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Article

Determining spatial heterogeneity and influencing factors in housing prices with geographically weighted regression method: A case of Erzurum

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ABSTRACT

Understanding the dynamics of the real estate market has emerged as a pivotal concern in urban economics for ensuring sustainable land management and effective investment strategies. The spatial heterogeneity of housing market determinants gives rise to variations in market activity and significant spatial differences in property values. However, global regression models are constrained in their ability to capture this heterogeneity and the spatial autocorrelation of housing prices. The aim of this study is to identify the spatial variability of housing prices and the potential factors influencing them. To this end, the study employs the Geographically Weighted Regression (GWR) model, which enables the analysis of spatial heterogeneity. In addition to conventional structural variables (floor area, age, heating type, number of floors, and floor level), measurable indicators, including network-based accessibility metrics (connectivity, betweenness, and closeness), distance to the central business district, and the remotely sensed Normalized Difference Vegetation Index (NDVI), are integrated into the model. The findings reveal the complexity of the housing market in Erzurum, showing that newly developing peripheral areas form high-priced clusters that reshape the center-periphery dynamics. While structural variables, including floor area and building age, emerge as dominant factors across the city, environmental determinants vary considerably by location. It is noteworthy that network-based accessibility metrics are critical infrastructural variables that shape market heterogeneity. NDVI highlights the decisive role of vegetation density and accessible and functional urban green spaces in determining housing values. In conclusion, this study offers novel insights into the role of environmental and infrastructural metrics in real estate research and provides guidance for policymakers in regulating housing values and designing more sustainable urban planning strategies.

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INTRODUCTION

Housing is not merely a physical structure that meets the need for shelter; it is also a fundamental component of individual well-being and social development (Ding et al., 2024). Housing markets, widely recognized as pivotal economic indicators, are closely monitored by governments due to their historic role as catalysts of major economic and financial crises (Güneş & Apaydın, 2022; Wang et al., 2022a). In this context, analyzing the spatial distribution of housing prices provides critical insights for a wide spectrum of urban land management practices, ranging from government regulation to individual purchase decisions, from land-use planning to urban renewal, and from tax and investment strategies to locational suitability assessments (Bovkir & Aydinoglu, 2018). Given that housing price dynamics serve as a strategic source of information for policymakers, market actors, and researchers, housing economics has long remained a central focus of interdisciplinary academic research (Hu et al., 2019; Tchuente & Nyawa, 2022).

Since the advent of housing price modeling and prediction methods, an extensive body of research has emerged, spanning several decades (Wang et al., 2022a). Among these, the Hedonic Price Model (HPM) has been the most frequently employed approach to capture the structural and environmental parameters that shape housing values (Du et al., 2018). Over time, versions of the HPM, originally a global regression model, have been enhanced with GIS-based spatial techniques and, increasingly, machine learning algorithms. These include Support Vector Machines (SVM) (Chen et al., 2017; Ho et al., 2021), Gradient Boosting, and Decision Trees (DT) (Zou et al., 2022; Liu et al., 2024), Random Forest (RF) (Dimopoulos et al., 2018; Adetunji et al., 2022; Ghamrawi & Nat, 2024), Multiple Regression Analysis (MRA) (Lisi, 2019; Yilmazer & Kocaman, 2020; Zhang, 2021), and Artificial Neural Networks (ANN) (Yang et al., 2023; Soegianto et al., 2024). While these models have demonstrated predictive potential across different geographical contexts, the majority fail to adequately account for spatial dependence, assuming instead that the relationship between housing prices and explanatory factors remains constant across the study area. However, the housing market inherently exhibits spatial heterogeneity, with the influence of factors varying across local contexts (Du et al., 2018; Tchuente & Nyawa, 2022; Wang et al., 2022a). For instance, while transportation accessibility may strongly influence prices in peripheral areas, proximity to green spaces may be more decisive in dense urban cores. Such diversity cannot be fully captured by global regression models, often resulting in misinterpretations of market dynamics and the design of unsustainable housing policies (Sisman & Aydinoglu, 2022). This underscores the necessity of employing local regression models capable of accommodating both spatial dependence and heterogeneity.

Against this backdrop, Geographically Weighted Regression (GWR) emerges as a particularly effective tool for capturing spatial variability in the influence of explanatory factors (Wang et al., 2022a; Comber et al., 2023). Unlike global models that apply a single coefficient across the study area, GWR estimates location-specific parameters, thereby illuminating the heterogeneity inherent to housing markets. This methodological advancement enables a more nuanced analysis of the structural and environmental determinants of housing values across diverse geographic contexts (Kopczewska & Ćwiakowski, 2021). Empirical evidence highlights its efficacy: For example, Sisman & Aydinoglu (2022) demonstrated that GWR outperformed Ordinary Least Squares (OLS) in explaining housing prices in Istanbul; Samad et al. (2020) found that local models better captured environmental effects in Malaysia; and Kopczewska & Ćwiakowski (2021), Cellmer et al. (2020), Zhang et al. (2019b), and Tomal (2020) all underscored GWR's capacity to delineate submarkets and explain spatial heterogeneity. Despite this growing body of work, much of the literature has focused on model comparisons. However, there is a clear need for further research to determine the impact of variables that generate spatial heterogeneity on housing prices.

Housing price determinants are broadly grouped into structural and environmental dimensions (Kopczewska & Ćwiakowski, 2021; Sisman & Aydinoglu, 2022; Lu et al., 2023). Structural characteristics typically include housing size, building age, number of floors, and construction quality (Zhang et al., 2019a; Kangalli-Uyar & Ketten, 2020; McCord et al., 2020). Environmental factors encompass distance to the city center, presence of green spaces, and accessibility (Du et al., 2018; Zhang et al., 2019b; Wang et al., 2020; Samad et al., 2020). Among these, distance to the city center remains one of the most frequently used variables, serving not only as a measure of location but also as a proxy for functional interaction zones that structure individuals' everyday practices (Zhang et al., 2019a; Tomal, 2020; Kopczewska & Ćwiakowski, 2021). Similarly, green spaces have consistently been shown to enhance property values (Payton & Ottensmann, 2015; Samad et al., 2020), with objective measures such as the Normalized Difference Vegetation Index (NDVI) serving as valuable indicators of environmental quality (Tian et al., 2017).

Accessibility, as a crucial environmental dimension, has often been narrowly defined as proximity to transport infrastructure (Sadayuki, 2018; Yang et al., 2018; Tomal, 2020; Wang et al., 2020). Yet the network topology—including how a street is connected to others or its position within the broader urban network—may better capture residents' spatial perceptions and valuation of housing. Metrics such as betweenness and connectivity offer a more robust representation of accessibility, as evidenced by Law et al. (2017) in the UK, Abdulla & Ibrahim (2023) in Kirkuk, and Liu et al. (2024) in Cardiff. However, these studies primarily relied

on global modeling approaches, paying limited attention to local spatial heterogeneity.

More broadly, despite strong evidence that housing prices may vary substantially across neighborhoods due to environmental and locational conditions, spatial heterogeneity has often been addressed only in a limited manner in the existing literature. Conventional global regression models and many machine learning approaches (Ho et al., 2021; Zou et al., 2022; Ghamrawi & Nat, 2024; Soegianto et al., 2024) implicitly assume spatial stationarity and therefore struggle to fully capture spatial dependence. As a result, empirical findings are frequently confined to numerical performance metrics, while the spatially differentiated impacts of key structural, environmental, and accessibility-related determinants remain largely overlooked. In this context, although the application of GWR has increased in recent years, several critical gaps persist. Firstly, much of the GWR-based literature (Samad et al., 2020; Kopczevska & Ćwiakowski, 2021; Cellmer et al., 2020; Zhang et al., 2019b; Tomal, 2020) has focused on comparing the performance of global and local models rather than explicitly identifying which structural, environmental, and accessibility-related variables drive spatial heterogeneity in housing prices. Secondly, accessibility has been functionalized primarily through simple distance-based measures (Tian et al., 2017; Tomal, 2020; Yilmazer & Kocaman, 2020; Sisman & Aydinoglu, 2022; Genc & Colak, 2025; Lee et al., 2025; Soltani et al., 2026), and the impact of street network topology on housing prices remains unclear. Thirdly, empirical evidence combining network-based accessibility indicators with regression models has identified global effects (Porta et al., 2009; Xiao et al., 2016; Kang, 2019; Tan et al., 2019; Ye et al., 2019; Zhang et al., 2021; Chakrabarti et al., 2022; Liu et al., 2024) while neglecting spatially varying effects.

In this context, the objective of this study is to investigate the impact of structural and environmental variables, alongside accessibility indicators derived from Spatial Design Network Analysis (sDNA), on housing prices. To this end, a GWR framework was employed to explicitly incorporate spatial heterogeneity. The contributions of this study are threefold: (i) Identifying the local-scale variations in the effects of structural and environmental determinants of housing prices, (ii) integrating sDNA-based street network accessibility metrics into housing market analysis, and (iii) providing policy-relevant insights that can inform urban planning and decision-making processes. Guided by this objective, the study addresses the following research questions: (1) How do the effects of structural and environmental characteristics on housing prices vary spatially within the city? (2) What is the role of network-based accessibility indicators derived from sDNA in explaining the spatial pattern of housing prices?

From this perspective, Erzurum was selected as the study

area because it has the most dynamic housing market, having recorded the highest annual increase in residential real estate prices of any province in Türkiye. In 2024, housing prices in Erzurum rose by 58.04%, more than double the national average of approximately 25% (Endeksa, 2025). Beyond its remarkable price dynamics, Erzurum provides a particularly suitable empirical context for examining spatial heterogeneity in housing markets. The city has a complex urban structure that includes a historic core with an organic urban fabric, as well as regularly and irregularly developed residential areas, newly planned growth areas, and officially designated urban regeneration zones. This pronounced morphological and functional diversity makes Erzurum an analytically rich case for investigating how structural, environmental, and accessibility-related factors shape housing prices in a spatially heterogeneous manner.

LITERATURE REVIEW

Housing prices are shaped by the interplay of supply-demand dynamics and a broad set of structural and environmental determinants (Wang et al., 2025). Within the housing economics literature, these determinants are commonly grouped into two main categories: (i) The physical and structural attributes of housing units and (ii) the locational and environmental characteristics of their surrounding context (Koramaz & Dökmeci, 2012; Uğurlar & Eceral, 2014; Genç & Çolak, 2025). Structural characteristics refer to the intrinsic physical properties of housings, such as floor area, building age, floor level, and the number of rooms and bathrooms, whereas locational and environmental characteristics encompass accessibility to transportation infrastructure, urban services, and green amenities that shape residential quality of life (Brown & Rosen, 1982; Kim et al., 2018; Lieske et al., 2021).

Structural attributes remain among the most consistently employed variables in empirical housing price models. Core physical characteristics, including housing size, age, and internal layout, have long been recognized as fundamental determinants of housing values (Can, 1990; Adair et al., 1996). Beyond these basic attributes, a growing body of research highlights the importance of building and neighborhood level amenities, such as elevators, covered parking, and location within a gated or secure site, which are generally found to exert positive price effects (Türel, 1981; Ebru & Eban, 2011; Ekşioğlu Çetintahra & Çubukçu, 2011; Kördiş et al., 2014; Genç & Çolak, 2025). Collectively, these findings suggest that housing market participants value not only physical space but also amenities that enhance comfort, security, and overall residential well-being.

Floor level constitutes another structural variable that has received substantial attention in the literature. Numerous empirical studies report a positive and linear relationship between floor level and housing prices, often interpreted as

reflecting privacy and reduced exposure to street-level disturbances (Hui et al., 2007; Cho et al., 2009; Du et al., 2018; Xiao et al., 2019; Yilmazer & Kocaman, 2020). However, this relationship is not universally linear. Chau et al. (2007), employing a Box-Cox transformation model, demonstrated that the price premium associated with higher floors varies according to contextual attributes such as scenic views. In housings lacking a view, marginal price gains diminish as floor level increases, whereas in units with a view, each additional floor generates a substantial price premium. These findings underscore the spatially heterogeneous nature of floor level effects and indicate that global linear specifications may fail to fully capture such localized dynamics.

Relatedly, the total number of floors in a building has been identified as an additional factor influencing housing prices. Several studies emphasize that high-rise developments may exert downward pressure on prices, particularly due to their association with higher density, crowding, noise exposure, perceived crime risk, and unfavorable microclimatic conditions. Wong et al. (2011) showed that, *ceteris paribus*, apartments in taller and denser buildings tend to transact at lower prices than those in shorter structures. Evidence from East Asian cities further suggests that clusters of high-rise buildings can exacerbate thermal discomfort by restricting natural ventilation and daylight access, thereby negatively affecting housing values (Li et al., 2018). Conversely, other studies report positive price effects associated with taller buildings, often reflecting prestige or panoramic views in specific urban contexts (Alkan Gökler, 2017; Kim & Tepe, 2026). Together, these mixed findings highlight the context-sensitive nature of vertical development and building density effects.

At finer spatial scales, housing prices emerge as the outcome of spatially varying processes in which location-specific attributes play a decisive role (Goodman, 1978; Simpson, 1992). A substantial portion of this literature is grounded in classical monocentric urban models, which posit that housing and land prices decline with increasing distance from the central business district (CBD) due to rising travel time and commuting costs (Alonso, 1964; Mills, 1972; Muth, 1969; De Palma et al., 2005). However, as metropolitan regions have increasingly evolved toward polycentric urban structures, the explanatory power of distance to CBD alone has weakened (Koramaz & Dökmeci, 2012). The expansion of automobile dependence, the decentralization of employment and services, and comparatively lower land costs in peripheral subcenters have complicated the traditionally assumed negative distance-price gradient.

Within this context, accessibility indicators, particularly proximity to highways and major transportation corridors, have become widely used in housing price studies (Srouf et al., 2002; Tomal, 2020; Yilmazer & Kocaman, 2020; Genç & Çolak, 2025; Soltani et al., 2026). While improvements in

transportation infrastructure can enhance accessibility and thereby increase housing values (Tsai, 2018), the literature also documents substantial negative externalities associated with living near main roads, including noise pollution, air quality degradation, and traffic congestion (Gan et al., 2021). For instance, empirical evidence from Utah indicates that these negative effects may outweigh accessibility benefits in certain contexts (Tian et al., 2017). Accordingly, prior studies report both positive and negative accessibility effects separately (Porta et al., 2009; Xiao et al., 2016; Tian et al., 2017; Kang, 2019; Abdulla & Ibrahim, 2023; Liu et al., 2024), suggesting pronounced spatial variability and highlighting the limitations of global modeling approaches that impose a single coefficient across space.

More recently, walkability has emerged as a prominent spatial determinant of housing demand and property values. Walkable urban environments are associated with health, environmental, and social benefits, which can be capitalized into higher housing prices (Kim & Kim, 2020; Huang et al., 2024). Empirical studies increasingly document positive associations between neighborhood-level walkability and housing values (Luo et al., 2025). While early research relied primarily on morphological indicators such as intersection density and block length, recent studies have emphasized network-based centrality measures, particularly closeness and betweenness, to more accurately capture pedestrian accessibility and movement potential (Zhang et al., 2021; Chakrabarti et al., 2022; Liu et al., 2024). Nevertheless, the majority of this literature continues to rely on global regression frameworks, which remain limited in their ability to detect spatially varying effects.

Visual and environmental attributes, particularly urban vegetation, have also gained increasing attention in housing price research (Aboelata & Sodoudi, 2019; Soltani et al., 2026). Among these, the NDVI has become one of the most widely used remote sensing indicators for quantifying urban green cover (Franco & Macdonald, 2018; Kim & Kim, 2020; Zambrano-Monserrate et al., 2021). Higher NDVI values generally indicate denser and healthier vegetation and are associated with improved air quality, urban heat island mitigation, and noise reduction (Strohbach et al., 2012; Haaland et al., 2015), as well as positive mental health and life satisfaction outcomes (Belcher & Chisholm, 2018; Wang et al., 2025). However, the effect of green amenities on housing prices is not uniform; prior studies emphasize that the magnitude and direction of this effect depend on contextual factors such as perceived safety, maintenance quality, and actual usage patterns (Chen & Jim, 2010), further underscoring spatial heterogeneity.

Table 1 synthesizes the key variables of prior studies on housing price determinants. Overall, the literature demonstrates that both structural and environmental variables exhibit spatially heterogeneous effects, with varying magni-

Table 1. Summary of empirical studies on structural, environmental, and network-based determinants of housing prices

Variable	
Floor area	Türel, 1981; Koramaz & Dökmeçi, 2012; Alkan Gökler, 2017; De Araujo & Cheng, 2017; Belcher & Chisholm, 2018; Yuan et al., 2018; Liu et al., 2019; Xiao et al., 2019; Gu et al., 2021; Barnes et al., 2025; Genc & Colak, 2025; Wang et al., 2025; Soltani et al., 2026
Number of rooms	Türel, 1981; Selim, 2009; Alkan Gökler, 2017; Belcher & Chisholm, 2018; Samad et al., 2020; Yilmazer & Kocaman, 2020; Sayın et al., 2022; Ben et al., 2023; Huang et al., 2024; Genc & Colak, 2025; Soltani et al., 2026
Age of building	Türel, 1981; Ebru & Eban, 2011; De Araujo & Cheng, 2017; Liu et al., 2019; Xiao et al., 2019; Kim & Kim, 2020; Gu et al., 2021; Sayın et al., 2022; Ben et al., 2023; Huang et al., 2024; Barnes et al., 2025; Genc & Colak, 2025; Kim & Tepe, 2026; Soltani et al., 2026
Number of floors	Alkan Gökler, 2017; De Araujo & Cheng, 2017; Belcher & Chisholm, 2018; Sayın et al., 2022; Huang et al., 2024; Genc & Colak, 2025; Wang et al., 2025; Kim & Tepe, 2026
Floor level	Kördiş et al., 2014; Du et al., 2018; Sadayuki, 2018; Xiao et al., 2019; Tomal, 2020; Yilmazer & Kocaman, 2020; Genc & Colak, 2025
Number of bathrooms	Alkan Gökler, 2017; Du et al., 2018; Kangallı-Uyar & Keten, 2020; Sayın et al., 2022; Sisman & Aydinoglu, 2022; Genc & Colak, 2025; Lee et al., 2025; Kim & Tepe, 2026
Heating type	Selim, 2009; Ebru & Eban, 2011; Ekşioğlu Çetintahra & Çubukçu, 2011; Alkan Gökler, 2017; Sayın et al., 2022; Ben et al., 2023; Genc & Colak, 2025
Covered parking availability	Selim, 2009; Ebru & Eban, 2011; Kangallı-Uyar & Keten, 2020; Tomal, 2020; Kopczewska & Ćwiakowski, 2021; Genc & Colak, 2025
Gated community	Ebru & Eban, 2011; Ekşioğlu Çetintahra & Çubukçu, 2011; Kördiş et al., 2014; Sayın et al., 2022; Genc & Colak, 2025
Smart home	Sadayuki, 2018; Kangallı-Uyar & Keten, 2020
Elevator availability	Türel, 1981; Selim, 2009; Kördiş et al., 2014; Liu et al., 2019; Tomal, 2020; Yilmazer & Kocaman, 2020; Gu et al., 2021; Sisman & Aydinoglu, 2022; Genc & Colak, 2025
Furnished	Ekşioğlu Çetintahra & Çubukçu, 2011; Kangallı-Uyar & Yayla, 2016; Önder & Turgut, 2018
Distance to CBD	Türel, 1981; Koramaz & Dökmeçi, 2012; Belcher & Chisholm, 2018; Du et al., 2018; Yuan et al., 2018; Liu et al., 2019; Xiao et al., 2019; Tomal, 2020; Sayın et al., 2022; Huang et al., 2024; Liu et al., 2024; Genc & Colak, 2025; Lee et al., 2025; Kim & Tepe, 2026; Soltani et al., 2026
NDVI	Franco & Macdonald, 2018; Kim & Kim, 2020; Zambrano-Monserrate et al., 2021; Soltani et al., 2026
Street network connectivity	Abdulla & Ibrahim, 2023; Abdulla et al., 2023
Betweenness centrality	Porta et al., 2009; Xiao et al., 2016; Kang, 2019; Tan et al., 2019; Ye et al., 2019; Zhang et al., 2021; Chakrabarti et al., 2022; Liu et al., 2024
Closeness centrality	Porta et al., 2009; Xiao et al., 2016; Kang, 2019; Tan et al., 2019; Zhang et al., 2021; Chakrabarti et al., 2022

tudes and directions across urban contexts. Despite this, a large share of empirical research continues to rely on global models that assume spatial stationarity, thereby neglecting localized relationships. To address this gap, the present study adopts a GWR framework to estimate location-specific parameters and incorporates network-based accessibility indicators derived from sDNA, enabling a more realistic representation of urban connectivity and mobility potential than conventional distance-based measures.

MATERIALS AND METHOD

Study Area

Erzurum's urban development historically reflects different planning approaches (Figure 1a). The city's earliest developed areas form its historical core and present-day city

center, exhibiting a predominantly concentric development pattern until the 1950s. Following this period, urban expansion shifted toward a more linear form, largely structured along main transportation axes (Çamur et al., 2023). In recent decades, there has been a pronounced increase in new housing development in the northern and southern parts of the city.

The 1/5000-scale Master Development Plan, approved in 2014 with a target year of 2045, sets out the principal planning decisions guiding Erzurum's spatial development (Figure 1b). Within this framework, housing development areas are primarily designated in the northwestern and southwestern parts of the city and extend toward the expressway. Urban regeneration areas are defined where newly designated development zones intersect with the existing urban

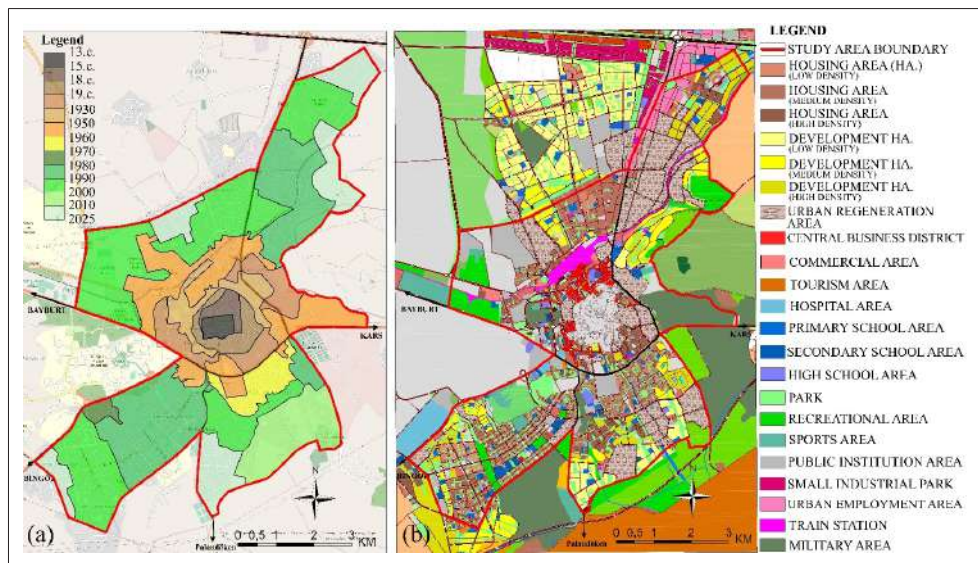


Figure 1. (a) The spatial development pattern of Erzurum, (b) 1/5000-scale Master Development Plan (Planevi Planning Office, 2014).

fabric, indicating that planning decisions directly shape the structure of housing supply and spatial density patterns. By contrast, housing areas expanding toward the urban periphery are generally planned at lower densities.

The southwestern development area began to develop after 1980, with the aim of providing an alternative to unplanned squatter settlements through cooperative housing projects that initially emphasized environmental balance (Terzi et al., 2025). However, the completion of the City Hospital investment in 2020 led to a rapid increase in housing demand in this area and generated strong pressure for intensive development. During this period, environmental considerations gradually weakened, and a tendency toward maximizing development density became evident. Accordingly, in the 2045 projection master plan, this area is defined as a high-density housing development area.

Another major development area is located in the north-eastern part of the city, where neighborhoods largely built during the 1980s have been designated as urban regeneration areas. In this zone, new housing development areas extending toward the expressway have also been proposed. This planning approach reflects a strategy that simultaneously promotes urban regeneration of the existing building stock and the spatial expansion of the city. Overall, planning decisions in Erzurum have played a decisive role in determining the location, density, and environmental characteristics of housing development areas, contributing to the emergence of differentiated housing market dynamics across the urban space.

For the purposes of this study, a cross-sectional dataset was compiled using complementary online real estate data sources. Endeksa.com, one of Türkiye's most comprehensive real estate analytics platforms, was initially consulted

to identify Erzurum as the province exhibiting the highest annual increase in housing prices in 2024, which motivated the selection of the study area. However, since Endeksa.com does not provide unit-level listing prices and detailed property attributes required for micro-scale spatial analysis, individual housing prices and property-specific characteristics were compiled from publicly available online real estate listings published on Sahibinden.com, one of the largest property advertisement platforms in Türkiye. The final dataset includes listing prices and property-specific characteristics for 1,596 apartments offered for sale in Erzurum during the June-July 2025 period. According to official statistics (TurkStat, 2025), housing market activity in Erzurum exhibits a concentration of both building permit issuance and transaction volumes during the summer months, which informed the selection of the study period. Moreover, the analysis adopts a narrow temporal window to ensure that observed price differences primarily reflect spatial and structural determinants rather than temporal variation.

To ensure data consistency and comparability, the analysis focused exclusively on residential properties categorized as apartments, excluding detached houses, duplexes, and basement units. The spatial distribution of the sampled properties in the study is illustrated in Figure 2. The spatial concentration of housing transactions exhibits a strong association with the city's urban development dynamics. The density map indicates a high concentration of transactions in areas surrounding the historical core of Erzurum and along its northwestern periphery. This pattern indicates that, despite the relatively older building stock in the central areas, regeneration pressures in adjacent neighborhoods and accessibility advantages continue to exert a significant

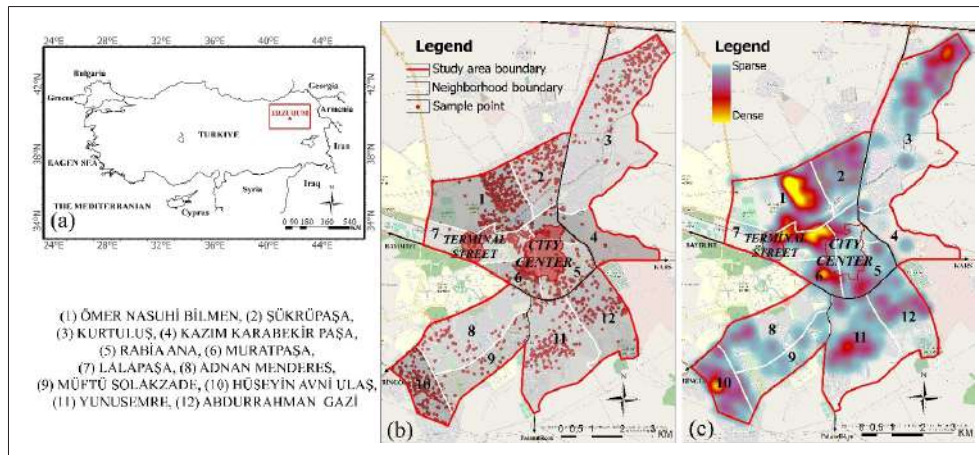


Figure 2. (a) The location of Erzurum, (b) Housing units' distribution, (c) Spatial heat map illustrating the concentration of housing units.

influence on housing market activity.

Furthermore, increasing concentrations of housing transactions are also observed in the northern and southern peripheral zones identified as development areas in the 1/5000-scale Master Development Plan. In particular, notable clusters of transactions emerge in the northwestern part of the city, especially within urban regeneration areas and around Terminal Street. These locations illustrate how new housing supply shaped by planning decisions, together with intensified commercial activity, generates spatially selective demand within the housing market.

The observed density pattern indicates that the housing market in Erzurum is not exclusively centered around the historical center. Instead, it displays a spatial configuration that evolves along planned development areas, regeneration zones, and major transportation corridors. This spatial pattern indicates a close relationship between housing market activity and urban planning decisions, thereby providing an essential contextual framework for interpreting the empirical findings of this study.

Explanatory Variables

To elucidate the determinants of housing prices, explanatory variables were systematically evaluated under two primary categories: Structural and environmental. The structural characteristics of a residence encompass its physical and equipment components, including the floor area (m^2), the number of rooms, the building age, the total number of floors, the floor level, the number of bathrooms, the heating type, the availability of covered parking, the location within a gated community, smart home features, elevator availability, and the presence of furnishings. These indicators, widely recognized in the literature as the fundamental parameters of hedonic price models, directly influence the market valuation of housing (Alkan Gökler, 2017; Kopczewska & Ćwiakowski, 2021; Sisman & Aydinoglu, 2022).

Environmental characteristics capture the locational and quality-of-life dimensions that shape housing values. Distance to the CBD (DCBD) was used to represent the monetary and temporal costs associated with access to the urban core (Alonso, 1964; Jin et al., 2022; Liu et al., 2024). In this study, the CBD was operationally defined as the historic and administrative core of Erzurum, where commercial activities and public services are most concentrated. Accordingly, the DCBD was calculated as the Euclidean distance from each housing unit to the CBD using the Near Distance tool in ArcGIS Pro.

Green area density was assessed via the NDVI, derived from Landsat 8/9 OLI satellite imagery. While many previous studies have defined green space indicators through official land-use classifications or planning inventories, this study directly measured vegetation density surrounding dwellings. In doing so, both the spatial concentration and ecological quality of greenery were incorporated into the model in an objective and fine-grained manner (Du et al., 2018; Samad et al., 2020).

Accessibility metrics were derived from connectivity, betweenness, and closeness indices, which capture the degree of spatial integration within the street network. As evidenced by Space Syntax and sDNA-based studies, these measures reflect not only spatial distance but also the positional importance of each housing within the urban network (Law et al., 2017; Abdulla & Ibrahim, 2023; Liu et al., 2024). In this study, the betweenness (TPbTA) and closeness (MAD) indices were calculated using the sDNA method with street network data obtained from Open Street Maps, using the widely accepted 800-meter walking distance threshold. This threshold is a commonly applied scale for pedestrian-level accessibility analyses (Li et al., 2023; Khosravi et al., 2024). To operationalize these indicators at the housing scale, network-based buffer zones with a 100-meter radius were defined around each property,

and the average index values within these buffers were assigned to the respective dwellings (Pozo et al., 2025). This approach preserved the theoretical 800 m pedestrian scale while generating housing-specific accessibility measures. The network-based buffer technique has been shown to offer a more realistic representation of spatial conditions than circular buffers, as it directly incorporates street network configurations (Güller, 2025).

In total, 17 candidate variables were initially considered (Table 2). Following statistical significance and multicollinearity diagnostics, nine variables were retained in the final model: Floor area, building age, number of floors, floor level, heating type, distance to the city center (DCBD), NDVI, connectivity, and TPBtA800. Multicollinearity was assessed using the Variance Inflation Factor (VIF) test, and variables with VIF values exceeding 7.5 were excluded (Wang et al., 2020). The retained variables yielded VIF scores between 1.04 and 1.96, indicating the robustness and reliability of the final model.

Geographically Weighted Regression

The empirical analysis began with an optimized hotspot

analysis, a spatial statistical technique designed to detect and visualize clustering patterns in housing prices (Figure 3). This procedure integrates both Global Moran’s I and Getis-Ord G_i^* statistics, enabling the identification of statistically significant concentrations of high and low values within the study area (Kortas et al., 2022; Hsieh & Yang, 2024). The Optimized Hotspot Analysis tool in ArcGIS Pro automatically determines the most appropriate distance band for the dataset, thereby minimizing the subjectivity associated with traditional hotspot methods (Esri, 2025).

Following this exploratory stage, GWR was employed to model the spatially heterogeneous relationships between structural and environmental variables and housing prices. Unlike conventional global regression models, which assume constant relationships across areas, GWR estimates location-specific coefficients, thus capturing the local variations that characterize housing market dynamics (Sisman & Aydinoglu, 2022).

A critical step in GWR calibration involves the selection of bandwidth. According to Bujanda & Fullerton (2017), the use of adaptive kernel bandwidths is preferable when ob-

Table 2. Summary of variables

Category	Variable	Variable definition and measurement method
Dependent Variable	PRICE	Total housing price
Structural variables	FLOOR AREA	Total usage area of the housing in the m ² unit
	NOROOM	Total number of rooms in the housing
	AGE	Time (year) from the date of construction of the apartment to the present day
	NOFLOOR	The total number of floors in the apartment
	FLOOR LEVEL	The floor level of the housing in the apartment
	NOBATHROOM	Total number of bathrooms in the housing
	HEATING TYPE	Stove-1, combi boiler-2, central heating-3, underfloor heating-4
	COVERED PARKING	Whether the apartment has a covered parking variable or not (available-1, not available-0)
	GATED COMMUNITY	Whether the apartment is in a gated community or not (within the gated community-1, others-0)
	SMART HOME	Whether the apartment is a smart home or not (smart home -1, others-0)
	ELEVATOR	Whether the apartment has an elevator variable (available-1, not available-0)
	FURNISHED	Whether the housing is furnished (furnished-1, unfurnished-0)
Environmental variables	DCBD	Distance to CBD (km)
	NDVI	Vegetation density index around housing
	CONNECTIVITY	Number of direct street links
	TPBtA	Betweenness index derived from sDNA, measuring how often a street lies on shortest paths
	MAD	Closeness index derived from sDNA, measuring average angular distance to all other nodes

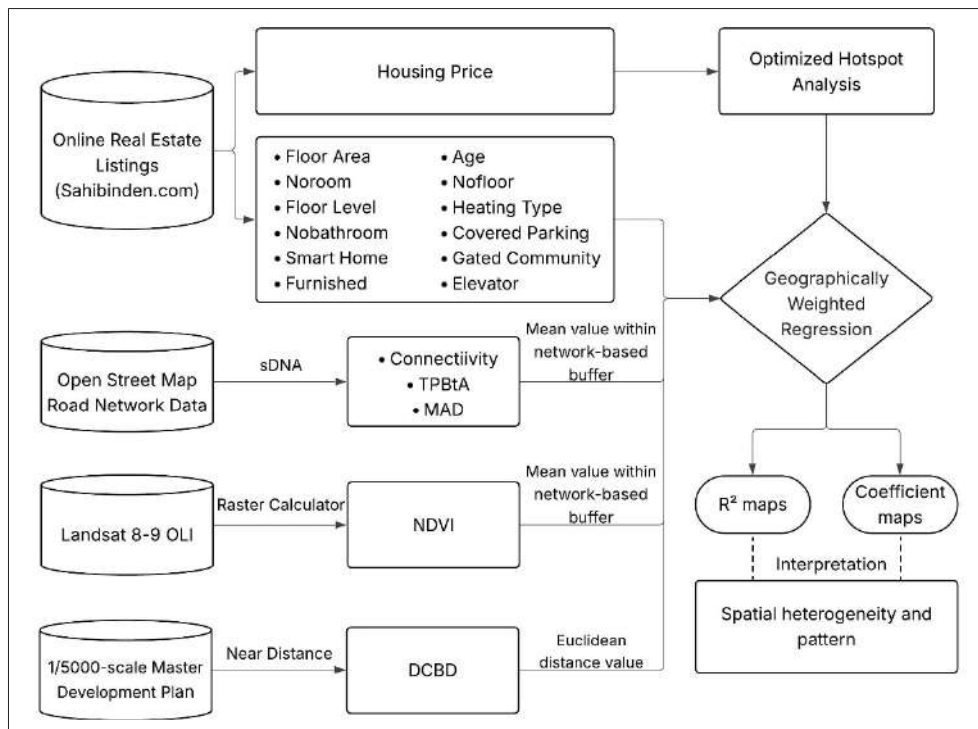


Figure 3. The method and procedure schema of the study.

servations are unevenly distributed, as it ensures that a fixed number of neighbors is considered for each location. This approach mitigates the biases that may arise from irregular densities. In contrast, fixed kernels apply the same spatial radius everywhere, which can distort results in contexts with clustered or sparse data (Moralı & Yılmaz, 2020; Güneş & Apaydın, 2022). In this study, an adaptive bandwidth with a Gaussian kernel weighting function was implemented. Bandwidth optimization was performed using the golden section search algorithm available in ArcGIS Pro, and the model specification with the lowest Akaike Information Criterion (AIC) value was selected for final analysis.

RESULTS AND DISCUSSION

Evolution of the Spatial Pattern of House Prices

The results revealed that residential property prices in Erzurum exhibited significant positive spatial autocorrelation, forming both high-high and low-low clusters (Figure 4). The southeastern part of the city was dominated by low-low clusters, whereas high-high clusters were concentrated in the northwestern and southwestern districts, corresponding to newly developed residential zones. Interestingly, the emergence of low-low clusters in certain northern districts—also classified as new development areas—highlighted the pronounced spatial heterogeneity in price formation.

In contrast, the central districts were largely characterized by low-low clusters or statistically significant but less coherent spatial groupings. This pattern diverges from the pre-

vailing tendency reported in the literature, which typically suggests a gradual decline in housing prices from the city center to the periphery (Kopczewska & Ćwiakowski, 2021; Wang et al., 2022b). Numerous studies indicate that high-price clusters tend to concentrate in urban cores, while low-price clusters are more frequently located in peripheral zones (Cui et al., 2018; Li et al., 2019; Zhang et al., 2019a).

However, these assumptions were insufficient to explain the Erzurum case. The findings suggest that the relatively aged and low-quality building stock in the city center, coupled with the shift in housing demand toward western development areas, has hindered the formation of high-price clusters in the core. Instead, new growth zones in the periphery have emerged as the focal point of price premiums. This dynamic indicates that Erzurum's spatial development dynamics differentiate the center-periphery relationship in the housing market. These findings provide an important contextual foundation for the first research question by demonstrating that housing price formation in Erzurum is inherently spatially heterogeneous and cannot be adequately explained by uniform center-periphery assumptions.

GWR Model Estimation and Fit Performance

The GWR model achieved strong explanatory performance, with an R^2 of 0.867 and an adjusted R^2 of 0.834, while the AICc value of 3661.98 confirmed the superiority of the local specification over global alternatives. Residual diagnostics further supported the robustness of the model: Standardized residuals followed an approximately normal

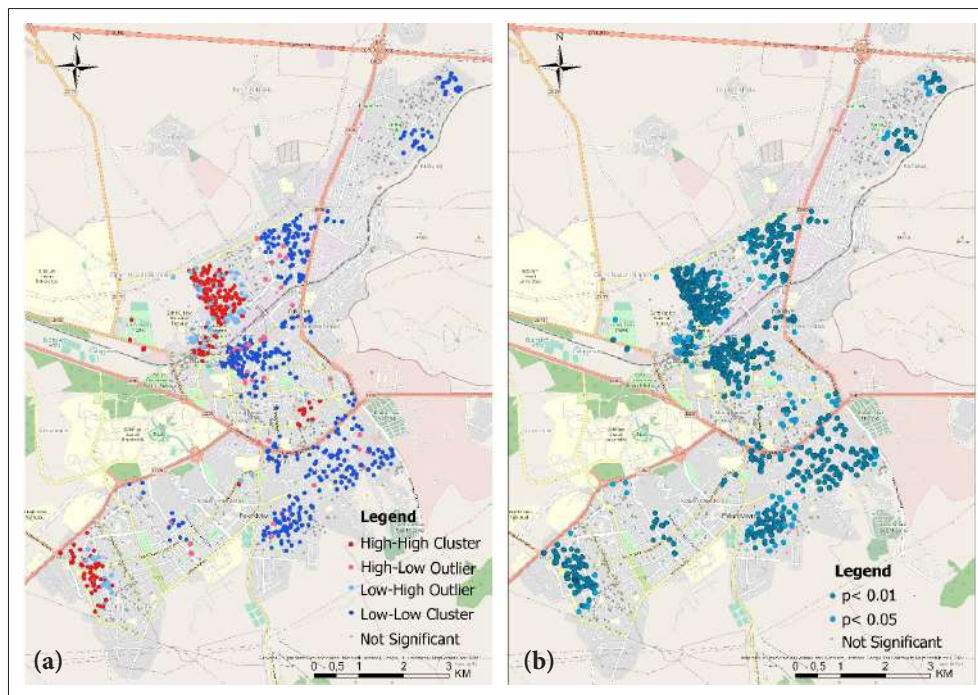


Figure 4. (a) Optimized outlier analysis and (b) p-values.

distribution, with most values within ± 2 standard deviations and only minor deviations at the tails, while the QQ plot showed close alignment with the theoretical normal line (Figure 5). Importantly, the Global Moran's I test of standardized residuals produced a non-significant result ($I = -0.009$, $z = -0.549$, $p = 0.583$). Moran's I measures whether model errors exhibit spatial clustering; a significant positive value would indicate that errors are spatially correlated and that the model failed to capture important spatial processes (Du et al., 2018; Güneş & Apaydın, 2022). In this study, the near-zero and insignificant Moran's I demonstrates that the residuals were randomly distributed across space, meaning that the GWR model had successfully captured the spatial dependence in housing prices and eliminated serious spatial autocorrelation in the errors. By effectively account-

ing for spatial dependence, the GWR framework provides strong evidence of the model's validity and reliability for addressing both research questions, particularly those concerning spatially varying effects.

The GWR model, by explicitly accounting for spatial heterogeneity, exhibited marked variation in its local explanatory capacity across the study area. The distribution of local R^2 values indicated that the model's explanatory power was not spatially uniform: Most observations exhibited a value between 0.70 and 0.90, with a mean of 0.76. This highlights areas where the model performs particularly well, as well as areas where unobserved local factors may weaken its explanatory strength. The GWR model recorded its highest explanatory values in the southwestern districts and the lowest in the northeast, while its per-

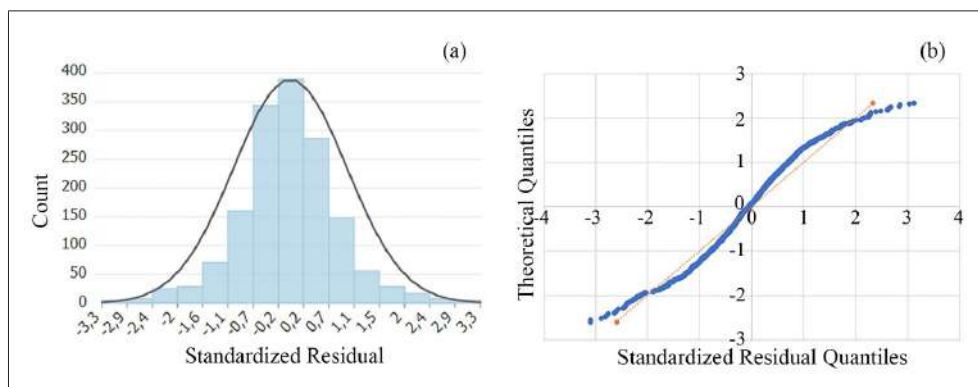


Figure 5. Residual diagnostics for the GWR model: (a) Histogram of standardized residuals with normal curve; (b) Normal QQ plot of standardized residuals against theoretical quantiles.

formance in the central and eastern parts of the city was relatively consistent (Figure 6).

Geographical Distribution of GWR Coefficient Estimates

The spatial distribution of GWR local parameters was examined by mapping only statistically significant results. The findings

indicated that the model's local coefficients varied across locations, demonstrating that the determinants of housing prices were heterogeneous in space (Figure 7a). In direct response to the first research question, these results confirm that the effects of structural and environmental characteristics are not spatially uniform but vary considerably across the urban fabric.

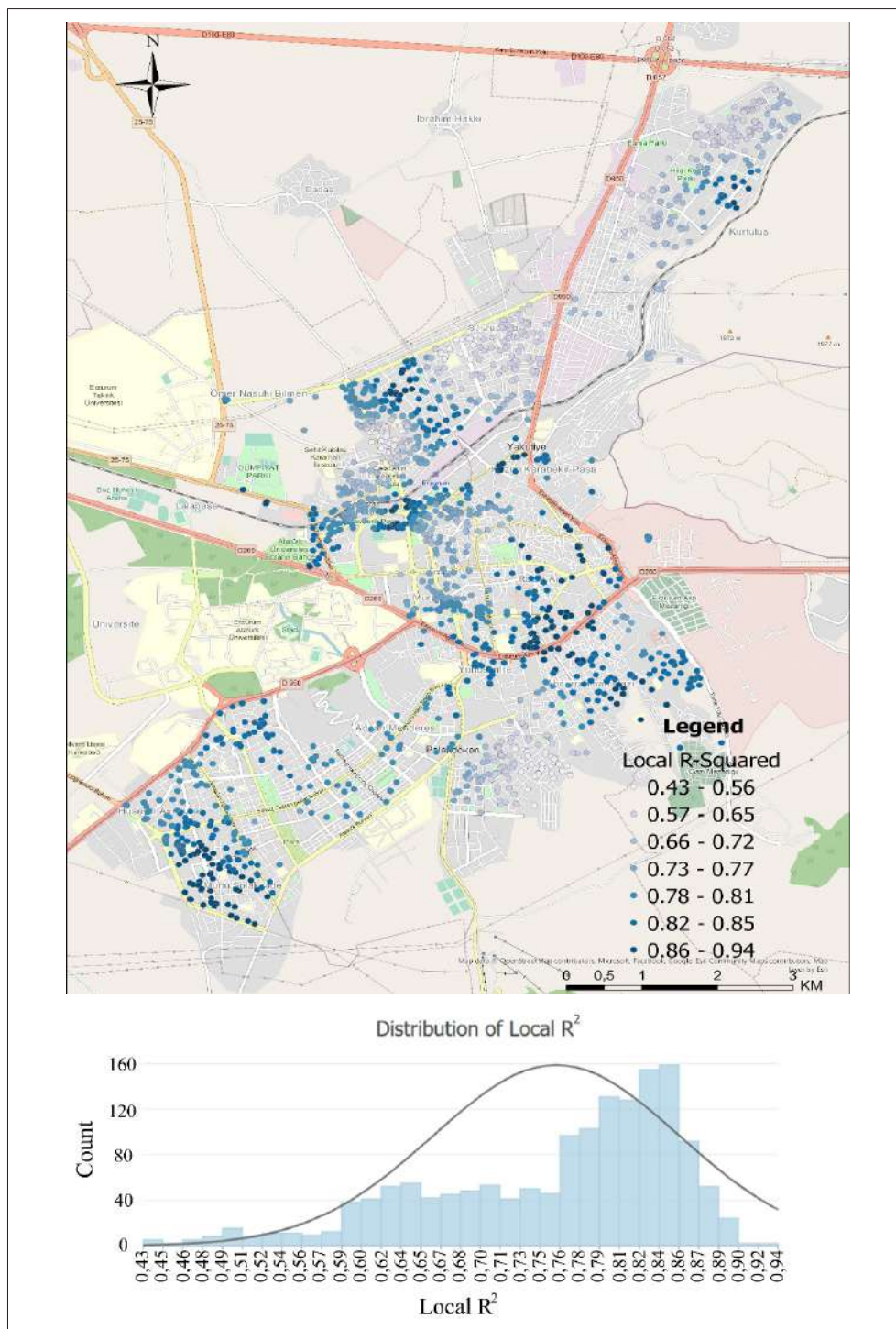


Figure 6. Geographical distribution of local R^2 values of the GWR model in the study area.

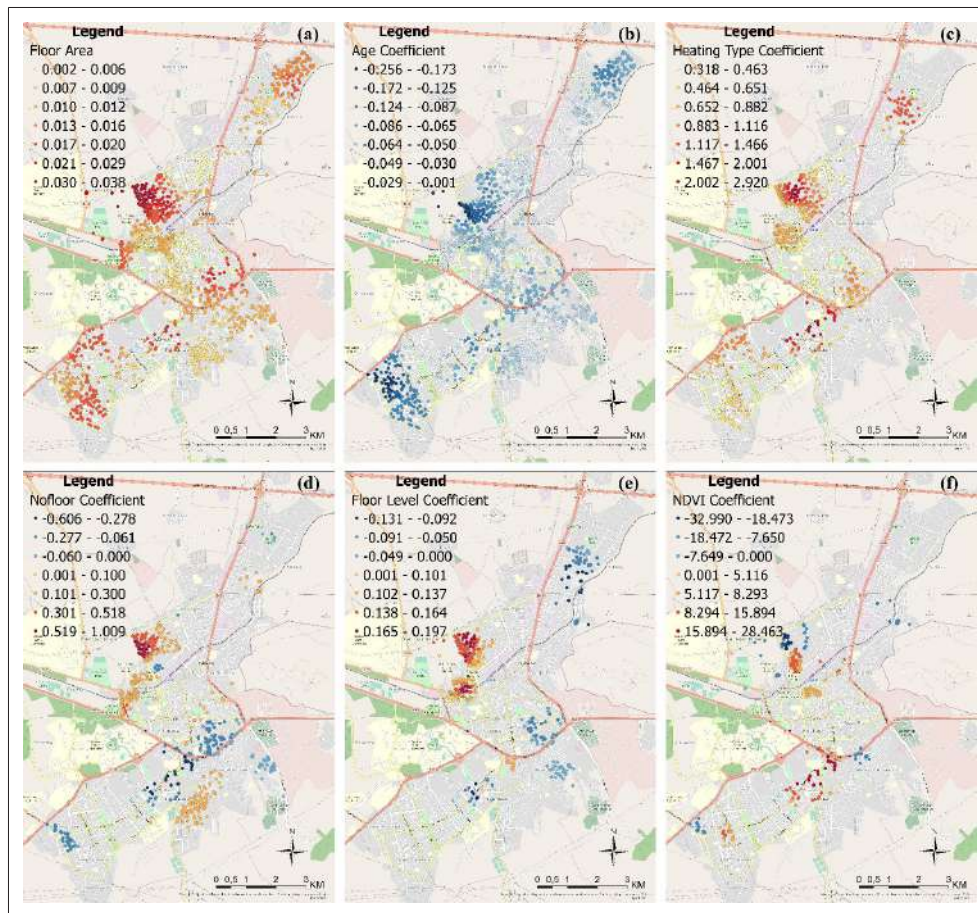


Figure 7. GWR model coefficients of (a) floor area; (b) age; (c) heating type; (d) Nofloor; (e) floor level; (f) NDVI.

Specifically, floor area (m²) and building age emerged as the most consistent predictors of housing values, both of which were found to be statistically significant in a large portion of the study area. This finding is consistent with the extant literature, which demonstrates a positive correlation between unit size and housing price (Moralı & Yılmaz, 2020; Sisman & Aydinoglu, 2022). A further examination revealed that floor area attained its highest coefficient values in the northwestern development zones. This phenomenon can be attributed to the diversity introduced by varying unit sizes (Zahirovich-Herbert & Gibler, 2014), which highlights how product heterogeneity increases price differentials and strengthens the role of square footage as a determinant of value.

The building age variable exhibited a negative correlation with prices, as expected (Figure 7b). This result may be explained by buyers' preference for newer buildings (Sisman & Aydinoglu, 2022; Wang et al., 2022a) and the advantages of reduced maintenance and improved equipment, particularly under Erzurum's severe winter conditions (Tian et al., 2017). The effect of building age was most pronounced in high-density development zones in the southwest and northwest, while its impact was weakest in the CBD and

the Terminal Street corridor, where commercial activity is particularly dense. In line with prior research, the mitigating influence of centrality indicates that the locational advantages of core districts offset the depreciation effect of older building stock (Tomal, 2020; Güneş & Apaydın, 2022). This pattern underscores the notion that the role of building age in shaping housing values is highly context-dependent. In areas proximate to urban centers, the location advantage mitigates the value loss associated with older buildings.

Heating type had a stronger influence on housing prices than both floor area and building age (Figure 7c). Local coefficients increased from individual systems to central heating, indicating that centrally heated buildings commanded higher values. This finding aligns with literature emphasizing that central systems enhance real estate value by improving energy efficiency, reducing costs, and lowering emissions (Noh et al., 2025). Given Erzurum's harsh climate, this result is unsurprising, yet the spatial distribution revealed variability: The strongest coefficients were recorded in northwestern development areas, while the effect in Yıldızkent was relatively weak. This suggests that

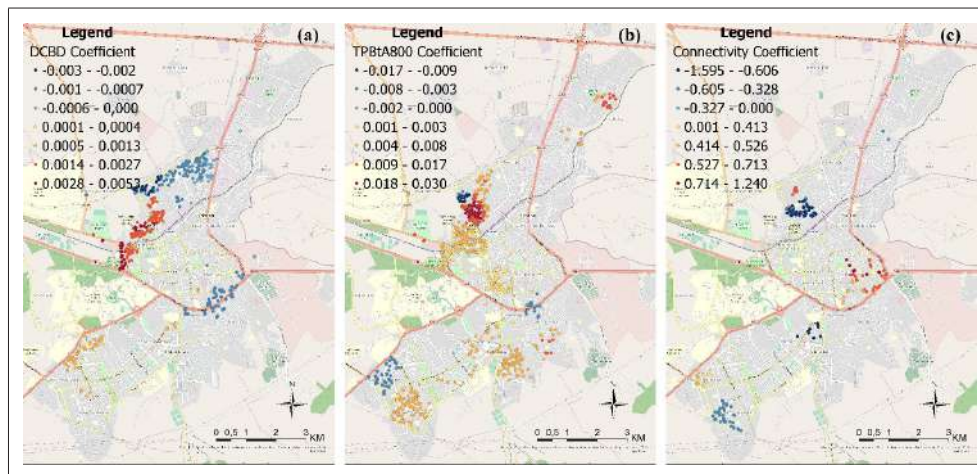


Figure 8. GWR model coefficients of (a) DCBD; (b) TPBtA800; (c) connectivity.

widespread adoption of central heating reduces local differentiation. Overall, heating infrastructure emerges as not merely a technical provision but also a strategic determinant of market value.

The nofloor variable exhibited a price-increasing role in the majority of the city (Figure 7d). In new development zones and commercial areas such as Terminal Street, additional floors significantly raised housing values. This finding is consistent with previous studies suggesting that nofloor exerts a positive influence in dense and centrally located neighborhoods (Sisman & Aydinoglu, 2022). Similarly, in Kayakyolu, located in the south, multi-story buildings contributed to higher values due to modern construction techniques, amenities such as elevators and parking, and the Palandöken views advantage. Conversely, in older neighborhoods, an increase in nofloor was associated with lower prices, particularly in Yenişehir and the eastern periphery. Here, multi-story stock appeared to be less desirable, likely due to structural deterioration and seismic risk concerns (Yiu & Cheung, 2022; Shi & Naylor, 2023). These patterns demonstrate that nofloor can be value-enhancing or value-reducing depending on neighborhood conditions.

The floor level variable demonstrated positive effects in new development areas but weaker or negative impacts in older districts (Figure 7e). Unlike earlier studies that generally reported uniformly positive effects (Li et al., 2019; Sisman & Aydinoglu, 2022), the present analysis indicated that higher floors reduced values in older neighborhoods. Poor insulation in upper floors of aged buildings under harsh winters appeared to drive this trend. Conversely, in new housing zones on the plain, upper floors became more desirable due to better air quality, views, and reduced noise (Saphores & Aguilar-Benitez, 2005; Lin et al., 2014; Cellmer et al., 2020). Even in areas with older stock near Buhara Hospital, upper floors were associated with a higher value, likely due to traffic and pollution lowering the attractiveness of ground-level units (Lu et al., 2023). These findings highlight that floor

level effects are mediated by both structural conditions and environmental quality.

NDVI generally emerged as a value-enhancing factor (Figure 7f). Greenery improves quality of life by mitigating noise and air pollution, thereby supporting housing values (Tian et al., 2017; Kopczevska & Ćwiakowski, 2021). The willingness of Erzurum residents to pay more for green amenities is consistent with prior findings (Du et al., 2018; Liebelt et al., 2019; Wu et al., 2019; Kim & Kim, 2020). Yet, in some peripheral development areas, higher NDVI was paradoxically linked to lower prices. This outcome reflects that the quantity and quality of vegetation matter: Agricultural plots, vacant land, and immature landscaping did not contribute to higher values. Thus, the decisive element in housing markets is not mere vegetation density but the availability of accessible, functional, and high-quality green spaces.

The findings indicated that DCBD coefficients were negative in the southern periphery of the city center and in the northern part of the city, confirming that prices decreased with distance (Figure 8a). This finding aligns with prior studies showing that residential proximity to commercial centers supports higher values (Du et al., 2018; Wu et al., 2019). However, this relationship weakened in new commercial hubs such as Yıldızkent and Terminal Street. The findings of the study indicate that local commercial sub-centers can offset distance to the historic core (Zhang et al., 2019a) and that buyers consider not only traditional centers but also commercial opportunities within their living environments.

With respect to the second research question, the spatial distribution of sDNA-based accessibility indicators reveals that street network characteristics play a context-sensitive role in shaping the spatial pattern of housing prices. The TPBtA800 index, representing pedestrian accessibility, generally emerged as a value-enhancing factor, though with spatial variations (Figure 8b). The findings indicated that

local coefficients were elevated in new development areas, while their effect remained comparatively constrained in the city center. This indicates that pedestrian-oriented accessibility contributes more strongly to price formation in areas where network maturity is still evolving (Tian et al., 2017). In contrast, it is noteworthy that the TPbtA800 index had a price-reducing effect on main boulevards. The observed outcomes can be attributed to a number of factors, including high traffic volumes, pedestrian-unfriendly street layouts, and environmental disadvantages in the area surrounding main boulevards. This suggests that buyers in these areas have a preference for human-scale environments and are willing to pay more for such conditions (Özüduru & Yücesoy, 2018; Liu et al., 2025). Moreover, the coexistence of high-rise density in these corridors further reinforced negative pricing effects, highlighting the market drawbacks of density-oriented regulations. Therefore, it is concluded that while the betweenness index is critical in explaining housing values, it should be supported by pedestrian-focused interventions.

Finally, the connectivity coefficients revealed that, in contrast to the betweenness index, higher connectivity along major streets increased prices (Figure 8c). These results demonstrate that sDNA-derived accessibility metrics contribute to explaining the spatial configuration of housing prices beyond traditional distance-based measures, thereby directly addressing the second research question. Moreover, the findings indicate that local access opportunities are more influential for housing markets than global centrality measures (Law et al., 2017; Yang et al., 2018; Abdulla & Ibrahim, 2023). In mature network contexts, connectivity enhanced accessibility advantages and market appeal. By contrast, in new development zones, higher connectivity failed to improve prices, largely because links often terminated in dead ends within an incomplete network structure. Thus, immature street networks produced fragmentation rather than functional benefits. This underscores that the relationship between local access and global centrality is highly context-sensitive, and spatial morphology can exert divergent effects depending on the developmental stage of the urban fabric.

CONCLUSION

This study reveals the spatial heterogeneity of structural and environmental determinants of housing prices, demonstrating that real estate markets are shaped not only by supply-demand dynamics but also by urban form, environmental quality, and infrastructure. The findings highlight the qualities households prioritize in their housing preferences, thereby offering concrete guidance for urban planning and housing policy design.

By employing network-based accessibility metrics, this research departed from conventional approaches that rely primarily on distance-based measures. The results indicate

that street networks function not merely as transport corridors but as integral components of urban infrastructure that influence housing market dynamics. In particular, spatial network indicators such as connectivity and betweenness illustrate how local access and global centrality differentially affect prices. Consistent with previous studies, higher levels of connectivity are associated with increased housing values in mature urban networks (Tian et al., 2017; Abdulla & Ibrahim, 2023). However, the findings further demonstrate that the effect of betweenness is highly context-dependent. In line with Liu et al. (2024) and Chakrabarti et al. (2022), pedestrian-oriented betweenness in newly developing areas is more likely to support housing price premiums, whereas increased betweenness along traffic-dominated corridors tends to generate negative externalities. These results emphasize that accessibility indicators are not inherently value-enhancing; rather, their effects depend on network configuration, environmental conditions, and broader urban form.

Beyond accessibility, this study provides key insights into the complex interplay between structural and environmental variables in shaping housing markets, generating several planning-oriented implications.

1. Contrary to typical expectations in the housing market (Cui et al., 2018; Li et al., 2019; Wang et al., 2025), the relocation of high-priced housing clusters toward the northwestern and southwestern peripheries of Erzurum reflects a shift in planning-driven housing attractiveness. When combined with the relative inadequacy of the aging central housing stock, this trend underscores the need for integrated planning strategies that simultaneously promote central area regeneration and carefully manage peripheral expansion. Achieving this balance is essential for achieving equitable and sustainable urban development.
2. The strong and spatially differentiated influence of heating systems highlights the critical role of energy infrastructure in housing markets, particularly in cold-climate cities. In line with Noh et al. (2025) and Ben et al. (2023), centralized heating systems are found to significantly increase housing values, suggesting that energy-efficient infrastructure should be treated as a core element of housing policy rather than a secondary technical consideration. Moreover, the locally varying effects of building height and floor level (Chau et al., 2001; Xiao et al., 2019) indicate that density regulations should be context-sensitive. It demonstrates the need to avoid uniform standards that do not take into account environmental conditions, building quality, and neighborhood characteristics.
3. The spatially heterogeneous effect of NDVI confirms the notion that environmental quality, rather than the mere presence of green space, exerts a pivotal influence on housing price formation. Consistent with Kim & Kim (2020) and Soltani et al. (2026), accessible, well-integrated, and function-

al green areas are associated with positive price premiums, whereas undeveloped or poorly integrated vegetation tends to exert weaker or even negative effects. This result highlights the importance of moving beyond quantitative green space targets toward qualitative planning approaches that emphasize accessibility, usability, and ecological integration.

Methodologically, the use of GWR allowed the study to effectively capture local-level price determinants while addressing both spatial heterogeneity and autocorrelation. Nevertheless, several limitations should be acknowledged. First, the analysis relied on cross-sectional data, and future research incorporating longitudinal datasets could provide insights into temporal dynamics. Second, a uniform bandwidth was applied across variables; adopting multiscale GWR would enable more nuanced detection of variable-specific effects. Finally, incorporating finer-grained classifications of social infrastructure variables, such as education and health facilities, may enhance explanatory power.

In conclusion, this study demonstrates the multidimensional link between urban planning and real estate markets and offers two key messages for planners: (i) Spatial context fundamentally alters the effect of the same variable on market outcomes; and (ii) structural investments should be coupled with environmental quality to foster sustainable and balanced growth in housing markets.

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