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Impact of Accessibility on Housing Prices in Dalian City of China Based on a Geographically Weighted Regression Model

YANG Jun[1, 2], BAO Yajun[1], ZHANG Yuqing[1], LI Xueming[1], GE Quansheng[2]

(1. *Human Settlements Research Center*, *Liaoning Normal University*, 116029 *Dalian*, *China*; 2. *Key Laboratory of Land Surface Pattern and Simulation*, *Institute of Geographic Sciences and Natural Resources Research*, *Chinese Academy of Sciences, Beijing* 100101, *China*)

Abstract: This paper studies the relationship between accessibility and housing prices in Dalian by using an improved geographically weighted regression model and house prices, traffic, remote sensing images, *etc*. Multi-source data improves the accuracy of the spatial differentiation that reflects the impact of traffic accessibility on house prices. The results are as follows: first, the average house price is 12 436 yuan (RMB)/m^2, and reveals a declining trend from coastal areas to inland areas. The exception was Guilin Street, which demonstrates a local peak of house prices that decreases from the center of the street to its periphery. Second, the accessibility value is 33 minutes on average, excluding northern and eastern fringe areas, which was over 50 minutes. Third, the significant spatial correlation coefficient between accessibility and house prices is 0.423, and the coefficient increases in the southeastern direction. The strongest impact of accessibility on house prices is in the southeastern coast, and can be seen in the Lehua, Yingke, and Hushan communities, while the weakest impact is in the northwestern fringe, and can be seen in the Yingchengzi, Xixiaomo, and Daheishi community areas.

Keywords: geographically weighted regression model; accessibility; house price; Dalian City

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1 Introduction

In the new era of people's ever-growing desire for better lifestyles, the demand for housing and travel has gradually increased. Residents tend to prefer fast, convenient modes of transportation, and traffic accessibility has become an important factor in housing prices within residential areas. This paper studies the relationship between accessibility and house prices based on a geographically weighted regression model.

When regression models are applied to geographic locations, sometimes regression coefficients are not spatially fixed, but are non-stationary. The British geographers Fotheringham et al. (1998) proposed the geographically weighted regression (GWR) model to address this phenomenon. GWR is a spatial variance regression model that includes geographic locations in regression parameters, and takes into account the different effects of the same explanatory variable at various locations. Brunsdon et al. (1999) compared the results obtained from the GWR model against a general linear regression model, while studying the relationship between floor areas and house prices in Kent County, UK. They confirmed that the GWR model is better suited for spatial modeling. In recent years, GWR models have been widely used to study cities (Kontokosta and Jain,

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Corresponding author: YANG Jun. E-mail: yangjun@lnnu.edu.cn

2015; De La Luz Hernández-Flores et al., 2017; Li et al., 2017), ecology (Propastin, 2012; Ajaz Ahmed et al., 2017; Sheng et al., 2017), environment (Avila-Flores et al., 2010; Guo et al., 2017; Wu S et al., 2017), health (Chalkias et al., 2013; Robinson et al., 2013; Tu et al., 2016), medical care and diseases (Jeon et al., 2017; Ramezankhani et al., 2017), geochemistry (Song et al., 2016; Emamgholizadeh et al., 2017), agriculture (Zhang et al., 2014; Jiang et al., 2015), transportation, and real estate. Researchers also have been making improvements to the GWR model (Harris et al., 2015; Lu et al., 2015; Chen Q et al., 2016; Geniaux and Martinetti, 2017).

Many studies have applied the GWR model to the area of transportation. Du and Mulley (2006) used GWR model to study the relationship between traffic accessibility and land value in the Tyne region of England and found that the accessibility of land has a positive impact on its value in some areas, but has negative impact or no impact on its value in some other areas. In another instance, Cardozo et al. (2012) used GWR model to predict traffic in a metro station in Madrid and found that the GWR model was more suitable for predicting station traffic than traditional ordinary least squares (OLS) models. Yet another study by Griffin and Jiao (2015) used a GWR model to evaluate the health effects of public bicycles in Travis County, Texas. Chiou et al. (2015) used OLS and GWR models to analyze key factors influencing the use of public transport and provided development strategies for improving the use of public transport.

A review of real estate literature also reveals the use of the GWR model to study spatial and temporal nonstationarity. Yu et al. (2007) used both GWR and OLS models to study the real estate price impact factors in Milwaukee, USA. Huang et al. (2010) added temporal factors to a GWR model to improve its performance in evaluating house prices over time. Based on data that spanned 19 years of house prices in London, Fotheringham, et al. (2015) used GWR model to explore the spatiotemporal changes in factors affecting house prices. Kestens et al. (2006) also used GWR model to study the factors that influence the prices of houses (Dziauddin et al., 2015). Luo (2007) and Lv (2016) both used GWR models to study the spatial variability of urban residential land prices and the factors that have an influence. Shen and Karimi (2017) conducted a study on the relationship between urban designs and house prices. Chen Y et al. (2016) studied urban housing leasing characteristics and found that rents decrease with increasing distance from the city.

With regard to the relationship between transportation and house prices, Ibeas et al. (2012) used multiple linear regression model, spatial autoregressive model, and other models to study the relationship between transportation and the value of real estate in urban systems. Dziauddin (2009) used a GWR model to study the impact of the light rail transit (LRT) system in Klang Valley, Malaysia, on house prices. Dai et al. (2016) studied the impact of Beijing's rail transit stations on the prices of surrounding houses. Jang and Kang (2015) studied the impact of retail accessibility and proximity effects on house prices in Korea. Wen et al. (2017) studied the impact of the accessibility of the Grand Canal in Hangzhou, China, on house prices and found that house prices have distance and regional heterogeneities. Wu C et al. (2017) analyzed the spatial impact of the accessibility to parks on housing prices in Shenzhen, China. Currently, when scholars use GWR models to study the impact of accessibility on house prices, they consider the distance from principal nodes to the destination (e.g., bus stations or road networks) or the number of nodes within a buffer distance from the destination, to represent accessibility. This measurement of accessibility is not accurate enough. Therefore, this paper will improve GWR modeling by using an accurate calculation of accessibility, and study the relationship between accessibility and the prices of houses.

2 Materials and Methods

2.1 Overview of the study area

The city of Dalian is located at the southern tip of the Liaodong Peninsula, People's Republic of China. Its geographic coordinates lie between 120°58′E and 123°31′E, and between 38°43′N and 40°10′N. The study area for this paper covers four districts of Dalian: Ganjingzi, Shahekou, Xigang, and Zhongshan (Fig. 1).

2.2 Data sources and processing

The data used for this study comprises two parts: one part is sample data on residential characteristics, and the other part is data on Dalian's infrastructure and transportation network.

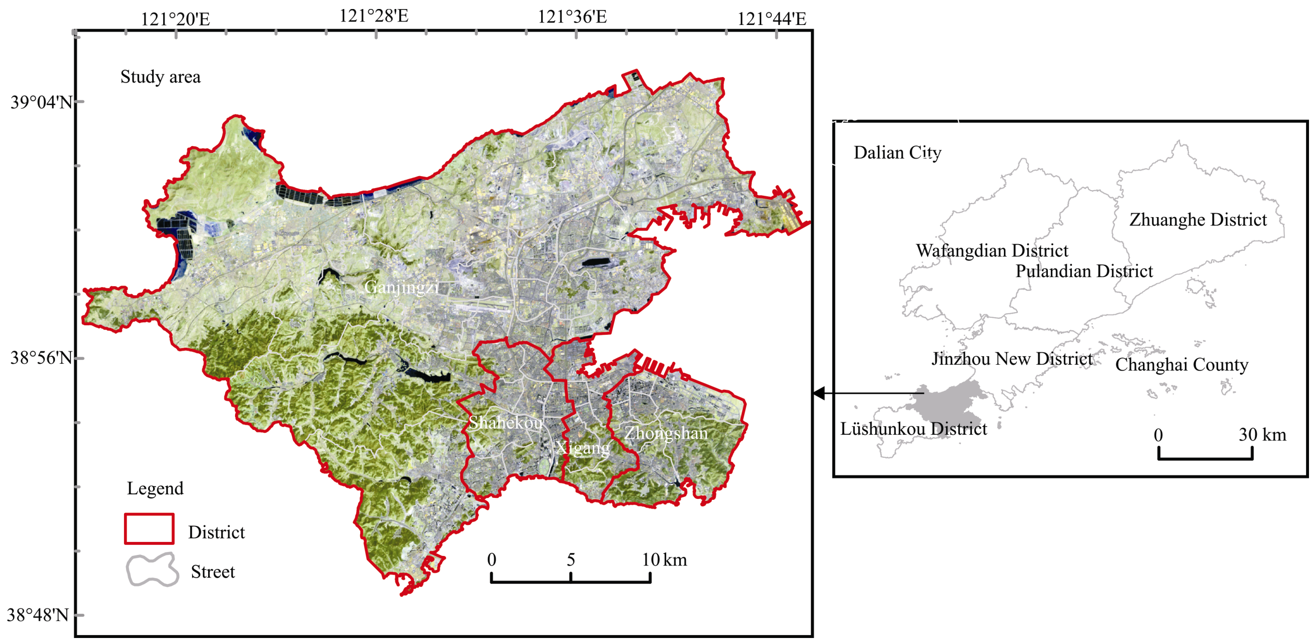

Fig. 1 The location of study area

Table 1 Data sources and description

Data	Data source
Residential property data	Soufang.com
Dalian traffic network	Dalian Planning Bureau
Distribution of infrastructure services	Dalian Planning Bureau
Administrative divisions of Dalian	Dalian Planning Bureau
Remote sensing images SPOT5	National Marine Monitoring Center
Remote sensing images Landsat 8	Geospatial Data Cloud

In December 2016, this study used web crawler tools to search for data from the Soufang website. The data thus procured was organized into tables, and included details of district attributes and spatial information (latitudes and longitudes). ArcGIS was used to generate sampling points on the map. According to the 'Code for design of urban road engineering (2016)', roads are categorized into three grades: main roads, secondary roads, and other roads. Main roads have a higher grade than county roads and urban roads. County roads and urban roads fall under the secondary roads category. Other roads include all the remaining lower grades roads. In order to set cost attributes for the different grades of roads, this study considered 'cost' as the time taken to pass a one kilometer distance on the different grades of roads (Interim Provisions on quota targets of urban planning, 1980). This enabled us to establish a 25 m × 25 m road 'cost grid' of traffic networks for the four districts.

2.3 Research methods

2.3.1 Technical process

This study is divided into four steps. The first step is to calculate accessibility using the sampling points. The second step is to analyze global regression and spatial autocorrelation to determine the explanatory variables for the GWR model, which will be used to study the relationship between accessibility and house prices. The third step is to conduct a kernel density analysis and a price interpolation analysis. The final step is to compare the results of the two methods (GWR model and price analysis) and analyze the relationship between accessibility and house prices. The diagram of the technical process is illustrated in Fig. 2.

2.3.2 Methods

(1) Calculation of accessibility

The measurement of intra-city accessibility is based on the choice of road networks and travel modes (Lin et al., 2014; AlKahtani et al., 2015). This paper chooses the cumulative cost weighted distance method to calculate the accessibility of each residential area. In the cumulative cost distance method, all the cost values on the path to the destination are accumulated, and the

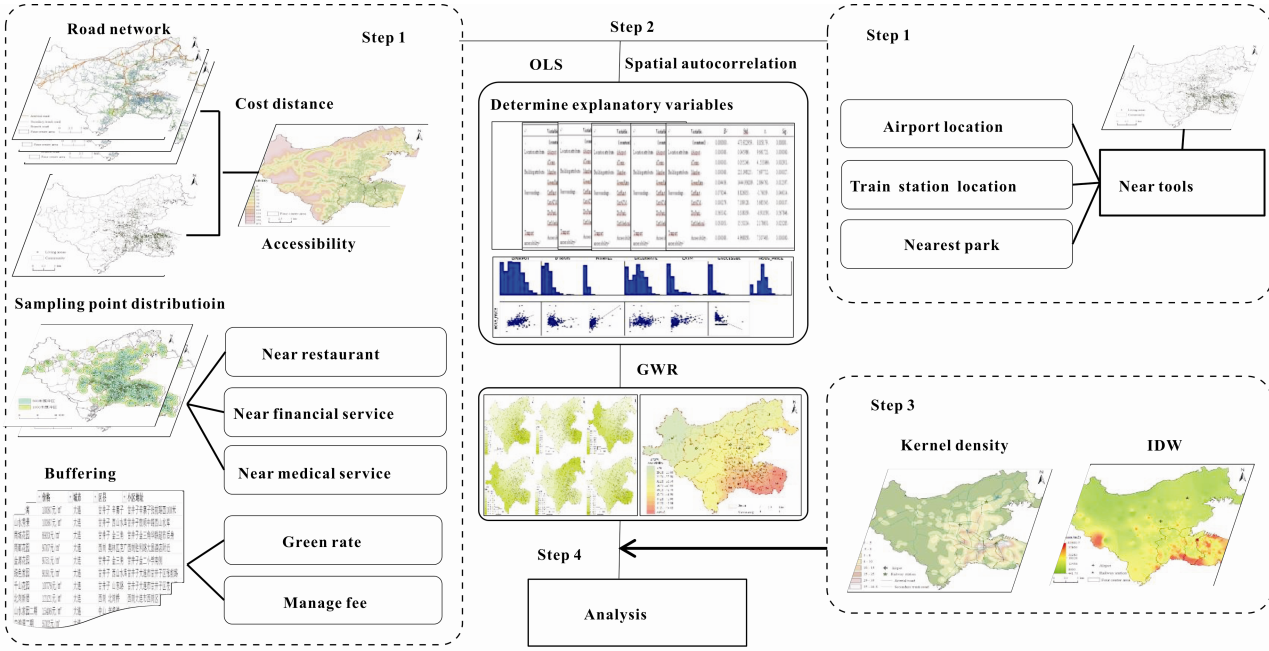

Fig. 2 Technology scheme

minimum cumulative value is selected as the destination accessibility metric. This paper uses time to measure the cost, which is the time taken to cross a distance of 1 km. The formula is as follows:

$$A = \begin{cases} \dfrac{1}{2}\displaystyle\sum_{i=1}^{n}(C_i + C_{i+1}) \\ \dfrac{\sqrt{2}}{2}\displaystyle\sum_{i=1}^{n}(C_i + C_{i+1}) \end{cases} \tag{1}$$

where C_i is the cost value of the i-th pixel, and C_{i+1} is the cost value of the next pixel in the path. The upper fraction calculates the cumulative cost of the next pixel in a horizontal or vertical direction. The lower fraction calculates the cumulative cost of the next pixel in a diagonal direction. In this paper, time is used to measure cost. The accessibility characterization variable is the cumulative minimum time value to reach the destination. Therefore, the greater the result, the poorer the accessibility. To make it more intuitive to understand, this study uses the reciprocals of the calculated results.

(2) Global regression model

The formula for the global regression model is as follows:

$$y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \tag{2}$$

where X_n is the coefficient of the n-th explanatory variable, β_n is the coefficient of the n-th explanatory variable, and ε is a random error.

The GWR model uses the following formula:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p}\beta_k(u_i, v_i)X_{i \cdot k} + \varepsilon_i \tag{3}$$

where (u_i,v_i) are the coordinates of the i-th sample point, and $\beta_k(u_i,v_i)$ is the k-th regression parameter on the i-th sample point, and a function of the geographic location, calculated as follows:

$$\begin{gathered} \boldsymbol{\beta}(u_i, v_i) = (\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{W}(u_i, v_i)\boldsymbol{X})^{-1}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{W}(u_i, v_i)y, \\ \boldsymbol{W}(u_i, v_i) = \begin{pmatrix} w_{i1} & 0 & 0 \\ 0 & ... & 0 \\ 0 & 0 & w_{in} \end{pmatrix} \end{gathered} \tag{4}$$

where X is the argument matrix, and $W(u_i, v_i)$ is the diagonal weighted matrix. A Gauss function was selected to calculate the weight (Equation 5), where b is referred to as the bandwidth, d_{ij} is the distance between i and j. The bandwidth is selected using the smallest *AICc* (Fotheringham et al., 2002).

$$W_{ij} = \exp(-(d_{ij}/b)^2) \tag{5}$$

(3) Modified GWR model geographically weighted accessibility model

In this paper, the accessibility calculation is substituted into the GWR model, and the GWR model is modified to analyze the relationship between accessibility and house prices more accurately. Thus, the formula can be expanded as:

$$y_i = \beta_{i0} + \sum_{k=1}^{n} \beta_{ik} X_{ik} + \sum_{k=n}^{p} \beta_{ik} A_{ik} + \xi \qquad (6)$$

where β_{ik} is the geographical position function, X_{ik} is a parameter of the explanatory variable, A_{ik} is the accessibility parameter, and ξ is the random error.

2.3.3 Model building

According to literature on the subject that identifies the factors that may affect house prices, we selected nine variables from three aspects. The overarching aspects included the location, residential property and traffic accessibility of the residential area, and the variables comprised two locational variables, six residential variables, and one traffic accessibility variable (Table 2).

Based on the global regression (Table 3) and spatial autocorrelation results, this study selected factors without large errors and established the GWR with six selected indexes.

Thus, the model was built as follows:

$$y_i = \beta_0 + \sum_{j=1,k} \beta_1 X_{ij}(\text{dAirpot}) + \sum_{j=1,k} \beta_1 X_{ij}(\text{dTrain}) + \sum_{j=1,k} \beta_1 X_{ij}(\text{Manfee}) + \sum_{j=1,k} \beta_1 X_{ij}(\text{GreenRate}) + \sum_{j=1,k} \beta_1 X_{ij}(\text{CntATM}) + \sum_{j=1,k} \beta_1 A_{ij}(\text{Accessibility}) \qquad (7)$$

Table 2 Selection and quantization of the factors

Aspects	Variable name	Quantitative method
Location attributes	dAirport	Distance to the airport
	dTrain	Distance to the railway station
Building attributes	Manfee	Property management fee
	GreenRate	Greening rate
Surroundings	CntRast	Number of restaurants within 500 m
	CntATM	Number of financial service stores within 1000 m
	DisPark	Distance from the nearest park
	CntMedical	Number of medical service facilities within 1000 m
Transport accessibility	Accessibility	Transport accessibility

Table 3 Results of global regression model 1

	Variable	B	SD	t	Sig.
	(constant)	0.000000*	473.922959	8.858079	0.000000*
Location attribute	dAirport	0.000000*	0.045986	9.661721	0.000000*
	dTrain	0.000010*	0.055246	4.533066	0.002911*
Building attribute	Manfee	0.000000*	221.098125	7.697712	0.000027*
	GreenRate	0.004436*	1444.936209	2.864761	0.012397*
Surroundings	CntRast	0.079244	8.826833	–1.76039	0.046114*
	CntATM	0.000279*	7.189128	3.683545	0.000107*
	DisPark	0.363142	0.308039	–0.910591	0.567846
	CntMedical	0.030031*	15.50214	2.178631	0.023285*
Transport accessibility	Accessibility	0.000000*	4.968858	7.307463	0.000000*

Note: * significant at the 0.05 level

3 Results and Analyses

3.1 Spatial differences of house prices

The residential areas of Dalian are mainly distributed in the districts of southeastern Ganjingzi, Shahekou, Xigang, and western Zhongshan (Fig. 3a). They are concentrated around Xigang District, and the density of houses in the south and east are higher than the north and west. Within this, the three main centers are: Zhicheng community area, Jiusan community area, and Fushou community area, and several secondary centers are: Xingjiapo community, Lanyuan community, Jingshan community, Fubing community, Bayi community, and Zhongxing community areas (Fig. 3b).

In December 2016, the average price of houses in the area was 12 436 yuan/m^2. In some areas on the margins, the price of houses was less than 8000 yuan/m^2. On the upper end of the price range, villas could cost more than 40 000 yuan/m^2, and high-end residential houses more than 20 000 yuan/m^2. The median price is 11 000 yuan/m^2, which can be seen in Fig. 3c. Owing to the unique geographical location of Dalian City, house prices generally decrease from the coast to inland, from east to west, and from south to north. However, the prices of houses around Guilin Street witness a local peak, decreasing from the center of the street to the periphery. The areas of peak house prices are mainly distributed in Xinghaiwan Street, Bayi Street, coastal areas along Laohutan Street, and areas around Guilin Street. The coastal area has great natural scenery, and is the main location for the construction of villas. Guilin Street is near Dalian's highly developed central area where there are many high-end residential areas, and the prices of houses are relatively high. There are also a few peak price areas near the airport and other transportation nodes.

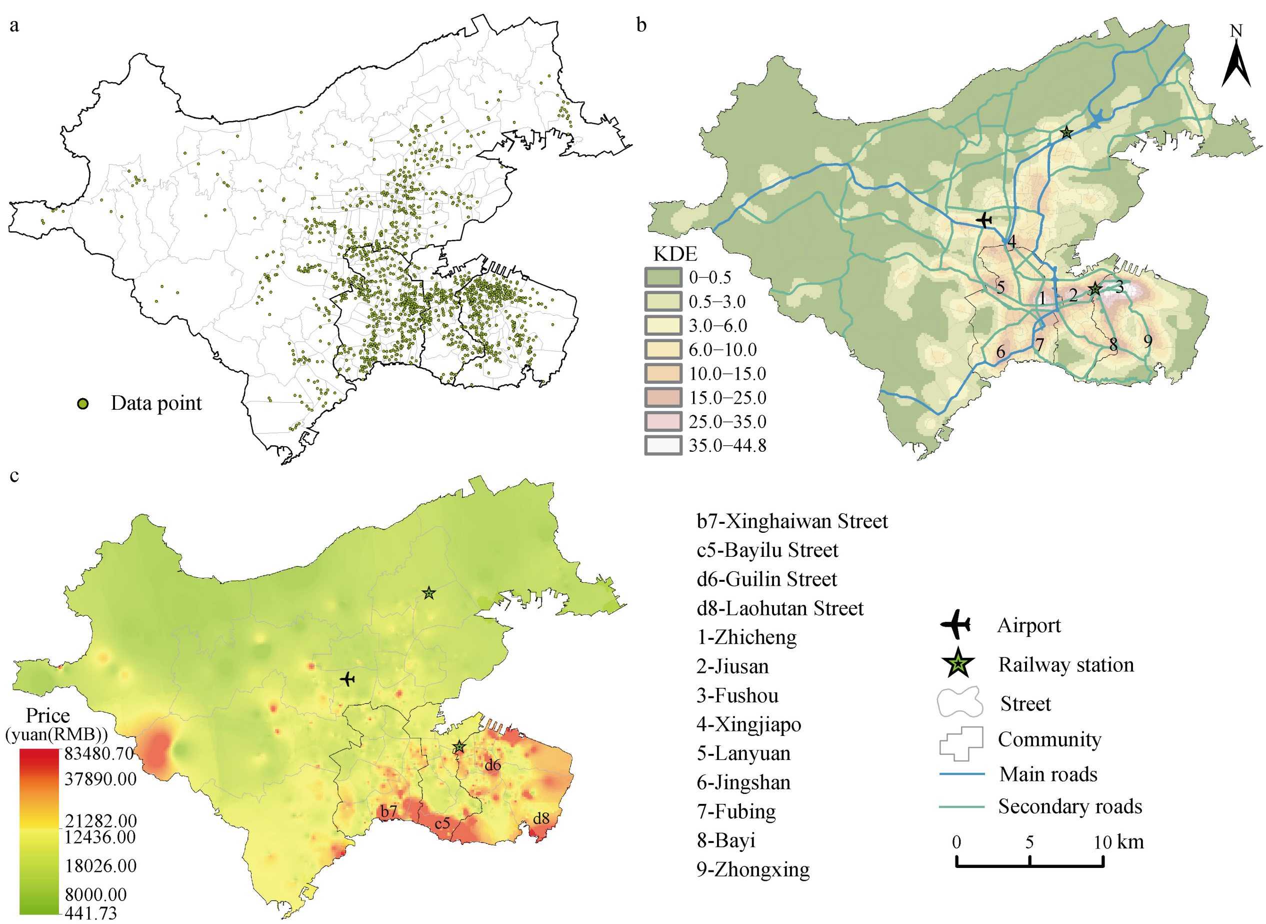

Fig. 3 Residential information. a: Distribution of residential sample points; b: Kernel density distribution of housing; c: Spatial variation of housing prices

3.2 Traffic accessibility of residential districts

The road network in the research area is shown in Fig. 4a, and Fig. 4b shows that mean accessibility is 33 minutes for all the residential areas in our study sample. Accessibility is within half an hour for more than two-thirds of the sample residential areas. The relatively low accessibility of some areas is around 50 to 70 minutes. Areas with the lowest accessibility are mainly in Yingchengzi, Maoyingzi, Qipanzi, Dalian Bay, and so on. Areas with accessibility of less than ten minutes are mainly in the middle of Xigang District, Navy Square community, Shuanghe community, Yingshan community, Huanghe community, and Zhongshan community. Shahekou and Xigang have dense transportation networks, and their residential areas enjoy relatively high accessibility, generally within 25 minutes. The areas near Huadong Road and Northeast Expressway also have relatively high accessibility, which is within 20 minutes. In comparison, the Zhongshan coastal area has relatively low accessibility, and the northern and western fringes of Ganjingzi district has the lowest accessibility of the areas studied.

3.3 Correlation analysis of accessibility and house prices

According to Equation 7, all the explanatory variables are used in the GWR model. The regression results are shown in Table 4. Compared with the global regression results (Table 5), R^2 was increased from 0.670 to 0.763, adjusted R^2 was increased from 0.665 to 0.749, and the local maximum reached 0.817, indicating that the GWR model is significantly better than the global regression model. The regression results are connected to the zoning of the Dalian community by spatial joining. Connecting the local regression coefficients of accessibility to each community and visualizing them clearly shows the impact of accessibility on house prices.

The study shows significant spatial correlation coefficient between accessibility and house prices. Accessibility has a positive impact on house prices. It can be seen from Fig. 5 that the impact of accessibility on house prices gradually increases in the east-southeast direction. The Yingchengzi, Xixiaomo, and Daheishi communities in the Ganjingzi district show the weakest correlations. The Lehua, Yingke, Hushan, Jianyuan, and Fujiazhuang communities in Zhongshan district show the strongest correlations. There is a stronger positive correlation between accessibility and housing prices in the districts of Shahekou, Xigang and Zhongshan. The impact of accessibility on housing prices in Ganjingzi area shows a certain degree of spatial heterogeneity. The impact of accessibility on house prices varies greatly, increasing significantly toward the southeastern direction. The impact is the biggest in Linghai, Xinyuan, Huichun, and Nanshan communities that are on the border of the Shahekou district; the impact is relatively low in the communities of Cha’ancun, Dadonggou, Youjia, and Xiajiahezi. The correlation coefficient of a bivariate correlation analysis of house prices and accessibility is 0.423 (Table 6).

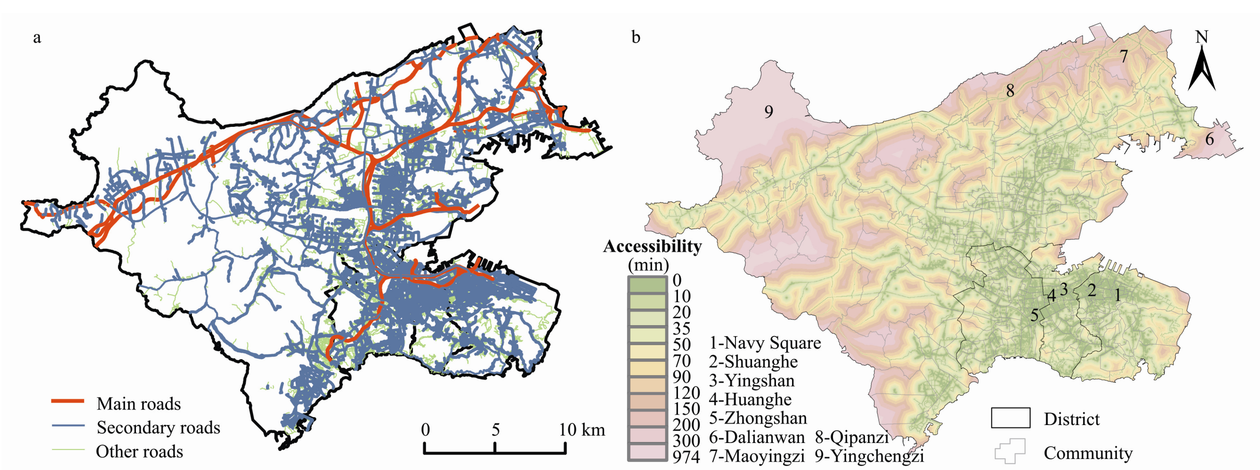

Fig. 4 Dalian road network (a) and transport accessibility in relation to distribution of housing (b)

Table 4 Results of geographically weighted regression

	Variable	Mean	SD
Location attributes	dAirport	0.49	0.15
	dTrain	0.46	0.08
Building attributes	Manfee	1589.88	321.70
	GreenRate	3752.63	1814.46
Surroundings	CntATM	21.19	10.26
Transport accessibility	Accessibility	42.40	5.56
	Bandwidth	10180.369	
	AICc	6516.936	
	R^2	0.763	
	Adjust R^2	0.749	

4 Conclusions

Based on the data of house prices in Dalian in December 2016, this paper uses an improved GWR model to study the correlation between accessibility and house prices, and arrives at the following conclusions:

(1) The residential areas of Dalian are mainly distributed in the districts of southeastern Ganjingzi, Shahekou, Xigang, and western Zhongshan districts. There are three main community areas, namely, Zhicheng, Sanjiu, and Fushou. House prices generally decrease from the coastal areas to inland areas, and from

Table 5 Results of global regression model 2

	Variable	B	SD	t	Sig.
	(constant)	0.000000	434.161916	10.536206	0.00000
Location attributes	dAirport	0.000000	0.044663	9.673525	0.000000
	dTrain	0.000004	0.050507	4.764881	0.001904
Building attributes	Manfee	0.000000	217.618935	7.413471	0.000056
	GreenRate	0.002070	1441.344270	3.105191	0.007089
Surroundings	CntATM	0.000000	3.431857	5.962908	0.000002
Transport accessibility	Accessibility	0.000000	4.727896	8.404865	0.000000
	R^2			0.670	
	Adjust R^2			0.665	

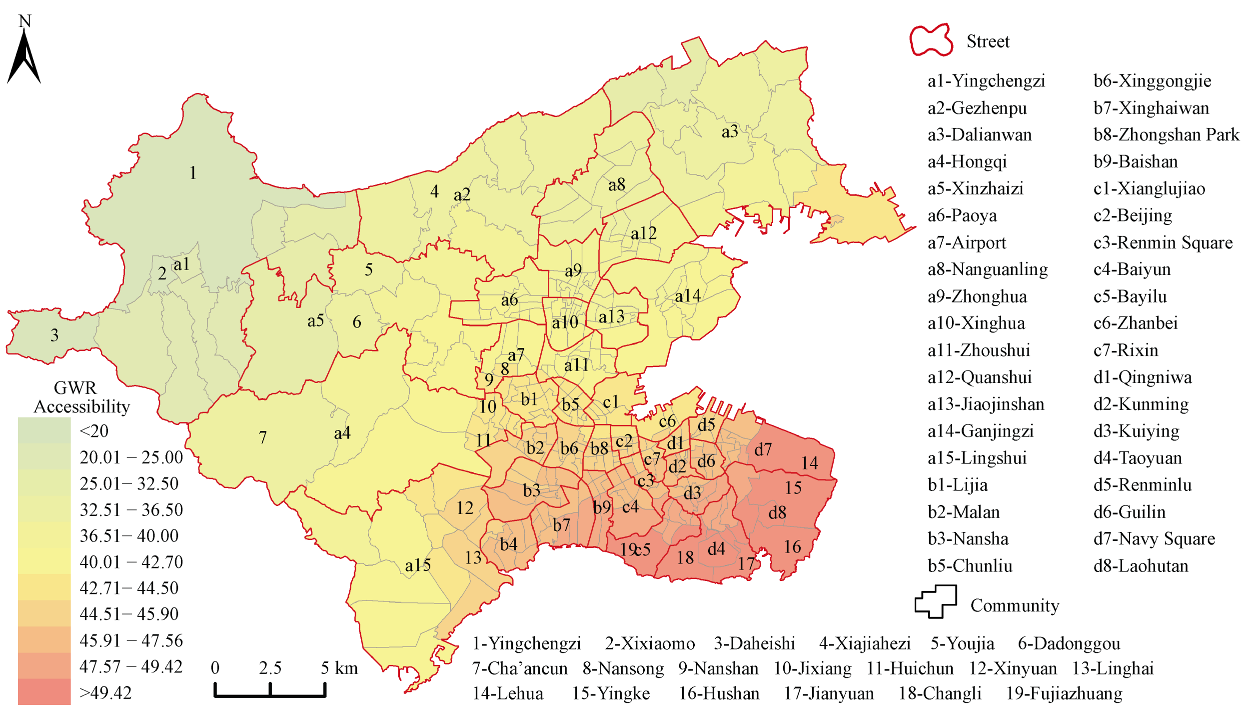

Fig. 5 Spatial correlations between accessibility and Dalian housing prices (community scale)

Table 6 Results of bivariate correlation analysis

Bivariate	Pearson correlation	Sig. (2-tailed)	Sum of squares and cross-products	Covariance	*N*
House price- Accessibility	0.423**	0.000	30152446.216	86149.846	351
Accessibility -House price	0.423**	0.000	30152446.216	86149.846	351

Note: ** Correlation is significant at the 0.01 level (2-tailed)

east to west, and south to north. There is a local peak around Guilin Street, where we observed that house prices also decline from the center of the street to the periphery. The areas with peak house prices are mainly located on and around Xinghaiwan Street, Laohutan Street, Navy Square Street, and Guilin Street.

(2) The accessibility of the study area is relatively good, an average of 33 minutes. The accessibility in areas with less dense transportation networks is relatively poor. The middle of Xigang district has a dense transportation network and possesses the best accessibility.

(3) The correlation coefficient between accessibility and house prices is 0.423, spatially positively significant. Accessibility has a positive impact on house prices, and the degree of impact extends in the east-southeast direction. As a result, the Yingchengzi, Xixiaomo, and Daheishi communities in the northeastern Ganjingzi District show the weakest impact, the Lehua, Yingke, Hushan communities and so on in southeastern Zhongshan District show the strongest impact. The impact of accessibility on house prices is more significant in the Shahekou, Xigang and Zhongshan districts than in Ganjingzi District.

Residential area accessibility has improved and housing prices show a growth trend, but the increase has a spatial differentiation. The improved GWR model indicates higher house prices relating to goodness-of-fit, while refining the impact of accessibility on house prices. Therefore, it more accurately reflects the degree of spatial differentiation of influence. This paper raises a few points for discussion and has implications for future studies. Firstly, the prices of houses change over time. This study only collected data of house prices at a single point in time, so the data does not represent the changes that occur over time. This is one of the limitations of this study. Secondly, this study uses dots to represent residential areas. The analysis will be more accurate if the boundaries of each area are captured. Thirdly, when grid costs were assigned to calculate accessibility, blank grids were directly assigned to the time cost values of other roads, without considering the obstructions created by buildings. Future studies can add some obstruction value for buildings in order to make the results of accessibility calculation even more accurate.

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