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Analysis of the Driving Forces of Urban Expansion Based on a Modified Logistic Regression Model: A Case Study of Wuhan City, Central China

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Abstract: Urban development policies and planning schemes are essential drivers of urban expansion in the contemporary world. However, they are usually investigated by qualitative analysis and it is difficult to use them in spatial analysis models. Within the advancement of technology regarding the geostatistical dataset, this study uses a field strength model to quantify policy-oriented factors and designs a modified logistic regression model to analyze the main drivers of urban expansion by selecting natural environment, socioeconomic development, and especially policy-oriented variables. Wuhan City in central China is taken as an example: the modified model is applied and compared with the classical model, and the driving mechanism of urban expansion in Wuhan from 2006 to 2013 is determined through spatial analysis. The results show that the urban system planning in combination with various anthropologic and environmental factors can be comprehensively quantified and described by the urban field strength. The methodological innovation of the classical logistic regression model is tested by statistical and spatial analysis methods, and the results verify that the modified regression model can be used more accurately to investigate the driving mechanism of urban expansion in the past and simulate the spatial pattern of urban evolution in the future.

Keywords: urban land use transformation; drivers; statistical method; spatial analysis; modified model

1. Introduction

Urban expansion, which is an important part of the land use and land cover change (LUCC) research promoted by the International Geosphere–Biosphere Program (IGBP) and the Global Environmental Change in the Humanities Program (IHDP) in 1995 [1], has been a research hotspot considering accelerating global urbanization during recent decades [2,3]. More scholars are trying to investigate the process of urban expansion [4–6] and predict the consequences of urban land use transformation [7], and then provide decision-makers with important information or assessment for the sustainable utilization of land resources and harmonious urban/regional development [8]. Analyzing the drivers of urban expansion becomes important to infer the urban growth mechanism in the past and simulate the spatial pattern of urban evolution in the future [9].

The existing literature has investigated the drivers of urban land use expansion. Land use change (LUC) is generally related to two aspects, natural environmental and anthropogenic drivers in the physical world [10]. Drivers related to the natural environment include topographical and hydrologic conditions [11–13] and natural hazards [14,15]. Anthropogenic drivers, such as demographic changes [7], economic development [16], industrial level [17], traffic systems [18], resident incomes [19], and land use policy [1,20], which are given close attention universally, generally play more crucial roles in affecting urban growth in the context of rapid urbanization and industrialization.

Many studies have focused on analyzing the spatial drivers of urban expansion worldwide from different perspectives and at different spatial scales [21–33]. Some researchers have collected social and economic panel data of administrative divisions of a city or country and developed quantitative models to analyze the driving forces of urban expansion at the regional scale [21–25]. With the development of geographic information systems and remote sensing techniques, other researchers have extracted geospatial data through spatial analysis software and used spatial analysis models to determine the driving forces of urban land expansion at the land patch scale [26]. Some classical methods, such as logistic regression analysis [27], cost-benefit framework analysis [28], space syntax-based analysis [29], and cellular automata (CA)-based analysis [30], are used in related research on drivers of urban land use change. In China, rapid urbanization in cities is partly reflected in statistical data on population increase, gross domestic product (GDP) growth, and transportation and real estate construction, which are led by a series of socioeconomic development planning schemes of the city. The most intuitive reflection of urban development is expressed in terms of the spatial pattern of urban expansion, which is guided by different types of planning schemes in different spatial scales, such as land use, city layout, and urban planning [31].

Although we can find good examples of quantitative analysis about the influence of urban development or land use polices on urban expansion, such as the experimental studies by Long et al. [32], García-Ayllon [33], and Deng et al. [31], the effects of spatial planning on urban expansion through quantitative analysis should be addressed more widely, since urban expansion is usually due to political drivers that can be investigated by qualitative analysis in spatial planning. The development of sustainable policies for urban transformation should be investigated by a mixed approach. Within the advancement of technology regarding the geostatistical dataset, it is easier to verify the amount of land urbanization through land use datasets in different time series, and geospatial data such as altitude and slope can be used in analyzing the effects of physical factors on land urbanization. Converting the socioeconomic statistical data, including GDP and population, and policy-oriented information from urban planning at the regional scale into spatial data at the land patch scale and combining them with geographic information data will improve the mixed approach to understand drivers of urban expansion. Developing such techniques is beneficial to investigate the driving mechanism of urban expansion and simulate the spatial pattern of urban evolution. Based on related research, this study proposes a modified method for determining the driving forces of urban expansion. The study aims to (1) quantify information on urban spatial planning and match up policy-oriented and socioeconomic data to urban land use changes at the land patch scale; (2) verify the feasibility of the new analytical method by comparing it with traditional ones, and (3) reveal the mechanism of urban spatial layout strategy and other outstanding factors of urban expansion based on the model results.

2. Methodology

2.1. Field Strength Model

The field strength model, as a derivative of the gravity model, is a powerful tool for investigating the interactions of different spatial units, especially in the absence of specific statistical data of socioeconomic factors that correspond to a rasterized plot in the study of land use change [34]. This study selected the field strength model to quantitatively describe the effects of urban planning on spatial units and address the deficiency of research on the effects of policy elements on urban expansion. Field strength describes the intensity of a rasterized plot influenced by regional radiation from surrounding subdistricts in a city [35]. The field strength model can be formulated as follows:

$$F_j = \sum_{i=1}^{n} \frac{M_i}{D_{ij}^{b}}, \tag{1}$$

where F_j denotes the field strength of rasterized plot j affected by all subdistricts in a city, M_i denotes the quality (generally referring to the evaluation of socioeconomic strength) of subdistrict i, D_{ij} is the distance from rasterized plot j to subdistrict i, and b is the distance friction coefficient that reflects the sensitivity of the field strength to distance and has a constant value.

Formula (1) is based on the assumption that any rasterized plot in the city receives regional radiation with equal opportunity; however, radiation in reality is often attenuated or blocked by obstacles, such as a natural (river, mountain) or administrative boundary [36], which may also rapidly increase along expressways. Therefore, regional radiation does not simply and smoothly decrease according to linear distance, but selects the path of least resistance to spread to any spatial unit in a city. The degree of radiation received by a spatial unit at the same linear distance from a town will also vary due to different resistance [37]. If the level of resistance to radiation transmission is described by the cumulative cost of traffic at each point, then D_{ij} can be replaced by the cumulative cost distance from rasterized plot j to subdistrict i in the city. When all spatial units are regular quadrilateral grids that are as large as rasterized plot j, the specific calculation steps are as follows:

(1) The weighted resistance of the rasterized plot is calculated according to the cost to pass through plot j. The cost to pass through the rasterized plot can be formulated as follows:

$$A_j = \frac{\sqrt{2}m}{V_j} \tag{2}$$

where A_j is the travel (time) cost of rasterized plot j measured in minutes, $\sqrt{2}m$ represents the travel distance through each plot (grid), and V_j is the travel speed measured by the minutes required to travel an average of 1 km.

(2) The weighted resistance of each rasterized plot to each subdistrict in the city is calculated through a cost distance-weighted analysis. Weighted resistance can be determined as follows:

$$C_j = \sum_{k=1}^{n} W_k A_{jk} \tag{3}$$

where C_j is the weighted resistance of rasterized plot j, A_{jk} is the travel cost of resistance factor k on rasterized plot j, W_k is the weight of resistance factor k, and n is the total number of resistance factors.

(3) The cumulative cost distance from one rasterized plot passing through other rasterized plots to any subdistrict in the city is calculated based on the cumulative cost distance algorithm. Cumulative cost distance (D_{ij}) can be calculated as follows:

$$D_{ij} = \begin{cases} \frac{1}{2}\Sigma\left(C_j + C_{j+1}\right) \\ \frac{\sqrt{2}}{2}\Sigma\left(C_j + C_{j+1}\right) \end{cases} \tag{4}$$

where C_j and C_{j+1} denote the weighted resistance of rasterized plots j and j + 1, respectively. The upper fraction of the formula represents the cumulative cost from j through the horizontal or vertical direction to j + 1, and the lower fraction represents the cumulative cost from j through the diagonal direction to j + 1.

2.2. Modified Logistic Regression Model

The logistic regression model is a statistical analysis tool for classifying variables and can be used to determine the intensity of independent variables that affect the probability of occurrence of dependent variables [38]. This model has been widely used in studies on the driving forces of urban expansion and its simulation [7,9]. In the present work, a binary logistic regression model was selected to estimate the contribution of the influencing factors to urban expansion. The model sets the dependent variable Y as 1 when urban expansion occurs (otherwise, Y is equal to 0) [39]. For the explanatory variables x_1, x_2, ... x_n, probability P when urban expansion occurs can be denoted as P (y = 1|x_1, x_2, ... x_n) or P (y = 1|x_i). The classical logistic regression model can be formulated as follows:

$$logit(P) = \ln\left(\frac{P}{1-P}\right) = \alpha + \sum_{i=1}^{n} \beta_i x_i \tag{5}$$

where $\alpha$is the constant term, and β_i is the linear regression coefficient of each explanatory variable and denotes the logarithmic variation of probability P when urban expansion occurs, i.e., one variable changes by one unit, while all other independent variables are fixed. The positive regression coefficient indicates that the odds ratio of urban expansion will increase correspondingly with each additional value of the explanatory variable. By contrast, the negative regression coefficient indicates that the odds ratio of urban expansion will decrease correspondingly with each additional value of the explanatory variable [40].

Based on the hypothesis of the classical logistic regression model, this study used the field strength variable to build a modified logistic regression model for spatial analysis of the driving forces of urban expansion. For any spatial unit j in urban expansion, the probability of its transformation, that is, y = 1, is denoted as P_j, which can be calculated as follows:

$$P_j = P_j\left(y = 1 \middle| x_i, F_j\right) = \frac{\exp\left(\alpha + \sum_{i=1}^{n} \beta_i x_i + \delta F_j\right)}{1 + \exp\left(\alpha + \sum_{i=1}^{n} \beta_i x_i + \delta F_j\right)} \tag{6}$$

The modified logistic regression model can be formulated as follows:

$$logit\left(P_j\right) = \ln\left(\frac{P_j}{1-P_j}\right) = \alpha + \sum_{i=1}^{n} \beta_i x_i + \delta F_j, \tag{7}$$

where δ is the regression coefficient of the field strength variable, and the other parameters are the same as those in Formula (6).

2.3. Verification of the Regression Model

The logistic regression coefficient does not reflect the importance of each variable to the dependent variable. When using related software such as SPSS and SAS for multiple logistic regression analysis, Wald statistics [41] are usually used to represent the relative weight of each explanatory variable in the model to evaluate their contribution to the prediction of the effect index [39]. After operating the logistic regression model, the degree of effective description of the response variable and the data of the model registration observation should be tested; that is, the goodness of fit of the model should be determined. The receiver operating characteristic (ROC) curve [42] is selected for testing because it comprehensively reflects the sensitivity and specificity of continuous variables. Sensitivity refers to the probability of accurately predicting the actual 1 to 1, and specificity refers to the probability of accurately predicting the actual 0 to 1. The ROC curve can be drawn to reveal the linear relationship between sensitivity and specificity, which is used to judge the diagnostic accuracy of the model. The ROC curve generally takes a diagonal line as the threshold in the coordinate system, above which the prediction effect of the curve is high. In this regard, the farther the ROC curve is from the diagonal line (the larger the area under the ROC curve), the higher the prediction accuracy will be.

To accurately test the regression effect, this study integrated the regression coefficient into the probability calculation of Formula (6) and applied the raster calculator tool of ArcGIS to simulate the spatial distribution of the probability of urban construction land expansion. The kappa coefficient was used to compare the real and simulated distribution of urban land and determine the optimal simulation model. For the two raster graphics, the calculation formula of kappa coefficient [43] is as follows:

$$K = \frac{P_o - P_c}{1 - P_c} \tag{8}$$

$$P_o = \frac{s}{n} \tag{9}$$

$$P_c = \frac{a_1 \times b_1 + a_0 \times b_0}{n \times n} \tag{10}$$

where K is the kappa coefficient and ranges from −1 to 1, n is the total number of raster pixels, a_1 represents the pixels with a real raster value of 1, a_0 represents the pixels with a real raster value of 0, b_1 represents the pixels with an analog grid value of 1, b_0 represents the pixels with an analog grid value of 0, and s is the number of pixels with equal values for the two raster graphics.

3. Study Area and Data Processing

3.1. Area Description

Wuhan, extending from 29°58′ to 31°22′ N latitude and 113°41′ to 115°05′ E longitude, is the capital of Hubei Province in central China and covers an area of 8494.41 km^2. Wuhan features mostly low hills and plains with a gently sloping terrain and abundant water resources, which make up approximately one-quarter of the total water resources of the entire city owing to the Yangtze (the world's third largest river) and Hanshui (its largest tributary) rivers. Wuhan is the largest transportation hub, with dozens of roads, expressways, railways, and airlines connecting with all the cities of China and with different countries worldwide. Wuhan is currently recognized as the financial, educational, and transportation center of central China and has a large population and a rapid growth rate of urbanization. According to the administrative division, Wuhan consists of 13 administrative districts, seven central urban and six suburban districts (Figure 1).

In recent years, the municipal government has implemented the General Land Use Plan of Wuhan City (2006–2020) to build a four-level urban system that consists of city center townships, key developing townships, suburban center townships, and general townships. The city center township is the core of urban development, which takes care of financial, technological, and educational functions and has a strong effect on the social and economic development of the surrounding areas. The key developing township is the most important area reflecting urban spatial expansion, where the population agglomeration and industrial concentration will increase rapidly with the development spillover of the urban center. The suburban center and general townships are the dominant areas for agricultural production. The former is the main area of urban transportation, tourism, and other functional spatial expansion, with a minor distribution of basic farmland and ecological land, and the latter is the primary area of urban agriculture development, with a major distribution of basic farmland and ecological land. In addition, the government has authorized a series of planning schemes—the Wuhan City Master Plan (2010–2020), the Strategic Plan of "1+6" Spatial Development in Wuhan Urban Area, and the Ecological Space Plan of Wuhan Urban Area—which propose classifying the entire city area into three distinct functional subareas: the central urban, urban development, and eco-agricultural subareas. The implementation of these policy-oriented plans will inevitably exacerbate the imbalance of regional development within Wuhan City and then affect the land use and urban expansion of the city in the next few years.

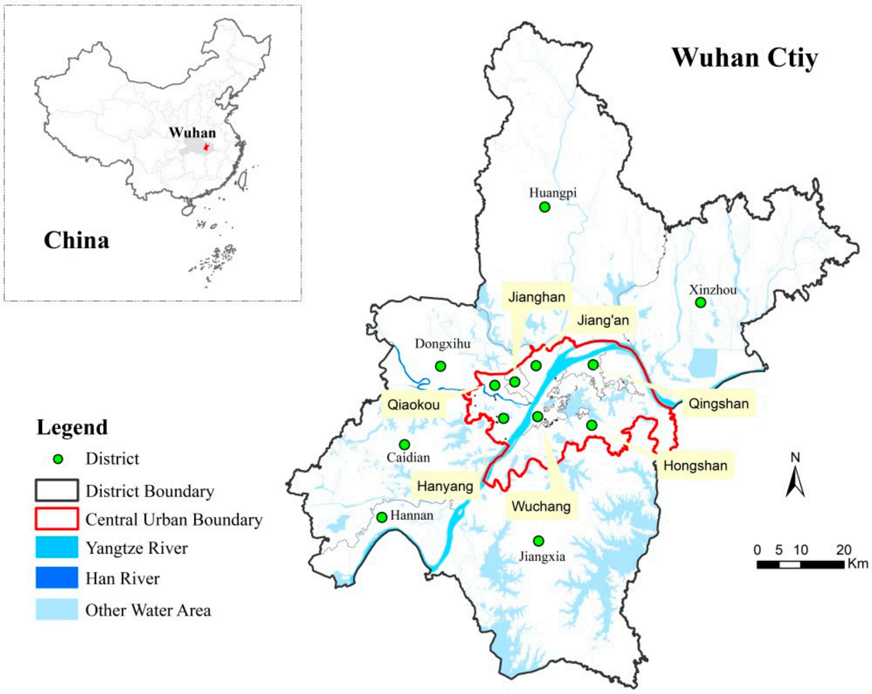


Figure 1. Location and administrative districts of Wuhan.

3.2. Data Sources and Preprocessing

This study analyzed systematic data on land use change in Wuhan based on two land use–land cover vector format maps at the 1:10,000 scale. The maps were obtained from land use data in 2006 and 2013 based on two nationwide land surveys. The land classification scheme consists of nine categories: cultivated land, forest, other agriculture land, urban construction land, rural construction land, other construction land, water area, and unused land. Table 1 shows the different types of land use during 2006 and 2013. Figure 2 shows the spatial distribution patterns of land use in 2006 and 2013. The two vector format maps were converted into raster format with a spatial resolution of 150 m × 150 m by applying the ArcGIS 10.0 (Esri, US) polygon to raster conversion tool. The variations in quantity and spatial distribution of urban construction land use were acquired by extracting the urban and nonurban construction land in two maps and conducting an overlay analysis. The digital elevation model (DEM) data of Wuhan City originated from Shuttle Radar Topography Mission (SRTM) elevation data with a spatial resolution of 90 m × 90 m in 2007. The data were converted into raster format with the same resolution as that of the land use map. The traffic network information was obtained from the vector data of the road traffic spatial distribution map in Wuhan in 2010. The spatial distributions of the functional subareas and the urban system were extracted from the related map in the planning documents of Wuhan City.

The 85 townships were reconfigured as research areas by regarding the six central urban districts (Jiang'an, Jianghan, Qiaokou, Hanyang, Qingshan, and Wuchang) and the city proper of Hongshan District as the consolidated townships to unify the caliber of statistical data among all types of socioeconomic information and related planning documents reconfigured in this study. The towns and the development zones under their jurisdiction are locally integrated in the suburban districts. The societal and economic data of the 85 townships were derived from the yearbook of each town and the Statistical Yearbook of Wuhan from 2007 to 2014. Data were partly collected from the contemporaneous Statistical Yearbook of Hubei. Accessibility to data in a few towns is relatively poor. Interpolation and data fitting were used to supplement the missing data and maintain data integrity.

Table 1. Land use quantitative and structural changes in Wuhan, 2006–2013 (unit: km^2).

Land Use Type	2006		2013		2006–2013
	Area	% Total	Area	% Total	Variation
Cultivated land	3659.72	42.82	3266.55	38.22	−393.18
Forest	887.88	10.39	975.54	11.41	87.66
Other agriculture land	1062.80	12.43	1204.28	14.09	141.48
Urban construction land	626.37	7.33	882.78	10.33	256.41
Rural construction land	506.53	5.93	561.07	6.56	54.55
Other construction land	262.58	3.07	345.90	4.05	83.33
Water area	1371.57	16.05	1227.51	14.36	−144.06
Unused land	169.67	1.99	83.48	0.98	−86.19

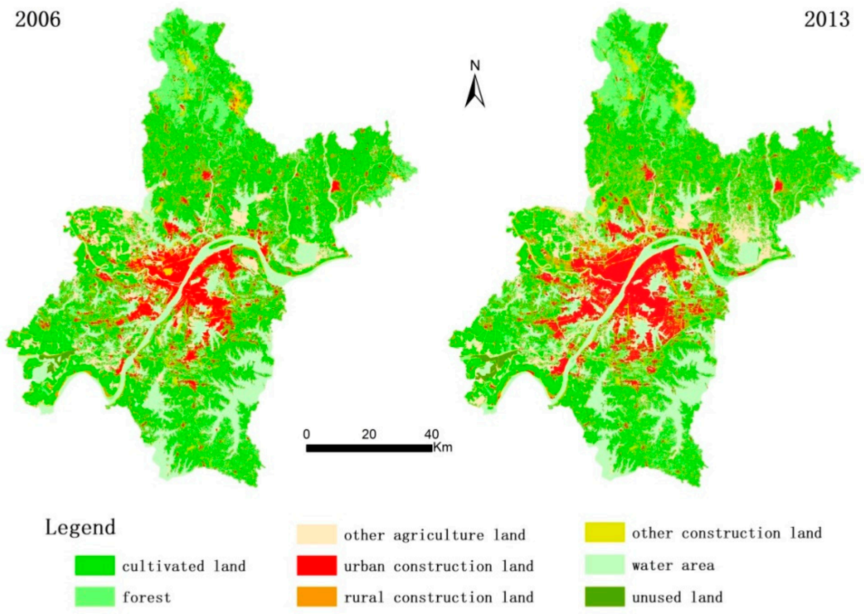


Figure 2. Classified land use/cover maps of Wuhan in 2006 and 2013.

3.3. Variable Selection and Spatial Quantification

This study selected the influencing factors from three aspects—natural, accessibility, and policy-oriented—to analyze the driving forces of urban expansion of Wuhan City. The specific independent variables were set as shown in Table 2.

Table 2. Independent variables of driving forces of urban expansion for different models.

Type	Variables		Applicable Model	
Natural environment factors	**Slope (xx_1)**		Classical logistic regression model	Modified logistic regression model
	Distance	from the main river (x_2) from the ordinary river (x_3) from the lake (x_4)		
Accessibility factors	Distance	from the arterial road (x_5) from the subarterial road (x_6) from the expressway (x_7) from the center of the city (x_8) from the center of the key developing town (x_9) from the center of the suburban center town (x_{10})		
Policy-oriented factors	Location of the overall layout of urban space (x_{11}) Degree of influence of the various grading townships (x_{12})			

3.3.1. Natural Environment Variables

A steeper slope of spatial units generally leads to a higher requirement for engineering technology, higher construction cost, and difficulty converting into urban land. The orography of Wuhan presents a certain degree of surface undulation, which has an effect on urban expansion. Furthermore, Wuhan is rich in water resources, particularly rivers and lakes, which are indispensable factors influencing urban construction and development. Therefore, slope (x_1) was selected as the topographic and geomorphic characteristic variable, and the distances of spatial units were selected from the major rivers (x_2), minor rivers (x_3), and lakes (x_4) as the resource and environment variables. Figure 3 shows the spatial distribution of the four natural environment variables in Wuhan.

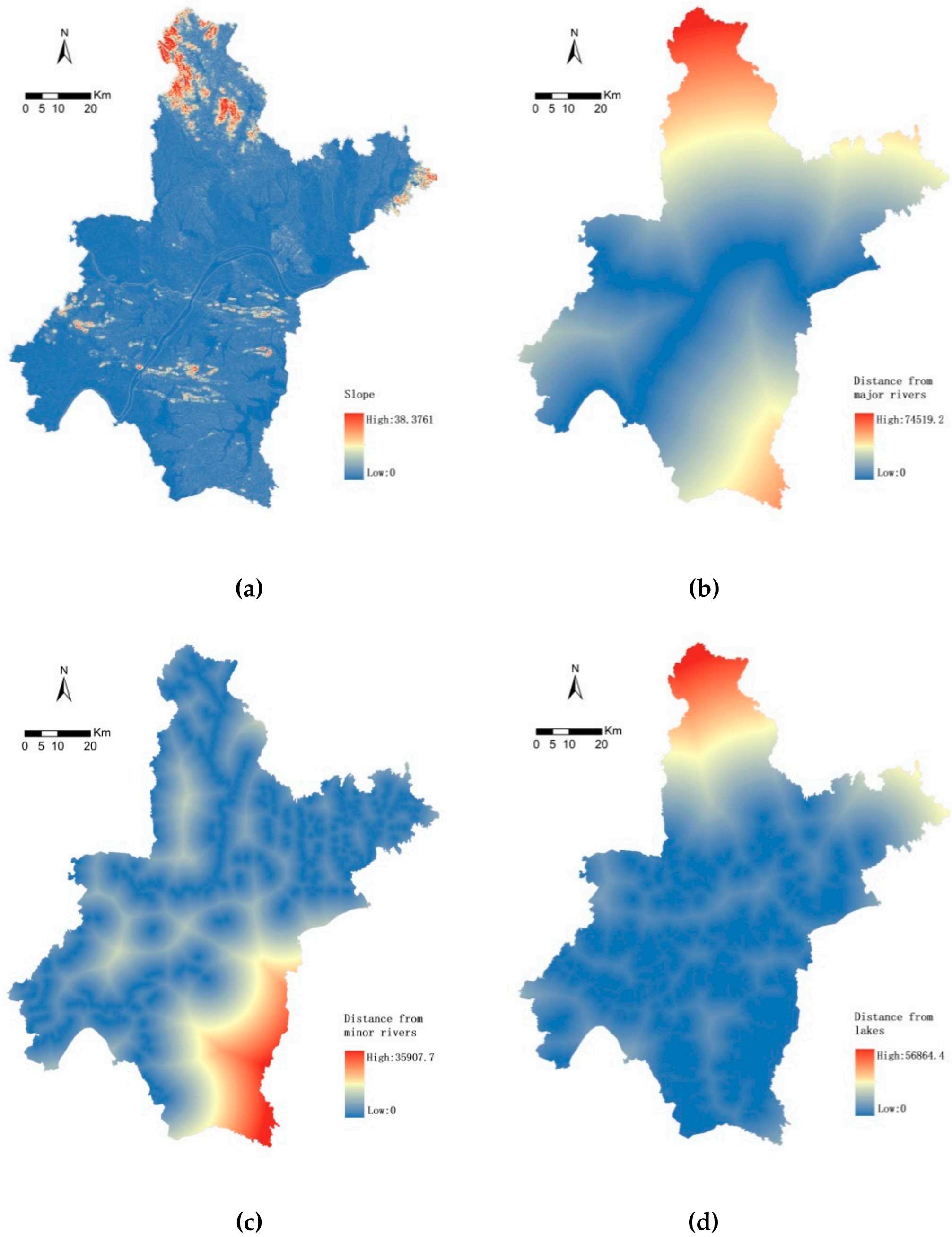
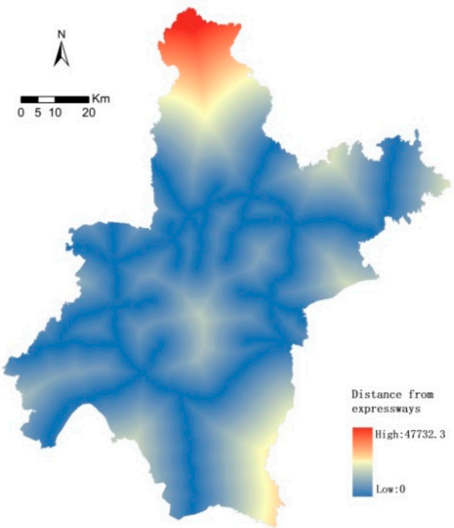


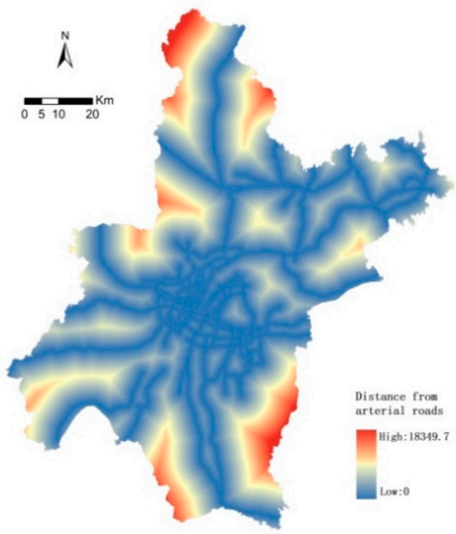
Figure 3. Spatial distribution of natural environment variables of urban expansion, Wuhan: (**a**) slope; (**b**) distance from major rivers; (**c**) distance from minor rivers; (**d**) distance from lakes.

3.3.2. Accessibility Variables

While urban expansion needs transportation as the infrastructure connection of towns and cities, transportation development can be a stimulating factor for the formation of towns and urban expansion. Railways and airlines affect the spatial distribution, because these traffic modes connect the towns within Wuhan City less than the highways with different levels. This study only considered the impact of and selected the distance of spatial units from the arterial roads (x_5), subarterial roads (x_6), and expressways (x_7) as the traffic development variables. The location of urban or rural settlements with different grades of urbanization is another important factor that promotes urban expansion. The distances of spatial units from the center of the city (x_8), the centers of the key developing towns (x_9), and the centers of the suburban center towns (x_{10}) were selected as the urbanization development variables. Figure 4 shows the spatial distribution of the six accessibility variables in Wuhan.



(a)



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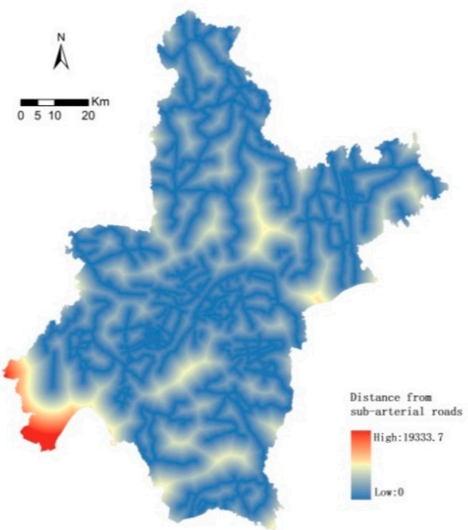
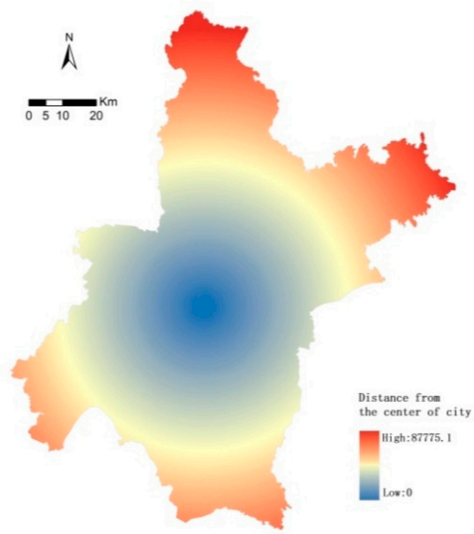
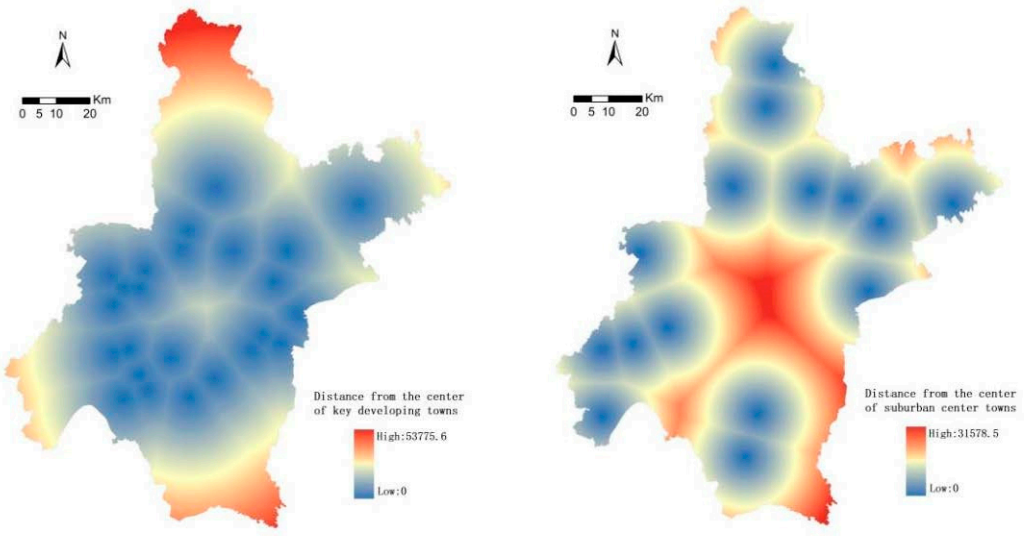


(c)



(d)

Figure 4. *Cont.*



(e) **(f)**

Figure 4. Spatial distribution of accessibility variables of urban expansion, Wuhan: (**a**) distance from expressways; (**b**) distance from arterial roads; (**c**) distance from subarterial roads; (**d**) distance from the center of the city; (**e**) distance from the centers of key developing towns; (**f**) distance from the centers of suburban center towns.

3.3.3. Policy-Oriented Variables

Policy-oriented factors are mainly reflected in the implementation of government planning programs, such as land use and comprehensive city and environmental plans, which restrict the quantity and spatial allocation of urban construction land use. Two types of policy-oriented variables were selected. The location of the overall layout of urban space (x_{11}) of the spatial units in research was used to represent the effect of functional zoning according to the urban space planning of Wuhan. Each spatial unit belonging to the central urban subarea, the urban development subarea, or the eco-agricultural subarea was directly assigned as 3, 2, or 1 based on the importance of the subarea at all levels in the urban space development. The degree of influence of various grading townships (x_{12}) was used to represent the effect of urban system planning. The indirect effect of urban planning was the focus and was calculated by the field strength model. The calculation steps were as follows:

(1) Considering the availability and authority of data, this study selected the population and local fiscal revenue of each township in 2010 as indices to measure comprehensive socioeconomic strength. After standardized data processing, the comprehensive strength of every town was calculated by a weighted average method with the same weight for the indices. Simultaneously, the townships were graded as 400, 300, 200, and 100, which correspond to the city center township, the key developing township, the suburban center township, and the general township, respectively. The quality (M_i) of every town is the product of the comprehensive strength and the grade value.

(2) Land use type and traffic conditions are the main factors that promote or restrict the radiation of townships. Transportation and urban construction lands have better access conditions than other types of land, and the travel cost of the former is relatively lower than that of the latter. Travel cost was measured in terms of travel speed through different land use types and roads by using Formula (2). The travel costs of different land use types and roads in Wuhan were calculated by referring to the relevant research results and according to the design speed of all levels of roads in the China Urban Road Engineering Design Specification (CJJ37-2012, Tables 3 and 4). The travel costs of land use types and roads were weighted as 0.6 and 0.4, respectively, and the weighted resistance of each spatial unit was calculated by overlaying the two resistance maps in ArcGIS 10.0 according to Formula (3). Figure 5a shows the spatial distribution of travel cost (C_j) of township radiation.

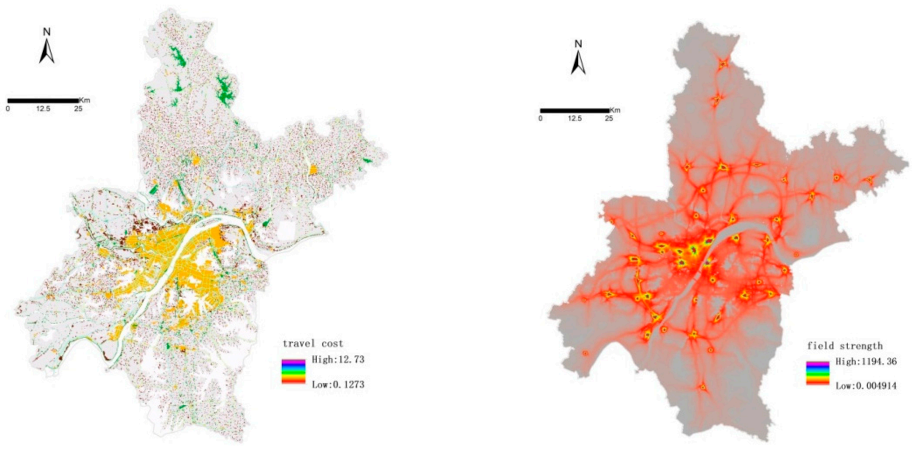
Table 3. Costs of different roads.

Road Grade	Expressway			Arterial Road			Subarterial Road		
Travel speed (km/h)	100	80	60	60	50	40	50	40	30
Travel cost (min)	0.13			0.21			0.25		

Table 4. Costs of different land use types.

Land Use Type	Traffic Land	Urban Construction Land	Rural Construction Land	Farmland	Water
Travel speed (km/h)	30	20	15	10	1
Travel cost (min)	0.42	0.64	0.85	1.27	12.73

(3) The cumulative cost distance (D_{ij}) from every spatial unit to the center of any township was calculated by the cost distance tool in ArcGIS 10.0 according to Formula (4). The distance friction coefficient *b* takes the standard value of 2. All coefficients were entered into Formula (1), and the degree of radiation of every spatial unit from all radiating towns was calculated. Figure 5b shows the spatial distribution of degree of radiation. The distribution of township radiation strength in Wuhan mainly corresponds to the distribution of the transportation network. There appears to be good strength in the town center, and it weakens when it is far away.



(a) **(b)**

Figure 5. Spatial distribution of travel cost and field strength of township radiation, Wuhan: (**a**) travel cost of radiation; (**b**) township radiation strength.

3.4. Data Sampling for Logistic Regression Analysis

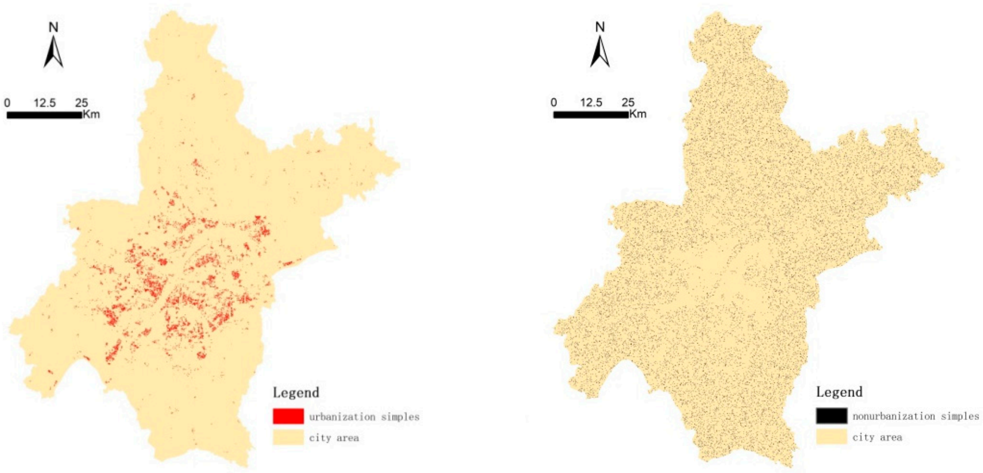
Data sampling is a key step in logistic regression analysis and requires the same amount of observational data valued as 1 and 0 because an unequal sampling rate would not affect the explanatory variables on the coefficient estimates in the regression model, but would affect the constant value of the model [38]. Stratified random sampling was used to select sample points to eliminate the subjectivity of data sampling as much as possible. The specific steps of sampling were as follows:

(1) Land types were divided into urban and nonurban land according to the land class attributes in the chart of the two land use vector maps in 2006 and 2013. Urban expansion was assumed to be irreversible. The urban construction land in 2006 was deemed to be unchanged. The value of the

nonurban land in 2006 converted into urban land in 2013 (referred to as urbanization land) was defined as 1, whereas the nonurban land in 2006 that remained unchanged (referred to as non-urbanization land) was defined as 0.

(2) The difference between the quantity of urbanization and non-urbanization lands was significant. A total of 10,689 effective grids were selected as random sample points from the total sample quantity of urbanization land by applying the create random raster tool in ArcGIS 10.0 to create random integer raster layers. According to the principle of equal sampling, 12,178 random sample points were selected from the total sample of non-urbanization land in accordance with the proportion of 5%. Figure 6 shows the spatial distribution of the extracted samples.

(3) The data of the sample values of urbanization and non-urbanization lands were extracted using the sample tool in ArcGIS 10.0, and the spatial attribute values of the driving force variables of urban expansion were imported into SPSS 20.0 (IBM, US). After eliminating a handful of invalid samples, 22,524 observation sample series were reserved for logistic regression analysis to ensure near equivalence of the quantities of both land types.



(a) **(b)**

Figure 6. Spatial distribution of extracted samples, Wuhan: (**a**) urbanization samples; (**b**) non-urbanization samples.

4. Results

4.1. Model Application and Regression Results

To compare the prediction results of different logistic regression models, this study labeled the classical logistic regression model only considering the natural environment and socioeconomic variables of urban expansion as Model 1, the modified logistic regression model adding the variable of the location of the overall layout of urban space as Model 2, and the modified logistic regression model incorporating the field strength variable as Model 3. Prior to regression analysis, the correlation among variables was tested. The correlation coefficient among effective variables was close to 0 when the significance level was 0.001, and the variables could enter the regression analysis. The binary regression analysis tool in SPSS 20.0 was used to analyze the data in different models. The specific results of the analysis and test are shown in Table 5.

Table 5. Coefficients of different models.

	Model 1		Model 2		Model 3	
	B	**Wald**	**B**	**Wald**	**B**	**Wald**
x_1	0.111844	138.60	0.084403	79.34	0.086460	83.43
x_2	−0.000011	17.36	−0.000004	2.20	−0.000001	0.20
x_3	0.000012	11.54	0.000010	8.10	0.000010	7.89
x_4	0.000020	15.94	0.000014	7.19	0.000005	1.03
x_5	−0.000309	1563.77	−0.000301	1461.24	−0.000287	1324.53
x_6	−0.000145	220.85	−0.000085	73.51	−0.000061	37.02
x_7	0.000041	55.02	0.000041	58.04	0.000047	74.58
x_8	−0.000072	1503.92	−0.000029	142.62	−0.000027	122.75
x_9	−0.000073	341.04	−0.000085	442.89	−0.000081	403.31
x_{10}	0.000010	12.86	−0.000007	5.74	−0.000002	0.39
x_{11}	/	/	−1.194718	676.04	−1.166769	640.45
x_{12}	/	/	/	/	0.164021	160.73
Constant	3.305632	1780.24	4.846721	2301.82	4.374762	1721.28

A comparison of the regression coefficients and Wald statistical values of the variables among the three models (Table 5) shows that the effects of the driving forces of socioeconomic development on urban expansion are significantly greater than those of the natural environment. The three variables of the driving forces of socioeconomic development, i.e., distance from arterial roads (x_5), from the center of the city (x_8), and from the centers of the key developing towns (x_9), have prominent roles in the interpretation of regression models. The regression coefficients of variables x_5, x_8, and x_9 are negative, indicating that the closer the arterial roads, the center of the city, and the centers of key developing towns, the greater the probability of urban expansion, and vice versa. Slope (x_1) is a more effective variable in urban expansion than other natural environment variables in Wuhan.

4.2. ROC Curve Verification of Models

As shown in Figure 7, the area under the ROC curve of Models 1, 2, and 3 increases successively, indicating that the regression results of Model 3 are the best and Model 2 is better than Model 1. Given that the policy-driving factors include the location of the overall urban space layout (x_{11}) and the degree of influence of various grading townships (x_{12}) entering the regression analysis, the model is suitable for explaining the driving mechanism of urban expansion in Wuhan.

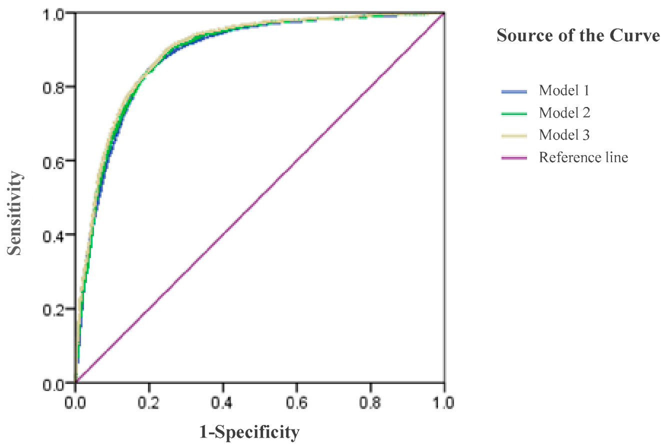


Figure 7. Receiver operating characteristic (ROC) curves of different regression models.

4.3. Kappa Coefficient Verification of Models

The regression coefficients that correspond to each explanatory variable in the different logistic regression models were integrated into the regression equation. The conditional probability of each regression model when the dependent variable is 1 was obtained, and the spatial distribution of the probability of urban construction land expansion in Wuhan between 2006 and 2013 was simulated by the ArcGIS 10.0 spatial analysis tool (Figure 8). The simulated predicted precision index–kappa coefficients (Table 6) show that the simulation precision of Model 3 is relatively higher than that of the other models.

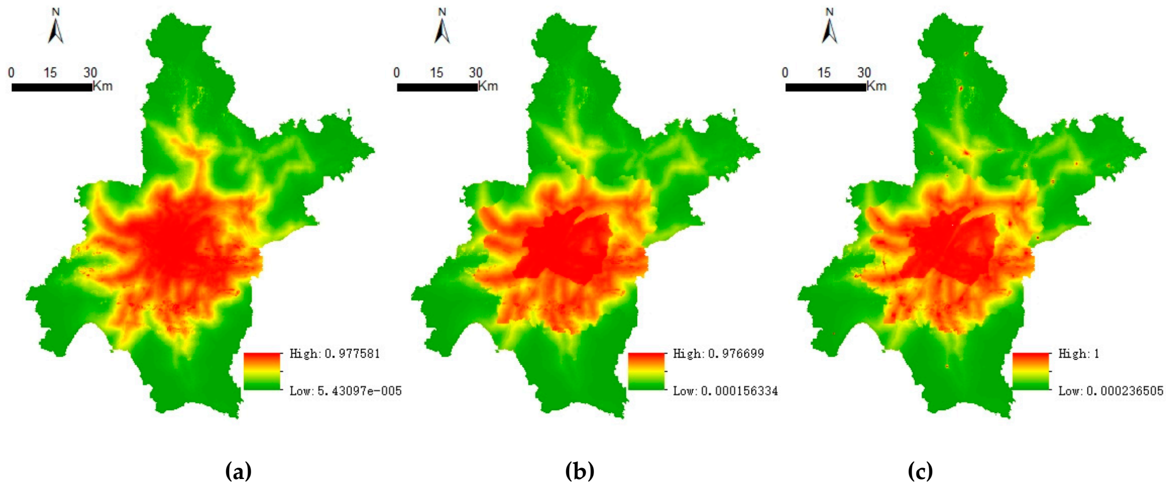


Figure 8. Spatial distribution of urban expansion simulation probability of Wuhan in 2013: (**a**) Model 1; (**b**) Model 2; (**c**) Model 3.

Table 6. Precision of different models.

	Model 1	Model 2	Model 3
Kappa coefficient	0.338	0.346	0.356

5. Discussion

5.1. Effects of Traffic System Development on Urban Expansion

According to the serial regression results, urban expansion is prominently affected by the distribution of urban arterial roads, less affected by the distribution of subarterial roads, and not affected by expressways due to strong closure. The distribution of traffic roads with different levels has varied influence on urban expansion in Wuhan. The promotion of transit-oriented development (TOD) in recent years guides urban expansion through the composited transport corridor of urban expressways, skeleton arterial roads, and urban rail traffic. A comparison of the distances between urban construction land and roads with different levels through statistical analysis shows that the most intensive urban expansion in Wuhan is mainly 0.5–1 km from arterial roads and 1–2 km from subarterial roads (Figure 9).

This finding reveals the distribution of urban expansion along the main trunk road within Wuhan City, which is similar to other regional research on different spatial scales, such as by Wang [34] and Huang [44] in China. The urban traffic network was taken as the main internal adaptive factor for urban space expansion. The construction of road infrastructure and improvement of traffic systems are bound to have an impact on the pattern and direction of urban expansion. Based on understanding the quantitative relationship between traffic system attribution and urban land expansion, planners can estimate the state of urban development, strictly control the building and renovation of roads, and then adjust the structure of the urban traffic network reasonably. In addition, the experience of

Wuhan indicates that both towns and cities, even urban agglomerations, can use the TOD mode to guide sustainable urban land utilization and control blind urban expansion.

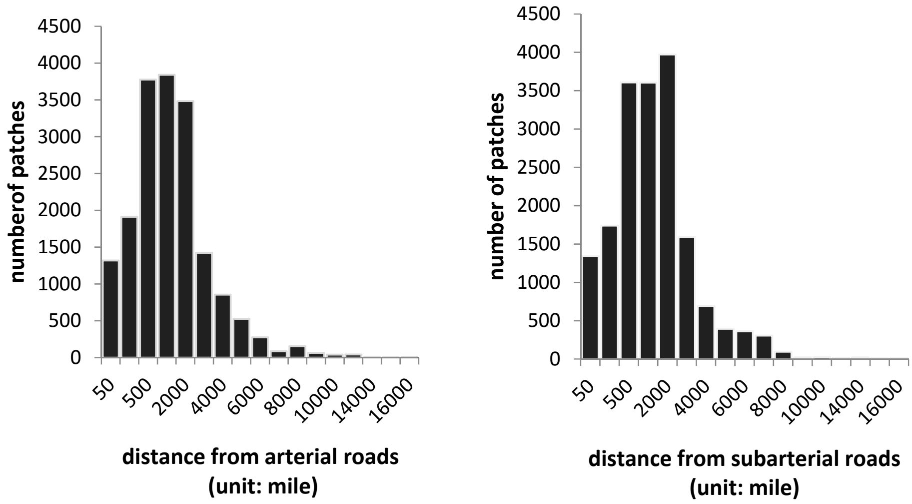


Figure 9. Histograms of distance between urban expansion land patches and two grades of road.

5.2. Various Urbanization Levels and Urban Expansion

The research of Akinobu et al. showed that the urbanization process helps to expand urban areas and increase the diversity of land use on the fringes of megacities [45]. In China, population urbanization is a strong driver of urban expansion, which has been seen in many cities, including Changchun, Chengdu, Hangzhou, and Harbin [18]. The urbanization level at different stages will affect the urban growth of a city, while the spatial diversity of the urbanization level can influence the urban land transformation of different regions within a city.

The logistic regression results show that the distance from the centers of the key developing towns is an important factor explaining urban expansion. Therefore, the spatial distribution of key towns is an important factor that drives urban expansion in Wuhan. According to the relevant socioeconomic statistical data, the population urbanization level of the key developing towns in Wuhan ranked second to that of the central city by 2013. The average urbanization level of the key developing townships is 46.51%, which is higher than the 28.79% of the suburban center towns and 16.28% of the general towns (Figure 10). The local fiscal revenue of the key developing towns is higher than that of the suburban center towns and general towns (Figure 11). With the guidance of planning and policy, socioeconomic development of the key developing towns promotes urban expansion. According to the analysis of the expansion characteristics of urban construction land of different levels of towns in Wuhan (Table 7), the urban expansion scale and intensity of the key developing towns and the level of land urbanization from 2006 to 2013 are higher than the other levels of towns.

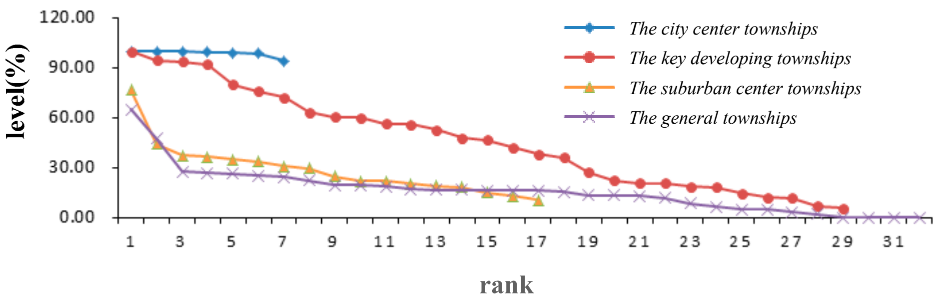


Figure 10. Population urbanization level of different levels of townships, Wuhan. Source: Statistical Yearbook of Wuhan (2014).

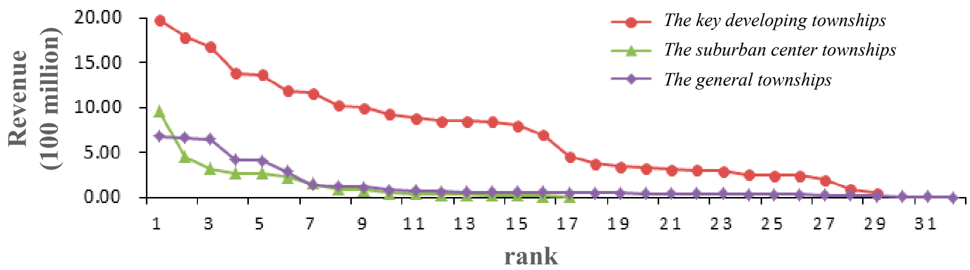


Figure 11. Local fiscal revenue of different levels of townships in Wuhan. Source: Statistical Yearbook of Wuhan (2014).

Table 7. Rate of urban construction land in four levels of townships.

	2006		2013	
	R	**R′**	**R**	**R′**
City center townships	45.69	43.38	60.97	40.42
Key developing townships	9.85	43.20	16.25	49.76
Suburban center townships	2.21	7.93	2.57	6.45
General townships	1.12	5.50	0.98	3.37

Note: R denotes the rate of urban land out of all urban land in the same level of township; R′ denotes the rate of urban land out of all urban land in Wuhan.

As shown in the histograms of the distance from the centers of the key developing towns, the most intensive urban construction land expansion in Wuhan is mainly located within 3–5 km from each key developing town. Urban construction land in the central urban area is almost saturated. The urban expansion land patches are most densely distributed in the region 1 km from the center of the city, and a range larger than 1 km presents a significant distance attenuation pattern (Figure 12).

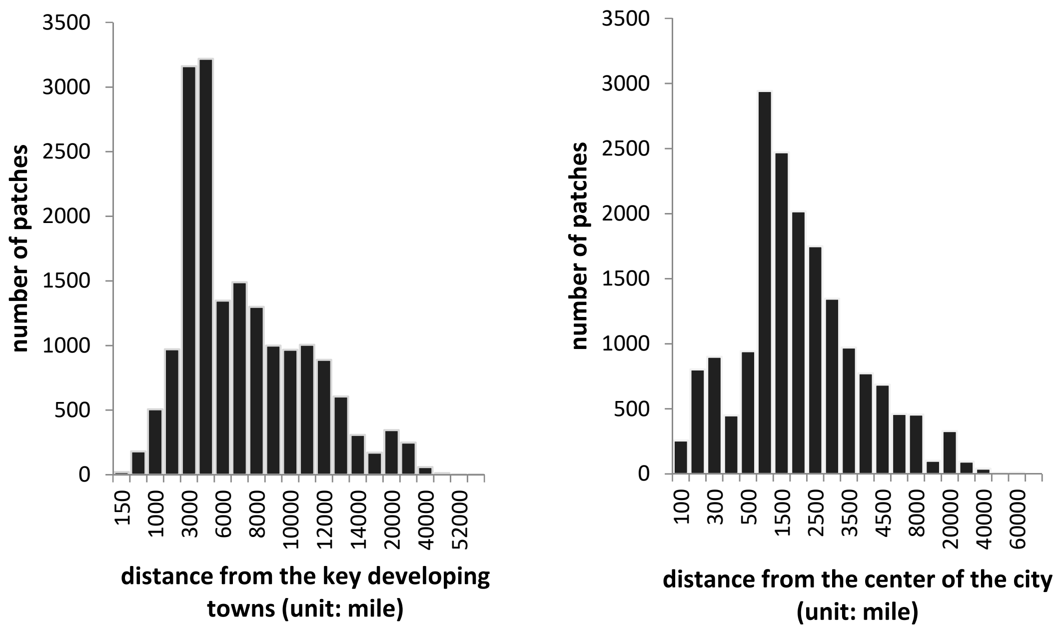


Figure 12. Histograms of distance between urban expansion land patch and two levels of township.

5.3. Drivers of Spatial Planning to Urban Expansion

Spatial policy influences the pattern of land transformation, because policies act as promoters and restrictors of urban development [22]. In accordance with the timing of development, spatial layout, and growth scale of cities, spatial planning aims at controlling the construction land in order to guide sustainable and rational development [31]. Among spatial planning and related policy, traffic planning and development zone planning generally play important roles in urban expansion [29].

The strong explanatory power of variables in the location of the overall layout of urban space and the field strength of towns in the regression model indicate that the urban spatial strategy of Wuhan plays an important role in the urban construction land expansion. Since 2006, planning schemes of land use, city layout, and spatial patterns of Wuhan have been implemented to realize the urban spatial strategy. The government strengthens the open space structure, which emphasizes not only the key role of the central townships of Wuhan, but also the coexistence of multiple subcenters where an increasing number of new industrial demonstration parks and general industrial parks will be built as part of the industrial economic development platform. The subcenters in the developing areas of Wuhan express a guiding role in socioeconomic development of the backward towns in the surrounding areas, thereby contributing to changes in the land use pattern and leading to further urban expansion. A number of high-grade roads, including rapid ground transit and rail transit, have been constructed to speed up the connections between central urban areas and suburban areas and thus support the urban spatial expansion. These infrastructures are important in promoting the rapid social and economic development of towns in suburban areas and enhancing the effects of urban radiation on urban land expansion in Wuhan.

The radiation field intensity of each land patch differs from others under the comprehensive effect of different levels of urban radiation fields. According to the statistical data of the radiation field intensity of every land patch, the largest number of land patches is acquired when the intensity reaches a value of 30, indicating the most intensive urban land expansion; the urban land expansion is relatively intensive when the value of urban radiation field intensity of the land patches is between 2 and 150 (Figure 13).

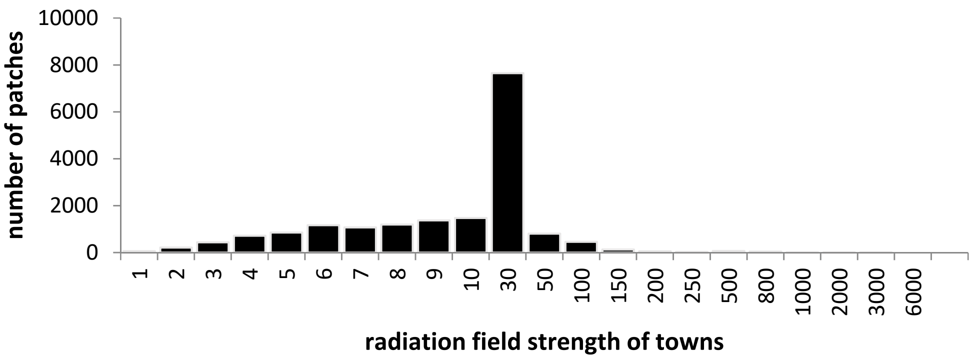


Figure 13. Histogram of radiation field strength of towns.

5.4. Natural Environment and Urban Expansion

The natural foundation and environmental background are important as both constraints and incentives of urban growth [46]. Terrain conditions and distribution of water resources have been regarded as factors that influence urban land expansion in China, although they are not the main drivers [12,47].

The logistic regression results show that the driving force of natural environmental factors such as slope and distance from rivers and lakes is weaker than that of socioeconomic and policy factors. The regression coefficient of slope is positive, which indicates a higher probability of urban expansion as the slope of terrain increases. This shows the characteristic of urban expansion in Wuhan, because steeper-sloped land generally means a higher cost of urban land development [23]. The gradient statistics of urban expansion land patches show that the largest value of slope of Wuhan is 22.73°, which is controlled below the suitable slope (25°) for the surface of urban construction land in China. The slope values of most urban expansion land patches are mainly concentrated in the range (0,4) (Figure 14a).

The regression coefficient of distance from the major river is negative; that is, the closer the major river is, the more intense the urban expansion will be. This condition is related to the historical fact that the development of Wuhan City depended on two major rivers, the Yangtze and the Han, and the distribution of urban land use is along them. The statistics show a uniform distribution and an agglomeration of urban expansion land patches from the major river of approximately 0.15 km to 80 km and 10 to 20 km, respectively (Figure 14b).

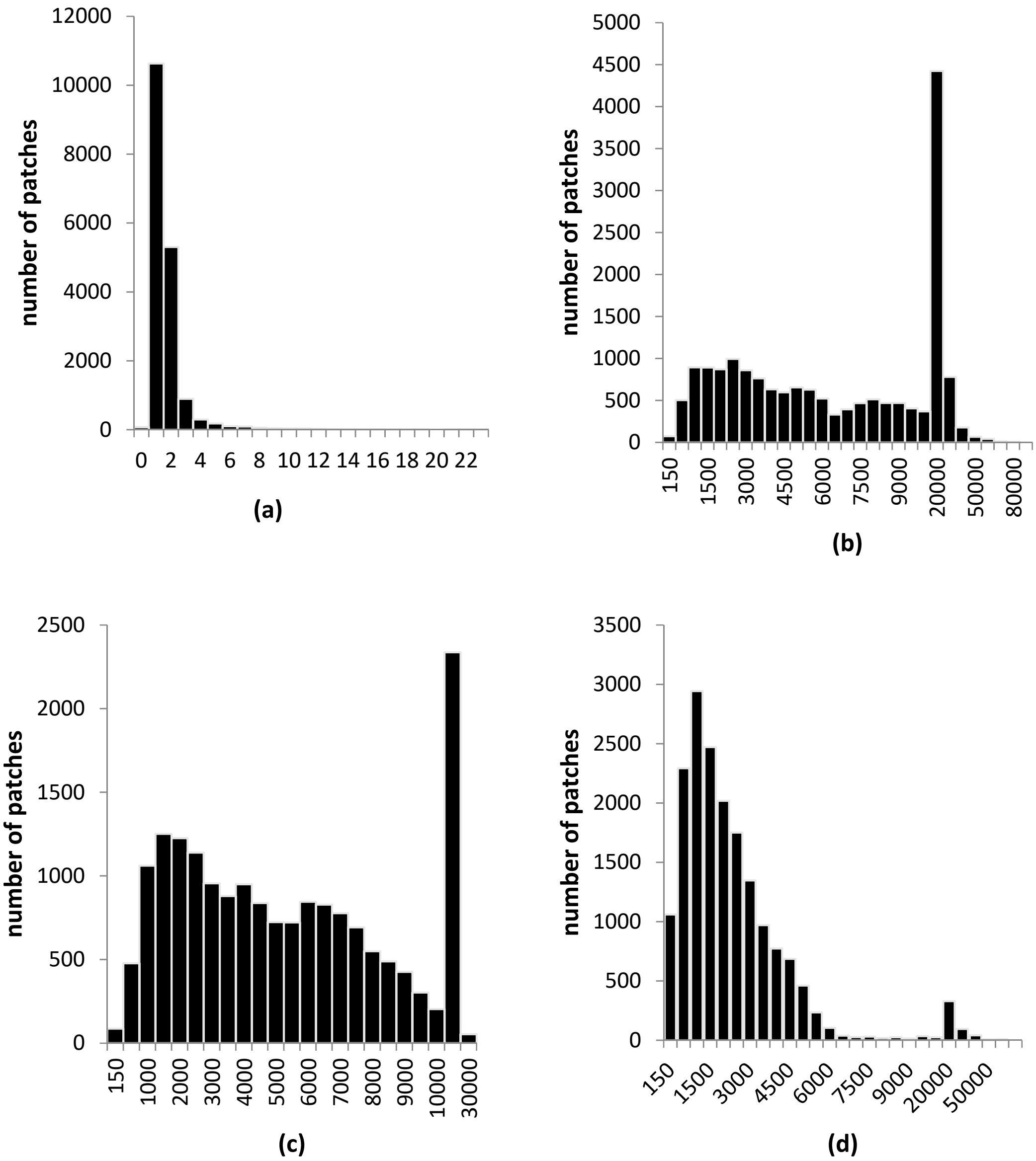


Figure 14. Histograms of spatial variables of natural factors: (**a**) slope (%); (**b**) distance from major rivers (miles); (**c**) distance from minor rivers (miles); (**d**) distance from lakes (miles).

5.5. Other Potential Drivers of Urban Expansion

This study applied the quantitative method to analyze the drivers of urban expansion in Wuhan City from four aspects, focusing on the effect of spatial planning on urban land use change. Due to the lack of statistical data on 85 townships within Wuhan, other potential factors have not been considered, such as industrial restructuring [23], foreign direct investment (FDI) [24], and even traditional culture [25]. Simulating spatial changes in urban land use under the effects of various planning policies is significant to make effective decisions in urban growth management [29]. In a follow-up study, other land use policies in China, such as economic and intensive land use, land consolidation and rehabilitation, and increasing versus decreasing the balance of urban–rural construction land [1,8,48], should be taken into account to research the determiners of urban expansion, especially using the quantitative analysis method.

6. Conclusions

This study adopted a modified model of classic logistic regression analysis combined with the field strength model to analyze the relationship between urban land use changes and their influencing factors in Wuhan City at the land patch scale. The research design helps to deal with difficulties outlined in the introduction. Three major findings were obtained:

(1) Two modes were applied to quantify the information of urban spatial planning. The first mode gives simple assignments to different functional division areas according to policy-oriented urban spatial planning, and the other mode designs the field strength variable to describe the comprehensive influence of policy factors on each grid of land use change under various promoting and resisting forces. The results of model application and verification show that the introduction of the field strength model is beneficial to match up the policy information with the urban land use change at the land patch scale.

(2) The modified logistic regression model integrates the field strength variable into the classical logistic regression model, which only considers the direct-viewing geographic information, to explain the policy driving force of urban expansion. Two testing methods, the ROC curve and kappa coefficient, were used to verify the availability of the modified model. The proposed method could be used to investigate the driving mechanism of urban expansion in the past and simulate the spatial pattern of urban evolution in the future with higher precision than other methods.

(3) Factors affecting the expansion of urban construction land in Wuhan were analyzed based on the outcomes of the modified model and combining the social and economic development and natural environmental characteristics of Wuhan. The factors include terrain, water resource distribution, population, social and economic development, traffic network patterns, and urban space development strategies, with urban system planning as the core. The spatial distribution of main roads and key towns has a prominent effect on urban expansion. Urban expansion in Wuhan is significantly affected by urban spatial development strategies and urban radiation field strength, but minimally influenced by natural environmental factors such as slope.

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