ISSN: 1648-715X / eISSN: 1648-9179

VILNIUS TECH
Vilnius Gediminas Technical University

INTERNATIONAL JOURNAL OF STRATEGIC PROPERTY MANAGEMENT

2025
Volume 29
Issue 3
Pages 215–231
https://doi.org/10.3846/ijspm.2025.24225

ENHANCING REAL ESTATE MASS APPRAISAL IN TYPE II METROPOLITAN CITIES: A GIS-MGWR APPROACH

Yu ZHAO, Jixiang ZHANG*, Xuejia SHEN, Miao YU, Wenbo ZHENG

School of Management, Shenyang Jianzhu University, Shenyang, China

Article History:
- received 22 October 2024
- accepted 30 April 2025

Abstract. At present, China's real estate appraisal sector confronts a number of challenges, including low appraisal efficiency, significant human influence, lack of objectivity, and absence of unified standards. Particularly, conducting a scientific, precise, and efficient mass appraisal of existing housing is vital for fostering the industry's healthy development. This study adopts Zhangjiakou City in Hebei Province as a case study, integrating Geographic Information Systems (GIS) and utilizing the Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), Semi-parametric Geographically Weighted Regression (SGWR), and Multiscale Geographically Weighted Regression (MGWR) models to assess the prices of existing housing. The research delves into the specific challenges in mass appraisal of real estate within Type II metropolitan cities. The study reveals spatial heterogeneity in the prices of existing housing in Zhangjiakou City and shows that the MGWR model excels in mass appraisal of housing prices in Type II metropolitan cities. This research offers strategic guidance for real estate market investment and transactions in Zhangjiakou City and provides valuable references for other Type II metropolitan cities in real estate appraisal practices, market analysis, and policy formulation.

Keywords: housing price, mass appraisal, real estate, Geographic Information Systems (GIS), Multiscale Geographically Weighted Regression (MGWR), spatial autocorrelation, Type II metropolitan cities.

*Corresponding author. E-mail: *jixiangzhang@stu.sjzu.edu.cn*

1. Introduction

Fluctuations in real estate prices not only directly impact the living standards of residents but also mirror the dynamic changes in urban development (Cardone et al., 2024). In the process of urbanization in China, the real estate market in large cities, as a vital component of urban economic development, is increasingly capturing attention (An et al., 2024). By 2014, megacities and super cities such as Beijing, Shanghai, and Guangdong Province had already begun to exhibit counter-urbanization trends, but these cities' development patterns, population scales, and economic levels significantly differ from those of Type II major cities, reflecting new tendencies in the urbanization process and highlighting the importance of conducting scientific appraisal of existing real estate in secondary large cities (Yu et al., 2024). Type II major cities face different problems and challenges in the urbanization process compared to megacities, thus requiring specific research to explore sustainable development paths suitable for these cities.

According to the "Notice on Adjusting the Standards for the Division of Urban Sizes" issued by the State Council, Zhangjiakou has been positioned as a Type II major city with significant geographical advantages, providing us with a research entry point. At the same time, the development of Zhangjiakou's real estate market has benefited from its local geographical advantages and is closely linked to the steady growth of its economy and the acceleration of urbanization. The successful hosting of the 2022 Beijing Winter Olympics has further enhanced Zhangjiakou's international image, injecting new vitality into the real estate market, offering us a unique window of observation. Therefore, against this backdrop, this study selects Zhangjiakou City in Hebei Province, China, as a representative of Type II major cities to explore the uniqueness and complexity of its real estate market prices.

In summary, this study takes Zhangjiakou City as a case study to simulate and verify the applicability of various geographically weighted regression models in the mass appraisal of real estate in Type II major cities, discussing the spatiotemporal heterogeneity of their influencing factors with scientific effectiveness. This is not only instructive for the real estate market management and planning of Zhangjiakou itself but also provides reference methods and tools for other cities of similar scale facing similar issues. With this scientific assessment framework, other Type II major cities will better understand the dynamics of their local real estate markets, consider the impact of spatial heterogeneity on housing prices, and thus more accurately formulate relevant policies and measures in urban planning, resource allocation, and economic development strategies, enhancing the competitiveness of the city and the quality of life for residents.

2. Literature review

2.1. Applications of geographically weighted regression

Spatial heterogeneity in housing prices has emerged as a key research focus in China, with Geographically Weighted Regression (GWR) and its extensions playing pivotal roles. Studies employing GWR models have investigated neighborhood characteristics' impact on housing resale prices in cities like Zhuhai and Hangzhou (Liu & Strobl, 2023; Wen et al., 2017), revealing significant spatial disparities and highlighting the models' superiority over traditional OLS methods. Research on factors such as human settlement suitability (Luo et al., 2021), cultural heritage (Franco & Macdonald, 2018), and urban appearance (Jia et al., 2022) has demonstrated their influence on property values and urban development across various regions (Zhao et al., 2023). These findings underscore the importance of considering spatial heterogeneity and scale effects for a comprehensive understanding and prediction of property value dynamics and sustainable urban planning. Moreover, GWR has proven valuable in assessing the impact of rapid urbanization and land expansion on residential land prices in cities like Wuhan, providing insights for urban planning and development (Yang et al., 2020).

On the international front, GWR and its extended models have also gained traction in addressing spatial heterogeneity in housing prices across different countries and regions. In Austria, for example, the Multiscale Geographically Weighted Regression (MGWR) model has provided insights into the spatial distribution of single-family housing prices, offering a nuanced understanding beyond traditional fixed-effects models (Helbich et al., 2014). Similarly, researchers have utilized MGWR to assess the influence of commuter rail accessibility on residential land prices (Le Boennec et al., 2022), thereby enriching urban planning initiatives geared towards fostering sustainable development (Kurkcuoglu, 2023). Furthermore, studies in diverse contexts such as India and Egypt have utilized GWR to explore the influence of environmental amenities and large-scale infrastructure projects on housing prices, highlighting the versatility of these models in different socio-economic settings (Bera et al., 2018).

2.2. Advancements in modeling and mass appraisal technologies

Technological advancements spurred the development of new models. For instance, researchers established a spatial autoregressive model incorporating quantile regression methods to examine the correlation between bus stations, real estate prices, and land value taxes (Hwang & Quigley, 2006). The integration of geographically weighted regression techniques into spatial hedonic models has further enabled the estimation of the impact of land-use conversion on housing prices (Geniaux et al., 2011). They utilized the Unilateral Geographic and Temporal Weighted Regression and its multi-scale extension to analyze the spatiotemporal characteristics of housing prices in Beijing (Zhang et al., 2021). To investigate the impact of visual contact with green spaces on housing prices, the study utilized machine learning and hedonic modeling methods (Wu et al., 2022). Additionally, researchers used online visual surveys and machine learning models to collect designers' perceptions of street design quality in Shanghai. They evaluated housing prices based on the predicted subjective perceptions (Qiu et al., 2022). Researchers also proposed a supervised regularized regression method that accounted for spatial autocorrelation to predict housing prices (McCord et al., 2022). Introducing an innovative composite modeling approach, the researchers emphasized integrating models rather than simply comparing them. This approach expands the mass appraisal paradigm and enhances appraisal performance (Hermans et al., 2022, 2023).

In addition, GIS technology has been widely applied in real estate mass appraisal, particularly leveraging its advantages in handling spatial data for pricing model research (Aladwan & Ahamad, 2019). The economic value of Singapore's urban green infrastructure was explored through the hedonic pricing method and integrated GIS methods (Dell'Anna et al., 2022). Sisman et al. (2023) used GIS to organize geographic and regional data of the area. They conducted a Pearson correlation analysis to evaluate standard development models and associated sub-criteria for bulk real estate mass appraisal.

In summary, GWR and its extended models are capable of capturing the spatial heterogeneity of real estate prices and have shown broad application prospects in real estate mass appraisal. GIS technology enables spatial analysis and visualization of these influencing factors, thereby enhancing the understanding of spatial relationships within cities. However, current research has mostly focused on megacities or super cities, neglecting the fact that the next-tier large cities, due to their unique economic, social, and geographical characteristics, may require different appraisal methods and model adjustments.

This study employs GIS technology along with OLS, GWR, SGWR, and MGWR models to conduct a comprehensive mass appraisal of existing housing in Zhangjiakou City, a typical Type II major city. By simulating and verifying the applicability of these models in the mass appraisal of Zhangjiakou's real estate, the study not only provides new perspectives and tools for real estate appraisal in Type II major cities, improving the efficiency and accuracy of appraisal, but also offers a scientific basis for the formulation of urban planning and economic policies in Zhangjiakou City.

3. Data sources and spatial analysis

3.1. Regional characteristics analysis

3.1.1. Regional overview

Zhangjiakou, located in the northwest of Hebei Province. Geographically situated between 113° 50′ to 116° 30′ East longitude and 39° 30′ to 42° 10′ North latitude, Zhangjiakou features a distinctive "mountain city" landscape. Spanning

36,357 km^2, it governs six districts and ten counties, with a permanent population of approximately 4.0746 million people as of the end of 2022. The development of Zhangjiakou's real estate market is significantly influenced by various factors, including geography, economy, and society, underscoring the practical importance of studying it.

3.1.2. Data selection and processing

The study primarily utilized the Gaode POI (Point of Interest) download tool and the Gaode Map Coordinate Picker to obtain the necessary POI data. Given the significant differences in housing prices between the county areas and the urban district of Zhangjiakou, spatial analysis focused on the sample data of existing housing in the Qiaoxi District and Qiaodong District of Zhangjiakou's urban area. The following process was adopted to collect and preprocess the sample data, as illustrated in Figure 1.

1. The characteristic variables of the housing samples were obtained from real estate transaction websites, primarily from housing data sourced from Lianjia.com for September 2023, supplemented by Anjuke.com.
2. To ensure consistency, only villa and apartment types were included in the sample selection, comprising typical second-hand residential houses with a 70-year property right.
3. During sample selection, 118 abnormal data entries and some duplicate data were removed, such as samples with excessively high or low housing prices, resulting in 883 remaining sample data entries. The study focused on the existing housing within the urban district.

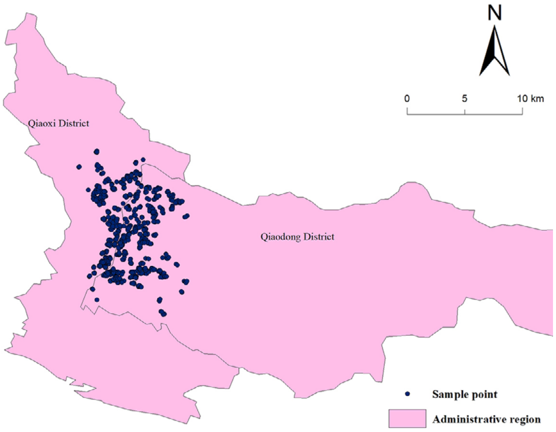


Figure 1. Sample distribution map

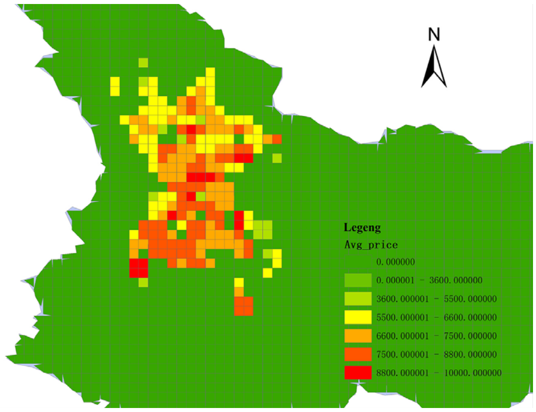


Figure 3. Fishnet analysis chart of housing prices in Zhangjiakou City

3.1.3. Normality test and spatial distribution trend analysis

Figure 2 indicates that the Q-Q plot of the original housing price data roughly aligns with the 45° reference line. This suggests that the housing prices in Zhangjiakou are approximately consistent with the characteristics of a standard normal distribution.

Fishnet analysis provides a clear and intuitive display of the spatial variation trends of data. In this study, based on the actual situation of Zhangjiakou City, a 500×500 m grid cell is selected to divide the study area into several grids and construct a fishnet analysis diagram. As shown in Figure 3, green and yellow grids are mostly located in the north, while orange and red grids are significantly more in the south than in the north, and dark-colored grids are more concentrated in the central area, that is, along the boundary between Qiaodong District and Qiaoxi District. It can be concluded that the prices of existing housing in the central and southern parts of Zhangjiakou City are higher than those in other areas. This result provides important support for the accuracy and effectiveness of future spatial analysis.

3.2. Spatial autocorrelation analysis based on GIS

3.2.1. Global spatial autocorrelation

Global spatial autocorrelation analysis is crucial for understanding the large-scale patterns of housing price distribution in Zhangjiakou. Utilizing the Global Moran's I index allows us to quantify the extent to which similar house prices are clustered in specific areas, thus identifying regions with

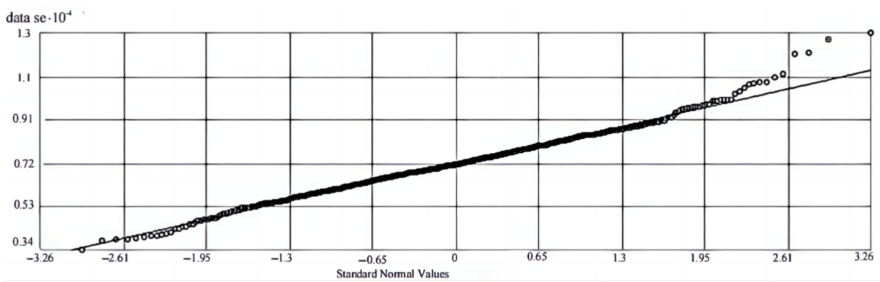


Figure 2. Normal Q-Q plot of raw data

consistent market behavior. The significance of the Global Moran's I index value is assessed using Z-values and P-values, with the calculation equation as follows:

$$I = \frac{n}{s_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}; \tag{1}$$

$$s_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}. \tag{2}$$

In this context, z_i represents the deviation of the attribute of a feature i from its mean value $\left(x_i - \bar{x}\right)$, z_j represents the deviation of the attribute of a feature from j its mean value $\left(x_j - \bar{x}\right)$, $w_{i,j}$ is the spatial weight matrix between feature i and j, n is the total number of features or the number of samples, and s_0 is the sum of all spatial weights.

The presence of spatial autocorrelation can be tested using the statistical quantity Z, which is calculated as follows:

$$E(I) = \frac{-1}{n-1}; \tag{3}$$

$$Z_I = \frac{I - E(I)}{\sqrt{V(I)}}; \tag{4}$$

$$V(I) = E(I^2) - [E(I)]^2. \tag{5}$$

Z-scores are standardized statistical measures, and their specific values and implications can be referenced from Jiao and Liu (2012).

3.2.2. Local spatial autocorrelation

Local spatial autocorrelation analysis can identify local clustering patterns in spatial data, allowing detailed study of micro-level changes within specific communities or areas in Zhangjiakou. This helps identify areas deviating from city-wide trends due to unique socio-economic conditions or localized urban development (Anselin, 1995). The equations are as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j} (i \neq j). \tag{6}$$

In the context of local spatial autocorrelation, x_i and x_j represent the attribute values of features i and j, respectively. $w_{i,j}$ is the spatial weight between feature i and j, n is the total number of features or the number of samples, and it is important that any i and j should not represent the same weight.

3.2.3. Spatial autocorrelation analysis

The Moran's I for housing prices in the study area is 0.343007, and the Z-score is 25.242283, indicating the presence of positive spatial autocorrelation. This suggests that similar housing prices tend to cluster spatially, with the city center or certain specific areas potentially having significantly higher housing prices than other regions, forming high-price clusters. A p-value of 0.000000 strongly suggests that the result of the Moran's I index test is highly significant.

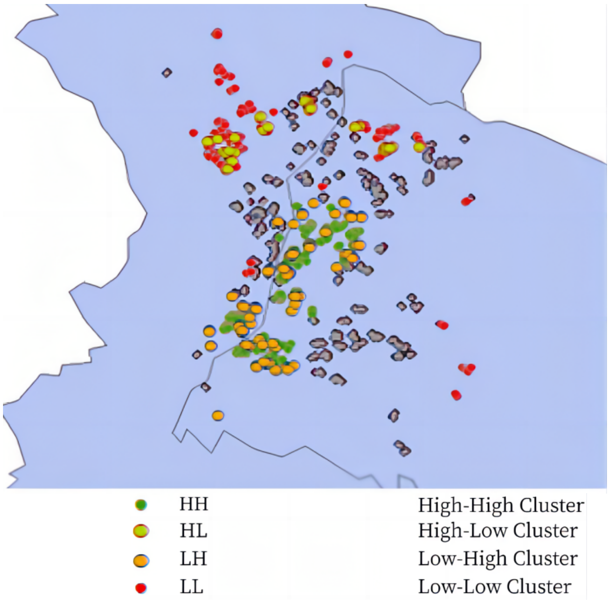


Figure 4. Results of local spatial autocorrelation analysis

Figure 4 illustrates the results of the local spatial autocorrelation analysis conducted on the collected data of existing housing prices in Zhangjiakou. Green indicates clusters of high values, while red signifies clusters of low values. From the cluster analysis chart, it can be observed that there is a pattern of clustering in both high and low housing prices, indicating the presence of local spatial autocorrelation in Zhangjiakou's housing prices. In summary, the spatial distribution of housing prices for existing homes in Zhangjiakou is not entirely random; instead, it exhibits significant spatial clustering.

4. Model construction and effectiveness verification

4.1. Establishment of the appraisal model indicator system

This study quantifies the characteristics that influence housing prices based on specific circumstances, employing methods such as actual values, dummy variable assignment, and value overlay. Detailed descriptions of the quantification methods and indicators can be found in Table 1. In particular, when evaluating the impact of elevators on housing prices, the effect of differing household numbers under the same elevator-to-household ratio is taken into account, with the elevator-to-household ratio serving as the baseline. The equation is as follows:

$$EH = \begin{cases} \dfrac{e}{h}, e = 1 \\ \dfrac{e}{h} \times 0.8, e \geq 2. \end{cases} \tag{7}$$

In this context, EH represents the quantified value of the elevator-to-household ratio, e denotes the number of elevators per unit, and h signifies the number of households per floor.

The quantification of the relationship between traffic and parking is a crucial factor in evaluating the overall livability and value of residential properties. These two factors are combined into one variable for quantification. The comprehensive quantification equation is as follows:

$$R = \begin{cases} \frac{p}{h}, \text{ Parking Space Ratio} \\ \frac{p}{h} + 1, \text{ Pedestrian-Vehicle Separation.} \end{cases} \quad (8)$$

In this context, R represents the quantified value of the traffic and parking relationship within the residential community, p denotes the number of parking spaces available in the community, and h signifies the total number of households in the community.

When evaluating the impact of hospitals and schools on housing prices, both distance and quantity are taken into account, along with the quality of the hospitals and schools. The equations are as follows:

$$H = n + q; \quad (9)$$

$$S = \begin{cases} d, \text{ School District} \\ d + 1, \text{ Non-School District.} \end{cases} \quad (10)$$

Additionally, specific local conditions, such as school district residency and the presence of hospitals, are taken into account, thereby enhancing the local adaptability and accuracy of the appraisal model. The quantified value for hospitals (H) considers the total number of hospitals n within a 2-km radius and the number of Grade-A hospitals q in the same area. The quantified value for schools (S) is based on the distance d to the nearest primary school.

Considering the characteristics of housing prices and their influencing factors, the significance level is set at 0.05 to reduce the risk of model interference. The results of the significance analysis can be found in Appendix Table A1. The significance levels of the variables for the number of rooms, halls, floor area ratio, and greening rate are all greater than 0.05. In addition, the significance of the area variable is 0.058. Based on common sense, location typically influences housing prices. Since 0.058 is less than 0.1, it can be considered significant at the 0.10 level of significance, suggesting that the area variable should be included in the study. After the screening process, collinearity diagnostics were conducted on the remaining 13 variables, with the results presented in Appendix Table A2. The findings indicate that all variables have VIF values significantly below 5, suggesting the absence of multicollinearity in the data. This allows for the continuation of further research.

4.2. Model category selection

This section examines the selection of appropriate spatial regression models for analyzing spatial data, a comparative analysis of four prominent models is presented:

1. OLS is a fundamental statistical method for modeling linear relationships between variables. It assumes no spatial dependence among the data, making it suitable for datasets where spatial effects are not significant.
2. GWR generates customized regression coefficients for each geographic location, allowing model parameters to vary spatially. This approach facilitates the identification of local spatial patterns.

Table 1. Indicator quantification and description

Variable	Quantification method	Range	Average value	Expected impact
Area	Ratio of total construction area to total number of households (m²)	39–280	100.05	+
Rooms	Total number of rooms per household	1–5	2.24	+
Halls	Total number of halls per household	0–3	1.6	+
Floor	High-rise: High 2, Medium 3, Low 1; Low-rise: High 1, Medium 2, Low 3	1–3	2.01	Unknown
Renovation	Bare 1; Simple 2; Fine 3; Luxury 4	1–4	2.17	+
Elevator	Ratio of elevators to households per floor	0–1.5	0.28	+
Traffic and parking	Equation (8)	0.03–2.8	0.83	–
Age	Difference between 2023 and the year of construction	1–33	12.24	–
Property fee	CNY/square meter month	0.16–2.9	1.3	+
Area	Ratio of total construction area to land use area (%)	10–60	31	–
Greening rate	Ratio of green area to occupied area (%)	0.87–4.5	2.1	+
Public transport	Number of bus stations within 0.5 km	1–16	6.28	+
Park	Number of parks within 1 km	0–4	0.96	+
Shopping center	Distance to the nearest shopping center (km)	0.04–4.5	1.51	+
Hospital	Equation (9)	0–9	3.48	+
Distance to government	Equation (9)	0.24–10	3.92	–
School	Equation (10)	0.08–3.8	2.23	–

3. SGWR incorporates both global and local spatial effects, enhancing the model's interpretability and flexibility. This distinction between fixed and space-varying effects provides a more nuanced understanding of underlying processes.
4. MGWR allows each variable in the model to have unique spatial weights based on its scale characteristics, accurately reflecting the complexities of spatial processes.

A comparative analysis of these models is shown in Table 2, highlighting their unique characteristics and applications.

Figure 5 illustrates the interrelationships among the four geographically weighted regression models, providing a clear conceptual framework for their application in spatial analysis.

Table 2. Comparison of spatial regression models

Model type	Equation
OLS	$y_i = \beta_0 + \sum_{k=1}^{k} \beta_k x_{ik} + \varepsilon_i,$ y_i: observed value at the i-th location; β_0: the intercept of the regression line; x_{ik}: the value of the k-th independent variable for the i-th observation; k: the total number of independent variables; ε_i: error term.
GWR	$y_i = \beta_0(\mathrm{u}_i, v_i) + \sum_{k=1}^{k} \beta_k (u_i, v_i) x_{ik} + \varepsilon_i (u_i, v_i),$ x_{ik}: value of the k-th variable at the i-th location; (μ_i, v_i): geographical coordinates of the i-th sample point; $\beta_k(\mu_i, v_i)$: spatially varying coefficient for the k-th variable;
SGWR	$y_i = \sum_{j=1}^{k_a} a_j x_{ij}(a) + \sum_{i=1}^{k_b} b_{il} x_{il}(b) + \varepsilon_i,$ k_a: the number of global variables; a_j: the regression coefficient for the j-th global variable; $x_{ij}(a)$: the i-th observation of the j-th global variable; k_b: the number of local variables; b_{il}: the regression coefficient for the l-th local variable at the i-th observation; $x_{il}(b)$: the i-th observation of the l-th local variable.
MGWR	$y_i = \sum_{j=1}^{k} \beta_{bwj} (u_i, v_i) x_{ij} + \varepsilon_i,$ b_{wj}: the bandwidth for the regression coefficients of the j-th variable.

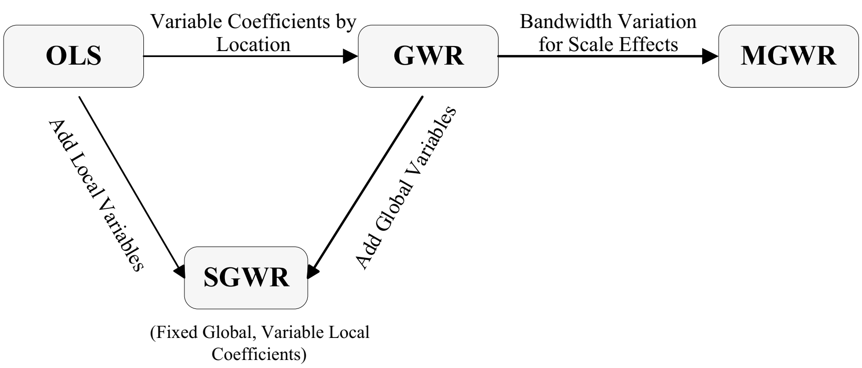


Figure 5. Interrelationships among geographically weighted regression models

4.3. Model evaluation and effectiveness verification

The International Association of Assessing Officers (IAAO) defines mass appraisal as a systematic process of estimating the value of a large number of properties on a specific date using standard methods, common data, and statistical testing. This process provides relevant ratio standards for evaluating the effectiveness of mass appraisal models. Specifically, it includes the Median Ratio (MR), Coefficient of Dispersion (COD), and Price Related Difference (PRD).

This study evaluates the efficiency of various models in mass appraisal of Zhangjiakou's existing housing stock by calculating these indicators. Furthermore, by considering the fit of each model to the sample data, a comprehensive assessment of the models' performance is conducted to identify the optimal mass appraisal model suitable for Zhangjiakou, a Type II city.

4.3.1. MR appraisal

MR refers to the value that is in the middle position of a dataset after it has been sorted. Due to its characteristic of being less influenced by extreme values, it is a stable and reliable indicator in data analysis. The equation is as follows:

$$M = \begin{cases} R_{(\frac{n+1}{n})}, \ n \text{ is odd} \\ \frac{1}{2}\left\{\frac{R_n}{2} + \frac{R_{n+1}}{2}\right\}, \ n \text{ is even.} \end{cases} \tag{11}$$

In this context, M represents the Median Ratio, R denotes the ratio of the assessed value to the actual value for each property, n signifies the total number of samples under examination. The acceptable range for MR is between [0.90–1.10], the closer the MR value is to 1, the closer the model's assessed values are to the actual values, indicating a better appraisal effect.

4.3.2. COD appraisal

The COD measures the degree of variability between the assessed and actual value ratios. Quantifying this dataset's volatility and spread using COD aids in understanding the distribution characteristics and the extent of variation. The equation is as follows:

$$COD = \frac{\sum \left| \frac{A_i}{S_i} - M \right|}{nM} \times 100. \tag{12}$$

In this context, A_i represents the estimated value for the i-th sample, and S_i is the actual value for the i-th sample. According to industry standards. According to mass appraisal standards, the recommended range for COD is [5–15], the lower the COD value, the less variability in the assessed values, indicating better stability and consistency of the model.

4.3.3. PRD appraisal

PRD is a fundamental indicator used to assess whether the sample appraisal values demonstrate progressiveness or regressiveness. When the PRD value exceeds 1, it suggests that the value of high-value real estate has been underestimated in the appraisal process. Conversely, if the PRD value is less than 1, it implies that the value of high-value real estate may have been overestimated. The equation is as follows:

$$PRD = \frac{\sum \frac{A_i}{S_i}}{n \sum \frac{A_i}{S_i}}. \tag{13}$$

According to standard ratio research, the typical range for PRD is [0.98–1.03], with values within this range suggesting a fair and reasonable appraisal process. The closer the PRD value is to 1, the less progressive or regressive the assessed values are, indicating higher accuracy in the appraisal.

5. Results and discussion

5.1. Existing housing batch appraisal effectiveness analysis

5.1.1. OLS model effectiveness analysis

The OLS model is the most fundamental model in econometrics. In this study, standardized data were first modeled using spatial relationships to construct an OLS model for the existing housing in Zhangjiakou. This model was used to explore the correlation between housing prices and various influencing factors. The results were then utilized to assess the suitability for geographically weighted regression model analysis.

From Tables 3 and 4, it can be seen that all VIF values are less than 5, indicating no multicollinearity among the variables. However, the coefficients for area and age of

Table 3. OLS analysis

Variable	Coefficient	Standard error	Robust *P*	VIF
Intercept	6878.25	572.05	0.000000*	–
Area	–1.69	2.01	0.582966	1.1128
Floor	318.63	64.44	0.000001*	1.0226
Age	–80.44	12.47	0.000000*	2.0607
Renovation	352.35	72.62	0.000007*	1.0278
Elevator	1235.68	229.32	0.000000*	1.6732
Traffic and parking	274.22	150.54	0.013491*	1.6897
Property fee	322.94	19.52	0.045048*	1.6206
Public transport	4.14	93.43	0.778214	1.6546
School	–454.10	39.47	0.000000*	1.5262
Hospital	330.45	79.61	0.000000*	2.3360
Shopping center	47.84	37.296	0.581511	1.7001
Park	216.98	68.37	0.006414*	1.1020
Distance to government	–308.02	27.91	0.000000*	1.4050

Note: * denotes statistical significance at the 5% level ($P < 0.05$).

Table 4. OLS model diagnostic

Model evaluation indicator	Value
AICc	15510
R^2	0.49
Chi-square statistic	1114.95
Koenker (BP) statistic	0.000000*
Jarque-Bera statistic	0.000000*

Note: * denotes statistical significance at the 5% level ($P < 0.05$).

the building are negative, which significantly deviates from actual observations. An R^2 of only 0.49 suggests that the OLS model has a poor fit and does not adequately explain the relationship between housing prices and various influencing factors in Zhangjiakou.

Furthermore, the significant BP statistic indicates inconsistent modeling relationships, suggesting that the impact of variables is pronounced in some areas and not in others, signifying significant spatial heterogeneity.

5.1.2. GWR model effectiveness analysis

For the remaining 13 variables obtained through screening, a VIF method was utilized to conduct multicollinearity analysis, with the VIF value used as the criterion for appraisal. The results show that all VIF values are significantly less than 5, indicating the absence of multicollinearity among the data.

In the GWR model, bandwidth is a crucial parameter, and it is essential to choose the optimal bandwidth calculation method when conducting GWR model analysis. This study evaluates two adaptive bandwidth methods for the GWR model: Cross-Validation (CV) and the Akaike Information Criterion (AICc). As can be seen from Table 5, there is little difference in the fit effect between the AICc and CV calculation methods. However, compared to the CV method, using AICc results in a higher R^2 and a reduced number of neighbors. Therefore, in this study, the Akaike Information Criterion AICc method is applied.

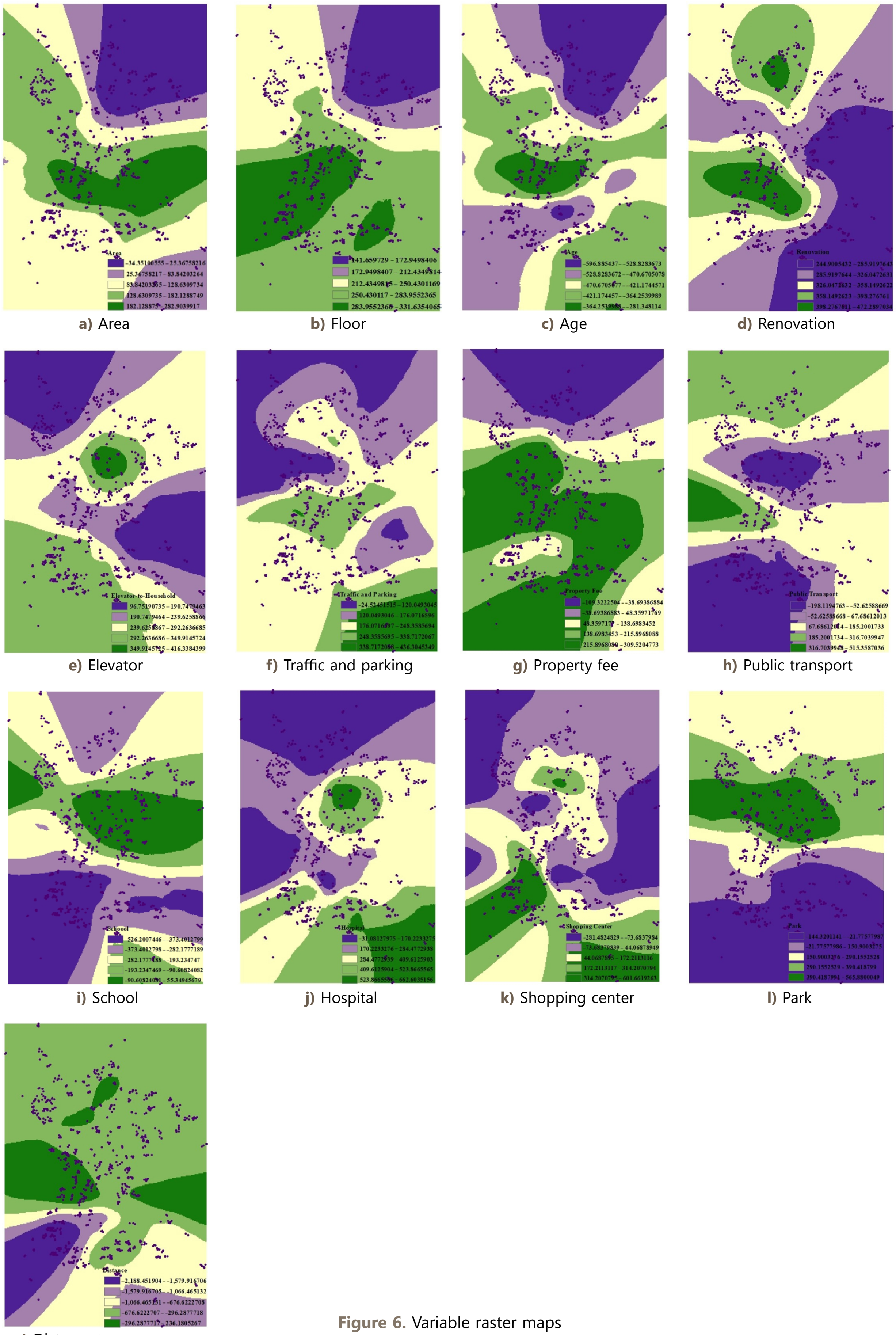
Table 6 provides the descriptive statistical analysis results of the GWR model, while Figure 6 displays the variable raster maps exported from the ArcGIS-GWR model, which, when analyzed together, illustrate the variation of variables across different regions. The B value (6187.462) in Table 6 represents the expected baseline value of housing prices, and the standardized coefficients represent the importance of each variable, with the strength of positive correlation being in the following order: Renovation > Hospital > Elevator > Floor > Traffic and Parking > Property Fee > Shopping Center > Public Transport > Area > Park. The strength of negative correlation is in the following order: Distance to Government < Age < School. Specifically, Figures 6a–m show the specific spatial variations

Table 5. GWR model diagnostic

Kernel type	Test value	Neighbors	R^2	R^2 adjusted	Residual sum of squares	Sigma estimate
AICc	14020.26	345	0.81488	0.79122	341313411	659.58
CV	14020.66	347	0.814587	0.791931	341854584	659.88

Table 6. GWR collinearity analysis

Coefficient	Unstandardized coefficients		Standardized coefficients	t	Significance	Collinearity statistics	VIF
	B	Standard error	Beta				
(Constant)	6187.462	267.986		23.089	0		
Area	2.868	0.94	0.055	3.051	0.002	0.898	1.113
Floor	304.984	30.219	0.174	10.092	0	0.977	1.024
Age	–68.815	5.835	–0.289	–11.793	0	0.487	2.053
Renovation	442.288	34.068	0.225	12.982	0	0.973	1.028
Elevator	899.894	107.581	0.185	8.365	0	0.597	1.675
Traffic and parking	307.867	50.314	0.136	6.119	0	0.592	1.690
Property fee	329.909	70.376	0.102	4.688	0	0.62	1.614
Public transport	24.685	9.148	0.059	2.698	0.007	0.604	1.655
School	–418.819	43.499	–0.203	–9.628	0	0.658	1.519
Hospital	154.388	18.458	0.218	8.364	0	0.431	2.322
Shopping center	113.345	37.296	0.068	3.039	0.002	0.59	1.696
Park	80.818	32.073	0.045	2.52	0.012	0.906	1.104
Distance to government	–201.718	13.082	–0.312	–15.419	0.000	0.713	1.403



a) Area **b)** Floor **c)** Age **d)** Renovation

e) Elevator **f)** Traffic and parking **g)** Property fee **h)** Public transport

i) School **j)** Hospital **k)** Shopping center **l)** Park

m) Distance to government

Figure 6. Variable raster maps

of these 13 variables. Figure 6a shows that Area has a particularly significant positive correlation in the central region and a negative correlation in the northeastern part. Figure 6b shows that the influence of Floor level decreases gradually from southwest to northeast. Figure 6c shows that the impact of Age on housing prices is negative, with the northern urban area being the most significant. Figure 6d shows that the influence of Renovation is positive across the space, with the eastern area being lower and the western area being higher. Figure 6e shows that the Elevator has a positive impact, with the most significant influence in the central urban area. Figure 6f shows that the Traffic and Parking ratio has a positive impact on housing prices in most areas except for a few houses in the southeast.

Figure 6g shows that Property Fee has negative values, mainly concentrated in the northern urban area. Figure 6h shows that the Public Transport coefficient is lower in the southeast and higher in the northwest. The higher the school composite score, the farther the distance and the less likely it is a high-quality school district; Figure 6i shows that in most areas, housing prices are negatively correlated with School. Figure 6j shows that the Hospital coefficient is lower in the northwest and higher in the southeast. Figure 6k shows that the Shopping Center coefficient is lower in the southeast and higher in the northwest. Figure 6l shows that the impact of Park is positively correlated in most areas, while negative values and low values are mainly distributed in the south. Figure 6m shows that the Distance to Government coefficient has significant polarization and is the variable with the greatest impact in the GWR model results.

5.1.3. SGWR model effectiveness analysis

Scatter plots of the SGWR model results are presented in Appendix Figure A1. Upon analysis, it was found that the relationships between area, traffic and parking availability, distance to city hall, and property fees with housing prices exhibit a clear trend. This indicates that these four variables have a relatively stable impact across the entire study area, and in this study, they are set as global variables. The remaining variables, such as building age, distance to bus stops, degree of renovation, floor level, distance to hospital, distance to shopping center, elevator, proximity to park, and school distance, may have a relationship with housing prices that varies significantly based on geographic location. These variables are defined as local variables. Calculations were performed, and the model diagnostic table (Table 7) and variable coefficient table (Table 8) were exported.

Table 8. SGWR model diagnostic

Model evaluation indicator	Value
R^2	0.746386
AICc	13894.37
Residual sum of squares	4.767×10^8
Bandwidth	99

5.1.4. MGWR model effectiveness analysis

The analysis results of the MGWR model are presented in Tables 9 and 10. The positive correlation strengths are in the following order: Hospital > Renovation > Floor > Elevator > Park > Property Fee > Shopping Center > Traffic and Parking > Area > Public Transport. The negative correlation strengths are in the following order: Distance to Government < Age < School. Among them, the variables of Floor, Age, Elevator-to-Household Ratio, Traffic and Parking, and Distance to Government have bandwidths exceeding 800, indicating that these variables are relatively stable on a global scale. The bandwidths for Area, Renovation, and Park are moderate, suggesting that these variables exhibit significant spatial heterogeneity. The bandwidths for Property Fee, Public Transport, School, Hospital, and Shopping Center are all less than 100, indicating that these variables show strong spatial heterogeneity, with substantial differences across various regions.

The coefficient of each variable is superimposed on the satellite image of Zhangjiakou City to reveal the spatial patterns of these coefficients, as seen in Figure 7. The residential areas of Zhangjiakou are distributed in a strip running from north to south. The green line represents the Qingshui River that flows through the city, and the red line represents Wei Yi Road, which serves as the boundary between the new and old urban areas.

Table 7. Variable coefficient

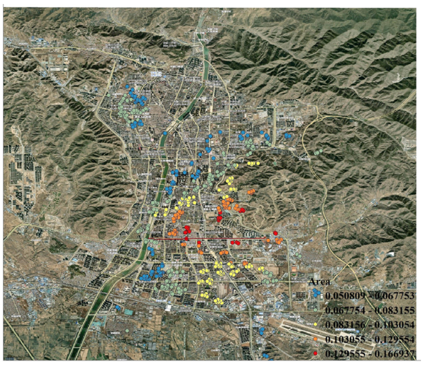
Variable	Average coefficient	Variable	Average coefficient
Intercept	7349.04	Traffic and parking Relationship	198.39
Area	80.33	Public transport	86.58
Floor	254.67	School	–295.94
Renovation	328.27	Shopping center	98.70
Age	–421.42	Property fee	148.60
Hospital	317.85	Park	66.05
Elevator	269.99	Distance to government	–455.51

Table 9. MGWR variable regression coefficient statistical description

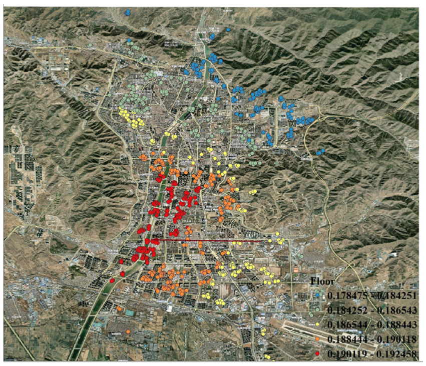
Variable	Average value	Standard deviation	Minimum value	Median value	Maximum value	Bandwidth	Proportion $p < 0.05$
Area	0.065	0.034	–0.021	0.067	0.167	279	63.13%
Floor	0.188	0.003	0.178	0.188	0.192	882	100%
Age	–0.300	0.001	–0.304	–0.300	–0.297	882	100%
Renovation	0.212	0.026	0.140	0.211	0.290	317	100%
Elevator	0.148	0.002	0.141	0.149	0.152	880	100%
Traffic and parking	0.114	0.004	0.102	0.115	0.120	880	100%
Property fee	0.130	0.176	–0.425	0.111	0.557	52	42.02%
Public transport	0.034	0.160	–0.408	0.040	0.604	77	28.65%
School	–0.094	0.355	–0.814	–0.168	1.263	43	56.06%
Hospital	0.355	0.431	–0.201	0.182	2.730	77	58.78%
Shopping center	0.122	0.478	–0.918	0.027	1.696	43	41.22%
Park	0.132	0.072	0.030	0.169	0.232	475	65.69%
Distance to government	–0.399	0.001	–0.402	–0.399	–0.396	882	100%

Table 10. MGWR model diagnostic table

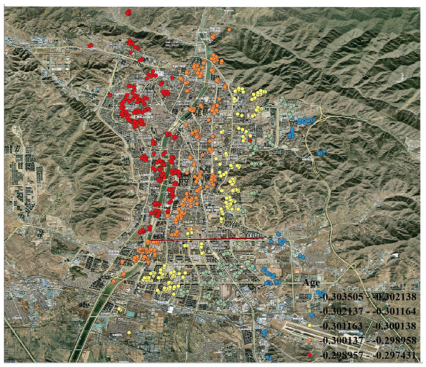
Model evaluation indicator	Value
R^2	0.885
R^2 adjusted	0.862
AICc	13807.936
Residual sum of squares	2.118×10^8
Sigma estimate	537.402



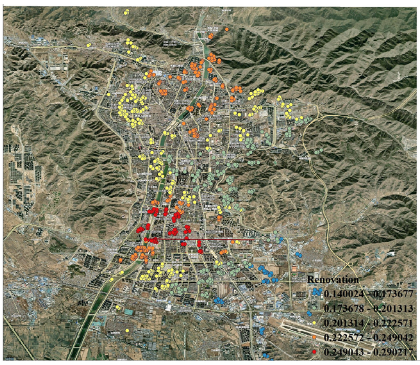
a) Area



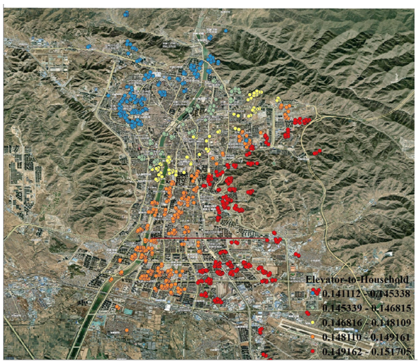
b) Floor



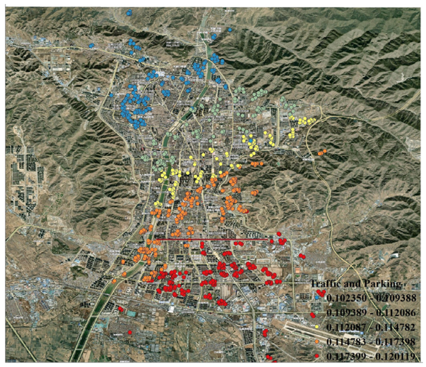
c) Age



d) Renovation

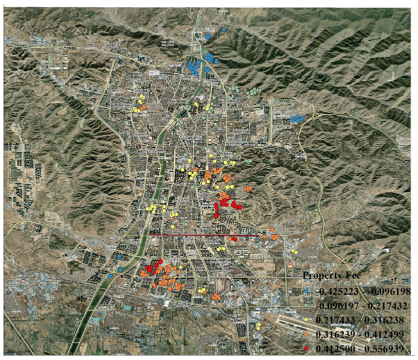


e) Elevator

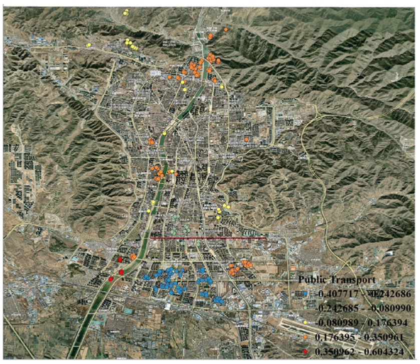


f) Traffic and parking

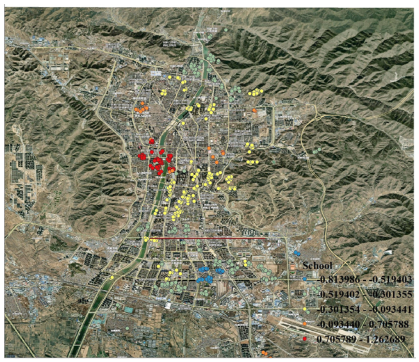
Figure 7. *To be continued*



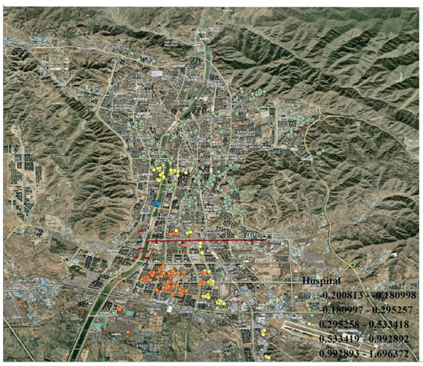
g) Property fee



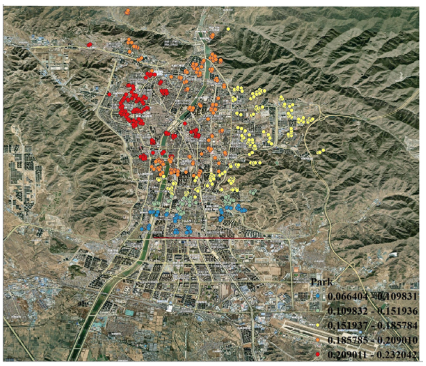
h) Public transport



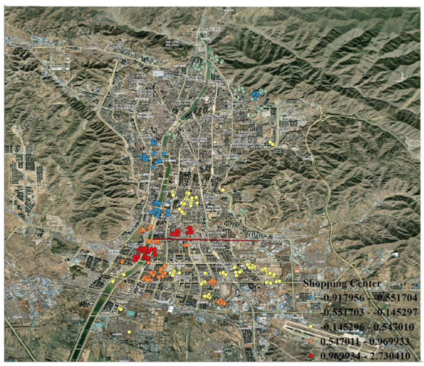
i) School



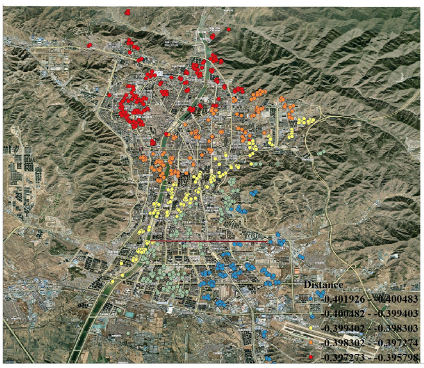
j) Hospital



k) Park



l) Shopping center



m) Distance to government

Figure 7. Spatial pattern of MGWR model coefficients

5.2. Comprehensive model assessment

5.2.1. Model accuracy

Firstly, a further spatial autocorrelation test was conducted on the OLS residuals to assess the effectiveness of the OLS model in capturing the characteristics of spatial data. The results showed that the global Moran's I index was greater than 0, at 0.26, indicating that there is still significant spatial autocorrelation in the residuals, reflecting that the OLS model failed to fully capture the spatial dependence structure in the data.

Secondly, we compared the outcomes of the OLS model, GWR model, SGWR model, and MGWR model, as presented in Table 11. It is observed that the model fit, as indicated by R^2, has significantly improved with the MGWR model compared to the other three models. Moreover, the difference in AICc values is substantially greater than 3, demonstrating the superior model fit and performance of the MGWR. In addition, the MGWR model, in contrast to the GWR model, accounts for the varying spatial scales of different variables, thereby yielding more reliable regression analysis results.

Table 11. Model comparison

Model	OLS	GWR	SGWR	MGWR
R^2	0.49	0.81488	0.746386	0.885
AICc	15510	14020.26	13894.37	13807.94
Residual sum of squares	6.493×10^8	3.413×10^8	4.767×10^8	2.118×10^8

5.2.2. Batch appraisal effectiveness validation

The effectiveness of real estate mass appraisal is assessed according to the IAAO ratio standards, and the results are

Table 12. MGWR model assessment capability measurement

Ratio indicator	MR	COD	PRD
International standard	0.9–1.1	5–15	0.98–1.03
OLS	0.64	23.51	0.71
GWR	0.97	11.37	0.94
SGWR	0.86	17.21	0.76
MGWR	1.08	8.34	1.006

shown in Table 12. Among the various models, the MGWR model's validation results outperform the others, with MR and PRD validation results being closer to 1, and the COD being the lowest within the standard range. This indicates that the MGWR model has better mass appraisal capabilities compared to other models, making it suitable for mass appraisal research of existing housing in Zhangjiakou.

5.2.3. Cross-validation

Yinchuan City, like Zhangjiakou City, is also a Type II major city and shares similarities in various aspects, such as the absence of a subway system and urban development planning. To verify the evaluative efficacy of the MGWR model in Type II major cities, this study selects existing housing in Yinchuan City for cross-validation analysis. During the model training phase, 80% of the data assessed by the MGWR model was used as the training set, and K-fold cross-validation was conducted. The results show that when the number of cross-validation folds K is 7, the MAE is minimized, indicating that the stability and accuracy of the trained model at this point are optimal. Furthermore, 177 sample data from Yinchuan City were quantified for indicators and used as the test set to evaluate the efficacy of the MGWR model in actual mass appraisal of existing housing. As shown in Figure 8, the test results show that the actual values and predicted values are essentially consistent with each other, with a small error (MAE of 379.19).

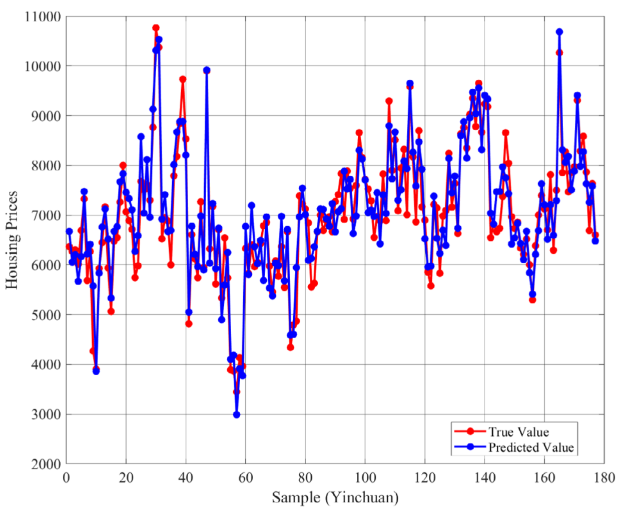


Figure 8. Model training test

These results indicate that the MGWR model can be effectively applied to the evaluation of the existing housing market in Yinchuan, a Type II city, providing a reliable tool for policy formulation and market analysis.

5.3. Discussion on the results of MGWR model variables

After comprehensively considering the accuracy and appraisal efficiency of each model, it has been found that the MGWR is the optimal model suitable for Zhangjiakou, a typical Type II city. Further discussion on the spatiotemporal heterogeneity of each variable is presented below.

In the MGWR model, Hospital is identified as the most significant positive correlation variable in Zhangjiakou City, with an average coefficient of 0.355. Low values are located in the central and northern urban areas, while high values are near the southern part of Wei Yi Road and the Qingshui River. Due to the uneven distribution and quality of medical resources in Zhangjiakou City, especially the concentration of top-tier hospitals in the central and northern urban areas, residents in these areas are accustomed to the proximity of hospitals and pay more attention to other factors such as floor level, renovation, public transport, and parks. In contrast, residents near the southern part of Wei Yi Road and the Qingshui River, who are farther from hospitals, have a higher concern for hospital accessibility. Renovation has an average coefficient of 0.212, with high values concentrated in the central and northern urban areas and low values in the southern part. This aligns with the overall development planning of Zhangjiakou in recent years, which has shifted southward, making southern residential areas relatively newer. Renovation has a relatively smaller impact on housing choices in the southern urban areas due to their modern and fashionable design, therefore for the southern urban areas residents, renovation in housing selection has a relatively smaller impact. Conversely, in the older central and northern urban areas with more aged housing, the condition of renovation becomes a more critical consideration in housing selection. Similarly, Floor, as the third most significant positive correlation variable (0.188), is most pronounced in the central urban area near the Qingshui River. This is attributed to the convenient central transportation facilities and the beautiful river and city views offered by higher floors, which have a higher potential for appreciation. The positive correlation intensity of elevator is 0.148, spatially greater in the east than in the west and in the south compared to the north. This is due to the presence of many older buildings without elevators in the northwestern old urban area, while the central and southern areas have more new residences with a higher rate of elevator usage, making the presence of an elevator more important.

The average coefficient of Park is 0.132, with high values located in the old central and southern urban areas, and minimal impact in the southern new urban areas. This is because the majority of parks in Zhangjiakou are located in the old urban area, where residents tend to be older and prefer living close to parks. Parks not only provide leisure and exercise spaces but also bring tranquility and comfort to the community, making the demand and preference for parks within 1 km more significant. In contrast, the southern new urban area, with very few parks, has a younger population that prefers modern entertainment facilities and commercial centers over traditional parks, resulting in a minimal impact on housing prices. The average coefficient of Property Fee is 0.13, gradually increasing from north to south. This is due to the relatively new residential areas in the south, which have higher infrastructure maintenance costs and a younger population leading to diversified demands for property services, resulting in higher property fees. Shopping Center shows a negative correlation in the central and southern areas, as the city of Zhangjiakou is relatively small, and the distance to shopping centers is usually short. Additionally, as the urban area gradually expands southward, several large shopping centers have not moved southward and remain in the central urban area. Therefore, for areas south of Wei Yi Road, despite being farther from shopping centers, the impact on housing prices is minimal. The relationship between cars and houses is similar to the elevator, significantly affecting residents in the new urban areas. The separation of vehicles and pedestrians increases comfort and convenience and improves management and order, which is particularly valued by the average-aged southern residents who prefer this feature. The average coefficient of Area is 0.065, indicating a relatively small impact on the existing housing stock in the city, with a slightly higher influence in the southeast direction. This is because the southeastern residential areas are newer and larger, making them the preferred choice for homebuyers, aligning with the latest trend of residents favoring larger and newer residences. Public Transport is statistically significant for only 28.65% of the total samples and has a positive impact on housing prices across various regions.

Distance to Government, as the strongest negatively correlated variable with an average coefficient of –0.399, indicates that an increase in the distance from government offices often results in a decrease in housing prices. In the northwestern urban area of Zhangjiakou, where it is farther from the city government center, housing prices are less affected. This phenomenon may be related to the fact that areas near government offices usually enjoy more policy inclination and resource concentration, equipped with high-quality educational facilities, advanced medical centers, and thriving commercial services, all of which collectively enhance property values. The impact of Age decreases gradually from east to west, but the overall variation is not significant (–0.30). Considering its bandwidth of 882, this variable includes almost all samples, indicating low spatial heterogeneity but a significant impact, making it an important factor for residents when purchasing homes. The comprehensive score of School being larger indicates a farther distance and non-high-quality school districts, so in most areas, housing prices are negatively correlated with school scores, with an average impact coefficient of –0.094. The five best primary schools in Zhangjiakou are all located in the old urban area, surrounded by many old communities. Under the guise of "school district housing," they also face the embarrassing situation of "old and small houses". Therefore, there is no apparent pattern in the spatial distribution of housing prices in relation to school scores.

6. Conclusions

This study takes the existing housing in Zhangjiakou, a typical Type II major city, as an example, and compares the applicability of OLS, GWR, SGWR, and MGWR models in mass appraisal in Type II major cities through their fit and IAAO mass appraisal standards. Among them, the MGWR model demonstrates superior assessment capabilities, laying a scientific foundation for urban planning and economic policies in Zhangjiakou. Furthermore, after cross-validation discussion in Yinchuan City, its extensibility in mass appraisal of existing housing prices using spatial data in China has been proven, providing innovative perspectives and methods for related research.

The model revealed varying degrees of impact of each variable within the study area. Various factors such as the number and quality of hospitals, renovation conditions, floor level scoring, elevator, access to parks, property fees, building age, and proximity to government facilities have a significant impact on housing prices. Bandwidths for variables such as floor level scoring, building age, elevator, traffic, and distance from government facilities are nearly universal, indicating relatively stable coefficients. Conversely, bandwidths for property fees, public transportation, schools, hospitals, and shopping centers are below 100, indicating strong spatial heterogeneity.

The mass appraisal of housing prices provides a scientific basis for urban planning decisions. It enables the government to identify areas where certain influential factors are lacking, such as transportation facilities in high-priced areas, and take appropriate measures to address these gaps. Furthermore, the data generated from this appraisal can inform policy formulation, especially in initiatives such as China's property tax reform. Additionally, in the housing transaction market, both buyers and sellers can benefit from a more transparent understanding of property values, which helps prevent blind or unfair transactions.

China's vast territory and diverse levels of urban development mean that the factors influencing housing prices and their extent vary across cities of different sizes. Currently, the mass appraisal of housing prices necessitates targeted research for each city to uncover urban characteristics and leverage the capabilities of GIS. This involves analyzing urban topography, spatial correlation and heterogeneity of housing prices, and the selection and quantification of evaluation indicators to enhance the precision and efficiency of research.

Acknowledgements

This study was supported by Humanities and Social Sciences Youth Foundation, Ministry of Education of China (22YJC630219), Liaoning Federation of Social Sciences (2025lslybwzzkt-150), and Liaoning Revitalization Talents Program (XLYC2203004).

References

Aladwan, Z., & Ahamad, M. S. S. (2019). Hedonic pricing model for real property valuation via GIS: A review. *Civil and Environmental Engineering Reports*, *29*(3), 34–47. https://doi.org/10.2478/ceer-2019-0022

An, B. W., Xu, P. Y., Li, C. Y., Zhang, L. Y., & Guo, Q. P. (2024). Assessing green production efficiency and spatial characteristics of China's real estate industry based on the undesirable super-SBM model. *Scientific Reports*, *14*(1), Article 16367. https://doi.org/10.1038/s41598-024-67506-8

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Bera, M. M., Mondal, B., Dolui, G., & Chakraborti, S. (2018). Estimation of spatial association between housing price and local environmental amenities in Kolkata, India using hedonic local regression. *Papers in Applied Geography*, *4*(3), 274–291. https://doi.org/10.1080/23754931.2018.1446354

Cardone, B., Di Martino, F., & Senatore, S. (2024). Real estate price estimation through a fuzzy partition-driven genetic algorithm. *Information Sciences*, *667*, Article 120442. https://doi.org/10.1016/j.ins.2024.120442

Dell'Anna, F., Bravi, M., & Bottero, M. (2022). Urban green infrastructures: How much did they affect property prices in Singapore? *Urban Forestry* & *Urban Greening*, *68*, Article 127475. https://doi.org/10.1016/j.ufug.2022.127475

Franco, S. F., & Macdonald, J. L. (2018). The effects of cultural heritage on residential property values: Evidence from Lisbon, Portugal. *Regional Science and Urban Economics*, *70*, 35–56. https://doi.org/10.1016/j.regsciurbeco.2018.02.001

Geniaux, G., Ay, J. S., & Napoléone, C. (2011). A spatial hedonic approach on land use change anticipations. *Journal of Regional Science*, *51*(5), 967–986. https://doi.org/10.1111/j.1467-9787.2011.00721.x

Helbich, M., Brunauer, W., Vaz, E., & Nijkamp, P. (2014). Spatial heterogeneity in hedonic house price models: The case of Austria. *Urban Studies*, *51*(2), 390–411. https://doi.org/10.1177/0042098013492234

Hermans, L. D., Bidanset, P. E., Davis, P. T., & McCord, M. J. (2022). Using property-level ratio studies for the incorporation of validation models in single-family residential real estate assessment. *Journal of Property Tax Assessment* & *Administration*, *19*(1), 3–20. https://doi.org/10.63642/1357-1419.1245

Hermans, L. D., McCord, M. J., Davis, P. T., & Bidanset, P. E. (2023). An exploratory approach to composite modelling for real estate assessment and accuracy. *Journal of Property Tax Assessment* & *Administration*, *20*(1), 4–23. https://doi.org/10.63642/1357-1419.1256

Hwang, M., & Quigley, J. M. (2006). Economic fundamentals in local housing markets: Evidence from US metropolitan regions. *Journal of Regional Science*, *46*(3), 425–453. https://doi.org/10.1111/j.1467-9787.2006.00480.x

Jia, J., Zhang, X., Huang, C., & Luan, H. (2022). Multiscale analysis of human social sensing of urban appearance and its effects on house price appreciation in Wuhan, China. *Sustainable Cities and Society*, *81*, Article 103844. https://doi.org/10.1016/j.scs.2022.103844

Jiao, L., & Liu, Y. (2012). Analyzing the spatial autocorrelation of regional urban datum land price. *Geo-spatial Information Science*, *15*(4), 263–269. https://doi.org/10.1080/10095020.2012.714103

Kurkcuoglu, M. A. S. (2023). Analysis of the energy justice in natural gas distribution with Multiscale Geographically Weighted Regression (MGWR). *Energy Reports*, *9*, 325–337. https://doi.org/10.1016/j.egyr.2022.11.188

Le Boennec, R., Bulteau, J., & Feuillet, T. (2022). The role of commuter rail accessibility in the formation of residential land values: Exploring spatial heterogeneity in peri-urban and remote areas. *The Annals of Regional Science*, *69*(1), 163–186. https://doi.org/10.1007/s00168-022-01113-1

Liu, N., & Strobl, J. (2023). Impact of neighborhood features on housing resale prices in Zhuhai (China) based on an (M) GWR model. *Big Earth Data*, *7*(1), 146–169. https://doi.org/10.1080/20964471.2022.2031543

Luo, X., Yang, J., Sun, W., & He, B. (2021). Suitability of human settlements in mountainous areas from the perspective of ventilation: A case study of the main urban area of Chongqing. *Journal of Cleaner Production*, *310*, Article 127467. https://doi.org/10.1016/j.jclepro.2021.127467

McCord, M., Lo, D., Davis, P., McCord, J., Hermans, L., & Bidanset, P. (2022). Applying the geostatistical eigenvector spatial filter approach into regularized regression for improving prediction accuracy for mass appraisal. *Applied Sciences*, *12*(20), Article 10660. https://doi.org/10.3390/app122010660

Qiu, W., Zhang, Z., Liu, X., Li, W., Li, X., Xu, X., & Huang, X. (2022). Subjective or objective measures of street environment, which are more effective in explaining housing prices? *Landscape and Urban Planning*, *221*, Article 104358. https://doi.org/10.1016/j.landurbplan.2022.104358

Sisman, S., Akar, A. U., & Yalpir, S. (2023). The novelty hybrid model development proposal for mass appraisal of real estates in sustainable land management. *Survey Review*, *55*(388), 1–20. https://doi.org/10.1080/00396265.2021.1996797

Wen, H., Jin, Y., & Zhang, L. (2017). Spatial heterogeneity in implicit housing prices: Evidence from Hangzhou, China. *International Journal of Strategic Property Management*, *21*(1), 15–28. https://doi.org/10.3846/1648715X.2016.1247021

Wu, C., Du, Y., Li, S., Liu, P., & Ye, X. (2022). Does visual contact with green space impact housing prices? An integrated approach of machine learning and hedonic modeling based on the perception of green space. *Land Use Policy*, *115*, Article 106048. https://doi.org/10.1016/j.landusepol.2022.106048

Yang, S., Hu, S., Wang, S., & Zou, L. (2020). Effects of rapid urban land expansion on the spatial direction of residential land prices: Evidence from Wuhan, China. *Habitat International*, *101*, Article 102186. https://doi.org/10.1016/j.habitatint.2020.102186

Yu, L., Wang, Y., & Li, M. (2024). The emergence of counter-urbanisation in China: Can it be a pathway for rural revitalisation? *Habitat International*, *144*, Article 102998. https://doi.org/10.1016/j.habitatint.2023.102998

Zhang, Z., Li, J., Fung, T., Yu, H., Mei, C., Leung, Y., & Zhou, Y. (2021). Multiscale geographically and temporally weighted regression with a unilateral temporal weighting scheme and its application in the analysis of spatiotemporal characteristics of house prices in Beijing. *International Journal of Geographical Information Science*, *35*(11), 2262–2286. https://doi.org/10.1080/13658816.2021.1912348

Zhao, Y., Shen, X., Ma, J., & Yu, M. (2023). Path selection of spatial econometric model for mass appraisal of real estate: Evidence from Yinchuan, China. *International Journal of Strategic Property Management*, *27*(5), 304–316. https://doi.org/10.3846/ijspm.2023.20376

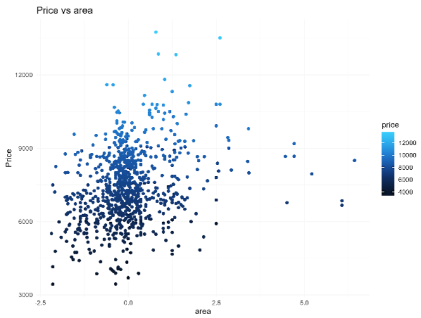
Appendix

Table A1. Significance analysis

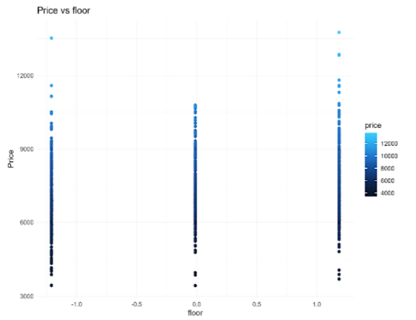
Variable	Unstandardized coefficients		Standardized coefficients	*t*	Significance
	B	Standard error	Beta		
Constant	6039.617	328.722		18.373	0
Area	126.707	66.735	0.047	1.899	0.058
Rooms	42.201	56.294	0.015	0.75	0.454
Halls	0.735	1.393	0.014	0.528	0.598
Floor	301.814	30.268	0.173	9.971	0
Age	–70.575	6.091	–0.296	–11.587	0
Renovation	444.399	34.187	0.226	12.999	0
Elevator	896.363	108.105	0.184	8.292	0
Greening rate	0.814	4.772	0.003	0.171	0.865
Area	–3.376	30.907	–0.002	–0.109	0.913
Traffic and parking	297.782	51.051	0.131	5.833	0
Property fee	324.716	70.568	0.1	4.601	0
Public transport	27.356	9.251	0.066	2.957	0.003
School	–415.043	43.839	–0.201	–9.467	0
Hospital	153.533	18.469	0.217	8.313	0
Shopping center	118.002	37.593	0.07	3.139	0.002
Park	80.274	32.101	0.045	2.501	0.013
Distance to government	–201.023	13.194	–0.311	–15.235	0

Table A2. Collinearity diagnostics

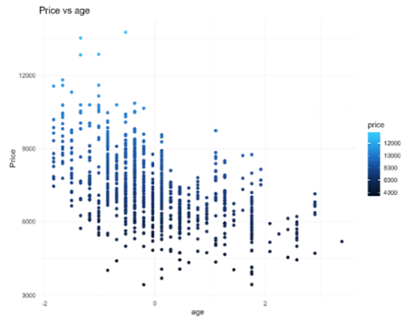
Variable	Unstandardized coefficients		Standardized coefficients	*t*	Significance	Collinearity statistics	VIF
	B	Standard error	Beta				
Constant	6187.462	267.986		23.089	0		
Area	2.868	0.94	0.055	3.051	0.002	0.898	1.113
Floor	304.984	30.219	0.174	10.092	0	0.977	1.024
Age	–68.815	5.835	–0.289	–11.793	0	0.487	2.053
Renovation	442.288	34.068	0.225	12.982	0	0.973	1.028
Elevator	899.894	107.581	0.185	8.365	0	0.597	1.675
Traffic and parking	307.867	50.314	0.136	6.119	0	0.592	1.69
Property fee	329.909	70.376	0.102	4.688	0	0.62	1.614
Public transport	24.685	9.148	0.059	2.698	0.007	0.604	1.655
School	–418.819	43.499	–0.203	–9.628	0	0.658	1.519
Hospital	154.388	18.458	0.218	8.364	0	0.431	2.322
Shopping center	113.345	37.296	0.068	3.039	0.002	0.59	1.696
Park	80.818	32.073	0.045	2.52	0.012	0.906	1.104
Distance to government	–201.718	13.082	–0.312	–15.419	0	0.713	1.403



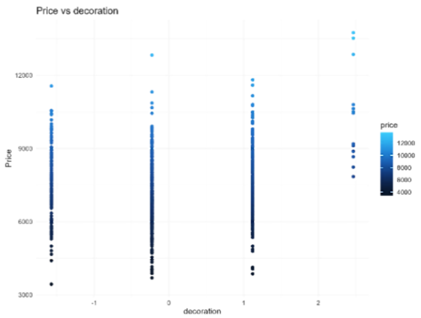
a) Area



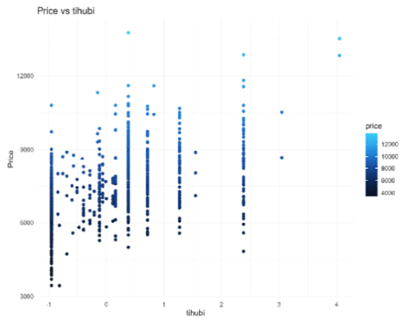
b) Floor



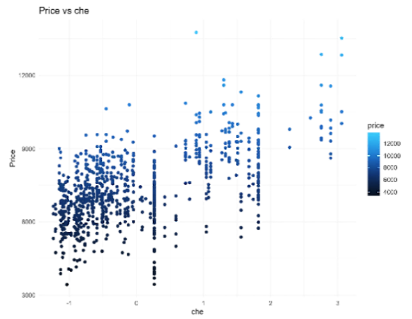
c) Age



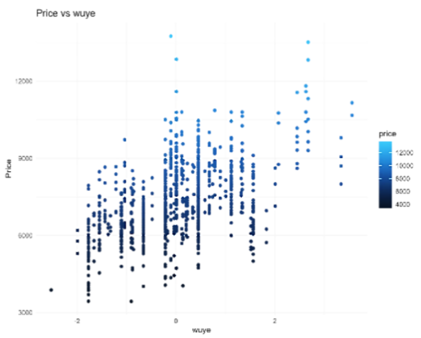
d) Renovation



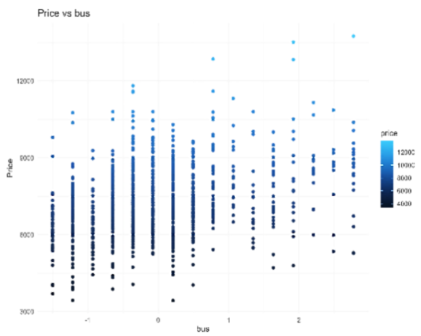
e) Elevator



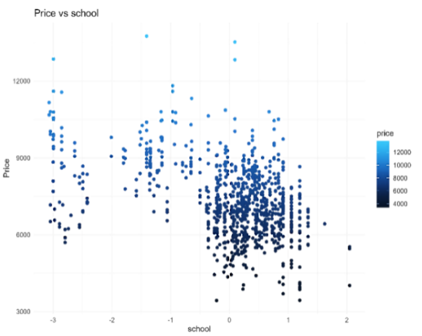
f) Traffic and parking



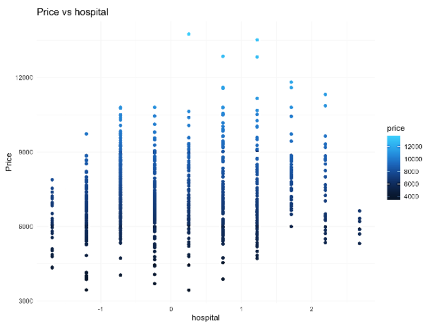
g) Property fee



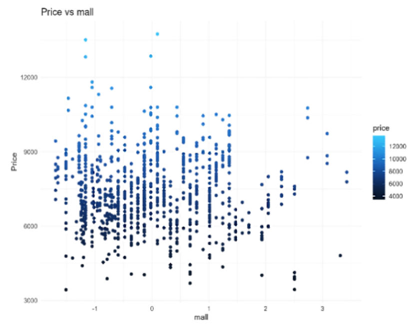
h) Public transport



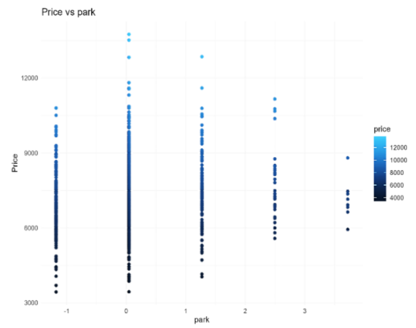
i) School



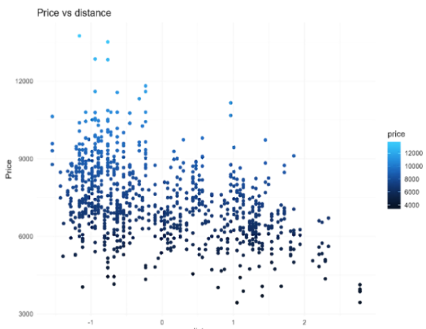
j) Hospital



k) Shopping center



l) Park



m) Distance to government

Figure A1. Scatter plots of housing prices and variables