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Geo-additive Semiparametric Regression for Modeling Property Price in Surabaya, Indonesia Using Marketplace Data

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Abstract The price growth of the property in Surabaya is the highest among the other cities in East Java, but demand in the residential sub-sector is still there. The value of a property is described by its price. Property price is one of the important factors considered in making an investment decision. The market value is determined by its physical and micro-neighborhood factors. It consists of location and environmental factors. Mass appraisal is an efficient and cost-effective way to value property fairly, transparently, and consistently, as properties with the same attributes will receive equal value. The existence of a price property model is vital in the context of mass appraisal. The objective of mass appraisal is to value a group of properties using data, valuation methods, and statistical tests. Mass appraisal is invaluable for the government to formulate taxes based on the market value. In this research, the Geo-aditive model is used to model property price based on its physical and location factors. The results show that the physical (number of bedrooms, number of bathrooms, land area, and building area) and location (longitude and latitude coordinates) factors significantly influence the property prices in Surabaya. The building area has more impact on the property price compared to the land area. The combined effect plot shows also that the properties located in the eastern of Surabaya have a relatively higher price than those in the western part.

Keywords Geoaditive, Mass Appraisal, Property Price

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1. Introduction

The residential property market in Surabaya, as highlighted by a survey conducted by Bank Indonesia, witnessed a slowdown in the increase of residential property prices during the fourth quarter of 2018, with a modest average growth rate of 5.85% (YoY). While small houses experienced a notable increase of 9.58%, medium and large houses saw comparatively lower increments of 4.28% and 3.75%, respectively. This price surge, most pronounced in East Java, coincided with a notable uptick in demand within the residential sub-sector despite the overall deceleration. Property value, a pivotal determinant in investment decisions, is encapsulated by its price and remains a cornerstone factor in investment decisions within the sector [1]. Market value, as underscored by the Indonesian Valuation Standards [16], serves as the primary basis for valuation, encompassing various factors including residential property products.

Li and Brown [21] delineate the significance of physical and micro-neighborhood factors, comprising location and environmental aspects, in shaping market values. Residential properties situated in appealing micro-neighborhoods tend to command higher market values compared to those in less attractive locales. Physical attributes such as type, size, shape, design, and construction quality also influence property valuation. The

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importance of location, the second factor, lies in its ability to foster industrial development and investor accessibility. Accessibility, as emphasized by [33], plays a crucial role in determining the attractiveness of a location, with factors like proximity to industrial zones, transportation networks, and amenities influencing property values. The environmental factor, while contributing positively to aesthetic appeal, also presents challenges, particularly in industrial zones where pollution levels can adversely impact property values. Air and noise pollution are key determinants, with higher pollution levels correlating with decreased property values. The US Environmental Protection Agency [27] recommends stringent noise limits to maintain environmental quality and protect property values.

In the domain of mass appraisal, the development of a robust property pricing model is indispensable. Unlike individual property valuation, which focuses on specific properties, mass appraisal aims to value property groups using data-driven methodologies. This approach, crucial for formulating fair and transparent taxation policies, ensures equitable valuation practices that are consistent across properties. The main aim of this study is to look into the impact of environmental factors on residential property values in Surabaya. Additionally, the research investigates the effectiveness of a modeling approach utilizing e-commerce data for mass appraisal purposes. Understanding these dynamics is essential for policymakers and investors to make sound judgments about urban development and investment strategies. Usually, the assessment process has relied on subjective reasoning, however the models developed by this research could help with this justification process. Mass assessment also plays an important role in promoting fair and transparent taxation policies by giving accurate and uniform property values. It enables governments and stakeholders to make educated decisions about taxation and urban planning. While earlier research has looked into many areas of property value, there is still a considerable vacuum in comprehending the unique dynamics of the Surabaya property market. This study aims to fill the gap by investigating the unique characteristics that influence property values in the region. Current property value methods in Surabaya and Indonesia typically include a combination of income, cost, and sales comparison methodologies, which are guided by local rules and appraisal standards.

2. Literature Review

Regression models are also applied for property valuation. In [6], a regression model was developed for property valuation to justify property taxes. Then [7] compared a weighted geographic regression model with a spatial lag regression in mass real estate valuation using residential property sales data during 2010-2012 in Norfolk, Virginia. Furthermore, [25] use regression to assess vacant land, which is one of the constraints in property valuation.

Appraisal/valuation is a process to provide estimates and opinions on the economic value of an object of valuation at a specific time by the Indonesian Valuation Standards Council. According to [33], valuation is an estimation process based on knowledge and experience of the value of comparable transactions and properties. The property value reflects the market and individual values. According to [14], there are three valuation approaches, the market approach, the income approach, and the cost approach. The market approach sets limits on the market value for the property by examining market data of prices usually paid by buyers for similar properties. In the market approach, the value of a property is estimated by comparing the subject property with similar or comparable properties sold at a specific time [10]. Statistical quantitative techniques with multiple linear regression methods are also applied in the market approach. Regression analysis is a method used to analyze the relationship between the dependent and the independent variables. Statistical regression methods are used to analyze the market through different locations and property attributes. Multiple linear regression methods also provide the highest analysis results by measuring the relationship between subjects and comparable sales data in each attribute [20]. Another previous study on property price prediction and valuation stated that Random Forest is the most successful machine learning algorithm which has better compatibility with the data situation [17].

The income approach is used for income-generating properties, analyzing income and expenditure data from comparison properties to obtain net income for the assessed property. The cost approach is used to determine the property value by estimating the acquisition and replacement costs for new developments with equal utilities or adapting old properties for the same usage. This approach does not consider costs caused by development delay and overtime. This approach calculates the estimated depreciation including physical depreciation and functional obsolescence for an older property. The analysis result of construction cost estimates and depreciation should determine the construction costs and depreciation in accordance with the market.

In property valuation, [9] states that physical, legal, and location factors affect property value. In the study of [8], the location factor is measured through the distance variable, one of which is the shopping center. The results show that the value of residential properties at a distance of 450 meters from the shopping center has decreased the closer it is to the shopping center. Residential properties with more than 450 meters from the shopping center get an increase in value. [31] states that environmental factors are measured through noise pollution variables. The results show that noise pollution has an effect (significant) on the market value of residential houses. The results showed that noise pollution has a negative coefficient. [24], physical factors are measured from the variables including land area, building area, number of bedrooms, and number of bathrooms. The land area and the number of bedrooms on a property have a positive effect on the market value of residential houses [11]. According to [15], the number of bathrooms on a property has a positive effect on the market value of residential houses. According to research by [4], building area affects the market value of residential houses in Surabaya.

The literature review explores various methodologies and factors influencing property valuation, with a focus on the Indonesian real estate landscape. Post-pandemic challenges in the Indonesian housing market are highlighted in Wiradinata's study [32], which investigates house price prediction in Surabaya using machine learning techniques. This research underscores the economic slowdown caused by the COVID-19 outbreak and its impact on property pricing dynamics, reflecting broader concerns within the Indonesian property industry. Utama's study [28] delves into the best models and variables affecting housing values in major Indonesian cities, including Surabaya and Denpasar. By analyzing web-based survey data, the research identifies critical factors such as electric power consumption and land area that influence property prices, providing valuable insights for consumers and investors navigating Indonesia's diverse real estate markets. Gnagey's investigation [12] into property-price determinants in Indonesia further enriches the literature review, offering insights into asking-price formation across the Indonesian archipelago. By examining residential, commercial, and undeveloped land markets, the study reveals the nuanced impact of property characteristics, land ownership status, and advertising methods on asking prices. These findings illuminate the intricacies of Indonesia's property market and highlight the need for context-specific valuation approaches tailored to diverse regional dynamics

Valuation is also closely related to consumer behavior in buying property. [5] note that only financial factors impact buyer decisions. In addition, this study also shows there exist significant differences in factors between buyers who want to live compared to those who want to invest. The factors include psychology, emotion, intuition, and evaluation. Then [2] investigated the home buying decision process based on demographic and life cycle factors. The result shows that multiple processes cannot be distinguished based on multi motives. However, demographic variables such as gender, age, education, and family life cycle show the differences in multiple processes. Furthermore, [3] further find that buyers have a consumption motive in buying a residence and behave rationally. But investors prefer to purchase apartments and tend to behave heuristically. The multi-time motives for buyers are not significant to the decision model.

3. Research Methodology

3.1. Data Collection

There are two primary sources for this research. The first is from the marketplace website and the other source is from the survey. Those two sources are necessary to get the price estimation, considering data from the websites tend to have higher prices. Data from the websites are obtained using API (*application programming interface*) technology. As for the survey, the target population is all residential houses in Surabaya, Then the purposive sampling method is used according to the criteria for residential houses transacted or offered in the last year from October 2018 to October 2019. Transaction data is obtained from the property broker. The rationale behind this decision lies in the need to target specific residential properties in Surabaya that were transacted or offered for sale within a defined timeframe (October 2018 to October 2019). This targeted approach ensures that the sample

Table 1. Concept, Definition and Indicator

Concept	Definition	Indicator
Location factor	Geographical coordinate of the property location	Latitude Longitude
Physical factor	The tangible features can be seen, touched, felt, or tangible attached to the property	Land area (m2) Building area (m2) Number of bedrooms (units) Number of bathrooms (units)

Source: Author's Decision

represents the relevant population of interest, optimizing the efficiency and relevance of the data collection process. Additionally, it allows for the inclusion of properties that may not be adequately represented in a simple random sample, such as those with unique characteristics or transaction histories.

3.2. Variable of Interest

The collected data from the website includes type, land area, building area, number of bedrooms, number of bathrooms, facilities, ownership status, and location coordinates. There are also additional data from the survey, as presented in Table 1.

3.3. Data Analysis

The geo-additive model is then used to model the collected data. geo-additive model is one of the semiparametric regression models containing parametric and nonparametric components. The semiparametric model can handle both linearity and nonlinearity relationships between the response and the sets of predictor variables [30]. The Geoaditive model is an extension of the additive model that can contain components of bivariate functions [19]. It can be written as:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + f_3(x_{3i}) + f_4(x_{4i}) + f_{56}(x_{5i} + x_{6i}) + \epsilon_i, \epsilon_i\ N(0, \sigma^2) \quad (1)$$

For $1 \leq i \leq n$ is Geoaditive model due to the bivariate function f_{56} of the predictor x_5 and x_6. Bivariate function corresponds to geographic coordinates such as longitude and latitude, which is the reason for the name Geoaditive. However, the term bivariate also refers to any pair of continuous predictors [13].

4. Analysis and Discussion

4.1. Residential Property Overview

23,433 residential property data were collected including the characteristics of the number of bedrooms, number of bathrooms, building area, land area, and property price. Several methods including descriptive analysis by using frequency are presented in this paper for the data analysis. The data descriptive analysis revealed that 81.4% of the total residential data are houses with a type of 3 to 5 bedrooms, only 11.5% are houses with less than 3 bedrooms, and the remaining 7.2% are houses with more than 5 bedrooms. Meanwhile, the characteristics of residential property based on the number of bathrooms in each house shows that 60.5% of the residential property in Surabaya has 3 to 5 bathrooms, 37.5% are houses with less than 3 bathrooms, and only 2.4% are houses with more than 5 bathrooms.

Table 2 provides the median property price based on the number of bedrooms and number of bathrooms. Table 2 shows that the more bedrooms and bathrooms, the higher the property price. Table 2(a) revealed that the median property price with less than 3 bedrooms is IDR 1.2 Billion, while the median of property price with more than 5

Table 2. Median of Residential Property price Based on House Type

Type	Median Property Price (a)	Median Property Price (b)
<3 Rooms	IDR 1.2 Billion	IDR 1.6 Billion
3-5 Rooms	IDR 2.7 Billion	IDR 3.4 Billion
>5 Rooms	IDR 4.9 Billion	IDR 6.5 Billion

Source: Author's Calculation

bedrooms is IDR 4.9 Billion. It is also shown in 2(b) that the median property price with less than 3 bathrooms is IDR 1.6 Billion, whereas the median property price with more than 5 bathrooms reaches IDR 6.5 Billion. Property price is based on criteria the number of bedrooms and bathrooms. The characteristics of building area, land area, and property price are visualized in the histogram. The histogram in Figure 1 revealed that the distribution of building area and land area of the residential data tends to be asymmetrical and highly left-skewed, in comparison, the distribution of the property price tends to be right-skewed. Most properties in Surabaya tend to have small building area and land area, while the price of the property is relatively high.

To further analyze the relation of these variables, the correlation between building area, land area, and property price needs to be visualized in Scatterplot. The scatterplot in Figure 2 informed that each variable has a positive correlation, this is indicated by a plot that tends to form a positive line. So, it can be interpreted that the higher the building area and land area, the higher the residential property price.

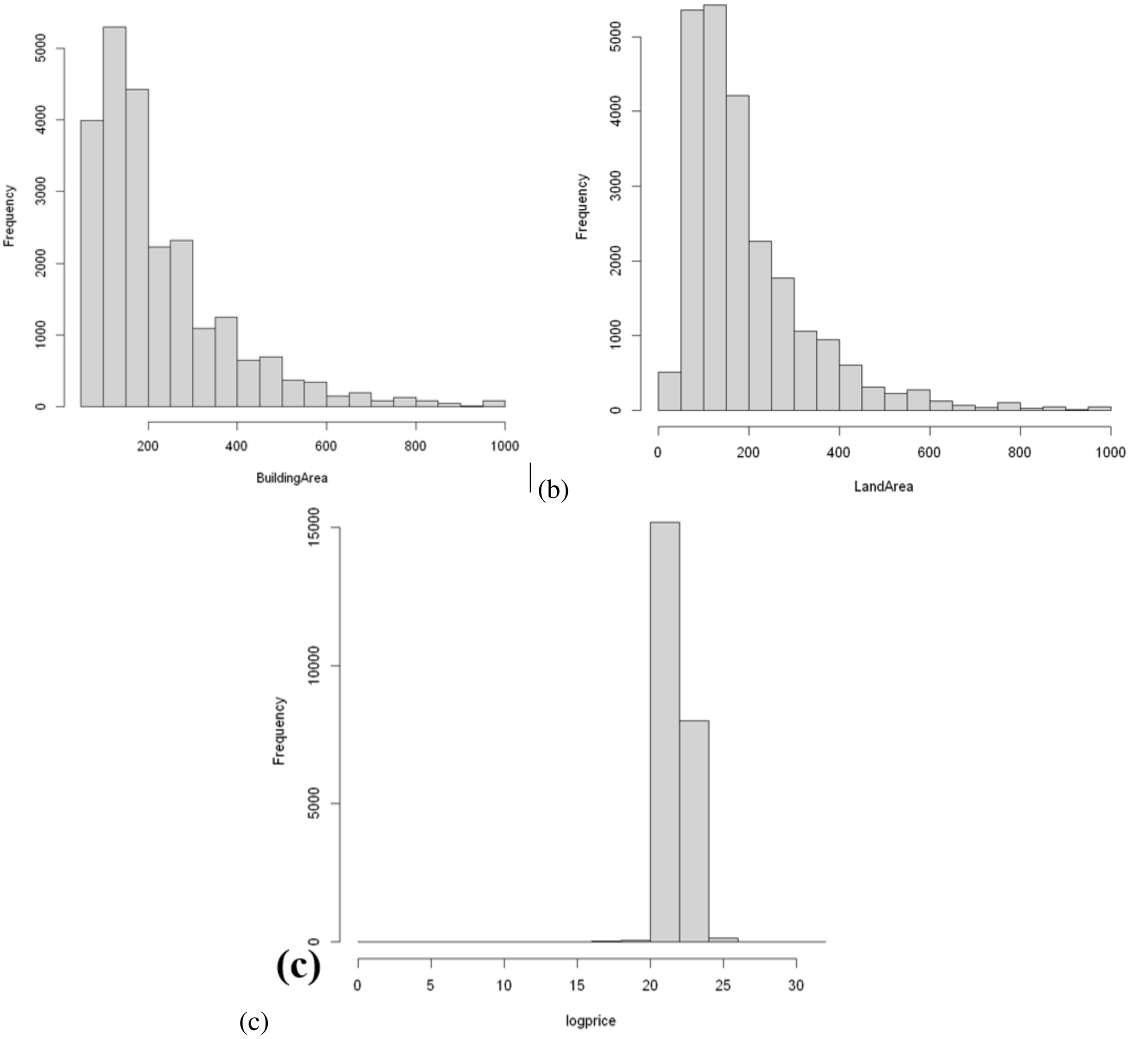
4.2. The Geo-additive Model

The geo-additive model is a semiparametric model that contains parametric and nonparametric components. This study defines the number of bedrooms and the number of bathrooms as parametric components, then building area, land area, and geographical coordinates of the property location as nonparametric components. The results of geo-additive modeling on property price in Surabaya based on those variables are presented in Table 3.

The analysis results from Table 3 of the geo-additive model indicate that the number of bedrooms, number of bathrooms, building area, land area, and property location collectively exert a significant influence on residential property prices in Surabaya. However, it's crucial to note that with a sample size of 23,433 houses, even minute effects can achieve statistical significance. The geo-additive model employed in this study integrates both parametric and nonparametric components to comprehensively capture the complex relationships between the predictor variables and property prices. Specifically, the number of bedrooms and bathrooms are considered as parametric components, while the building area, land area, and geographical coordinates of the property location are treated as nonparametric components. Interestingly, while it was initially hypothesized that factors like land area and the number of bedrooms would positively affect property prices, the negative estimate for the number of bedrooms in Table 3 suggests a more nuanced relationship. This discrepancy underscores the importance of delving into the intricacies of the model's results and interpreting them in the context of the broader real estate market dynamics in Surabaya. In summary, the geo-additive model provides valuable insights into the determinants of residential property prices in Surabaya, shedding light on both expected and unexpected relationships between various predictor variables and market values.

An adjusted R-squared value (R-sq.(adj)) of 0.729 and a deviance explained percentage of 72.9% indicate that the geo-additive model fits the data well. The Restricted Maximum Likelihood (REML) value of 13262 reflects the method used to estimate model parameters, while the sample size (n) of 23,433 denotes the number of residential properties analyzed.

Table 4 compares the performance of several models from prior studies to the suggested model in the current study. Each row represents a separate study, which includes the author, sample time/country, sample size, and performance metric (Adjusted R-squared). The performance indicator measures how effectively each model predicts variations in property values. The proposed model in the current study, which employs a geo-additive technique, has an R-squared adjusted value of 0.729. This means that the model explains about 72.9% of the



(a) (b) (c)

Figure 1. Histogram of (a) Building Area (b) Land Area and (c) Property Price

Table 3. The Results of geo-additive Modelling on Property Price

Parametric Components				
Variable	Estimate	Std. Error	t-value	P-value
Intercept	21.668	0.012	177.370	0.000
Number of bedrooms	-0.078	0.003	-23.980	0.000
Number of bathrooms	0.125	0.003	36.970	0.000
Nonparametric Components				
Variable	edf	Ref. df	F-value	P-value
Building Area	8.793	8.985	272.883	0.000
Land Area	7.833	8.587	866.620	0.000
Property Location (Latitude, Longitude)	8.487	10.935	8.357	0.000
R-sq.(adj)=0.729; Deviance explained=72.9%; REML=13262; n=23,433				

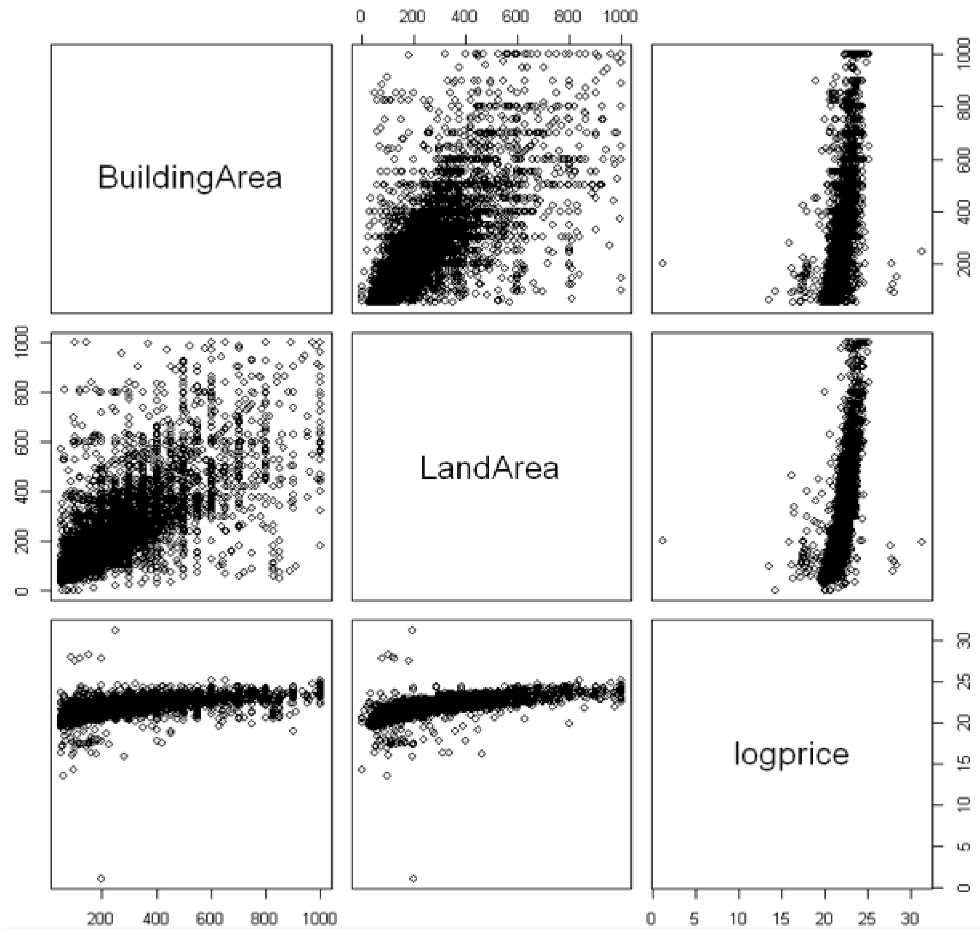
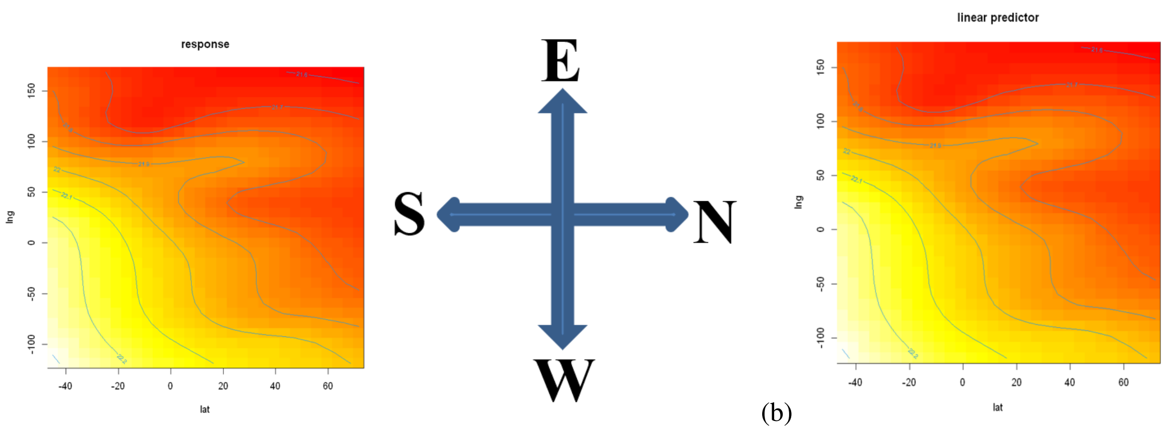


Figure 2. *Scatterplot* of Building Area, Land Area, and Property Price



(a) (b)

Figure 3. The Joint Effects of Latitude and Longitude on (a) Property Price (b) Fitted Price

variation in property prices in Surabaya, Indonesia. The model's visibility is fairly high, indicating that it catches a major fraction of the factors driving property prices in the area.

Table 4. Comparison of Property Valuation Model Performance with Previous Studies

Author	Country	Sample	Performance (R-sq. (adj))
Pi-Ying, L. (2011).	Kaohsiung City, China	2,470	MRA: 0.649 ANN: 0.758
William et al. (2014)	Johor, Malaysia	387	MRA: 0.720
Zhang et al. (2015)	Shenzhen, China	537	MRA: 0.717
Morano et al. (2019)	Bari, Italy	200	EPR: 0.634
Wang et al. (2020)	Beijing, China	3,064	MRA: 0.565 GWR: 0.201
Yilmazer & Kocaman (2020)	Ankara, Turkey	1,162	MRA: 0.710 RF: 0.749
Yacim & Boshoff (2020)	Cape Town, South Africa	3,225	SVM: 0.547 NNSVM: 0.652
Torres-Pruñonosa et al. (2021)	Catalonia, Spain	188,652	ANN: 0.584 SLR: 0.715 QR: 0.536
Purposed Model (2024)	Surabaya, Indonesia	23,433	Geo-additive: 0.729

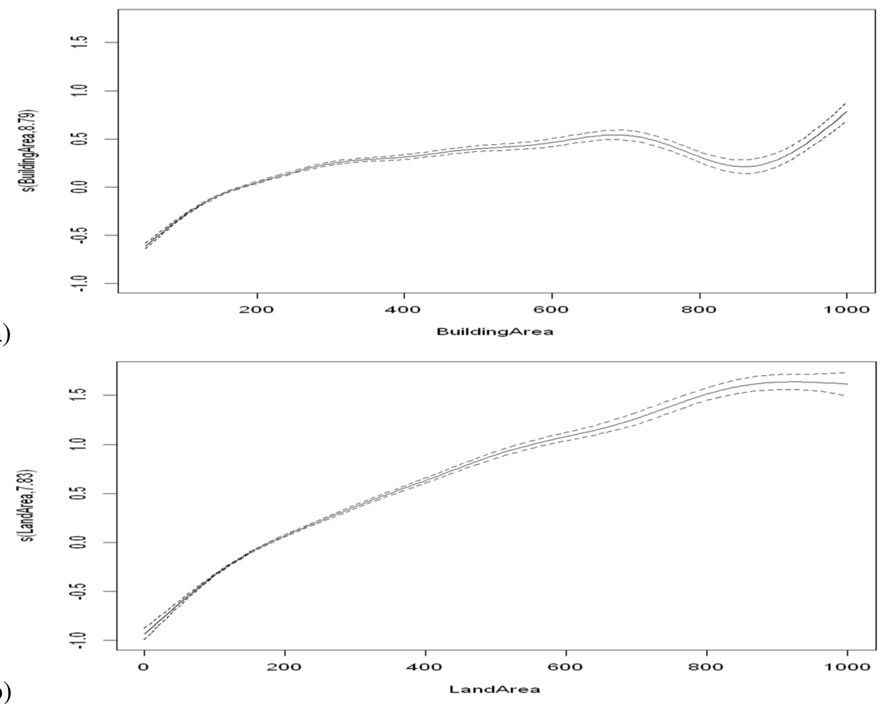
Note. ANN: Artificial Neural Network; MRA: Multiple Regression Analysis; EPR: Evolutionary Polynomial Regression; GWR: Geographically Weighted Regression; RF: Random Forest; SLR: Semi-Log Regressions; QR: Quantile Regressions; NNSVM: Neural Networks Support Vector Machine; SVM: Support Vector Machine.

When compared to earlier experiments, the proposed model appears to perform competitively. For example, it beats models created in Beijing, China (R-squared adjusted of 0.565 for MRA and 0.201 for GWR) and Catalonia, Spain (R-squared adjusted ranging from 0.536 to 0.715 for various models). However, it falls short of the results of other research, such as those conducted in Kaohsiung City, China (R-squared adjusted ranging from 0.694 to 0.758 for various models) and Ankara, Turkey (R-squared adjusted of 0.710 for MRA and 0.749 for RF). It is worth noting that the suggested geo-additive model in this study incorporates variables relating to property location or coordinates, which may contribute to its success in explaining property price variances in Surabaya, Indonesia. This use of location variables improves the model's prediction power by capturing spatial and geographic influences on property prices.

Figure 4 shows the effects of building area and land area on property price. The component function of the building area is vertically centered about zero, this means the building area has little effect on property price. Meanwhile, the component function of the land area is monotonic increasing. It indicates that land area has more significant effects on property prices. Properties with a larger land area will significantly have a higher price. The component function of the property location is not displayed because it does not contain sufficient information. The joint effects of latitude and longitude coordinates on property prices in Surabaya are visualized in Figure 3 and Figure 5.

The joint effects of latitude and longitude coordinate on response and fitted property price based on the results of geo-additive modeling shown in Figure 3 give the same results. Figures 3 and 5 show that residential properties located at high longitude coordinates also have higher prices, while latitude coordinates have relatively small effects. Thus, it can be defined that the property prices in East Surabaya are higher than property prices in West Surabaya, while property prices in South Surabaya are not much different from property prices in North Surabaya.

Several locations of the properties are then mapped in the map of Surabaya. Red dots symbolize properties with high prices, green dots indicate properties with low prices, and yellow dots symbolize properties with medium prices. Several points in Figure 6 represent the administrative area of Surabaya (The Heroes Monument is located in North Surabaya, The Great Mosque is located in South Surabaya, Bungkul Park is located in Central Surabaya, ITS



(a)

(b)

Figure 4. Estimated univariate smooth function components for the geo-additive model fit of (a) Building Area and (b) Land Area

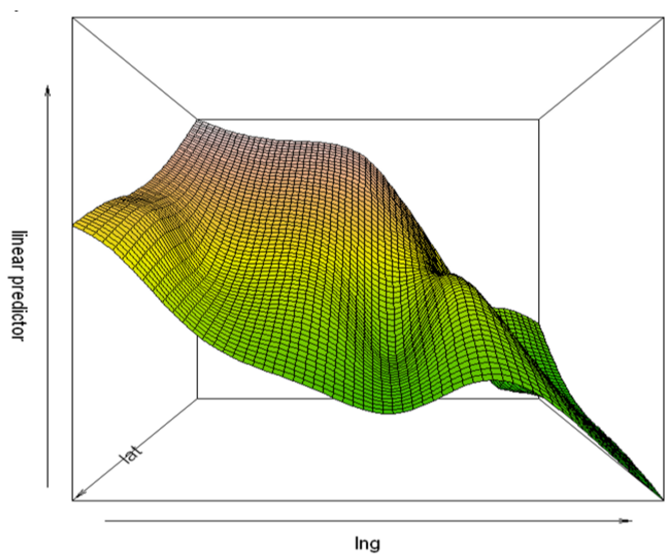


Figure 5. The Joint Effects of Latitude and Longitude on Property Price for The geo-additive Model Fit to The Data

Campus is located in East Surabaya, and Lenmarc Mall is located in West Surabaya). The results of mapping the latitude and longitude coordinates on response and fitted property price show the same result that most properties with high prices are located in East Surabaya.

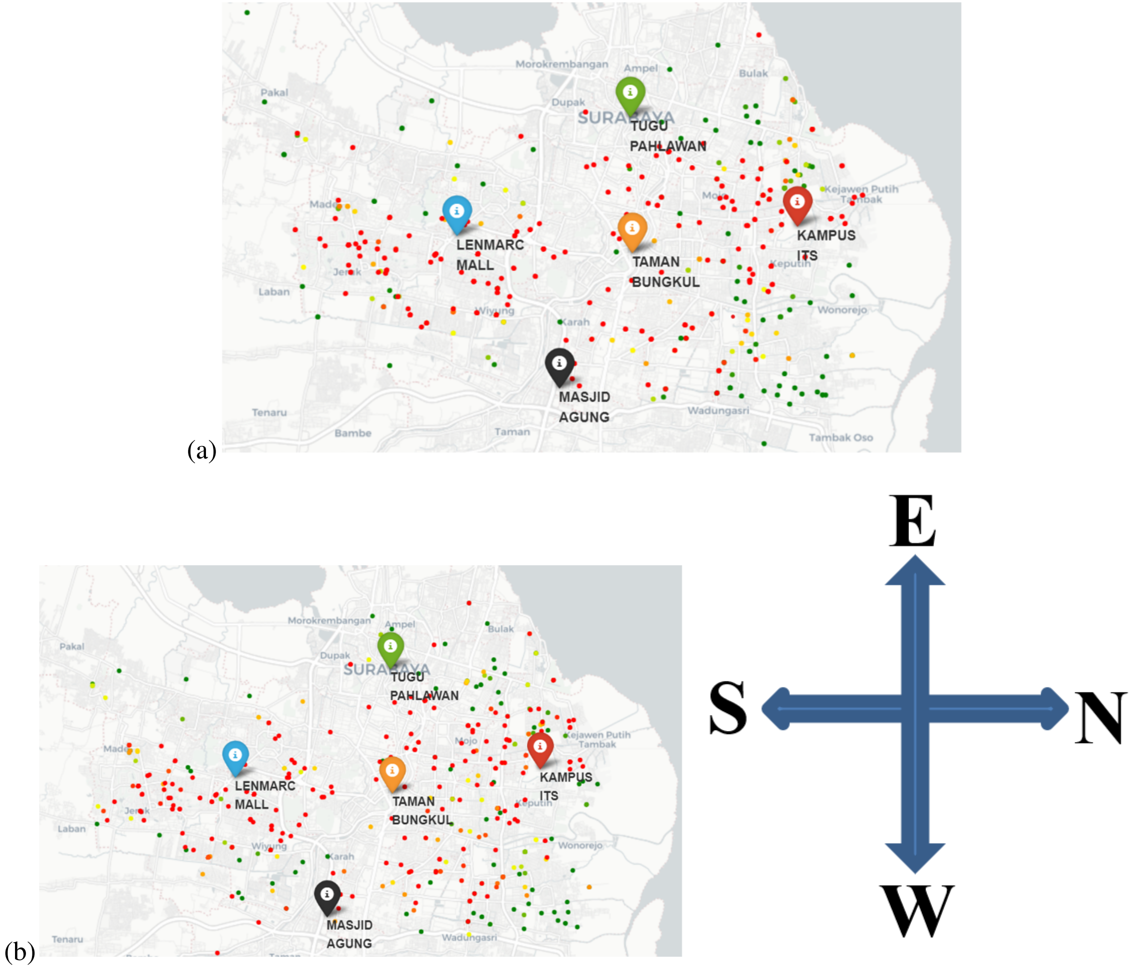


Figure 6. Mapping (a) Property price (b) Fitted property price by Property Location Coordinates

4.3. Goodness of Fit

This study looks further into the diagnostic plots from the responses, residuals, and fitted values obtained from the geo-additive model to see the goodness of fit of the model. The diagnostic plots are presented in Figure 7.

Figure 7 revealed that autocorrelation and heteroscedasticity cases are not found in residuals generated by the geo-additive model. However, the Q-Q plot and histogram of the residuals clearly show that the residuals are not normally distributed, the Q-Q plot is particularly concave on the left indicating that the residuals are left-skewed. The skewness coefficient for the entire set of residuals is -5.78, indicating a fairly severe left-skewed case. The determination coefficient (R-squared) shown in Table 3 reaches 0.729, it can be interpreted that the geo-additive model can explain 72.9% variability of the data, in large sample sizes, highly significant predictors are not always very predictive of the response, so it can be inferred that the R-squared value from the geo-additive model is quite good.

5. Conclusion

The research analyzed the impact of environmental elements on property values in Surabaya and assessed the efficacy of a geo-additive modeling approach for mass appraisal using e-commerce data. The investigation indicated

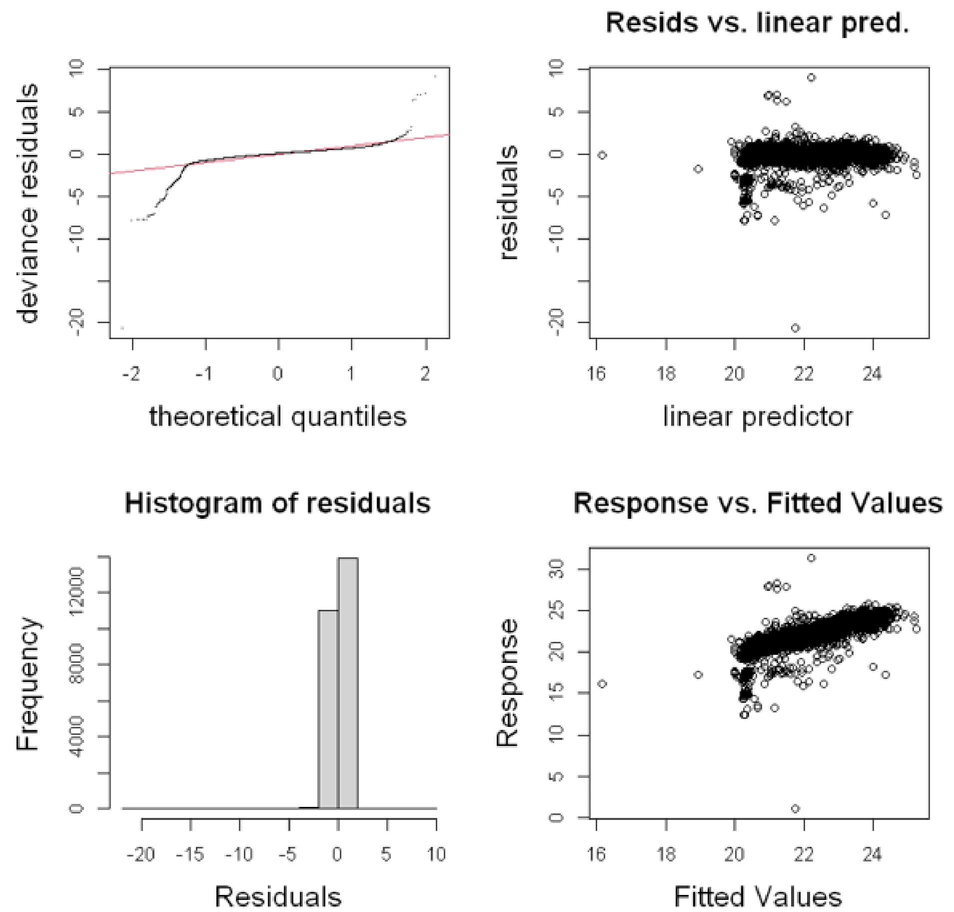


Figure 7. Diagnostic Plots for The geo-additive Model

that both physical and geographical characteristics had a significant impact on property prices, with land acreage having a stronger influence than building area. Notably, property values varied according to longitude coordinates. The established modeling approach has shown promising accuracy in estimating property values, giving useful insights for improving appraisal practices in Surabaya and potentially expanding its applicability abroad. This approach should be refined and explored further to fully realize its promise in the field of mass appraisal".

Data Availability

"The property prices data.xlsx" data used to support the findings of this study have been deposited in the Mendeley repository (DOI:10.17632/k6h4fp832b.1).

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