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Analysis of Factors Influencing Housing Prices in Mountain Cities Based on Multiscale Geographically Weighted Regression—Demonstrated in the Central Urban Area of Chongqing

Yiduo Chen [1,2,3,4], Qingyuan Yang [1,2,*], Li Geng [1,2] and Wen Yin [1,2]

1 School of Geographical Sciences, Southwest University, Chongqing 400715, China; chenyiduo@cqdky.com (Y.C.); gengli@swu.edu.cn (L.G.); yinwenaa@swu.edu.cn (W.Y.)
2 Key Laboratory of Monitoring, Evaluation and Early Warning of Territorial Spatial Planning Implementation, Ministry of Natural Resources, Chongqing 401147, China
3 Chongqing Institute of Geology and Mineral Resources, Chongqing 401120, China
4 China Chongqing Huadi Engineering Investigation Designing Institute, Chongqing 401120, China
* Correspondence: yizyang@swu.edu.cn; Tel.: +86-023-68253911

Abstract: By leveraging a multiscale geographically weighted regression (MGWR) model, this paper delves into the intricate factors that influence housing prices in the prototypical mountainous cityscape of Chongqing's central urban area. The key findings are as follows: Firstly, the distribution of housing prices in the study region exhibits pronounced spatial heterogeneity, with the core area exhibiting a distinct "high-high" clustering pattern and manifesting characteristics of a multicenter group distribution. Secondly, the MGWR model effectively assigns an individual bandwidth to each feature quantity, allowing for a more nuanced portrayal of the varying influence scales exerted by diverse variables. Lastly, the study reveals that factors such as property cost, greening rate, building age, and proximity to rivers have a notable negative impact on housing prices, whereas, educational facilities exert a marked positive influence. Elevation, floor area ratio, and distance from the Central Business District (CBD) exhibit a more complex influence on housing prices.

Keywords: MGWR model; mountain city; housing price; influencing factors

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1. Introduction

The activity degree of the urban housing market is an important measure of the urban economy because of its direct effect on the urban economy. In the past 20 years, China's real estate industry has developed rapidly and has gradually become a pillar industry of national economic development. Changes in commercial housing prices have deep impacts on social and economic development. At the same time, such changes receive widespread attention from the public, the government, enterprises, and research institutions.

The spatial differentiation of urban commodity housing prices is a key research direction of urban geography [1]. To date, scholars have carried out many studies on the spatial differentiation of urban commercial housing prices, focusing mainly on the factors influencing housing price differentiation in large and medium-sized cities. (1) Transportation infrastructure has an impact on the spatial differentiation of housing prices. The findings of this study indicate that transport infrastructure has a universal premium effect on nearby housing prices worldwide. From preconstruction to the completion and operation of urban rail transit, the spatiotemporal effect of urban rail transit on housing prices occurs within 2 km around each station. Urban rail transit has a significant value-added effect on housing prices along routes, and medium- and high-priced housing markets are most obviously affected by urban rail transit [2]. Additionally, scholars have found that traffic sites must be within the scope of housing prices; for example, authors have studied the impact strength in the U.S. city of Minneapolis [3] and the northern British city of South East London [4]. Housing price analyses have found that in the vicinity of a light rail site, within certain limits, housing prices will reach a certain premium that increases with closer distances. When the research perspective is extended to the accessibility of public facilities, the findings indicate that these facilities have a certain impact on nearby housing prices, as has been shown in empirical studies of certain cities in South Korea [5], Chongqing [6], Xiamen [7], etc. (2) Urban spatial structure has an impact on the spatial differentiation of housing prices. Scholars studied the spatial differentiation characteristics of urban housing prices at different spatial scales and analyzed the leading factors of the spatial differentiation of housing prices by constructing a hedonic price model (HPM). Their findings indicated that the spatial distribution of housing prices was consistent with the polycentric structure at the scale of the main urban area, and three high-priced housing areas were formed within each center [8]. Some scholars also tried to build a residential space division index system at the block scale with three dimensions: population, physical facilities, and economic environment [9]. Google Street View plays an important role in the analysis of urban spatial structure, and a deep learning algorithm can be used to predict the residential spatial pattern of residents based on material environmental information, such as housing building types and parking lot models in the community [10]. (3) Urban microfactors have an impact on the spatial differentiation of housing prices. Previous studies have shown that the kriging spatial interpolation method has a unique role in analyzing the factors influencing housing prices, and the impact of characteristic factors on housing prices has significant spatial heterogeneity [11,12]. On this basis, some scholars improved the assessment of the marginal housing characteristic price and residual housing price volatility by creating a housing characteristic quality index and proposed a method to measure residual housing price volatility [12]. Others have made innovations in analysis methods, used a spatial quantile model for reference for quantitative analysis, and conducted a detailed analysis of various influencing factors [13]. Great progress has also been made in the analysis of the domestic market. Through the analysis of a large number of county-level housing price samples, a housing price model was established in combination with the supply and demand of housing and the market situation, and the impact of land prices on housing prices was discussed. The findings indicated that the land supply plan is the internal driving force that determines urban land prices. Land prices influence housing prices through supply and demand and market mechanisms [14].

In terms of methodology, the HPM, the geographically weighted regression (GWR) model, and the multiscale geographically weighted regression (MGWR) model based on the GWR model are mainly used. The HPM is well suited to analyzing the heterogeneity of housing prices and uses consumption theory to better explain the heterogeneity of hedonic prices [15]. Subsequently, to expand the applicable scope of the HPM, the hidden market was introduced into hedonic price analysis and an empirical framework was constructed, laying a theoretical foundation for the HPM [16]. Freeman [17] empirically explained the HPM in the housing market from a theoretical perspective. The GWR model is a spatial linear model that adds a spatial weight matrix to the linear regression model. Its purpose is to better display differences in spatial structure [18]. The main role of the GWR model is to explore the influence of different characteristic factors on housing prices and their spatial differentiation rules [19]. Through empirical analysis, the spatial distribution and influence of housing price factors were analyzed with the help of the GWR model. Based on the HPM, many scholars [20,21] have compared the spatial expansion model with the GWR model and found that the GWR model is superior in terms of explanatory power and forecasting accuracy. However, a classical GWR model cannot fully reveal the spatial scales of different influencing factors. There has been little research on the scale differences in the spatial heterogeneity of different influencing factors. The MGWR model, proposed by Fotheringham [22] in 2017, can subdivide the global and local scales of each factor. Yu et al. [23] supplemented and improved the statistical inference of the MGWR model so that it could be applied to empirical analysis. With the increasing popularity of the

MGWR model, some scholars have begun to use it to explore the spatial scale and spatial differentiation of the factors influencing housing prices [24]. Previous studies based on the classical GWR model may be unstable, while the MGWR model reflects the scale of the influence of different variables on the dependent variable, and its results are more reliable [25,26].

The analysis and summary of previous studies show that the research results regarding factors influencing urban housing prices have been rich, but the studies have concentrated mostly on large and medium-sized plains cities, whereas fewer analyses have considered factors influencing housing prices in mountain cities. This paper takes the central city of Chongqing, a typical mountain city in China, as the research object. Based on the traditional HPM, this paper introduces the terrain location index to construct the MGWR model and analyzes the influence intensity and influence range of characteristic measurements, such as elevation, slope, and terrain location index, on housing prices. The results of this paper are expected to provide theoretical guidance and a scientific basis for housing price regulation, urban planning, and real estate development in mountainous cities in Western China, which are greatly influenced by topographic location and other factors.

2. Materials and Methods

2.1. Study Area

Chongqing, located in Southwest China, is the only municipality directly within both the central and western regions of China, with a total area of 8.24 × 104 km^2. The topography is mainly hilly and mountainous, and the mountainous areas account for 76% of the total area. The Yangtze River runs throughout Chongqing, with a transit length of 691 km. In 2020, the city's permanent population was 3.20893 million, the GDP was CNY 25,279 million, the ratio of primary, secondary, and tertiary industries was 6.9:55.6:37.5, the forest coverage rate was 52.5%, the annual average precipitation was 1181.4 mm, and the annual average temperature was 19.2 °C. The central urban area of Chongqing (including Yubei District, Yuzhong District, Jiangbei District, Beibei District, Shapingba District, Jiulongpo District, Dadukou District, Banan District, and Nan'an District), with a total area of 4403.19 km^2, is the "two rivers and four shores" core area of Chongqing, setting the historical context and providing a landmark for the Chongqing showcase. It is also the centralized embodiment of the core functions of this national central city.

2.2. Data Sources

The data in this paper are mainly point of interest (POI) data, housing price data, and DEM data. Among them, the housing price data come from the open data of the manual search network, the registration data of the real estate trading center, and the listing and transaction data provided exclusively by Home Arrived (https://cq.daojiale.com/ (accessed on 10 December 2021)). The data intercept time node is 10 December 2021. POI data, including the average price of sample residential housing, building age, residential green rate, floor area ratio, property costs, and latitude and longitude, are derived from Amap. Python software (3.12.3) is used to carry out real-time crawling of supermarkets, subway stations, bus stations, park squares, gas stations, schools, general hospitals, the CBD, and other locations in downtown Chongqing. DEM data come from the Resources and Environment Science and Data Center (http://www.resdc.cn/Default.aspx (accessed on 10 December 2021)) and have a resolution of 30 m × 30 m. After the difficulty of data acquisition was resolved and duplicate and erroneous data were eliminated, 4711 available sample points remained.

3. Methods

3.1. Model Selection

The MGWR model has strong flexibility and adaptability. It not only inherits the advantages of the GWR model in dealing with spatial heterogeneity but can also measure the scale difference in the spatial variation relationship between independent variables and dependent variables. The GWR model uses the weighted least squares estimation method, but the estimation of the MGWR model is quite different. The MGWR model can be regarded as a generalized additive model [27] that can detect the influence of nonlinear regression and can be calibrated by a backward fitting algorithm [28,29]. Compared with the MGWR model, the GWR model is an improved spatial linear regression model. Since it introduces the spatial geographic location information of sample data [30,31], its main advantage is reflected in the reference provided by the spatial weight matrix to the linear regression model. The GWR model explores the spatial nonstationarity relationship and provides a measure of the spatial scale of the model operation by determining the optimal bandwidth [32].

The formula for calculating the MGWR is as follows:

$$Y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i) X_{ij} + \varepsilon_i$$

where Y_i is the average housing price of the ith sample plot, X_{ij} is the index value of the jth influencing factor of the ith sample plot, (u_i, v_i) is the coordinate of sample plot i, $\beta_{bwj}(u_i, v_i)$ is the regression coefficient of the jth housing price influencing factor fitted by a specific bandwidth, bwj represents the bandwidth of the jth housing price influencing factor, and ε_i is the random error. Compared with GWR, each regression coefficient of the MGWR model is obtained based on local regression, with all factors using the same bandwidth and each influencing factor using its exclusive bandwidth when fitting, which reflects the regression coefficient of different variables at different spatial scales [22,30,33]. To maintain consistency of fit, an adaptive bandwidth is adopted in the process of fitting the MGWR model and GWR model in this paper. The kernel function and bandwidth selection criteria of the MGWR model are based on an adaptive Gaussian function and corrected Akaike information criterion (AICc), which are commonly used in classical GWR models.

In this paper, the MGWR model is selected as the research method. Compared with the traditional GWR model, the MGWR model makes the following three main improvements. First, the defects of the GWR model are solved by allowing different spatial smoothing levels for each variable. Second, the specific bandwidth of each variable can be used as an indicator of the spatial scale at which each spatial process acts. Third, the multibandwidth approach yields spatial process models that are closer to reality and more useful. The MGWR model directly reflects the role of the differentiation between different characteristic scales, while the GWR model reflects the characteristic function of the average of the scales, which is fundamentally different from the spatial heterogeneity of dependent and independent variables. This homogenizing effect ignores the essence of the geographical research scale effect, as the spatial and temporal heterogeneity are not explained at a sufficiently fine scale [22]. The MGWR model assigns a dedicated bandwidth to each feature quantity to reflect the influence scale of different feature quantities, effectively avoiding the convergence problem of the influence range of feature quantities in the GWR model.

3.2. Variable Setting

The variable reference features price model used to study the factors affecting housing prices at the microlevel is one of the most commonly used models. Its object is to assess different characteristics under different conditions. Through the price of the object and the special relationships between different attributes of regression analysis, the effect of each factor affecting housing prices can be more effectively measured, and the action intensity and direction of each characteristic quantity in relation to housing prices can be obtained [22,28,34–39].

The reference feature price model for residential price variables includes four variables: topographic features, architectural features, area features, neighborhood features. To fully reflect the characteristics of mountainous cities in Chongqing, this paper incorporates factors such as slope and elevation into the Topographic features. The role of distance plays an important role in the housing market and has been reflected in existing research [40]. This paper proposes Neighborhood features, refines distance factors, and analyzes the forms of interaction between residential communities and surrounding facilities.

By referring to relevant research results [22,28,35,37,39] and comprehensively considering issues such as data availability and local collinearity, the average housing price in sample plots is taken as the dependent variable; the selection of independent variables is shown in Table 1. The factors affecting housing prices in downtown Chongqing are determined as characteristic quantities. Since the constant terms of the GWR and MGWR models represent the impact of the spatial attributes of different points on the dependent variable when other independent variables are determined, the constant terms can capture the impact of factors determined by unique locations, such as education level and environment, that to a certain extent are not included in the model of housing prices [22].

Table 1. Quantification table of sample residential housing price characteristics.

Tag Sort of Characteristics	Variable Attributes	Assignment Description/Unit	Expected Symbol
Topographic features	Topographic potential index	The topographic potential index is extracted from the digital elevation model	−
	Altitude	The elevation of the plot is extracted from the DEM (m)	+
	Slope	The slope of the plot is extracted from the digital elevation model (°)	−
Architectural features	Plot ratio	Objective value of plot floor area ratio	−
	Property fee	Objective value of residential property management fee (CNY/m^2/month)	+
	Greening rate	Objective value of green rate in the community	+
	Year	Community completion time (year)	+
Area features	Educational resources	Number of schools within 1 km of the neighborhood	+
	Medical resources	Number of general hospitals within 1 km of the community	+
	Landscape resources	Distance from community to the nearest park or square (m)	−
	Travel facilities	Number of gas stations within 1 km of the neighborhood	+
	Living facilities	Number of supermarkets within 1 km of the neighborhood	+
Neighborhood features	Rivers	The distance from the community to the Jialing River or the Yangtze River as the crow flies (m)	−
	CBD	The rectilinear distance from the residential area to the nearest CBD (m)	−
	Metro	Linear distance from the cell to the nearest orbital station (m)	−
	Bus	Number of bus stops within 500 m of the neighborhood	+

4. Results

4.1. Spatial Pattern of Housing Prices in Downtown Chongqing

The distribution of housing prices in the central urban area of Chongqing has an obvious polycentric structure (Figures 1 and 2), which can be shown as follows: housing prices are high-value centers distributed mainly in the study area, and there are several obvious high price points in Jiefangbei Business District in Yuzhong District, Central Park in Yubei District, the university town in Shapingba District, Guanyinqiaoi, and Jiangbei Mouth in Jiangbe District. These regions of Chongqing have developed rapidly in recent years, and housing prices in other regions are relatively low. ArcGIS 10.2 software was used to conduct global autocorrelation analysis on 4711 sample points, and the results are shown in Table 2. The global Moran's I index is 0.22, indicating that housing prices have a strong positive correlation in space. The Z score is 144.56, which is greater than the positive critical value of 2.58 at a significance level of 1%, indicating that there is significant positive autocorrelation in housing prices. The local Moran's I index was further used to analyze the spatial autocorrelation of housing prices in the central urban area of Chongqing [41]. According to the analysis results of the local Moran's I index, those housing prices show significant spatial heterogeneity, as shown in Figure 2, indicating obvious positive spatial autocorrelation in housing prices. In the center of the study area is a significant "high-high" aggregation, showing a multicentric trend, including mainly the Jiefangbei business circle in Yuzhong District, Nanbin Road and Chayuan in Nan'an District, and the Zhaomushan Plate in western Yubei District. These areas are core areas of commercial activities in Chongqing, with an active real estate market and large transaction volume. "Low-low" clusters appear mainly at the edges of the central city.

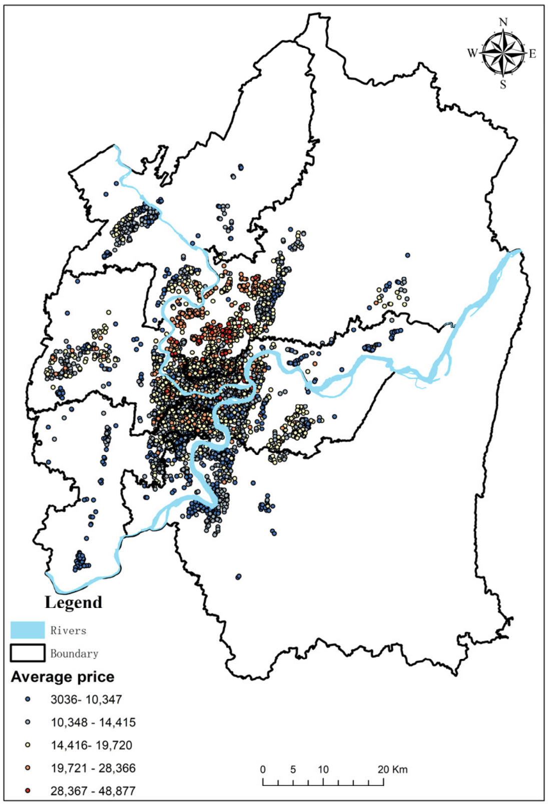

Figure 1. Housing price diagram of the Chongqing city center.

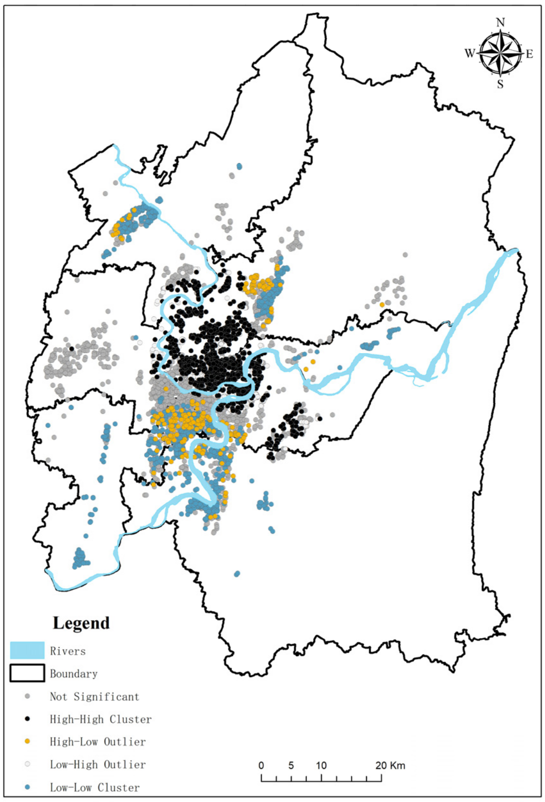

Figure 2. LISA map of housing prices in the Chongqing city center.

Table 2. Moran's I index table for global autocorrelation analysis.

Name of Index	Exponent
Moran's I Index	0.223556
Expectations index	−0.000212
Variance	0.000002
Z score	144.561290
p value	0.00000

4.2. Regression Coefficient Analysis

According to the regression coefficient results of the MGWR model (Table 3, Figure 3), elevation, floor area ratio, property fee, greening rate, building age, and distance from the river have an impact on housing prices.

(1) Elevation. Elevation reflects our results to a certain extent, verifying our hypothesis. Terrain factors have a certain impact on housing prices, and the impact is not fixed. The impact also has some regional features that vary in different regions of influence. In some areas, housing prices increase with elevation, while in other regions, elevation has the opposite effect. The elevation coefficient ranges from −0.118 to 0.141, with an average of −0.001. The standard deviation is 0.099, indicating that in the central urban area of Chongqing, every 1 m increase in the elevation of a housing community increases the price by CNY 1410 at most, decreases it by CNY 1180 at most, and decreases it by CNY 10 on average. This influencing factor varies greatly among different regions. Figure 3a shows that the prices of housing communities in areas such as Yubei District and Jiangbei District increase with increasing elevation, especially in the emerging development areas of Chongqing centered on Zhaomushan Plate, Renhe Street, and Caijia, as these areas have short construction times and better supporting facilities. At the same time, the higher the elevation of a community is, the lower the probability of external pollution, which drives up housing prices. However, in Jiefangbei Business District, Guanyinqiao Business District, the tea garden in Nan'an District, and Shapingba District, housing prices decrease with

elevation due to the relatively smooth terrain and convenient transportation in this area. A lower elevation level means more convenient communication between the district and the outside world. This series of factors directly affects the housing price level in these areas. The absolute value of the regression coefficient indicates that elevation is not the dominant factor in the characteristic quantification of housing prices, but it has a certain influence on housing prices.

Table 3. Statistical description of multiscale geographic weighted regression coefficients.

Variable	Mean	STD	Min	Median	Max
Intercept	0.219	0.101	0.043	0.218	1.257
Topographic potential index	0.057	0.019	0.056	0.056	0.498
Altitude	−0.001	0.099	−0.118	−0.037	1.195
Slope	−0.068	0.061	−0.583	−0.068	0.125
Plot ratio	−0.041	0.182	−0.821	0.005	0.451
Property fee	0.264	0.192	−0.149	0.231	1.073
Greening rate	0.084	0.070	−0.043	0.067	0.404
Year	2.912	1.380	−0.715	2.870	10.450
Education	−0.049	0.089	−0.171	−0.059	0.100
Medical	0.015	0.020	0.015	0.015	0.471
Landscape	−0.032	0.013	−0.336	−0.031	−0.031
Travel	−0.028	0.014	−0.029	−0.029	0.284
Living	0.086	0.017	0.085	0.085	0.465
River	0.010	0.126	−0.201	−0.038	0.318
CBD	−0.143	1.000	−3.818	−0.076	5.379
Metro	−0.055	0.004	−0.055	−0.055	0.041
Bus	−0.011	0.005	−0.134	−0.011	−0.011

(2) Plot ratio. The floor area ratio of a housing district is subject to relevant planning control and is fixed at the beginning of construction. However, an excessively high floor area ratio will generally cause crowding in the district, and an excessively low floor area ratio will lead to high housing prices, making it difficult for low-income groups to afford housing. As shown in Figure 3b, the plot ratio has a significantly negative impact on the prices of most housing communities that are concentrated in newer areas, such as Zhaomushan Plate and Caijia. Because the plots in the above areas are relatively new, the plot ratio has little variation, but the higher the plot ratio, the lower the price of unit floor space. The areas with a positive impact of the floor area ratio on housing prices are concentrated in the central area of Chongqing, distributed in the old campus of Chongqing University, Chongqing Tiandi in Yuzhong District, and other places. This area has a mature and complete real estate market. A higher floor area ratio means that the community can accommodate more households, and a more central location and more convenient supporting facilities can attract more residents to buy housing, leading to higher housing prices. The mean value of the regression coefficient of the floor area ratio is −0.041, ranging from −0.821 to 0.451, and the standard deviation is 0.182, indicating that housing prices decrease by CNY 410 on average for every unit increase in the floor area ratio. The absolute value of the coefficient analysis indicates that the influence intensity of the plot ratio is in the middle of all the characteristic quantities.

(3) Property fees. Property fees significantly affect housing prices and are positively correlated; that is, housing prices in areas with higher property fees also show a higher trend. This trend reflects the general perception that higher property fees represent a higher level of community environment, management, and other services, thereby driving up housing prices. As shown in Figure 3c, the property fee regression coefficient has clear spatial heterogeneity. Areas with a significant impact of property fees on housing prices are concentrated mainly in the core areas of downtown Chongqing, including the Jiefangbei business circle in Yuzhong District, Guanyinqiao business circle in Jiangbei District, Binjiang Road in Nan’an District, and the garden and area of Vientiane City in Jiulongpo District.

The eastern and western regions show scattered distributions, and there are more housing sample points with regression coefficients of 0.179–0.312. The value of the property fee coefficient is between 0.179 and 1.073, with an average of 0.264, indicating that with an increase of CNY 1 in the property fee, the housing prices will increase by CNY 1790–10,730, with an average increase of CNY 2640. Although property fees have an obvious positive effect on housing prices, the spatial difference in the degree of the effect is large, and the spatial distribution of the impact degree is uneven.

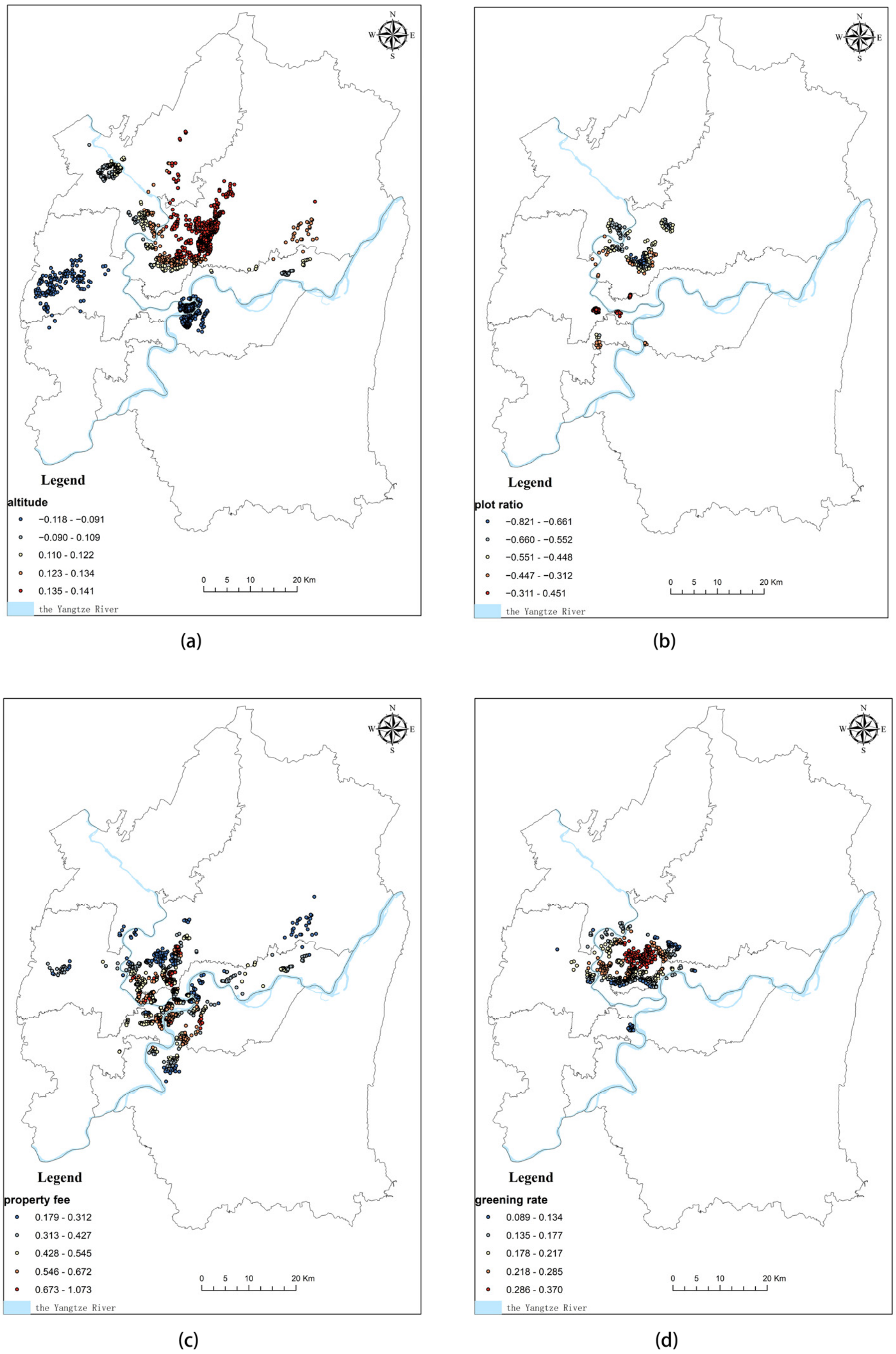

Figure 3. *Cont.*

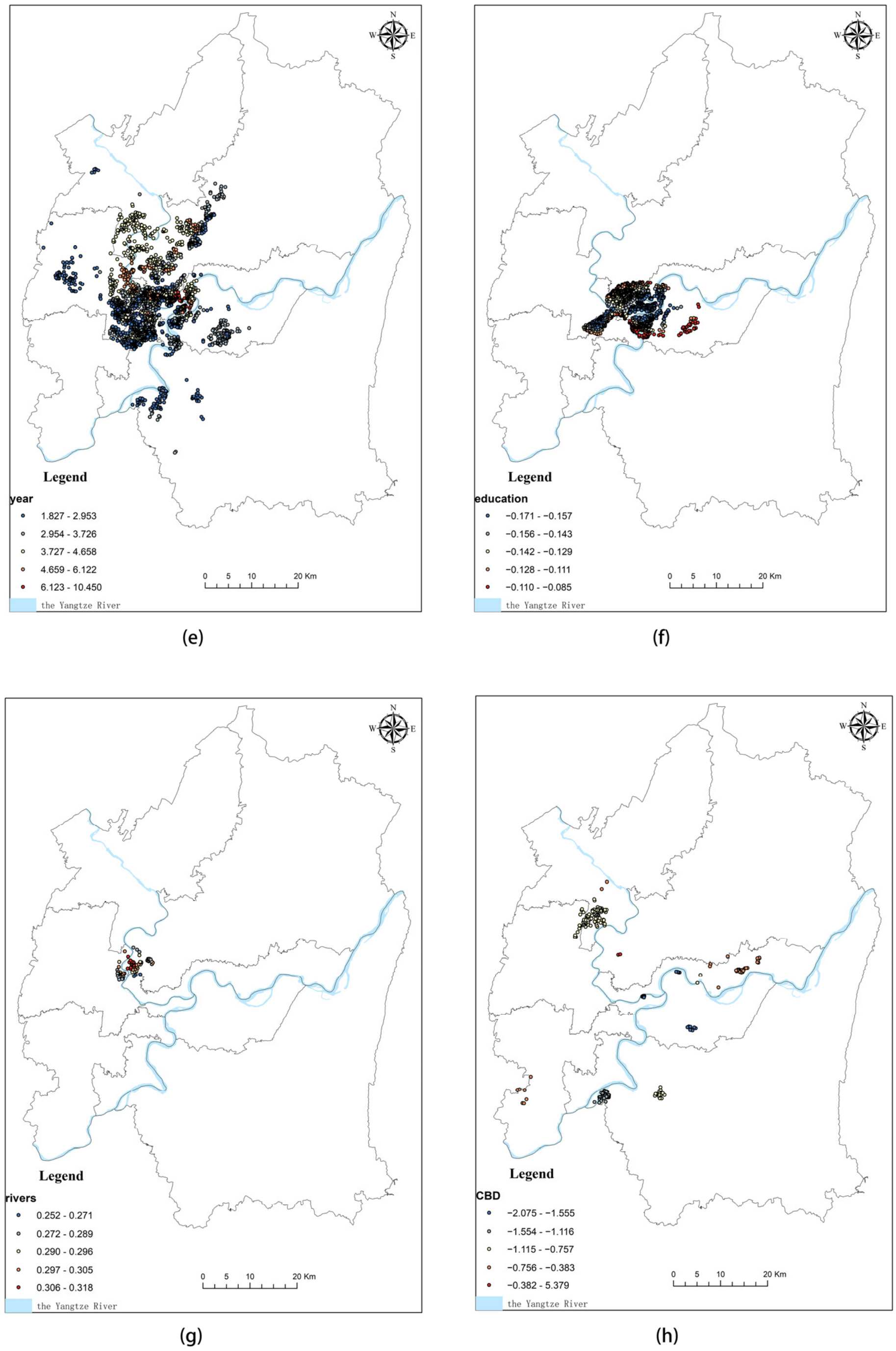

Figure 3. Spatial patterns of MGWR regression coefficients. (Picture (**a**) represents Altitude; Picture (**b**) represents Plot ratio; Picture (**c**) represents Property fee; Picture (**d**) represents Greening rate; Picture (**e**) represents Year; Picture (**f**) represents Education; Picture (**g**) represents River; Picture (**h**) represents CBD).

(4) Greening rate. The greening rate also significantly affects housing prices and presents a positive correlation (Figure 3d). The area with a significant effect of the greening rate on housing prices in the central urban area of Chongqing is concentrated in Yubei District, and the distribution of the regression coefficient also shows a certain spatial trend, with the Zhaomushan group as the center and the outward-direction coefficient gradually decreasing. In the area with a concentrated distribution of residential buildings, the population and building density are higher, and higher greening rates of residential areas can effectively drive up housing prices. The regression coefficient of the greening rate

has an average value of 0.084 and a standard deviation of 0.07, ranging from 0.089 to 0.37, indicating that under the same conditions, every 1% increase in the greening rate will increase housing prices by CNY 890 to 3700, with an average increase of CNY 700.

(5) Construction age. Construction age has a significant positive impact on housing prices, as shown in Figure 3e. From the perspective of spatial location, the influence degree of Yubei District and Jiangbei District is much higher than that of other areas, indicating that the traditional housing district is less affected than new districts, which means that the impact of the housing depreciation rate on housing prices is decreasing; that is, when housing is built, housing prices first fall faster, and the speed of this decrease then gradually slows. The regression coefficient of building age ranges from 1.827 to 10.45, with an average value of 2.912 and a standard deviation of 1.38, indicating that the housing price decreases by CNY 18,270 to 104,500 for every year that housing age increases. The influence intensity of construction age is the largest among all the characteristic quantities, with obvious spatial heterogeneity. The positive effect of housing age on housing prices varies greatly in different regions.

(6) Educational facilities. Supporting educational facilities have a significant negative impact on housing prices (Figure 3f). The significant influence range of educational facilities is highly concentrated in the center of the study area, including Yuzhong District, Nan'an District, Jiangbei District, Jiulongpo District, and the southern part of Yubei District. This is due to the rich educational resources in the central urban area of Chongqing, ranging from basic education to higher education and vocational education, but the relative location is concentrated in the central urban area. Therefore, the spatial distribution of the regression coefficients shows a relative tendency of aggregation. In the central urban area of Chongqing with highly developed educational resources, in order to attract more residents, most communities will introduce price reduction measures; thus, the supporting educational facilities have a negative impact. The value of educational facilities ranges from −0.171 to −0.085, with a mean value of −0.049 and a standard deviation of 0.089. For every additional school distributed within 1 km of the neighborhood, the housing price decreases by CNY 850 to 1710, with an average decrease of CNY 490.

(7) Distance from rivers. As shown in Figure 3g, as a local variable, this variable has a small effect scale. The coefficient ranges from 0.271 to 0.318, indicating that the housing price increases by CNY 2710–3180 for every 1 unit increase in distance from the river. The absolute value of the coefficient indicates that its influence is weak. However, this does not mean that the price of the view is lower. The reason is that the sample of this paper is the average price of housing in the community. Generally, "view" refers to a single house.

(8) Distance from the CBD. The housing price and distance from the CBD show a certain degree of spatial agglomeration (Figure 3h), and the regression coefficient is negative in most areas and appears to be positive only in the vicinity of Zhaomushan Plate. Zhaomushan Plate, as a younger and more active real estate market in the central urban area of Chongqing, is close to Zhaomushan Park, meaning it is close to nature and a beautiful environment. Therefore, the farther the distance from the CBD, the higher the housing price is, while the closer the distance to the CBD, the lower the price is. The value ranges from −2.075 to 5.379, with an average value of −0.143, indicating that the housing price decreases by CNY 1430 for each additional 1 km from the CBD. The absolute value of the regression coefficient reveals that its influence intensity is one of the largest of all the characteristic quantities.

5. Conclusions and Discussion

5.1. Conclusions

Taking the central city of Chongqing as an example, this paper discusses the spatial differentiation and spatial scale difference in housing prices in sample residential areas. The results are as follows. (1) The spatial distribution of housing prices in sample residential areas in downtown Chongqing has obvious spatial heterogeneity. The analysis of the local Moran's I index reveals that housing prices show significant "high-high" clustering in the core of the study area and a polycentric trend, while "low-low" clustering appears at the edges of the study area, which is consistent with the current situation of the real estate market in the Chongqing city center. (2) The MGWR model assigns a dedicated bandwidth to each feature quantity. The topographic location index, medical resources, landscape resources, transport facilities, living facilities, rail station distance, and bus station distance are all global variables, and their spatial heterogeneity is weak. (3) The regression coefficient analysis results show that property cost, greening rate, building age, and distance from a river have a significant positive impact on housing prices, while educational facilities have a significant negative impact on housing prices. The impact of elevation, floor area ratio, and distance from the CBD on housing prices is complex. Of all the significant factors affecting housing prices, the strongest is building age, followed by property management fees, plot ratio, and distance from the CBD. Greening rate and elevation have the weakest impact on housing prices, but to a certain extent, the housing prices of mountain cities are still affected, so these factors cannot be ignored.

5.2. Discussion

The findings of this paper are consistent with the conclusions of previous studies regarding greening rate [42], building age [21], distance from the CBD [43], educational facilities [18], and other factors that have a significant impact on housing prices. Chongqing is a typical mountain city in China located in a hilly and mountainous area of Southwest China. The characteristics of the housing market and housing prices in the central urban area are different from those in central and eastern plain cities. In the context of a large number of previous studies [10,13,14], this paper considers the regional characteristics of Chongqing [44] in the selection of feature quantities and adds topographic factors to the range of defined features in attempting to explain the mechanism of topographic factors in the formation of housing prices in mountainous cities. Chongqing is located in a hilly and mountainous area, and the terrain is complex and varied, but this study found that the impacts of the terrain index and slope in the sample plots of Chongqing housing prices are not significant. Elevation has a significant effect on housing prices and shows that in the study of urban housing price factors, reflecting regional characteristics can more accurately reflect the uniqueness of the local housing market. As shown by the research results of this paper, it is clear that Chongqing has formed several urban subcenters with an active real estate market and a large number of housing communities, including Guanyinqiao, Yangjiaping, Shapingba, Nanping, and the tea garden, which are among the "six subcenters" proposed in the Outline of Chongqing 2020—Urban Master Plan for the Metropolitan Area (2004–2020). These regions are still hot spots for future development, and the conclusions of this paper provide decision-making support for the development of these regions.

By comparing the calculation results of the GWR model and MGWR model, this paper finds that the MGWR model results are significantly better than those of the previous GWR model and are more suitable for the study of the factors influencing real estate prices, which is consistent with the results of previous studies. Zhang and Wu et al. [32,44,45] found that the scale effect plays an important role in geographical research. The MGWR model can more intuitively explain the spatiotemporal differentiation of housing prices. Incorporating spatial attributes into the analysis of housing price characteristic quantities can lead to better and more explanatory results by combining the spatial and other characteristics of housing prices while simultaneously considering the dynamic change process [46].

From a policy point of view, Chongqing provides public housing for non-local migrant workers to ease the pressure of renting. Due to the special properties of public rental housing, workers who do not buy houses in the central urban area of Chongqing can apply for public rental housing, which provides impetus for the diversified development of Chongqing's housing market, which has similar conclusions to previous studies [47]. Therefore, in addition to the quantifiable indicators listed in this paper, there are also some non-quantifiable policy factors that play an important role in the development of the housing market and the trend of housing prices.

Taking Chongqing as an example, this paper investigates and analyzes the housing prices in mountain cities, analyzes the spatial distribution of housing prices in Chongqing by using the Moran index model, and analyzes the distribution characteristics and driving factors of housing prices by constructing an index model. The research results of this paper have guiding significance to enrich research practice regarding housing prices, and can provide a theoretical basis for further exploring the development trend of housing prices in mountain cities and formulating policies. It provides technical support for establishing a more in-depth understanding of the development law of housing markets in mountain cities.

There are two possible limitations of this study. (1) The Euclidean metric is used to measure the characteristics of housing sample points rather than the distance based on accessibility, which may lead to some errors in the measurement of the distance to surrounding facilities. This will be a direction of further research. (2) This paper studies the characteristics of the proposed quantitative amounts; however, social factors are also important characteristics of housing prices, and their important role in the research process cannot be ignored. Factors such as policy [44], for example, in future studies, can be added as important variables for a more comprehensive analysis of the factors influencing housing prices. In the meantime, the research direction can be adjusted appropriately, and individual factors can be considered as important influencing factors in the housing market. For example, policy factors such as public rental housing and factors such as housing quality can be emphasized as research directions to explore whether relevant factors in mountainous cities have an impact on housing choices.

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