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ANALYSIS OF LAND VALUE DISTRIBUTION IN EAST JAKARTA WITH A SPATIAL MODELING APPROACH

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ABSTRACT

This study aims to analyze the distribution of land value in the Administrative City of East Jakarta through spatial modeling. With the increasing concentration of economic activities in East Jakarta, the demand for land also continues to increase, which has an impact on the increase in land values in the area. This study uses market data and Tax Object Selling Value (NJOP) from 1,522 land sample points, with variables that affect land value, such as land area, building area, and distance to the village and sub-district administrative centers. The spatial analysis approach with the Geoda application is used to evaluate spatial dependencies through the Classic, Spatial Lag, and Spatial Error models. The results of the study show that the variables of building area and distance to the village have a significant influence on market prices and NJOP in East Jakarta. The spatial dependency test carried out by the Lagrange Multiplier (LM) Lag and LM Error methods indicated the existence of spatial autocorrelation in the dependent variables. In addition, the results of Moran's I and LISA indices identified areas with high (hot spots) and low (cold spots) value patterns, which describe the spatial distribution of land values in the region. This research is expected to contribute to spatial planning and property tax policy and become the basis for more focused infrastructure development. By understanding the factors that affect land value, the government and property developers can make more effective decisions in the management of urban areas of East Jakarta.

KEYWORDS *Distribution of Land Value, Spatial Dependence, East Jakarta, Spatial Modeling, Geoda Analysis*

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INTRODUCTION

Based on data from the Central Statistics Agency in 2022, the number of urban residents has reached 56.39% due to high urbanization (Badan Pusat Statistik, 2022). According to Saladin (1989), the factors that are the attraction of urbanization are due to environmental factors, the attractiveness of city life and the availability of many jobs in the city (Obi-Ani & Isiani, 2020; Raihan & Tuspekova, 2022; Riad, 2024). In addition, the city also offers a variety of dynamic activities ranging from socio-cultural to urban economy. The increase in the concentration of urban economic activity in a city has a wide impact, including on the property sector (Gamal et al., 2024).

Urban economic activity also affects the high level of housing demand. The increasing concentration of economic activity is related to increased population growth which creates a greater demand for housing (Korostin & Grishin, 2021; Li et al., 2021). In this case, land is a significant need for housing because land is a fundamental element in building a house (Bamakan et al., 2022; Barnard & Woodburn, 2024).

The increasing need for land ownership in line with the increasing population and the need for housing causes land to become a very valuable commodity and affects land prices in urban areas. In addition, other factors can also affect land prices such as road infrastructure. According to Sutawijaya (2004a), the wider the road in front of a land property, the higher the value of the land. This is possible because the width of the road in front of a land property makes the location very strategic and has quite high accessibility compared to land located on small roads and alleys (Sutawijaya, 2004). In addition, according to Setiawan (2023), the closer the land price is to the collector's road, the higher the land value.

In addition, the proximity to the city center, with the location of the land will further increase the value of the land (Surya et al., 2021; Wang et al., 2021). This is possible because of its high accessibility and its location is also considered strategic due to the ease of reaching the city center. The availability of transportation facilities is related to the ease of carrying out activities or mobility, so that the existence of transportation facilities causes the value of land to be valuable or valuable. Furthermore, a flood-free environment also has a positive effect on the location of the land. Land and properties that have a flood-free environment are more appreciated than land locations that are often affected by floods (Sutawijaya, 2004).

According to Marine (2021) the city of Jakarta has a high population density, increasing demand for land has become a common phenomenon accompanied by an increase in land value. In fact, the increase in land value in Jakarta is estimated to reach 22-33% per year (Rumah.com, 2021). If examined further based on the property price index data report in DKI Jakarta in 2021, the East Jakarta Administrative City is the area with the highest property market price index compared to other administrative cities as seen in graph 1 below.

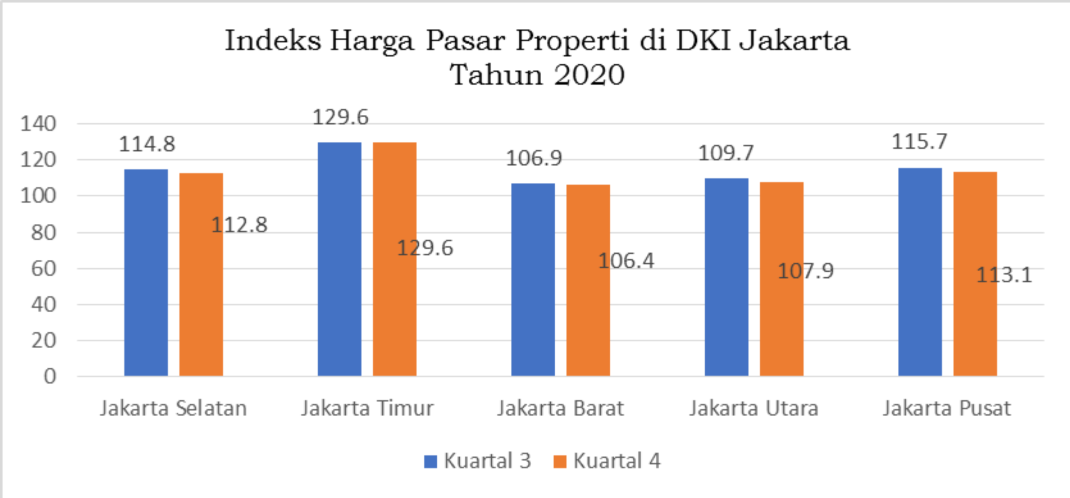

Figure 1. Property Market Price Index in DKI Jakarta in 2020
Source: Rumah.com

According to Marine (2021), even during the Covid-19 pandemic, the market price index in 2020 reached 113.7 in the 1st and 2nd quarters and increased to 129.6 in the 3rd and 4th quarters compared to other cities in DKI Jakarta which experienced a decline (Rumah.com, 2021).

According to Marine (2021), factors that affect the land price index in the East Jakarta Administrative City include the construction of housing for the middle and upper middle class in alternative areas with more affordable prices. The residential construction is located close to public transportation facilities such as stations, terminals, or bus stops. In addition, the public also does not have a problem with properties with minimum facilities, as long as the price is cheaper (Rumah.com, 2021). In addition to residential development, according to Shafirra (2020) land value offers offered through property buying and selling sites have increased in price. The value offered is higher than the value in the land value zone (Shafirra, 2020).

With the increasing demand for land in East Jakarta, a study is needed to see the influence of land area, building area, and distance factors on land prices by comparing the market price with the Selling Value of Tax Objects (NJOP) of land in the East Jakarta Administrative City. The results of this study are expected to describe the value of land in the East Jakarta Administrative City and the factors that affect land prices in the region. In this case, the study will use spatial analysis.

Spatial analysis can explain geographical phenomena on the earth's surface that have complex conditions so that to facilitate the understanding of these phenomena and spatially use complete data (Syaeful Hadi, 2015). In addition, research in the form of spatial modeling can predict and provide an overview of the development of residential areas in the future, so that it will make it easier to formulate appropriate policies to minimize the impact that occurs (Lestari & Pratomoatmojo, 2019).

Previous studies have explored the determinants of land value using various quantitative and spatial approaches. Fitriani and Agustina (2020) examined land prices in urban areas using hedonic pricing models and found that proximity to roads, public facilities, and the city center significantly influenced land values. Similarly, Mardiansjah et al. (2022) investigated land price patterns in Jakarta and revealed that accessibility and building size were strong predictors of property values. However, most of these studies used either general regression methods or focused on a macro perspective without specifically comparing market prices to the Selling Value of Tax Objects (NJOP).

This research presents a novel approach by applying spatial analysis to compare NJOP and market land prices in East Jakarta, a region with the highest price index growth in DKI Jakarta (Atiqi et al., 2022; Dewi et al., 2024; Utami et al., 2022). By analyzing the relationship between land area, building area, and distance from the city center using spatial techniques, this study provides deeper insights into localized property valuation and offers practical implications for tax policy and urban planning adjustments.

This study was conducted to see the influence of land area, building area, and distance factors on land prices by comparing the market price with the Selling Value of Tax Objects (NJOP) of land in the East Jakarta Administrative City. The results of this study will describe the value of land in the Administrative City of East Jakarta and what factors affect land prices. The results of this study will assist the government in Spatial Planning and Zoning and provide input for changes or adjustments to property tax policies as a basis for infrastructure development or improvement, and a basis for developing a more effective and sustainable regional development plan. This study aims to analyze the distribution of land value in the Administrative City of East Jakarta through spatial modeling.

METHOD

This study uses a quantitative approach with spatial analysis using the Geoda application. This study aims to analyze spatial patterns and compare market prices with the Selling Value of Tax Objects (NJOP) in the Administrative City of East Jakarta. East Jakarta Administrative City has a northern border with North Jakarta City and Central Jakarta, east with Bekasi Regency (West Java Province), south of Bogor Regency (West Java Province), and west with South Jakarta City which has 10 sub-districts and 65 sub-districts as seen in figure 3 below (Badan Pusat Statistik, 2022).

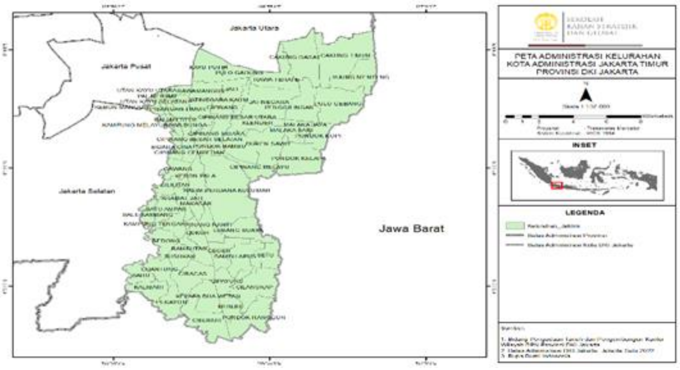

Figure 2. East Jakarta Administrative City Administration Map
Source: processed by the author based on Jakarta Satu, 2022.

This analysis uses dependent variables and independent variables, the dependent variables used are the Market Price and Selling Value of Tax Objects (NJOP) from 1,522 sample points of land plots in the East Jakarta Administrative City taken from the Land Value Zone data of the East Jakarta Administrative City Land Office in 2021. The independent variables include information about the area of the land (land), the area of the building, the distance to the village and the distance to the sub-district. The incorporation of this data will form the basis for an in-depth analysis of the spatial pattern of land prices in the Administrative City of East Jakarta. Dependent and independent variables can be seen in table 1 below.

Table 1. Research Variables

No.	Variable	Kind
1.	Land Market Price	Variabel Depend (Y1)
2.	NJOP	Variabel Depend (Y2)
3.	Area of the Earth (Land Area)	Independent Variable (X_1)
4.	Building Area	Independent Variable (X_2)
5.	Distance to Village	Independent Variable (X_3)
6.	Distance to Sub-district	Independent Variable (X_4)

Source: Author (2023)

Classic Regression

In this study, the initial regression is in the form of regression with the classic category which is carried out by determining dependent variables in the form of market prices and Selling Value of Tax Objects (NJOP) in 2021 which are influenced by the area of land (land), building area, distance to the village and distance to the sub-district. At this stage, it was seen that the R-squared results were close to 100% and the Prob (F-statistic) was below 5% and the Probability check on each variable with a limit of < 5% (significant data).

Advanced checking by looking at LM-Lag and LM-Error

After running data using the classic regression model, the next check refers to the LM-Lag and LM Error values. LM-Lag and LM-Error become significant when the value is below 5%.

Spatial Effect Checking

Spatial effect is a depiction of the influence on the areas around the observation. The process of checking the spatial effect can be illustrated in the diagram as follows:

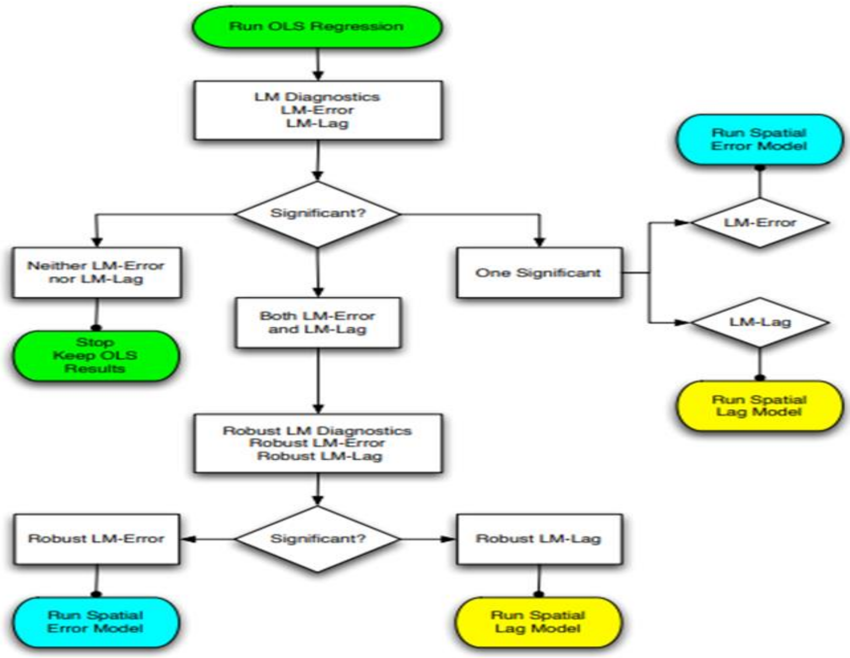

Figure 3. Spatial Model Lag and Spatial Model Error Process Flow
Sumber : Anselin and Rey (2014)

The flow diagram above shows the flow of the determination process in the analysis of the Spatial Lag Model and Spatial Lag Error, including:

a. if the LM-Leg and LM Error values, then the process flow stops until the OLS result.
b. if the LM Leg value is significant then the process is continued using the Spatial Lag Model and if the LM error value is significant then the process is continued using the Spatial Error Model
c. If the LM Leg and LM error values are significant, then the next check is to see the Robust LM Error and Robust LM Lag values. If the Robust LM Error value is more significant, the next process uses the Spatial Error Model and if the Robust LM Lag value is significant, the process continues using the Spatial Lag Model.

Local Indicator of Spatial Association (LISA) Index

In the observation, the LISA index will divide the area into four categories between High-high or in quadrant I, identifying areas with high value categories and around areas that have high observation values; Low-High category (Quadrant II) with the condition of the area with low observation value and surrounded by an area with high observation value; High-Low (Quadrant III) with high observation value area conditions and surrounded by areas with low observation value; Low-Low category (Quadrant IV) with the condition of the area with low observation value and surrounded by an area with low observation value.

RESULT AND DISCUSSION

Comparison of Classic, Spatial Lag and Spatial Error Model Results on Land Prices.

In table 2, it can be seen that the observation results using the Classic Model affect the area of land, building area, distance to the sub-district and distance to the sub-district on land prices. Based on the data in table 1, the R-squared value is 18.50% with Adjusted R-Squared of 15.91% and Prob (F Statistic) below 5%.

Table 2. Results of the Determination Coefficient (R2) Test, F classical regression using Geoda software

Model Summary

R-squared	Adjusted R-Squared	F-Statistic	Prob (F-Statistic)
0.018505	0.015917	7.15025	1.05763E-05

Source: Author's preparation, 2023 (Geoda Output)

Furthermore, in table 3, the probability of land area (land size area) is 0.41137 or >5% and the distance to the sub-district is 0.34509 or >5% which explains that the land area (land area) and distance to the sub-district do not affect the land price while the building area is 0.00017 and the distance to the sub-district is 0.01342. With the probability value of the two variables each below 5%, it is explained that it has an influence or attachment to the increase in land prices.

Table 3. Results of Individual Variable Coefficient Test Using Geoda Software

	Coefficient	*Std.Error*	*t-Statistic*	*Probability*
Constant	9.75838e+06	249622	39.0926	0.00000
LUAS_BUMI	-1382.03	1681.88	-0.821714	0.41137
LUAS_BGN	95,4489	25.3096	3.77126	0.00017
JRK_KEL	-173648	70153.9	-2.47525	0.01342
JRK_KEC	73462	77781.9	0.944461	0.34509

Source: Author's preparation, 2023 (Geoda Output)

Table 4 is the results of the spatial dependency test with results showing that the land area (land area) does not affect the increase in land prices with a probability value of 0.37946 or >5%, the probability of distance to the sub-district is 0.28216 or >5% and the probability of the distance to the sub-district is 0.66712 or >5%. The area of the building greatly affects the price of land, as seen from the probability of 0.01106 or below 5%.

Table 4. Results of Variable Coefficient Spatial Dependency Test

Variable	*Coefficient*	*Std.Error*	*z-value*	*Probability*
W-MEAN	0.0746236	0.0441043	16.9197	0.00000
CONSTANT	2.53235e+06	482095	5.2528	0.00000
LUAS_BUMI	-1343.86	1529.02	-0.878898	0.37946
LUAS_BGN	58.4711	23.0125	2.54084	0.01106
JRK_KEL	-68608.9	63793.2	-1.07549	0.28216
JRK_KEC	30416.3	70719.2	0.430099	0.66712

Source: Author's preparation, 2023 (Geoda Output)

Furthermore, a spatial dependency test was carried out, namely the Lagrange Multiplier test to determine the effect of spatial dependence. Based on the test seen in table 5, the result is that the probability value for Lagrange Multiplier (LM) Lag and for LM Error is 0.00000**. It shows that statistically there is spatial autoregression with lag in the dependent variable. For this reason, the next observation uses the Spatial Lag Model and the Spatial Error Model.

Table 5. Lagrange Multiplier and Robust LM Test Results

Test	**MI/DF**	**Value**	**Prob.**
Moran's I (error)	0.1649	27.4952	0.00000
Lagrange Multiplier (lag)	1	722.4475	0.00000
Robust LM *(lag)*	1	115.6638	0.00000
Lagrange Multiplier (Error)	1	649.7839	0.00000
Robust LM *(error)*	1	43.0001	0.00000
Lagrange Multiplier (SARMA)	2	765.4477	0.00000

Source: Author's preparation, 2023 (Geoda Output)

Furthermore, in table 6 is the spatial analysis of the Error Model which shows that the land area (land area) does not affect the increase in the Selling Value of Tax Objects (NJOP) with a probability value of 0.48749 or >5%, the probability of distance to the sub-district is 0.28216 or >5% and the probability of the distance to the sub-district is 0.66712 or >5%. The area of the building significantly affects the price of land, as seen from the probability of 0.03704 or below 5% and the Lambda of 0.00000.

Table 6. Results of the Spatial Test Error Model

Variable	*Coefficient*	*Std.Error*	*t-Statistic*	*Probability*
CONSTANT	9.70252e+06	648586	14.9595	0.00000
LUAS_BUMI	-1073.22	1545.73	0-0.694309	0.48749
LUAS_BGN	48.466	23.2411	2.08536	0.03704
JRK_KEL	-28410.4	68281.4	-0.416079	0.67735
JRK_KEC	9023.62	75714.4	0.11918	0.90513
LAMBDA	0.755575	0.0432327	17.4769	0.00000

Source: Author's preparation, 2023 (Geoda Output)

Comparison of Classic Results, Spatial Lag, and Spatial Error Model to the Selling Value of Tax Objects (NJOP).

In table 7, it can be seen that the results of observations using the Classic Model on the influence of land area, building area, distance to sub-districts and distance to sub-districts on the Selling Value of Tax Objects, the R-squared value is 6.88% with Adjusted R-Squared of 6.63% and Prob (F Statistic) is below 5%.

Table 7. Results of the Determination Coefficient (R2) Test, F classical regression using Geoda software

Model Summary			
R-squared	Adjusted R-Squared	F-Statistic	Prob (F-Statistic)
0.068813	0.0066358	28.0258	1.7395e-22

Source: Author's preparation, 2023 (Geoda Output)

Based on table 8, the probability of land area (land size area) is 0.98142 or >5% which explains that the land area (land area) does not affect the increase in the Selling Value of Tax Objects (NJOP).

Table 8. Results of Individual Variable Coefficient Test Using Geoda Software

	Coefficient	*Std.Error*	*t-Statistic*	*Probability*
CONSTANT	4.82859e+06	189121	25.5317	0.00000
LUAS_BUMI	-29.7795	1274.25	-0.0233703	0.98142
LUAS_BGN	176.222	19.1753	9.19004	0.00000
JRK_KEL	-250846	53150.7	-4.71952	0.00000
JRK_KEC	282095	58929.9	4.78696	0.00000

Source: Author's preparation, 2023 (Geoda Output)

Table 9 shows the results of diagnostics for spatial dependence in checking the spatial lag model, with results showing that the land area (land area) does not affect the increase in the Selling Value of Tax Objects (NJOP) with a probability value of 0.71250 or >5%. The probability building area is 0.00000 or below 5%, the distance to the village probability is 0.0003 or below 5%, and the distance to the sub-district is 0.00000 or below 5%. These three variables greatly affect the Selling Value of Tax Objects (NJOP).

Table 9. Results of Variable Coefficient Spatial Dependency Test

Variable	*Coefficient*	*Std.Error*	*z-value*	*Probability*
W-NIR_REAL	0.788314	0.0373109	21.1283	0.00000
CONSTANT	429955	255228	1.68459	0.09207
LUAS_BUMI	417.542	1133.1	0.368494	0.71250
LUAS_BGN	149.325	17.0701	8.74777	0.00000
JRK_KEL	-197744	47467.7	-4.16585	0.00003
JRK_KEC	272153	52649.6	5.16913	0.00000

Source: Author's preparation, 2023 (Geoda Output)

In table 10, based on the results of the spatial dependency test, namely the Lagrange Multiplier test to determine the effect of spatial dependence. The probability value for Lagrange Multiplier (LM) Lag and LM Error is 0.00000. It shows that statistically there is spatial autoregression with lag in dependent variables. For this reason, the next observation uses the Spatial Lag Model and the Spatial Error Model.

Table 10. Lagrange Multiplier and Robust LM Test Results

TEST	MI/DF	Value	Prob.
Moran's I (error)	0.1987	33.1191	0.00000
Lagrange Multiplier (lag)	1	926.5864	0.00000
Robust LM *(lag)*	1	15.2515	0.00000
Lagrange Multiplier (Error)	1	944.4047	0.00000
Robust LM *(error)*	1	33.0698	0.00000
Lagrange Multiplier (SARMA)	2	959.6561	0.00000

Source: Author's preparation, 2023 (Geoda Output)

Furthermore, in table 10 is the spatial *analysis of the Error Model* which shows that the land area (land area) does not affect the increase in the Selling Value of Tax Objects (NJOP) with a probability value of 0.66466 or >5. The probability building area is 0.00000 or below 5%, the distance to the sub-district is 0.00003 or below 5%, the distance to the sub-district is 0.00000 or below 5% and Lambda is 0.00000. The area of the building, the distance to the sub-district and the distance to the sub-district greatly affect the Selling Value of Tax Objects (NJOP).

Table 11. Results of the Spatial Test Error Model

Variable	*Coefficient*	*Std.Error*	*z-value*	*Probability*
CONSTANT	4.60632e+86	572225	8.04983	0.00000
LUAS_BUMI	495.795	1143.73	0.43349	0.66466
LUAS_BGN	146.632	17.1977	8.52625	0.00000
JRK_KEL	-211819	50615.7	-4.18485	0.00003
JRK_KEC	302270	56127.8	5.38538	0.00000
LAMBDA	0.797229	0.0380534	20.9503	0.00000

Source: Author's preparation, 2023 (Geoda Output)

Percentile Map Observation Results.

1) Percentile Map for Market Prices.

Based on observations using *a percentile map* , from a sample of 1,522 land plot points in the East Jakarta Administrative City, in figure 1 it can be seen that the mean (market price) ranges from Rp7,991,317 to 868 sample points, the mean (market price) ranges from Rp7,991,317 to 13,659,150 as many as 390 sample points, the mean (market price) ranges from Rp13,659,150 to 24,153,390 as many as 188 sample points, and the mean (market price) ranges from greater than equal to Rp24,153,390 A total of 76 sample points.

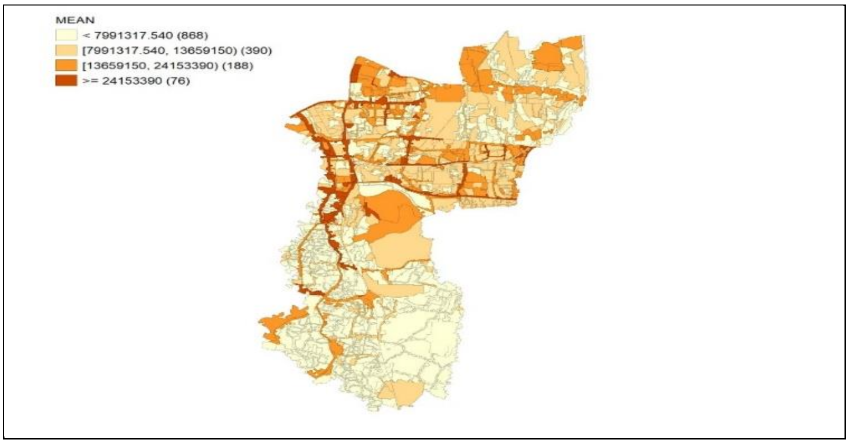

Figure 4. Market Price Percentile Map

Source: Prepared Author, 2023

2) Percentile Map for Selling Value of Tax Objects (NJOP)

Based on observations using *a percentile map* , from a sample of 1,522 points in the East Jakarta Administrative City, in figure 2 it can be seen that the Nir_Real (NJOP) ranges from Rp4,605,000 to 901 sample points, the Nir_Real (NJOP) ranges from Rp4,605,000 to 11,305,000 as many as 450 sample points, the Nir_Real (NJOP) ranges from Rp11,305,000 to 20,755,000 as many as 126 sample points, and the Nir_Real (NJOP) ranges from Rp20,755,000 to 45 sample points.

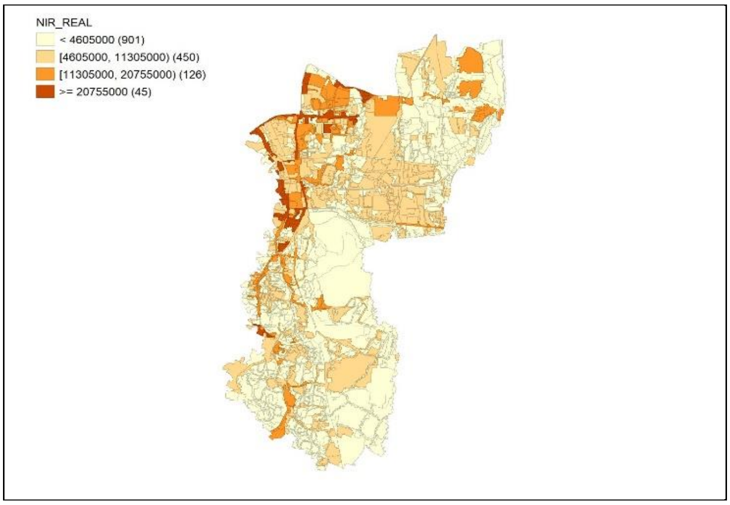

Figure 5. Percentile Map NJOP
Source: Prepared Author, 2023

Observation Results *of LISA and Moran's I*

1) LISA and Moran's I for Market Prices.

Based on figure 3, it can be seen that the value of Moran's I is 0.200 with 436 sample points that fall into the insignificant category. There were 268 samples in the High-high category, 550 sample points in the Low-low category, 226 sample points in the Low High category and 42 sample points in the High Low category.

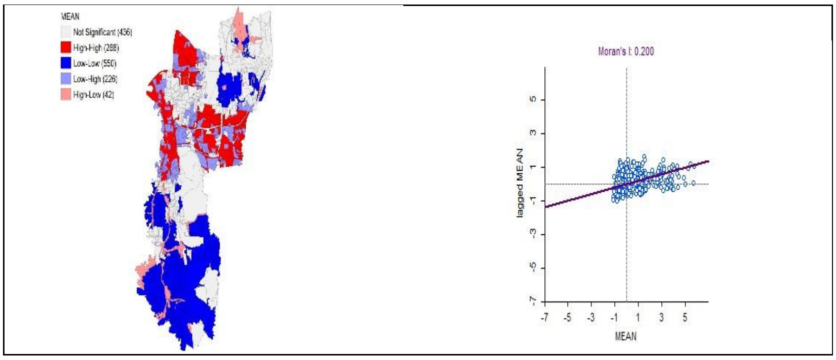

Figure 6. LISA Moran's I Market Price
Source: Prepared Author, 2023

2) LISA and Moran's I for the Selling Value of Tax Objects (NJOP).

Based on the data in figure 4, it can be seen that the value of Moran's I is 0.217 with 645 sample points that fall into the insignificant category. 177 samples fell into the High-high category, the Low-low category of 475 sample points, the Low High Category of 164 sample points and the High Low category of 61 sample points.

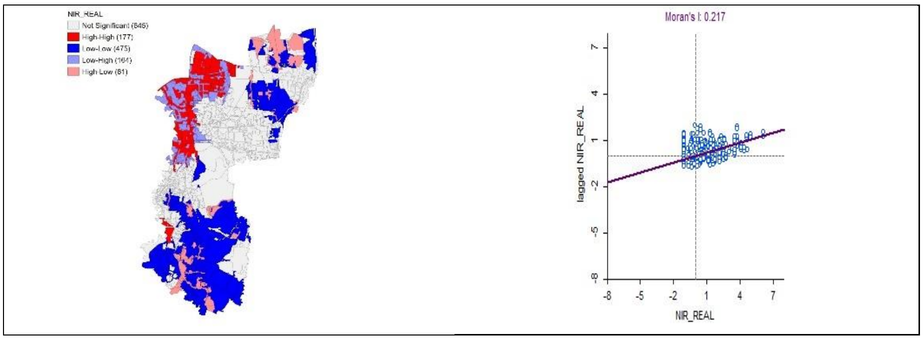

Figure 6. LISA Moran's I NJOP
Source: Prepared Author, 2023

The comparison of classical regression models with spatial regression approaches, namely the Spatial Lag Model and the Spatial Error Model, demonstrates the importance of accounting for spatial dependence in modeling land prices and the Selling Value of Tax Objects (NJOP) in East Jakarta. The classical regression model showed relatively low explanatory power, with an R^2 of only 18.50% for land prices and 6.88% for NJOP, suggesting that traditional linear models are insufficient in capturing spatial heterogeneity and autocorrelation. In contrast, both spatial lag and error models provided significantly stronger evidence of spatial effects, as supported by high values in Lagrange Multiplier tests and improved significance of coefficients. Notably, building area consistently had a significant and positive effect on both market land prices and NJOP, while land area showed no significant influence in all model variations. The results from Moran's I and LISA analysis also confirm spatial clustering patterns, indicating that land value disparities are not randomly distributed but follow discernible spatial structures. High-high clusters, especially for market prices, are concentrated in areas with better accessibility and infrastructure, aligning with previous theories of urban land value formation. These findings highlight the necessity for incorporating spatial analysis in land valuation to improve planning accuracy and support more equitable and data-driven policy decisions regarding urban development and property taxation.

CONCLUSION

Based on the results of spatial analysis using the Geoda application, this study concludes that among the analyzed variables, building area and distance to the village significantly influence both market land prices and the Selling Value of Tax Objects (NJOP) in the East Jakarta Administrative City, as revealed through the Spatial Error Regression Model applied to 1,522 sample points. These findings underscore the importance of integrating spatial variables in understanding urban land valuation patterns. The implication is that urban planning and policy decisions must not only consider economic variables but also spatial characteristics that directly affect property valuation.

For future research, it is recommended to include additional spatial variables, such as access to public transportation, proximity to commercial zones, and environmental quality. Incorporating temporal data could also reveal trends in land price evolution, allowing for dynamic modeling. Furthermore, machine learning or spatial panel models may enhance predictive accuracy and policy simulation for land-use planning.

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