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KEYWORDS	ABSTRACT
Spatial Durbin model; Greenhouse gases; Human development index; Geographically weighted regression; Developing countries	Increasing carbon dioxide and air pollution emitted by human activities are the two greatest impediments to human development worldwide, particularly in developing economies. This study examines the spatial effects of CO ₂ emissions and air pollution on human development index in 112 developing nations. Consequently, the spatial econometric models of global and local Moran's I, spatial Durbin model, and geographically weighted regression are utilised in this study. The results revealed significant spatial associations in terms of CO ₂ emissions, air pollution, and HDI. The empirical findings of SDM indicate that CO ₂ emissions have a positive local and spillover effects on HDI, whereas air pollution has a negative local and spillover effects on HDI. In addition, GWR analysis revealed that the coefficient magnitude of CO ₂ emissions and air pollution differs between developing nations. The positive effect of CO ₂ emissions is found to be highly sensitive in South American and African developing economies, while the negative effect of air pollution is found to be highly sensitive in a number of Asian and African developing nations. Based on these findings, this study provides policy recommendations to governments in order to reduce CO ₂ emissions and air pollution to improve HDI by prioritising the most vulnerable areas.
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Introduction

Over the past few decades, the world's total energy production and consumption have remarkably increased which put magnificent pressure on the ecological environment (Bilgen, 2014; Khan et al., 2021). The greenhouse gases (GHGs) and climate change such as carbon dioxide (CO₂) emissions, ambient temperature, air pollution, energy consumption, and wind pressure have been considered to be significant concerns throughout the globe (Den Elzen, Olivier et al., 2013; Enzler & Diekmann, 2019; Ramanathan & Feng, 2009). Among these, CO₂ emissions is the most influential factor of GHG that play a pivotal role to determine economic growth and human development (Adekoya et al., 2021; Asongu & Odhiambo, 2020; Madaleno & Nogueira, 2023; Mohammed et al., 2019). The excessive burning of fossil energy sources produced a huge quantity of CO₂ in the atmosphere which becomes the primary cause of the GHG effects (Flower & Sanjayan, 2007; Hanif, 2018; Lin & Xu, 2020). The contribution of CO₂ emissions to the total GHG emissions is about 60 percent worldwide which ranks at the top among all the environmental attributes in the planet (Bedir & Yilmaz, 2016). Such a high contribution towards GHG significantly influenced the human development of any country (Kutlu & Wang, 2021). Consequently, this intends policymakers to focus on the relationship between human development and CO₂ emissions. Because the first human development report (HDR) of the United Nations development program (UNDP) states that “people are the real asset of the nations. The prime objective of human development is to provide a sustainable environment for residents to live long and healthy”.

Climate change is characterised as one of the key components of sustainable development goals (SDGs) founded by the UNDP in 2015. The main objective of **SDG 13 “take urgent action to combat climate change and its impacts”** is to promote climate resilience, mitigate GHG emissions and adaptive capacity (UNDP, 2015a). The dramatic increase in energy-related CO₂ emissions by 6 percent in year 2021 (reaching the highest level ever) has significantly boosted the air pollution worldwide (UNDP, 2015a, 2015b). CO₂ emissions is considered a major subset of air pollutants including particulate matter, nitrogen oxide, sulfur dioxide, and volatile organic compounds (Jacobson, 2010; Phan et al., 2021). These air pollutants encompass various harmful substances from different sources, including burning fossil fuels which affect human health/wellbeing and environment (Ghorani-Azam et al., 2016; Kampa & Castanas, 2008; Mabahwi et al., 2014). Various wellbeing indicators can be affected by air pollution among which human development index (HDI) is most commonly used. Air pollution has an inverse impact on HDI in the form of life expectancy, particularly in low- and middle-income countries (Gürlük, 2009; Hill et al., 2019; Wang et al., 2013). In comparison with developed economies, the ambient air pollution is a great problem with developing nations. Based on the importance of SDG 13, the contribution of CO₂ towards human development and prosperity is twofold. The excessive burning of fossil energy sources increases CO₂ emissions which directly mitigate the health outcomes and human development. On the other hand, CO₂ emissions indirectly affect the human health and development by increasing the air pollution in atmosphere. In other words, CO₂ emissions pollute the clean air which in turn adversely affect human development. There is a need to assess the

impact of both CO₂ emissions and air pollution on human development, particularly, in developing nations.

CO₂ emissions and air pollution varies across the nations throughout the globe. Developing economies have higher CO₂ emissions and air pollution as compared to the advanced countries (Ahmad, Ismail et al., 2021; Khan & Ozturk, 2021). There are several reasons of higher CO₂ and air pollutions in developing nations such as industrialization, lack of environmental regulations, dependence on traditional energy resources, limited access to clean technology, populations growth and urbanization, but the industrialization and use of traditional energy resources are the two main grounds that enhance the CO₂ and air pollution significantly (Bauer et al., 2019; Li & Lin, 2015; Raihana et al., 2022; Shahbaz et al., 2014). Developing nations often experience rapid industrialization which lead to increase energy consumption and higher GHG emissions (Khan et al., 2020). Similarly, many industries in developing economies mainly rely on fossil fuels which release substantial amount of CO₂ and other air pollutants (Li et al., 2021; Shen et al., 2020). CO₂ emissions and air pollution not only differ between the developing and advanced nations, variations also exist within the developing economies which mainly depending upon how fast a nation produces energy by traditional resources. Consequently, the influence of varied CO₂ emissions and air pollution on human development and economic growth is also differ across the nations (Aye & Edoja, 2017; Shaojian et al., 2018). Variations in amounts of CO₂ and air pollutions across developing nations and their varied impact on human development is a regional/spatial phenomenon (Chen & Bi, 2022; Ge et al., 2022; Wang & Zheng, 2021; Xu & Lin, 2021). Therefore, it is needed to study the association between GHG and human development from spatial perspectives.

Spatial analysis earned its reputation after the “first law of geography” presented by Waldo Tobler in 1970, which states that everything is related to everything else but the distant things are associated less as compared to the nearer things (Dempsey, 2014; Miller, 2004). The dominant feature of the spatial analysis (as compared to the conventional/nonspatial analysis) is that it incorporates information on locations of all observations in the sample size. The extraordinary difference between the conventional and spatial analysis suggest to re-examine the nexus between GHG (CO₂ emissions and air pollution in our study) and human development. Spatial analyses are helpful in many ways. Firstly, it identifies the spatial dependence/spillover (hotspots) and heterogeneity (cold spot) clusters concerning CO₂, air pollution and human development across the study observations. Secondly, it disaggregates the total impact of independent variables into direct (local/own region) and indirect (neighboring regions) effects on dependent variable. Thirdly, it provides the separate coefficients of all the study observations which is not possible in conventional and/or nonspatial analysis. Previous literature has mostly focussed on the relationship between CO₂ emissions, air pollution and human development in nonspatial perspectives. Therefore, with the massive importance of spatial analysis, the main concentration of this study is to re-estimate the impact of CO₂ emissions and air pollution on human development across the selected developing economies.

By considering the importance of UNDP's thirteenth SDG (**Goal 13: climate action**) in conjunction with advanced spatial techniques, this study has three primary objectives. Firstly, it aims to identify spatial dependence (clusters) and spatial heterogeneity (outliers) of CO₂ emissions, air pollution and human development across the selected developing countries. Second, it seeks to examine the spatial spillover (both direct and indirect) effects of CO₂ emissions and air pollution on human development. Lastly, it aims to measure the spatial inequalities by examining the local varying coefficients of CO₂ emissions and air pollution that affect the human development.

As the present study aims at estimating the spatial association of CO₂, air pollution and human development, the marginal contributions of this work to the existing literature are based on two key points. Firstly, relationship between CO₂, air pollution and human development has been rarely studied in spatial perspectives especially in developing economies. Secondly, instead of conventional/non-spatial econometric models, this study applies advanced spatial regression models to explore the effects of CO₂ emissions and air pollution on human development. These two contributions make present study the first pioneering attempt to investigate the performance of CO₂ emissions and air pollution in determining human development in developing economies. The rest of the paper is divided into several sections. Section 2 provides a detailed review of previous studies concerning the nexus between CO₂, air pollution, and human development. Section 3 elaborates on the complete methodology, including data sources, variables of the study, and the spatial models used for regression purposes. Section 4 and 5 present the results and discussions, respectively. Section 6 describes the limitations of the study, followed by the conclusion in section 7.

Literature review

The focus of this paper is to recognize the effects of CO₂ emissions and air pollution on human development in developing economies in spatial perspectives. Based on this theme, this paper mainly reviews the previous studies that link CO₂ emissions and air pollution to human development. This chapter has three sub-sections. Section 2.1 explains the association of CO₂ emissions and human development, section 2.2 describes the relationship between air pollution and human development and section 2.3 highlights the nexus between CO₂ emissions, air pollution and human development from spatial perspectives.

CO₂ emissions and human development index

Despite the privilege of developing economies to contribute in efforts aimed at reducing CO₂ emissions and avoiding distressing environmental change, the consequences of CO₂ lessening goals in Human Development Index (HDI) of developing economies persist a major concern (Hossain & Chen, 2021). Asongu & Odhiambo, (2020) investigated the relationship between governance, CO₂ emissions and human development in 44 sub-Saharan African countries for a period of 2000–2012. They recognized that CO₂ emissions have a negative association with inclusive human development. The key energy consumption throughout the globe is related to the human activities. It is needed to quantify how renewable energy consumption determine human development. In this regard, Wang et al., (2018) conducted research on renewable energy consumption, economic

growth and human development in Pakistan for a period of 1990-2014. Their findings revealed that renewable energy consumption has no influence on human development, however, they found that CO₂ emissions have significantly determined human development index. Akbar et al., (2021) inspected the bidirectional connection among healthcare expenditure, CO₂ emissions and HDI in 33 OECD countries for a period of 2006-2016. Results of the study exhibited a unidirectional inverse causality between CO₂ and HDI which infers that CO₂ emissions have substantially worsened the human health and wellbeing. Pervaiz et al., (2021) explained the relationship between health expenditure, Gross Domestic Product (GDP), CO₂ emissions, HDI, renewable energy, financial development and electricity consumption in Brazil, India, South Africa and China. According to their findings, HDI and renewable energy negatively influenced the carbon emissions. Furthermore, they obtained a bidirectional causality between human development index and carbon emissions. As HDI is a composite index of GDP per capita, life expectancy and education, CO₂ emissions may influence life expectancy and/or GDP per capita which in turn affect HDI. Mahalik et al., (2022) investigated the association between life expectancy and CO₂ in 68 developing and emerging countries for period of 1990-2017. Their findings showed an inverse impact of CO₂ emissions on life expectancy. This output occurred both for consumption-based and production-based emissions of CO₂. Environmental sustainability depends on improved human development. Recently, Opoku et al., (2022) examined the contribution of human development towards environmental sustainability in OECD countries for a period of 1996 to 2016. Their findings showed that improvement in HDI enhanced the environmental sustainability by reducing CO₂ and total GHG emissions. Similarly, Van Den Bergh & Botzen, (2018) assessed the impact of per ton CO₂ emissions on human development in developing countries. Findings of the study showed that effect of CO₂ emissions on HDI poor countries is higher than countries with a high HDI score.

Air pollution and human development index

Air pollution has a significant contribution towards HDI, especially in the context of life expectancy. Săndică et al., (2018) examined the association between human development (in the context of life expectancy at birth) and ambient PM_{2.5} concentration in 29 European countries by reshaping the concept of HDI into a new measure of Pollution Human Development Index (PHDI). The inclusion of ambient PM_{2.5} in HDI, significantly influenced the ranking of the countries. According to their study outcomes, higher the effect of air pollution in HDI scores, higher the impact the pollution has on rankings. Environmental pollution substantially affects human development. Recently, Li & Xu, (2021) investigated the association between the composite environmental quality (including air pollution) and human development in China. For better understanding, they constructed Environmental Degradation Index (EDI) and HDI to measure environmental pollution and human development respectively. They found an inverted U-shaped association between EDI and HDI. Further, the results established that environmental pollution, in turn, deferred the regional economic growth. Most of the previous studies proved that air pollution mainly affects the life expectancy which in turn deteriorate HDI. For instance, Correia et al., (2013) measured the effect of air pollution control on life expectancy in U.S by analysing 545 counties for

period of 2000–2007. Their results showed negative relationship between air pollution and life expectancy. In other words, a decline in ambient air pollution significantly improved the life expectancy which in turn enhance the HDI. In addition, they noted that this inverse relationship is higher in more urban and densely populated counties. Control on air pollution positively improved the public health in terms of life expectancy. Similar study by Wen & Gu, (2012) has also been conducted for older adults in China. Their study mainly focused on the association between life expectancy and outdoor air pollution. The study outcomes showed that exposure to outdoor air pollution severely reduced the life expectancy. The effect of air pollution was stronger for women. Life expectancy was considerably different between the regions with good and moderate quality of air. Air pollutants are growing rapidly in recent decades that significantly determine the per capita income. To understand such association between economic condition and air pollutants, Luo et al., (2014) investigated gross regional product per capita, the concentration of air pollutants such as PM₁₀, SO₂, and NO₂, and air pollution index in big cities of China. Their findings showed that concentration of air pollutants per ten thousand yuan with multiplying of gross regional product per capita in provincial cities. Furthermore, their outcomes also exhibited that the concentration of air pollutants as well as air pollution index showed a decreasing trend with the rise of gross regional product per capita. (Nazeer et al., (2016) assessed the causal relationship between pollution and sustainable growth in the context of human development index. for this purpose, they performed causality analysis to generate combined pollution index series and human development index series. Their findings indicated that the two series are co-integrated. Furthermore, they also found the two-way causality between the pollution and development with stronger causality flowing from human development index to pollution index.

CO₂ emission, air pollution and HDI from spatial perspectives

The excessive burning of traditional fossil fuels and rapid industrialization in developing economies emit an extensive amount of CO₂ and air pollution which ultimately influence the human development. The amount of CO₂ emissions and air pollution varies from country to country, mainly relies on how fast a country grow. As a result, the association between CO₂, air pollution and human development varies geographically. Liu et al., (2021) constructed the China's Human Development Index (CHDI) and measured the HDI level of 31 provinces from 1990 to 2017. By applying the exploratory spatial data analyses, they found a number of significant outcomes. Human development significantly varied across different regions and CHDI in eastern China was far ahead of other regions. The 31 provinces had positive spatial dependence on one another. Furthermore, they concluded that urbanization, financial expenditure on education and health professionals has positive spatial effects on CHDI whereas CO₂ emissions have negatively spatially influenced the CHDI. Chen et al., (2017) investigated the spatial spillover effects of air pollution on public health in 116 cities of China. Their study findings showed an adverse impact of air pollution and its spatial spillover effects on public health. Recently, Luo et al., (2023) examined the HDI from spatial perspectives in China by applying the spatial hierarchical factor model from 2000 to 2018. Results of the study revealed that provinces having high regional integration and population densities have higher rankings and low uncertainties of HDI. Moreover, HDI has a spatial spillover effect and

this association increases year by year. Also, Shengyun et al., (2022) constructed a carbon intensity index of human wellbeing to explore the pattern of its spatial evolution as well as the characteristics of its spatial clusters. Results of the study concluded that with spatial heterogeneity between high-high and low-low clusters, the carbon intensity of human wellbeing declined significantly. Economic development has the most significant positive impact on the carbon intensity of human wellbeing in Latin American developing countries, followed by Asian developing and developed countries. This impact was found to be smallest in African developing countries (or regions). Moreover, they found spatial spillover effects of human wellbeing's carbon intensity. Energy consumption, trade, and industrialization in surrounding countries raised a nation's carbon intensity of human wellbeing whereas, economic development, wealth accumulation, and lower mortality rates reduce the carbon intensity of human well-being. Kutlu & Wang, (2021) examined the spatial spillover effects of human development index on the efficiency of greenhouse gas emissions of 38 European countries between 2005 to 2014. Findings of the study showed positive significant impact of HDI on greenhouse gas efficiency level. Moreover, the efficiency levels differed across the countries as well as over time. However, the spatial spillover shape was parallel among all the European countries over time. Zhang et al., (2021) examined the spatial effects of environmental regulation on city air pollution treatment in 280 cities of China. They found that the air pollution is significantly spatially clustered across the study cities. The findings also confirmed a significant inverted U-shaped association between economic development and air pollution in southern cities. Shaobin et al., (2022) investigated spatiotemporal patterns in life expectancy in 134 countries for a period of 1960 to 2016 by applying Bayesian spatiotemporal modelling. Their results showed heterogenous spatiotemporal trends in life expectancy in African and South-East Asian countries. further, different factors showed varied coefficients of life expectancy in 134 countries. The spatial coefficient of economic growth and air pollution on life expectancy is substantially different across six WHO regions.

In a nutshell, numerous studies have investigated the intricate connection between CO₂ emissions, air pollution, and human development in both developing and developed economies. While efforts to reduce CO₂ emissions and promote renewable energy are essential for environmental sustainability, the effects on the Human Development Index (HDI) in developing economies continue to be a major concern. According to research, CO₂ emissions have a negative relationship with inclusive human development, impacting variables such as life expectancy and GDP per capita. It has been determined that air pollution, notably in the form of ambient PM_{2.5} concentration, has a significant effect on HDI, particularly in terms of life expectancy. In addition, spatial factors play a role in this relationship, with varying levels of human development and environmental impact across regions. Positive effects can result from efforts to enhance human development and reduce greenhouse gas emissions, but these relationships are complex and can vary between countries and regions.

Spatial distribution of CO₂ emissions, air pollution and HDI

Generally, advanced countries have higher HDI scores as compared to the developing economies (Hou et al., 2015). HDI is basically a composite index that measures an economy's wellbeing in three basic dimensions of 1) health, 2) education, and 3) standard of living. Geographical variations in any of these three domains can change the HDI (Anand & Sen, 1994). Figure 1a shows the spatial distribution of human development index (HDI) scores of developing economies across various continents. HDI scores of the selected developing economies are categorized in five groups named, 1) very low, 2) low, 3) moderate, 4) high, and 5) very high. Developing economies from Europe, Asia and South America have showed a spatial pattern of very high and high ranked HDI scores. In other words, these developing countries are better off in terms of HDI scores. There are multiple factors that can contribute to the higher Human Development Index (HDI) observed in Asian and South American emerging countries in comparison to African countries (Shah, 2016). In recent decades, several Asian and South American countries have experienced rapid economic growth and development, leading to an increase in per capita income and improved living standards for their populations (Darku & Yeboah, 2018). The aforementioned economic advancement has resulted in a notable increase in their HDI scores. Education plays a crucial role in the calculation of the HDI. Asian and South American nations have made significant financial commitments to the field of education, leading to significant advancements in educational achievements, heightened levels of literacy, and enhanced overall human capital (Ozturk, 2008). Besides, the presence and quality of healthcare services and infrastructure can influence life expectancy. Asian and South American countries have achieved prominent progresses in healthcare infrastructure and life expectancy by implementing enhanced disease management strategies, immunisation initiatives, and expanding healthcare accessibility (Freeman et al., 2020; Hao et al., 2020; Khan & Hussain, 2020). Moreover, political stability and effective governance can contribute to the facilitation of economic development and social progress. Certain Asian and South American nations exhibit outstanding political stability, thereby fostering conducive conditions for the implementation of development initiatives (Cooray, 2009). In contrast, developing countries from African (and some of the Asian) continent displayed a spatial pattern of low and very low HDI scores. African countries face several challenges that hinder their economic development. Some African countries struggle with low economic growth rates, high levels of poverty, and limited job openings, which impact their HDI scores (Matekenya et al., 2021; Meyer et al., 2017). Several African countries have experienced political instability, armed conflicts, and civil wars, which disrupt social and economic development and exacerbate poverty (Sarkodie & Adams, 2020). Similarly, the prevalence of infectious diseases, such as HIV/AIDS, malaria, and other health issues, have significantly impacted the life expectancy and overall human development in African countries (Ajide et al., 2022). Poor and inadequate access to quality education, high dropout rates, and limited educational opportunities have hindered progress in improving educational indicators for certain African nations (Grisolia et al., 2022). It is important to note that Africa is a vast and diverse continent, and there are significant variations in HDI scores among its countries. Some African countries have made substantial progress in improving their HDI over the years, and various development initiatives are ongoing to address the challenges and promote human development

across the continent. However, the factors mentioned above provide some context for the observed disparities in HDI between Asian and South American developing countries and African countries.

Figure 1b display the spatial distribution of CO₂ emissions (measured in metric tons per capita) of developing nations. Like HDI, CO₂ emissions presented atypical clusters of developing economies. Most of the Asian countries are categorized in high and very high CO₂ emission groups. South American countries emitted less CO₂ and presented a pattern of moderate and low CO₂ economies. However, most of the African countries presented a spatial pattern of the countries which emit very low CO₂ amount. The overall picture showed considerable variations in the quantity of CO₂ emissions across developing economies. These disparities can occur due to several reasons. The process of industrialization and economic development has been observed to occur at a faster pace in developing Asian and South American countries in comparison to African countries. CO₂ emissions are generated as a result of various activities such as manufacturing processes, energy consumption, and industrial operations. China, India, as well as various South American countries, are characterized by substantial populations and are currently experiencing a rapid process of urbanization. Increased emissions can be attributed to higher energy usage, transportation activities, and consumption patterns within urban areas (Chandran & Tang, 2013). Besides, the selection of energy sources for power generation and transportation has a substantial influence on emissions. Coal, oil, and natural gas are significant sources of CO₂ emissions, and they are extensively utilized for energy generation in several Asian and South American nations (Dong et al., 2019). Some African nations may opt to increase their reliance on renewable energy sources or implement energy conservation measures as they experience economic growth. Moreover, the implementation of cleaner and more advanced technology leads to a reduction in pollutants (Suki et al., 2022). Certain African countries have the potential to opt for environmentally friendly alternatives instead of hazardous technology. Deforestation, land-use alterations, and agricultural practices are all factors that can contribute to the escalation of emissions. The deforestation of agricultural land in South America has resulted in increased emissions (Raihan et al., 2022). The transportation sector is a significant contributor to CO₂ emissions. Similarly, the level of emissions is impacted by factors such as public transportation and the use of fuel-efficient vehicles (Chandran & Tang, 2013).

Figure 1c display the spatial distribution of air pollution (PM_{2.5}) measured in micrograms per cubic meter of emerging economies. Air pollution is ranked as low or very low in upper Asian and South American developing nations. The lower Asian countries such as Pakistan, India, China and Afghanistan, and most of the African countries have high or very high air pollution. The varied amount of air pollution (PM_{2.5}) among various developing nations can occur due to many factors. It is conceivable that the presence of diversified economies and substantial industrial bases in certain Asian and South American nations contributes to the dispersion of pollution. Nevertheless, it is important to note that several African nations heavily depend on industries or activities that serve as significant contributors to environmental pollution (Bauer et al., 2019). Also, in Asian and South American economies, there is a greater prevalence of renewable energy sources and cleaner fossil fuel technology, while certain African countries exhibit a higher reliance on traditional biomass

burning or lower-quality fuels. Moreover, the dissemination of air pollution can be influenced by various factors, including topography and wind patterns prevailing across marine environments (Wu et al., 2022). Countries with environments that are better suited for the dispersal of pollutants may exhibit lower pollution levels (Wallace et al., 2010). The level of pollution in a specific region is influenced by economic development as well as the accessibility of advanced technologies and infrastructure. Developed nations often exhibit advanced waste management systems and allocate greater financial resources towards the implementation of environmentally sustainable technologies.

Figure 1a-c show the spatial patterns of the study variables across the emerging economies which indicate that HDI, CO₂ emissions and air pollution of contiguous countries are associated with one another. However, it is not confirmed whether these atypical spatial clusters are significant or not. Various spatial techniques are used (in methodology section) to measure the spatial dependence (or heterogeneity) of the study indicators.

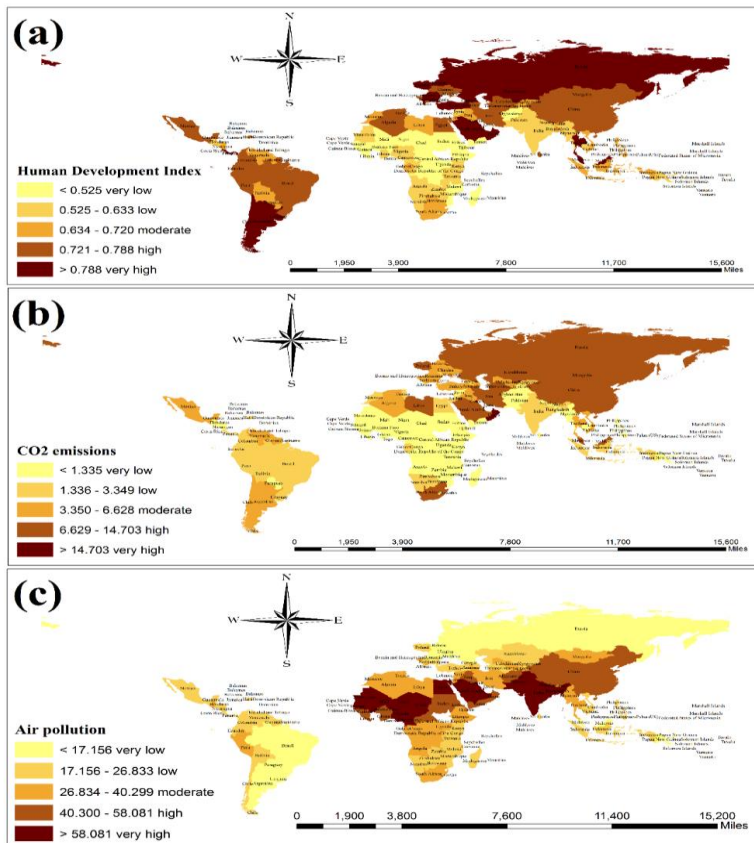


Fig. 1 Spatial representation of (a) Human Development Index (HDI), (b) Carbon Dioxide (CO₂) emissions, and (c) Air Pollution in developing economies.

Methodology

Data source

This section presents the dataset and econometric models applied for present study. Data on HDI, CO₂ emissions and air pollution are extracted from the World Bank database for 142 developing economies across various continents for year 2020. The variable HDI represents the overall human wellbeing as it is the composite index of three different dimensions of health, education and standard of living. CO₂ shows the per capita emissions of carbon dioxide measured in metric tons per capita. Air pollution (PM2.5) displays the mean annual exposure of air quality measured in microgram per cubic meter ($\mu\text{g}/\text{m}^3$).

Global spatial autocorrelation

The Global Moran I statistic (Anselin, 1995) was used to check if the developing countries are spatially agglomerated with one another regarding the HDI, CO₂ emissions and air pollution. The Moran's I is statistically written as under;

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2}, i \neq j \dots \dots \dots (1)$$

Where n in equation (1) is the number of developing economies, x_i and x_j are respectively the i^{th} and j^{th} adjacent nation's HDI score (or CO₂ emissions or air pollution), $\bar{x}$ is the mean of HDI (or CO₂ or air pollution) across all the emerging nations, and w_{ij} is the weighted spatial matrix. If the i^{th} and j^{th} districts have a shared boundary, the value of w_{ij} is set to 1; otherwise, it is set to 0. The score of Global Moran's I is denoted within the range of +1 to -1. The closer the Moran's I score is to +1 or -1, the stronger the spatial interconnectivity, and hence the more the surrounding districts are spatially agglomerated in terms of any of the study indicators. If Moran's I statistic is zero, then either of the study variables are spread throughout developing economies at random. In other words, there is no spatial association among the countries.

Local spatial autocorrelation

The Local Indicators of Spatial Autocorrelation (LISA), commonly referred to as local Moran's I, were employed to detect significant spatial clusters and/or outliers within the contiguous developing economies in relation to HDI (or CO₂ or air pollution). In econometrics, the LISA statistic is represented as follows:

$$I_i = \frac{n(x_i - \bar{x}) \sum_{i=1}^n w_{ij}(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}, i \neq j \dots \dots \dots (2)$$

Where n represents the number of countries, x_i and x_j denote the quantity of HDI (or CO₂ or air pollution) in the i^{th} and j^{th} nations, respectively. $\bar{x}$ represents the average score of any of the study indicators across all nations, w_{ij} represents the spatial weight matrix. l_i is the extent of a spatial relationship between each i^{th} and its surrounding developing economies. The outcomes of LISA can be categorised into four quadrants: high-high (HH), commonly referred to as a hot spot, low-low (LL) or cold spot, high-low (HL), and low-high (LH), both known as outliers (Anselin, 1995). The (HH) and (LL) quadrants indicate a high level of spatial agglomeration in HDI (or CO₂ or air pollution) and its neighbouring countries. On the other hand, the (HL) and (LH) quadrants suggest heterogeneity among contiguous developing countries (Anselin, 1995).

Spatial Durbin Model

(LeSage & Pace, 2009) proposed the Spatial Durbin Model (SDM) which includes the lagged dependent variable as well as the independent variables. Generally, the SDM is written in Eq. (3) as under,

$$y_i = \alpha + \rho W y_i + \beta X_i + \theta W X_i + \varepsilon_i, \varepsilon_i \sim N(0, \sigma_u^2) \dots \dots \dots (3)$$

Where $i=1, 2, 3, \dots, n$, α is the constant term, y_i is a vector of observations on the dependent term, $X_i = [X_{1i}, X_{2i}, \dots, X_{Ki}]$ is the vector of K independent variables, $\beta = [\beta_1, \beta_2, \dots, \beta_K]$ is the vector of parameters at explanatory variables, ε_i is the error term, ρ is the spatial autoregression parameter, W is the spatial weight matrix of $n \times n$ dimensions with zero diagonal elements, and θ is the vector of spatial parameters of spatially lagged explanatory variables.

The SDM in Eq. (3) is specified to our study variables. The specification of the SDM model in econometric form is written in Eq. (4) as under,

$$HDI_i = \alpha + \rho \sum_{j=1}^n W_{ij} HDI_j + \beta_1 CO2_i + \beta_2 AP_i + \theta_1 \sum_{j=1}^n W_{ij} CO2_j + \theta_2 \sum_{j=1}^n W_{ij} AP_j + \varepsilon_i, i \neq j \dots \dots \dots (4)$$

Where HDI_i is the human development index, i and j are neighbouring developing countries, and W_{ij} is the spatial weight matrix (symmetrical in the upper right and lower left) as detailed in Equation 5. ρ is the spatially lag coefficient of HDI that reflects the degree (and direction) of spatial spillover across adjacent countries. α is the constant term, $W_{ij} HDI_j$ is the dependent variable's spatial autocorrelation matrix, displaying the effect of HDI_j of j country next to HDI_i of i district. CO₂ and AP are the carbon dioxide emissions per capita and air pollution, respectively. β_1 and β_2 are the coefficients of explanatory variables, θ_1 and θ_2 are the spatial autocorrelation coefficients of independent variables reflecting the impact of all explanatory variables in neighbouring

countries on the local country's HDI, and ε_i is the random error term normally distributed with zero mean and constant variance.

Spatial weight matrix

This study uses the spatial queen contiguity weight matrix define as, the districts that share common boundaries as well as a common diagonal. The symmetric spatial weight matrix $W_{n \times n}$ for n districts is shown in Eq. (5) as under,

$$W_{ij} = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \omega_{n1} & \omega_{n2} & \cdots & \omega_{nn} \end{bmatrix} \dots \dots \dots (5)$$

Geographically Weighted Regression

GWR, an extension of the conventional OLS method, introduces a higher level of modelling sophistication by allowing the relationships between dependent and explanatory variables to vary by locality. This technique serves as an exploratory tool, facilitating the visualization of stimulus-response relationships and their spatial fluctuations. Additionally, it considers the spatial autocorrelations of variables.

To put it simply, GWR constructs separate OLS equations for each location within the study area, incorporating the dependent and explanatory variables of neighboring locations falling within a specified bandwidth. This bandwidth can be either manually specified by the user or determined automatically by statistical software. The significance of GWR lies in its ability to identify spatial non-stationarity, a property not accounted for by the conventional OLS technique. In previous studies, GWR has been extensively used due to its capability to address spatial geographical variability effectively (Antczak, 2019; Antczak & Miszczyńska, 2020; Khan & Sheikh, 2023; Muche et al., 2021; Raza et al., 2019).

In our current study, we aim to investigate the spatial impact of CO₂ emissions and air pollution on HDI (Human Development Index). As this analysis requires capturing geographical variability, we have employed the most sophisticated version of GWR to fulfill our research interests. By doing so, we can uncover spatial patterns and variations that would otherwise remain hidden when assuming a constant and homogenous spatial association between explanatory and dependent variables, which is the assumption made by traditional OLS. The GWR model in an econometric form is written in equation (6) as under;

$$Y_i = \beta_o(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)X_{ik} + \varepsilon_i \dots \dots \dots (6)$$

where (u_i, v_i) denotes the coordinates (longitudes and latitudes) of i th location.

The GWR model in equation (6) has been tailored to explore the factors influencing Human Development Index (HDI). In the context of our study variables, the specific econometric representation of the GWR model is as follows;

$$HDI_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)CO2_i + \beta_2(u_i, v_i)AP_i + \varepsilon_i \dots \dots \dots (7)$$

Where (u_i, v_i) are the coordinates of i th country, $i = 1, 2, 3, \dots, 142$, $\beta_1(u_i, v_i)$ and $\beta_2(u_i, v_i)$ are the local varying coefficients of the weighted regression model at location i , and ε_i is the error term at location i which is normally and independently distributed with zero mean and constant variance. HDI is the nation's human development, CO₂ is the emission of per capita carbon dioxide, and AP is the air pollution.

Results

This section presents the spatial effects of CO₂ emissions and air pollution on HDI in 142 developing economies of the world. Further, this section also explores the variations in the extent of impacts of CO₂ emissions and air pollution on HDI across developing countries. Before proceeding, it is needed to check the spatial autocorrelation in the study variables.

Global spatial autocorrelation results

The Moran's I score of all the study variables showed that the contiguous developing countries have significant spatial dependence (Table 1). This association is higher (73 percent) for air pollution following by HDI which is about 66 percent. The lowest spatial dependency score of 43 percent is recorded for CO₂ emissions. Figure 2 shows that all the three variables have positive spatial association which means that economies with higher (lower) levels of HDI (or CO₂ or air pollution) are surrounded by the neighboring regions having higher (lower) levels of HDI (or CO₂ or air pollution). This spatial association is clustered into four different quadrants as shown in the figure. These quadrants are the low-high (LH), high-high (HH), low-low (LL) and high-low (HL). HH and LL quadrants are respectively known as the hotspots and cold spots. These quadrants cover the countries with high (low) levels of HDI (or CO₂ or air pollution) bounded by the neighboring regions having high (low) levels of HDI (or CO₂ or air pollution). The LH and HL quadrants are the outliers. These quadrants cover the regions with low (high) levels of HDI (or CO₂ or air pollution) surrounded by the economies having high (low) levels of HDI (or CO₂ or air pollution). However, the global Moran only shows the spatial dependence or spatial heterogeneity concerning HDI, CO₂ and air pollution across developing economies. It does not provide the exact locations of various countries lies in different quadrants. To better understand the location (or cluster) of each country, local autocorrelation analysis has been performed.

Table 1. significance test of spatial associations with 999 random permutations

Variable	Moran's I	E(I)	Sd(I)	z-scores	Pseudo p-value
HDI	0.659	-0.009	0.074	8.963	0.001
CO ₂ emission	0.435	-0.009	0.069	6.446	0.001
Air pollution	0.732	-0.009	0.073	10.062	0.001

Source: Author own computations based on the world band indicators

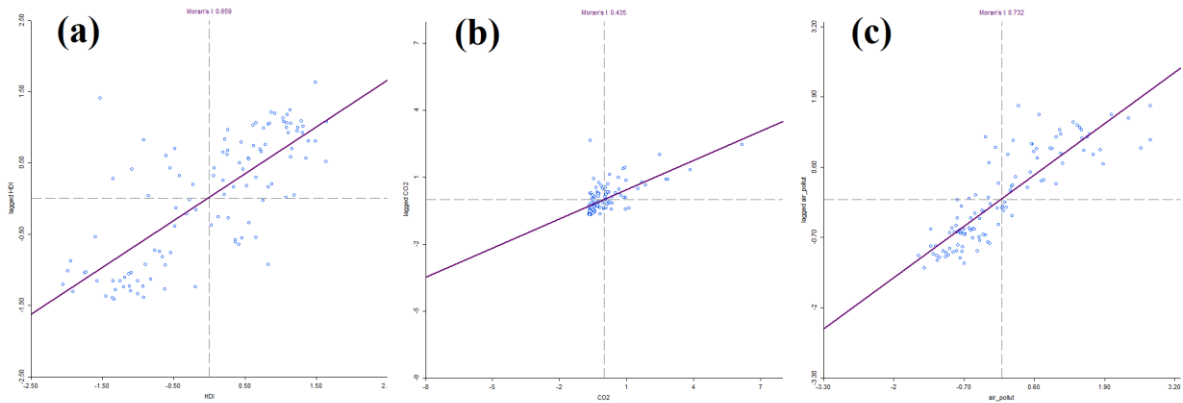


Fig. 2 Moran scatterplots of (a) Human Development Index (HDI), (b) Carbon Dioxide (CO₂) emissions, and (c) Air Pollution in developing countries.

Local spatial autocorrelation results

Figure 3 presents the LISA results of HDI, CO₂ and air pollution. Most of the south American developing countries (Brazil, Chile, Argentina, Uruguay, Peru and Bolivia) and the upper Asian countries like Russia have displayed an HH significant spatial cluster in terms of HDI (figure 3a). These countries have higher HDI scores which are substantially surrounded by their neighbors having higher HDI scores. Most of the south African countries (Tanzania, Uganda, Kenya, Malawi, Zambia, Congo etc.) have presented the cluster of LL developing countries. these nations have lower HDI values and substantially bounded by LL HDI score countries. However, there is only one Asian country (Yemen) that has low level HDI score but is significantly surrounded by the countries with high level of HDI scores. The respective significance level of all these developing countries concerning HDI is shown in figure 3d.

Figure 3b displays the hotspots and cold spots of CO₂ emissions across the developing economies. It is shown in the figure that Asian countries such as Russia, Saudi Arab, Kuwait and Indonesia have made a substantial hotspot (HH) cluster concerning CO₂ emissions. These countries emit high level of CO₂ which are significantly surrounded by the neighboring countries emitting high level of CO₂. In contrast, most of the south African countries (Mali, Burkina Faso, Senegal, Nigeria, Liberia, Guinea, Tanzania, Uganda, Kenya, Congo etc.) are contiguously agglomerated in the spatial cluster

of LL (also known as cold spot) developing economies. These emerging economies emit lower amount of CO₂ which are spatially surrounded by the regions with the low level of CO₂ emissions. Moreover, the south American developing countries have presented the insignificant spatial clusters in terms of CO₂ emissions (figure 3e).

Finally, figure 3c displays the LISA results of air pollution across developing countries. The lower Asian countries such as Pakistan, India, Bhutan, and Saudi Arabia and most of the south African countries (Libya, Niger, Chad, Mali, Sudan, Cameroon, Nigeria, Burkina Faso etc.) have made a spatial pattern of HH air polluted countries. The air pollution in these countries is spatially highly associated with their adjacent regions. Belarus, Ukraine, Moldova, Romania and almost all developing countries from south America have presented a cluster of cold spots (LL clustered countries). In other words, these countries are low air pollution which are significantly bounded by the low air polluted developing countries. The spatial significance of each country in terms of air pollution is shown in figure 3f. However, very few countries like Algeria from south Africa and Myanmar from Asia are clustered in LH spatial quadrant. These countries have lower air pollution but their contiguous developing economies have significantly high level of air pollution.

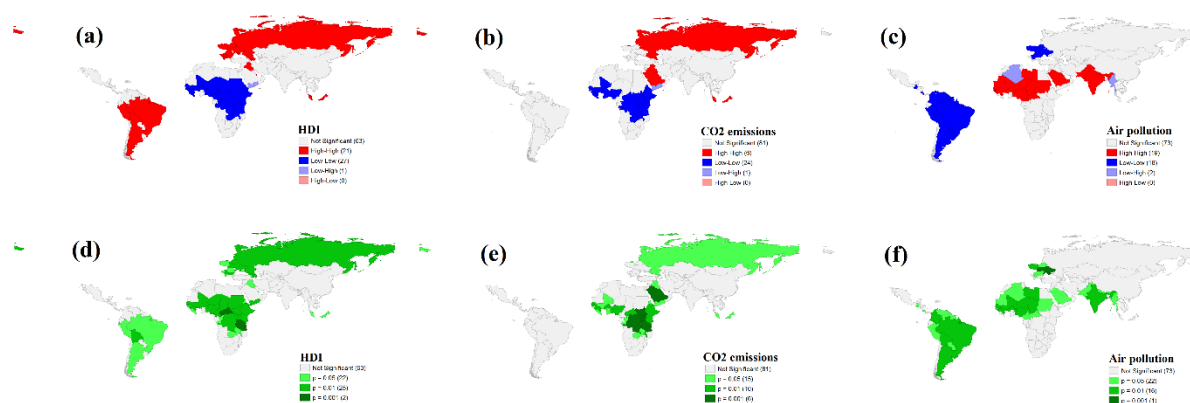


Fig. 3 Map displaying Local Indicators of Spatial Autocorrelation (LISA) analysis of (a) Human Development Index (HDI), (b) Carbon Dioxide (CO₂) emissions, and (c) Air Pollution in selected developing economies

Spatial Durbin Model results

Giving importance to the spatial spillover effects of CO₂ emissions and air pollution on human development index, the non-spatial Ordinary Least Square (OLS) technique does not provide consistent outcome which may cause the results biased and inconsistent. It is because the conventional OLS neither incorporate the coordinate information of various locations under study nor add average of lag explanatory variables into account. Thus, it become difficult to split the size of the total effect into direct and indirect effects. SDM has the ability to incorporate the lags of both

dependent and independent variables in the model, allowing the coefficient to be segregated in direct and spillover effects.

As figure 2 and 3 showed that there is significant spatial dependence and heterogeneity across the contiguous developing economies, it is expected that CO₂ emissions and air pollution have spatial spillover effects on human development. Table 2 presents the direct and spillover results of CO₂ emissions and air pollution on HDI across emerging economies. Overall, the model is best fitted as the goodness-of-fit (F-test) is statistically significant at a 1% level of significance. The spatially lagged coefficient ρ is highly significant, demonstrating spatial association between the distribution of HDI in developing countries, which confirms the rationality of integrating the spatial spillover effects into the econometric model. CO₂ emissions has a significant positive effect on HDI, whereas the air pollution has adversely influenced the human development index.

The direct and indirect impact of CO₂ emissions and air pollution: Emissions of carbon dioxide has a positive and considerable direct and indirect effect. On average, an increase in the per capita CO₂ emissions leads to an increase in the HDI score by 0.006 units in a local country, whereas for each incremental per capita CO₂ emission in the neighbouring countries raise the local district's HDI score by 0.017 units. The total (Direct + Indirect) impact of the per capital CO₂ emissions is highly significant at a 1% level of significance. Unlike the CO₂ emissions, air pollution has adverse direct and indirect effects on human development index. The total impact of air pollution is significant at a 1% level of significance. On average, an incremental micrograms per cubic meter air pollution in a local economy reduce human development by 0.002 units and a one percent increase in micrograms per cubic meter air pollution in surrounding developing economies significantly reduces HDI score by 0.003 units in a local country.

Table 3. Spillover results of Spatial Durbin Model

Variables	Direct effects	
	Coefficient	z-value
CO ₂ emissions	0.006	4.645***
Air pollution	-0.002	-1.989*
Constant	0.748	31.183***
	Indirect (spillover) effects	
CO ₂ emissions	0.011	3.966***
Air pollution	-0.003	-2.366*
	Total effects	
CO ₂ emissions	0.017	7.129***
Air pollution	-0.004	-7.401***
Spatial ρ		0.38***
Log-likelihood		-3249.41
AIC		4718.02
BIC		4727.28

R-Squared	0.54
Adjusted R-Squared	0.52
F-statistic	31.90***

Note: Dependent variable = Human Development Index (HDI)

“***”, “**”, and “*” denote level of significance at “1%”, “5%”, and “10%” respectively.

Geographically Weighted Regression results

Prior to delving into the intricate outcomes of Geographically Weighted Regression (GWR), it is imperative to initially juxtapose the non-spatial regression model, namely simple Ordinary Least Squares (OLS), with the spatial regression model of GWR. Based on the findings presented in Table 3, it is evident that the results obtained from the GWR method demonstrate a higher level of robustness and accuracy. This is supported by the notable reductions observed in various metrics, including the residual sum of squares, maximum likelihood-based global sigma estimates, $-2 \log$ likelihood, and AIC, and BIC scores, upon the application of GWR. Furthermore, it is worth noting that the R^2 (coefficient of determination) has exhibited a substantial enhancement, increasing from 58 percent to 69 percent in the geographically weighted regression outcomes. Based on the global OLS results, it can be observed that both CO₂ emissions and air pollution exhibit a significant correlation with human development index. However, CO₂ emissions have a positive impact on HDI while air pollution has adversely determined the human development index in developing countries. The GWR results are specific to each country, with individual coefficients assigned accordingly. The following results are interpreted in figure 4 in detail.

Table 4. Diagnostic test for GWR vs OLS results

Ordinary Least Square (OLS) results					
Variable	Coeff.	St.er	t-value	Residual sum of squares	0.820
Intercept	0.721	0.019	37.79***	Number of parameters	3
CO ₂ emissions	0.017	0.001	9.88***	ML based global sigma estimates	0.085
Air pollution	~	0.001	-7.38***	Unbiased global sigma estimates	0.086
	0.003				
				-2 log likelihood	-232.73
				AIC	-224.35
				BIC	-213.85
				CV	0.008
				R ²	0.58
Geographically Weighted Regression (GWR) results					
Summary statistics for local coefficients				Bandwidth size	57.90
Variable	Mean	STD	Median	Residual sum of squares	0.395
Intercept	0.688	0.081	0.721	ML based global sigma estimates	0.059
CO ₂ emissions	0.024	0.011	0.019	Unbiased global sigma estimates	0.063
Air pollution	~	0.001	-0.003	-2 log likelihood	-314.49

0.003				
AIC				-286.38
BIC				-256.09
CV				0.004
R ²				0.69
GWR Anova				
Source	SS	DF	MS	F
Global Residuals	0.821	109.00		
GWR improvement	0.425	11.377	0.037	
GWR residuals	0.396	97.623	0.004	9.225

Source: Author's own computations based on the world bank indicators. "****", "**", and "*" denote level of significance at "1%", "5%", and "10%" respectively.

A regression analysis was conducted to examine the relationship between CO₂ emissions, air pollution, and the human development index (HDI) in developing economies. The results pertaining to CO₂ emissions and air pollution are presented in Figure 4a and Figure 4b, respectively. The empirical findings indicate a positive association between CO₂ emissions and HDI scores, while air pollution is found to be inversely correlated with human development. The statistical analysis reveals that both variables exhibit a high level of significance in developing countries. On average, there is a significant positive relationship between a one unit increase in per capita CO₂ emissions and human development, with an increase ranging from 0.011 to 0.043 percent, all other factors held constant (see figure 4a). The impact size is relatively higher in developing countries in North America and certain economies in South Africa, ranging from 0.033 to 0.043. On the other hand, there is a cluster of countries in Asia that have a relatively lower impact. Furthermore, the carbon dioxide (CO₂) emissions in several developing nations in South Africa have a diverse range of impacts on human development, ranging from 0.016 to 0.043. Figure 4c illustrates that the local varying coefficients of all the study economies exhibit a high level of significance, specifically at the 1 percent level. In a similar vein, it can be observed from figure 4b that when all other variables are held constant, a one-unit increase in air pollution (measured in micrograms per cubic metre) resulted in an average decrease in the human development index ranging from -0.005 to -0.001 units. A significant highest impact of -0.005 has been observed in several developing countries in Asia and South Africa. The economies with the lowest impact (-0.001) are situated in the southern regions of Asia and certain countries in southern Africa. The size of the coefficient for air pollution in developing nations in South Africa exhibits significant variation, similar to CO₂ emissions. The impact of air pollution on the Human Development Index (HDI) is statistically significant at both the 1 percent and 5 percent levels in nearly all countries, with the exception of certain developing countries in southern South Africa (refer to figure 4d).

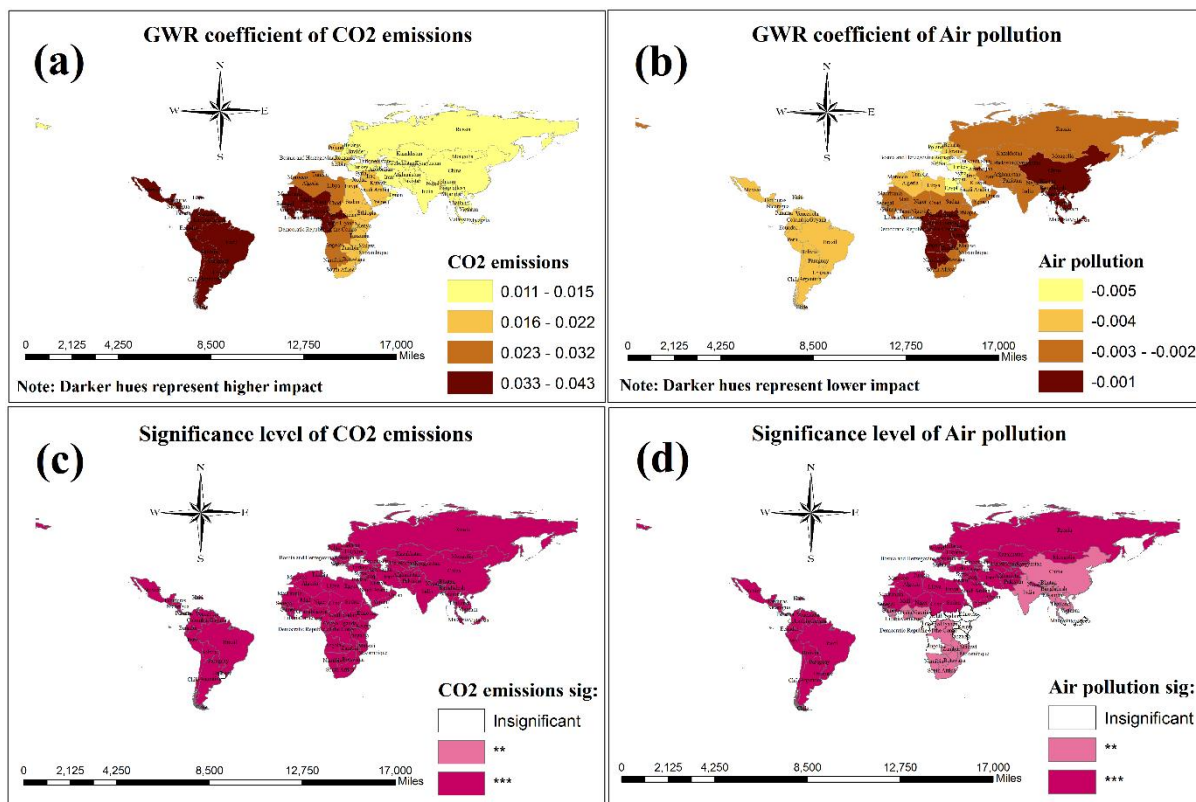


Fig. 4 Map representing the (a) Geographically Weighted Regression (GWR) coefficients of Carbon Dioxide (CO₂) emissions, (b) Geographically Weighted Regression (GWR) coefficients of Air Pollution, (c) significance level of CO₂ emissions, and (d) significance of Air Pollution in selected developing economies.

Discussion

This study is attempted to investigate the spatial impact of CO₂ emissions and air pollution on human development index in 112 developing economies. The investigation of GHGs has gained an insightful importance as the United Nations member countries unanimously agreed upon the **SDG 13 "take urgent action to combat climate change and its impacts"** to promote climate resilience and mitigate GHG emissions (UNDP, 2015a, 2015b). Globally, nations try to combat the increasing amount of GHGs such as CO₂ emissions and air pollution but it is hard to mitigate. However, it is possible to reduce the GHGs by promoting towards advanced technology of renewable energy production (Yu & Du, 2019; Zhang et al., 2013). Due to lack of technological innovations, CO₂ emissions are relatively higher in developing economies as compared to advanced countries. It is obvious from our results that the amount of CO₂ emissions significantly varies among the developing countries (figure 1b). For instance, our study results confirmed that Asian countries emit a larger amount of CO₂ emissions. China and India are widely recognised respectively as the first

and third contributor to global CO₂ emissions, due to their substantial population size and quick pace of economic expansion (Mirza et al., 2022). These nations are primarily dependent on coal and fossil fuels as a primary source of energy generation, resulting in a substantial contribution to its overall carbon emissions (Hanif et al., 2019). Several Asian emerging nations, including Indonesia, Vietnam, and the Philippines, are currently witnessing a rise in CO₂ emissions due to their ongoing processes of industrialization and urbanisation (Sikder et al., 2022). In contrast, figure 1b also showed that African developing countries emit relatively lower CO₂ emissions. South Africa is the largest CO₂ emitter in Africa, primarily due to its reliance on coal for electricity generation. The country has been making efforts to diversify its energy mix and invest in renewable energy. While Africa's overall carbon emissions are relatively low, some countries like Nigeria, Egypt, and Algeria are among the continent's highest emitters due to industrial activities and energy consumption (Yusuf et al., 2020). Majority of the Asian and African countries (Pakistan, China, India, Nepal, Bangladesh, Nigeria, Chad, Mali etc.) release higher air pollution (figure 1c) due to their industrial emissions, vehicle exhaust, burning of agriculture products, and particulate matters in atmosphere (Anjum et al., 2021; Babayemi et al., 2016; Ji et al., 2019). The variations in CO₂ emissions and air pollution across developing countries have spatially determined the human development index.

Our study results of Global and Local Moran confirmed the significant spatial dependence and heterogeneity across developing countries in terms of HDI, CO₂ emissions and air pollution (Table 1). The Moran scatterplots clearly showed positive existence of spatial relationship among the neighboring countries. In other words, countries with higher or lower amount of HDI (or CO₂ or air pollution) have been clustered at one point in space (Zeng et al., 2021). This means that developing economies under the hotspot clusters either use coal and fossil fuels as primary sources of energy production or the industrialization and urbanization is very fast. The higher amount of CO₂ emissions and air pollution may cause due to the violation of green technology and environmental protection agency rules (Du & Li, 2019; Lee et al., 2022). The LISA analysis is useful in identification of the locations of such clusters. Russia, Saudi Arabia, Iraq and Indonesia and all their neighboring countries emitted higher carbon dioxide, while, the African developing economies such as Ethiopia, Djibouti, central Africa, Uganda, Kenya, Mali, Senegal, Mauritania, etc. have presented a spatial significant cluster that emitted lower amount of CO₂ (figure 3a). The reason may be because African countries are relatively economically poor as compared to the Asian and south American countries, or these developing economies are less industrialized. Emissions of higher CO₂ pollute the air significantly (Guan et al., 2023). Our study results revealed that due to higher CO₂ emissions in Asian developing countries, Pakistan, India, Nepal and Bhutan have significantly presented a cluster of higher amounts of air polluted economies. Similar hotspot of air pollution is also found in African emerging economies. In contrast, south American developing countries where the CO₂ emissions are relatively lower have presented substantial spatial cold spot of economies with lower amount of air pollution (figure 3c). These countries either follow the environmental rules and green technology or directly emit low carbon dioxide due to less industrialization. More interestingly, the spatial hotspots of human developing index are found almost in those developing nations where both CO₂ emissions and air pollution were higher and vice versa. Such type of spatial

connection confirmed that there exist spillover effects of CO₂ emissions and air pollution on HDI across emerging economies.

The SDM results evidenced a positive spatial spillover impact of CO₂ emissions on HDI in emerging countries. The coefficients (both direct and indirect), although quite small but are statistically significant at 0.01 level (table 3). This empirical finding is in line with the previous works of (Mikayilov et al., 2018; Nosheen et al., 2021; Onofrei et al., 2022) in which CO₂ emissions was shown to be detrimental to the HDI in emerging economies. However, our results are different from the findings of (Das & Debanth, 2023; Mahalik et al., 2022; Pervaiz et al., 2021) where CO₂ emissions have negatively influenced the life expectancy. The association between CO₂ and HDI is not unique as HDI is the combination of health, education and income, and different academicians and researchers use HDI in different form. However, none of these studies investigated the direct and indirect impact of CO₂ emissions on HDI, which may explain this differently. Our study results showed that the weighted average of CO₂ emissions in neighboring developing economies have a positive spillover impact on the local developing country (Table 3). Higher level of CO₂ emissions lead to higher economic growth but severely pollute the environmental quality and air quality. As our study findings showed that developing countries with higher CO₂ emissions have higher amount of air pollution. The varied amount of air pollution across developing economies may have significant impact on human development. The empirical findings of the study showed an inverse direct and spillover impact of air pollution on HDI. Like carbon dioxide, the direct and indirect coefficients are quite small, but they are statistically significant at 5 and 1 percent level. This inverse relationship is supported by the (Li & Xu, 2021; Luo et al., 2014), in which HDI in the context of economic development is inversely determined by air pollution. Higher air pollution in the neighboring countries may affect the life expectancy in the local developing nation (Chen et al., 2017). However, none of these studies concentrated to find out the role of neighboring countries in relationship between the air pollution and HDI. The empirical findings of SDM model showed that higher amount of air pollution has significantly influenced the human development index (Table 3). As it is apparent from the figure 1 that CO₂ emissions and air pollution vary across the developing countries, the sensitivity of these factors towards human development may differ across the study nations.

As the ordinary least square (OLS) technique is non-spatial, the GWR model was applied to spatially evaluate the impact of CO₂ emissions and air pollution on human development index in emerging economies. Results of the study revealed that emissions of carbon dioxide significantly and positively determined the human development index. Such direct relationship between CO₂ emissions and HDI is supported by (Nosheen et al., 2021). However, the size of the impact was found to be different across developing economies (figure 5). For instance, CO₂ emissions was highly sensitive towards human development across the south American and African developing countries as compared to the Asian and central Asian developing countries. Due to low emissions of carbon dioxide gas in African countries, a slight development in the construction and technological advancement sectors improve the human development (Edziah et al., 2022). On the other hand, as the Asian countries have already achieved relatively high CO₂ and HDI scores, an increase in CO₂

emissions are less responsive towards human development. Likewise, figure 5 also confirmed that the negative association between air pollution and human development index is spatially varied across developing economies (Samadder, 2011). Higher amount of CO₂ in Asian and African countries produced higher air pollution in Asian developing economies that in turn effected the human development (Liu et al., 2021). However, the impact size is lower either these developing nations either implement the green technology or follow the rules of environmental protection. On the other hand, the impact size was found to be higher in south American emerging economies as these nations have lower air pollution. In case of lower pollution, slight changes are highly sensitive towards human development. The high sensitivity may result from the violations of green technology and burning of fossil fuels that pollute the overall environment (Perera, 2018).

The present study is subject to certain limitations. This study exclusively examined the spatial implications of CO₂ emissions and air pollution on human development within emerging economies. There may be additional significant variables related to greenhouse gas emissions, however, they were not included in the study. The lack of available data posed a challenge for numerous developing countries. Given the spatial nature of this study, it is imperative to ensure that data availability is consistent across all neighboring regions in order to prevent the occurrence of inconsistent and biased coefficients. Furthermore, this study was exclusively conducted during the year 2020, as the primary objective of the present study was to examine the regional (direct and spillover) disparities in the impact of CO₂ emissions and air pollution on the Human Development Index (HDI) in developing countries. This study has excluded several developing countries from the present analysis due to their separate geographical locations. To clarify, these countries do not possess a contiguous border with the global community. In order to assess the spatial impacts, it is imperative that every developing nation possesses at least one neighboring country.

Conclusion

The majority of prior research has focused on examining the relationship between carbon dioxide emissions, air pollution, and the human development index (HDI) in emerging economies, primarily from a non-spatial standpoint. By taking into account the existing regional differences, this study focused to investigate the influence of CO₂ emissions and air pollution on spatial perceptions. Hence, we utilized spatial econometric methodologies such as univariate global Moran's I, Local Indicators of Spatial Association (LISA) cluster analysis, Spatial Durbin Model (SDM), and Geographically Weighted Regression (GWR) model to evaluate potential spatial discrepancies in the association between CO₂ emissions, air pollution, and the human development index within the chosen developing nations.

The immediate findings concluded the presence of notable regional inequalities among emerging nations with regards to CO₂ emissions, air pollution, and HDI ratings. Clusters with high-high values of HDI and carbon dioxide emissions were predominantly observed in developing countries in Asia and South America, whereas nations with low-low values of CO₂ emissions were primarily situated in the African continent. The empirical findings also concluded that the regions with elevated concentrations of air pollutants were predominantly observed in African nations and

Asian countries. On the other hand, the countries with low levels of air pollutants were observed to be concentrated in the South American continent. The empirical data derived from the SDM indicated that the average level of carbon dioxide (CO₂) emissions from bordering developing nations has had a notable positive impact on human development. On the contrary, the proximity-based mean of atmospheric air pollution has resulted in a decline in the human development index inside emerging economies. Furthermore, the magnitude of the effects of both carbon dioxide emissions and air pollution differed among developing countries. The immediate findings determined that CO₂ emissions exhibited a high level of sensitivity in relation to developing nations in South America and Africa. In contrast to carbon dioxide emissions, air pollution exhibited heightened sensitivity in many Asian and African emerging nations.

The aforementioned outcomes yield a set of policy recommendations. Firstly, the promotion of clean energy through the restrictions of fossil fuel combustion is a crucial measure that governments should undertake to enhance environmental conditions. Secondly, nations characterized by elevated levels of carbon dioxide emissions contribute to a more substantial degree of air pollution. It is recommended that all governments consider the implementation of a carbon tax as a means to effectively mitigate CO₂ emissions. The revenue generated from this tax could then be used towards enhancing the development and utilization of clean energy sources. Thirdly, it is imperative for each government to impose limitations on their industrial zones, ensuring compliance with the regulations set forth by green technology organizations. This entails giving precedence to regions that exhibit higher levels of CO₂ emissions and air pollution.

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