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# Spatially non-stationary relationships between urban residential land price and impact factors in Wuhan city, China

Shougeng Hu [a, b, *, 1], Shengfu Yang [a, 1], Weidong Li [c], Chuanrong Zhang [c], Feng Xu [a]

[a] Department of Land Resources Management, China University of Geosciences (CUG), Hubei, Wuhan 430074, China
[b] Institute of Geographic Sciences and Natural Resources Research(CAS), Beijing 100101, China
[c] Department of Geography, Center for Environmental Sciences and Engineering, University of Connecticut, 215 Glenbrook Rd, Unit 4148, Storrs, CT 06269, USA

A R T I C L E I N F O

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A B S T R A C T

Land price plays an important role in guiding land resource allocation for urban planning and development, particularly in big cities of fast developing countries where infrastructures and populations change frequently. Therefore, detecting spatially implicit information in the spatial pattern of relationships between land price and related impact factors is critical. Geographically weighted regression (GWR) analysis was conducted in this study for the purpose in Wuhan, China, by using a 10-year panel data set of residential land price. Based on twelve factors in three aspects (land attributes, location factors and neighborhood attributes), an evaluation index system of resident land price was established. The spatial distributions of estimated coefficients and pseudo t-values of three major explanatory variables (floor area ratio, distance to nearest center business district (CBD) and distance to nearest lake), obtained from GWR analysis, indicated that their relationships of the impact factors with land price are spatially non-stationary. The positive impact of floor area ratio on land price is more significant in highly developed areas than in less developed areas. Conversely, the negative impact of distance to nearest CBD on land price is larger in highly developed areas than in less developed areas. Moreover, wealthier dwellers may be willing to pay a higher price for a good lake view (especially views of small lakes), but infrastructure barriers (near some large lakes) cause negative effect. The outputs of this study, which provide detailed information on the relationships between land price and impact factors in local areas, are promising for urban planners to scientifically evaluate land price and make area-specific strategies.


## 1. Introduction

Urbanization is one of the most significant changes occurred in contemporary human society. China, like some other countries, has witnessed the urbanization process with a variety of changes in many aspects, such as urban population, land resource, economy and environment. Particularly, China is urbanizing at an unprecedented rate. It is perhaps the greatest human-resettlement experiment in history (Bai, Shi, & Liu, 2014). The current sizes and number of cities in China are showing a growing trend, and the rapid change in urban land use has impressed the world. As we have seen, urban land use change is known as a complex interactional product of natural, economic, environmental and social factors, while land price as an important driving force affects the direction and strength of urban land use change expressed by urban horizontal expansion and vertical development (Hu, Cheng, Wang, & Xu, 2013; Morris & Michael, 2008).

Urban land price, as an indicator for the land market development degree of a city or region, is an important reference to guide the planning authority to make land use policy and home buyers to purchase their houses. During the past several years, the issues

*Abbreviations:* GWR, geographically weighted regression; OLS, ordinary least squares regression; $R^2$, coefficient of determination; AICc, corrected Akaike Information Criteria; EBK, Empirical Bayesian kriging; VIF, Variance Inflation Factor; CBD, central business district; D_CBD, distance to nearest CBD; D_lake, distance to nearest lake.

* Corresponding author. Department of Land Resources Management, School of Public Administration, China University of Geosciences (CUG), Hubei, Wuhan 430074, China.

*E-mail addresses:* husg2009@gmail.com (S. Hu), yangsf2049@126.com (S. Yang), weidongwoody@gmail.com (W. Li), chuanrong.zhang@uconn.edu (C. Zhang), 307945179@qq.com (F. Xu).

[1] These authors contributed equally to this work and should be considered co-first authors.

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associated with the spatial distribution of urban land price have been of interest to investigators for optimizing land use management. There is growing literature on the temporal and spatial distributions of land price and the underlying driving mechanism (McMillen, 2003; Wen & Goodman, 2013). In most studies, inverse distance weighting (IDW), kriging interpolation and some other mathematical methods were popularly used to describe the temporal and spatial distributions of land price. Recently, the multifractal interpolation method was used to explore the distribution of urban residential land price, and proved to be suitable for characterizing the local anomalies of land price (Hu, Cheng, Wang, & Xie, 2012).

It is obvious that the complexity of the spatial difference of the land price results from the combined effects of many driving factors. Thus, driving factors of the spatial-temporal variation of land price become another hot research topic. As we all know, all factors that affect the distribution of urban land price are intricate and uncertain. These factors include not only international environment, national policies, and social and economic development at the macro level, but also traffic conditions, community stability, and land speculation at the micro level. So far, many researches have been done to explore the influencing factors of land price from different perspectives. At the macro-level, for example, McDonald and McMillen (1998) carried out a comparison study of the land prices in Chicago before and after the land-use zoning system was adopted in 1923 in order to explore the influence of policy; Atack and Margo (1998) discussed the influence of the American Civil War to land price in New York. Factors are much easier to be detected quantitatively at the micro-level than at the macro-level. Many studies at the micro-level were focused on the floor area ratio, parcel area, and distance to nearest CBD (Colwell & Munneke, 1999), among others. However, it was found that good outdoor environment, including green space provision, proximity to parks, and views of green space and water, carried significant hedonic values (Bond, Seiler, & Seiler, 2002; Jim & Chen, 2007; Lansford & Jones, 1995). Thus, increasing researches began to focus on landscape and infrastructure factors, such as sea (Benson & Hansen, 1998), lake (Bond et al., 2002), forest (Sharma, 2013), and park (Tian & Jim, 2012). A very popular method is the hedonic price method, which was used to measure the hidden values of driving factors. But the existing literature has also suffered from a lack of consideration of regional variations of land price in the rapidly changing land market.

Geographically weighted regression (GWR), a local spatial statistical method, emerged in recent years for evaluating how the relationships between a dependent variable and one or more explanatory variables change spatially (Brunsdont, Fotheringham, & Chariton, 1998). Since the study of Brunsdont et al. (1998), there has growing literature concentrating on residual analysis (Zhang, Gove, & Heath, 2005), stationary test (Leung et al., 2013), arithmetic exploration (Mei, He, & Fang, 2004) and other related theoretical studies for GWR. Because of the obvious superiorities of GWR, it has been widely utilized in many fields in recent years. For example, the Geographic variation and impact factors of land use change (Tu & Xia, 2008), deforestation (Jaimes, Sendra, Delgado, & Plata, 2010), burglary (Breetzke, 2012), childhood drowning (Dai, Zhang, Lynch, Miller, & Shakir, 2013), residents' recreation demand (Lee & Schuett, 2014), urban space (Nilsson, 2014), male suicide (Trgovac, Kedron, Bagchi-Sen, 2015), municipal water consumption (Connolly and Hagelman, 2015) and mapping of population (Cockx and Canters, 2015) have been investigated using GWR.

Although many studies indicated that the influencing factors of land price are complex and their impacts on land price are difficult to be identified accurately, the research in spatial heterogeneity of influence factors of land price has received little attention so far. More importantly, land price plays an important role in guiding land resource allocation for urban planning and development, particularly in big cities of developing countries where infrastructures and populations change frequently. In addition, spatially implicit information on the spatial pattern of relationships between land price and related impact factors is critical and should be detected. Therefore, the general purpose of this paper is to detect the spatially non-stationary relationships between land price and related impact factors using the GWR approach, so that we can better characterize the spatial distribution of land price, analyze related local impact factors and their influencing mechanisms, improve the forecast level of urban land price, and optimize the allocation of land resources.

The whole paper is arranged as follows: Section 2 presents the methods for data collection and processing. Section 3 discusses the spatial variation of urban residential land price, examines the advantages of geographically weighted regression in exploring the spatially varying relationships, and analyzes the spatially varying correlations of the three main factors (floor area ratio, distance to nearest CBD and distance to nearest lake) with land price. Finally, the conclusions and discussion derived from this analysis are given in Section 4.

## 2. Materials and methods

### *2.1. Study area*

As shown in Fig.1, this study was carried out in the Wuhan metropolis, which lies in the east-central Hubei Province in central China (at 29°58′–31°22′N and 113°41′–115°05′E). The Yangtze River, the largest river in China, and the Han River both cross this city. The central region of the city is divided by these two rivers into three geographical parts, namely Hankou, Wuchang, and Hanyang. In view of functional zoning, Wuchang is the provincial administrative and educational center, Hankou is the commercial, financial and city administrative center, and Hanyang is the industrial base. The main city area of Wuhan is divided into seven administrative districts: Jianghan, Jiang'an, Qiaokou, Hanyang, Wuchang, Hongshan, and Qingshan. This city possesses abundant water resources and typical water landscape. There are 166 lakes in the administrative region, among which 65 lakes are bigger more than 5 $km^2$. The East Lake is the largest one, with an area of 33 $km^2$. The total water area accounts for a quarter of the whole city land area. According to the Great Wuhan Development Strategy towards 2049 (WMG, 2012), Wuhan will focus on the development of its water network, and strive to build a livable water landscape city. All of the natural factors play a key role in the land price distribution. Therefore, considering the rate of city expansion of Wuhan, the distribution of samples and the scale requirements of the methods, the area within the third ring road of Wuhan was chosen as our study area.

### *2.2. Data collection and processing*

#### *2.2.1. Land price*

In China, residential, commercial and industrial lands are the three main land use classes, and they are located in different areas. Residents get their land use rights mainly through land transfer in the primary land market by four ways, namely, auction, bidding, listing and leasing. Since 1990s, after the tangible real estate market began to appear on the Chinese economic stage, the statistical, analytical and releasing information of residential land price has been always an important part of urban land management. Therefore, based on the sample distributions of price features in

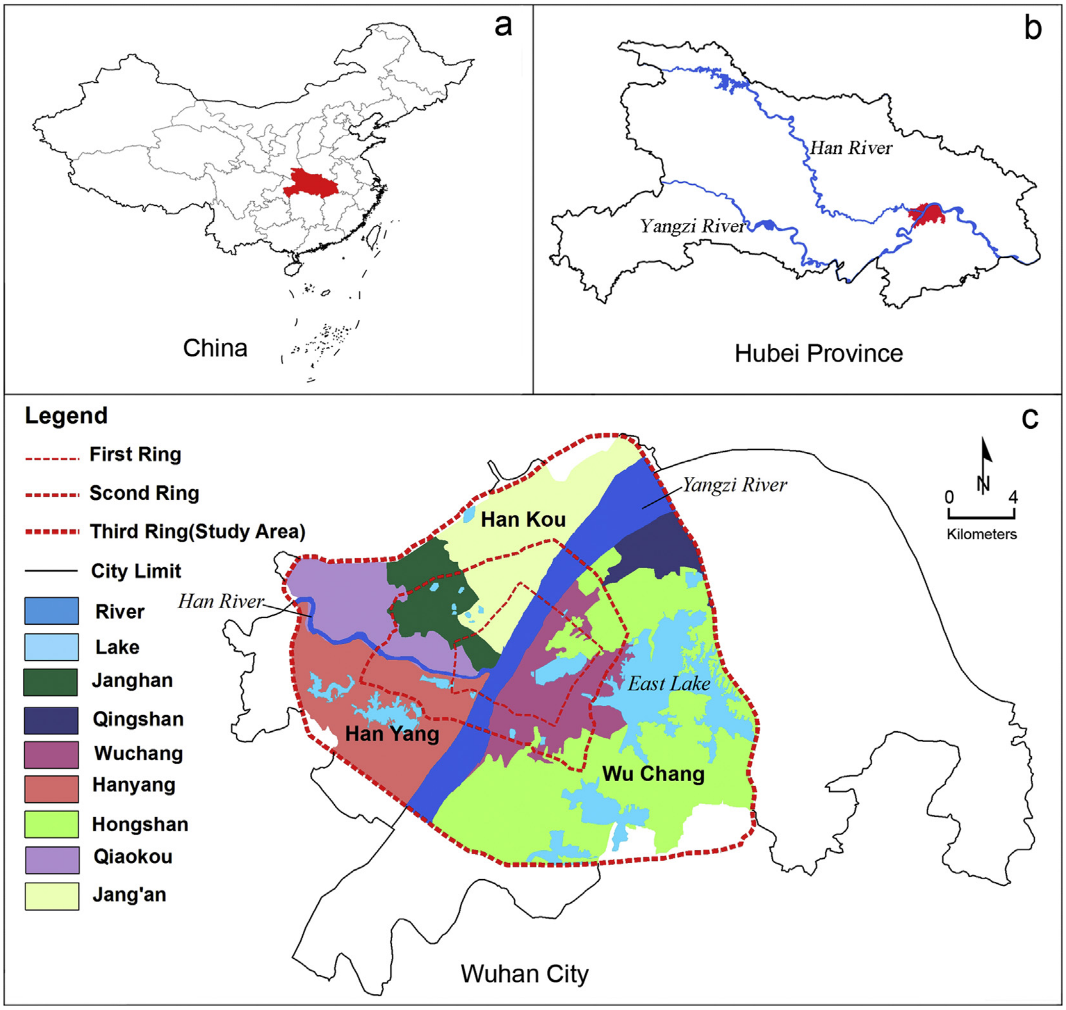


**Fig. 1.** Location of the Wuhan city in China (a) and Hubei province (b). The study area is within the third ring road of Wuhan (c).

Wuhan, we selected the urban residential land price as our study example and built a database, which includes remising price, area, planned floor area ratio, turnover time and other land use characteristics. All of the data, namely 475 land samples, were obtained from the Wuhan Land Resource and Planning Bureau, and they were collected during January 2003 to December 2013.

To meet the requirement of the ArcGIS-based GWR module, all GIS layers for samples, which were raster or statistical data initially, were converted to the vector format. The three steps for data conversion and test are as follows: Firstly, the land prices of samples were carefully calculated one by one based on routine methods and relative standards, and the unit land price (in CNY ¥$\cdot$m$^{-2}$) was selected as the dependent variable in this research. Secondly, because of the differences in transaction date, sample prices were corrected into standardized prices. To deal with this issue, the prices of all of the samples were amended to the same date (31 December 2013) through the real estate price indices of Wuhan (Table 1). Finally, because the GWR approach assumes the normal distribution for variables, non-normally distributed data were processed before they were analyzed using statistical methods. To eliminate abnormal data points, the frequency distribution curve (Fig. 2) was constructed for samples' normality test. The quantile–quantile (Q–Q) plot showed that the majority of land price values from the 475 samples follow a lognormal distribution, but the values near the two tails do not. Because this study only discusses the land price trends of ordinary residence, a few of samples at places for building villas were removed after we conducted the normality test of sample data. We finally decided that 460 data points were used for GWR analysis after 15 extreme data were removed as outliers.

### 2.2.2. Impact factors

*2.2.2.1. Land attributes.* Floor area ratio (ratio of total building area to floor area) is one of the key planning factors restricting land use intensity. It has important impact on land price through the influence of land profits and supply-demand relationship. In general, the greater the planned floor area ratio, the higher is the land utilization efficiency, the more expensive is the transaction price and the lower is residents' comfort level.

In this study, the variable “area” represents the overall region that connects some coordinate points along parcel boundaries. Therefore, land area data is a kind of basic and important data for land price and may be obtained from trading information.

*2.2.2.2. Location factors.* The CBD for a city is the most sophisticated and intensive land use area forming in the urban center of a city. As widely known, there is a reasonable conjecture that the land price gradient would vary with the change of the direction from the CBD (Mills, 1971). These previous efforts have provided valuable contributions to examining the directional variation and

**Table 1**
Real estate price indices of Wuhan used to correct sample price.

| Time | | Jiangan | Jianghan | Qiaokou | Hanyang | Wuchang | Hongshan | Qingshan |
|---|---|---|---|---|---|---|---|---|
| …… | | | | | | | | |
| 2012 | 1st quarter | 3825.2 | 4353.6 | 3046.8 | 4048.3 | 4561.8 | 4505.8 | 3780.2 |
| | 2nd quarter | 3654.5 | 4195.4 | 3075.3 | 3941.3 | 4255.2 | 4732.5 | 3532.4 |
| | 3rd quarter | 3359.6 | 3826.3 | 3461.4 | 3863.4 | 3730.7 | 4956.0 | 3574.1 |
| | 4th quarter | 3165.1 | 3657.8 | 3366.5 | 3915.5 | 3619.2 | 4926.2 | 4354.8 |
| 2013 | 1st quarter | 3616.3 | 3800.4 | 3874.9 | 3830.8 | 3626.5 | 4670.0 | 4823.4 |
| | 2nd quarter | 3645.7 | 4114.1 | 4368.2 | 3956.8 | 3700.4 | 5005.8 | 5285.2 |
| | 3rd quarter | 3898.4 | 4287.3 | 4659.1 | 4162.9 | 3997.2 | 5190.0 | 5736.0 |
| | 4th quarter | 4253.9 | 4535.9 | 4402.4 | 4281.1 | 4233.0 | 5080.0 | 6188.0 |
| …… | | | | | | | | |

Note: The real estate price indices are a series of relative values that are used to reflect the change trends and levels of real estate price in Wuhan. This study used the real estate price index to correct sample price data because it has the following advantages: First, the real estate price index data were made for four quarters and seven administrative regions, which may be more detailed and reasonable than the annual land price index and consumer price indices to characterize the subtle differences in land price change. Second, it is an important reference for the price indices in Wuhan real estate market, accepted and approved by workers in this field for many years. Sample prices are corrected by $V = V_0 \times k_0/k_t$, where $V$ represents the unit price in specific date (here 31 December 2013), $V_0$ expresses the transaction unit price, $k_0$ denotes the land price index of specific date, and $k_t$ is the land price index of transaction date.

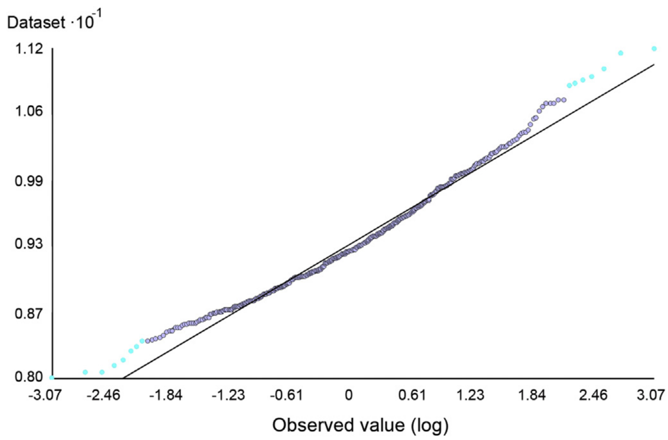


**Fig. 2.** The Q–Q plot of urban residential land price for 475 samples. Data are base 10 log-transformed.

strength of land price gradient around the center of a city (Colwell and Colwell, 2009). But the relation between land price and CBD is increasingly complicated due to the polycentric development pattern. The Jianghan Road area is the original commercial center in Wuhan. With the function transfer of the city center in recent decades, a polycentric development pattern has been formed in Wuhan, with new commercial subcenters such as Wuhan Square, Guanggu Square, and Wangjiadun.

Metro has become popular as a cost-effective alternative to urban road investments in China in recent years. Metros can facilitate the land price premium with different marginal prices at different regions (Cardozo, García-Palomares, & Gutiérrez, 2012). Wuhan's metro system has greatly facilitated daily trips of local residents since the Wuhan Metro Line One was put into use on July 28, 2004. In view of the development of Wuhan's metro system, we took the Metro lines one and two (45 stations including Guanggu and Zhongnan) as our research subjects.

In social and economic activities, people usually actualize their spatial activities through road networks. A high-density evenly distributed road network provides more advantages in transportation flow and capacity than does a low-density road network. Transportation accessibility directly guides residents' choices as one of several infrastructure elements. In this study, we used the density of urban main roads (abbreviation: RD), which was calculated as the urban main road area per grid area unit of $2 \times 2$ km$^2$, to characterize the transportation accessibility in a certain region.

In addition, the social welfare systems such as education and health services are also attributable to land appreciation. In this perspective, the D_hospital (road distance to nearest class-A hospital) and the D_school (road distance to nearest class-A high school) were selected as explanatory variables to detect theirs marginal prices.

*2.2.2.3. Neighborhood attributes.* Lake landscape has been pointed out as an influencing factor to residential land price because it provides an open and comfortable view to residents. Early study on the marginal price of a water park by Darling (1973) indicated that water front properties demand a significant premium price. In view of accessibility and visibility, later studies showed that negative correlation may exist between land price and lake landscape (Bond, Seiler, & Seiler, 2002; Nilsson, 2014; Platter & Camobell, 1978; Rodriguez & Sirmans, 1994). In Wuhan, the wealth of lake resource brings about rich landscape supply, a large number of lake recreational and esthetic resources are still semi-developed or undeveloped, except for those lakes within or close to commercial districts. Based on the potential supply-demand relationship in Wuhan's real estate market, one can expect that more and more real estate projects will be conducted near lakes for bigger profits in the coming years. That is why the distance to nearest lake (abbreviation: D_lake) was selected as an explanatory variable.

River and park, as important urban open spaces in Wuhan City, have profound impacts on the urban landscape ecosystem. Hence, the distance to nearest river (abbreviation: D_river) and the distance to nearest park (abbreviation: D_park) were consequently selected as open space factors that affect land price.

Wuhan has vast higher education resources and ranks as the top in terms of the number of college students (more than eighty colleges or universities and one million students) over the world. An increasing number of residents will live around colleges, especially some key universities. So the distance to nearest college (abbreviation: D_college) was selected as an explanatory variable.

Finally, disadvantageous factors, such as airport noise and water pollution ((Espey & Lopez, 2000; Leggett & Bockstael, 2000), have been investigated to reveal their relationships with the values of residential properties in crowded, congested regions. Many industrial enterprises are located in our research area and the industrial production usually brings along a great deal of noise or air pollution. Therefore, there is no doubt that further quantitative research about the influence of industrial pollution on land price is necessary.

The Pearson's correlation coefficients between land price and explanatory variables were calculated, as shown in Table 2. All the

**Table 2**
Impact factors of land price, their Pearson correlation coefficients with land price, and variance inflation factors.

| Variable name definition | Abbreviation | Description | Geometrical features | Descriptive statistics | | |
|---|---|---|---|---|---|---|
| | | | | r | p_value | VIF |
| **Land attributes** | | | | | | |
| Land use area | AREA | The size of parcel area ($m^2$) | Polygon | −0.16 | 0.01 | 1.16 |
| Floor area ratio | FAR | Ratio of total building area to floor area | – | 0.47 | 0.01 | 1.17 |
| **Location factors** | | | | | | |
| Distance to nearest CBD | D_CBD | Straight-line distance to the geometric center of urban commercial area (m) | Polygon | −0.41 | 0.01 | 2.97 |
| Distance to nearest metro | D_metro | Distance along road network to nearest metro stations (m) | Plot | −0.37 | 0.01 | 1.68 |
| Road density | RD | Main road are per grid unit of 2 × 2 $km^2$. Here main road area = length × width, and road width including 20 m, 30 m, 50 m | – | 0.33 | 0.01 | 1.45 |
| Distance to nearest hospital | D_hospital | Distance along network to class-A hospital (m) | Plot | −0.39 | 0.01 | 2.23 |
| Distance to nearest school | D_school | Distance along network to class-A school (m) | Plot | −0.30 | 0.01 | 1.97 |
| **Neighborhood attributes** | | | | | | |
| Distance to nearest college | D_college | Straight-line distance to nearest boundary of key university (m) | Plot | −0.16 | 0.01 | 1.86 |
| Distance to nearest park | D_park | Straight-line distance to nearest boundary of park (m) | Polygon | −0.40 | 0.01 | 4.10 |
| Distance to nearest river | D_river | Straight-line distance to the boundary of river (m) | Polygon | −0.10 | 0.05 | 1.56 |
| Distance to nearest lake | D_lake | Straight-line distance to the boundary of lake (m) | Polygon | −0.17 | 0.01 | 1.98 |
| Distance to nearest industry district | D_industry | Straight-line distance to the boundary of industry district (m) | Polygon | 0.32 | 0.01 | 1.84 |

Note: r is the Pearson's correlation coefficient; p_value is the pseudo-significance level, which is computed using a randomization algorithm; VIF is the variance inflation factor.

related factors exhibit significant correlation with land price. Therefore, based on the results of Pearson's correlations, twelve explanatory variables are suitable predictors of residential land price over space. In addition, according to the results of multi-collinearity tests, all dependent and explanatory variables meet the condition (i.e., VIF < 8), which means they are suitable for regression analysis.

### 2.3. Methods

#### 2.3.1. Spatial dependency index

To assess the spatial dependence between land prices of samples, spatial correlation measures are necessary. The most often used global index for spatial autocorrelation is the Moran's I coefficient (Pasculli, Palermi, Sarra, Piacentini, & Miccadei, 2014), which is calculated using the following formula:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})\left(y_j - \overline{y}\right)}{\sum_{i=1}^{n}(y_i - \overline{y})^2},$$

where $n$ represents the total number of observations; $y_i$ and $y_j$ denote the variable values at locations $i$ and $j$, respectively; $\overline{y}$ is the mean value of $y$ over the $n$ locations; and $w_{ij}$ is the element of spatial weight matrix.

#### 2.3.2. Geographically weighted regression

The GWR method is a technique for exploring the spatial variation of the statistical associations between a dependent variable and a set of explanatory variables. Traditional regression methods such as the ordinary least squares (OLS) regression method are global statistics, which assume that the relationships under study are constant over space. In contrast to a global model, GWR permits the relationships between the dependent variable and independent variables to vary spatially (Brunsdont et al., 1998). In the study, the fixed Gaussian kernel was been use to estimate weight and the corrected Akaike Information Criteria was adopted to determine the fixed bandwidth.

#### 2.3.3. Empirical Bayesian kriging

Empirical Bayesian kriging (EBK) is a geostatistical interpolation method that automates the most difficult aspects of building a valid kriging model. EBK automatically calculates the parameters that should be manually adjusted in other kriging methods in Geostatistical Analyst to obtain accurate results through a process of subsetting and simulation (Esri, 2015). One of the most important advantages of EBK is that it can reduce the smoothing effect of spatial interpolation and allows accurate predictions of moderately non-stationary data. In this study, because of the spatial non-stationarity of samples, all of spatial interpolation maps were produced using the EBK method to visualize the relationships of land price and impact factors.

## 3. Results and analysis

### 3.1. Spatial variation of urban residential land price

The Moran's $I$ index for the land price data was 0.368, passing the Monte Carlo significance test at 0.01 level. Because the Moran's $I$

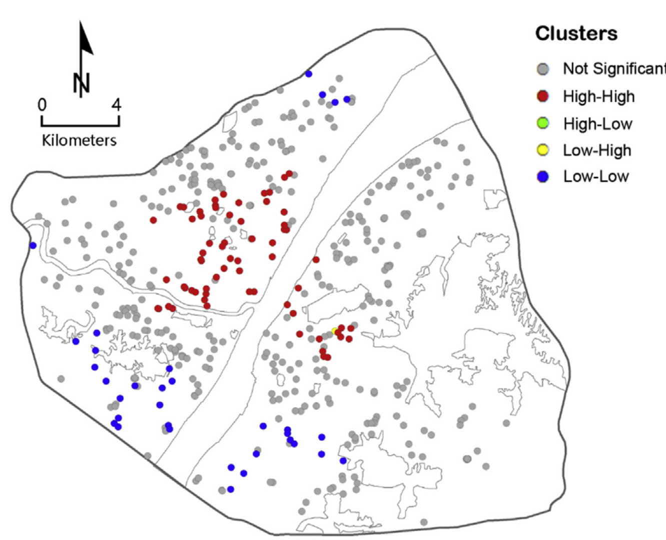


**Fig. 3.** The cluster map of sample sites for residential land price.

is a global spatial autocorrelation index, it does not reflect the local characteristics of spatial autocorrelation. Further details of the spatial pattern of the geographical clustering in land price can be noticed by examining the spatial variation of local spatial associations. Based on the cluster map of sample data (Fig. 3), it is clear that hot spots (i.e., high land prices being surrounded by high land prices: HH) are located in the central area of Wuhan city and cold spots (i.e., low land prices surrounded by low land prices: LL) are located in the peripheral areas (mainly southwest) of Wuhan city.

The urban residential land price varies spatially over different regions in Wuhan. Fig. 4 shows the spatial variation pattern of the original (non-transformed) values of urban residential land price, interpolated using the EBK method. The highest land price values are mainly concentrated in the central area (mostly in Hankou), while the regions at the edge of the city generally are evidenced by lower values.

### 3.2. GWR results

A more reliable local fitting to the spatial distribution of residential land price was obtained through modeling using the GWR approach. In this study, geographical variability for each varying coefficient was tested by model comparison. To test the geographical variability of the *k*th varying coefficient, a model comparison was carried out between the normally fitted GWR model in which all coefficients can vary (i.e., estimated locally) and a special GWR model in which the *k*th coefficient is fixed (i.e., estimated globally) (Nakaya, 2014). The model comparison indicator used for this test is the same as the one used for bandwidth selection, that is, the AICc. The result table (Table 3) consists of rows of indices for explanatory variables (including GWR model's intercept) with a “Diff of Criterion” item. A positive “DIFF of Criterion” value, especially when it is greater than or equal to 2.0, suggests no spatial variability in terms of model selection criteria. All of the values of “Diff of Criterion” for different explanatory variables are negative in our conduct, suggesting that the related coefficient is better not assumed to be global.

Moran's *I* test was used to detect spatial autocorrelation among residuals. Table 4 provides the testing results, which show the Moran's *I* of GWR residuals is −0.06, much lower than that of the OLS model (0.24). Obviously, the residuals of GWR have little autocorrelation compared with the residuals of OLS. In other words, GWR outperformed OLS in this study. Usually, a model can be considered better than another model if its AICc value is at least 3 points lower. Here the AICc of GWR is much smaller than that of OLS. A higher $R^2$ value means that the explanatory variables can explain more variance in land price. The $R^2$ value for GWR analysis is 0.81, while it is 0.41 for OLS analysis. This means that the global OLS model can capture only 41 percent of the influence of the explanatory variables, but the GWR method represents a significant improvement. In general, above results prove that the GWR model performed much better than the OLS model did, which is consistent with findings in previous studies (Jaimes, Sendra, Delgado, & Plata, 2010; Oliveira, Pereira, San-Miguel-Ayanz, & Lourenço, 2014; Qu, Li, Zhang, Huang, & Zhao, 2014; Wang, Zhang, Li, Lin, & Zhang, 2014).

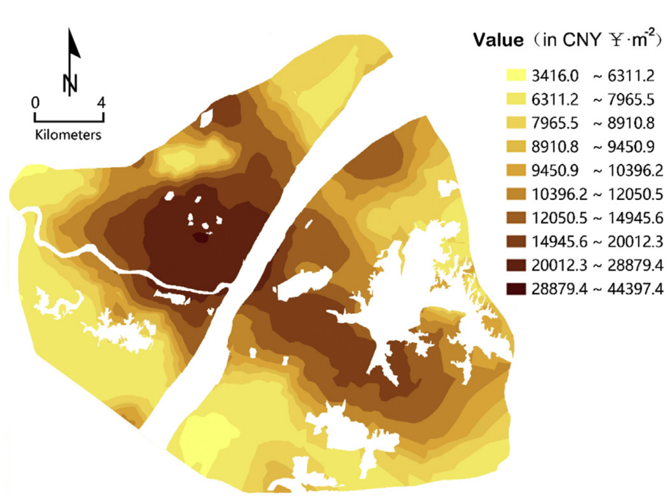


**Fig. 4.** The spatial distribution of land price generated by the EBK interpolation method.

**Table 3**
Significant test of coefficient variation.

| Variable | F | $Df_1$ | $Df_2$ | DIFF of criterion |
|---|---|---|---|---|
| Intercept | 26.288 | 6.79 | 264.209 | −223.863 |
| AREA | 1.214 | 16.25 | 264.209 | −0.628 |
| FAR | 2.752 | 17.43 | 264.209 | −41.886 |
| D_CBD | 323.218 | 6.257 | 264.209 | −980.219 |
| D_metro | 1.339 | 11.35 | 264.209 | −3.037 |
| RD | 1.892 | 12.39 | 264.209 | −14.318 |
| D_hospital | 2.138 | 8.773 | 264.209 | −14.009 |
| D_school | 1.881 | 10.02 | 264.209 | −11.673 |
| D_college | 9.100 | 6.917 | 264.209 | −84.472 |
| D_park | 2.154 | 9.296 | 264.209 | −15.023 |
| D_river | 76.996 | 6.926 | 264.209 | −494.325 |
| D_lake | 3.169 | 8.49 | 264.209 | −27.634 |
| D_industry | 3.882 | 7.886 | 264.209 | −34.668 |

Note: The F statistics follows the F distribution of degree of freedom; $Df_1$ and $Df_2$ denotes degree of freedom one and denotes degree of freedom two respectively; Positive value of Diff-Criterion suggests no spatial variability in terms of model selection criteria.

**Table 4**
Indices for comparing OLS and GWR.

| | Bandwidth | Residuals Moran's I | p | $AIC_c$ | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|---|---|---|
| GWR | 1345.73 | −0.06 | <0.01 | 9130.53 | 0.81 | 0.62 |
| OLS | | 0.24 | <0.01 | 9299.46 | 0.41 | 0.39 |

Note: p: the pseudo-significance level. AICc: corrected Akaike Information Criteria. $R^2$: the coefficient of determination.

### 3.3. Local effects of main factors on land price

Spatially varying relationships between land price and related factors were explored using GWR. Consequently, the spatially non-stationary relationships between land price and related factors were mapped. Figs. 5–7 show how the local coefficients of three major impact factors vary in magnitude and sign spatially. It is easy to see that these factors have varying coefficient values over space, which means that they have different degrees of influence on land price over different places. Further significance level is provided by the maps of t-statistics, obtained by dividing each local estimate of a regression coefficient by its corresponding local standard error. Although twelve impact factors were considered in GWR analysis, here we chose three major impact factors - floor area ratio, D_CBD, and D_lake, to explain and visualize the spatially non-stationary relationships between land price and impact factors.

#### 3.3.1. Floor area ratio

Floor area ratio is an effective indicator for urban administrators to control the urban space density and have a strong association with land price. The impact of the floor area ratio on land price may weaken with increasing distance from the city center. Fig. 5 shows the maps of local estimates of the regression coefficient of this

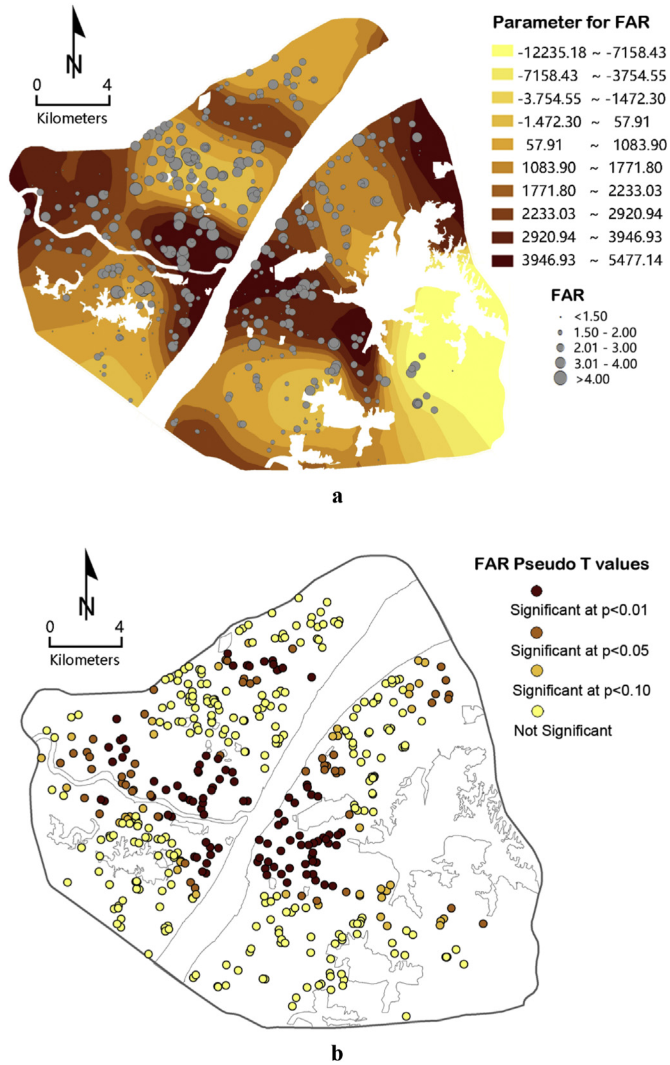


Fig. 5. The spatial distribution of local estimates for the regression coefficient (a) and the pseudo t-values (b) of floor area ratio.

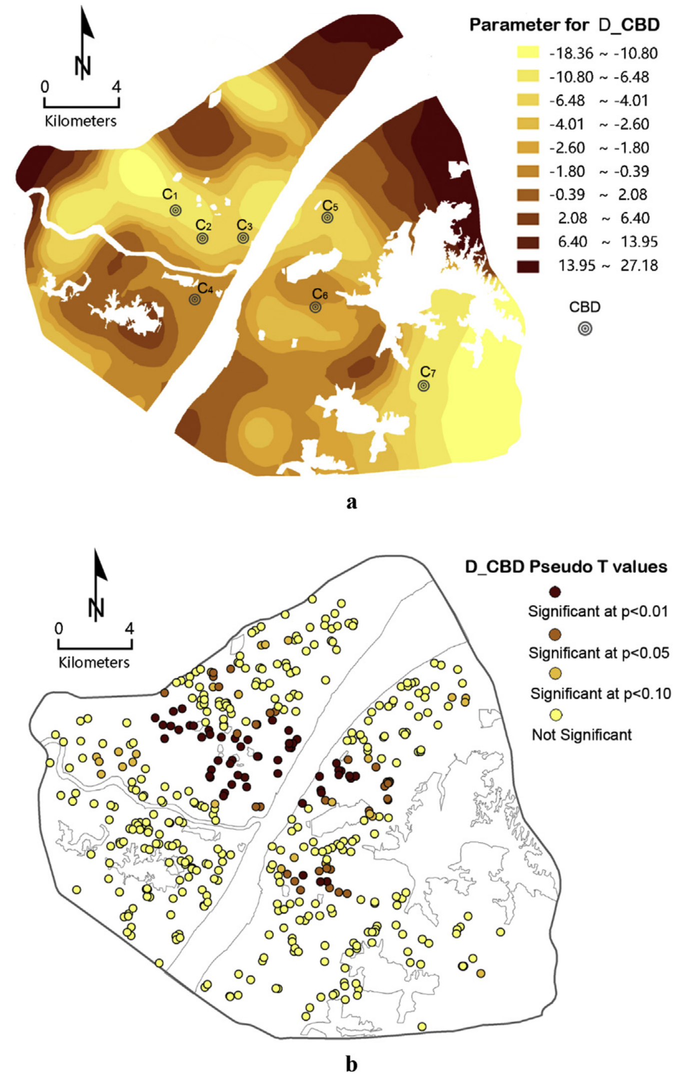


Fig. 6. The Spatial distribution of local estimates for the regression coefficient (a) and the pseudo t-values (b) of D_CBD. Note, Name of studied CBDs: $C_1$:Wangjiadun, $C_2$: Wuguang, $C_3$: Jianghanlu, $C_4$: Zhongjiacun, $C_5$: Xudong, $C_6$: Zhongnanlu, $C_7$: Guanggu.

variable in GWR analysis and its t-test values at sampled locations. Fig. 5a shows that both positive and negative correlations occur in the study area, and a clear spatial pattern can be identified. The areas surrounding the confluence of two rivers, mainly the metropolitan area, and the northeast and southwest corners of the study area have positive correlations, indicating that land price increases with increasing value of floor area ratio in these places. On the other hand, the southeast part of the study area, which is a city suburb and located in a large forest park, shows negative correlations, suggesting that higher floor area ratio is related to lower land price. In other words, in the areas surrounding the confluence of the two rivers, which are highly developed, higher floor area ratio may make a contribution to higher land premium. Besides, when we consider the confidence levels for the t-values, most of the correlations are significant (Fig. 5b) (significant at $p < 0.05$), especially in the areas surrounding the confluence of the two rivers.

From the spatially varying floor area ratio values, we can approximately derive the spatial distribution of building heights in Wuhan. The spatially varying correlation information between land price and floor area ratio provides a guide to the planning authority in Wuhan on where they should plan the urban land-use layout for land intensive use.

### 3.3.2. Distance to nearest CBD

Fig. 6 shows the map of local regression coefficients of the impact factor D_CBD, and the map of the t-test values at sampled locations. Both were obtained from the GWR analysis. Obvious negative local correlations between land price and D_CBD are observable at most of the sample sites, indicating that the closer to the CBD the higher land price. However, only those negative correlations occurring in the highly developed regions around C1, C2, C3, C5 and C6 (i.e., CBD sub-centers) are significant at the 95% confidence level (Fig. 6b). These results suggest that D_CBD has a negative impact on land price and the impact is more significant in highly developed areas than in less developed areas.

Nowadays, many city sub-centers have formed in Wuhan. The development of CBD shows a decentralized trend, namely, some specific functions of CBD spread out from the original center and re-assemble in some other areas. There is no doubt that the separation and movement of city sub-centers (C1, C2, C4, C5, C6 and C7) from the original center (C3) will drive the spatial variation of land price. From the non-stationary spatial distribution of the GWR coefficient (Fig. 6a), we can find that the spatial distribution of land price has been reshaped by the interactions between CBD sub-centers and

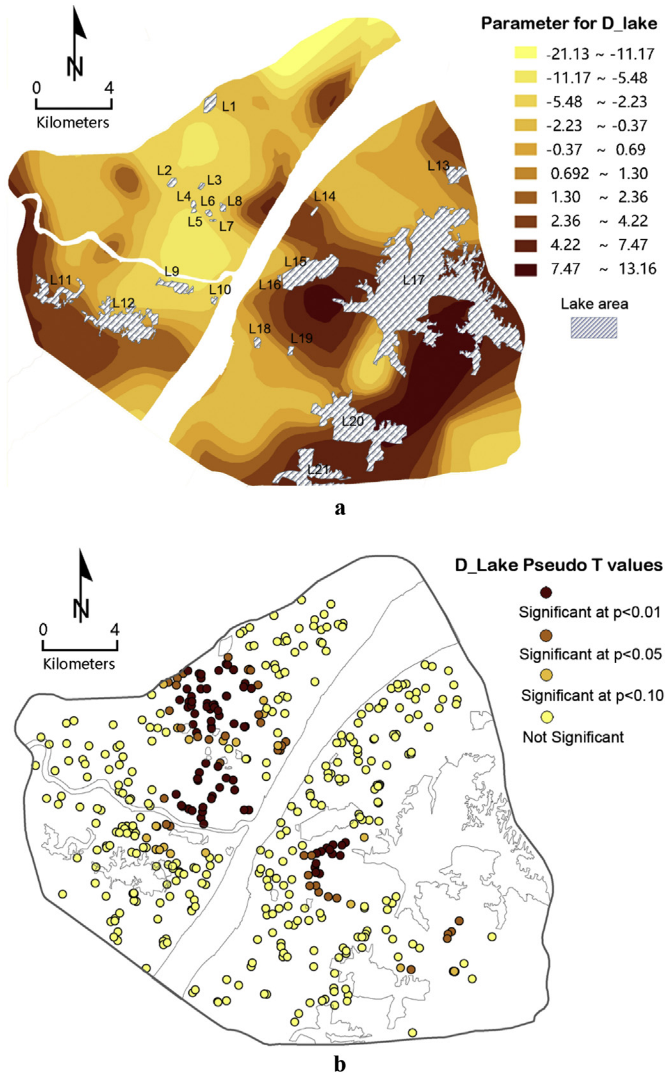


**Fig. 7.** The spatial distribution of local estimates for the regression coefficient (a) and the pseudo t-values (b) of D_lake. Note, Name of studied lakes: L1:Tazihu, L2:Houxianghu, L3:Lingjiaohu, L4:Xihu, L5:Jiqidangzihu, L6:Beihu, L7:Xiaonanhu, L8:Huanzihu, L9:Yuehu, L10:Lianhuahu, L11:Longyanghu, L12:Moshuihu, L13:Yangchunhu, L14:Simeihu, L15:Shahu, L16:Neishahu, L17:Donghu,L18:Ziyanghu, L19:Saihu, L20:Nanhu, L21:Yezhihu.

land price.

### 3.3.3. *Distance to nearest lake*

For another critical impact factor, D_lake, both positive and negative correlations are observed in the GWR analysis (Fig. 7a and b). Most of sample sites close to lake areas have no high land prices (see Fig. 4). However, significant negative correlations with land price appear at sample sites surrounding the small lakes L1 to L10 and L12. Obviously, this negative correlation indicates that being closer to a lake means higher land price. This phenomenon should be caused by lake landscapes with a quiet, peaceful, and comfortable dwelling environment, where property developers would like to develop more real estates. The scarcity of landscape resource and higher resident's purchasing power usually contribute to the land premium. In contrast, in a few areas around large lakes the relationship between D_lake and land price is positive. It is possible that others factors have stronger influence than the residents' requirement to the benefits of lake landscape so that lake landscape does not obtain significant premium for land price.

For large lakes (e.g., L17, L20, L12), the premium form of lake landscape is anisotropic in different directions. The main reason for this spatial characteristic may be that while wealthier dwellers are willing to pay a higher price for a good lake view, the immature infrastructure (e.g., transportation barriers) imposes a negative impact on their intention.

## 4. Conclusions and discussion

Quantitatively understanding the spatially varying relationships between residential land price and related factors is crucial to land resource management and urban development planning. Wuhan has experienced rapid urbanization since China's reform and opening up which began in 1978, and has formed a complicated spatial pattern of residential land price. The influence mechanism of impact factors on residential land price has broken by special landscape structures. New city sub-centers appeared, and they not only dramatically increased the land price but also caused significant regional difference. In this study, we intended to obtain a better understanding of the spatial variation of land price caused by long-term urbanization and major impact factors in Wuhan, China, using a local spatial statistical method – GWR.

In the analysis we found considerable evidence indicating that neighboring land parcels have similar patterns of value visitation and high spatial autocorrelation. GWR can capture the spatial variation of a phenomenon under study and reveal the local patterns of the influences of particular impact factors. By accounting for the spatial non-stationarity of the relationships between the land price and the impact factors, it may provide more accurate prediction than global regression does.

Clear spatial patterns of regression coefficients were obtained from the GWR analysis. The results indicated that the relationships between land price and impact factors vary over space, and they are negative at some locations but positive as other locations. The maps of the estimated coefficients of three major explanatory variables (floor area ratio, D_CBD and D_lake) obtained from GWR analysis demonstrated the spatial non-stationarity in their relationships with land price. For example, the positive impact of floor area ratio is more significant in highly-developed areas than in less developed areas. Conversely, the negative impact of D_CBD is more significant in highly-developed areas than in less developed areas. Moreover, wealthier dwellers may be willing to pay a higher price for a good lake view (especially views of small lakes), but infrastructure barriers (near some large lakes) cause negative effect. In general, the outputs of this study provided detailed information on the relationships between land price and impact factors in local areas of Wuhan, and such information is helpful to urban planners to scientifically evaluate land price and make area-specific policies.

Several limitations of this study should be mentioned here. (1) The results obtained in this study only partially reflect the influences of related factors on urban residential land price, particularly within the third ring road of Wuhan, at the study time. For places where the explanatory variables considered do not show significant effects, other social-economic factors should be investigated and considered. (2) Because the sample data of urban residential land price were derived from governmental statistical databases and mapped manually, data accuracy issues may arise. At present, specific spatial data such as land price dynamic supervising information is not readily available, so the development of spatial databases that can help explain and predict the variation of land market is needed for future research. (3) The geographical discontinuities in Wuhan, such as river channels, lakes and ring road, may reduce the power of the GWR approach in this study. While existing methods may not be sufficient to obtain a comprehensive assessment on the spatial variation of residential land price, this study has made a further step towards the goal.

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