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THE ROLE OF PUBLIC TRANSPORTATION IN SHAPING URBAN PROPERTY VALUES: A CASE STUDY OF THU DUC CITY, VIETNAM

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ABSTRACT

This study investigates the factors shaping real estate values in Thu Duc City, located in Ho Chi Minh City, Vietnam, over the past five years (2019–2024), focusing on a comparative analysis of econometric models to identify the most suitable framework for the data and research assumptions. Drawing on data from various online real estate platforms in Thu Duc, the analysis employs spatial autoregressive models (SAR, SEM, SDM) alongside multiple linear regression (MLR) to explore the interplay between transportation accessibility, central location, and property prices. Findings reveal that spatial autoregressive models significantly outperform MLR, which displays spatial autocorrelation in its residuals. Among these, the SEM model with the Queen matrix emerges as the most effective, demonstrating that property prices rise when closer to public transport routes, decline when farther from commercial hubs, and are adversely impacted by proximity to train stations. Highlighting the importance of spatial models, this study emphasizes their role in reducing biases and achieving more accurate insights in urban real estate analysis, particularly in rapidly developing areas like Thu Duc.

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1. Introduction

Alonso (1964) and Muth (1969) were among the first to introduce classical urban economic theory related to real estate values. Their work suggests that property values are influenced by a trade-off between proximity to central business districts and the available spatial area. Properties closer to Central Business District (CBD) tend to command higher unit values, as some individuals are willing to pay a premium for accessibility. This highlights a significant insight: improvements in transportation infrastructure not only boost accessibility but also directly affect real estate values.

Essential to the empirical validation of hypotheses in urban economic theory and now firmly established as a foundational econometric tool for estimating the determinants of real estate value (Malpezzi, 2008) is the application of hedonic studies - a methodological approach designed to isolate and quantify the impact of individual attributes on the overall value of a product or service. Originating from the pioneering work of Court (1939) and Lancaster's (1966) consumer behavior theory, this approach was later formalized by Rosen (1974). Central to Rosen's framework is the premise that real estate value is defined by a functional relationship of its attributes, encompassing not only structural characteristics but also the features of the surrounding environment and the degree of accessibility to diverse land uses.

Urban economic theory suggests that accessibility positively influences apartment market values, proposing that improved accessibility leads to higher property prices. Accessibility is typically measured using three indicators: cumulative opportunities, gravity-based metrics, and travel time to the central business district (CBD), while also considering the effects of traffic congestion. In addition to public transit systems such as rail and BRT, several studies have emphasized the importance of road networks and peak-hour travel times in determining real estate values. For instance, Martínez and Viegas (2009) demonstrate that longer commuting times during

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congestion significantly reduce housing prices in Lisbon. Similarly, Ibeas et al. (2011) find that accessibility based on travel time is a critical determinant in housing demand models. These findings support the inclusion of travel time variables, such as TTTM, in hedonic regression models, especially in polycentric urban contexts like Ho Chi Minh City. This study utilizes four hedonic regression models to assess how accessibility impacts real estate valuation. Nonetheless, the hedonic regression method encounters methodological challenges, particularly in accounting for spatial relationships among observations, which conflict with the assumption of residual independence in linear regression (LeSage & Pace, 2010). Anselin (1988) highlighted two key types of spatial relationships: spatial autocorrelation, representing interactions among neighboring phenomena, and spatial heterogeneity, reflecting instability in model parameters or errors across locations. These spatial effects are common in real estate markets due to factors such as housing supply-demand imbalances across urban areas (Bitter et al., 2007), price spillovers from adjacent regions, or omitted variables stemming from data limitations or quality issues. Therefore, employing spatial econometric models is crucial to ensure unbiased and efficient parameter estimation in studies where spatial effects are significant (LeSage & Pace, 2009).

After the introduction, the article is organized as follows: Section 2 reviews various regression models used to estimate the effect of accessibility on real estate prices, emphasizing hedonic regression models that do not consider spatial dependence. Section 3 discusses the outcomes of multivariate linear regression (MR) based on the hedonic framework, highlighting significant spatial autocorrelation in the residuals. To mitigate this issue, spatial autoregressive models are employed. The study explores three primary research questions:

- Does considering spatial dependence clarify the impact of public transportation and local factors on real estate prices while improving data fit?
- Which spatial model best balances accuracy and practicality in real estate valuation, especially for public transportation policies?
- How do control variables such as size, amenities, or specific location affect the accuracy of spatial models in estimating real estate values?

Section 4 details the spatial autoregressive models - SAR, SEM, and SDM - and examines the results to address the research questions. Section 5 concludes by discussing the evidence of spatial effects in modeling real estate markets and emphasizes the potential applications of these models in urban planning and property valuation.

This study offers several noteworthy contributions to the existing body of literature. First, it presents a novel empirical application of spatial econometric techniques to investigate the nexus between public transportation infrastructure and urban real estate values in Thu Duc City - a rapidly developing municipality within Ho Chi Minh City, Vietnam. By doing so, the study adds empirical evidence from an under-researched Southeast Asian context, thereby addressing a notable geographical gap in the literature.

Second, the research enhances methodological discourse by systematically comparing four distinct regression frameworks - namely, Multiple Linear Regression (MLR), Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). This comparative approach underscores the critical role of accounting for spatial dependence in hedonic pricing models, particularly in polycentric and transitioning urban settings.

Third, the findings yield actionable insights for urban planners and policymakers by identifying key transportation accessibility factors that significantly influence real estate values. These insights support more evidence-based decision-making in transport infrastructure investment and urban land-use planning.

Collectively, these contributions enrich academic understanding while strengthening the policy relevance of transport–real estate linkages in rapidly urbanizing regions.

2. Literature Review

Research on the relationship between transportation and real estate prices can be categorized into two primary approaches. The first, rooted in von Thünen's (1826) theory and later expanded by Alonso (1964), Muth (1969), and Mills (1972), examines the trade-off between transportation costs to central business districts and spatial expenses through a rent function. The second approach focuses on empirical analysis, employing hedonic regression models (Rosen, 1974) to evaluate how transportation impacts property values. For instance, studies such as Debrezion et al. (2007) have found that commercial properties tend to experience larger price increases than residential properties, and suburban stations have a greater influence compared to light rail or subway stations. However, these findings might be exaggerated if the effects of other transportation modes are not taken into account.

In addition to studies focusing on rail-based systems and BRT, the literature also emphasizes the role of road networks and average travel time to central areas during peak hours as critical factors influencing property values. For instance, Giuliano (2004) and Levinson (2007) highlight that road accessibility, measured through travel time rather than distance alone, significantly affects housing demand in congested urban areas. Similarly, Páez et al. (2012) demonstrate that travel time reliability and congestion levels are strong predictors of residential location choices. In the context of Southeast Asia, Nguyen and Kim (2020) and Nguyen (2022) found that the average peak-hour travel time to the CBD was negatively associated with apartment prices in Hanoi. These findings justify the inclusion of road-based accessibility indicators - such as average commute duration or road network density - in hedonic models, particularly in cities with mixed modal transport systems like Ho Chi Minh City.

Recent studies have emphasized the spatial impact of public transportation systems on urban housing prices in both developed and developing contexts. Kim and Lee (2021) explored the light rail system in Korea and also confirmed a price premium near stations. Liu and Zhang (2022), through a meta-analysis, emphasized the relevance of spatial modeling in explaining transit-induced price changes.

Senior (2009) concluded that the Metrolink system had no significant effect on housing prices in Greater Manchester, while Ovenell (2007) observed a positive impact within a 0.5 to 1 km radius of train stations. Similarly, Andersson et al. (2010) found that high-speed rail in Taiwan had limited influence on property values, contrasting with findings by Debrezion et al. (2011) in the Netherlands, where the effect was more substantial. Banister and Thurstain-Goodwin (2011) noted that rail investments can enhance land values but may also lead to negative consequences, such as increased noise and crime near stations, as discussed by Bowes and Ihlanfeldt (2001), with effects reaching up to 1 km, as suggested by Ovenell (2007). According to Colin Buchanan & Partners (2003), only major infrastructure investments have a notable impact on housing markets.

Several studies have investigated the effect of Bus Rapid Transit (BRT) systems on property values. Rodríguez and Mojica (2009) reported a 13-14% increase in real estate prices in Bogotá, Bolivia, after the introduction of a BRT system. Munoz-Raskin (2010) observed that while properties immediately adjacent to bus stations were 4.5% less valuable, those within a five-minute walking distance experienced an 8.7% increase in value compared to properties located farther away (5-10 minutes walking distance). This indicates that households are willing to pay a premium for proximity to the system. Similarly, Cervero and Kang (2011) found in their research on Seoul, South Korea, that property prices rose by up to 10% within 300 meters of BRT stations.

Although hedonic regression models are considered valuable tools for analyzing real estate values, they still face three major challenges: omitted variables, the choice of functional form, and spatial autocorrelation (Armstrong & Rodríguez, 2006). The omission of relevant variables can lead to biased parameter estimates (Gujarati & Porter, 2009), especially when crucial factors such as accessibility provided by alternative transportation modes are overlooked (Debrezion et al., 2007). The challenge of selecting an appropriate functional form arises from the lack of clear theoretical foundations, with common recommendations including linear forms (Cropper et al., 1988) and log-linear forms (Malpezzi, 2008), which aim to minimize errors and enhance interpretability. Furthermore, spatial autocorrelation in sample observations can distort estimation results, necessitating the use of spatial econometric models to address this issue effectively (LeSage & Pace, 2009).

3. Research Methodology and Data

3.1. Data

Estimated data for the hedonic regression models in this study was collected from the urban area of Thu Duc City. Household samples were obtained from various online real estate platforms in December 2022, including information on listing prices and structural attributes such as area, number of rooms, and construction status for 730 urban properties[1]. The sample includes only apartment-type residential properties. Other types such as detached houses, townhouses, and vacant land plots were excluded to ensure consistency and reduce structural heterogeneity. This scope also aligns with the dominant property type transacted in Thu Duc City during the

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[1] Reliable online real estate platforms you may consider include Batdongsan.com.vn, Alonhadat.com.vn, Muaban.net, and Nhatot.com.

survey period. In addition to real estate attributes extracted from online platforms, several contextual variables were constructed using external data sources and spatial processing techniques. Specifically, the Hansen-type accessibility index, which reflects the gravitational pull of employment opportunities, was calculated based on job density and travel impedance using a simplified gravity model. Employment data were aggregated at the ward level using statistics from the Ho Chi Minh City Department of Labor and Social Affairs (2022).

The share of foreign residents and population density indicators were derived from 2021 demographic reports published by the General Statistics Office of Vietnam and geo-referenced at the district and ward levels. Spatial proximity variables - such as distances from each property to the nearest metro station, park, or commercial center - were computed using GIS software based on geocoded property coordinates. These spatial features were incorporated to capture neighborhood-level accessibility and urban amenities. Thu Duc City, a newly established administrative unit of Ho Chi Minh City, features several distinct residential clusters with varying urban characteristics. Thao Dien, located along the Saigon River, is characterized by high-end real estate and a concentration of international residents, with listing prices reaching up to 150 million VND/m². Thu Thiem, situated near the city center, is known for its large-scale infrastructure investments and is envisioned as a new financial and administrative hub. In the Southeast, developments such as Vinhomes Grand Park and Nam Rach Chiec offer well-planned green urban spaces and modern amenities. The Northwest zone includes areas like Van Phuc and Long Binh, which integrate ecological lakes, public parks, and commercial zones into the residential layout. To support spatial analysis and enhance interpretability, the study includes a series of maps illustrating the key spatial features of Thu Duc City.

Figure 1 shows the geographical location of Thu Duc City within the national territory of Vietnam, providing contextual orientation for international readers unfamiliar with the country’s administrative divisions. Location, living environment, and amenities are key factors shaping real estate values in Thu Duc. Areas with relatively low property prices - such as Binh Chieu, Linh Dong, Tam Phu, and Hiep Binh Phuoc - offer convenient access to the city center and industrial zones but lack premium amenities and desirable living conditions (Figure 2). Similarly, neighborhoods adjacent to industrial zones or river ports, including Hiep Binh Chanh, Tam Binh, and Linh Xuan, are negatively affected by traffic congestion, air pollution, and noise, which reduce their residential appeal. Consequently, housing price prediction models should not rely solely on proximity to the city center but must also account for quality-of-life factors, transportation infrastructure, and local market demand.

One key limitation of this study is that it uses listing prices rather than actual transaction prices. However, Hometrack (2005) suggests that listing prices are highly correlated with final sales prices, typically averaging around 90% of the market equilibrium value. This approximation is therefore unlikely to significantly bias the model's estimates. The dataset was collected during a period of rapid real estate appreciation - estimated at 13–15% per year - driven by urban planning initiatives and major infrastructure projects. A further limitation concerns the availability of detailed property-level characteristics. Currently, no publicly accessible official database provides comprehensive information on real estate transactions in Vietnam. Table 1 summarizes the variables included in the hedonic pricing models. The HAI index was constructed from employment accessibility data derived from census-based labor statistics. Variables such as WORKS, PFR, and PDK were calculated using GIS-based population data from the Ho Chi Minh City Statistics Office. To support interpretation of spatial patterns, Figure 2 provides an overview of residential area distribution across Thu Duc, while Figure 3 highlights Thao Dien - a premium riverside neighborhood notable for its high property values and sophisticated living environment.

The dependent variable in the research model is the real estate listing price, which has been converted into logarithmic form in line with Malpezzi's (2008) methodology. This transformation enables the interpretation of the estimated parameters as the percentage change in price corresponding to a one-unit change in an independent variable. Significant independent variables associated with transportation conditions include: D6, TTTM, D7, and HAI.

Fig. 1. Geographical location of Thu Duc City in the national context of Vietnam. *Source:* Author's elaboration using base map from Wikimedia Commons (accessed July 2024).

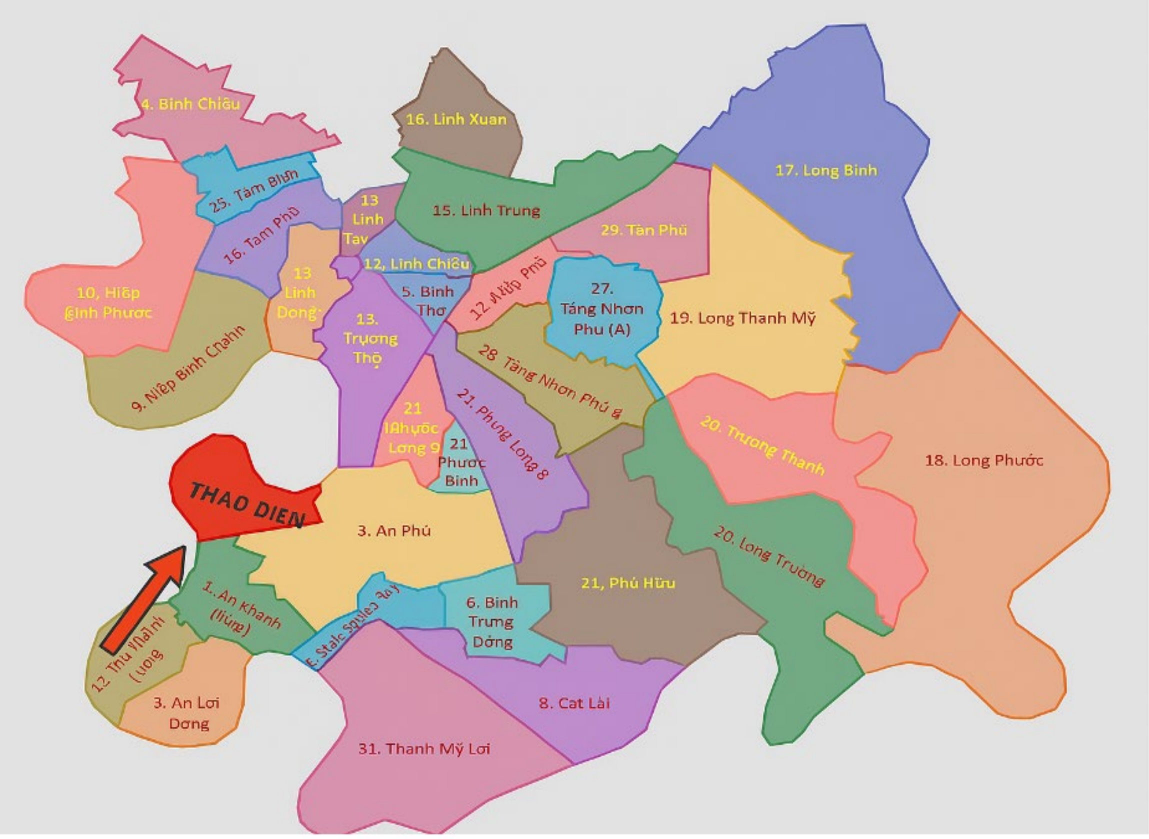

Fig. 2. Location of Thao Dien Ward highlighted in red within Thu Duc City, Ho Chi Minh City. The ward serves as the main study area in this research. *Source:* Author's elaboration based on administrative map of Thu Duc City. Original base map adapted from Thuthiemlocation.com (accessed 2024).

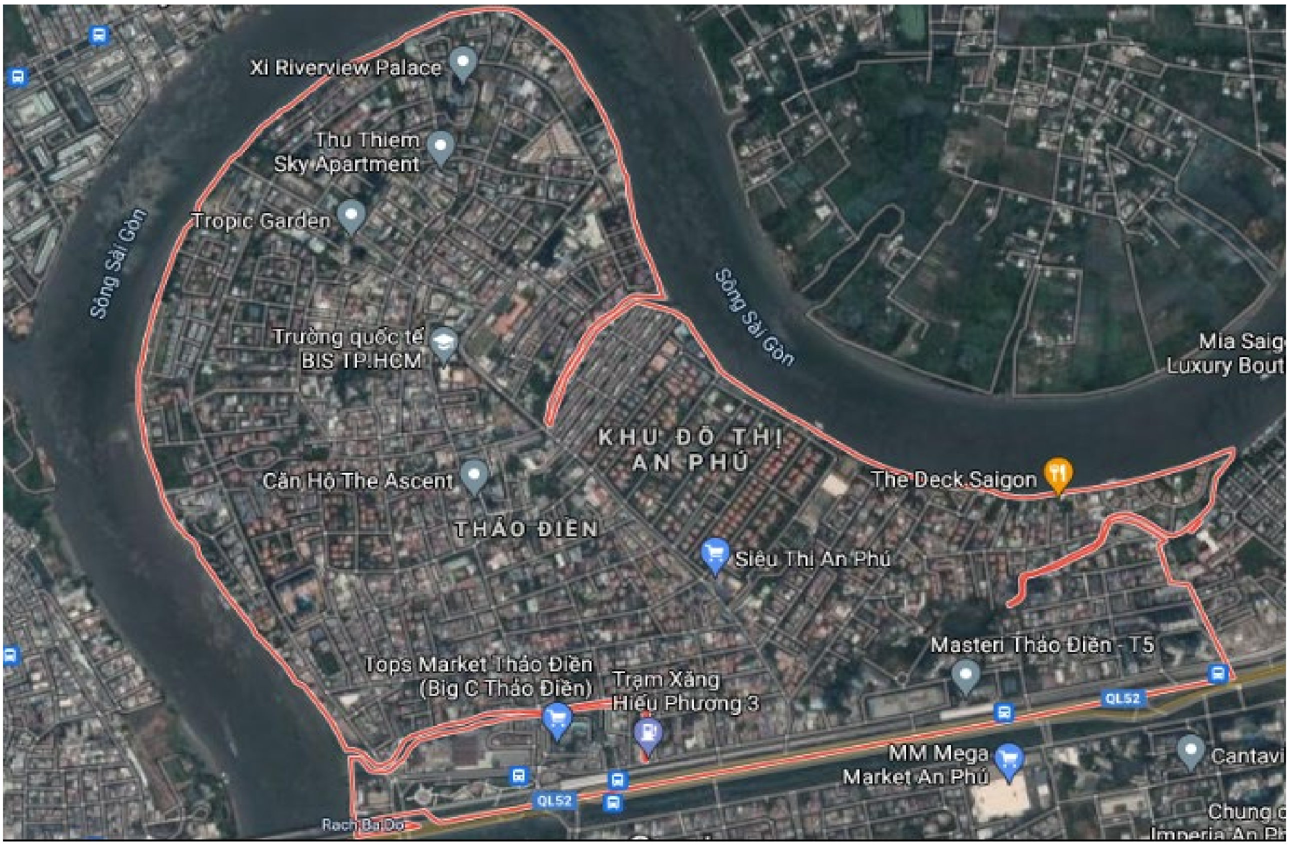

Fig. 3. Satellite map showing Thao Dien Ward outlined in red, located within Thu Duc City, Ho Chi Minh City. The ward represents the main study area. *Source: Screenshot captured by the authors using Google Maps (accessed July 2024).*

Table 1

Variable Definitions and Measurement Units in the Models

Variable Types	Variables in the Model	Symbol	Unit of Measurement	Description
D. Variable	Asking price of the property	**LN(P)**	Ln (bn VND)	Malpezzi (2008).
Control variable	A binary variable set to 1 if the property requires renovation	**D1**	–	
	A binary variable set to 1 if the property is a standalone house	**D2**	–	
	Binary variable set to 1 if the building housing the property includes an elevator.	**D3**	–	
	Number of bedrooms in the property	**ROOMS**	No. of beds	Rosen (1974)
	Number of bathrooms in the property	**BATHS**	No. of baths	Rosen (1974)
	Number of floors the property is located on within the building	**FLOORS**	No.of floors	Rosen (1974)
	Property size measured in square meters.	**SBD**	m^2	Muth (1969)
	Travel time (in minutes) required to reach the shopping mall (TTTM) from the property during morning peak hours using the road network, accounting for congestion	**TTTM**	minutes	Alonso (1964)
	Binary variable set to 1 if the property is situated within 500 meters of a suburban railway station.	**D7**	–	Handy & Niemeier (1997)
	Binary variable set to 1 for properties positioned along the Saigon River.	**D9**	–	
	Hansen-type index (gravity-based) measuring accessibility to employment opportunities.	**HAI**	–	Hansen (1959)
	Number of jobs available in the area where the property is located.	**WORKS**	No. Jobs	Waddell et al. (2007)
	Percentage of foreign residents living in the area where the property is located.	**PFR**	%	Rosen (1974)
Variable	Binary variable set to 1 if the property features a terrace.	**D4**	–	

of interest	Binary variable set to 1 if the property includes a garage.	**D5**	–	
	Binary variable set to 1 if a bus stop is located within 400 meters of the property, combined with the total number of bus routes serving that stop.	**D6**	No. of lines	
	Binary variable set to 1 for properties situated in the city center.	**D8**	–	
	Population density index of the area, calculated as the number of residents per unit area.	**PDK**	People/km^2	Rosen (1974)

Source: Compiled by the author from previous studies.

3.2. Multivariate Linear Regression Model

The hedonic pricing model is grounded in urban economic theory, which posits that the price of a real estate asset is determined by a bundle of its characteristics. These characteristics can be broadly classified into structural attributes, accessibility factors, and neighborhood features. In this study, a multivariate linear regression (MLR) framework is employed to estimate the influence of these factors on apartment prices in Thu Duc City. The general form of the hedonic regression model is specified as follows:

$$Ln(P_i) = \beta_0 + \beta_1 X_i + \beta_2 A_i + \beta_3 N_i + \varepsilon_i \qquad (1)$$

Where, *P*i represents the price per square meter of property *i*; *Xi* denotes the vector of structural variables, such as area, number of rooms, and floor level; *Ai* captures accessibility variables, including proximity to metro stations or travel time to the central business district; *Ni* refers to neighborhood characteristics, such as population density or the proportion of foreign residents; *εi* is the error term, assumed to be normally distributed.

Given the typical right-skewed distribution of property prices, the logarithmic transformation of the dependent variable (lnPi) is adopted to linearize the relationships.

$$Ln(P_i) = \rho W ln(P) + \beta_0 + \beta_1 X_i + \beta_2 A_i + \beta_3 N_i + \varepsilon_i \qquad (2)$$

SEM model: Assumes that spatial dependence exists in the error term, representing unobserved factors with spatial patterns.

$$Ln(P_i) = \beta_0 + \beta_1 X_i + \beta_2 A_i + \beta_3 N_i + \varepsilon_i, u_i = \lambda W u + \xi_i \ (3)$$

Where λ is the spatial error coefficient, and ξi is an independently and identically distributed error term.

SDM model: Extends the SAR model by including spatial lags of the explanatory variables, capturing both direct and indirect spatial effects.

$$Ln(P_i) = \rho W ln(P) + \beta_0 + \beta_1 X_i + \beta_2 A_i + \beta_3 N_i + \theta W(X_i, A_i, N_i) + \varepsilon_i \qquad (4)$$

Prior to estimating these models, the presence of spatial autocorrelation is tested using Moran's I statistic

relationships and reduce heteroscedasticity. Moreover, the log-linear specification allows for a more intuitive interpretation of the estimated coefficients as semi-elasticities, which is particularly useful for policy implications and comparative analysis across studies (Malpezzi, 2008; Cropper et al., 1988).

3.3. Spatial Econometric Models

While the multivariate linear regression model provides a foundational framework for estimating property values, it assumes that observations are independent and identically distributed. However, in spatial contexts - such as urban housing markets - this assumption is often violated due to spatial dependence and spillover effects. Ignoring such spatial autocorrelation may lead to biased or inefficient parameter estimates. To address this issue, spatial econometric models are introduced, which explicitly incorporate spatial structures into the regression framework. Three commonly used spatial models are considered in this study: the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). Each model accounts for spatial effects in a different manner:

SAR model: Introduces a spatially lagged dependent variable to capture direct spillover effects of neighboring property prices.

Where ρ is the spatial autoregressive coefficient, and W is the spatial weights matrix defining neighborhood

on the residuals of the MLR model. A significant Moran's I would confirm the need to account for spatial effects. The spatial weight matrix W used in this study is based on inverse distance between centroids of the observed properties, standardized to ensure row sums equal one. Model estimation is carried out using maximum likelihood techniques available in spatial econometric packages.

Figure 4 summarizes the conceptual differences among the three spatial econometric models. While SAR includes spatial lags of the dependent variable, SEM introduces spatial dependence in the error terms. SDM, in contrast, incorporates spatial lags of both the dependent and independent variables, making it the most comprehensive among the three.

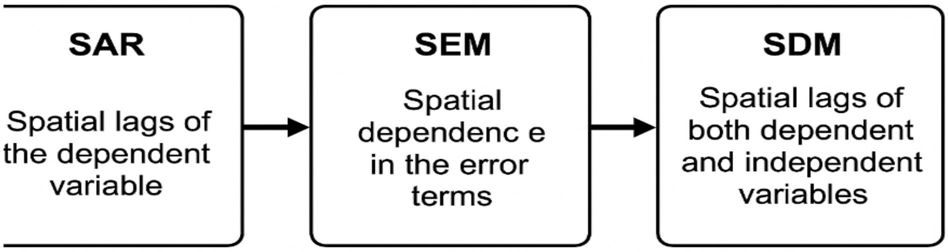

Fig. 4. Conceptual comparison of SAR, SEM, and SDM models. *Source*: own study.

4. Results

This section examines spatial autocorrelation in the residuals of the MR, SAR, SEM, and SDM models, using the specifications of MR4, which provided the best model fit. Accessibility is represented by travel time to the central business district to account for spatial relationships.

4.1. Descriptive Results

This section provides the descriptive statistics for the key variables employed in the empirical analysis. These statistics serve to offer a foundational understanding of the sample's characteristics, encompassing critical dimensions such as property typology, locational features, and indicators of transportation accessibility. The summary table that follows supports the interpretation of subsequent regression results by highlighting prevailing trends and the distributional structure of the dataset.

Emerging from the data in Table 2 is a clear depiction of diversity and disparities in real estate, spanning price, size, location, and structure. Prices range from 56.96 to 388.82 million VND/m^2, averaging 129.58 million VND/m^2, with a large standard deviation (2.565) reflecting significant variation driven by location and amenities. Property sizes range from 100 to 850 m^2 (average 124.41 m^2), with an average distance to the city center of 15.22 minutes, 2–7 rooms, and 3.16 floors on average. Evident is the transition from small houses to luxury villas. Dummy variables (D1, D2, D3, ...) capture key features like ground floors, proximity to main roads, and amenities, making this dataset a robust tool for regression analysis and evaluating factors influencing real estate values.

Table 2

Descriptive Statistics of Variables in the Model

Variable	Min	Max	Mean	Std
LN(P)	4.043	5.958	4.868	2.315
D1	0	1	0.061333	0.240101
D2	0	1	0.216	0.411789
ROOMS	0	7	2.972	1.115
BATHS	0	6	1.862	0.834
FLOORS	0	12	6	3.761941
D3	0	1	0.533333	0.499221
D4	0	1	0.249333	0.432916
D5	0	1	0.378667	0.485379
SBD	54	850	124.451	78.388
D6	0	15	7.441333	4.77797
TTTM	5.47	29.73	15.22	6.42
D7	0	1	0.301333	0.459143
HAI	5.031531	48.02225	25.84372	12.52304
D8	0	1	0.081333	0.273529
D9	0	1	0.16	0.366851
PDK	0.02555	9.319072	4.846994	2.708963
WORKS	0.006665	4.596254	2.282953	1.304893
PFR	0.00838	0.321235	0.12575	0.052515

Source: Author's calculations using Stata 16 software.

4.2. Estimation Results Using Multivariate Linear Regression

Table 3 summarizes the findings of the initial multivariate linear regression model (MR1), which includes 18 independent variables. While the estimated parameters generally align with theoretical expectations, the variables D2, HAI, PDK, and WORKS are found to be statistically insignificant. Additionally, the accessibility-related variables TTTM and HAI exhibit a high correlation, with a coefficient of -0.77 and VIF values of 3.7 and 6.8, respectively, suggesting potential multicollinearity in MR1. To address this concern, D2, PDK, and WORKS were removed in the subsequent models (MR2 and MR3). In these models, only one accessibility variable was retained: TTTM in MR2 and HAI in MR3. Although HAI was statistically insignificant in MR1, it was retained in MR3 for comparative analysis and due to its theoretical relevance in polycentric urban studies. Both variables are statistically significant at the 95% confidence level, with their signs aligning with theoretical predictions.

The MR2 model demonstrates better fit based on adjusted R^2 and AIC, with VIF values in both models below 3, eliminating the risk of severe multicollinearity. To enhance accuracy and validity, outlier observations with residuals exceeding three standard deviations were removed, resulting in the improved MR4 and MR5 models - refined versions of MR2 and MR3. These improved models are less influenced by outliers, allowing for more precise parameter estimation. After removing outlier observations with residuals exceeding ±3 standard deviations, the sample size was reduced from 730 to 692 properties.

Table 3

Presentation of Regression Results from Multivariate Models

VARIABLE	MR1	MR2	MR3	MR4	MR5
Constant	4.367*(0.000)	4.393*(0.000)	4.227*(0.000)	4.402*(0.000)	4.240*(0.000)
D1	—0.085*(0.002)	—0.080*(0.004)	—0.087*(0.002)	—0.079*(0.004)	—0.086*(0.002)
D2	0.038*(0.167)				
ROOMS	0.069*(0.000)	0.068*(0.000)	0.068*(0.000)	0.058*(0.000)	0.058*(0.000)
BATHS	0.131*(0.000)	0.134*(0.000)	0.136*(0.000)	0.123*(0.000)	0.125*(0.000)
FLOORS	0.011*(0.009)	0.010*(0.012)	0.012*(0.003)	0.009*(0.019)	0.011*(0.005)
D3	0.144*(0.000)	0.132*(0.000)	0.153*(0.000)	0.135*(0.000)	0.156*(0.000)
D4	0.044*(0.004)	0.042*(0.005)	0.034*(0.016)	0.041*(0.007)	0.035*(0.021)
D5	0.1067*(0.000)	0.113*(0.000)	0.108*(0.001)	0.109*(0.003)	0.106*(0.000)
SBD	0.004*(0.000)	0.005*(0.000)	0.005*(0.000)	0.005*(0.000)	0.005*(0.000)
D6	0.030*(0.000)	0.031*(0.000)	0.031*(0.000)	0.031*(0.000)	0.032*(0.000)
TTTM	— 0.010*(0.000)	—0.011*(0.000)		—0.011*(0.000)	
D7	—0.060*(0.001)	—0.062*(0.000)	—0.076*(0.000)	—0.065*(0.000)	—0.075*(0.000)
HAI	0.002(0.269)		0.005*(0.000)		0.005*(0.000)
D8	0.123*(0.001)	0.145*(0.000)	0.088*(0.009)	0.140*(0.000)	0.084*(0.011)
D9	0.338*(0.000)	0.336*(0.000)	0.315*(0.000)	0.326*(0.000)	0.305*(0.000)
PDK	—0.008(0.130)				
WORKS	0.002(0.903)				
PFR	—0.570*(0.001)	—0.638*(0.000)	—0.875*(0.000)	—0.631*(0.000)	—0.863*(0.000)
R^2(adj)	0.767	0.767	0.763	0.773	0.770
R2	0.765	0.764	0.761	0.771	0.768
F	281.68	367.292	345.94	376.15	366.37
p-value F	0.0001	0.0000	0.000	0.0003	0.0005
Moran’s I	0.0001	0.0000	0.0003	0.0003	0.0005
AIC	434.75	435.56	456.10	352.748	377.7
Log-likelihood	—158.37	—160.88	—169.55	—113.114	—133.85
N	730	730	730	692	692

Note: p-values in ().

Source: Author's calculations using Stata 16 software.

The removal of outlier observations improves the model to ensure that such anomalies do not negatively impact parameter estimation and the accuracy of the model. As a result, the MR4 and MR5 models are labeled as (5) and (6), respectively:

$$Log(\hat{P}_i) = \beta_0 + \beta_1 D_{1_i} + \beta_2 ROOMS + \beta_3 BATHS_i + \beta_4 FLOORS_i + \beta_5 D_{3_i} + \beta_6 D_{4_i} + \beta_7 D_{5i} + \beta_8 SBD_i + \beta_9 D_{6_i} + \beta_{10} TTT + \beta_{11} D_{7_i} + \beta_{12} D_{8_i} + \beta_{13} D_{9_i} + \beta_{14} PFR_i + \varepsilon_i \quad (5)$$

$$Log(\hat{P}_i) = \beta_0 + \beta_1 D_{1_i} + \beta_2 ROOMS + \beta_3 BATHS_i + \beta_4 FLOORS_i + \beta_5 D_{3_i} + \beta_6 D_{4_i} + \beta_7 D_{5i} + \beta_8 SBD_i + \beta_9 D_{6_i} + \beta_{10} HAI_i + \beta_{11} D_{7_i} + \beta_{12} D_{8_i} + \beta_{13} D_{9_i} + \beta_{14} PFR_i + \varepsilon_i \quad (6)$$

In the MR4 and MR5 models, all variables are statistically significant and display signs that align with theoretical predictions (refer to Table 3). Within the group of variables related to structural conditions, the variable D1 has a negative sign, indicating that the value of buildings requiring renovation decreases by 7.5% to 8.2%. Variables with positive impacts include: adding a bathroom, which increases the average value by 12%; having a garage, which raises the value by approximately 10%; and installing an elevator, which contributes an additional 20% to the property value.

The parameter related to elevators not only highlights the importance of this amenity but also reflects the age and quality of the building. Environmental factors, including geographic location, scenic views, or nearby features, typically have a positive effect if the property is situated in an economic hub or provides a view of the Saigon River. Results from MR4 indicate that riverfront properties can see an average price increase of up to 38%. Conversely, the variable PFR has a negative sign with a large magnitude, indicating the adverse effects of high population density, poor urban service quality, or a lack of public infrastructure, which diminish property values despite these areas' potential for long-term development.

Most transportation parameters in Thu Duc City align with the hypothesis that improved transportation enhances property values. The variable D7, however, exhibits a negative coefficient, suggesting that properties within 500 meters of a railway station experience a 6-7% reduction in value. This finding, which deviates from traditional theory, could be due to the incomplete state of railway infrastructure and the underdeveloped surroundings near the stations. For instance, many stations along Metro Line 1 (Ben Thanh - Suoi Tien) remain under construction, with nearby areas suffering from a lack of cohesive planning and challenges such as noise, visual blight, and suboptimal living conditions (Armstrong & Rodríguez, 2006). Additionally, railways constitute a minor share of the transportation modes in Thu Duc, where residents predominantly rely on motorcycles and private cars. However, once Metro Line 1 is completed and public transportation is further developed, positive impacts on property values are likely to emerge.

The parameter D6 indicates that each additional public transportation route can increase property values by 2.2%. This reflects the high demand in central areas with a concentration of businesses, commerce, and services, particularly in major urban centers. In Thu Duc, although public transportation is not yet dominant, central areas retain high value due to their strategic location and vibrant economic activities. The indicators of road transportation accessibility in Thu Duc demonstrate logical significance: the TTTM variable in MR4 has a negative sign, while the HAI variable in MR5 has a positive sign. The TTTM parameter reveals that each extra minute of travel time to the city center (Districts 1 and 3) reduces property values by more than 1%, supporting the theory that property values diminish with greater distance from the central area. Conversely, the HAI parameter indicates that each unit increase in the reasonable commuting radius to access employment opportunities raises property values by 0.5%. This underscores that areas with well-connected transportation networks tend to have higher property values.

In the MR4 and MR5 models, the TTTM and HAI coefficients exhibit expected signs and are statistically significant, demonstrating their usefulness in explaining property value variations. The TTTM variable is better suited for traditional monocentric urban designs, while the HAI variable is more appropriate for areas with a polycentric urban framework (Ottensmann et al., 2008).

In this study, the new urban areas in Thu Duc have not yet developed sufficiently to compete with Ho Chi Minh City's traditional economic centers. Currently, the old central districts (District 1 and District 3) account for over 20% of total employment and approximately 65% of the city's high-value jobs, highlighting that Thu Duc still exhibits characteristics of a monocentric urban structure, with accessibility to the central business district serving as a critical indicator. The MR4 model, with higher R² and lower AIC, was selected as the reference model for analyzing spatial models. This reflects the reality that while urban developments such as the High-Tech Park, Thu Thiem, and the Vietnam National University area are emerging, Thu Duc has yet to rival the role of traditional economic centers.

To examine spatial autocorrelation in the residuals of the MLR regression model, employed are Moran's I index and the Lagrange Multiplier (LM) test. Constructed is the spatial weight matrix based on geographic coordinate information, which is then transformed into regional data using the Thiessen polygon method. Applied in the urban context are three types of matrices:

1. First-Order Queen Matrix, identifying observations sharing a boundary, with an average of 5-7 connections.
2. K8 Matrix, identifying the 8 nearest observations, with an average of 8 connections.
3. D1700 Matrix, relying on an average radius of 1700 meters, ensuring at least one neighbor per observation, with an average of 14 connections.

   Chosen as the minimum threshold is the 1700-meter distance to prevent spatial isolation and ensure comprehensiveness (Ángel Ibeas et al., 2011).

Calculated for all three matrices is Moran's I index, with results showing statistically significant values in all cases (see Table 3). Detected by the LM test is spatial autocorrelation in both the dependent variable and the residuals, affirming spatial dependence in the data, as confirmed through robust tests.

4.3. Spatial Regression Results

LeSage and Pace (2009) emphasized that the Spatial Autoregressive (SAR) model is a representative framework in the field of spatial economics, capturing the influence of economic characteristics at one location on neighboring locations through a "spillover" mechanism. In this study, an empirical SAR model is developed based on the detailed specification of the MR4 model as follows:

$$Log(\hat{P}_i) = \rho W log(\hat{P}_i) + \beta_0 + \beta_1 D_{1_i} + \beta_2 ROOMS + \beta_3 BATHS_i + \beta_4 FLOORS_i + \beta_5 D_{3_i} + \beta_6 D_{4_i} + \beta_7 D_{5i} + \beta_8 SBD_i + \beta_9 D_{6_i} + \beta_{10} TTTM_i + \beta_{11} D_{7_i} + \beta_{12} D_{8_i} + \beta_{13} D_{9_i} + \beta_{14} PFR_i + \varepsilon_i \tag{7}$$

Here, ρ is the spatial autoregressive parameter; W is the spatial weights matrix representing the spatial structure. To address the issue of spatial autocorrelation in errors, the study proposed an empirical Spatial Error Model (SEM), developed based on the detailed specification of the MR4 model, with the following representation:

$$Log(\hat{P}_i) = \beta_0 + \beta_1 D_{1_i} + \beta_2 ROOMS + \beta_3 BATHS_i + \beta_4 FLOORS_i + \beta_5 D_{3_i} + \beta_6 D_{4_i} + \beta_7 D_{5i} + \beta_8 SBD_i + \beta_9 D_{6_i} + \beta_{10} TTTM_i + \beta_{11} D_{7_i} + \beta_{12} D_{8_i} + \beta_{13} D_{9_i} + \beta_{14} PFR_i + \varepsilon_i \tag{8}$$

$$u = \lambda W u + \varepsilon \tag{9}$$

Where, λ is the spatial error coefficient; W is the spatial weights matrix; ε is the independent error term. Finally, the Spatial Durbin Model (SDM) stands out for its close relationship with the two previously mentioned spatial autoregressive models. Based on the specification of the MLR4 model, the SDM is developed and represented as follows:

$$Log(\hat{P}_i) = \rho W log(\hat{P}_i) + \beta_0 + \beta_1 D_{1_i} + \beta_2 ROOMS + \beta_3 BATHS_i + \beta_4 FLOORS_i + \beta_5 D_{3_i} + \beta_6 D_{4_i} + \beta_7 D_{5i} + \beta_8 SBD_i + \beta_9 D_{6_i} + \beta_{10} TTTM_i + \beta_{11} D_{7_i} + \beta_{12} D_{8_i} + \beta_{13} D_{9_i} + \beta_{14} PFR_i + \gamma_1 W D_{1_i} + \gamma_2 WROOMS + \gamma_3 WBATHS_i + \gamma_4 WFLOORS_i + \gamma_5 W D_{3_i} + \gamma_6 W D_{4_i} + \gamma_7 W D_5 + \gamma_8 WSBD_i + \gamma_9 W D_{6_i} + \gamma_{10} WTTTM_i + \gamma_{11} W D_{7_i} + \gamma_{12} W D_{8_i} + \gamma_{13} W D_{9_i} + \gamma_{14} WPFR_i + \varepsilon_i \tag{10}$$

LeSage and Pace (2009) recommend applying the SDM model due to two notable advantages: its greater stability in the presence of missing key independent variables, which is particularly beneficial in experimental studies where data is often incomplete or inaccurate, and its more generalized nature compared to SAR and SEM models. They also emphasize two critical aspects of spatial econometrics: the stability of parameter estimates, requiring that estimates remain largely unaffected by the specification of the weight matrix (Anselin, 1988), and the use of an appropriate estimation method. In this context, the maximum likelihood (ML) method is recommended over OLS, as spatial dependence can cause OLS to violate the assumption of independent residuals, leading to biased parameter estimates.

Each model was estimated using three types of neighborhood matrices: Queen, K8, and D1700, resulting in nine combinations of SAR, SEM, and SDM models to assess spatial dependence. The estimated parameters from SAR and SEM models closely resemble those from OLS in MR4; however, two variables, D7 and FLOORS (in the SEM model with the D1700 matrix), are not statistically significant at the 95% confidence level. In the SDM model, several parameters lack statistical significance, notably TTTM and D7 in SDM-QUEEN and SDM-D1700. However, SDM-K8 yields results where all variables are significant and maintain signs consistent with SAR, SEM, and MR4. Some variables, such as D1, D5, and SBD, exhibit signs or significance levels that do not align with theoretical expectations, warranting further examination and explanation.

The estimated parameters from the neighborhood matrices (Table 4) generally retain the same signs as in the MR model, except for TTTM and D7 in SDM-D1700 compared to SDM-QUEEN and SDM-K8. However, this change is negligible due to the low significance of these parameters in the SDM. Among the three models, the Queen matrix outperforms K8 and D1700, as reflected in the log-likelihood and AIC values, affirming the effectiveness of the Queen matrix in modeling spatial relationships. As noted by LeSage and Pace (2009), understanding the effects of independent variables in SAR and SDM models necessitates decomposing the impacts into direct, indirect, and total effects. This method ensures precise interpretation and effective use in spatial econometric analyses.

Table 4 reveals that Moran's I is not statistically significant in the SEM-QUEEN, SEM-D1700, SDM-QUEEN, and SDM-D1700 models, suggesting that these models successfully mitigate spatial autocorrelation in the residuals. In the remaining models, residual spatial autocorrelation remains significant, but Moran's I values are lower than those of the MR model, indicating that spatial factors have substantially reduced autocorrelation. SAR and SEM with the QUEEN matrix are highly regarded for their fit, parameter significance, and ability to eliminate residual autocorrelation. For SDM, while SDM-K8 has a lower fit compared to SDM-QUEEN and SDM-D1700, it is preferred because the variables D6, TTTM, and D7 are all statistically significant.

Table 4

Presentation of the results from estimating spatial regression models

VARIABLE	SAR MODEL			SEM MODEL			SDM MODEL		
	QUEEN	K8	D1700	QUEEN	K8	D1700	QUEEN	K8	D1700
Constant	6.507*	6.520*	4.313*	8.443*	8.430*	8.469*	4.607*	5.643*	2.812*
D1	-0.098*	-0.095*	-0.082*	-0.093*	-0.090*	-0.085*	-0.092*	-0.096*	-0.089*
ROOMS	0.061*	0.054*	0.059*	0.060*	0.054*	0.057*	0.059*	0.051*	0.058*
BATHS	0.109*	0.120*	0.117*	0.118*	0.126*	0.123*	0.114*	0.126*	0.118*
FLOORS	0.011*	0.009*	0.008*	0.009*	0.010*	0.006	0.010*	0.009*	0.006
D3	0.212*	0.228*	0.242*	0.196*	0.225*	0.232*	0.193*	0.221*	0.229*
D4	0.035*	0.038*	0.034*	0.034*	0.040*	0.036*	0.033*	0.037*	0.032*
D5	0.104*	0.110*	0.113*	0.114*	0.108*	0.127*	0.112*	0.108*	0.135*
SBD	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*
D6	0.017*	0.020*	0.022*	0.018*	0.020*	0.015*	0.004	0.018*	0.014*
TTTM	-0.009*	-0.007*	-0.007*	-0.011*	-0.009*	-0.010*	-0.008	-0.005*	0.001
D7	-0.052*	-0.052*	-0.017	-0.051*	-0.047*	-0.006	-0.000	-0.028*	0.013
D8	0.094*	0.140*	0.104*	0.129*	0.133*	0.076*	0.065	0.131*	0.086*
D9	0.223*	0.245*	0.205*	0.295*	0.264*	0.227*	0.084	0.195*	0.269*
PFR	-0.288*	-0.609*	-0.547*	-0.505*	-0. 710*	-1.00*	-0.213	-0.683*	-1.12*
W.D1							0.118*	0.144	0.134
W.ROOMS							-0.047*	0.004	0.061
W.BATHS							-0.031	-0.072	0.102
W.FLOORS							-0.006	-0.000	-0.031
W.D3							0.037	-0.015	0.049

W.D4							0.034	-0.020	-0.051
W.D5							-0.077*	0.054	-0.031
W.SBD							-0.001*	-0.000	-0.001
W.D6							0.009	-0.000	0.015
W.TTTM							0.005	-0.083	-0.001
W.D7							-0.057	- -	-0.065
W.D8							0.005	0.014	0.890*
W.D9							0.099	0.090	-0.163*
W.PFR							-0.224	0.935*	0.963*
ρ	0.235	0.232	0.406				- 0.224	0.935	0.963
λ				0.459	0.413	0.775			
p-Value ρ/λ	0.0003	0.0004	0.0004	0.0002	0.0003	0.0004	0.0005	0.0002	0.0006
Moran´ s I	0.0001	0.0001	0.0001	0.078	0.000	0.891	0.078	0.000	0.731
Log-likelihood	-48.56	-65.91	-76.01	-24.45	-75.45	-36.480	8.989	-41.542	-5.06
AIC	137.33	165.82	183.44	77.902	181.67	107.78	58.457	148.85	67.613

Note: * - At the 0.05 level, statistically significant.

Source: Author's calculations using Stata 16 software.

Table 5

Estimation of direct, indirect, and total effects from SAR and SDM models

VAR	SAR- QUEEN Model			SDM-K8 Model		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
D1	—0.099*	—0.029*	—0.128*	—0.088*	0.158	0.070
ROOMS	0.062*	0.018*	0.080*	0.053*	0.029	0.082
BATHS	0.110*	0.032*	0.143*	0.123*	—0.046	0.077
FLOORS	0.011*	0.003*	0.015*	0.009*	0.003	0.012
D3	0.214*	0.063*	0.277*	0.225*	0.074	0.300
D4	0.036*	0.010*	0.046*	0.036*	—0.012	0.024
D5	0.105*	0.030*	0.136*	0.113*	0.122	0.236*
SBD	0.003*	0.001*	0.004*	0.003*	0.000	0.004*
D6	0.017*	0.005*	0.022*	0.018*	0.003	0.022*
TTTM	—0.009*	—0.002*	—0.012*	—0.005*	—0.001	—0.007
D7	—0.052*	—0.015*	—0.068*	—0.033*	—0.127*	—0.161*
D8	0.095*	0.028*	0.124*	0.135*	0.076	0.212*
D9	0.225*	0.066*	0.292*	0.204*	0.210*	0.414*
PFR	—0.291*	—0.085*	—0.376*	—0.637*	1.00*	0.365

Source: Author's calculations using Stata 16 software.

Table 4 reveals that Moran's I is not statistically significant in the SEM-QUEEN, SEM-D1700, SDM-QUEEN, and SDM-D1700 models, suggesting that these models successfully mitigate spatial autocorrelation in the residuals. In the remaining models, residual spatial autocorrelation remains significant, but Moran's I values are lower than those of the MR model, indicating that spatial factors have substantially reduced autocorrelation. SAR and SEM with the QUEEN matrix are highly regarded for their fit, parameter significance, and ability to eliminate residual autocorrelation. For SDM, while SDM-K8 has a lower fit compared to SDM-QUEEN and SDM-D1700, it is preferred because the variables D6, TTTM, and D7 are all statistically significant.

A comparison of Table 4 and Table 5 reveals minor differences in the estimated parameters, which do not affect the main conclusions, affirming the stability of the models. However, for variable D9, the direct or indirect effects may vary in significance, necessitating careful interpretation within the spatial context. The SAR-QUEEN model stands out due to its significant indirect effects and theoretically consistent signs, accurately reflecting spatial relationships and ensuring stability, thereby enhancing the reliability of the results. Meanwhile, the SEM-QUEEN model is rated the highest for three reasons: strong data fit, theoretically consistent signs, and the complete elimination of spatial autocorrelation in the residuals.

5. Discussion

The results of this study confirm the significance of several structural and locational attributes in determining property values in Thu Duc City. In particular, proximity to metro lines shows a positive association with apartment prices, aligning with findings from Debrezion et al. (2007), who highlighted the price premiums generated by improved rail accessibility. However, the spatial models reveal that this effect is not uniform across space, suggesting the presence of spatial spillovers.

Interestingly, our findings diverge from those of Munoz-Raskin (2010), as the presence of BRT stations in Thu Duc does not appear to significantly influence real estate prices. This contrast may be attributed to the relatively low service frequency or perceived quality of BRT in the local context, compared to rail infrastructure. The limited statistical significance of some accessibility indicators, such as the Housing Accessibility Index (HAI), further suggests that accessibility alone does not guarantee higher property values unless supported by infrastructure quality and integration with urban amenities.

Moreover, the spatial Durbin model (SDM) results emphasize that both direct and indirect effects of accessibility are at play, underscoring the importance of considering spatial interactions in urban valuation studies, as advocated by LeSage and Pace (2009).

These insights highlight the need for targeted infrastructure investments that account not only for proximity, but also for service quality and urban context. Future studies may consider incorporating dynamic factors such as transport usage patterns and perceptions of safety to further refine the analysis.

6. Conclusion

This study utilizes four hedonic models—multiple linear regression (MLR), spatial autoregressive (SAR), spatial error (SEM), and spatial Durbin (SDM) regression models—to evaluate the influence of transportation conditions on property values in Thu Duc City. Empirical data was estimated and compared to identify the most suitable model, ensuring the stability of the parameters. The experimental results highlight key factors influencing real estate prices in Thu Duc in recent years.

First, the estimation models indicate that transportation characteristics significantly influence real estate values in Thu Duc City. The variable D6, representing bus accessibility, has a positive impact, increasing property values by 1.4% to 2.2%, with an average of 1.8% based on the SEM-QUEEN model. Thu Duc's transportation system is undergoing rapid development, with bus routes connecting peripheral areas like Linh Trung and Binh Chieu to the city center. Notably, the Ben Thanh–Suoi Tien metro line is expected to further enhance accessibility, shaping property values in the region.

Second, travel time to the city center reduces real estate prices by 0.5%–1.1% per minute, reflecting higher property values in areas closer to the center. Rail accessibility (D7) also decreases property values by 2.7%–6% due to negative impacts such as noise and vibration. However, with the operation of the Ben Thanh–Suoi Tien metro line, this effect is expected to diminish, and property values near stations like the High-Tech Park, Suoi Tien, and Binh Thai are anticipated to rise significantly in the long term.

Third, the study reveals that real estate prices in Thu Duc City tend to decrease as the distance from the center increases and transportation connectivity diminishes. Areas near metro stations or central locations, such as Thao Dien and the High-Tech Park, have significantly higher values compared to more remote areas like Long Binh and Linh Xuan, reflecting a preference for convenient transportation and public amenities.

Fourth, a comparison between the multivariate linear regression (MR) model and spatial models (SAR, SEM, SDM) indicates that spatial models address the issue of ignoring spatial dependence inherent in MR. The estimated parameters from spatial models show consistent values and signs when using different neighborhood matrices, demonstrating their stability. However, in the SDM model, some parameters are close to zero, lack statistical significance, and change signs when the matrix configuration is altered, indicating that SDM is more sensitive to the choice of the neighborhood matrix.

Fifth, the SEM-QUEEN model was selected as the optimal model due to its ability to accurately reflect real estate data in Thu Duc City, with parameters that are statistically significant and consistent with theoretical expectations. The SEM model outperforms the MR model by better accounting for local environmental factors, avoiding misvaluation of real estate in certain areas. Additionally, SEM achieves a higher fit based on log-likelihood and AIC, while reducing spatial autocorrelation in residuals (Moran's I). This study makes an important contribution to evaluating the role of spatial factors in real estate valuation in urban areas.

In conclusion, the SEM-QUEEN model proves to be the most suitable approach, providing reliable and theoretically consistent estimations of real estate values in Thu Duc City. It not only addresses spatial autocorrelation but also outperforms traditional models in terms of fit and explanatory power. These findings underscore the significant role of transportation infrastructure in shaping urban property markets.

Nevertheless, this study has certain limitations that future research may address. First, a temporal comparison of property values before and after the implementation of major public transport policies—such as subsidies or metro development—could offer deeper insights into policy effectiveness. Second, examining the risks and implementation challenges associated with large-scale transportation projects, including financial constraints, delays, and public resistance, would enhance the practical relevance of such studies. These aspects go beyond the scope of the current analysis and warrant further investigation.

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