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Urban growth pattern modeling: a case study of Wuhan city, PR China

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Abstract

Urban expansion has been a hot topic not only in the management of sustainable development but also in the fields of remote sensing and geographic information science (GIS). After land reform initiated in 1987, Chinese cities are facing a new development wave, which is the mixture of urban expansion and redevelopment. Local urban planners are also facing a huge challenge to require the understanding of complex urban growth process, which involves various actors with different patterns of behavior. Modeling an urban development pattern is the prerequisite to understanding the process. This paper presents a spatial data analysis method to seek and model major determinants of urban growth in the period 1993–2000 by a case study of Wuhan City in PR China. The method comprises exploratory data analysis and spatial logistic regression technique. The former is able to visually explore the spatial impacts of each explanatory variable. The latter can provide a systematic confirmatory approach to comparing the variables. The study shows that the major determinants are urban road infrastructure and developed area, and master planning is losing its role in the specific period.

Keywords: Growth pattern; Exploratory data analysis; Spatial logistic regression; Wuhan

1. Introduction

The economic reform and 'Open Door' policy initiated in 1978, and especially its land reform launched in 1987 had a profound impact on the China's urbanization. From official report, the urbanization level of China has increased from 22% in 1983 to 33% in 1999 according to the formula: the non-agricultural divided by the total population (Cheng et al., 2001). The number of mega-cities (>1 million population) has added up to 37 in 1998 from 13 in 1978. It is estimated the urbanization level may reach 75% by the middle of 21st century.

So rapid urbanization brings opportunities to new urban developments. However, it also brought about serious losses of arable land, which has occurred in other developed countries like USA and UK before 1950 (Firman, 1997). For instance, China's cultivated land per capita has decreased significantly from 1800 in 1949 to 1133 m^2 in 1995 (Zhang, 2000). The redevelopment stimulated by Chinese land reform has proven that the traditional urban planning is not able to deal with the rapid urban restructuring. As a result, Chinese urban planners are facing a huge challenge to require a modification of the urban planning system from a centrally planned to transitional economy (Yeh and Wu, 1999), which centers on the understanding urban development process of Chinese cities in transformation. The rapid physical and socio-economic

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restructuring of Chinese cities have been attracting more and more attentions of not only Chinese scholars but international urban researchers as well, e.g. (Laurence and Edward, 1981; Kirkby, 1985; Victor, 1985; Chan, 1994; Hsu, 1996; Khakee, 1996; Wu and Yeh, 1997; Yao, 1998; Gaubatz, 1999; Wu, 2000a, 2001; Zhang, 2000; Xu, 2001).

These studies may fall into the following four points when related to the urban growth of Chinese cities. Firstly, urban development process of Chinese cities is differentiated as two distinguishing periods before and after 1978/1987 (Laurence and Edward, 1981; Victor, 1985; Wu and Yeh, 1997; Gaubatz, 1999). It means that the economic reform in 1978 and land reform in 1987 are the key factors impacting the urban development process. The change of urban landscape systems is driven by complex political, social and economic systems.

Secondly, most cases focus their studies on the impacts of relevant policies or actors on urban development, such as the interplay between state and market on urban development in Shanghai (Han, 2000), foreign investment on urbanization in the Pearl River Delta (Victor and Yang, 1997), foreign investment on the real estate industry (Jiang et al., 1998), the roles of local government in sprawl in China (Zhang, 2000), foreign investment and changing urban governance on urban restructuring in Shanghai (Wu, 2000a), state policies (investment source, development organisation and planning regime) on urban landscape in Guangzhou (Wu, 1998), urban planning transition before and after land reform (Yeh and Wu, 1999), housing reform (Chen, 1996; Wu, 1996; Wang and Murie, 1999), etc.

Thirdly, some utilized population data as the indicator of urban growth (Hsu, 1996) for descriptive analysis in particular when the analysis spanned a longer period, e.g. since 1949. Partial reasons are that population statistical information is relatively more accessible than geo-referenced information as most spatial information is only available during 1980s when geographic information science (GIS) was introduced in their organizations.

Finally, the selected cases mostly are located in economically much stronger regions or mega-cities like Guangzhou, Shanghai, Beijing and Shenzhen.

These pioneering studies have found some determinant policies such as investment structure, industry structure, housing commercialization, land leasing, urban planning, decentralization of decision making and main development actors such as state, local governments, developers, work units and investors which are changing the urban space of Chinese cities. These may provide some valuable evidences for further comparative study and a guideline for specific applications to other cases and even to new planning schemes. However, as the main concern of urban planning, urban spatial systems at landscape level must be recognized and also linked with various policies because political, social, economic and institutional variables finally have to be projected onto landscape system when they are implemented. Moreover, with the rapid advances in remote sensing and geographic information science and techniques, modern satellite imagery, together with traditional aerial photos are becoming possible to be provided with rich multi-resolution and scales of data sources for monitoring urban development processes (Masser, 2001). By using GIS, it is technically feasible to integrate large quantities of data for further spatial analysis related to urban development.

For example, Wu and Yeh (1997) applied aerial photos, GIS and statistical analysis methods for modeling land development pattern in the periods 1978/1987 and 1987/1992. They found that the main determinants of land development have changed from distance from the city center to closeness to the city center; from proximity to inter-city highways to proximity to city streets; and from more related to less related to physical condition of the sites. Urban planning is playing a less important role in development control. Before land reform, land development tended to be located away from areas of high population density in the city center and close to industrial areas. After land reform, more urban redevelopment has taken place in the densely populated city center and the influence of industrial development has declined. Residential development tends to be located in good neighbourhoods away from industrial areas in meeting the demands of the housing and land markets in the new socialist market economy. Similar changes in the spatial distribution of land development are occurring in other Chinese cities, such as Beijing and Shanghai (Gaubatz, 1999).

Hence, as a fresh case, Wuhan city has not been systematically studied so far on the published literature especially its urban growth pattern. The cities stressed in former studies have highly distinguishing social, economic and political environment from Wuhan. The systematic research of Wuhan can be beneficial to local planning system and also comparable with other Chinese cities as urbanization is not a universal process with similar attributes in all world regions but a set of complicated phenomena conditioned by various cultural and historical forces in different places (Laurence and Edward, 1981).

Given these considerations, the paper is organized into five main sections. Following the introduction, Section 2 presents a spatial data analysis method, which comprises exploratory data analysis and spatial logistic regression analysis. Section 3 focuses on the detailed description of data source, data classification and GIS analysis with a case study. The fourth section discusses major findings, which are able to uncover the determinants of urban growth pattern in this specific period. The paper ends with issues left for the future research.

2. Methodology

Since a main objective is to seek and compare determinants of urban growth pattern in this specific period, causal-effect interpretation capacity of modeling technique is of vital importance. The major methodology developed here consists of exploratory and confirmatory data analysis.

2.1. Exploratory data analysis

The real power of GIS resides in their display facilities; they still lack the facility to visually explore relationships between multivariate data. Graphical representation of spatial relationships is generally more easily interpreted than numerical output. Towards this direction, exploratory spatial data analysis (ESDA) technique is utilized to detect spatial patterns in data, and to suggest hypothesis, which may be tested in a later confirmatory stage (pre-modeling exploration). In modeling patterns, ESDA has been receiving more and more attention (Bell et al., 2000; Goodchild, 2000; Brunsdon, 2001).

$$f(x) = \beta\, e^{-\lambda x} \tag{1}$$

In urban theories, a widely accepted assumption is the negative exponential decrease of density of development units such as building, people and resources illustrated in Eq. (1), where x is the radial distance from the central business district (CBD) situated at the core, and λ is the density gradient. The density gradient quantifies the extent of the urban spread around the central core. Urban models based on economic theory (Muth, 1969), discrete choice theory (Anas, 1982) and other approaches such as entropy maximization (Wilson, 1970) have made widespread use of the negative exponential function. Here, we extend CBD to other development factors such as major road, minor road, developed areas, etc and also extend density to probability of change (here it is defined as the possibility of land cover transited from developable land to urban use at any pixel). We assume that probability of change is characterized with exponential increase or decrease in relation to each development factor. In this case, function $f(x)$ could be transferred to $p(x)$ (probability) through the procedure in Eq. (2):

$$\begin{aligned} f(x) &= \lim_{\Delta x \to \infty} \frac{\Delta p}{\Delta x} \approx \Delta p = \frac{\mathrm{CH}_{\Delta x}}{\mathrm{CH}_{\Delta x} + \mathrm{NCH}_{\Delta x}} \\ &= \beta\, e^{\lambda x} = p(x) \end{aligned} \tag{2}$$

where $p(x)$ is the change probability function, Δp the probability of change in the scope $(x, x + \Delta x)$. When Δx is very small, $p(x)$ could be approximately equal to Δp. Δx is a radial distance interval, which should be as small as possible. $\mathrm{CH}_{\Delta x}$ counts the total amount of land cover change located in the scope $(x, x + \Delta x)$, $\mathrm{NCH}_{\Delta x}$ is the total amount of developable land without change in the same scope. Δx is actually the buffering distance interval. After logarithmically transforming, we can calculate the density gradient λ (Eq. (3)), which exhibits the spatial influence of each factor on growth.

$$\log(\Delta P) = \log(\beta) + \lambda x \tag{3}$$

The slope λ indicates the degree of spatial influences; $\lambda > 0$ means a positive influence; $\lambda < 0$ indicates a negative effect. The correlation coefficient R indicates its accuracy or reliability. From the standpoint of probability theory, ΔP represents probability value of the event of land cover change in the scope $(x, x + \Delta x)$.

The distance-decay effect of each factor can be visualized for pattern detection and hypothesis formation by displaying scatter plot $(\log(\Delta P), x)$. Spatial outlier can be detected for detailed data check. When a curve has multiple peaks, it may result from unreasonable definition of spatial indicator. In this case, the indicator should be split or merged (see Section 4.1). Slope λ indicates the growth pattern in relation to its development factor. Steeper slope may imply more compact pattern, otherwise more dispersed or scattered pattern. Intercept b $(= \log(\beta))$ represents the initial value of probability. Systematic comparisons of λ and b among various factors can offer deep insights into the spatial patterns of urban growth.

It should be noted that the formula defined above principally reflect the global spatial influences. In some cases, we need to focus on local extent such as 0–1000 m. Local pattern exploration can provide more insights into spatial heterogeneity.

2.2. Spatial logistic regression

Traditional statistical analysis techniques like linear regression, logistic regression and log-linear regression, are still widely used in pattern analysis. For example, Lopez et al. (2001) employed linear regression for exploring the relationship between urban growth and population growth. Wu and Yeh (1997) and Wu (2000b) applied logistic regression methods for explaining land development pattern and industrial firm location, respectively. The techniques have been proven effective in seeking some determining variables for the occurrence of certain spatial phenomena such as urban development.

Compared with linear regression and log-linear regression (see Table 1), logistic regression is advantageous in dependent variable, explanatory variables and normality assumption. As a complex social-economic system, urban growth phenomena does not usually follow normal assumption. Its influential factors are mostly the mixture of continuous and categorical variables. The general form of logistic regression is described as follows:

$$y = a + b_1x_1 + b_2x_2 + \cdots + b_mx_m \tag{4}$$

$$y = \log_e\left(\frac{P}{1-P}\right) = \mathrm{logit}(P) \tag{5}$$

$$P = \frac{e^y}{1+e^y} \tag{6}$$

where $x_1, x_2, x_3, \ldots, x_m$ are explanatory variables, y a linear combination function of the explanatory variables representing a linear relationship (Eq. (4)). The parameter $b_1, b_2, \ldots, b_m$ are the regression coefficients to be estimated. If we denote z as a binary response variable (0 or 1), vaule 1 ($z = 1$) means the occurrence of new unit such as transition from rural to urban, and value 0 ($z = 0$) indicates no change. The P means the probability of occurrence of a new unit, i.e. $z = 1$. Function y is represented as logit(P), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1 (Eq. (5)). In logistic regression, the probability value can be a non-linear function of the explanatory variables (Eq. (6)). This is a strictly increasing function, probability P will increase with value y. Regression coefficients $b_1 - b_m$ imply the contribution of each explanatory variable on probability value P. A positive sign means that the explanatory variable will help to increase the probability of change and a negative sign means the opposite effect. The statistical technique is a multivariate estimation method in examining the relative strength and significance of the factors (explanatory variables).

However, as the primary data sources regarding urban growth come from remotely sensed imagery, the spatial heterogeneity is a main concern. Logistic regression has to consider spatial statistics like spatial dependence and spatial sampling. Ignoring these issues will lead to unreliable parameter estimation or inefficient estimates and false conclusions regarding hypothesis tests (Irwin and Geoghegan, 2001). This

Table 1
Comparison of multi-regression, log-linear and logistic regression

Type of regression	Dependent variable	Independent variable	Computation method	Normality assumption	Relationship
Multivariate regression	Continuous	Only continuous	OLS[a]	Yes	Linear
Log-linear regression	Categorical	Only categorical	GLS[b]	No	Non-linear
Logistic regression	Binary categorical	Mixture	GLS[b]	No	Non-linear

[a] OLS: ordinary least square.
[b] GLS: generalized least square.

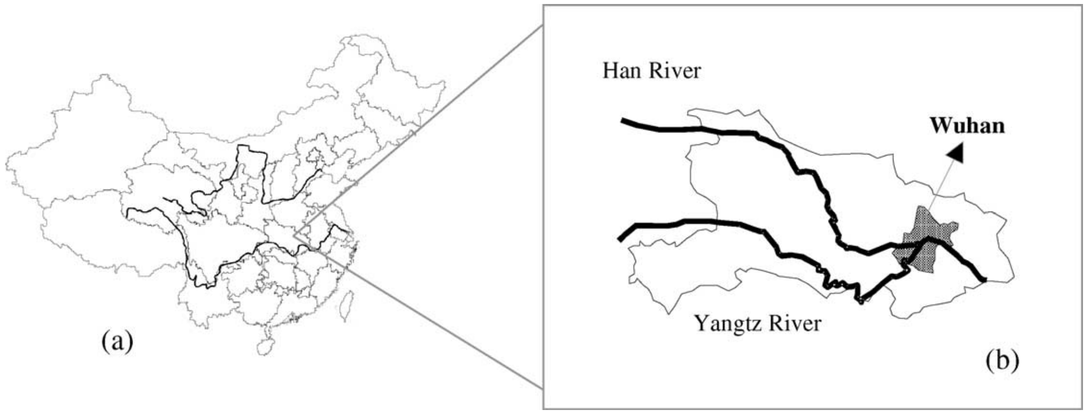

Fig. 1. Location of Wuhan city (a) in China; (b) in Hubei Province.

paper will design a spatial sampling scheme to reduce spatial dependence phenomena.

3. Study materials

3.1. Study area

As the capital of Hubei Province, Wuhan is the largest mega-city in central China and in the middle reaches of Yangtze River (Fig. 1). In 1999, it had more than 4 million non-agricultural population, four times more than that of 1949. Wuhan municipality is administratively stratified as district, sub-district (organized by street committee) and neighbourhood (by residential committee). In 1993, the urban administration of Wuhan consisted of seven districts (*Qiaokou*, *Jianhan*, *Jiangan*, *Hanyang*, *Wuchang*, *Hongshan*, and *Qiangshan*). The district *Qiaokou* comprised 13 sub-districts and one township. The sub-district *Baoqing* included 19 neighbourhoods (see Fig. 2). These spatial units are the major statistical sources of social and economical data (Cheng, 1997).

3.2. Data sources

SPOT PAN/XS imagery is an ideal source from which to produce land cover maps at the urban–rural

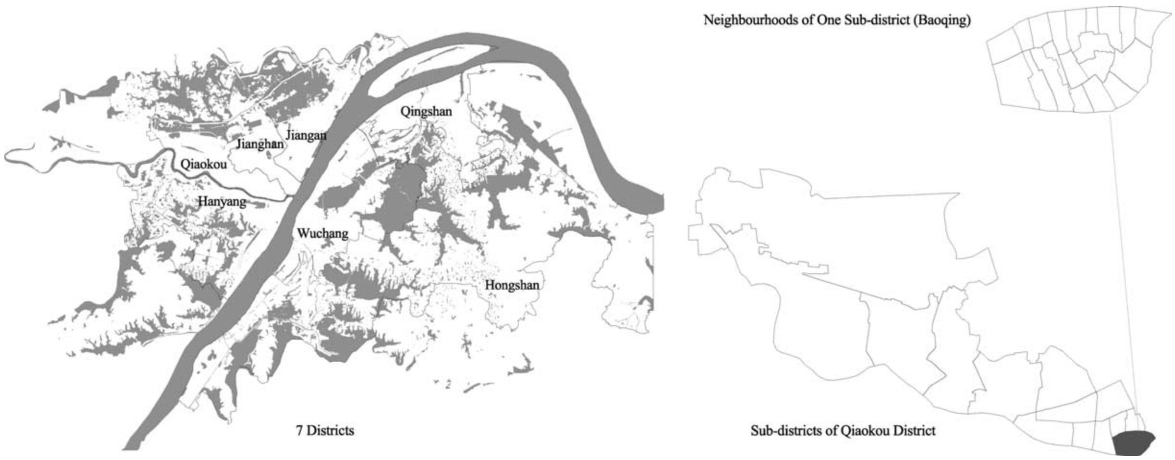

Fig. 2. Illustration of Wuhan Municipal Administration Hierarchy.

fringe. The imagery employed here includes SPOT PAN/XS of 2000, which cover the whole study area. The images are treated as the primary data source for creating land cover change map from 1993 to 2000. The topographic map (1:10,000) of 1993 was used for imagery geo-coding registration and also for producing the land cover map of 1993. The secondary sources include planning scheme maps, traffic/tourism maps, street boundary maps and population census and statistical data, etc. The image processing for land cover change is implemented through ERDAS IMAGINE 8.4 package.

The original images have been rectified using some 50 points systematically chosen and evenly distributed over the images to guarantee enough points in the center and corners of the images. A second order polynomial model was chosen for the image rectification and re-sampled using the nearest-neighbor algorithm. The root means square (RMS) error is strictly limited to 0.3 pixels. The projection system of WGS84 NORTH with Zone 50 was selected for Wuhan.

Image fusion is the combination of different digital images in order to create a new image by using a certain algorithm. Image fusion takes the advantages of both higher spatial resolution and spectral information for effective visual interpretation of images. It was implemented to comprehensively harness the spectral information from SPOT XS (three bands and 20 m) and spatial information from SPOT PAN (10 m). Before fusion, the accurate co-registration is vital for the accuracy of fusion. A map-to-image strategy is applied for higher resolution of SPOT PAN based on the topographic map (scale 1:10,000), and then the image-to-image method is used for the geo-referenced registration of SPOT XS. Adequate ground control points could guarantee the accurate position match of two images. Among the three techniques (multiplicative, principal component, brovey transform) in ERDAS, the multiplicative was chosen for the fusion as being better for highlighting urban features.

Before interpretation and digitizing, the fused images are transferred into RGB images as color composites and then a supervised classification (maximum likelihood) is made to identify pixels with land cover change. Visual interpretation (with local knowledge) is carried out to remove errors of the mis-supervised classification.

3.3. Data classification

The main information requirements available for the model comprise land cover of 1993, land cover change in 1993–2000 (Fig. 3), proximal factors (Figs. 4 and 5), physical constraints (water body and protected areas), social factor (population), and institutional factors (administration, master planning) (Fig. 6), which are extracted and processed from primary and secondary sources. Proximal factors include road network, railway network, city centers/sub-centers, industrial centers, bridges and rivers. Land cover is classified here as water body, town/village, agricultural land, urban built-up area (industrial and warehouse, and others) and protected area (including green, sands, special uses). There is no universal standard of road classification as it is determined by quite a number of indefinite factors like adjacent land use, traffic volume, road width, and construction materials. It is the same for the definition of city centers/sub-centers. In this research, in order to reduce the uncertainty in classification, only two classes (major and minor) are identified. The determination of major roads and major city centers are principally based on the local knowledge available from master and transportation planning schemes, and tourism maps. Some interviews with local planners are also necessary for further confirmation.

From the viewpoint of temporal dimension, few layers do not have a certain degree of fuzziness in their definitions in particular when study area is large and its period is long. For instance, the construction of roads may occur in different phases. Their construction time should be taken into account. In this research, a major road linking with the third bridge over the Yangtze River (*Baishazhou*) was completed in early 2000, which is clearly seen in the SPOT images of 2000. This major road should not be included in the layer of major road network because it did not create any practical impacts on urban growth in the period 1993–2000. This judgement is also confirmed by very sparse land cover change surrounding the road. Other layers are spatially defined by following the similar regulation.

In the case of Wuhan city, it can be treated as flat landscape as its elevation ranges from 22 to 27 m a.s.l. except for few hills with higher elevation. Hence, slope is not an influential factor. However, water

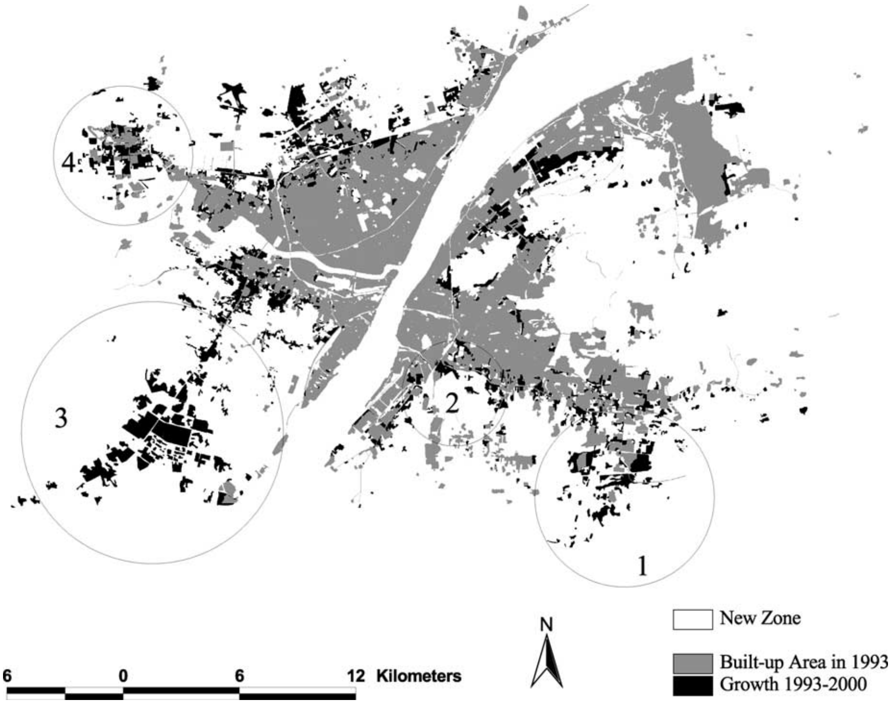

Fig. 3. Urban growth from 1993 to 2000.

body takes major percentage as can be seen from Fig. 6. Consequently, physical constraint principally comprises water body, which will be analyzed in the Section 3.4.

As for population data, the detailed population census at sub-district level is only available for 1990 but not accessible for 2000, population yearly statistical report at district level is accessible for each year from 1993 to 2000. In the Section 3.4, we will disaggregate population information to each pixel. The master plan scheme was approved by Central Government in 1996 and will be valid till 2020. This scheme map includes detailed land use classification.

3.4. Variables and GIS data analysis

Being focused on methodology, this paper only describes the spatial indicators, which can be measured from available data. All variables are listed in Table 2. They are created via the spatial analyst module in ArcView 3.2a based on 10 m × 10 m cell size, which results in a 6100 × 4000 grid.

Dependent variable: CHANGE is a binary variable. Its value “1” represents land cover change from 1993 to 2000, value “0” is the unchanged developable land in 2000 (= agricultural + villages + water body − protected− excluded). Here the layer ‘excluded’ is created through certain GIS operations. Theoretically, water bodies should be completely excluded from land cover change. However, in this special case study, 18% land cover change in the period 1993–2000 came from water bodies, which include ponds and lakes. As they are mostly from small-scale water body or the fringe of large lake, a general procedure can be designed for defining this specific layer:

- extracting water body from land cover layer (Fig. 6b);
- neighbourhood statistics (based on a circular neighbourhood with a 200 m radius);
- selecting sum >800 (if totally neighbouring 800 cells are also water).

The layer created is named ‘excluded’, which is utilized as physical constraint from water body. Another

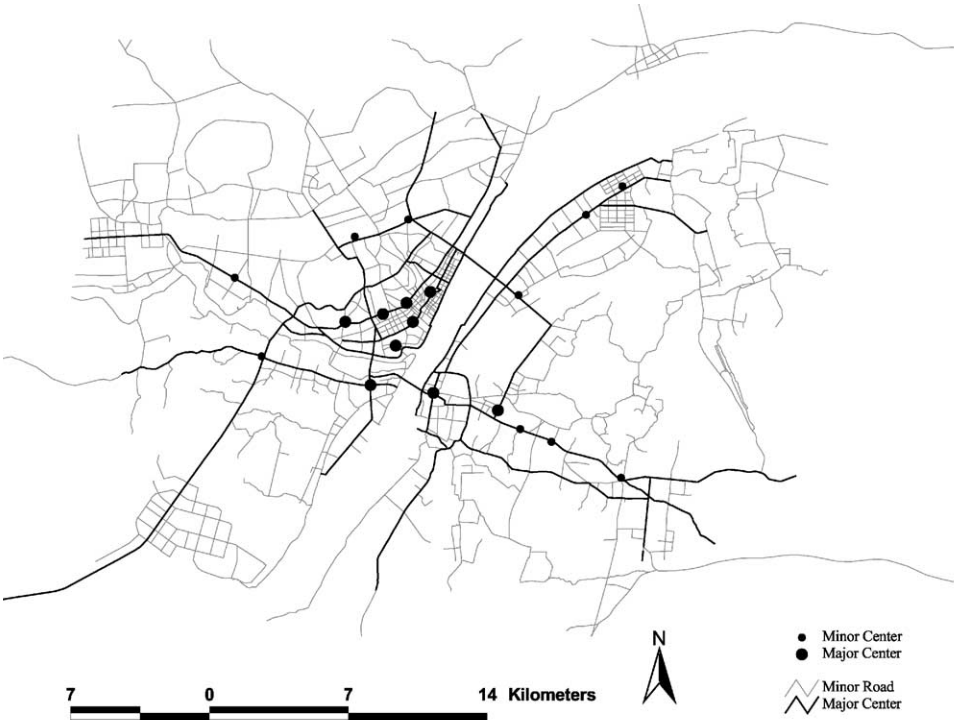

Fig. 4. Spatial distribution of road network and centers.

physical constraint lies in protected areas, which do not constitute developable land.

Fig. 3 shows that the urban growth in 1993–2000 was characterized by a large-scale spatial agglomeration. There are four new development zones (i.e. (1) *Guandong and Guannan* industrial parks; (2) *Nanhu and Changhong* industrial parks; (3) *Zuankou* car manufacturing base; (4) *Wujiashan* Taiwanese economic development zones).

Explanatory variables: firstly, proximity is a prime cause of urban expansion; transport and communication changes represent a major explanatory variable in helping to account for the continuing demand for urban land (Kivell, 1993). Here, the proximity variables measure the direct access to city centers/sub-centers, industrial centers, major roads, minor roads, rail lines, the Yangtze/Han rivers, constructed bridges over the Yangtze River and planned bridges on Yangtze River, respectively. The constructed bridges are: No. 1 in 1957, and No. 2 in 1994 bridge over the Yangtze River. The planned ones are *Baishazhou* (lower reach) and *Tianxinzhou* (upper reach). The spatial distribution of the explanatory variables can be seen from Figs. 4–6. The physical indicators equip any site with necessary development potential. Its spatial analysis is implemented through 'Find Distance' sub-menu in ArcView 3.2a.

Secondly, urban growth patterns, for instance, are largely a function of the availability of usable sites. The likelihood that a specific site will be developed varies according to its own availability for development, but also according to the availability of other sites located at different distances from various activity centers or generators of demand for development. A neighbourhood variable quantifies the spatial effect of neighbouring cells. From the aspect of urban development, the spatial influence (promotion or constraint) principally comes from the spatial agglomeration of the developed areas, industrial sites, developable land, and water constraint. They are density-oriented/ based indicators. Its spatial measure is based on the neighbourhood statistics technique.

Fig. 5. Spatial distribution of railway, bridges and industrial centers.

The type and size of selected neighbourhood reflect the distance-decaying mechanism of various factors. Here, a circular neighbourhood with a 500 m radius is chosen to calculate the density value towards a normal distribution.Thirdly, the social and economic activities are the main driving forces of urban development. These indicators include land value, employment opportunity, population pressure, etc. Here only population data is available. The indicator of cumulative population density is represented by the area under a graph of population density change between 2 years. The variable provides a better measure of population pressure (continued habitation and use of land for development) than does a single time measurement of population density (Arlinghaus, 1996). The population census data in 1990 is employed to disaggregate the accumulated population density from district to sub-district level for the period 1993–2000 although it will affect accuracy of information. The disaggregation formula is listed as follows in Eq. (7):

$$\mathrm{DAPD}_{ij}(1993-2000) = \frac{\mathrm{POPU}_{ij}(1990)}{\mathrm{POPU}_{i}(1990)} \frac{\mathrm{AP}_{j}(1993-2000)}{\mathrm{AREA}_{ij}} \tag{7}$$

where DAPD means disaggregated accumulated population density (unit: person/ha). AP is the accumulated population of each district in the period 1993–2000. The sub-script i, j indicate the ith sub-district in the jth district. POPU means the total population in 1990 at district or sub-district level. AREA is the total area (excluding water body) of ith sub-district. Totally, seven districts and 95 sub-districts were included in the study area but two of sub-districts have no data available. CPOPU_DENS is the net accumulative population density of each pixel computed from DAPD.

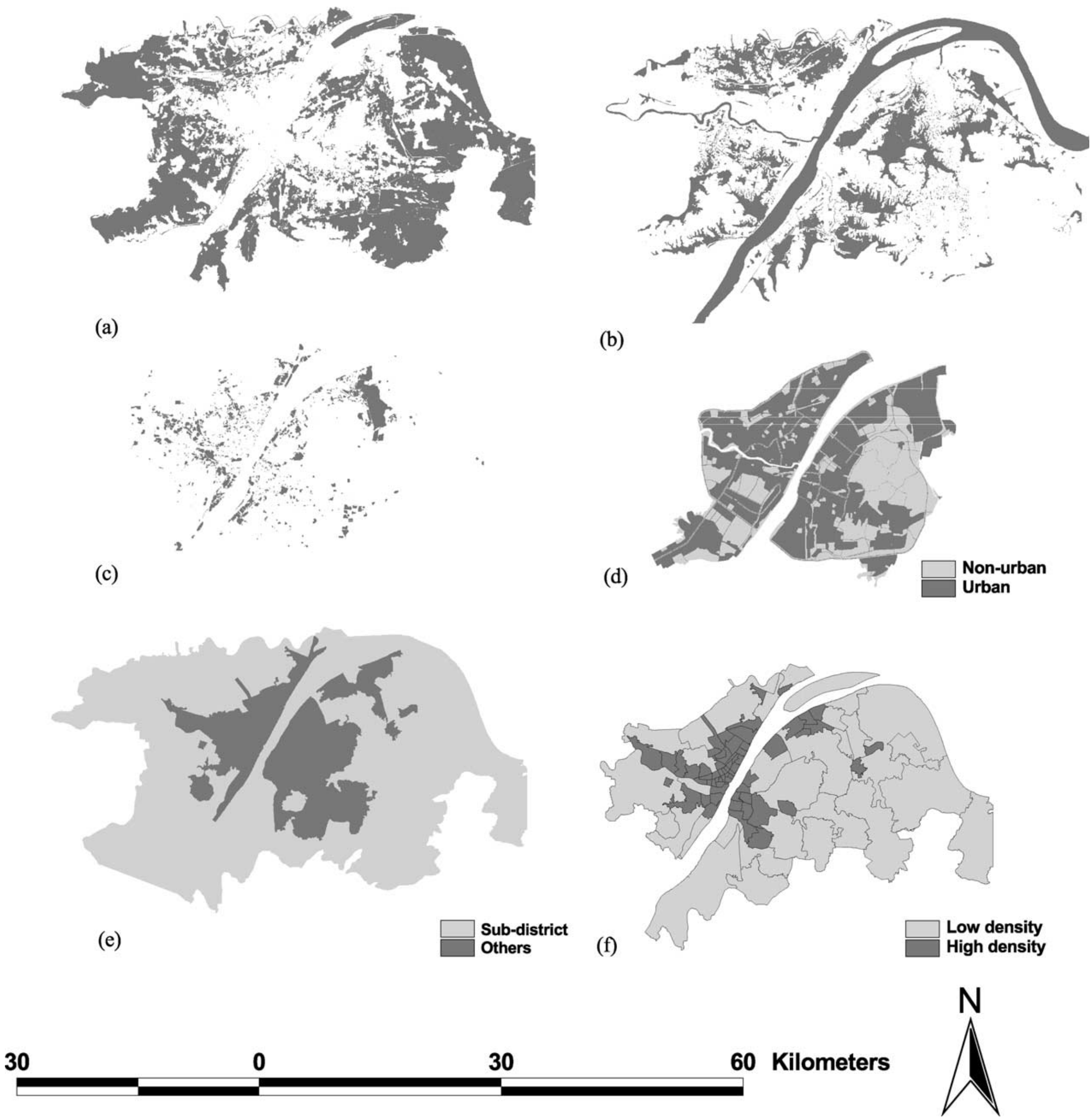

Fig. 6. Spatial distribution of other explanatory variables: (a) developable land; (b) water body; (c) industrial sites; (d) master plan; (e) administration; (f) accumulative population density.

Unfortunately, CPOPU_DENS does not cover the whole study area due to the fact that the population census in 1990 could not cover the present municipal boundary due to rapid urbanization. Consequently, it is better to treat them as categorical variable so that local knowledge regarding the spatial distribution of population density can be utilized for semi-quantifying (order variable). Its frequency distribution enables us

Table 2
Varibales and descriptions

Variables	Descriptive
Dependent variable	
CHANGE	Binary variable (1: change from developable to urban; 0: no-change)
Proximity Variable	
DIST_RAIL	Continuous variable, distance to railway lines
DIST_INDUC	Continuous variable, distance to industrial centers
DIST_CENT	Continuous variable, distance to city center/sub-centers
DIST_MCEN	Continuous variable, distance to major centers
DIST_OCEN	Continuous variable, distance to minor centers
DIST_MRD	Continuous variable, distance to major roads
DIST_ORD	Continuous variable, distance to minor roads
DIST_RIVER	Continuous variable, distance to Yangtze/Han rivers
DIST_YZ	Continuous variable, distance to Yangtze river
DIST_HAN	Continuous variable, distance to Han river
DIST_PBRID	Continuous variable, distance to planned bridges
DIST_CBRID	Continuous variable, distance to constructed bridges
DIST_CBRI1	Continuous variable, distance to No. 1 bridge
DIST_CBRI2	Continuous variable, distance to No. 2 bridge
Neighbourhood variable	
DENS_WATER	Continuous variable, density of neighbouring waters
DENS_DEVE	Continuous variable, density of neighbouring areas developed
DENS_INDU	Continuous variable, density of neighbouring industrial areas
DENS_AVAIL	Continuous variable, density of neighbouring developable areas
Categorical variable	
PLAN_NO	Binary variable (1: planned as built-up area; 0: not)
STREET_NO	Binary variable (1: sub-district; 0: not (town, township and farm)
CPOPU_DENS	Order variable (1: high density; 0: low density)

to reclassify it into two classes: (1) high density and (0) low density. In this way, the sites with missing value can be assigned with 1 or 0 according to local knowledge. This qualitative or subjective judgement is principally based on the comparison between the site and other sites with known value.

Finally, urban development is under the control of master planning and municipal administration management, which are generalized as macro policy variables. Whether a site is planned as built-up (1) or un-developable area (0), will essentially decide its change possibility. Whether a site is within the administrative boundary of sub-district or others such as town, township and farms, will also influence its development scale and speed in a specific period. The spatial distribution of three variables (STREET_NO, PLAN_NO and CPOPU_DENS) can be seen from Fig. 6.

4. Findings

4.1. Exploratory data analysis

In Eq. (2), $CH_{\Delta x}$ and $NCH_{\Delta x}$ in each Δx are processed by using 'Tabulate areas' between the layers (land cover change and buffering theme) in ArcView package. Here $\Delta x = 100$ m is defined for proximity variables and $\Delta x = 2\%$ for neighbourhood variables. The table file created is exported into the software STATISTICA 5.0 for calculating ΔP of Eq. (3) in Section 2.1. The scatter plots ($\log(\Delta P)$, x) are able to explore in detail the spatial influences of each variable (see Fig. 7). The significance of slope λ, intercept b and correlation coefficients R are shown in Table 3. P_R will be explained in Section 5.

From Fig. 7and Table 3, firstly, it is clearly seen that most variables have statistically significant linear trend

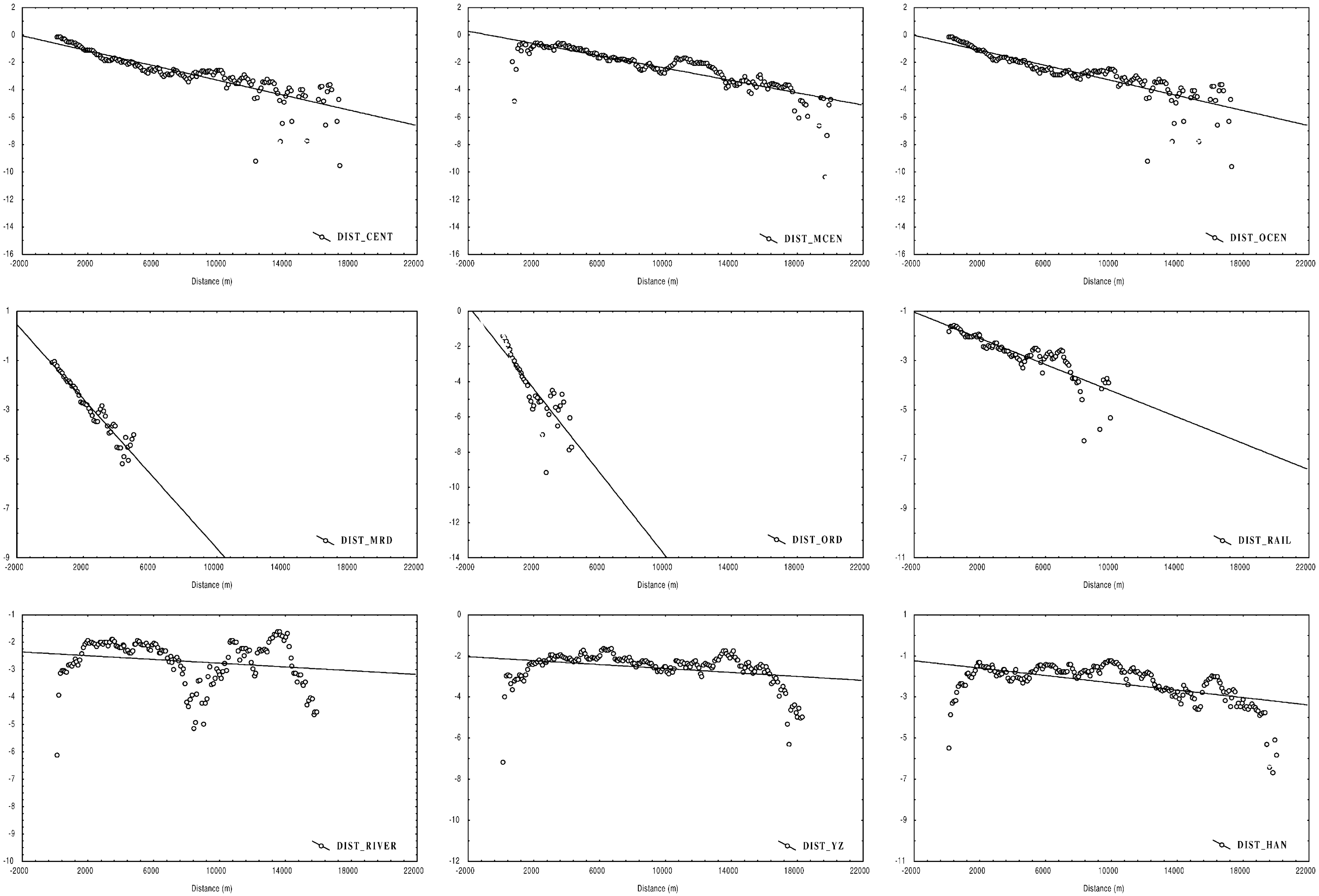

Fig. 7. Scatter plots of all continuous variables.

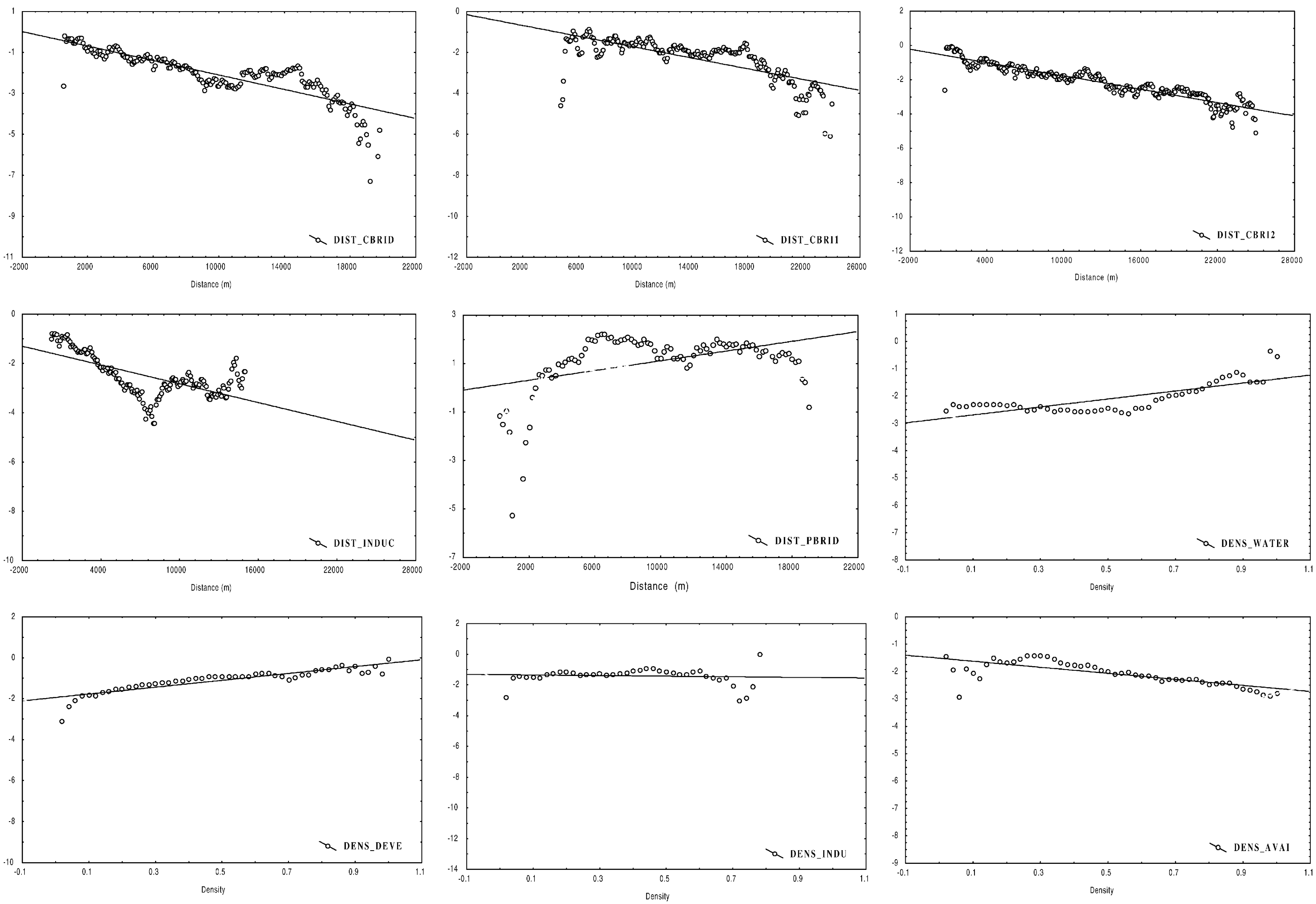

Fig. 7. (*Continued*).

Table 3
Exploratory data analysis

Variables	Slope (λ)[b]	Intercept (b)	Correlation coefficient (R)	P_R[a]
DIST_RAIL	−2.7	−1.57	−0.84	−0.73
DIST_INDUC	−1.3	−1.56	−0.65	−0.78
DIST_CENT	−2.72	−0.61	−0.85	−0.79
DIST_OCEN	−2.75	−0.57	−0.85	−0.78
DIST_MCEN	−2.25	−0.17	−0.85	−0.69
DIST_MRD	−7.6	−1.05	−0.96	−0.9
DIST_ORD	−12	−2.06	−0.83	−0.84
DIST_RIVER	−0.3	−2.43	−0.19	**
DIST_HAN	−0.9	−1.42	−0.55	−0.21
DIST_YZ	−0.5	−2.14	−0.31	**
DIST_PBRID			**	**
DIST_CBRID	−1.78	−0.35	−0.84	−0.75
DIST_CBRI1	−1.9	0.01	−0.86	−0.74
DIST_CBRI2	−1.3	−0.48	−0.93	−0.86
DENS_WATER	1.46	−2.84	0.77	0.54
DENS_DEVE	0.465	1.01	0.88	0.97
DENS_INDU			**	**
DENS_AVAIL	−1.1	−1.51	−0.74	−0.52

[a] P_R: correlation co-efficient from inverse power function.
[b] λ: λ for DENS_variables and λ/10,000 for DIST_variables.
** $p > 0.01$.

(negative exponential function) except two variables (** in Table 3). In particular, the distance to major roads and to the second bridge over the Yangtze River show over 90% accuracy. Spatial outliers are indeed existent in some variables but they are not removable because urban growth itself inevitably creates a certain degree of randomness. Not only R but also slope λ and intercept b show much spatial variation among variables. Slope λ is a major indicator for exploring varied probability. Steeper slope indicates more compact urban expansion in relation to the factor considered.

Secondly, the variable DIST_RIVER has two peaks, which results in a lower R. It indicates that two rivers may have different density gradient. So, it needs to be separated into two variables, each with one river. The separated two variables: DIST_YZ and DIST_HAN, especially the latter exhibits a better trend. Following this principle, we create DIST_MCEN, DIST_OCEN from DIST_CENT, and DIST_CBRI1, DIST_CBRI2 from DIST_CBRID. Such division is able to seek more accurate spatial determinants. For instance (in terms of slope):

- Sub-centers were making more effective impacts than major centers.
- Yangtze river was decreasing its role in contrast to Han river.
- No. 1 bridge over the Yangtze River is more influential than No. 2.

Summing up, we are able to make the following preliminary conclusions:

- Minor road network, major road network, minor city center, rail line network, No. 1 bridge, industrial centers and No. 2 bridge show a ranked order from high to low value in negatively affecting the probability of land cover change (the nearer, the more).
- Density of neighbouring water body and developed area show statistically significant positive impacts on probability of change (the greater, the more).

These results clearly show some significant differences among explanatory variables, which enable us to make a hypothesis that road infrastructure is still playing a crucial role in urban growth. The other three categorical variables (STREET_NO, PLAN_NO, CPOPU_DENS) are further confirmed to be statistically significant by using t-test (continuous) and Chi-square test (categorical).

4.2. Logistic regression modeling

Traditional logistic regression does not take spatial dependence into account, e.g. (Wu and Yeh, 1997; Tang and Choy, 2000; Wu, 2000b). There are few selective alternatives to consider spatial dependence. One is to build a more complex model incorporating an autogressive structure, e.g. (Gumpertz et al., 2000). Another is to design a spatial sampling scheme to expand the distance interval between sampled sites. The latter results in a much smaller size of sample, which will lose certain information. However, the maximum likelihood method, upon which logistic regression is based, relies on a large-sample of asymptotic normality. It means the result may not be reliable when the sample size is small. Consequently, a conflict occurs in applying logistic regression: the removal of spatial dependence and large size of sample. A reasonable design of spatial sampling scheme is becoming a crucial point of spatial statistics. This has attracted more and more researchers in various areas (Stehman and Overton, 1996). Frequently adopted schemes in logistic regression modeling are either stratified random sampling (Atkinson and Massari, 1998; Dhakal et al., 2000; Gobin et al., 2001) or systematic sampling (Li et al., 1999; Sikder, 2000). Their advantages and drawbacks were in detail reviewed and compared by Stehman and Overton (1996). Unlike the spatial prediction purpose in the area of geo-statistics, the population studied here is completely known, spatial sampling aims to reduce the size of samples (here the population is 6100×4000 cells, which is computationally intensive) and remove spatial auto-correlation. Systematic sampling is effective to better reduce spatial dependence but may lose some important information like relatively isolated sites when population is not spatially homogeneous. In particular, its ability representing the population may decrease when the distance interval increases significantly. Conversely, random sampling is efficient in representing population but low in efficiency in reducing spatial dependence especially local spatial dependence. Following the idea, we argue that the integration of both systematic and random sampling is better able to balance sample size and spatial dependence.

Firstly, a systematic sampling is implemented for the population. When a 20th order lag (20 pixels or 200 m distance interval in east–west and north–south directions) is reached, Moran' *I* index are significantly reduced for all continuous variables. After the systematic sampling, the ratio between the size of samples with value 1 and 0 becomes 1:11. To gain unbiased parameter estimation, we continue to randomly select another 10% from sample 0. This random sampling create nearly 1:1 ratio for final sample. Its total size is 3002 pixels. Systematic and random sampling is implemented under the spatial module of ArcInfo 8.0.

Regarding multi-collinearity, subsequently, of all pairs of variables with a correlation over 0.80, one is omitted. Of all pairs of variables with a correlation over 0.50, only one is allowed to enter a regression equation. Here, we found higher correlation exists between developable land and developed area (−0.73), developed area and industrial sites (0.72), rivers and Yangtze River (0.64). Three centers variables (>0.77), three bridge variables (>0.88), railway and industrial centers (0.66), the second bridge and sub-centers (0.68). It means that we still need to choose fewer representative variables, which can refer to the results of exploratory analysis (Table 3). The others are kept remaining as the correlation coefficients are less than 0.6. The use of a stepwise regression procedure aims to optimize combination of significant variables. A forward stepwise variable selection is employed via SPSS 10.0 package.

After 10, 6 and 5 steps, the results of three models were calculated separately as listed in Table 4. Model-I systematically explores the spatial influences of each independent variable on urban growth. Model-II and model-III aim to test the robustness of estimated parameters in model-I by comparing with only proximal variables and the rest, respectively.

4.3. Major determinants

The logistic regression model is estimated by maximum likelihood algorithm. There are various ways to assess the goodness-of-fit of logistic regression. One way is to cross-tabulate prediction with observation and to calculate the percentage correctly predicted (PCP). Table 4 shows the estimated logistic regression models. The overall percentage of correctness is about 83, 81.4 and 76%, respectively for model-I, -II and -III.

Table 4
Logistic regression results of three models

Models	Model-I (all variables)	Model-II (proximity variables)	Model-III (the others)
Steps of regression	10	6	5
Sample size	3002	3002	3002
Co-efficient	B (S.E.[a], Wald)	B (S.E.[a], Wald)	B (S.E.[a], Wald)
DIST_RAIL	–[b]	–[b]	
DIST_INDUC	3.37 (0.55, 37.5)	2.37 (0.48, 24.3)	
DIST_CENT	–[b]	–[b]	
DIST_OCEN	−6.86 (0.82, 69.9)	−6.6 (0.74, 79)	
DIST_MCEN	–[b]	–[b]	
DIST_MRD	−7.1 (0.52, 194)	−7.8 (0.5, 243)	
DIST_ORD	−48.8 (4, 149)	−57.1 (3.9, 212)	
DIST_RIVER	–[b]	–[b]	
DIST_HAN	2.93 (0.62, 22)	3.3 (0.58, 32.8)	
DIST_YZ	–[b]	–[b]	
DIST_PBRID	**	**	
DIST_CBRID	–[b]	–[b]	
DIST_CBRI2	–[b]	–[b]	
DIST_CBRI1	−3.43 (0.62, 30.5)	−2.97 (0.52, 32)	
DENS_WATER	−0.65 (0.29, 5)		1.3 (0.2, 39.7)
DENS_DEVE	1.68 (0.46, 14)		4.65 (0.38, 149.4)
DENS_INDU	–[b]		–[b]
DENS_AVAIL	–[b]		–[b]
CPOPU_DENS(1)	**		
STREET_NO (1)	0.79 (0.2, 15)		0.486 (0.18, 7.2)
PLAN_NO (1)	−0.82 (0.12, 49)		−1.77 (0.1, 350)
CONSTANT	11 (0.66, 276)	12.1 (0.51, 568)	−0.02 (0.2, 0.011)
Tests			
−2 LL[c]	2341	2447	3218
Cox & Snell R^2	0.455	0.435	0.27
Nagelkerke R^2	0.61	0.58	0.36
PCP (%)[d]	83	81.4	75.7

[a] S.E.: standard error.
[b] –: Not selected.
[c] -2LL refers to the two times log likelihood.
[d] PCP: percentage correctly predicted.
** Non-statistically significant ($p > 0.01$).

The major determinants include four negative variables (distance to minor road, distance to major road, distance to minor centers, distance to No. 1 bridge in order; The nearer it is, the greater the probability of change will be) and two positive variables (density of developed area and sub-district (street) administration. The greater density of developed area it is, the greater the probability of change is. The developable land located in urban sub-districts is able to change with greater probability than that in rural administration. The distance to Han River and to industrial centers are statistically significant but practically not significant. Density of water body shows a weak impact. Master planning is proven here to be out of control for the urban growth in this period.

The results from logistic regression modeling are basically consistent with these of the exploratory data analysis (see Table 2). However, The latter to some extent confirms the accuracy or reliability of the former and also is able to model the relative importance of each independent variable in a systematic way.

5. Discussion and conclusions

The major determinants discovered above are consistent with theoretical evidences. Firstly, after 1993, Wuhan entered a new era of urban development, which was characterized with rapid urban growth on the fringe and redevelopment in inner city; moreover, the urban growth in this period has shifted its focus from industrial to multi-function new zones (Cheng et al., 2001). They are different from traditional sub-urban centers. They are large, diverse, information-age cities with high-order retailing, entertainment, services and housing. This change is largely stimulated by the improvement of urban infrastructure.

Secondly, the first wave of foreign direct investment in China (1980–1991) was forced largely on investments in industrial growth, the second wave, beginning in 1992, has been directed as well towards infrastructure and land development (Gaubatz, 1999). In Wuhan, major infrastructure projects include new *Tianhe* international airport, New *Hankou* Railway Station, New Wuhan Passenger Harbor Station, The second highway bridge over Yangtze River, The fourth bridge over Han River (*yuehuqiao*), third highway bridge on Yangtze River (*Bashazhou daqiao*), cross-bridges on *Hangkong* road (Hankou town), cross-bridges on *Dadongmen* road (Wuchang town). They were constructed in the period 1993–2000. Other projects like the fourth and fifth bridges over Yangtze River are already planned in this period. These projects not only strengthen its role to be the center of transportation in China but also improve its investment environment as the systematic accessibility inside Wuhan has been considerably improved. As land values begin to emerge, accessibility is becoming a determinant of land development.

Finally, the dual land system (Han, 2000) leads to the fact that local government will often relax development control and simplify permit application procedures to attract foreign investors (Wu and Webster, 1998); moreover, the concurrent decentralization of decision making, increase of development actors and conflicts among developers, local residents, and government are ever-increasingly weakening the role of urban planning in urban development. The land development based on market principle frequently leads to the delay of planning scheme behind the undesirable constructions. The former results in the encroachment of protected areas like green space. The latter leads to the encroachment of arable land. In this period, *Wujiashan* new development zones (No. 4 in Fig. 3.) was not planned in the master planning 1996–2020.

In urban theories, another geographical law, inverse power function is also frequently applied for density gradient modeling (Makse et al., 1998). When compared with negative exponential function, Eqs. (1) and (4) are correspondingly modified as follows in Eqs. (8) and (9):

$$f(x) = \beta x^{-\lambda} \tag{8}$$

$$\log(\Delta P) = \log(\beta_1) + \lambda_1 \log(x) \tag{9}$$

The linear correlation coefficients P_R of both proximity- and neighbourhood variables are also computed and listed in Table 3. It clearly indicates that generally negative exponential function has higher accuracy than inverse power function. As a consequence, this research suggests that urban growth better obeys a law of negative exponential function in terms of probability of change.

Unlike natural science, urban development like other social sciences is in essence not a completely random or stochastic process. Hence, complete removal of spatial dependence is impossible. As Jacquez (1999) argued that spatial auto-correlation is almost always present and its strength varies considerably from one kind variable to another. A feasible way is to compare various sampling schemes for a compromised alternative.

This research also found that logistic regression analysis is very sensitive to its multi-stages such as data transformation and spatial sampling. The logarithm data transformation $\log(y + \beta$; β is to be determined by experiments) and various combinations of sampling type and size may significantly influence parameter estimation and model accuracy. Here, the proximity variables sampled are transformed by using $\log(y+1)$. Then, all continuous variables are standardized according to the formula: $(y - \min)/(\max-\min)$. So all independent variables are universally transformed into the range (0–1) for further logistic regression modeling. The selection or design of reasonable data transformation and spatial sampling scheme still needs further systematic research for spatial logistic regression. Spatial exploratory data analysis, like a simple approach proposed in this paper, can facilitate testing the detected patterns with the outcome of logistic regression. Exploratory spatial data analysis is able to discover the influence of each continuous variable but not systematic ranking. Logistic regression is efficient in systematically evaluating their relative contribution.

In this research, remotely sensed imagery is an ideal primary data sources for urban growth modeling although pattern analysis need more other socio-economic attributes. Timely and inexpensive satellite images make dynamic monitoring of urban growth more operational. GIS is proven to be highly limited in spatial data analysis including exploratory and confirmatory types except for its advantages of developing spatial indicators or variables (such as proximity or neighbourhood-based), designing spatial sampling and data integration. However, a loose-coupling strategy is frequently preferred by modeler as GIS can not and also do not need to completely incorporate powerful and flexible statistical software. In the future, the findings discovered here are expected to link with process modeling, such as cellular automata (CA) and multi-agent (MA) for further exploration of dynamic process. The gradient of density λ can be directly input into CA model.

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