in SDM-RE. These results are consistent with the literature on the nexus between environmental degradation factors such as CO_2 emissions (Rafiq et al., 2016; Yang et al., 2018; Lin et al., 2017; Ma et al., 2017; Salim et al., 2017; Ghazali & Ali, 2019), sulfur dioxide (Wang et al., 2016), PM2.5 (Hao & Liu, 2016) and economic development.

A positive relationship exists between temperature variability and energy intensity. As energy intensity increase by 1 unit, temperature variability increases by 0.1 percent. Industrialization increases energy consumption, which further leads to increased temperature variability. Cole and Neumayer (2004) found a positive relationship between energy intensity and CO_2 emission for 86 countries over 24 years. Rafiq et al. (2016) and Sadorsky (2014) also found a positive relationship between CO_2 emission and energy intensity.

The study found a negative relationship between industrial value-added and temperature variability. One-unit increase in industrialization value-added of the GDP decreases temperature variability by 0.06 percent in selected countries considered in the analysis. These results highlight that the industrial value-added percent of the GDP doesn't augment temperature variability similarly to carbon emission. Instead, it tends to decrease temperature variability. This might be the case that industrialization affects average temperature through carbon emissions but a change in temperature variability decrease from its long-run average of 30 years. Another possible reason for the decline in the pace of variability is the period considered in the analysis, i.e., 1991 to 2018, in which major international organizations came up with emission reduction agreements. Industrialization based on renewable energy resources picked momentum in this era. The fall in the pace of variability is due to the stringent measures adopted globally to contain temperatures below 1.5 degrees Celsius.

The total population has a significant positive relationship with temperature variability. One percent increase in total population increases temperature variability by 0.1 percent. An increase in population increases pressure on existing natural resources and industrial, residential, and transportation energy consumption. An increase in population also exacerbates the demand for other resources (Roy et al., 2017). More exploitation leads to more variability in environmental factors, such as temperature variability.

Urbanization decreases the pace of temperature variability by 0.2 percent as more urbanized societies lead to efficient use of resources in the form of resource sharing in transportation, house buildings, and urban planning. Besides this, when society shifts from rural to urban areas, household income and overall standard of living increase. With a better sense of utilization of resources, environmental regulations, and awareness of environmental policies, changes in temperature variability tend to decrease. Sharma (2010) estimated the relationship between urbanization and CO_2 emission for a global panel of 69 countries and found a negative relationship between urbanization and CO_2 emissions.

The coefficients of the SDM model don't represent marginal effects. They include the country's explanatory variable effect, feedback from neighboring countries, and its repercussions on individual countries. This can be examined as SDM coefficients differ from the direct effect coefficients. For example, the GDP per capita coefficient in the SDM model is 0.28, while the coefficient of direct effect is 0.33, showing a feedback effect of 0.05. Therefore, the study examines the direct, indirect, and total impact of drivers of temperature variability.

Energy intensity, total population, and urban population are the critical spatial determinants of temperature variability for spillover effects. Countries surrounded by neighbors with high energy intensity tend to increase domestic countries' climate variability. The indirect impact of the energy intensity coefficient is more elevated than the direct, indicating a more significant spillover effect of the neighboring country's energy intensity on climate variability. Countries with high populations also exert a positive spillover effect on the climate variability of nearby locations. An increase in the population size of neighboring countries increases the exploitation of natural resources, leading to increased energy consumption. Thus, the domestic country's climate variability increases. Urbanization decreases temperature variability in the domestic country; if urbanized economies surround a country, it also reduces temperature variability.

The key spatial determinant is rainfall variability in the model (3), GDP per capita, and energy intensity. The spatial auto correlated parameter is significant at a 1 percent level, indicating that it will increase the rainfall variability of the domestic country. A country's GDP per capita and energy intensity increase its rainfall variability. All other variables, such as industrialization, trade, population, and urban population, are insignificant in the case of rainfall variability. For spillover and indirect effects, an increase in trade liberation of nearby countries increases rainfall variability in the domestic country. All other variables considered are insignificant in determining rainfall variability.

In the case of model 5, the dependent variable is carbon intensity is spatially driven by GDP per capita, its square term, trade liberalization, population, and urban population.

Energy intensity shows a positive spillover effect on nearby countries' carbon intensity for the indirect effect. As energy intensity increases, countries move to more fossil fuel-driven production, further exacerbating neighboring countries' carbon intensity. The spatial auto correlated parameter is significant at a 1 percent level, indicating that carbon intensity increases as the carbon intensity of neighboring counties increases. GDP per capita and its square term satisfy the inverted U EKC. Energy intensity has an insignificant relationship with carbon intensity; however, it has a significant and robust spillover effect on neighboring county energy emissions. As nearby countries' energy intensity increases, domestic countries' carbon intensity also increases. This is due to the reason that carbon emissions are homogenously distributed irrespective of the country emitting them. If neighboring countries have polluting industries that use fossil fuels, this will affect the environmental quality of an individual country.

Table 3.5a: Estimation Results of Spatial Durbin Model with Alternative Dependent Variables

Variable	SDM fixed effect (1)	SDM random effect (2)	SDM fixed effect (3)	SDM random effect (4)	SDM fixed effect (5)	SDM random effect (6)
	Temperature variability		**Rainfall variability**		CO_2 **intensity**	
ρ	0.934*** (80.19)	0.932*** (78.54)	0.215*** (10.51)	0.614*** (11.64)	0.410** (5.73)	0.430*** (6.16)
GDP_{pc}	0.283** (2.1)	0.221*** (2.61)	2.266* (1.85)	2.211** (2.09)	0.160** (11.81)	0.170*** (12.97)
GDP_{pc}^2	-0.01 (-1.22)	-0.011** (-2.27)	-0.086 (-1.17)	-0.096 (-1.59)	-0.009** (-10.66)	-0.009*** (-12.33)
EI	0.131*** (4.8)	0.084*** (4.83)	0.585** (2.46)	0.269 (1.24)	-0.007 (-1.20)	-0.009 (-1.56)
$TRADE$	0.010 (0.57)	-0.006 (-0.37)	-0.17 (-1.11)	-0.112 (-0.73)	-0.006** (-3.00)	-0.006** (-3.00)
IND	-0.063** (-2.26)	-0.052** (-2.32)	-0.342 (-1.40)	-0.465** (-1.96)	-0.005 (-1.33)	-0.003 (-0.81)
POP	0.145** (2.35)	-7.7E-05 (-0.01)	0.394 (0.74)	-0.208 (-1.46)	0.011* (1.95)	0.002 (0.56)
URP	-0.231*** (-3.09)	-0.031 (-0.76)	-0.39 (-0.57)	-0.551 (-1.01)	0.061** (6.87)	0.061*** (7.36)
$W * GDP_{pc}$	0.056 (0.08)	1.268** (2.3)	-3.018* (-1.74)	-3.789 (-0.63)	0.090 (0.12)	-0.012 (-0.17)
$W * GDP_{pc}^2$	0.0124 (0.3)	-0.069** (-2.23)	0.145 (1.42)	0.179 (0.53)	0.002 (0.4)	0.003 (0.75)
$W * EI$	0.455*** (2.87)	0.369*** (5.4)	-0.257 (-0.64)	0.013 (0.01)	0.214** (5.88)	0.216*** (6.87)
$W * TRADE$	-0.024 (-0.41)	0.072 (1.5)	0.464** (2.13)	0.569 (1.17)	0.008 (1.26)	0.008 (1.15)
W*IND	-0.21 (-1.22)	-0.457*** (-3.23)	-0.144 (-0.35)	0.028 (0.02)	-0.036 (-1.64)	-0.033 (-1.56)
W*POP	1.242*** (4.54)	0.135*** (3.1)	-0.774 (-1.28)	-0.244 (-0.32)	-0.013 (-0.51)	0.028** (2.02)
W*URP	-2.255*** (-4.31)	0.164 (0.8)	0.376 (0.35)	1.749 (0.67)	-0.029 (-0.45)	-0.095** (-2.05)
log L	384.72		-6643.60		8166.77	
Hausman	21.71 (0.003)		12.95 (0.073)		115.82 (0.0000)	

Note: All variables are in log form. t-statistics in parentheses. * P-Value < 0.10, ** P-Value < 0.05, *** P-Value < 0.01

Table 3.5b: Spatial Direct, Indirect and Total Effect of the SDM Model

Variables	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
Dependent variable	**Temperature variability**			**Rainfall variability**			CO_2 **intensity**		
GDP_{pc}	0.330**	4.502	4.832	2.165*	-3.161	-0.996	0.161***	0.121	0.282**
	(2.22)	(0.45)	(0.48)	(1.76)	(-1.63)	(-0.51)	(11.80)	(1.06)	(-2.52)
GDP_{pc}^2	-0.010	0.081	0.071	-0.082	0.162	0.08	-0.009***	-0.003	-0.011*
	(-1.05)	(0.13)	(0.12)	(-1.11)	(1.42)	(0.71)	(-10.59)	(-0.44)	(-1.81)
EI	0.215***	9.001***	9.216***	0.596***	-0.131	0.465	-0.004	0.359***	0.355***
	(6.04)	(3.31)	(3.36)	(2.64)	(-0.28)	(0.89)	(-0.72)	(5.48)	(5.42)
$TRADE$	0.007	-0.253	-0.246	-0.15	0.516**	0.366	-0.006***	0.010	0.004
	(0.68)	(-0.30)	(-0.29)	(-1.03)	(2.07)	(1.46)	(-3.08)	(0.90)	(0.38)
IND	-0.100***	-4.032	-4.132	-0.352	-0.237	-0.588	-0.005	-0.063	-0.069*
	(-2.62)	(-1.50)	(-1.52)	(-1.52)	(-0.47)	(-1.03)	(-1.52)	(-1.63)	(-1.74)
POP	0.338***	20.84***	21.18***	0.375	-0.876	-0.501	0.0112**	-0.017	-0.006
	(5.07)	(3.89)	(3.93)	(0.75)	(-1.49)	(-0.98)	(2.05)	(-0.41)	(-0.14)
URP	-0.575***	-37.37***	-37.94***	-0.38	0.414	0.034	0.061***	-0.005	0.056
	(-5.07)	(-3.66)	(-3.69)	(-0.56)	(0.33)	(0.03)	(6.83)	(-0.04)	(0.52)

Note: ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

3.6.4 Spatial Econometric Regression Results for Climate

Following Tol (2021) study considers climate as the thirty-year average of climatic variables such as temperature and rainfall. We have averaged 30 years (1989-2018) for 114 countries worldwide for climate analysis. This section measures the spatial determinants of climate. To measure the presence of spatial dependence in our data, we analyzed the Moran I test statistic. For climate analysis, binary maritime borders[31] weight matrix is used. All the key-dependent and related covariates are tested for spatial dependence. Results of the univariate Moran-I test are shown in Table 3.6. Annual thirty-year average temperature and rainfall have positive and statistically significant spatial dependence. Thus, countries that experience high temperatures are surrounded by neighbors who are also experiencing warming. For other explanatory variables, results show the presence of spatial autocorrelation in the data.

Table 3.6: Results of Univariate Moran I Test

Variables	Moran Statistics
$CLIMATE_{temp}$	74.16***
$CLIMATE_{rain}$	91.34***
CO_2	26.87***
GDP_{pc}	54.95***
GDP_{pc}^2	55.84***
$POPD$	39.00***
$TRADE$	3.45*
IND	24.17***

Note: All variables are taken in log form. * P-value < 0.10, ** P-value < 0.05, *** P-value < 0.01

For spatial regression, we have analyzed the drivers of climate by using alternate models such as spatial autoregressive (SAR), spatial error (SEM), and spatial lag of explanatory variables (SLX). The SAR model shows the presence of spatial autocorrelation as the ρ is positive and statistically significant, indicating that the increase in the temperature of neighboring countries has repercussions for increasing the temperature of individual countries. Population density, trade, and industrialization are key spatial determinants of climate led by temperature. GDP per capita and its square terms are in line with EKC but

[31] We have constructed the weight matrix of 114 countries that share common border land or maritime. We have used maritime borders of those countries that have no land border.

remained insignificant in the case of climate. Population density is positively associated with an increase in temperature. One unit increase in population density across countries increases temperature change by 0.07. These results are consistent with earlier literature by Rahman (2017); Sapkota and Bastola (2017). Trade liberalizations tend to decrease the pace of climate led by temperature. As countries liberalize, they tend to integrate technology and skill transfers using better technologies, and environmental quality can be improved. An increase in the value-added share of industrialization in the GDP increases temperature change by 0.2 percent. If industrial expansion is based on fossil fuels, it augments warming faster.

Table 3.7b shows the marginal effects of the SAR model. Direct effects are different from coefficients in the SAR model as direct effect encompasses the spillover effect of the spatially lagged dependent variable. In the present case of industrialization, the direct effect is 0.233, and its coefficient in the SAR model is 0.199; thus, the feedback effect for industrialization is 0.034. The indirect impact shows that an increase in the population density of nearby countries will increase the temperature in the domestic country, while trade liberalization of neighboring countries will decrease the temperature. Trade and environmental regulations are not the same across countries. Therefore, some of the polluting industries are being shifted to economies having less restrictive ecological regulations (You & Lv, 2018)

SEM results depicted in model (3) show positive and significant spatial autoregressive terms indicating that climate is affected by unknown factors and spillover effects of nearby countries. In the case of SEM, population density is the key driver of climate that increases temperature by 0.05 percent. The SLX model lag of covariates remained insignificant, indicating no spillover effects on climate.

In the case of climate-driven rainfall, the SAR model (6) indicates the presence of spatial autocorrelation as the coefficient of an autoregressive term is positive and significant. Population density increases while trade liberalization decreases the pace of climate. The indirect effect of SAR models indicates that the increase in population density of nearby countries increases temperature while countries surrounded by more liberalized countries have decreased the pace of climate-driven rainfall. For the SEM model, population density is the key determinant causing a change in average rainfall across countries. SLX model (8) shows a significant positive relationship between rainfall with GDP per capita and a negative association with its square term. Population density has a positive and significant relationship with rainfall.

For carbon intensity results of the SAR, the model depicts the presence of spatial autocorrelation as ρ is positive and statistically significant, indicating that an increase in the carbon intensity of neighboring countries has a positive spillover effect on individual countries. GDP per capita and square term are important and satisfy the EKC showing positive linear and negative nonlinear relationships between CO_2 intensity and GDP. As countries grow, they tend to move towards more environmentally friendly technologies. Industrialization drives and augments CO_2 intensity in the present case. The indirect effect shows that GDP per capita has a spillover effect on carbon intensity. SEM and SLX models consider GDP per capita and its square term an important determinant of CO_2 intensity.

Table 3.7a: Regression Results for Climate (Temperature and Rainfall) and CO_2 Intensity

Variables	OLS (1)	SAR (2)	SEM (3)	SLX (4)	OLS (5)	SAR (6)	SEM (7)	SLX (8)	OLS (9)	SAR (10)	SEM (11)	SLX (12)
	Climate (temperature)				Climate (rainfall)				carbon intensity			
GDP_{PC}	0.058	0.118	-0.035	0.042	1.656	0.575	-0.231	1.968*	0.275***	0.277***	0.259***	0.295***
	(0.14)	(0.36)	(-0.11)	(0.1)	(1.56)	(0.79)	(-0.37)	(1.85)	(5.91)	(6.35)	(5.63)	(6.56)
GDP_{pc}^2	-0.010	-0.01	-0.001	-0.005	-0.083	-0.027	0.016	-0.101*	-0.015***	-0.015***	-0.014***	-0.016***
	(-0.41)	(-0.54)	(-0.03)	(-0.19)	(-1.36)	(-0.64)	(0.45)	(-1.65)	(-5.48)	(-5.88)	(-5.21)	(-6.20)
$POPD$	0.079**	0.073***	0.054*	0.099**	0.368***	0.247***	0.167***	0.284***	0.00148	0.003	-0.001	-0.001
	(2.42)	(2.86)	(1.83)	(2.37)	(4.4)	(4.24)	(2.83)	(2.64)	(0.4)	(0.92)	(-0.33)	(-0.20)
$TRADE$	-0.0998	-0.153***	-0.0133	-0.076	-0.0325	-0.362***	-0.033	0.001	0.005	-0.007	0.006	-0.005
	(-1.39)	(-2.69)	(-0.25)	(-0.93)	(-0.18)	(-2.79)	(-0.34)	(0.01)	(0.67)	(-0.76)	(0.79)	(-0.51)
IND	0.199	0.218*	0.119	0.195	-0.362	-0.057	-0.461*	-0.516	0.024	0.031*	0.013	0.018
	(1.26)	(1.75)	(0.89)	(1.06)	(-0.89)	(-0.20)	(-1.81)	(-1.08)	(1.34)	(1.86)	(0.71)	(0.9)
intercept	2.716	1.15	2.884**	2.304	-1.881	0.427	8.203***	-2.186	1.124***	0.980***	1.236***	1.018***
	(1.64)	(0.87)	(2.2)	(1.4)	(-0.44)	(0.15)	(3.24)	(-0.51)	(6.06)	(5.4)	(6.68)	(5.66)
ρ		0.425***				0.587***				0.0611***		
		(7.39)				(10.38)				(2.84)		
Λ			0.575***				0.792***				0.336***	
			(9.51)				(17.51)				(3.54)	
$W * GDP_{pc}$				0.305				-0.41				-0.0197
				(1.18)				(-0.61)				(-0.70)
$W * GDP_{pc}^2$				-0.0242				0.0244				0.00165
				(-1.54)				(0.6)				(0.96)
$W * POPD$				-0.0172				0.214				0.00901
				(-0.31)				(1.5)				(1.49)
$W * TRADE$				-0.142				-0.404				-0.0072
				(-1.13)				(-1.24)				(-0.52)
$W * IND$				-0.039				0.658				0.0443*
				(-0.16)				(1.07)				(1.7)
Log L		-46.2	-38.75	-63.6		-140.6	121.06	171.02		184.4	185.9	186.3
Pseudo-R2		0.1	0.1	0.2		0.2	0.1	0.3		0.5	0.5	0.5
N	113	113	113	113	113	113	113	113	113	113	113	113

Note: t-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7b: Direct, Indirect and Total Effect of SAR Model on Climate (Temperature & Rainfall) and CO_2 Intensity

Dependent variable	Climate-Temperature			Climate-Rainfall			CO_2 intensity		
Variables	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
GDP_{pc}	0.127	0.078	0.204	0.669	0.716	1.384	0.278***	0.018**	0.295***
GDP_{pc}^2	-0.011	-0.007	-0.017	-0.031	-0.033	-0.064	-0.015***	-0.001**	-0.016***
$POPD$	0.078***	0.048**	0.127***	0.287***	0.307***	0.594***	0.003	0.000	0.003
$TRADE$	-0.164***	-0.101**	-0.265**	-0.421***	-0.450**	-0.871**	-0.007	0.000	-0.007
IND	0.233*	0.144	0.377*	-0.066	-0.071	-0.137	0.031*	0.002	0.033*

Note: ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

Table 3.8: Summary of Results for Direct and Indirect Effects of Climate, Climate Variability, and Carbon Intensity

Determinants	Temperature variability		Climate-Temperature		Rainfall variability		Climate-Rainfall		Carbon intensity panel		Carbon intensity cross-sectional	
	Direct	indirect	Direct	Indirect	Direct	indirect	direct	indirect	direct	indirect	direct	indirect
GDP_{pc}	**(+)	(+)	(+)	(+)	*(+)	(-)	(+)	(+)	*****(+)**	(+)	*****(+)**	*****(+)**
GDP_{pc}^2	(-)	(+)	(-)	(-)	(-)	(+)	(-)	(-)	***(-)	(-)	***(-)	***(-)
EI	***(+)	***(+)	Not included		***(+)	(-)	Not included		(-)	***(+)	Not included	
IND	***(-)	(-)	*(+)	(+)	(-)	(-)	(-)	(-)	(-)	(-)	(+)	(+)
$TRADE$	(+)	(-)	***(-)	**(-)	(-)	**(+)	***(-)	**(-)	***(-)	(+)	(-)	(+)
POP	***(+)	***(+)	Not included		(+)	(-)	Not included		**(+)	(-)	Not included	
URP	***(-)	***(-)	Not included		(-)	(+)	Not included		***(+)	(-)	Not included	
$POPD$			***(+)	***(+)			***(+)	***(+)			(+)	(+)

Source: Author's work

3.6.5 Spatial Econometric Regression Results for Climate Change

In the present section, we have calculated climate change by taking the square deviation of thirty years' annual temperature and rainfall from their respective long-run mean (1961-90). Cross sectional data from 114 countries are used. We have tested for the presence of spatial relationship by the univariate Moran I test. Results indicate the presence of a spatial relationship. To gauge the driving factors of climate change and their spillover effects, we have tested for alternative model specifications in spatial settings by employing spatial autoregressive (SAR), spatial error (SEM), and spatial lag of explanatory variables (SLX). We have employed SBC/AIC criteria to choose between alternative model specifications. Results for temperature change indicate the absence of significant spatial relationship indicating the heterogeneous nature of climate change across countries considered in the analysis. The SEM model shows a spatial error relationship with the average error of nearby countries. All other variables included in the analysis are insignificant in explaining temperature change.

In the case of rainfall change, the SAR model shows the presence of spatial autocorrelation as the ρ is positive and statistically significant, indicating that the increase in the rainfall of neighboring countries has repercussions for increasing the rainfall of individual countries. GDP_{pc} and its square term is the key spatial determinant of climate change led by temperature. GDP_{pc} and its square terms are in line with EKC. SEM also indicates that spatial relationship is due to neighboring countries' errors or unobserved factors.

In the case of rainfall change, SAR model, we found a positive and statistically significant ρ value which shows that increased rainfall change has a positive spillover effect on nearby locations. GDP_{pc} and its square term is in with the EKC showing that economic activity initially amplifies change, but this relationship tends to decay at a higher level of GDP_{pc}. In the case of SEM, the positive and significant spatial autoregressive term indicates that climate is affected by unknown factors, and spillover effects of a nearby country's population density and industrialization are the key determinants of rainfall change. SLX model reveals GDP_{pc}, and its square term, a population density determines changes in rainfall. Also, trade openness has a spillover effect in decreasing rainfall change. For choosing between models, we applied the SBC/AIC criteria results, suggesting SEM is the best fit in the case of rainfall variability.

Table 3.9: Regression Results for Climate Change (Temperature and Rainfall)

Variables	OLS(1)	SAR(2)	SEM(3)	SLX(4)	OLS(5)	SAR(6)	SEM(7)	SLX(8)
	Temperature Change				Rainfall Change			
GDP_{PC}	-0.012	-0.0114	-0.012	-0.019	7.018**	4.295*	2.981	7.367**
	(-0.87)	(-0.89)	(-0.90)	(-1.43)	(3.15)	(2.32)	(1.48)	(3.28)
GDP_{pc}^2	0.001	0.001	0.001	0.001	-0.386**	-0.234*	-0.151	-0.397**
	(1.16)	(1.18)	(1.12)	(1.53)	(-3.02)	(-2.21)	(-1.31)	(-3.08)
IND	-0.011	-0.010	0.008	-0.003	-1.722	-1.474	-3.140**	-2.123
	(-1.58)	(-1.50)	(1.08)	(-0.38)	(-1.43)	(-1.51)	(-2.89)	(-1.57)
$TRADE$	0.0002	0.0003	0.004	0.002	-0.0281	0.208	0.615	0.402
	(0.07)	(0.07)	(0.92)	(0.58)	(-0.04)	(0.39)	(1.1)	(0.59)
$POPD$	(-0.001)	-0.001	-0.002	-0.001	1.101***	0.764***	0.633**	0.875**
	(-0.98)	(-0.92)	(-0.95)	(-0.57)	(4.85)	(4.00)	(2.71)	(3.05)
intercept	2.390***	2.379***	2.369***	2.387***	-22.19*	-14.02	-0.492	-24.84**
	(44.77)	(42.67)	(43.75)	(45.74)	(-2.45)	(-1.89)	(-0.06)	(-2.77)
ρ		0.003				0.472***		
		(0.54)				(6.59)		
Λ			0.333**				0.560***	
			(2.94)				(7.5)	
$W * GDP_{pc}$				0.0118				-0.583
				(1.18)				(-0.34)
$W * GDP_{pc}^2$				-0.00045				0.024
				(-0.75)				(0.23)
$W * IND$				-0.00724				2.481
				(-0.72)				(1.43)
$W * TRADE$				-0.00903				-1.771*
				(-1.81)				(-2.07)
$W * POPD$				-0.000				0.603
				(-0.01)				(1.59)
Log L		325.13	323.04	330.02		-243.7	-242.54	-256.55
Pseudo R^2		0.147	0.134	0.22		0.28	0.21	0.31
N	114	114	114	114	114	114	114	114

Source: Author's work.

3.6.6 Spatial Econometric Regression Results across regions-Temperature Variability

The results of the regional analysis are depicted in table 3.10. In the case of region 1, that is, Europe and the Asia Pacific, the spatial correlation coefficient indicates the positive and statistically significant relationship between the temperature variability of a country to its nearby locations. As the coefficient of SDM–FE and SDM–RE represents the variable explanatory effect, feedback effect, and its repercussions on a country, marginal effects are calculated by our explanatory variable's direct, indirect, and total effect. The relationship between GDP_{pc} and its square term in both the regions satisfies the EKC, which indicates that initially, GDP_{pc} in the country increase, but after a certain period, a rise in GDP_{pc} tends to reduce temperature variability.

In the case of Europe, energy intensity has a direct positive relationship with temperature variability, indicating that high energy use exacerbates temperature variability. In contrast, in the case of region-2, the Asia Pacific increase in energy intensity tends to decrease temperature variability. The results indicate that the type (quality) of primary energy used to produce goods matters instead of the amount of energy used. Trade openness increases temperature variability in the case of Europe, while in the Asia Pacific, it tends to decrease it. European countries trade in high energy-intensive products like machinery, cars, and electrical equipment, while the Asia Pacific is mostly part of the global value chain and an important destination for foreign firms that transfer advanced knowledge and techniques. Also, newly industrialized countries that are part of Asia have increased their share in global renewable energy resources, as depicted in Figure 2.16. An increase in the total population tends to increase temperature variability as existing resources are over-exploited to influence the balance of our ecosystem.

In the case of Europe,GDP_{pc}, energy intensity, trade openness, and urbanization have significant spillover effects on the temperature variability of nearby countries (and vice versa). Countries initially exert the negative impact of temperature variability in their nearby locations, but this relationship tends to weaken as GDP grows. The trade openness of other European countries increases the temperature variability of their neighbors. While in the case of Asia Pacific, GDP_{pc}, and trade openness have significant spillover effects.

Trade openness is more beneficial in the case of Asia Pacific countries as it tends to decrease their temperature variability.

Table 3.10: Results of Climate Variability (Temperature) Spatial Durbin Model – across the Regions

Variables	Region 1		Region 2	
	SDM fixed effect	SDM random effect	SDM fixed effect	SDM random effect
	Temperature Variability			
ρ	0.867***	0.876***	0.454***	0.438***
	(41.95)	(44.65)	(5.85)	(5.51)
GDP_{PC}	0.090	-0.04	0.045	0.0534*
	(1.24)	(-1.19)	(1.29)	(2.11)
GDP_{pc}^2	-0.002	0.003	-0.004	-0.0034**
	(-0.50)	(1.43)	(-1.88)	(-2.62)
EI	0.106***	0.043*	-0.083**	-0.038
	(4.52)	(2.55)	(-3.22)	(-1.66)
$TRADE$	0.022*	-0.002	-0.011	-0.003
	(2.44)	(-0.30)	(-1.50)	(-0.60)
IND	-0.048**	-0.011	0.021	-0.002
	(-2.72)	(-0.86)	(1.26)	(-0.15)
POP	0.125***	-0.005	0.074**	-0.000
	(4.16)	(-1.72)	(2.81)	(-0.16)
URP	0.024	0.028	0.032	0.023
	(0.46)	(1.15)	(1.02)	(1.29)
$Intercept$		-2.154		-0.784
		(-1.94)		(-1.27)
$W * GDP_{pc}$	0.985***	0.480*	0.289	0.217
	(3.5)	(2.44)	(1.69)	(1.84)
$W * GDP_{pc}^2$	-0.055***	-0.029**	-0.021*	-0.017*
	(-3.62)	(-2.80)	(-2.16)	(-2.47)
$W * EI$	0.320*	-0.031	0.017	0.121
	(2.55)	(-0.44)	(0.14)	(1.38)
$W * TRADE$	0.064*	0.035	-0.051*	-0.053*
	(2.25)	(1.46)	(-2.13)	(-2.43)
W*IND	-0.097	-0.001	0.0515	0.035
	(-1.03)	(-0.02)	(0.77)	(0.57)
W*POP	-0.085	-0.039	-0.094	0.008
	(-0.56)	(-1.60)	(-1.16)	(0.79)
W*URP	0.732*	0.273	0.222	0.24
	(2.23)	(1.88)	(0.97)	(1.88)
L	1723.1059		1212.811	
Hausman	44.70(0.0000)		130(0.0000)	

Source: Author's work.

Table 3.11: Results of Spatial Direct, Indirect and Total Effect of Climate Variability (Temperature) SDM Model-across the Regions

Variables	Region 1			Region 2		
	Temperature Variability					
	Direct	Indirect effect	Total effect	Direct	Indirect effect	Total effect
GDP_{pc}	0.282*** (3.81)	7.802*** (3.65)	8.084*** (3.74)	0.0633 (1.71)	0.534* (1.97)	0.597* (2.12)
GDP_{pc}^2	-0.0123** (-2.96)	-0.415*** (-3.57)	-0.428*** (-3.63)	-0.005* (-2.47)	-0.040* (-2.42)	-0.045** (-2.66)
EI	0.183*** (5.95)	3.073*** (3.43)	3.256*** (3.56)	-0.082** (-3.01)	-0.023 (-0.11)	-0.105 (-0.45)
$TRADE$	0.037*** (3.83)	0.609** (2.76)	0.645** (2.87)	-0.014* (-2.01)	-0.100* (-2.33)	-0.114** (-2.58)
IND	-0.072** (-2.72)	-1 (-1.41)	-1.072 (-1.47)	0.025 (1.46)	0.118 (0.93)	0.143 (1.07)
POP	0.129*** (3.89)	0.142 (0.15)	0.271 (0.27)	0.071** (2.7)	-0.119 (-0.85)	-0.048 (-0.32)
URP	0.159 (1.75)	5.603* (2.13)	5.762* (2.13)	0.046 (1.14)	0.44 (1.05)	0.486 (1.08)

Source: Author's work.

3.6.7 Spatial Econometric Regression Results across regions-Rainfall Variability

In the case of region-1, Europe, and region-2, Asia Pacific, the spatial correlation coefficient indicates the positive and statistically significant relationship of the rainfall variability of a country to its nearby locations. In the case of Europe, energy intensity directly affects rainfall variability, while trade openness tends to reduce rainfall variability in the case of Asia. There is no significant spillover effect of variables considered in the analysis for Europe and the Asia Pacific.

Table 3.12: Results of Climate Variability (Rainfall) Spatial Durbin Model – across the Regions

Variables	Region 1		Region 2	
	SDM fixed effect	**SDM random effect**	**SDM fixed effect**	**SDM random effect**
	Rainfall Variability			
ρ	0.546***	0.532***	0.395***	0.382***
	(8.8)	(8.42)	(4.9)	(4.66)
GDP_{PC}	3.386	1.042	-0.459	0.572
	(1.22)	(0.76)	(-0.17)	(0.270)
GDP_{pc}^2	-0.185	-0.071	0.005	-0.067
	(-1.21)	(-0.97)	(0.03)	(-0.57)
EI	1.547	-0.83	1.542	-0.765
	(1.72)	(-1.32)	(0.8)	(-0.46)
$TRADE$	0.373	-0.057	-2.063***	-1.299*
	(1.08)	(-0.21)	(-3.77)	(-2.56)
IND	0.13	-1.054*	2.455	2.079
	(0.19)	(-2.07)	(1.88)	(1.85)
POP	0.597	-0.394***	0.915	-0.515*
	(0.52)	(-3.47)	(0.46)	(-2.22)
URP	-0.72	0.32	3.719	1.668
	(-0.36)	(0.34)	(1.58)	(1.06)
$Intercept$		-50.52		31.53
		(-1.23)		(0.64)
$W * GDP_{pc}$	-1.49	15.96*	-2.209	3.925
	(-0.14)	(2.29)	(-0.17)	(0.41)
$W * GDP_{pc}^2$	0.175	-0.751*	-0.194	-0.478
	(0.3)	(-2.01)	(-0.26)	(-0.86)
$W * EI$	1.793	9.200***	-9.22	-11.02
	(0.38)	(3.41)	(-1.00)	(-1.47)
$W * TRADE$	-0.851	0.468	2.141	0.764
	(-0.78)	(0.53)	(1.2)	(0.46)
W*IND	-5.661	-9.684**	-2.208	0.138
	(-1.54)	(-3.22)	(-0.44)	(0.03)
W*POP	-7.362	0.0417	-7.254	-1.567
	(-1.28)	(0.04)	(-1.19)	(-1.51)
W*URP	-1.037	-3.263	20.23	7.946
	(-0.08)	(-0.56)	(1.18)	(0.78)
L	-2257.35		-1123.54	
Hausman	42.02 (0.0000)		108.72 (0.0000)	

Source: Author's Work.

Table 3.13: Results of Spatial Direct, Indirect and Total Effect of Climate Variability (Rainfall) SDM Model-across the Regions

Variables	Region 1			Region 2		
	Rainfall Variability					
	Direct	Indirect effect	Total effect	Direct	Indirect effect	Total effect
GDP_{pc}	3.488 (1.3)	0.0531 (0.00)	3.541 (0.17)	-0.512 (-0.19)	-5.191 (-0.28)	-5.703 (-0.30)
GDP_{pc}^2	-0.188 (-1.26)	0.216 (0.18)	0.027 (0.02)	-0.008 (-0.06)	-0.221 (-0.20)	-0.23 (-0.21)
EI	1.730* (2.03)	6.015 (0.63)	7.745 (0.8)	1.33 (0.67)	-13.03 (-0.88)	-11.7 (-0.74)
$TRADE$	0.339 (1.05)	-1.514 (-0.66)	-1.175 (-0.52)	-2.016*** (-3.81)	2.136 (0.77)	0.12 (0.04)
IND	-0.055 (-0.08)	-11.76 (-1.52)	-11.81 (-1.48)	2.388 (1.88)	-1.551 (-0.18)	0.837 (0.09)
POP	0.339 (0.32)	-15.63 (-1.37)	-15.29 (-1.35)	0.657 (0.33)	-12 (-1.25)	-11.34 (-1.11)
URP	-0.782 (-0.37)	-1.99 (-0.07)	-2.772 (-0.09)	4.81 (1.64)	36.78 (1.26)	41.59 (1.31)

Source: Author's work.

3.6.8 Spatial Econometric Regression Results across regions-Carbon Intensity

The spatial autocorrelation coefficient is negative and statistically significant, indicating that CO_2 intensity varies across space in Europe and the Asia Pacific. Countries with high carbon intensities tend to be surrounded by countries with low carbon intensities (and vice versa). GDP per capita and its square terms satisfy the EKC in the European and Asia Pacific regions. Energy intensity positively influences carbon intensities in both regions. Trade openness reduces carbon intensity in Europe while it increases carbon intensity in the Asia Pacific. These results are in contrast to the openness effect on temperature variability. This is because carbon emitted once in the atmosphere affects temperature variability despite the reduction in emissions. In the case of carbon intensity, openness helps reduce carbon emissions. Liberalization policy in Europe allowed firms to move to countries with less restrictive environmental regulations. Also, most Asian emerging economies are important destinations for the global value chain. High production costs for low environmental regulation have led to increased carbon emissions. Increased industrial value added decreases carbon intensity of Asian pacific countries while it has a negative and statistically insignificant relationship in the case of Europe. Urban population increases CO_2 intensity in Europe while it tends to decrease in the case of the Asia pacific region.

The spillover effect of carbon intensity indicates that in the case of Europe, GDP_{pc}, trade openness, size of the total, and urban population have a spillover effect on nearby locations. GDP_{pc}, its square term, industrialization, and the size of the total population have spillover an individual country's carbon intensity in Asia Pacific countries.

Table 3.14: Results of Carbon Intensity Spatial Durbin Model –across the Regions

Variables	Region 1		Region 2	
	SDM fixed effect	SDM random effect	SDM fixed effect	SDM random effect
	CO_2 intensity			
ρ	-0.596***	-0.579***	-0.540***	-0.493***
	(-4.18)	(-4.07)	(-3.77)	(-3.42)
GDP_{PC}	0.171***	0.171***	0.388***	0.374***
	(8.35)	(8.54)	(23.24)	(21.31)
GDP_{pc}^2	-0.009***	-0.009***	-0.022***	-0.021***
	(-7.99)	(-8.27)	(-23.32)	(-21.43)
EI	0.059***	0.058***	0.059***	0.065***
	(8.89)	(8.66)	(4.94)	(5.28)
$TRADE$	-0.009***	-0.009***	0.015***	0.012***
	(-3.40)	(-3.82)	(4.37)	(3.43)
IND	-0.006	-0.005	-0.027**	-0.030***
	(-1.15)	(-1.10)	(-3.28)	(-3.63)
POP	0.006	0.003	0.010	0.012
	(0.71)	(0.73)	(0.86)	(1.33)
URP	0.074***	0.073***	-0.090***	-0.065***
	(5.01)	(5.13)	(-6.20)	(-3.98)
$Intercept$		2.344***		-0.327
		(3.41)		(-0.42)
$W * GDP_{pc}$	-0.067	-0.050	-0.197*	-0.332***
	(-0.82)	(-0.61)	(-2.34)	(-3.58)
$W * GDP_{pc}^2$	0.005	0.004	0.015**	0.022***
	(1.21)	(0.92)	(3.06)	(4.17)
$W * EI$	0.001	-0.011	0.109	0.083
	(0.02)	(-0.35)	(1.89)	(1.4)
$W * TRADE$	-0.032***	-0.030***	-0.021	-0.016
	(-3.97)	(-3.78)	(-1.88)	(-1.39)
W*IND	0.126***	0.125***	0.086**	0.098**
	(4.54)	(4.47)	(2.77)	(3.07)
W*POP	0.203***	0.177***	0.327***	0.223***
	(4.79)	(5.73)	(8.67)	(4.86)
W*URP	-0.663***	-0.620***	-0.421***	-0.227
	(-7.18)	(-7.10)	(-3.97)	(-1.92)
L	3242.6716		1532.4396	
Hausman	26.60		12.40	
P-Value	0.0322		0.6483	

Source: Author's work.

Table 3.15: Results of Spatial Direct, Indirect and Total Effect of Carbon Intensity SDM Model-across the Regions

Variables	Region 1			Region 2		
	CO_2 emission					
	Direct	Indirect effect	Total effect	Direct	Indirect effect	Total effect
GDP_{pc}	0.174***	-0.112	0.0627	0.390***	-0.360***	0.030
	(7.92)	(-1.96)	(1.4)	(21.17)	(-5.59)	(0.47)
GDP_{pc}^2	-0.009***	0.007*	-0.002	-0.022***	0.023***	0.001
	(-7.60)	(2.28)	(-0.89)	(-20.96)	(6.02)	(0.24)
EI	0.060***	-0.022	0.038	0.065***	0.036	0.101*
	(9.12)	(-0.99)	(1.87)	(5.57)	(0.86)	(2.32)
$TRADE$	-0.009**	-0.018**	-0.026***	0.013***	-0.015	-0.002
	(-3.26)	(-2.92)	(-5.21)	(3.56)	(-1.66)	(-0.24)
IND	-0.008	0.084***	0.076***	-0.034***	0.077***	0.043
	(-1.67)	(4.96)	(4.51)	(-4.22)	(3.4)	(1.94)
POP	0.003	0.129***	0.131***	0.006	0.153***	0.159***
	(0.3)	(4.61)	(5.4)	(0.65)	(4.35)	(4.63)
URP	0.087***	-0.457***	-0.370***	-0.059***	-0.142	-0.201*
	(5.79)	(-7.25)	(-5.83)	(-4.21)	(-1.71)	(-2.19)

Source: Author's work.

3.7 Conclusion

In the present study, we estimated spatial determinants of climate, climate variability, climate change, and carbon intensity. For climate variability, we have used the panel of 116 countries from 1991 to 2018. The study measures the climate variability of the average temperature difference from the long-run mean. At the same time, climate change is calculated by the thirty-year average of temperature, rainfall, and carbon intensity in cross-sectional data of 114 countries.

Spatial Determinants of Climate Variability include GDP per capita, energy intensity, industrialization, total population, and urban population. Energy intensity, total population, and urban population are the key spatial determinants of temperature variability for spillover effects. Countries surrounded by neighbors with high energy intensity tend to increase domestic countries' climate variability. Countries with high populations also exert a positive spillover effect on the climate variability of nearby locations. Urbanization decreases temperature variability in the domestic country; if urbanized economies surround a country, it also reduces temperature variability.

The key spatial determinants for rainfall variability are GDP per capita and energy intensity. For spillover and indirect effects, an increase in trade liberation of nearby countries increases rainfall variability in the domestic country. Carbon intensity is spatially driven by GDP per capita, its square term, trade liberalization, population, and urban population. Energy intensity shows a positive spillover effect on nearby countries' carbon intensity for the indirect effect. As energy intensity increases, countries move to more fossil fuel-driven production, further exacerbating neighboring countries' carbon intensity.

Spatial Determinants of Climate led by temperature find population density positively associated with increased temperature change. Trade liberalizations tend to decrease the pace of climate change led by temperature change. An increase in the value-added share of industrialization in the GDP increases temperature change by 0.2 percent. The indirect effect shows that an increase in the population density of nearby countries will increase the temperature in domestic countries. In contrast, trade liberalization of neighboring countries will decrease the pace of climate change.

Climate change led by rainfall shows that population density and trade liberalization are the key determinants. Population density increases while trade liberalization decreases the pace of climate change. The indirect effect of SAR models indicates that the increase in population density of nearby countries increases temperature change while countries surrounded by more liberalized countries have decreased the pace of climate change driven by rainfall. For carbon intensity in a cross-sectional setting, GDP per capita and square term are significant and satisfy the EKC showing a positive linear and negative nonlinear relationship between CO_2 intensity and GDP. Industrialization drives and augments CO_2 intensity in the present case. The indirect effect shows that GDP per capita has a spillover effect on carbon intensity.

Climate variability (temperature) shows that the short-term fluctuation in climate is affected by GDP per capita, energy intensity, total population, and urbanization, while industrialization decreases variability in the short run. Climate change intensified because of industrialization and increased population density in the long run. Economic growth raises temperature variability while having an insignificant positive effect on climate change in the long run.

Economic growth increases carbon intensity in the panel and the cross-sectional setting. For short-term policy suggestions, results highlight the need to consider energy consumption, energy mix, population growth, and urban planning as the key factors to slow the pace of climate variability; however, for long-run climate change, countries need to consider policies aim to handle population density and urban planning. In the long run, trade openness decreases the pace of climate change.

A cross-regional determinants

Europe and the Asia Pacific both satisfy the EKC relation with temperature variability. Energy intensity in Europe exacerbates temperature variability, while in the Asia Pacific, it helps reduce the pace of variability. The quality of energy being used to produce also matters. Trade openness increases temperature variability in Europe while it decreases in the case of Asia Pacific. Industrial value-added decreases temperature variability in Europe while it increases in the case of Asia Pacific. GDP, energy intensity, trade, and urban population have the key spillover. While in the case of Asia, GDP_{pc}, and trade have spillover effects. In the case of Europe, rainfall variability is explained by positive changes in energy intensity. In the case of Asia Pacific, trade openness affects rainfall variability. GDP_{pc}, GDP_{pc}^2, EI, $TRADE$, IND, and URP are the key determinants for carbon intensity in Europe. While GDP_{pc}^2, $TRADE$, IND, URP, and total POP size have a spillover effect. GDP_{pc}, GDP_{pc}^2, EI, $TRADE$, IND, and URP are the key driving factors for carbon intensity, while GDP_{pc}, GDP_{pc}^2, IND, and POP size have a spillover effect.

Spillover effects suggest that countries must devise their environmental policies and regulations, keeping in view neighboring countries' energy policies, energy mix, and energy consumption patterns. Coordination in energy policies for countries at the regional level is central to reducing climate variability and change. Climate change policies need to consider the spillover effect of nearby locations to implement better regulations, adaptation, and mitigation measures. For climate change, densely populated neighboring countries increase climate change's pace. This needs to be considered part of urban planning. Sustainable economic growth must be regarded as, in all cases, improvement in per capita income increases climate change, variability, and carbon intensity. The difference in temperature variability and carbon intensity determinants indicates that both should be analyzed in formulating the policy target for climate change. Also, the adaptation measures should be according to existing temperature variability faced by countries. Variability, positive or negative, creates short-term uncertainty and increases cost.

3.8 Key Takeaways

In the panel of 116 countries, increase in the GDP per capita has direct impact on climatic variability irrespective of the alternative dependent variables considered in the analysis. However, the magnitude varies with the type of dependent variable considered. One percent increase in GDP per capita increase temperature variability by 0.3 percent, rainfall variability by 2.2 percent and CO_2 intensity by 0.2 percent.

Among the indirect impact, temperature variability is more sensitive to changes in energy intensity of any neighboring countries. One-unit increase in the energy intensity of neighboring country increases temperature variability of a given country. In case when CO_2 emission were used as dependent variable, energy intensity of neighboring country increases CO_2 intensity by 0.4 percent. The result also indicates that neighboring countries energy intensity is more on temperature variability rather than CO_2 intensity.

Results of the regional analysis shows that in Region-1 i.e. the European countries, the magnitude of spillover effects of increase in GDP, energy intensity, trade openness on temperature variability are more as compare to Asia Pacific region. Interestingly, the magnitude of spillover effect is more than direct effect of these determinants indicating that European countries need to devise a common climate adaptation and mitigation policies as neighboring countries GDP, energy intensity, and trade liberalization impact a given country’s temperature variability. Contrary to the existing literature energy intensity of a given country in case of Asia Pacific lowers the temperature variability while there is no spillover effect on other countries. The reason can be the diverse geographical spread, regional climates (tropical and artic), industrial structures, and energy consumption patterns. The relationship needs to be explored further in terms of long run and short run.

In both the regions Europe and Asia Pacific GDP per capita, energy intensity, trade openness and urbanization are the key direct determinants of CO_2 intensity. In case of Europe trade liberalization tends to decrease the CO_2 intensity by 0.01 percent while in case of Asia Pacific trade liberalization increase CO_2 intensity by 0.01 percent. In Europe, the clean energy mix, regulatory measures for climate change and trade liberalization also encourage easy access to cleaner technologies and practices, thereby decreasing CO_2 intensity. Among the spillover effect, in both the regions, industrialization and population increase augments CO_2 intensity.

Chapter 4

IMPACT OF CLIMATE CHANGE ON FOOD PRODUCTION: AN ANALYSIS BASED ON SPATIAL ECONOMETRIC MODEL

4.1. Introduction

Food security, in general, and food production, are central to any country's sustainable economic development and national security. Food security encompasses food production, food access, and its utilization. Climate change affects all components of food security as climate variables such as temperature, humidity, and precipitation are major factors affecting food production processes. Climate change indirectly affects food access as disruption in the food supply chain creates a food shortage, exacerbates prices, and creates uncertainty for farmers' income. Climate change also affects food's nutritional quality, affecting food security's food utilization component.

Few countries dominate the global grain market for rice, maize, and wheat. All these crops constitute the major food basket for most of the world's daily calorie intake. Simultaneous shock in the form of a global rise in temperature will change the projection of future grain production in the world market. Although globalization has increased food availability for countries even with limited food production, the global pandemic COVID-19 and recent Russia and Ukraine war-driven food inflation have led countries to rethink food security in terms of food production.

Achieving the global sustainable development goal of achieving zero hunger by 2030 needs stringent policy action in the post-pandemic era. According to FAO[32], around 720 to 811

[32] FAO, IFAD, UNICEF, WFP and WHO. 2021. The State of Food Security and Nutrition in the World 2021. Transforming food systems for food security, improved nutrition and affordable healthy diets for all. Rome, FAO. https://doi.org/10.4060/cb4474en

million people are expected to face hunger in 2020. Besides the global pandemic, certain climate-related challenges such as locust outbreaks, floods, and drought have added additional pressure on limited resources used to feed the increasing population. The world population is increasing at a high rate compared to crop yield per hectare. (Arora, 2019). With the additional burden of unexpected climate-related changes, food production, price hikes, and food shortage are the major challenges to ensuring global food security.

Food security and its sustainability have been important agendas for countries around the globe. However, despite existing bottlenecks for its smooth functioning, climate change is one of the most challenging threats for this sector. Climate change is not confined to the geographical boundaries of countries, and its impacts are heterogeneously distributed across space. Increases in temperature and rainfall affect plant growth, soil fertility, and water availability, and are more prone to pests' attacks. Rising temperature leads to multiple implications for the world agriculture system. For colder regions away from the equator where the temperature is increasing, fertilization effects will aid a conducive environment for agriculture production, while already hot and humid countries will face water scarcity. More rainfall will benefit countries with semi-arid, arid, and rain-fed land holdings. In contrast, less rainfall and a high temperature in these areas will be detrimental to agriculture (Agovino et al., 2019).

Also, the world economy relies on the temperate zone while most of the world population resides in the tropical zone. Initially, temperate zones might benefit from climate change, while tropical zones may in occur losses. However, as termed by Tol (2009), this benefit is a 'sunk benefit' that ultimately dies out with escalating carbon emissions. Climate change and technological advancement will likely shift world agriculture production to temperate zones. Developing and least developed economies are situated in tropical and equatorial belts. Most of them depend heavily on agriculture as a primary source of their livelihood. In addition, they have a high poverty level and minimum capacity for adaptation.

Climate change affects the crop cycle, growth, production, and yield. Crop production and yields are directly affected by climate change through certain factors such as temperature, precipitation, carbon dioxide, temperature and precipitation variability, and surface water availability. Both temperature and rainfall are important inputs for crop growth; however, a decrease in precipitation affects freshwater availability and soil moisture. High rainfall reduces the yield gap between irrigated and rain-fed farms and can cause flooding beyond certain limits. The length of the growing period and water requirements are also determined by temperature and soil moisture. High temperature reduces the crop cycle and decreases crop productivity and yield (IPCC, 2007; Calzadilla et al., 2010).

The positive impact of climate change due to increased carbon emissions in the atmosphere is also highlighted in the literature. Nordhaus (2013) pointed out that crops like wheat, rice, and soybeans can increase yields from 10-15 percent if carbon emissions are doubled. This is because plants need carbon dioxide for growth. More carbon emissions in the atmosphere will stimulate photosynthesis and speed up the plant growth cycle. In addition to carbon emission, other determinants of plant growth should be adequately available for the beneficial use of increased carbon emissions. Increased CO_2 emissions benefit C3 (rice, wheat, oats, barley, cotton) plants whose photosynthesis expedites with increased CO_2 emissions. The C4 (maize, sugarcane, pearl millet, sorghum) plant type is negatively affected by CO_2 emissions (Calzadilla et al., 2010).

Population growth and climate change are the two serious concerns for future food availability. Most of the studies in the literature identified a reduction in wheat yields in South Asia while improvement in the yield across Europe owing to the increase in global temperatures. Major cereal and staple food consumption worldwide comprise wheat, maize, and rice. The present study considers these crops to evaluate the impact of various climatic and non-climatic factors in determining the level of crop production. Globalization, economic and technological integration, increased communication, and information sharing have created a spillover effect of any economic activity on the country itself and its nearby regions more than ever before. Agriculture activity especially has a greater spillover effect as countries share common ecological and climatic conditions. Therefore, unlike traditional panel models that ignore the spillover effect of neighboring countries in proximity, we apply spatial panel models that incorporate the spatial dependency between regions.

4.2. Review of Literature

The agriculture sector in general and food production, in particular, depend on climate and environmental conditions. Being the basic input and public good by nature of climatic conditions, its impact on the agriculture sector has been extensively researched in the past few decades. The present section discusses existing studies on the impact of climate change on the agriculture sector regarding crop yields, productivity, and farm profits. Numerous studies have been conducted at regional and country levels using different data sets, models, and estimation methodologies. Some studies found a negative relationship between climate change and agriculture. High temperature and increased precipitation affect crop productivity at growth stages, increasing production costs and lowering farmers' profits. At the same time, others reveal a positive impact. However, the net impact climate change exerts on food production remains inconclusive. For this, the present section highlights the existing studies and their conflicting evidence on the impact of climate change on agriculture and food production in general.

One of the prime SDGs is to ensure zero hunger for all. Owing to the natural climate or artificial financial or economic crisis, food prices face upward pressure and are subject to volatility. Food generating resources are under pressure as the world population is increasing faster than agricultural land growth. High-income levels and high food demand have added to existing challenges for food security and access. It has been estimated that food demand will surge to 300 percent by 2080. In the presence of climate change, food production will create a wedge between supply-demand followed by a surge in food prices, consequently worsening the food security situation. (Sanchez, 2000; Siwar et al., 2013; Bandara & Cai, 2014).

The green revolution in the 1960s equipped many developing countries with better crops and farming practices and ensured the availability of better inputs. However, the quality of natural endowments, such as climate and soil fertility, plays an important role in gaining true benefits. Yields, along with input intensity, also varies with change in the climate. Mendelsohn and Wang (2017) estimated farm input intensity in the presence of climate change by using 8400 farms' data sets across China. Results suggest that if climate change benefits crop productivity, farmers will increase their crop intensity and vice versa.

Most developing and less developed countries depend on agriculture for income and revenue generation. In addition, their geographical location (low altitude), rising temperature, water shortages, and low adaptive capacity make them more vulnerable (IPCC, 2014; Mendelsohn et al., 2006). Unfortunately, more than half of poor HH of the world live in the South Asian region. The agriculture sector has an important contribution to GDP and employment generation. Further, this sector helps in poverty reduction. Climatic change-induced factors such as drought, floods, and rising temperatures in this region have been observed in subsequent years.

The impact of climate change on food production is heterogeneously distributed among regions and countries. For example, Bandara and Cai (2014) studied the impact of climate change on crop productivity and its repercussion on food prices and security in the South Asian region with a computable general equilibrium model. Without incorporating the adaptive capacity, the study found a negative impact of climate change on the food production of all five countries in this region. In addition to this, the study examined food shortages by 2030 with a major decline in wheat (11%), cereal (7%), and rice (4%) from the baseline scenario. For the price of these commodities major increase is forecasted for cereal grains (45%), wheat (25%), and rice (10%). Food demand for these commodities is likely to decrease from 0.5 to 5 percent, while GDP is projected to decline in all five countries.

Chandio and Gokmenoglu (2022) estimated the impact of climatic and non-climatic factors on rice production in Asian economies from 1961 to 2016. Results indicate that temperature and carbon emission increase has a detrimental effect on rice production in the long run, while the increase in precipitation positively affects rice production. Increased non-climatic factors such as labor, fertilizer consumption, and cultivated land area increase rice production in Asian economies.

Climate change impact assessment studies reveal that the impact of climate change varies in low and high-altitude countries. (Kolstad & Moore, 2019). Rosenzweig and Parry (1994) simulated the impact of climate change scenarios on the global food supply. Results suggest that developing countries lying at low altitudes are more affected by climate change than developed countries despite employing adaptive strategies by farmers. Ginbo (2022) analyzed the impact of climate change on various crop yields located in different agroecological zones of Ethiopia. The study analyzed the future impact of climate change on cash crops (coffee) and major cereals (wheat, maize, barley, and sorghum) for 2041–2060 compared to 1988–2018. Wheeler and Kay (2010) suggested that crop area will shift towards the north by 50kms for every 1-degree increase in temperature.

Also, the least developed countries in sub-Saharan Africa (SSA) are agrarian economies that attain 40% of their GDP from the agriculture sector while it employs more than half of their labor force. The temperature in these economies is consistently increasing with low rainfall. Extreme climatic events such as drought and floods are frequent. The inability to access modern technology makes them worse off than the rest of the world.

Barrios et al. (2008) examined the impact of climate change on agriculture production in sub-Saharan Africa (SSA) and non-sub-Saharan African (NSSA) developing countries for the years 1961 to 1997. Climate change is accessed through changes in rainfall and temperature from the long-run mean. Other inputs include labor, livestock, mechanization, land, and fertilizer use. Results indicate that changes in rainfall and temperature in the country are major determinants of agriculture production in SSA.

Ward et al. (2014) examined the impact of temperature and diurnal temperature range on the cereal yield of sub-Saharan African economies. The study found that by the end of this century increase in temperature and diurnal temperature range will decrease cereal yields by 36 percent. Simulation results suggest that the negative effect on yield can be reduced by employing better irrigation facilities.

Ray et al. (2019) studied the impact of climate change on the crop yields of ten major crops, including maize, rice, wheat, and others, for 20,000 political units. Crop yields in Australia, Europe, and South Africa negatively impact climate change, while Latin America has a positive impact. Asia and northern and central America have mixed results. Globally, results show a decline in rice yields by 0.3 percent and wheat by 0.9 percent. For maize, a slight increase of 0.2 MT annually is found in the analysis. Further, the study evaluated the changes in global consumable crop calories and found a decrease in rice calories by 0.4 percent, wheat by 0.5 percent, and maize by 0.7 percent annually.

Fei et al. (2020) estimated the impact of climate change on wheat, maize, and rice production potential. The study found that wheat crop production potential has declined since 1960 because of climate change, while the production potential of rice and maize has improved in China. Wheat is sensitive to high temperatures (maximum and minimum) in its flowering stage, while maize and rice have a beneficial effect of higher temperatures at the flowering stage. Changes in precipitation have a negative impact on the production potential of all the crops.

Lobell et al. (2011) estimated the yield responses of major crops (maize, wheat, rice, and soybeans) to changes in climate variables for all countries of the world from 1980 to 2008. Results indicate a reduction in maize and wheat yield for a net global loss of 3.8 percent and 5.5 percent, respectively. For rice, the study found that gains compensate for the insignificant impact of loss in global production by others. Among climatic variables, trends in temperature drive impact, while the trend in precipitation influences internal annual variability.

Some of the studies in the literature have measured the spatial spillover effect of crop production (Donfouet et al., 2017), total factor productivity (Zhong et al., 2019), land values (Nicita et al., 2020), and food security (Qingshi & Akbar, 2022). Donfouet et al.

(2017) studied the impact of crop diversity on crop production in the presence of climate change in France using a spatial autoregressive model with the spatial autoregressive error term (SAC). The study found that crop diversity cushions the negative impact of the reduction in rainfall. The study concluded that the unobserved factors and shocks are responsible for spillover effects for spatial effects. Nicita et al. (2020) investigated the impact of climate change and agrobiodiversity on farmland values using the Ricardian spatial Durbin model for Sicily. The study incorporated the spatial relationship and heterogeneity of farms. Results indicate that farm values have a significant relationship with climate and agro-biodiversity, and spillover effects contribute to the difference in farm values.

Zhong et al. (2019) investigated the impact of climate change on province-wise agricultural total factor productivity for China. The data envelope method is used to access the average total factor productivity. The Spatial Durbin Model (SDM) is applied to evaluate the impact of climatic variables (temperature, rainfall, evaporation) at the regional level for China.

Qingshi and Akbar (2022) investigated the determinants of food security with a particular focus on political risk factors for food security and its repercussion on neighboring countries using the spatial Durbin model for 35 Asian countries. Results suggest that environmental and political risk negatively affects the food security of a particular country and its neighbors. Countries deteriorating the environment through polluting industries affect regional food security. Trade openness benefits a particular country, but its spillover effects on neighboring Asian countries are negative.

Long Ji et al. (2018) studied the factors responsible for causing structural changes in vegetable production in the case of China using SDM. The study employed climatic factors, rural labor, urban population, and road density as important determinants of vegetable production. Results indicate that rural labor and road density positively spillover effect on nearby provinces' vegetable production.

Exiting studies in the literature have focused on the spatial clusters of agriculture crops with a country-specific study incorporating the spillover effect of nearby farmland. Unlike the existing studies, we have evaluated the impact of climate change on food production by taking into account the countries that produce a particular crop and are located close by. We have considered wheat, rice, and maize as they constitute the major portion of staple food being consumed globally. In addition to the country's own effect, the spillover effect of a country that produces the same crop is missing in literature to the best of our knowledge. Thus, the present study evaluates the climatic and non-climatic factors affecting a country's production and the spillover effect of nearby countries producing the same crop.

4.3. Theoretical Framework

The economic impact of climate variables on the agriculture sector is widely assessed through the Ricardian (hedonic) and production function approach, subject to the scope and objective of the study. Studies that aimed to analyze the impact of climate change on agriculture yields have employed the production function approach, while Mendelsohn et al. (1994); Sanghi and Mendelsohn (2008); Mendelsohn and Dinar (2009) use the Ricardian (hedonic) approach to access agriculture productivity by using profit or land values.

The production function approach and crop simulation models analyze crop yield sensitivity to climate change. The major focus in the crop simulation models is on physiological aspects and plant growth under changing climate change scenarios. These models ignore that farmers undergo adaptation strategies while confronting climate change (Salvo et al., 2013). Moreover, they require daily data on climate and other farm management activities that are not readily available. For the production function approach, agriculture inputs such as fertilizers, climate, and other soil-related variables are used to access changes in crop yields. The basic limitation of this model lies in the '*dumb farmer hypothesis*' that ignores the adaptation strategies in the form of changing cropping patterns and crops due to climate change. For the present case, we have explicitly accounted for adaptation strategies by adding fertilizer and mechanization as proxy variables for adaptation. Integrated assessment models have also been developed to examine the repercussion of climate variables on the entire economy. Other models used in literature include positive mathematical programming and the general equilibrium model (for detail, see Salvo et al., 2013).

Considering our study's objective, the production function approach is most appropriate as it explicitly accounts for agriculture inputs. Following Barrios et al. (2008) and Kahsay and Hansen (2016), we assume the Cobb Douglas production function converts inputs to output.

$$Q = A\, L^{\beta 1}\, K^{\beta 2} \tag{4.1}$$

Where Q represents production[33]; L shows the amount of labor employed in agriculture; K shows the capital and machinery used; A represents other variables, including climate variables in our case. $\beta_1, and\ \beta_2,$ are the production elasticity concerning the country's input.

The log-linear reduced form of the model in our case becomes.

$$lnFP_{it} = \beta_{\circ} + \beta_1 lnFERT_{it} + \beta_2 lnMACH_{it} + \beta_3 lnAGRL_{it} + \beta_4 lnOPEN_{it} + \beta_5 lnTEMP_{it} + \beta_6 lnRAIN_{it} + \beta_7 lnTVAR_{it} + \beta_8 lnRVAR_{it} + \lambda_t + \mu_i + \eta_{it} \tag{4.2}$$

As in the present case, we are interested in measuring and accounting for neighborhood effect, i.e., the spillover effect of neighboring countries' crop production, inputs, and climatic variables on domestic countries' crop production. Therefore, we have used a spatial econometric model in a panel setting.

[33]Crops considered are wheat, rice, maize. While cereal production index is also used as dependent variable.

4.4. Methodology

Standard panel econometric methodologies such as fixed effect and random effect models are extensively used to assess the impact of climatic variables on agriculture production yield, total factor productivity, farm profits, and agriculture sector efficiency. However, traditional panel models assume no spatial autocorrelation across space. To measure spillover or neighborhood effects affecting food production in any given country, the traditional panel fails to consider. Therefore, we have used spatial econometric models incorporating the spillover effect by considering the cross-sectional dependence and heterogeneity across space. (Elhorst & Vega, 2013). In spatial autocorrelation, the error term is no longer normal, while the standard error becomes high, leading to the acceptance of a false hypothesis.

Spatial autocorrelation is a major concern if one location's dependent variable, error term, or explanatory variables correlate with its neighboring locations. Most empirical studies that measure the spatial effects of climate change on agriculture production, farm values, and profitability have applied the spatial Durbin model. For example, Qingshi and Akbar (2022) applied the spatial Durbin model to evaluate the role of political risk and other determinants of food security in the spatial context. Nicita et al. (2020) highlighted the importance of the spatial relationship between farm values while studying the climate impact assessment. Certain inputs such as soil, climate, and irrigation facilities cross space. While the value of land is also affected by the value of nearby land area thus, the study employed a spatial Durbin model that includes spatial lag exogenous factors and a spatial lag dependent variable. Tang et al. (2021) examined the spatial/spillover effect of farm use transition on grain production in the case of China.

In the present case, we have analyzed the spatial relationship between food production determinants measured by wheat, rice, and maize production. Food production factors include agriculture inputs such as fertilizer usage, irrigation system, mechanization, climatic variables, prices, and trade decisions. Most of the variables used as input have similar behavior across nearby spaces. In addition, most geographical locations, soil fertility, and climate change variables are not limited to the country's geographical boundaries. The food production area in one country is near another; thus, to capture the spillover effect of neighboring countries' agriculture production and other factors, we use a more generalized form of spatial model that includes spatial interaction of exogenous and dependent variables.

Following Elhorst and Vega (2013) methodology for selecting an appropriate spatial model, we initially employed a non-spatial model, i.e., OLS, for selecting an appropriate model. LM lag and LM error test and their subsequent robust forms are used to choose between non-spatial and spatial lag and the spatial error model. If the spatial models better fit the data than the non-spatial model, we have used Wald and LR tests to choose the most appropriate model. For the present case, we have used a more generalized model that is the spatial Durbin model, and test two hypotheses; first, is spatial Durbin model can be simplified to the SLM model (Ho= γ =0), and can the spatial Durbin model can be reduced to spatial error model (Ho= γ +$\delta\beta$).

For the present case, we have used the generalized spatial Durbin model:

$$FP_{it} = \mu_i + \lambda_t + \delta \sum_{j=1}^{N} w_{ij} FP_{jt} + \gamma \sum_{j=1}^{N} w_{ij} x_{jt} + \beta x_{it} + \varepsilon_{it} \qquad (4.3)$$

$$i = 1,2,3, \dots, N; \; t = 1,2,3, \dots, T$$

Our model equation can be rewritten as this:

$$\begin{aligned} lnFP_{it} = {} & \beta_o + \mu_i + \lambda_t + \rho \sum_{j=1}^{N} W_{ij} lnFP_{jt} + +\beta_1 lnFERT_{it} + \beta_2 lnMACH_{it} + \\ & \beta_3 lnAGRL_{it} + \beta_4 \ln OPEN_{it} + \beta_5 lnTEMP_{it} + \beta_6 lnRAIN_{it} + \\ & \beta_7 lnTEMP_{var\,it} + \beta_8 \ln RAIN_{var\,it} + \gamma_1 \sum_{j=1}^{N} W_{ij} lnFERT_{jt} + \\ & \gamma_2 \sum_{j=1}^{N} W_{ij} lnMACH_{jt} + \gamma_3 \sum_{j=1}^{N} W_{ij} lnAGRL_{jt} + \gamma_4 \sum_{j=1}^{N} W_{ij} lnOPEN_{jt} + \\ & \gamma_5 \sum_{j=1}^{N} W_{ij} lnTEMP_{jt} + \gamma_6 \sum_{j=1}^{N} W_{ij} lnRAIN_{jt} + \gamma_7 \sum_{j=1}^{N} W_{ij} lnTEMP_{var\,jt} + \\ & \gamma_8 \sum_{j=1}^{N} W_{ij} lnRAIN_{jt} + \varepsilon_{it} \end{aligned} \qquad (4.4)$$

FP represents the food production (wheat, rice, and maize production), FERT fertilizer usage; $MACH$ is the machinery used for agriculture production; $AGRL$ shows employment in the agriculture sector under agriculture; $OPEN$ measures the ratio of trade volume (exports + imports) of each crop to country's GDP; W_{ij} non-stochastic, non-zero, and exogenously determined weight matrix used to explain the nature of the spatial relationship between country i and j. We used the inverse square distance weight matrix that shows as distance increases. The spillover effects tend to decay.

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}$$

d_{ij} represents the distance between location i and j measured by their respective latitude and longitudes. At the same time, n indicates the number of countries. Matrix is row standardized as per standard procedure, and a weighted average of nearby locations calculates the spatial value of variables.

In matrix notation, it can be written as.

$$FP = \rho WY + X\beta + XW\gamma + \mu I_n + \varepsilon \tag{4.5}$$

Y is the $(N \times 1)$ vector of crop yield for each country i (i= 1,2,…,n); ρ is the scalar spatial lag dependent variable coefficient, W is the weight matrix of $(N \times N)$ dimension; X is $(N \times K)$ vector of explanatory variables, β and γ are the unknown coefficient vector $(K \times 1)$ of fixed X that is to be estimated. μ represents the individual fixed effect while ε is the random error term. WY and WX capture the spatial endogenous and exogenous interaction effects.

As highlighted earlier, the coefficients of the SDM model include both countries' own explanatory variable effect and feedback from neighboring countries and its repercussions on the individual country. SDM calculates average direct, indirect, and total effects for marginal effects. Direct effects measure changes in explanatory variables of country i. Indirect effect measures changes in explanatory variables of other locations j that affects the dependent variable of country i. Total impact combines both direct and indirect effects. Equation 4.5 can be rewritten as:

$$(I_n - \rho)FP = X\beta + XW\gamma + I_n\mu + \varepsilon \tag{4.6}$$

$$FP = \sum_{r=1}^{k} Q_r(W)\, X_r + T(W)I_n\mu + T(W)\varepsilon$$

(4.7)

$$Q_r(W) = T(W)(I_n\beta_r + W\theta_r)\ and\ T(W) = (I_n - \rho W)^{-1} \tag{4.8}$$

Equation (4.7) can be rewritten as:

$$\begin{bmatrix} FP_1 \\ FP_2 \\ \vdots \\ FP_n \end{bmatrix} = \sum_{r=1}^{k} \begin{bmatrix} Q_{r\,(W)_{11}} & Q_r(w)_{12} & \cdots & Q_r(w)_{1n} \\ Q_r(w)_{21} & Q_r(w)_{22} & \cdots & Q_r(w)_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Q_r(w)_{n1} & Q_r(w)_{n2} & \cdots & Q_r(w)_{nn} \end{bmatrix} \begin{bmatrix} X_{1r} \\ X_{2r} \\ \vdots \\ X_{nr} \end{bmatrix} + \text{v (w)}\varepsilon$$

(4.9)

Direct effects are calculated by the summation of the diagonal terms of $Q_r(W)$ matrix, while total impact can be calculated by the average of the sum of the rows or columns of the $Q_r(W)$ matrix. The difference between total and direct is used to calculate the indirect effect.

$$\bar{N}(r)_{total} = n^{-1} I_n S_r(\text{w}) \tag{4.10}$$

Direct impact

$$\bar{N}(r)_{direct} = n^{-1} t_r(S_r(\text{w})) \tag{4.11}$$

Indirect impact/spillover

$$\bar{N}(r)_{spillover} = \bar{N}(r)_{total} - \bar{N}(r)_{direct} \tag{4.12}$$

4.5. Data Description

To assess the spatial impact of climate change on food production, we have used crop production of cereals, i.e., wheat, rice, and maize, as a proxy for food production.

Following Zhang et al. (2017) we have weighed crop production by agricultural land in each country to capture the productivity of crops. The data on crop production was taken from the Food and Agriculture Organization (FAO). For climatic variables, we have employed annual average temperature and annual average rainfall. Climate variability is measured by the average annual temperature (rainfall) difference from its long-run mean of 30 years. The period considered in the analysis is 1995 to 2020. Countries considered in each crop type are given in Appendix D1, D2, and D3. For wheat, we have analyzed 114 wheat-producing countries, 93 rice-producing countries, and 126 maize-producing countries as per the FAO database. Other explanatory variables in the analysis include agriculture inputs such as fertilizer, machinery, agriculture labor, and crop-wise trade openness. Climate variables include temperature, rainfall, and temperature and rainfall variability. (Detail definitions of variables, their unit of measurement, and data sources are mentioned in Appendix C1).

4.6. Empirical results

4.6.1 Spatial Autocorrelation Test

The spatial autocorrelation in crop production is examined by applying the global Moran-I test. A positive value of Moran statistics indicates a spatial relationship between sample countries. This indicates that countries with the same crop production level are clustered geographically, while a negative value of a Moran test shows that high values are spatially linked to low values and no spatial relationship within countries considered. In the present analysis, we have performed the Moran test on wheat, rice, and maize production for sample countries from 1995 to 2020 (See Table 4.1). In the case of all three crops, we found a positive and significant spatial relationship between cereal production worldwide.

Table 4.1: Moran-I Test of Spatial Autocorrelation

Year	Wheat production per agriculture land		Rice production per agriculture land		Maize production per agriculture land	
	Moran's I	**Z**	**Moran's I**	**Z**	**Moran's I**	**Z**
1995	0.297***	20.933	0.216***	11.567	0.117***	8.676
1996	0.287***	20.274	0.207***	11.1	0.116***	8.621
1997	0.299***	21.123	0.206***	11.047	0.130***	9.63
1998	0.298***	21.05	0.207***	11.102	0.119***	8.824
1999	0.292***	20.604	0.205***	10.972	0.125***	9.262
2000	0.295***	20.797	0.207***	11.075	0.121***	9.002
2001	0.297***	20.92	0.205***	10.963	0.135***	9.947
2002	0.299***	21.073	0.202***	10.822	0.146***	10.741
2003	0.281***	19.824	0.203***	10.878	0.119***	8.814
2004	0.299***	21.082	0.202***	10.815	0.144***	10.6
2005	0.291***	20.518	0.204***	10.948	0.147***	10.796
2006	0.285***	20.162	0.202***	10.801	0.132***	9.723
2007	0.288***	20.302	0.203***	10.863	0.120***	8.939
2008	0.299***	21.109	0.198***	10.599	0.137***	10.13
2009	0.293***	20.657	0.193***	10.362	0.133***	9.839
2010	0.287***	20.258	0.191***	10.272	0.127***	9.385
2011	0.290***	20.472	0.189***	10.171	0.142***	10.442
2012	0.284***	20.039	0.191***	10.274	0.126***	9.328
2013	0.289***	20.368	0.188***	10.125	0.122***	9.038
2014	0.293***	20.641	0.189***	10.169	0.127***	9.413
2015	0.295***	20.784	0.187***	10.056	0.113***	8.414
2016	0.294***	20.766	0.181***	9.727	0.134***	9.881
2017	0.291***	20.546	0.184***	9.917	0.118***	8.72
2018	0.283***	19.952	0.180***	9.695	0.127***	9.359
2019	0.288***	20.319	0.168***	9.075	0.121***	8.998
2020	0.284***	20.021	0.170***	9.189	0.124***	9.202
N	**114**		**93**		**126**	

Considering the limitation[34] of the global Moran-I test, we have analyzed the relationship graphically through a scatter plot. The top right quadrant shows that countries with high crop production are clustered around neighbors also experiencing better production, while the top left quadrant indicates that countries with low crop production are surrounded by neighbors experiencing high crop production. The bottom left quadrant shows that countries with low average crop production accompany low crop-producing countries, while the bottom right quadrant countries are those with high production levels surrounded

[34] As Moran I tests the presence of overall spatial autocorrelation. Negative and positive value of index for some countries might cancel each other and value of index turns out to be zero, indicating no spatial auto correlation.

by countries with low production, indicating the non-existence of spatial autocorrelation. I and III quadrants show positive spatial autocorrelation. The II and IV quadrants present negative spatial autocorrelation or spatial dispersion.

We have plotted the crop production (wheat, rice, and maize) for the years 1995, 2005, 2015, and 2020 to examine the changes in crop production spatial dependence in the past two decades. As most of the points in figure 4.1 lie in the I and III quadrant, positive spatial autocorrelation was observed graphically in 1995. High-quantity wheat-producing countries are surrounded by neighbors having high average wheat production.

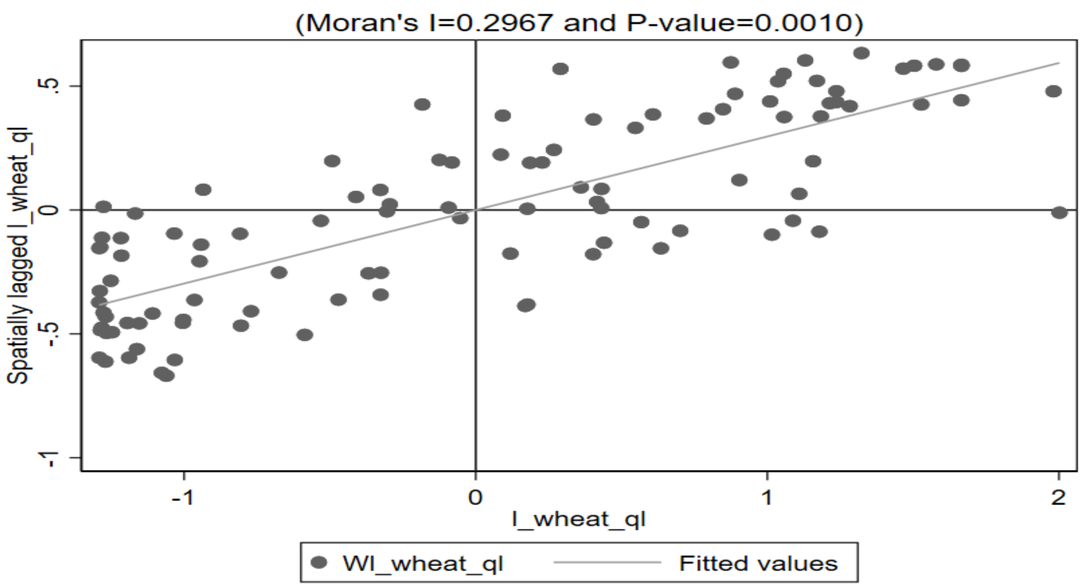
In 2005, most values lay in the I and III quadrant. Moran-I and p-value indicate positive spatial autocorrelation. High wheat-producing countries are clustered around neighbors with high average wheat production values.

In 2015, most values lay in the I and III quadrants. Moran-I and p-value indicate positive spatial autocorrelation. High wheat-producing countries are clustered around neighbors with high average wheat production values.

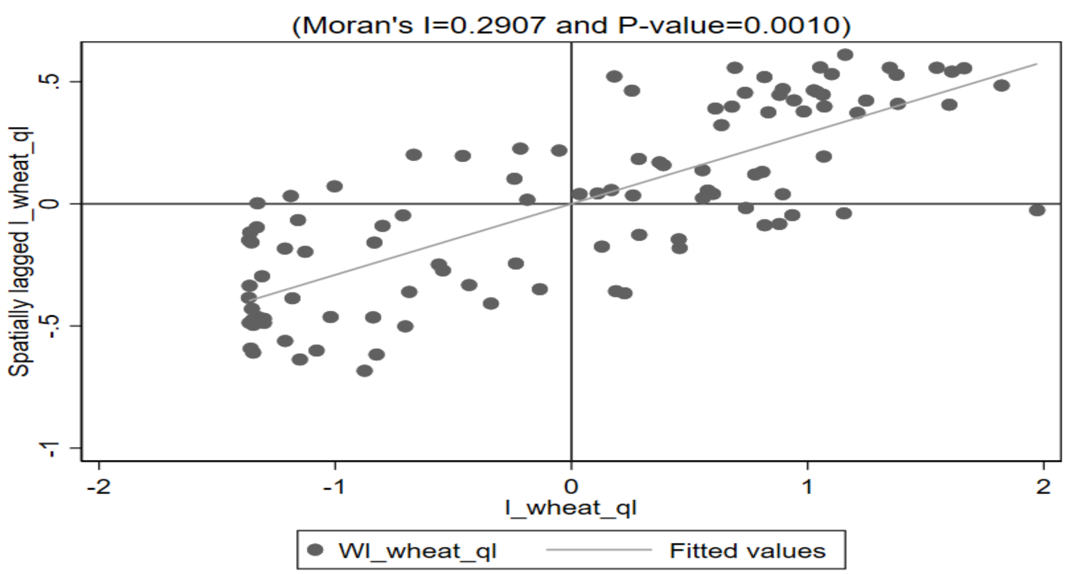
In 2020, most of the values lie in Moran-I's I and III quadrants, and the p-value significance level indicates positive spatial autocorrelation. High-crop-producing countries are clustered around neighbors with high average wheat production values.

Figure 4.1: Moran I Scatter Plot for the Log of Wheat Production per Agriculture Land for Various Spatial Lags

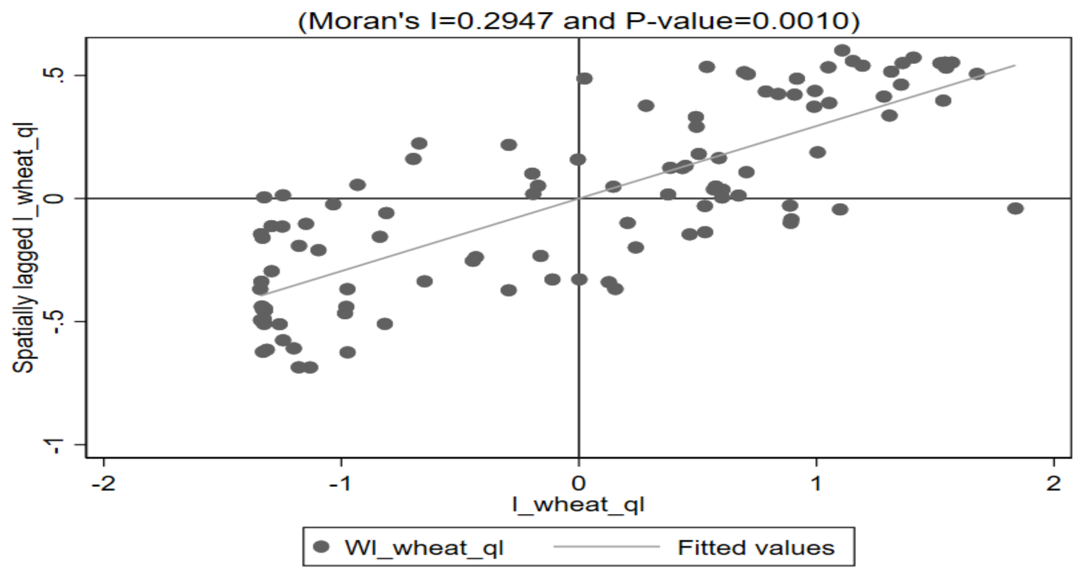
1995



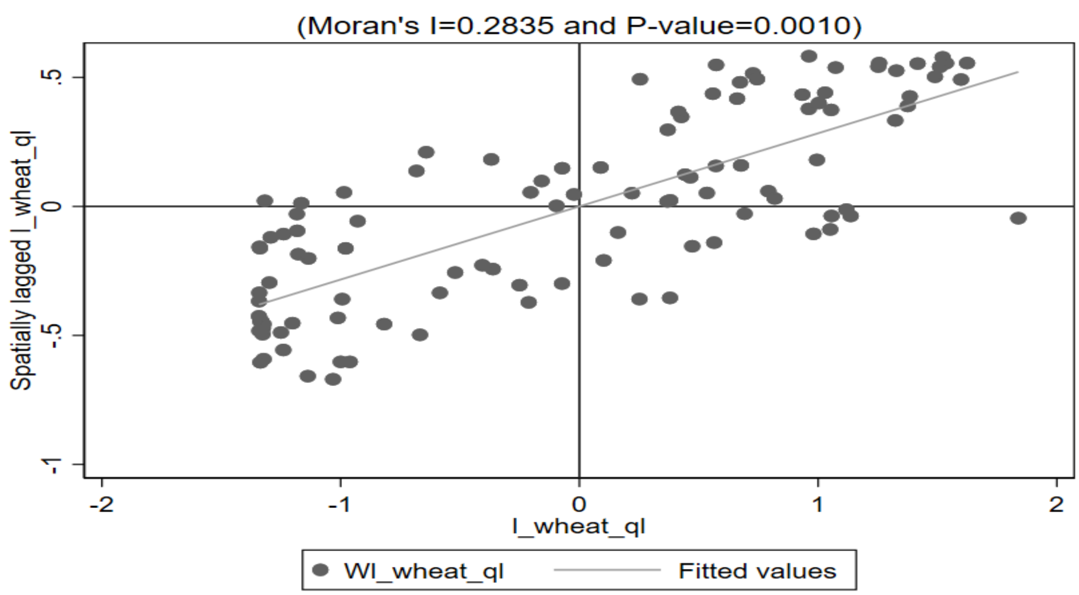
2005



2015



2020



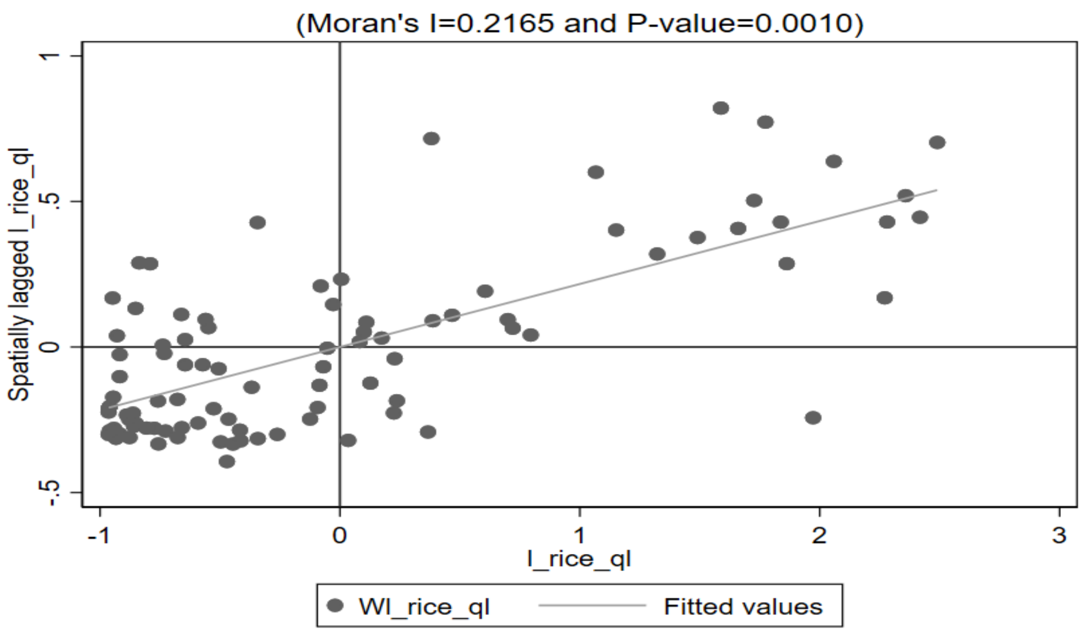
In the case of rice production in 1995, most of the values lie in the I and III quadrants, and the p-value of the Moran-I test is less than 0.1, indicating positive spatial autocorrelation. Countries producing more rice are clustered around neighbors having high average rice production (and vice versa).

In the case of rice production in 2005 and 2015, most of the values lie in the III quadrant showing that countries with low rice production are clustered around neighbors with low average rice production. Some countries lie in the first quadrant indicating that neighbors surround high rice-producing countries with high rice production on average.

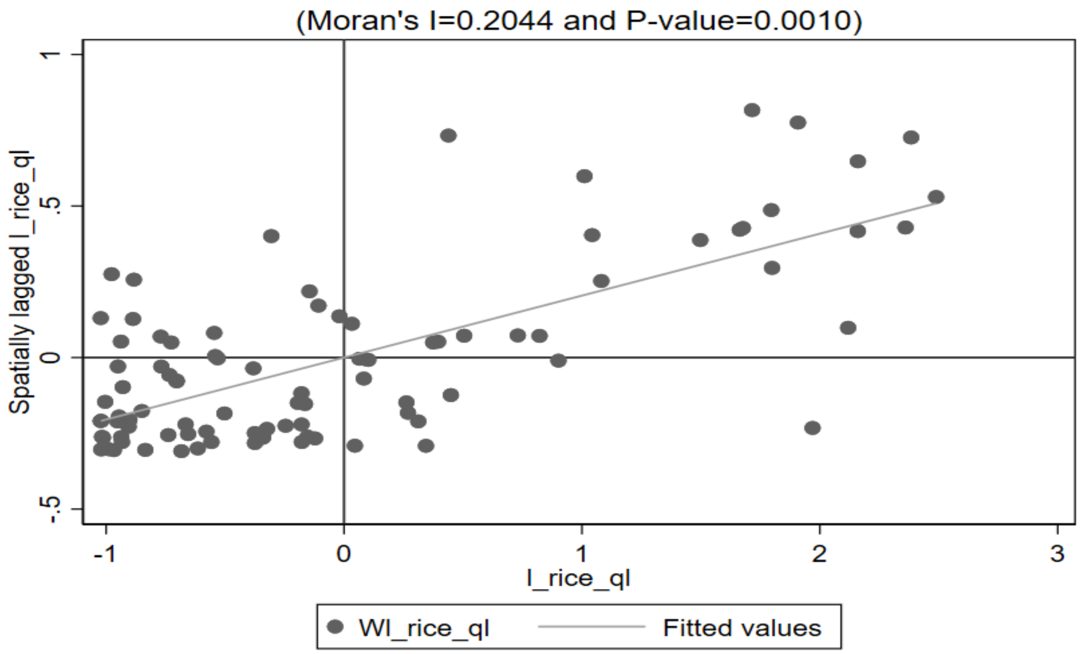
In 2020, although most of the values lie in the III quadrants, the value of Moran-I statistics is decreasing. Countries with low rice yields are clustered around neighbors with low average rice production (and vice versa). The pattern of spatial dependence has remained the same for rice-producing countries for the past two and half decades.

Figure 4.2: Moran I Scatter Plot for the log of Rice Production per Agriculture Land for Various Spatial Lags

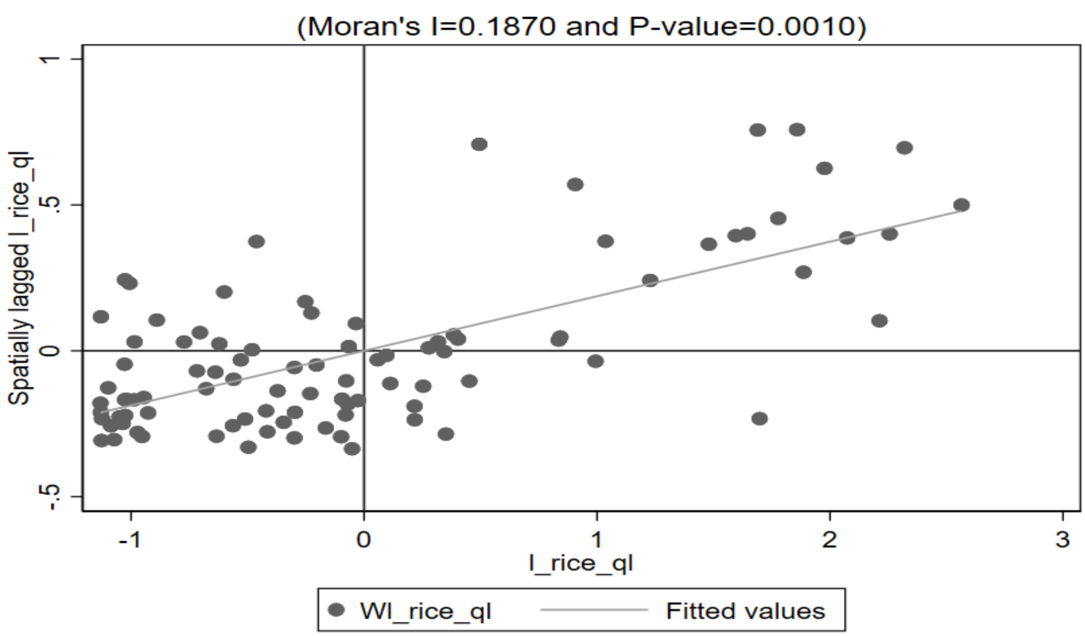
1995



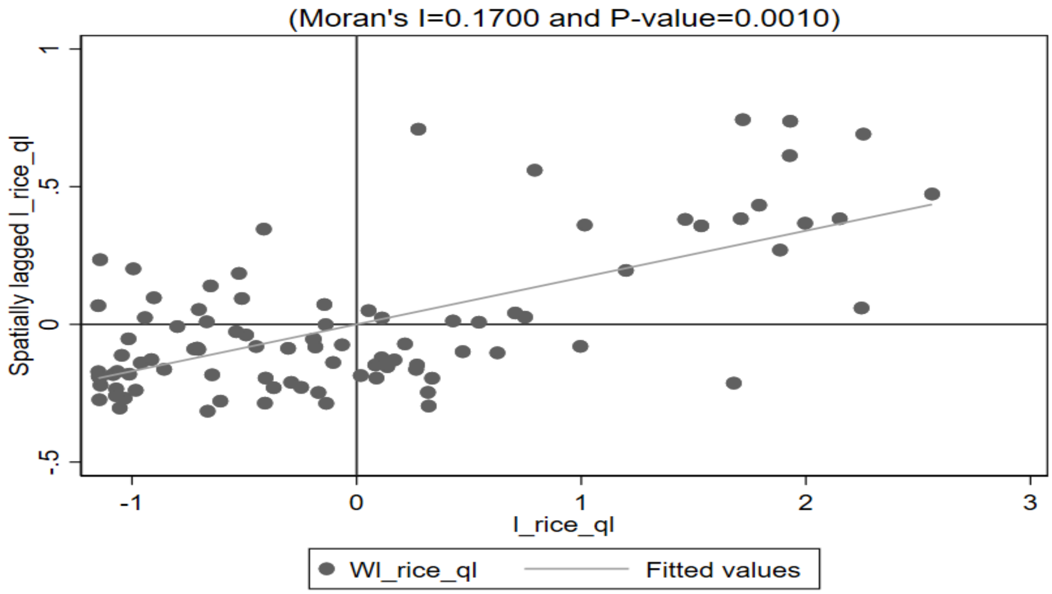
2005


(Moran's I=0.2044 and P-value=0.0010)
Spatially lagged l_rice_ql
l_rice_ql
Wl_rice_ql
Fitted values

2015


(Moran's I=0.1870 and P-value=0.0010)
Spatially lagged l_rice_ql
l_rice_ql
Wl_rice_ql
Fitted values

2020

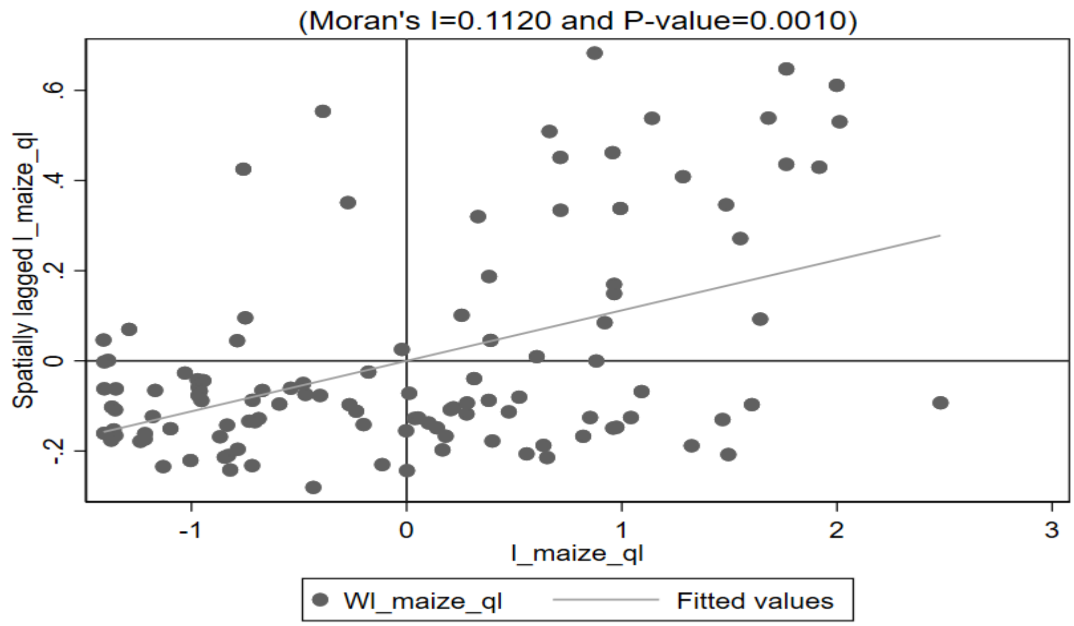


In the case of maize production across sample countries in 1995, most of the values lie in the I and III quadrants, and the p-value of the Moran-I test is less than 0.1, indicating positive spatial autocorrelation. Countries with high maize production cluster around neighbors with high average maize production (and vice versa).

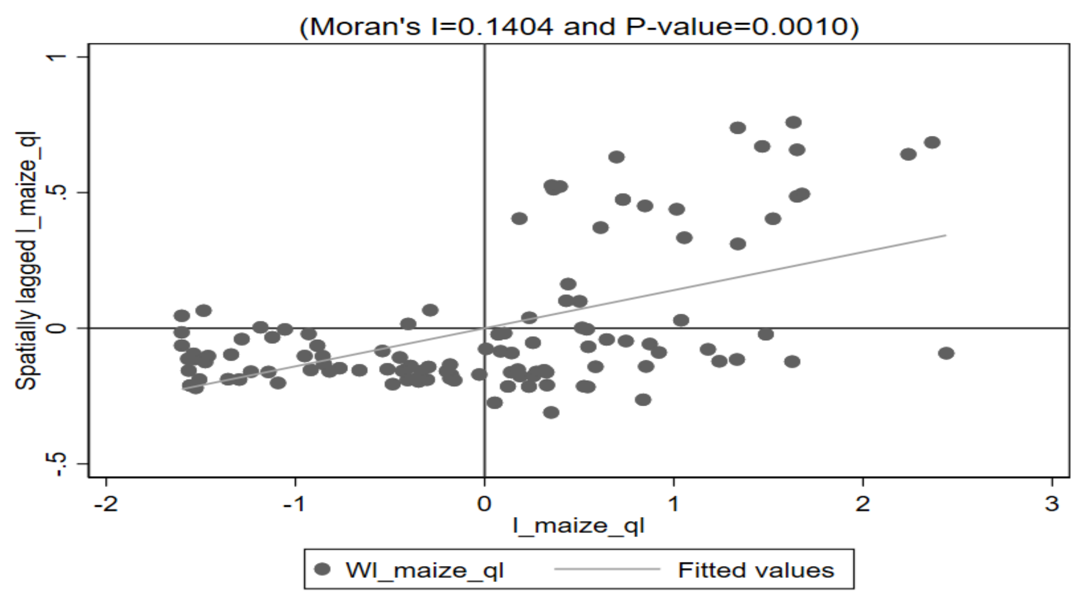
In 2005 and 2015, most sample countries lie in the I and III quadrants, indicating positive spatial autocorrelation at a 1% significance level. In 2020, most of the values lie in the I and III quadrants indicating positive spatial autocorrelation. Countries with high maize production are clustered around neighbors with high average maize value (and vice versa).

Figure 4.3: Moran-I Scatter Plot for the log of Maize Production per Agriculture Land for Various Spatial Lags

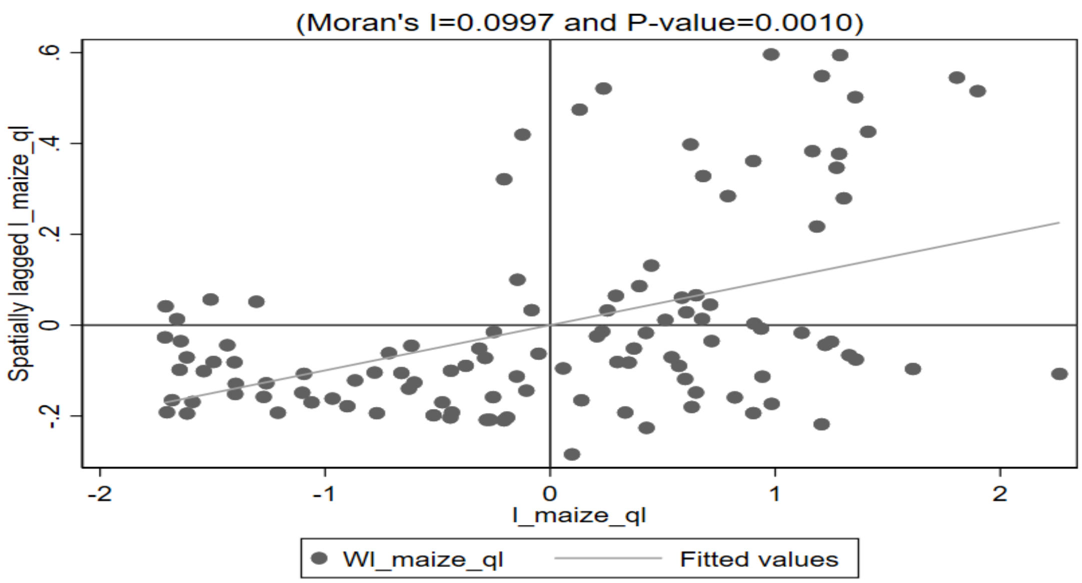
1995



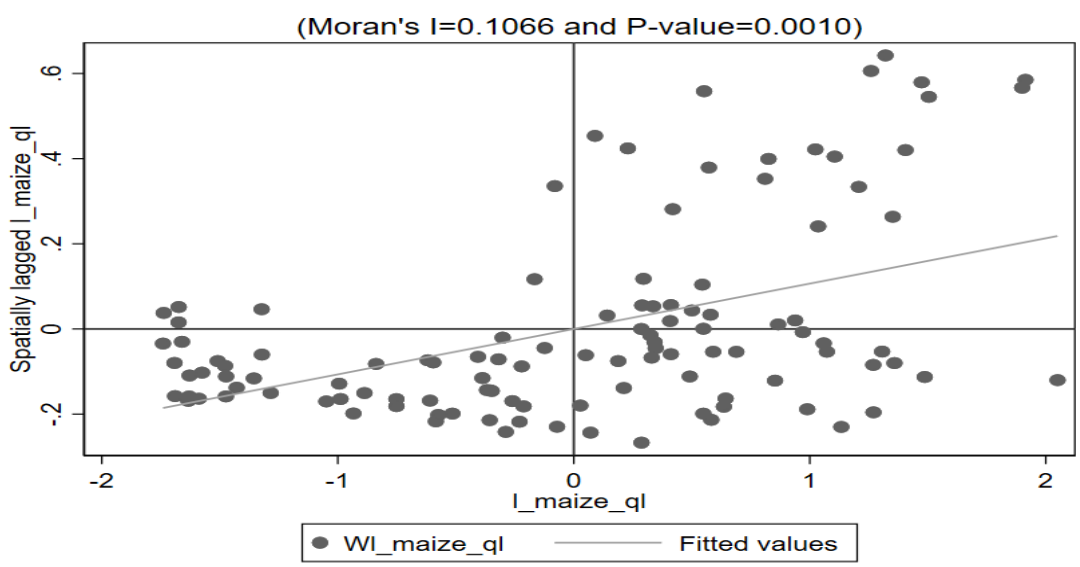
2005



2015


(Moran's I=0.0997 and P-value=0.0010)
Spatially lagged l_maize_ql
-.2
0
.2
.4
.6
-2
-1
0
1
2
l_maize_ql
Wl_maize_ql
Fitted values

2020

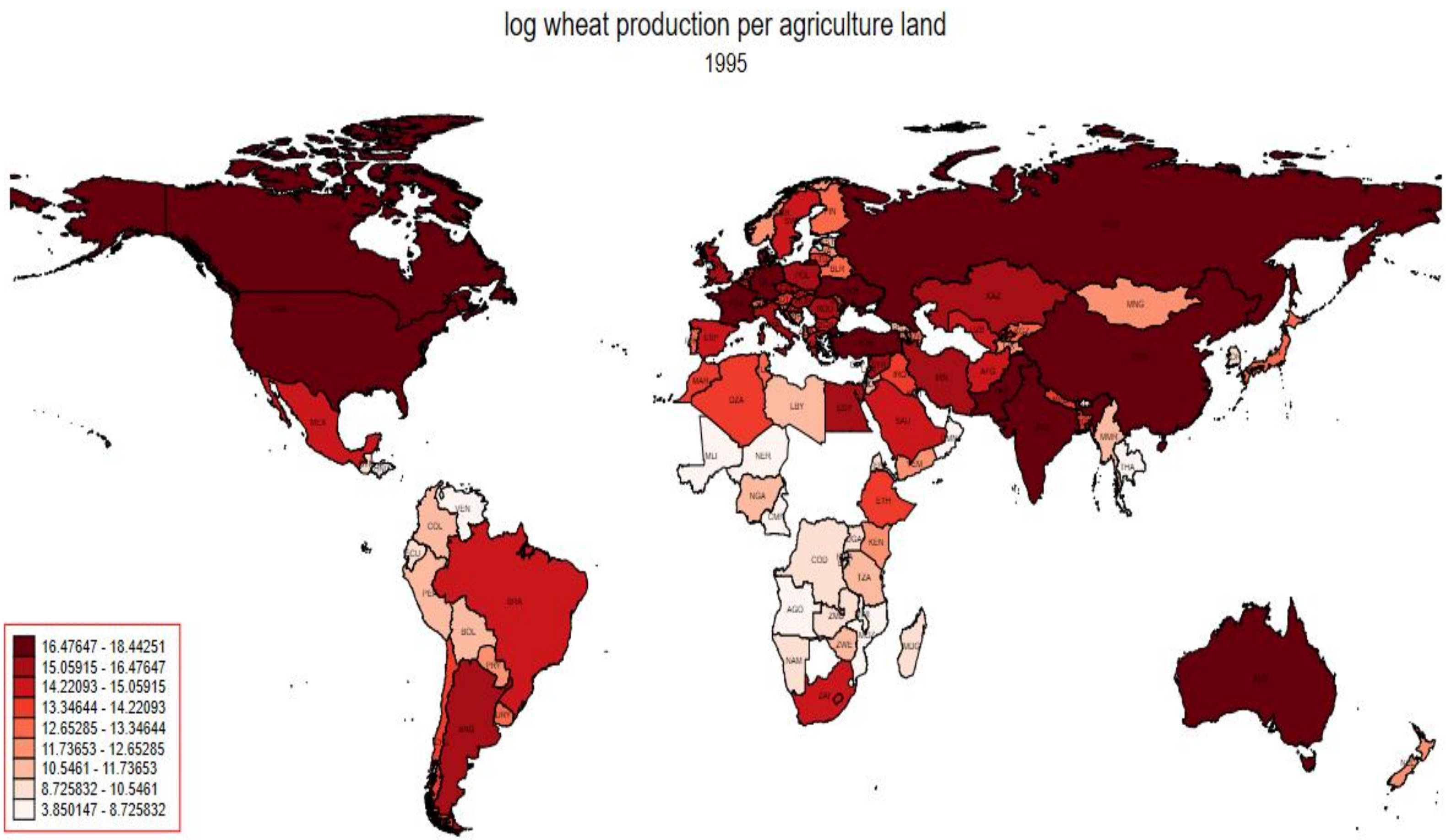

(Moran's I=0.1066 and P-value=0.0010)
Spatially lagged l_maize_ql
-.2
0
.2
.4
.6
-2
-1
0
1
2
l_maize_ql
Wl_maize_ql
Fitted values

To evaluate the spatial distribution of crop production, we have averaged the data for wheat, rice, and maize production per agricultural land from 1995 to 2020. The legend in each case indicates class breaks which show quantiles of the distribution of crop production.

Spatial distribution in the case of wheat production shows that countries with similar production per agricultural land are in close proximity to each other. European countries and Canada are more productive in producing wheat, followed by Asia. Africa and some parts of Latin American countries lie in the lower quantiles in the case of wheat. For rice production per agricultural land, Pakistan, India, China, Bangladesh, and East Asian economies are more productive in producing rice crops as they lie in the upper quantile and are in close proximity. Central Asian and African economies have low productivity in producing rice.

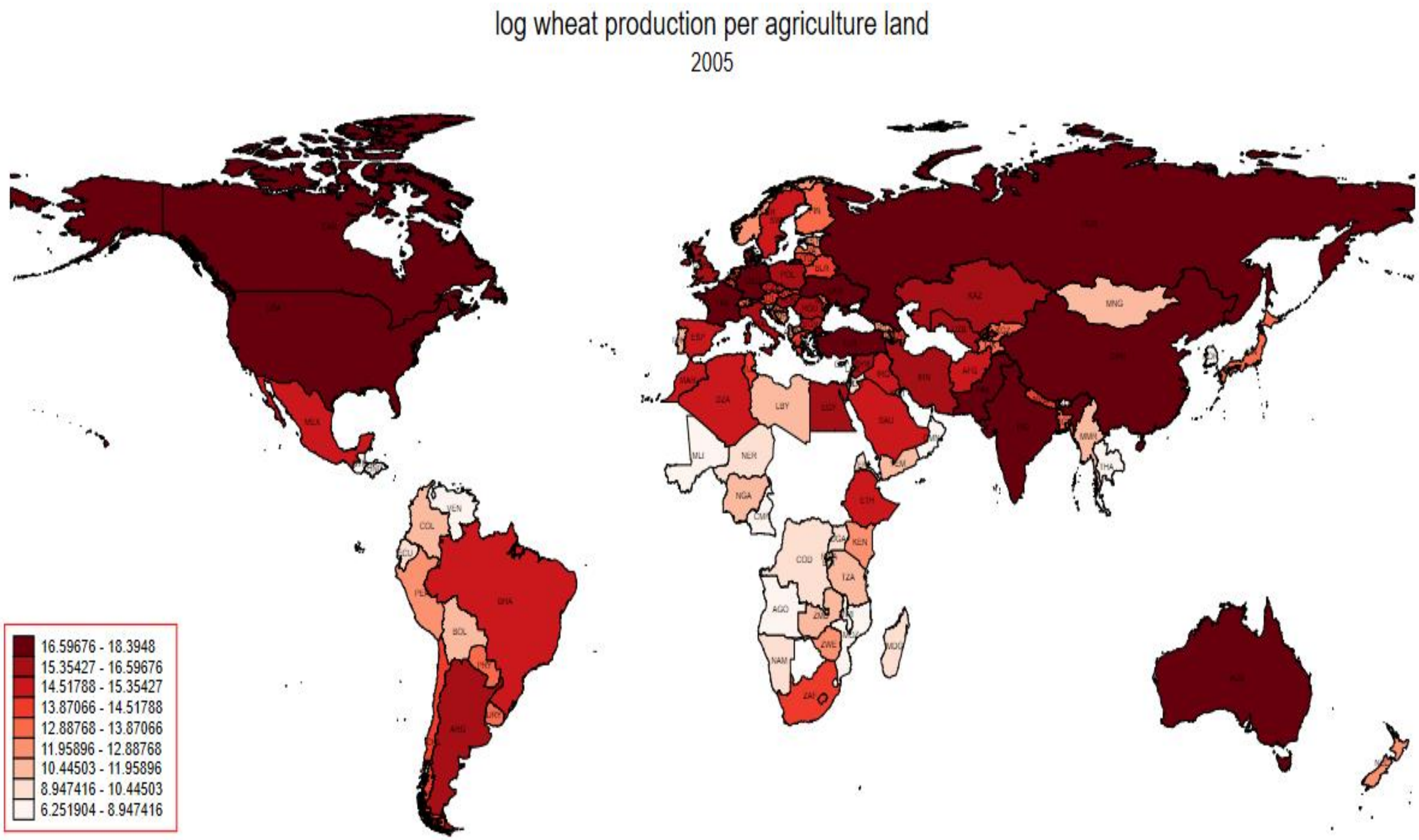
For maize, the USA, China, East Asian countries, and part of Europe are more productive than the rest of the world as they lie in the upper quantile. Latin American countries, including Mexico and Canada, are in the middle quintile of the countries producing maize. Central Asia, parts of the Middle East, and Australia have low productivity in producing maize.

Figure 4.4a: Spatial Distribution of Wheat Production per Agriculture Land (1995)



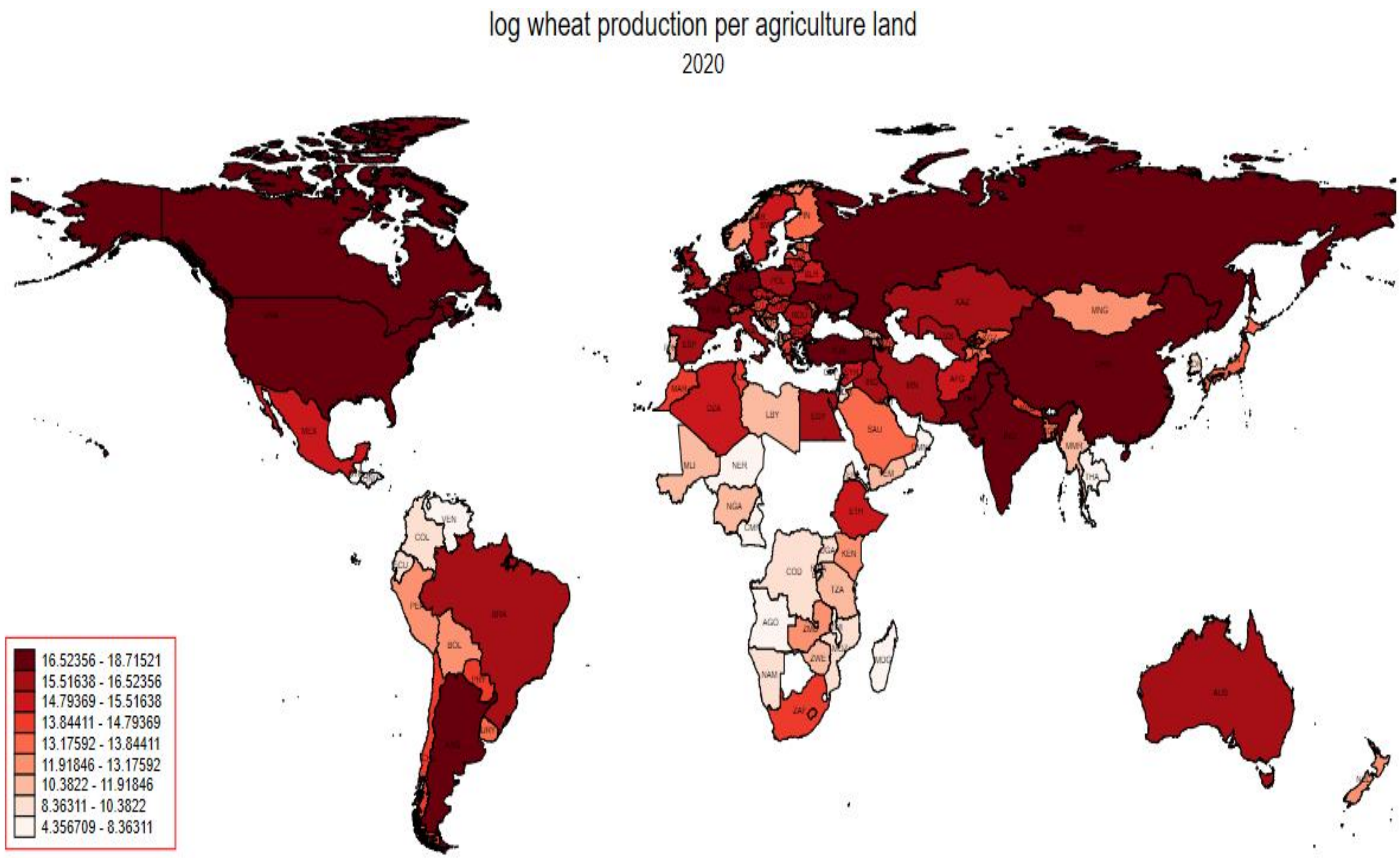
Source: Author's calculation from FAO database

Figure 4.4b: Spatial Distribution of Wheat Production per Agriculture Land (2005)



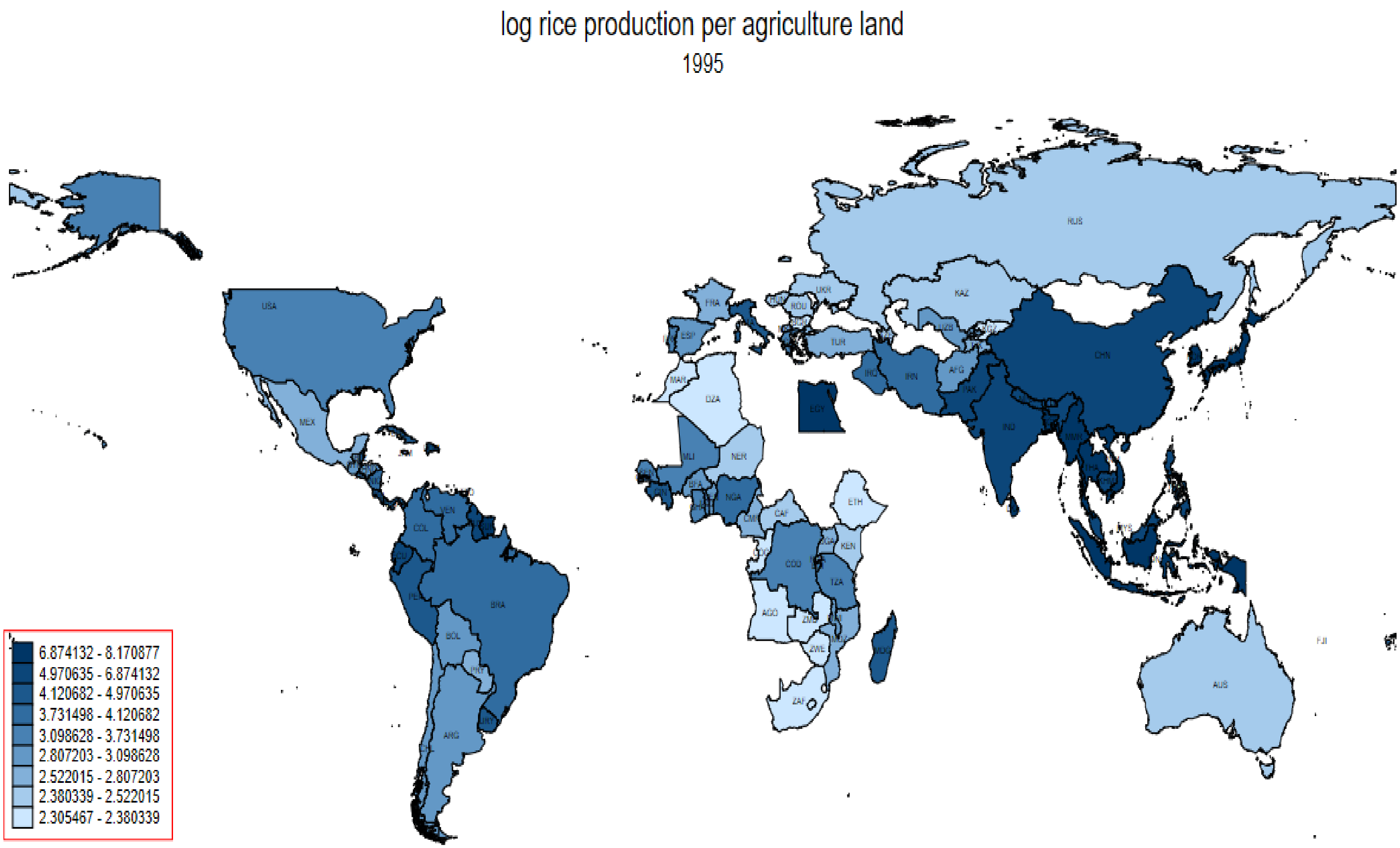
Source: Author's calculation from FAO database

Figure 4.4a: Spatial Distribution of Wheat Production per Agriculture Land (2020)



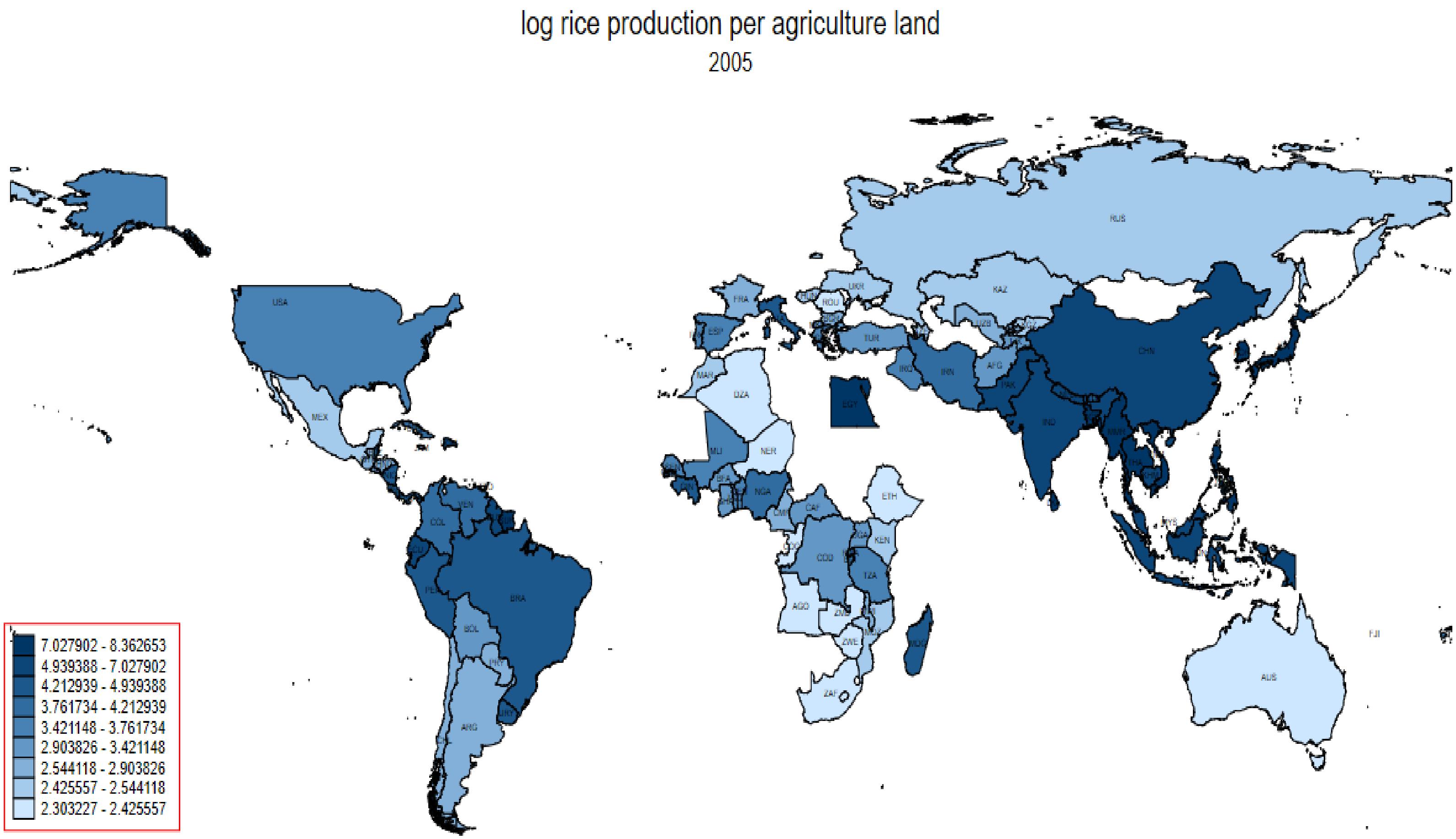
Source: Author's calculation from FAO database

Figure 4.5a: Spatial Distribution of Rice Production per Agriculture Land (1995)



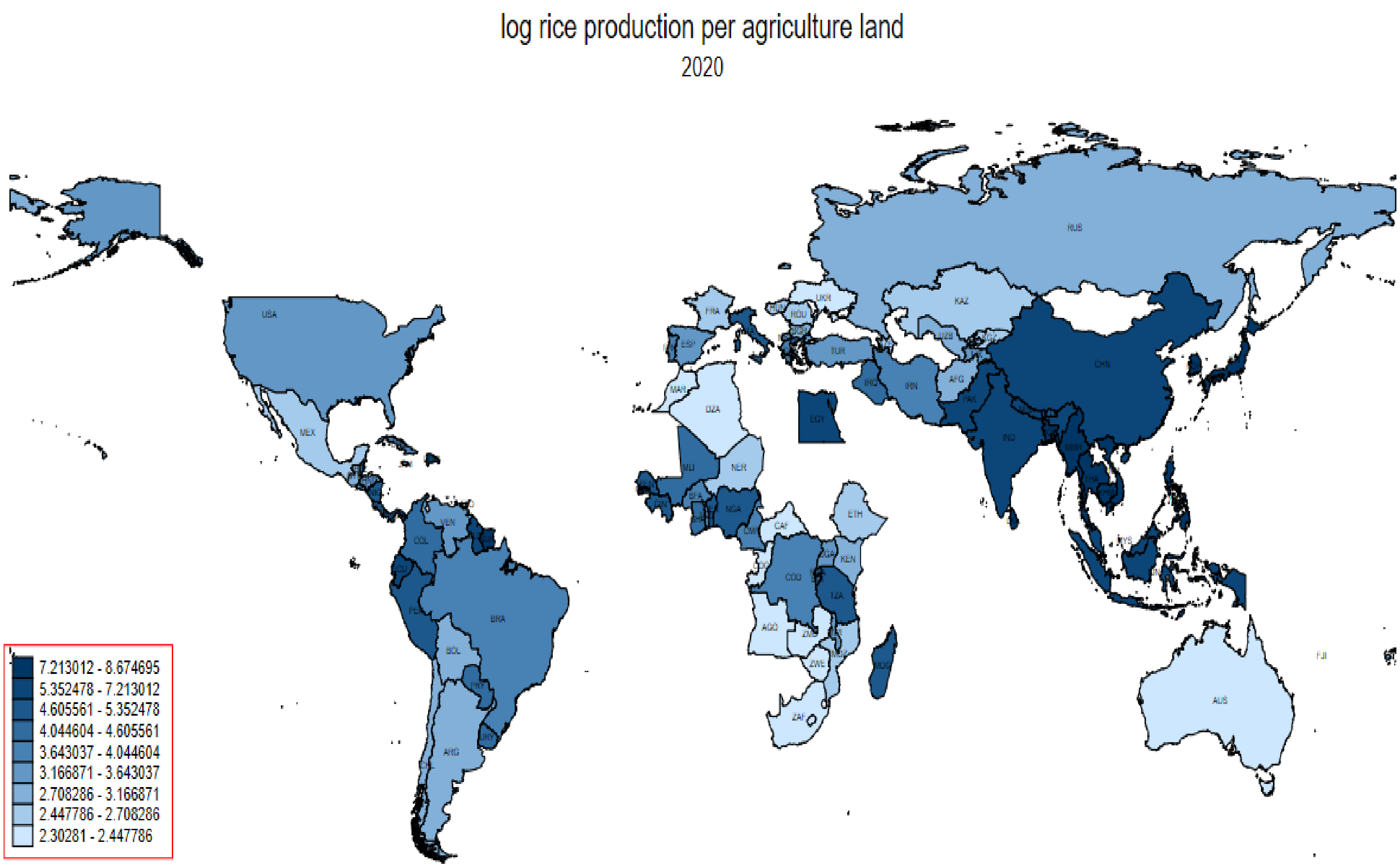
Source: Author's work from FAO database

Figure 4.5b: Spatial Distribution of Rice Production per Agriculture Land (2005)



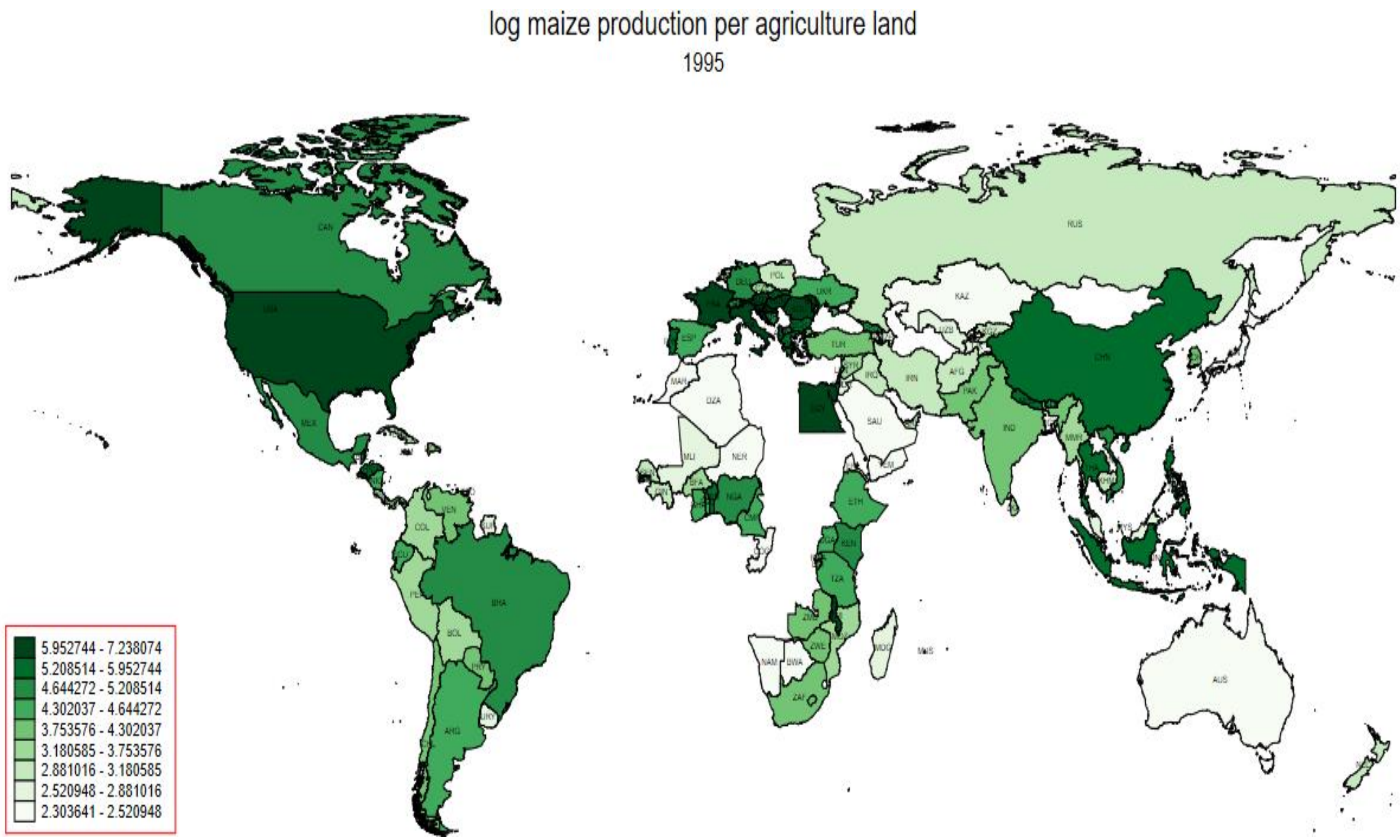
Source: Author's work from FAO database

Figure 4.5c: Spatial Distribution of Rice Production per Agriculture Land (2020)



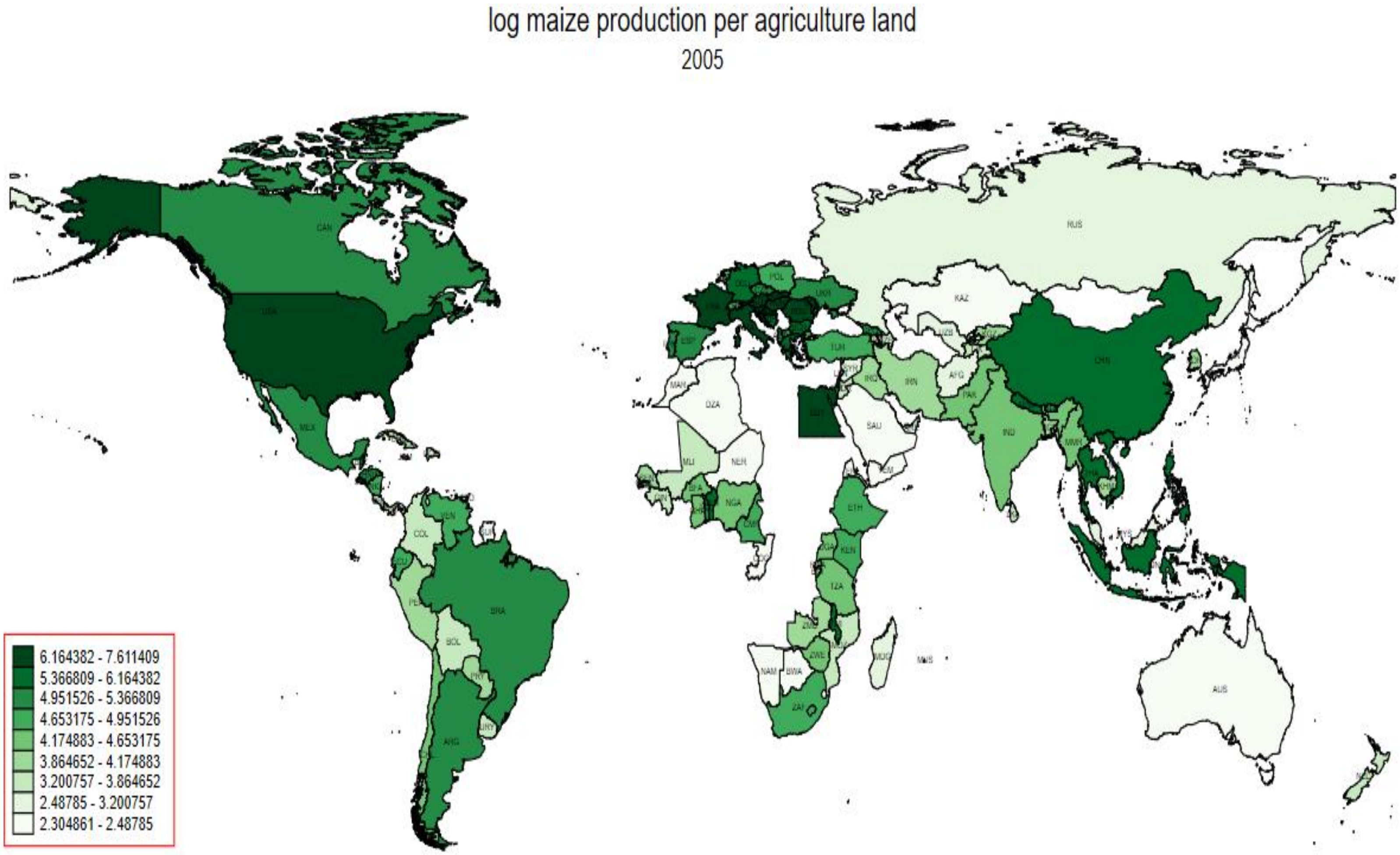
Source: Author's calculation from FAO database

Figure 4.6a: Spatial Distribution of Maize Production per Agriculture Land (1995)



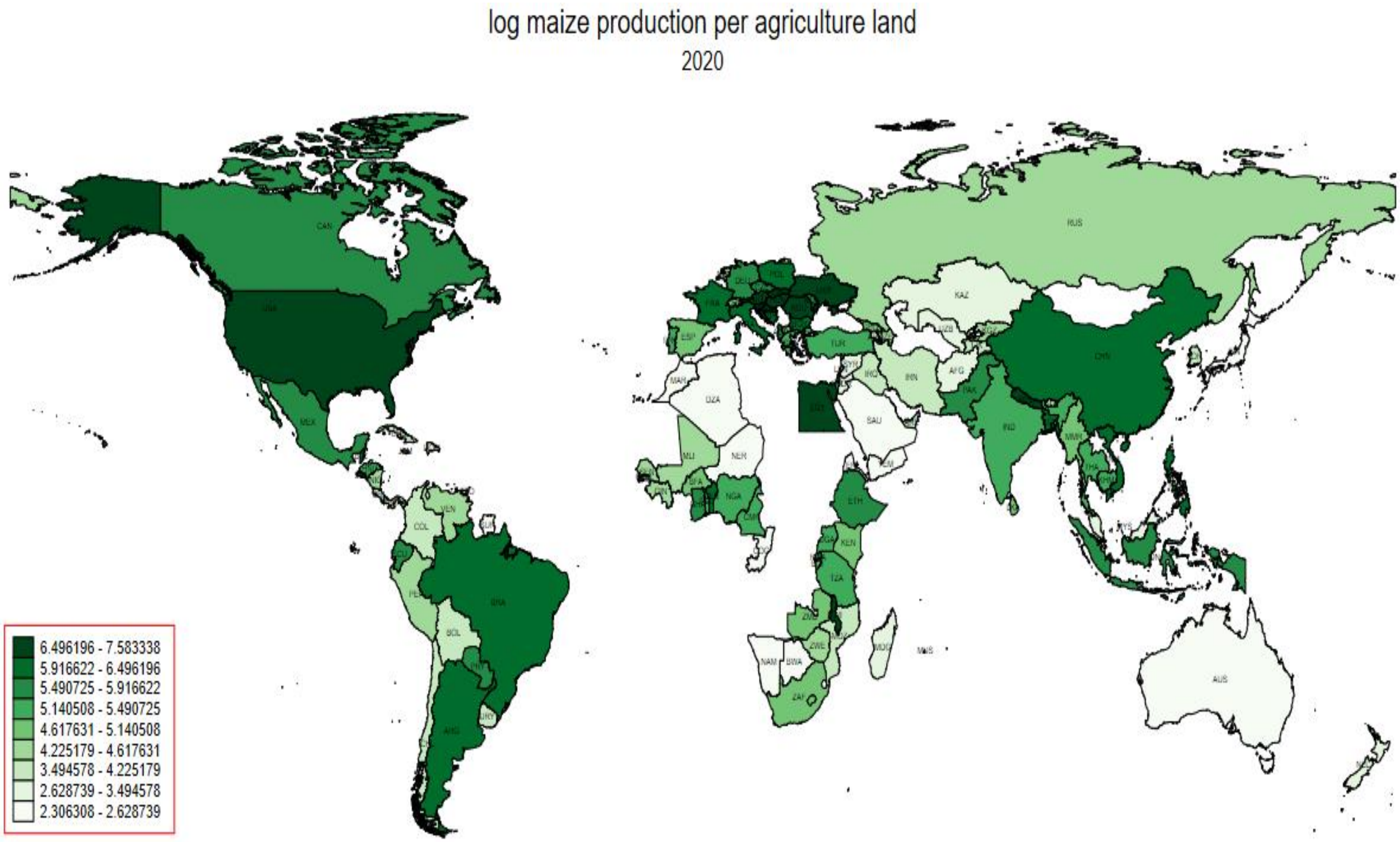
Source: Author's work from FAO database

Figure 4.6b: Spatial Distribution of Maize Production per Agriculture Land (2005)



Source: Author's calculation from FAO database

Figure 4.6c: Spatial Distribution of Maize Production per Agriculture Land (2020)



Source: Author's calculation from FAO database

4.6.2 Cross-sectional Dependence Test

To further examine the presence of dependence across countries without considering the spatial weight matrix, we have applied the cross-sectional dependence test (CD). All the variables included rejects the null hypothesis of no cross-sectional dependence at a 1% significance level.

Table 4.2 Cross-Sectional Dependence Test

Variables	**CD test**		
	Wheat	Rice	Maize
$WHEAT$	35.92***		
$RICE$		82.246***	
$MAIZE$			132.141***
$FERT$	44.085***	63.633***	48.266***
$MACH$	16.699***	179.4***	47.458***
$AGRL$	2.891***	133.768***	2.507**
$OPEN$	114.348***	10.771***	122.523***
$TEMP$	119.858***	126.43***	152.438***
$VTEMP$	106.524***	115.684***	139.495***
$RAIN$	8.446***	10.934***	9.34***
$VRAIN$	41.569***	16.758***	23.9***

Notes: Under the null hypothesis of cross-section independence, CD ~ N (0, 1). ***, **, * indicates the significance level at 1%, 5% and 10% respectively. All variables are taken in log form.

4.6.3 Spatial Econometric Regression for Food Production

Following Elhorst and Vega (2013), we first test for the non-spatial panel model against the spatial model (spatial lag and spatial error models). The LM diagnostics test, i.e., LM lag and LM error test in wheat, rice, and maize production, significantly reject the presence of no spatial lagged dependent variable and reject the null hypothesis of no spatial auto correlated error term (see table; 4.4). Both Robust LM lag and Robust error test reject the null hypothesis, but the test value of robust LM error is higher than LM lag; therefore, in the case of wheat, rice, and maize yield spatial error test statistic strengthen the existence of spatial effects in the data as highlighted by Moran-I test.

Estimation results of non-spatial panel models are shown in Table 4.3. Alternative model specifications, such as pooled OLS, fixed effect, and random effect models, are presented. All model specifications from (1) – (9) Hausman test suggest a fixed-effect model for non-spatial factors affecting crop production.

Table 4.3: Estimation Results of Non-Spatial Models

Variables	Wheat production per agriculture land			Rice production per agriculture land			Maize production per agriculture land		
	OLS (1)	**Fixed Effect (2)**	**Random Effect (3)**	**OLS (4)**	**Fixed Effect (5)**	**Random Effect (6)**	**OLS (7)**	**Fixed Effect (8)**	**Random Effect (9)**
FERT	-0.0145	0.0576***	0.0641***	0.148***	0.107***	0.108***	0.138***	0.122***	0.123***
	(-22.85)	(6.91)	(7.64)	(13.37)	(16.11)	(16.18)	(14.70)	(14.19)	(14.46)
MACH	0.385***	-0.0584	0.0941	14.38***	-3.116	-1.857	-0.249	2.757***	2.613***
	(8.98)	(-0.34)	(0.55)	(5.26)	(-1.08)	(-0.66)	(-1.61)	(12.85)	(12.61)
AGRL	6.151***	-0.573	-0.537	3.146***	1.050***	1.193***	5.764***	-1.563*	-1.027
	(12.51)	(-0.83)	(-0.80)	(27.49)	(7.32)	(8.53)	(11.96)	(-1.78)	(-1.24)
OPEN	0.116	0.257***	0.249***	0.591	0.148	0.146	1.081***	0.619***	0.621***
	(1.33)	(8.3)	(7.87)	(1.17)	(1.24)	(1.22)	(9.08)	(12.720)	(12.65)
TEMP	-2.058***	0.601**	-1.101***	1.253***	1.218***	1.352***	-0.664***	2.504***	0.551**
	(-30.95)	(2)	(-5.46)	(12.47)	(2.83)	(4.35)	(-9.34)	(5.89)	(2.26)
VTEMP	3.531***	0.267**	0.779***	-2.185***	-0.0837	-0.138	2.940***	-0.0825	0.493***
	(15.28)	(2.54)	(9.37)	(-5.24)	(-0.56)	(-1.12)	(10.86)	(-0.56)	(4.52)
RAIN	-0.369***	0.343***	0.297***	0.534***	0.127***	0.150***	0.416***	0.306***	0.300***
	(-11.77)	(9.42)	(8.34)	(13.58)	(3.43)	(4.12)	(14.61)	(6.71)	(6.97)
VRAIN	0.0235	0.0301***	0.0295***	-0.0284*	-0.0142***	-0.0145***	-0.0469***	0.00318	0.00288
	(1.62)	(6.75)	(6.45)	(-1.83)	(-3.85)	(-3.91)	(-3.56)	(0.65)	(0.59)
Intercept	-15.77***	-0.296	3.714**	-42.35***	2.44	-1.288	-20.01***	-11.55***	-7.344***
	(-11.60)	(-0.16)	(2.2)	(-6.44)	(0.35)	(-0.19)	(-14.82)	(-4.67)	(-3.44)
N		2756			2418			2964	
Hausman		149.81			30.01			70.74	
P-Value		0.0000			0.0000			0.0000	

Note: ***, **, * indicates the significance level at 1%, 5%, and 10%, respectively.

Table 4.4: Spatial Diagnostics

Diagnostics	Wheat	Rice	Maize
Spatial error			
Moran's I	60.125***	38.117***	48.913***
Lagrange multiplier	3371.781***	1365.999***	2270.941***
Robust Lagrange multiplier	2540.692***	665.498***	852.713***
Spatial lag			
Lagrange multiplier	987.557***	704.488***	1420.513***
Robust Lagrange multiplier	66.467***	3.987**	2.285

Note: ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

As the non-spatial panel model is rejected in the presence of spatial panel models in all three crop production considered, the study chooses between alternative spatial panel models that best describe the data. We first estimate the spatial Durbin fixed (SDM-FE) and random effect model (SDM-RE) for wheat, rice, and maize production. Hausman test is employed to choose between fixed and random effect models. Results show that SDM-FE is more applicable in the case of wheat and maize, while SDM RE is the best fit in the case of rice (see Table 4.5).

Following Belotti et al. (2017), we test whether SDM is the best representative of our data. We test two hypotheses to identify if SDM can be reduced to SLM or SEM. The study employs the Wald test in all three crop productions to conclude whether SDM can be reduced to SLM and if SDM can be simplified to SEM. As SAC[35] and SDM are non-nested models, AIC SBC information criteria are used to choose between SAC and SDM models.

In wheat production, the hypothesis that SDM can be simplified to SLM is significantly rejected at 5 percent significance (Wald; 19.65, p=0.0118), while the hypothesis that SDM can be reduced to SEM is also rejected at 1 percent (Wald; 33.43; p-value 0.001). To choose between SAC and SDM models, we applied Akaike's Information Criterion, which revealed that SDM has a lower AIC than SAC. Thus, the SDM model is applied in the case of wheat production.

[35] Spatial Autoregressive model with auto regressive disturbances, SAC.

In the case of rice production, the Wald test (Wald; 62.59; p-value 0.0000) rejects the null hypothesis that SDM can be simplified to SLM at a 1% significance level. Wald test (Wald; 77.37; p-value 0.0000) also rejects the null hypothesis that SDM can be reduced to SEM. Thus, the SDM model is applied in the case of rice.

In the case of maize production, SDM is preferred over SLM (Wald; 32.20, p-value 0.0001), and Wald tests (Wald; 71.58; p-value 0.0000) also reject the hypothesis that SDM can be reduced to SEM. In the case of maize, both AIC and SBC for SDM are lower than SAC. Thus, we employed the SDM model for maize production.

4.6.3.1 Spatial Econometric Regression Results for Food Production-Wheat

SDM-FE and SDM RE are estimated in wheat production per agricultural land, while the Hausman test preferred SDM-FE. Results are shown in Table 4.5. Fertilizer, labor, trade openness, rainfall, and variability are major input factors affecting wheat production in countries considered in the analysis.

The spatial autocorrelation coefficient indicates that high wheat production in a neighboring country has a positive spillover effect in the home country. Countries with high wheat per land production are clustered around countries with similar production patterns (and vice versa). The coefficients of the SDM model don't represent marginal effects. They include the country's explanatory variable effect, feedback from neighboring countries, and its repercussions on the individual country. This can be examined as the coefficient of SDM are different from the direct effect coefficients. Therefore, the study examines the direct, indirect, and total effects of wheat production

The direct effect in the case of wheat indicates that increased fertilizer use increases wheat production by 0.05 percent. In contrast, increasing labor will decrease wheat production by 0.2 percent. Marginal productivity decreases as more labor inputs are employed per unit of land. The agriculture sector usually employs unskilled labor with low adaptation to technological and farm management skills; thus, increased labor reduces the country's wheat production. These results are in line with Zouabi and Peridy (2015).

Trade openness in wheat exports and imports positively impacts the country's wheat production. For climate variables, average annual rainfall and its variability have a significant positive relationship with wheat production. This shows a positive impact if rainfall is higher or lower than expected. Major wheat-producing countries that makeup 70 percent of total wheat production are in temperate and subtropical zones (see figure; 4.5), mostly dependent on precipitation and irrigation systems (Asseng et al., 2015). An increase in rainfall will create a conducive environment for the wheat crop.

The indirect effect shows neighborhood and spillover effects. The study found that an increase in trade openness and fertilizer usage of neighboring countries impact domestic countries' wheat production. While the change in the expected temperature measured by temperature variability of the nearby country negatively affects the domestic country's wheat production. If neighbors surround a country with an open trade policy for the wheat crop, it will encourage farmers to grow more wheat because of increased market access and size. An increase in temperature variability in one region will decrease wheat production in the neighboring regions. Countries in nearby locations face the same geography and environmental inputs. Uncertain increase or decrease in temperature negatively affects nearby countries. Countries that are rain-fed or irrigated are spatially connected. Also, information sharing through increased technology access between countries enables farmers to take proactive measures to benefit from increased rainfall variability.

There is a negative spillover effect of increased use of labor by neighboring countries on individual countries' wheat production. If the labor supply is mobile across countries, increasing labor in the agriculture sector in one country will decrease the labor availability for other countries. This can be true in the case of the EU, US, Mexico, and Canada, where agriculture labor is mobile. However, in Asia, where agriculture labor is not mobile, the geographical, economic, and skill development of agriculture labor is the same, and the farmer is strongly likely to imitate the practices being followed by neighboring countries. If neighboring countries employ more labor, domestic farmers also follow the same pattern and employ more labor. This might end up reducing their wheat output as well as labor productivity decrease with additional labor. The total effect indicates that labor productivity, trade openness, and annual average temperature and rainfall are the key factors determining wheat production. We have also evaluated the impact of non-climatic and climatic factors on wheat yield (for details, see Appendix C2 and C3).

4.6.3.2 Spatial Econometric Regression Results for Food Production-Rice

In case of rice production per agricultural land, the Hausman test preferred SDM-RE. Results in the Table 4.5 indicates that the key inputs affecting rice producing countries include fertilizer usage, agriculture sector labor, annual average temperature, temperature, and rainfall variability from the long-run mean. Positive sign of spatial autocorrelation coefficient shows that high rice producing countries are clustered around countries with similar production patterns (and vice versa).

The direct effect shows that inputs such as fertilizer and climate factors such as temperature, rainfall, and rainfall variability significantly affect domestic country rice production. Increasing fertilizer usage by one unit increases rice production by 0.05 percent. An increase in the annual average temperature increases rice production by 1.4 percent. However, temperature variability has a negative impact on rice production per land area. This shows that uncertainty created by the temperature movement means the cost of reducing rice production by 0.5 percent. Annual average rainfall has a positive but insignificant impact. Rainfall variability decreases rice production by 0.001 percent. Uncertainty created by climate variables negatively affects rice production

For indirect effects in the case of rice production, the use of mechanization, increase in annual average rainfall, and its variability are the key factors having spillover effects on the home country's rice production. Increasing mechanization by nearby countries decreases rice production in the home country. As the production will be more efficient by neighbors, the farmers in the home country will shift to other crops that might end up decreasing their rice production. Secondly, most of the agricultural machinery is imported from other regions. The increased use of agriculture machinery might create competition among countries acquiring agriculture machinery. An increase in annual rainfall in a neighboring country positively affects rice production in the home country. Rice is a water-intensive crop that requires consistent water intake. Rainfall variability of nearby locations or countries will deter rice cultivation in the home country as climate factors are homogenous across nearby locations. The total effect indicates that fertilizer, mechanization, rainfall, and its variability are the key determinants of rice production in the countries considered in the analysis. We have also evaluated the impact of non-climatic and climatic factors on rice yield (for details, see Appendix C2 and C3).

4.6.3.3 Spatial Econometric Regression Results for Food Production-Maize

SDM-FE in the Table 4.5 indicates that fertilizers, mechanization, agriculture labor, trade openness, annual average temperature, annual average rainfall, and their variability are the key factors affecting maize producing countries. The spatial autocorrelation coefficient is positive and reflects that countries will similar pattern of production are clustered around each other.

The direct effect of maize production indicates that increased fertilizer use increases maize production by 0.06 percent. Fertilizer is an important input that provides resilience against changing climate conditions. It is also used to access adaptation measures adopted by countries to overcome the negative impact of climate change. The increased use of mechanization in maize cultivation increases maize production by 0.3 percent. At the same time, an increase in labor employment in the agriculture sector will decrease maize production by 0.3 percent. Marginal productivity decreases as more labor inputs are employed. Trade openness in maize exports and imports positively impacts the country's maize production. An open export policy for maize expands the market for farmers, while an open import policy also creates healthy competition for domestic farmers and low prices of maize to consumers. For climate variables, annual average temperature and rainfall increase maize production per hectare by 2.6 and 0.2 percent, respectively. Annual average temperature and precipitation are known to the farmers at the time of cultivation of crops; however, variability in terms of temperature deviation and precipitation from their long-run mean negatively affects maize production by 0.9 and 0.01 percent, respectively (Moore & Lobell, 2014).

For spillover effects, increased fertilizer use, mechanization, and trade openness in the neighboring country promote maize production in the home country. A country surrounded by neighbors with an open trade policy for maize has a positive spillover effect on its production. As the market size of maize for domestic farmers increase. In addition, the import of maize tends to equalize maize prices to international price levels that benefit both the growers and consumers. Climatic variables have no spillover effect in the case of maize crops. An increase in labor in neighboring countries' maize production has a profound positive impact on maize production in the home country. This shows that labor sharing and coordination efforts among maize growers are also made. The total effect indicates that fertilizer, mechanization, and trade openness are the key factors determining maize production. We have also evaluated the impact of non-climatic and climatic factors on maize yield (for details, see Appendix C2 and C3).

Table 4.5: Estimation Results of Spatial Durbin Model – Food Production

Variables	Wheat Production per Agriculture land				Rice Production per Agriculture land				Maize Production per Agriculture land			
	SDM-FE		SDM-RE		SDM-FE		SDM-RE		SDM-FE		SDM-RE	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
ρ	0.300***	(4.26)	0.311***	(4.44)	0.441***	(7.6)	0.486***	(8.6)	0.522***	(9.84)	0.550***	(10.63)
$FERT$	0.0535***	(6.21)	0.0568***	(6.49)	0.0483***	(7.66)	0.0478***	(7.45)	0.0567***	(7.29)	0.0569***	(7.21)
$MACH$	-0.0267	(-1.26)	0.00948	(0.45)	-0.00775	(-0.34)	-0.00266	(-0.12)	0.284***	(12.21)	0.265***	(11.77)
$AGRL$	-0.170***	(-6.82)	-0.188***	(-7.73)	0.159***	(8.74)	0.155***	(8.55)	-0.271***	(-8.39)	-0.232***	(-7.48)
$OPEN$	0.145***	(4.64)	0.143***	(4.48)	0.0937	(0.88)	0.101	(0.94)	0.234***	(5.22)	0.242***	(5.29)
$TEMP$	0.362	(1.2)	-0.575**	(-2.25)	1.061***	(2.64)	1.414***	(4.06)	2.621***	(6.37)	1.716***	(5.42)
$VTEMP$	0.112	(1.02)	0.401***	(4.02)	-0.446***	(-2.82)	-0.551***	(-3.77)	-0.879***	(-4.93)	-0.582***	(-3.75)
$RAIN$	0.326***	(9.3)	0.313***	(8.92)	0.0219	(0.6)	0.037	(1.01)	0.215***	(4.64)	0.234***	(5.09)
$VRAIN$	0.0179***	(4.06)	0.0177***	(3.93)	-0.00674**	(-2.04)	-0.00634*	(-1.89)	-0.0134***	(-3.06)	-0.0136***	(-3.05)
$W * FERT$	-0.131**	(-2.55)	-0.145***	(-2.79)	-0.0221	(-0.77)	-0.0261	(-0.91)	0.0715**	(2.07)	0.0663*	(1.9)
$W * MACH$	0.0228	(0.11)	0.0901	(0.46)	-0.629***	(-3.30)	-0.466**	(-2.48)	0.215*	(1.83)	0.200*	(1.85)
$W * AGRL$	-0.660***	(-3.77)	-0.593***	(-3.40)	0.00381	(0.04)	0.0406	(0.47)	0.365***	(2.85)	0.270**	(2.21)
$W * OPEN$	0.224*	(1.88)	0.225*	(1.85)	-0.39	(-0.87)	-0.359	(-0.79)	0.380**	(2.12)	0.339*	(1.89)
$W * TEMP$	1.319	(1.46)	1.795**	(2.06)	-1.459	(-0.82)	-1.481	(-1.04)	-1.422	(-1.11)	-1.265	(-1.25)
$W * VTEMP$	-0.616*	(-1.90)	-0.766**	(-2.38)	0.0381	(0.07)	0.128	(0.28)	0.71	(1.64)	0.548	(1.44)
$W * RAIN$	0.0702	(0.38)	0.0464	(0.25)	0.302**	(2.3)	0.305**	(2.36)	-0.0661	(-0.40)	-0.125	(-0.79)
$W * VRAIN$	-0.00725	(-0.32)	-0.0068	(-0.30)	-0.137***	(-8.48)	-0.134***	(-8.16)	0.0059	(0.25)	0.00862	(0.36)
intercept			2.531	(0.8)			2.287	(0.49)			-6.544**	(-2.32)
Hausman	53.71				23.83				129.03			
P-Value	0.0004				0.1240				0.0000			

Source: Author's calculation based on FAO database

Table 4.6: Spatial Direct, Indirect and Total effect of SDM model- Food Production

Variables	Wheat Production per Agriculture land			Rice Production per Agriculture land			Maize Production per Agriculture land		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
$FERT$	0.0530***	-0.159**	-0.106	0.0480***	-0.00365	0.0443	0.0589***	0.216***	0.275***
	(5.99)	(-2.14)	(-1.42)	(7.3)	(-0.07)	(0.79)	(7.37)	(3.13)	(3.94)
$MACH$	-0.0276	0.0127	-0.0149	-0.0133	-0.929***	-0.943***	0.290***	0.757***	1.047***
	(-1.33)	(0.04)	(-0.05)	(-0.61)	(-2.61)	(-2.62)	(13.1)	(3.55)	(4.97)
$AGRL$	-0.173***	-1.018***	-1.191***	0.159***	0.212	0.370**	-0.264***	0.449*	0.185
	(-7.12)	(-4.31)	(-4.89)	(9.05)	(1.4)	(2.41)	(-8.58)	(1.84)	(0.76)
$OPEN$	0.147***	0.390**	0.537***	0.0932	-0.686	-0.593	0.244***	1.047***	1.291***
	(4.8)	(2.22)	(3.09)	(0.89)	(-0.81)	(-0.70)	(5.54)	(3.02)	(3.73)
$TEMP$	0.376	1.992	2.367*	1.397***	-1.619	-0.222	2.622***	-0.202	2.42
	(1.29)	(1.55)	(1.84)	(4.23)	(-0.62)	(-0.09)	(6.6)	(-0.08)	(0.99)
$VTEMP$	0.111	-0.817*	-0.706	-0.549***	-0.295	-0.844	-0.869***	0.525	-0.344
	(1.04)	(-1.75)	(-1.54)	(-3.90)	(-0.37)	(-1.12)	(-5.01)	(0.63)	(-0.44)
$RAIN$	0.328***	0.225	0.552**	0.0435	0.615**	0.658***	0.216***	0.0789	0.295
	(9.01)	(0.86)	(2.08)	(1.17)	(2.49)	(2.79)	(4.61)	(0.25)	(0.99)
$VRAIN$	0.0177***	-0.00423	0.0135	-0.00914***	-0.261***	-0.270***	-0.0136***	-0.00267	-0.0163
	(4.21)	(-0.13)	(0.42)	(-2.85)	(-6.76)	(-6.95)	(-3.32)	(-0.05)	(-0.33)

Note: ***, **, * indicates the significance level at 1%, 5% and 10%, respectively.

4.7. Spatial Econometric Regression Results- across Regions

4.7.1. Spatial Econometric Regression Results of Wheat Production across Regions

In the present section, we have tested for spatial determinants of wheat production across Asia-Africa and Europe. Region 1 includes Asia and Africa, and region 2 includes Europe. The spatial autocorrelation term is positive and statistically significant, showing that a country's wheat production has a positive spillover effect on its neighboring countries in regions 1 and 2. Increase use of fertilizer increases wheat production in both regions. An increase in mechanization has a positive impact on region-1's production, while it is insignificant in the case of region-2.

African and Asian countries use traditional or less capital-intensive techniques for production. Increasing the use of mechanization can enhance their production. Trade openness has a direct detrimental effect on region-1's agriculture production while it has a positive impact in the case of region-2. Asia and Africa both have a high cost of wheat production increased liberalization creates competition for domestic farmers. This can lead to a decrease the wheat production in region-1. In climatic variables, wheat production is positively influenced by rain in both regions, while temperature variability negatively affects wheat production in region-2. Most Africans and Asian countries depend on rain water for irrigation. An increase in rain enchases wheat production in this region.

Results of the indirect effect reveal that in region-1, fertilizer, temperature, variability, and rainfall spillover affect neighboring countries. Region-2 wheat production is positively influenced by neighboring country temperature and rainfall, but their respective variability that causes uncertainty decreases wheat production.

Table 4.7: Results of Wheat production Spatial Durbin Model –across the regions

Variables	Region 1		Region-2	
	Wheat production per agriculture land			
	SDM-FE	SDM-RE	SDM-FE	SDM-RE
ρ	0.205**	0.269***	0.410***	0.416***
	(2.24)	(3.04)	(4.91)	(4.97)
$FERT$	0.0268**	0.0284**	0.0890***	0.107***
	(2.46)	(2.56)	(2.68)	(3.26)
$MACH$	0.139***	0.213***	-0.0378	-0.0238
	(3.23)	(5.08)	(-1.07)	(-0.69)
$AGRL$	0.00203	-0.00266	0.0958	0.0248
	(0.04)	(-0.05)	(1.37)	(0.4)
$OPEN$	-0.157***	-0.143***	0.677***	0.636***
	(-3.72)	(-3.32)	(9.83)	(9.16)
$TEMP$	-3.546	-3.353**	-0.208	-0.143
	(-1.48)	(-2.54)	(-0.43)	(-0.40)
$VTEMP$	0.113	0.115	0.326*	0.305**
	(0.27)	(0.43)	(1.78)	(1.97)
$RAIN$	0.232***	0.186***	0.174**	0.168**
	(4.58)	(3.63)	(2.49)	(2.38)
$VRAIN$	-0.00977	-0.0141*	0.0432***	0.0439***
	(-1.29)	(-1.82)	(5.28)	(5.28)
$Intercept$		-22.31		-8.151**
		(-1.48)		(-2.09)
$W * FERT$	-0.119**	-0.112**	0.215	0.243
	(-2.22)	(-2.11)	(1.35)	(1.55)
$W * MACH$	0.0211	0.162	-0.372*	-0.348
	(0.11)	(0.88)	(-1.65)	(-1.58)
$W * AGRL$	0.00505	-0.29	-0.018	0.0807
	(0.02)	(-1.27)	(-0.09)	(0.4)
$W * OPEN$	0.221	0.260*	0.00355	0.0539
	(1.57)	(1.83)	(0.01)	(0.2)
$W * TEMP$	17.62***	10.98**	3.363***	2.734**
	(3.04)	(2.14)	(2.61)	(2.2)
$W * VTEMP$	-2.340**	-1.253	-1.109***	-0.938**
	(-2.41)	(-1.44)	(-2.86)	(-2.50)
$W * RAIN$	0.21	0.0985	0.309**	0.289*
	(1.33)	(0.64)	(2.03)	(1.88)
$W * VRAIN$	0.0475	0.0239	-0.198***	-0.191***
	(1.16)	(0.59)	(-3.88)	(-3.70)
Hausman	38.56		65.27	
P-Value	0.0021		0.0000	

Source: Author's work.

Table 4.8: Spatial Direct, Indirect and Total effect of Wheat Production SDM model-across the Regions

	Wheat production per agriculture land					
	Region 1			Region2		
Variables	Direct Effect	Indirect effect	Total effect	Direct Effect	Indirect effect	Total effect
	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE
$FERT$	0.026**	-0.136**	-0.11	0.098***	0.449	0.547*
	(2.29)	(-2.01)	(-1.55)	(2.79)	(1.64)	(1.92)
$MACH$	0.138***	0.053	0.19	-0.050	-0.65	-0.7
	(3.26)	(0.21)	(0.73)	(-1.35)	(-1.58)	(-1.62)
$AGRL$	0.007	-0.017	-0.010	0.104	0.040	0.144
	(0.13)	(-0.06)	(-0.03)	(1.54)	(0.12)	(0.4)
$OPEN$	-0.155***	0.248	0.093	0.687***	0.496	1.183**
	(-3.80)	(1.31)	(0.48)	(9.64)	(1.11)	(2.57)
$TEMP$	-3.303	21.18***	17.88***	-0.115	5.419***	5.304**
	(-1.41)	(2.97)	(2.58)	(-0.24)	(2.59)	(2.51)
$VTEMP$	0.088	-2.892**	-2.804**	0.304*	-1.619**	-1.316**
	(0.22)	(-2.39)	(-2.45)	(1.69)	(-2.54)	(-2.12)
$RAIN$	0.235***	0.323*	0.558***	0.185***	0.628***	0.813***
	(4.49)	(1.72)	(2.94)	(2.59)	(2.77)	(3.57)
$VRAIN$	-0.009	0.057	0.047	0.038***	-0.306***	-0.269***
	(-1.25)	(1.08)	(0.87)	(4.56)	(-3.43)	(-2.92)

Source: Author's work.

4.7.2. Spatial Econometric Regression Results of Rice production across regions

The present section includes rice production in Asia, north and South America. We consider Asia as region-1 and the Americas as region 2. The spatial autocorrelation term is negative and significant in the case of Asia, indicating that rice production is not clustered. Regions surrounding countries have high rice production with low rice production. In the case of the Americas, high productive regions are surrounded by high rice-producing countries. In the case of region 1, labor productivity increases rice production as most countries depend on labor-intensive techniques, while it has an insignificant impact on region-2's rice production. An increase in temperature is beneficial for rice production in both regions. However, uncertainty regarding temperature decreases rice production.

Rainfall variability and increased use of labor and agriculture machinery have a positive spillover effect in the case of region-1, while openness exerts a negative spillover effect on nearby countries. The increased use of fertilizer and rainfall variability has a spillover effect in the case of region-2.

Table 4.9: Results of Rice Production Spatial Durbin Model –across the Regions

Variables	Region 1		Region 2	
	Rice production per agriculture land			
	SDM-FE	SDM-RE	SDM-FE	SDM-RE
ρ	-0.284**	-0.344**	0.200*	0.202*
	(-2.09)	(-2.47)	(1.8)	(1.81)
$FERT$	-0.008	-0.004	0.116***	0.111***
	(-0.47)	(-0.26)	(4.91)	(4.62)
$MACH$	-0.005	0.003	-0.205	-0.226*
	(-0.05)	(0.04)	(-1.61)	(-1.83)
$AGRL$	0.107***	0.117***	0.032	-0.021
	(3.37)	(3.65)	(0.46)	(-0.34)
$OPEN$	-0.239	-0.272	0.042	0.021
	(-0.68)	(-0.76)	(0.33)	(0.17)
$TEMP$	2.303**	2.889***	2.896*	3.316***
	(2.23)	(4.14)	(1.85)	(3.11)
$VTEMP$	-0.758***	-0.894***	-1.225***	-1.375***
	(-2.71)	(-4.22)	(-2.60)	(-3.50)
$RAIN$	0.063	0.097*	0.027	0.034
	(1.12)	(1.68)	(0.4)	(0.49)
$VRAIN$	-0.003	-0.001	0.009	0.009
	(-0.49)	(-0.24)	(1.45)	(1.31)
$Intercept$		-0.66		3.166
		(-0.08)		
$W * FERT$	-0.059	-0.069	0.262***	0.229**
	(-0.80)	(-0.92)	(2.7)	(2.33)
$W * MACH$	0.723**	0.743**	0.536	0.319
	(2.4)	(2.52)	(1.09)	(0.66)
$W * AGRL$	0.548***	0.570***	-0.042	-0.005
	(3.62)	(3.79)	(-0.22)	(-0.03)
$W * OPEN$	-4.852***	-5.043***	0.513	0.45
	(-2.58)	(-2.63)	(1.26)	(1.08)
$W * TEMP$	1.823	1.381	-4.215	-3.824
	(0.65)	(0.57)	(-1.09)	(-1.08)
$W * VTEMP$	-0.783	-0.702	1.056	0.959
	(-0.99)	(-1.00)	(0.93)	(0.89)
$W * RAIN$	0.0265	-0.015	-0.359*	-0.337
	(0.17)	(-0.09)	(-1.74)	(-1.61)
$W * VRAIN$	0.142***	0.147***	-0.042	-0.044
	(5.01)	(5.11)	(-1.57)	(-1.59)
Hausman	8.93		27.32	
P-Value	0.3481		0.0536	

Source: Author’s work.

Table 4.10: Spatial Direct, Indirect and Total effect of Rice Production SDM model-across the Regions

	Rice production per agriculture land					
Variables	Region 1			Region 2		
	Direct Effect	Indirect effect	Total effect	Direct Effect	Indirect effect	Total effect
	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE
$FERT$	-0.002	-0.049	-0.051	0.122***	0.368***	0.490***
	(-0.14)	(-0.85)	(-0.87)	(5.03)	(3.04)	(3.91)
$MACH$	-0.014	0.558**	0.544**	-0.2	0.663	0.463
	(-0.17)	(2.43)	(2.46)	(-1.60)	(1.04)	(0.68)
$AGRL$	0.111***	0.398***	0.509***	0.038	-0.058	-0.020
	(3.6)	(3.71)	(4.65)	(0.56)	(-0.24)	(-0.08)
$OPEN$	-0.179	-3.947***	-4.125***	0.051	0.679	0.73
	(-0.53)	(-2.78)	(-2.69)	(0.42)	(1.23)	(1.26)
$TEMP$	2.879***	0.257	3.136*	2.824*	-4.754	-1.93
	(4.21)	(0.14)	(1.76)	(1.87)	(-1.02)	(-0.39)
$VTEMP$	-0.877***	-0.315	-1.191**	-1.187**	1.081	-0.106
	(-4.14)	(-0.62)	(-2.37)	(-2.57)	(0.75)	(-0.07)
$RAIN$	0.099	-0.043	0.055	0.022	-0.453*	-0.431
	(1.64)	(-0.33)	(0.44)	(0.31)	(-1.78)	(-1.64)
$VRAIN$	-0.004	0.113***	0.108***	0.009	-0.050	-0.042
	(-0.84)	(5.61)	(5.33)	(1.39)	(-1.36)	(-1.09)

Source: Author's work.

4.7.3. Spatial Econometric Regression Results of Maize production across regions

In the present section, we have tested for spatial determinants of maize production across Europe and Africa. Region 1 includes Europe, and region 2 includes Africa. The spatial autocorrelation term is positive and statistically significant, showing that an increase in maize production of a country has a positive spillover effect on its neighboring countries in regions 1 and 2. Increase use of fertilizer increases maize production in both regions. Increase mechanization has a positive impact on region-1's production while it is insignificant in the case of region-2. Trade openness and labor are important determinants of maize production in region-1. In the case of climatic variables, average annual temperature, variability, and annual average rainfall determine the changes in maize production in Europe. In region 2, annual average rainfall positively impacts maize production, while its variability negatively affects maize production in region 2. Most of the countries in region 2 are rain-fed. Thus, uncertainty reduces maize production.

Results of the indirect effect reveal no spillover effects of the determinants considered in region-1, while in region-2, increased use of machinery, trade openness in maize crops, and increased rainfall exert positive spillover on nearby countries.

Table 4.11: Results of Maize Production Spatial Durbin Model – across the Regions

Variables	Region 1		Region 2	
	Maize production per agriculture land			
	SDM-FE	SDM-RE	SDM-FE	SDM-RE
ρ	0.348***	0.323***	0.168*	0.173*
	(3.42)	(3.1)	(1.65)	(1.71)
$FERT$	0.101***	0.099***	0.023**	0.028***
	(3.52)	(3.45)	(2.38)	(2.74)
$MACH$	0.089*	0.051	-0.142	-0.098
	(1.78)	(1.04)	(-1.08)	(-0.92)
$AGRL$	-0.199**	-0.158*	-0.043	0.029
	(-2.11)	(-1.96)	(-0.43)	(0.33)
$OPEN$	0.663***	0.676***	-0.039	-0.035
	(7.78)	(7.91)	(-0.55)	(-0.49)
$TEMP$	4.151***	2.312***	-9.460**	-2.378
	(5.7)	(4.51)	(-2.02)	(-0.93)
$VTEMP$	-1.203***	-0.597**	0.406	-0.775
	(-4.24)	(-2.51)	(0.49)	(-1.51)
$RAIN$	0.296***	0.330***	0.300***	0.298***
	(2.96)	(3.28)	(3.67)	(3.73)
$VRAIN$	-0.005	-0.005	-0.016*	-0.019**
	(-0.44)	(-0.43)	(-1.87)	(-2.10)
$Intercept$		-6.405		-34.58
		(-0.92)		(-1.19)
$W * FERT$	0.080	0.048	0.011	0.017
	(0.7)	(0.41)	(0.29)	(0.44)
$W * MACH$	0.282	0.078	1.791***	1.579***
	(0.63)	(0.19)	(3.32)	(3.26)
$W * AGRL$	-0.033	-0.111	-0.114	-0.159
	(-0.17)	(-0.58)	(-0.26)	(-0.39)
$W * OPEN$	0.052	0.035	0.514**	0.514**
	(0.18)	(0.12)	(2.4)	(2.35)
$W * TEMP$	-3.009	0.088	13.26	10.27
	(-1.18)	(0.04)	(1.17)	(1.11)
$W * VTEMP$	0.681	-0.268	-0.549	-0.119
	(1.01)	(-0.42)	(-0.25)	(-0.06)
$W * RAIN$	0.002	-0.040	0.404*	0.421*
	(0.01)	(-0.22)	(1.65)	(1.68)
$W * VRAIN$	0.067	0.054	-0.055	-0.054
	(1)	(0.86)	(-1.55)	(-1.52)
Hausman	110.02		24.62	
P-Value	0.0000		0.1036	

Source: Author's work.

Table 4.12: Spatial Direct, Indirect and Total effect of Maize Production SDM model-across the Regions

	Maize production per agriculture land					
	Region 1			Region 2		
Variables	Direct Effect	Indirect effect	Total effect	Direct Effect	Indirect effect	Total effect
	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE	SDM-FE
$FERT$	0.106***	0.189	0.294	0.0282***	0.0271	0.0553
	(3.48)	(1.09)	(1.6)	(2.74)	(0.6)	(1.21)
$MACH$	0.097*	0.486	0.582	-0.0812	1.831***	1.749***
	(1.65)	(0.67)	(0.76)	(-0.79)	(3.12)	(2.86)
$AGRL$	-0.192**	-0.161	-0.353	0.036	-0.15	-0.114
	(-2.12)	(-0.60)	(-1.25)	(0.42)	(-0.30)	(-0.22)
$OPEN$	0.673***	0.436	1.109***	-0.029	0.593**	0.564**
	(7.81)	(1.08)	(2.65)	(-0.41)	(2.38)	(2.2)
$TEMP$	4.115***	-2.518	1.597	-2.249	10.7	8.451
	(5.71)	(-0.64)	(0.39)	(-0.89)	(0.98)	(0.74)
$VTEMP$	-1.189***	0.424	-0.765	-0.762	-0.151	-0.912
	(-4.24)	(0.4)	(-0.72)	(-1.48)	(-0.07)	(-0.39)
$RAIN$	0.299***	0.157	0.456**	0.304***	0.548*	0.852***
	(2.94)	(0.68)	(1.98)	(3.68)	(1.79)	(2.72)
$VRAIN$	-0.003	0.098	0.095	-0.0199**	-0.066	-0.0861*
	(-0.30)	(1.07)	(1)	(-2.28)	(-1.56)	(-1.94)

Source: Author's work.

4.8. Conclusion

The present section studies the responsiveness of food production (wheat, rice, and maize) per unit of the land area towards spatial climatic and non-climatic inputs involved in the production process. The key input factors examined in the analysis are fertilizers, mechanization per unit of agricultural land, labor per unit of agricultural land, trade openness, temperature, precipitation, and their respective variability calculated by deviation from their long-run mean. We have employed a separate analysis for each crop from 1995 to 2020. The non-spatial panel model is rejected in the presence of spatial panel models in all three crop production. Within spatial models, the SDM model fits the data well. Hausman test is employed to choose between fixed and random effect models. Results show that SDM-FE is more applicable in the case of wheat and maize, while SDM RE is the best fit in the case of rice. The spatial analysis measures spatial correlation coefficient, direct, indirect, and total effect. The spatial correlation coefficient in all three crops is positive and statistically significant, showing that neighbors surround high crop-producing countries with high crop production (and vice versa).

For wheat production per unit of land area, fertilizer usage, labor, trade openness for the wheat crop, rainfall, and its variability are major input factors affecting wheat production. Increased fertilizer use by the home country has a direct positive and significant impact on the country's wheat production, while increased fertilizer use by neighboring countries has a negative significant spillover effect on the domestic country's production. This is due to the competition and availability of input in the international market. As most of the countries considered are dependent on imported fertilizers. An increase in labor employment has a negative impact on the country's wheat production, while an increase in labor usage by neighboring countries negatively affects wheat production in the home country. Openness, i.e., free movement and access of wheat in domestic and neighboring countries, positively impacts wheat production in domestic countries. An increase in rainfall variability in one region and its neighboring countries increases wheat production in the domestic country.

For rice production, fertilizer, agriculture labor, average annual temperature and its variability, and rainfall variability from the long-run mean are major input factors affecting rice production. Increased fertilizer use by the home country has a direct positive and significant impact on the country's rice production, while increased fertilizer use by neighboring countries has no significant spillover effect on the domestic country's production. Increased machinery has a negative but insignificant impact on domestic country rice production, while neighboring countries' increased machinery usage reduces rice production in the home country. Rice-producing countries mostly use labor for the crop sowing and harvesting process. Thus, mechanization is not helpful in rice-producing countries that also require labor training to operate machinery. An increase in the annual average temperature of the domestic country increases rice production, while an increase in a neighboring country's temperature has no significant spillover effect on domestic country rice production. An increase in temperature variability of the home country negatively affects domestic rice production, while neighboring countries' temperature variability has a negative but insignificant spillover effect. An increase in rainfall variability of the home country negatively affects domestic rice production, while neighboring countries' rainfall variability also has a negative spillover effect on domestic rice production. This shows that uncertainty about the temperature and rainfall conditions of domestic and neighboring countries creates additional costs for domestic rice growers.

Fertilizers, mechanization, agriculture labor, trade openness, annual average temperature, annual average rainfall, and their variability from the long-run mean are the major determinants of maize production. Increased use of fertilizer by the home country has a direct positive and significant impact on the country's maize production, while increased use of fertilizer by neighboring countries also has a significant positive spillover effect on the domestic country's production. An increase in the use of machinery has a positive impact on domestic country maize production, while neighboring countries' increased usage of machinery has a positive effect on maize production in the home country. An increase in labor in the home country negatively affects maize production as unskilled agriculture labor marginal productivity diminishes. Increasing agricultural labor by neighboring countries positively affects domestic maize production. Trade openness in home and neighboring countries positively impacts domestic maize production.

Climatic variables such as temperature and rainfall of domestic countries positively affect maize production with no significant spillover effect on neighboring countries' climate. However, climate variability in terms of temperature and rainfall change in the domestic country negatively affects domestic production, while neighboring countries' uncertain climate conditions have no significant effect on maize production.

Chapter 5

CONCLUSION & POLICY IMPLICATIONS

Climate change is considered the 21st century's biggest challenge as countries worldwide struggle to achieve sustainable economic growth. It has been widely discussed in multidisciplinary literature that artificial factors are responsible for the past century's increase in global temperature. In addition, numerous studies concluded that developed countries that led their industrialization based on fossil fuels and transited to higher income levels also augmented the pace of climate change. Carbon emissions emitted in one part of the world are homogenously distrusted in space irrespective of the country emitting it. Thus, it makes global warming-driven climate change a global problem that requires global solutions and collaboration. Consequently, in the last decade of the 20th- century, international organizations were formed to increase the pace of climate adaptation and mitigation measures worldwide.

Impact assessment studies reveal that impact of climatic change is disproportionately distributed over geographical space and income levels of countries. The possible impact is still the debate in the literature, with a greater consensus that developing countries near the equator are likely to bear the brunt of climate change more than developed countries towards the poles. Another aspect of the ecosystem and environment is that it has a public good nature that incurs a free rider problem. The negative externality of countries emitting carbon emissions and causing climate change needs to be considered in policy formation at regional and global levels. The spillover effect of economic activities on neighboring countries gives important insights that need to be addressed while outlining the global policy framework for climate change.

Also, the existing literature takes several proxies to measure climate change, such as carbon emissions, sulfur dioxide, nitrogen peroxide, and other pollutants. WMO and other international organizations have distinguished between climate change and climate variability based on the time involved in a change. Literature provides mixed evidence on the use of climate change and variability interchangeably.

The current research systematically takes up all the issues discussed above and empirically tests the interplay of climatic variables with economic activities. First, the study analyzes climatic variability (climate anomalies) across different geographical locations, income, and industrialization levels of countries within specific regimes based on breakthroughs (Kyoto Protocol and Paris Agreement) in global climate change policies. Results show that warming constantly increases irrespective of the policy regime, income and industrialization level, and geographical location. However, the two significant climate change policy measures (Kyoto Protocol and Paris Agreement) have decelerated the rate of additional warming in the world. When countries were bifurcated according to their income level, results found that high income group countries experienced greater climate variability (temperature).

Similarly, when countries are separated according to their level of industrialization, climate variability (temperature) in highly industrialized countries is more pronounced than in others. The speed of warming as calculated by percentage change between different periods shows that LIC's pace of climate variability (temperature) is more as compared to other income levels. Also, the amount of carbon emission by LICs is the lowest among all income groups. Climate variability expressed by rainfall shows volatile behavior in all categories considered. There is no clear pattern in rainfall behavior throughout the time used in the analysis, thus, adding to the existing challenges. Regional results show that Europe and Central Asian countries are experiencing greater temperature variability, followed by the Middle East and North African countries, North America, Sub-Saharan Africa, South Asia, East Asia Pacific, Latin America, and the Caribbean.

Another important aspect examined in the study is the identification of drivers of climate variability, change, and carbon intensity. The mitigation and adaptation process calls for a deeper analysis of factors responsible for climate change. Therefore, the study highlights both non-spatial and spatial determinants. For climate variability, we have considered panel data for 116 countries from 1991 to 2018. While for climate change, we have cross-sectional data averaged for 30 years (1989 to 2018). Results show that GDP per capita, energy intensity, population, industrialization, and urbanization are significant determinants of climate variability (temperature), while energy intensity, population size, and proportion of urban population spillover effect nearby countries' climate variability. For climate variability expressed by rainfall is affected by energy intensity, trade openness has a spillover effect on nearby countries' climate variability (rainfall). Carbon intensity over the same period is influenced by the GDP per capita, trade openness, population size, and urbanization, while energy intensity has a spillover effect on the carbon intensity of nearby countries. For climate change (temperature), population density and trade are key spatial determinants.

Climate variables also serve as an input for various sectors, among which the agriculture sector is considered the most vulnerable in literature. To effectively capture the impact, the present study has considered the spillover effect of climatic and non-climatic variables for wheat, rice, and maize production per agricultural land. In the case of wheat, fertilizer, agriculture labor, trade openness for wheat, annual average rainfall, and its variability are key inputs for a country to increase its wheat production. However, the spillover effect of increased fertilizer usage, openness, labor, and the presence of rainfall variability in countries near it are important. Similarly, in the case of rice production per agricultural land, fertilizer, labor, temperature and its variability, and rainfall variability are key determinants to enhancing rice production. At the same time, the spillover effect of increased use of machinery, rainfall, and its variability affect the domestic country’s rice production. Maize production is affected by fertilizer usage, labor, machinery, openness, and climatic variables and their respective variability. In addition, neighboring countries' fertilizer labor and machinery usage also affect maize production in the home country.

Industrialization policy in all income groups, especially in developing and LICs, should encourage sustainable industrialization by introducing good business practices and incentivizing those industries that use renewable energy resources. International agreements such as GSP plus EBA for developing and least developed countries can be used as an instrument to help them adapt to climate change. Instead of making it a compulsory part of the agreement, which creates additional costs for developing countries, it should be incentivized because they may grant additional access to industries applying environmentally friendly technology.

Results show that global collaboration in the Kyoto Protocol and the Paris Agreement has reduced countries' carbon emissions; consequently, climate variability has reduced in almost all country groups. In addition to the NDGs, there should be region-specific goals to achieve as countries of the same region undergo similar climatic changes. Regional climate change summits and good practices need to share on a common platform. This will create a sense of commitment and competition among countries.

UNEP, WB, ADB, and other donor agencies should aid in developing and LIC that is majorly affected by climate change. Carbon tax being imposed by rich and high-income countries should be used to build the adaptive capacity of lower-income countries. Developed countries should invest in developing countries' renewable energy resources. Developed and emerging economies relocating their polluting industry to developing countries should be penalized and discouraged. IPCC should play its role in knowledge transfer to developing countries in manufacturing and building renewable energy resources through collaborations between higher education institutions of developed and developing countries.

Green technologies, renewable energy initiatives, proper management of industrial waste, and better industrial practices that cause less harmful environmental effects should be prioritized to contain the drivers of climate variability at the individual country level. Development plans of countries should be initiated in a manner that should have a minimum fixed proportion of green initiatives with year-wise targets.

Researchers also need to develop methods to quantify green GDP that could be used to assess a country’s progress towards sustainable development. In the case of LICs and developing countries, green GDP could be used as an instrument to ease their debt repayments to international financial institutions. Results indicate that countries must initiate environment-inclusive urban planning to contain climate variability. As unplanned urban slums add pressure to the existing resources.

The energy intensity, population size, and urbanization spillover effect call for integrated efforts at a regional level where countries are nearby. Renewable energy policies at the regional level can be initiated where countries can set joint targets for their annual investment. Besides investment, there is a need to harmonize and change the energy mix towards environmentally friendly resources. A regional platform can serve as a free trade zone and business partnership platform for green technologies. Also, regional awareness campaigns, workshops, and conferences can be coordinated to exchange better energy solutions.

For wheat crop-producing countries, a fertilizer policy should be initiated to improve the quality of fertilizers used by farmers. The policy should set a target to increase organic fertilizer in production. Further, policy should fix R&D targets in producing better fertilizers that are more resilient to climate change. As in the present case, the trade liberalization policy improves wheat production in the country. Therefore, policy measures to facilitate the export and import of wheat crops will be conducive to enhancing wheat competitiveness. Farmers' training center needs to develop in countries with courses to provide crop-specific knowledge, changing crop patterns, better and sustainable farming techniques, and sophisticated technologies. Early warnings on pest attacks can take adaptive measures to reduce crop losses should be dispersed through technology. As most depend on rain-fed irrigation, water management policy must be ensured in wheat-producing countries. Water pricing and water-saving technologies in the form of drip irrigation, water recycling, and the construction of dams will help take further benefits from rainwater. As for the spillover effect, integrated efforts are needed to improve labor productivity by initiating joint seminars, workshops, and field visits among regional countries to transfer knowledge and share best practices in wheat production. Regional trade liberalization and forming a common agriculture market can give farmers greater market access and competitive prices. Increase competition within the region with help in efficient resource allocation.

Rice is sensitive to climate changes, especially rainfall uncertainty negatively affects rice production. Rice is water-intensive; timely crop water availability and management practices must be dispersed among farmers. Climate resilient rice varieties should be developed through R&D. Private organizations, in collaboration with government departments, should build the capacity to develop climate-resilient rice varieties. Maize is also climate sensitive crop that responds negatively to climate uncertainty; therefore, better weather forecasting and dissemination of information need to be ensured for maize cultivators. Climate uncertainty can be hedged through crop insurance and agricultural commodity exchange markets.

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Appendix A: Description of the variables

Name of the variable	Definition of the variable	Unit of Measurement	Source
$TEMP$	Mean temperature	Degree Celsius (°C)	Climate Research Unit University of East Anglia
RAIN	Mean rainfall	Millimeters (mm)	Climate Research Unit University of East Anglia
Industry ranking	**Industrialized economies** having adjusted manufacturing value added (MVA) per capita greater than 2,500 or a gross domestic product higher than USD 20,000 (PPP) **Emerging industrial economies** are the ones with adjusted MVA per capita between 1,000 and 2,500 or whose share of the world MVA is higher than 0.5 percent. **The least developed** are structured as united nations assembly decisions **Developing** all the rest is structured as developing	Ranking 1=Industrialised 2=emerging Industrialise 3=developing 4=least Lower Middle Income	Industrial Development Report 2018 United Nations Industrial Development Organization (UNIDO)
Country Ranking	**High-Income** countries with GNI of USD 12,375 or more **Upper middle income** with GNI between USD 3,996 - 12,375 **Lower middle income** USD 1,026 - 3,995 **Low income** with GNI of USD 1,025 or less	Ranking 1= High Income 2= Upper middle income 3 Lower middle income 4= Low income	World Bank 2019 and World bank 1990

Appendix B: Description of the variables

Variable	Description	Unit of measurement	Sources
Dependent Variables			
$VTEMP$	Square deviation of annual average temperature from its long-run mean (30 years)	Degree Celsius	Climate research unit TS 4.03
$VRAIN$	Square deviation of annual average rainfall from its long-run mean (30 years)	millimeters	Climate research unit TS 4.03
CC_{temp}	The average annual temperature of thirty years (1989-2018)	Degree Celsius	Climate research unit TS 4.03
CC_{rain}	Average annual rainfall of thirty years (1989-2018)	millimeters	Climate research unit TS 4.03
CO_2	Carbon dioxide emissions from solid fuel consumption refer mainly to emissions from the use of coal as an energy source	Weighted average	WDI
Independent Variable			
GDP_{pc}	Gross domestic product in current USD divided by population	Weighted average	World Development Indicators (WDI)
EI	The ratio between primary energy supply and GDP at PPP.	Weighted average	WDI
IND	Industry value added as a percentage of the GDP. The net output of the industrial sector after deducting intermediate inputs. Industry includes manufacturing, mining, construction, electricity, water, and gas.	Weighted average	WDI
POP	Includes residents living in a country irrespective of their citizenship	number	WDI
$POPD$	A population divided by the land area in square km	Weighted average	
URP	The ratio of urban population to the total population. The urban population includes people living in	Weighted average	WDI
$OPEN$	Sum of exports and imports as a percentage of the GDP in current USD	Weighted average	WDI

Appendix C1: Description of the variables

Variable	Description	Unit of measurement	Sources
Dependent Variables			
$WHEAT$	The amount of wheat production sold in the market is divided by agricultural land	Tonnes/1000 hectare	FAO stat
$RICE$	Amount of rice production sold in the market divided by agricultural land	Tonnes/1000 hectares	FAO stat
$MAIZE$	Amount of maize production sold in the market divided by agricultural land	Tonnes/1000 hectares	FAO stat
Independent Variable			
$FERT$	Sum of N, P2O5, and K2O nutrients for fertilizer consumption	Kgs/hectare	FAO stat
$MACH$	Farm inventories of farm machinery, measured in thousands of metric horsepower (1000 CV) in tractors, combine-threshers, and milking machines	unit	United states department of agriculture, USDA
$AGRL$	Employment in agriculture, forestry, and fishing –total ILO modeled estimates	1000 persons	FAO stat
$OPEN$	Sum of exports and imports of the crop (wheat, rice, and maize) as a percentage of the GDP in current USD	USD	FAO
$TEMP$	Annual average temperature	Degree Celsius	Climate research unit TS 4.05
$RAIN$	Annual average temperature	millimeters	Climate research unit TS 4.05
VTEMP	Deviation of annual average temperature from its long-run mean (30 years)	Degree Celsius	Climate research unit TS 4.05
VRAIN	Deviation of annual average rainfall from its long-run mean (30 years)	millimeters	Climate research unit TS 4.05

Appendix C2: Estimation Results of spatial Durbin model for crop yield

Variables	SDM-FE		SDM-RE		SDM-FE		SDM-RE		SDM-FE		SDM-RE	
	Wheat yield				Rice yield				Maize yield			
P	0.218**	(2.57)	0.245***	(2.95)	0.226***	(2.68)	0.222***	(2.67)	0.188**	(2.2)	0.324***	(4.48)
FERT	0.0490***	(3.78)	0.0585***	(4.7)	-0.0241	(-1.41)	-0.0113	(-0.71)	0.0229	(1.39)	0.0385**	(2.46)
MACH	0.0179	(0.56)	0.0271	(0.84)					0.200***	(4.92)	0.196***	(4.77)
IRRI	0.0579*	(1.78)	0.0368	(1.4)	0.0960**	(2.13)	0.143***	(4.6)	0.00791	(0.19)	0.0603*	(1.82)
AGRL	-0.0863***	(-2.71)	-0.111***	(-4.20)	-0.100***	(-2.29)	-0.123***	(-3.74)	-0.111***	(-2.83)	-0.197***	(-5.89)
TEMP	0.851	(0.78)	-0.187	(-0.54)	5.152***	(2.72)	0.601	(1.53)	0.689	(0.46)	-0.587	(-1.30)
RAIN	0.247***	(5.9)	0.175***	(4.96)	0.167***	(2.65)	0.149***	(3.66)	0.290***	(5.64)	0.273***	(6.45)
VTEMP	-0.213	(-0.53)	0.12	(0.53)	-1.433*	(-1.96)	0.157	(0.42)	-0.743	(-1.38)	-0.295	(-1.00)
VRAIN	-0.0112***	(-3.61)	-0.0112***	(-3.52)	0.001	(0.26)	0.002	(0.33)	-0.0054	(-1.36)	-0.00486	(-1.20)
INTERCEPT			-3.516	(-0.57)			-14.74**	(-2.57)			-12.75*	(-1.81)
W*FERT	0.182***	(2.88)	0.137**	(2.24)	0.303***	(4.96)	0.256***	(4.5)	0.0619	(0.83)	-0.038	(-0.53)
W*MACH	-0.0988	(-0.43)	0.145	(0.65)					0.604**	(2.35)	1.061***	(4.38)
W*IRRI	0.870***	(4.14)	0.531***	(2.79)	-0.003	(-0.01)	0.136	(0.75)	1.526***	(4.61)	0.819***	(3.25)
W*AGRL	-0.354	(-1.37)	-0.17	(-0.78)	0.102	(0.37)	-0.019	(-0.11)	0.418	(1.38)	-0.0945	(-0.38)
W*TEMP	-2.643	(-1.05)	1.785	(0.88)	6.02	(1.19)	4.530**	(2.42)	-0.953	(-0.25)	2.73	(1.15)
W*RAIN	-0.318	(-1.50)	-0.271	(-1.32)	0.209	(0.87)	0.067	(0.36)	0.0992	(0.41)	-0.0591	(-0.27)
W*VTEMP	1.386	(1.25)	0.186	(0.19)	-1.914	(-0.88)	-0.884	(-0.74)	1.178	(0.75)	0.465	(0.38)
W*VRAIN	-0.0164	(-0.94)	-0.0146	(-0.82)	0.002	(0.11)	0.004	(0.17)	-0.00214	(-0.10)	0.00136	(0.06)
N	2156		2156		1342		1342		1958		1958	
Hausman	116.88				12.2				40.75			
P-Value	0.0000				0.1427				0.0000			

Note: ***,**,* indicates the significance level at 1%, 5%, and 10%, respectively.

Appendix C3: Spatial direct, indirect and total effect of SDM model for crop yield

Variable	wheat yield			rice yield			Maize yield		
	Direct Effect	**Indirect Effect**	**Total Effect**	**Direct Effect**	**Indirect Effect**	**Total Effect**	**Direct Effect**	**Indirect Effect**	**Total Effect**
FERT	0.05***	0.26***	0.31***	-0.02	0.379***	0.359***	0.02	0.09	0.112
	(3.81)	(3.31)	(3.96)	(-1.19)	(5.06)	(4.75)	(1.41)	(0.98)	(1.22)
MACH	0.0158	-0.131	-0.115				0.202***	0.789**	0.991***
	(0.5)	(-0.44)	(-0.37)				(5.1)	(2.46)	(3.02)
IRRI	0.0663**	1.125***	1.192***	0.094***	0.037	0.132	0.02	1.851***	1.871***
	(2.14)	(4.49)	(4.64)	(2.12)	(0.11)	(0.37)	(0.52)	(5.34)	(5.25)
AGRL	-0.0892***	-0.456	-0.546	-0.095**	0.095	0.0004	-0.110***	0.513	0.403
	(-2.91)	(-1.30)	(-1.53)	(-2.25)	(0.27)	(0)	(-2.89)	(1.29)	(0.99)
TEMP	0.847	-3.252	-2.405	5.224***	8.925	14.15**	0.702	-1.121	-0.419
	(0.8)	(-1.09)	(-0.84)	(2.84)	(1.4)	(2.3)	(0.48)	(-0.26)	(-0.10)
RAIN	0.248***	-0.33	-0.0827	0.170***	0.336	0.505	0.291***	0.17	0.46
	(5.99)	(-1.17)	(-0.29)	(2.78)	(1.05)	(1.57)	(5.44)	(0.58)	(1.55)
VTEMP	-0.208	1.702	1.494	-1.433*	-2.869	-4.302	-0.728	1.321	0.593
	(-0.53)	(1.3)	(1.18)	(-1.99)	(-1.06)	(-1.60)	(-1.38)	(0.68)	(0.32)
VRAIN	-0.0114***	-0.0235	-0.0349	0.0012	0.0049	0.006	-0.00552	-0.00352	-0.00905
	(-3.87)	(-1.01)	(-1.49)	(0.25)	(0.17)	(0.21)	(-1.46)	(-0.13)	(-0.33)

Note: ***, **, * indicates the significance level at 1%, 5%, and 10%, respectively

Appendix D1: List of countries included in the estimation of wheat production

1	Afghanistan	37	Germany	73	Oman
2	Albania	38	Greece	74	Pakistan
3	Algeria	39	Guatemala	75	Paraguay
4	Angola	40	Honduras	76	Peru
5	Argentina	41	Hungary	77	Poland
6	Armenia	42	India	78	Portugal
7	Australia	43	Iran (Islamic Republic of)	79	Republic of Korea
8	Austria	44	Iraq	80	Republic of Moldova
9	Azerbaijan	45	Israel	81	Romania
10	Bangladesh	46	Italy	82	Russian Federation
11	Belarus	47	Japan	83	Rwanda
12	Belgium	48	Jordan	84	Saudi Arabia
13	Bhutan	49	Kazakhstan	85	Slovakia
14	Bolivia	50	Kenya	86	Slovenia
15	Bosnia and Herzegovina	51	Kuwait	87	South Africa
16	Brazil	52	Kyrgyzstan	88	Spain
17	Bulgaria	53	Latvia	89	Sweden
18	Burundi	54	Lebanon	90	Switzerland
19	Cameroon	55	Libya	91	Syrian Arab Republic
20	Canada	56	Lithuania	92	Tajikistan
21	Chile	57	Madagascar	93	Thailand
22	China	58	Malawi	94	Tunisia
23	Colombia	59	Mali	95	Türkiye
24	Croatia	60	Mexico	96	Uganda
25	Cyprus	61	Mongolia	97	Ukraine
26	Czechia	62	Morocco	98	United Kingdom
27	Democratic Republic of the Congo	63	Mozambique	99	United Republic of Tanzania
28	Denmark	64	Myanmar	100	United States of America
29	Ecuador	65	Namibia	101	Uruguay
30	Egypt	66	Nepal	102	Uzbekistan
31	Eritrea	67	Netherlands	103	Venezuela (Bolivarian Republic of)
32	Estonia	68	New Zealand	104	Yemen
33	Ethiopia	69	Niger	105	Zambia
34	Finland	70	Nigeria	106	Zimbabwe
35	France	71	North Macedonia		
36	Georgia	72	Norway		

Appendix D2: List of countries included in the estimation of Rice Production

1	Afghanistan	35	Greece	69	Portugal
2	Algeria	36	Guatemala	70	Republic of Korea
3	Angola	37	Guinea	71	Romania
4	Argentina	38	Guyana	72	Russian Federation
5	Australia	39	Honduras	73	Rwanda
6	Azerbaijan	40	Hungary	74	Senegal
7	Bangladesh	41	India	75	South Africa
8	Belize	42	Indonesia	76	Spain
9	Benin	43	Iran	77	Sri Lanka
10	Bhutan	44	Iraq	78	Suriname
11	Bolivia	45	Italy	79	Tajikistan
12	Brazil	46	Jamaica	80	Thailand
13	Bulgaria	47	Japan	81	Togo
14	Burkina Faso	48	Kazakhstan	82	Trinidad and Tobago
15	Burundi	49	Kenya	83	Türkiye
16	Cambodia	50	Kyrgyzstan	84	Uganda
17	Cameroon	51	Madagascar	85	Ukraine
18	Central African Republic	52	Malawi	86	Tanzania
19	Chile	53	Malaysia	87	United States of America
20	China, mainland	54	Mali	88	Uruguay
21	Colombia	55	Mexico	89	Uzbekistan
22	Congo	56	Morocco	90	Venezuela
23	Costa Rica	57	Mozambique	91	Viet Nam
24	Cuba	58	Myanmar	92	Zambia
25	Democratic Republic Congo	59	Nepal	93	Zimbabwe
26	Dominican Republic	60	Nicaragua		
27	Ecuador	61	Niger		
28	Egypt	62	Nigeria		
29	El Salvador	63	North Macedonia		
30	Ethiopia	64	Pakistan		
31	Fiji	65	Panama		
32	France	66	Paraguay		
33	Gambia	67	Peru		
34	Ghana	68	Philippines		

Appendix D2: List of countries included in the estimation of Maize Production

1	Afghanistan	41	Ghana	81	Poland
2	Albania	42	Greece	82	Portugal
3	Algeria	43	Guinea	83	Republic of Korea
4	Argentina	44	Honduras	84	Republic of Moldova
5	Armenia	45	Hungary	85	Romania
6	Australia	46	India	86	Russian Federation
7	Austria	47	Indonesia	87	Rwanda
8	Azerbaijan	48	Iran (Islamic Republic of)	88	Saudi Arabia
9	Bangladesh	49	Iraq	89	Senegal
10	Belize	50	Israel	90	Slovakia
11	Benin	51	Italy	91	Slovenia
12	Bhutan	52	Jamaica	92	South Africa
13	Bolivia	53	Japan	93	Spain
14	Bosnia and Herzegovina	54	Jordan	94	Sri Lanka
15	Botswana	55	Kazakhstan	95	Suriname
16	Brazil	56	Kenya	96	Switzerland
17	Bulgaria	57	Kyrgyzstan	97	Syrian Arab Republic
18	Burkina Faso	58	Lebanon	98	Tajikistan
19	Burundi	59	Madagascar	99	Thailand
20	Cambodia	60	Malawi	100	Togo
21	Cameroon	61	Malaysia	101	Trinidad and Tobago
22	Canada	62	Mali	102	Türkiye
23	Chile	63	Mauritius	103	Uganda
24	China	64	Mexico	104	Ukraine
25	Colombia	65	Morocco	105	United Arab Emirates
26	Congo	66	Mozambique	106	United Republic of Tanzania
27	Costa Rica	67	Myanmar	107	United States of America
28	Croatia	68	Namibia	108	Uruguay
29	Cuba	69	Nepal	109	Uzbekistan
30	Czechia	70	Netherlands	110	Venezuela
31	Dominican Republic	71	New Zealand	111	Viet Nam
32	Ecuador	72	Nicaragua	112	Yemen
33	Egypt	73	Niger	113	Zambia
34	El Salvador	74	Nigeria	114	Zimbabwe
35	Eritrea	75	North Macedonia		
36	Ethiopia	76	Pakistan		
37	France	77	Panama		
38	Gambia	78	Paraguay		
39	Georgia	79	Peru		
40	Germany	80	Philippines		