Public Infrastructure Accessibility and Property Price Disparities in Jakarta: A Composite Index and Spatial Regression Approach

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Abstract. This study analyzes spatial inequality in public infrastructure accessibility and Property price in Jakarta Province using a Composite Index and spatial econometric modeling. A data-driven spatial approach is employed to examine the distribution of property price and accessibility to health, education, and transportation facilities. Accessibility is measured using the Entropy Weight Method, while spatial inequality patterns are assessed through Moran's I and Local Indicators of Spatial Association (LISA). Results reveal significant clustering of high property price and accessibility in central Jakarta, contrasted with low values in peripheral areas, indicating pronounced spatial disparities. Furthermore, Geographically Weighted Regression (GWR) and the Spatial Lag Model (SLM) demonstrate that improved accessibility is positively associated with higher property price, although the magnitude of this effect varies spatially. These findings provide empirical evidence to support data-based spatial planning and infrastructure development policies aimed at reducing urban spatial disparities and promoting more equitable urban growth in Jakarta.
Keyword: Accessibility, Composite Index, Jakarta Province, Property price, Spatial Regression

1. Introduction

The province of DKI Jakarta plays an important role in national development as it serves as the country's capital city. DKI Jakarta is a metropolitan city that continues to experience high population growth due to urbanization and migration [1]. Based on data from the Badan Pusat Statistik (2024), the population of DKI Jakarta in mid-2024 reached 10.68 million, with the productive age group (15-64 years) dominating at 71.4% of the total population. In addition, the population density reached more than 16,000 people/km2, making DKI Jakarta one of the most densely populated cities in the world [2], [3], [4], [5].

In its function as the national capital, Jakarta is also the core area of the Greater Jakarta region with a large agglomeration that supports national and global economic activities. Jakarta's rapid growth as a metropolitan city is often not matched by equitable public infrastructure development, resulting in spatial disparities in the distribution of accessibility and property price. Infrastructure development focused on business centers and high-value economic areas has caused disparities in the quality of public services between regions [5]. This inequality in accessibility has resulted in longer travel times and higher transportation costs for residents in suburban areas, exacerbating traffic congestion and reducing productivity.

Jakarta's rapid development is inseparable from structural challenges such as land scarcity, rising property price, and the uneven distribution of public infrastructure. This is partly due to the high and increasing population growth in Jakarta. Property price distribution in urban areas is greatly influenced by factors such as accessibility, land use intensity, and the availability of public facilities, which creates a classification of areas with very high property price in the city center and along transportation corridors, while other areas lag behind with low property price [6]. This condition is also exacerbated by the construction of new transportation infrastructure such as the MRT, which has been proven to drive up property price unevenly along the corridor.

On the other hand, densely populated areas in Jakarta with low incomes have limited public infrastructure and low access to economic activity centers [7]. As a result, Jakarta experiences pronounced spatial inequality in both accessibility and property price. High-purchasing-power populations tend to concentrate in strategic and well-connected urban cores, whereas low-income groups are pushed toward suburban peripheries characterized by lower land values, inadequate transportation networks, and limited public services. Although several studies have examined spatial inequality and property price distribution in Jakarta and other megacities most have treated accessibility and property value as separate issues or focused only on transport-related factors. Consequently, limited attention has been given to how disparities in multi-sectoral public facilities such as health, education, and transport jointly influence property price polarization. This study addresses that gap by constructing a Composite Accessibility Index and applying spatial econometric models to explain how accessibility inequality shapes property price variation in Jakarta [8].

Several previous studies have examined spatial inequality, particularly in relation to property price and accessibility. The distribution of property price in urban areas is influenced by factors such as accessibility, land use intensity, and the availability of public facilities [8]. Other studies have classified areas based on variations in property price, with more emphasis on identifying the determinants of property price or general area classification [6]. In addition, recent findings highlight the limitations of public infrastructure and the lack of access to economic activity centers in low-income, densely populated areas [7]. The novelty of this study lies in the development and application of a Composite Index specifically designed to analyze spatial inequality in accessibility and property price in DKI Jakarta, with the support of Moran's I spatial analysis to assess global spatial relationships and Local Indicators of Spatial Association (LISA) to identify property price clusters on a local scale.

This research seeks to evaluate the uneven distribution of access to public infrastructure and real estate costs in DKI Jakarta, and to investigate their spatial interconnections via a data-centric strategy. The outcomes are poised to deliver concrete evidence for implementing fairer, data-supported policies in spatial planning and infrastructure growth, which in turn will assist in alleviating urban inequalities and strengthening Jakarta's position as a globally integrated capital city.

2. Research Method

The research method used includes an explanation of the study area, the type of data used, and the stages of analysis carried out. All data was obtained from official institutions and selected based on its suitability for the research objectives. The analytical approach was used to examine spatial relationships and identify differences in patterns between study areas.

2.1. Research Location

This research is located in the Province of DKI Jakarta, which is administratively divided into five cities Central Jakarta, North Jakarta, South Jakarta, East Jakarta, and West Jakarta and one regency, namely the Thousand Islands. The selection of DKI Jakarta as the study area is based on its characteristics as the national center of economic, governmental, and transportation activities, which exhibits a high degree of spatial complexity. This complexity is reflected in the unequal distribution of public infrastructure accessibility and property price disparities between regions, making the area representative for examining the relationship between accessibility and land value dynamics in a metropolitan urban context.

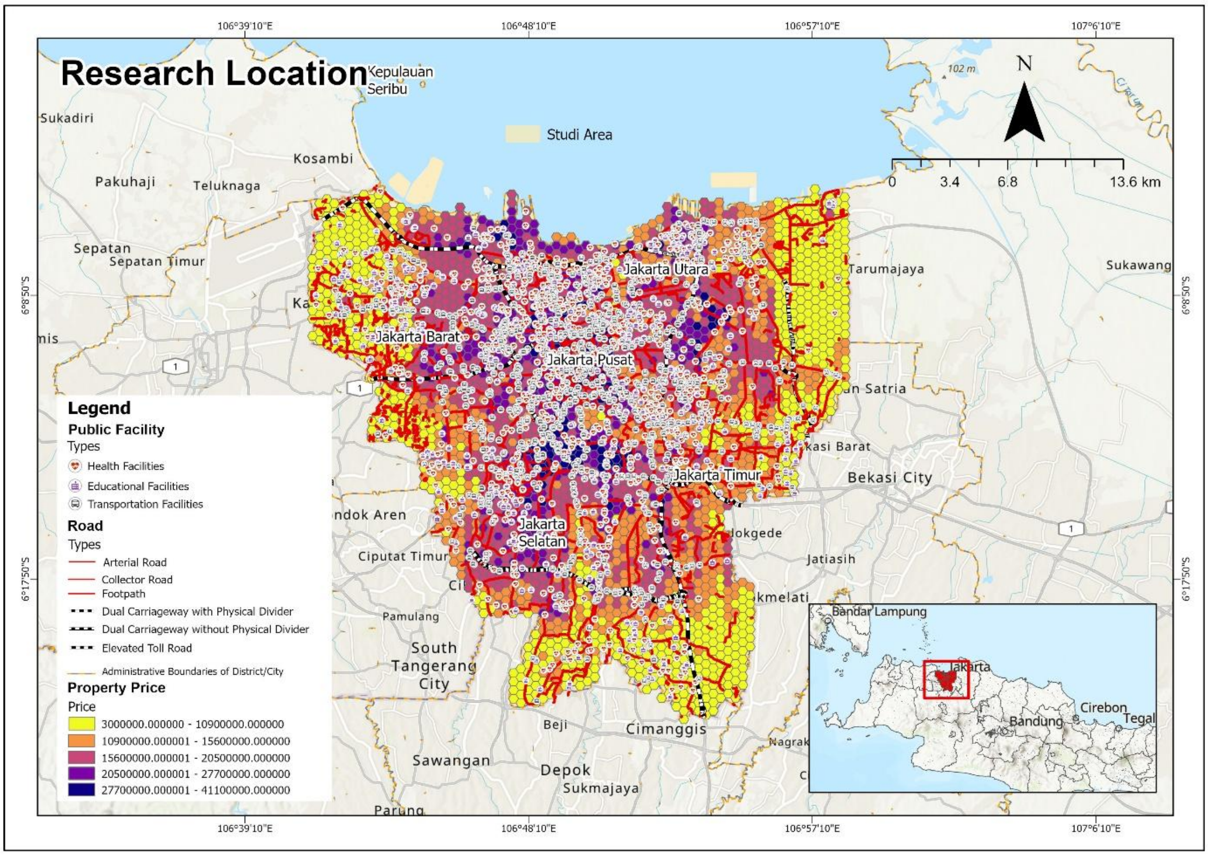

Figure 1. Research location

2.2. Data

The data used in this study includes secondary data in the form of property price data, public infrastructure accessibility point data (such as transportation networks and public facilities) obtained from BIG, DKI Jakarta Province population density data from BPS, and administrative spatial data in the form of shapefiles of regencies and cities in DKI Jakarta Province. The data used in this study is presented in Table 1.

Table 1. Research data

No	Data	Type	Spatial Resolution	Temporal Resolution	Source
1	Provincial Administrative Boundaries	Vector	1:25.000	2024	(BIG, 2024)
2	Road Network	Vector	1:25.000	2024	(BIG, 2024)
3	Educational Facilities Points	Vector	1:25.000	2024	(OSM, Jakarta Satu 2024)
4	Population Density	Raster	100 m	2023	(GHSL, 2023)
5	Property price	Vector	1:25.000	2022	(XProperti, 2022)
6	Health Care Facility Points	Vector	1:25.000	2024	(OSM, Jakarta Satu 2024)
7	Transportation Facility Points	Vector	1:25.000	2024	(OSM, Jakarta Satu 2024)

Based on Table 1, the datasets used in this study vary in their reference years. This variation is due to differences in data availability across institutions and data platforms. Each dataset was obtained from the most recent and relevant sources to ensure reliability and spatial comparability among variables. For instance, population density data were obtained from the 2023 Global Human Settlement Layer (GHSL), which provides the latest estimation of population distribution, while property price data were derived from the 2022 XProperti dataset, representing the most updated market information available. Meanwhile, administrative boundaries, road networks, and facility point data were taken from the 2024 updates of BIG, OSM, and Jakarta Satu to maintain consistency with the most recent spatial infrastructure data of DKI Jakarta. Therefore, the variation in reference years reflects an effort to utilize the most up-to-date data available for each variable.

2.3. Method

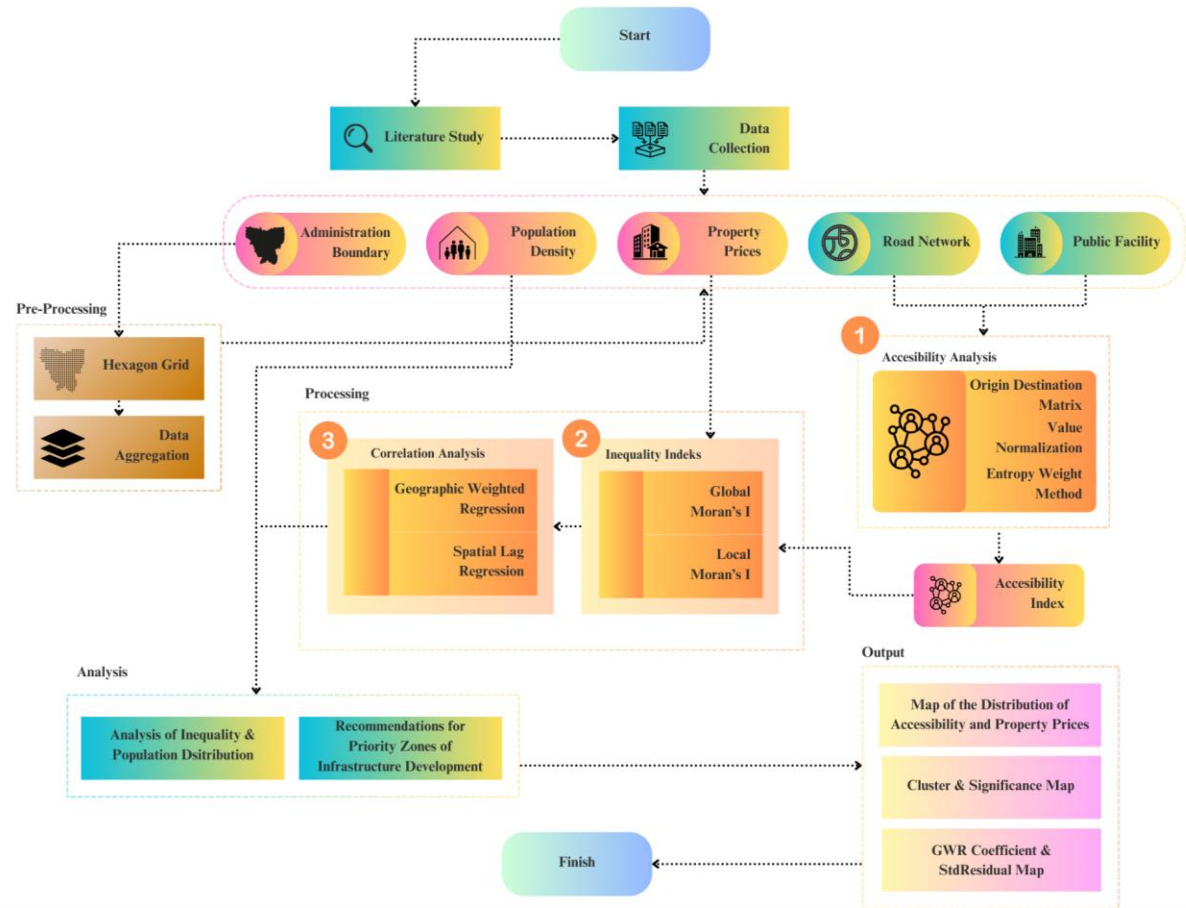

Figure 2. General flowchart

The research workflow follows several sequential stages as illustrated in the flow diagram. (1) The process begins with a literature review and data collection, which include datasets on administrative boundaries, population density, property prices, road networks, and public facilities. (2) Next, data pre-processing is conducted by aggregating all datasets into a hexagonal grid, which serves as the spatial unit of analysis. (3) Accessibility analysis is then performed using the Origin Destination Matrix, normalization of accessibility values, and the Entropy Weight Method to produce a composite accessibility index. (4) Subsequently, spatial inequality analysis is carried out using Global and Local Moran's I to identify clustering patterns between accessibility and property price. (5) The spatial relationship modeling between property price and accessibility is examined using Geographically Weighted Regression (GWR) and the Spatial Lag Model (SLM), capturing both local variations and spatial spillover effects. (6) Finally, the outputs include accessibility and property price distribution maps, cluster and significance maps, and GWR coefficient maps, which form the basis for interpreting inequality, population distribution, and recommending priority zones for infrastructure development.

2.3.1. Moran's I

Spatial Autocorrelation (Global Moran's I) is a statistical measure used to evaluate spatial correlation by considering the proximity of features along with their associated attribute values simultaneously. With a standardized spatial weight matrix, the Moran Index values range from $-1 \leq I \leq 1$. Values within the range $-1 \leq I < 0$ indicate negative spatial autocorrelation, meaning the data distribution tends to be dispersed. Conversely, values between $0 < I \leq 1$ indicate positive spatial autocorrelation, suggesting that the data tends to cluster. A value of zero implies that the data distribution does not exhibit clustering [9]. The results of spatial autocorrelation measurement consist of five key values, namely Moran's Index, Expected Index, Variance, z-score, and p-value for significance testing [10]. . The spatial autocorrelation calculation using Moran's I can be performed using the following formula [9].

$$I = \frac{n \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i \neq j} w_{ij}\right) \sum_i (x_i - \bar{x})^2} \tag{1}$$

where: I = Moran's Index, n = number of locations/events, wij = spatial weight element between regions i and j , xi = value of variable x at location i ; i = 1,2,3, ... , n , xj = value of variable x at location j ; j = 1,2,3, ... , n , and x = mean of variable values.

Moran's I is used to measure the global spatial autocorrelation of property price and accessibility data across DKI Jakarta Province. This test identifies whether there are significant spatial clustering patterns in property price distribution that may indicate spatial inequality.

2.3.2. Local Indicators of Spatial Association (LISA)

Local Indicators of Spatial Association (LISA) is a method for measuring spatial autocorrelation at the local level, used to analyze spatial relationships between an observation point and its neighboring points. LISA functions as a statistic that indicates significant spatial clustering, representing groups of similar values around a certain location. Furthermore, the sum of LISA values across the entire study area is proportional to the global Moran's index, allowing LISA to reveal specific spatial patterns at each observation location [10]. The LISA for each location ii is expressed as follows:

$$Li = \frac{z_i}{m_2} \sum_j w_{ij} z_j \tag{2}$$

$$m_2 = \sum_{i=1}^{n} \frac{z_i^2}{n} = \sum_{i=1}^{n} \frac{(x_1 - \bar{x})^2}{n} \tag{3}$$

$$z_j = \left(x_j - \bar{x}\right) \tag{4}$$

where Li = LISA value, zi and zj = deviations from the mean, xi = value of variable x at location i; i=1,2,3,…,n i=1,2,3,…,n, xj = value of variable x at location j; j=1,2,3,…,n, j=1,2,3,…,n, x¯ = mean of the variable values, wij = spatial weight element between areas i and j, n = number of locations or events, and m2 = variance.

For more detailed spatial cluster analysis, LISA is used to detect local clusters of areas with high or low property price, as well as regions displaying spatial outlier patterns. This analysis helps identify hotspots of inequality and patterns of accessibility and price disparities at the district and city levels.

2.3.3. Geographically Weighted Regression (GWR)
Geographically Weighted Regression (GWR) is a statistical method used to model the relationship between a response variable and predictor variables while taking into account the geographical location or spatial context (Brunsdon, C., Fotheringham, A.S. and Charlton, M.E., 1996). Unlike traditional regression models that assume constant relationships across the entire study area, GWR allows regression coefficients to vary at each location, thereby capturing spatial variation in the data. The strength of GWR lies in its ability to provide localized models that reflect the influence of spatial or geographic characteristics on the response variable. As a result, GWR can identify spatial heterogeneity patterns that cannot be detected by conventional regression models. The mathematical formulation of GWR is presented by [11], as follows :

$$Y_i = \beta_0(u_i, v_i) + \sum_{i=1}^{p-1} \beta_k(u_i, v_i)\, X_{ik} + \varepsilon_i, i = 1, 2, 2, \dots, n, \tag{5}$$

where:

Yi	: the dependent variable value at location	
Xik	: the value of the independent variable *k* at location	
$\beta 0\ (ui, vi)$	: the intercept coefficient at location	
$\beta k\ (ui, vi)$	: the slope coefficient of the independent variable *k* at location	
(ui, vi)	: the coordinates (longitude, latitude) of location	
$p - 1$	: the number of independent variables	
εi	: the random error at location	

GWR is applied to examine the spatial relationship between public accessibility and property price locally. This model allows regression coefficients to vary across locations, capturing spatial heterogeneity in the influence of accessibility on property price and identifying areas most sensitive to the variable. GWR is compared with the OLS model to determine the best fit.

2.3.4. Spatial Lag Regression (SLM)
Spatial Lag Regression (SLM) is a spatial regression model used to analyze the relationship between dependent and independent variables while accounting for spatial dependence in the dependent variable itself. The value of a dependent variable in one location is not only determined by internal factors within that location but is also influenced by dependent variable values in neighboring areas [12]. For example, in property price analysis, the price in one area is influenced not only by its own conditions but also by prices in surrounding areas. The linear regression model taking into account the spatial lag effect on the dependent variable ($\lambda = 0$) is expressed by the following equation (6) (Anselin, L., 2013):

$$Y = \rho W_1 Y + X\beta + \epsilon \tag{6}$$

where:

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Y : vector of dependent variables
ρ : spatial lag coefficient measuring the direction of spatial dependence in the dependent variable
W_1 : spatial weight matrix defining neighborhood relationships between locations
$W_1 Y$: spatial lag variable of the dependent variable
X : matrix of independent variables
β : vector of regression coefficients for independent variables
ε : vector of error terms assumed to be normally distributed and independent with variance constant σ^2

2.3.5. Composite Accessibility Index (CAI)

A location can reach facilities within a certain time or distance threshold. An isochrone is defined as a polygon representing the area that can be accessed from an origin point within a specified travel time or distance through the transportation network [13]. Using this method, the number of facilities accessible from each unit of analysis such as the centroid of a hexagonal grid can be calculated based on specific categories of facilities, such as education, healthcare, or transportation.

To construct a Composite Accessibility Index, a method is required to integrate various types of facilities into a single measure. The method employed is the Entropy Weighted Method (EWM), an objective weighting technique that assigns indicator weights based on the degree of variation or information contained in each variable [14]. After obtaining normalized indicators and their respective objective weights, the composite accessibility index per grid is calculated using the following linear formula:

$$IAK_i = \sum_j w_j \, . x'_{ij} \tag{7}$$

where:
$IAKi$: the index value or specific indicator for location or unit
$\sum_j$: summation over all units or variables associated with location
w_j : the weight assigned to variable or location *j*
x'_{ij} : the normalized value of variable *x* in unit *j* relevant to unit

Thus, each grid obtains a single index value representing the combined accessibility to hospitals, schools, and transportation facilities, which can then be applied in subsequent spatial analyses such as Geographically Weighted Regression (GWR) on property price.

3. Result and Discussion

This study began with the mapping of property price provided by the open platform X-Properti, which offers predictions of property price based on a hexagonal grid (Figure 3). The map illustrates the spatial distribution of property prices across Jakarta, with clearer administrative boundaries to distinguish each municipality. The results reveal a pronounced disparity, where the highest property values are concentrated in Central and South Jakarta dominated by commercial and governmental functions while peripheral regions such as North, East, and parts of West Jakarta exhibit lower property prices due to limited accessibility and higher exposure to flood-prone zones.

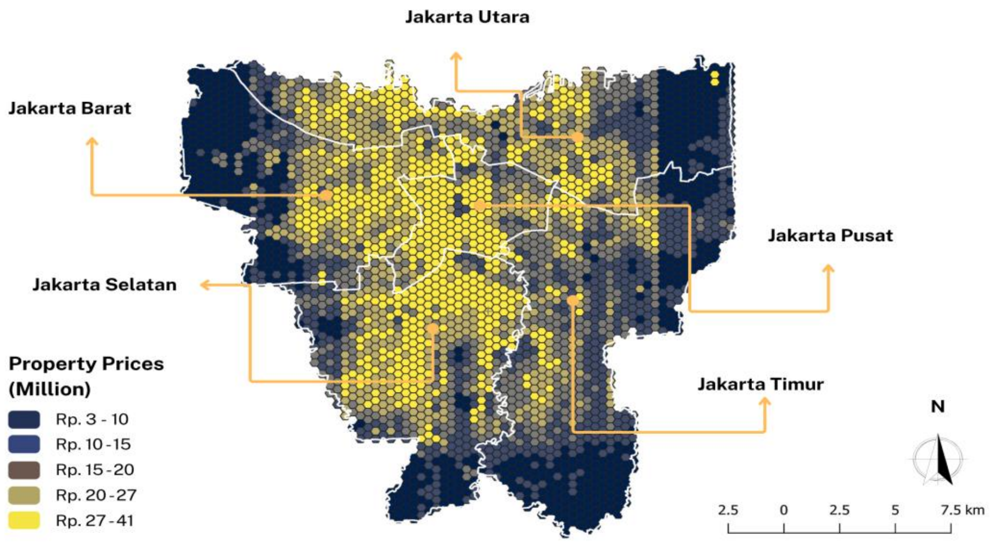

Figure 3. Property price hexagonal grid map of DKI Jakarta Province.

Property prices vary significantly across space, with this variation partly attributable to differential access to public infrastructure. By examining the spatial distribution of property prices in relation to infrastructure locations, we can identify how accessibility (measured through distance or travel time) influences property valuations, consistent with hedonic pricing theory which posits that property values reflect both structural and locational attributes. Accordingly, the subsequent analysis focuses on the construction of an accessibility index, followed by spatial inequality testing, and finally an examination of inter-variable relationships using spatial regression approaches.

3.1.1. Composite Accessibility Index

The weighting process using the Entropy Weighting Method (Table 2) produced different relative weights for each accessibility indicator. Transportation facilities received the highest weight (34.7%), slightly higher than healthcare facilities (34.5%), followed by educational facilities (30.8%). These values indicate that spatial variation in accessibility across Jakarta is strongly influenced by the distribution of public transport networks, particularly MRT, BRT Trans Jakarta, and commuter rail (KRL). This is reasonable, as the availability of public transport not only facilitates mobility but also directly impacts land economic values.

Table 2. Accessibility indicator’s weight

Indicator	Entropy	Divergence	Weight
Health Facilities	0.99007081	0.0099292	0.345
Educational Facilities	0.99113194	0.0088681	0.308
Transportation Facilities	0.99000294	0.0099971	0.347

The distribution map of the Composite Accessibility Index (Figure 4) shows a stark spatial contrast. Areas with high index values are concentrated around the city center and along major transport corridors such as Sudirman–Thamrin, Kuningan, Senayan, and MRT and TransJakarta routes. In contrast, peripheral regions such as Marunda, Cilincing, and Cipayung exhibit low accessibility values due to their distance from service centers and mass transport networks.

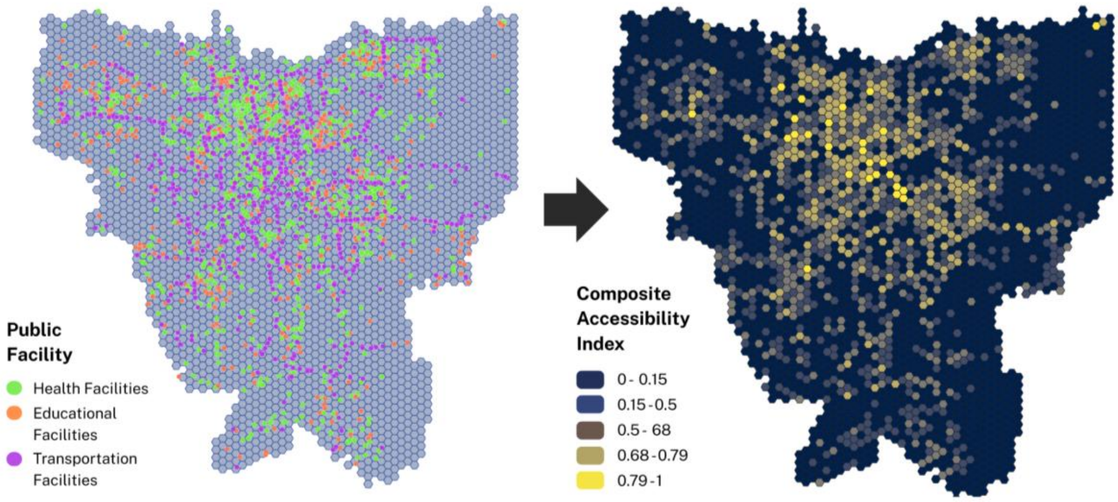

Figure 4. Public facilities distribution & composite accessibility index map.

These findings indicate that public infrastructure development in Jakarta remains highly concentrated in the urban core, resulting in spatial disparities between central and peripheral areas. An important implication is that low-income groups, who often reside in the periphery, not only face lower property price but also limited accessibility to public facilities, exacerbating the persistence of the “urban divide” in Jakarta.

3.2. Spatial Distribution of Property Price and CAI Inequality

Global Moran’s I analysis was applied to identify spatial autocorrelation in property price and accessibility index data across Jakarta. The results show a Moran’s I value of 0.788 for property price with high statistical significance, indicating a strong clustering tendency. This means that high-value areas tend to be located near other high-value areas, while low-value areas cluster with other low-value areas.

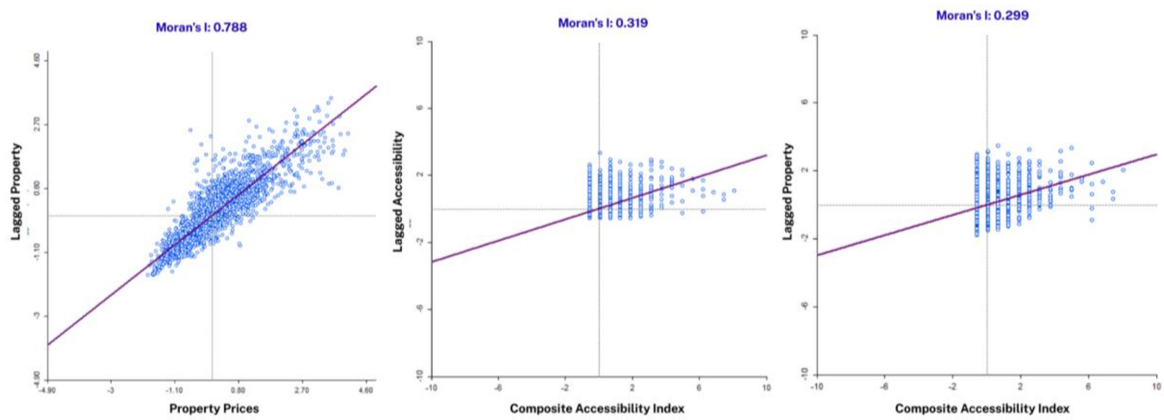

Figure 5. Univariate & bivariate Moran’s I of property price and CAI.

For the accessibility index, Moran's I was 0.319, also significantly positive, suggesting that accessibility to public facilities is unevenly distributed, with concentrations of both high-access and low-access areas. The bivariate Moran's I between property price and accessibility index was 0.299, indicating a moderate spatial correlation area with higher accessibility also tend to have higher property price, although the relationship is weaker than the autocorrelation of property price alone.

These results are further supported by Local Moran's I (LISA), which maps spatial clusters in greater detail. The LISA map of property price reveals a High-High pattern concentrated in Central Jakarta and parts of South Jakarta, where high-value areas cluster together. Conversely, Low-Low clusters appear in peripheral areas such as North Jakarta and parts of East and West Jakarta, where low-value areas are grouped. A similar pattern emerges for accessibility, with High-High clusters along mass transit corridors and Low-Low clusters in peripheral areas with limited access to public transport and facilities.

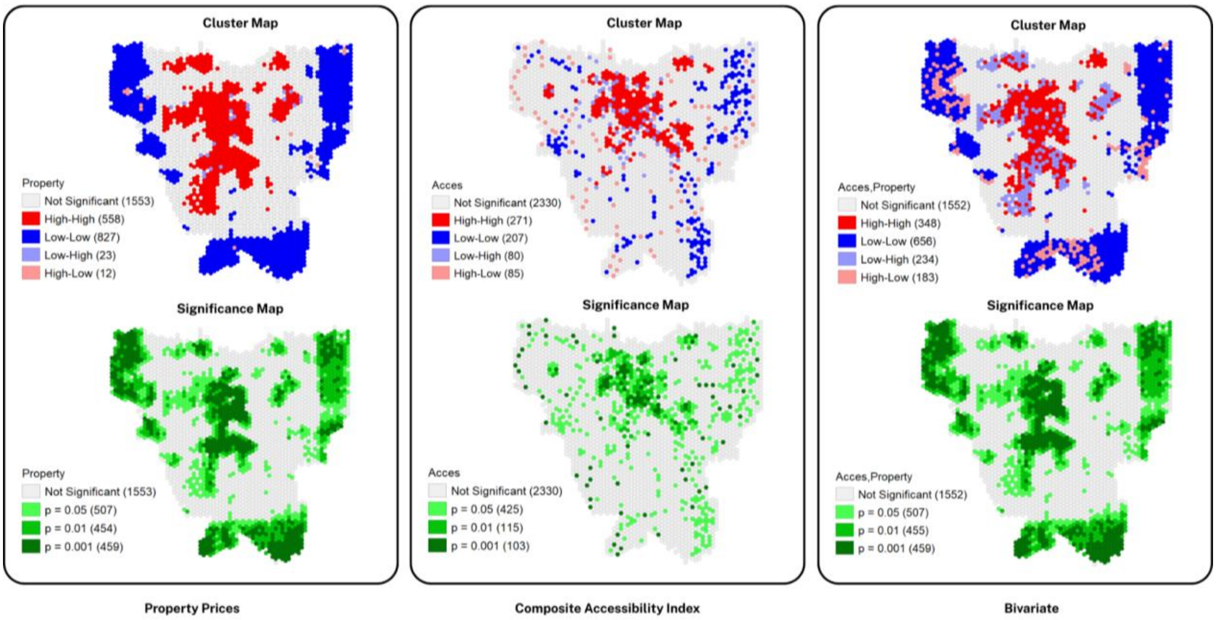

Figure 6. Cluster & Significance map Local Indicator Spatial Autocorrelation (LISA).

In the bivariate LISA between property price and accessibility, High-High clusters in the city center highlight the strong relationship between accessibility and property price, while Low-Low clusters in the periphery illustrate areas with both limited access and low property price. Interestingly, some areas show a High-Low pattern, where high accessibility coexists with relatively low property price. These areas represent potential zones for future development, as infrastructure availability is not yet reflected in market property price.

3.3. Spatial Correlation Between Property price and Composite Accessibility

The Geographically Weighted Regression (GWR) was applied instead of simple spatial correlation because diagnostic tests revealed spatial non-stationarity and local variation in the relationship between public facility accessibility and property prices (Anselin, 1988; Fotheringham et al., 2002). Preliminary checks, including tests of normality, multicollinearity, and spatial dependence, confirmed that the model assumptions were satisfied. Unlike global regression models, GWR allows the coefficients to vary across locations, making it suitable for identifying local differences in how accessibility affects property values. The coefficient map (Figure 7) shows that areas in the south and east of Jakarta have higher positive coefficients, meaning that improvements in accessibility strongly increase property prices. Conversely, areas with negative coefficients (darker colors) indicate that increased accessibility does not significantly correspond with price growth, likely due to other influencing factors such as population density, environmental quality, or distinct market dynamics.

Meanwhile, the residual map shows a relatively scattered distribution of model errors, although some high deviation clusters (> 2.5 Std. Dev.) remain in central areas, suggesting the influence of additional variables not captured by the model.

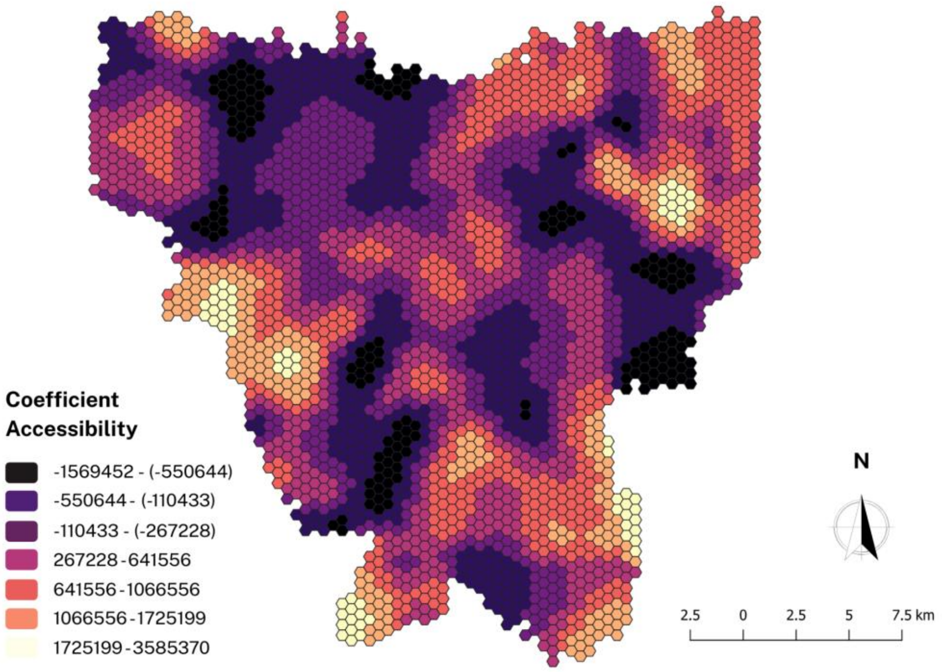

Figure 7. Geographically Weighted Regression (GWR) coefficient map.

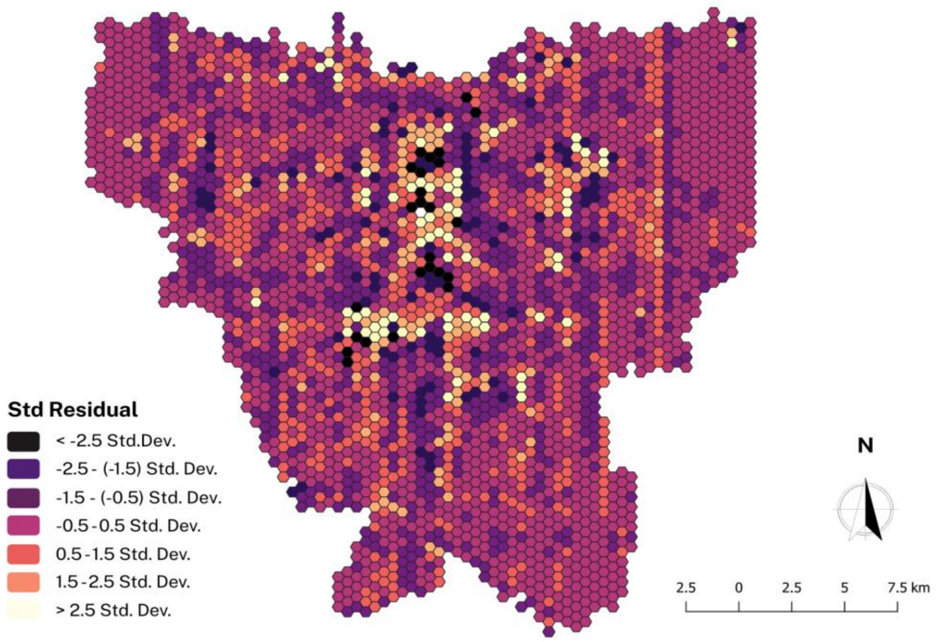

Figure 8. Standard residual of Geographically Weighted Regression (GWR).

On the other hand, the Spatial Lag Model (SLM) analysis confirms that the relationship between accessibility and property price remains globally significant when accounting for spatial dependence. SLM captures interdependence in property price between neighboring areas, meaning that even when accessibility in a particular location has little influence, property price can still be affected by prices in adjacent areas. However, because SLM is a global model, it does not capture local variations as GWR does. Therefore, SLM is more effective in explaining aggregate patterns, while GWR is better suited for identifying local heterogeneity.

Table 3. Spatial Lag Model (SLM) coefficient.

Variable	Coefficient	Std. Error	z-value	Probability
W_Property (Rho)	0.882708	0.009394	93.963	0.0000
Constanta	1,631,260	153,001	10.662	0.0000
Accessibility	173,534	33,614	5.162	0.0000

Table 4. Goodness of Fit Model SLM.

Statistic	Value
R-squared	0.7859
Log Likelihood	-48,840.1
Akaike Information Criterion (AIC)	97,686.3
Schwarz Criterion (SC)	97,704.3
Sigma²	8.72×10^{12}
Std. Error of Regression	2,953,360

The SLM results (Tables 3 and 4) reinforce the GWR findings. The spatial lag coefficient (ρ) of 0.8827 is highly significant, indicating that property price in one area are strongly influenced by neighboring prices. Moreover, accessibility is also significantly positive, with a coefficient of 173,534, confirming that higher accessibility leads to higher property values. The SLM model achieves an R^2 of 0.7859, demonstrating strong explanatory power. In other words, variations in property price across Jakarta are largely explained by a combination of accessibility factors and spatial dependence among regions.

3.4. Discussion and Recommendations

Before discussing the spatial relationship between accessibility and property prices, a comparative analysis was also conducted by overlaying the Composite Accessibility Index (CAI) with population density data from the Global Human Settlement Layer (GHSL, 2023). This analysis aimed to assess whether accessibility inequality is also related to population distribution patterns. The results are illustrated in Figure 9, showing that approximately 72.3% of Jakarta's population lives in zones with medium to low accessibility. This finding indicates that spatial inequality is reflected not only in differences in land value but also in the unequal distribution of access to public infrastructure across densely populated areas.

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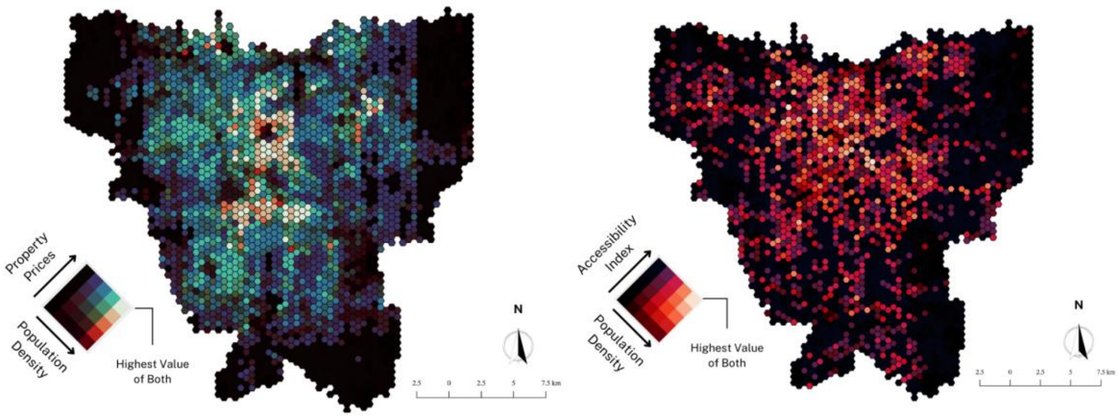

Figure 9. Bivariate map of the relationship between accessibility index and property price in relation to population density.

When compared with the literature, these findings are consistent with studies conducted in major global cities. Research in Tokyo has shown that the presence of the MRT network can significantly increase property price, but only at locations with sufficiently high population density (18) . In Bogotá, the development of the BRT system has also been proven to raise property price, although the increase was more evident in areas with concentrated residential settlements [16]. Thus, the effect of accessibility on property price is influenced not only by proximity to public infrastructure but also by the intensity of the population that can utilize such infrastructure.

From a methodological perspective, the comparison between Geographically Weighted Regression (GWR) and the Spatial Lag Model (SLM) highlights differences in analytical perspectives. GWR reveals local variations: in South Jakarta and parts of East Jakarta, accessibility has been found to be a significant factor driving property price increases, whereas in the city center its effect is relatively weak due to the dominance of non-accessibility factors (prestige, CBD). SLM, on the other hand, shows that property price in one area are strongly influenced by prices in surrounding areas (spatial spillover), with a very high spatial lag coefficient ($\rho = 0.8827$). These two approaches complement each other: GWR emphasizes local heterogeneity, while SLM underscores the structural interconnections between regions. The combination of both provides a more comprehensive understanding of the dynamics of urban property price.

Based on the results of the inequality analysis (Moran's I and LISA) and spatial relationships (GWR and SLM), several policy recommendations can be considered:

1. Low-Low areas with high population density (North Jakarta: Cilincing, Koja; East Jakarta: Cipayung, Ciracas): should be prioritized for the development of new public infrastructure (mass transportation, schools, healthcare facilities) to reduce spatial inequality.
2. High-Low areas (high accessibility, low property price): should be directed toward inclusive Transit-Oriented Development (TOD), for example through the development of affordable housing and public facilities, ensuring that existing infrastructure can be utilized more optimally.
3. High-High areas (city center: Central Jakarta, parts of South Jakarta): policy focus should be on land control and gentrification mitigation, with strategies such as incentives for vertical housing, provision of green open spaces, and equitable spatial planning regulations.
4. Spatial integration across regions: since the SLM results indicate spillover effects, infrastructure development should adopt a regional and cross-boundary approach rather than focusing solely on the city center.
5. Population-density-based priorities: infrastructure interventions should target areas with a combination of low accessibility and high population density, so that investments provide direct benefits to a larger number of residents.

4. Conclusion

This research uncovers a marked disparity in the relationship between access to public infrastructure and property values across Jakarta. Elevated property prices are primarily found in the central and southern districts, which benefit from excellent connectivity to transportation, healthcare, and educational services, whereas the outlying northern, eastern, and western areas feature lower prices due to restricted access, flood vulnerabilities, and minimal land development. The Composite Accessibility Index demonstrates that transportation systems have the most substantial impact on differences in accessibility, highlighting their pivotal role in influencing urban land values. Analyses using Geographically Weighted Regression (GWR) and Spatial Lag Models (SLM) validate that improved accessibility boosts property prices and that interactions between adjacent regions amplify this effect. Overall, these results indicate that Jakarta's urban disparities are fundamentally caused by uneven infrastructure allocation and regional spatial interactions. Consequently, policy measures should emphasize investing in infrastructure for regions with poor access and high population density, foster combined transportation and housing initiatives, and implement coordinated regional strategies to promote fairer and more sustainable urban expansion.

Spatial analysis also shows the presence of positive spatial autocorrelation in both property price and accessibility indices, where High-High clusters are concentrated in the city center and Low-Low clusters are located in peripheral areas. The results of the Spatial Lag Model (SLM) show that property price are significantly influenced by accessibility and spatial dependence between regions, with an R^2 value of 0.7859, indicating the model's strong explanatory power for variations in property price. Therefore, spatial inequality in property price cannot be separated from the distribution of public infrastructure accessibility, and policy interventions in the development of mass transportation have the potential to serve as an important instrument in reducing spatial inequality in property price in DKI Jakarta.

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