Convergence in Global Environmental Performance: A Spatial Econometric Analysis

By

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198-SE/PhD/F18

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INTERNATIONAL INSTITUTE OF ISLAMIC ECONOMICS (IIIE)
INTERNATIONAL ISLAMIC UNIVERSITY ISLAMABAD (IIU)

2023

Statistical methods

Environmen[illegible]

impact analysis

Econometrics

Spatial analysis (statistics)

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A Dissertation Submitted to the School of Economics, International Institute of Islamic Economics, International Islamic University, Islamabad, in Partial Fulfillment of the Requirements for the Award of the Degree of Doctor of Philosophy in Economics

2023

APPROVAL SHEET

CONVERGENCE IN GLOBAL ENVIRONMENTAL PERFORMANCE: A SPATIAL ECONOMETRIC ANALYSIS

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DECLARATION

I, **Faisal Azeem Abbassi** S/O **Muhammad Rahim** Registration No. **198-SE/PhD/F18**, student of Ph.D. Economics at the School of Economics, International Institute of Islamic Economics, International Islamic University Islamabad, do hereby solemnly declare that the thesis entitled "**Convergence in Global Environmental Performance: A Spatial Econometric Analysis**", submitted by me in the partial fulfillment of the requirements for the award of Ph.D. degree in Economics. It is my original work, except where otherwise acknowledged in the text, and has not been submitted, printed or published earlier and shall not, in future, be submitted by me for obtaining any degree from this or any other university or institution.

Signature: _______________

Dated: August 07 , 2023

Faisal Azeem Abbassi

DEDICATION

To my beloved sons, Abul Raafae and Wahaj Faysal, who always waited with open arms for me to emerge from my study room during my Ph.D. thesis, turning my study breaks into moments of pure joy.

ACKNOWLEDGEMENT

There are many people without whose support it would have been impossible for me to complete such a gigantic task as Ph.D. The most important of those people is my supervisor, Dr. Mirajul Haq. I was truly blessed to have him as my supervisor. He is a passionate researcher, great mentor and a very kind human being. His vast experience of teaching and supervision has helped me in timely completion of my research thesis. I am deeply thankful to him for his guidance, encouragement and faith in me during the entire course of my research work. May he live long and continue to inspire generations to come.

The other most important person in this journey was my colleague, Dr.Muhammad Jamil. Having such an enthusiastic and accomplished colleague by my side has been a true blessing for me. I am obliged to him for always being there to help me. His friendship, constant motivation and support were of immense importance for my research work. I would also like to thank the entire faculty of International Institute of Islamic Economics. All of them are very competent, kind and humble. I would like to particularly mention Dr. Abdul Jabbar, Dr. Abdul Rasheed and Dr. Arshad Ali Bhatti for inspiring me with their exceptional talent and gentle mentoring. I would like to sincerely thank Dr. Tauqeer Ahmad and Mr.Niaz Ali Shah from graduate research office of IIIE for their kind cooperation.

At the end, I would like to thank my parents, Muhammad Rahim and Nasreen Begum, for their unconditional love, support and countless sacrifices for my education. May Allah bless them with good health and long lives! Lastly, I would like to thank my wife, Tasneem, who would always be a source of relief in the time of stress and pressure during my Ph.D. She took on more family responsibilities than her fair share to help me make more time for my study. I am truly fortunate to have her in my life.

Faisal Azeem Abbassi

August, 2023

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List of Abbreviations

IPCC	Intergovernmental Panel on Climate Change
EP	Environmental Performance
EKC	Environmental Kuznet Curve
EPI	Environmental Performance Indicator
PBA	Production-Based Accounting
CBA	Consumption-Based Accounting
EF	Ecological Footprints
PHH	Pollution Haven Hypothesis
LM	Lagrange Multiplier
SURE	Seemingly Unrelated Regression Equations
DEA	Data Envelope Analysis
OLS	Ordinary Least Squares
MENA	Middle East and North Africa
MPK	Marginal Product of Capital
SDM	Spatial Durbin Model
SAR	Spatial Autoregressive
SEM	Spatial Error Model
MISE	Mean Integrated Square Error
WDI	World Development Indicators
PWT	Penn World Tab
PS	Phillips and Sul

ABSTRACT

This study explores the convergence in global environmental performance using spatial econometric techniques. In this context, the study has explored the existence of spatial β and σ-convergence using distribution and club convergence approaches. To explore spatial β-convergence, we have applied Lagrange Multiplier test to make a choice among Spatial Durban Model, Spatial Autoregressive Model or Spatial Error Model. Likewise, to analyze spatial σ-convergence using intra-distribution dynamics approach, we followed Gerolimetto and Magrini (2010). Finally, the methodology developed by Phillips and Sul (2007) has been used to study spatial club convergence. The empirical analysis was carried out for 88 countries covering 1978-2017.The results of Moran's I indicates that there is substantial positive spatial dependence in the environmental performance of the sample countries. Estimated results reveal that spatial β-convergence exists at the aggregate level and in each dimension of environmental performance . The estimated results of the intra-distribution dynamics approach confirm the existence of bimodality at the aggregate level. While there is existence of bimodality for cropland footprint and built up land footprint, persistence for CO_2 footprints, and convergence for grazing land footprints, forest land footprints, and fishing ground footprints. The results of club convergence analysis show that countries are converging into two clubs in their overall environmental performance. A disaggregated analysis of convergence shows that countries are converging into four clubs in their cropland footprints, into two clubs in their grazing land footprints and forest land footprints, and into three clubs in their fishing ground footprints and CO_2 footprints. Based on the findings it is recommended that a differentiated set of environmental policies should be formulated for different dimensions of environmental performance and for different clubs. Furthermore, there is a need to improve cross-border communication and cooperation among countries. It will enhance clean technology's spatial spillover which will improve the environment.

Key Words: Environmental Performance, Spatial Green Solow Model, Moran's I, β-Convergence, Spatial Durbin Model, Club Convergence, Stochastic Kernel

Gel Classification: F64, O44, Q40, Q50

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CHAPTER 1

INTRODUCTION

1.1 Background

Since the industrial revolution in the mid-eighteen century, countries have experienced huge economic growth, but on the flip side, it has brought many environmental problems with it. Increased industrialization caused global warming, which in turn caused glaciers to melt, sea levels to rise, and weathers to have irregular patterns. This climatic change has raised concerns for food security and water availability for humans (Ray et al., 2014). Moreover, it has also increased the frequency of natural disasters such as floods, hurricanes, storms, and droughts (Kreft et al., 2104). Daily (1997); and Ehrlich and Pringle (2008) pointed out that increased environmental degradation has caused the loss of habitats for many species, thereby fastening their extinction. This extinction of species has negative consequences for the ecosystem services that are crucial for the quality of life for humans.

Most of the received literature on the subject reached the consensus that acceleration in human economic activities is the key reason for environmental degradation. For instance, Intergovernmental Panel on Climate Change (IPCC) year (2007) carried out a comprehensive study in 2007 and came to the conclusion that human economic activities are the driver force of environmental degradation, and if it is left alone, it would be disastrous (IPCC, 2007). Because of this, there are growing concerns about environmental degradation in developed and developing countries. This has put them on the dialogue tables under initiatives like 'The framework Convention on Climate Change', 'Kyoto Protocol' and more recently, 'Paris Agreement'. Under these initiatives, countries are committing themselves to reduce the emission of greenhouse gases which are thought to be a chief culprit for environmental degradation.

In this context, studying the convergence of countries' environmental performance (EP) is important chiefly for four reasons. Firstly, convergence in the EP of the countries implies that per capita environmental degradation would be the same in all countries. This existence of convergence in EP will make the international environmental protection agreements less contentious as most of the burden-sharing proposals under such agreements are based on a per capita basis (Stegman and McKibbin, 2005; Aldy, 2006; Romero-Avila, 2008). Whereas in the case of divergence, disputes on burden sharing are bound to arise among developed and developing countries if allocation were made on a per capita basis. It is because such a rule would favor developing countries as they currently have a low level of environmental degradation per capita. Per capita allocation will allow them to continue with economic growth to uplift the standards of living of their masses and pull their population out of poverty. On the other hand, such a rule would be resisted by developed countries as it would put immense pressure on them to reduce their per capita environmental degradation to the level of developing countries (Payne et al. 2014). This dispute eventually vanishes if the EP of the countries converges (Barassi et al., 2011).

Secondly, convergence in important variables like income, energy, and emissions is assumed by default in many environmental models (Apergis and Payne, 2017; Pettersson et al., 2013; Zhou and Wang, 2016). In this association, a reflective analysis of convergence is important in order to check the validity of the existing models. To direct policy regarding environmental protection, the validity of these models may prove beneficial. Thirdly, the presence of environmental convergence ensures environmental sustainability as sustainability requires environmental degradation to be finite and bounded (Criado et al. 2011). These two conditions of sustainability will be met in the event of environmental convergence. It is because if the environmental performance of the countries converges, we can work out total environmental degradation. We can then examine whether this level of total environmental degradation exceeds the total assimilative capacity of the environment or not. If it exceeds the total assimilative capacity of the environment, then per capita targets of emission reduction can be assigned to individual countries. So, in order to examine sustainability, the study of environmental convergence becomes imperative. Lastly, a complete landscape of environmental degradation is crucial to understand to design environmental protection policies. In this context, convergence analysis of EP is appealing to provide comprehensive analysis regarding the environmental performance of different countries.

1.2 Research Problem

At the beginning of the environmental movement (the 1960s and 1970s), economic growth was blamed as the primary cause of environmental degradation (Ehrlich, 1968; Meadows et al., 1972). It was argued that increased economic growth and growing population put immense pressure on the environment. This 'overshoot and collapse' model predicted that a day would come when the earth would run out of resources necessary to support life, like water, habitat, clean air, cultivable land, and other natural resources (Dryzek 1999). This school of thought usually recommended deindustrialization and de-growth as policy prescriptions for environmental improvement. But a great turn has occurred regarding understanding the interrelationship between the environment and economic growth with the seminal work of Grossman and Krueger (1991). They found that the environment indeed gets degraded with economic growth. However, it does not last forever. This occurs until a certain point when the environment starts improving with economic growth. The result is an inverted U-shaped curve known famously as Environmental Kuznet Curve (EKC).

With the advent of the EKC, a large number of empirical studies tested the EKC hypothesis. These studies stand with an optimistic view and, at large, accept the EKC hypothesis. For example, Luo et al. (2017); Narayan and Narayan (2010); Apergis and Ozturk (2015); Wang et al. (2016), and Fujii and Managi (2016), among others. Most of these studies explain the existence of EKC in their own way; hence different reasons are available in the received literature. For example, Grossman and Krueger (1995) and Brock and Taylor (2005), explain the existence of EKC with the concepts of scale effect, technical effect, and composition effect. According to this argument, environmental degradation rises with increased economic activity *(the scale effect)*. However, with increased economic activities, the economy shifts from polluting industries to cleaner ones *(composition effect)*, and investment in environmentally friendly technologies increases *(technical effect)*. This indicates that environmental degradation decreases after a certain period with increased economic activity.

Another set of literature underlines the hypothesis of "pollute today and clean tomorrow". The basic idea is that countries with a certain income level can allocate reasonable resources to environmental improvement projects. In addition, it is argued that with an increase in income level, a large segment of the population becomes more aware and concerned about the environment, which can put pressure on the government to control pollution and environmental degradation (Baldwin, 1995; Roca, 2003). Another strand of literature stresses the importance of regulation as the underlying reason behind the existence of the EKC relationship (Arrow et al. 1995 and Dasgupta et al. 2002). According to this argument, rising income levels help strengthen the institutions responsible for enforcing environmental regulations.

There is yet another explanation for the existence of the EKC relationship, which is based on the economy's structural transformation as it grows. Dinda (2004), for example, argued that at the initial stage of economic growth, the country is largely agrarian, so it has low pollution, however, graduating to the second stage (industrialization), pollution emission rises. Whereas at the third stage of development (stage of service economy), pollution reduces again. Thus, the country's EP forms an inverted U-shaped curve (EKC).

The ECK predication of the interdependence of economic growth and environmental performance and the conditional convergence forecasting of the neoclassical growth model should lead to the convergence of the environmental performance. In the long run, if countries with similar initial conditions are expected to have similar levels of income, they must also have similar levels of environmental quality. This study is devoted to testing the convergence of environmental performance empirically. In this context, the study aims to achieve the following objectives.

1.3 Research Objectives

This study aims to extend the literature on the following:

- To test the spatial dependence of environmental performance in a global sample of countries
- To test the spatial β-convergence hypothesis in global environmental performance
- To quantify direct and spillover effects of different variables in spatial β-convergence

- To test the convergence hypothesis in global environmental performance using intra-distribution dynamics approach while taking spatial factors into account
- To test the spatial club convergence hypothesis in global environmental performance

1.4 Research Questions

To achieve the objectives of the research, this study will try to explore the answers to the following questions:

- Does the environmental performance of the countries depend on their neighbors?
- Does the environmental performance of the world's countries exhibit a pattern of spatial β-convergence?
- What is the role of space in causing β-convergence in environmental performance?
- How the distribution of environmental performance has evolved over the period of time?
- Does the distribution of environmental performance exhibit convergence?
- What role does space play in shaping the distribution of environmental performance?
- Does the environmental performance of the world's countries exhibit a pattern of spatial club convergence?

1.5 Research Hypotheses

This study aims at testing the following null hypotheses:

- Space does not have any role to play in determining the environmental performance of the countries.
- The environmental performance of the countries does not exhibit spatial β-convergence.
- There are no spillover effects of different variables in spatial β-convergence.
- The distribution of environmental performance does not exhibit convergence.

- The environmental performance of the countries does not exhibit spatial club convergence.

1.6 Research Gap and the Contributions of the Study

Due to the vital importance of the issue, many studies have been conducted in the past to examine the convergence of environmental performance. For example, List (1999), Brock and Taylor (2010), Aldy (2006), Barassi *et al.* (2008), Romero-Avila (2008), Westerlund and Basher (2008), and Yavuz and Yilanci (2013). However, these studies have four main limitations.

The first shortcoming observed in existing studies is that they have utilized Environmental Performance Indicator (EPI) based on Production Based Accounting (PBA). For example, Aldy (2006), Yavuz and Yilanci (2013), Acar and Lindmark (2017), and Apergis and Payne (2017). The problem with PBA is; it only considers where the production of goods and services has been made and disregards where actual consumption has taken place. In the present era of globalization and international trade, there can be a huge difference between the production and consumption of the economies. Studies have estimated that emissions embodied in trade can be as high as 25-30% (Zhang et al., 2017; Peters and Hertwich, 2008). These effects are too huge to be ignored (Liddle, 2018). Hence, EPI is needed based on Consumption-Based Accounting (CBA) instead of PBA.

The use of PBA based EPI in convergence studies gives misleading or, at best incomplete results due to the possibility of 'leakage' as predicted by the 'Pollution Haven Hypothesis (PHH)". The leakage occurs because countries have made mitigation commitments based on PBA under international commitments like the Kyoto protocol and the more recent Paris agreement. They must also prepare and share their emission record based on PBA (Afionis et al., 2017). In order to fulfill these commitments, the high emitting countries/developed countries are induced to outsource the emission intensive industries to low emitting countries/developing countries (Copeland and Taylor, 2013). This effect is augmented with liberalization, integration, and globalization, because of which pollution intensive technology diffusion occurs in developing economies (Levinson and Taylor, 2008; Cole and

Elliott, 2005). It decreases reported emissions in developed countries and increases in developing countries. This would cause the researchers to conclude the presence of convergence in EP when it may not be the case. It is, therefore, imperative to use EPI, which is based on CBA. Only then we can isolate the effect of leakage from convergence. So, present study has utilized Ecological Footprint (EF) of consumption as EPI. This will help us carry out convergence analysis in EP more accurately.

The second contribution of the present study is the incorporation of the role of space in the convergence analysis of EP. Most of previous studies on EP have assumed that the EP of the countries is independent of space. But in fact, this is not the case, as indicated by Li et al. (2017) and Maddison (2006). There are several reasons why the environmental performance of the countries is spatially dependent. For example, technological spillovers among neighboring spatial units (Ertur and Koch, 2007; Ezcurra and Rios, 2015) cause production methods to change, hence the byproduct, pollution level (Fischer, 2011). Similarly, there are factors of production flows, especially among neighboring spatial units. This also strengthens the spatial dependence of cross sectional units. Moreover, even the governments of neighboring units mimic the policies of each other (Costa et al., 2015; Shipan and Volden, 2012). In the presence of spatial dependence, the conventional way of estimation is not appropriate (LeSage and Pace, 2009). Hence, instead of conventional estimation, spatial econometrics is more appealing.

The third limitation of past studies is that most of them are based on the utilization of a single variable as an environmental performance indicator (EPI). Examples of such studies are Aldy (2006), Yavuz and Yilanci (2013), Acar and Lindmark (2017), and Apergis and Payne (2017). These single variable studies are mainly confined to the utilization of carbon emission (CO_2) as a sole EPI. There is no denying fact that the level of CO_2 is indeed very crucial for the overall health of the environment. Still, this only presents a partial picture of the EP (Ahmed *et al.*, 2019; Ozcan, Ulucak, & Dogan, 2019). Considering this missing dot, the current study utilizes the broader environmental degradation concept of "Ecological Footprints" (EF) developed by Wachernagel & Rees (1996). Ecological Footprint aims at measuring human demand and nature's supply of resource provisioning. This index is based on six components:

cropland, grazing land, fishing grounds, built-up land, forest area, and carbon demand on land. Unlike CO_2, which represent only a partial effect of human demand for resources on the environment, the EF addresses the full impact of human demand for resources on environmental health. Hence, using this variable as a measure of EP of the countries will better enable us to make the interregional comparisons of EP, and consequently, it will enable us to advance more informed policy suggestions.

Few recent studies have utilized the concept of EF as EPI. These studies include; Erdogan and Okumus (2021), Haider and Akram (2019), Biligili and Ulucak (2018), and Ulucak and Apergis (2018). These studies have used only absolute EF as the EPI and ignored the component-wise analysis. Making the component-wise analysis is important because each component of EF has different determinants. These different components often pose different sorts of challenges to the environmental health of an economy. Hence, only component-wise analysis of EF will enable the policy makers to design policies that effectively tackle the specific environmental challenges. The present study intends to carry out convergence analysis using EF at aggregate as well as disaggregated levels by examining the convergence of each of the six components of the EF that prove beneficial to analyze the convergence of EP more comprehensively.

Lastly, there are pros and cons to each of the concepts of convergence. The chief advantage of β-convergence is that using this concept of convergence (conditional β-convergence) we can study the role of different factors in causing convergence. However, β-convergence may not guarantee the reduction of dispersion of the distribution. The second problem with the β-convergence hypothesis is, it assumes that countries with similar structural characteristics (technology, preferences, population growth, etc.) will converge to the same steady state. There is no role for the initial conditions of the individual countries. For this to hold, we must assume that each economy has a unique and globally stable equilibrium. For the plausibility of this assumption, the conditional convergence assumes that individuals are homogenous, and a constant saving rate of output causes the saving curve to be strictly concave, like the shape of the production function. These assumptions achieve a unique, stable, steady state (Glaor, 1996).

To solve the first problem caused by β-convergence, σ-Convergence is calculated. For σ-Convergence to hold, β-convergence is a necessary condition, but it is not sufficient (Barro and Sala-i-Martin, 2004). β-convergence implies σ-Convergence only if the initial variance of the cross section is greater than the steady state variance. Although the use of σ-Convergence is an important improvement in the literature on convergence, the way in which σ-Convergence is tested has its own limitations. Specifically, it has been tested in most previous studies by just using some measure of dispersion such as variance and standard deviation (Quah 1993, 1996b). Using variance or standard deviation cannot reveal the bimodality, stratification, or polarization. To solve this problem, another approach to convergence is formed, known as the intra-distribution dynamics approach. This approach can be used to reveal bimodality, stratification, or polarization in the data. In this way distribution approach points towards the clusters, known as "clubs", in the data.

However, the distribution approach cannot classify which country belongs to which club. To overcome this limitation of the distribution approach, another approach known as 'club convergence' is used. This approach solves the problem of club membership identification and removes the restrictive assumption of individual homogeneity of β-convergence. Here, heterogeneity among individuals is permitted instead of assuming homogeneity among individuals. With the relaxation of this assumption, we will have multiple locally stable equilibria known as convergence clubs. These clubs act as basins of local attractions for different countries. Hence, if countries differ in their initial conditions (e.g., per capita income and literacy rate, etc.), they would converge to different steady states. In this way, countries would form different clubs.

No study has been carried out that has tested the convergence using the beta, intra-distribution dynamics, and club convergence approach. In this study, we have carried out a complete analysis of convergence using all these approaches. This will leave no blind spot in viewing the convergence in EP, which will enable us to conclude the existence of convergence with greater confidence.

1.7 Organization of the Study

In the next chapter, we will survey the literature on the subject to review the methodology adopted in these studies and their findings and we will identify gap in the existing literature that we intend to bridge in the current study. Chapter 3 will describe the material and methods used to test convergence through various approaches. In chapter 4, we will present results on spatial dependence and β-convergence of EP. Chapter 5 presents results of convergence found through the intra-distribution dynamics approach, while the penultimate chapter presents results found using the club convergence approach. The last chapter will conclude the study and recommends policy measures for the improvement of EP.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews existing studies on the subject of convergence in environmental performance. Literature on convergence in EP has applied approaches as the literature on convergence in economic growth has adopted. The empirical literature on the economic growth convergence hypothesis is broadly divided into three concepts: Beta, Sigma, and Stochastic Convergence. The upcoming sections present a review of the past studies which have utilized these approaches in assessing the convergence in environmental performance.

2.1 β-Convergence in Environmental Performance

The concept of β-convergence has emerged from the neo-classical growth model of Solow (1956). According to this model, the per capita income growth in developing countries would be higher than that of rich countries. This would cause the developing countries to 'catch-up' with the per capita income of the rich countries. This forecast of the Solow and Swan model is called absolute beta convergence. But if it occurs only among countries with similar characteristics like saving rate, population growth rate, and technological progress, then it is termed conditional beta convergence. This notion of convergence in the Solow model rests on the crucial assumption of diminishing marginal product of capital. Along with the well-known studies by Barro and Sala-i Martin (1992) and Mankiw et al. (1992), many studies have been conducted to test beta convergence in economic growth, including Bernard and Durlauf (1995); Higgins et al. (2006), Young et al. (2007).

Emulating the concept of beta convergence in economic growth, many studies have been carried out in environmental economics to test the β-convergence in EP. β-convergence in EP will occur when developing countries' environment is degraded faster than their rich counterparts. Hence, developing countries will catch–up with the level of environment degraded by the rich countries. It is called absolute beta convergence in EP if this occurs across the world countries. But if it occurs among countries with similar characteristics, it is called conditional beta convergence.

To test this concept of β-convergence in EP, Strazicich and List (2003) carried out one of the earliest studies. This study used CO_2 emission data as EPI for 21 industrialized countries from 1960 to 1997 and found evidence supporting conditional convergence. Similarly, Nguyen Van (2005) used both cross-sectional and panel data analysis to test β-convergence for 26 high-emission countries from 1966 to 1996. The study found evidence for convergence in the cross-sectional cases, while the β-coefficient for panel data case was found to be insignificant; hence this study was inconclusive in the case of panel data analysis.

In their influential study, Brock and Taylor (2010) tested absolute and conditional β-convergence for OECD countries by using the data from 1960 to 1998. This study used cross sectional approach and came up with the findings that both absolute and conditional β-convergence holds in the sample countries. In another study, Stegman and McKibbin (2005) tested β-convergence using data from 1900 to 1999 for OECD countries, while global sample data was used from 1950 to 1999. They found support for convergence for OECD countries and insignificant results regarding convergence for the global sample. On the other hand, Jobert *et al.* (2010) used a shrinkage estimator to test the β-convergence for a group of European countries from 1971 to 2006. They found evidence for both absolute and conditional convergence.

Similarly, Brannlund and Karimu (2018) derived an environmental performance index using production theory to test the existence of β-convergence in the world. They used the data from 1971 to 2008 for 94 developed and developing countries. This study also found the existence of convergence at a global level. However, the convergence rate was lower for high-income countries than for their low-income counterparts.

Using a similar production theory framework, Brannlund et al. (2015) tested the existence of β-convergence across the Swedish manufacturing sectors from 1990 to 2008. This study has also found that the presence of β-convergence and the speed of convergence are inversely related to the capital intensity of the sector. Acar and

Lindmark (2017) tested the presence of β-convergence concerning the type of fuel used by the OECD countries. They came with the findings of convergence conditional upon GDP during 1973-1991 (the cold war period), but it was not conditional upon GDP during 1992-2010 (during the post-cold war period). Considering the single-country case, Wang and Zhang (2014) examined the existence of β-Convergence in environmental performance in 28 provinces of China for six sectors from 1996 to 2010. The study found the existence of unconditional β-convergence for most of the sectors.

In another study, Li and Lin (2013) examined conditional and unconditional β-convergence utilizing a global sample of 110 countries from 1971 to 2008. The study found no evidence for the existence of unconditional convergence. There is, however, ample evidence for the presence of conditional convergence. Tiwari and Mishra (2017) studied β-Convergence using CO_2 as EPI for Asian countries from 1972 to 2010. They came up with the findings of the presence of convergence. Yu et al. (2018) investigated convergence in environmental performance in 24 sub-sectors of industry in China from 1995 to 2015. This study has also found evidence of conditional convergence in different industrial sectors of China.

2.2 σ-Convergence in Environmental Performance

This is the second concept of convergence used by empirical studies. It tests whether the variance of the series among cross-sections decreases or not. The original concept of σ-Convergence was put forward by Barro and Sala-i-Martin (1992). For σ-Convergence to hold, β-convergence is a necessary condition, but it is not sufficient (Barro & Sala-i-Martin, 2004).

One of the most influential studies to test the presence of σ-Convergence in emission is carried out by Aldy (2006). The author has used various cross-sectional distributional techniques to achieve this objective in this study. For this purpose study used two samples, one of 23 OECD countries and the other global sample of 88 countries. This study found evidence of convergence for OECD countries, while divergence in emission is found for the global sample. Following a similar approach of using two samples, Stegman and McKibbin (2005) also tested σ-Convergence for two samples, one of 26 OECD countries for 1900-1999 and a global sample of 97 countries for the period 1950-1999. This study also found the divergence for the global sample during convergence for the OECD countries. Nguyen Van (2005) tested σ Convergence for 26 high-emission countries worldwide from 1966-1996. The study's results are: countries with high initial emissions tend to have decreasing emissions over time, while countries with low initial emission levels tend to stay in their position. Li et al. (2017) have also found the presence of σ-Convergence at the prefecture-level of the Yangtze River delta in China from 2000 to 2010. Similarly, Wang and Zhang (2014) studied the existence of σ-Convergence in 28 provinces of China for six sectors from 1996 to 2010. The study found that the standard deviation declined in each sector across the study period, confirming the existence of σ-Convergence.

There is another approach to σ-Convergence known as the 'intra-distribution dynamics approach'. This approach was suggested by Quah (1993, 1996b). This approach devises a more rigorous procedure to test σ-Convergence than the conventional σ-Convergence. The conventional σ-Convergence, in a simple case, relies on plotting cross-sectional variance or standard deviation. There are many benefits of using the intra-distribution dynamics approach for studying convergence. For example, it can reveal whether the distribution is bimodal or if polarization and stratification exist. This cannot be studied using traditional plots of variance or standard deviation.

Many studies have then been conducted using intra-distribution dynamics approach of Quah. Stegman (2005) utilized the methodology developed by Quah to explore the intra-distributional aspects of CO_2 emission for a sample of 97countries for the period 1950-1999. The author has utilized stochastic kernels for the analysis. The study could not confirm the presence of convergence. Ezcurra (2007) has also studied the distribution dynamics of CO_2 for a sample of 87 countries from 1960-1999. This study has found evidence for the presence of convergence. This study also found that polarization across the countries decreased during the study period. In a similar study by Criado and Grether (2011), the authors applied different measures to study the distributional and intra-distributional characteristics of a huge sample of 166 countries from 1960 to 2002. Authors found the distribution of CO_2 to be non-stationary before 1970s oil price shocks, while stable and symmetric shapes were found after that. Tiwari and Mishra (2017) used Asian countries' data to study the existence of σ-Convergence by utilizing the intra-distribution dynamic approach from 1972 to 2010. For this purpose study made use of kernel density estimate. This study confirmed the presence of convergence.

Phillips and Sul (2007) developed another approach to study σ-convergence known as club convergence. This approach tests conditional σ-convergence. Using a log t-test, this method divides per capita income into an idiosyncratic term and a common factor. In this way, these methods test whether the idiosyncratic term converges or not. By doing so, the component is tested against the panel average to check whether the series has the same transition path. Many studies have utilized this club convergence approach to study environmental performance. Panopoulou and Pantelidis (2009) have applied the club convergence approach developed by Phillips and Sul (2007) using a sample of 128 countries from 1960 to 2003. The study's results confirm the presence of club convergence in CO_2 emission for OECD and EMU countries. But convergence cannot be found for developing countries.

Another study by Camarero *et al.* (2013) also utilized the methodology developed by Phillips and Sul (2007) to test club convergence in CO_2 emission for OECD countries from 1960 to 2008. The study found four different convergence clubs for the countries. Ulucak and Apergis (2018) have also applied this club convergence methodology to test the existence of convergence in environmental performance in European Union countries from 1961 to 2013. This study utilizes a comprehensive measure of 'ecological footprint' to measure the countries' environmental performance. The results indicate the presence of club convergence in the environmental performance of the European Union countries. In another study, Herrerias (2013) tested the notion of club convergence in CO_2 emission for a sample of 162 countries from 1980 to 2009. For many countries, evidence for the presence of club convergence was found. However, there were still some countries where CO_2 emissions diverged.

Emir *et al.* (2019) have also used Phillips and Sul approach for studying club convergence in CO2 intensity in 28 EU countries from 1990-2016. This study does not find any evidence of the convergence of all countries into a single club. Therefore, this study also confirms the existence of multiple steady states for EU countries. In a country study, Wang et al. (2014) tested the club convergence hypothesis for the Chinese provinces from 1995 to 2011. This study found evidence of divergence in CO_2 emission. Payne and Apergis (2021) have also studied the convergence of CO_2 emission per capita for countries with different income levels. This study also confirms the existence of convergence clubs among countries with different income levels. Ulucak et al. (2020) studied the convergence of EF and its components for Sub-Saharan African countries from 1961 to 2014. This study also found multiple convergence clubs of countries based on EF and its components.

2.3 Stochastic Convergence in Environmental Performance

This is the most widely tested concept of convergence in empirical studies. This concept is based on testing the properties of univariate time series. In particular, the presence of unit roots in the time series or the penal data is tested. The idea is to test to what extent the value of a series converges to its long-run hypothesized value once it deviates from it due to some shock. The rejection of the unit root hypothesis implies the series's tendency to mean reversion, hence implying convergence. Empirical studies have utilized a variety of ways to test the presence of unit roots.

List (1999) conducted one of the earliest studies to test the stochastic convergence in the EP of the regions across the USA between 1929 and 1994. By utilizing SO_2 (sulfur dioxide) and NO_2 (nitrogen dioxide) as EPI, the study found some evidence for convergence. Heil and Selden (1999) used a sample of 135 countries from 1950 to 1992. The study found the CO_2 emission series to be stationery. Hence, the study found support for convergence. This study utilized the tests of panel unit root developed by Im *et al.* (1995). McKitrick and Strazicich (2005) used a panel of 121 countries from 1950 to 2000. They found results that support the notion of convergence at a global level. However, during testing for individual countries, it is found that emissions in 26 countries are non-stationary, which means they aren't converging to any steady state.

Barassi *et al.* (2008) carried out an exhaustive exercise to test the convergence by using a very similar data set of the very similar 21 OECD countries as of Strazicich and List (2003) for the period 1950 to 2002. This study applied different unit root tests and found that applying different tests gives different conclusions for convergence in emission data. Hence, this study warns the researchers to be careful while selecting the tests for their analysis as the results depend substantially on the testing procedure choice.

Similarly to Strazicich and List (2003), Romero-Avila (2008), in their study for testing the stochastic convergence for OECD countries for the period 1960 to 2002, has shown that the results of convergence differ when you allow for the possibility of the presence of structural break and when you do not allow. They found divergence when they excluded the possibility of structural breaks and found convergence when they allowed for structural breaks. Thus this study has also demonstrated the importance of the methodology used for testing convergence. The importance of the choice of testing methodology for the convergence study is evident in another example by Lee and Chang (2008) and Chang and Lee (2008). Lee and Chang (2008) have applied the Seemingly Unrelated Regressions Augmented Dickey-Fuller (SURADF) test for 21 OECD countries from 1960 to 2000. The authors found that time series are non-stationary. It means OECD countries are diverging in emissions. But Chang and Lee (2008), similar authors, found evidence for stochastic convergence when they allowed for the possibility of structural breaks by using the Lagrange Multiplier (LM) test.

Westerlund and Basher (2008) have employed different panel unit root tests and found evidence that supports the notion of convergence in groups for 16 OECD countries and 28 developed and developing countries from 1870 to 2002. For G-7 countries (Canada, France, Germany, Japan, Italy, the United Kingdom, and the United States of America), Yavuz and Yilanci (2013) investigated the presence of convergence in CO_2 emission for the period 1960 to 2005. This study utilized the non-linear panel analysis by employing the threshold autoregressive (TAR) unit root test. This test allows data to be divided into two data regimes. The results of the study show convergence for one regime and divergence for the other. In another study, Camarero *et al.* (2008) utilized seemingly unrelated regression equations (SURE) to test convergence in OECD countries from 1971 to 2002. The authors have used data envelope analysis (DEA) for the constructions of indices they used in SURE. This study found mixed results regarding convergence. In a country-specific study, Li et al. (2017) used prefecture-level data from the River delta in China to study the convergence of carbon intensity during 2000-2010. Using the stochastic convergence approach, the authors found the existence of convergence.

Ahmed et al. (2016), using a global sample of 162 countries, studied the presence of stochastic convergence in CO_2 during 1960-2010. This study utilized the wavelet analysis and found convergence for only 38 countries. For the remaining countries, the study found divergence. Similarly, Acaravci and Erdogan (2016) have also used non-linear unit tests to test stochastic convergence in the environmental performance of the seven world regions during 1960-2011. The study used the KPSS unit root test. This study found evidence of stochastic convergence when structural breaks were allowed. In a country study by Hao et al. (2015), the authors used panel unit root tests to test the stochastic convergence in 29 provinces of China from 1995 to 2011. This study found evidence for the presence of convergence. To focus on developing countries, Tiwari et al. (2016) used CO_2 data to study the environmental performance of 35 Sub-Saharan African countries during 1960-2009. This study utilized panel unit root and non-linear time series tests that also allow for structural breaks. The study's results found evidence for the presence of convergence in CO_2 in Sub-Saharan African countries. Christidou et al. (2013) have also found strong evidence for the existence of convergence in the global sample of 35 countries for the period 1870-2006. In another country-specific study, Baldwin and Wing (2013) used the index decomposition approach to study the convergence of CO_2 at the state level in the United States of America for the period 1963-2008. The authors found that although the determinants of CO_2 are not converging, there is convergence at the aggregate level of emission of CO_2.

Bilgili *et al.* (2019) have utilized Ecological Footprint (EF) as EPI in the study of convergence of EP and found stochastic convergence for the continental data for the period 1961-2014. On the other hand, Cai and Wu (2019) have found mixed results regarding convergence in CO2 emission for OECD and emerging economies for the period 1960 to 2014. In another recent study by Erdogan and Acaravci (2019), the authors tested the presence of stochastic convergence in 28 OECD countries using the Fourier panel KPSS test and found evidence of convergence in the period 1960-2014. Using SO2 as EPI, Solarin and Tiwari (2020) tested the presence of stochastic convergence for OECD countries from 1850 to 2005. This study has also found evidence of convergence. In another recent study by Yilanci, V., and Pata (2020), the authors tested the presence of stochastic convergence in EF of ASEAN-5 countries for the period 1961 to 2016. This study found that the EF series of these countries is non-linear and has two regimes. There is convergence in the first regime, while divergence is found in the second regime.

2.4 Spatial Convergence in Environmental Performance

As seen in previous sections of the chapter, there is a vast amount of literature that focuses on the convergence of environmental performance, but literature has largely ignored the role of space that it has to play in the determination of the environmental performance of the countries. In other words, existing literature has assumed that the cross sectional observations are independent spatially. But due to technological spillover, labor and commodity flow among neighbors, and because the government mimicking the policies of the neighboring government, the environmental performance is spatially dependent (Li et al., 2016). Due to this, an important assumption of independence of ordinary least squares (OLS) gets violated. Hence, inference based on OLS estimation would not be valid.

However, some studies have taken spatial factors into account while studying environmental convergence. Li et al. (2017), using prefecture-level data from the Yangtze River delta in China, studied the convergence of carbon intensity during 2000-2010. The authors used both conventional and spatial econometric methods to study convergence. They confirmed that there is spatial dependence on carbon intensity. And found beta convergence by applying spatial econometric methods.
Similarly, Huang and Meng (2013) used spatial econometric techniques to investigate unconditional spatial beta convergence in carbon emission in urban China for the

period 1985 to 2008. The study allowed spatial effects to vary over time. This study also confirmed spatial dependence among cross sectional units and that spatial beta convergence exists. Evans and Kim (2015) studied the convergence of CO_2 emissions during 1972-2009 in Asian countries using spatial econometric analysis. They have also confirmed that CO_2 emission data is spatially dependent. They have also found evidence of convergence in Asian countries regarding the convergence of environmental performance.

In a comprehensive study, Rios and Gianmoena (2018) studied the existence of beta and club convergence in CO_2 at the global level using a sample of 141 countries for the period 1970-2014, employing standard econometric techniques as well as using spatial econometric techniques. In line with the results of other studies, this study also found that spatial factors play an important role in determining CO_2 emission patterns at the global level. This study also found evidence of global beta convergence and the existence of club convergence. In another study, Behboudi et al. (2017) applied spatial econometric techniques to study convergence in CO_2 in MENA (Middle East and North Africa) countries from 1970-2010. The study found that considering the spatial dimension increases the speed of conditional convergence. This, however, does not affect the level of steady-state emission.

Guo and Luo (2021) studied the existence of spatial beta convergence in environmental efficiency in 99 Chinese cities from 2005-2017. The results of the study indicated the existence of convergence. Xu *et al.* (2020) have included spatial consideration in testing absolute and conditional beta convergence for a different region of China for 2005-2106. This study has found the existence of both conditional and absolute beta convergence. In another study, Tang *et al.* (2020) explored the role of spatial factors in the convergence of environmental efficiency in 262 Chinese cities from 2003 to 2016. The results found the existence of club convergence. Cui *et al.* (2021) has made a dynamic spatial analysis for the study of NO2 pollution in China and confirmed the existence of absolute and conditional beta convergence in Chinese regions during 2004-2020.

2.5 Conclusion

A review of the studies on the subject shows that there is no consensus regarding the convergence of EP[1]. The results of the studies are sensitive to the choice of approach to convergence (β-convergence, σ-Convergence, or stochastic convergence), length of time, and geographic coverage of the study. Regarding different approaches to convergence, studies using β-convergence approach and spatial econometric techniques to convergence tend to support the notion of convergence in EP while studies using distribution dynamic approach, club convergence approach and stochastic convergence approach found mixed results regarding presence of convergence. Regarding choice of sample countries it clearly emerges that there is convergence in EP of developed countries like OECD countries while no such clear evidence of convergence in EP of developing countries. Hence, there is no verdict regarding convergence in environmental performance. This calls for further research on the issue with better methodology and a broader data set that covers the analysis comprehensively.

The review of the literature on the subject indicates important shortcomings in the existing studies on the subject. For example, there is no past study that has used an EPI which is based on CBA consequently none of them can truly isolate the 'leakage effect' from convergence. Secondly, the overwhelming majority of past studies have ignored the role of space in analyzing environmental performance that causes serious model misspecification problems and, therefore, biased results. Then past studies have mostly used a single variable (mainly CO2) as EPI. However, no single variable can fully capture the overall environmental performance. To amend these shortcomings, the present study has used EF of consumption, a comprehensive EPI covering six dimensions of EP. Moreover, we have used spatial econometric techniques which take into account the role of space in environmental performance.

[1] Summary of the studies on convergence in environmnteal performance is given as appendix C.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Theoretical Framework

This section is devoted to developing a theoretical framework for our empirical models. The theoretical framework is mainly based on the 'Spatial Green Solow Model' developed by Rios and Gianmoena (2018). The Rios and Gianmoena model is rooted in the 'Green Solow Model' of Brook and Taylor (2010), which introduces the spatial dependence of the economies for their environmental performance. Spatial Green Solow Model assumes spatial interdependence of the economies in their production technologies. This assumption of the technological spillover is the departure of the 'Spatial Green Solow Model' from Brook and Taylor (2010).

Consider following Cobb-Douglas with a constant return to scale:

$$Q_{it} = K_{it}^{\alpha}(B_{it}L_{it})^{1-\alpha} \qquad 0 < \alpha < 1 \tag{3.1}$$

Where Q_{it} is the total output of country 'i' in period 't', K_{it} is the total stock of physical capital, L_{it} is the total labor, B_{it} is the level of technology, α = Elasticity of output with respect to capital, and finally $1 - \alpha$ = Elasticity of output with respect to labor.

Following the neo-classical growth model of Solow (1956), we assume that labor is growing at a constant exogenous growth rate of population:

$$L_{it} = L_{i0}e^{n_{it}} \tag{3.2}$$

Taking natural log on both sides:

$$\ln(L_{it}) = \ln(L_{i0}e^{n_{it}})$$
$$\ln L_{it} = \ln L_{i0} + n_{it}\ln e$$

Taking the time derivative on both sides of the equation will take the from:

$$\frac{1}{L_{it}}.\frac{dL_{it}}{dt} = \frac{1}{L_{i0}}.\frac{dL_{i0}}{dt} + \frac{dn_{it}}{dt}$$

If we denote $\frac{dL_{it}}{dt}$ by $\dot{L}_{it}$ which is a growth of labor over time, then the above equation can be written as:

$$\frac{\dot{L}_{it}}{L_{it}} = n_i \tag{3.3}$$

Equation 3.3 shows that labor is growing at a constant exogenous growth rate of 'n', which is the population growth rate. To introduce the presence of spatial spillover in production technology, we are following Yu and Lee (2012). Following equation 3.4 shows technological growth and spatial spillover effects:

$$B_{it} = B_{i0}e^{g_b t}\prod_{j\neq 1}^{N} B_{jt}^{\phi w_{ij}} \qquad 0 < \phi < 1 \tag{3.4}$$

Equation 3.4 shows that the technological growth in country $'i'$ in period $'t'$, $'B_{it}$', depends on three factors. Firstly, the initial level of technology in country 'i', $'B_{i0}$'. Secondly, a constant exogenous growth rate of technology $'g_b'$. And thirdly, at the technology level of neighboring countries $'B_{jt}$' The neighboring countries spillover effect is captured through spatial weight matrix $'w_{ij}'$. This matrix captures the spatial interdependence of the economies on each other. The detail of spatial weight matrix for our study is given in section 3.4. The parameter 'ϕ' shows the intensity of technological spillover among the spatial units.

Taking natural log on both sides of equation 3.4 will take the form:

$$lnB_{it} = lnB_{i0} + g_b t l_n + \phi W_{ij} lnB_{it}$$

$$lnB_{it} = [I_n - \phi W]^{-1} lnB_{i0} + \frac{g_b t}{1-\phi} l_n$$

In above equation l_n is the Nx1 vector of ones and 'W' is row normalized therefore:

$$\frac{\dot{B}_{it}}{B_{it}} = \frac{g_b}{1-\phi} \tag{3.5}$$

Since the spillover effect, ϕ, is restricted between '0' and '1' therefore the technological growth rate in country 'i' and period 't' would be greater than g_b. Hence, allowing for spatial spillover of technological growth causes technology to grow at a greater rate than treating spatial units as independent.

Following Brook and Taylor (2010), we integrate the environment into the Solow model. We assume that during economic activity, a bad in the form of environmental degradation is co-produced with the production of the good. Aghion and Howitt (1998) have also made this assumption. To model this, let's assume that during the production of each unit of good $'Q'$ environment is degraded by 'Ω_{it}' if no abatement is made. The environmental degradation, however, will reduce if abatement is made. Assume that after the abatement, a unit of 'Q_{it}' degrades the environment by $\Omega_{it}a(\theta)$ in period't'. The abatement is assumed to be a constant return to scale activity. Further, it is assumed to be a positive and concave function of economic activity and abatement effort. Hence, $a(0) = 1$, $\acute{a}(\theta) > 1$ *and* $\acute{\acute{a}}(\theta) < 1$. It is also assumed that $a(\theta) = (1-\theta)^{\epsilon}$ where $\epsilon > 1$.

The output left for consumption and investment after the abatement effort will be:

$$Y_{it} = (1-\theta)Q_{it} \tag{3.6}$$

After abatement, the total environmental degradation would be:

$$D_{it} = Q_{it}\Omega_{it}a(\theta) \tag{3.7}$$

Equation 3.7 indicates that total environmental degradation is the function of both levels of production $'Q_{it}'$ and technique of production $'\Omega_{it}a(\theta)'$ Hence, reduction in environmental degradation does not necessarily need 'limit to growth' or 'de-growth'. It can also be achieved by improvement in production techniques. Following Brook and Taylor (2010), we assume a constant growth rate of abatement technology. In addition, technological progress is taken as exogenous, hence, Ω_{it} in equation 3.6 is being specified as follows:

$$\Omega_{it} = \Omega_{i0}e^{-g_a t}$$

In the above equation, Ω_{i0} denotes the initial level of technology, and it is growing at each point in time at the rate of g_a. Taking natural log on both sides gives:

$$\ln(\Omega_{it}) = \ln(\Omega_{i0}e^{-g_a t})$$
$$\ln \Omega_{it} = \ln \Omega_{i0} - g_a t \ln e$$

Taking the time derivative on both sides of the equation will give:

$$\frac{1}{\Omega_{it}} \cdot \frac{d\Omega_{it}}{dt} = \frac{1}{\Omega_{i0}} \cdot \frac{d\Omega_{i0}}{dt} - \frac{dg_a t}{dt}$$

Let the term $\frac{d\Omega_{it}}{dt}$ replaced with $\dot{\Omega}_{it}$ which is a growth of abatement over time, then the above equation can be written as:

$$\frac{\dot{\Omega}_{it}}{\Omega_{it}} = -g_a \qquad (3.8)$$

Regarding the evolution of physical capital, we will follow the standard assumption of the Solow (1956) growth model that physical capital accumulates with new investment but reduces with the depreciation of existing capital. This can be written as:

$$K_{it} = I_{it} - \delta_i K_{it}$$

Where 'I' is the investment in physical capital, which like the Solow growth model, is assumed to depend on an exogenously fixed rate of saving 's' such that:

$$K_{it} = s_i Y_{it} - \delta_i K_{it}$$

As discussed earlier, a fixed portion of output produced 'Q_{it}' is assumed to be devoted to abatement, so the above equation can be re-written as:

$$K_{it} = s_i(1-\theta)Q_{it} - \delta_i K_{it} \tag{3.9}$$

The model described so far can be solved in intensive form by specifying output, environmental degradation, and equation of motion of capital per unit of effective labor. This can be done by dividing 3.1, 3.6, 3.7, and 3.9 by units of effective labor $(B_{it}L_{it})$.

The intensive form of these variables are presented as follows;

$$q_{it} = k_{it}{}^{\alpha} \tag{3.10}$$

$$y_{it} = (1-\theta)q_{it} \tag{3.11}$$

$$d_{it} = q_{it}\Omega_{it}a(\theta) \tag{3.12}$$

$$\dot{k}_{it} = s_i(1-\theta)q_{it} - \left(n_i + \frac{g_b}{1-\phi} + \delta_i\right)k_{it} \tag{3.13}$$

Like Green Solow Model, our assumptions of positive but diminishing marginal products of factors and constant return to scale implies that the economy will eventually converge to following steady-state level of capital and output per effective labor;

$$k_i^* = \left[\frac{s_i(1-\theta)}{\frac{g_b}{1-\phi}+n_i+\delta_i}\right]^{\frac{1}{1-\alpha}} \tag{3.14}$$

$$y_i^* = \left[\frac{s_i(1-\theta)}{\frac{g_b}{1-\phi}+n_i+\delta_i}\right]^{\frac{\alpha}{1-\alpha}} \tag{3.15}$$

From steady-state equations 3.14 and 3.15, it can be seen that capital and output per effective labor would be the same in all economies if they have the same level of saving rate (s_i), population growth rate (n_i) and depreciation rate (δ_i). This is what the convergence of income hypothesis of the neo-classical model is about. It does not matter what the initial capital stock is in the economies. As long as they have similar characteristics in the form of saving rate, population growth rate, and depreciation rate, they would converge to similar per capita income. Further, it can be seen that steady state values of per capita capital and output of our model are higher than that of Brook and Taylor (2010) model. This is because of our assumption of spatial spillover of the production technology (ϕ).

Equation 3.11 implies that the growth rate of aggregate environmental damage would be:

$$g_{D,i} = \frac{g_b}{1-\phi} + n_i - g_a \tag{3.16}$$

The above equation shows that the growth rate of aggregate environmental degradation depends on two factors: growth rate of production technology and the growth rate of abatement technology. The first factor is popularly known as the scale effect (effect of an increase in production on the environment) in literature, while the second factor is known as the technique effect (effect of improvement in abatement technology). The growth rate of production technology degrades the environment, while the growth rate of abatement technology improves the environment. Hence, to have sustainable growth (where both income and environmental quality improve), g_a (growth in abatement technology) should be greater than $\frac{g_b}{1-\phi} + n_i$ (growth in production technology). This will ensure that environment is getting more benefit from the growth of abatement technology than it is degraded by growth in production technology.

To see the relationship between the neo-classical growth model of Solow and environmental degradation, we specify the differential equation for environmental degradation as:

$$D_{it} = B_{i0}L_{i0}\Omega_{i0}a(\theta)e^{g_{Di}t}k_{it}^{\alpha} \tag{3.17}$$

Differentiating 3.17 with respect to time will give us the following:

$$\frac{\dot{D}_{it}}{D_{it}} = g_{D_i} + \alpha\frac{\dot{k}_i}{k_i} \tag{3.18}$$

And $\frac{\dot{k}_i}{k_i}$ can be found from equation 3.13 as:

$$\frac{\dot{k}_i}{k_i} = s_i k_i^{1-\alpha}(1-\theta) - \left(n_i + \frac{g_b}{1-\phi} + \delta_i\right) \tag{3.19}$$

Equations no 3.18 and 3.19 can be used to interlink capital dynamics with environmental degradation dynamics. The interrelationship between these two when there is no spatial spillover effect and when we assume the spatial spillover of the production technology is drawn in figure 3.1. Let us first discuss the case when there is no spatial spillover. There are two panels of the figure. In panel (a), on the y-axis, we have plotted (α times) growth rates of capital ($\alpha\frac{\dot{k}_i}{k_i}$) and the growth rate of aggregate environmental degradation ($\frac{\dot{D}_{it}}{D_{it}}$). On the x-axis, we have plotted 'k'. The negatively sloped curve labeled as '$\alpha s_i k_i^{1-\alpha}(1-\theta)$', is the ($\alpha$ times) actual investment in physical capital. The horizontal line labeled as $'\alpha(n_i + g_b + +\delta_i)'$ is the (α times) break-even investment needed to keep the level of physical capital constant. The difference between the negatively sloped actual investment curve and this break-even investment line will give us a capital growth rate per effective labor.

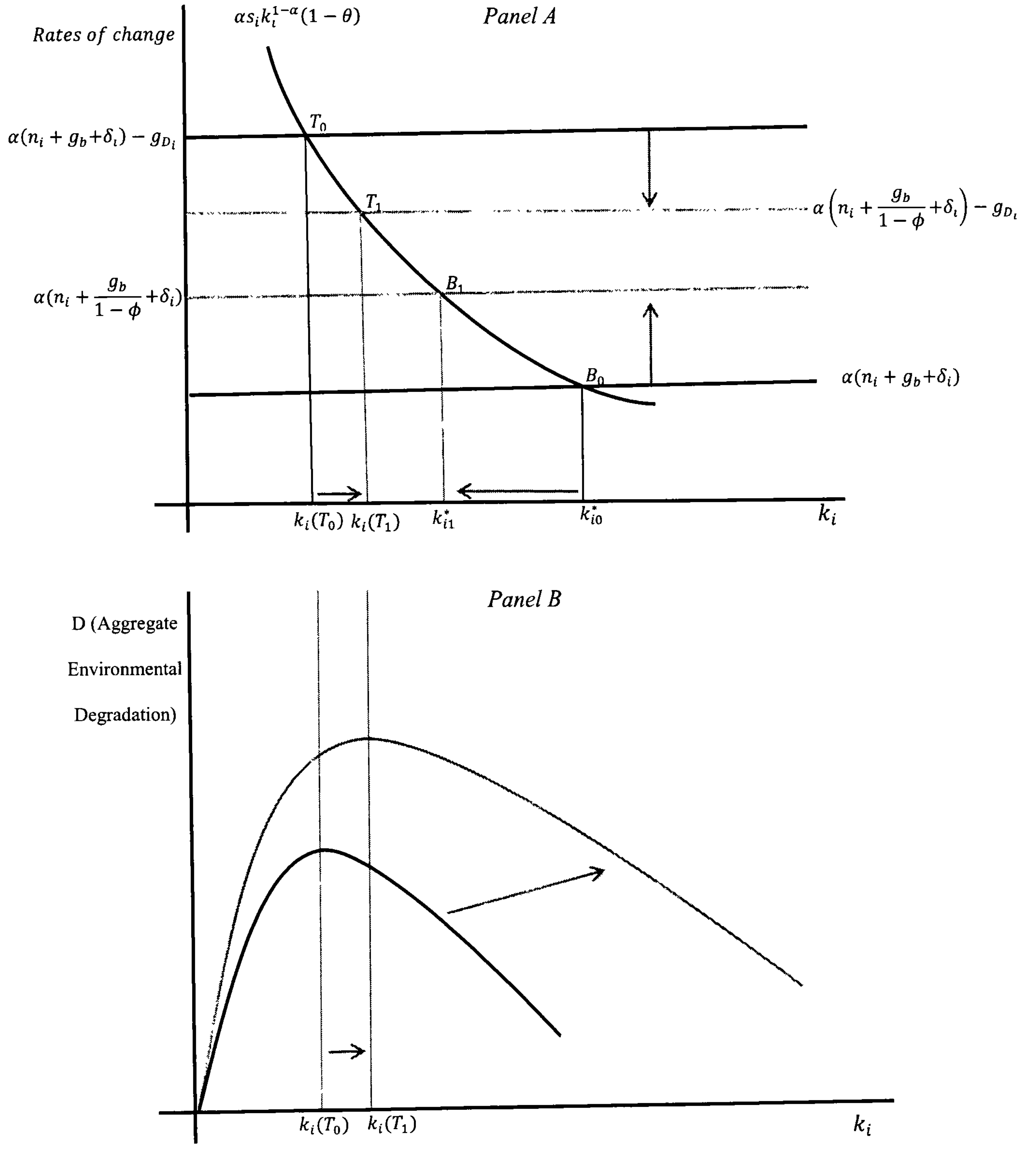
Actual investment in physical capital and break-even investment are equal at point 'B_0'. This gives us the steady state level of capital per effective labor, 'k_{i0}^*'. The growth rate of 'k' is positive below this level of'k' and negative above this level of 'k'. This growth rate of 'k' is higher at a lower level of 'k' and smaller at a higher level of 'k'. Equation 18 shows that $g_{D_i}$is constant and hence $\frac{\dot{D}_{it}}{D_{it}}$ would inherit most of the properties of $\frac{\dot{k}_i}{k_i}$. So, the difference between negatively sloped actual investment in physical capital and the horizontal line labeled as $'\alpha(n_i + g_b + \delta_i) - g_{D_i}'$ will give us the growth rate of aggregate environmental degradation if there is no spatial spillover effect. Actual investment in the physical capital curve intersects the as $'\alpha(n_i + g_b + \delta_i) - g_{D_i}'$ line at point $k(T_0)$. This intersection gives us the level of the capital where the environmental degradation level is at its peak. The growth rate of environmental degradation is positive below this level of 'k' and negative above this level of 'k'. Moreover, the growth rate of environmental degradation would be higher at a lower level of 'k' and smaller at the higher level of 'k'.

The bottom panel of figure 3.1 plots this relationship between aggregate environmental degradation and the level of capital per effective labor. We can see that our model implies the existence of EKC. Without any spatial spillover of production technology, an increase in capital per effective labor will cause environmental degradation to increase till $k_i(T_0)$ and after $k_i(T_0)$ increase in capital per effective labor will cause environmental degradation to reduce.

This is because we have assumed sustainability in our model. That is, we have assumed growth in abatement technology (g_a) is higher than the growth rate of production technology ($n_i + \frac{g_b}{1-\phi}$). Our assumption of diminishing MPK implies that at a lower level of 'k' there is a stronger scale effect, so output rises rapidly, which degrades the environment faster than what is restored by abatement.

This continues to happen till $k_i(T_0)$. At this level of 'k' environment degraded by the extra production equals what is restored by the abatement. This is where the peak of the so-called EKC will occur. Before this level of 'k' the negative effect of output growth on the environment outweighs the positive effect of growth in abatement technology on the environment. After this level, the positive effect of growth in abatement technology on the environment will outweigh its negative effects caused by the growth of output. The introduction of spatial spillover in production technology will shift EKC upwards, as indicated by arrows in figure 3.1. This is because introducing spatial spillover causes output to grow faster, causing the environment to degrade more at each level of capital. This would cause the peak level of environmental degradation to shift from T_0 to T_1.

Figure 3.1: Steady State Dynamics



Source: Rios and Gianmoena, (2018)

To examine the properties of these turning points of EKC more formally, we can specify income per effective labor as:

$$y_{it} = (1-\theta)k_{it}^{\alpha}B_{i0}B_{jt}^{\phi w_{ij}} \tag{3.20}$$

The level of capital per effective labor where the peak of environmental degradation (k_T) will occur can be found by substituting equation 3.19 in 3.18 and setting the level of aggregate environmental degradation ($\frac{\dot{D}_{it}}{D_{it}}$) equal to zero.

This will give us the following:

$$k_{iT} = \left[\frac{s_i(1-\theta)}{n_i+\frac{g_b}{1-\phi}-\delta_i-\frac{g_{D_i}}{\alpha}}\right]^{\frac{1}{1-\alpha}} \tag{3.21}$$

The value of k_i at any time 't' can be found by solving equation 3.19. It will give the value:

$$k_{it} = \left[k_i^{*(1-\alpha)}\left(1-e^{-\lambda_{it}}\right)+k_{i0}^{(1-\alpha)}e^{-\lambda_{it}}\right]^{\frac{1}{1-\alpha}} \tag{3.22}$$

In the above equation, 'λ_i' is the convergence rate or speed of adjustment of country 'i' to its balanced growth path, and it is equal to:

$$\lambda_i = (1-\alpha)\left(n_i+\frac{g_b}{1-\phi}-\delta_i\right) \tag{3.23}$$

Capital per effective labor at peak time 'T' can be found by substituting 'T' for 't' in 3.22. Hence;

$$k_{iT} = \left[k_i^{*(1-\alpha)}\left(1-e^{-\lambda_{iT}}\right)+k_{i0}^{(1-\alpha)}e^{-\lambda_{iT}}\right]^{\frac{1}{1-\alpha}} \tag{3.24}$$

The time required to reach the peak of environmental degradation, 'T', can be found by solving equation 3.24 for the following implicit equation:

$$T = \frac{1}{\lambda_i} ln \left[\frac{k_i^{*(1-\alpha)} - k_{io}^{(1-\alpha)}}{k_i^{*(1-\alpha)} - k_i^{T(1-\alpha)}}\right] \tag{3.25}$$

Equation 3.25 shows that the higher the convergence rate of the economy lower is the time required (T) to reach the peak of environmental degradation. It also shows that farther the 'k_{io}' from 'k_i^*' or closer the k_{iT}' to 'k_i^*', more time would be required to reach the peak of environmental degradation.

Finally, to find the peak level of environmental degradation, substitute 3.23 into 3.17. This will give us the following:

$$D_{it} = B_0 L_0 \Omega_0 a(\theta) e^{g_{Di}t} \left[k_i^{*(1-\alpha)}\left(1 - e^{-\lambda_{it}}\right) + k_{io}^{(1-\alpha)} e^{-\lambda_{it}}\right]^{\frac{1}{1-\alpha}} \tag{3.26}$$

And environmental degradation at the peak would be:

$$D_{iT} = B_0 L_0 \Omega_0 a(\theta) e^{g_{Di}T} [k_{iT}]^{\alpha} \tag{3.27}$$

Equation 3.26 shows that the peak of environmental degradation is the positive function of capital intensity and the negative function of peak time required (T) for environmental degradation.

3.2 Defining Environmental Performance

The EF data provided by Global Footprint Network has been used in this study as the EPI of the countries. The majority of the past studies have used only emissions as EPI of the countries, e.g., Yavuz and Yilanci (2013), Acar and Lindmark (2017), and Apergis and Payne (2017). Although emissions are a crucial indicator of EP, this only presents a partial picture (Ahmed *et al.*, 2019). EF is a comprehensive indicator that measures all pressure on the environment. The concept of EF measures how many ecological assets are required for the generation of resources humans consume and to absorb the waste they generate, the most important of which is carbon emission. The

EF uses six categories of productive surface for this purpose, i.e., cropland, grazing land, fishing grounds, built-up land, forest area, and carbon demand on land.

Using this variable as a measure of EP serves two crucial purposes. Firstly, unlike emissions, which represent only a partial effect of human demand for resources on the environment, the EF addresses the full impact of human demand for resources on environmental health. Hence, using this variable as a measure of EP of the countries will better enable us to make the interregional comparisons of EP, and consequently, it will enable us to advance more informed policy suggestions. Secondly, emissions utilized as EP are normally calculated under production-based accounting (PBA). Hence, under PBA, environmental responsibility for the emissions rests with the country of production and completely ignores where goods and services are consumed. The problem with utilizing this production-based accounting (PBA) system is; as countries grow, they do not change their consumption. They shift the production of CO_2-intensive goods and services to low-income countries. In this way, the reported emissions reduce in rich countries and increase in developing countries. This causes the researcher to inaccurately conclude that EP is converging between rich and developing countries.

Using EF of consumption as the measure of EP solves this problem. It is because accounting methodology will then allocate the environmental responsibility to the country where the resources are consumed instead of where they are produced. To do this, adjustments for international trade are made i.e. first, the production footprints of the country are calculated, then the import footprints of the country are added, and the export footprints are subtracted. This makes our EPI grounded on a consumption-based accounting (CBA) system. CBA is a more accurate system to study the convergence of EP than the production-based accounting (PBA) system as it would only conclude convergence in EP if environmental pressure from consumption of goods and services converged among countries.

3.3 Spatial Dependence

In order to determine whether or not a series is spatially dependent, the most commonly used statistic is Moran's I index. The Moran's I index value will tell us whether or not the overall EP is spatially dependent.

It can be calculated using the following formula:

$$I_t = \frac{n\sum_i \sum_j w_{ij} z_i z_j}{S\sum_i z_i^2} \quad (3.28)$$

Where z_i is the deviation of country *'i'* EP from its mean at period *'t'*, z_j= Deviation of country *'j'* EP from its mean at period *'t'*, W_{ij}= Neighborness of the country 'i' to country 'j' as measured by spatial weight matrix (discussed in section 3.4 in detail) and finally *S*= Sum of all elements of the weight matrix.

In the case of a row standardized spatial weight matrix, 'S' becomes equal to *'n'* in the formula; hence the formula of global Moran's I becomes,

$$I_t = \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2} \quad (3.29)$$

The value of Moran's I can be between '-1' to '+1'. The value close to '-1' indicates a negative spatial autocorrelation i.e. EP of the neighboring region negatively affects EP of the region under consideration. In this case, a country with a poor EP will be neighbored by a country with a high EP. And if the value of Moran's I is close to '+1', it indicates that the neighboring region positively affects the EP of the region under consideration. In this case, a country with poor EP will be neighbored by a country with poor EP. Lastly, closer Moran's 'I' value to zero indicates no spatial autocorrelation, and the standard econometric analysis would do the job. The significance of Moran's 'I' can be checked using the standard 'Z-test'.

3.4 Spatial Weights

The spatial weights matrix imposes the neighborhood structure in spatial data analysis. The construction of spatial weights is a very crucial task in any spatial econometric analysis.

There are primarily three ways to define spatial weights:

- **a.** Weights based on boundaries
- **b.** Weights based on distance
- **c.** Weights based on the combination of boundary and distance

3.4.1 Weights Based on Boundaries

This is a very popular method of constructing spatial weights. It is because, in many cases, the shared boundaries between spatial units determine the spatial influence between the spatial units. Hence, it is natural to use these boundary relationships to determine the spatial relation between spatial units. Following are two types of such weights that have been used in literature:

3.4.1.1 Contiguity Binary Weights

This is the simplest form of spatial weights. In the case of the so-called 'Queen Binary Contiguity Matrix' the two spatial units are neighbors if they share a common border or any corner, while according to a 'Rook Binary Contiguity Matrix' two spatial units must share a border, in order to be termed as neighbors. If the shared length of the boundary is denoted by 'b_{ij}' then spatial contiguity weight matrix can be defined as:

$$w_{ij} = \begin{cases} 1, & b_{ij} > 0 \\ 0, & b_{ij} = 0 \end{cases}$$

In spite of being very popular in the literature, contiguity weights have one very obvious disadvantage. That is while assigning the neighborhood relationship to the spatial units. All this weighting scheme looks at is; the contiguity. This scheme does not differentiate between the spatial units sharing a very large boundary or sharing a very small one. The contiguity weighting scheme would treat both as exerting the same level of spatial dependence. In the case of macroeconomic data, where countries are the spatial units, this can be misleading. It is because countries with lengthy borders are generally tied more closely than countries with shorter borders.

3.4.1.2 Shared Boundary Weights

As discussed above, one of the shortcomings of the contiguity weighting scheme is that it treats all spatial units sharing borders equally important. This problem can be solved using shared boundary weights. The strength of the spatial relationship between two units '*i*&*j*' can be done by calculating the ratio of the length of the shared boundary between '*i*&*j*' to the total length of the boundary of '*i*'. This will directly show the relative importance of unit '*j*' for unit '*i*'.

If the shared length of the boundary is denoted by 'b_{ij}' and the total shared length of boundary shared with all other spatial units are denoted by $\sum_{i \neq k} b_{ik}$ then such weights can be defined as:

$$w_{ij} = \frac{b_{ij}}{\sum_{i \neq k} b_{ik}}$$

3.4.2 Weights Based on Distance

The second most popular criterion to determine weights is using different distances between spatial units. Distance weights solve the problem that contiguity weights cause, i.e., it ensures that there are no islands. That is one of the reasons these distance weights are frequently used in macroeconomic data studies. Some of the most popular distance-based weight matrices are as under:

3.4.2.1 K-Nearest Neighbor (KNN) Weights

In this method, a specific number (k) of neighbors is selected, and then the k-nearest units are identified as neighbors. This '*k*' can be any number 2, 4, 10, etc. In such cases, the distance between the spatial units is measured by specifying some important point in spatial units, such as the capital city or simply the centroid of the unit.

The chief advantage of using this weighting scheme is that it ensures that every spatial unit does have k-neighbors. So, no spatial unit is excluded from the spatial econometric analysis. But there are costs as well that are associated with the use of the KNN weighting scheme. One problem with using the KNN matrix is that it assigns an equal number of neighbors to all spatial units; hence, it treats all spatial units equally spatially integrated. This is not the case in most practical cases. This is especially problematic in the case of country-level analyses. This is because we know that some countries are much more integrated with the rest of the world than others.

3.4.2.2 Radial Distance Weights

Another way of forming spatial weights is using radial distance weights. This method specifies a distance within which spatial units are treated as neighbors. This distance can be any arbitrary number say 10 km, 15 km, 100 km, etc. If '*d*' is the cut-off distance, then the spatial weights can be defined as:

$$w_{ij} = \begin{cases} 1, & 0 < d_{ij} < d \\ 0, & d_{ij} > d \end{cases}$$

Hence, a spatial unit with more neighbors in the pre-specified distance would be considered subject to more spatial influence than the other spatial unit with fewer neighbors in the pre-specified distance. This is a huge advantage of radial distance weights over the KNN weights.

KNN weighting scheme would assign an equal number of neighbors to all the spatial units no matter how far or near they are located from the said spatial unit. So for one spatial unit, all the neighbors can be located in the near vicinity, and for the other, they can be located distantly. KNN weighting scheme would treat both of these spatial units subject to equal spatial influence from the neighbors. This can be misleading, particularly in the case of country-level data. Here gravity model of international trade predicts that countries located closer distances would have more trade among them and hence have more spatial influence among each other. The treatment of equal spatial influence under the KNN weighting methodology would be flawed.

3.4.2.3 Inverse Distance Weights

One of the criticisms on radial distance weights is; these assume that spatial influence on units is the same up to the cut-off distance, and it vanishes abruptly soon as the cut-off distance is reached. It is more logical to assume spatial dependence to be diminishing. One way to model this is to specify spatial weights in the form of the inverse of the distance between spatial units.

Hence, weights can be specified as:

$$w_{ij} = d_{ij}^{-\alpha}$$

'α' is normally assumed to be '1' or '2'. In this case, all the spatial units are neighbors to some degree.

One disadvantage of this weighting scheme, particularly for macroeconomic data is that it makes every country a neighbor of all the other countries of whatever degree. We know that at the country level, the distant spatial units rarely have any economic relationship among them.

3.4.3 Weights Based on the Combination of Boundary and Distance

Lastly, the spatial relationships between different units can be specified as the combination of boundary and distance. One such weighting scheme was introduced by Cliff and Ord (1969).

They introduced the following spatial weights:

$$w_{ij} = \frac{b_{ij} d_{ij}^{-\alpha}}{\sum_{i \neq k} b_{ik} d_{ik}^{-\alpha}}$$

'α' was assumed to be '1'.

Although this type of spatial weight is the most accurate conceptually, these are complicated to calculate. That is why these are rarely used in literature.

3.4.4 Standardization of Spatial Weights

Weights constructed in the manner described above are unit-dependent. In order to make these weights unit-free, standardization of weights is carried out. The most popular method of weight standardization is 'row standardization. In a row, standardization weights are standardized to have a sum of 1 for each row.

In symbols row standardization will look like this:

$$\sum_{j=1}^{n} w_{ij} = 1, \qquad i = 1,2, \dots, n$$

In this way, a spatial weight 'w_{ij}' signifies the relative importance of 'jth' unit in spatial influence for unit 'i'. This row standardization is so popular that the weights described above are row standardized by default. For example, shared boundary weights are row standardized. Similarly, the combined distance and boundary weight of Cliff and Ord (1969) discussed above are also row standardized. Practically, studies using 'k-nearest neighbors' weights also use '$1/k$' as weight instead of '1' to ensure row standardization.

Although row normalization is very popular, it does have its drawbacks. Specifically, it alters the internal weighting structure so that the comparison between rows becomes impossible. For example, if country 'i' and country 'j' are neighbors to each other, but each of them has a different number of neighbors, then they would be assigned different weights in their respective rows, i.e., in order to have a sum of row equal to 1 'w_{ij}' would be different then 'w_{ji}'. It is counter-intuitive that one country is more spatial dependent on another than the other.

To conclude, we can safely say that no spatial weighting methodology is perfect. Every method of constructing spatial weights has its pros and cons. That is why for the spatial econometric analyses, the present study has utilized different spatial weight matrices to check the robustness of the results.

3.5 Testing Spatial Beta Convergence

As one of our objectives is to test spatial β-convergence, the present section presents the methodology to test the presence of spatial β-convergence, which consists of four subsections. The first subsection is meant to describe the model specification. The second subsection will discuss the estimation technique used to estimate the model. The third subsection will describe the study's variables, and the last subsection is meant to describe how the results of the models would be interpreted.

3.5.1 Model Specification

If we disregard the effect of space in the convergence of EP, unconditional Beta convergence can be tested using the following model (Adhikari & Chen, 2014):

$$\Delta lnY_{it} = \alpha + \beta lnY_{it-1} + \varepsilon_{it} \tag{3.30}$$

Where ΔlnY_{it} is the growth rate of EF of country "i" in period "t", lnY_{it-1}= initial period EF, α = Constant , β= slope coefficient and ε_{it}= error term. If β is negative and significant in equation 3.30, this will imply the presence of unconditional beta convergence (Wang & Zhang, 2014). This means that all countries, irrespective of their structural characteristics (e.g., saving rate, population growth rate, technology, etc.), would converge to the same steady state.

Similarly, conditional beta convergence can be tested using the following model.

$$\Delta lnY_{it} = \alpha + \beta lnY_{it-1} + X_t\theta + \varepsilon_{it} \tag{3.31}$$

Where:

X_t = $N \ x \ K$ matrix of the set of controlled variables

θ= K X 1 vector of response parameters of the matrixX_t.

The above two models, 3.30 and 3.31, cannot capture the effect of space in EP as measured by EF. To introduce the effect of space in the model, we will proceed by adopting the general to the specific approach of model specification. Hence, we will first specify Spatial Durbin Model (SDM), as Lesage and Pace (2009) advised.

$$\Delta lnY_{it} = \alpha + \rho W\Delta lnY_{it} + \beta lnY_{it-1} + X_t\theta + WX_t\eta + \varepsilon_{it} \tag{3.32}$$

Where ρ= spatial autoregressive coefficient, W= weight matrix, η= K X 1 vector of response parameters of the matrix X_t of a neighboring country. All of the rest of the variables have the same definition as above. The model specified in 3.32 is a general model encompassing two other spatial models: the spatial lag model (SAR) and the spatial error model (SEM).

Model specifications of 3.32 can be used to test whether SDM can be reduced to either SAR or SEM. In this context following two hypotheses are tested:

i) H_0: η= 0 and
ii) H_0: $\eta + \rho\beta = 0$.

Accepting the first null hypothesis would imply that SDM can be reduced to a simple SAR. Hence 3.32 would take the form:

$$\Delta lnY_{it} = \alpha + \rho W \Delta lnY_{it} + \beta lnY_{it-1} + X_t\theta + \varepsilon_{it} \qquad (3.33)$$

The acceptance of the second null hypothesis would imply that SDM can be reduced to simple SEM, and 3.32 would become:

$$\Delta lnY_{it} = \alpha + \beta lnY_{it-1} + X_t\theta + \varepsilon_{it} \qquad (3.34)$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + V_{it} \qquad (3.35)$$

The rejection of both hypotheses indicates that SDM is the true model and cannot be reduced to either SAR or SEM.

3.5.2 Estimation Technique

The empirical models (equations 3.32-3.35) hold spatial and temporal lag terms ($W\Delta lnY_{it}$, lnY_{it-1}), which leads to simultaneity and endogeneity. Hence cannot be estimated with OLS.

We use Quasi Maximum Likelihood (QML), or Bias Corrected Maximum Likelihood (BCML) estimations to deal with this problem. Elhorst (2003) developed a Maximum Likelihood (ML) estimator for the dynamic spatial panel data model. According to this technique, the first difference of the reduced form of the model is taken, and then the unconditional likelihood function is estimated. Later, Yu et al. (2008) utilized this ML estimator, and by utilizing the rigorous asymptotic theory, they proved that the estimator developed by Elhorst (2003) gives biased results. Yu et al. (2008) suggested a mechanism to correct this bias and developed BCML or QML estimator for spatial fixed effects. Lee and Yu (2010) then extended this QML estimation technique to include time fixed effects and spatial-fixed effects. This estimator does bias correction with or without the normality assumption of the error term. This modified BCML/QML estimator can be used even if we eliminate the temporal lag (lnY_{it-1}) from the model.

This is the most appropriate estimator to estimate Spatial Dynamic Panel Data Model. This has been used by (Yesilyurt and Elhorst, 2017; Lv and Li, 2021; Karman *et al.*, 2020; Postiglione *et al.*, 2020). This study will also use the BCML estimator to estimate Dynamic Spatial Panel Data model to test the β-convergence in EP.

3.5.3 Description of the Variables under Consideration

This section provides a detailed description of the variables under consideration.

3.5.3.1 Dependent Variable

This study has tested the presence of β-convergence at the aggregate level as well as at the disaggregated level. To test the existence of β-convergence at the aggregate level, EF has been used as EPI, whereas for disaggregate analysis, footprint data of each of the six components of EF has been used to measure EP of the countries in relevant dimensions.

3.5.3.2 Explanatory Variables

The following explanatory variables have been used as the determinants of EP in the sample countries.

i. Physical Capital (PC_{it})

This variable is directly taken from Green Solow Model, as discussed in section 3.1. GSM assumes environmental degradation to be the byproduct of economic output, and the standard neo-classical model considers physical capital to be one of the primary determinants of economic output and its growth (Solow, 1956). Hence, this will be a primary determinant of the EP of the countries. Since physical capital has positive impacts on economic output, it would also have a positive impact on environmental degradation. Brook and Taylor (2010) and Evans and Kim (2015) confirm these results in their studies. For present study, gross capital formation to GDP ratio at current PPPs has been used as a proxy for physical capital the data for which have been taken from Penn World Table (PWT) 9.1.

ii. Break Even Investment (BEI_{it})

In standard neo-classical growth model of Solow (1956), break even investment is calculated by summing up population growth rate (n), growth rate of production technology (g) and depreciation rate (δ). For empirical analysis this study assumes $(g + \delta)$ eqalling 5% following Mankiw et al. (1992). Like physical capital, the population growth rate is also considered one of the primary determinants of output and economic growth in the neoclassical economic growth model. That is why it is also considered the primary determinant of environmental performance in GSM, which takes environmental degradation as the byproduct of economic activity.

Solow's model predicts the negative effects of population growth rate on per capita output, implying that it would also reduce per capita environmental degradation. Using this variable is popular in literature. Evans and Kim (2015) and Wang and Zhang (2013), among others, have utilized this variable in environmental convergence analysis. These studies confirm a negative relationship between population growth rate and environmental degradation per capita. Brook and Taylor (2010) have found either a negative or insignificant effect of population growth rate on environmental degradation per capita. Data for population growth rate is taken from Word Devlopment Indicators (WDI).

iii. Human Capital (HC_{it})

In our theoretical framework, the Green Solow Model, human capital can affect environmental degradation in two ways. On the one hand, increased human capital is expected to affect output per capita positively. This will also positively impact environmental degradation, which is treated as the byproduct of economic activity. On the other hand, an increase in human capital is expected to improve abatement technology as well. Which will then affect environmental degradation negatively. Hence, the impact of human capital on environmental degradation is ambiguous, and it depends upon which effect is stronger. Present study uses data of human capital index provided by Penn World Table (PWT) 9.1 which is based on years of schooling and return on education.

iv. Trade Openness (TO_{it})

Like human capital, trade openness will also affect environmental degradation in two ways. On the one hand increase in trade and openness is expected to affect economic activity positively, and hence it is expected to affect environmental degradation positively. On the other hand, due to greater trade openness, multinationals may introduce newer and cleaner technologies to developing countries, which will affect environmental degradation negatively. Hence, the net effect of trade openness on environmental degradation is ambiguous. It would depend on which of the two effects is stronger. Present study uses total trade volume (imports plus exports) to GDP ratio as a measure of trade openness. The data for which is taken from word development indicators (WDI).

v. Urbanization (UP_{it})

Theoretically, urbanization too can affect the environment in either way. If urbanization is planned and it provides access to energy-efficient production technology to producers and energy-efficient durables to consumers, then it may improve the environment; otherwise, it would degrade the environment (Shahbaz *et al.*, 2014). However, the empirical literature has mostly found that urbanization degrades the environment (Adebayo *et al.*, 2021; Azam and Khan, 2015). In present study, percentage of population residing in urban areas is used as a measure of urbanization. The data for which is taken from WDI.

3.5.4 Decomposing of Total Effect into Direct and Indirect Effect (Spillover Effect)

This study has decomposed the total effect of the explanatory variables on EF into direct and spillover effects. The basic idea is that traditional convergence studies rely simply on the interpretation of the slope coefficient, β, which is not valid in the case of SDM. This may be due to the reason that the growth rate of EF of country 'i' in period 't' not only depends on the EF of country 'i' in period '$t-1$' but also on the EF of country 'j' in period 't' which in turn depends on its own EF in period '$t-1$'. Lesage and Pace (2009) argued that in such cases, the interpretation of SDM should be based on the calculation of direct effect and spillover effects (indirect effect). Where direct effect captures the effect on EF by exogenous variables of country 'i' and the spillover effect (indirect effect) captures the effect on EF of country 'i' by exogenous variables of country 'j' (all neighboring countries).

3.6 Testing Spatial Sigma Convergence

Sigma convergence refers to a situation where the distribution spread reduces over time (Hart, 1995; Sala-i-Martin, 2004). Sala-i-Martin (2004) argued that β-convergence is necessary but insufficient for sigma convergence. Sigma convergence is often used in the convergence analysis along with beta convergence to complement the analysis. Empirical indications of Sigma convergence fall into two broad categories. The first category of studies used a single measure of dispersion to study the spread of the CO_2 distribution (Li *et al.*, 2016). Most studies have used standard deviation or coefficient of variation measures to measure dispersion. If the standard deviation or coefficient of variation reduces over time, it signifies the reduction of the spread of the distribution, and hence the presence of sigma convergence is concluded. The problem with this approach is based on the crucial assumptions of normality and linearity of data. Hence, the results of such studies would not be reliable if data do not fulfill these assumptions.

The second category of the studies that analyzed the sigma convergence is the use of the dynamic distribution approach developed by Quah (1995a, 1995b, 1996, 1997, 2000). This approach emphasizes intra distributional dynamics of the data. In this approach, the evolution of full cross-country distribution is analyzed. Hence, convergence is thought to be the collapsing distributions to a point limit over time. The use of non-parametric methods allows the data to be non-normal and/or non-linear.

Kernel density estimates are the most widely used non-parametric method to analyze the intra-distributional characteristics of the data. These estimates do not assume the fixed structure of the data and are based on all data points. A usual form of Kernal density estimator is:

$$f(x)=\frac{1}{hn}\sum_{i=1}^{n} k\left[\frac{x_i-x}{h}\right] \tag{3.36}$$

Where f(x) is the density estimator, $'x'$ is the variable whose density is to be estimated, $'n'$ is the number of observations, and finally $'h'$ is bandwidth, and $k(.)$ is the smooth and symmetric kernel function. The choice of $'h'$, the bandwidth, is very important in kernel density estimation. It is because this determines the degree of smoothness produced. The higher the value the more smoothness produced. The literature proposes various methods for the optimal choice of $'h'$. For example, the use of the Gaussian kernel is based on minimizing the mean integrated square error (MISE) in the derivation of $'h'$ (Silverman, 1978, 1986).

Density plots are very important in the analysis of sigma convergence, but the limitation with the use of density plots is that these only tell the evolution of the shape of a distribution. They do not tell the intra-distribution dynamics. Hence, the two very different data sets, one having persistence and the other having mobility, may have the same shape of density plots. These two data sets, though, have very different implications for policy. The former would not be very sensitive toward the policy options, but the latter would be.

This limitation of kernel density estimation can be removed by estimating stochastic kernel density estimates. In this process, a transition function is obtained using kernel density estimates. Thus allowing us to estimate a conditional density function. The greatest benefit of using the stochastic density function is that it is the only way to study the intra-distribution dynamics by utilizing information on all the data points.

The other two concepts of convergence aren't able to do this. Beta convergence studies the distribution behavior only compared to the initial value without considering the last. While sigma convergence bases its conclusion using all data points but it does so only in terms of standard deviation (Weber, 2009). The stochastic kernel density estimation does both tasks. It shows how the external shape of the distribution changes, as well as it also shows how the intra-distribution dynamics are changing.

Let two random variables $'X'$ and $'Y'$ describe the relative EP (relative to group mean) at period 't' and '$t + s$' for a group of $'N'$ economies. Let denote the distributions of $'X'$ and $'Y'$ with $F(X)$ and $F(Y)$ and assume these distributions admit density functions $f(X)$ and $f(Y)$.

If the dynamic of $F(\cdot)$ or equivalently $f(\cdot)$ can be modeled as a first-order process, then the density at a time '$t + s$' will be:

$$f(Y) = \int_{-\infty}^{\infty} f(Y|X) f(X) dX \tag{3.37}$$

In 3.38 $f(Y|X)$ maps the density at time 't' into the time '$t + s$'. Its estimations not only provide the information regarding the external shape of the distribution but it will also provide information regarding the transition of the economies from one part of a distribution to the other, which occurs from time 't' to '$t + s$'. Then convergence analysis can be made by utilizing the 3D plot of stochastic kernel estimates or from the contour plot.

The stochastic kernel of the equation of 3.37 is the conditional density function. Its non-parametric estimate can be obtained by:

$$f(Y|X) = \frac{f(X,Y)}{f(X)} \tag{3.38}$$

Where $f(X,Y)$ is the joint probability density function and $f(X)$ is the marginal density function. The kernel density estimator is the most common way to get such an estimate. If we denote the explanatory variable by 'X' and the dependent variable by 'Y' then we can write:

$$Y = m(X) + u \tag{3.39}$$

One of the most popular techniques used to estimate $m(X)$ is the Naddarya-Watson estimator:

$$m\hat{}\,(x) = \frac{\sum_{j=1}^{n} k\left(\frac{x-X_j}{h}\right)Y_j}{\sum_{j=1}^{n} k\left(\frac{x-X_j}{h}\right)} \tag{3.40}$$

Whereas usual 'h' is the parameter that determines the degree of smoothness. The problem with the Naddarya-Watson estimator is that it gives biased estimates on the boundary of 'X' space and the interior. It is known as the mean bias of conditional density estimators. To lower this mean bias, other smoother with better bias properties have also been suggested.

One such smoother is:

$$\hat{m}\,(x) = \frac{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)Y_j}{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)} + (x - X_w)\frac{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)(X_j-X_w)Y_j}{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)(X_j-X_w)^2} \tag{3.41}$$

Where;

$$X_w = \frac{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)X_j}{\sum_{j=1}^{n} K\left(\frac{x-X_j}{h}\right)} \tag{3.42}$$

The asymptotic properties employed to estimate $m\hat{}\,(x)$ are based on the assumption that error terms of 3.39 have zero means and uncorrelated variables. This assumption may be reasonable in an ordinary case. But when data is spatially dependent, as is assumed in our case, this assumption obviously will get violated.

To tackle this problem, Gerolimetto and Magrini (2010) devised a procedure for nonparametric regression when data has spatial dependence. It does not require any prior parametric assumptions. This study will follow that procedure. It consists of the following steps:

i. At first, a pilot fit is made. For this, a local polynomial smoother is used to estimate $m\ (x)$. Here, the bandwidth would be a nearest neighbor smoothing parameter. The degree of the polynomial is usually kept to 1. This gives: $\hat{u} = y - \hat{m}(x)$

ii. By using *a* spline correlogram $\hat{V}$ is obtained. This is the spatial covariance matrix of $\hat{u}$.

iii. A modified regression, $z = \hat{m}(x) + L^{-1}\hat{u}$, is run. Where 'L' is obtained by using the Cholevsky decomposition of $\hat{V}$. The residual autocorrelation criterion developed by Ellner and Seifu (2002) is used to choose the bandwidth parameter for obtaining the non-parametric estimate of $\hat{m}$ in this second fit.

3.7 Testing Spatial Club Convergence

This convergence phenomenon states that only those economies will converge to similar balance growth paths with similar structural characteristics (e.g., government policies, preference, technology, etc.) as well as similar initial conditions (Galor, 1996; Azariadis and Drazen, 1990). Thus, the economies that differ in their initial conditions will converge to different steady states despite having similar structural characteristics. Hence, economies will converge to each other in groups which are called 'clubs'. The mainstream literature has focused on the convergence of economies to form clubs with similar initial values of the variables like GDP per capita and human capital (Durlauf and Johnson, 1995). Applying this concept of club convergence of economic growth, many studies on EP have applied similar techniques. Studies have generally applied two approaches to identify countries' clubs according to their EP.

First, studies identified clubs according to a *priori* criteria (Pan et al., 2014). Second, some studies have used techniques to identify the clubs endogenously (Wang et al., 2014). One of the most popular ways to identify the clubs endogenously is using Phillips and Sul (2007) methodology of club convergence (Panopoulou and

Pantelidis, 2009; Payne and Apergis, 2020; Ulucak et al., 2020). One of the chief advantages of this methodology is that it is based on a non-linear time-varying factor model, which gives robust results in individual heterogeneities (Burnett, 2016).

Previous studies on convergence in EP, which have applied Phillips and Sul methodology, have ignored space's role in forming clubs. There are many reasons why space matters in the club formation of EP. Firstly, the state of technology is closely linked with EP as it determines the production methods used in the countries. Hence, it has a key role to play in convergence. But technological diffusion strongly depends on spatial factors like travel time and distance between countries. So, space is crucial in forming clubs of countries with similar EP (Coe and Helpman, 1995). Secondly, the state of institutions and the initial level of technology also tend to have spatial dependence (Easterly & Levine, 1998; Temple, 1999).

Thirdly, there are other types of spillover effects among neighbors, e.g., socioeconomic and political factors in neighboring cross-sectional units (Lall and Yilmaz, 2001; Murdoch and Sandler, 2002).

3.7.1 Spatial Filtration

Given that EP of the countries is spatially dependent. This study will perform spatial filtration using the Postiglione *et al.* (2009) technique. According to this approach, spatial filtration is carried out in two steps.

Step 01: In the first step, the nature of spatial dependence is examined, whether the data has spatial lag or spatial error. For this purpose, LM tests in simple and robust forms can be used.

Step 02: In the second step using equations 3.43 and 3.44, spatial filtration is carried out using Spatial Lag or Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) relationship depending upon the findings of step 1.

$$g(\Delta lnY_{it}) = \Delta lnY_{it} - \rho W \Delta lnY_{it} \tag{3.43}$$

In equation 3.43, $g(\Delta lnY_{it})$ is a spatially filtered variable calculated by using the SAR model relationship. $W, \rho\ and\ \varepsilon_{it}$ are the same as described in section 3.6.

This spatial filtration can also be done using the SEM model relationship specified in 3.44.

$$h(\Delta lnY_{it}) = \Delta lnY_{it} - \lambda W\varepsilon_{it} \tag{3.44}$$

Similarly, $g(\Delta lnY_{it})$ is a spatially filtered variable that is calculated with an SEM model relationship. W, λ and ε_{it} are the same as described in section 3.6.

3.7.2 Phillips and Sul (2007) Club Convergence Methodology

Usually, in panel data, Y_{it} is decomposed in the following way:

$$Y_{it} = g_{it} + \alpha_{it}; \qquad i = 1,2,\dots,N \quad and \quad t = 1,2,\dots,T \tag{3.45}$$

Where; $'g_{it}'$ is a permanent or systematic component and $'\alpha_{it}'$ is a transitory or idiosyncratic component. Phillips and Sul (2007) reformulated equation (3.45) to separate the common component from the idiosyncratic component as follows:

$$Y_{it} = \left(\frac{g_{it}+\alpha_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \qquad for\ all\ i\ and\ t \tag{3.46}$$

In equation (3.46) δ_{it} is an idiosyncratic component while μ_t is a common component. Both of these components are time-varying. The idiosyncratic component, δ_{it}, measures the distance of the individual cross section Y_{it} from common component $'\mu_t'$. This dynamic factor design separates the common component from the idiosyncratic one, δ_{it}, is the transition path of the individual cross section to a common steady state determined by μ_t. This common growth component $'\mu_t'$ may follow a stationary trend process or a non-stationary stochastic process with drift. There is no need to have a specific assumption about the behavior of $'\mu_t'$.

The estimation of $'\delta_{it}'$ is the key to testing the convergence of different economies. Phillips and Sul (2007) state that the estimation of $'\delta_{it}'$ is not possible without imposing additional assumptions and structural restrictions. To achieve this end, the following relative transition component is proposed by them:

$$h_{it} = \frac{Y_{it}}{\frac{1}{N}\sum_{i=1}^{N} Y_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \qquad (3.47)$$

Equation (3.47) computes what is called 'relative transition path'. This can be computed from the data directly. It enables the computation of the trajectory for each cross-section $'i'$ relative to the average of the panel. In this way, it is possible to abolish $'\mu'$, the common steady-state trend. So, this relative transition path describes both the departure of individual cross-sections $'i'$ from the common growth path $'\mu'$ as well as relative individual behavior.

The transition path of each economy should have a common limit in case of convergence. The coefficient $'h_{it}'$ should converge towards unity for all $i = 1,2,\ldots,N$ as $t \to \infty$. The cross-section variance should approach zero:

$$H_t = \frac{\sum_{i=1}^{N}(h_{it}-1)^2}{N} \to 0 \quad as\, t \to \infty \qquad (3.48)$$

Equation (3.48) shows that variance is computed as a quadratic distance from the common limit for the panel. For the formal statistical test, Phillips and Sul (2007) make the following semi-parametric specification for $'\delta_{it}'$:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^a}, \qquad t \geq 1,\ \sigma_i > 0\ for\ all\ i \qquad (3.49)$$

Where $'\delta_{it}'$ is time-invariant and ξ_{it} is a random variable that is assumed to be independently and identically distributed $[N \sim (0,1)]$. This is weakly dependent on $'t'$ while $L(t)$ is a slowly increasing function with $L(t) \to \infty$ when $t \to \infty$. The convergence rate is measured by $'a'$ which measures the decay rate.

The Null and alternative hypotheses can be written as follows:

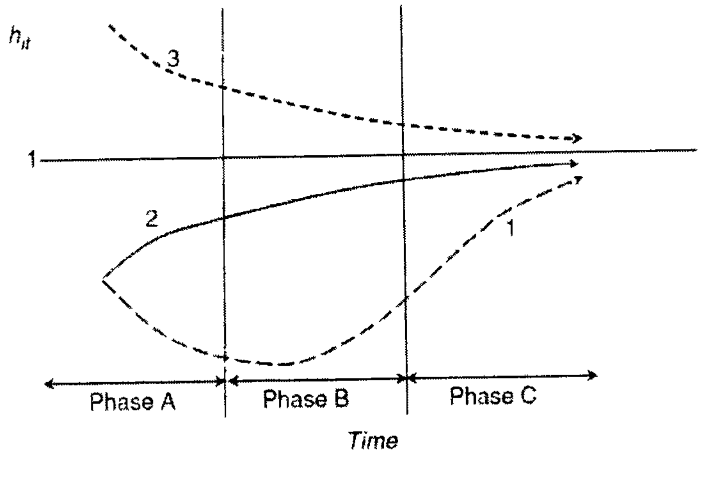
$$H_{0:}\delta_i = \delta \qquad a \geq 0$$
$$H_{1:}\delta_i \neq \delta \;\; for\ all\ 'i'\ or \qquad a < 0$$

In this case, there are different transitional paths under null hypothesis possibilities. This includes the possibility of temporary divergence. They may converge in the fashion shown in figure 3.2.

Formally, Phillips and Sul (2007) suggested the following regression model test the convergence hypothesis:

$$log\frac{H_1}{H_t} = -2\log(\log t) = \alpha + \beta \log t + u_t\,,\ for\ t = [rT], [rT]+1, \dots, T \qquad (3.50)$$

Figure 3.2: Possible Transition Paths and Transition Phases



Source: Phillips and Sul (2007)

Where $H_t = \frac{\sum_{i=1}^{N}(h_{it}-1)^2}{N}$, $\frac{H_1}{H_t}$ is the ratio of cross sectional variance, β is the convergence speed of δ_{it}, $-2\log(log\ t)$ is the penalization function which improves the performance of the test under the alternatives, r assumes the value between 0 and 1.

This discards the first block of observation from the estimation, $[rT]$ is the integer part of rT. Phillips and Sul (2007) suggest using $r \in [0.2,0.3]$ for a small sample T< 50.

Hence, null and alternative hypotheses are set as follows:

$$H_0: \delta_i = \delta \leftrightarrow a > 0$$

$$H_1: \delta_i \neq \delta \leftrightarrow a < 0$$

This procedure is generally called a log t-test. This implies a one-sided test with the limit distribution being:

$$t_b = \frac{\hat{b} - b}{s_b} \sim N(0,1)$$

The null hypothesis would be rejected if t_b < -1.65. The rejection of the null hypothesis would imply an absence of convergence in the whole sample. If so, Phillips and Sul (2007) suggest that club convergence should be tested by repeating the testing procedure according to the four steps clustering mechanism described in the next subsection.

3.7.2.1 Club Clustering

Upon the rejection of convergence in the overall sample following four steps procedure is carried out to test the existence of club convergence:

Step 1: Cross-Section Sorting

First, cross-sections are sorted in descending order according to the last observation in the panel.

Step 2: Core Group Formation

This step consists of two sub-steps. In the first sub-step, 'k' is found such that calculated 't' for $\log(t)$ regression $t_k > -1.65$ with individuals in subgroup $\{k, k+1\}$. If no such 'k' is found, the algorithm is stopped, and the conclusion is drawn that there are no convergence subgroups in the data. On the other hand, if the algorithm finds 'k' in the first sub-step, then we move to the second sub-step. Here, start with 'k' identified in the first sub-step and perform $\log(t)$ regression again for the individuals $\{k, k+1, \ldots, k+j\}$ where $j \in \{1, 2, \ldots, N-k\}$. For choosing a value of 'j' such a value is searched for that test statistic for $\{k, k+1, ..., k+j\}$ individuals' subgroup is maximum. These individuals $\{k, k+1, ..., k+j\}$ are known as the core group.

Step 03: Sieve Individuals for Club Membership

After the formation of the core group, add one more individual to it and run $\log(t)$ regression and find the value of 't'. If this calculated value of 't' is greater than a critical value of 't' which is equal to -1.65, then keep adding the individuals and finding the value of 't' as long as it is greater than -1.65. These individuals of the core group, plus newly added, form the first convergence club.

Step 04: Recursion and Stopping Rule

Select a group of individuals from the remaining individuals of step 3 and run the $\log(t)$ regression. If the value of 't' is found to be greater than -1.65, then this group forms another convergence club. If not, then repeat steps 1 to 3 for this sub-group. The remaining panel units diverge if no further club can be found.

3.7.2.2 The Merging Algorithm

The total number of clubs found using club clustering algorithm mentioned in section 3.7.2.1 strongly depends on the chosen critical value c^*. Where c^* shows the level of conservativeness. Higher the value higher would be the level of selectiveness and lower the probability of including individuals in the wrong clubs, but at the same time, in case of a higher value of c^* there is an increased probability that we may find more clubs than they exist. To avoid this, Phillips and Sul (2007) recommended the use of a club merging algorithm, which attempts to merge the adjacent clubs in the following three steps:

Step 01: First, we have to add the members of the first two clubs and run the $\log(t)$ regression in order to obtain the value of 't'. If the estimated value of 't' is greater than -1.65, these two clubs can be added to make one broader club.

Step 02: This should be repeated by adding one more club to these newly formed clubs until the value of 't' is greater than -1.65.

Step 03: When the convergence hypothesis is rejected, this implies that the previously found clubs are correct and start merging from the club where the convergence hypothesis did not hold.

3.8 Sample and Sample Selection Criteria

The sample contains 88 developed and developing countries[2] for which data has been taken for the period 1978 to 2017. The sample size results from the effort to maximize the time and the availability of data on the study variables.

3.9 Data and Data Sources

Data on variables under observation have been taken from three different sources. The data for EF, our dependent variable, has been taken from Global Footprint Network[3]. Data for human capital and physical capital have been taken from Penn World Table (PWT) 9.1[4] and data for population growth, urbanization, and trade openness has been taken from World Development Indicators (WDI)[5].

[2] See appendix A for country list.
[3] Available at: https://www.footprintnetwork.org/licenses/public-data-package-free/
[4] Available at: https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt9.1?lang=en
[5] Available at: https://databank.worldbank.org/source/world-development-indicators

CHAPTER 4

RESULTS ON β-CONVERGENCE IN ENVIRONMENTAL PERFORMANCE

This Chapter presents estimated results on the first three objectives and their interpretation. These objectives are the determination of the spatial dependence of EP, examining the role of different factors in spatial β-convergence, and decomposition of the total effect of these factors into direct and spillover effects. The first section presents the results and its interpretation of these objectives for overall EP, while the second section repeats the analysis for component-wise analysis.

4.1 β-Convergence in Overall Environmental Performance

This study uses aggregate EF to measure overall EP. This section presents results on convergence in the overall EP of the countries. In this context, this section first presents summary statistics of the variables used then it explores the spatial dependence of EP and finally it presents regression results.

4.1.1 Summary Statistics

Table 4.1 presents summary statistics for the study variables. It is evident from the statistics that there is great variation in the data of different indicators of the countries. This sufficiently diverse data set makes it a good case to study convergence in EP as well as to explore the role of different factors in determining the convergence behaviour.

4.1.2 Spatial Dependence

To explore the spatial dependence of the countries with regard to their EP, Moran's I stat have been used. Table 4.2 shows the estimated results of Moran's I test.

Table 4.1: Summary Statistics

Variable	Definition	N	Mean	SD	Min	Max
		Dependent Variable				
ln_EF	Natural log of ecological footprint	704	0.91	0.70	-0.42	2.76
		Explanatory Variables				
ln_PC	Natural log of physical capital	704	-1.65	0.57	-6.36	-0.58
ln_BEI	Natural log of break-even investment $(n + g + \delta)$	704	1.88	0.17	1.32	2.32
ln_HC	Natural log of human capital	704	0.76	0.33	0.02	1.32
ln_UP	Natural log of urban population as a % of total	704	3.90	0.57	1.47	4.58
ln_TO	Natural log of trade openness (trade volume as a % of GDP)	704	4.1	0.54	2.41	5.96

Source: Authors' calculations from the data

Moran's I have been calculated over the span of 5 years over the study period. It is highly significant and quite high in the said years. It authenticates our conjecture that the EP of the countries is spatially dependent. Although, it fluctuated over the study period, it always remained quite high.

Table 4.2: Moran's I for Ecological Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.667***	0.0000	2002	0.623***	0.0000
1987	0.659***	0.0000	2007	0.603***	0.0000
1992	0.652***	0.0000	2012	0.599***	0.0000
1997	0.617***	0.0000	2017	0.59***	0.0000

*Note: *** indicates a 1% level of significance*

4.1.3 Regression Results

Our analysis of spatial dependence utilizing Moran's I proves that the study of the EP calls for the utilization of spatial econometric methods. Ignoring this in carrying out any regression analysis would cause serious problems in estimations. Hence, following Lesage and Pace (2009), we started our estimation with Spatial Durbin Model (SDM) and then tested whether this SDM could be reduced to Spatial Lag Model (SAR) or Spatial Error Model (SEM). For SDM, we have used all possible specifications: SDM with spatial fixed effects, SDM with time fixed effects, and SDM with both time and spatial fixed effects. We then used minimum AIC and SIC criteria to select among these specifications. This model selection procedure is given in Table 4.3.

Table 4.3: Model Selection for Ecological Footprint

Model	AIC	SIC
SDM with spatial fixed effects	-1386.768	-1324.842
SDM with time fixed effects	-1247.310	-1185.385
SDM with both spatial and time fixed effects	-1422.499	-1360.574
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 13.60 (0.018)**	Chi^2= 11.64 (0.040)**
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=56.30 (0.000)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

Table 4.3 shows that minimum AIC and SIC are found for SDM with both spatial and time fixed effects. For this model, our Wald hypothesis testing has led us to conclude that SDM cannot be reduced to the SAR or SEM models. Furthermore, the Hausman test has been performed to choose between random and fixed effects. The results of the Hausman test direct for fixed effects instead of random effects. Hence, we are left with SDM with both spatial and time fixed effects. Regression results for this model are presented in Table 4.4.

Table 4.4 presents our chosen spatial model's results for studying spatial β-convergence in EP. We have found evidence of conditional convergence in the EP of the countries as the coefficient of 'ln_EF_l' (lag of EF) is negative and significant. The estimated result shows that countries with a higher initial per capita ED have lower growth rates in ED. Our conditional convergence findings align with the findings of Guo and Luo (2021). The historical development may justify the results from 1978 to 2017. This is the period when the environmental movement began and gained momentum. It began in the 1960s, and till the late 1970s, different economies, particularly developed ones, were sensitized enough to consciously include environmental considerations in their policies (Dreiling & Wolf, 2001). Moreover, developed countries have committed themselves to reduce ED in international agreements like the Kyoto protocol and the Paris agreement.

Table 4.4: Regression Results of SDM for Ecological Footprint

Variables	Coefficient	SE	Variables	Coefficient	SE
ln_EF_l	-0.244***	0.027	W*ln_ef_l	0.061	0.044
ln_PC	0.063***	0.010	W*ln_pc	0.011	0.020
ln_BEI	-0.002	0.052	W*ln_bei	-0.147*	0.079
ln_HC	0.225***	0.081	W*ln_hc	-0.327**	0.131
ln_UP	0.049	0.040	W*ln_up	-0.054	0.048
ln_TO	0.001	0.018	W*ln_to	0.047	0.030
			ρ	0.242***	0.049

*Dependent Variable: Δln_EF=Growth Rate of Ecological Footprint. ln_EF_l= Logged Value of Ecological Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

On the other hand, this is when developing countries have witnessed a huge increase in their economic growth. Among other notable cases are Brazil, Russia, India, and South Africa (de Medeiros & Trebat, 2017). This increase in income of developing countries has created a huge middle class whose consumption increased many folds and thereby increasing the ecological footprint of these countries. These developments in developed and developing countries caused convergence in EP. The effect of both physical and human capital is positive for the aggregate level of EF. The effect of other variables is not found to be significant.

The coefficient of spatial lag (ρ) is found to be positive and highly significant statistically. Similar results have been found by Xu et al. (2020) and Behboudi et al. (2017). Our findings align with Moran's I findings that the neighboring countries' EP positively affects the countries' EP. This finding is completely fathomable because the period of study is the era when communication technology revolutionized the world. Communication technology experienced unprecedented growth in the 1990s and 2000s. This immense growth of communication technology has made the world a global village. Now, any policy action taken by one country in one part of the world gets immediately visible to the rest of the world (Mikail and Aytekin 2016). If one country takes a bad policy action, it gets backlash from the rest of the world. Similarly, if there is any environmental friendly development, it catches the attention of consumers and producers globally. This better communication causes the spatial spillover of policies and actions among economies to increase.

Table 4.5: Effects Decomposition for Ecological Footprint

Variables	Direct Effects		Spillover Effects		Total Effects	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
ln_EF_l	-0.243***	0.028	0.003	0.053	-0.240***	0.058
ln_PC	0.064***	0.009	0.032	0.025	0.096**	0.028
ln_BEI	-0.006	0.049	-0.177*	0.095	-0.183*	0.107
ln_HC	0.207**	0.081	-0.329**	0.158	-0.122	0.177
ln_UP	0.046	0.038	-0.055	0.056	-0.009	0.067
ln_TO	0.005	0.018	0.062	0.040	0.067	0.048

*Dependent Variable: Δln_EF=Growth Rate of Ecological Footprint. ln_EF_l= Logged Value of Ecological Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

In the case of SDM, there is a feedback effect, so the coefficients don't provide marginal effects on the dependent variable (LeSage & Pace, 2009). Because of this, the direct interpretation of coefficients is less meaningful. It is, therefore, customary to estimate total effects and break them into direct and spillover effects. This has been done, and the results are presented in Table 4.5.

The direct effects presented in Table 4.5 show the effect of explanatory variables of the local country on its EP. At the same time, spillover effects capture the effect of change in the neighboring countries' explanatory variables on the local country's EP. In contrast, the total effect shows how an overall change in the dependent variable would occur if the explanatory variable changed in all the countries. The direct effect of the temporal lag of EF is found to be -0.243, which is negative and significant. The spillover effect is insignificant, whereas the total effect remains negative and significant. This negative sign and significant coefficient of temporal lag of the dependent variable implies convergence in EP. The direct effect of physical capital is found to be 0.064, which is positive and significant. This was expected because, as per our theoretical model, physical capital positively impacts economic output, so it would also positively impact ED, which is assumed to be the byproduct of economic activity. Brook and Taylor (2010) and Evans and Kim (2015) came up with the same findings while analyzing the impact of physical capital on ED.

The direct effect of population growth turned out to be insignificant. Other studies like Rios and Rios and Gianmoena (2018) have the same findings. The population growth rate's indirect effect is negative and significant. The estimated results may be justified in the perspective of the neo-classical growth model, according to which an increase in "BEI" will adversely impact economic output and positively affect EP (a negative coefficient of ED). The spillover of this positive impact will also benefit the environment of the local country. The direct effect of human capital is found to be highly significant, and it is equal to 0.207. Human capital can affect ED in two ways. On the one hand, it can degrade the environment as it will positively affect output and hence its byproduct ED. On the other hand, it can improve the environment by positively impacting the development of abatement technologies. Since we have found a positive sign of human capital for ED, this shows that, in our case, human capital has benefitted the development of production technology more than abatement technology.

The output growth of developing countries during the last decades bears witness to this. As indicated by Nazeer et al., (2016) and Adedoyin et al. (2020a, b). increasing output growth has caused increased ED in developing countries. The spillover effect of human capital is found to be negative and significant. This shows that an improvement in neighbors' human capital benefits abatement technologies more than benefits production technology development. Due to spatial spillover, this beneficial effect reaches to domestic country and lowers its EF too. Sun et al. (2021) has also found that the spillover effect of human capital from neighboring countries is beneficial for the EP of the country. Other variables are not found to affect EF significantly.

4.1.4 Robustness Analysis

In order to check the robustness of our results, we have used two other distance-based weighting matrices to check whether or not our results are sensitive to the choice of neighborhood relationship, which we have imposed by adopting a binary contiguity weight matrix.

In this regard, we have used two alternative weight matrices. We first used an inverse distance weight matrix with a cut-off distance of 3000 kilometers. Then we used "K-Nearest Neighbors" method to construct a weight matrix by setting KNN=5. Using these two matrices, we first calculated Global Moran's I and presented the results in Table 4.6. After that, these newly created weight matrices are used to estimate regression, and results are presented in Table 4.7.

It is evident from the results presented in Table 4.6 that Moran's I results are almost the same when we have used inverse distance weight matrix or KNN weight matrix as we have found previously using contiguity weight matrix. Hence, it validates our results found earlier and proves that our results regarding the spatial dependence of EP are robust to the weight matrix choice.

Table 4.6: Robustness Analysis of Moran's I for Ecological Footprint

Inverse Distance Weight Matrix (d=3000)					
Year	**Moran's I**	**P-Value**	**Year**	**Moran's I**	**P-Value**
1982	0.657***	0.0000	2002	0.652***	0.0000
1987	0.668***	0.0000	2007	0.663***	0.0000
1992	0.659***	0.0000	2012	0.672***	0.0000
1997	0.633***	0.0000	2017	0.666***	0.0000
K-Nearest Neighbors Weight Matrix (KNN=5)					
Year	**Moran's I**	**P-Value**	**Year**	**Moran's I**	**P-Value**
1982	0.621***	0.0000	2002	0.591***	0.0000
1987	0.615***	0.0000	2007	0.595***	0.0000
1992	0.609***	0.0000	2012	0.609***	0.0000
1997	0.573***	0.0000	2017	0.595***	0.0000

Note: *** *indicates* a 1% level of significance.

Table 4.7, which presents the robustness of regression results, shows that our results of SDM remain the same even after the change of the weight matrices. Hence, we can confidently assert that the results of SDM based on the binary contiguity weight matrix presented earlier are not sensitive to the choice of neighborhood structure.

Table 4.7: Robustness Analysis of Regression Results for Ecological Footprint

Variables	Inverse Distance Weight Matrix (d=3000)		KNN Weight Matrix (KNN=5)	
	Coefficient	**SE**	**Coefficient**	**SE**
ln_EF_l	-0.254***	0.028	-0.234***	0.027
ln_PC	0.063***	0.010	0.061***	0.010
ln_BEI	-0.009	0.051	-0.014	0.052
ln_HC	0.199**	0.079	0.171**	0.079
ln_UP	0.057	0.038	0.037	0.038
ln_TO	0.002	0.018	0.000	0.018
W*ln_EF_l	0.130***	0.049	0.097**	0.046
W*ln_PC	0.044	0.031	0.043*	0.025
W*ln_BEI	-0.133	0.103	0.002	0.096
W*ln_HC	-0.355*	0.183	-0.082	0.182
W*ln_UP	-0.098	0.073	-0.059	0.069
W*ln_TO	0.018	0.037	0.048	0.037
ρ	0.281***	0.057	0.255***	0.057

*Dependent Variable: Δln_EF=Growth Rate of Ecological Footprint. ln_EF_l= Logged Value of Ecological Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

4.2 β-Convergence at Disaggregated Level

In order to make the convergence analysis at a disaggregated level, convergence in different components of EF is tested. This component-wise analysis will make us more certain regarding the exact dimension where intervention is needed to improve the EP. Based on this, a tailored set of policies may be opted to target specific dimensions of the EF to enhance the EP.

4.2.1 Convergence in Crop Land Footprint

The first dimension in which we have tested the presence of β-convergence is cropland footprint. The cropland footprint measures the land needed to grow all crops for human and livestock consumption. Results obtained from the convergence analysis are presented as under.

4.2.1.1 Spatial Dependence

In order to check whether the EP of the countries in cropland footprint is spatially dependent or not, Moran's I have been calculated. The results are presented in Table 4.8. It can be observed that spatial dependence in crop footprints of the countries is quite high throughout the study period. Hence, the spatial econometric methodology should be adopted to study convergence.

Table 4.8: Moran's I for Crop Land Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.663***	0.0000	2002	0.647***	0.0000
1987	0.727***	0.0000	2007	0.674***	0.0000
1992	0.708***	0.0000	2012	0.628***	0.0000
1997	0.680***	0.0000	2017	0.591***	0.0000

Note: *** *indicates* a 1% level of significance.

4.2.1.2 Regression Results

Since we have found that crop footprint has significant spatial dependence, we have used spatial econometric models to test the presence of β-convergence in cropland footprints. For model selection, we have followed the same procedure as adopted in the case of overall EF. The results of the model selection are presented in Table 4.9.

Results presented in Table 4.9 indicates that SDM with both spatial and time fixed effects has minimum AIC and SIC. Hence, we started with this model, and then we tested whether this model could be reduced to SAR or SEM model through the Wald test. We found that the null hypotheses of spatial lag or spatial error are rejected at 10% significance; therefore, SDM cannot be reduced to either SAR or SEM.

Table 4.9: Model Selection for Crop Land Footprint

Model	AIC	SIC
SDM with spatial fixed effects	-933.3246	-875.4267
SDM with time fixed effects	-825.6905	-767.7926
SDM with both spatial and time fixed effects	-948.4084	-890.5105
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 9.93 (0.0773)*	Chi^2= 9.84 (0.0798)*
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=40.69 (0.0001)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

In the next step, we apply the Hausman test in order to test whether fixed or random effects are more appropriate. The Hausman directs for fixed effects. Hence, we are left with SDM with spatial and time fixed effects as our final model. This model is used for regression, and the results are given in Table 4.10.

Results presented in Table 4.10 confirm the existence of conditional β-convergence in the cropland footprints of the countries. This is confirmed by the negative sign of the coefficient of variable 'ln_CRP_l' which is significant at 1%. This shows that environmental pressure caused by the human need for food would eventually become the same across developed and developing countries. Physical capital has a positive effect on the cropland footprint. This finding is similar to the role of physical capital in determining aggregate EF, where its coefficient was also positive and significant. Human capital is found to affect crop footprints negatively. Hence, it is beneficial for environmental improvement in this dimension. Other variables are not found to affect cropland footprints significantly.

The direct interpretation of the coefficient of SDM is not meaningful because these coefficients do not give correct marginal effects due feedback effect. Hence, total effects are segregated into direct and spillover effects, and results are presented in Table 4.11.

Table 4.10: Regression Results of SDM for Crop Land Footprint

Variables	Coefficient	SE	Variables	Coefficient	SE
ln_CRP_l	-0.348***	0.038	W*crp_l	0.127**	0.052
ln_PC	0.084***	0.018	W*ln_pc	-0.015	0.033
ln_BEI	-0.058	0.068	W*ln_bei	0.047	0.087
ln_HC	-0.287**	0.113	W*ln_hc	0.470***	0.166
ln_UP	-0.037	0.049	W*ln_up	-0.047	0.062
ln_TO	-0.001	0.024	W*ln_to	0.044	0.035
			ρ	0.031	.051

*Dependent Variable: Δln_CRP=Growth Rate of Crop Land Footprint. ln_CRP_l= Logged Value of Crop Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

Estimated results in Table 4.11 show that the temporal lag of crop footprint affects crop footprint directly and indirectly through its spillover effects. The temporal lag of crop footprint negatively affects crop footprint directly, while it positively affects it indirectly through the spillover effect. It shows that even the previous period cropland footprint of neighboring spatial units significantly affects the current period cropland footprints of the country. This shows the extreme importance of spatial factors in determining EP in this dimension. The total effect of temporal lag remained significantly negative.

Physical capital is found to have only a direct positive effect which is significant at 1%. Its total effect is also positive. This means that physical capital has a detrimental effect on this component of the environment and overall EP as measured by EF. Human capital is found to affect crop footprint both directly and indirectly. It negatively affects crop footprints directly, while the spillover effect is positive. The result indicates that 'technique effect' dominates the 'scale effect' in countries with relatively more human capital.

Hence, increased human capital improves abatement technology more than it benefits production technology. For neighboring countries, the country's capital negatively impacts its crop footprint. Here, it is positively related to crop footprint, which shows the dominance of the scale effect. Another aspect that deserves the comment is that the spillover effect of human capital for crop footprint is close to double than that of the direct effect. This shows the importance of spatial factors for human capital. Other factors are not found to affect cropland footprint significantly.

Table 4.11: Effects Decomposition for Crop Land Footprint

Variables	Direct Effects		Spillover Effects		Total Effects	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
ln_CRP_l	-0.346***	0.039	0.120**	0.052	-0.226***	0.061
ln_PC	0.083***	0.017	-0.014	0.031	0.070*	0.036
ln_BEI	-0.051	0.065	0.053	0.087	0.002	0.103
ln_HC	-0.281**	0.113	0.487***	0.165	0.207	0.185
ln_UP	-0.037	0.046	-0.051	0.061	-0.088	0.068
ln_TO	0.001	0.024	0.048	0.038	0.049	0.048

*Dependent Variable: Δln_CRP= Growth Rate of Crop Land Footprint. ln_CRP_l= Logged Value of Crop Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

4.2.2 Convergence in Grazing Land Footprints

The second dimension in which we have tested the presence of β-convergence is grazing land footprint. Grazing land footprint measures the total land required for grazing livestock reared by humans. Results obtained from the convergence analysis are presented as follows.

4.2.2.1 Spatial Dependence

Table 4.12 presents Moran's I result in cropland footprints of the sample countries. For all data points, Moran's I is significant, indicating that grazing land footprints have spatial dependence. Hence, spatial econometric models are appropriate for investigating β-convergence in grazing land footprints.

4.2.2.2 Regression Results

To choose an appropriate model for our regression, we used the criterion of minimum AIC and SIC, which are presented in Table 4.13. We can see that the SDM model with both spatial and time fixed effects has a minimum value of AIC and SIC. This model is selected and tested to determine whether it can be reduced to SAR or SEM through the Wald test. It was found that it cannot be reduced to either as the null hypotheses of the presence of spatial lag or spatial error are rejected at 10% significance. Finally, regarding the appropriateness of fixed or random effects, the Hausman test results have shown that fixed effects are more appropriate. Hence, our final model for testing the β-convergence in grazing land footprint is SDM with both spatial and time fixed effects.

Table 4.12: Moran's I for Grazing Land Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.624***	0.0000	2002	0.608***	0.0000
1987	0.637***	0.0000	2007	0.615***	0.0000
1992	0.629***	0.0000	2012	0.620***	0.0000
1997	0.625***	0.0000	2017	0.615***	0.0000

*Note: *** indicates a 1% level of significance.*

Regression results for the selected model are presented in Table 4.14. Our results confirm the existence of β-convergence for grazing land footprint. This is evident because the coefficient of 'ln_GRZ_l' enters the model negatively and is statistically significant. This indicates that countries with a higher growth rate of grazing land footprints in the previous period have a lower growth rate of grazing footprint. Thus, this confirms the existence of β-convergence. The population growth rate holds a positive sign that is statistically significant, which shows that demand for grazing land increases with an increase in population. Hence, the population growth rate increases the demand for environmental resources. Other factors are not found to affect grazing land footprints significantly.

Since the coefficients of SDM do not give us marginal effects, we have computed direct effects, spillover effects, and total effects of the factors presented in Table 4.15. Our results show that the temporal lag of grazing land footprint affects grazing land footprint only directly, and there is no spillover effect. This shows that neighbors' grazing land footprint of the previous period does not significantly affect the country's current grazing land footprint. Population growth rate affects grazing land footprint both directly and indirectly. The positive direct effect shows that a country's population growth increases its grazing land footprints.

Table 4.13: Model Selection for Grazing Land Footprint

Model	AIC	SIC
SDM with spatial fixed effects	-371.0414	-313.1435
SDM with time fixed effects	-228.7024	-170.8044
SDM with both spatial and time fixed effects	-384.302	-326.4041
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 10.06 (0.0736)*	Chi^2= 10.04 (0.074)*
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=36.04 (0.0006)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

It implies that animal-based food is prevalent in our sample countries, and with an increase in population growth, demand for animals increases, increasing demand for grazing land and hence increasing grazing land footprints. The spillover effect of the population growth rate is found to be negative. Since direct and indirect effects are almost of the same magnitude but opposite, the total effect of population growth rate is insignificant for grazing land footprint.

Table 4.14: Regression Results of SDM for Grazing Land Footprint

Variables	Coefficient	SE	Variables	Coefficient	SE
ln_GRZ_l	-0.291***	0.035	W*ln_grz_l	-0.051	0.060
ln_PC	0.051	0.033	W*ln_pc	0.047	0.058
ln_BEI	0.245**	0.126	W*ln_bei	-0.308*	0.160
ln_HC	-0.068	0.207	W*ln_hc	-0.811***	0.303
ln_UP	0.028	0.090	W*ln_up	0.025	0.112
ln_TO	-0.005	0.044	W*ln_to	-0.067	0.065
			ρ	-0.002	0.056

*Dependent Variable: Δln_GRZ=Growth Rate of Grazing Land Footprint. ln_GRZ_l= Logged Value of Grazing Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

Human capital holds a negative coefficient (-0.783) which is statistically significant. The coefficient of human capital is found to have only a spillover effect with a coefficient of -0.783. The estimated results show that improving neighbors' human capital benefits the local environment in the grazing land dimension. This implies that improvement in neighbors' human capital causes the development of environmental friendly technology in neighboring countries, and spatial spillover diffuses it to a local country which helps reduce the grazing footprints.

Table 4.15: Effects Decomposition for Grazing Land Footprint

Variables	Direct Effects		Spillover Effects		Total Effects	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
ln_GRZ_l	-0.289***	0.035	-0.050	0.059	-0.339***	0.063
ln_PC	0.049	0.032	0.046	0.056	0.095	0.065
ln_BEI	0.259**	0.121	-0.297**	0.157	-0.038	0.182
ln_HC	-0.063	0.207	-0.783***	0.298	-0.845**	0.326
ln_UP	0.030	0.085	0.021	0.109	0.051	0.117
ln_TO	-0.003	0.044	-0.061	0.069	-0.064	0.086

*Dependent Variable: Δln_GRZ=Growth Rate of Grazing Land Footprint. ln_ GRZ _l= Logged Value of Grazing Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

Another thing to stress is that this spillover effect of human capital is strong enough to make the total effect of human capital significant and beneficial for EP. The coefficients of other variables are insignificant for grazing land footprint.

4.2.3 Convergence in Forest Land Footprint

After testing β-convergence in cropland and grazing land footprints, convergence in forest land footprint is tested. Forest footprint measures the land required to produce the total forest products demanded by humans. Results are presented in the following subsection.

4.2.3.1 Spatial Dependence

Moran's I statistic is calculated to explore the spatial dependence of forest land footprints of the sample countries. Results are presented in Table 4.16. Like the previous two components of EF, forest land footprint also has spatial dependence as the values of Moran's I are highly significant throughout the study period.

Table 4.16: Moran's I for Forest Land Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.281***	0.002	2002	0.234***	0.008
1987	0.281***	0.002	2007	0.224**	0.011
1992	0.250***	0.006	2012	0.277***	0.003
1997	0.231***	0.010	2017	0.311***	0.001

*Note: *** indicates a 1% significance level, and ** represents a 5% significance level.*

4.2.3.2 Regression Results

The results of Moran's I show that spatial factors are the significant determinant of forest land footprints; hence, spatial econometric models need to be used. To select the most suitable spatial econometric model among the options available, we have carried out a model selection exercise, and the results are presented in Table 4.17. It can be seen that SDM with both spatial and time fixed effects have minimum AIC and SIC; hence, this model is selected for testing the presence of β-convergence in forest land footprints. The results of the Wald test show that SDM cannot be reduced to either SAR or SEM as a null hypothesis of the presence of spatial lag or spatial error is rejected at a 5% significance level or better. Further, the results of the Hausman test show that the fixed effect model is more appropriate. So, the final choice for testing the convergence in forest footprint is SDM with spatial and time fixed effects. This model is used for regression analysis, and the results are presented in table 4.18.

Regression results show the tendency of conditional convergence in the forest land footprint of the countries. It is because the coefficient of 'ln_FST_l' is negative and significant at 1%. This implies that EP in the dimension of forest land footprint would be similar among the countries with similar characteristics. For forest land footprint, only physical capital is found to be significant. All other factors have an insignificant effect on the forest land footprint.

To interpret the marginal effects of our model correctly, effects decomposition is carried out, and results are presented in table 4.19. Decomposition analysis shows that the temporal lag of forest footprints has a negative and significant direct effect on them, while the spillover of the effect of it is insignificant. This implies that the previous period's performance of neighbors does not matter for forest land footprint.

Table 4.17: Model Selection for Forest Land Footprint

Model	AIC	SIC
SDM with spatial fixed effects	-457.088	-399.190
SDM with time fixed effects	-324.512	-266.614
SDM with both spatial and time fixed effects	-467.415	-409.517
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 15.50 (0.0084)***	Chi^2= 14.38 (0.0134)**
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=142.09 (0.0000)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

Physical capital's direct effect is found to affect forest land footprints positively. It implies that an increase in physical capital similarly affects forest land footprint as it affects the aggregate EF of the countries. The only other factor which is found to be significant is the population growth rate which has a negative spillover effect. These results show that forest land footprint may have different determinants than aggregate EF or other components of EF

Table 4.18: Regression Results of SDM for Forest Land Footprint

Variables	Coefficient	SE	Variables	Coefficient	SE
ln_FST_l	-0.358***	0.035	W*ln_fst_l	0.120*	0.070
ln_PC	0.091***	0.030	W*ln_pc	-0.070	0.053
ln_BEI	0.178	0.120	W*ln_bei	-0.338**	0.154
ln_HC	0.239	0.192	W*ln_hc	-0.073	0.279
ln_UP	0.001	0.083	W*ln_up	-0.142	0.108
ln_TO	0.038	0.040	W*ln_to	0.036	0.059
			ρ	0.081	0.059

*Dependent Variable: Δln_FST=Growth Rate of Forest Land Footprint). ln_FST_l= Logged Value of Forest Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

Table 4.19: Effects Decomposition for Forest Land Footprint

Variables	Direct Effects		Spillover Effects		Total Effects	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
ln_FST_l	-0.355***	0.036	0.099	0.074	-0.255***	0.087
ln_PC	0.088***	0.029	-0.069	0.055	0.019	0.064
ln_BEI	0.181	0.116	-0.332**	0.160	-0.151	0.191
ln_HC	0.241	0.192	-0.034	0.288	0.207	0.334
ln_UP	-0.000	0.079	-0.153	0.108	-0.153	0.125
ln_TO	0.042	0.041	0.048	0.068	0.090	0.086

*Dependent Variable: Δln_FST=Growth Rate of Forest Land Footprint. ln_FST_l= Logged Value of Forest Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

4.2.4 Convergence in Fishing Ground Footprint

Fishing ground footprint measures the equivalent surface area required to sustainably support the country's total fish catch from the aquatic ecosystem. To analyze the β-convergence in the fishing ground footprint, we first tested spatial dependence in the fishing ground footprint, then we carried out a model selection exercise, and finally, the selected model was used for regression.

4.2.4.1 Spatial Dependence

Table 4.20 presents the results of Moran's I values for fishing ground footprint. We can see that fishing ground footprints have high spatial dependence, like aggregate EF and other components. Therefore, it is imperative to use spatial econometric techniques to explore convergence in fishing ground footprints.

Table 4.20: Moran's I for Fishing Ground Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.301***	0.001	2002	0.352***	0.000
1987	0.360***	0.000	2007	0.332***	0.000
1992	0.313***	0.001	2012	0.326***	0.001
1997	0.328***	0.001	2017	0.374***	0.000

Note: *** *indicates* a 1% level of significance.

4.2.4.2 Regression Results

For regression, first, we carried out an exercise to select the appropriate model for the fishing ground footprint and presented results in Table 4.21.Results in table 4.21 show that SDM with both spatial and time fixed effects gives the lowest values for AIC and SIC. Hence, this model is selected and further tested for its possible reduction to SAR or SEM model through the Wald test. Results of the Wald test show that SDM can be reduced to both specifications. P-values show that results are more in favor of SEM; hence we have specified SEM with different possibilities. We again used minimum AIC and SIC criteria to find the best possible specification among these. Results show that SEM with both spatial and time fixed effects gives minimum AIC and SIC. Hausman test shows that fixed effects are more appropriate than random effects. Hence, our final model is SEM with both spatial and time-fixed effects. Regression results for this chosen model are presented in table 4.22.

Table 4.21: Model Selection for Fishing Ground Footprint

Model	**AIC**	**SIC**
SDM with spatial fixed effects	303.4146	361.3125
SDM with time fixed effects	313.527	371.425
SDM with both spatial and time fixed effects	254.488	312.386
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 3.78 (0.5813)	Chi^2= 3.05 (0.6928)
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2= 54.58 (0.0000)***
Model	**AIC**	**SIC**
SEM with spatial fixed effects	304.476	337.560
SEM with time fixed effects	312.678	345.762
SEM with both spatial and time fixed effects	247.795	280.879
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2= 23.93 (0.001)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

One important limitation of SEM is that using this model country spillover effect of factors can't be found (Yesilyurt and Elhorst, 2017). Overall spatial effects are captured by λ (spatial lambda). SEM results confirm conditional convergence in fishing ground footprints as the coefficient of ln_FSH_l is found to be -0.263, which is statistically significant. This finding implies that in the long run, EP in this dimension would be the same across countries.

Table 4.22: Regression Results of SEM for Fishing Ground Footprint

Variables	Coefficient	SE
ln_FSH_l	-0.263***	0.039
ln_PC	0.090	0.066
ln_BEI	-0.397	0.246
ln_HC	-0.238	0.406
ln_UP	0.197	0.170
ln_TO	0.062	0.086
λ	0.147***	0.052

*Dependent Variable: Δln_FSH=Growth Rate of Fishing Ground Footprint. ln_FSH_l= Logged Value of Fishing Ground Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

Spatial lambda was found to be significant and have a positive value. It is significant at 1%. This shows that the fishing ground footprint of a country will increase if its neighbors' footprint goes up and decrease if its neighbors' footprint goes down. Other factors are found to be insignificant determinants of fishing ground footprint.

4.2.5 Convergence in Built-Up Land Footprint

Built-up land footprints measure the total land occupied for human activities. β-convergence in built-up footprint has also been tested using the same sequence of analysis carried out so far in testing convergence in aggregate EF and other components.

4.2.5.1 Spatial Dependence

Spatial dependence in built-up footprint is found using Moran's I stat, the results of which are presented in Table 4.23.

Table 4.23: Moran's I for Fishing Ground Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.496***	0.000	2002	0.426***	0.000
1987	0.491***	0.000	2007	0.440***	0.000
1992	0.436***	0.000	2012	0.460***	0.000
1997	0.411***	0.000	2017	0.513***	0.000

*Note: *** indicates a 1% level of significance.*

Results in Table 4.23 confirm the existence of spatial dependence for the entire study period. This presence of spatial dependence in built-up footprint necessitates using a spatial econometric model to test β-convergence.

4.2.5.2 Regression Results

An appropriate regression model is needed to test the presence of β-convergence in built-up land footprints. Model selection is made by specifying SDM with different possibilities and selecting the one with minimum AIC and SIC. Table 4.24 shows that SDM with both spatial and time fixed effects is found to have minimum AIC and SIC, and the Wald test shows that this model can be reduced to SEM. SEM with both spatial and time fixed effects is found to have minimum AIC and SIC. Hausman test shows that fixed effects are more appropriate than random effects; hence SEM with both spatial and time fixed effects is selected for regression. Table 4.25 presents the results of the chosen model.

Results of table 4.25 confirm the existence of convergence in built-up land footprints as the coefficient of 'ln_BLT_l' is found to be -0.352, which is statistically significant. This result implies that EP in this dimension of EP will eventually be the same across countries. Physical capital is found to increase the built-up land footprints of the countries. Hence, the role of physical capital for this dimension of EP is the same as for overall EP measured by aggregate EF. The spatial lambda is found to be positive and significant at 1%. This shows that spatial factors significantly determine the countries' built-up footprints.

Table 4.24: Model Selection for Built-Up Land Footprint

Model	AIC	SIC
SEM with spatial fixed effects	-581.072	-547.987
SEM with time fixed effects	-484.298	-451.213
SEM with both spatial and time fixed effects	-600.681	-567.596
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=21.93 (0.0026)***
Model	**AIC**	**SIC**
SDM with spatial fixed effects	-582.860	-524.962
SDM with time fixed effects	-483.863	-425.965
SDM with both spatial and time fixed effects	-599.394	-541.496
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 10.09 (0.0726)*	Chi^2= 9.11 (0.1047)
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=72.94 (0.0000)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

Table 4.25: Regression Results of SEM for Built-Up Land Footprint

Variables	Coefficient	SE	P-Value
ln_BLT_l	-0.352***	0.040	0.000
ln_PC	0.083***	0.026	0.001
ln_BEI	-0.092	0.098	0.346
ln_HC	-0.048	0.164	0.770
ln_UP	-0.061	0.068	0.370
ln_TO	-0.031	0.034	0.372
λ	0.156***	0.054	0.004

*Dependent Variable: Δln_BLT=Growth Rate of Built-Up Land Footprint. ln_BLT_l= Logged Value of Built-Up Land Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

4.2.6 Convergence in CO_2 Footprint

CO_2 footprints measure the total forest land required to sequester the carbon dioxide emitted due to human activities. The results of β-convergence in CO_2 footprint are presented as follows.

4.2.6.1 Spatial Dependence

Moran's I is calculated to test the spatial dependence of CO_2 footprints, and the results are presented in table 4.26.

Table 4.26: Moran's I for CO_2 Footprint

Year	Moran's I	P-Value	Year	Moran's I	P-Value
1982	0.762***	0.000	2002	0.762***	0.000
1987	0.766***	0.000	2007	0.733***	0.000
1992	0.770***	0.000	2012	0.688***	0.000
1997	0.768***	0.000	2017	0.670***	0.000

Note: *** represents a 1% level of significance.

The results of Moran's I presented in Table 4.26 show that countries have high spatial dependence in their CO_2 footprints. This is evident from the high values of Moran's I, which are statistically significant throughout the study period. This necessitates using spatial econometric models to test β-convergence in CO_2 footprints.

4.2.6.2 Regression Results

First of all, the appropriate model was searched for to carry out regression analysis. This has been done by specifying SDM with various possibilities and selecting the SDM with minimum AIC and SIC. In the second step, the selected SDM is tested for the possibility of its reduction to the SAR or SEM model through the Wald test. Table 4.27 shows that SDM with both spatial and time fixed effects have minimum AIC and SIC. This model was selected and further tested for its possible reduction to SAR or SEM model. The results of the Wald test show that it can't be reduced to either of these models. The Hausman test shows that the fixed effect model is more appropriate; hence the final model selected for testing β-convergence in CO_2 footprints is SDM with both spatial and time fixed effects. Regression results for this model are presented in Table 4.28.

Results in Table 4.28 confirm the existence of conditional β-convergence, which is evident from the negative and significant coefficient of the temporal lag. This result has important implications as countries' performance on this dimension of EF is a global concern. This is because CO_2 has the lion's share in greenhouse gases which are known to be the chief culprit for climate change. Convergence in this important dimension raises the prospects that countries would agree to per capita emission allocation in global environmental agreements. This would foster global cooperation in the fight against climate change and ED. The coefficients of physical capital, population growth, human capital, and urban population are all found to affect the CO_2 footprints of the countries positively. In the case of spatial factors also, most of the variables are found to be significant. Spatial roh, the coefficient of spatial lag, is found to be highly significant.

To better interpret each factor's results in determining CO_2 footprint, we have decomposed each factor's total effects into direct and spillover effects. The result of this effects decomposition is presented in table 4.29

Table 4.27: Model Selection for CO_2 Footprint

Model	AIC	SIC
SDM with spatial fixed effects	-298.630	-240.732
SDM with time fixed effects	-314.945	-257.047
SDM with both spatial and time fixed effects	-433.341	-375.443
Model	**Wald Test for SAR**	**Wald Test for SEM**
SDM with both spatial and time fixed effects	Chi^2= 16.76 (0.005)***	Chi^2= 22.85 (0.0004)***
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=121.32 (0.0000)***

*Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses..*

The results show that the direct effect of temporal lag is found to be -0.364 while the spillover effect of this is found to be 0.316, and both of these coefficients are statistically significant. This shows that country's performance depends on the past performance of its neighbors. Physical capital affects CO_2 footprints positively, both directly and through its spillover effect. Hence, we can say that no matter whether physical capital increases in own country or neighboring countries, this is detrimental to the CO_2 footprints of the country. This is not surprising given the importance of physical capital in production, and this increase in production increases its byproduct CO_2. Our results on the role of physical capital in determining CO_2 footprints align with the findings of Evans and Kim (2015).

Table 4.28: Regression Results of SDM for CO_2 Footprint

Variables	Coefficient	SE	Variables	Coefficient	SE
ln_CO2_1	-0.364***	0.036	W*ln_co2_1	0.316***	0.052
ln_PC	0.237***	0.031	W*ln_pc	0.166***	0.056
ln_BEI	0.268**	0.117	W*ln_bei	-0.002	0.152
ln_HC	0.437**	0.194	W*ln_hc	-0.420	0.299
ln_UP	0.287***	0.086	W*ln_up	-0.300***	0.107
ln_TO	0.060	0.041	W*ln_to	0.042	0.061
			ρ	0.360***	0.044

*Dependent Variable: Δln_CO2=Growth Rate of CO_2 Footprint. ln_ CO2= Logged Value of CO_2 Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

The population growth rate is found to have a direct positive effect on CO2 footprints, which shows that if a country's population growth rate increases, it is detrimental to its CO_2 footprints. This finding has very important implications for EP of the developing countries as they typically have higher population growth rates than their developed counterparts. So, greater environmental degradation in this dimension is expected from developing countries.

Human capital is also found to affect the CO_2 footprint of the countries positively. This implies that country's human capital has a greater 'scale effect' than the 'technique effect'. In the case of the urban population, direct and indirect effects are opposite in their influence on CO_2 footprint. Urban population positively affects CO_2 footprints directly and negatively affects spillover effects. This result implies that with an increase in urban population, demand for energy increases, increasing the CO_2 footprints of the countries. Similar results have been found by Dogan and Turkekul (2016). However, in our study, the negative spillover effects of the urban population pacify its direct positive effects.

Table 4.29: Effects Decomposition for CO_2 Footprint

Variables	Direct Effects		Spillover Effects		Total Effects	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
ln_co2_l	-0.338***	0.038	0.266***	0.076	-0.073	0.094
ln_PC	0.269***	0.031	0.356***	0.075	0.625***	0.093
ln_BEI	0.294***	0.117	0.156	0.211	0.450**	0.268
ln_HC	0.407***	0.202	-0.342	0.427	0.065	0.523
ln_UP	0.261***	0.080	-0.286**	0.142	-0.024	0.171
ln_TO	0.072	0.045	0.100	0.099	0.172	0.128

*Dependent Variable: Δln_CO2=Growth Rate of CO_2 Footprint. ln_ CO2_l= Logged Value of CO_2 Footprint in previous period, ln_PC=Logged Value of Physical Capital, ln_BEI= Logged Value of Break Even Investment, ln_HC= Logged Value of Human Capital, ln_UP= Logged Value of Urban Population and ln_TO=Logged Value of Trade Openess. Note: ***, **, and * indicate 1%, 5%, and 10% significance, respectively.*

4.3 Conclusion

This chapter presented results on three objectives: assessing spatial dependence of EP, testing β-convergence in the EP, and finally segregating the total effects of the determinants of EP into direct and spillover effects. In this context, the spatial dependence was investigated through Moran's I, while spatial β-convergence and effects decomposition was carried out using SDM. The overall EP is measured with the aggregate EF, while EP in different dimensions is measured through different components of EF. A binary contiguity weight matrix has been used to establish the neighborhood relationship among the countries.

The results of Moran's I show that there is substantial spatial dependence in the EP of the countries both at the aggregate level as well as at each of its dimensions. A positive spatial autocorrelation in the EP at an aggregate level and each of the six dimensions has been found. This means countries with good EP surround countries with good EP, and other countries with bad EP surround countries with bad EP. Regression results have shown that spatial β-convergence exists both at an aggregate level and in each dimension of ED. Regarding the role of different variables in the convergence of EP, this study found it differs from dimension to dimension and from aggregate to component level. The bottom line is that this chapter found evidence supporting the spatial dependence of EP and the existence of conditional convergence in the EP. However, each level and dimension of EP has its determinants.

4.4 Limitations

Although the use of spatial econometric techniques used in this chapter is an important step forward toward the analysis of convergence of EP but β-convergence or regression approach is criticized by many researchers. Quah (1996, 1997) argued that the problem with the regression approach is that it only concentrates on the study of average behavior. It is uninformative regarding the dynamics of the distribution. It can only inform about the behavior of the representative economy but cannot inform about the behavior of the entire distribution. This becomes a particularly serious problem if the distribution exhibits 'multimodality'. Multimodality means that over some time, Distribution has several local maxima instead of one global maximum. Another problem with the regression approach is its restrictive assumption that the underlying distribution is linear and normal. Such an assumption is rarely met.

To overcome these limitations of the regression approach, Quah (1996) suggests using the distribution approach instead of the regression approach to study convergence. The distribution approach captures the convergence process's dynamics instead of just static average behavior. Hence, multimodality can be revealed using this approach. Moreover, the distribution approach uses a non-parametric technique to study the convergence phenomenon. The use of non-parametric methods allows the data to be non-normal and/or non-linear. Here convergence is thought to be the collapsing of distributions to a point limit over time. In this way use of the distribution the approach does not rest on the restrictive assumption of linearity and normality of the data.

To overcome the limitations of β-convergence in this study, the distribution approach is applied to the study of convergence in EP of the countries, and results are presented in the next chapter.

CHAPTER 5

RESULTS ON CONVERGENCE IN ENVIRONMENTAL PERFORMANCE: INTRA-DISTRIBUTION DYNAMICS ANALYSIS

This Chapter of the study presents estimated results on the convergence analysis of EP using the distributional approach. Like the β-convergence analysis of EP, distributional analyses are applied at aggregate and component levels of EP. In this association, the first section of the chapter is devoted to the results of the overall level of EP, while the second section presents the analysis at a component level.

5.1 Convergence in Overall Environmental Performance

Overall EP is measured through the use of aggregate EF. This section presents results on convergence in the overall EP of the countries.

5.1.1 Spatial Dependence

In the previous chapter, we used Moran's I to investigate the presence of spatial dependence in the EP of the countries. In this chapter, we used the distribution approach for the same analysis. In this connection, a stochastic kernel can be used to explore the role of different factors in forming the specific shape of the distribution. We have to condition the original distribution with the factor of our interest and then plot this conditioned distribution against the original distribution. If the plot shows that the distribution is parallel to the axis of the original distribution around the value of 1 of the conditioned distribution axis, then we conclude that the conditioning factor significantly affects the distribution (Magrini 2004). We are particularly interested in exploring spatial factors' role in the convergence of EP of the sample countries. For this, the present study plots original distribution against spatially conditioned distribution in both the initial (1978) and terminal (2017) years.

Figure 5.1: Role of Spatial Factors in Ecological Footprint in 1978

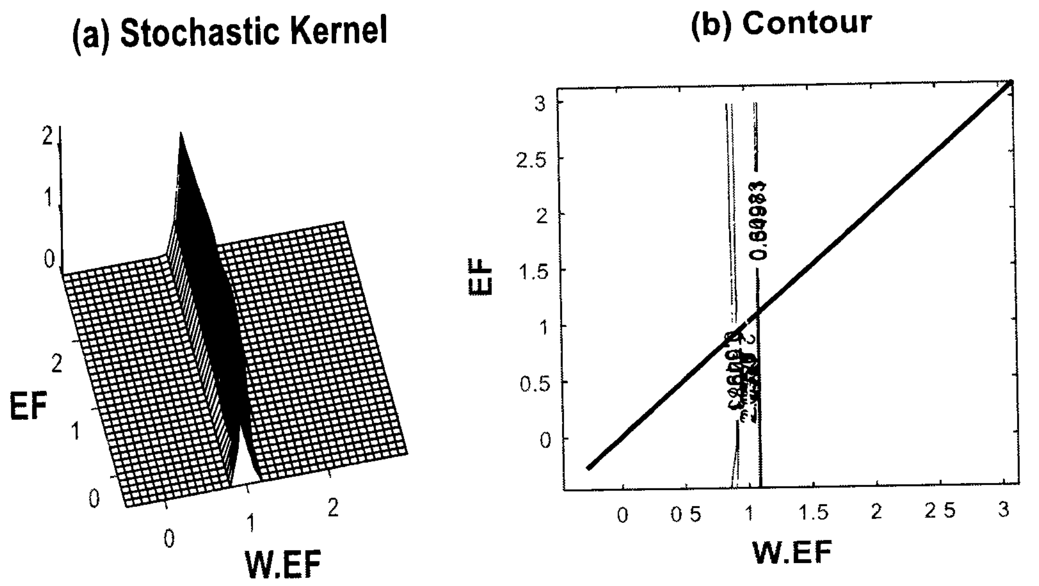


Figure 5.2: Role of Spatial Factors in Ecological Footprint in 2017

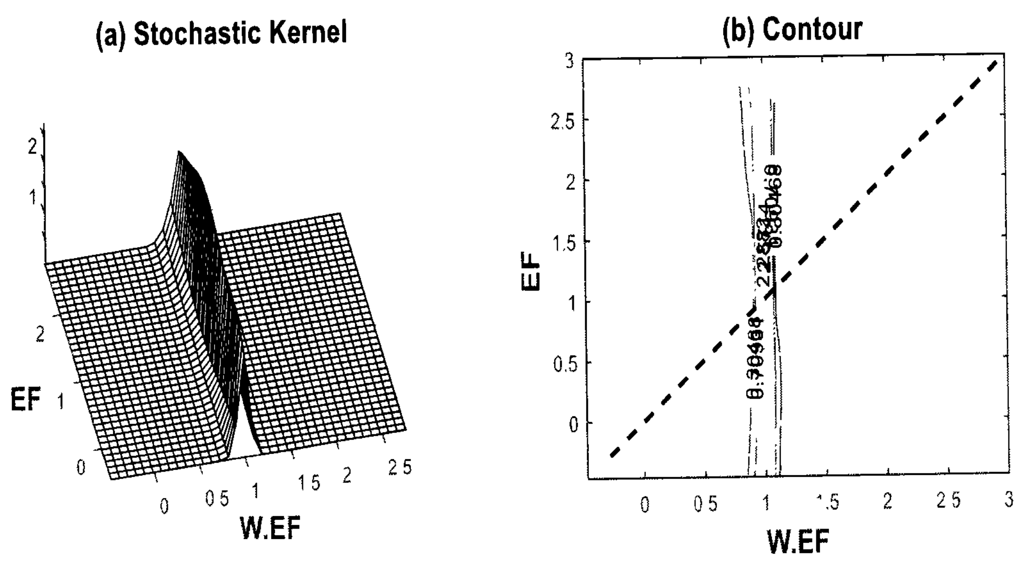


Figure 5.1 presents the original distribution of EF against the neighbors' distribution of EF for the initial year (1978). From part (a) of the figure, it can be seen that the distribution of EP for 1978 is parallel to the original distribution axis around the value of 1 of the neighbors' distribution of EF. This shows that spatial factors are important for the overall EP of the countries. Part (b) of figure 5.2, which plots the contours of the distribution, confirms this. This demonstrates that the EP of the countries in the initial period under consideration strongly depends on their neighbors.

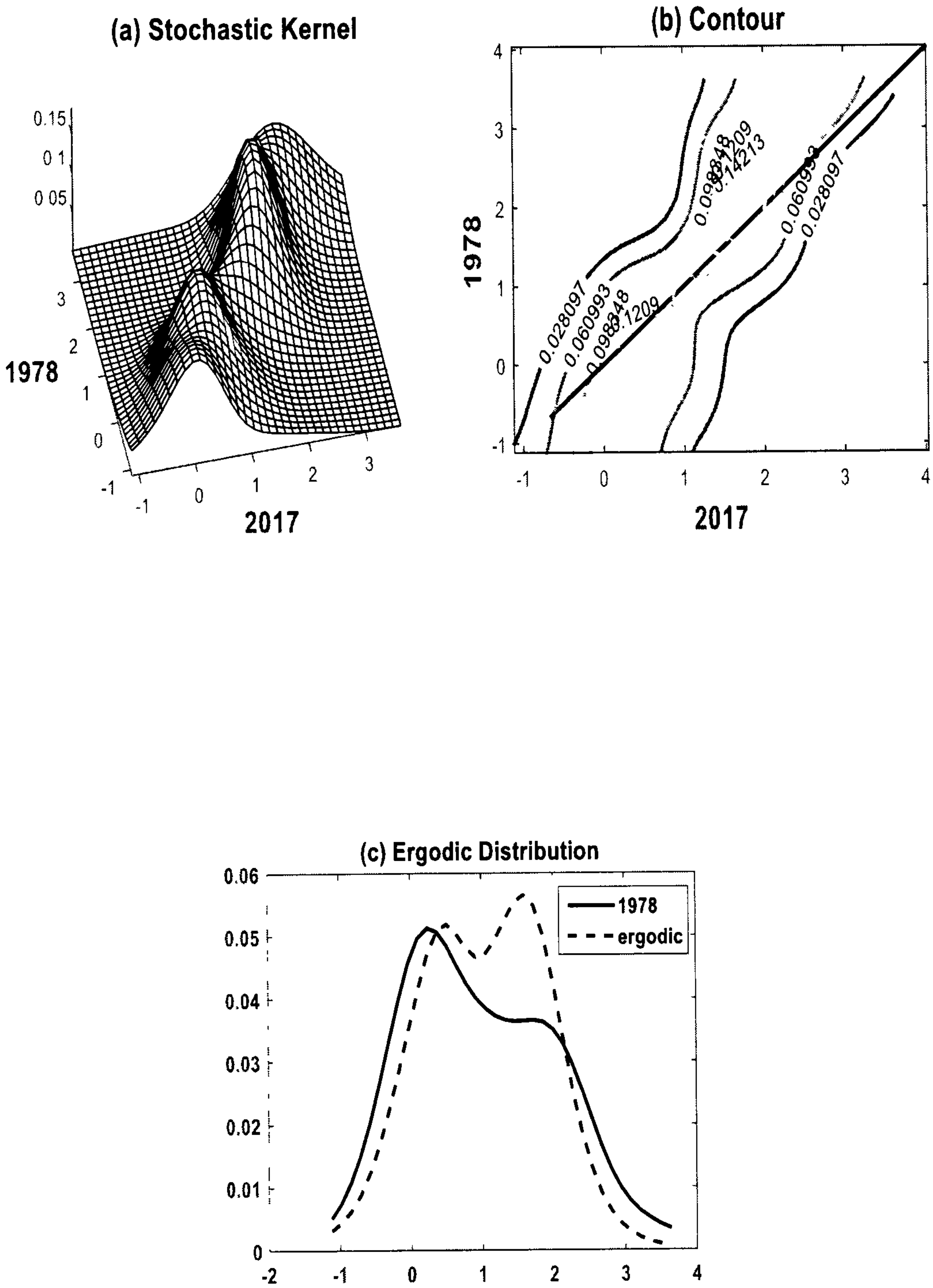
To verify that spatial factors remain important in the determination of EP in the terminal period of the study, the same analysis has been repeated for the year 2017 as well. Figure 5.2 presents space's role in the EP of the countries for the year 2017. It can be seen that, like the initial period, the distribution is parallel to the original distribution axis around the value of 1 of the conditioned distribution. It shows that spatial factors also play a role in determining EP in the terminal year. The contour of the distribution in part (b) confirms this fact. Hence, this evidence of spatial dependence demands the use of accommodation of spatial factors in the analysis of convergence in EP.

The upcoming subsection (5.1.2) presents the distribution analyses to test the convergence in EP.

5.1.2 Convergence Analysis

Once it is established that spatial factors are important in the determination of EP of the countries, we have analyzed how spatially conditioned EP of the countries has evolved over the period. This is shown in figure 5.3. It shows the transition dynamics of spatially conditioned EP of the sampled countries as measured by EF. Specifically, it demonstrates how the distribution of EP has evolved in sample countries from 1978 to 2017. Part (a) of the figure shows the evolution of the distribution of EP during these 40 years. It is evident from the 3D figure of the stochastic kernel surface that no unique equilibrium and bimodality exist in the EP of the sample countries.

Figure 5.3: Convergence of Spatially Conditioned Ecological Footprint



There are two peaks in figure 5.3 (a). The first peak comprises a group of countries with a low level of ED, and the second peak comprises a group of countries with a higher level of ED. This can be witnessed with even greater clarity in part (b) of the figure. This figure plots the contour of the stochastic kernel presented in part (a). By observing contours, we can see that both peaks lie on a 45-degree line, which shows that both groups have remained in a terminal year where they have been in the initial year. There is persistence in their EP.

Moreover, there is a dip between these two peaks, which has a flatter density mass compared to the surroundings of the peaks. This shows that countries in the middle converge toward lower or higher peaks. This shows the existence of club convergence in EP, and the hypothesis of EP convergence to a single point is rejected. A conventional regression approach to convergence would have been unable to uncover this feature of polarization which studies the average behavior of representative economy only.

To enrich our convergence analysis further, we estimated the ergodic distribution, which shows long-run equilibrium. Ergodic distribution for EF is presented in part (c) of figure 5.3. This figure compares the initial distribution (labeled '1978') to the ergodic one. In the initial year, only one peak was overwhelmingly prominent, but the ergodic distribution shows that EF would converge into two clubs in the long run. Albeit, these two clubs would get nearer to each other in the long run.

5.2 Convergence at Disaggregated Level

In the previous section, we presented the convergence of global EP using overall EF as EPI. However, to better understand the dynamics of the EP, we have carried out a disaggregated analysis of the convergence of EP. The results of the component-wise analysis are presented in this section.

Figure 5.4: Role of Spatial Factors in Crop Land Footprint in 1978

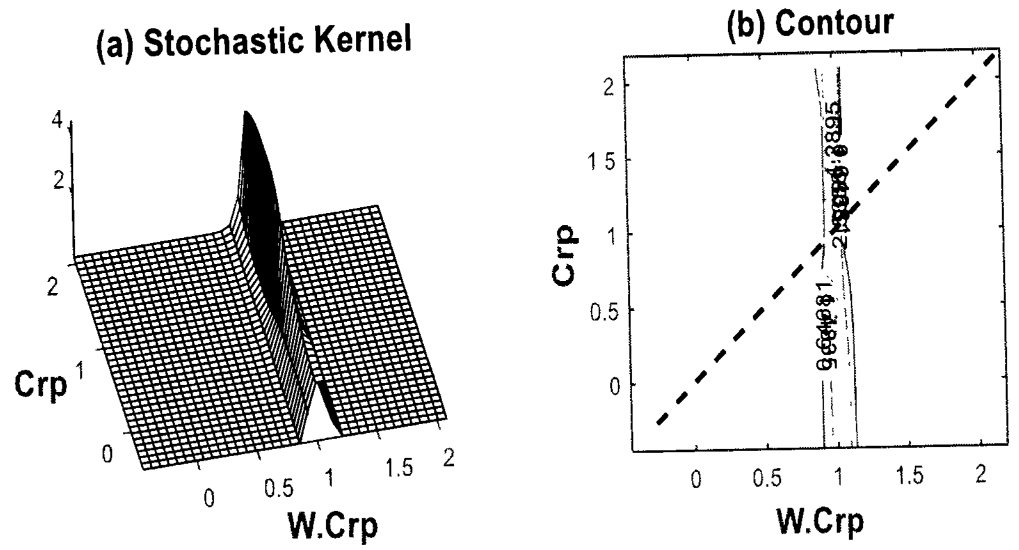
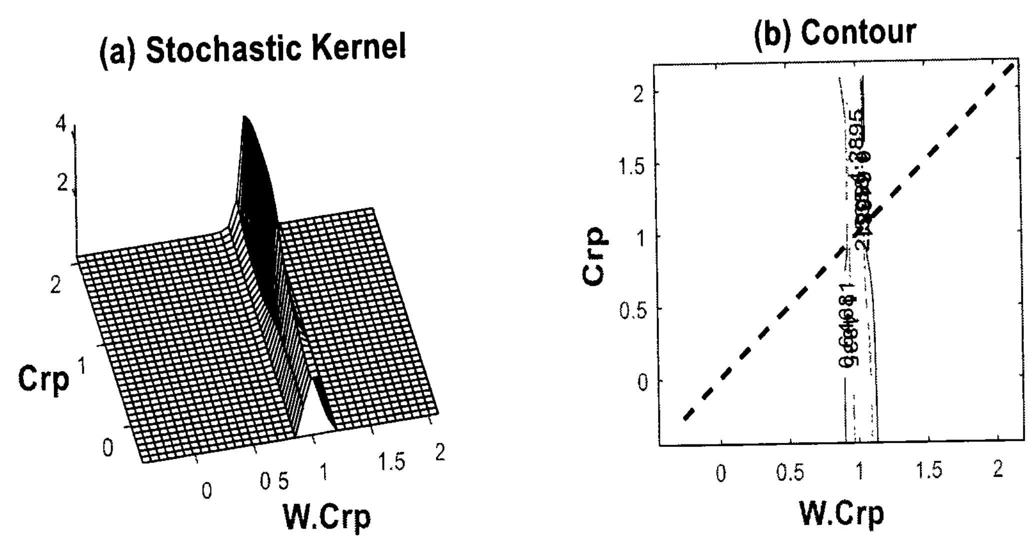


Figure 5.5: Role of Spatial Factors in Crop Land Footprint in 2017



5.2.1 Convergence in Crop Land Footprint

The first dimension we tested convergence using the distribution approach is cropland footprint. Cropland footprint measures the land needed to grow all the crops required for human and livestock consumption (Lin et al., 2019). Results obtained from the convergence analysis are presented as under.

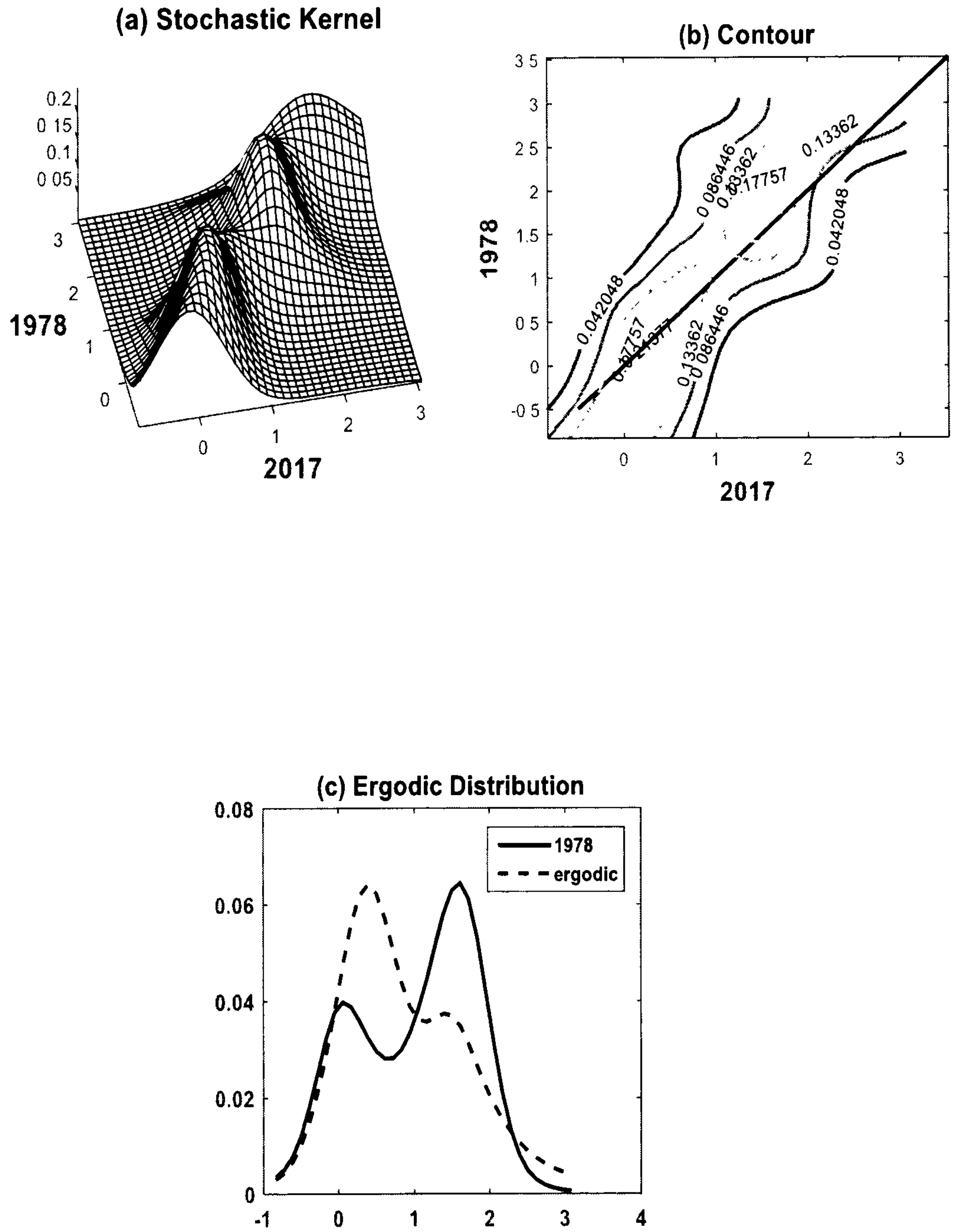
5.2.1.1 Spatial Dependence

The spatial dependence of EP in cropland footprint is tested using a distribution approach for both the study's initial period (1978) and the terminal year (2017). The results are presented in figure 5.4 and figure 5.5. Y-axis in both figures plots the original distribution of crop footprints, while X-axis plots the neighbors' crop footprint distribution. Figure 5.4 shows that space determines the EP of the sample countries in the initial period because we found the crop footprint distribution parallel to the original distribution axis on the value of '1' of the spatially conditioned distribution axis. Part (b) of the figure plots the contour and shows the same results. The same result for the terminal (2017) is presented in figure 5.5. We can conclude that spatial factors are important in determining the cropland footprint of the sample countries.

5.2.1.2 Convergence Analysis

Having found that spatial factors are important in determining crop land footprints, the distribution approach is used to study the cropland footprint's transition dynamics and long-run equilibrium. The evolution of cropland footprint distribution between 1978 and 2017 is presented in parts (a) and part (b) of figure 5.6. Part (a) shows the surface of the stochastic kernel, which shows two prominent peaks, one at a lower level of cropland footprint and the other at a higher level of cropland footprint. Moreover, it is found that the density mass around the peaks is steeper, and it is flatter in the dip between these two peaks.

Figure 5.6: Convergence of Spatially Conditioned Crop Land Footprint



This phenomenon is more noticeable in part (b) of the figure, which plots the contours of the stochastic kernel. Here, two peaks in crop footprint are even more evidence regarding mobility; these peaks are located along the diagonal with a minor anticlockwise tilt of the upper peak. The existence of twin peaks at the 45-degree line shows that countries with lower and higher crop footprints converge towards different equilibriums. This indicates the presence of club convergence for cropland footprint, which implies that there are local basins of attraction at both lower and higher levels of ED, attracting countries nearing them to converge with them.

The long-run equilibrium for the cropland footprint is shown by ergodic distribution in part (c) of figure 5.6. This figure compares the initial distribution with the ergodic one, which shows that although in the long, twin peaks would still exist, more countries would join club 1, and there would be few in club 2. Hence, although there won't be complete convergence in the cropland footprints of the countries in the long run, most countries would be in a single club. Moreover, since it indicates greater membership for club 1 (a club with a lower cropland footprint), it is also beneficial for the environment.

5.2.2 Convergence in Grazing Land Footprints

The second dimension in which we have tested the existence of convergence through a distributional approach is the grazing land footprint which is the total land required for the grazing of livestock reared by humans (Lin et al., 2019). Results obtained from the convergence analysis are presented as under.

5.2.2.1 Spatial Dependence

Spatial dependence of grazing land footprint is assessed through the distribution approach, and results of this are presented for the initial year and the terminal year of study in figures 5.7 and 5.8, respectively.

Figure 5.7: Role of Spatial Factors in Grazing Land Footprint in 1978

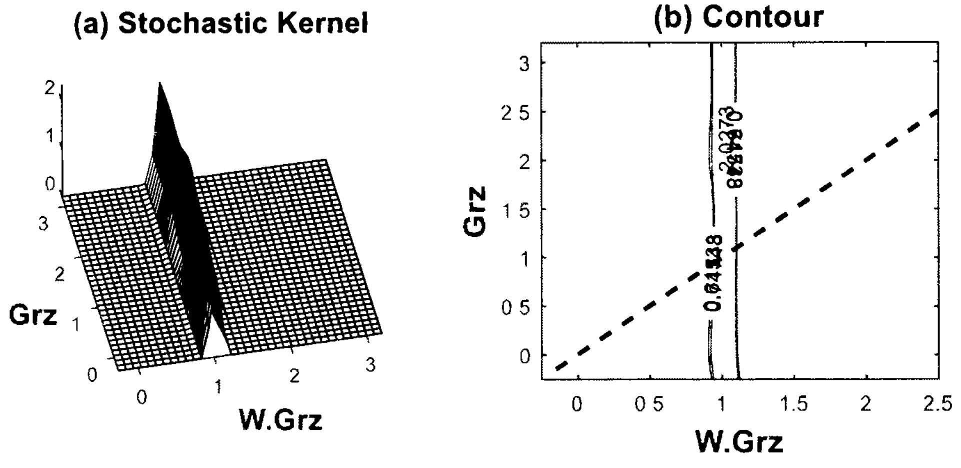
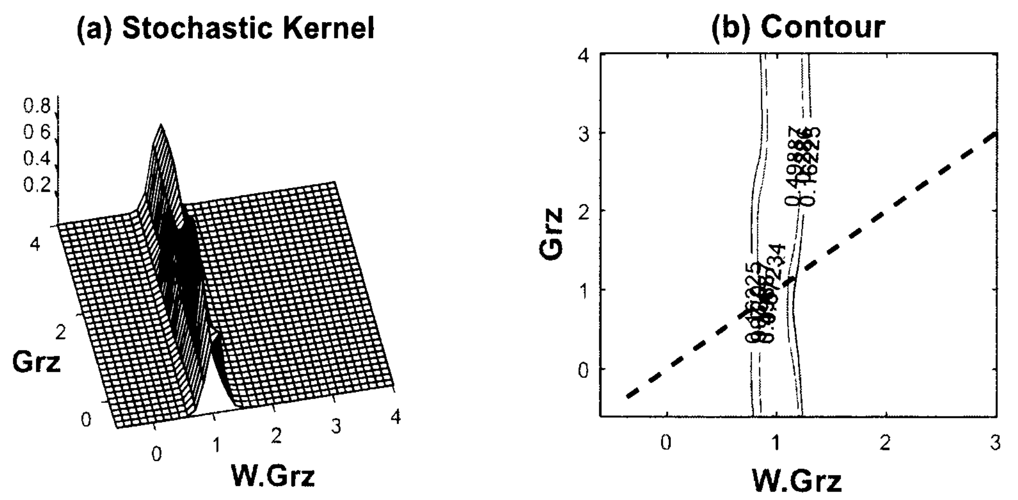


Figure 5.8 Role of Spatial Factors in Grazing Land Footprint in 2017



The results show that neighbors' grazing land footprints are the significant factor explaining the shape of the distribution of grazing footprints of a given country for both initial and terminal years. It is because the stochastic kernel and contour of grazing footprints are parallel to the Y-axis, which plots the original distribution against the value of 1 of the conditioned distribution.

5.2.2.2 Convergence Analysis

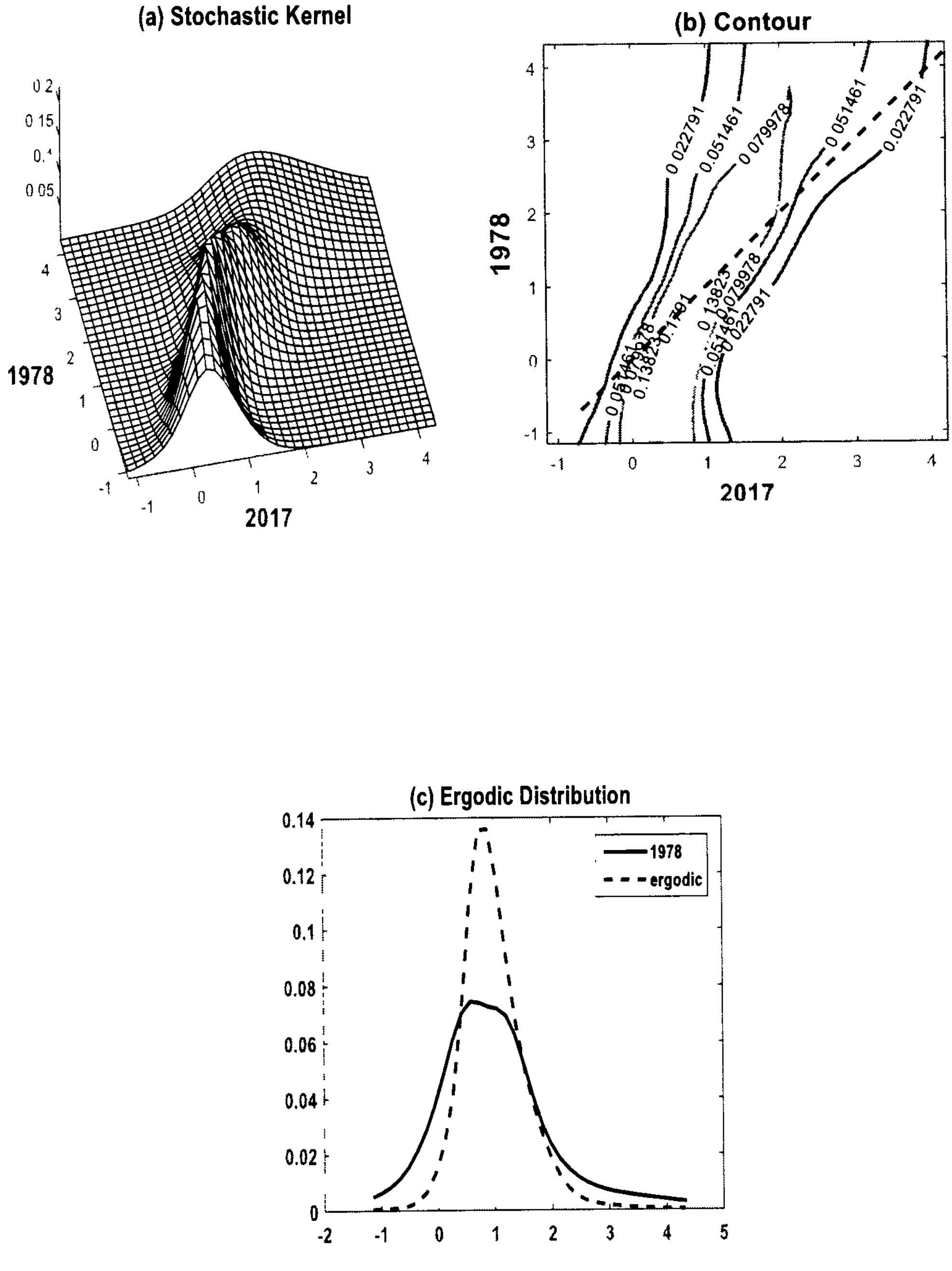
Having understood the importance of spatial factors in explaining the grazing land footprints, we used a distribution approach to assess the existence of convergence in grazing land footprint in the period under consideration. The evolution of spatially conditioned grazing land footprint is presented in figure 5.9. The plot of a stochastic kernel in part (a) of the figure shows that contrary to EF and cropland footprints. There is only one peak of the grazing land footprint with a counter-clockwise rotation. This shows that all countries in the sample are converging to a single level of grazing land footprints. Part (b) of the figure, which plots the distribution contours, supports the convergence of the sample countries to a single level. This means the environmental pressure caused by livestock reared by humans has become increasingly the same across the globe over the period under consideration.

The plot of ergodic distribution in part (c) of figure 5.9 confirms this existence of convergence in grazing land footprint for the long run. This shows that compared to the initial period, the grazing land footprint would have a more pointed single peak in the long run, and there would be a reduction in cross-sectional variance. The conclusion can be drawn is that human reliance on animal-based food would be similar across sample countries in the long run.

5.2.3 Convergence in Forest Land Footprint

Like cropland footprints and grazing land footprints, convergence in the forest land footprint is tested through a distribution approach. Forest land footprint measures the land required to produce the total forest products demanded by humans (Lin et al., 2019). The results of the distribution approach are presented in the upcoming subsection.

Figure 5.9: Convergence of Spatially Conditioned Grazing Land Footprint



5.2.3.1 Spatial Dependence

Figure 5.10 presents the results of spatial dependence for the initial year (1978) are presented in figure 5.10. In the figure, both the stochastic kernel in part (a) and the contour plot in part (b) confirm the existence of spatial dependence in the forest land footprint. The same results are found for a terminal year (2017), presented in figure 5.11. Hence, we can conclude that the forest land footprints of the countries hold spatial dependence.

5.2.3.2 Convergence Analysis

After finding the evidence of spatial dependence in forest land footprint, this study has conditioned the forest footprint data spatially, and then convergence in this data is tested using a distribution approach. The results are presented in figure 5.12. Part (a) of the figure shows the plot of the stochastic kernel, and part (b) plots contours while part (c) plots the ergodic distribution of forest land footprint.

For forest land footprint, there are two peaks of the stochastic kernel. The first peak is found at a lower level of forest land footprint, while the second is at a higher level of forest land footprint. However, the rotation of the distribution is anticlockwise. Part (b) of the figure, which plots the contour of the distribution, confirms the counter-clockwise rotation of the distribution. This indicates convergence in the forest land footprint of the countries under consideration. The result implies that demand for forest products would be the same across the globe, and the environment would face the same level of pressure in this dimension in all countries.

Part (c) of figure 5.12, which shows the ergodic distribution, also predicts the existence of convergence. It can be seen that the forest land footprint had stretched distribution in the initial period, while in the long run (ergodic distribution), the single period peaked with much lower variance. This implies convergence of forest land footprints in the long run.

Figure 5.10 Role of Spatial Factors in Forest Land Footprint in 1978

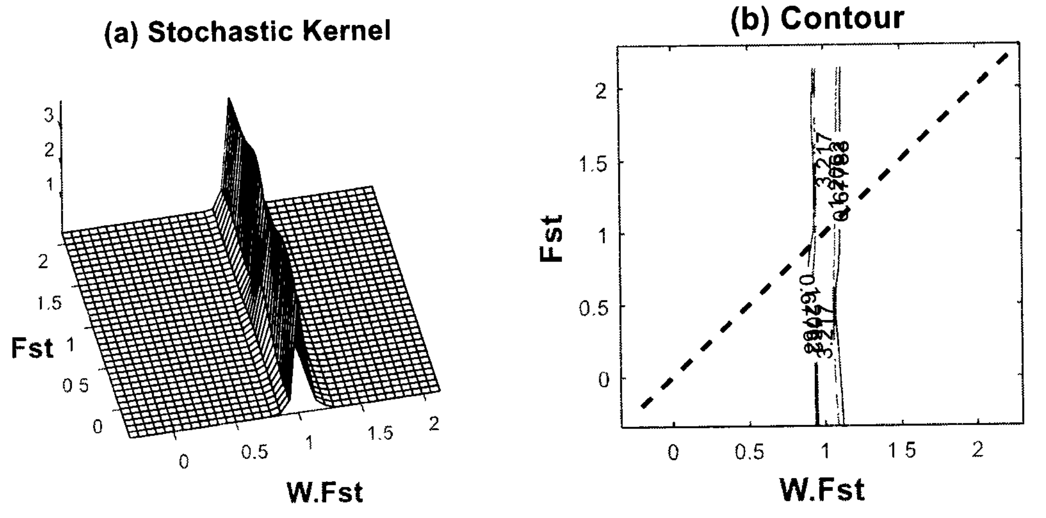


Figure 5.11: Role of Spatial Factors in Forest Land Footprint in 2017

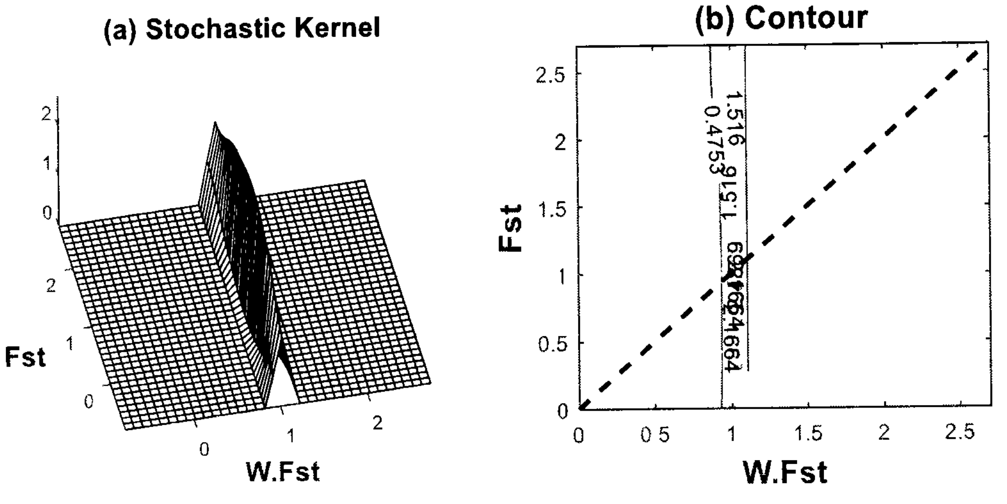
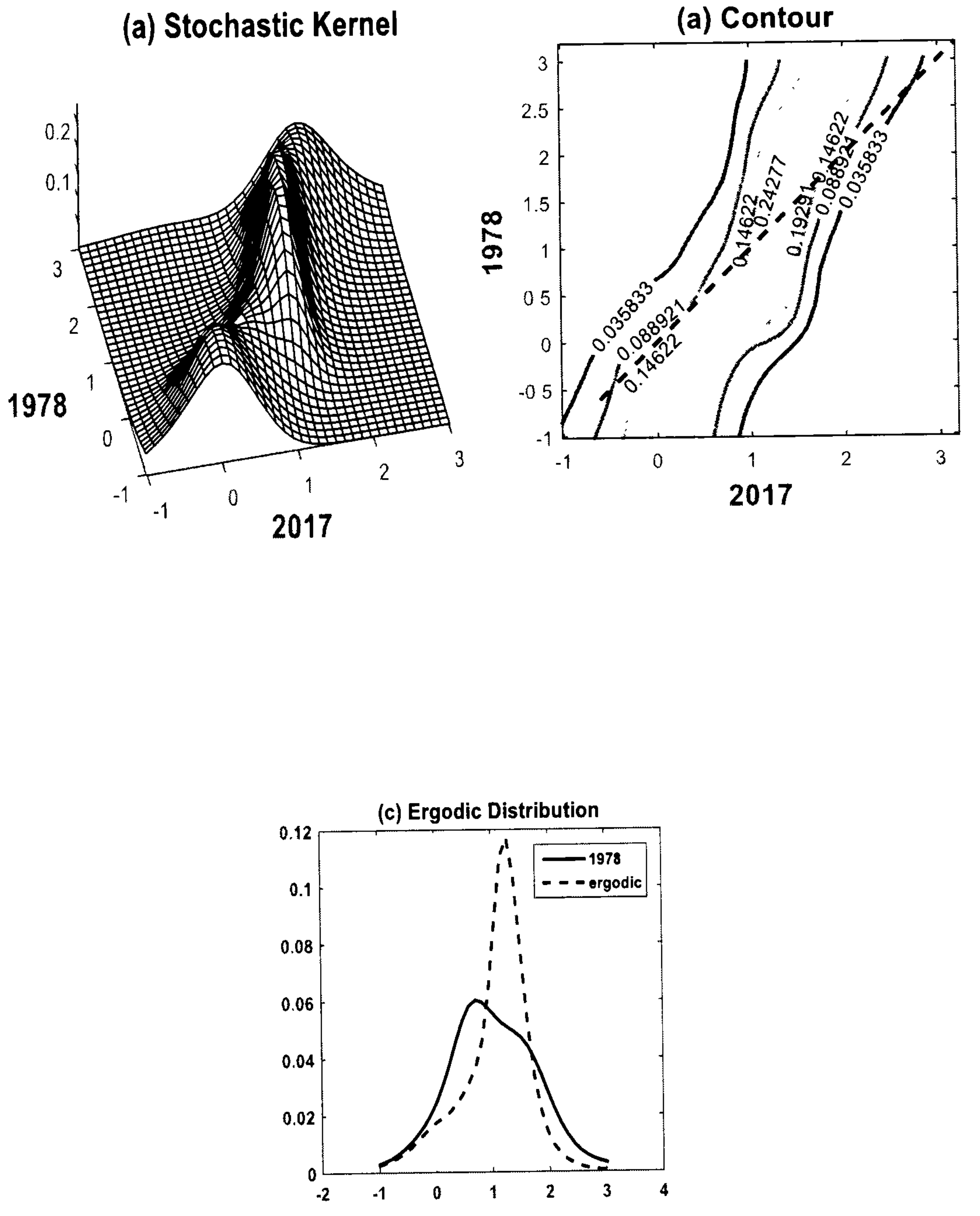


Figure 5.12: Convergence of Spatially Conditioned Forest Land Footprint



5.2.4 Convergence in Fishing Ground Footprint

Fishing ground footprint measures the equivalent surface area required to sustainably support the country's total fish catch from the aquatic ecosystem (Lin et al., 2019). To analyze the convergence in fishing ground footprint, firstly, we examined spatial dependence then we tested convergence using the distribution approach.

5.2.4.1 Spatial Dependence

The distribution approach explores the importance of spatial factors in determining the fishing ground footprint. The testing of spatial dependence has been carried out by plotting the original distribution of the fishing ground footprint of the countries to the footprints of their neighbors. Figure 5.13 and 5.14 presents the results of the initial and terminal year, respectively. It can be seen from both part (a) and part (b) of these figures that the plots are parallel to the axis which contains the original distribution. This depicts the significance of spatial factors' role in determining fishing ground footprints.

5.2.4.2 Convergence Analysis

After the findings of spatial dependence of fishing ground footprints, we conditioned the fishing ground footprint data spatially and then applied a distribution approach to test the existence of convergence. Figure 5.15 presents the results. Part (a) shows three peaks, one at the lower, one at the medium, and one at the higher fishing ground footprints.

This indication reveals that there are multiple clubs in the fishing grounds' footprint. This phenomenon is more clearly visible in part (b) of the figure, which plots the contours of the stochastic kernel. We can see a counter-clockwise rotation of the distribution of the fishing ground footprint. This implies the existence of convergence in this dimension of EP.

The long-run equilibrium of the fishing ground footprint is examined through ergodic distribution plotted in part (c) of figure 5.15. A single peak of ergodic distribution shows convergence in the long run for the fishing ground footprint.

Figure 5.13: Role of Spatial Factors in Fishing Ground Footprint in 1978

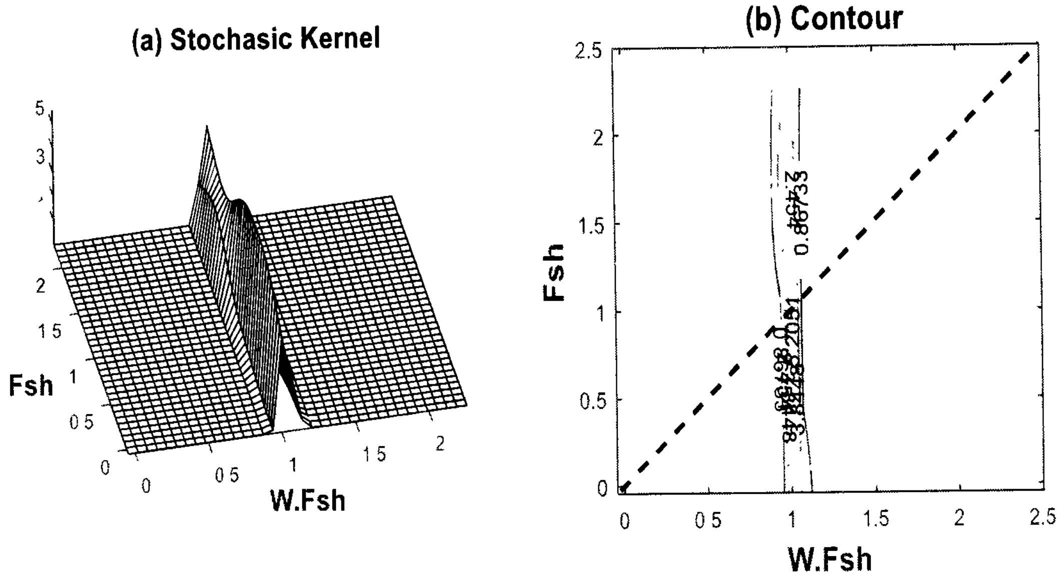


Figure 5.14: Role of Spatial Factors in Fishing Ground Footprint in 2017

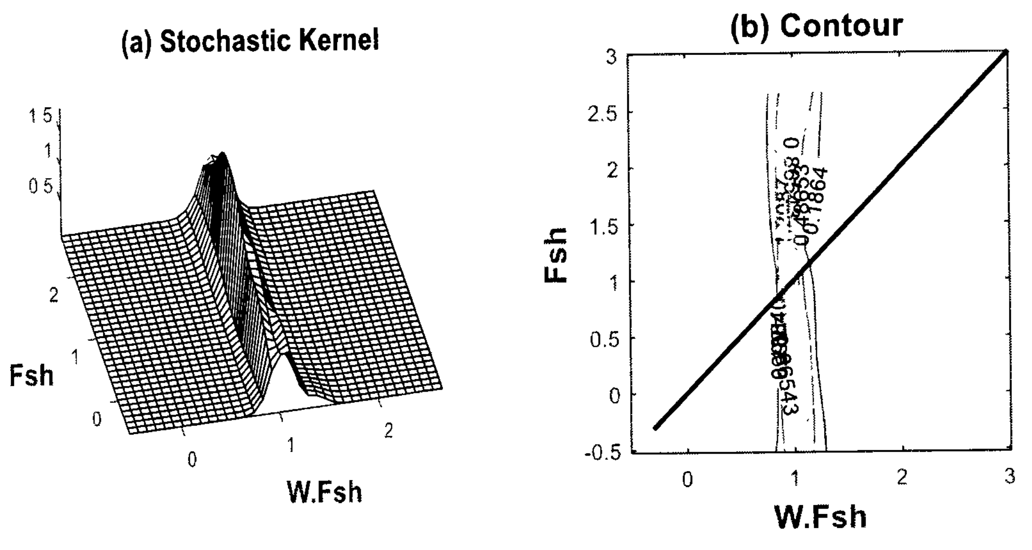
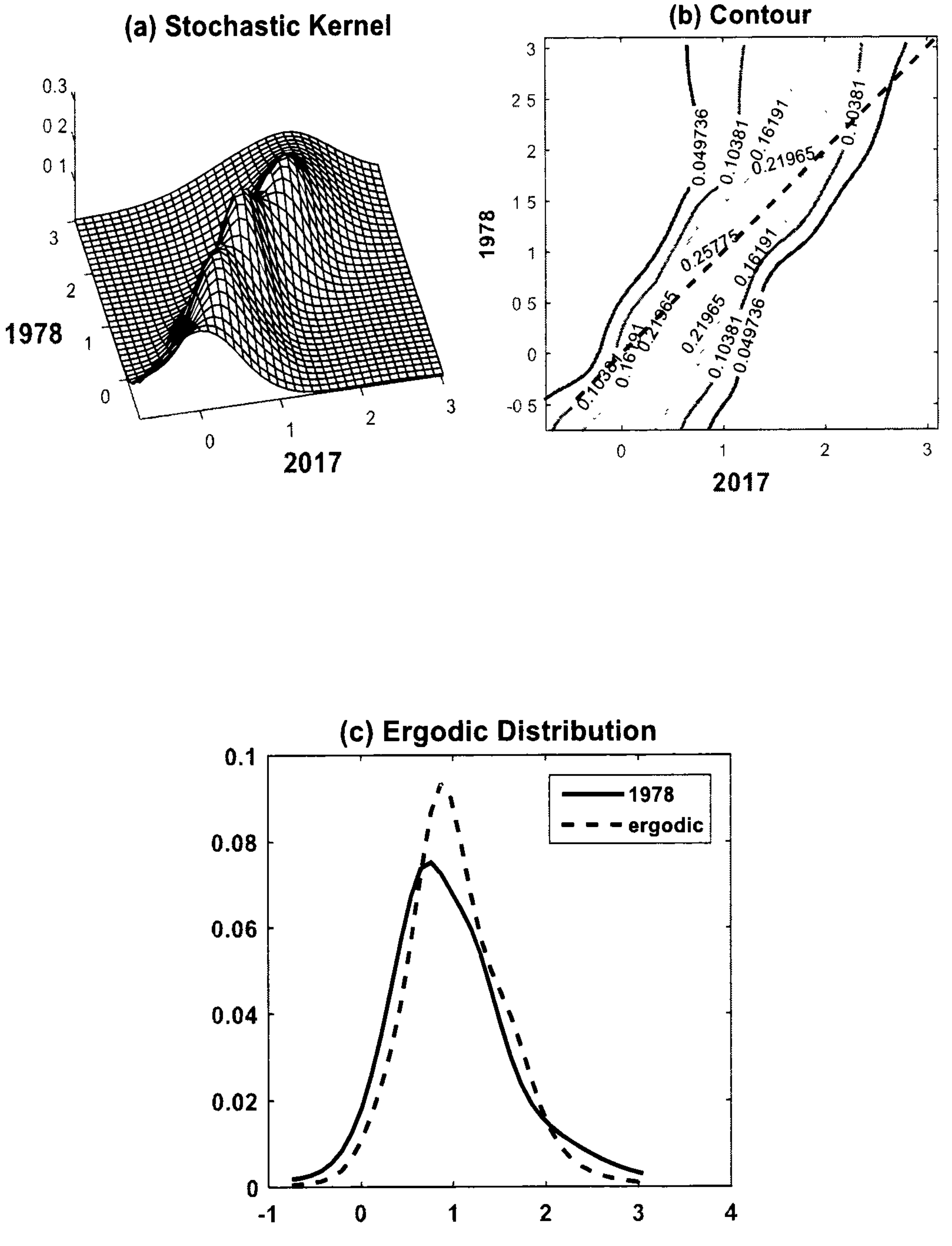


Figure 5.15: Convergence of Spatially Conditioned Fishing Ground Footprint



5.2.5 Convergence in Built-Up Land Footprint

Built-up land footprints measure the total land occupied for human activities (Lin et al., 2019). The convergence in the built-up footprint is tested through the distribution approach. In this context, first, the stochastic kernel is used to confirm spatial dependence of the built-up footprint and then for convergence analysis.

5.2.5.1 Spatial Dependence

Before carrying out the convergence analysis, we first used the stochastic kernel to test the role of spatial factors in the built-up footprint in the initial year and the terminal year. The results are presented in Figures 5.16 and 5.17. The table shows that spatial factors primarily determine the built-up land footprint for both years. As in both figures, stochastic kernel and contour plots are parallel to the axis that has the original distribution. This finding requires us to treat our data for spatial dependence and then use it for convergence analysis.

5.2.5.2 Convergence Analysis

The evolution of the built-up footprint between 1978 and 2017 has been shown in figure 5.18. This shows the existence of bimodality for spatially conditioned built-up footprints. One peak is situated at the lower level of the built-up footprint, while the other is at a higher level of the footprint. The transition dynamics of the built-up footprint show that countries largely show persistence in their built-up footprint as most of the density mass lies around the diagonal. Part (b) of the figure, which plots the contour of the distribution, also confirms the persistence of the countries in their built-up footprints. Only a slight downward movement of the lower peak from the 45-degree line. Hence, the twin peaks phenomenon is at work for the built-up footprint, and there is no evidence of convergence towards a single level.

Part (c) of figure 5.18 plots the ergodic distribution showing the built-up footprint's long-run equilibrium. This indicates that although there would be two clubs of countries in the long term, according to their built-up footprint, a club with a higher footprint would overwhelmingly dominate the club with a lower footprint.

Figure 5.16: Role of Spatial Factors in Built-Up Land Footprint in 1978

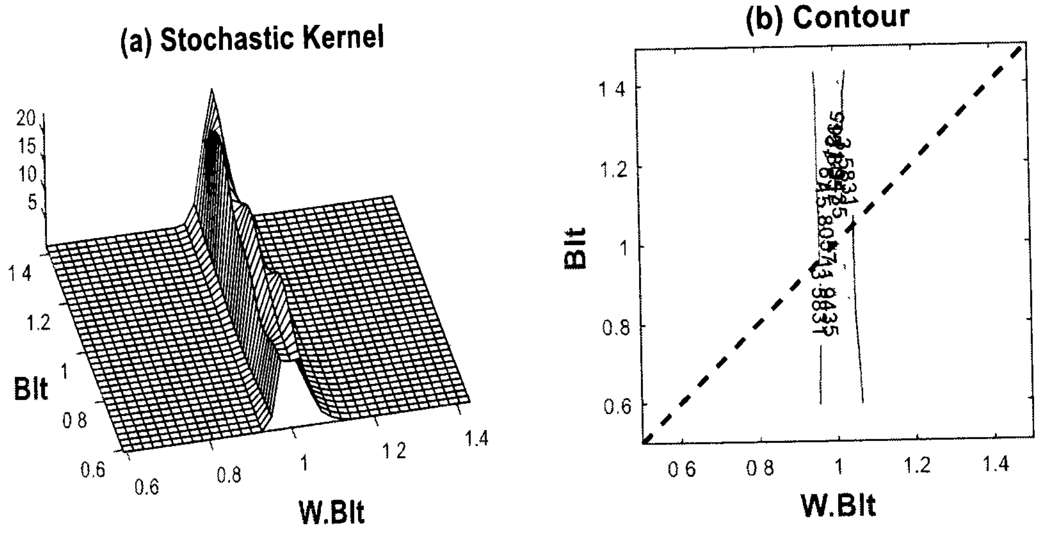
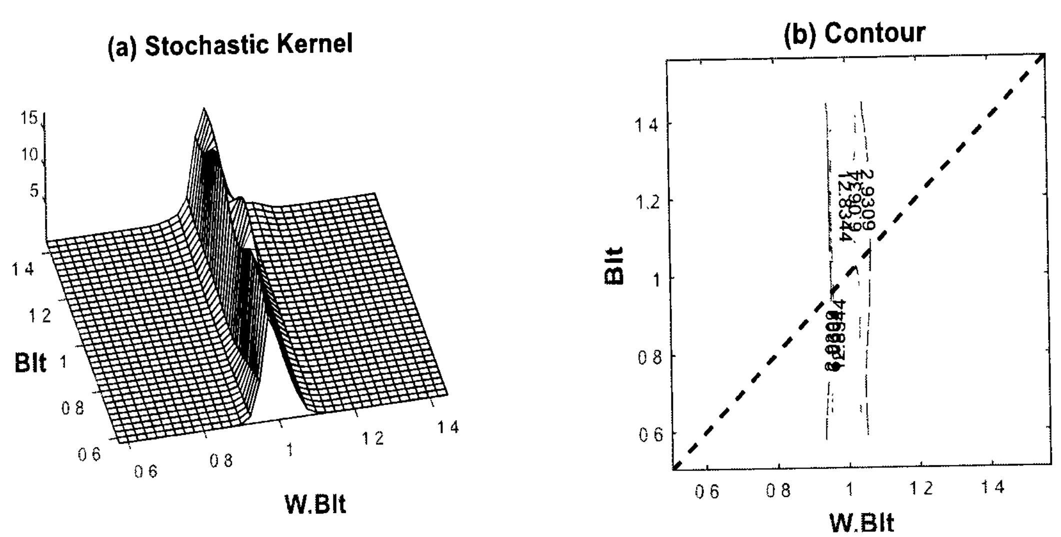


Figure 5.17: Role of Spatial Factors in Built Up Land Footprint in 2017



5.2.6 Convergence in CO_2 Footprint

CO_2 footprint measures the total forest land required to sequester the carbon dioxide emission from human activities (Lin et al., 2019). Like previous cases, convergence in CO_2 footprint is tested using the usual sequence. The upcoming section presents the results of the convergence of CO_2.

5.2.6.1 Spatial Dependence

To test the convergence in CO_2 footprint, we have first tested the existence of spatial dependence in both the initial and terminal years of the study using the distribution approach, whose results are presented in Figures 5.19 and 5.20. Both stochastic kernels and contour plots for each year show that spatial factors have a significant role in determining CO_2 footprint.

5.2.6.2 Convergence Analysis

Figure 5.21 shows how the evolution of CO2 footprint distribution occurred once we conditioned it for spatial factors. We can see that the hump of the stochastic kernel lies along the diagonal line, which shows that there is persistence in the CO_2 footprint in our whole sample. This is more easily noticeable in part (b), which plots the contour of the stochastic kernel. This finding is in contrast to the findings of Jobert *et al.* (2010), Tiwaria and Mishra (2017), and Brannlund and Karimu (2018). These studies have found convergence in the CO_2 footprint of the countries.

One potential explanation for this difference is that these studies have utilized the CO_2 footprint of production while the current study has utilized the CO_2 footprint of consumption. This implies that developed countries may have shifted CO_2-intensive production sectors to developing countries but have kept using goods produced by those sectors via trade. Hence, their CO_2 footprint might have reduced as measured by their products, but there is persistence in their CO_2 footprint as measured by their consumption. Part (c) of figure 5.21, which plots the ergodic distribution of CO_2, confirms this.

Figure 5.18: Convergence of Spatially Conditioned Built-Up Land Footprint

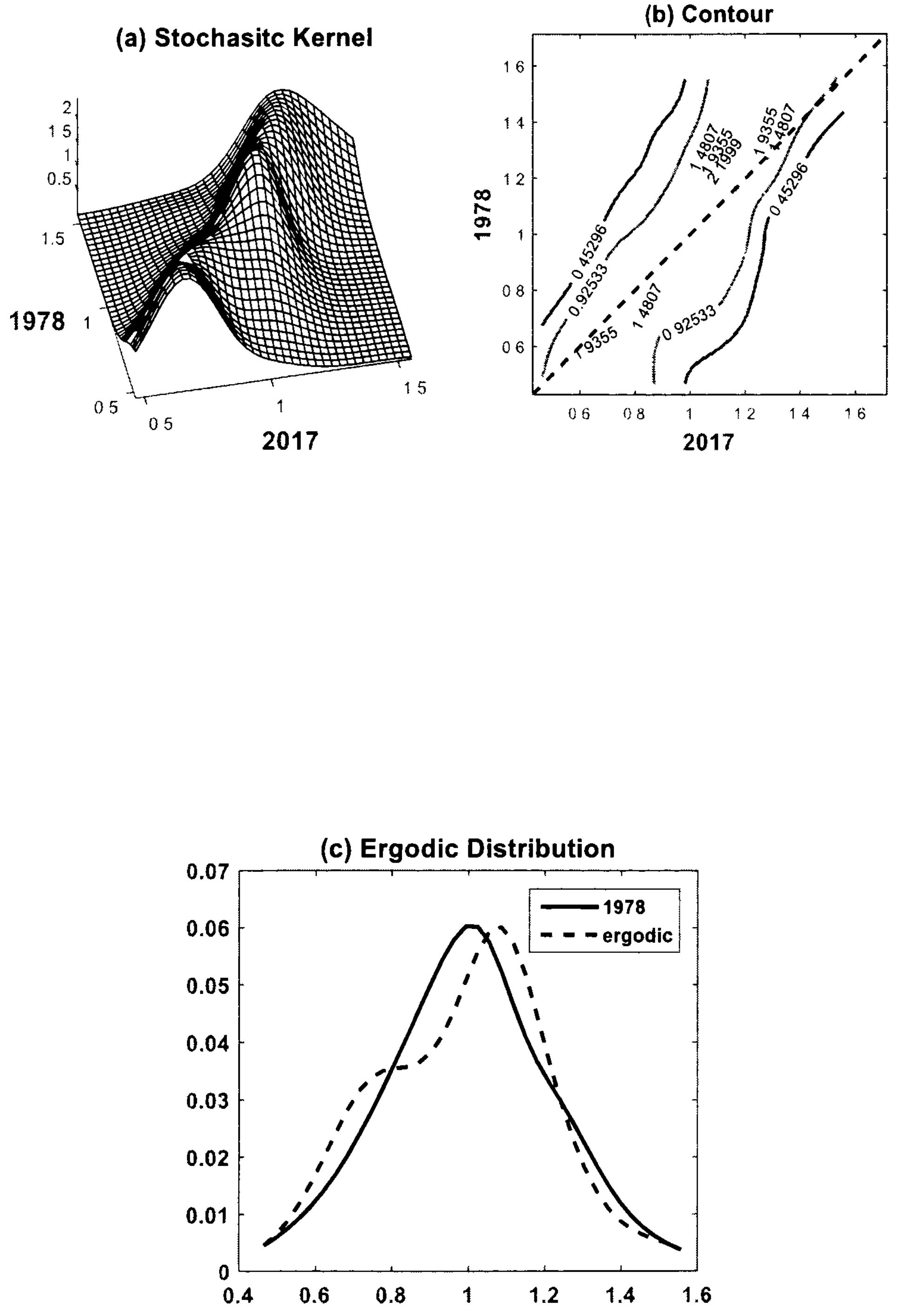


Figure 5.19: Role of Spatial Factors in CO_2 Footprint in 1978

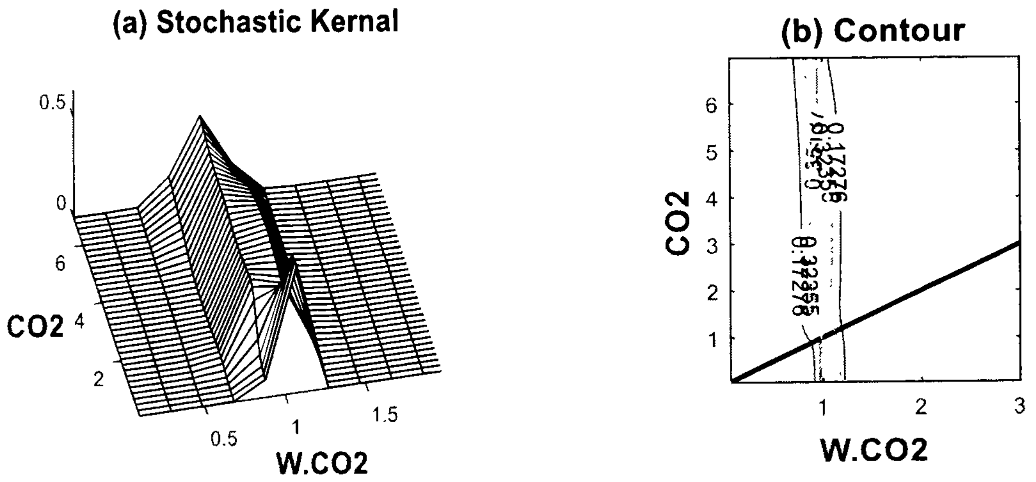


Figure 5.20: Role of Spatial Factors in CO_2 Footprint in 2017

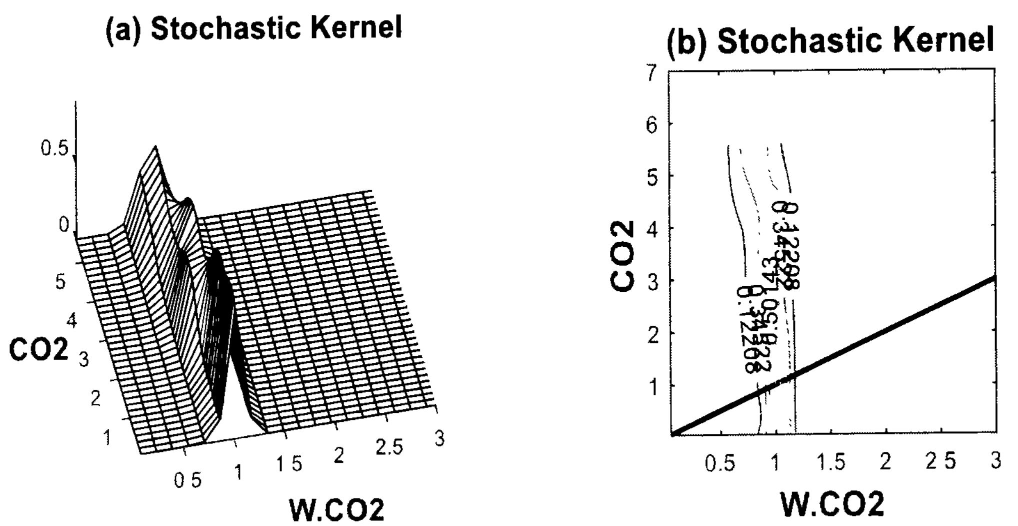
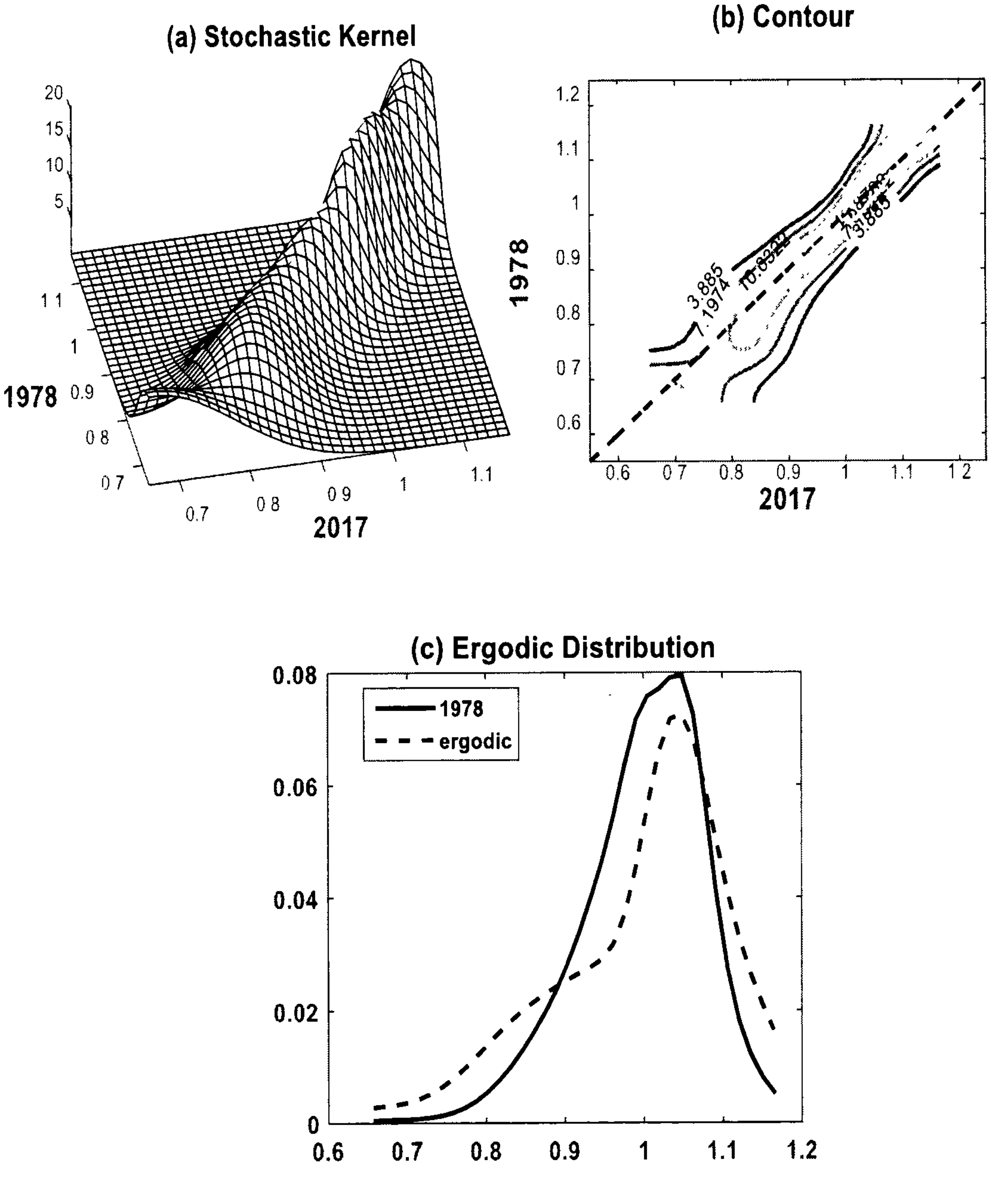


Figure 5.21: Convergence of Spatially Conditioned CO_2 Footprint



5.3 Conclusion

This study chapter was devoted to testing the existence of convergence in the overall global EP and its disaggregated analysis using the distribution approach. In this context, we explored the role of spatial factors in the determination, and upon finding spatial dependence, we conditioned data for spatial factors and tested convergence. Our estimates reveal that space is the significant determinant of overall EP and each of its six dimensions. This directed incorporating the spatial factors in the analysis of EP of the countries under consideration.

Regarding the convergence process in overall EP, bimodality is found as the countries form two clubs according to their overall EP- one at a lower level of ED and the other at a higher level of ED. Hence, no evidence of convergence to a single level of ED was found. Ergodic distribution has also formed two clubs in the long run. The disaggregated analysis of the components of EP has revealed that spatial factors are a significant determinant of EP in each of them. Regarding convergence, this study found the existence of bimodality for cropland footprint and built-up land footprint. Ergodic distribution confirmed this pattern. Persistence was found in the CO_2 footprint of the countries over the study period. For other components of EF, this study has found support for convergence. For these components, Ergodic distribution also confirms the existence of convergence in the long run.

The conclusion that can be drawn from this chapter is that this study found mixed results regarding the presence of convergence in overall EP and its different components of it.

5.4 Limitations

This chapter shows that the distribution approach can reveal data features that β-convergence cannot reveal. Particularly, the present study distribution approach has shown that there is polarization and stratification in the EP of the countries, which points out the existence of club convergence in the EP of the countries. β-convergence in the last chapter was unable to find it because it studies only the average behavior of the representative economy. Although the distribution approach successfully uncovered the feature of club convergence in EP, the limitation is that we cannot find which countries among our sample belong to which club. To discover this, we have applied Phillips and Sul (2007) club convergence approach to our EP data, and the results are presented in the next chapter.

CHAPTER 6

RESULTS ON CLUB CONVERGENCE IN ENVIRONMENTAL PERFORMANCE

Results of the distribution approach presented in chapter 5 revealed that the EP of the sample countries is not converging to a single level. Rather there is the existence of club convergence. The distribution approach cannot make a specification of country and club; hence keeping in view this limitation of the distribution approach, in this chapter, club convergence analysis has been carried out using Phillips and Sul (2007) methodology, which gives the detail of membership of each club. We approach club convergence in two steps: Firstly, given our evidence of spatial dependence in EP of the countries, we have filtered our data for spatial dependence following the methodology of (Postiglion *et al.*, 2010). Secondly, Phillips and Sul (2007) methodology of club convergence was applied to spatially filtered data.

6.1 Club Convergence at Aggregate Level of Environmental Performance

First, we test the club convergence at the aggregate level of EP for which EF is used as EPI.

6.1.1 Spatial Filtration

Using Moran's I statistic and distribution approach, we have found strong evidence of spatial dependence in chapters 4 and 5. However, the main issue with both approaches is that they do not uncover the type of spatial dependence in the data, without which the outlined methodology of spatial filtration cannot be carried out. We have used the LM test to determine the type of spatial dependence in the data. The results of the LM test are presented in Table 6.1.

Table 6.1: Spatial Dependence in Ecological Footprint

Test	Statistic	P-Value
LM Error	93.59***	0.0000
LM Error (Robust)	176.40***	0.0000
LM Lag	0.3028	0.5821
LM Lag (Robust)	83.11***	0.0000

Table 6.1 presents the results of the LM test, both in its simple form and robust form, to find the type of spatial dependence in EF. In its simple form, LM shows that the null hypothesis of 'no spatial lag' cannot be rejected; however, it is rejected for spatial error. This means EF data has a spatial error. There is no need to use the results of the robust form of LM as LM in its simple form has given results decisively in favor of the presence of spatial error (Anselin, 1988). This means EF data should be filtered using SEM.

Table 6.2: Model Selection and Spatial Coefficient for Ecological Footprint

Model	AIC	SIC
SEM with spatial fixed effects	4862.156	4905.319
SEM with time fixed effects	12118.74	12161.9
SEM with both spatial and time fixed effects	4678.123	4721.286
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic	Chi^2=11.75 (0.068)***	
Results SEM with both spatial and time fixed effects		
λ	0.3003234 (0.0000)***	

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. P-Values are given in parentheses.*

The evidence of spatial dependence in error has been found in EF data. In the first step, SEM was to be estimated to find the spatial lambda (λ), which would then be used for spatial filtering. In this context, the SEM model is specified with different alternatives, and AIC and SIC criteria are used to choose the minimum AIC and SIC specifications. Table 6.2 presents AIC and SIC results which show that SEM with time and spatial fixed effects have minimum AIC and SIC. Hence the spatial lambda is estimated with this model. The estimated value of spatial lambda is 0.30, which is statistically significant at 1 percent and is used for spatial filtration.

6.1.2 Convergence Analysis

Once spatially filtered data has been found, Phillips and Sul (2007) club convergence methodology has been used to test club convergence in the EF, for which results are presented in Table 6.3 to Table 6.5. First, convergence in EF in the overall sample is tested, and results are presented in Table 6.3. Results presented in Table 6.3 show that as the t-stat value is below -1.65, countries under consideration cannot converge to a single level of EF. The absence of convergence in the overall sample means that instead of converging to any single level in EF, countries converge to different levels and form clubs. To uncover the details of this, the club convergence test has been applied to the EF data of the countries. Table 6.4 presents results on club convergence.

Table 6.3: Regression Results for Convergence in Ecological Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-0.3410	0.0270	-12.6318

Results presented in Table 6.4 show that regarding the overall EP as measured by EF, countries are converging into two clubs. The estimated t-stat values are 1.48 and 7.88 for club 1 and club 2, respectively. The estimated results indicate that there is indeed club convergence in the EF of the countries. It means the convergence paths of the two clubs to their respective equilibriums are significantly different. If the membership of these clubs is closely observed, it shows that clubs formed for overall EP are broadly based on the economic development of the countries where economically developed countries form one club while economically less developed countries form other clubs[6]. This substantiates the postulation of our theoretical model, which treats ED as the byproduct of economic output.

[6] See appendix B for club membership.

Table 6.4: Regression Results for Ecological Footprint Club Identification

log(t)	Club1	Club2
Coeff	0.072	6.544
T-stat	1.482	7.884

As per the suggestion of Phillips and Sul (2007), the possibility of merging these two clubs into a single club is tested, and the results are presented in Table 6.5. The result shows that such a club would not be convergent as the value of the t-stat is -12.552, which is less than -1.65. That means we can reject the null hypothesis of convergence. Hence, previously found that two clubs cannot be merged to form one club.

Table 6.5: Regression Results for Ecological Footprint Club Mergence

log(t)	Club1+2
Coeff	-0.339
T-stat	-12.552

6.2 Club Convergence at Disaggregated Level

To make our analysis more profound, we carried club convergence analysis of different components of the EF. The same procedure has been carried out as in the case of overall EF. Firstly, the type of spatial dependence in the relevant component is examined. Secondly, the spatial filtering of the data is carried and finally, club convergence is tested using Phillips and Sul (2007) approach.

6.2.1 Club Convergence in Crop Land Footprints

Cropland footprint is the first dimension in which club convergence is tested among the components. Cropland footprint measures the land needed to grow all the crops required for human and livestock consumption. Results obtained from the convergence analysis are presented as under.

6.2.1.1 Spatial Filtration

To carry out spatial filtration in cropland footprint, we have to determine its type of spatial dependence. In this context, the first LM tests are used in simple and robust forms to identify the type of spatial dependence in cropland footprint. Results are presented in Table 6.6.

Table 6.6 shows that there is a spatial error in the cropland footprint. Hence, SEM is the right model to carry out spatial filtration. To do this, SEM with different possibilities is specified, and AIC and BIC criteria have been used to find the best specification. The results of the model selection are given in table 6.7.

Table 6.6: Spatial Dependence in Crop Land Footprint

Test	Statistic	P-Value
LM Error	70.50***	0.0000
LM Error (Robust)	350.47***	0.0000
LM Lag	0.8431	0.3585
LM Lag (Robust)	280.81***	0.0000

Table 6.7: Model Selection and Spatial Coefficient for Crop Land Footprint

Model	AIC	SIC
SEM with spatial fixed effects	-2090.212	-2049.062
SEM with time fixed effects	1455.634	1496.784
SEM with both spatial and time fixed effects	-2121.19	-2080.04
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic	Chi^2=11.21 (0.0821)*	
Results SEM with both spatial and time fixed effects		
λ	0.1784007 (0.0000)***	

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

Results of the model selection show that SEM with both spatial and time fixed effects has minimum AIC and SIC. Moreover, the Hausman test shows that the fixed effect model is better suitable. Hence SEM with both spatial and time fixed effect models was used to find out the coefficient to be used for spatial filtration. The spatial lambda was found to have a value of 0.1784, which is highly significant. This value of spatial lambda is used for spatial filtration.

6.2.1.2 Convergence Analysis

After finding the spatially filtered data, club convergence analysis was carried out in a cropland footprint. The estimated results are presented in table 6.8 to table 6.11. Table 6.8 presents the result of the overall sample convergence.

Table 6.8: Regression Results for Convergence in Crop Land Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-0.6972	0.0313	-22.3076

Results presented in Table 6.8 show that the convergence does not hold in the cropland footprint in the overall sample. As the value of the t-stat is -22.3076, which is less than -1.65, we reject the null hypothesis of convergence in the overall sample. Due to this result, we further tested the presence of multiple clubs in this cropland footprint of the sample countries, presented in table 6.9.

Table 6.9 shows that based on cropland footprint, the sample countries can be divided into four convergent clubs and one non-convergent group[7]. This means that the dynamics of club formation for cropland footprint are quite different from EF's. Apart from club 1 of cropland footprints which has all of its members be rich other clubs have mixed membership of the countries as far as their economic status is concerned. For example, Japan is classified into club 4 along with India and Sri Lanka, and Mali and Niger are classified into club 2 along with Australia and United Kingdom. For this dimension of EP, we have found one non-convergent group as well, although it has only one country, Argentina. This country's cropland footprints are not converging towards any club. Among the six convergent clubs, the strongest convergence occurred in club 5, which contains many less developed countries. Because for this club, the calculated value of 't' is the farthest from its critical value of -1.65.

To test whether or not these clubs can be merged into broader and bigger clubs, Phillips and Sul (2007) methodology for club emergence is applied. The results are presented in Tables 6.10 and 6.11.

[7] See appendix B for club membership.

Table 6.9: Regression Results for Crop Land Footprint Club Identification

log(t)	Club1	Club2	Club3	Club4	Club5	Club6
Coeff	5.208	-0.054	-1.445	0.841	2.313	-0.180
T-stat	4.526	-0.977	-0.703	7.061	9.970	-0.739

Table 6.10: Regression Results for Crop Land Footprint Club Mergence

log(t)	Club1+2	Club2+3	Club3+4	Club4+5	Club5+6	Club6+G~7
Coeff	-0.366	-0.032	0.490	0.255	1.033	-2.078
T-stat	-9.743	-0.494	3.979	1.957	4.358	-21.825

Results presented in Table 6.10 show that Clubs 1 and 2 and club 6 and group 7 cannot be merged, whereas other clubs can be merged. This results in four broader convergence clubs[8]. The respective t-values and members of these clubs are given in table 6.11. If initially found, clubs are compared to these final clubs. It is found that although new clubs are broader than the previously found ones, there are similarities as well. Particularly, even in new club classifications, countries of different economic statures are found to be in the same club. Moreover, Argentina is again found to be non-converging. The strongest convergence among these final clubs occurs among the developed countries of club 1.

Table 6.11: Regression Results for Final Crop Land Footprint Club Identification

log(t)	Club1	Club2	Club3	Club4
Coeff	5.208	-0.054	0.255	-0.180
T-stat	4.526	-0.977	1.957	-0.739

6.2.2 Club Convergence in Grazing Land Footprints

Grazing land footprint is the second dimension of EP for which this study has explored the presence of club convergence. First, spatial filtration of the grazing land footprint is made, and then club convergence is tested in this spatially filtered data.

[8] See appendix B for club membership.

6.2.2.1 Spatial Filtration

Before doing the spatial filtration, we need to know the type of spatial dependence in grazing land footprint. To achieve this, simple and robust LM tests are employed for the grazing land footprint data. Table 6.12 presents the results.

Table 6.12: Spatial Dependence in Grazing Land Footprint

Test	Statistic	P-Value
LM Error	76.12***	0.0000
LM Error (Robust)	186.18***	0.0000
LM Lag	0.4435	0.5054
LM Lag (Robust)	110.50***	0.0000

The table results show spatial dependence in error, which directs the use of SEM to carry out spatial filtration. To find the appropriate form of SEM, we made different specifications of SEM and found AIC and SIC for each. Table 6.13 illustrates the results.

Robust Hausman test shows that the fixed effects model is more appropriate than the random effect model. Among the various possibilities of fixed effects, the results show that AIC and SIC are minimum for SEM with both spatial and time fixed effects. Hence, this model is used to determine the spatial filtration coefficient. The coefficient of spatial error (λ) is 0.1532 for grazing land footprint, which is significant at 1%. The spatially filtered data of grazing footprint is then used to test club convergence.

6.2.2.2 Convergence Analysis

For convergence analysis, first, we tested the presence of convergence in grazing land footprint in the overall sample. The results are presented in Table 6.14, which shows that grazing land footprints are also not converging in the overall sample. This led us to proceed towards testing club convergence in grazing land footprint.

Table 6.13: Model Selection and Spatial Coefficient for Graning Land Footprint

Model	AIC	SIC
SEM with spatial fixed effects	659.0087	700.1584
SEM with time fixed effects	6977.305	7018.454
SEM with both spatial and time fixed effects	524.8319	565.9816
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=19.04 (0.0041)***
Results SEM with both spatial and time fixed effects		
λ		0.1531733 (0.0000)***

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

Table 6.14: Regression Results for Convergence in Grazing Land Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-0.2723	0.0136	-20.0308

The results of club convergence are given in Table 6.15. Results show that our sample countries are classified into two clubs regarding grazing land footprints. Most countries converge to form club 1, and only five developing countries form club two. This result shows that the environment will face a similar level of distress in the grazing land dimension among almost all countries. This probably implies that human dependence on an animal, chiefly for food, would become similar across the globe.

Table 6.15: Regression Results for Grazing Land Footprint Club Identification

log(t)	Club1	Club2
Coeff	-0.009	-0.127
T-stat	-0.348	-1.511

Table 6.16: Regression results for Grazing Land Footprint Club Mergence

log(t)	Club1+2
Coeff	-0.272
T-stat	-20.031

The possibility of margining these two convergence clubs into one is tested, and results are given in table 6.16. Results show that the calculated value of ‘t’ is -20.031. This is substantially less than the critical value of ‘t’, -1.65. Hence, we can conclude that these two clubs can’t be merged to form one broader club.

6.2.3 Club Convergence in Forest Land Footprint

After testing club convergence in cropland and grazing land footprints, cub convergence is examined in forest land footprints. The results are presented as under.

6.2.3.1 Spatial Filtration

To filter spatial dependence from forest land footprint, we first explored the nature of spatial dependence through LM tests. The results of LM tests are presented in table 6.17.

Table 6.17: Spatial Dependence in Forest Land Footprint

Test	Statistic	P-Value
LM Error	23.36***	0.0000
LM Error (Robust)	70.17***	0.0000
LM Lag	0.0429	0.8359
LM Lag (Robust)	46.85***	0.0000

Results of LM tests show that there is a spatial error in the sample countries' forest land footprint. This requires the use of SEM for spatial filtering. The appropriate form of SEM is searched for, and model selection results are presented in table 6.18.

The robust Hausman test results show that fixed effects are more appropriate than random effects. Among various fixed effects specifications, the values of AIC and SIC are minimum for SEM with both spatial and time fixed effects. This model is used for the estimation of spatial lambda. The value of spatial lambda is found to be 0.1128942, and it is significant at a 1% level of significance. This coefficient value is used for spatial filtration. Club convergence is then applied to spatially filtered forest land footprint data.

Table 6.18: Model Selection and Spatial Coefficient for Forest Land Footprint

Model	AIC	SIC
SEM with spatial fixed effects	-251.4771	-210.3274
SEM with time fixed effects	4815.722	4856.871
SEM with both spatial and time fixed effects	-321.4389	-280.2892
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic		Chi^2=19.90 (0.0029)***
Results SEM with both spatial and time fixed effects		
λ		0.1128942 (0.0000)***

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

6.2.3.2 Convergence Analysis

First of all, convergence in the overall sample is tested. Table 6.19 presents the results of convergence in the overall sample. The value of the t-stat was found to be -4.0143. This is less than -1.65. So, we also reject the null hypothesis of convergence to a single level in forest land footprint. This has led us to move and test the presence of convergence clubs. The presence of convergence club in forest land footprint is tested, and results are presented in table 6.20.

Table 6.19: Regression Results for Convergence in Spatially Filtered Forest Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-0.1995	0.0497	-4.0143

Table 6.20 shows that for forest land footprint, although there are two clubs into which our sample countries are converging in their EP, club 2 is overwhelmingly dominant[9]. About 90% of the sample countries belong to this club, and the remaining 10% of very rich countries, except Chile, are converging to club 1. This shows that environmental pressure on this dimension would be the same in most countries. This sort of finding is discouraging, especially on the part of developed countries. Because these countries can't only reduce their dependence on forest products, but at the same

[9] See appendix B for club membership.

time, they can invest in reforestation as well. The possibility of the mergence of these two clubs into one broader club is tested, and results are presented in Table 6.21.

The results indicate that they can't be merged into one larger convergence club. Hence, although there are only six countries in club one, their convergence dynamics are different enough that they can't be included in club 2 with most countries.

Table 6.20: Regression Results for Forest Land Footprint Club Identification

log(t)	Club1	Club2
Coeff	3.292	0.022
T-stat	8.414	0.337

Table 6.21: Regression Results for Forest Footprint Club Mergence

log(t)	Club1+2
Coeff	-0.199
T-stat	-4.014

6.2.4 Club Convergence in Fishing Ground Footprint

Club convergence in the fishing ground footprint is tested after finding the type of spatial dependence in the fishing ground footprint and filtering that out from the data. The following results are found regarding the existence of club convergence in it.

6.2.4.1 Spatial Filtration

LM tests were applied to fishing ground footprint data to determine the type of spatial dependence. This will enable us to use the appropriate model to estimate a spatial parameter that would be used for spatial filtration. The results of LM tests are presented in table 6.22.

Table 6.22: Spatial Dependence in Fishing Ground Footprint

Test	Statistic	P-Value
LM Error	19.67***	0.0000
LM Error (Robust)	76.70***	0.0000
LM Lag	0.0817	0.7750
LM Lag (Robust)	57.11***	0.0000

Results show that there is a presence of spatial error in the fishing ground footprint. This implies that SEM is the right specification to estimate spatial factors' role in determining fishing ground footprint. To comply with this, SEM was specified with different alternatives to search for the appropriate form of SEM. The results of the model selection are given in table 6.23.

Table 6.23: Model Selection and Spatial Coefficient for Fishing Ground Footprint

Robust Hausman test for selection of random vs. fixed effects	
Ho: difference in coefficients not systematic	Chi^2=7.85 (0.2491)
Results SEM with both spatial and time fixed effects	
λ	0.1508561 (0.000)***

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

The results of the robust Hausman test show that the random effect model is more appropriate than the fixed effect model. SEM with random effects was used to estimate spatial lambda. Its value is found to be 0.1508561. It is significant at 1%. Fishing ground footprint data was spatially filtered using this value of spatial lambda.

6.2.4.2 Convergence Analysis

After finding the spatially filtered data of fishing ground footprints club convergence test of Phillips and Sul (2007) has been applied. In doing so, convergence in the overall sample is tested first. Table 6.24 presents the results for that.

Table 6.24: Regression Results for Convergence in Fishing Ground Footprint in Overall sample

Variable	Coeff	SE	T-stat
log(t)	-0.0872	0.0414	-2.1054

The results for fishing ground footprint also show the absence of countries' global convergence to a single fishing ground footprint level. This has led us to test the club convergence hypothesis in the data. Table 6.24 shows the results of the club convergence test.

Table 6.24 shows that based on fishing ground footprints, the sample countries of the present study can be divided into three different clubs[10]. If we look at the composition of the clubs, we find that countries' environmental performance in fishing ground footprint has little to do with their economic performance. Each club has a combination of countries with very different economic statures. For example, Belgium and Switzerland are classified along with Congo and Uganda in club 1. Denmark is classified in club 2 with Sri Lanka; finally, countries like Australia and Italy are classified with Nigeria and Zimbabwe in club 3.

We have tested the possibility of merging these clubs to make broader clubs. The results are presented in table 6.25. This table shows that these clubs cannot be merged. Hence, the initial classification of the countries into different clubs is final.

Table 6.24: Regression Results for Fishing Ground Footprint Club Identification

log(t)	Club1	Club2	Club3
Coeff	0.021	0.431	0.031
T-stat	0.529	5.868	0.546

Table 6.25: Regression Results for Fishing Ground Footprint Club Mergence

log(t)	Club1+2	Club2+3
Coeff	-0.378	-0.187
T-stat	-15.287	-4.276

6.2.5 Club Convergence in Built-Up Land Footprint

A built-up land footprint is a penultimate dimension in which club convergence is tested. For this, too, first of all, spatial filtration is made then convergence analyses are carried out.

[10] See appendix B for club membership.

6.2.5.1 Spatial Filtration

As usual, we have employed LM tests to find the true type of spatial dependence in built-up land footprint. The results of LM tests are presented in table 6.26.

Table 6.26: Spatial Dependence in Built-Up Land Footprint

Test	Statistic	P-Value
LM Error	95.03***	0.0000
LM Error (Robust)	232.20***	0.0000
LM Lag	0.0074	0.9313
LM Lag (Robust)	137.10***	0.0000

Results show that there is a presence of spatial error in the built-up land footprint. Hence, SEM should be used to find out the spatial dependence coefficient. To do so, SEM with different alternatives has been specified. The results of the model selection exercise are presented in table 6.27.

The results of robust Hausman show that the random effect model is more appropriate than the fixed effects. Hence, SEM with random effects is used to estimate spatial lambda. Its value is 0.2103309, which is significant at 1%. This value of the spatial dependence parameter is used for spatial filtration of built-up land footprint.

Table 6.27: Model Selection and Spatial Coefficient for Built Up Land Footprint

Robust Hausman test for selection of random vs. fixed effects	
Ho: difference in coefficients not systematic	Chi^2=3.95 (0.6834)
Results SEM with both spatial and time fixed effects	
λ	0.2103309 (0.000)***

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

6.2.5.2 Convergence Analysis

Once spatially filtered data of built-up land footprint is found, convergence analyses are carried out. First, convergence in the overall sample is tested, and results are given in table 6.28.

Table 6.28: Regression Results for Convergence in Built-Up Land Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-0.5234	0.0228	-22.9660

The calculated value is -22.9660, substantially less than the critical value of 't', equaling -1.65. This has led us to reject the null hypothesis that built-up land footprint converges in the overall sample. Upon finding this absence of convergence in the overall sample, we have further tested the presence of club convergence in built-up footprints. Table 6.29 presents the results. Table 6.29 shows that based on the built-up land footprint sample, the countries of the present study can be divided into three convergence clubs[11]. If we look at the membership of the clubs, we can see that the economic stature of the countries has little to do with their EP in the dimension of built-up land footprint.

For example, highly developed countries like Germany and Belgium are classified with least developed countries like Nepal and Niger in club 1. In club 2, very high-income countries like France and The United States of America are classified with low-income countries like Burkina Faso and Pakistan. This phenomenon is present in club 3 as well. In this club, highly developed countries Japan and Switzerland are classified with least developed countries like the Central African Republic and Burundi. As far as the strength of the convergence process is concerned, it is strongest in club 3, as we have the highest value of 't' for this club.

Table 6.29: Regression Results for Built-Up Land Footprint Club Identification

log(t)	Club1	Club2	Club3
Coeff	0.053	0.051	0.202
T-stat	0.918	0.809	14.457

The possible merging of these three clubs of countries into fewer clubs is tested, and table 6.30 presents the results. This can be seen that none of the two clubs can be merged to form a new and broader club.

[11] See Appendix B for club membership.

Table 6.30: Regression Results for Built-up Land Footprint Club Mergence

log(t)	Club1+2	Club2+3
Coeff	-0.187	-0.271
T-stat	-3.560	-7.472

6.2.6 Club Convergence in CO_2 Footprint

The final dimension of the EP of the countries in which club convergence is tested for CO_2 footprint. The results are presented as under.

6.2.6.1 Spatial Filtration

To carry out the club convergence analysis, spatial filtration was needed. For spatial filtration, the knowledge of the exact type of spatial dependence was the requirement. To find that this study employed LM tests. The results of which are presented in table 6.31.

Table 6.31: Spatial Dependence in CO_2 Land Footprint

Test	Statistic	P-Value
LM Error	74.91***	0.0000
LM Error (Robust)	127.47***	0.0000
LM Lag	0.63	0.4279
LM Lag (Robust)	53.20***	0.0000

Table 6.32: Model Selection and Spatial Coefficient for CO_2 Footprint

Model	AIC	SIC
SEM with spatial fixed effects	-310.7349	-269.7623
SEM with time fixed effects	4083.605	4124.755
SEM with both spatial and time fixed effects	-478.3461	-437.1963
Robust Hausman test for selection of random vs. fixed effects		
Ho: difference in coefficients not systematic	Chi^2=17.61 (0.0073)***	
Results SEM with both spatial and time fixed effects		
λ	0.2910498 (0.0000)***	

*Note: ***, **, and * represent 1%, 5%, and 10% significance, respectively. P-Values are given in parentheses.*

The results of LM tests show spatial dependence of countries in error. Hence, SEM is the right model to determine the spatial dependence coefficient. We have specified

SEM with different alternatives to find the right form of SEM. The results of this model selection are presented in table 6.32.

Results show that the fixed effect model is more appropriate, and among fixed effects, a model with both time and spatial fixed effects has minimum AIC and SIC. So, SEM with both spatial and time fixed effects was used to estimate the coefficient of spatial dependence. The value of spatial lambda is found to be 0.2910498, and it is highly significant. This value of spatial lambda was used to carry out spatial filtration.

6.2.6.2 Convergence Analysis

After finding spatially filtered data on CO_2 footprint, convergence analyses are made using this data. First, the possibility of convergence of CO_2 footprint to a single level is tested, and results are presented in table 6.33.

Table 6.33 Regression Results for Convergence CO_2 Footprint in Overall Sample

Variable	Coeff	SE	T-stat
log(t)	-3.5801	0.1059	-33.8146

Results show that the calculated value of 't' is -33.8146. This is less than the critical value of 't', equaling -1.65. This indicates the absence of convergence of the CO_2 footprint of the countries to any single level. After finding this present study has tested the presence of club convergence in the CO_2 footprint of the countries. The results are presented in table 6.34.

The results in table 6.34 indicate seven convergent clubs for CO_2 footprint and one divergent group[12]. Except for clubs 2 and 5, all other clubs have fewer than five members. Although this club formation in CO_2 is sparse, one pattern is clear: countries with similar income levels are in the same club with few exceptions. Hence, economic activity appears to be a primary determinant of the CO_2 footprints of the countries.

[12] See appendix B for club membership.

Table 6.34: Regression Results for CO_2 Footprint Club Identification

log(t)	Club1	Club2	Club3	Club4	Club5	Club6	Club7	Group 8
Coeff	-0.159	1.667	1.004	0.351	0.738	2.355	1.143	-2.787
T-stat	-1.531	159.647	4.194	16.602	15.548	7.332	28.176	-6.968

Apart from these convergent clubs, three countries are in the divergent group. This means that these countries are neither converging to any of the seven convergent clubs nor their CO_2 footprints are converging to another similar level to form their club.

Since the initial findings on club convergence in CO_2 footprints of the countries show a large number of clubs with rather a small number of countries in many of them, the possibility of merging these small clubs into broader clubs is tested. The results of these merging of clubs are presented in table 6.35.

Table 6.35: Regression Results for CO_2 Footprint Club Mergence

log(t)	Club1+2	Club2+3	Club3+4	Club4+5	Club5+6	Club6+7	Club7+G~8
Coeff	1.321	2.666	0.347	-0.397	0.478	-2.389	-0.767
T-stat	52.946	93.556	1.195	-5.487	5.360	-21.267	-15.113

Table 6.36: Regression Results for Final CO_2 Footprint Club Identification

log(t)	Club1	Club2	Club3	Group 4
Coeff	2.300	2.355	1.143	-2.787
T-stat	1.043	7.332	28.176	-6.968

The results in Table 6.35 show that these initial seven convergent clubs and one divergent group can be merged into three convergent clubs and one divergent group. This final club classification is shown in table 6.36[13].

As expected, many sparse clubs can be merged into a few broader clubs. Specifically, seven convergent clubs can be merged into three broader convergent clubs. Although

[13] See appendix B for club membership.

the existence of multiple convergence clubs in CO_2 of the countries was verified, club one is overwhelmingly prominent as it contains close to 90% of the countries. Hence, we can conclude that once spatial factors are controlled, almost all countries will have the same level of EP in this important dimension.

6.3 Conclusion

Chapter 5 covered the analysis of convergence in overall EP and its components using a distribution approach which revealed that the EP of the countries is not converging to any single level. Instead, countries were found to be to multiple equilibriums forming different clubs. However, through the distribution approach, it is impossible to find convergence of specific countries to a specific club. This chapter aimed to cope with this issue using Phillips and Sul (2007) approach. Before applying convergence club methodology in this chapter, we first made spatial filtration of the data, and club convergence was then tested using this spatially filtered data. The estimated results revealed two broader clubs in the case of overall EP. Mostly, countries with the same standard of living are also members of the same club, which shows that economic activities are one of the primary determinants of ED.

The disaggregated analysis of convergence in EP shows four different convergence clubs in the case of cropland footprint. Cropland footprints are not found to be affected by the economic affluence of the countries, as most of the cropland footprint clubs have countries with different economic statuses. In the case of grazing land footprint and forest land footprint, countries converge into two clubs. However, in both cases, one club overwhelmingly dominates the other. On the other hand, in the case of fish ground footprint, there are three clubs, each of which is respectable. These clubs' formation can also not be explained by the economic might of the countries. The results for built-up land footprints are very similar to fishing ground footprints. Lastly, for CO_2 footprints, countries are also converging into three different clubs. But here again, most of the countries join one club. This shows that our sample countries are converging to an almost similar level in this important dimension of EP.

CHAPTER 7

CONCLUSION AND POLICY RECOMMENDATIONS

This chapter presents key insights extracted from the study's findings, accompanied by policy recommendations derived from these insights.

7.1 Conclusion

Existing empirical insights on the global EP have four main limitations. Firstly, past studies have used production-based EPI instead of consumption-based EPI. In contrast, due to globalization and increased trade among countries, production and consumption now vary substantially; hence, consumption-based EPIs are conceptually more accurate to be used. Secondly, past studies ignored the role of spatial factors in the determination of EP of the countries, which become more important due to increased globalization, trade, and improved information technology. Thirdly, most of the existing studies have used uni-dimensional EPI, mostly CO_2, which does not capture EP at its full length. Such uni-dimensional measures can only partially capture the EP ignoring important dimensions of EP, for example, natural resource utilization compared to their regenerative capacity. Lastly, there are different approaches to testing convergence across countries, with each having its pros and cons; however, none of the received studies on the subject has used all of them in the analysis of convergence in EP.

The motivation for carrying out this study is to fill these presented gaps in the literature. To overcome the limitation of using uni-dimensional measures as EPI, the present study has used comprehensive EF as EPI, which covers six different dimensions. Similarly, instead of production, this study used consumption EF. The use of consumption EF allocates environmental degradation to the countries where actual consumption is taking place instead of producing such goods and services. This makes our EPI reflect the EP of the countries more accurately. Moreover, this study utilizes spatial econometric techniques to capture the role of spatial factors in convergence analysis. Finally, this study utilizes different approaches to convergence together, intending to leave no blind spot.

This study first explored spatial dependence in EP using Moran's I to explore β-convergence in EP. After finding the evidence of spatial dependence, the appropriate spatial model, as suggested by the model selection procedure, was used to test β-convergence in EP. β-convergence was tested both for EP at an aggregate level and at a disaggregate level to capture EP of the countries in different dimensions of the environment. For σ-convergence, present study used intra-distribution dynamics approach by utilizing stochastic kernel and ergodic distribution tools. Although, the intra-distribution dynamics approach can reveal bimodality and multimodality in the data (or the presence of different clubs), the limitation of the distribution approach is that it is uninformative regarding the cross sections that form these clubs. This means that in the present case, it does not inform about the names of the countries in different clubs. To overcome this limitation, the present study used Phillips and Sul (2007) approach to study club convergence in the EP of the countries.

Moran's I results showed positive spatial autocorrelation at aggregate and disaggregated levels, implying that neighboring countries tend to have similar EP. This finding calls for the need to use spatial econometric methods to analyze convergence in EP. Using such methods, the results of β-convergence confirm the existence of convergence at aggregate and disaggregate levels of EP. At the aggregate level, physical capital was found to degrade the environment directly. Population growth was found to improve the environment through its spillover effect. Similarly, human capital was found to harm the environment directly while it improves the environment through its spillover effect.

The estimated results of the disaggregated analysis of EP indicate that for cropland footprint, physical and human capitals are significant determinants. Physical capital has a direct positive effect on cropland footprint, while human capital has a direct negative and positive spillover effect. For grazing land footprint, the population growth rate has positive direct and negative spillover effects. Human capital was found to have a negative spillover effect. Physical capital was found to positively impact forest land footprint, while the population growth rate negatively affected forest land footprint. No significant variable except the positive spatial error coefficient was found for the fishing ground footprint. Physical capital and spatial error coefficients positively affected the built-up footprint. For CO_2 footprint, physical capital, population growth rate, human capital, and urbanization are found to increase it directly. Regarding the spillover effect, physical capital was found to have a positive effect, while urbanization has a negative impact.

Like β-convergence, results of the distribution approaches have also shown that the spatial factors are a significant determinant of the EP of the countries under consideration both at aggregate and disaggregate levels. We conditioned our data for spatial factors and tested convergence using the distribution approach. Our estimated results show the existence of bimodality at an aggregate level where countries form two clubs, one at the lower level of ED and the other at a higher level of ED. For the disaggregate level, the estimated results indicate the existence of bimodality for cropland footprint and built-up land footprint. For CO_2 footprint, persistence was found to exist. This study has found support for convergence for other components of EF.

Results of the club convergence methodology of Phillips and Sul (2007) revealed members of the clubs. The results revealed that in overall EP, countries form two broader clubs. Mostly, countries with the same standard of living are members of the same club. This shows that economic activities are one of the primary determinants of ED. The disaggregated analysis of convergence in EP shows four different convergence clubs for cropland footprint. Cropland footprints seem to be affected little by the economic affluence of the countries, as most of the clubs have countries with different economic statuses.

Regarding grazing land footprint, although two clubs were found, one has more than 90% of the country. So, in the grazing land footprint, most sample countries seem to converge to an almost similar level. Similar results were found for forest land footprints also.

In fishing ground footprints, there are three clubs, each of which is of respectable size. The membership of these clubs seems to be affected little by the countries' standard of living. The results for built-up land footprints are similar to those of fishing ground footprints. Lastly, for CO_2 footprints, countries are converging into three different clubs, with most of the countries joining one club.

7.2 Policy Recommendations

Based on our findings, the following are some policy implications that may direct the relevant authorities to take action to improve the EP of the countries.

- This study found the existence of convergence in the EP of the countries. However, this convergence is not taking place at any single level. This is rather taking place in different clubs. This may be due to differences in resource endowments, available technology, and socio-economic determinants (such as GDP per capita, quality of human capital, work ethics, and cultural habits) at the club level. Hence, there is a need to have a differentiated set of policies at the club level. These members of the same clubs will be better able to fight against the environmental challenge collectively.
- This study has found a strong positive spatial correlation in the EP of the countries under consideration. Hence, there is a need to improve cross-border communication and cooperation among countries to enhance the spatial spillover of clean technology and thereby improve the environment. This improved cross-border communication will enable the policymakers of the different countries to share their knowledge and experience in forming environmental policies in their respective countries.
- The direct effect of human capital is found to be positive on the ED of the country. This suggests that growth in the country's human capital benefits the development of production technology more than the development of abatement technology. Hence, there is a need to attract educated and skilled human resources to develop the abatement technology sector. More public spending and tax incentives will enable this sector to be economically more sound and thereby attract better human resources by offering them better compensations.

- This study found that convergence behavior is different for different dimensions of EP, which implies that each dimension of EP is affected differently by different factors. Such a finding necessitates formulating a differentiated set of policies for each dimension. Hence, while devising environmental policy, policymakers should carefully chalk out initiatives specifically targeting the needful in each dimension.

7.3 Limitations of the Study and Suggestions for Future Research

In convention to previous literature in spatial econometrics this study has also modeled the spatial dependence among countries using fixed spatial weight matrices. Recent contributions in spatial panel econometrics by Lee and Yu (2012), Wang and Yu (2015) and Han and Lee (2016) allow the spatial dependence among the spatial units to be captured through time varying spatial weight matrices. Future research on convergence in EP may be carried out using these time varying spatial weight matrices. The use of time varying spatial weight matrices will enable us to capture the change in spatial dependence over time which may be occurring due to change in the production technologies and economic structure of the countries. Another, limitation of current study is, it did not explore the determinants of clubs membership. Hence, we were unable to find why different countries are getting together to form clubs. Future studies may be carried out to accomplish this task.

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Appendix A: List of the Countries

S.No.	Name of the Country	S.No.	Name of the Country
1	Albania	45	Italy
2	Algeria	46	Jamaica
3	Argentina	47	Japan
4	Australia	48	Jordan
5	Austria	49	Kenya
6	Belgium	50	Republic of Korea
7	Benin	51	Luxembourg
8	Bolivia	52	Madagascar
9	Botswana	53	Malaysia
10	Brazil	54	Mali
11	Bulgaria	55	Malta
12	Burkina Faso	56	Mauritania
13	Burundi	57	Mauritius
14	Côte d'Ivoire	58	Mexico
15	Cameroon	59	Morocco
16	Canada	60	Nepal
17	Central African Republic	61	Netherlands
18	Chile	62	New Zealand
19	China	63	Nicaragua
20	Colombia	64	Niger
21	Congo	65	Nigeria
22	Costa Rica	66	Norway
23	Cyprus	67	Pakistan
24	Denmark	68	Panama
25	Dominican Republic	69	Paraguay
26	Ecuador	70	Peru
27	Egypt	71	Philippines
28	El Salvador	72	Portugal
29	Eswatini	73	Rwanda
30	Fiji	74	Senegal
31	Finland	75	South Africa
32	France	76	Spain
33	Gabon	77	Sri Lanka
34	Gambia	78	Sweden
35	Germany	79	Switzerland
36	Ghana	80	Thailand
37	Greece	81	Togo
38	Guatemala	82	Tunisia
39	Honduras	83	Turkey
40	India	84	Uganda
41	Indonesia	85	United Kingdom
42	Iran	86	United States of America
43	Ireland	87	Uruguay
44	Israel	88	Zimbabwe

Appendix B: Club Membership of Different Convergence Clubs

Appendix B1: Club Membership at Aggregate Level of Environmental Performance

Club 1 Membership (74)
Albania, Algeria, Argentina, Australia, Austria, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Côte d'Ivoire, Cameroon, Canada, Chile, China, Colombia, Congo, Costa Rica, Cyprus, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Eswatini, Fiji, Finland, France, Gabon, Germany, Ghana, Greece, Guatemala, Honduras, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Republic of Korea, Luxembourg, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Morocco, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Panama, Paraguay, Peru, Portugal, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States of America, Uruguay.
Club 2 Membership (14)
Burkina Faso, Burundi, Central African Republic, Gambia, Kenya, Madagascar, Nepal, Pakistan, Philippines, Rwanda, Senegal, Togo, Uganda, Zimbabwe.

Appendix B2: Club Membership in Crop Land Footprint (Initial Clubs)

Club 1 Membership (9)
Austria, Belgium, Denmark, Greece, Luxembourg, Netherlands, Norway, Sweden, United States of America
Club 2 Membership (36)
Albania, Australia, Benin, Bolivia, Brazil, Côte d'Ivoire, Cameroon, Canada, Chile, China, Colombia, El Salvador, Fiji, France, Germany, Ghana, Indonesia, Israel, Italy, Jordan, Republic of Korea, Malaysia, Mali, Nepal, Niger, Panama, Paraguay, Peru, Portugal, Rwanda, Spain, Switzerland, Thailand, Tunisia, Turkey, United Kingdom
Club 3 Membership (2)
Burkina Faso, Nigeria
Club 4 Membership (11)
Botswana, Central African Republic, Costa Rica, Dominican Republic, India, Japan, Mexico, Nicaragua, Philippines, Sri Lanka, Togo
Club 5 Membership (5)
Burundi, Congo, Kenya, Pakistan, Uganda
Club 6 Membership (2)
Madagascar, Zimbabwe
Not Convergent Group 7 (1)
Argentina

Appendix B3: Club Membership in Crop Land Footprint (Final Clubs)

Club 1 Membership (9)
Austria, Belgium, Denmark, Greece, Luxembourg, Netherlands, Norway, Sweden, United States of America
Club 2 Membership (38)
Albania, Australia, Benin, Bolivia, Brazil, Burkina Faso, Côte d'Ivoire, Cameroon, Canada, Chile, China, Colombia, El Salvador, Fiji, France, Germany, Ghana, Indonesia, Israel, Italy, Jordan, Republic of Korea, Malaysia, Mali, Nepal, Niger,

Nigeria, Panama, Paraguay, Peru, Portugal, Rwanda, Spain, Switzerland, Thailand, Tunisia, Turkey, United Kingdom
Club 3 Membership (16)
Botswana, Burundi, Central African Republic, Congo, Costa Rica, Dominican Republic, India, Japan, Kenya, Mexico, Nicaragua, Pakistan, Philippines, Sri Lanka, Togo, Uganda
Club 4 Membership (2)
Madagascar, Zimbabwe
Not Convergent Group 5 Membership (1)
Argentina

Appendix B4: Club Membership in Grazing Land Footprint

Club 1 Membership (61)
Albania, Argentina, Australia, Austria, Belgium, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Côte d'Ivoire, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Congo, Costa Rica, Denmark, Dominican Republic, El Salvador, Fiji, France, Germany, Ghana, Greece, Indonesia, Israel, Italy, Japan, Jordan, Kenya, Republic of Korea, Luxembourg, Madagascar, Malaysia, Mali, Mexico, Nepal, Netherlands, Nicaragua, Niger, Nigeria, Norway, Panama, Paraguay, Peru, Philippines, Portugal, Rwanda, Spain, Sweden, Switzerland, Togo, Tunisia, Turkey, Uganda, United Kingdom, United States of America, Zimbabwe.
Club 2 Membership (5)
Benin, India, Pakistan, Sri Lanka, Thailand.

Appendix B5: Club Membership in Forest Land Footprint

Club 1 Membership (6)
Austria, Canada, Chile, Luxembourg, Norway, Sweden
Club 2 Membership (60)
Albania, Argentina, Australia, Belgium, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Côte d'Ivoire, Cameroon, Central African Republic, China, Colombia, Congo, Costa Rica, Denmark, Dominican Republic, El Salvador, Fiji, France, Germany, Ghana, Greece, India, Indonesia, Israel, Italy, Japan, Jordan, Kenya, Republic of Korea, Madagascar, Malaysia, Mali, Mexico, Nepal, Netherlands, Nicaragua, Niger, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Rwanda, Spain, Sri Lanka, Switzerland, Thailand, Togo, Tunisia, Turkey, Uganda, United Kingdom, United States of America, Zimbabwe

Appendix B6: Club Membership in Fishing Ground Footprint

Club 1 Membership (13)
Belgium, Congo, Fiji, France, Germany, Israel, Norway, Philippines, Portugal, Sweden, Switzerland, Uganda, United Kingdom
Club 2 Membership (7)
Denmark, Indonesia, the Republic of Korea, Malaysia, Panama, Peru, Sri Lanka
Club 3 Membership (46)
Albania, Argentina, Australia, Austria, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Côte d'Ivoire, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Costa Rica, Dominican Republic, El Salvador, Ghana, Greece, India, Italy, Japan, Jordan, Kenya, Luxembourg, Madagascar, Mali, Mexico, Nepal,

Netherlands, Nicaragua, Niger, Nigeria, Pakistan, Paraguay, Rwanda, Spain, Thailand, Togo, Tunisia, Turkey, United States of America, Zimbabwe

Appendix B7: Club Membership in Built-Up Land Footprint

Club 1 Membership (16)
Argentina, Belgium, Brazil, Côte d'Ivoire, Cameroon, Chile, China, Colombia, Denmark, Germany, Ghana, Jordan, Nepal, Niger, Paraguay, and Peru.
Club 2 Membership (30)
Albania, Australia, Austria, Benin, Bolivia, Burkina Faso, Canada, Costa Rica, Dominican Republic, France, Greece, India, Indonesia, Kenya, Luxembourg, Madagascar, Malaysia, Mali, Netherlands, Nicaragua, Nigeria, Pakistan, Philippines, Rwanda, Sri Lanka, Sweden, Thailand, Togo, United Kingdom, United States of America.
Club 3 Membership (20)
Botswana, Burundi, Central African Republic, Congo, El Salvador, Fiji, Israel, Italy, Japan, Republic of Korea, Mexico, Norway, Panama, Portugal, Spain, Switzerland, Tunisia, Turkey, Uganda, Zimbabwe.

Appendix B8: Club Membership in CO_2 Footprint (Initial)

Club 1 Membership (2)
Australia, Luxembourg
Club 2 Membership (38)
Albania, Argentina, Austria, Belgium, Bolivia, Botswana, Brazil, Canada, Chile, China, Colombia, Costa Rica, Denmark, El Salvador, France, Germany, Greece, India, Israel, Italy, Japan, Republic of Korea, Malaysia, Mexico, Netherlands, Norway, Panama, Peru, Portugal, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States of America
Club 3 Membership (4)
Congo, Dominican Republic, Ghana, Jordan
Club 4 Membership (4)
Benin, Fiji, Indonesia, Nicaragua,
Club 5 Membership (10)
Côte d'Ivoire, Cameroon, Kenya, Mali, Nigeria, Pakistan, Paraguay, Philippines, Togo, Zimbabwe.
Club 6 Membership (3)
Burkina Faso, Uganda, Nepal.
Club 7 Membership (2)
Burundi, Madagascar
Not convergent Group 8 Membership (3)
Central African Republic, Niger, Rwanda.

Appendix B9: Club Membership in CO_2 Footprint (Final)

Club 1 Membership (58)
Albania, Argentina, Australia, Austria, Belgium, Benin, Bolivia, Botswana, Brazil, Côte d'Ivoire, Cameroon, Canada, Chile, China, Colombia, Congo, Costa Rica, Denmark, Dominican Republic, El Salvador, Fiji, France, Germany, Ghana, Greece, India, Indonesia, Israel, Italy, Japan, Jordan, Kenya, Republic of Korea, Luxembourg, Malaysia, Mexico,

Netherlands, Nicaragua, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Togo, Tunisia, Turkey, United Kingdom, United States of America, Zimbabwe
Club 2 Membership (3)
Burkina Faso, Nepal, Uganda
Club 3 Membership (2)
Burundi, Madagascar
Club 4 Membership (3)
Central African Republic, Niger, Rwanda.

Appendix C: Summary of the Studies on Convergence in Environmental Performance

Study	Period	Scope	EPI	Finding
		β-Convergence in Environmental Performance		
Strazicich and List (2003)	1960-1997	21 industrialized countries	CO_2	Conditional convergence
Nguyen Van (2005)	1966-1996	26 high-emission countries	CO_2	Convergence for cross sectional data and insignificant results for panel data
Brock and Taylor (2010)	1960-1998	OECD countries	CO_2	Absolute and Conditional β-convergence
Stegman and McKibbin (2005)	1900-1999	OECD countries and a global sample	CO_2	Convergence for OECD countries and insignificant results for global sample
Jobert *et al.* (2010)	1971-2006	European countries	CO_2	Absolute and Conditional β-convergence
Brannlund and Karimu (2018)	1971-2008	94 developed and developing countries	Environmental Performance Index	Conditional β-convergence
Brannlund et al. (2015)	1990-2008	Swedish manufacturing sectors	CO_2	Convergence
Acar and Lindmark (2017)	1973-2010	OECD countries	CO_2	Convergence
Wang and Zhang (2014)	1996-2010	Six sectors of China	CO_2	Unconditional β-convergence
Li and Lin (2013)	1971-2008	110 countries	CO_2	Conditional convergence
Tiwari and Mishra (2017)	1972-2010	Asian countries	CO_2	Convergence
Yu et al. (2018)	1995-2015	Industrial sectors of China	CO_2	Conditional convergence
		σ-Convergence in Environmental Performance		
Aldy (2006)	1960-2000	23 OECD countries and the other global sample of 88 countries	CO_2	Convergence for OECD countries and divergence for global sample

Stegman and McKibbin (2005)	1950-1999	26 OECD countries and a global sample of 97 countries	CO_2	Convergence for OECD countries and divergence for global sample
Nguyen Van (2005)	1966-1996	26 high-emission countries	CO_2	Convergence
Li et al. (2017)	2000-2010.	Prefectures of the Yangtze River delta in China	CO_2	Convergence
σ-Convergence in Environmental Performance using Intra-distribution Dynamics Approach				
Stegman (2005)	1950-1999	97countries	CO_2	Convergence for developed countries and no convergence for whole sample
Ezcurra (2007)	1960-1999	87 countries	CO_2	Convergence
Criado and Grether (2011)	1960-2002	166 countries	CO_2	Convergence in EU countries while divergence in the world
Tiwari and Mishra (2017)	1972-2010	Asian countries	CO_2	Convergence
σ-Convergence in Environmental Performance using Club Convergence Approach				
Panopoulou and Pantelidis (2009)	1960-2003	128 countries	CO_2	Club Convergence for groups (e.g. OECD, EMU etc. but not in developing countries) and divergence for global sample
by Camarero *et al.* (2013)	1960-2008.	OECD countries	CO_2	Club Convergence
Ulucak and Apergis (2018)	1961-2013	European Union countries	Ecological Footprint	Club Convergence
Herrerias (2013)	1980-2009	162 Countries	CO_2	Club Convergence
Emir *et al.* (2019)	1990-2016	28 European Union countries	CO_2	Club Convergence
Wang et al. (2014)	1995-2011	Chinese Provinces	CO_2	Club Convergence
Payne and Apergis (2021)	1972-2014	65 Developing Countries	CO_2	Club Convergence
Ulucak et al. (2020)	1961-2014	Sub-Saharan African countries	Ecological Footprint	Club Convergence
Stochastic Convergence in Environmental Performance				
List (1999)	1929-1994	USA	SO_2 and NO_2	Convergence

Heil and Selden (1999)	1950-1992	135 countries	CO_2	Convergence
McKitrick and Strazicich (2005)	1950-2000	121 countries	CO_2	Convergence in global sample and no convergence for 26 individual countries
Barassi *et al.* (2008)	1950-2002	21 OECD countries	CO_2	No Convergence
Romero-Avila (2008)	1960-2002	OECD countries	CO_2	Divergence without structural breaks and convergence with structural breaks
Lee and Chang (2008)	1960-2000	21 OECD countries	CO_2	Divergence
Chang and Lee (2008)	1960-2000	21 OECD countries	CO_2	Convergence
Westerlund and Basher (2008)	1870-2002	16 OECD countries and 28 developed and developing countries	CO_2	Convergence
Yavuz and Yilanci (2013)	1960-2005	G-7 countries	CO_2	Convergence for one regime and divergence for other regime
Camarero *et al.* (2008)	1971-2002	OECD countries	CO_2	Mixed results
Li et al. (2017)	2000-2010.	Prefectures of the Yangtze River delta in China	CO_2	Convergence
Ahmed et al. (2016)	1960-2010	162 countries	CO_2	Divergence for most countries
Acaravci and Erdogan (2016)	1960-2011	Seven regions from the world	CO_2	Convergence with structural breaks
Hao et al. (2015)	1995-2011	29 provinces of China	CO_2	Convergence
Tiwari et al. (2016)	1960-2009	35 Sub-Saharan African countries	CO_2	Convergence with structural breaks
Christidou et al. (2013)	1870-2006	Global sample of 35 countries	CO_2	Convergence
Baldwin and Wing (2013)	1963-2008	States of USA	CO_2	Convergence
Bilgili *et al.* (2019)	1961-2014	60 countries	Ecological Footprint	Convergence
Cai and Wu (2019)	1960-2014	OECD countries and emerging economies	CO_2	Mixed Results
Erdogan and Acaravci	1960-2014	28 OECD countries	CO_2	Convergence

(2019)				
Solarin and Tiwari (2020)	1850-2005	OECD countries	SO2	Convergence
Yilanci, V., and Pata (2020)	1961-2016	ASEAN-5 countries	Ecological Footprint	Convergence in one regime and divergence in other
Spatial Convergence in Environmental Performance				
Li et al. (2017)	2000-2010.	Prefectures of the Yangtze River delta in China	CO_2	Spatial β-Convergence
Huang and Meng (2013)	1985-2008	Urban China	CO_2	Spatial β-Convergence
Evans and Kim (2015)	1972-2009	Asian Countries	CO_2	Spatial Convergence
Rios and Gianmoena (2018)	1970-2014	141 countries	CO_2	Spatial beta convergence and spatial club convergence
Behboudi et al. (2017)	1970-2010	MENA (Middle East and North Africa) countries	CO_2	Spatial β-Convergence
Xu *et al.* (2020)	2005-2106	Chinese regions	Environmental efficiency index based on NO_x, PM2.5, SO2, waste water and solid wastes	Spatial conditional and unconditional β-Convergence
Tang *et al.* (2020)	2003-2016	262 Chinese cities	CO_2	Spatial club convergence
Cui *et al.* (2021)	2004-2020	China	NO2	Spatial conditional and unconditional β-Convergence

Source: Author's own review of literature