Sustinere
Journal of Environment and Sustainability
Volume 8 Number 2 (2024) 150-165

Print ISSN: 2549-1245 Online ISSN: 2549-1253
Website: https://sustinerejes.com E-mail: sustinere.jes@uinsaid.ac.id

RESEARCH PAPER

Spatial dependency of air pollution in Jabodetabek urban agglomerates cities

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Article history:
Received 14 March 2024 | Accepted 26 July 2024 | Available online 31 August 2024

Abstract. Poor air quality is a major issue in the core city of the Jabodetabek urban agglomeration, Jakarta. Unfortunately, this problem is not limited to Jakarta. Other cities in Jabodetabek also face similar challenges, where they have experienced similar fluctuations in their annual average $PM_{2.5}$ concentrations based on historical data. This indicates that the air quality problem is dependend on the region. The integration of systems and activities among these cities may explain this problem. This spatial dependency is dangerous and can lead to transboundary health effects. Therefore, this research aims to find evidence of this spatial dependency in Jabodetabek. The results show that $PM_{2.5}$ concentration in Jabodetabek is spatially dependent and exhibits a clustered pattern. The highly concentrated core of the cluster is Depok, the connecting city between the buffer cities and the core city of Jabodetabek. Cities with high-point and mobile hotspot sources, such as South Jakarta, East Jakarta, Bogor, and Bogor City, surround Depok, leading to this concentration.

Keywords: Air pollution; $PM_{2.5}$; Spatial dependency; Spatial pattern; Urban Agglomeration; Jabodetabek

1. Introduction

Living in urban areas can enhance person's quality of life by providing convenience and flexibility. However, urbanization also has its drawbacks, such as air pollution, which can significantly impact the health of urban communities (Haryanto, 2018; Y. Kim et al., 2017; C. Li et al., 2019; Piracha & Chaudhary, 2022; Sierra-Vargas & Teran, 2012; Susanto, 2020). WHO (2022) claimed that Air pollution is more dangerous than smoking, tuberculosis, and HIV/AIDS. $PM_{2.5}$, a type of air pollution, can cause respiratory and cardiovascular problems and even hinder the growth of young children, leading to increased healthcare costs for the community (Guo et al., 2018; Hamanaka & Mutlu, 2018; Kashima et al., 2010; Pun et al., 2021; Sacks et al., 2011; Soleman et al., 2023; Wei & Tang, 2018; Y. Wu et al., 2019; S. Zhang et al., 2022). The risk of morbidity and stunting can impact the quality of human resources and labor productivity, leading to a slowdown in economic growth in the short and long term (Aragón et al., 2017; Y. Kim et al., 2017; Pun et al., 2021).

Air quality in 65% of urban areas worldwide from 2000 to 2019 has been deteriorating, particularly in the Middle East, sub-Saharan Africa, and Southeast Asia (Sicard et al., 2023). This increase in air pollution can be attributed to the growing demand for energy in urban economies,

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DOI: https://doi.org/10.22515/sustinere.jes.v8i2.393

which result in higher emissions from both point and mobile sources (She et al., 2021; Zeduo et al., 2022). Higher urban economic activities from industries and households are the main sources of pollution in urban areas (Farabi & Abdullah, 2020; Qi et al., 2023). Meanwhile, the complex structure of urban areas causes traffic congestion, leading to high levels of air pollution from mobile sources (Liang & Gong, 2020; Lu et al., 2021; Qiang et al., 2020; Zhou et al., 2018).

Air pollution can easily spread from one place to another, including across borders, especially $PM_{2.5}$. Unlike other pollutants, $PM_{2.5}$ can be transported over long distances (Chen & Ye, 2019; D. Zhao & Sing, 2017). Evidence from Kim (2019) shows that $PM_{2.5}$ concentrations in the coastal cities of China can be transported to South Korea and affect air quality in the country. The movement of air pollution particles is mainly influenced by the wind speed and direction (Kusumaningtyas et al., 2021). Therefore, the $PM_{2.5}$ concentration in a city can affect the air quality of its neighbors (Chen & Ye, 2019; Ding et al., 2019; Feng et al., 2020; Jiang & Bai, 2018; L. Yang et al., 2022; Y. Yang et al., 2019; Zeduo et al., 2022; Zezhou & Xiaoping, 2017; Zhan et al., 2017; S. Zhao et al., 2018).

Transboundary or spatial dependencies of $PM_{2.5}$ concentration can lead to transboundary health impacts, slow down the turning point of EKC's curve, and attenuate the effect of a city's pollution control policy (Ding et al., 2019; He et al., 2021). The transboundary health impact is a negative spillover effect in public health that is suffered by neighbors of a high $PM_{2.5}$ concentrated city or country. The transported $PM_{2.5}$ to neighbors cities will lead to deterioration in air quality and cause a public health problem (J. Jung et al., 2022; Liu et al., 2020; S. Wu, 2020). Jung et al. (2022), demonstrated a transboundary impact of China air pollution on South Korea's public health. Meanwhile, Liu et al. (2020) and Wu, (2020) presented the transboundary impact in the China region.

The spatial dependence of air pollution can cause changes in the Environmental Kuznets Curve (EKC) relationship (Ding et al., 2019). The original (EKC) model suggests that economy growth initially increases environmental damage, such as air pollution. However, there is a turning point where environmental damage peaks and then decreases as the economy continues to grow. Negative spillover effects from surrounding cities can slow down the turning point of the EKC curve when those cities are still in an increasing stage. Ding et al. (2019) explained that surrounding cities that have not yet reached a turning point, which will continue to suffer from air pollution which will spill over into bordered cities. Spatial dependency can also lead to inaccurate identification of potential driving factors for air pollution or inaccurate effects of driving factors, which can hinder the development of effective solutions to air pollution (Feng et al., 2020; F. Li et al., 2022; She et al., 2021; Y. Yang et al., 2019).

Controlling air pollution in a city can be challenging because of ot transboundary impact. When a city implements mitigation or prevention measures without considering air pollution spillovers from neighboring cities, its efforts may be ineffective. For instance, tightening emission regulations in a city may prompt emitters to relocate their businesses to surrounding cities with more relaxed policies, resulting in an increase in air pollution concentrations in those areas. This can lead to spillover effects in cities with stricter regulations (Fang et al., 2019; Feng et al., 2020).

Metropolitan areas, such as the Jabodetabek Urban Agglomeration, face significant challenges in controlling air pollution. In addition to the natural characteristics of $PM_{2.5}$ that cause air pollution to spread further, urban agglomerations can intensify spillover effects between cities. An urban agglomeration can shape the spatial pattern of urban land use to become more clustered, and use in an agglomeration changes into a clustered area with a specific type of use such as an industrial area, commercial area, residential area, etc (M. C. Jung et al., 2019; Rustiadi et al., 2021). An urban agglomeration area that becomes more clustered requires transportation to link from one are to another or high mobility to facilitate integration in urban agglomerations (Huang & Du, 2018; M. C. Jung et al., 2019; C. Li et al., 2019; Liao et al., 2015; Lu et al., 2021; Rustiadi et al., 2021; Y. Wang et al., 2021; Zezhou & Xiaoping, 2017; Zhou et al., 2018). Such complexity and integration in an urban agglomeration can cause severe spatial dependency of air pollution concentration between cities or a transboundary effect of air pollution in an urban agglomeration.

As urban areas grow in complexity, new challenges arise, such as traffic congestion. Unfortunately, this problem has a significant impact on air quality due to the accumulation of mobile source emissions in areas with high traffic density, particularly as it relates to PM2.5 (da Schio et al., 2019; Huang & Du, 2018; Qi et al., 2023). Interestingly, diesel-powered vehicles emit higher levels of $PM_{2.5}$ at low speeds, while CO emissions are higher at high speeds (Batterman et al., 2015). As a result, low-speed traffic congestion tends to generate higher $PM_{2.5}$ emissions and create concentration hotspots. It is crucial to remember that these mobile-source emissions do not just come from the city where the traffic is located but can also come from surrounding areas, leading to spillover effects that impact populations beyond the immediate vicinity.

Apart from traffic congestion, urban sprawl in urban agglomerations can also lead to negative spillover effects of $PM_{2.5}$. This phenomenon occurs when growth points emerge in urban agglomeration areas, causing additional point source emissions and contributing to increased air pollution concentrations. As a result, both the city centre and surrounding areas may suffer from air pollution spillover effects. To address this issue, many studies recommend joint regulations for all cities within urban agglomeration areas to mitigate spatial dependency (Chen & Ye, 2019; He et al., 2021; F. Li et al., 2022; Zeduo et al., 2022).

Jakarta is the core of Indonesia's largest urban area, with Jabodetabek as its capital. Jakarta has been grappling with severe air pollution since 1990. It is important to recognise that this is not just a local issue confined to Jakarta, as traffic congestion plays a significant role in exacerbating air pollution, not only within the city but also in buffer zones. The worsening air pollution in these buffer cities can have a negative spillover effect on Jakarta and vice versa, and the concentration of point source emissions caused by clustering in Jabodetabek may intensify the problem.

Controlling Jakarta's air pollution requires joint regulation in Jabodetabek, which requires proving the spatial dependency of air pollution in the region. However, there is currently no empirical evidence to support this claim, highlighting the need for research to identify such evidence. Therefore, this research identifies the spatial dependencies within the Jabodetabek urban agglomeration.

2. Research method

3.2. Spatial weighting method

Spatial dependency, also known as spatial autocorrelation, refers to the relationship between a variable in one location and variables in surrounding areas. The presence of spatial autocorrelation can affect the way in which a variable and related factors are modelled. The W matrix represents this spatial relationship and describes spatial weighting. The spatial weighting method can be contiguity-based such as rook, queen, and Distance-based such as inverse distance, exponential distance model, and K-nearest neighbors, etc. The W matrix can take the form of a variable or binary matrix depending on the type of spatial weighting applied. Spatial weighting methods, such as fixed distance, K nearest neighbors, Delaunay triangulation, contiguity, or space-time window, use a binary W matrix. In contrast, the variable W matrix is used for the inverse distance, exponential distance, and zone of indifference.

To analyze the spatial distribution of $PM_{2.5}$ and the spatial relationships between different locations in Jabodetabek, this study used the contiguity matrix and inverse distance matrix. The contiguity matrix demonstrates that spatial dependence only exists among cities that share borders. On the other hand, the inverse distance matrix shows that spatial dependence can occur not only between neighboring cities but also between more distant cities, which is influenced by their distance.

3.2. Moran's Index

There are various methods for testing spatial autocorrelation. To determine its presence, Moran's I or Geary's C index was used. Moran's I use standardized spatial covariance, whereas Geary's C uses the sum of square distances. On the other hand, spatial regression can be used to gauge the strength of spatial dependency. This study will identify the existence of spatial dependency in air pollution within the Jabodetabek urban agglomeration. Therefore, the Moran I index is used because it is both widely used and powerful.

Getis (2010) explained that Moran's I index is a highly effective and widely used method for detecting the spatial independence of residuals. It is a modified version of the Pearson correlation coefficient is commonly used to establish the relationship between two variables. By incorporating a weight matrix, Moran's I can identify correlations in single variables while considering the spatial context. The proposed method not only detects spatial autocorrelation in data but also measures its strength. There are two types of Moran's I index used to identify spatial dependency: Global Moran's I, which detects spatial dependency in the entire data, and local Moran's I, which determines the spatial dependency between each area and its surroundings. The formula of Global Moran's I is in Equation 1.

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\,(y_i - \bar{y}) - (y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}\; i \neq j \tag{1}$$

Where I is the value of Global Moran's I, n is the number of observations, i is the index for the observed city, j is for neighboring cities of i, W_{ij} is a spatial weight for the observed city i and neighboring j, y is the value of the variable, and $\bar{y}$ is a mean of the variable.

To assess the significance of the global Moran's I index, the z-score and p-value can be utilized. The null hypothesis being tested is whether the data are randomly distributed. Rejecting the null hypothesis indicating spatial dependency. The value of Global Moran's I reflects the degree of such spatial dependency, typically ranging from 1 to 1 but potentially being outside this range. A positive value denotes clustering or relationship within the data, and a higher value indicates a stronger spatial relationship. Conversely, negative values indicate dispersed data, and a value of zero indicates no spatial dependency.

Differing from Global Moran's I, Local Moran's I focuses on the relationship between each area and its immediate surroundings. By detecting clustered areas, Local Moran's I can provide a dependency value for each area individually, enabling a more detailed analysis of spatial patterns. Essentially, this statistic measures the spatial clustering of high or low values in a dataset, making it a valuable tool for identifying hotspots and spatial outliers. The Local Moran's I is in Equation 2.

$$I_i = \frac{\sum_{j=1}^{n} W_{ij}\,(y_i - \bar{y}) - (y_j - \bar{y})}{\sum_{j=1}^{n}(y_j - \bar{y})} \tag{2}$$

where I_i is the value of Local Moran's I of i's city.

The Local Moran's I is a specialized version of the Global Moran's I, which exclusively examines the spatial dependence of each area-i and is a decomposition of the Global Moran's I. Depending on the outcome, the Local Moran's I can be positive or negative. Positive values denote high or low clustering, and negative values denote spatial outliers.

To understand the clustering area in greater depth, we can use Moran's scatterplot. Moran's scatterplot is a visualization of the interaction between y variables and the spatial lag of y variables. The pattern in the scatter plot represents the relationship between an area and its surroundings. Moran's scatterplot can also show whether one area is clustered, such as a High-High value type, which means a high-value area surrounded by high-value areas or a Low-Low value type, where a low-value area is surrounded by low-value areas, or whether the area is an outlier with a High-Low value type, where a high-value area is surrounded by low-value areas or a Low-High value type, where a low-value area is surrounded by high-value areas. The high-High value type shows that the point is located in the 1st quadrant, the 2nd quadrant is for the Low-High value type, the 3rd quadrant is for the Low-Low value type, and the 4th quadrant is for the High-Low value type.

3.5. Data sources

The data used in this research comprise the annual average $PM_{2.5}$ levels in the cities within Jabodetabek. The data were obtained from aqli.epic.uchicago.edu, an open data source maintained by the Energy Policy Institute of the University of Chicago. The data were processed using satellite-derived $PM_{2.5}$ data by the Atmospheric Composition Analysis Group at the University of Washington (Hammer et al., 2020). These data are ideal for analyzing patterns of $PM_{2.5}$ concentrations in urban areas caused by human activities, such as transportation and industry, as they are claimed to be free from natural sources of emission like forest fires and volcanoes. The data cover an annual time series from 1998 to 2021.

3. Result and discussion

3.5. Change in $PM_{2.5}$ concentration of Jabodetabek urban agglomeration cities in 1998-2021

$PM_{2.5}$ concentrations in Jakarta and its neighboring cities have exceeded the WHO guidelines for an annual average concentration of $PM_{2.5}$ which is 5 μg/m³ since 1998, as shown in Figure 1. According to historical data on Jabodetabek's $PM_{2.5}$ concentration, the concentration of $PM_{2.5}$ during 2998-2021 was almost 5 to 7 times from WHO guidelines. Figure 1 depicts the average annual concentration pattern in Jabodetabek, which exhibits a consistent upward fluctuation. Sicard et al. (2023) confirmed this trend, reporting a 1%-3% increase in $PM_{2.5}$ concentrations across Southeast Asia from 1998 to 2019. In the case of Jabodetabek cities, before the 2000s, the region's average annual $PM_{2.5}$ concentration was 20 μg/m³ to 25 μg/m³, which increased to 30 μg/m³ till 36 μg/m³ in the 2010s and beyond. This indicates a sharp increase in $PM_{2.5}$ concentration before 2006, followed by a gentler slope with wider fluctuations thereafter.

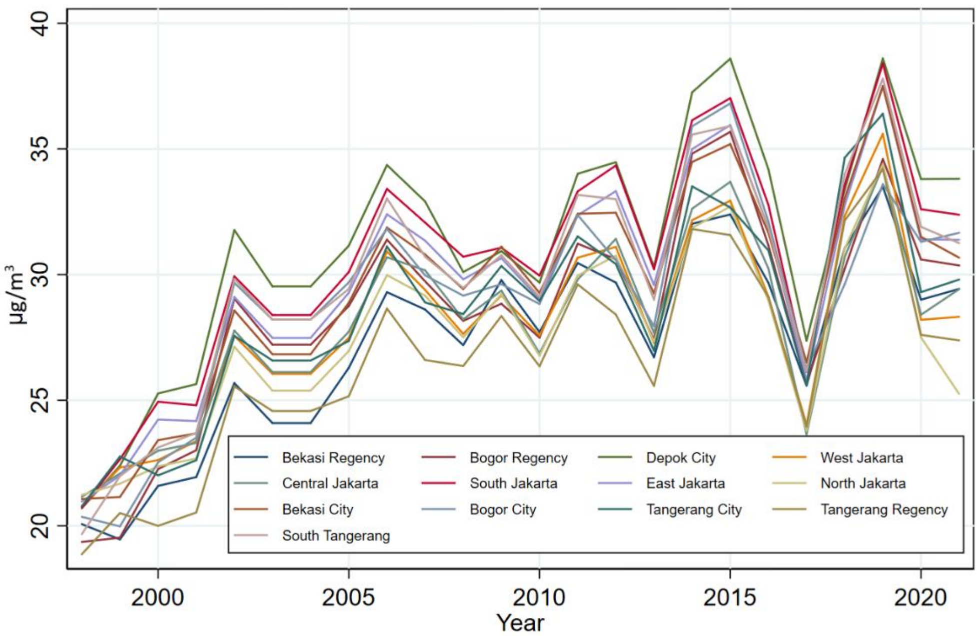

Figure 1. Annual average of $PM_{2.5}$ concentration of Jabodetabek cities from 1998 to 2021 (Hammer et al., 2020)

Changes in the yearly average $PM_{2.5}$ concentration can be attributed to variations in the number of rainy days. Rainfall has a negative relationship with atmospheric $PM_{2.5}$ concentrations, as supported by studies by Tian et al. (2021), R. Wang et al. (2023), and Yu et al. (2021). Rain can disperse harmful gases and deposit particulate matter onto the wet earth's surface. During rainfall, the concentration of $PM_{2.5}$ in the atmosphere can decrease by approximately 20%-50% (Tian et al., 2021; R. Wang et al., 2023). Figure 2 depicts how the level of $PM_{2.5}$ concentration in Jabodetabek interacts with the number of rainy days each year. This figure shows that a higher number of rainy days correspond to a lower annual average $PM_{2.5}$ concentration, and vice versa.

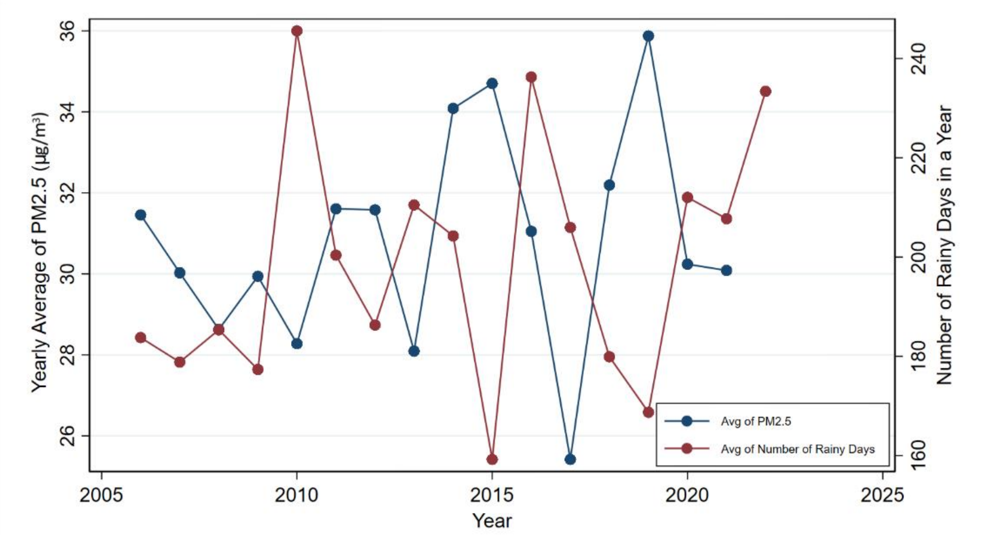

Figure 2. Annual average of $PM_{2.5}$ concentration and number of rainy days in a year of Jabodetabek from 2006 to 2021 (Funk et al., 2015; Hammer et al., 2020)

In Figure 1, it can be observed that the fluctuation patterns of the 13 cities are uniform. This uniformity indicates a correlation between the $PM_{2.5}$ concentrations in these cities. Specifically, the high and low annual average $PM_{2.5}$ concentrations of a city are dependent on the concentration levels of surrounding cities. This spatial pattern is also visible in Figure 3, which presents the annual average concentration of $PM_{2.5}$ in Jabodetabek. The maps in Figure 3 show clustering of high-concentration areas in the middle of the Jabodetabek region, specifically in Depot, Tangerang South, East Jakarta, and South Jakarta. To confirm this spatial correlation, global and local Moran calculations can be examined.

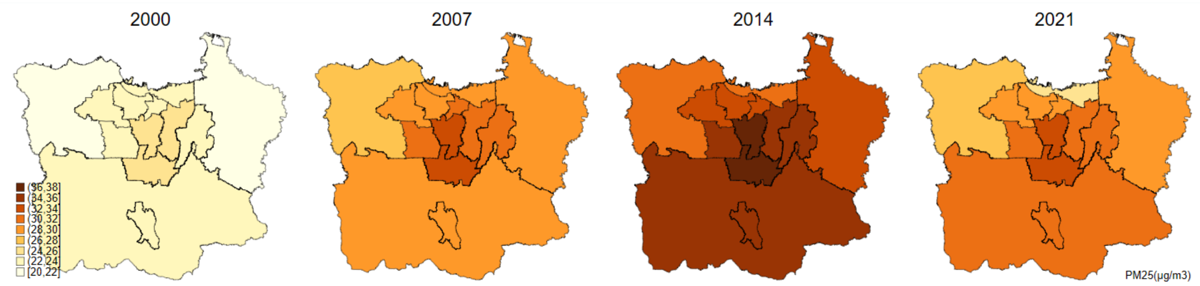

Figure 3. Annual average of $PM_{2.5}$ concentration map of Jabodetabek urban agglomeration (Hammer et al., 2020)

3.2. Spatial correlation trend of the annual average $PM_{2.5}$ in Jabodetabek from 1998 to 2021

The result of the Jabodetabek urban agglomeration's global Moran's *I* indicates that the value of global Moran's *I* is mostly positive (see Table 1). A positive global Moran's *I* value indicates a clustered spatial pattern of $PM_{2.5}$ concentration in the Jabodetabek urban agglomeration. According to Table 1, with a 95% confidence level, there is a spatial dependency of the annual average of $PM_{2.5}$ concentration between cities that share borders in the Jabodetabek urban agglomeration. The most significant value of the global Moran's index on the contiguity-weighted matrix is evidence of this. However, in the inverse distance matrix, the only significant global Moran index values are 1999 and 2018. This indicates that cities that do not share similar borders do not have a spatial dependency of annual average $PM_{2.5}$ concentration on each other.

Table 1. Result of Global Moran *I* for 13 Cities in Jabodetabek 1998-2021

Year	Contiguity	Inverse distance	Year	Contiguity	Inverse distance
1998	0.1634	0.1041	2010	0.1932	0.0344
1999	0.423**	0.3457**	2011	0.25*	0.1142
2000	0.2388*	0.1197	2012	0.2394*	0.1522
2001	0.1839	0.0692	2013	0.2372*	0.1465
2002	0.2187*	0.1229	2014	0.3208*	0.1946
2003	0.2267*	0.1073	2015	0.2925*	0.2102
2004	0.2191	0.0555	2016	0.3157**	0.116
2005	0.2375*	0.1328	2017	0.3798**	0.213
2006	0.2262*	0.0816	2018	0.3497**	0.3517**
2007	0.247*	0.1153	2019	0.253*	0.1766
2008	0.2139	0.0633	2020	0.3443**	0.1903
2009	0.2169	0.118	2021	0.3033**	0.1137

t statistics in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

The calculated Global Moran's *I* value fell within the range of 0.2–0.4, indicating a relatively weak to medium spatial relationship among $PM_{2.5}$ concentrations in Jabodetabek. Note that the global Moran's Index range is 1 to 1, where negative values indicate sparse patterns and positive values indicate clustered patterns. Additionally, the results show that, over time, the global Moran's I value increases, indicating that the positive spatial correlation strengthens.

3.5. Spatial pattern of $PM_{2.5}$ concentration in Jabodetabek

To gain a better understanding of the spatial distribution of $PM_{2.5}$ concentrations in the Jabodetabek urban agglomeration, it can be through a Moran scatterplot. The scatterplot is based on spatial lag calculations from previously calculated global Moran's *I* result. Figure 4 shows Moran's *I* scatterplot, which displays the correlation between a city's $PM_{2.5}$ concentration and its spatial lag. The slope of the linear line in the scatterplot indicates the level of spatial correlation; an increasing slope indicates a positive correlation. After identifying cluster points or outliers via local Moran's *I* calculations, we can further discuss the Moran scatterplot. The Moran scatterplot depicts data from 2000 to 2021, presented in seven-year intervals, and provides an overview of pattern changes from 1998 to 2022, with each year displaying a significant Moran value.

In the Jabodetabek area, cities can be divided into two categories: High-High value type or Low-Low value type. This implies that Jabodetabek is typically surrounded by neighbours with similar $PM_{2.5}$ concentrations. To determine which local dependency is significant, we perform Local Moran's *I* calculation. Table 2 displays the results of local Moran's *I* for Jabodetabek cities per seven years from 2000 to 2021, which were used in Moran's scatterplot.

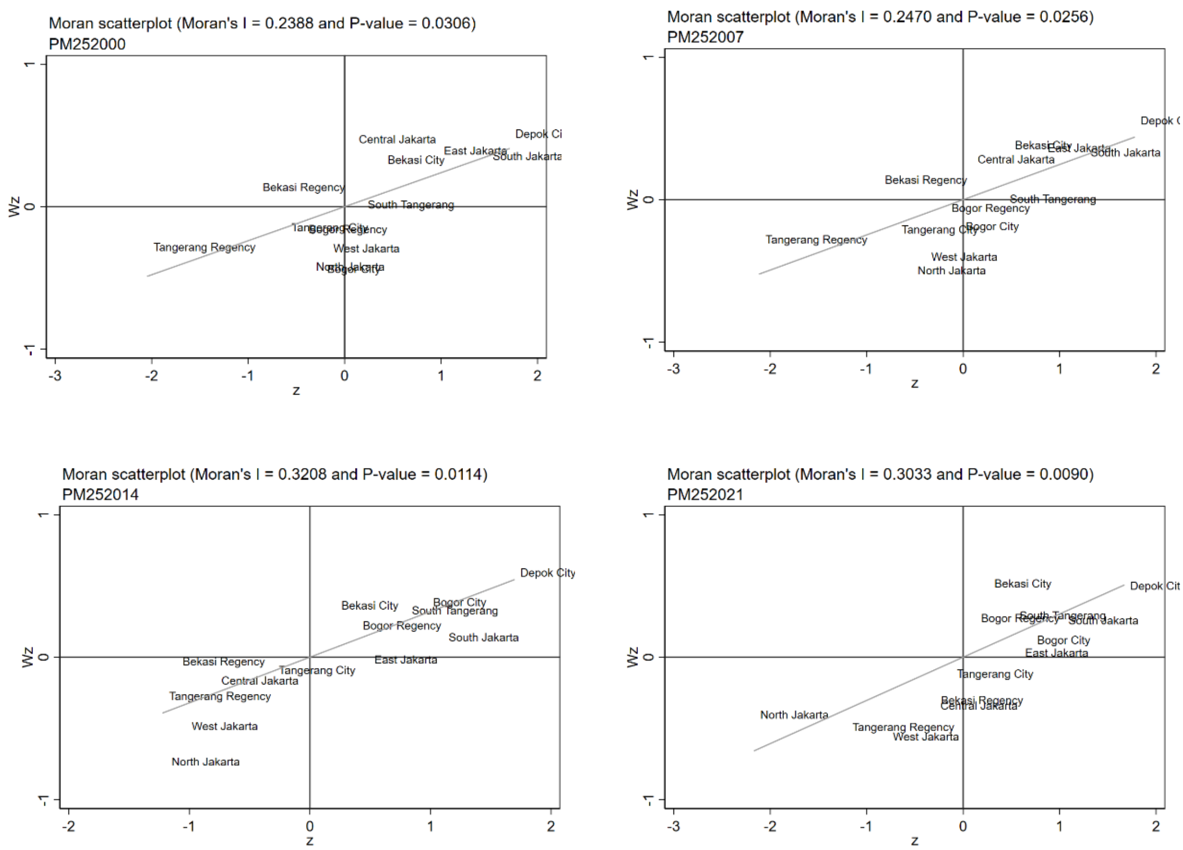

Figure 4. Moran's *I* scatterplot of $PM_{2.5}$ concentration and spatial lag of $PM_{2.5}$

Table 2. Result of Local Moran's *I* of 13 cities in Jabodetabek per seven years from 2000-2021

City	2000	2007	2014	2021
Bekasi Regency	-0.14	-0.135	0.0339	0.0955
Bogor Regency	0.07	0.0116	0.0944	0.0367
West Jakarta	0.06	0.1704	0.5378	0.4754
Central Jakarta	0.04	0.0272	0.1367	0.1088
South Jakarta	0.57*	0.4554	0.1689	0.2881
East Jakarta	0.41	0.3221	-0.007	0.021
North Jakarta	0.16	0.2868	0.95**	0.94**
Bekasi City	0.14	0.1976	0.084	0.1473
Bogor City	0.11	0.0071	0.408	0.0939
Depok City	0.95**	1.07***	1.09***	0.91**
Tangerang City	0.09	0.1568	0.0296	0.0157
South Tangerang	0.0032	0.0035	0.2852	0.1671
Tangerang Regency	0.625*	0.637*	0.357	0.640*

t statistics in parentheses: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

According to the local Moran's *I* result presented in Table 2, it was discovered that the pattern over a year is similar. The four cities had significant local Moran's *I* value with a *p*-value of 0.05, as shown in Table 2. Most of the samples had a positive local Moran value, indicating that this city is surrounded by a similar annual average of $PM_{2.5}$ concentration. Depok City is the core of the cluster area where a high concentration of $PM_{2.5}$ is clustered, followed by a low value of $PM_{2.5}$ concentration cluster city in the outer area of the Jabodetabek urban agglomeration. This result is also depicted in the map in Figure 5 to show the spatial pattern.

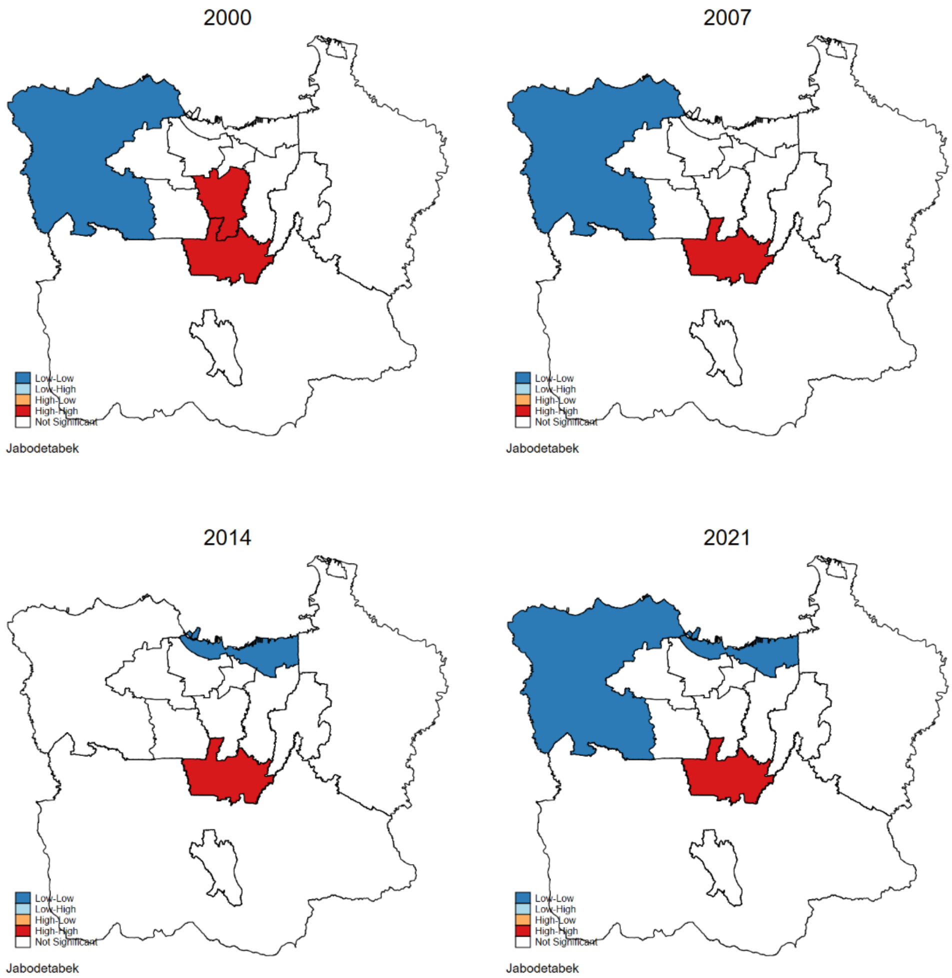

Figure 5. Local Moran's *I* Clustered Map of $PM_{2.5}$ Concentration of Jabodetabek Urban Agglomeration

In 2000, besides Depok City, South Jakarta was also found as a local cluster with a high-to-high value type, while Tangerang regency was found to be a low-to-low value cluster type. Seven years later, in 2007, it was found that the local Moran's *I* value for South Jakarta was not significant, but Depok City and Tangerang Regency remained the same. In 2014, there was a shifting pattern in the Low-Low cluster core. In 2000 and 2007, Tangerang Regency was found to be significant, but in 2014, a significant low-low value cluster type was found in North Jakarta. High-High-value cities in 2014 remained the same as in 2007. The significant value of local Moran's *I* was found again in Tangerang Regency in 2021, where this year three areas were found to be significant: Depok with a High-High value type of cluster, and North Jakarta and Tangerang Regency with a Low-Low value type of cluster.

3.5. Spatial correlation pattern of $PM_{2.5}$ concentration in Jabodetabek before and during social restriction

A study by Pramana et al (2020) found that social restriction policies implemented during the COVID-19 pandemic in Jabodetabek positively affected air quality. This led researchers to hypothesize that there may have been changes in the patterns of $PM_{2.5}$ concentrations in the area.

Understanding these changes in spatial patterns can be obtained by analyzing the previous results for Global and Local Moran's *I*.

Upon comparing the results in Figure 4 from 2021, when social restrictions were in place for the entire year, to the previous year, the study found a small change in the pattern of $PM_{2.5}$ concentration during the social restrictions. Comparing the patterns between 2014 and 2021, we found that Tangerang Regency returned to be a cluster point of low-value concentration of $PM_{2.5}$. This indicated that the pattern was largely the same but with a narrower high $PM_{2.5}$ concentration cluster area.

In the context of spatial dependency, we did not find any significant impact on the power of dependency. The global Moran's *I* result showed no significant change in spatial dependency in Jabodetabek and the value of global Moran's *I* followed years before social restrictions were implemented for the entire year.

3.5. Discussion

$PM_{2.5}$ emissions in different cities throughout Jabodetabek have distinct sources and characteristics. In DKI Jakarta, $PM_{2.5}$ emissions are mainly composed of black carbon and sulphate, which are caused by diesel vehicle usage (Santoso et al., 2020). TomTom's report on the TomTom website shows that traffic congestion was higher in Central Jakarta and South Jakarta during October 2022 than in surrounding cities. The MoEF's (MoEF) continuous industrial emissions monitoring information system data revealed that there are many point source emissions originating primarily from the processing industry in East Jakarta, North Jakarta, Benasi, and Bogor Regency. In numerous areas within Bogor Regency, dust from multiple cement factories dominates $PM_{2.5}$ pollution (Suhariyono, 2016). South Tangerang has many residential areas where the primary sources of $PM_{2.5}$ emissions are motorised vehicles, road dust, and diesel power plants. However, the sources of emission in South Tangerang are not only from residential areas but also from industrial areas (Santoso et al., 2011). In contrast to other cities in Jabodetabek, Bogor, Tangerang, and Bekasi, the annual average of $PM_{2.5}$ relatively lower. Although all three regencies have several point sources of emissions, such as industrial and residential areas, the total area of the three regencies is vast, and the population density is dispersed. Hence, the concentration of $PM_{2.5}$ can vary significantly within a regency area, resulting in small results when calculating the annual average of $PM_{2.5}$ concentrations in these areas.

Based on global Moran's *I* calculations and testing, it has been confirmed that there exists a spatial correlation between $PM_{2.5}$ concentrations in Jabodetabek. This correlation was found to be positive or clustered. However, as the cluster area expanded or the observation area moved further away, the strength of the correlation weakened. This is due to the diffusion of $PM_{2.5}$ and the direction and speed of the wind carries. As $PM_{2.5}$ diffuses, it spreads from the emission source to surrounding areas. Further transport via wind decreases pollutant concentration (Chen & Ye, 2019; Kusumaningtyas et al., 2021; Sirithian & Thanatrakolsri, 2022; J. Wang et al., 2023; S. H. Yang et al., 2020; Z. Zhang et al., 2023).

Over the years, there has been a significant increase in the spatial correlation of $PM_{2.5}$ concentrations in Jabodetabek. Before 2010, the global value of Moran's *I* was less than 0.25, but it began to increase after 2010. This shift can be attributed to the massive development of Jabodetabek and changes in the urban form of the region, specifically due to the type of urban expansion in Jabodetabek. The urban expansion type in Jabodetabek is known as a conurbation, meaning that the buffer city is united with the core city through transportation integration that connects the cities (Rustiadi et al., 2021). This has resulted in the formation of cluster areas with specific land uses like industrial, commercial, and residential areas, leading to an accumulation of $PM_{2.5}$ concentrations in each area caused by the concentration of point source emissions (M. C. Jung et al., 2019; Park & Ko, 2018). Consequently, there is a higher risk of spillover effects on the air quality of surrounding areas.

The integration of cities in Jabodetabek leads to higher mobility, as the clustering of areas during urban expansion creates complexity in urban form. This complexity encourages mobility within an area and drives the number of commuters in urban agglomeration areas (Batterman et al., 2015; Lu et al., 2021). However, this increase in mobility can lead to a high use of private vehicles if public transportation is insufficient, resulting in an increase in the number of mobile sources of emissions. In addition, traffic congestion is a common problem in the area, and it can cause hotspots for mobile sources of $PM_{2.5}$ emissions. During traffic hours, diesel vehicles emit higher levels of $PM_{2.5}$ due to low speeds, which can worsen air quality (Gately et al., 2017). This increase in mobility also indirectly increases spatial correlation, as mobile-source emissions that worsen the air quality of an area can come from the surrounding area (F. Li et al., 2022; She et al., 2021).

After examining the results of local Moran's *I* calculations for $PM_{2.5}$ concentrations in Jabodetabek, it was evident that the epicentre of the high $PM_{2.5}$ concentration cluster area was Depok, which was positioned in the center of the Jabodetabek area when viewed from its latitude and longitude. This can be explained by the transportation network in which Depok acts as a link between several regions and serves as a gateway to the core of the agglomeration, or Jakarta, leading to a high volume of commuter traffic flows through Depok. A report from Indonesia Statistics (2019) shows that approximately 800.000 commuter workforces originating or passing through Depot. Furthermore, public transportation outside of Jakarta, such as Depot, Bogor city and district, South Tangerang, and other cities, tends to be less developed than in DKI Jakarta, leading to more individuals opting to use private vehicles for their daily activities, thereby contributing to high mobile-phone sources.

Although Depok has fewer point sources than other areas, it is surrounded by cities with high point sources, such as East Jakarta, which has numerous sources of $PM_{2.5}$ in the industrial sector, South Jakarta with high traffic hours, South Tangerang, which is primarily used as a residential area, and Bogor district, which has numerous factories. Therefore, the $PM_{2.5}$ that is emitted from neighboring cities of Depok can be transported to Depok, and it has a negative spillover effect on air quality by increasing the $PM_{2.5}$ concentration.

During the social restrictions, there was a noticeable change in the spatial patterns of air pollution in Jabodetabek. Areas with high pollution concentrations became smaller, while areas on the outskirts experienced a decrease in pollution concentration. This change is supported by the findings of Local Moran's *I* analysis, which indicated the emergence of a low-low value cluster in West Jakarta and the disappearance of Bogor city as part of the center of the high $PM_{2.5}$ concentration cluster. This change is due to limited activities and reduced mobility, which have decreased emissions from point and mobile sources. This agrees with the findings of previous studies that have shown that social restrictions have a positive impact on air quality (Keshtkar et al., 2022; Pramana et al., 2020).

Based on the results and discussion, it was established that there is a spatial correlation in $PM_{2.5}$ in Jabodetabek. This correlation has been validated, indicating that further consideration is necessary to effectively mitigate and control pollution. The presence of spatial correlation can result in transboundary public health risks throughout the Jabodetabek region. Additionally, it can reduce the effectiveness of pollution control policies due to the canceling effect caused by spatial dependency.

Therefore, it is recommended that pollution control policies with joint regulations be implemented in the Jabodetabek area. This suggestion aligns with previous studies that recommended implementing joint regulation of pollution control policies in urban agglomeration regions (Huang & Du, 2018; M. C. Jung et al., 2019; C. Li et al., 2019; Liao et al., 2015; Lu et al., 2021; Y. Wang et al., 2021; Zezhou & Xiaoping, 2017; Zhou et al., 2018). By doing so, air quality problems can be resolved more effectively.

4. Conclusion

The findings reveal a clear spatial correlation between $PM_{2.5}$ concentrations in the Jabodetabek urban agglomeration. Over time, this correlation has become stronger as Jabodetabek's cities have become more interconnected. Notably, the highest concentration of $PM_{2.5}$ is at the center of Jabodetabek, in the city of Depot. This city experiences significant commuter traffic and is surrounded by other cities with $PM_{2.5}$ emission hotspots. This situation is likely due to changes in Jabodetabek's shape, which have resulted in the creation of point source emission areas, as well as increased mobility and commuter flows. These factors have led to increased spillover effects from point source emissions and private vehicles, worsening regional air pollution. The presence of this spatial correlation also raises concerns about potential transboundary health risks. To tackle air pollution in Jabodetabek, it's essential to develop joint regional policies that can address the spatial correlation and avoid canceling effects. Limitation: This study does not take into account the impact of variations in the size of each city and district because the calculation of $PM_{2.5}$ concentration is done by averaging the concentration value per pixel in the satellite image data. Additionally, the distance between city districts is determined using the center point of latitude and longitude for each city and district. The observation of the spatial patterns of $PM_{2.5}$ concentrations is also limited to geographical location factors, without considering other socioeconomic factors that may affect the spatial patterns of $PM_{2.5}$ concentrations.

Acknowledgment

I am grateful to Ms. Pini Wijayanti (IPB University), who has always supported, guided, and provided valuable feedback to me in my research. I am also thankful to Prof. Yusman Syaukat (IPB University) for his continuous guidance and insightful suggestions. Additionally, I want to express my gratitude to LPDP Indonesia for providing financial support to me pursue my master's degree.

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