ANALYZING THE IMPACT OF ACCESSIBILITY ON RESIDENTIAL PROPERTY PRICE: A CASE STUDY OF HANOI'S CENTRAL DISTRICTS

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ABSTRACT

This research focuses on real estate values in central Hanoi, aiming to analyze factors influencing real estate prices, with particular emphasis on locational characteristics, for the case of Hanoi's central districts. A geographically weighted regression (GWR) model is employed to address the limitations of traditional Hedonic Pricing Models (HPM), based on data from 1,545 properties across 12 central districts of Hanoi during the period from November 2024 to March 2025. The study evaluates the impact of 7 accessibility variables: distance to hospitals, parks, schools, universities, shopping centers, administrative offices at various level, and the city center. Results show that the relationship between distance to public amenities and property prices varies significantly across geographic locations – a characteristic not reflected in traditional HPM models. Notably, many variables that lack statistical significance in the HPM model show differentiated impacts at specific locations in the GWR model, with higher coefficients of determination, demonstrating better explanatory power for real estate price variations. The research has demonstrated spatial heterogeneity in the relationships between valuation variables, indicating that location characteristics and spatial variation have not been adequately considered in current valuation methods in Vietnam. These findings not only address the limitations of HPM models but also provide important reference perspectives for policymakers regarding the significance of spatial factors.

Keywords: *Geographically weighted regression; GWR; hedonic; HPM; real estate; valuation; Hanoi.*

PHÂN TÍCH TÁC ĐỘNG CỦA KHẢ NĂNG TIẾP CẬN ĐẾN GIÁ BẤT ĐỘNG SẢN NHÀ Ở: NGHIÊN CỨU TRƯỜNG HỢP TẠI CÁC QUẬN TRUNG TÂM HÀ NỘI

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TÓM TẮT

Nghiên cứu này tập trung vào giá trị bất động sản tại khu vực trung tâm Hà Nội, nhằm phân tích các yếu tố ảnh hưởng đến giá bất động sản, đặc biệt chú trọng đến đặc điểm vị trí đối với trường hợp các quận trung tâm của Hà Nội. Mô hình hồi quy có trọng số theo địa lý (GWR) được sử dụng để khắc phục những hạn chế của Mô hình Định giá Hedonic (HPM) truyền thống, dựa trên dữ liệu từ 1.545 bất động sản tại 12 quận trung tâm của Hà Nội trong giai đoạn từ tháng 11 năm 2024 đến tháng 3 năm 2025. Nghiên cứu đánh giá tác động của 7 biến số về khả năng tiếp cận: khoảng cách đến bệnh viện, công viên, trường học, trường đại học, trung tâm mua sắm, cơ quan hành chính các cấp và trung tâm thành phố. Kết quả cho thấy mối quan hệ giữa khoảng cách đến các tiện ích công cộng và giá bất động sản thay đổi

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đáng kể giữa các vị trí địa lý – một đặc điểm không được phản ánh trong các mô hình HPM truyền thống. Đáng chú ý, nhiều biến số không có ý nghĩa thống kê trong mô hình HPM cho thấy tác động khác biệt tại các vị trí cụ thể trong mô hình GWR, với hệ số xác định cao hơn, thể hiện khả năng giải thích tốt hơn cho sự biến động giá bất động sản. Nghiên cứu đã chứng minh tính không đồng nhất về mặt không gian trong mối quan hệ giữa các biến định giá, cho thấy đặc điểm vị trí và biến động không gian chưa được xem xét đầy đủ trong các phương pháp định giá hiện tại ở Việt Nam. Những phát hiện này không chỉ giải quyết những hạn chế của mô hình HPM mà còn cung cấp góc nhìn tham khảo quan trọng cho các nhà hoạch định chính sách về tầm quan trọng của các yếu tố không gian.

Từ khóa: *Hồi quy có trọng số theo địa lý; GWR; hedonic; HPM; bất động sản; định giá; Hà Nội.*

1. INTRODUCTION

As an intertwined sector involving various industries and stakeholders, the real estate market plays an important role in every economy. But it is also one of the most notorious sectors for its market failures and misinformation (Zhang 2015), especially in developing economies where related regulations are often underdeveloped. Indeed, Vietnam's real estate market currently faces significant challenges. Severe supply-demand imbalances exist, causing abnormally high property prices particularly in major cities like Hanoi and Ho Chi Minh City (Savills 2023). A notable issue is the substantial gap between the government's official valuation methods and actual market prices, with state-established prices typically amounting to only about 30% of market prices in urban areas[1]. Not only does this discrepancy show how outdated some of the state-led valuation methods are in reflecting real estate prices but, it also creates confusion and difficulties in real estate market management.

In recent years, the Communist Party of Vietnam as well as the Government of Vietnam have paid great attention to the operation of the real estate markets (both land and property) in adherence to market-based mechanisms, such as Resolution No. 18 on effective land management and use (Vietnam Central Committee 2022) and Resolution No. 33 to promote safe, functional and sustainable real estate market (The Government of Vietnam 2023). In particular, the three newly amended laws, including the 2023 Law on Real Estate Business and the 2023 Law on Housing and the 2024 Law on Land (Vietnam National Assembly 2023a, 2023b, 2024), have helped to establish a synchronous legal corridor for the development of the real estate market. On real estate valuation, the Government continues to update the official (state-led) valuation methodology on both land (The Government of Vietnam 2024) and property (Vietnam Ministry of Finance 2024). These specific orientations and policies have shown high determination, efforts and concrete actions to facilitate a competitive and effective real estate market focusing primarily on reflecting the true value of real estate properties.

Despite ongoing revisions, the methodologies remain inadequate for reflecting the real-world dynamics of property price formation Real estate differs fundamentally from other goods in that its value is inseparably bound to its physical location. Accordingly, the valuation of real estate is shaped by property-specific attributes, most notably its structural

[1] According to an expert interview. URL: https://reatimes.vn/gstskh-dang-hung-vo-khong-phai-truong-hop-nao-cung-ap-dung-gia-dat-thi-truong-20225010915403321 4.htm. Last accessed: May 15, 2025.

characteristics (e.g., size, room configuration, and orientation), together with locational qualities such as accessibility to amenities and neighborhood conditions. Evaluation of real estate properties based on these above mentioned characteristics makes the essence of Hedonic Pricing Models (HPM) as has been popularly examined in literature. Nonetheless, traditional HPM methods often assumes that the impact of factors influencing property prices is uniform across the spatial plane. Empirical evidence shows that the real estate market is characterized by pronounced spatial heterogeneity, whereby the impact of a given factor on property prices varies according to geographic context. In this light, utilizing the Geographically Weighted Regression (GWR), which recognizes the spatial variation of constituent factors (thus, better reflects real-life determination of property price), is a notable alternative to overcome the limitations of traditional HPM methods.

In short, official state-led valuation methodologies have largely overlooked critical determinants of property prices, including both physical traits and locational attributes, while traditional HPM, although incorporating these factors, have insufficiently accounted for their spatial heterogeneity. Accordingly, this study seeks to furnish policymakers with empirical evidence on the influence of accessibility on property prices – an aspect omitted from current state-led valuation approaches – through the application of both HPM and GWR models to residential properties in central Hanoi, thereby contributing to the advancement of valuation methodologies and addressing a notable gap in the existing literature.

The study employs both the traditional HPM and the GWR model, with HPM serving as the baseline for comparison. HPM, a specific application of the multiple linear regression framework, estimates property values by regressing prices on structural and locational attributes. However, it assumes that the influence of these factors is spatially uniform across the study area. By contrast, GWR allows regression coefficients to vary across geographic locations, thereby capturing spatial heterogeneity in the effects of accessibility and neighborhood characteristics on real estate prices. Integrating GWR with detailed geographic information system (GIS) data, the study offers a comprehensive analysis of how locational attributes shape residential property values in central Hanoi. The findings not only highlight the limitations of state-led and conventional valuation methods but also provide a methodological framework applicable to other major Vietnamese cities, contributing to both improved valuation practice and the advancement of real estate valuation theory in the context of modern urbanization.

GWR was suggested as the superior and more accurate method to HPM by Tran (2025), although it was not explored in details. Our paper contributes to the literature by outlining key aspects of the GWR approach and, to the best of our knowledge, is one of the first comprehensive studies to explore the use of GWR and its application in the determinants of residential real estate prices in Vietnam. This is the main contribution to this research gap in literature; the nature of the paper is thus both empirical and exploratory.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 presents the conceptual framework together with the model specification and data sources. Section 4 reports and discusses the empirical findings. Finally, conclusion offers concluding remarks and highlights key policy implications.

2. LITERATURE REVIEW

Real estate valuation constitutes a multifaceted area of inquiry that continues to draw significant scholarly interest internationally. Traditional valuation models typically rely on employing a multivariate linear regression, most notably the HPM.

This approach assumes that the purchase of a property is associated with a level of pleasure or utility from it (hence, “hedonic”). So, variations in the attributes of a property and its locational characteristics are therefore reflected in the willingness to pay for such property and, ultimately, its price. Despite being widely used, traditional HPM models are typically estimated using Ordinary Least Squares (OLS), which assumes homoscedasticity and independence of error terms. In real estate markets, however, these assumptions are violated because property prices in proximate locations tend to move together, creating spatial dependence and leading to biased or inefficient estimates (LeSage & Pace 2009). In simpler terms, HPM imposes a single set of coefficients across the entire study area, which prevents it from being able to reflect real life because real estate prices in different locations tend to show similarities or disparities depending on proximity measurements. Although these models can incorporate location effects through fixed-effect dummy variables by region, they cannot perfectly capture the inherent spatial heterogeneity in housing markets (Helbich et al. 2014). This limitation arises because models are constrained by boundaries that location variables impose, while property characteristics typically have much more uneven and complex distributions, especially in urban areas (Wheeler & Tiefelsdorf 2005).

The limitations of HPM can be addressed by GWR model which allows regression parameters to vary spatially (Bellefon & Floch 2018), (Brunsdon et al. 1996), (Fotheringham et al. 1998). In GWR, a separate regression is estimated at each observation point, with closer observations assigned greater weights in the estimation process. As a result, the relationship between property prices and explanatory variables is permitted to change by location. Fotheringham et al. (1998) describes GWR as “Local” model for spatial data, in contrast to HPM method as “Global” model.

Several studies analyzing the influence of spatial factors on property prices have highlighted the value of GWR in capturing spatial variations in the relationship between geographical factors and housing prices. For instance, Du & Mulley (2012) used GWR to analyze public transportation’s impact on house prices in Tyne and Wear, England. They discovered that public transportation’s influence on house prices varied across the region, with prices increasing 5-15% above average in areas with convenient connections and high-quality services, while decreasing 2-8% near stations or railways due to noise and pollution. In Malaysia, Dziauddin and Idris (2017) employed GWR to analyze the relationship between house prices and various location factors using data from over 2,500 property transactions. Their analysis revealed that in high-income areas in the eastern part of the city, proximity to high-quality schools had the strongest influence, with each kilometer closer increasing house prices by up to 12%. Meanwhile, in densely populated central areas, distance to parks and green spaces became the most important factor, potentially increasing property values by 7-15%.

Other studies focused on socioeconomic and environmental factors affecting property values. Basu and Thibodeau (1998) found that properties in areas with clean air and proximity to large parks were valued 15-25% higher than similar properties in areas with poorer environmental quality. Air pollution impact was strongest in high-income areas but less significant in middle and low-income areas. Helbich et al. (2014) applied GWR for analysis of Austria’s real estate market, finding evidences in proving that factors such as per capita income, unemployment rates, and transportation infrastructure quality all impacted property values. In central areas with high average income and low unemployment, property values were 20-30% higher than the city average. However, the influence of these factors decreased in suburban areas where living space and transportation connections became more important.

Some studies have shown GWR to be more efficient than traditional regression methods. Farber & Yeates (2006) analyzed the spatial relationship between housing characteristics and sales prices in Toronto, Canada using data from over 19,000 housing transactions. It is shown that GWR significantly outperformed traditional approaches like OLS and spatial autoregressive models, explaining over 90% of housing price variation (specifically 93.5% compared to 82.4% with OLS). They found that housing attributes varied considerably across different city areas, with stronger influences in high-income areas near the center.

In the case study of Calgary, Canada, Yu et al. (2019) also demonstrated that GWR significantly improved explanatory power for house price variation, with adjusted R^2 increasing from 0.75 in OLS to 0.93 in GWR. They identified spatial variation in factors like floor area (coefficients from 0.28 to 0.45) and distance to center (coefficients from -0.32 to -0.11) depending on location. Similarly, Bitter et al. (2007) using data from 11,732 housing transactions in Tucson, Arizona found that GWR significantly reduced forecast errors, with mean-absolute-error decreasing by 17.6% and root mean-squared-error by 13.2% compared to OLS. Their research also highlighted substantial differences in school quality impact (coefficients from 0.052 to 0.217) between areas with different income levels, reflecting complex spatial structures in real estate markets that traditional models cannot detect.

Some works extended or modified GWR models to achieve better precision and practical relevance. Griffith (2008) incorporated temporal effects into the GWR framework, resulting in Geographically and Temporally Weighted Regression (GTWR), which allows regression coefficients to vary across both space and time[2]. With advancement in information technology and big data processing capabilities, GWR is being integrated with emerging approaches like machine learning and big data analytics. This opens new possibilities for real estate price analysis and prediction, offering enhanced accuracy and performance[3].

In Vietnam, literature on real estate evaluation is diverse but remains somewhat fragmented in case studies and design. Yet, they can be broadly categorized into three main groups. The first group consists of studies focusing on exploring factors (or determinants) affecting real estate prices across different regions. Vu & Nguyen (2024) found that environmental quality, area, distance to everyday amenities (markets, schools, stations) and plot location significantly influence coastal land prices in Quang Ninh province. Dao (2023) identified six statistically significant factors affecting high-end apartment prices in Nam Tu Liem district (Hanoi), which are: developer capability, location, physical characteristics, surrounding environment, service quality, and market conditions. Pham (2023) explored that new transportation projects increase real estate prices by 15-25% within a 2-kilometer radius in Hanoi's suburban areas, while Nguyen & Tran (2024) discovered a correlation between natural disaster risks and property value decreases in coastal central Vietnam areas affected by climate change.

The second group consists of studies focusing on various valuation

[2] Abbreviated "GTWR", this approach is also employed in studies by Huang et al. (2010), Wang et al. (2020) and Wu et al. (2014). This approach is particularly useful when analyzing time-series real estate data, enabling researchers to capture both spatial and temporal changes in variables.

[3] A study by McCluskey et al. (2013) showed that the combination of GWR and machine learning techniques can reduce mean absolute error to below 12% in mass appraisal models, a significant improvement over traditional OLS methods with average errors above 20%.

methodologies and approaches. Tran et al. (2024) developed a multiple variable regression model explaining 78.2% of land price variations using variables such as location, distance to center, lot frontage width, and area. Nguyen (2023) applied the hedonic pricing model to residential properties in Hanoi, and identified variables including usable area, building age, location, amenities, and accompanying services as the most important variables. Pham (2023) compared four main valuation methods, concluding that direct comparison method remains the most common while income approaches are increasingly used for commercial properties. Le (2022) compared machine learning algorithms for property price forecasting in Da Nang, finding XGBoost most accurate with mean error below 7%. Hoang & Nguyen (2024) combined GIS with statistical models to develop land valuation tools in Bac Ninh province, improving accuracy by 15% compared to traditional methods.

The third group are studies on buyer behavior and purchasing decisions, and some of these works have revealed important insights. Nguyen (2023) identified 14 factors influencing young people's home buying decisions in Hanoi, with price, financial situation, and location being the strongest determinants. Nguyen & Nguyen (2023) found five factors that positively affecting apartment purchase decisions in Khanh Hoa: location, apartment characteristics, finances, beliefs and surrounding environment. Pham & Nguyen (2024) found evidence that developer reputation has the strongest impact on apartment purchasing decisions among non-locals moving to Hanoi, followed by living environment, finances, family, location, and infrastructure. Le & Tran (2022) Le Hoang Minh (2022) discovered that developer reputation, appreciation potential, and rental potential are the top three factors influencing vacation property purchase decisions in Da Nang and Nha Trang.

Overall, the Vietnamese literature has primarily concentrated on examining how various factors – both endogenous and exogenous to the property – affect real estate prices, drawing on perspectives from consumption behavior as well as valuation methodologies.

The majority of studies rely on a single quantitative approach, with the hedonic pricing model (HPM) being the most widely applied. The use of Geographic Information Systems (GIS) has largely remained at a descriptive or illustrative level, with relatively limited integration into advanced analytical frameworks. In particular, the combination of GIS with contemporary quantitative models such as Geographically Weighted Regression (GWR) has yet to be systematically developed or fully explored in the Vietnamese.

3. CONCEPTUAL FRAMEWORK AND MODEL SPECIFICATION

3.1 Conceptual framework

We developed a research conceptual framework as shown in Figure 1.

In studies employing the HPM approach, scholars typically examine either the group of physical characteristics of a property (e.g., number of floors, number of rooms, house orientation, construction quality), the group of locational characteristics (e.g., distance to the city center, accessibility to urban amenities), or a combination of both. When data availability is comprehensive and accessibility is ensured, the most robust and methodologically sound approach is to incorporate both groups of factors in the analysis, thereby capturing the full spectrum of influences on property values. In this study, we emphasize locational characteristics as the decisive factor in property valuation, while assuming that physical attributes exert a negligible effect on property prices. Within the Vietnamese context, this assumption can be justified on three grounds.

First, locational characteristics are more durable and predictable making them a more

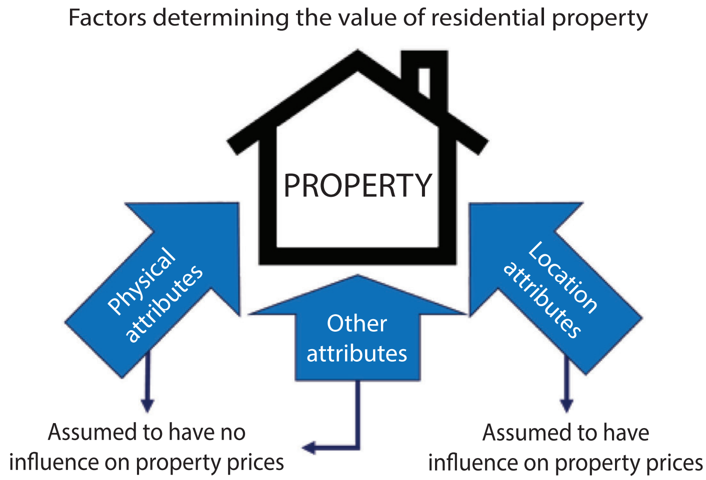

Figure 1: Conceptual framework
Source: rendered by authors

reliable determinant residential property prices. By contrast, physical characteristics can change over time due to renovation, upgrading or deterioration. This pattern is evident in the Vietnamese housing market, where homebuyers frequently renovate or even restructure their homes to suit personal preferences. Furthermore, location attributes can be collected objectively and accurately through modern GIS tools. This creates a great advantage in terms of data reliability compared to collecting information on physical characteristics, which ensures higher reliability compared to physical characteristics that often rely on self-reported, unverifiable information from homeowners.

Secondly, as has been imbued in Vietnamese culture, homebuyers in Vietnam often prioritize busy neighborhood, rating locational features as "*Best (home) is near the market, second best is near the river, third best is near the road*"[4]. Buyers value convenience – proximately to workplaces, schools, urban amenities, or relatives – over design or construction quality. Once a suitable area is secured, they typically adapt the house through renovations.

Thirdly, the majority of properties are bought and sold mainly for shelter, not as an investment assets. While certain properties with exceptional architectural or historical value are highly prized, they rarely enter the open market[5]. Meanwhile, buildings – even with poor construction quality – attract strong demand if located in prime areas. This demonstrates that geographical location remains the dominant factor shaping property value, whereas physical attributes often play a secondary role, particularly when the property is intended for long-term residence rather than speculative investment.

3.2. An overview of HPM approach and GWR model

The HPM property valuation approach is the process of estimating the relationship between a dependent variable – and one or more independent variables. The general formula of the HPM usually takes the form:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon_i \quad (3.1)$$

[4] In Vietnamese text: "Nhật cận thị, Nhị cận giang, Tam cận lộ".

[5] Many real-life examples illustrate this case, such as the case of French colonial Indochina-style villas in Hanoi; old planned-economy era apartment buildings in Kim Lien or Giang Vo, or rural houses in remote villages.

In which, is the dependent variable – usually the monetary value of the property $x_1, x_2, \ldots, x_n$ are dependent variables and $\beta_1, \beta_2, \ldots, \beta_n$ are coefficients to be estimated in the model.

Model 3.1 can be rewritten in the more general matrix form as followed:

$$Y = X\beta + \epsilon \tag{3.2}$$

In which, is the matrix of size *n*x*1* containing the values of observed dependent variables. *X* is the matric of size *n* x *(k+1)* containing observed independent variables. β is the matrix of size *(k+1)* x *1* containing variable coefficients and ϵ is matrix of size *n* x *1* with residual terms. In mathematical form, these matrices are written as:

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ . \\ . \\ Y_n \end{pmatrix},$$

$$X = \begin{pmatrix} 1 & x_{11} & x_{21} & \ldots & x_{k1} \\ 1 & x_{12} & x_{22} & \ldots & x_{k2} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & x_{1n} & x_{2n} & \ldots & x_{kn} \end{pmatrix},$$

$$\beta = \begin{pmatrix} b_0 \\ b_1 \\ . \\ . \\ b_k \end{pmatrix},$$

$$\epsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ \varepsilon_n \end{pmatrix}$$

The estimation process of the impact of each independent variable in X on Y, i.e. estimation of β values, is shown as:

$$\hat{\beta} = \frac{Y}{X} = X^{-1}Y \tag{3.3}$$

And since these matrices are not of the same size, we multiply both sides with transposed matrix X^T to achieve:

$$\hat{\beta} = \frac{X^TY}{X^TY} = (X^TX)^{-1}X^TY \tag{3.4}$$

β in formular 3.4 is the vector of coefficients $\beta_1, \beta_2, \ldots, \beta_n$ in the model. In the conventional HPM approach, the value of these coefficients is *global* in the whole study area.

The GWR extends this model by incorporating spatial factors into the model, to take into account *local* factors within the study area. First, for each observation point, the GWR model assigns spatial coordinates to the model:

$$y_i = \beta_0 + \beta_1(u_i, v_i)x_{1i} + \beta_2(u_i, v_i)x_{2i} + \cdots + \beta_k(u_i, v_i)x_{ki} + \varepsilon_i \tag{3.5}$$

Similarly, we can rewrite the general form of GWR model as:

$$y_i = \beta_0(u_i, v_i) + \sum\beta_k(u_i, v_i)x_{ki} + \varepsilon_i \tag{3.6}$$

where geographical coordinates (u_i, v_i) are the assigned to each observation point *i*. This allows the relationship between the dependent variable and the independent variables to vary from location to location. In matrix form, the GWR model is shown as:

$$Y = (\beta \otimes \mathrm{X}) + \varepsilon \tag{3.7}$$

Where β is a matrix of coefficients that vary with geographic location, and $\otimes$ is a logical matrix multiplication (between two matrices of the same size): each value of β is multiplied by the corresponding value of *X*. Matrix β now take a new updated form:

$$\beta = \begin{pmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \ldots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \ldots & \beta_k(u_2, v_2) \\ \ldots & \ldots & \ldots & \ldots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \ldots & \beta_k(u_n, v_n) \end{pmatrix}$$

The values in each row of β is now estimated as:

$$\hat{\beta} = (X^T W(i) X)^{-1} X^T W(i) Y \quad (3.8)$$

$$W(i) = \begin{bmatrix} w_{1i} & 0 & \cdots & 0 \\ 0 & w_{2i} & \ddots & 0 \\ . & . & \cdots & . \\ 0 & 0 & \ldots & w_{ni} \end{bmatrix}$$

Where the matrix $W(i)$ is a diagonal matrix of size *n x n*, where w_{ij} is the weight assigned to the observation data point j at location i, based on coordinates (u_i, v_i). This weight[6] reflects the influence of observation point j on point i. The weight of a point close to i will be higher than a point far from i. The weight of a location decreases with increasing distance from i.

The fundamental difference between the HPM and the GWR model is shown in equations 3.4 and 3.8. In the conventional HPM, the estimated coefficients are spatially constant ($\beta = [\beta_0, \beta_1, \ldots, \beta_n]$), while in the GWR model, the estimated coefficients can vary spatially – expressed numerically as taking values within a range ($\beta = [\beta_0(u_0, v_0), \beta_1(u_1, v_1), .., \beta_n(u_n, v_n)]$) This spatial variation is adjusted through the weight matrix $W(i)$. The main results of the GWR analysis are usually presented in the form of multiple maps. Each independent variable requires at least one map to represent the variation of the estimated coefficients in space.

3.3. Model specification

From the conventional HPM approach (Model 3.1) we first define the standard HPM with the following form:

$$PRICE_i = \beta_0 + \beta_1 SDHOS_i + \beta_2 SDPRK_i + \beta_3 SDSCH_i + \beta_4 SDUNI_i + \beta_5 SDSHP_i + \beta_6 SDCENL_i + \beta_7 SDCEN_i + \varepsilon_i \quad (3.9)$$

Where *PRICE* is the advertised selling price of residential property i (measured in million VND/m²), *SDHOS, SDPRK, SDSCH, SDUNI, SDSHP* are independent variables respectively represent the shortest distance as-the-crow-flies from real estate i to the nearest urban services which are hospitals, parks and green spaces, schools, shopping centers, universities. *SDCENL, SDCEN* are independent variable representing shortest distance of real estate i to the nearest local people's committee location and to the Hanoi People's committee location[7]. ε is the error term and $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$ are coefficients to be estimated in the model.

Access to these urban services – or amenities – (Figure 2), we argue, are basic and essential matter-of-fact need that everyday life requires to happen: medical facilities in case of sickness; education for themselves and family members; green spaces and shopping as utility enhancers; engagement with public institution for essential daily services and information. The selection of these variables align with other empirical works which include several variables to measure accessibility based on distance to different amenities such as by Wu et al. (2019) with variables representing distance to central business district, district center, high-speed rail, metro station, density, park, hospital, school. Wang et al. (2020) distinguished between distance to shopping mall, food market, supermarket

[6] For calculation of weightings applied, we used the default settings in ArcGIS to select bandwidth and applied the Akaike Information Criterion (AIC) for optimal calculation based on works by Fotheringham et al. (1998) and Bellefon & Floch (2018) which argued for AIC as a reliable and most efficient settings.

[7] "SD" is short for "shortest distance", with HOS, PRK, SCH, UNI, SHP, CENL, CEN correspondingly stand for Hospital, Park, School, University, shopping malls (shopping centers), Center (local) – the position of district level people's committee buildings, and Center (Hanoi) – the position of Hanoi people's committee building.

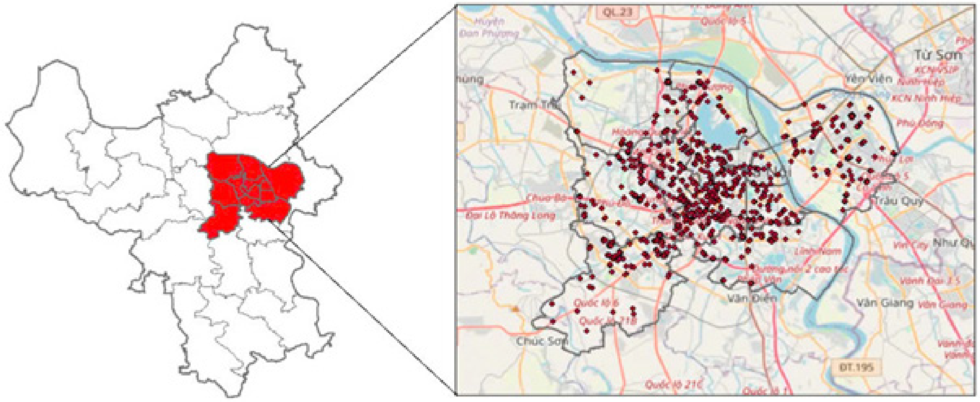

Figure 2: Research area and observation points (residential properties)
Source: rendered by authors

and restaurant, although with a specific boundary limit of 2km from real estate observation i. Cao et al. (2019) particularly designed a model with primarily variables proxying for accessibility. In their research, 6 out of 9 variables represent distance to nearest amenities.

From model 3.5, we define our GWR model with the following form:

$$PRICE_i = \beta_0 + \beta_1(u_i, v_i)SDHOS_i + \beta_2(u_i, v_i)SDPRK_i + \beta_3(u_i, v_i)SDSCH_i + \beta_4(u_i, v_i)SDUNI_i + \beta_5(u_i, v_i)SDSHP_i + \beta_6(u_i, v_i)SDCENL_i + \beta_7(u_i, v_i)SDCEN_i + \varepsilon_i \quad (3.10)$$

Where *PRICE, SDHOS, SDPRK, SDSCH, SDUNI, SDSHP, SDCENL, SDCEN* are the dependent and independent variables similar to model 4.1. But compared to model 4.1, coefficients β_1, β_2, β_3, β_4, β_5,β_6, β_7 in model 4.2 are specifically estimated for each location, as assigning specific (u_i, v_i) to each observation is the basis for the GWR model to calculate β_1, β_2, β_3, β_4, β_5, β_6, β_7 with inclusive weights.

Naturally, for both models 4.1 and 4.2, the expected sign of coefficients is negative, which means an increased proximity to these amenities (smaller shortest distance) should bring about an increase in the value of a residential property.

3.4. Research area and data source

This study focuses on 12 central districts of Hanoi including Hoang Mai, Long Bien, Ha Dong, Cau Giay, Hai Ba Trung, Hoan Kiem, Ba Dinh, Bac Tu Liem, Nam Tu Liem, Dong Da, Thanh Xuan and Tay Ho as study area. In Vietnamese context, prior to 01st July 2025, a city consists of districts and wards, where administratively districts are urban and wards are rural (World Bank 2020). So, these 12 districts represent the most central and developed urban areas of Hanoi, where the real estate market is vibrant and diverse (Figure 2). While these central districts account for a small geographical area but most economic, cultural and social activities of the city are concentrated in these districts. Furthermore, data on real estate transactions in central areas are often more abundant and accessible, increasing the number of available observations for the study.

Data was systematically collected and processed from variable open and reliable sources. We collected listed selling residential property price *(PRICE)* as advertised on website "batdongsan.com.vn" [8]. The site was chosen as the main data

[8] URL: https://batdongsan.com.vn. (Last accessed: 15/05/2025)

source because it is one of the most popularly accessed sites in Vietnam with large database and is regularly updated. Besides, listed properties on this site are accompanied with specific coordinates *(u_i,v_i)* needed for our GWR mode. The collection process took place from November 2024 to the end of March 2025. This is the 5-month span from before to after Lunar New Year in Vietnam (*Tết*), which is arguably the most popular window for selling and buying properties, hence selected to maximize the number of observed data.

Advertisements on batdongsan.com.vn may be posted directly by homeowners or through third-party agents, which introduces the risk of price bias. To mitigate this issue, we restricted our dataset to listings that satisfied both the "Verified Listings" and "Professional Broker" filters provided by the platform. According to the website's official guidelines, "Verified Listings"[9] are postings that have been examined and authenticated by its expert team, ensuring accuracy in legal documentation, property characteristics, images, addresses, and, critically, conformity of listed prices with prevailing market levels. The "Professional Broker"[10] designation, meanwhile, is granted to brokers who meet the platform's standards of activity, reliability, and professional conduct. This recognition functions both as a branding tool for brokers and as a trust-enhancing mechanism for prospective buyers, who can engage with them more confidently. By applying both filters, our study reduces potential price distortion while still leveraging one of the most comprehensive publicly accessible real estate data sources in Vietnam.

Collected information includes: selling price (in million VND), lot size (m²), geographical location (WGS coordinate system), and property type (house/apartment). In total, there are 1,545 observations with variables on housing prices and distance to public amenities (as shown in Table 1).

Spatial data was collected via the QuickOSM plugin in QGIS, allowing information retrieval from OpenStreetMap. The process began by extracting the geographical locations of 7 types of public services in Hanoi (hospitals, parks, schools, universities, shopping centers, local people's committee locations, Hanoi people's committee locations,) through specific keywords. These layers are displayed in Figure 3. Data from QuickOSM was converted to the VN-2000 coordinate system. The Euclidean distance from each property to amenities was calculated using the "Near" tool to achieve seven independent variables: *SDHOS, SDPRK, SDSCH, SDUNI, SDSHP, SDCENL* and *SDCEN*.

For the collected dataset to work with our models, and in consistence with our conceptual framework (Figure 1) we further assume that information collected from batdongsan.com.vn and OpenStreetMap (via QuickOSM plugin in QGIS) is up-to-date and accurately reflect the actual state of Hanoi's real estate market. Ideally, the most reliable source of data for residential property prices would be official housing transaction information recorded by government agencies or reputable research organizations[11]. Yet, this database is currently not available nor publicly accessible in Vietnam. Thus, we utilized data available on public and community-based domains as the next best alternative source of data.

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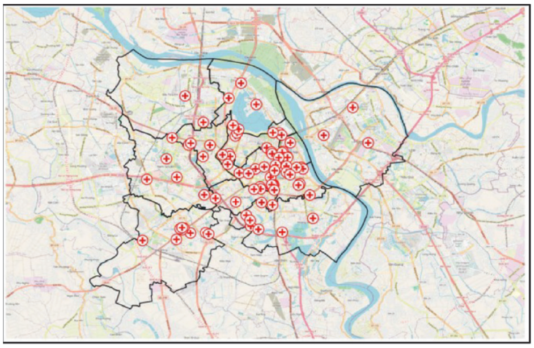
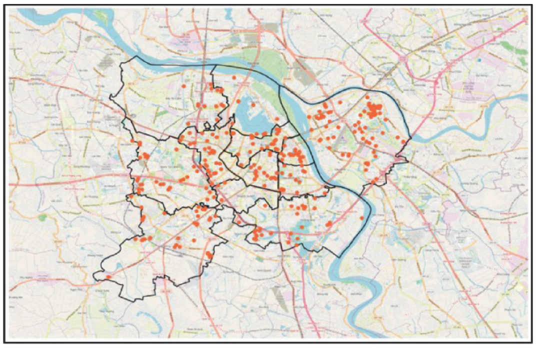
[9] Verified Listings – original Vietnamese: "Tin xác thực". URL: https://trogiup.batdongsan.com.vn/docs/gioi-thieu-ve-tin-dang-xac-thuc

[10] Professional Broker – original Vietnamese: "Môi giới chuyên nghiệp". URL: https://trogiup.batdongsan.com.vn/docs/danh-hieu-moi-gioi-chuyen-nghiep-la-gi

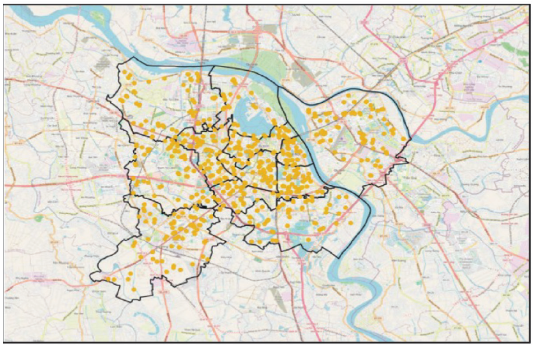
[11] As in study by Cellmer (2012) using official transaction price recorded and kept by Olsztyn City Office, Poland.



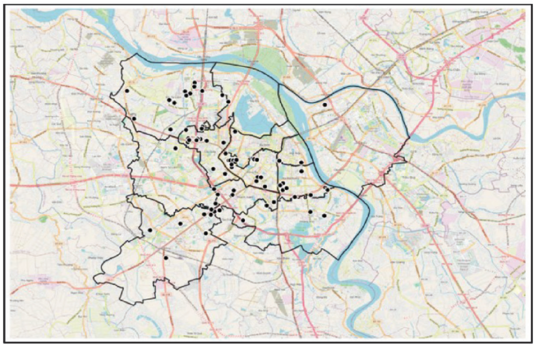
(A) Hospitals



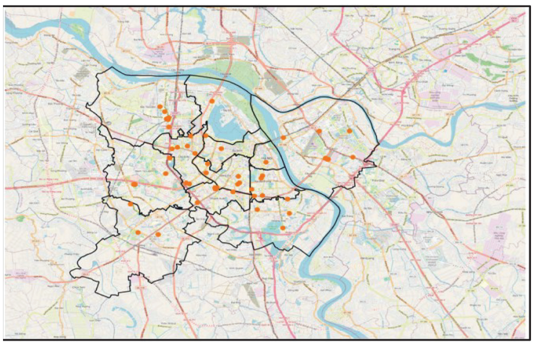
(B) Parks and green spaces



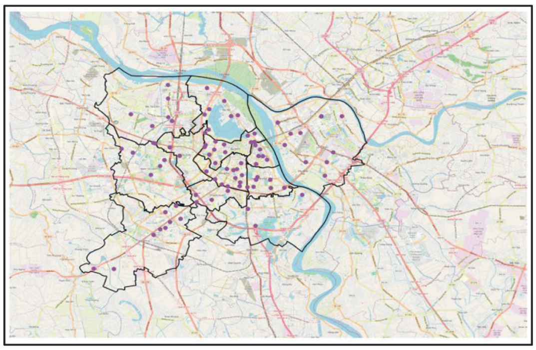
(C) Schools



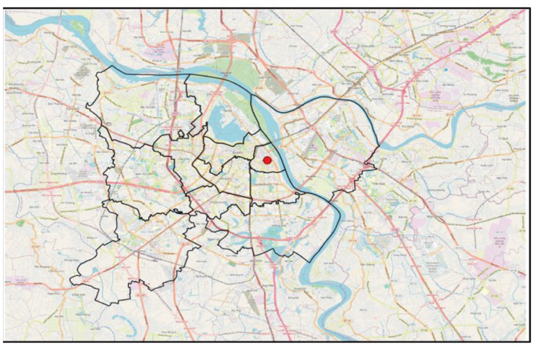
(D) Universities



(E) Shopping centers



(F) Locations of People's Committee headquarters



(G) Location of Hanoi People's Committee headquarters

Figure 3: Spatial distributions of amenities in 12 central districts in Hanoi
Source: rendered by authors

4. ANALYSIS AND DISCUSSION

4.1. Results analysis

The Koenker test yielded a studentized Breusch–Pagan statistic of 31.6, which is statistically significant at the 1% level, indicating the presence of heteroskedasticity (Koenker 1981). To address this issue, we report robust probability estimates of the coefficients to ensure the validity of the inference. The results of estimating HPM (model 3.9) using OLS method[12], and of estimating GWR (model 3.10) are shown respectively in Table 2 and Table 3.

Table 2 shows an inverse relationship between property prices and distance to hospitals (*SDHOS*), universities (*SDUNI*), and the city center (*SDCEN*), and local people's committee locations (*SDCENL*), aligning to our expectations. Meanwhile, the coefficients of *SDPRK*, *SDSCH*, *SDSHP* are positive, which is in contrast to our sign expectation, hinting preferences for properties not too close to these amenities. In independent variables, the relationship between property prices and shopping malls (*SDSHP*) is positive (0.008) but not statistically significant (p-value = 0.257). The coefficient value of β s from the HPM is 'global' – or universal – across the entire study area. For instance, the coefficient of *SDHOS* is -0.031 and is statistically significant at 1% level, implying that, *ceteris paribus*, if a residential property is 100m closer to a hospital, its price would increase by 4.4 million VND/m^2 and vice versa.

All selected amenities generate positive externalities for urban residents, including public health benefits (hospitals), community and leisure spaces (parks), educational opportunities (schools and universities), and enhanced security and administrative services (local government offices). However, in large metropolitan areas such as Hanoi, the high concentration of people and activities inevitably gives rise to negative externalities, which in some cases may outweigh the positive effects. Within the standard Hedonic Pricing Model (HPM), estimated via Ordinary Least Squares (OLS), these net externalities – defined as the balance of perceived positive and negative effects by prospective property buyers – are assumed to be spatially uniform across the study area. At face value, the results suggest that buyers tend to associate higher property prices with proximity to amenities that provide net positive externalities, particularly hospitals, government offices, and universities. These specific amenities are noteworthy in that, despite the high density of people around them, most related activities remain largely contained within their premises, thereby limiting potential negative spillovers.

Conversely, lower property prices are often associated with proximity to amenities where net negative externalities are more pronounced. Non-university schools, public parks, and shopping centers typically attract large daily inflows and outflows of people, and due to management-related factors, the surrounding areas are particularly vulnerable to adverse spillovers. For example, illegal parking and unsafe pupil pick-up behaviors by parents have been identified as major contributors to congestion and heightened traffic accident risks in the vicinity of Vietnamese schools (Hiep et al. 2020). Similarly, a survey-based study of four parks in Hanoi by Pham et al. (2019) found that even among younger residents (aged 18 – 24), issues such as heat, crowded sidewalks, heavy traffic, and unsafe street crossings were perceived as significant barriers to park access. With regard to shopping centers, Chung et al. (2018), in a comparative study of Ho Chi Minh City and Hanoi, observed that proximity to malls in Ho Chi Minh City was positively associated with housing prices, partly because malls function as cultural and social hubs where residents can enjoy air-conditioned environments in a tropical climate. However, this dynamic may differ in Hanoi, where seasonal variation alters the relative value of such amenities. Taken together, these findings highlight that if accessibility is understood not solely in terms of physical distance but also in terms of convenience and perceived usability, the way externalities are evaluated – and thus their influence on property prices – can vary significantly across amenities and contexts.

[12] We employ the "Ordinary Least Square" tool in ArcGIS to estimate the HPM.

Table 1: Summary Statistics

Category	Variable	Definition	No. of observations	Min	Mean	Median	Max	Standard Deviation
Property characteristics	House price	The total amount of money to pay for a house or real estate. House price is calculated in million VND	1,545	2,350	32,179	14,950	510,000	49,210.779
	Area	The dimensions of the house or real estate, measured in square meters (m^2)	1,545	11.4	117	90.2	1,329	166.779
Dependent variable	House price per m^2	An index representing the value of one square meter in a house or real estate	1,545	30,05	256,89	217,9	2571,43	205,36
Locational conditions of observed real estate	SD_HOS	Distance to the nearest hospital	1,545	31.9	1,013.5	844.4	5,353	660.53
	SD_PRK	Distance to the nearest park	1,545	12	519.14	444.8	4,605.8	373.9
	SD_SCH	Distance to the nearest school	1,545	2	306.41	260	1,600	197.09
	SD_UNI	Distance to the nearest university	1,545	35	1,371	909	7,192	1,277.29
	SD_SHP	Distance to the nearest shopping malls	1,545	14	1,122.13	955	5,663.73	697.55
	SD_CENL	Distance to the nearest People's Committee (local levels)	1,545	212	6,637.88	6,111	18,514	3,016.5
	SD_CEN	Distance to the City People's Committee	1,545	26	872.9	673	3,402	642.52

Source: assembled by authors

Note: Distance measured in meter

Table 2: Hedonic Pricing Model Regression Results (OLS)

Dependent variable: Property price per m² ($PRICE$)

Independent Variable	Coefficient	Std. Error	t-Value	p-Value
$SDHOS$: Shortest distance to the nearest hospital	-0.031	0.010	-3.258	0.001***
$SDPRK$: Shortest distance to the nearest park or green space	0.036	0.012	3.086	0.000***
$SDSCH$: Shortest distance to the nearest school	0.036	0.015	2.400	0.002**
$SDUNI$: Shortest distance to the nearest university	-0.014	0.005	-3.034	0.000***
$SDSHP$: Shortest distance to the nearest shopping center	0.008	0.008	1.024	0.257
$SDCENL$: Shortest distance to the nearest local People's committee location	-0.015	0.004	-4.385	0.000***
$SDCEN$: Shortest distance to Hanoi People's committee location	-0.020	0.002	-10.977	0.000***
Intercept	441.542	12.909	34.204	0.000***

Model Parameters

Number of Observations	1545
Adjusted R^2	0.163853

***, ** denote statistical significance at 1%, 5% levels, respectively.

Source: calculated by authors

Note: Estimated robust probability of coefficients is reported

Table 3: Geographically Weighted Regression Results (GWR)

Dependent variable: Property price per m² ($PRICE$)

Independent Variable	Min	Q1	Mean	Q3	Max
$SDHOS$: Shortest distance to the nearest hospital	-0.090	-0.061	-0.041	-0.023	0.006
$SDPRK$: Shortest distance to the nearest park or green space	-0.053	-0.030	-0.010	0.008	0.040
$SDSCH$: Shortest distance to the nearest school	-0.082	-0.015	0.013	0.039	0.088
$SDUNI$: Shortest distance to the nearest university	-0.028	-0.009	-0.003	0.003	0.042
$SDSHP$: Shortest distance to the nearest shopping center	-0.012	0.004	0.019	0.027	0.048
$SDCENL$: Shortest distance to the nearest local People's committee location	-0.029	-0.024	-0.010	0.008	0.012
$SDCEN$: Shortest distance to Hanoi People's committee location	-0.047	-0.035	-0.030	-0.025	-0.016
Model Parameters					
Number of Observations	1545				
RSS	52241222.924				
AICc	20530.283893				
Adjusted R^2	0.192015				

Source: calculated by authors

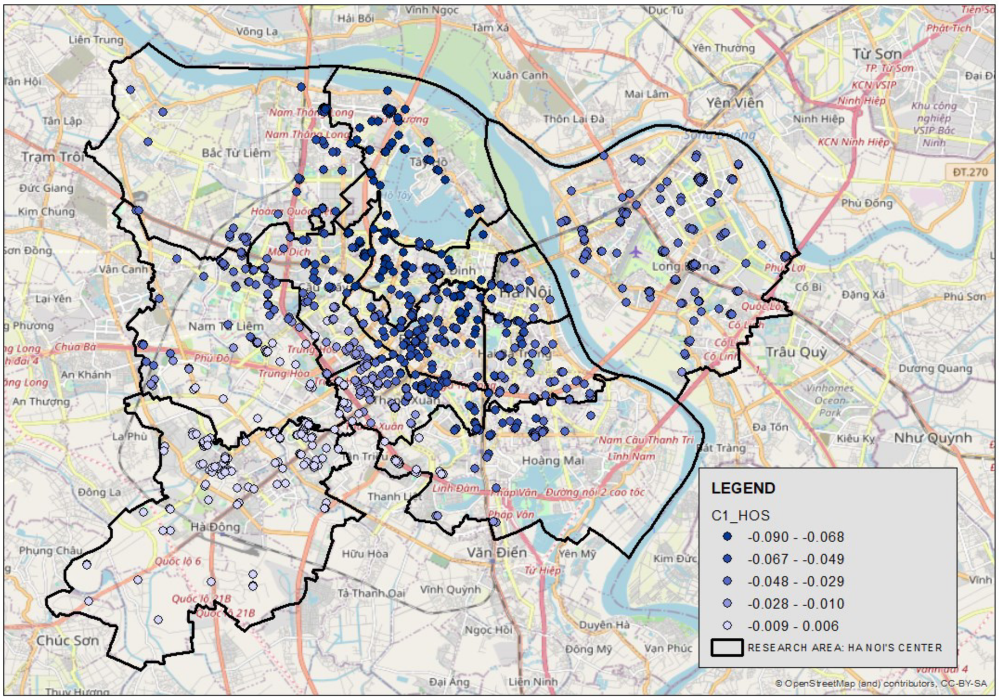


Figure 4: Spatial distribution of GWR coefficients illustrating the relationship between distance to hospitals (SDHOS) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

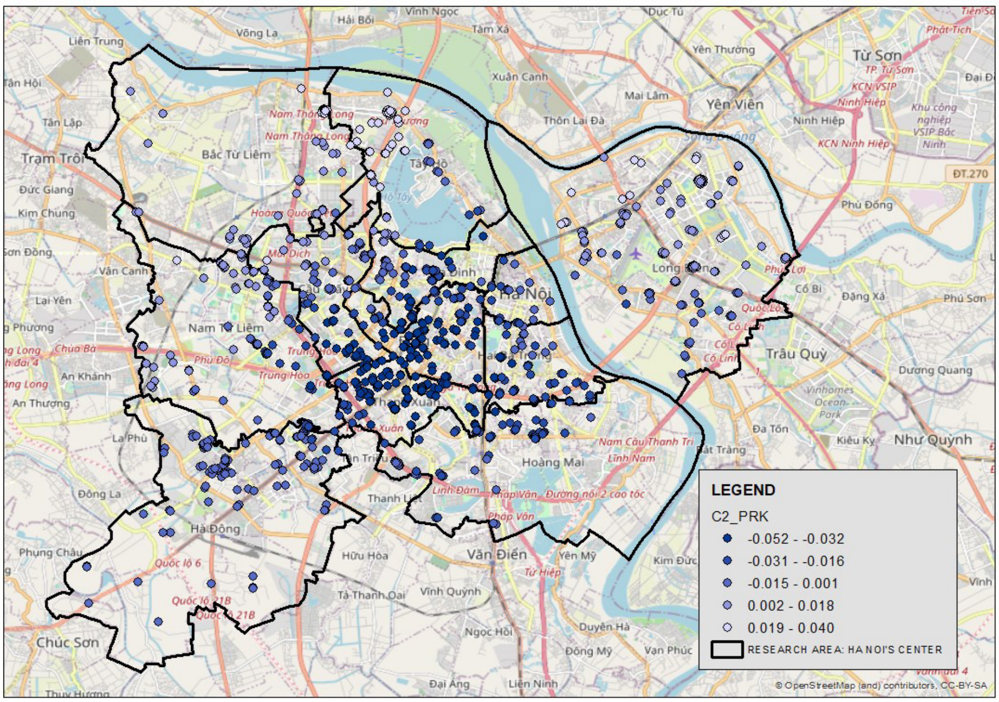


Figure 5: Spatial distribution of GWR coefficients illustrating the relationship between distance to parks (SDPRK) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

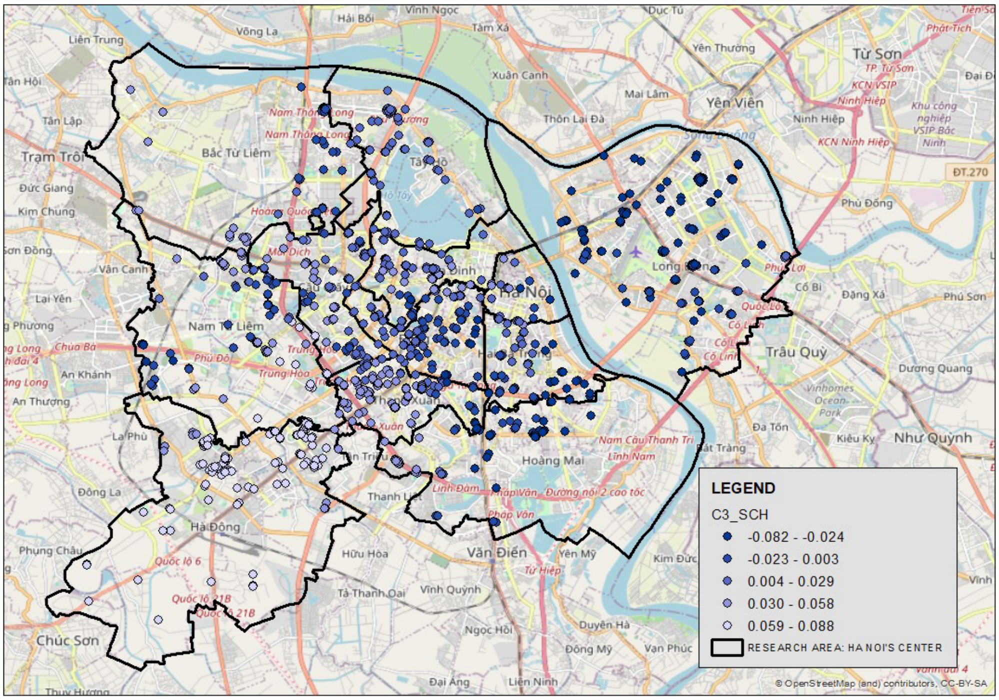


Figure 6: Spatial distribution of GWR coefficients illustrating the relationship between distance to schools (primary, secondary, high school) (SDSCH) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

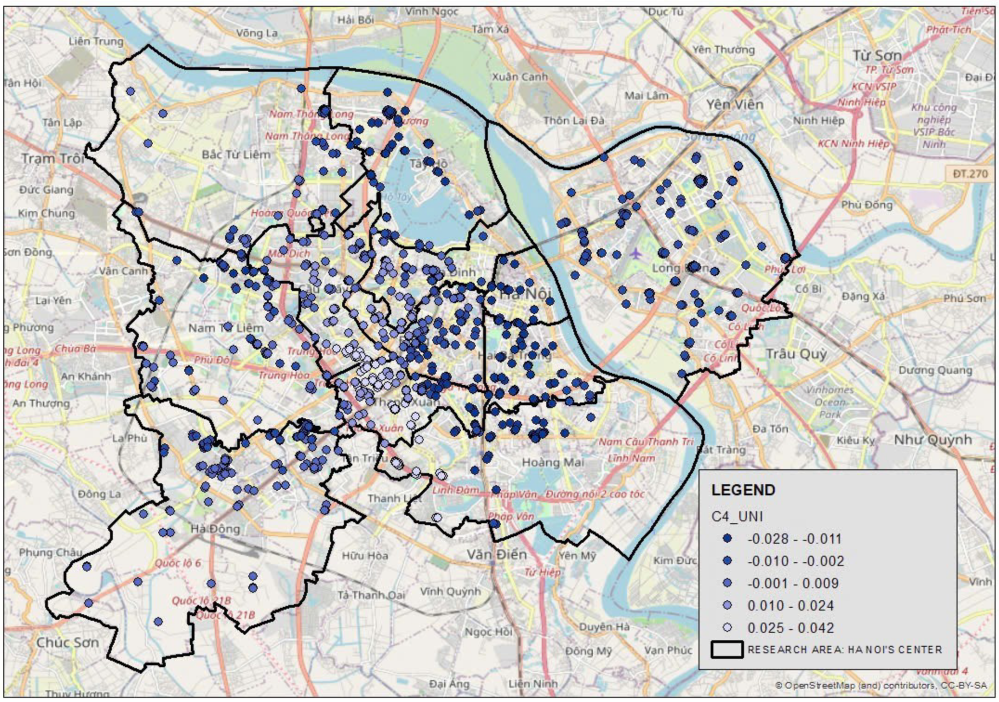


Figure 7: Spatial distribution of GWR coefficients illustrating the relationship between distance to universities (SDUNI) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

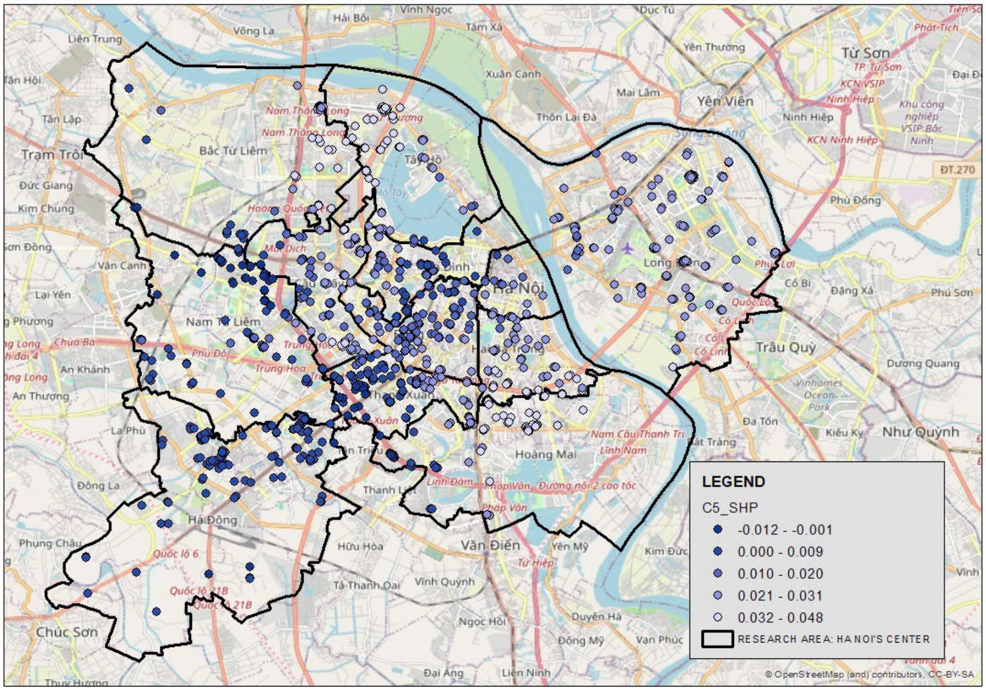


Figure 8: Spatial distribution of GWR coefficients illustrating the relationship between distance to shopping centers (SDSHP) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

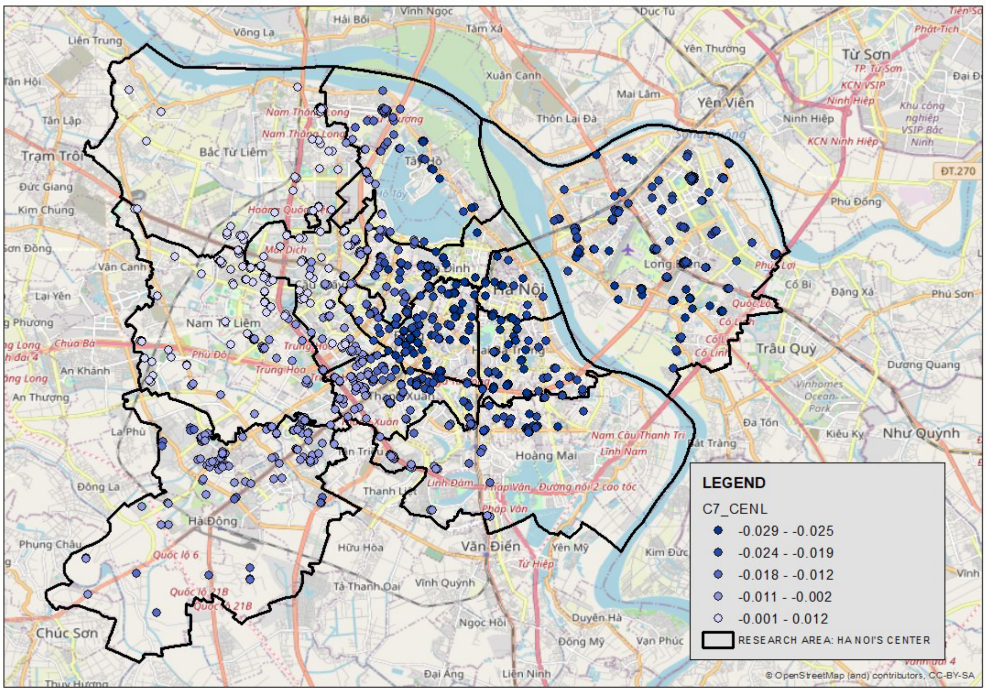


Figure 9: Spatial distribution of GWR coefficients illustrating the relationship between distance to People's Committees at various levels (SDCENL) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

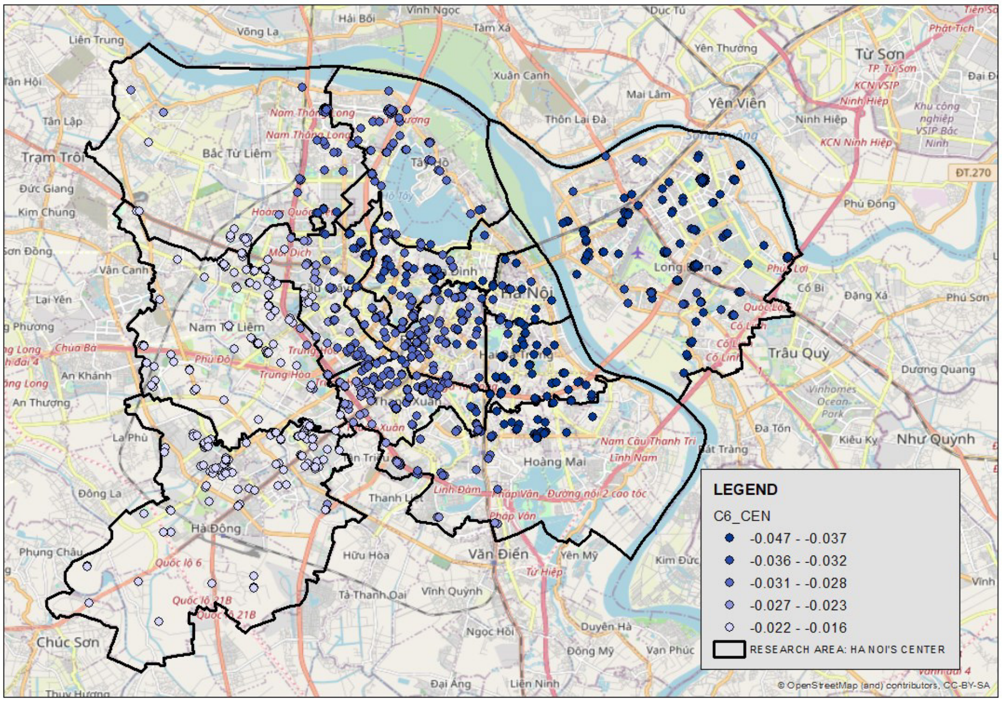


Figure 10: Spatial distribution of GWR coefficients illustrating the relationship between distance to Hanoi city center (SDCEN) and property prices in Hanoi
Source: results from GWR analysis, rendered by authors

Unlike the traditional HPM, the GWR model estimates β values that vary within a range (as shown in Table 3). Consequently, the coefficients β_1, β_2, β_3, β_4, β_5, β_6 and β_7 fluctuate between minimum and maximum values, exhibiting positive or negative magnitudes depending on the spatial location *i*. A significant p-value from the Koenker test (as discussed above) is frequently interpreted as evidence of spatial nonstationarity, indicating that the relationships between the dependent and independent variables are not consistent across the study area. This finding provides the primary rationale for employing the Geographically Weighted Regression (GWR) approach. Adjusted R^2 value of the HPM is 0.164, while in the GWR model it is 0.192, indicating the latter's better explanatory power by accounting for spatial heterogeneity. This result aligns with several studies that have also indicated the higher explanatory capability of GWR (Brunsdon et al. 1996b), (Wu et al. 2019), (Yu et al. 2007).

The GWR model captures the *spatially varying* coefficients, reflecting geographic variability. Because of this, as discussed above, a series of spatial distribution maps of estimated coefficients are rendered to illustrate the impact of accessibility to each amenity *SDHOS, SDPRK, SDSCH, SDUNI, SDSHP, SDCENL, SDCEN* on property prices depending on specific geographic locations of each factor. This is demonstrated in Figures 4, 5, 6, 7, 8, 9, 10 correspondingly.

Compared to the conventional HPM, estimated β values can range from negative to positive (Table 3), showing that increased accessibility to amenities could increase as well as decrease residential property prices. The color in Figures 4 to 10 is assigned to each individual property *i*, and the color scheme is also rendered to showcase this phenomenon. Darker colors tend to show that property price benefits from increased accessibility and, on the contrary, lighter colors imply that property *i* benefits less or even experience value depreciation from increased accessibility. For example, for the case of accessibility to nearest hospital (*SDHOS*), in central districts such as Hoan Kiem, Ho Tay, Ba Dinh, Cau Giay, Dong Da, and Hai Ba Trung, the estimated coefficients range from -0.09 to -0.068, implying that for every 100 meters closer to hospitals, property prices increase by 6.8 to 9 million VND/m². In outer districts Tu Liem, Hoang Mai, and Thanh Xuan districts, coefficients range from -0.048 to -0.029, meaning that property price increases from 2.9 to 4.8 million VND/m² per 100 meters closer to hospitals. Conversely, in Ha Dong district – the southernmost district from the center, coefficients fluctuate between -0.009 and 0.006, indicating that prices decrease by approximately 0.6 million VND/m² for every 100 meters closer to hospitals.

In Thanh Xuan and Dong Da districts, *SDPRK* coefficients are negative (-0.052 to -0.032). Proximity to parks and green spaces has a slight positive influence on property prices, with an increase of 5.2 million VND/m² per 100 meters closer. In Hoan Kiem, Ba Dinh, Hai Ba Trung, Cau Giay, and Nam Tu Liem districts, coefficient values are positive (ranging from -0.031 to near 0). In these districts, for every 100 meters closer to parks, property prices increase by 3.1 VND/m². In Bac Tu Liem and Ho Tay districts, coefficients are strongly positive (from 0.019 to 0.04), so the opposite effect is true for this area: for every 100 meters farther from parks, property prices increase by 1.9 to 4 million VND/m².

While the HPM model only provides universal regression coefficients, GWR demonstrates the spatial variation of these variables. Variable such as *SDSHP* are not statistically significant in the OLS model, but in the GWR model, they exhibit different levels of influence at different locations. This indicates that in some areas, the distance to shopping malls has a significant impact on the dependent variable, while in other areas, this impact is insignificant or even reversed. Similarly, the negative coefficients of *SDHOS* and *SDUNI* in the OLS model indicate a general trend where the value residential property value decreases as the distance to these facilities increases. However, the GWR model shows that for *SDHOS*, in some areas, this relationship can be positive, demonstrating the complexity of spatial relationships. The GWR model provides a more detailed and specific picture of the relationships between variables compared to the OLS model, especially when examining spatial data. The significant improvement in explanatory capability and the ability to capture spatial variations in relationships between variables make GWR a more effective spatial analysis tool in this case.

4.2. Further discussions

Naturally, there are certain limitations in our study. We tested for multicollinearity among the independent variables, using the Variance Inflation Factor (VIF) reported in ArcGIS software (see Appendix A). While there are debates on the optimal threshold, a VIF value below 10 is generally the acceptable level of multicollinearity (“rule of 10”, i.e. see O’Brien 1992). Three variables indeed have high VIF values, indicating the existence of multicollinearity in our model (which might make coefficient estimates unstable), but the mean VIF value is 9.99, which is just sufficient for this threshold. Having said that, high VIF values are acknowledged as a limitation but it is not solely a sufficient reason to exclude these variables from the model, as the common “treatment” to variables with high VIF values. For our case, accessibility to healthcare, education facilities and green spaces (respectively represented by *SDHOS, SDPRK, SDSCH*) are basic, grounded considerations for house buyers in real life and has been commonly included in previous empirical research (Basu & Thibodeau 1998), (Dao 2023), (Dziauddin & Idris 2017), (Vu & Nguyen 2024). Removing these variables would lead to mis-specified model and incomplete picture of the phenomenon studied. Besides, some research cautioned against adhering rigidly to the "rule of 10" as the basis for variable inclusion or exclusion. Gujarati and Porter (2009: 340) noted that "VIF (or tolerance) as a measure of collinearity is not free of criticism […] a high VIF is neither necessary nor sufficient to get high variances and high standard errors. Therefore, high multicollinearity, as measured by a high VIF, may not necessarily cause high standard errors". Similarly, O'Brien (1992: 673) remarked that "threshold values of the VIF (and tolerance) need to be evaluated in the context of several other factors that influence the variance of regression coefficients. Values of the VIF of 10, 20, 40, or even higher do not, by themselves, discount the results of regression analyses". For exploratory purpose, our model aims to describe a collective explanatory contribution of locational attributes to residential property prices. Keeping these variables in the model helps to better provide the picture of complex relationships involved, especially in the absence of physical and other attributes (Figure 1). Of course, our exploratory work can be used to inform more complicating research in the future, when collinearity can be addressed more effectively.

Besides, the scope and design of this study could be broadened and the assumptions taken unbundled as suggestions for future research. A potential research direction is to consider the effect of determining factors on other types of residential real estate, such as apartments. Compared to residential housing a fundamental difference with apartments is that it is more difficult to renovate or change the physical attributes of the property, hence structural physical features of apartments, such as design, construction quality, internal amenities, and management systems would be more relevant on property value. Applying the GWR model to analyze the spatial variation of these factors will provide deeper insights into the price formation mechanism in the apartment segment, a type that is rapidly developing in major urban areas of Vietnam, although it would also require more detailed data.

Furthermore, future research could expand to consider other factors beyond physical characteristics and location (Figure 1). In the context of an increasingly developed and diverse real estate market, people's housing preferences may be changing. Factors such as construction quality, interior design, and even intangible values like *fengshui* may be playing important roles in home purchasing decisions. Other factors such as legal status, market liquidity, buyer psychology, and even macroeconomic conditions like credit policies and bank interest rates can also significantly impact real estate prices. Incorporating these variables into the GWR model could create a more comprehensive analytical framework, examining not only traditional attributes but also the dynamic factors of the market. Alternatively, with more data, future works may explore determinants of real estate prices in non-linear nature; using non-Euclidean distances, or enhance analysis with qualitative data from interviews or surveys, especially with urban planners or officials. Public engagement could help to identify factors that the model has yet covered or to validate findings against lived experiences of participants in residential property markets.

5. CONCLUSION

While more attention has been paid for better operation and management of the real estate markets in Vietnam, a notable challenge persists: the considerable disparity between state-regulated real estate prices and actual market prices. Meanwhile, in the research sphere, traditional valuation methods such as the HPM model have shown limitations as they assume that factors affecting real estate prices have a uniform, universal impacts across the entire research area. In reality, the impact of these factors varies according to geographical location, which the HPM model cannot fully reflect.

In our paper, we explored the application of the GWR model as an alternative, more efficient solution to take spatial factors into account. The GWR model allows for examination of how influencing factors vary by region and location, thereby improves the ability to explain and predict real estate prices. While there have been some studies applying GIS in the real estate valuation, these applications have mainly been limited to projection and illustration functions. To the best of our knowledge, this is the pioneering research in discussing, developing and applying the GWR model to real estate valuation for the case of Hanoi.

In doing so, the paper has utilized a case-specific GWR model to analyze factors affecting real estate prices and found evidence that the influence of factors such as distance to schools, hospitals, administrative offices, and amenities is not uniform across all areas. We found that variables that are not statistically significant in the traditional HPM approach show different impacts at specific locations in the GWR model. In addition, in the Vietnamese context, state-led land and property valuation methods of the state and businesses in Vietnam (discussed above) have yet to address the locational characteristics of real estate and the spatial variation of factors affecting real estate prices. Thus, the capability of the GWR model to optimize data also provides an additional perspective and reference for policy makers. Hopefully, our paper would engage more academic participation exploring potential applications of GWR in the future.

STATEMENT OF CONTRIBUTION

Author Le Minh Son: Research design, direction, organization and supervision; Editing of final manuscript.

Author Le Thi Hoa Ly: Original idea conception; Literature review; Data collection and software operation (QuickOSM, QGIS, ArcGIS); Preparation of tables, figures and result analysis; Editing of first manuscript draft.

Author Doan Thu Trang: Original idea conception; Literature review; Data collection and software operation (QuickOSM, QGIS, ArcGIS); Preparation of tables, figures and result analysis; Editing of first manuscript draft.

All authors participated at every stage of this research, discussed research results and contributed to the final version of this manuscript.

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The authors have no conflicts of interest to declare.

REFERENCES

Basu, S., & Thibodeau, T. G. (1998). Analysis of spatial autocorrelation in house prices. *The Journal of Real Estate Finance and Economics*, *17*(1), Article 1. https://doi.org/10.1023/A:1007703229507

Bellefon, M.-P., & Floch, J.-M. (2018). Geographically Weighted Regression. In *Handbook of Spatial Analysis Theory and Application with R: Vol. Insee Méthodes N°131* (pp. 231–254). https://www.insee.fr/en/information/3635545

Bitter, C., Mulligan, G. F., & Dall'erba, S. (2007). Incorporating spatial variation in housing attribute prices: A comparison of geographically weighted regression and the spatial expansion method. *Journal of Geographical Systems*, *9*(1), Article 1. https://doi.org/10.1007/s10109-006-0028-7

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, *28*(4), Article 4. https://doi.org/10.1111/j.1538-4632.1996.tb00936.x

Cao, K., Diao, M., & Wu, B. (2019). A Big Data–Based Geographically Weighted Regression Model for Public Housing Prices: A Case Study in Singapore. *Annals of the American Association of Geographers*, *109*(1), 173–186. https://doi.org/10.1080/24694452.2018.1470925

Cellmer, R. (2012). The Use of the Geographically Weighted Regression for the Real Estate Market Analysis. *Folia Oeconomica Stetinensia*, *11*(1), 19–32. https://doi.org/10.2478/v10031-012-0009-6

Chung, Y. S., Seo, D., & Kim, J. (2018). Price Determinants and GIS Analysis of the Housing Market in Vietnam: The Cases of Ho Chi Minh City and Hanoi. *Sustainability*, *10*(12), 4720. https://doi.org/10.3390/su10124720

Dao, V. K. (2023). Research on factors affecting the selling price of Class A apartments in Nam Tu Liem district, Hanoi. *Journal of Science and Environmental Resources*, *47*, Article 47.

Du, H., & Mulley, C. (2012). Understanding spatial variations in the impact of accessibility on land value using geographically weighted regression. *Journal of Transport and Land Use*, *5*(2), Article 2. https://doi.org/10.5198/jtlu.v5i2.225

Dziauddin, M. F., & Idris, Z. (2017). Use of Geographically Weighted Regression (GWR) Method to Estimate the Effects of Location Attributes on the Residential Property Values. *Indonesian Journal of Geography*, *49*(1), Article 1. https://doi.org/10.22146/ijg.27036

Farber, S., & Yeates, M. (2006). A comparison of localized regression models in a hedonic house price context. *Canadian Journal of Regional Science 29.3*, 405–420.

Fotheringham, A. S., Charlton, M., & Brunsdon, C. (1998). Geographically Weighted Regression: A Natural Evolution of The Expansion Method for Spatial Data Analysis. *Environment and Planning A*. https://www.paperdigest.org/paper/?paper_id=doi.org_10.1068_a301905

Griffith, D. A. (2008). Spatial-Filtering-Based Contributions to A Critique of Geographically Weighted Regression (GWR). *Environment and Planning A*. https://www.paperdigest.org/paper/?paper_id=doi.org_10.1068_a38218

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5. ed). McGraw-Hill Irwin.

Helbich, M., Brunauer, W., Vaz, E., & Nijkamp, P. (2014). Spatial Heterogeneity in Hedonic House Price Models: The Case of Austria. *Urban Studies*, *51*(2), Article 2. https://doi.org/10.1177/0042098013492234

Hiep, D., V. Huy, V., Kato, T., Kojima, A., & Kubota, H. (2020). The Effects of Picking Up Primary School Pupils on Surrounding Street's Traffic: A Case Study in Hanoi. *The Open Transportation Journal*, *14*(1), 237–250. https://doi.org/10.2174/1874447802014010237

Hoang, X. Q., & Nguyen, T. M. A. (2024). GIS application in building land value maps in Bac Ninh province. *Journal of Surveying and Cartography*, *53*, Article 53.

Huang, B., Wu, B., & Barry, M. (2010). Geographically and Temporally Weighted Regression for Modeling Spatio-temporal Variation in House Prices. *International Journal of Geographical Information Science*. https://www.paperdigest.org/paper/?paper_id=doi.org_10.1080_13658810802672469

Koenker, R. (1981). A note on studentizing a test for heteroscedasticity. *Journal of Econometrics*, *17*(1), 107–112. https://doi.org/10.1016/0304-4076(81)90062-2

Le, H. M., & Tran, Q. T. (2022). Consumer behavior model in the decision to buy resort real estate in Da Nang and Nha Trang. *Journal of Economics and Management*, *41*, Article 41.

Le, T. B. N. (2022). Application of machine learning model in real estate price forecasting in Da Nang. *The University of Danang – Journal of Science and Technology*, *20*(9), Article 9.

LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Econometrics* (0 ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781420064254

McCluskey, W. J., McCord, M., Davis, P. T., Haran, M., & McIlhatton, D. (2013). Prediction accuracy in mass appraisal: A comparison of modern approaches. *Journal of Property Research*, *30*(4), Article 4. https://doi.org/10.1080/09599916.2013.781204

Nguyen, T. D. L., & Nguyen, A. D. (2023). Factors affecting customers' decision to buy apartments in Khanh Hoa. *Thai Nguyen University of Economics and Business Administration*, *28*, Article 28.

Nguyen, T. H. G. (2023). Application of hedonic pricing model in residential real estate valuation in Hanoi. *Journal of Economics and Development*, *306*, Article 306.

Nguyen, T. T. (2023). Analysis and evaluation of factors affecting home buying decisions of young people in Hanoi. *Construction Economics and Management Workshop: Connect – Innovate – Develop*.

Nguyen, T. T., & Tran, V. Q. (2024). The impact of climate change on real estate prices in the central coastal region of Vietnam. *Journal of Climate Change Science*, *19*, Article 19.

O'Brien, R. (1992). *Global financial integration: The end of geography*. Royal Institute of International Affairs.

Pham, N. H. Q., & Nguyen, V. P. (2024). Factors affecting the decision to buy apartments of people from other provinces living and working in Hanoi. *Ho Chi Minh City Open University Journal of Economics and Business Administration*, *19*(11), Article 11. https://doi.org/10.46223/HCMCOUJS.econ.vi.19.9.2971.2024

Pham, T. H. H. (2023). Assessing the impact of transport infrastructure on real estate prices in suburban areas of Hanoi. *Journal of Transportation*, *5*, Article 5.

Pham, T.-T.-H., Labbé, D., Lachapelle, U., & Pelletier, É. (2019). Perception of park access and park use amongst youth in Hanoi: How cultural and local context matters. *Landscape and Urban Planning*, *189*, 156–165. https://doi.org/10.1016/j.landurbplan.2019.04.021

Pham, V. M. (2023). Comparing the effectiveness of real estate valuation methods in the Vietnamese market. *Finance Review*, *7*(759), Article 759.

Savills. (2023, July 27). *The Savills Blog: Income growth gap and housing prices in Hanoi*. https://vn.savills.com.vn/blog/article/212655/vietnam-%20viet/khoang-cach-tang-truong-thu-nhap-va-gia-nha-tai-hn.aspx. Last accessed: May 2025.

The Government of Vietnam. (2023). *Resolution No. 33/NQ-CP dated 11/03/2023 on Certain Solutions to resolve difficulties and promote the real estate market to develop safely, healthily, and sustainably*.

The Government of Vietnam. (2024). *Decree No. 12/2024/ND-CP dated 05/02/2024 on Amendments to decree 44/2014/ND-CP dated 15/05/2014 of the Government on Land prices and Decree No. 10/2023/ND-CP dated 03/04/2023 of the Government on Amendments to decrees on guidelines for the Law on Land*.

Tran, N. L. D. (2025). *Methodology for assessing the impact of heritage on real estate located in core and buffer zones*. 276–289.

Tran, T. M. C., Pham, G. T., Nguyen, B. N., & Ngo, V. H. (2024). Building a model of urban land prices in Thuy Duong ward, Huong Thuy town, Thua Thien Hue province. *Journal of Agricultural Science and Technology*, *8*(3), Article 3. https://doi.org/10.46826/huaf-jasat.v8n3y2024.1191

Vietnam Central Committee. (2022). *Resolution No. 18-NQ/TW of the Fifth plenum of the 13th CPV central committee dated 16/06/2022 on "Ongoing Innovation and Improvement in Regulatory Institutions and Policies; Enhancement of Efficiency and Effectiveness in Management and Use of Land, serving as the driving force in developing our country into a High-income Economy"*.

Vietnam Ministry of Finance. (2024). Circular *42/2024/TT-BTC dated 20/06/2024 Promulgating Vietnam's valuation standard on Real Property Valuation*.

Vietnam National Assembly. (2023a). *Law on Housing (Law No. 27/2023/QH15 dated 27/11/2023)*.

Vietnam National Assembly. (2023b). *Law on Real Estate Business (Law No. 29/2023/QH15 dated 28/11/2023)*.

Vietnam National Assembly. (2024). *Law on Land (Law No. 31/2024/QH15 dated 18/01/2024)*.

Vu, D., & Nguyen, V. L. (2024). Factors affecting coastal land prices in Quang Ninh province. *Vietnam Soil Science*, *42*, Article 42.

Wang, D., Li, V. J., & Yu, H. (2020). Mass Appraisal Modeling of Real Estate in Urban Centers by Geographically and Temporally Weighted Regression: A Case Study of Beijing's Core Area. *Land*, *9*(5), 143. https://doi.org/10.3390/land9050143

Wheeler, D., & Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems*, *7*(2), Article 2. https://doi.org/10.1007/s10109-005-0155-6

World Bank. (2020). *Vietnam's Urbanization at a Crossroads*. World Bank, Washington, DC. https://doi.org/10.1596/34761

Wu, B., Li, R., & Huang, B. (2014). A geographically and temporally weighted autoregressive model with application to housing prices. *International Journal of Geographical Information Science*, *28*(5), 1186–1204. https://doi.org/10.1080/13658816.2013.878463

Wu, C., Ren, F., Hu, W., & Du, Q. (2019). Multiscale geographically and temporally weighted regression: Exploring the spatiotemporal determinants of housing prices. *International Journal of Geographical Information Science*, *33*(3), 489–511. https://doi.org/10.1080/13658816.2018.1545158

Yu, D., Wei, Y. D., & Wu, C. (2007). Modelling Spatial Dimensions of Housing Prices in Milwaukee, WI. *Environment and Planning B: Planning and Design*, *34*(6), Article 6. https://doi.org/10.1068/b32119

Yu, H., Fotheringham, A. S., Li, Z., Oshan, T., Kang, W., & Wolf, L. (2019). Inference in Multiscale Geographically Weighted Regression. *Geographical Analysis*. https://www.paperdigest.org/paper/?paper_id=doi.org_10.1111_gean.12189

Zhang, L. Y. (2015). *Managing the City Economy: Challenges and Strategies in Developing Countries*. Taylor & Francis.

APPENDIX A. Testing for multicollinearity

During the process of developing the linear regression model, we test for multicollinearity among the independent variables. VIF values are calculated and reported by ArcGIS software.

	Dependent variable: $PRICE$	VIF
Independent variables	$SDHOS$	12.83
	$SDPRK$	15.57
	$SDSCH$	24.36
	$SDUNI$	3.79
	$SDSHP$	9.36
	$SDCEN$	1.84
	$SDCENL$	2.17
	Mean VIF	9.99

Source: assembled by authors