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Study on Spatial Distribution Characteristics and Influencing Factors of Housing Prices in Longgang District, Shenzhen

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Abstract: *Housing prices have a direct impact on both the national economy and people's livelihoods. An in-depth exploration of the spatial distribution and influencing factors of housing prices is crucial for promoting the healthy development of the real estate industry. This study utilizes housing price data and POI (Point of Interest) big data, employing GIS spatial analysis methods to examine the distribution characteristics and spatial correlations of housing prices in Longgang District, Shenzhen. Furthermore, it explores the mechanisms by which various factors contribute to housing price heterogeneity. The findings are as follows: (a) Longgang District exhibits a polycentric spatial structure, with the housing prices peaks located in the western urban core and the eastern Longgang Central City; (b) Housing prices display significant spatial agglomeration, with high-value clusters located in Longcheng, Bantian, Buji, Jihua, and Nanwan Subdistricts, while low-value clusters are found at the junctions of Pingdi, Baolong, Longcheng, and Longgang Subdistricts; (c) The relative influence of factors on housing prices within the district ranks as follows: economic factors > transportation factors > neighborhood environment factors.*

Keywords: *Housing prices, Shenzhen, Space distribution, Multi-scale geographically weighted regression*

1. Introduction

In 1998, China fully implemented housing reforms to promote the marketization of urban residential housing, resulting in a gradual increase in urban housing prices. In 2010, the Chinese government issued a notice on "Resolutely Curbing the Rapid Rise of Housing Prices in Some Cities," introducing purchase restrictions to temper the overheated real estate market. By 2016, the Chinese government had introduced the concept of "housing is for living, not for speculation," emphasizing the establishment of a long-term management mechanism. By 2020, the Chinese government further highlighted the necessity to address significant issues within the housing sector of major cities[1]. By 2024, the Chinese government mandated "coordinated research on policies to reduce existing housing inventory and optimize new housing supply," which was interpreted externally as a sign of "de-stocking."[2] These actions illustrate China's continuous efforts to ensure the stability and healthy development of housing prices through macro-control measures.

Regional housing prices are influenced by variable and complex factors[3]. At the macro-regulatory level, elements such as residential land supply, purchase restrictions, and financial adjustment measures can partially regulate the cost of home purchases, thereby affecting housing prices[1,4,5]. Additionally, within regional contexts, socioeconomic conditions, population distribution, transportation accessibility, and educational resources are key considerations for residents when selecting residential locations. In-depth analysis of National Bureau of Statistics data further confirms that indicators like per capita GDP and the tertiary industry's share are critical factors driving spatial disparities in housing price[6]. The impact of transportation on housing prices differs between suburban and urban areas, with various modes of transport exerting distinct effects. Research indicates that rail transit has a more significant impact on suburban housing prices than on those in city centers, demonstrating broader coverage[7]. High-speed rail exhibits positive effects on housing prices, whereas conventional rail exhibits negative impacts[8]. Moreover, the proximity of infrastructure like parking lots and supermarkets also affects housing prices[5]. It is revealed that comprehensive hospitals significantly boost housing prices, with spatial heterogeneity

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observed[9]. Beyond infrastructure convenience, the quality of the surrounding environment is a key determinant of housing prices[10]. Housing prices display significant spatial characteristics related to "location," and a range of spatial analysis techniques, such as Exploratory Spatial Data Analysis (ESDA)[11], multiple linear regression[12], the spatial Durbin model[6], Geographically Weighted Regression (GWR)[10,13], Geospatial Time-Weighted Regression (GTWR), and Multi-Scale Geographically Weighted Regression (MGWR)[14], have been utilized to understand their spatial positioning and interactions. ESDA aids in the investigation of spatial correlations and agglomeration phenomena within data, whereas the MGWR model reliably reflects the influence of independent variables on dependent variables across various scales. The MGWR model exhibits a higher model fit compared to the GWR model, allowing for a more precise revelation of spatial relationships between dependent and independent variables[14].

As a window city for China's reform and opening-up and a core city in the Guangdong-Hong Kong-Macao Greater Bay Area, Shenzhen's Longgang District is situated in the northeast, bordering Dongguan and Huizhou, and has attracted numerous high-tech enterprises and higher education institutions. According to the 2022 Shenzhen Statistical Yearbook, both real estate development investment and commercial housing sales area in Longgang District rank within the top three in Shenzhen. Based on this, the study selects Longgang District as its research subject, employing ESDA methods and the MGWR model to investigate the comprehensive impact of factors categorized into three sectors—surrounding environment, transportation conditions, and economic demographic—on housing prices.

2. Data Sources and Methods

2.1. Data Sources

The dataset primarily comprises residential property prices, POI (Points of Interest) for surrounding facilities, transportation infrastructure, and administrative divisions in Longgang District. Residential property prices were obtained from Lianjia.com and Baidu Maps, with fields including neighborhood names, average prices, geographic coordinates, and nearby commercial areas. After data cleaning, 708 residential property price records were finalized. Location data for six public facilities—shopping malls, parks, middle schools, primary schools, hospitals, and subway stations—was sourced from Baidu Maps' POI database. Transportation road vector data was sourced from OpenStreetMap, while administrative division vector data was obtained from the National Center for Basic Geographic Information. The GDP and population grid data were sourced from the Resource and Environmental Science Data Registration and Publishing System[15].

2.2. Methods

2.2.1. Inverse Distance Weighting

This study employs inverse distance weighting (IDW) on housing price data to generate a continuous spatial surface of property values in the region. The IDW method posits that geographic proximity between objects correlates with their similarity. The information value of an unknown point is calculated by weighting the values of adjacent sample points, with weights determined by distance decay principles. The underlying formula is presented in Equation (1):

$$Z = \sum_{i=1}^{n} Z_i \left((1/{D_i}^p) / \sum_{j=1}^{n} (1/{D_j}^p) \right) \tag{1}$$

where Z denotes the estimated value at the interpolation point; Z_i represents the information value of the i-th known neighboring sample point; D_i indicates the distance between the i-th sample point and the current interpolation point; p is the power of the distance between the interpolation point and the i-th sample point, which adjusts the distance weight. When p approaches 0, the weights of all sample points become equal; as p increases, the weights of more distant sample points decrease rapidly[16].

2.2.2. Spatial Autocorrelation

Spatial autocorrelation examines the relationship between a study object and its spatial distribution, typically categorized into two types: positive and negative correlations. Positive correlation indicates that the information values of a study unit show the same variation trend as its adjacent spatial units, while negative correlation[17] demonstrates the opposite pattern. In housing price spatial correlation analysis, higher autocorrelation suggests significant spatial clustering of housing prices.

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1) Global spatial autocorrelation

Global spatial autocorrelation measures the spatial characteristics of information values across an entire region. This study employs Moran's I method to analyze residential price autocorrelation in Longgang District. The Equation (2) illustrates the principle of global Moran's I spatial autocorrelation:

$$I = (n/S_0)\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j} Z_i Z_j / \sum_{i=1}^{n} Z_i^2\right) \tag{2}$$

where I denotes the Moran's I index, Z_i represents the deviation of the information value x_i of cell i and its mean value $\bar{X}$; $W_{i,j}$ is the spatial weight between elements i and j, n is the total number of cells, and S_0 is the sum of all spatial weights. The Moran's I index ranges from -1.0 to +1.0. A positive value indicates spatial positive correlation in the studied information, a negative value indicates spatial negative correlation, and a value of 0 indicates spatial randomness[18].

2) Local spatial autocorrelation

Global spatial autocorrelation analysis reveals consistent overall spatial clustering patterns, yet housing prices exhibit localized heterogeneity. To investigate local clustering characteristics, This study employ local spatial correlation analysis to examine the spatial differentiation of housing prices in Longgang District. The local Moran's I spatial autocorrelation principle is specifically expressed in Equation (3):

$$I_i = ((x_i - \bar{X})/S_i^2)\sum_{j=1, j\neq i}^{n} W_{i,j}\left(x_j - \bar{X}\right) \tag{3}$$

where I_i denotes the local Moran's I index, with x_i, $W_{i,j}$, $\bar{X}$, and n defined as in Equation (2). The variance S_i^2 is given by Equation (4):

$$S_i^2 = \sum_{j=1, j\neq i}^{n}(x_i - \bar{X})/(n-1) \tag{4}$$

Agglomeration represents a spatial connectivity pattern. High-high agglomeration occurs when units with high observed values are surrounded by other units exhibiting similarly high values. High-low agglomeration describes situations where units with higher observed values are encircled by units with lower values. Low-low agglomeration refers to spatial connections where units share identical low-value characteristics. Conversely, low-high agglomeration occurs when units with observed lower values are surrounded by units with higher values.

2.2.3. Multi-scale geographically weighted regression

The MGWR model demonstrates superior reliability compared to traditional GWR models by simultaneously accounting for bandwidth variations across variables during modeling and analysis[14]. As a critical threshold for spatial weight calculation, bandwidth values directly determine the precision of spatial weight parameters. When processing observational data, the MGWR model comprehensively considers the geographical locations of each observation point, assigning appropriate bandwidths to individual variables and conducting linear regression analysis for each. This method allows the model to precisely determine the influence coefficients of various factors on housing prices at different sample points, thus uncovering the distinct impact of each factor on housing prices across various regions. The operational principles of the MGWR model are detailed in Equation (5):

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)\, x_{i,j} + \varepsilon_i \tag{5}$$

where y_i denotes the housing price of the i-th unit; $x_{i,j}$ represents the j-th housing price driver index value for the i-th unit; (u_i, v_i) indicates the spatial coordinates of the i-th unit; ε_i denotes the random error; and β_{bwj} represents the bandwidth of the regression coefficient for the j-th housing price driver.

3. Results

3.1. Spatial Distribution of housing prices

Figure 1 below shows the spatial distribution of housing prices in Longgang District, calculated using IDW interpolation. The data indicates a multi-center pricing pattern: prices in the urban core of the southwest are significantly higher than in other areas, whereas the northwestern region exhibits relatively lower costs. The central area adjacent to Dongguan also shows higher housing prices, while the northeastern and southern regions have slightly lower price levels.

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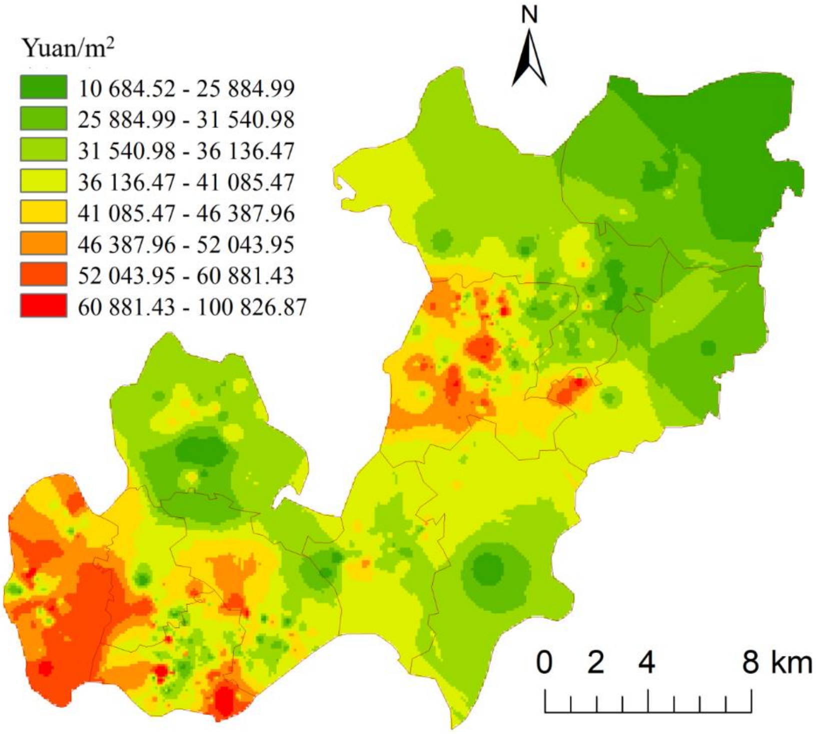

Figure 1: Distribution surface of housing prices in Longgang District.

3.2. Spatial Heterogeneity of Housing Price

The Moran's I index for housing prices in Longgang District was calculated to be 0.379, with a p-value < 0.01 and z-score of 4.65, indicating significant spatial positive correlation in the district's housing market.

As shown in *Figure 2*, the high-high housing price agglomeration phenomenon is mainly concentrated in the southwest and central regions, while the low-low housing price agglomeration phenomenon is mainly found in the northwest and northeast. Other regions show no significant agglomeration characteristics, and there is almost no low-high and high-low housing price agglomeration phenomenon in the whole region.

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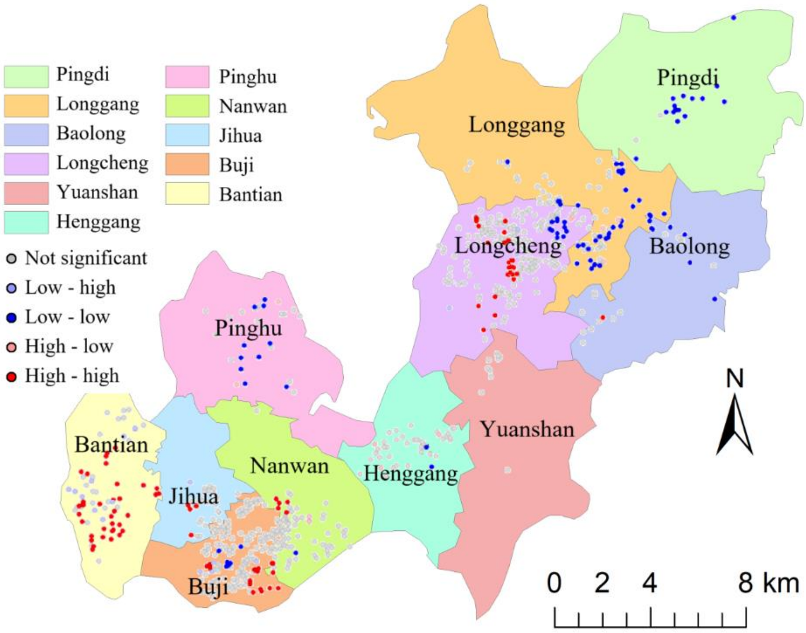

Figure 2: Local spatial autocorrelation analysis results of housing prices in Longgang District.

3.3. Influencing Factors of housing prices

Housing prices are generally higher in urban centers due to dense populations and access to quality infrastructure, such as transportation, education, and healthcare. In these areas, the impact of various factors is relatively balanced. However, in suburban areas, the influence of a single factor becomes more pronounced[19].

Based on data availability and representativeness, this study selects influencing factors from three dimensions: the surrounding environment, transportation conditions, and economic demographic (as shown in *Table 1*). The entire research area is divided into 1km×1km grids, with the mean housing prices and corresponding factor values calculated for each grid. Subsequently, a MGWR analysis is conducted.

Table 1: Influencing factors explanation of housing prices.

Influencing factors		Calculation and Descriptions
Surrounding environment	Shopping malls	The average distance cost per square kilometer between shopping malls and residences.
	Parks	The average distance cost per square kilometer between the parks and residences.
	Middle schools	The average distance cost per square kilometer between the middle schools and residences.
	Primary schools	The average distance cost per square kilometer between the primary schools and residences.
	Hospitals	The average distance cost per square kilometer between the hospitals and residences.
Transportation conditions	Subway stations	The average distance cost per square kilometer between the subway stations and residences.
	Road length	The sum of road length per square kilometer.
Economic demographic	GDP	The sum of GDP per square kilometer.
	Population	The sum of population per square kilometer.

Several experiments with the MGWR model demonstrated that the combination of an adaptive kernel type (Adaptive) with cross-validation (CV) for bandwidth optimization produced the most robust fitting results, as illustrated in *Table 2* and *Figure 3*. The MGWR analysis revealed small residual sum of squares, a low Sigma value, and a low AIC value, with an adjusted R^2 exceeding 0.4. This indicates the model

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passed significance testing and met optimal model parameter criteria[14]. Therefore, the MGWR model for Longgang District housing prices is validated as effective.

Table 2: Coefficients of influencing factors by MGWR.

Factors	Mean	Standard deviation	Minimum	Median	Maximum	Bandwidth
Shopping malls	0.099	0.19	-0.138	0.153	0.308	121
Parks	-0.038	0.05	-0.099	-0.054	0.022	141
Middle schools	-0.055	0.11	-0.201	-0.11	0.119	118
Primary schools	-0.04	0.012	-0.059	-0.04	-0.021	147
Hospitals	-0.029	0.149	-0.377	-0.018	0.174	59
Subway stations	-0.086	0.321	-0.625	-0.132	0.686	48
Road length	0.086	0.012	0.071	0.083	0.102	147
GDP	0.147	0.042	0.084	0.146	0.213	147
Population	0.083	0.023	0.057	0.085	0.113	147

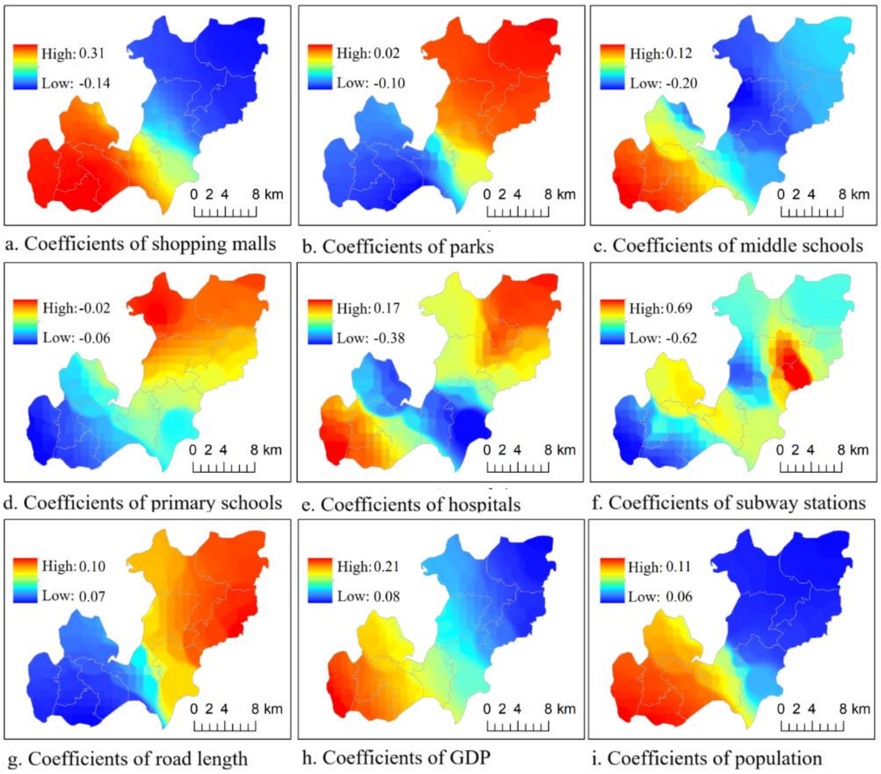

Figure 3: Results of MGWR Coefficients.

4. Discussion

4.1. Influence of surrounding environment on housing prices

As indicated in *Figure 3-a*, the coefficient range of shopping mall proximity on housing prices spans from -0.138 to 0.308, with negative values accounting for 43.31% of the cases. The median coefficient is 0.153, signifying considerable spatial variation. The areas with negative coefficients are predominantly concentrated in the central city of Longgang, extending outwards to the eastern regions, including Pingdi, Longgang, Baolong, Longcheng, and the northern part of Yuanshan. The infrastructure and commercial zones of Longgang Central City are still in a phase of ongoing development and refinement, featuring relatively few shopping malls and cultural entertainment facilities, which makes it more attractive to residents. In the central-western urban core of Shenzhen, where high population density and convenient transportation are common, shopping malls exert a suppressive effect on housing prices, rendering them more susceptible to other influencing factors.

As indicated in *Figure 3-b*, the coefficient of park distance on housing prices varies from -0.099 to 0.022, with 54.36% of the values being negative and a median of -0.054. This coefficient signifies the smallest spatial variation among all factors, suggesting relatively minor regional disparities in the impact of parks. In western subdistricts such as Bantian, Buji, Jihua, Nanwan, Pinghu, and Henggang, parks have notably positive effects on housing prices. This effect may be due to the severe environmental pollution in urban centers, which makes park green spaces particularly valuable. It also illustrates how high-quality recreational environments in the surrounding areas increase housing market values.

As indicated in *Figure 3-c*, the regression coefficient range of the impact of middle school proximity on housing prices spans from -0.201 to 0.119, with negative values constituting 63.76% and a median of -0.11. In summary, the influence of middle schools on housing prices is notably significant. Chart analysis suggests that, aside from urban core areas, neighborhoods in proximity to middle schools generally exhibit higher housing prices. The majority of key middle schools in Longgang District are situated in the central-eastern regions. Despite the presence of key middle schools in urban core areas, housing prices there are predominantly affected by other factors.

As indicated in *Figure 3-d*, the regression coefficients for the proximity of primary schools on housing prices range from -0.059 to -0.021, with all coefficients being negative (100% of the total). The median coefficient is notably low at -0.04. In general, primary school educational resources exert a significant positive influence on housing prices. Compared to the eastern regions, this effect is particularly pronounced in the western areas, which not only host multiple key primary schools but also have higher per capita income levels. This underscores the strong emphasis that Shenzhen residents place on their children's education.

As indicated in *Figure 3-e*, the regression coefficients for hospital proximity on housing prices vary from -0.377 to 0.174, with negative values constituting 52.35% of the total. The median coefficient is -0.018, suggesting considerable spatial variation. The negative coefficients are predominantly found in the Pinghu, Henggang, and Yuanshan. In these regions, hospitals appear to have a significant positive effect on housing prices, potentially because of their earlier development schedules. In contrast to recently developed areas, these locales already have more established medical resources.

4.2. Influence of transportation conditions on housing prices

As illustrated in *Figure 3-f*, the regression coefficients for the proximity of subway stations to housing prices range from -0.625 to 0.686. Negative values constitute 61.07% of the total, with a median coefficient of -0.132. Overall, with the exception of the eastern Baolong area and the intersection of Longgang and Longcheng subdistricts, which exhibit positive coefficients, all other regions display negative values. This trend may be attributed to the ongoing construction of the planned Phase II of Line 16, anticipated to open in 2025. Although current housing prices in these areas are relatively low, they exhibit significant potential for appreciation. The positive effect of proximity to subway stations on housing prices is especially evident in the eastern and western regions, mainly because these areas are concentrated residential zones where the convenience of subway access greatly enhances the mobility of residents.

As indicated in *Figure 3-g*, the regression coefficient for road length on housing prices varies between 0.071 and 0.102, with all values being positive and a median of 0.083. This suggests a significant positive correlation between road length and housing prices. The eastern part of Longgang District exhibits the most pronounced impact, mainly because of its relatively sparse subway coverage and its role as a key transportation hub connecting Shenzhen, Dongguan, and Huizhou. This hub handles crucial intercity passenger, cargo, and information flows. In contrast, the western area experiences a lesser impact, characterized by dense residential clusters and numerous subway stations. Most residents in this region work in areas such as Futian and Nanshan, where subway travel is more convenient than road transportation.

4.3. Influence of Economic demographic on housing prices

As indicated in *Figure 3-h*, the regression coefficients of GDP on housing prices range from 0.084 to 0.213, all positive and accounting for 100% of the total, with a median value of 0.146. The influence exhibits a decreasing trend from west to east, peaking in the western regions, which signifies the most substantial impact of GDP on housing prices in this area. This outcome further corroborates the dominant role of economic factors in housing price fluctuations[20].

As indicated in *Figure 3-i*, the regression coefficients of population on housing prices range from 0.057 to 0.113, all of which are positive (100% positive), with a median value of 0.085. This suggests a positive correlation between population density and housing prices. The growth of urban populations often results in a shortage of housing supply, which in turn increases property values. When comparing residential areas, residents typically favor locations that offer better living conditions, leading to higher population densities in areas with superior regional advantages. The graph shows a gradual decline in the impact of population on housing prices from west to east. This could be due to the fact that western regions, as core urban areas with more convenient transportation, proximity to Shenzhen's urban core, and being key development zones in Longgang District, possess more favorable regional conditions compared to eastern areas.

From an overall average perspective, the proximity of schools, hospitals, and parks in the surrounding environment positively impacts housing prices, reflecting urban residents' preference for educational, medical, and recreational facilities, which aligns with existing research findings[9]. However, shopping malls in some areas exhibit a suppressive effect on housing prices, similar to previous studies showing that supermarket proximity inhibits housing prices[5]. This may be because some large shopping malls are built in suburban areas with relatively lower land prices or rents. Additionally, with the prevalence of online shopping, people's reliance on mall shopping has decreased. Regarding transportation convenience, proximity to subway stations positively influences housing prices, consistent with research by Zhang Weiyang et al[7]. The impact coefficient of road length further indicates that transportation accessibility benefits housing prices. In terms of economic demographic factors, areas with more developed economies and higher population density generally have higher housing prices, with economic level being the most significant factor affecting housing prices.

5. Conclusions

This study initially employs the inverse distance weighting interpolation method to estimate the spatial distribution of housing prices across Longgang District. It then utilizes the MGWR model to conduct regression analysis on the influencing factors of housing prices, leading to the following conclusions: (a) The overall housing price situation in the residential communities of Longgang District is as follows: the housing price range spans from 9,597 yuan/m^2 to 106,127 yuan/m^2, with an average price of 40,004.17 yuan/m^2 and a median of 38,300 yuan/m^2. The overall housing price distribution exhibits a multi-center pattern. (b) Spatial autocorrelation analysis indicates that housing prices in Longgang District generally display significant agglomeration characteristics; there are distinct differences in the distribution of housing prices across the region, which manifest as high-high agglomeration and low-low agglomeration. (c) Analysis from the MGWR model reveals that six types of public facilities, road length, and economic demographic factors exhibit significant spatial variations in their impact on housing prices in Longgang District. Overall, economic factors demonstrate the most pronounced influence, followed by transportation factors, while the impact of surrounding environmental factors is relatively weaker.

The methodology used in this study exhibits strong generalization capabilities, though constrained by data accessibility, and shows city-specific variations. Future research could incorporate more big data to achieve more reliable and precise outcomes. The study aims to offer actionable insights for optimizing housing resource allocation, providing robust data support to governments. These findings will enable effective macro-regulation of the housing market, ensuring sustainable development and long-term stability in the real estate sector.

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