Exploration of the spatial pattern of urban residential land use with geographically weighted regression technique: a case study of Nanjing, China

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Abstract: As the traditional methods and technical means cannot meet the quantitative research needs of the urban land use patterns, quantitative research methods for the urban land use pattern are established via the GIS (geographic information system) technique combined with the related theories and models. Taking the city of Nanjing as an example, a spatial database of urban land use and other environmental and socio-economic data is constructed. A multiple linear regression model is developed to determine the statistically significant factors affecting the residential land use distributions. To explain the spatial variations of urban land use patterns, the geographically weighted regression (GWR) is employed to establish spatial associations between these significant factors and the distribution of urban residential land use. The results demonstrate that the GWR can provide an effective approach to the exploration of the urban land use spatial patterns and also provide useful spatial information for planning residential development and other types of urban land use.

Key words: urban residential land use; GIS (geographic information system); multiple linear regression; geographically weighted regression

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Cities have been at the centre of economic growth, social and political interchange, technological advances and cultural production. They represent and support most of human activity. Urban spatial structure is highly complex and varies considerably from city to city. However, most urban land is devoted to residential use. The spatial pattern of residential land use contributes to the city's size, shape, and distributions of other types of land use, and determines the relationships of people, transport, neighbourhoods, economic activities and the environment. Therefore, the study of urban residential land use is essential in urban planning.

Urban studies has a long history, evolving from the school of human ecology in the 1920s to the schools of location theory, social behaviour and political economy in the 1970s and 1980s. Many studies have been done on the physical, social, economic and political space of urban areas, focusing on the understanding of urban land use structures and their dynamic changes as well as the drivers of the changes[1-10]. However, the research on urban residential land uses has been largely limited to descriptive analysis of land use spatial distribution and its determinants [11-13]. Some quantitative analysis and modellings have been conducted to simulate and predict urban land use change and urban growth. For example, celluar automata (CA) simulation is a popular method for modelling urban land use change based on local land use transition rules [14-17]. However, CA itself does not involve the identification and examination of the factors that drive land use change, and thus it does not provide insight into the urban development process.

In recent years, regression models have been widely used for quantitative analysis of urban land use change and its driving forces [18-20]. They assume that independent variables have no multicollinearity and no correlation. The regression coefficients are global. Therefore, conventional regression does not take into account spatial variations of parameters, and the results will not fully reflect the true nature of the spatial pattern of urban land use and influencing factors. In order to overcome the limitations with conventional regression analysis, this research applied the geographically weighted regression (GWR) technique to understand the spatial pattern of urban residential land use and the underlying factors. GWR estimates a regression equation for each location, where weights are assigned to the observations surrounding the location[21]. It is essentially a regression analysis with spatially varying or local parameters, and therefore can reveal spatially varying relationships between the distribution of urban residential land use and the factors that may affect the distribution. Nanjing, the capital city of Jiang-

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su Province, China, is used as a case study.

1 Methodology

In this research, GIS was used to construct a spatial database of urban land use and other urban environmental and socio-economic data. It first developed a multiple linear regression model to determine the statistically significant factors affecting the urban residential land use distributions, and then applied the GWR technique to establish spatial associations between these significant factors and the distribution of urban residential land use; and to explain the spatial variations in the urban residential land use pattern and their underlying driving forces. The results from multiple regression and GWR were also compared.

1.1 Study area

Nanjing was once the capital of six dynasties in Chinese history, and is now the capital city of Jiangsu Province. It is one of the most important political, economic, and cultural centres in the Yangtze Delta, one of the largest economic zones of China [22]. The Nanjing municipality covers over 6 500 km^2, including eleven urban districts and two rural counties. It has an urban population of over 5.25 million according to the 2010 Chinese Census. We limit our study to within the city as shown in Fig. 1, where most of the residential land use is located.

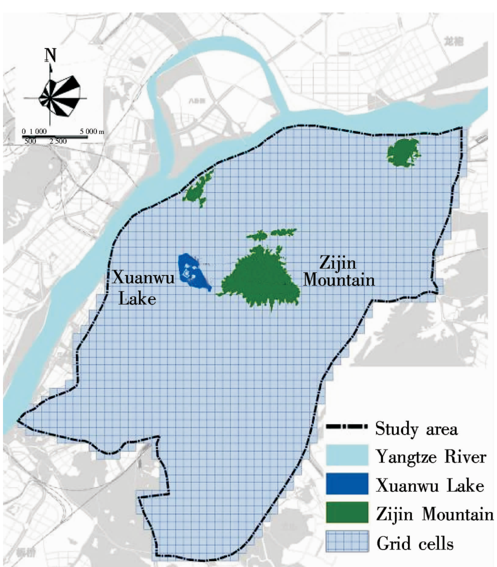

Fig. 1 Grid cells in the study area

1.2 Multiple linear regression model

The multiple linear regression attempts to model the relationship between two or more explanatory or independent variables. A general form of the multiple linear regression equation can be expressed as

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i$$

where i denotes the i-th observation; x_{ij} is the j-th independent variable; y_i is the dependent variable; k denotes the number of independent variables; β_0 and β_j represent the intercept and coefficients, respectively; and ε_i is an error term. The values of the parameters β_j ($j = 0, 1, \cdots, k$) can be found by solving

$$\boldsymbol{\beta} = (\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X})^{-1}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{Y}$$

$$\boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1k} \\ 1 & x_{21} & \cdots & x_{1k} \\ 1 & \vdots & & \vdots \\ 1 & x_{n1} & \cdots & x_{nk} \end{bmatrix}, \quad Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

where $\boldsymbol{\beta}$ is the vector of $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$, to be estimated; $\boldsymbol{X}$ is a matrix of observations on the independent variables; $\boldsymbol{Y}$ is the vector composed of observations on the dependent variable; n is the sample size or number of observations.

A multiple linear regression model can be constructed step by step through automatic selection of independent variables based on the t-statistics of their estimated coefficients [23], which is called stepwise regression. It is often achieved either by testing one independent variable at a time and including it in the regression model if it is statistically significant, or by including all potential independent variables in the model and removing those that are not statistically significant. This study used stepwise regression to identify the statistically significant factors determining the spatial pattern of urban residential land use.

1.3 Geographically weighted regression model

With multiple regression, $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$ are considered to be constant over space. However, in geographical analysis, these parameters may themselves be functions of geographical locations, as geographical phenomena such as urban land uses and their determinants are different across space. The relationships between the distribution of urban residential land use and particular social, economic or environmental factors determining the distribution may vary from location to location. GWR extends traditional "global" multiple regression analysis by producing a set of local parameter estimates for each relationship at every data point or location in a region, and therefore can effectively model the spatial variations of the relationships between geographically distributed phenomena. With GWR, a regression equation is estimated for every particular location, where weights are calculated for observations surrounding that location. A GWR model can be written as

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i$$

where (u_i, v_i) is the coordinates of location i; $\beta_0(u_i, v_i)$ is the intercept; $\beta_j(u_i, v_i)$ is the locally estimated coefficient for independent variable j at location i, which indicates that the parameter is specific to location i; and ε_i

denotes error at location i. $\beta_j(u_i, v_i)$ ($j = 0, 1, \cdots, k$) is derived by solving

$$\boldsymbol{\beta}(u_i, v_i) = (\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W}(u_i, v_i)\boldsymbol{X})^{-1}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W}(u_i, v_i)\boldsymbol{Y}$$

$$\boldsymbol{W} = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ 0 & \vdots & & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \cdots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \cdots & \beta_k(u_2, v_2) \\ \vdots & \vdots & & \vdots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \cdots & \beta_k(u_n, v_n) \end{bmatrix}$$

where n is the number of observations and w_{ij} denotes the weight of the observed data at location j for location i. The weights can be determined by several methods, but the most commonly used method uses the Gaussian function as expressed below [21]:

$$w_{ij} = \mathrm{e}^{(-1/2)(d_{ij}/b)^2}$$

where d_{ij} denotes the distance between location i and location j, and b is the distance threshold, also known as the the bandwidth.

The bandwidth may be chosen by minimizing the Akaike information criteria (AIC) score [21], given as

$$\mathrm{AIC_c} = 2n\ln(\hat{\delta}) + n\ln(2\pi) + n\left\{\frac{n + \mathrm{tr}(S)}{n - 2 - \mathrm{tr}(S)}\right\}$$

1.4 Rasterization of GWR parameters

The map of each independent variable was rasterized into a raster data layer. The cost distance method was selected to calculate the independent variable values, and the method needs source data and a cost surface. The source data was an independent variable, and the cost surface was created by calculating the impedance value in European space distance.

In this research, the study area is divided into a set of grid cells, as shown in Fig. 1. Each cell covers an area of 600 m × 600 m. Each cell is identified with its centroid whose Cartesian map coordinates are known. In addition, each cell is associated with the values of the dependent and independent variables, such as population and accessibility to transport. GWR formulates a separate regression equation for every grid cell incorporating the dependent and independent variables. The use of grid cells instead of natural plots delineated by roads is because the size of the plots varies significantly from 38 995 794.5 to 72.4 m^2 in the study area, which may lead to the loss of details or distortion of the spatial variations of the GWR parameters. As the average size of the natural plots is around 360 000 m^2, the cell size of 600 m is used.

The grid cell value of each independent variable was calculated in the following way, the values of the independent variable were extracted from the raster data layer at the centroid of a grid cell and other 10 randomly selected locations within the grid cell. Finally, the average of these values was calculated and assigned to that cell, representing the cell value of the independent variable. This process was repeated for every independent variable and for each grid cell in the study area.

The dependent variable is residential land use. The grid cell value of the dependent variable was calculated as the proportion of residential land use in the cell, which was captured by the 2007 Nanjing land use map with the grid cells. Xuanwu Lake and Zijin Mountain are excluded from modelling because they are two important and protected natural areas (see Fig. 1).

2 Results

2.1 Factors affecting the residential land use pattern and their significance

Generally speaking, residential areas should be located with good natural conditions. The topographic, geological and hydrological conditions should be suitable for the construction of residential houses. A good residential area should avoid flooding, earthquake, landslides and other natural hazards to minimize the construction costs, and should have nice natural surroundings. Transport network is one of the major factors determining the urban structure, the urban form and the pattern of residential land use evolves with the development and expansion of the transport network [24-25]. In addition, in order to facilitate the accommodation of residents, residential areas should have easy access to urban infrastructure, employment, heath care, educational and recreational opportunities, and should be compatible with the functional structure of the existing urban area. Urban sprawl mostly occurs along the natural and artificial corridors. The growth and distribution of population also affects the pattern of residential land use development.

There were sixteen major factors driving the spatial distribution of residential land use in Nanjing, which include slope, aspect, elevation, water resources, mountain resources, railway stations, metro stations, main roads, secondary roads, minor roads, cultural and entertainment facilities, sports facilities, health facilities, education and scientific research facilities, population, and existing residential land use. Nanjing has a single commercial and business centre, and the largest supermarket chain, Suguo, has retail outlets almost evenly distributed in the city. Therefore, commercial facilities are not a major factor affecting the distribution of residential land use, which are excluded from the analysis. Nanjing Railway Station is at the same location as the Nanjing metro station. Thus, train stations are removed from the analysis. As a result, fifteen factors are used in regression analysis. Tab. 1 lists the results of stepwise regression. With stepwise regression at a significance level of 0.05, if a coefficient's P-

value is less than 0.05 and its VIF (variance inflation factor) is less than 7.5, the corresponding independent variable will be statistically significant. According to Tab. 1, nine factors are statistically significant.

Tab. 1 Coefficients of the factors affecting the distribution of residential land use

Variable	Coefficient	Std error	t-statistic	Probability	VIF
Intercept	0.250		3.967	0	
Present residential land use	-4.930×10^{-5}	-0.387	-13.079	0	1.727
Population	-2.259×10^{-7}	-0.710	-3.020	0.003	1.080
Elevation	-1.361×10^{-6}	0.082	3.272	0.001	1.236
Health facilities	7.239×10^{-6}	0.120	3.660	0	2.119
Education and research facilities	-9.756×10^{-6}	-0.126	-4.082	0	1.883
Minor road	-1.301×10^{-5}	-0.134	-3.909	0	2.316
Recreation	4.418×10^{-6}	0.103	2.746	0.006	2.784
Secondary road	6.590×10^{-6}	0.074	2.456	0.003	1.808
Metro station	3.829×10^{-6}	0.062	2.928	0.004	1.111

2.2 GWR analysis of the significant factors

The GWR analysis was conducted in ArcGIS, the Kernel type was set as ADAPTIVE, and the bandwidth method as AIC. The outputs of the GWR analysis were written into a statistical report, which include the observed and estimated values of the dependent variable, residual, R-squared, AIC and bandwidth. The results indicated that the AIC value for the GWR analysis was -2 386.479, which is smaller than the AIC value for the multiple regression analysis, -2 081.338. Therefore, the GWR model provided a better fit to the observed data than the multiple regression model.

2.2.1 Elevation

The variation of elevation in the study area is generally small except the Zijin Mountain and the surrounding area. Fig. 2 shows the distribution of the coefficients of elevation obtained from the GWR analysis, and residential land use has a strong positive correlation relationship with elevation in the middle and southwest of the study area, but a negative correlation relationship occurs in the north-east of the area where the residential land use decreases as the elevation increases.

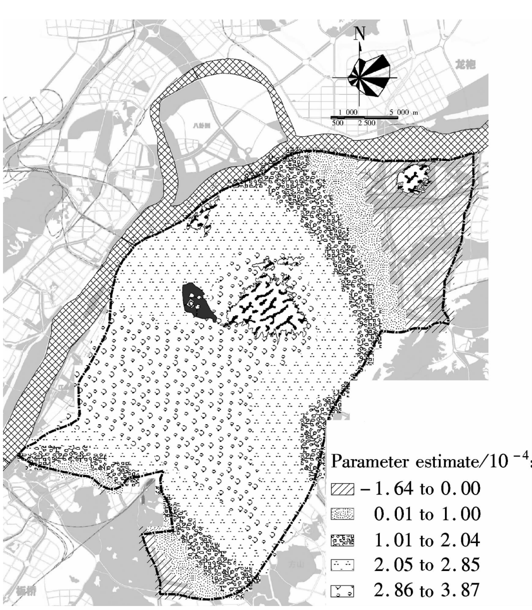

Fig. 2 Elevation

The positive relationship with elevation is weakens gradually from the central area to the north. That is because the north is by the Yangtze River and largely occupied by industrial land use. Residential land in the north is only used by workers in nearby factories, and is not as clustered as in the central area. Therefore, the significance of elevation on residential land use shows a decreasing trend towards the north.

2.2.2 Metro stations

The GWR parameter estimated for the factor of metro station is mapped in Fig. 3.

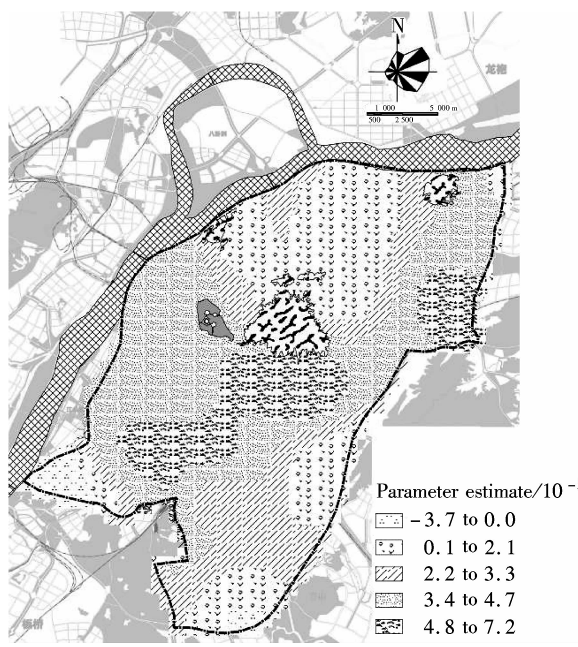

Fig. 3 Metro stations

From the map, it can be seen that the existence of metro stations is positively related to residential land use. Residential land use tends to be distributed closer to metro stations, particularly, in the central and eastern part. Metro stations have a weak relationship with residential land use in the area north to Zijin Mountain, but a strong relationship in the area south to the mountain. This is because the metro line is far from the area north to Zijin Mountain. Across the study area, the impact of metro stations decreases from the centre to the north and south.

2.2.3 Secondary roads

There are often more secondary roads than other classes of roads in an urban area. Together with main roads, they form the urban transport networks. Compared with main roads, secondary roads do not have strict requirements for the distance between road intersections. They have smoother traffic flows than minor roads and are suitable for entry to residential areas.

As shown in Fig. 4, residential land uses have a strong positive correlation relationship with secondary roads in the south, a weak positive relationship in the southwest, and a strong negative relationship in the east. Secondary roads have a positive relationship with residential land use in the north near the Yangtze River, where industrial land use dominates. The density of secondary roads is sparse and there is not much residential land. However, they have a very strong positive correlation relationship with residential land use in the south, where the Dongshan urban sub-centre is located with a high concentration of residential land use and high density of secondary roads. The southern part of the study area is a new development zone. There is a moderate density of secondary roads and less residential land use, which leads to a negative correlation relationship between secondary roads and residential land use.

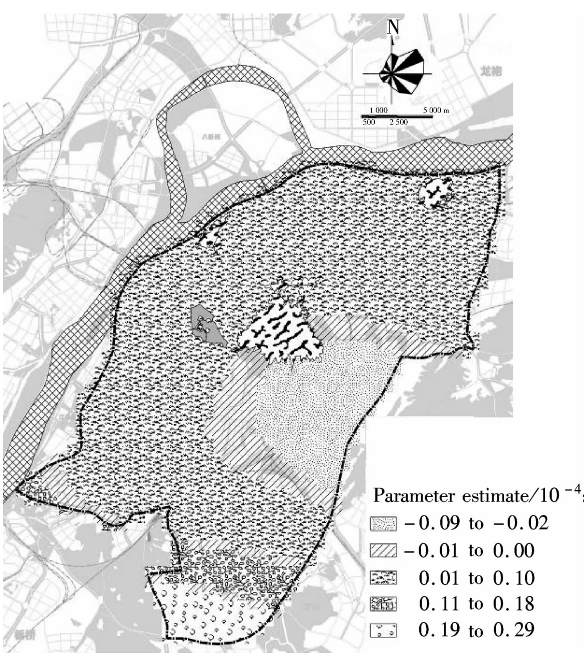

Fig. 4 Secondary roads

2.2.4 Minor roads

Minor roads are at the lowest level of urban road classification. The GWR parameter estimated for the factor of minor roads are shown in Fig. 5.

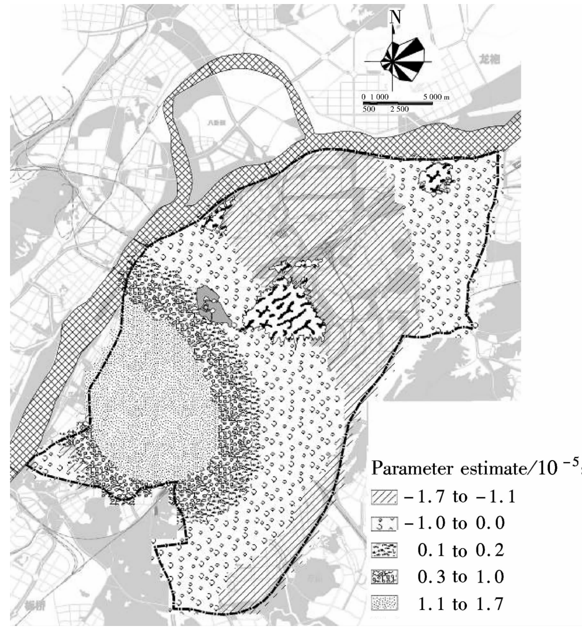

Fig. 5 Minor roads

It is evident that minor roads have a strong positive correlation relationship with residential land use in the central west, from which the influence of minor roads decreases outwards. In the north and southeast, the factor and residential land use demonstrated a negative correlation relationship. The central west is the CBD of Nanjing with evenly distributed residential land and dense minor road networks, and therefore, shows the strong positive influence of minor roads. The northern and south-eastern areas are occupied by the Xianlin University Town and industrial land use, with a medium density of minor roads and a sparse distribution of residential land use, and thus minor roads are negatively correlated with residential land use.

2.2.5 Present residential land use

As shown in Fig. 6, the present residential land use is strongly positively correlated with the distribution of residential land use.

The strength of the positive relationship decreased from the southwest to the northeast. It indicated that the present residential land use had an agglomeration function to the pattern of residential land use in the study area. The present residential land use is mainly concentrated in the areas near the Xuanwu Lake, but the maximum value of the parameter estimates does not appear in those areas. On the other hand, the northeast region has a low concentration of present residential land use, where the parameter values estimated are small. Therefore, the distribution of residential land use does not necessarily increase with the increasing concentration of the present residential land use.

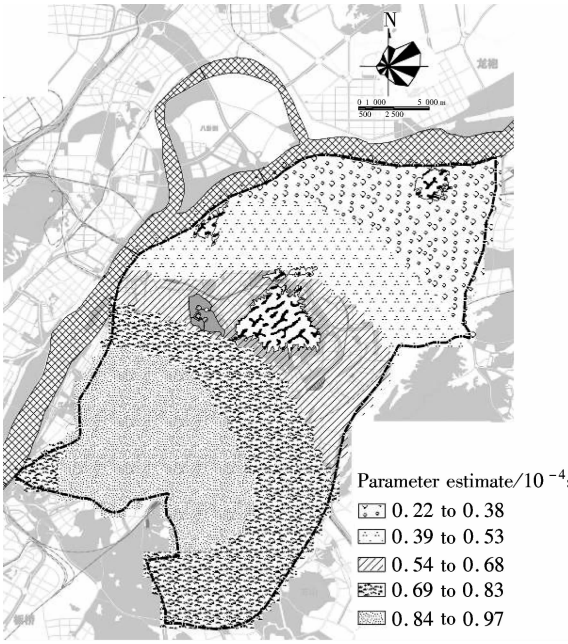

Fig. 6 Present residential land use

2.2.6 Population

Theoretically, the population size and distribution are closely related to the distribution of residential land use. Fig. 7 indicated that the population was not related to the residential land use distribution in most of the study areas. The area, northeast to Zijin Mountain, is the Jiangning District, a rapidly urbanised area, where residential areas scatter. The southern part of the study area has a small population, where industrial land dominates. The two areas demonstrate a negative relationship between population and residential land use.

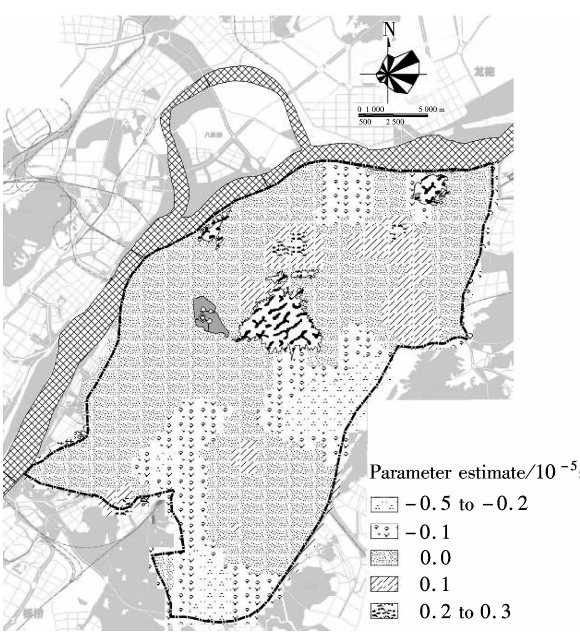

Fig. 7 Population

2.2.7 Health facilities

Health facilities are one of the essential public services in China. Their distribution is associated with residential land use.

As shown in Fig. 8, the strength of the association was strongest in the southeast and gradually weakened outwards. The southeast area where health facilities are positively and strongly associated with residential land use is a new development area with relatively high concentrations of health facilities and residential land use. In the CBD area, both health facilities and residential land use are distributed evenly, therefore, having a weak correlation relationship.

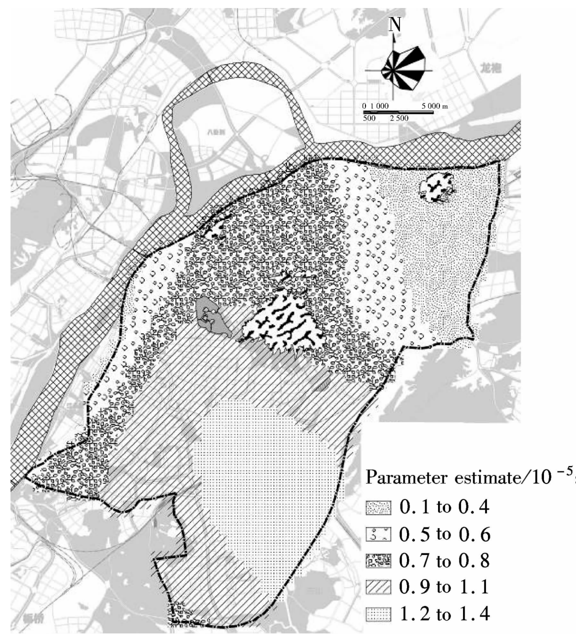

Fig. 8 Health facilities

2.2.8 Education and research facilities

Education and research facilities (including schools, universities and research institutes) in Nanjing are often accompanied by residential development. Fig. 9 reveals that this factor had a significantly strong and positive correlation relationship with residential land use in the southeast of the study area, i. e. that closer to education and research facilities there would be used for more residential land use. But education and research facilities and residential land use show significant negative relationships in the north where the Xianlin University Town is situated with limited residential development, and in the southwest where there is a high density of residential land use and very few education and research institutions.

2.2.9 Recreation

Recreation facilities may include playgrounds, sport grounds, parks, cinemas and theatres, libraries, etc. Generally, recreational and residential land use shows a positive correlation relationship over the study area. More residential land use attracts more recreational facilities, as illustrated in Fig. 10.

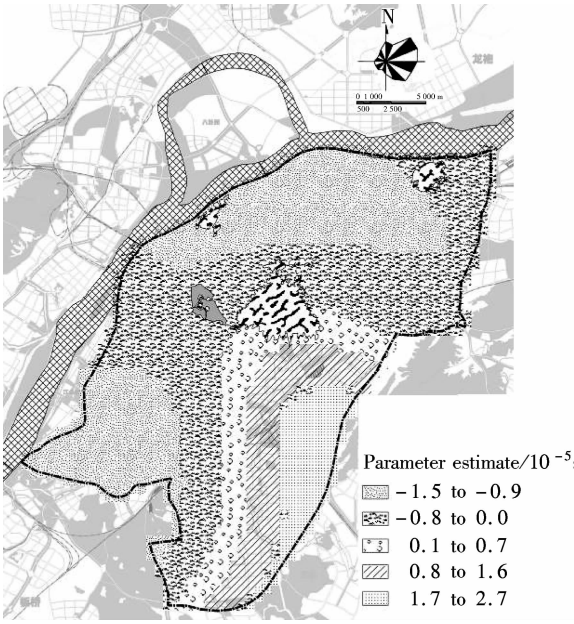

Fig. 9 Education facilities

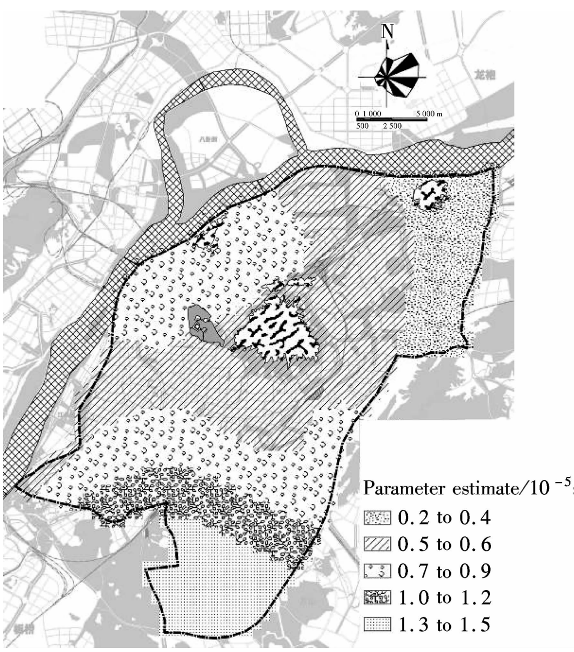

Fig. 10 Recreation

The area in the north facing the Yangtze River, part of the city core, has a high value for this parameter. In this area, the density of residential land use is high and there are many recreational facilities in the scenic area of Mufu Shan. The parameter is also significant in the south, where many industries and some new university campuses are located, but the density of residential land use is low and there are few recreational facilities.

3 Conclusion

This research applied GWR to explore the distribution in urban residential land use, and to explain the spatial variations in urban land use patterns and their underlying driving forces, taking Nanjing as a case study. The results demonstrate that the spatial statistic model is more effective in analyzing the factors affecting the spatial distribution of residential land use than global multiple regression analysis. Multiple regression analysis assumes that there are no spatial variations in dependent and independent variables. It provides global parameter estimates, which cannot reveal the local variations and ignores the existence of spatial autocorrelation. Therefore, multiple regression analysis cannot characterize the spatial pattern of urban land uses and its underlying driving factors. GWR overcomes the limitations with multiple regression analysis. It estimates parameter values with higher levels of significance and smaller residuals, and describes the spatial variations of all the regression variables.

In the case study, GWR was used to explore the spatial patterns of urban residential land use in Nanjing. Nine factors were determined through multiple linear regression that affect the urban residential land use distribution with statistical significance, including elevation, existing residential land use, metro stations, population, health facilities, education and scientific research facilities, cultural and entertainment facilities, secondary roads and minor roads. The coefficients or parameter values for each of the factors were estimated. The results are a set of coefficient maps. These maps depict the spatial variations of the impacts of each of the nine significant factors on the urban residential land use.

Residential land use plays an important role in urban development. This paper quantitatively explored the relationships between the distribution of urban residential land use and a number of environmental and socio-economic factors, based on which the patterns and evolution of residential land use at different locations can be derived. The research demonstrates that GWR modelling provides a new approach to the exploration of urban land uses based on geographical data and the modelling results can provide useful information for planning residential development and other types of urban land use.

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基于地理加权回归的南京市居住用地分布规律研究

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摘要:针对传统方法和技术手段难以满足城市用地格局定量研究需要的不足,建构了基于 GIS 技术与相关理论和模型方法相结合的城市用地格局定量研究方法. 以南京市为例,建立居住用地及其影响因子空间数据库. 在此基础上,运用多元回归模型进行全局估算,确定对现状居住用地统计显著的影响指标因子. 然后建立现状居住用地和统计显著的影响指标因子地理加权回归模型,对居住用地空间分布进行定量模拟和分析. 研究结果表明,CWR 能提供一种有效的城市土地利用空间格局研究方法,并为城市土地利用规划提供有效的空间信息.

关键词:居住用地; GIS; 多元线性回归;地理加权回归
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