

## Research Article

# GIS-Based Spatial Autocorrelation Analysis of Housing Prices Oriented towards a View of Spatiotemporal Homogeneity and Nonstationarity: A Case Study of Guangzhou, China

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In the past decades, the booming growth of housing markets in China triggers the urgent need to explore how the rapid urban spatial expansion, large-scale urban infrastructural development, and fast-changing urban planning determine the housing price changes and spatial differentiation. It is of great significance to promote the existing governing policy and mechanism of housing market and the reform of real-estate system. At the level of city, an empirical analysis is implemented with the traditional econometric models of regressive analysis and GIS-based spatial autocorrelation models, focusing in examining and characterizing the spatial homogeneity and nonstationarity of housing prices in Guangzhou, China. There are 141 neighborhoods in Guangzhou identified as the independent individuals (named as area units), and their values of the average annual housing prices (AAHP) in (2009–2015) are clarified as the dependent variables in regressing analysis models used in this paper. Simultaneously, the factors including geographical location, transportation accessibility, commercial service intensity, and public service intensity are identified as independent variables in the context of urban development and planning. The integration and comparative analysis of multiple linear regression models, spatial autocorrelation models, and geographically weighted regressing (GWR) models are implemented, focusing on exploring the influencing factors of house prices, especially characterizing the spatial heterogeneity and nonstationarity of housing prices oriented towards the spatial differences of urban spatial development, infrastructure layout, land use, and planning. This has the potential to enrich the current approaches to the complex quantitative analysis modelling of housing prices. Particularly, it is favorable to examine and characterize what and how to determine the spatial homogeneity and nonstationarity of housing prices oriented towards a microscale geospatial perspective. Therefore, this study should be significant to drive essential changes to develop a more efficient, sustainable, and competitive real-estate system at the level of city, especially for the emerging and dynamic housing markets in the megacities in China.

## 1. Introduction

Since the 1990s, the reform of real-estate system and land-use system in China have been implemented, leading to a continuous booming growth of the real-estate market, which has grown into one of the pillar industries in the national economic development. After decades of the dramatic development of housing market, the housing prices in China has been driven to consistent increasing, especially in the mega cities, such as Beijing, Shanghai, Shenzhen, and Guangzhou. Currently, the tremendous changes of housing prices in China are increasingly being watched by relevant research

organizations, scholars, and other interest groups, as it is not only a crucial economic issue related to the benign development of the housing market and the optimization and adjustment of the national economic structure but also a paramount social issue related to the urban residents' livelihood [1, 2]. Especially, the long-run urban spatial expansion, large-scale urban infrastructural construction, and fast-changing urban planning have been deriving the rapid changes of housing prices in the megacities in China. This triggers the significant need to examine the specific affecting factors in the context of urban spatial development, infrastructure layout, and planning for promoting the governing

policy and spatial controlling mechanism of housing market, and the reform of real-estate system and land-use system in the level of city.

Scholars have conducted research on the effects of housing prices from two perspectives, i.e., the national level and the city level. At the national level, the factors influencing on the changes in housing prices generally include monetary, fiscal, and housing policies [3–7], while the specific factors affecting the housing prices at the level of city mainly involve with urban development, land use, population, housing supply and demand, and urban planning [8–12]. At the level of city, the study on the fluctuations of housing prices and the correlations to the influencing factors has been a hot topic in the fields of governing policy of housing market and the reform of real-estate and related urban systems, e.g., land-use system, as well as the hotspots in urban spatial layout, urban planning, and sustainability development [10]. Due to the commodity attribute of the house, since the late 1970s, the traditional regressive models for asset pricing, i.e., hedonic price models [13], have been widely used in the evaluation of house values [14–17]. Hedonic price models define that the price of a specific commodity should be constituted by several different elements in which their number and combination are discrepant, leading to unequal prices for different commodities. The application of hedonic price models in housing market aims at decomposing the key components of housing prices and applying a regression analysis to quantitatively measure the impact of each element [13]. Currently, hedonic price models have been adopted and extended widely to investigate the complex effects on housing prices in the context of urban neighborhoods and submarkets. As an example, Basu and Thibodeau examine the spatial autocorrelation in transaction prices of single-family properties in Dallas, Texas, by an empirical analysis which applies a semilog hedonic house price equation and a spherical autocorrelation function with the data for over 5000 transactions of homes sold. This study reveals a strong evidence of spatial autocorrelation in transaction prices within submarkets [10]. Can utilizes the traditional econometric models based on a hedonic price regressive analysis extended to incorporate spatial neighborhood dynamics to model the housing price determination process from an explicit geographic perspective, leading to characterize the spatial variation with respect to the influence of housing attributes on housing prices [11]. To more precisely clarify the boundaries of the housing submarkets, Leishman introduces an application of the multilevel hedonic model as a tool to identify housing submarkets, and a method for identifying temporal changes within the submarket system [9]. Importantly, the complex environmental factors affecting housing prices have been increasingly kept getting attention by some professionals and researchers, who are actively looking for a new paradigm in exploring the influencing factors and regional differences of housing prices for effectively regulating housing markets and constructing the scientific governing policy for the real-estate system and other related urban systems, such as the land-use system. For instance, Keskin et al. develop a novel extension of the standard use of hedonic price models in

event studies to investigate the impact of natural disasters on real-estate values, aiming to explore the impact of a recent earthquake activity on housing prices and their spatial distribution in the Istanbul housing market on introducing a multilevel approach with the extension of hedonic models. Such an approach allows the isolation of the effects of earthquake risk and explores the differential impact in different submarkets, resulting in better capturing the granularity of the spatial effects of environmental events than the standard approach [18]. Furthermore, to examine the existence of the ripple effect from the change of housing prices between different regional housing markets, Larm et al. (2017) uses the autoregressive distributed lags (ARDL) cointegration and causality techniques [19] to characterize the ripple effect as a lead-lag effect and a long-run convergence between the regional and Amsterdam housing prices in the Netherlands [20]. The abovementioned studies are of significance to promote the traditional econometric models that utilize the hedonic price regression to reveal the direction of causality between housing prices and the complex affecting factors and further detect the spatial differentiation and spatial nonlinear characteristics of housing prices. With the rapid development of spatial econometric models, the spatial properties of housing prices have received increasing attention. For instance, Barreca et al. propose a new perspective on the spatial relationship between urban vibrancy and neighborhood services and the real-estate market. In this study, a Neighborhood Services Index (NeSI) is provided to identify the most and least vibrant urban areas in a city, and spatial autoregressive models are used to manage spatial effects and to identify the variables that significantly influence the process of housing price determination.

Indeed, it is complex and difficult to explore the influencing factors that trigger the housing price changes and spatial differentiation, particularly for the emerging and dynamic housing markets in China [21]. In the 1990s, most of the research studies oriented to evaluate the influencing factors of housing prices at the level of city conducted by Chinese scholars focused on the qualitative analysis on the correlations between the housing supply and demand, the composition of housing prices, the reform of housing system, and the effects of real-estate policy. Since the early 2000s, some scholars in China have gradually used hedonic price models to quantitatively characterize the influencing factors of housing prices [22, 23]. However, the spatiality of a house makes it different from the ordinary commodities, mainly reflected in the fact that the housing value usually shows spatial homogeneity and nonstationarity. For example, the houses located in the developed urban area usually possess the favorable geographical location and the well-developed urban infrastructure, leading to much higher prices than those of the houses located in the newly developing urban area even with better building structure design and construction quality. This implies that the traditional regression of hedonic price models without the consideration of spatial differentiation and spatial nonlinear characteristics is difficult to identify the determinations of housing prices. In recent years, spatial econometric models,

such as spatial interpolation, spatial autocorrelation analysis model, ESDA (Exploratory Spatial Data Analysis), and geographically weighted regression (GWR) model, have been widely applied to characterize the spatiality of housing prices and the spatial autocorrelation among the influencing factors [24–28]. Among the spatial econometric models, the local spatial autocorrelation analysis models, e.g., GWR model, have obvious advantages in characterizing the changes and spatial differentiation of housing prices. The GWR model extends the traditional regression models by introducing the local location factors of housing prices, leading to better deal with the issue of quantifying the spatial heterogeneity of housing prices under the affecting factors which are identified with specific spatial correlations [29]. Furthermore, the GWR model has been an effective way to achieve the spatial nonstationarity analysis of housing price changes [30].

Currently, many studies on the determinations of housing prices and the correlations to the influencing factors have been implemented by introducing the locations of houses and the spatial adjacency relations into hedonic price models [31–35]. Moreover, various theories and methods of spatial econometric models, such as ESDA and spatial autocorrelation analysis, are applied to examine the spatiality of housing prices [21, 36–42]. Nevertheless, under the environment of long-run urban spatial development, large-scale construction of urban infrastructure, and rapid transformation of urban planning in the megacities in China, the connections which are not limited to spatial links between adjacent areas within the city have become effective reflections of the spatial correlation among the housing prices in the context of neighborhoods. Although the traditional hedonic price models and spatial autocorrelation analysis models have been extended to use local spatial weights as the parameters of regression analysis, they only consider the spatial correspondence between the given dependent variables and the independent variables. Relevant research studies in recent years have focused on the identification of urban areas characterized by urban development and housing prices, which can effectively support the revision of the urban development plan and its regulatory acts, as well as the strategic urban policies and actions [12]. Nevertheless, at the level of a city, how the urban development differences, particularly with a microscale geospatial perspective (i.e., in the context of neighborhoods), triggers varying degrees of impact on housing prices, especially what and how to determine the spatial heterogeneity and nonstationarity of housing prices are still lacking attention. This presents the urgent need to explore how the intense urban spatial expansion, large-scale urban infrastructure development, and fast-changing urban planning determine and characterize the housing prices changes and spatial differentiation, which is of great significance to promote the governing policy and spatial controlling mechanism of housing markets and the reform of the real-estate system and land-use system.

Therefore, at the level of city, this paper implements an empirical analysis with the integration and comparative discussion of the traditional econometric models of

regressive analysis and GIS-based spatial autocorrelation analysis tools, focusing in exploring and characterizing the spatial homogeneity and nonstationarity of the housing prices in 2009–2015 in the context of the neighborhoods in Guangzhou, China. There are total 141 neighborhoods in Guangzhou identified as area units, and their average annual housing prices (AAHP) at different points in time (2009–2015) are defined as dependent variables. Simultaneously, the factors including geographical location condition, transportation accessibility, commercial service intensity, and public service intensity are identified as independent variables in the context of urban spatial expansion, infrastructural layout, land use, and urban planning, leading to examine the spatial correlations to the AAHP in neighborhoods. This aims to examine and characterize what and how to determine and characterize the spatial homogeneity and nonstationarity of housing prices, resulting in promoting the governing policy and spatial controlling mechanism of the housing markets and the reform of real-estate and land-use systems in Guangzhou, China. This would support a deep knowledge of the spatial heterogeneity and nonstationarity of housing prices identified and characterized by the regional differences in urban spatial expansion, infrastructural layout, land use, and urban planning. It is of great significance to trigger significant changes to develop a more efficient, sustainable, and competitive governing policy and spatial controlling mechanism for the real-estate system and land-use system at the level of city, especially in the megacities in China.

## 2. Study Area and Methodology

*2.1. Study Area.* The main building area of Guangzhou is composed of 8 administrative districts with 141 neighborhoods, which have a considerable population of about ten million and a large number of residential areas. Among the districts, Yuexiu District is the historical urban center of the city and forms the urban core with Liwan, Haizhu, and Tianhe Districts (see Figure 1). The Central Business District (CBD), which includes the neighborhoods of Liede, Yuncun, and Licun, is the business center of the city and located in Tianhe District. Other administrative districts surround the urban core, i.e., Baiyun and Huadu Districts in the north, Huangpu District in the east, and Panyu District in the south. As shown in Figure 1, the primary urban functional areas are illustrated, which include the CBD, Baiyun New Town, and University Town.

*2.2. Data Sources and Preprocessing.* The data adopted in this study is collected and preprocessed from different data sources. The average annual housing prices (AAHP) mainly comes from the “Report on the Operation of Guangzhou Real Estate,” which is issued by the Guangzhou Municipal Housing and Urban-Rural Development Bureau at each month through the government website of “Sunshine Family” ([http://zfcj.gz.gov.cn/data/Category\\_623/Index.aspx](http://zfcj.gz.gov.cn/data/Category_623/Index.aspx)). The report provides the specific data of the monthly average housing prices of all neighborhoods in

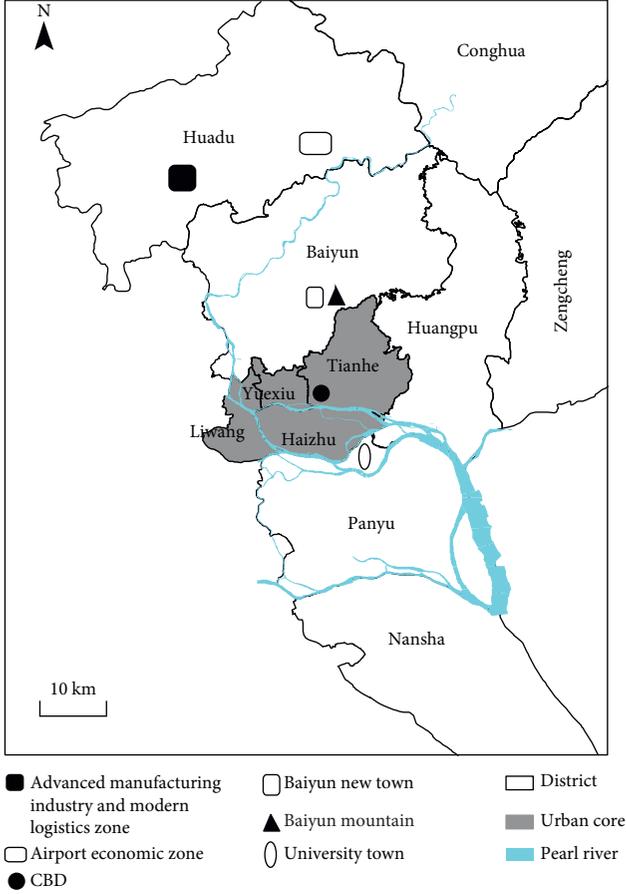


FIGURE 1: Study area.

Guangzhou, including the monthly average transaction prices of new housing, stock housing, and second-hand housing. The data of the monthly average prices in the neighborhoods can better present the spatial and temporal fluctuation of housing prices and accurately characterize the overall evolution of the housing prices in Guangzhou. In addition, the geographical spatial data of Guangzhou are extracted through vector digital processing, remote image nesting, and coordinate registration based on the OpenStreetMap database, and the medium and high resolution remote sensing images of the city of Guangzhou, which include the neighborhoods, urban transportation data (involving roads, bus stops, and metrostations), residential areas, buildings, and other urban infrastructure, and land-use data, e.g., the financial institutions (such as banks), restaurants, retail stores, supermarkets, educational institutions (such as primary and secondary schools), medical institutions (such as clinics and hospitals), government agencies (such as the administrative service centers at all administrative grades), parks, and squares. Particularly, in the environment of ArcGIS 10.2, the administrative area of each neighborhood is built as a polygon with its geometric center point, which stores all the information of the neighborhood, including the AAHP, number of bus stops and metrostations, and road density. Moreover, the road network is based on ArcGIS for topology modelling to fit the

network analysis for searching the shortest path between two given points. Other data, i.e., bus stops and metrostations, residential areas, buildings, and other urban infrastructure data, are represented as points in GIS, leading to calculate their density indexes in the context of neighborhoods.

### 2.3. Methodology

**2.3.1. Regression Model.** The regression model is a mathematical tool for the quantitative description of the statistical relations between given observation values (i.e., variables). Especially, it can provide the calculation method and theory for regression analysis to study the specific dependence of one explained variable (dependent variable) on another (independent variable). Regression linear analysis including multiple regression variables is identified as a multiple linear regression model, and its general equation is presented as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon, \quad (1)$$

where  $Y$  is a random variable,  $K$  is the number of independent variables,  $\beta_0$  is a constant term, and  $\beta_j$  ( $j = 1, 2, \dots, k$ ) is the regression coefficient.

Hedonic price model is a multiple regression model, which regresses on a specific price through quantifying the different properties of the price by multiple explanatory variables (independent variables). Hedonic price models mainly have three functional forms: linear model, log-linear model, and semilog model. In a specific application, therefore, the effective variables and function equations need to be selected properly according to different functional forms [34].

**2.3.2. GWR Model and Factor Selection.** The GWR model assumes that the regression coefficient is a function of the geographic location of the observation point and incorporates the spatial characteristics of the data into the regression model, leading to realizing the analysis of the spatial differences of the explained variables (dependent variables) [43]. The general formula of the model is listed as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^p \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i, \quad i = 1, 2, \dots, n, \quad (2)$$

where  $(\mu_i, v_i)$  is the coordinate of observation point  $i$  and  $\beta_k(\mu_i, v_i)$  is its  $k$ th regression parameter, which is a function describing the geographic location of observation point  $i$ .

Indeed, the changes of housing prices are affected by the rapid operation of urban systems, especially by the intense urban spatial expansion, large-scale urban infrastructural development, and fast-changing urban planning in megacities in China. To ensure the quantitative analysis under the framework of the geographically weighted regression model, in the context of urban spatial development, land use, infrastructure layout, and planning, four factors including geographical location condition, transportation accessibility, commercial service intensity, and public intensity are selected. Particularly, the specific variables which measure the intensity of each factor are shown in Table 1.

TABLE 1: Selection of the influencing factors and their variables.

Factor	Variable
Geographical location condition ( $D$ )	Distance away from the CBD ( $d_1$ )
Transportation accessibility ( $T$ )	Bus stop density ( $t_1$ )
	Number of metro station ( $t_2$ )
	Road weighted density ( $t_3$ )
Commercial service intensity ( $B$ )	Commercial building density ( $b_1$ )
	Financial institution density ( $b_2$ )
	Restaurant density ( $b_3$ )
	Retail store/supermarket density ( $b_4$ )
Public service intensity ( $p$ )	Educational institution density ( $p_1$ )
	Medical institution density ( $p_2$ )
	Government agency density ( $p_3$ )
	Park/square density ( $p_4$ )

In Table 1, the distance away from the CBD ( $d_1$ ) is identified as the length of the minimum travel-time path between the neighborhood and the CBD. Such a path is attained by the algorithm of Dijkstra with an average speed of 60 km/hour of cars through the road network topology model of Guangzhou in the environment of GIS. The application of Dijkstra shortest path algorithm and road network modelling can be found in our previous works [44–46]. In the factor of transportation accessibility, the value of bus stop density ( $t_1$ ) is calculated by the total number of bus stops located in the neighborhood divided by its area ( $\text{km}^2$ ). Under a microscale geospatial perspective, the neighborhood usually has only one or two metrostations; therefore, the number of metro stations ( $t_2$ ) is used as one of its transportation accessibility variables. The road weighted density ( $t_3$ ) in each neighborhood in the city of Guangzhou is calculated as follows:

$$M_j^w = \frac{\sum_{i=1}^n l_i^\alpha w_i}{S_j}, \quad i = 1, 2, \dots, n, \quad (3)$$

where  $M_j^w$  is the road weighted density of neighborhood  $j$  ( $\text{km}/\text{km}^2$ ),  $l_i^\alpha$  presents the length of road  $i$  with a grade of  $\alpha$  and a weight of  $w_i$  in neighborhood  $j$ ,  $n$  is the total number of roads, and  $S_j$  is defined as the area of neighborhood  $j$ . In this paper, the urban roads are classified into four grades, Expressway (EX), Main Road (MR), Secondary Road (SR), and Internal Road (IR), according to “Highway Engineering Technical Standards” (JTG B01-2014), which are issued by the Ministry of Transport of China. Furthermore, the weight of each grade of road is implemented by the Analytic Hierarchy Process (AHP) [47] and the expert scoring method, as shown in Table 2. The AHP is given by Thomas Saaty (1980) and is usually referred to as the Saaty method. As a systematic method, the analytic hierarchy process (AHP) takes a complex multiobjective decision-making problem as a system and then decomposes the objective into multiple objectives or criteria. Furthermore, the criterium are resolved into several levels of multiobjective (or criteria constraints), and the single rank (weight) and the total rank can be calculated by the fuzzy quantitative method of qualitative index, to be used as the system method of objective (multi index) and multischeme optimization decision [48, 49]. Therefore, this study adopts the analytical

TABLE 2: Grades and weights of the urban roads in the study area.

Road	EX	MR	SR	IR
Grade	1	2	3	4
Weight	0.5	0.25	0.2	0.1

hierarchical process (AHP) to evaluate the significance of the urban road for promoting the result of the calculation of road weighted density in neighborhood.

For the factor of commercial service intensity, commercial buildings, financial institutions, restaurants, retail stores, supermarkets, educational institutions, medical institutions, government agencies, parks, and square areas, respectively, are represented as point objects. For instance, the commercial building density index ( $b_1$ ) can be attained through the number of points (which represent the commercial buildings) in the neighborhood divided by the neighborhood’s area ( $\text{km}^2$ ). Following this method, therefore, other variables, including financial institution density ( $b_2$ ), restaurant density ( $b_3$ ), retail store/supermarket density ( $b_4$ ), educational institution density ( $p_1$ ), medical institution density ( $p_2$ ), government agency density ( $p_3$ ), and park/square density ( $p_4$ ), can be processed and calculated.

To access the relative development intensity of each neighborhood, the variables measuring the intensity of each factor are further processed, respectively, and the general formulation can be presented as follows:

$$A_i = \frac{x_i}{\left(\sum_{i=1}^N x_i\right)/n}, \quad i = 1, 2, \dots, n. \quad (4)$$

$A_i$  identifies the relative development level in neighborhood  $i$  based on  $x_i$ , which is defined as a specific variable of the factors, such as the road weighted density ( $t_3$ ), and  $n$  is the total number of neighborhoods. Therefore, for each factor, the indicator measuring its intensity in neighborhood  $i$  can be characterized as the arithmetic mean of  $A_i$ . For example, the indicator measuring the intensity of the factor of transport accessibility in neighborhood  $i$  can be calculated by

$$K_i^T = \frac{A_i^{t_1} + A_i^{t_2} + A_i^{t_3}}{3}. \quad (5)$$

In terms of formula (5), all indicators measuring the intensity of the factors of location condition, transport accessibility, commercial service intensity, and public service intensity are represented by  $K_i^D, K_i^T, K_i^B$ , and  $K_i^P$ , respectively.

**2.3.3. Spatial Autocorrelation Analysis Model.** The spatial autocorrelation analysis can be divided into global spatial autocorrelation and local spatial autocorrelation. The key index of the global spatial autocorrelation analysis is Moran's I index, which can be calculated by [50]

$$I = \frac{n}{\sum_{i=1}^n (y_i - \bar{y})^2} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y}) w_{ij} (y_j - \bar{y})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}}, \quad (6)$$

where  $y_i$  is the attribute value of observation point  $i$  and  $w_{ij}$  is the adjacency matrix. The value of Moran's I ranges from  $-1$  to  $1$ , when  $I > 0$ , it means that a given area has a positive correlation with its surrounding areas, and they tend to spatial agglomeration, otherwise, it implies that the areas tend to spatial dispersion. When  $I = 0$ , it illustrates that there is no spatial correction between the given area and its surrounding areas. However, the global spatial autocorrelation analysis cannot detect whether the observation values are high aggregation or low aggregation in space [31]. It is necessary to further explore the local spatial homogeneity or heterogeneity between a given area and its surrounding areas through the local spatial autocorrelation analysis, so as to clarify how the spatial dependence among the areas in space.

Anselin proposed the local indicators of spatial association (LISA) in 1995 to detect the aggregation in local space and analyze its nonstationarity [51]:

$$I_i = \frac{(y_i - \bar{Y})}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij} (y_j - \bar{Y}), S_i^2 = \frac{\sum_{j=1, j \neq i}^n (y_j - \bar{Y})^2}{n-1} - \bar{Y}^2, \quad (7)$$

where  $y_i$  is the value of observation point  $i$ ,  $\bar{Y}$  is the average value of the associated value, and  $w_{ij}$  represents the spatial weight of observation points  $i$  and  $j$ . The LISA provides four spatial association patterns, in which high-high (HL) level and low-low (LL) level associations define the positive spatial autocorrection and high-low (HL) level and low-high (LH) level associations are identified as the negative spatial autocorrection.

Spatial autocorrelation analysis is the basis for constructing the geographically weighted regression model. When the spatial correlation of observation points is not significant, it demonstrates that the distance between the points has a weak influence on their correlation, resulting in being unnecessary to use the geographically weighted regression.

### 3. Results and Analysis

**3.1. Spatial and Temporal Changes of Housing Prices in Guangzhou.** In 2008, the global financial crisis slowed down the economic growth of China. As a result, the State Council of China launched the "Four Trillion" economic stimulus

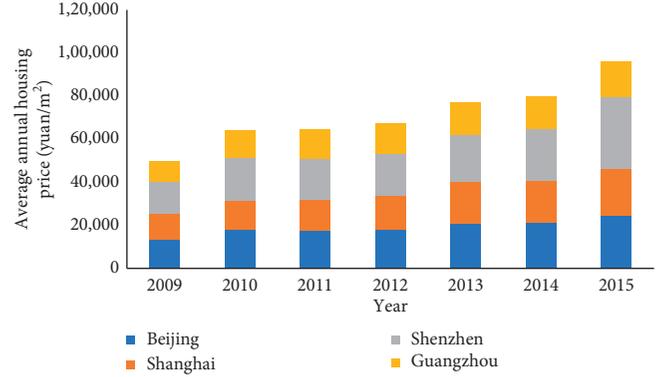


FIGURE 2: Increasing of housing price in 2009–2015.

plan in 2009, which prompted the real-estate market to recover after the financial crisis and the housing prices to return on the upward trend. Figure 2 shows the trend of AAHP in China's major metropolitans, including Beijing, Shanghai, Guangzhou, and Shenzhen in 2009–2015. As illustrated in Figure 2, since 2009, the AAHP in the four cities has been rising up. Simultaneously, it can be found that the AAHP in Guangzhou has the slowest growth among these cities. Particularly, it is significantly different from Shenzhen, which is also located in the Pearl River Delta and nearby Guangzhou. During this period, the AAHP in Shenzhen presents a fluctuating increasing and shows the change range is the largest among the four cities.

Through using the Kriging spatial interpolation model of ArcGIS 10.2, the spatial pattern of the average annual housing price (AAHP) in Guangzhou is illustrated in Figure 3. The results show that, in 2009–2015, the area with the higher AAHP in Guangzhou was concentrated in the urban core, i.e., Yuexiu, Liwang, Haizhu, and Tianhe Districts. Furthermore, the CBD in Tianhe District is highlighted with the highest AAHP in Guangzhou, involving with the neighborhoods of Liede, Licun, and Yuancun, which are nearby the Pearl River. As shown in Figure 3, the favorable location of the neighborhoods of Tangxia, Xintang, and Changxing, which are located in the east of Tianhe District and adjacent to the CBD, drives a sharp increasing of the AAHP. According to the perspective of spatiotemporal evolution, the spatial pattern of AAHP in Guangzhou evolved into a ring structure with the center of CBD in 2009–2015.

Figure 3 further demonstrates the existence of spatial differences in the rising of AAHP in 2009–2015. That is, the AAHP of the neighborhoods located in Baiyun, Tianhe, and Huangpu District increased rapidly in 2009–2015, and the area with the slowest growing is concentrated in Panyu District, which has an obvious advantage of location and is an important hub connecting the cities of Shenzhen and Hong Kong. Therefore, as early as 2000, the housing market in Panyu District has been developed and grew rapidly. After nearly ten years of booming growth, the AAHP in the district of Panyu in 2009–2015 is in a relatively stable increasing.

Furthermore, the AAHP in Tonghe and its surrounding neighborhoods of Yongping, Jiahe, and Huangshi in Baiyun

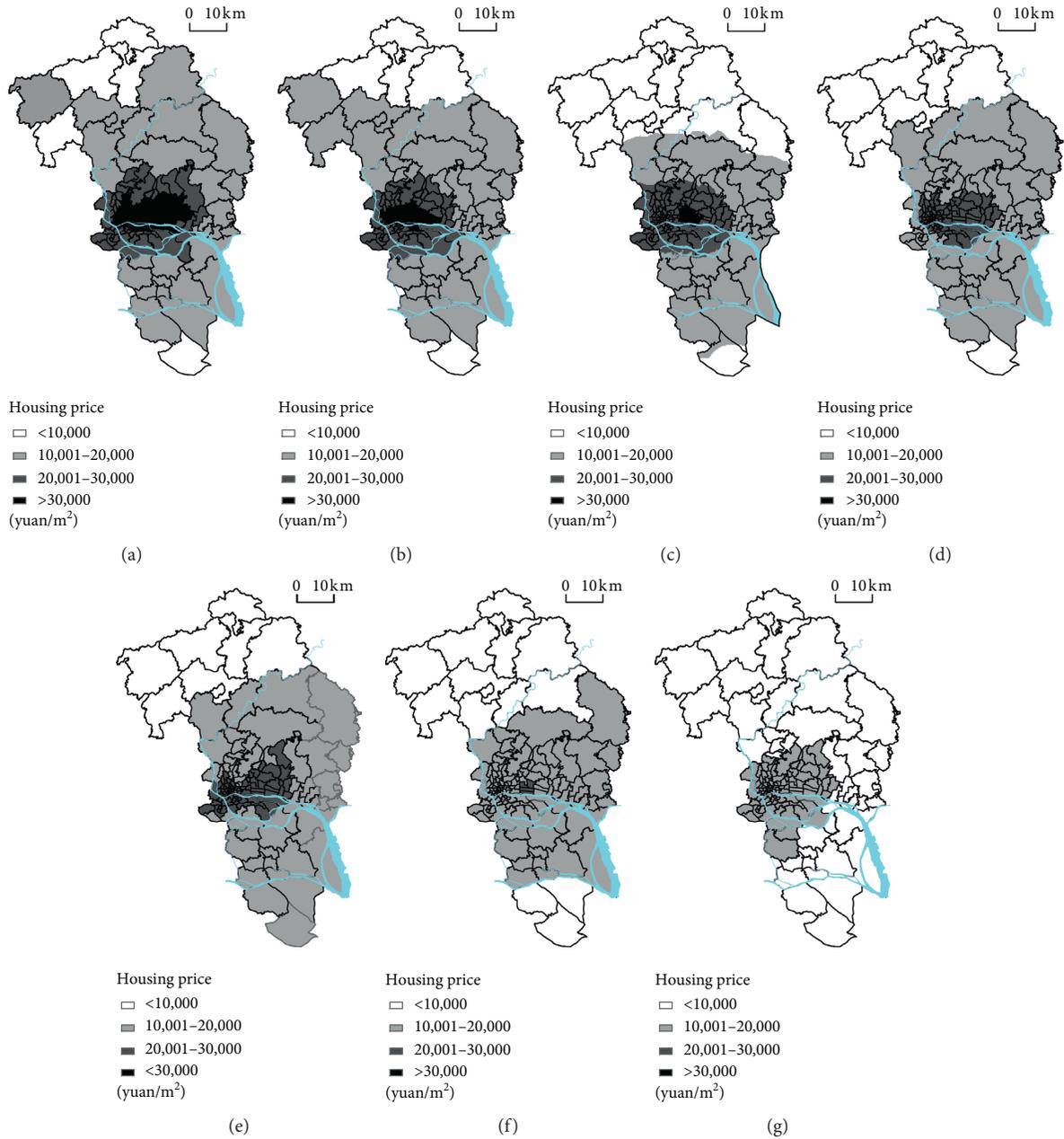


FIGURE 3: Spatial and temporal evolution of housing price in 2009–2015. (a) 2015. (b) 2014. (c) 2013. (d) 2012. (e) 2011. (f) 2010. (g) 2009.

District rapidly increased in 2009–2015, as the central area of the neighborhood of Tonghe in BaiYun District is the Baiyun mountain, which has outstanding natural environment and tourism resources. Especially, the neighborhoods of Yongping, Jiahe, and Huangshi are planned as another business center in the north of the city, i.e., Baiyun New Town (BNT). According to the 2015–2020 Urban Development Plan of Guangzhou, the BNT has been designated as the hug of spatiality, transportation, logistics, and business of the Central Comprehensive Service Function Zone (i.e., the urban core), the Northern Airport Economic Zone (i.e., the New Baiyun International Airport), the Western Advanced Manufacturing Industry, and the Modern Logistics Area (Huadu). Clearly, the transportation infrastructure

inside the BNT, especially the rapid development of metronetwork and urban public service facilities stimulates the booming growth of its housing markets.

As shown in Figure 4, the northwestern neighborhoods of Baiyun District also have a high increasing trend of AAHP in 2009–2015, mainly including Jinshazhou and Luochongwei, which are an important connection point between Guangzhou and Foshan City. This area once became the main region for the construction of resettlement houses (i.e., noncommercial houses), to arrange for residents who have been relocated because of the renewal of the urban core. However, with the promotion of the strategic goals of the integration of Guangzhou-Foshan City, the internal transportation networks in this region have been continuously

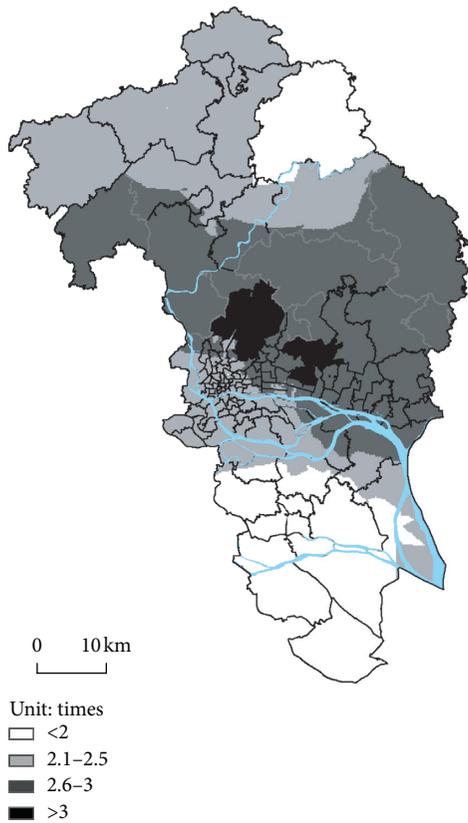


FIGURE 4: Spatial differences in housing prices in Guangzhou (2009–2015).

improved, and the region has gradually grown into a transportation hub for a primary link between Guangzhou and Foshan City. In Figure 4, nevertheless, it is interesting to find that the AAHP growth in 2009–2015 in the urban core including Yuexiu, Liwan, and Haizhou Districts has been relatively flat, but remains at a high level. The excellent geographical location, outstanding urban infrastructure, and favorable public service resources have kept the housing prices at a high level in Yuexiu, Liwan, and Haizhou Districts. Therefore, the increasing space of the AAHP is in line with the expectation and smaller than newly developed areas, such as Baiyun District.

Comparing the spatial differences in the rising of the AAHP in the city of Guangzhou, the AAHP increasing spatial patterns in Beijing, Shanghai, and Shenzhen (see Figure 5) in 2009–2015 are also demonstrated in Figure 6. In these metropolitans, the administrative districts are identified as unit areas, respectively.

As shown in Figure 6(a), the highest growth of AAHP in Shenzhen is highlighted in Nanshan District, which is the innovational center for science and technology in the city. Correspondingly, the AAHP in its adjacent districts, i.e., urban historical center (i.e., Futian District) and the emerging urban center (i.e., Longgang District) also grow rapidly. Compared with the highest increase of housing prices in the CBD in Tianhe District and the BNT in Baiyun District in Guangzhou, which is driven by the robust high-end service industry clusters, mainly including finance and



FIGURE 5: Locations of the study cities.

trade, Nanshan District in the city of Shenzhen is known as a scientific and technological manufacture and innovation center in Shenzhen and even across the country. It gathers a large number of high-tech industrial groups such as IT (Information Technology), communications, new materials, new energy, biomedicine, instruments, medical equipment, and mechatronics, resulting in being referred as China's most "Silicon Valley temperament" region. The city of Shenzhen is a young city which was established in 1979; nevertheless, its GDP has approached \$ 400 billion after the booming development of 40 years based on high-tech manufacturing industries. Triggered by the urban development and planning strategy in Shenzhen, Nanshan District has gradually shifted from an industrially oriented urban area to a fully functioning urban central area consisting of the economic center, science-technology center, cultural center, and international communication center, and particularly constitutes the dual main center of the city with Futian District. The area of Shenzhen's administrative district (1997 km<sup>2</sup>) is much smaller than the area of Guangzhou's (the total administrative area 7,436 km<sup>2</sup> and the area of the study area in this paper is 3,061 km<sup>2</sup>), leading to the spatial distribution pattern of the AAHP in the inner area is concentrated at two levels, i.e., Nanshan, Futian, and Luohu Districts in the urban core area around 50,000 yuan/m<sup>2</sup> (about \$ 7,200), and Longgang, Baoan, and Lantian Districts are all around 30,000 yuan/m<sup>2</sup> (about \$ 4,300). Therefore, the influence of the locations on the AAHP in the city of Shenzhen is not obvious. Aside from the factors, such as housing policies and the structure and materials of the

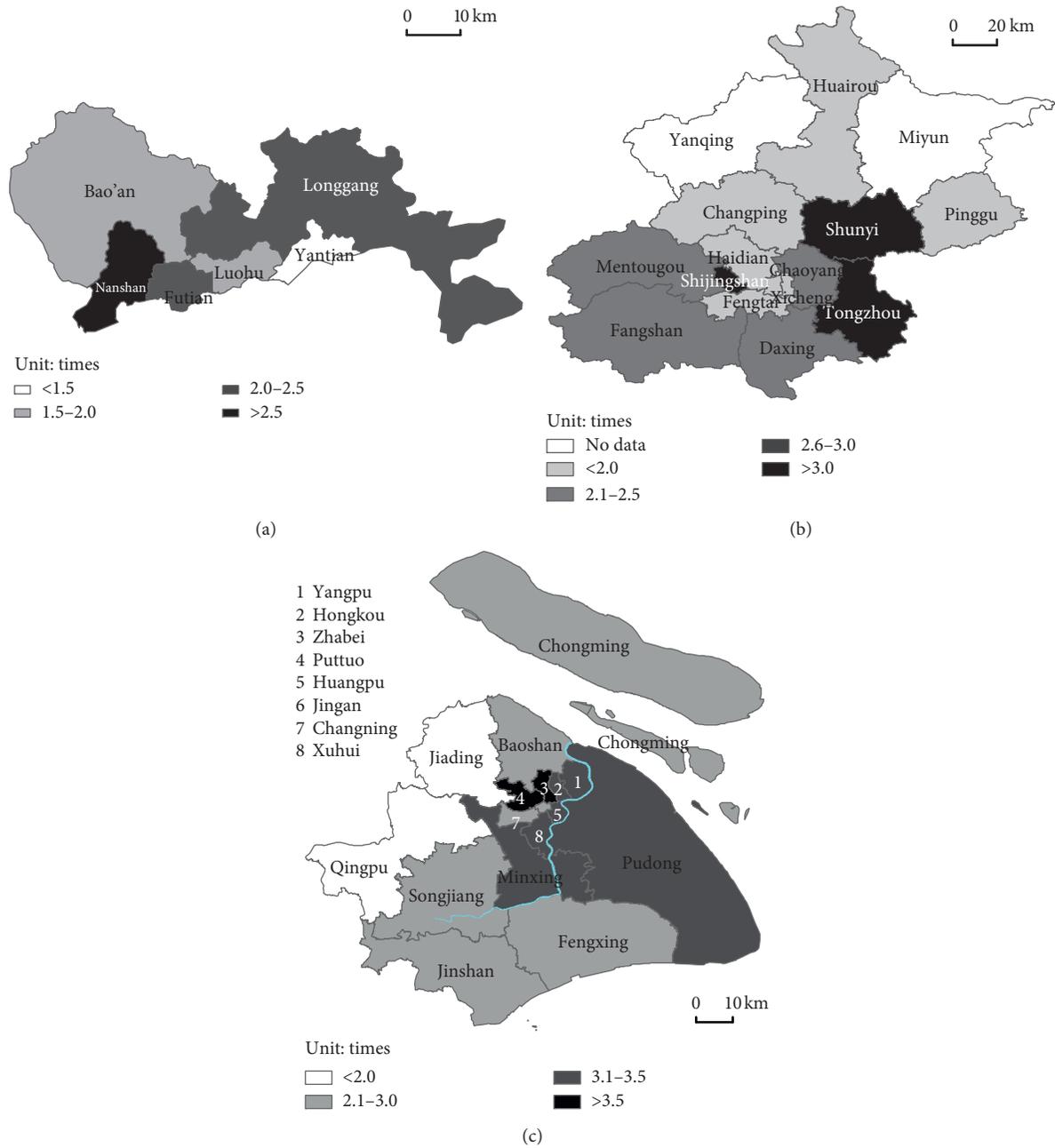


FIGURE 6: Spatial differences in the rise of housing prices in Beijing, Shanghai, and Shenzhen in 2009–2015. (a) Shenzhen. (b) Beijing. (c) Shanghai.

house itself, the affecting impacts are mainly derived from the urban strategic planning and functional area layout in the urban development of Shenzhen.

Figure 6(b) reveals that the areas with the fastest-growing housing prices in Beijing are Tongzhou and Shunyi Districts, which are identified as the subcenters in urban planning, as well as Shijingshan District, which has the well-developed urban infrastructure, favorable geographical location (the urban core in Beijing), and excellent landscape resources (the urban leisure and entertainment zone). In 2009–2015, the increase of AAHP in Shanghai was the fastest among the four cities. Compared with the area where the

rapidest growth of AAHP is the emerging urban center in Guangzhou, Shenzhen, and Beijing, the highest increase of the AAHP in Shanghai is highlighted in Putuo and Zhabei Districts, which are the urban historical center (see Figure 6(c)). Furthermore, it is similar to Guangzhou that the river crossing the center of the city; this provides an excellent landscape and plays the significant influencing on the rise of housing prices.

According to the comparative analysis of the spatial patterns of housing prices increasing in the four major cities of China, it can be found that the urban spatial development, urban infrastructure layout, urban planning, and land use

should play a significant role in the changes of housing prices. From this perspective, this paper further takes 141 neighborhoods in Guangzhou as area units to further explore the spatial correlation of housing prices within the city, and then quantify the impacting factors in the context of urban spatial development, infrastructural layout, planning, and land use, to characterize the spatially nonstationarity and heterogeneous characteristics of the housing prices in the city of Guangzhou.

### 3.2. Spatial Autocorrelation Analysis of Housing Prices in Guangzhou

**3.2.1. Global Spatial Autocorrelation Analysis.** Using the global Moran's I index analysis tool of ArcGIS 10.2, the global spatial autocorrelation analysis for the average annual housing price (AAHP) in 141 neighborhoods of Guangzhou in 2009–2015 is achieved, in which the first-order adjacency of polygon is adopted as the spatial relationship criterion.

As shown in Table 3, in 2009–2015, Moran's I index is more than 0. This illustrates that the AAHP in Guangzhou presents the positive spatial autocorrelation characteristic and demonstrates a significant statistical phenomenon of spatial clustering ( $Z > 1.96$ ,  $P < 0.001$ ), that is, when the AAHP of a neighborhood is high, that of its surrounding neighborhoods is correspondingly high, and vice versa.

**3.2.2. Local Spatial Autocorrelation Analysis.** Although the global spatial autocorrelation analysis can better detect the spatial clustering characteristics of the AAHP in Guangzhou with the spatial aggregation patterns of similar values of observation points (positive correlation) or nonsimilarity values (negative correlation), the spatial homogeneity, i.e., whether the AAHP is a high-value cluster or a low-value cluster cannot be explored clearly. Therefore, this paper further applies the local spatial correlation analysis tool, i.e., the local indicator of spatial association (LISA), to provide a better understanding of the spatial homogeneity of the AAHP in Guangzhou, as shown in Figure 7. In Figure 7(a), the high-high (HH) clustering area is mainly concentrated in Yuexiu District (i.e., the historical urban center), the Central Business District (i.e., the urban economic center), the Pearl River coast in Haizhu District, and the Baiyun New Town (BNT). Furthermore, the HH clustering area is surrounded by the low-high (LH) clustering area, but no high-low (HL) clustering area is found (see Figure 7(b)). This implies that the high housing prices have a certain effect on spatial spillover. The low-low (LL) clustering area is concentrated in the northern mountainous area and the southern region. There is no significant clustering characteristic in the East, indicating that the housing prices of the neighborhoods are more homogeneous in this region.

### 3.3. Geographically Weighted Analysis of the Housing Prices in Guangzhou

**3.3.1. Linear Regression Analysis of the Influencing Factors of Housing Prices.** To examine the global (average) influence of

the four factors of “location condition,” “transport accessibility,” “commercial service intensity,” and “public service intensity” on the formation of housing price, a linear regression model is used. In the regression model, the quantitative indexes of the factors are set as the explanatory variables (independent variables), i.e.,  $K_i^D$ ,  $K_i^T$ ,  $K_i^B$ , and  $K_i^P$ , and the AAHP of each neighborhood in 2015 is the explanatory variable (dependent variable), and the results are illustrated in Table 4.

As shown in Table 4, the value of Adjusted  $R^2$  is 0.60, which indicates how well the regression line fits the observations. Furthermore, it can be found that the values of P in the observations of  $K_i^T$  and  $K_i^P$  are much higher than 0.05, which implies the poor linear fitness, and especially reveals nonsignificant impacts of the transportation accessibility ( $K_i^T$ ) and public service intensity ( $K_i^P$ ) on the housing prices in the context of linear regression analysis. As shown in Figures 8(a) and 8(b), the Line Fit Plots of  $K_i^T$  and  $K_i^P$  to AAHP in neighborhoods show a strong log-fitting trend, respectively. For the factor of commercial service intensity, the value of P in the observations of  $K_i^B$  is lower than 0.05, but close to 0.01. Although it reflects the significant impact of the commercial service intensity on the house prices, Figure 8(c) shows that the Line Fit Plot of  $K_i^B$  to AAHP in neighborhoods presents the extremely significant log curve fitting instead of linear fitting. Figure 8 reveals that when the urban infrastructure development level of the neighborhood is lower, the influence of the factors oriented towards the perspective of urban infrastructure layout (i.e., transportation accessibility, public service intensity, and commercial service intensity) on the housing prices is more significant, that is, with the urban infrastructure development, the influence is getting weaker. This demonstrates that regional urban infrastructure development differences have varying degrees of impact on housing prices, further revealing that housing prices are spatially heterogeneous and nonstationarity. It is a fact that, with the intense urban spatial expansion, a large number of residential areas are bound to extend outward from the urban core into the city of Guangzhou, leading to the development of urban infrastructure lagging the spread of urban areas. Furthermore, the scarcity and uneven distribution of high-quality education resources, which are highly concentrated in the center of the city of Guangzhou, causes strong impacts on the AAHP in the developing neighborhoods with poor educational infrastructure, but causes weak impacts on the developed neighborhoods with complete educational infrastructure. Especially, in the Chinese traditional concept, the proximity of a house to a medical institution such as the hospital is not a favorable condition, and it even has a negative impact on the housing prices.

In Table 4, the factor of geographical location condition (i.e., the distance away from the CBD) presents the extreme significant impact on the housing prices, in terms of the value of P in cis much lower than 0.01, as well as the significant linear fitness on  $K_i^D$  to the AAHP of neighborhoods (see Figure 9). Specifically, every 1 km decrease in the distance between the neighborhood and the Central Business District (CBD), leading to its housing price to rise by about

TABLE 3: Results of the global Moran's I index analysis.

Value	Year						
	2009	2010	2011	2012	2013	2014	2015
Moran's I index	0.195145	0.365298	0.268577	0.288585	0.272338	0.346694	0.549534
Exp. index	-0.009901	-0.009901	-0.009901	-0.009901	-0.007143	-0.007143	-0.007143
Variance	0.004628	0.004643	0.004591	0.004643	0.002473	0.002483	0.002465
Z-score	3.014119	5.506398	4.109836	4.380566	5.620302	7.101614	11.211547
P value	0.002577	0.000000	0.000040	0.000012	0.000000	0.000000	0.000000

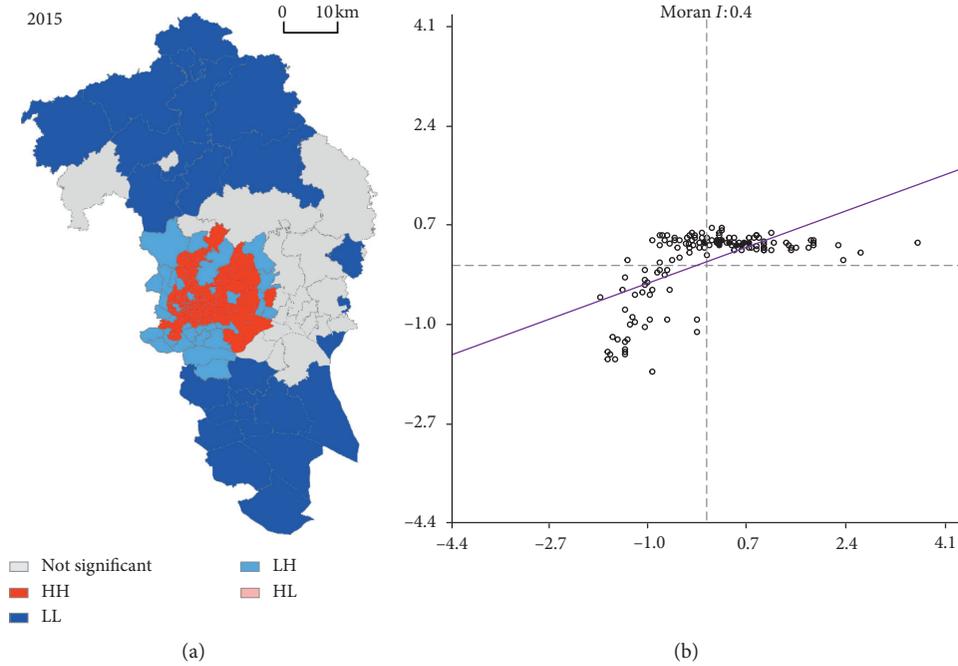


FIGURE 7: Local spatial autocorrelation analysis of housing price (2015). (a) LISA aggregation chart. (b) Moran scatter chart.

TABLE 4: Results of regression model analysis.

	Coefficients	Standard error	t-Stat	P value
Intercept	30388.85677	1543.939504	19.68267325*	1.25352E-41
$K_i^D$	-636.54367	75.18006459	-8.466921031*	3.59862E-14
$K_i^T$	219.1213257	157.9274463	1.387480966*	0.167564468
$K_i^P$	6.55650564	125.9266689	0.052066061*	0.958552453
$K_i^B$	346.8583018	135.4364537	2.561040932*	0.01152663
Adj. $R^2$			<b>0.60</b>	
Significance F			<b>2.03E-26</b>	

\*Significance at the level of 0.05.

636 yuan (about 90 dollars) per square meter in the neighborhood.

According to the linear regression analysis, it can be found that housing prices have obvious spatial differentiation and spatial nonlinear characteristics. Therefore, in the following content in this paper, the geographically weighted regression (GWR) model is further applied to more clearly and accurately interpret and characterize the spatial heterogeneity and nonstationarity of housing prices.

**3.3.2. Geographically Weighted Analysis of the Influencing Factors of Housing Prices.** In the environment of ArcGIS

10.2, the geographically weighted regression model is utilized to characterize the spatial homogeneity and nonstationarity of the housing prices with the AIC identified as the criterion for bandwidth optimization. In the GWR mode, the AAHPs of neighborhoods in Guangzhou in 2015 are identified as the dependent variables, and the independent variables being the observations in  $K_i^D$ ,  $K_i^T$ ,  $K_i^B$ , and  $K_i^P$ . The result shows that the value of  $R^2$  is 0.63, which is higher than the fitness of the traditional linear regression analysis (0.60). The residuals of the results derived from the global spatial autocorrelation analysis in the GWR model illustrate that Moran's I

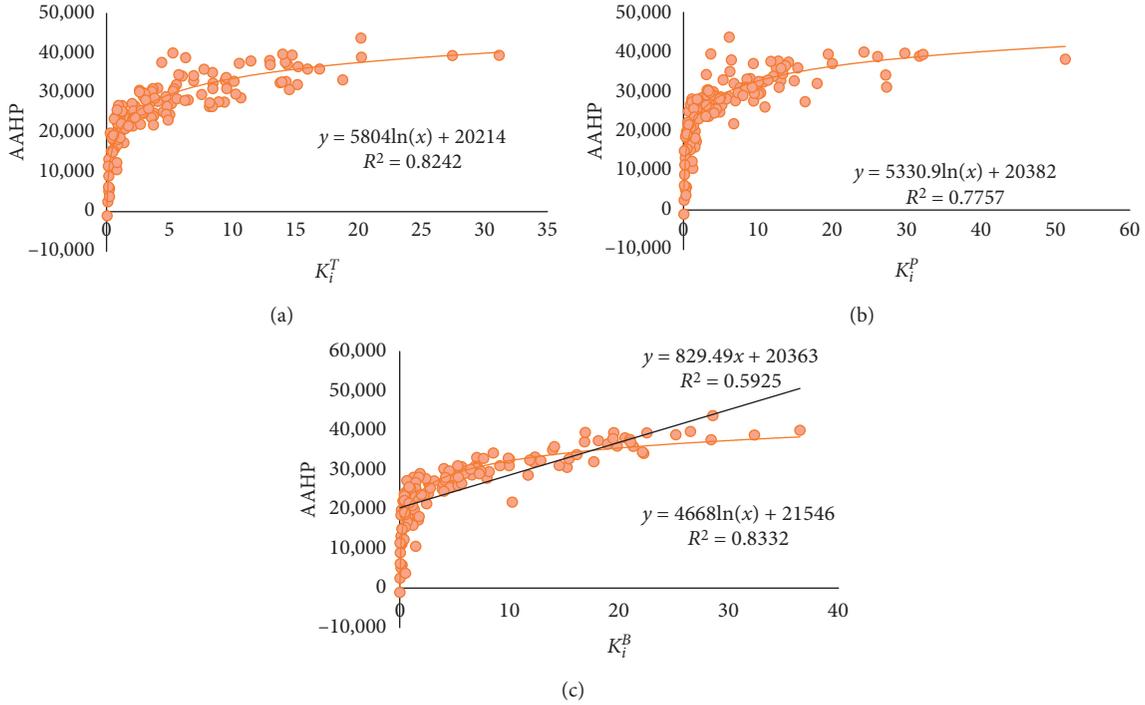


FIGURE 8: The Line Fit Plots of  $K_i^T$ ,  $K_i^P$ , and  $K_i^B$ . (a) Transportation accessibility. (b) Public service intensity. (c) Commercial service intensity.

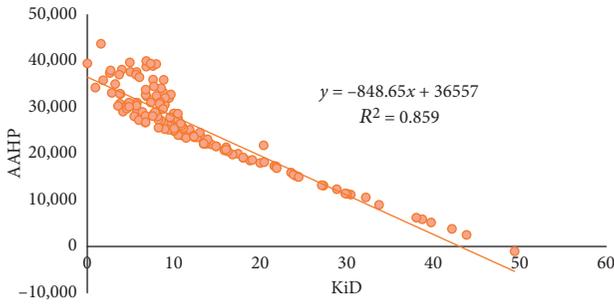


FIGURE 9: The line fit plots of  $K_i^D$ .

index is 0.03, the z-score is 0.5, and the  $P$  value is 0.4, indicating that the residuals exhibit spatial random distribution characteristics.

To clarify the impact of  $K_i^D$ ,  $K_i^T$ ,  $K_i^B$ , and  $K_i^P$  on the spatial nonstationarity of the housing prices in Guangzhou, Figure 10 illustrates, respectively, the equivalent partition based on the geographically weighted regression coefficient. In Figure 10(a), the distance away from the CBD has a significant effect on the housing prices in the eastern and southern neighborhoods, while the weakest impact on the housing prices is in Huadu District because of the longest distance between its neighborhoods and the CBD. Although the districts of Yuexiu, Liwan, and Haizhu in the west are adjacent to the CBD, their AAHP is rather less affected than that in Huangpu District and Panyu District. The reason is that the districts of Yuexiu, Liwan, and Haizhu are urban developed areas, in which the housing price is more affected by their own factors, such as the favorable location and well-developed urban infrastructure. As shown in Figure 10(b), it

is revealed that the transportation infrastructural development in Yuexiu, Liwan, and Haizhu Districts is flawless, leading to the highest level of transportation accessibility which plays the significant effect on the housing prices. Furthermore, the housing prices in the outstanding urban functional areas with the well-developed transportation infrastructure, such as the CBD, the BNT, and the University Town in Guangzhou, are highlighted by the significant influence of the factor on transport accessibility. Figure 10(c) demonstrates that the spatial distribution characteristic of the geographically weighted regression coefficient of  $K_i^B$  is similar to  $K_i^T$ . Moreover, the influence of the factor on commercial service intensity radiates outward from the urban core and shows the attenuation law based on the increasing of distance. As shown in Figure 10(d), the influence of the public service intensity on housing prices presents an interesting spatial heterogeneity and non-stationarity characteristic, that is, the east is strong and the west is weak. This phenomenon further characterizes the imbalance in the public service resources, that is, more resources are concentrated in the west (i.e., urban core) and less in the east. As the public service resources in the east are scarcer, its housing prices is more significantly affected by the public service intensity.

#### 4. Conclusion and Discussion

The consistent booming growth of the housing market in China highlights the urgent need to examine and detect how the intense urban spatial expansion, large-scale urban infrastructural development, and fast-changing urban planning determine and characterize the changes and spatial

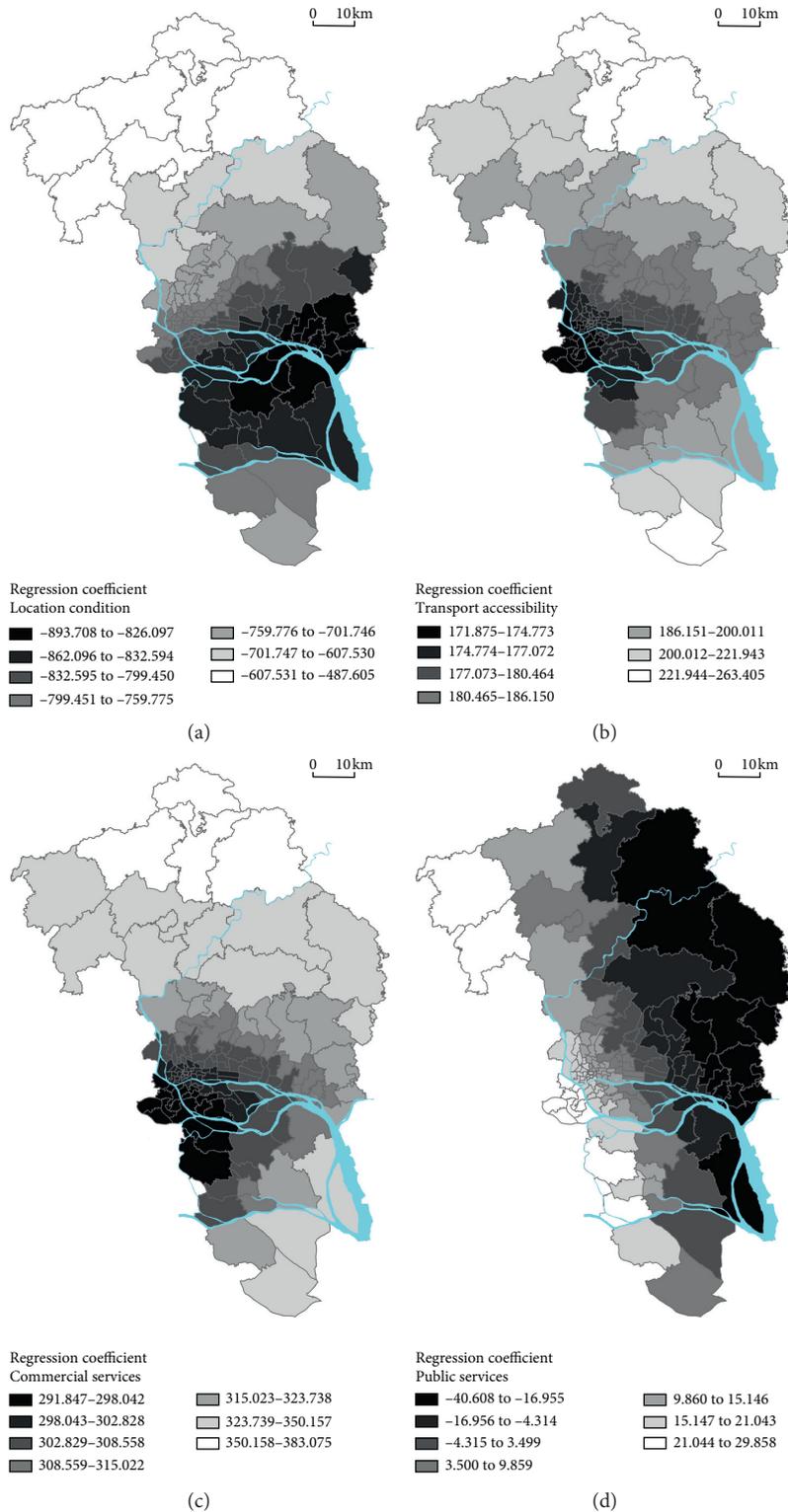


FIGURE 10: Spatial differences of geographically weighted regression coefficients. (a)  $K_i^D$ . (b)  $K_i^T$ . (c)  $K_i^B$ . (d)  $K_i^P$ .

differentiation of housing prices. This should be of great significance to promote the governing policy and spatial controlling mechanism of housing markets and the reform of the real-estate system and related urban systems, such as the land-use system. At the level of city, therefore, this paper

implements an empirical analysis with the using of the traditional econometric models of regressive analysis and GIS-based spatial autocorrelation analysis tools, focusing in exploring and characterizing the spatial homogeneity and nonstationarity of the housing prices in 2009–2015 in the

context of the neighborhoods in Guangzhou, China. In Guangzhou, there are total 141 neighborhoods identified as area units, and their average annual housing prices (AAHP) in 2009–2015 are represented as dependent variables. Simultaneously, the factors including geographical location condition, transportation accessibility, business service intensity, and public service intensity, which are identified in the context of urban development and planning, are defined as independent variables, leading to explore the spatial correlation between the AAHP in neighborhoods (area units). Furthermore, the quantitative analysis models, including multiple linear regression models, spatial autocorrelation analysis models, and geographically weighted regression (GWR) models in the environment of ArcGIS 10.2 are integrated and applied.

Firstly, in the environment of GIS (ArcGIS), the Kriging spatial interpolation method is used to reveal the spatio-temporal evolution of the average annual housing prices (AAHP) in 2009–2015, especially with the comparative analysis of the spatial patterns of housing prices increasing in the major cities of China, including Beijing, Shanghai, Guangzhou, and Shenzhen. It aims to reveal that the urban spatial expansion, urban infrastructure development, urban planning, geographical location, transportation accessibility, and land use have significant roles in the changes of housing prices. Furthermore, the global and local spatial autocorrelation models are used to explore the spatial clustering characteristics of the AAHP in the city of Guangzhou in 2015, integrating with the traditional linear regression model and geographically weighted regression model (GWR model). Finally, the in-depth investigation and discussion of the influencing factors on the housing prices in Guangzhou is achieved by characterizing the spatial heterogeneity and nonstationarity of the housing prices caused by these factors.

The specific results derived from this study show that (1) the temporal and spatial evolution of the AAHP in Guangzhou shows the circle characteristic with the center of the urban core; (2) there are obvious spatial differences in the growth of AAHP in Guangzhou, which is closely related to the urban planning and the spatial pattern of urban functional area; (3) the global spatial autocorrelation analysis reveals that the housing prices has significant spatial aggregation, and the local spatial autocorrelation analysis further characterizes the spatial homogeneity in the aggregation which highlights the critical characteristic of the high aggregation in the urban core; however, no area with a high-low aggregation is found, indicating that the housing price has a spatial spillover effect; (4) the analysis of the traditional linear regression model illustrates that when the urban infrastructure development level of neighborhood is lower, the influence of the factors oriented towards a perspective of urban infrastructure layout (i.e., transportation accessibility, public service intensity, and commercial service intensity) on the housing prices is more significant, that is, with the urban infrastructure development, the influence is getting weaker; (5) the factor of geographical location (i.e., the distance away from the CBD) presents the extreme significant impact on the housing prices; (6) the analysis based on the geographically weighted regression model

further illustrates the specific effect of each factor on the spatial heterogeneity and nonstationarity of the housing prices, that is, the spatial pattern of the regression coefficients of  $K_i^D$  and  $K_i^P$  shows “the east is strong and the west is weak,” while that of the regression coefficients of  $K_i^T$  and  $K_i^B$  is “the west is strong and the east is weak;” moreover, the spatial heterogeneity and nonstationarity of the housing prices demonstrates a ring structure with the center of urban core and the decreasing law with the increasing of distance.

All the abovementioned results can better reflect the elementary spatial characteristics and influencing factors of the housing prices within Guangzhou. The contribution of our study is to examine and characterize what and how to determine the spatial homogeneity and nonstationarity of housing prices oriented towards a microscale geographical perspective, i.e., in the context of neighborhoods, aiming to promote the governing policy and spatial controlling mechanism of the housing markets and the reform of real-estate and land-use systems in Guangzhou, China. The empirical analysis supports a deep knowledge of the spatial heterogeneity and nonstationarity of housing prices determined under the spatial differences in urban spatial development, infrastructural layout, land use, and urban planning. This is significant to drive significant changes to develop a more efficient, sustainable, and competitive governing policy and spatial controlling mechanism for the real-estate system and land-use system at the level of city, especially in the megacities in China.

However, the selection and processing of quantitative indicators are still in exploratory, and the existing research literature does not have a sound basis and solution. Therefore, the fitness of the regression models is not very satisfactory (around 6.0), which may cause deviations in the analysis of influencing factors. Therefore, the future work of this paper needs to do more in-depth analysis and investigation on the selection and quantification of related indicators and compare and analyze more cities to improve the current study.

## Data Availability

The data used to support the findings of this study are available from the first author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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