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Development of Land Price Model with Geographically Weighted Regression on the Existence of Spatial Planning Zones: A Case Study in the Eastern Bandung City

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***Abstract*— One of the methods used to estimate land prices is the Geographically Weighted Regression (GWR). The GWR method is built based on the dependent and independent variables (land prices) (the spatial proximity between the land object and other facilities). However, this study will develop the independent variable by adding a spatial planning zone to provide the complexity of land price estimation. This study proposes an implementation mechanism by setting each zone type as an independent variable. Based on the spatial planning zones in Eastern Bandung City, there are five spatial planning zones. Thus, 15 variables were used in this GWR model, with ten variables from public facilities and five from spatial planning zones. The variables are categorized into worship, industry, government offices, health, sports/recreation, education, prisons, defense offices, terminals, trade and service zones, industrial zones, and low-residential, medium, and high-residential zones. The results of this study indicate that the implementation of the spatial planning zone variable has a better accuracy rate than the GWR model without involving the spatial planning zone variable. The approach with the proposed mechanism gives better accuracy of 8.6%. Spatial planning zone variable can be a new perspective in making a GWR-based land price estimation model in addition to the physical object variable in the form of public or social facilities, especially to improve the quality of the model formed.**

***Keywords*—GWR; spatial planning zone; determining variable; Eastern Bandung City.**

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I. INTRODUCTION

Land is an especially important natural resource for human life. Various human activities depend on land management to fulfill their needs [1]. The importance of land, besides public needs, is that it has economic implications according to its availability [2]. Differences in land conditions, in terms of location and property, lead to variations in land prices. Specifically, land prices have very dynamic changes in urban areas [3]. This phenomenon occurs due to swift economic activity, especially in services, trade, and industry. The need for land is not only for activities in that field but also impacts other related fields, especially housing. This situation will eventually lead to changes in land prices where the need for land is high, but the availability of land is limited.

This predicament encourages further understanding of the dynamics and variations of land prices. One method that can be used to review this is a modeling approach that considers the location aspect [4], [5]. This aspect of fixed location is essential in understanding the spatial distribution of land prices so that land prices will depend on the location. Each location has variations in land prices with various driving factors, such as accessibility, environment, politics, socio-economics, utilities, and public facilities [3], [6]–[10].

One model that can be used to understand land prices, especially to estimate land prices, is the Geographically Weighted Regression (GWR) model. The GWR model can find a relationship between driving factors' impact and spatial relationships' variations [5], [10]–[12]. The construction of the GWR model for land price estimation considers driving factors as independent variables and land price data as dependent variables. The review of independent variables is often limited to the relationship between the location of land parcels with various other objects in terms of distance, such as distance to education, commerce, industry, or other locations of interest [3], [5], [13]–[16].

Besides the approach mentioned above, the review of independent variables that can affect land prices can also be determined by other approaches, such as economic, social, and other aspects not determined by the spatial distance approach [17]. Some use the conditions or attributes of the location, such as the number of floors and bedrooms [18]. The condition of this location is represented by a value obtained using a certain mechanism. This value is then used in the GWR model. In general, integrating various reviews of independent variables can enrich the analysis and validity of a study, especially in understanding land prices [19].

Freemark [20] generally states that the implications of changes in land prices are influenced by how the transaction process in a certain zone, such as a spatial planning zone. On the other hand, how the influence of several areas in spatial planning affects land prices have been investigated [21]–[23]. In addition, a statement from the Ministry of Agrarian Affairs and Spatial Planning of the Republic of Indonesia [24] also reinforces at the implementation of spatial planning zones that can be involved in forming the land price model. This is possible due to the significant contribution of spatial planning zones to land price variations.

Based on the influence of the spatial planning zone on land prices, this study aims to involve spatial planning zones in GWR modelling. This effort aims to improve land price models that do not involve spatial planning zone factors, especially in Indonesia. In addition, the contribution of this study is in the form of building a GWR model by involving qualitative factors. This qualitative understanding means that the data used is in the form of classification (categorical) and not on a ratio scale. The categories of spatial planning zones are very diverse, such as industrial and trade zones. Therefore, this study also attempts to develop a mechanism that involves zoning data characteristics in the GWR model.

II. Material and Method

The study area of this research is East Bandung in Bandung City, West Java Province-Indonesia (Fig. 1). Generally, this region has experienced many changes in land use from agricultural to non-agricultural uses. The population density and urban growth rates are increasing [25]. This condition indicates an increase in the need for space. This space is necessary to meet the demand for land as a place to live or in other sectors such as services, trade, or industry. With this phenomenon, the study area is expected to have variations in land prices.

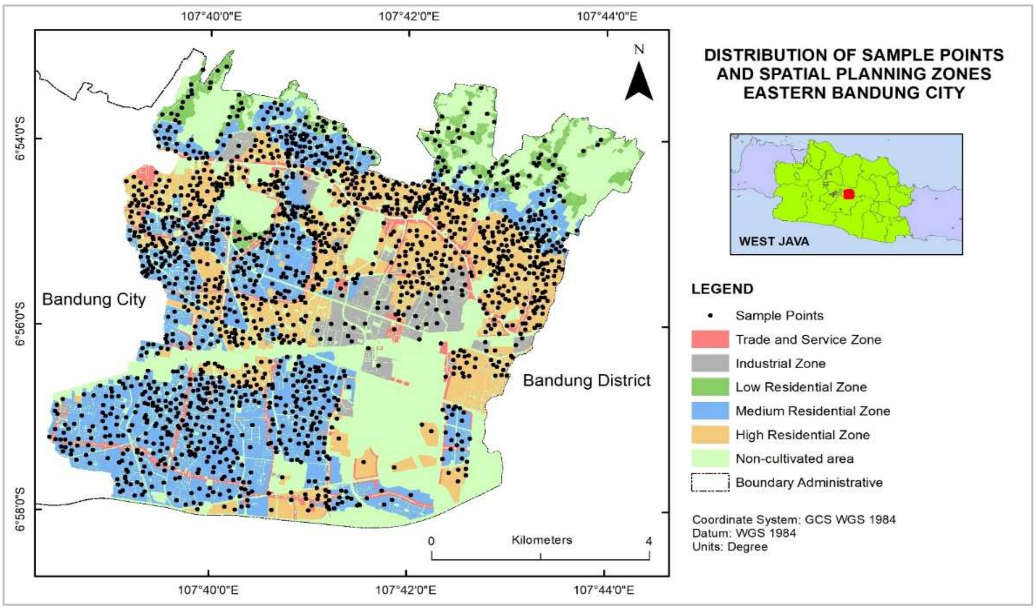

Fig. 1 Study area (Eastern Bandung City) with the distribution of sample points and spatial planning zones

This study uses several data to build a GWR-based land price estimation model, namely:

- Land parcels amounted to 13,702.
- Physical parameters, namely the location of the object used as a proximity factor, namely religious facilities, industry, government offices, health facilities, commercial facilities, sports/recreation facilities, educational facilities, prisons (penal institutions), defense offices, and terminals.
- Zoning parameters, namely data on spatial patterns (zoning pattern) of Bandung City, such as trade and service zones, industrial zones, low residential zones, medium residential zones, and high residential zones. In this case, the spatial planning zoning parameters are determined based on the cultivation area in the Bandung City spatial pattern.

The modeling process uses several land parcel samples taken based on a smaller administrative area, namely the sub-city in East Bandung. This sampling method is done because each sub-district has a different number and distribution. This effort was made so that the number and distribution of samples could represent the conditions in the study area. The number of samples was obtained using the Slovin formula (Eq. 1) for each sub-district with a margin of error of 0.05 [26].

$$n = \frac{N}{1 + Ne^2} \quad (1)$$

Where:
n = minimum value of sample point
N = number of population points
e = margin of error

The spatial distribution of the sample in each sub-district was determined using the simple random sampling method. This method is used considering that each member of the population has the same probability of being a sample [27]–[29]. Sample data can be obtained by converting land parcel data from polygon form to center points with the centroid principle. Based on these calculations, we obtained a sample of 1,884 plots of land with distribution, as shown in Fig. 1. Land price data was collected at the sample point locations. This land price data assigns a value to the GWR dependent variable (y). In addition to land price data, distance measurements from the centroid of each sample data to the nearest physical parameters are also carried out. This distance measurement uses the near analysis method with the formula as in Eq. 2. The results of this measurement could be used to assign the value of the independent variable (x_i) to each physical parameter in GWR.

$$d = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \quad (2)$$

Where:
d = nearest distance
X_1 = abscissa value of 1st data
X_2 = abscissa value of 2nd data
Y_1 = ordinate value of 1st data
Y_2 = ordinate value of 2nd data

Another measurement based on sample points is determining the closest distance to each zone adjacent to the zone of the observed land parcel. The measurement of the closest distance of land parcels to each zone was carried out as data for developing the GWR model in this study. This principle will find the shortest distance from a land parcel centroid to the line from each of its closest zones (Fig. 2). In the illustration, each line represents the shortest distance from the point of the land parcel to each zone line. The results of this measurement could also be used to assign the value of the independent variable (x_i) to each zone parameter in GWR.

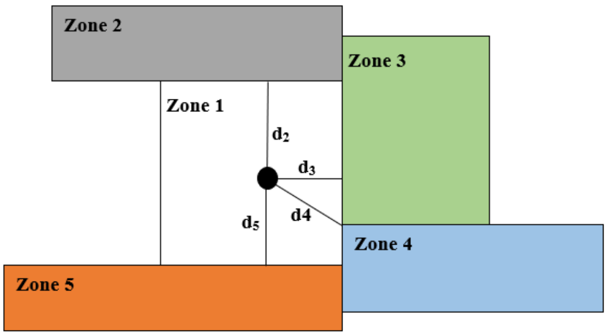

Fig. 2 Illustration of the closest distance measurement of land parcels to each zone

Based on the data collection that has been carried out, 16 types of data are obtained for each land parcel sample: one land price data, ten distance data to physical parameters, and five distance data to spatial planning zones. This data will then be processed in the GWR model with Eq. 3 [11]:

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{n} \beta_k(u_i,v_i)x_{ik} + \epsilon_i \quad (3)$$

Where:
n = number of observations
y_i = dependent variable on observation of-*i*
x_{ik} = independent variable of-*k* on observation of-*i*
(u_i,v_i) = coordinate values in easting and northing for the observation of-*i*
$\beta_0(u_i,v_i)$ = regression constant at the observation location of-*i*
$\beta_k(u_i,v_i)$ = regression coefficient of-*k* at the observation location of-*i*
ϵ_i = observation error of-*i*

The GWR model is built based on one dependent variable (y) and 15 independent variables (x_i). The independent variables will be divided into two types according to the parameters used: the type of physical object with ten independent variables (x_1 to x_{10}) and the type of spatial planning zone with five independent variables (x_{11} to x_{15}). Grouping the types of variables is intended to facilitate the development of the model carried out in this study.

Specifically for the independent variable from the spatial planning zone, the data value is not the distance from each land parcel to the nearest zoning. This study implements the effect of spatial planning zoning using Tobler's first law of geography. The rule is that everything is related to other things, but those close together are more related than others [30]. Based on this, the value given is an inverse comparison of the distance for the spatial planning zoning variable, namely:

$$x_i = \frac{1}{d_{ij}} \quad (4)$$

Where:
x_i = the value of variable of-*i*
d_{ij} = the distance between the points of land parcels in the zone-*i* and zone-*j*

The provision of 1/d is intended that other zones will also affect the value of land parcels in a zone but not as big as the zone of the land price itself. Suppose the observed land parcel is in a residential zone close to the industrial zone. In that case, it is expected that the industrial zone can also affect the value of the land object. This assumption is since various activities could be an attraction in the industrial zone in price assessments.

As an illustration, if a parcel of land is in an industrial zone, the value for the industrial zone variable will be assigned a value of 1. It is different for other zones, where the value given is an inverse ratio of distance. This is because other zones can affect the observed land parcels but are not larger than the zone of the land parcels themselves. In general, for spatial planning, zone variables refer to the following rules:

- The spatial planning zone variable from the observed land parcels is given a value of 1
- The spatial planning zone variable around the land parcel will be assigned a value of 1/d

The GWR model uses a fixed approach with Gaussian kernel weighting in this study. This approach refers to the density of data points that depend on a fixed radius for each regression point [11]. The GWR weighting is built with the weighted least square, as shown in Eq. 5 [11].

$$\hat{\beta}(u_i,v_i) = \left(X^T W(u_i, v_i) X\right)^{-1} (X^T W(u_i, v_i) y_i) \quad (5)$$

Where:
$\beta(u_i,v_i)$ = matrix of estimation coefficient
i = 1, 2, ..., n (number of observations)
X = parameter value matrix (independent variables)
y = empirical land price matrix (vector)
$W(u_i,v_i)$ = matrix of weighting diagonal

This equation forms the matrix for the weight values based on the Gaussian function. The weight value will decrease continuously as the distance from each independent variable increases to the bandwidth value limit. The Gaussian weighting function with bandwidth is [11]:

$$w_{ij} = \exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right] \quad (6)$$

Where:
w_{ij} = the weight between the regression point of-*i* and the data point of-*j*
d_{ij} = the distance between the regression point of-*i* and the data point of-*j*
b = bandwidth

The corrected akaike information criterion (AICc) method determines the optimum bandwidth value. AICc is the development of the akaike information criterion method, which has been corrected based on the maximum likelihood estimation (MLE) method [31]. This method will limit the number of variables to avoid overfitting so that this method provides a better value with a smaller estimated error variation [32]. Furthermore, numerical analysis with a golden section search is carried out, which proceeds iteratively to obtain the optimum bandwidth. The AICc equation is [11]:

$$AIC_c = 2n\log_e(\hat{\sigma}) + n\log_e(2\pi) + n\left\{\frac{n + tr(\mathbf{S})}{n - 2 - tr(\mathbf{S})}\right\} \quad (7)$$

Where:
n = number of observations
$\hat{\sigma}$ = estimated standard error resulting from dividing the residual sum of square (RSS) by the number of observations
tr(**S**) = trace of hat matrix **S** is the ranking or rank of the projection matrix, which contains the independent variables

The bandwidth value of the GWR process using sample points is 446.618 m. The amount of bandwidth is then used for model validation using several test points. As with the sample point selection process, the number and location of test points are selected the same way as the sample points. In the process of selecting test points, the land parcel data used are data that are not included as sample points. The number of test points data is 336 points. After going through the process of calculating the coefficient of land price estimation for each of these points, the quality control of the GWR model between the estimated and actual land prices can be performed through the calculation of the Root Mean Square Error (RMSE) value with Eq. 8 [3], [33]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}} \quad (8)$$

where:
i = 1, 2, ..., n (number of observations)
$\hat{Y}_i$ = estimated land price
Y_i = empirical land price
n = total number of observations

III. Result and Discussion

The results of the comparison of models can be seen in Table 1.

TABLE I
COMPARISON OF RMSE VALUES AT TEST POINTS

Model Type	Number of Sample Points	Number of Test Points	Bandwidth (m)	RMSE (Rp/m^2)
Without Spatial Planning Zone (10 Variables)	1,884	336	430.583	259,334
With Spatial Planning Zone (15 Variables)	1,884	336	446.618	237,113

Model testing is done by comparing the GWR model with spatial planning zones (10 physical variables and five spatial planning zone variables) against the GWR model without spatial planning zones (10 physical variables). The model without spatial zones was constructed using the same amount and spatial data distribution as the model with spatial zones.

From the RMSE value, the model that involves the influence of the spatial planning zone will give a smaller error value than the model without the spatial planning zone. Based on the comparison of the test results, this model can reduce the error by 8.6% compared to the model without spatial planning zones. In other words, adding new variables and procedures for their implementation in this model can further improve accuracy. However, it is still necessary to work out a mechanism for adding this zoning parameter in the modeling to obtain a better estimate.

The GWR model testing shows the diversity of the influence of spatial planning zone variables for each test point. The most influential zoning at each test point can be determined through the magnitude of the parameter value from the GWR equation for that point (nominally, not notation). Based on the results, the zone from the test point is not always the most influential in GWR. In the northern part of Eastern Bandung City (Fig. 3), some land prices located in the middle residential zone are most influenced by the industrial zone. Therefore, the industrial zone has a strong enough role to influence variations in land prices in the medium residential zone. This phenomenon shows that each location has a variety of spatial planning zones that affect it the most, which is not necessarily the zone that it is located.

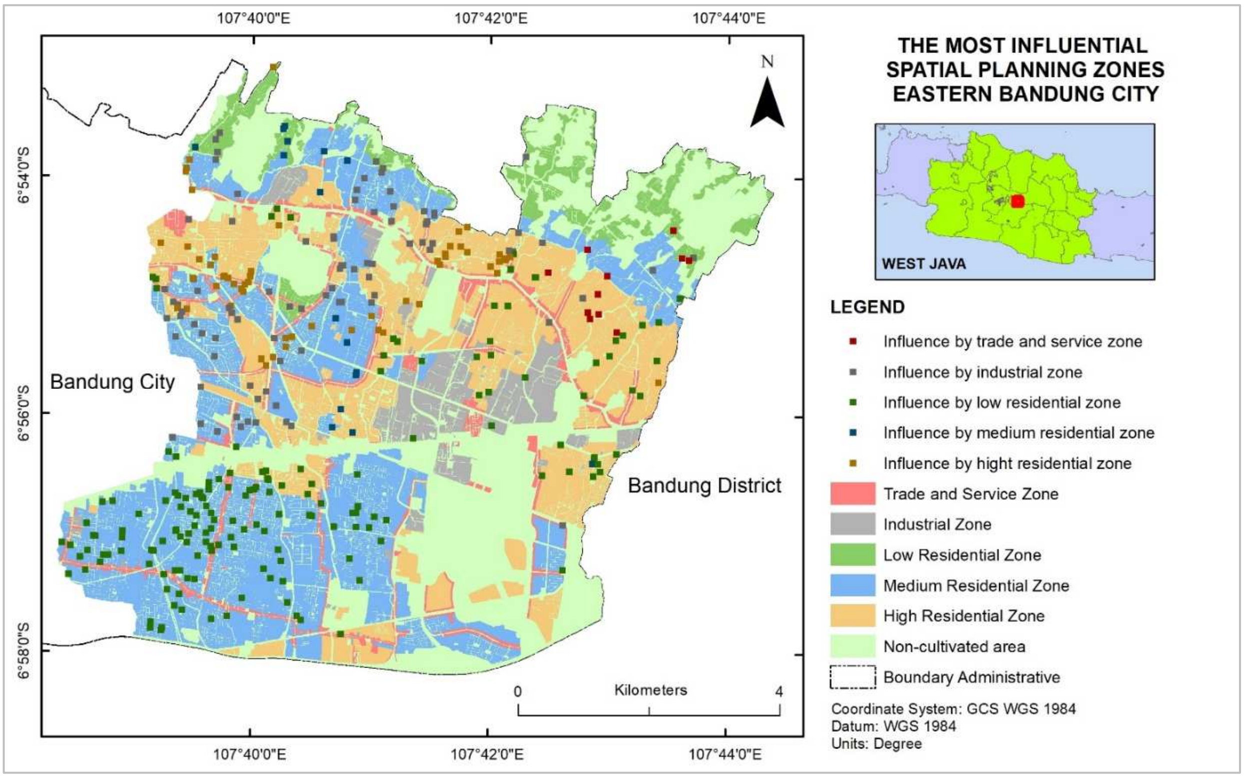

Fig. 3 The distribution of the most influential zoning variables in Eastern Bandung City

Based on the test results, most spatial planning zones that have the most influence on land prices in sequence are low residential zones, industrial zones, high residential zones, medium residential zones, and trade and service zones. This sequence is obtained by cross-tabulating the spatial planning zone data at each point of the most influential spatial planning zone (Table 2).

From Table 2, the number of diagonal areas of 37 land parcels shows the most influential zoning, the same as the zone where the test point is. On the other hand, as many as 299 other land parcels are most affected by zones that differ from the spatial planning zone of the parcels themselves. In other words, different zones can be more powerful in influencing the pattern and variation of land prices at several land parcel points.

TABLE II
CROSS-TABULATION ZONING RELATIONSHIP FROM TEST POINT TO MOST INFLUENTIAL ZONE

Spatial Planning Zone		**The Most Influential Zone**					**Grand Total**
		A	B	C	D	E	
Location Test Point	A	0	0	3	0	0	3
	B	10	0	12	0	11	33
	C	8	3	0	4	1	16
	D	39	2	107	8	16	172
	E	31	6	42	4	29	112
Grand Total		88	11	164	16	57	336

Note: A: Industrial Zone, B: Trade and Service Zone, C: Low Residential Zone, D: Medium Residential Zone, E: High Residential Zone

Another thing from the table is the low residential zone which is the zone that has the biggest influence on land price assessment, which is 164. This zone also has the biggest influence on land prices in the medium residential zone. The table shows the characteristics of the diversity of spatial planning zones that are the most influential in assessing land prices.

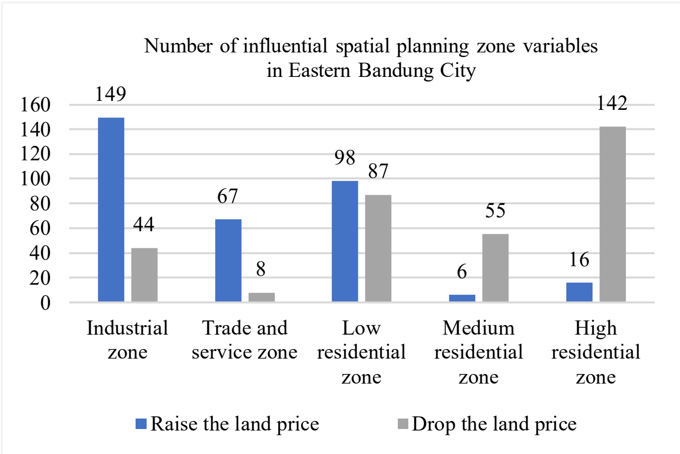

Fig. 4 Number of influential spatial planning zone variables in Eastern Bandung City

The characteristics of the diversity of spatial planning zone effects can be seen based on the parameter values of the GWR model at each point. Based on the value of the model parameters, the influence of the spatial planning zone has the character of increasing or decreasing land prices for each test point. The results show that the industrial zone is the most widely used spatial planning zone in terms of increasing land prices. A total of 44.3% (149 of 336) of the total land parcels are affected by this zone to increase land prices. This condition indicates that the land price will tend to be higher the closer to the industrial zone. In detail, these characteristics are presented in the form of a diagram shown in Fig. 4.

On the other hand, in spatial planning zones, the most influential in reducing land prices is the high residential zone. This zone influences as much as 42.2% of the total land parcels (142 of 336) in lowering prices. This phenomenon shows that the closer to the densely populated zone, the lower the land price. However, some land parcels will increase in price if they are close to high residential zones. This condition indicates the existence of spatial heterogeneity in determining land prices. This heterogeneity shows that each determination of land prices in a location can only be assessed based on the surrounding conditions, in this case, represented by the size of the bandwidth.

IV. Conclusion

Based on the study's results, the land price estimation model using the GWR method, which considers the spatial planning zone, will be better than without the spatial planning zone. This model provides a better accuracy of 8.6% for the study area used. This achievement is obtained if the modeling mechanism is carried out by placing each type of zone as an independent variable in the GWR equation. From the view of the mechanism of building the GWR model, it is still possible to use other methods that can increase the accuracy of spatial planning zoning in land price models. One of them is by setting the zone as an independent variable.

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