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Impact of Urban Form on CO_2 Emissions Using a STIRPAT Model:

Focusing on 15 cities in South, Southeast and West Asia*

Hyemi Yang** · Naeun Lee*** · Jaemin Song****

Abstract: The United Nations (UN) estimates that an additional 2.5 billion people will reside in urban areas by 2050. Due to rapid economic development and urbanization, urban areas are responsible for more than 70% of global greenhouse gas (GHG) emissions from final energy use. Rapid urbanization will predominantly occur in emerging nations, particularly in Asia, where more than four billion people reside, accounting for around 55% of the world's population. However, the temporal and spatial characteristics of urban structure in emerging cities and their correlations with GHG emissions are hardly understood, despite the fact that urban form is an important determinant of urban sustainability. Given this context, the study aims to evaluate the dynamics of urban form using three key measurements—population density, Moran's index, and population gradient coefficient—in the capital cities of South, Southeast, and West Asia and investigate how urban form affects CO_2 emissions. The study employs a modified STRIPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model as its major framework, using panel data from 2000 to 2019 with a five-year gap. The results indicate that the evolution of urban form varies from city to city while the population density continues to increase with slight variations in Moran's and population gradient coefficients. Considering the changes in the three indicators over time in the cities under study, it can be concluded that urbanization in the researched areas is generally getting more compact. Moran's index is a statistically significant factor concerning CO_2 emissions, indicating that CO_2 emissions could be lowered in cities with more clustered forms. The findings of this research have major implications for urban policy-makers seeking to explain the dynamics of urban form, how it evolves in developing countries, and how CO_2 emissions are affected.

Key Words: Urban form, CO_2 emissions, STIRPAT model

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** First Author, Ph.D student, Graduate School of Environmental Studies, Seoul National University

*** Co-Author, Master's degree student, Graduate School of Environmental Studies, Seoul National University

**** Corresponding Author, Associate Professor, Graduate School of Environmental Studies, Seoul National University

I. Introduction

Urbanization has accelerated substantially over the past decades, increasing from 30% in 1950 to 55% in 2018 (United Nations [UN], 2018). The UN expects an additional 2.5 billion people to dwell in metropolitan areas by 2050. With the increased economic development and urbanization, urban areas are responsible for more than 70% of the global greenhouse gas (GHG) emissions from final energy use (Seto et al., 2014).

Rapid urbanization will occur predominantly in developing countries, particularly Asia (UNDP, 2017), which is home to more than four billion people, or approximately 55% of the global population. By 2050, the urban population in the region is projected to increase from its current level of 2.1 billion to as high as 3.4 billion. Moreover, urbanization is often accompanied by a rapid increase in energy demand (International Energy Agency [IEA], 2019). Therefore, sustainable urbanization in three Asia sub-regions, namely Southeast, South, and West Asia, is critical for global climate change mitigation, given Asia's rapid urbanization and vast population. Nevertheless, the data and knowledge required to comprehend the climate change mitigation risk and opportunities in these areas are significantly lacking. Many prior studies have concentrated on developed countries, with little attention dedicated to other regions.

The urban dynamics in these under-developed areas is another research gap in climate change mitigation studies. Urban form is the pattern of human activities (Tsai, 2005), an important determinant of urban sustainability. The advantages of compact urban form are well-known from the sustainability perspective (OECD, 2012). Much empirical research on cities in developed countries has demonstrated that a compact urban form adds to the effective use of resources and decreases environmental pollution (Song and Nam, 2009; Kim and Song, 2015; Shin and Yoon, 2022). Urban form is intrinsically related to travel demand, hence spatial planning is vital for lowering GHG emissions (Ewing and Cervero, 2010; Seto et al., 2014; Song, 2021). Buildings are another major source of urban GHG emissions. Mixing mid- and high-rise buildings in a compact city reduces energy use. However, the temporal and spatial characteristics of urban structure in emerging cities and their associations with GHG emissions are hardly understood. The populations of cities in developing nations will continue to grow in the near future; therefore, examining the direction of their urban development and making appropriate suggestions for the future are essential.

Given this background, this study aims to assess the dynamics of urban form in the capital cities of South, Southeast, and West Asia and examine the effect of urban form on CO_2 emissions. The study employs a modified STIRPAT(Stochastic Impacts by Regression on Population, Affluence, and Technology) model as its main framework to examine the effect of urban form on CO_2 emissions using panel data from 2000 to 2019 with a five-year gap. This paper is constructed as follows. Section II reviews previous studies on the IPAT model and the relationship between urban form and CO_2 emissions. Section III describes the data collection and analysis, while Section IV reports and interprets the results from the analysis. Finally, conclusions are presented in Section V, along with policy implications.

Ⅱ. Literature Review

1. IPAT Model

The IPAT model is a popular empirical model for analyzing the effect of economic development on the environment. IPAT is a framework for analyzing the effects of population *P*, affluence *A*, and technology *T* on the environment *I*. Ehrlich and Holdren (1971) were the first to suggest the IPAT model, which Dietz and Rosa (1997) transformed into STIRPAT, a probability model, by adding an error component. Ehrlich and Holdren's argument was to refute the notion that people's contribution to environmental degradation was negligible. Thus, they placed population at the center of the equation, highlighting its significant impact on the environment. The researchers then extended their equation to show the interaction of population, affluence, and technology and their nonlinear relationships. In addition to the standard IPAT model, various versions have been proposed, including the IPBAT by Schulze (2002) and IPACT by Waggoner and Ausubel (2002) as shown in 〈Table 1〉. IPBAT extends the basic IPAT model with a variable B describing behavior, whereas IPACT adds a variable C reflecting consumption. 〈Table 1〉 illustrates the evolution of the IPAT model throughout time.

STIRPAT is a stochastic model used for empirically testing human impacts on the environment, in contrast to the original IPAT, which comprises accounting equations. STIRPAT model specifications are as follows:

$$I = aP_i^b A_i^c T_i^d e_i \cdots\cdots\cdots\cdots (1)$$

where *I* is the total environmental impact, *a* is the model's scale, *b*, *c*, and *d* are the coefficients of *P*, *A*, and *T*, respectively, that must be evaluated for the ith observation, and *e* is the error term. As indicated by the subscript *i*, these variables (*I*, *P*, *A*, *T*, and *e*) vary among the observations. Estimation and hypothesis testing are simplified by an incremental regression model with logarithmic values for all variables. STIRPAT model has been applied to numerous research to examine how economic development affects the environment (Lee and Kang, 2012; Yoon and Song, 2015; Shahbaz et al., 2016; Wang et al., 2017; Ding et al. 2022). Furthermore, to test the impact of urban form or urbanization on environment such as CO_2 emissions, those urban factor could be added as a additional independent variable on the equation.

〈Table 1〉 Evolution of IPAT Model

Authors	Model	Explanation
Ehrlich and Holden (1971)	$I = PF$	Total environmental impact explained by population *P* and impact per capita *F*
Ehrlich and Holden (1972)	$I = PAT$	Total environmental impact explained by population *P*, affluence *A*, and technology *T*
Schulze (2002)	$I = PBAT$	An extended version of IPAT, taking into consideration behavior *B*
Waggoner and Ausubel (2002)	$I = PACT$	An extended version of IPAT, taking into consideration consumption per unit of Gross Domestic Product[GDP] *C*
Dietz and Rosa (1994)	$I = aP_i^b A_i^c T_i^d e_i$	A stochastic model for IPAT model

2. Urban Form and Energy Consumption

The quantity and characteristics of GHG emissions vary by city based on population, socioeconomic status, spatial structure, and infrastructure (Seto et al., 2014). Spatial planning is crucial for reducing GHG emissions since urban form is inextricably linked to travel demand (Ewing and Cervero, 2010; Seto et al., 2014; Song, 2021). Another critical source of GHG emissions in cities is the building sector. Building energy usage can be reduced by mixing mid- and high-rise structures in a compact metropolitan area. Effective urban mitigation strategies should integrate various spatial planning features, such as high-density residential and employment areas placed together, diverse land use, enhanced accessibility, and efficient public transportation (Seto et al., 2021).

Numerous cities have been the subjects of empirical studies on the effect of urban patterns on energy and GHG emissions. For example, cross-sectional data analysis of Korean cities revealed that compactness characteristics contribute to a reduction in transportation energy (Kim and Song, 2015; Song and Nam, 2009). Population density has the greatest impact on the usage of public transit and non-motorized travel in Korea, according to a meta-analysis of historical empirical data for Korean cities (Song, 2021). Ye et al. (2015) explored the impact of compactness on urban household energy use using remote sensing data for China and found similar results—a considerable reduction in energy usage in areas with higher densities of development.

While some research has employed an IPAT model to quantify the influence of urbanization on the environment, few studies have integrated the impact of urban form with this approach. Using a STIRPAT model, Wang et al. (2017) explored the effect of urban form on CO_2 emissions for four Chinese mega cities—Beijing, Tianjin, Shanghai, and Guangzhou—using total urban area, the number of patches, edge density, and population density as major metrics. Interestingly, the results indicated that urban density is positively correlated with CO_2 emissions, contrasting the conventional view in which a compact urban form is more beneficial for energy consumption and associated GHG emissions. Furthermore, Ding et al. (2022) tested the impact of urban compactness on CO_2 emissions for 295 cities in China using a STIRPAT model. Five metrics were used to measure urban compactness, including patch density, landscape shape index, the coefficient of the patch area, patch cohesion index, and aggregation index. Their findings showed that, beyond a certain threshold, the effect of urban compactness on CO_2 emissions declines.

In summary, few studies have been conducted on the effect of urban form on CO_2 emissions using the STIRPAT model, particularly for rapidly expanding cities in the three sub-Asian regions. In addition, recent research undertaken on growing cities in China has revealed conflicting findings about the effect of urban form. Our study contributes to this body of knowledge by evaluating the dynamics of urban form changes and examining their effects on CO_2 emissions in understudied Asian cities.

Ⅲ. Data and Methodology

1. Study Scope

Our investigation encompasses the capital cities of Southeast, South, and Western Asia. Based on the availability of data, fifteen cities have been chosen for analysis, as depicted in 〈Figure 1〉 and 〈Table 2〉. To explore the dynamics of urban form changes and their associations with GHG emissions, the temporal scope of the research covers from 2000 to 2019, with a five-year data collection gap.

〈Figure 1〉 Study Area

〈Table 2〉 List of Cities

Region	City
South Asia	Delhi (India), Kathmandu (Nepal), Dhaka (Bangladesh)
Southeast Asia	Bangkok (Thailand), Jakarta (Indonesia), Kuala Lumpur (Malaysia), Manila (Philippines), Phnom Pehn (Cambodia)
West Asia	Ad Dawhah (Qatar), Al Kuwayt (Kuwait), Amman (Jordan), Baghdad (Iraq), Beirut (Lebanon), Manama (Bahrain), Muscat (Oman)

2. Data and Model

To examine the impact of urban form on CO_2 emissions, we modified the STIRPAT model developed by Dietz and Rosa (1994) by adding urban form factors. Additionally, to test the validity of urban form factors as significant variables, the study started with an original STIRPAT model for fifteen cities. Since the impact of urban form on CO_2 emissions is of interest, the dependent variable is CO_2 emissions. The basic STIRPAT model is specified as Eq. (2):

$$\ln CE_{it} = \ln a + b_1 \ln POP_{it} + b_2 \ln GDP_{it} + b_3 \ln Eff_{it} + u_i + e_{it} \cdots\cdots (2)$$

where CE_{it} is the CO_2 emissions of city i at year t (t = 2000, 2005, 2010, 2015, and 2019); POP_{it}, GDP_{it}, and Eff_{it} are the control variables of population, gross domestic product (GDP) per capita, and GDP per energy, respectively; and u_i and e_{it} are the fixed effect and random error, respectively.

The CO_2 emissions of each city were estimated by combining two datasets: national CO_2 emissions from IEA and the urban share of CO_2 emissions from Guerny et al. (2022). No public data was available for urban CO_2 emissions, in particular for cities in developing countries. Thus, we estimated them by multiplying national CO_2 emission values with the urban share estimated by Guerny et al. (2022), which presented the CO_2 urban share based on a combination of the urban population share, urban carbon footprint, SSP-based national CO_2 emissions, and recent analysis of per capita urban CO_2-eq trends. In addition, GDP per capita represents A, and the energy efficiency, defined as the GDP per unit of energy consumption, serves as T in our STIRPAT model. The expanded model that includes urban form factors are specified in Eq. (3). We have used three indicators to measure urban form based on Tsai (2005): population density, Moran's index and coefficient of population gradient curve. The following is the final model for the analysis.

$$\ln CE_{it} = \ln a + b1\ln POP_{it} + b_2\ln GDP_{it} + b_3\ln Eff_{it} + b_4\ln Density_{it} + b_5\ln Moran_{it} + b_6\ln Gradient_{it} + u_i + e_{it} \cdots\cdots\cdots\cdots\cdots\cdots (3)$$

where $Density_{it}$, $Moran_{it}$, and $Gradient_{it}$ are the population density, Moran's index, and coefficient of population gradient curve of city i at year t, respectively.

Without annual public data available for the urban population in the studied area, we used WorldPop data, open-source data that offers grid population data from 2000 to 2020 with a high resolution of 1km units(WorldPop, 2022). The WorldPop research programme, housed in the School of Geography and Environmental Science at the University of Southampton, is a multi-sector team of researchers, technicians and project specialists that produce data on population distributions and characteristics at high spatial resolution. The gridded population data was clipped and extracted using a city boundary obtained from DIVA-GIS (2022) for the urban form factor calculations.

Density is a commonly used indicator to measure urban form, owing to its easy measurement and usefulness in controlling urban development intensity (OECD, 2012). Moran's index represents the degree of clustering, measured by the spatial auto-correlation coefficient using ArcGIS. It ranges from −1 to 1, with a high positive value representing areas with similar densities that are highly clustered; a Moran's index near zero indicates random dispersal, and a value of −1 denotes a "chessboard" pattern of development (Tsai, 2005). Lastly, we estimated the population gradient coefficient by fitting the negative exponential model to the equation using the population density and distance from the CBD (central business district). Clark (1951) first proposed the concept of a population gradient curve to measure urban density. This curve illustrates how urban population density varies with distance from the CBD. Considering that the CBD is the center of population and business agglomeration, the grid cell with the highest population was considered the CBD of each city (Jang and Song, 2022). Finally, we determined the gradient coefficient by fitting a negative exponential model to the equation using population density and distance from the CBD. 〈Table 3〉 lists the variables and their descriptions.

〈Table 3〉 Data Description

Variables		Description	Unit	Transformation	Source
Impact (*CE*)		Urban CO_2 emissions	ton CO_2	logged	IEA
Affluence (*GDP*)		GDP per capita	US$ in 2022	logged	World Bank
Technology (*Eff*)		$\frac{GDP}{Total\ Energy}$	US$/TJ	logged	World Bank
Population (*POP*)		Population	Person	logged	World pop
Urban Form	Population Density (*Density*)	$\frac{Population}{Administrative\ Area}$	Person/㎢	logged	
	Moran's Index (*Moran*)	$I = \frac{1}{s^2}\frac{\sum_i\sum_j (y_i-\overline{y})(y_j-\overline{y})}{\sum_i\sum_j W_{ij}}$	-	logged	
	Population Gradient Coefficient (*Gradient*)	$\ln D_x = \ln D_0 - gx$ $g = \frac{\ln D_0 - \ln D_x}{x}$	-	logged	

Ⅳ. Empirical Result

1. Descriptive Statistics

According to the descriptive statistics, a noticeable difference is present in the variables among the research areas 〈Table 4〉. The average population of each study area is 3,137,440 persons. The GDP per capita is an average of US$10,392, ranging from US$229 to US$67,403. The average energy efficiency is US$122,015/TJ, while the difference in energy efficiency between the lowest- and highest-performing cities is greater than 15 times.

〈Table 4〉 Descriptive Statistics

Variables	Category	Obs	Mean	Std. dev.	Min	Max
Impact	overall	75	103478.7	222330.7	903.5	1311000.0
	between	15		208973.8	2778.2	833034.4
	within	5		90118.9	-320015.5	581444.3
Affluence	overall	75	10392.3	15231.0	229.5	67403.1
	between	15		14994.9	646.9	54830.2
	within	5		4391.9	-14461.6	22965.3
Population	overall	75	3137440.0	4549330.0	97298.7	19000000.0
	between	15		4604172.0	99495.0	16000000.0
	within	5		802411.8	297379.9	6132236.0
Technology	overall	75	122015	62180.3	16317.2	252072.7
	between	15		44301.5	36859.8	193743.4
	within	5		44831.4	27856.7	230255.8
Population Density	overall	75	12996.28	13612.47	219.6359	63510.84
	between	15		12271.87	224.5937	42680.7
	within	5		6545.299	-8507.535	51255.48
Moran's index	overall	75	0.6239476	0.275002	-0.045344	0.943288
	between	15		0.281953	0.0167862	0.9383646
	within	5		0.020633	0.5275954	0.6735874
Population Gradient Coefficient	overall	75	-131.8904	226.6943	-959.2775	-4.557199
	between	15		230.8975	-937.8175	-6.614693
	within	5		30.95889	-262.1596	44.46492

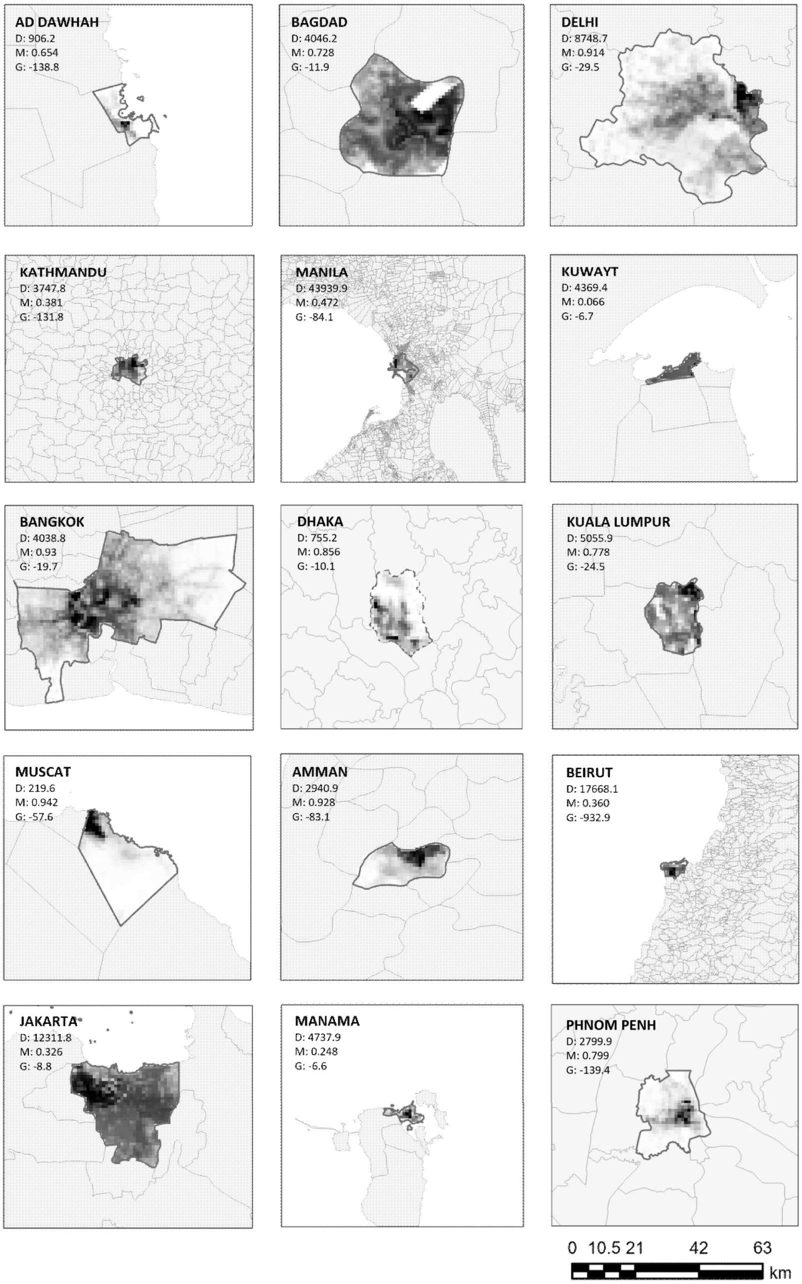
2. Characteristics of Urban Form

This section explores the urban form characteristics of the region's capital cities and analyzes their dynamic changes from 2000 to 2019. 〈Figure 2〉 depicts the 2019 1×1 km grid population distribution used to calculate urban form indicators for each city. The cities have varied characteristics in terms of population, area, and population distribution. The following provides a more detailed analysis of the three major urban form indicators.

Population density is a commonly used indicator in urban planning, providing a proxy for urban compactness. While higher density is generally known to contribute to urban sustainability, a standard threshold for optimal urban density is not established. 〈Figure 2〉 shows that some of the studied cities in the region have relatively high densities. For example, if we compare the densities of studied areas with the density of Seoul, Korea, having one of the highest densities of 15,699 people/km^2(OECD, 2012), Beirut and Manila are even denser as of 2019. The density of Jakarta is relatively similar to Seoul at 12,311 people/km^2. On the other hand, Ad Dawha and Muscat have very low densities, with less than 1,000 people/km^2. The densities of other cities under study are similar to that of Busan in Korea, the second largest and densest city in the country.

Although population density is a valuable metric of urban density, it fails to reflect the distributional characteristics of the population. In this regard, Moran's index is a useful metric for measuring the degree of clustering within a city. As illustrated in 〈Figure 2〉, the population distribution in the majority of cities show high level of spatial autocorrelation, indicating a continuous development pattern rather than a leap frogging pattern. In particular, the Moran's index for four cities, namely Amman, Bangkok, Delhi, and Muscat, was greater than 0.9, indicating a very strong spatial autocorrelation. Among a total of fifteen cities included in this study, nine had a Moran's index greater than 0.5.

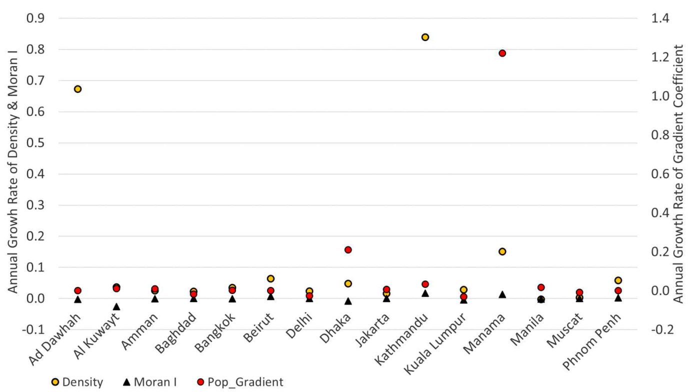
〈Figure 2〉 Distribution of Population in 2019



D-population density(pp/㎢); M-Moran's Index; and G-Coefficient of population gradient curve
Source: WorldPop(2022)

The slope of the population gradient curve is a useful measure of centrality. The population density gradient function is a modified version of the distance-decay model that depicts the decrease in population density at a specific urban site as its distance from the city center increases (Yoon and Lee, 2013). The urban population density and its slope rely on the city's characteristics. Consequently, the slope of the population gradient curve reflects the spatial structure characteristics of the city. However, a comparison of the coefficients between cities should be made with caution since the values can be sensitive to city size. In fact, the results indicate that smaller cities, such as Beirut, Manama, and Manila, have much larger gradient curve coefficients than other cities.

〈Figure 3〉 Annual Growth Rate of Urban Form Indicators (2000-2019)



〈Figure 3〉 depicts the annual growth rate of three urban form indices for each city between 2000 and 2019. With the exception of Manila, all cities experienced a significant increase in population density. Specifically, the population densities of Ad Dawhah and Kathmandu expanded over tenfold. In terms of Moran's index, average yearly growth rates of 0.018% were observed for all cities during the examined time period. Although half of the cities suffered a decrease in Moran's index, the absolute changes are not noteworthy.

In terms of the coefficient of the population gradient curve, the average yearly growth was 0.031%, excluding Manama, which experienced a significant increase. In addition, all cities except Baghdad, Delhi, Kuala Lumpur, and Muscat saw an increase in population gradient curve coefficients. Given that a gradient curve's coefficient is a proxy for centrality, we may conclude that the centrality of the capital cities in the three Asia sub-regions increases with time.

A compact urban form is generally characterized by a higher population density (Jang and Song, 2020; Ewing and Cevero, 2010; OECD, 2012), higher Moran's index (Tsai, 2005), and larger coefficient of population gradient curve (Yoon and Lee, 2013). However, given the multi-dimensional characteristics of a compact city, three factors are insufficient to determine whether a city is compact. Nevertheless, based on the changes in the three indicators over time, evaluating whether the overall urban form is becoming more compact or expanding is a reasonable approach. From 2000 to 2019, density grew in all cities except one, Manila, and Moran's index did not change much, with an annual growth rate between −0.01 and 0.01, except Al Kuwayt. Most of the cities except Bagdad, Delhi, and Kuala Lumpur experienced slight increase in population gradient coefficients, indicating that their centrality has been somewhat strengthened. In addition, the CBDs of those three cities with decreased population gradient coefficients have been intensified with increased density. Thus, the changes in the three indicators generally suggest that urbanization in the research area is generally becoming more compact.

3. Impact of Urban Form on CO_2 emissions

In this research, we performed a panel analysis using the STIRPAT model and conducted an empirical analysis to determine the impact of urban form on CO_2 emissions. As previously noted, the STIRPAT model incorporated three urban form-related variables. The coefficient in this model can be interpreted as elasticity of CO_2, which is the percentage change in CO_2 emissions due to the change in the independent variables, since all variables have been replaced by logarithms. To fit the best model for the analysis, we conducted tests shown in 〈Table 5〉. The results demonstrated that M3, the model including urban form indicators, had a better ability to explain the impact on CO_2 emissions better than the standard STIRPAT model.

〈Table 5〉 Model Fitting

Model	M1: Unconditional	M2: I-PAT	M3: I-PATU
	CO_2 Emissions	CO_2 Emissions	CO_2 Emissions
Population		0.432*** (-0.07)	0.710*** (-0.21)
Affluence		0.926*** (-0.11)	0.895*** (-0.10)
Technology		-0.469*** (-0.14)	-0.429*** (-0.13)
Population density			-0.775*** (-0.21)
Moran's Index			-2.715** (-1.04)
Population Gradient Coefficient			0.032 (-0.05)
_cons	10.398*** (-0.39)	2.103* (-0.95)	-0.704 (-1.26)
N	75	75	75
sigma_u	1.504	0.981	0.912
sigma_e	0.476	0.180	0.174
rho	0.909	0.967	0.965

Standard errors in parentheses.
*p〈 0.05, **p〈 0.01, ***p〈 0.001

The F test result for pooled OLS (Ordinary Least Squares) assuming homoscedasticity of the error terms was found to be rejected at the 1% significance level as a result of analysis using pooled OLS, fixed-effects model (FEM), and random-effects model (REM). This finding suggests that fixed- and random-effects models are more appropriate than pooled OLS. The fixed-effect model is optimal because the random-effect model was rejected by the Hausman test at a significance level of 1%. The effect of each variable on CO_2 emissions is as follows.

〈Table 6〉 Result of Panel Analysis

Independent Variable		CO_2 Emissions		
		Pooled OLS	FEM	REM
Population		0.731*** (−4.77)	0.375*** (−5.67)	1.187*** (−5.60)
Affluence		0.341*** (−3.46)	1.068*** (−9.96)	0.911*** (−8.79)
Technology		0.588** −2.72	−0.592*** (−4.77)	−0.446*** (−3.54)
Urban Form	Population density	−0.122 (−0.63)	0 (.)	−0.775*** (−3.63)
	Moran's Index	−0.0785 (−0.07)	−2.737* (−2.41)	−2.715** (−2.61)
	Population Gradient Coefficient	−0.347** (−3.08)	0.042 (−0.96)	0.032 (−0.69)
Cons		−7.003** (−3.01)	4.263*** (−4.65)	−0.704 (−0.56)
R^2−within		0.7374	0.8780	0.8731
R^2−between			0.0799	0.4865
R^2−overall			0.1113	0.5114
Test of Pooled OLS		−	Prob 〉 F = 0.0000	Prob 〉 chi2 = 0.0000
Hausman Test		−	Prob 〉 chi2 = 0.0001	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$*

First, population, affluence, and energy efficiency have statistically significant effects on CO_2 emissions. Population and GDP per capita were found to have a positive effect on CO_2 emissions, while the effect of energy efficiency was negative. Our findings, shown in 〈Table 6〉, are congruent with those of earlier research. For instance, Wu et al. (2021) conducted a panel data study on industrialized countries using an enhanced STIRPAT model and indicated that population and economic expansion lead to an increase in CO_2 emissions, whereas energy efficiency plays a key role in reducing CO_2 emissions. The analysis revealed that the traditional factors, *P*, *A*, and *T*, have similar effects on emissions in emerging countries as in wealthy nations.

Only the Moran's index among the urban form factors had a statistically significant effect on CO_2 emissions in fixed-effect model. Specifically, a 1% increase in the Moran's index reduced CO_2 emissions by approximately 3%. The size of elasticity is the largest compared with the other traditional variables, confirming the significance of urban form on GHG emissions. In the meantime, population density variable dropped due to collinearity in the fixed-effect model. However, its significance in the random-effect model indicates its potential contribution to urban GHG emissions. Both of significant urban form factors, population density and Moran's Index, have negative elasticity, meaning that higher density and Moran's Index contributing to a reduction in CO_2 emissions in a city. Thus, urban population distribution as well as population density should be considered a critical urban planning factor to reduce CO_2 emissions and achieve sustainable development.

Ⅴ. Conclusion

As cities are considered major contributors and potential remedies for CO_2 emissions, understanding the dynamics of urban form and how it affects CO_2 emissions in developing nations is vital. Much research, however, has focused on either national or city levels in developed countries. To fill the gap, the current study aims to capture the dynamics of urban form and its impact on CO_2 emissions of 15 cities in South, Southeast, and West Asia from 2000 to 2019.

The study reports that the densities of the cities under study are steadily increasing while the rate of urban population growth varies from city to city. Our study also analyzed dynamic changes in the distribution of population using Moran's index and the population gradient curve from the CBD to the edge of the city. Considering the changes in the three indicators over time in the studied cities, we may conclude that urbanization in the research area is generally becoming more compact, which is typically regarded as a positive trend.

Using a modified STIRPAT model, we also conducted a panel study to investigate how urban form affects CO_2 emissions. The Moran's index was identified as a significant variable influencing CO_2 emissions, with a negative sign. Notably, its elasticity is stronger than that of other traditional variables, such as population, affluence, and technological efficiency. While the result is consistent with previous findings that a compact city has lower CO_2 emissions (Baur et al., 2015; Makido et al., 2012; Christen et al., 2011; Ewing and Rong, 2008), a strong elasticity of an urban form variable reflects its relative importance even when compared to other factors regarded as critical determinants of CO_2 emissions, especially in developing countries.

This paper has significant policy implications for governments, developers, municipalities, and urban planners in developing countries to understand the dynamics of urban form and its transformation over time, along with their impact on CO_2 emissions. Our empirical study indicates that spatial planning can play a significant role in mitigating climate change in rapidly growing cities. For a better understanding of urban dynamics on CO_2 emissions, additional research is required, particularly an investigation of the relationship between urban form and CO_2 emissions per sector in developing nations. To conduct such research, however, various data including CO_2 emissions by sectors and economic status must be collected and disclosed at the urban level (Creutzig et al., 2019). When the updated data collected, a follow-up research could be delivered more deeply in linkage between urban form and CO_2 emissions.

▌References ▌

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Hyemi Yang: Ms. Yang received her Master of Engineering in Urban Planning and Design from University of Seoul. She is currently a Ph.D student at Seoul National University Graduate School of Environmental Studies. Her area of research is sustainable development of developing countries and climate change impact, mitigation, and adaptation at the global and local level(hmyang@snu.ac.kr).

Naeun Lee: Ms. Lee is a master student at the department of urban and regional planning in Soeul National University. Her fields of interest include urban regeneration, energy and urban planning(naeun21@snu.ac.kr).

Jaemin Song: Dr. Jaemin Song is an associate professor at Seoul National University Graduate School of Environmental Studies. She obtained her Ph.D in Engineering System from Massachusetts Institute of Technology(MIT). Her research interests include sustainable and smart cities(jaemins@snu.ac.kr).

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