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Driving forces and their interactions of built-up land expansion based on the geographical detector – a case study of Beijing, China

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ABSTRACT

Scientific interpretation of the driving forces of built-up land expansion is essential to urban planning and policy-making. In general, built-up land expansion results from the interactions of different factors, and thus, understanding the combined impacts of built-up land expansion is beneficial. However, previous studies have primarily been concerned with the separate effect of each driver, rather than the interactions between the drivers. Using the built-up land expansion in Beijing from 2000 to 2010 as a study case, this research aims to fill this gap. A spatial statistical method, named the geographical detector, was used to investigate the effects of physical and socioeconomic factors. The effects of policy factors were also explored using physical and socioeconomic factors as proxies. The results showed that the modifiable areal unit problem existed in the geographical detector, and 4000 m might be the optimal scale for the classification performed in this study. At this scale, the interactions between most factors enhanced each other, which indicated that the interactions had greater effects on the built-up land expansion than any single factor. In addition, two pairs of nonlinear enhancement, the greatest enhancement type, were found between the distance to rivers and two socioeconomic factors: the total investment in fixed assets and GDP. Moreover, it was found that the urban plans, environmental protection policies and major events had a great impact on built-up land expansion. The findings of this study verify that the geographical detector is applicable in analysing the driving forces of built-up land expansion. This study also offers a new perspective in researching the interactions between different drivers.

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Geographical detector; interactions; driving force; built-up land expansion; Beijing

1. Introduction

Built-up land expansion, as an active part of land-use and land-cover (LULC) change, has great importance given its significance to economic, social and environmental

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development. Understanding the driving mechanism of land-use change, including that of built-up land expansion, is one of the key objectives of land-use/-cover change (LUCC) research (Lambin *et al*. 1999). Although built-up land expansion stimulates the socio-economic development and improves the living standards of residents, it simultaneously causes problems such as resource shortages, population explosion, environmental pressure, and health problems (Kalnay and Cai 2003, Fernández 2007, Chan and Yao 2008, Christensen *et al*. 2008, Grimm *et al*. 2008, Li *et al*. 2013b). To solve these problems rationally and realise sustainable development, we must explore the driving forces of built-up land expansion. Such an analysis is also critical for modelling and predicting the pattern and process of built-up land growth. For example, some cellular automaton-based models, such as the SLEUTH urban growth model, require pre-known drivers as input (Clarke and Gaydos 1998, Herold *et al*. 2003). Many researchers also choose factors that are suggested by either the literature or experts to model built-up land expansion using different methods (Hu and Lo 2007, Luo and Wei 2009, Dubovyk *et al*. 2011). Overall, predicting the dynamics of built-up land expansion is the first step toward solving the ecological and human-dimensional problems of the expansion (Fang *et al*. 2005); therefore, identifying and understanding the effects of driving forces on built-up land expansion is crucially important for effective urban planning and management (Long *et al*. 2012, Li *et al*. 2013b).

Typically, the driving forces of built-up land expansion are discussed in detail with qualitative analysis (Liu *et al*. 2010, Shrestha *et al*. 2012). However, it is difficult to compare the driving forces of different periods and regions with qualitative analysis. Furthermore, the results of qualitative analysis can be easily influenced by researchers' personal opinions. As a result, quantitative analysis, usually in combination with qualitative descriptions, is largely used in analysing the drivers of built-up land expansion (Shi *et al*. 2009, Wu and Zhang 2012, Shu *et al*. 2014). Such a combination improves the objectivity and accuracy of the results and facilitates comparisons of different periods and regions. Numerous studies have examined the driving mechanism of built-up land expansion with various quantitative methods, such as bivariate regression (BR) (Cai *et al*. 2012, Haregeweyn *et al*. 2012, Wu and Zhang 2012), multiple linear regression (MLR) (Dewan and Yamaguchi 2009, Müller *et al*. 2010, Seto *et al*. 2011), logistic regression (LG) (Fang *et al*. 2005, Dubovyk *et al*. 2011, Long *et al*. 2012, Li *et al*. 2013b), boosted regression tree (BRT) (Linard *et al*. 2013) and analytic hierarchy process (AHP) (Thapa and Murayama 2010). Most of these methods can quantitatively calculate the relative importance of different factors except BR. Both BR and MLR explore the drivers from the perspective of the time dynamic, so they require long time-series socioeconomic and LULC data. In addition, the two methods can only use numerical variables. In contrast, LR and BRT investigate factors from the perspective of spatial heterogeneity, so they can be run without time-series of socioeconomic indicators or LULC data sets. Moreover, these two methods perform better in terms of analysing different types of factors because their input data can be both continuous and categorical variables. In contrast to the above methods, AHP determines the relative importance of each factor based on pair-wise comparison (Thapa and Murayama 2010). This method requires no data of factors and LULC, but its results depend largely on expert knowledge.

However, few of the above methods are able to determine the effects of the interactions between driving factors. In most ecosystems, factors are usually interrelated due to physical, chemical, biological, ecological and social principles and reasons, so the functions of a factor can be enhanced or reduced depending on the conditions of other factors in the same system (Fang *et al*. 2005). Interactions among physical and socio-economic factors also exist in the LUCC system, at different spatio-temporal scales (Shao *et al*. 2006). Understanding the interactions among the drivers is very important because it can help model and predict urban growth patterns more accurately. Fang *et al*. (2005) verified that interactions between factors can significantly improve the spatial simulation of urban sprawl by using logistic regression with a cellular automata model. However, methods to quantitatively assess the interactions among different factors are limited due to the complicated functions of the urban system.

The geographical detector is a spatial statistical method that can assess the relationships of different geographical strata. The method was originally used to explore the causes of regional disease (Wang *et al*. 2010). It has subsequently been applied to a variety of problems, such as the potential factors involved in the under-five mortality in the 2008 Wenchuan earthquake (Hu *et al*. 2011), the relationships between planting patterns and antibiotics in soil (Li *et al*. 2013a), the spatial correlations among ecological factors and urban forest landscape connectivity (Ren *et al*. 2014), and the effects of individual habitat factors and two-factor interactions on grasshopper occurrence in Inner Mongolia (Shen *et al*. 2015). The method has also been applied in the mechanism research of county urbanisation in China (Liu and Yang 2012), but only for determining the relative importance of factors without analysing the interactions between factors. These studies have shown that the geographical detector has two main advantages. First, it can identify relationships between a complex set of factors and a variety of geographical phenomena without any assumptions or restrictions (Hu *et al*. 2011, Liu and Yang 2012, Wang and Hu 2012, Li *et al*. 2013a, Ren *et al*. 2014, Shen *et al*. 2015). Second, it can quantitatively characterise the interactions between pairs of factors and obtain valuable results (Hu *et al*. 2011, Ren *et al*. 2014).

The present study aims at testing the applicability of the geographical detector in exploring the impacts of physical and socioeconomic factors of built-up land expansion and the interactions between these factors. The study also discusses the effects of policies using physical and socioeconomic factors as proxies. In this study, we will first provide details on the method of the geographical detector. Then, we will test the applicability of the geographical detector with a real case study of built-up land expansion in Beijing over the period of 2000–2010. Finally, we will discuss the driving mechanism of built-up land expansion in Beijing over the 10-year period based on the results of the geographical detector. Policy and methodological implications will be highlighted thereafter.

2. Geographical detector

The geographical detector is a spatial statistical method used to test the relationships between geographical phenomena and their potential driving factors. It includes four detectors: the factor detector, risk detector, ecological detector and interaction detector. When the method is applied to built-up land expansion, we assume that the spatial distribution of built-up land expansion is similar to that of its potential drivers. In this study, we mainly use the factor detector, the risk detector and the interaction detector to explore which factors are more important, where the built-up land expands more rapidly, and how different factors interact with each other. Free software to implement the geographical detector can be downloaded from http://www.sssampling.org/Excel-Geodetector.

Figure 1 illustrates the mechanism of the geographical detector (Wang *et al.* 2010). First, the study region A is divided with a grid system $G = \{g_i; i = 1, 2, \ldots, n\}$, and the built-up land expanded area of every grid cell is calculated: $y_1, y_{1..}y_n$. $D = \{D_i; i = 1, 2, 3\}$ is the geographical stratum of potential factors that can be both continuous and categorical variables. Then, the distribution of the built-up land expansion is overlaid with the geographical stratum D. Every grid cell in G records the built-up land expanded area in it and each factor's attribute that takes up the largest proportion of area in the grid cell. For neighbourhood factors, the values are the proportion of each land-use type in the grid cell, and the size of the neighbourhood is defined as equal to that of the grid cells. The mean value and the dispersion variance over sub-regions D_i are denoted as $\bar{y}_{D,i}$ and $\sigma^2_{D,i}$ (i = 1, 2, 3), respectively. Let n be the total number of grid cells over the entire region A, and let $n_{D,i}$ be the number of grid cells in sub-region D_i. The global variance of built-up land expansion in the region A is σ^2.

2.1. *The factor detector*

The factor detector can quantitatively indicate the relative importance of determinants. In this study, the power determinant (PD) (Wang *et al.* 2010) is defined as the difference between one and the ratio of accumulated dispersion variance of the built-up land expansion area over each sub-region to that over the entire study region:

$$\mathrm{PD} = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{3} n_{D,i}\sigma^2_{D,i} \tag{1}$$

If factor D is one determinant of built-up land expansion, the dispersion variance of the built-up land expansion area of each sub-region will be small, whereas the variance between sub-regions will be large. For example, if factor D completely controls the spatial pattern of built-up land expansion and $\sigma^2 \neq 0$, then $\sigma^2_{D,i}=0$ and PD = 1; if factor D is completely unrelated to built-up land expansion, then PD = 0. The value of PD lies

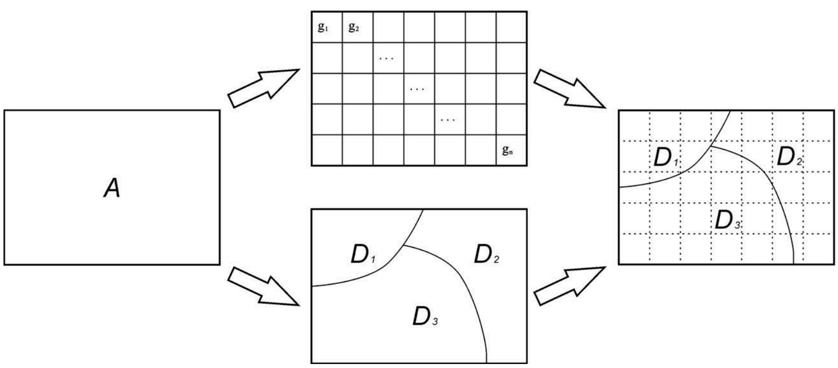


Figure 1. The study region A, the grid system G, the geographical stratum of potential factors D and the overlaid A, G and D (Wang *et al.* 2010).

between 0 and 1. The larger the PD value, the more important the factor of built-up land expansion. In this study, PD values represent the consistency of the spatial distribution between built-up land expansion and its factors.

2.2. *The risk detector*

The risk detector uses a *t*-test to compare the difference in average values between sub-regions of factor *D* (Wang *et al*. 2010). However, this study mainly uses the average value ($\bar{y}_{D,i}$) to calculate the built-up land expansion speed (E_d), which is the average percentage of built-up land expanded area of the grid cells in a sub-region D_i:

$$E_d = \frac{1}{Sn_{D,i}} \sum_{1}^{n_{D,i}} y_{D,i} \times 100\% \tag{2}$$

where $y_{D,i}$ denotes the built-up land expanded area of a grid cell in sub-region D_i, $n_{D,i}$ denotes the number of grid cells in the sub-region, and S denotes the area of a grid cell of the geographical detector. With E_d values, it is more convenient to compare the effects of different levels of a factor. The greater the E_d value is, the more rapidly the built-up land expands.

2.3. *The interaction detector*

The interaction detector determines whether two factors work independently or not, or if their effects are weakened or enhanced when they occur in space together. The interaction detector defines the interaction between two factors as follows (Spatial Analysis Group, IGSNRR 2013):

$$\left.\begin{array}{l}
\text{Nonlinear-weaken}: \mathrm{PD}(\mathrm{A} \cap \mathrm{B}) < \mathrm{Min}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) \\
\text{Uni-enhance/weaken}: \mathrm{Min}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) < \mathrm{PD}(\mathrm{A} \cap \mathrm{B}) < \mathrm{Max}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) \\
\text{Bi-enhance}: \mathrm{Max}(\mathrm{PD}(\mathrm{A}), \mathrm{PD}(\mathrm{B})) < \mathrm{PD}(\mathrm{A} \cap \mathrm{B}) < (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B})) \\
\text{Independent}: \mathrm{PD}(\mathrm{A} \cap \mathrm{B}) = (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B})) \\
\text{Nonlinear-enhance}: \mathrm{PD}(\mathrm{A} \cap \mathrm{B}) > (\mathrm{PD}(\mathrm{A}) + \mathrm{PD}(\mathrm{B}))
\end{array}\right\} \tag{3}$$

where the symbol '∩' denotes the interaction between A and B. Model (3) can be implemented in a GIS environment by overlaying layers A and B. The combined attributes of A and B are written to a new layer C. Then, PD values of layers A, B and C can be calculated using Equation (1), and the results can be judged using Equation (3). It should be noted that the three types of enhancement are different. For example, if PD (A) < PD (A∩B) < PD (B) < (PD (A) + PD (B)), this indicates that B enhances A, and A weakens B; if PD (A) and PD (B) < PD (A∩B) < (PD (A) + PD (B)), this indicates that A and B enhance each other; and if PD (A∩B) > (PD (A) + PD (B)), this implies nonlinear enhancement of A and B. Thus, 'nonlinear-enhancement' interactions are the strongest, whereas 'uni-enhancement' interactions are the weakest.

2.4. *The modifiable areal unit problem of the geographical detector*

The modifiable areal unit problem (MAUP) exists universally in geographical and spatial analysis. This problem arises from the fact that areal units of geographical objects are arbitrary and modifiable at choice, and thus, different aggregated sizes or spatial arrangements can yield different results (Jelinski and Wu 1996). The MAUP has two related yet distinctive components: the scale effect and the zoning effect. The scale effect is 'the variation in results that can often be obtained when data for one set of areal units are progressively aggregated into fewer and larger units for analysis' (Jelinski and Wu 1996). The zoning effect, in contrast, is 'any variation in results due to the use of alternative units of analysis when the number of units is held constant' (Jelinski and Wu 1996). The geographical detector, as a spatial statistical method, is based on grids to analyse the spatial relationships of geographical phenomena and factors, so it is essential to calculate how the MAUP affects the results of the geographical detector. In this study, both the scale effect and the zoning effect are analysed, with all factors being classified into the same number of classes.

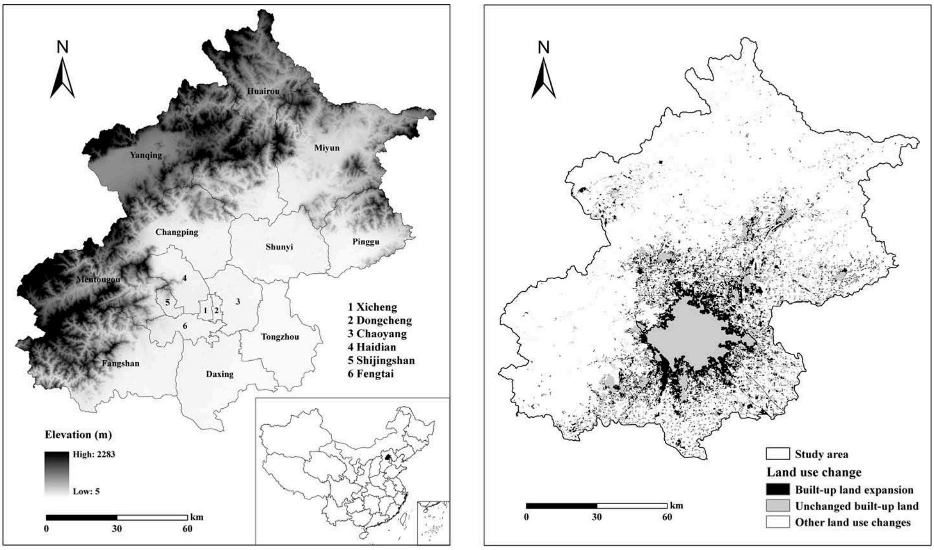
First, the scale effect is analysed to find an optimal scale of the geographical detector. The PD values are the relative importance of factors, so stable ranks of the PD values are important during the subsequent analysis. According to the resolution of LULC data and the extent of the study region, six grid sizes of the geographical detector are selected to analyse the scale effect of the PD values and their ranks (grid sizes: 1000 × 1000, 2000 × 2000, 3000 × 3000, 4000 × 4000, 5000 × 5000, 6000 × 6000 square metres, resulting in the following number of grid cells: 15,565, 3906, 1724, 973, 623, 431, respectively).

Second, the zoning effect of the geographical detector is tested with selected factors of different types under the optimal scale. For a specified number of classes, different methods generally define the cutting values differently. In this test, three methods are used: the natural-breaks method, the quantile method and the manual method. The natural-breaks method decides the cutting values by minimising within-class variance and maximising between-class variance in an iterative series of calculations (Brewer and Pickle 2002). The quantile method places an equal number of enumeration units into each class (Brewer and Pickle 2002), and the manual method decides the classes using prior knowledge or divides the classes at random without any rules.

3. Application of the geographical detector

3.1. *Study area*

Beijing is located between 115.7°E–117.4°E and 39.4°N–41.6°N at the northern tip of the North China Plain, covering 16 districts and counties. Beijing's average elevation is 43.5 m, with mountainous areas in the north and west and plains in the centre and southeast (Figure 2(a)). The city has a monsoon-influenced humid continental climate with hot, humid summers and cold, dry winters. As the nation's political, cultural and educational centre, Beijing has been developing at an incredible speed in the early twenty-first century. The permanent population increased from 11.08 million in 2000 to 19.61 million in 2010, and the proportion of the urban population grew from 77.54% to 85.96%. The gross domestic product (GDP) also experienced a rapid increase from



(a) (b)

Figure 2. Maps of the study area in Beijing showing (a) its location and topography and (b) land-use change.

316.17 billion renminbi (RMB) in 2000 to 1411.36 billion RMB in 2010. Accompanying the rapid socioeconomic development was the fast growth of the built-up land area (Figure 2(b)). The area of built-up land in Beijing rose by 47.16% from 2241.28 km^2 to 3298.23 km^2 in the same period.

The study area in this article excludes the built-up urban area of 2000 for higher accuracy when using the spatial statistical method. The built-up urban area refers to the administrative area that has already been constructed continuously in space with basic municipal public infrastructure and public facilities (Ministry of Construction, PR China 1998). Therefore, the built-up urban area, where built-up land expansion is finished under certain drivers, should be excluded when applying the spatial statistical method. In addition, this exclusion can avoid the inconsistency of socioeconomic data between 2000 and 2010 caused by the change in administrative division because the Dongcheng and Xicheng Districts are located entirely in the built-up urban area of 2000 (Beijing adjusted its administrative division in 2010 by merging the Chongwen and Xuanwu Districts into the Dongcheng and Xicheng Districts, respectively).

3.2. *Potential driving factors and data*

Factors leading to built-up land expansion are diverse and complex. After a literature review, we find that three main types of factors drive built-up land expansion: physical factors, socioeconomic factors and policy factors (Table 1). The three types of factors interact with each other, resulting in built-up land expansion (Figure 3). Based on the literature review and available data, 12 potential physical and socioeconomic factors are selected to run in the geographical detector (Table 1). Policy factors, which also have a significant influence on built-up land expansion, are not included in the geographical

Table 1. Summary of drivers of built-up land expansion in literature and the selected factors in the geographical detector.

Category	Factors of built-up land expansion in literature	Factors in the geographical detector	Abbreviation
Physical factors	Topographic factors (e.g. elevation and slope) (Fang *et al.* 2005, Liu *et al.* 2005, Braimoh and Onishi 2007, Dewan and Yamaguchi 2009, Dubovyk *et al.* 2011, Li *et al.* 2013b)	Elevation	ELV
		Slope	SLP
	Neighbourhood factors (e.g. urban land in the surrounding area or undeveloped land in the surrounding area) (Fang *et al.* 2005, Braimoh and Onishi 2007, Dubovyk *et al.* 2011, Li *et al.* 2013b)	Built-up land in the surrounding area in 2000	BULD
		Cropland in the surrounding area in 2000	CPLD
	Distance to rivers (Fang *et al.* 2005, Braimoh and Onishi 2007)	Distance to rivers in 2000	D_RV
Socioeconomic factors	Population (Liu *et al.* 2005, Braimoh and Onishi 2007, Dewan and Yamaguchi 2009, Dubovyk *et al.* 2011, Seto *et al.* 2011, Cai *et al.* 2012, Haregeweyn *et al.* 2012, Wu and Zhang 2012).	Change in permanent population between 2000 and 2010	P_POP
	Economy (e.g. distance to socioeconomic centres, GDP and income) (Liu *et al.* 2005, Dewan and Yamaguchi 2009, Seto *et al.* 2011, Cai *et al.* 2012, Wu and Zhang 2012, Li *et al.* 2013b)	Distance to the downtown area in 2000	D_DA
		Change in GDP between 2000 and 2010	GDP
		Change in disposable income per citizen between 2000 and 2010	ICM
		Change in proportion of secondary and tertiary industry in GDP between 2000 and 2010	S_T_INDU
		Change in total investment in fixed assets between 2000 and 2010	T_FAI
	Access to roads (Fang *et al.* 2005, Braimoh and Onishi 2007, Dubovyk *et al.* 2011, Li *et al.* 2013b)	Distance to main roads in 2000[1]	D_ROAD
Policy factors	Urban planning, Land-use policy (Fang *et al.* 2005, Liu *et al.* 2005, Braimoh and Onishi 2007)	–	–

[1]Distance to the main roads include main railway and expressway. Subway was excluded because Beijing subway before 2010 was mainly distributed within the built-up urban area of 2000, which was not the study area of this article.

detector because they are difficult to express quantitatively and spatially. To overcome this difficulty, this study uses the physical and socioeconomic factors as proxies of the policy factors because policy factors interact with physical and socioeconomic factors.

Based on the selected factors, the data used in this study include (i) land-use data of Beijing in 2000 and 2010, with six first level types (cropland, woodland, grassland, water bodies, built-up land and unused land). Built-up land comprises three second-level types: urban, rural settlement and industry-traffic land. The data are obtained from the National Land Use/cover Database of China, mapped by visual interpretation based on multiple sources of remote sensing data (Zhang *et al.* 2014). Land-use data are raster files with a 100-m resolution. (ii) Vector data of the main roads and rivers for the year 2000, and a digital elevation model (DEM) from the 1:250,000 topographic database, developed in the 1980s, provided by the National Fundamental Geographical Information System of China. The DEM is in raster format, with a 100-m resolution. (iii) Socioeconomic data of 14 districts and counties of Beijing in 2000 and 2010, including GDP, permanent population, disposable income per citizen, proportion of secondary

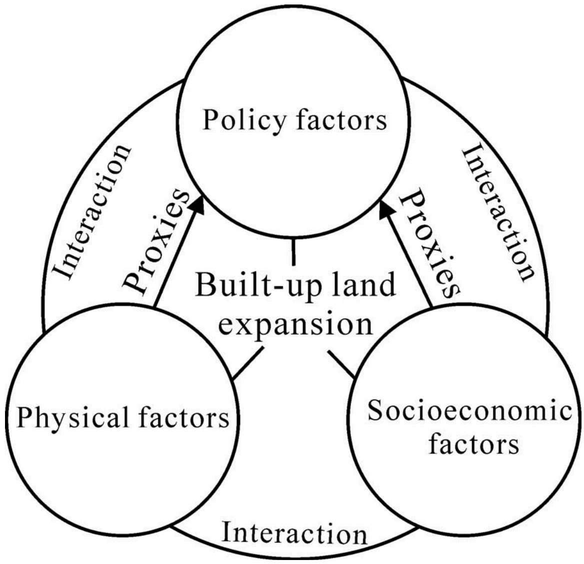


Figure 3. Relationships between factors of built-up land expansion.

industry and tertiary industry in GDP, and total investment in fixed assets (Beijing Municipal Statistical Bureau 2001, 2011, Beijing Municipal Statistical Bureau and National Bureau of Statistics Survey Office in Beijing 2008).

4. Results

4.1. *MAUP of the geographical detector*

For both the scale effect and the zoning effect tests, the number of classes for each factor was set at five. This was mainly because the socioeconomic data were acquired at the district level, which resulted in only 14 different spatial units in Beijing. More classes might make the data scattered in space, and fewer classes might not be sufficient to reflect the spatial heterogeneity.

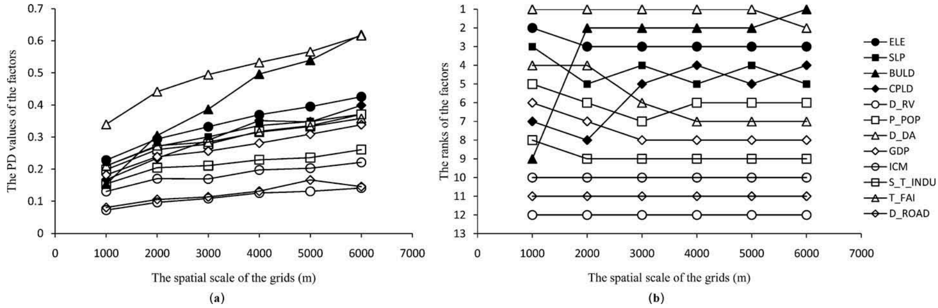


Figure 4. Scale effects on (a) the PD values and (b) the ranks of the factors (Acronyms are defined in Table 1.).

The scale effects of the PD values and the ranks of 12 factors were tested using six scales (Figure 4). The PD values of all factors tended to increase with increasing grid size, and that of the built-up land in the surrounding area increased faster than any other factor. In contrast, the ranks of different factors showed different relationships with the grid size. The ranks of the neighbourhood factors increased with increasing grid size, whereas the ranks of some other factors, such as the total investment in fixed assets and GDP, decreased. Note that the ranks of these factors remained relatively stable when the grid size was larger than 4000×4000 m^2, and larger grid sizes might mask meaningful geographic variation of built-up land expansion. Thus, 4000 m was chosen as the optimal grid size of the geographical detector in this study.

The results of the zoning effect showed that the PD values varied with different classifications, but no explicit relationships were found between the PD values and the classifications (Table 2). Previous studies stated that optimal classification algorithms and prior knowledge were needed to classify the quantitative variables when using the geographical detector (Wang *et al*. 2010). Arbitrary classifications might not characterise the actual associations between factors and geographical phenomena (Hu *et al*. 2011). In this study, the optimal classification was defined with both the optimal algorithm and prior knowledge. The 'natural break (Jenks)' method in ESRI's ArcView GIS software was used to classify five socioeconomic factors (GDP, permanent population, disposable income per citizen, proportion of secondary industry and tertiary industry in GDP and total investment in fixed assets), and prior knowledge as well as the range and distribution of the data were considered to classify the other factors (Figure 5 and Figure 6).

4.2. *The factor and risk detectors*

The factor detector calculated the PD values to represent the relative importance of the potential factors of built-up land expansion (Table 3), whereas the risk detector disclosed the built-up land expansion speed of different sub-regions of each factor (Figure 5 and Figure 6). Overall, the effects of physical and socioeconomic factors on built-up land expansion were consistent with those of previous research. Here, we mainly discuss the most important effects.

First, physical factors had significant effects on the built-up land expansion, especially the neighbourhood and topographic factors. Built-up land in the surrounding area was

Table 2. The zoning effect of the geographical detector.

Category	Factor [range]	Cutting values	Method	PD value
Physical factors	CPLD	0.1, 0.2, 0.4, 0.7	Manual	0.3514
	[0–0.9119]	0.1, 0.25, 0.45, 0.7	Natural break	0.3341
		0.01, 0.07, 0.23, 0.63	Quantile	0.2862
	ELE	200, 500, 800, 1000	Manual	0.3494
	[0–2283]	185, 443, 721, 1082	Natural break	0.4464
		39, 123, 428, 689	Quantile	0.3724
Socioeconomic factors	D_DA	20, 40, 60, 80	Manual	0.5326
	[0,120]	30, 60, 80, 100	Manual	0.4312
		10, 30, 60, 90	Manual	0.5615
	P_POP	11, 34, 83.7, 129	Natural break	0.3178
	[2.9–202.3]	5.3, 20.2, 58.7, 129	Quantile	0.2981
		5.6, 34, 123.3, 166.5	Manual	0.3027

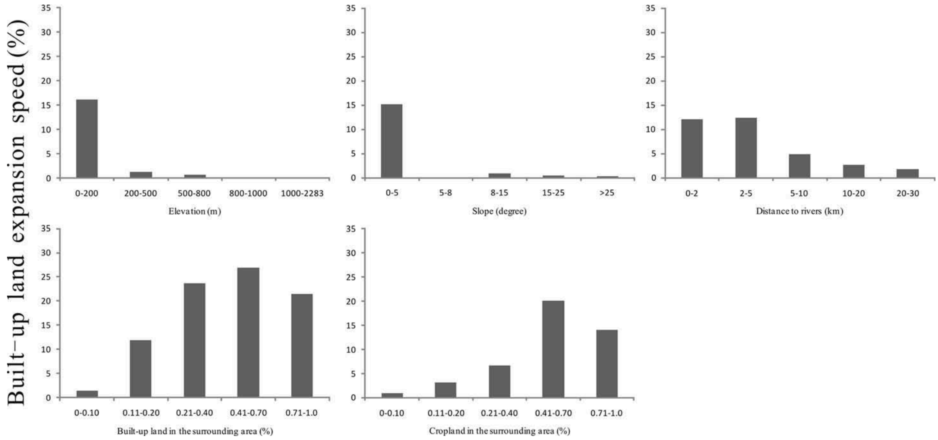


Figure 5. The built-up land expansion speed of the physical factors.

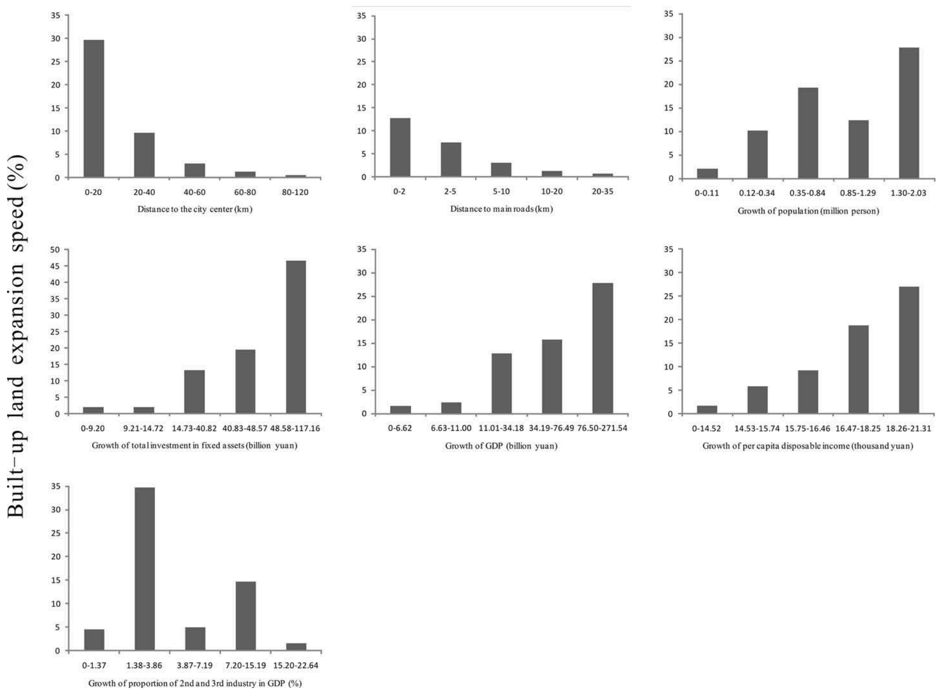


Figure 6. The built-up land expansion speed of the socioeconomic factors.

the most influential physical factor, and its expansion speed was generally higher than those of the other physical factors. The largest expansion speed was found where 40–70% of the surrounding area consisted of built-up land. This indicates that built-up land expansion tended to occur near developed areas. This phenomenon has been observed in many other studies as well (Braimoh and Onishi 2007, Hu and Lo 2007, Li *et al*. 2013b). However, the expansion speed decreased in areas where a higher proportion of built-up land was in the neighbourhood. It may be that these places have already experienced a

Table 3. The PD values of physical and socioeconomic factors.

Physical factors	PD value	Socioeconomic factors	PD value
BULD	0.4962	D_DA	0.5326
ELV	0.3694	P_POP	0.3179
CPLD	0.3514	T_FAI	0.3155
SLP	0.3360	GDP	0.2810
D_RV	0.1257	S_T_INDU	0.2291
		ICM	0.1975
		D_ROAD	0.1314

high-speed expansion of built-up land, with little land area of other types remaining. Compared with built-up land, cropland in the surrounding area was less influential. Its expansion speed also peaked where 40–70% of the surrounding area was cropland. According to the LULC data, built-up land expansion occupied approximately 1005 km^2 of cropland over the 10 years, which contributed to 80% of the expanded built-up land in Beijing.

Second, socioeconomic factors were also related to the built-up land expansion in Beijing. The factor detector showed that the distance to the downtown area was the most influential factor, followed by population, total investment in fixed assets, and GDP. Meanwhile, the expansion speed was positively correlated with the growth of total investment in fixed assets, GDP and per capita disposable income in space, whereas it was negatively correlated with the distance to the downtown area and the main roads. In contrast, the expansion speed was not correlated well with the growth of the proportions of secondary and tertiary industry in GDP in space.

The distance to the downtown area was the most influential factor. It reflected the concentric circle expansion pattern of Beijing. Its great influence could be explained in two ways. First, the distance to the downtown area represented the distance to the socioeconomic centre in Beijing. Areas closer to the downtown area became developed more easily because they had more economic, human and facility resources. Second, the distance to the downtown area also indicated the strong effects of urban planning in Beijing, as discussed below.

The impact of other physical and socioeconomic factors on built-up land expansion was generally consistent with the results from other studies. As explained, the effects of single factors were not the emphasis of this research; here, we only provide a brief description to explain the applicability of the geographical detector and the overall results of the relative importance and the expansion speed of the factors.

4.3. *The interaction detector*

In total, 60 pairs of interactions were calculated between 12 factors. We divided these interactions into three types: pairs of physical factors, pairs of socioeconomic factors and pairs of physical and socioeconomic factors. Interactions between pairs of physical factors and pairs of socioeconomic factors all enhanced each other when driving built-up land expansion, whereas two pairs of physical and socioeconomic factors exhibited nonlinear enhancement (Table 4). In addition, the average interaction was strongest between pairs of physical and socioeconomic factors and weakest between pairs of socioeconomic factors. Based on these findings, we first explain some important

Table 4. Interactions between factors of built-up land expansion.

Factors		Physical factors					Socioeconomic factors						
		BULD	ELE	CPLD	SLP	D_RV	D_DA	P_POP	T_FAI	GDP	S_T_INDU	ICM	D_ROAD
Physical factors	BULD												
	ELE	0.5356											
	CPLD	0.5501	0.4499										
	SLP	0.5217	0.3858	0.3970									
	D_RV	0.5519*	0.4161	0.4429	0.3947								
Socioeconomic factors	D_DA	0.6479	0.6280	0.6581*	0.6397	0.5724							
	P_POP	0.5892	0.4818	0.5196	0.4806	0.4420	0.5694						
	T_FAI	0.5871	0.5034	0.5258	0.5020	0.4583↗	0.6080*	0.3582					
	GDP	0.5705	0.4813	0.5142	0.4764	0.4225↗	0.5780	0.3393	0.3184				
	S_T_INDU	0.5698	0.4245	0.4483	0.4250	0.3546	0.5910	0.3756	0.3662	0.3714			
	ICM	0.5608	0.4625	0.4865	0.4626	0.3075	0.5477	0.3402	0.3321	0.2961	0.3495		
	D_ROAD	0.5244	0.4273	0.4269	0.4011	0.2268	0.5528	0.3839	0.3860	0.3555	0.3498	0.2712	

[a] '↗' denotes nonlinear enhancement of factors A and B; i.e. $PD(A \cap B) > (PD(A) + PD(B))$. All other interactions are bi-enhancing type; i.e. $Max(PD(A),PD(B)) < PD(A \cap B) < (PD(A) + PD(B))$.
[b] The symbol '*' denotes the largest interaction of each type (pairs of physical factors, pairs of socioeconomic factors and pairs of physical and socioeconomic factors).
[c] The average interaction of each type is calculated by averaging the interactions of each type: pairs of physical factors: 0.4646, pairs of socioeconomic factors: 0.4114, and pairs of physical and socioeconomic factors: 0.4917.

interactions of each type, which were all bi-enhancing interactions; then we discuss two pairs of nonlinear enhancement.

Interactions between pairs of physical and socioeconomic factors were generally stronger than those of the other two types, especially when the physical factors interacted with the distance to the downtown area. For instance, the largest four interactions were the distance to the downtown area interacting with the following physical factors: cropland in the surrounding area (0.6581), built-up land in the surrounding area (0.6479), slope (0.6397) and elevation (0.6280). This result indicates that over 60% of the spatial distribution of built-up land expansion was consistent with that of these physical factors intersecting with the distance to the downtown area. These interactions had greater effects on built-up land expansion than any factor alone. When the distance to the downtown area and the neighbourhood factors interacted, they enhanced the effects of each other. Locations near the downtown area and surrounded by more built-up land were more likely to be developed for the convenience of accessing resources. In addition, cropland near the downtown area was easier to construct on because it was cheaper than built-up land. After being converted into built-up land, such as residential buildings, commercial industry or rural settlement, the land could create greater profit and better promote the local economy. When the distance to the downtown area interacted with topographic factors, their effects were both enhanced. Low and flat areas close to the downtown area were suitable for built-up land development. This was because these areas usually had adequate resources and few physical obstacles. Simultaneously, the largest interaction between pairs of socioeconomic factors was the distance to the downtown area with the total investment in fixed assets (0.6080). One reason for this could be that government or enterprises tended to invest money in areas near the downtown area. In addition, the largest interaction between pairs of physical factors was built-up land in the surrounding area with the distance to rivers (0.5519). Typically, more developed regions along rivers could be converted to built-up land more easily because rivers could serve as tourist attractions and provide convenient transportation.

Nonlinear enhancement, the strongest type of enhancement, was found for two pairs of factors. When rivers interacted with factors of the total investment in fixed assets and GDP, their effects on built-up land expansion were significantly improved. This result suggests that activities such as government or private business investment in fixed assets along rivers or local economic growth near rivers would further stimulate the built-up land expansion. The combination of physical and economic advantages might create strong enhancement that an individual factor could not achieve alone.

5. Discussion

5.1. *The policy factors*

Policy factors play an important role in built-up land expansion, and their effects can be reflected by physical and socioeconomic factors (Figure 3). Based on the above results, we find that several policies and a major event considerably affected the expansion of the built-up land in Beijing during this period.

The distance to the downtown area, as the most influential factor, required further exploration of its effects. The high PD value of the distance to the downtown area indicated the consistent spatial distributions between the factor and the built-up land expansion, i.e. the built-up land in Beijing generally developed in a concentric circle. After the establishment of China, six urban master plans were formed to guide the development of Beijing. The first plan, created in 1954, established the concentric circle pattern of urban development in Beijing, and its effects are still observed today, e.g. ring roads. The construction of the fifth and the sixth ring roads was finished in 2003 and 2009, respectively. During this period, the problem of low-density urban expansion between these two ring roads was especially serious (Kuang *et al*. 2009). Although the subsequent plan attempted to convert the spatial pattern to a 'two axes – two zones – multi-centre' pattern (Beijing Municipal Commission of Urban Planning 2005), the actual developing pattern of Beijing deviated substantially from that of the subsequent plans (Long *et al*. 2012). Overall, the large influence of the distance to the downtown area actually reflected the significant effects of the historical urban master plans of Beijing.

Environmental protection policies also played an important role in Beijing's built-up land development. The topographic factors were influential, and the expansion speed was relatively low in higher and steeper districts in the northwest of Beijing (Figure 2(a) and Figure 7). According to the sub-regional division of the 'Beijing Master Plan (2004–

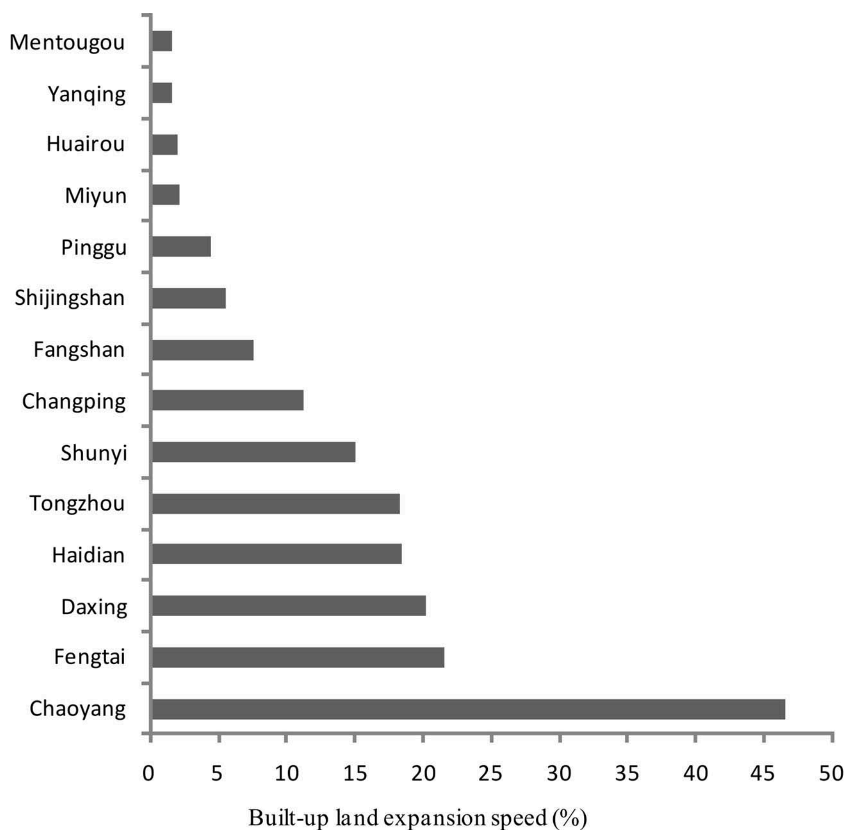


Figure 7. The built-up land expansion speed of 14 districts and counties in Beijing.

2020)', the mountain sub-region, including mountains in north Huairou, north Miyun, north Changping, west Mentougou, west Fangshan and Yanqing, was the ecological shelter of the city. Environmental protection policies such as the Sloping Land Conversion Programme and the Beijing and Tianjin Sandstorm Source Control Project were implemented in these areas. These policies restricted the built-up land construction because exploitation in mountain areas required additional financial and human resources and would degrade the ecosystem. As a consequence, the government promoted afforestation and ecological restoration in these areas (Beijing Municipal Commission of Urban Planning 2005).

The total investment in fixed assets was the second-most influential socioeconomic factor. As the financial base of built-up land construction, the investment in fixed assets was largely determined by the government in China, which reflected the political inclinations. According to official statistics, the Chaoyang district experienced the largest growth of the total investment in fixed assets during the period (Beijing Municipal Statistical Bureau 2001, 2011). The expansion speed was also greatest in the Chaoyang district, with a significant difference between it and the other districts (Figure 7), which also implied the influence of the government. In the year 2001, Beijing was elected the host city for the 2008 Olympic Games, and the main Olympic Games venues were located in the Chaoyang district. This event influenced Beijing's economy and urban development enormously, both during the preparation period and afterwards. The Olympic Games promoted the infrastructure construction in Beijing and stimulated the economic growth by attracting large amounts of investment and tourists (Li *et al*. 2009), which led to the expansion of built-up land.

5.2. *The implications of the geographical detector*

This study tests the applicability of the geographical detector for analysing the mechanism of built-up land expansion. The method is capable of identifying the relative importance of different factors, the expansion speed of different levels of each factor and the interactions between factors.

Compared with other methods, the geographical detector has two main advantages. First, it extracts the implicit interrelationships between factors and geographical phenomena without any assumptions or restrictions with respect to explanatory and response variables (Wang and Hu 2012). Like other spatial statistical methods, the geographical detector can analyse both continuous and categorical factors with only two sets of historical data. Developing such spatial statistical methods to analyse the drivers of built-up land expansion is essential, especially for places without long time-series data. In this study, we analysed only one period because historical socioeconomic data at the district level of Beijing were not available. We suggest that future studies focusing on larger areas with historical data available could analyse the spatiotemporal variation of factors using the geographical detector.

The second advantage is the innovative feature of the geographical detector in that it can detect the interactions between different factors. Complex interactions universally exist in the system of built-up land expansion. It is important to identify how physical, socioeconomic and policy factors interact with each other because these results may offer useful information to manage or predict built-up land expansion.

Several issues should be considered when using the geographical detector to analyse the driving force of built-up land expansion. First, the geographical detector is a statistical method that does not reveal the causality or the process of built-up land expansion. It is essential to identify the underlying reasons based on the results. For one thing, the effects of policy factors are difficult to be quantified and spatialised. In this study, we analysed the policy effects and obtained reasonable results using physical and socioeconomic factors as proxies. For another, it should be noted that some socio-economic factors may be the result of built-up land expansion. For example, the growth of GDP can be a consequence of built-up expansion in the form of annual land sales of the local government. Further studies are necessary to clarify the associations between built-up land expansion and some socioeconomic factors. Second, it is essential to test the MAUP (including the scale effects and the zoning effect) in the geographical detector before its application. Unlike previous studies using the geographical detector without any test of the MAUP (Hu *et al*. 2011, Liu and Yang 2012, Li *et al*. 2013a, Ren *et al*. 2014, Shen *et al*. 2015), this article attempts to analyse the MAUP of the geographical detector comprehensively. However, the scale effect of the data, such as LULC and DEM data, requires further exploration. It is likely that the optimal scale of the method will be different when the resolution of the input data varies. The above results are restricted to the scale of the geographical detector and the input data used in this study. Third, a limitation of the geographical detector is that it cannot predict or model either the area or the spatial distribution of built-up land expansion. In contrast, other methods such as bivariate regression or multiple linear regression can calculate the area of built-up land, and logistic regression can predict or model built-up land expansion in space.

6. Conclusions

Using Beijing as a case study, this study proves that the geographical detector is an effective method for analysing the driving forces and their interactions of built-up land expansion. New knowledge related to the modifiable areal unit problem of the geographical detector is gained, which is necessary to determine the optimal scale when using this method. Moreover, this new method is particularly useful for quantitatively characterising the interactions between a complex set of factors of built-up land expansion.

The results of our analysis show that, for our study region, the optimal scale of the geographical detector is 4000 m. Distance to the downtown area is the most influential spatial determinant, followed by the neighbourhood factors, topographic factors, population and total investment in fixed assets. Different factors show different characteristics of the built-up land expansion speed in space. The interactions between most factors enhance the effects of each other, and a few interactions show nonlinear enhancement. The most influential interactions are between the distance to the downtown area and physical factors. Finally, the urban plans, environmental protection policies and a major event exhibited a considerable impact on the expansion of Beijing's built-up land during this period.

In this study, we explored the driving mechanism of only one period at a regional scale for the reasons discussed above. Future studies may use the geographical detector to explore the spatial heterogeneity and temporal dynamics of drivers in larger areas with multi-period data sets. This study also offers a new perspective in researching the driving forces of land-use change and their interactions.

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References

Beijing Municipal Commission of Urban Planning, 2005. *Beijing master plan(2004-2020)* [online]. Available from: http://www.bjghw.gov.cn/web/static/catalogs/catalog_233/233.html [Accessed 16 January 2014]. (in Chinese).

Beijing Municipal Statistical Bureau, 2001. *Beijing statistical yearbook 2001*. Beijing: China Statistics Press. (in Chinese).

Beijing Municipal Statistical Bureau, 2011. *Beijing statistical yearbook 2011*. Beijing: China Statistics Press. (in Chinese).

Beijing Municipal Statistical Bureau, and National Bureau of Statistics Survey Office in Beijing, 2008. *The 30th anniversary of reform and opening up*. Beijing: China Statistics Press. (in Chinese).

Braimoh, A.K. and Onishi, T., 2007. Spatial determinants of urban land use change in Lagos, Nigeria. *Land Use Policy*, 24 (2), 502–515. doi:10.1016/j.landusepol.2006.09.001

Brewer, C.A. and Pickle, L., 2002. Evaluation of methods for classifying epidemiological data on choropleth maps in series. *Annals of the Association of American Geographers*, 92 (4), 662–681. doi:10.1111/1467-8306.00310

Cai, Y., *et al*., 2012. Urban expansion and its influencing factors in natural wetland distribution area in Fuzhou City, China. *Chinese Geographical Science*, 22 (5), 568–577. doi:10.1007/s11769-012-0564-7

Chan, C.K. and Yao, X., 2008. Air pollution in mega cities in China. *Atmospheric Environment*, 42 (1), 1–42. doi:10.1016/j.atmosenv.2007.09.003

Christensen, D.L., *et al*., 2008. Obesity and regional fat distribution in Kenyan populations: impact of ethnicity and urbanization. *Annals of Human Biology*, 35 (2), 232–249. doi:10.1080/03014460801949870

Clarke, K.C. and Gaydos, L.J., 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, 12 (7), 699–714. doi:10.1080/136588198241617

Dewan, A.M. and Yamaguchi, Y., 2009. Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. *Applied Geography*, 29 (3), 390–401. doi:10.1016/j.apgeog.2008.12.005

Dubovyk, O., Sliuzas, R., and Flacke, J., 2011. Spatio-temporal modelling of informal settlement development in Sancaktepe district, Istanbul, Turkey. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66 (2), 235–246. doi:10.1016/j.isprsjprs.2010.10.002

Fang, S., *et al*., 2005. The impact of interactions in spatial simulation of the dynamics of urban sprawl. *Landscape and Urban Planning*, 73 (4), 294–306. doi:10.1016/j.landurbplan.2004.08.006

Fernández, J.E., 2007. Resource consumption of new urban construction in China. *Journal of Industrial Ecology*, 11 (2), 99–115. doi:10.1162/jie.2007.1199

Grimm, N.B., *et al*., 2008. Global change and the ecology of cities. *Science*, 319 (5864), 756–760. doi:10.1126/science.1150195

Haregeweyn, N., *et al*., 2012. The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: a case study of Bahir Dar, Ethiopia. *Landscape and Urban Planning*, 106 (2), 149–157. doi:10.1016/j.landurbplan.2012.02.016

Herold, M., Goldstein, N.C., and Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment*, 86 (3), 286–302. doi:10.1016/s0034-4257(03)00075-0

Hu, Y., *et al*., 2011. Geographical detector-based risk assessment of the under-five mortality in the 2008 Wenchuan earthquake, China. *PLoS ONE*, 6 (6), e21427. doi:10.1371/journal.pone.0021427

Hu, Z. and Lo, C.P., 2007. Modeling urban growth in Atlanta using logistic regression. *Computers, Environment and Urban Systems*, 31 (6), 667–688. doi:10.1016/j.compenvurbsys.2006.11.001

Jelinski, D.E. and Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, 11 (3), 129–140. doi:10.1007/BF02447512

Kalnay, E. and Cai, M., 2003. Impact of urbanization and land-use change on climate. *Nature*, 423 (6939), 528–531. doi:10.1038/nature01675

Kuang, W., *et al*., 2009. Spatio-temporal patterns and driving forces of urban expansion in Beijing central city since 1932. *Journal of Geo-Information Science*, 11 (4), 428–435. (in Chinese). doi:10.3724/SP.J.1047.2010.00428

Lambin, E.F., *et al*., 1999. Land-use and land-cover change (LUCC): implementation strategy//a core project of the international geosphere-biosphere programme and the international human dimensions programme on global environmental change. *IGBP report 48. IHDP report 10*. Stockholm.

Li, H., Wang, Y., and Wan, X., 2009. Review of Beijing Olympic games and urban development. *Beijing City Planning & Construction Review*, 2009 (2), 34–39. (in Chinese).

Li, X., *et al*., 2013a. Influence of planting patterns on fluoroquinolone residues in the soil of an intensive vegetable cultivation area in northern China. *Science of the Total Environment*, 458–460, 63–69. doi:10.1016/j.scitotenv.2013.04.002

Li, X., Zhou, W., and Ouyang, Z., 2013b. Forty years of urban expansion in Beijing: what is the relative importance of physical, socioeconomic, and neighborhood factors? *Applied Geography*, 38, 1–10. doi:10.1016/j.apgeog.2012.11.004

Linard, C., Tatem, A.J., and Gilbert, M., 2013. Modelling spatial patterns of urban growth in Africa. *Applied Geography*, 44, 23–32. doi:10.1016/j.apgeog.2013.07.009

Liu, J., *et al*., 2010. Spatial patterns and driving forces of land use change in China during the early 21st century. *Journal of Geographical Sciences*, 20 (4), 483–494. doi:10.1007/s11442-010-0483-4

Liu, J., Zhan, J., and Deng, X., 2005. Spatio-temporal patterns and driving forces of urban land expansion in China during the economic reform era. *AMBIO: A Journal of the Human Environment*, 34 (6), 450–455. doi:10.1579/0044-7447-34.6.450

Liu, Y. and Yang, R., 2012. The spatial characteristics and formation mechanism of the county urbanization in China. *Acta Geographica Sinica*, 67 (8), 1011–1020. (in Chinese). doi:10.11821/xb201208001

Long, Y., Gu, Y., and Han, H., 2012. Spatiotemporal heterogeneity of urban planning implementation effectiveness: evidence from five urban master plans of Beijing. *Landscape and Urban Planning*, 108 (2–4), 103–111. doi:10.1016/j.landurbplan.2012.08.005

Luo, J. and Wei, Y.H.D., 2009. Modeling spatial variations of urban growth patterns in Chinese cities: the case of Nanjing. *Landscape and Urban Planning*, 91 (2), 51–64. doi:10.1016/j.landurbplan.2008.11.010

Ministry of Construction, PR China, 1998. *Standard for basic terminology of urban planning GB/r 50280-98*. Beijing: China Architecture & Building Press. (in Chinese).

Müller, K., Steinmeier, C., and Küchler, M., 2010. Urban growth along motorways in Switzerland. *Landscape and Urban Planning*, 98 (1), 3–12. doi:10.1016/j.landurbplan.2010.07.004

Ren, Y., *et al*., 2014. Geographical modeling of spatial interaction between human activity and forest connectivity in an urban landscape of southeast China. *Landscape Ecology*, 29 (10), 1741–1758. doi:10.1007/s10980-014-0094-z

Seto, K.C., *et al*., 2011. A meta-analysis of global urban land expansion. *PloS ONE*, 6 (8), e23777. doi:10.1371/journal.pone.0023777

Shao, J., Wei, C., and Xie, D., 2006. An insight on drivers of land use change at regional scale. *Chinese Geographical Science*, 16 (2), 176–182. doi:10.1007/s11769-006-0014-5

Shen, J., *et al*., 2015. Construction of a GeogDetector-based model system to indicate the potential occurrence of grasshoppers in Inner Mongolia steppe habitats. *Bulletin of Entomological Research*, 105 (3), 1–12. doi:10.1017/S0007485315000152

Shi, L., *et al*., 2009. Urban three-dimensional expansion and its driving forces —a case study of Shanghai, China. *Chinese Geographical Science*, 19 (4), 291–298. doi:10.1007/s11769-009-0291-x

Shrestha, M.K., *et al*., 2012. Land fragmentation due to rapid urbanization in the phoenix metropolitan area: analyzing the spatiotemporal patterns and drivers. *Applied Geography*, 32 (2), 522–531. doi:10.1016/j.apgeog.2011.04.004

Shu, B., *et al*., 2014. Spatiotemporal variation analysis of driving forces of urban land spatial expansion using logistic regression: a case study of port towns in Taicang City, China. *Habitat International*, 43, 181–190. doi:10.1016/j.habitatint.2014.02.004

Spatial Analysis Group, IGSNRR, 2013. *Excel-GeoDetector* [online]. Chinese Academy of Sciences. Available from: http://www.sssampling.org/Excel-Geodetector/ [Accessed 10 October 2015].

Thapa, R.B. and Murayama, Y., 2010. Drivers of urban growth in the Kathmandu valley, Nepal: examining the efficacy of the analytic hierarchy process. *Applied Geography*, 30 (1), 70–83. doi:10.1016/j.apgeog.2009.10.002

Wang, J.F., *et al*., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. *International Journal of Geographical Information Science*, 24 (1), 107–127. doi:10.1080/13658810802443457

Wang, J.-F. and Hu, Y., 2012. Environmental health risk detection with GeogDetector. *Environmental Modelling & Software*, 33, 114–115. doi:10.1016/j.envsoft.2012.01.015

Wu, K.Y. and Zhang, H., 2012. Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978–2008). *Applied Geography*, 34, 137–145. doi:10.1016/j.apgeog.2011.11.006

Zhang, Z., *et al*., 2014. A 2010 update of national land use/cover database of China at 1:100000 scale using medium spatial resolution satellite images. *Remote Sensing of Environment*, 149, 142–154. doi:10.1016/j.rse.2014.04.004