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Forty years of urban expansion in Beijing: What is the relative importance of physical, socioeconomic, and neighborhood factors?

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A B S T R A C T

Urban expansion is one of the major causes of many ecological and environmental problems in urban areas and the surrounding regions. Understanding the process of urban expansion and its driving factors is crucial for urban growth planning and management to mitigate the adverse impacts of such growth. Previous studies have primarily been conducted from a static point of view by examining the process of urban expansion for only one or two time periods. Few studies have investigated the temporal dynamics of the effects of the driving factors in urban expansion. Using Beijing as a case study, this research aims to fill this gap. Urban expansion from 1972 to 2010 was detected from multi-temporal remote sensing images for four time periods. The effects of physical, socioeconomic, and neighborhood factors on urban expansion and their temporal dynamics were investigated using binary logistic regression. In addition, the relative importance of the three types of driving factors was examined using variance partitioning. The results showed that Beijing has undergone rapid and magnificent urban expansion in the past forty years. Physical, socioeconomic, and neighborhood factors have simultaneously affected this expansion. Socioeconomic factors were the most important driving force, except during the period of 1972–1984. In addition, the effects of these driving factors on urban expansion varied with time. The magnitude of the unique effects of physical factors and neighborhood factors declined while that of socioeconomic factors increased along with the urbanization process. The findings of this study can help us better understand the process of urban expansion and thus have important implications for urban planning and management in Beijing and similar cities.

Introduction

Currently, more than half of the world's population resides in cities, and this figure is projected to reach 67.2% in 2050 (United Nations, 2012). Along with the rapid growth of urban populations comes rapid urban expansion. The total global urban area quadrupled during the period from 1970 to 2000 (Seto, Fragkias, Güneralp, & Reilly, 2011). Though urbanization promotes socioeconomic development and improves quality of life, urban expansion inevitably converts the natural and semi-natural ecosystems into impervious surfaces and thus has tremendous ecological and environmental consequences, such as forest loss and fragmentation (Miller, 2012; Zhou, Huang, Pickett, & Cadenasso, 2011), local and regional climate change (Kalnay & Cai, 2003; Kaufmann et al., 2007), hydrological circle alteration (Jacobson, 2011; Yang, Bowling, Cherkauer, & Pijanowski, 2011), and biotic homogenization (McKinney, 2008, 2006). While urban land covers only less than 3% of the global terrestrial surface, the ecological and environmental impacts of urban expansion are global (Grimm et al., 2008).

Understanding the process of urban expansion and its driving factors is crucial for effective urban growth planning and management in order to mitigate expansion's adverse impacts. A considerable amount of research has been conducted all around the world to understand the spatial patterns, the driving factors, and the ecological and social consequences of urban expansion (e.g., Pickett et al., 2011; Seto et al., 2011; Wang, He, Liu, Zhuang, & Hong, 2012). In particular, there has been an increasing interest in identifying and understanding the effects of the driving factors of urban expansion, as this understanding is crucially important for the design of effective urban planning and management strategies (Dubovyk, Sliuzas, & Flacke, 2011; Long, Gu, & Han, 2012; Tavares, Pato, & Magalhães, 2012; Thapa & Murayama, 2010).

Many approaches have been used and developed to identify and examine the effects of driving factors on urban expansion,

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including bivariate regression (BR) (Haregeweyn, Fikadu, Tsunekawa, Tsubo, & Meshesha, 2012; Wu & Zhang, 2012), multiple linear regression (MLR) (Dewan & Yamaguchi, 2009; Müller, Steinmeier, & Küchler, 2010; Seto et al., 2011), analytic hierarchy process (AHP) (Thapa & Murayama, 2010), adaptive Monte Carlo (aMC) (Chen et al., 2002), redundancy analysis (RDA) (Hietel, Waldhardt, & Otte, 2007), canonical correspondence analysis (CCA) (Fu et al., 2006), and logistic regression (Dendoncker, Rounsevell, & Bogaert, 2007; Dubovyk et al., 2011; Long et al., 2012; Reilly, O'Mara, & Seto, 2009). Of these methods, the most widely used is logistic regression, which has the following advantages: 1) it is an effective method to handle binary dependent variables, which is the case in LULC change (change or no change); 2) there is no assumption of normality or a linear relationship between the dependent and independent variables (Cheng & Masser, 2003); 3) the results of logistic regression can be directly used to predict the locations of future urban expansions (Dubovyk et al., 2011; Hu & Lo, 2007).

Using these methods, four types of driving factors have been generally identified: physical factors, socioeconomic factors, neighborhood factors, and land use policy and urban planning factors (Table 1).

Urban expansion is a temporal dynamic process, in which not only its spatial patterns but also its driving factors vary over time. There is a proliferation of studies focusing on the temporal dynamics of spatial patterns of urban expansion (e.g., Bhatta, 2009; Geymen & Baz, 2008; Maktav & Erbek, 2005; Seto & Fragkias, 2005; Tv, Aithal, & Sanna, 2012). However, fewer studies have focused on the temporal changes in the driving factors of urban expansion. The study of Reilly et al. (2009) reported that along with the process of urbanization, the effects of distance to the highway and the percentage of urban land within a 1 km window on urban expansion changed from positive to negative after 1948 in Silicon Valley in the U.S. Current studies on the driving factors behind urban expansion have been mostly conducted from a static point of view by examining the process of urban expansion for only one or two time periods. The temporal dynamics of the effects of driving factors on urban expansion are far from being thoroughly understood.

This study aims to investigate the effects of physical, socioeconomic, and neighborhood factors on urban expansion in Beijing from 1972 to 2010. Specifically, we attempted to address two questions: 1) What is the relative importance of the three types of driving factors? and 2) Do the effects of these driving factors change along with the process of urbanization? Urban expansion during four time periods (1972–1984–1992–2000–2010) was detected based on multi-temporal remote sensing images. Seven variables of physical, socioeconomic, and neighborhood factors were selected as the potential driving factors of urban expansion. A logistic regression model was built for each time period to test the effects of the selected variables on urban expansion. We applied variance portioning to examine the relative importance of the three types of driving factors.

Method

Study area

Beijing (between 39°28′–41°25′ N and between 115°25′–117°30′ E) is located in the northeast of the North China Plain, with a total area of approximately 16,410 km^2; roughly 38% is flat and 62% is mountainous. The mountainous areas are mostly located in the north and west, with an average elevation of approximately 1000–1500 m, while the plains areas are in the center and southeast, with an elevation ranging from 20 to 60 m (Fig. 1). Beijing has a monsoon-influenced humid continental climate, characterized by a hot and humid summer but a dry and cold winter. The mean annual temperature is 12 °C and the mean annual precipitation is 600 mm.

Beijing city has a 3000 year history and has been the capital city of China for more than 850 years. Its urbanization rate was low, and the urban area was mainly confined to the area within the second ring road before 1949. After that, China experienced considerable socioeconomic transformation (e.g., the foundation of the People's Republic of China in 1949 and the implementation of the Open and Reform Policy in 1978), which led to significant socioeconomic development in Beijing. The total population increased by 125% from 8.72 million in 1987 to 19.62 million in 2010, and the percentage of the urban population increased from 55% to 86% (Beijing Municipal Statistical Bureau, 2011). The gross domestic product (GDP) also increased rapidly from 10.88 billion RMB in 1978 to 1411.36 billion RMB in 2010 (Beijing Municipal Statistical Bureau, 2011). Along with this rapid socioeconomic development was the fast expansion of Beijing city. The area of developed land in

Table 1
Summary of the driving factors of urban expansion in the literature.

Types of factors	Driving factors
Physical factors	Slope and elevation (Aspinall, 2004; Batisani & Yarnal, 2009; Braimoh & Onishi, 2007; Dubovyk et al., 2011; He et al., 2006; Hu & Lo, 2007; Huang et al., 2009; Müller et al., 2010; Reilly et al., 2009; Wu, Huang, & Fung, 2009; Ye et al., 2011)
	Distance to river and water (Aspinall, 2004; Batisani & Yarnal, 2009; Cheng & Masser, 2003; Luo & Wei, 2009)
	Flood risk area (Poelmans & Van Rompaey, 2009)
Socioeconomic factors	Population (Batisani & Yarnal, 2009; Dewan & Yamaguchi, 2009; Dubovyk et al., 2011; Huang et al., 2009; Liu & Zhou, 2005; Seto et al., 2011; Wu et al., 2009; Wu & Yeh, 1997; Wu & Zhang, 2012)
	Gross domestic product (GDP) (Dewan & Yamaguchi, 2009; Wu & Zhang, 2012; Liu & Zhou, 2005; Seto et al., 2011)
	Distance to socioeconomic center, such as central business district (CBD), city center, subcity center, etc. (Aspinall, 2004; Batisani & Yarnal, 2009; Braimoh & Onishi, 2007; Cheng & Masser, 2003; Dubovyk et al., 2011; He et al., 2006; Hu & Lo, 2007; Luo & Wei, 2009; Reilly et al., 2009; Vermeiren, Van Rompaey, Loopmans, Serwajja, & Mukwaya, 2012; Wu et al., 2009; Wu & Yeh, 1997; Ye et al., 2011)
	Distance to road (Batisani & Yarnal, 2009; Cheng & Masser, 2003; Dubovyk et al., 2011; He et al., 2006; Hu & Lo, 2007; Huang et al., 2009; Liu & Zhou, 2005; Luo & Wei, 2009; Müller et al., 2010; Poelmans & Van Rompaey, 2009; Reilly et al., 2009; Vermeiren et al., 2012; Wu et al., 2009; Wu & Yeh, 1997; Ye et al., 2011)
	Travel time (distance) to airport or harbor (Braimoh & Onishi, 2007; He et al., 2006)
Neighborhood factors	Proportion of urban land in the surrounding area (Braimoh & Onishi, 2007; Cheng & Masser, 2003; Dubovyk et al., 2011; Hu & Lo, 2007; Liu & Zhou, 2005; Luo & Wei, 2009; Müller et al., 2010; Reilly et al., 2009; Wu et al., 2009)
	Proportion of undeveloped land (e.g., farmland, forest) in the surrounding area (Braimoh & Onishi, 2007; Dubovyk et al., 2011; Huang et al., 2009; Luo & Wei, 2009)
Land use policy and urban planning	Development control zone (Huang et al., 2009)
	Conservation area (Hu & Lo, 2007; Long et al., 2012)
	Master plan (Cheng & Masser, 2003; Long et al., 2012; Tavares et al., 2012)

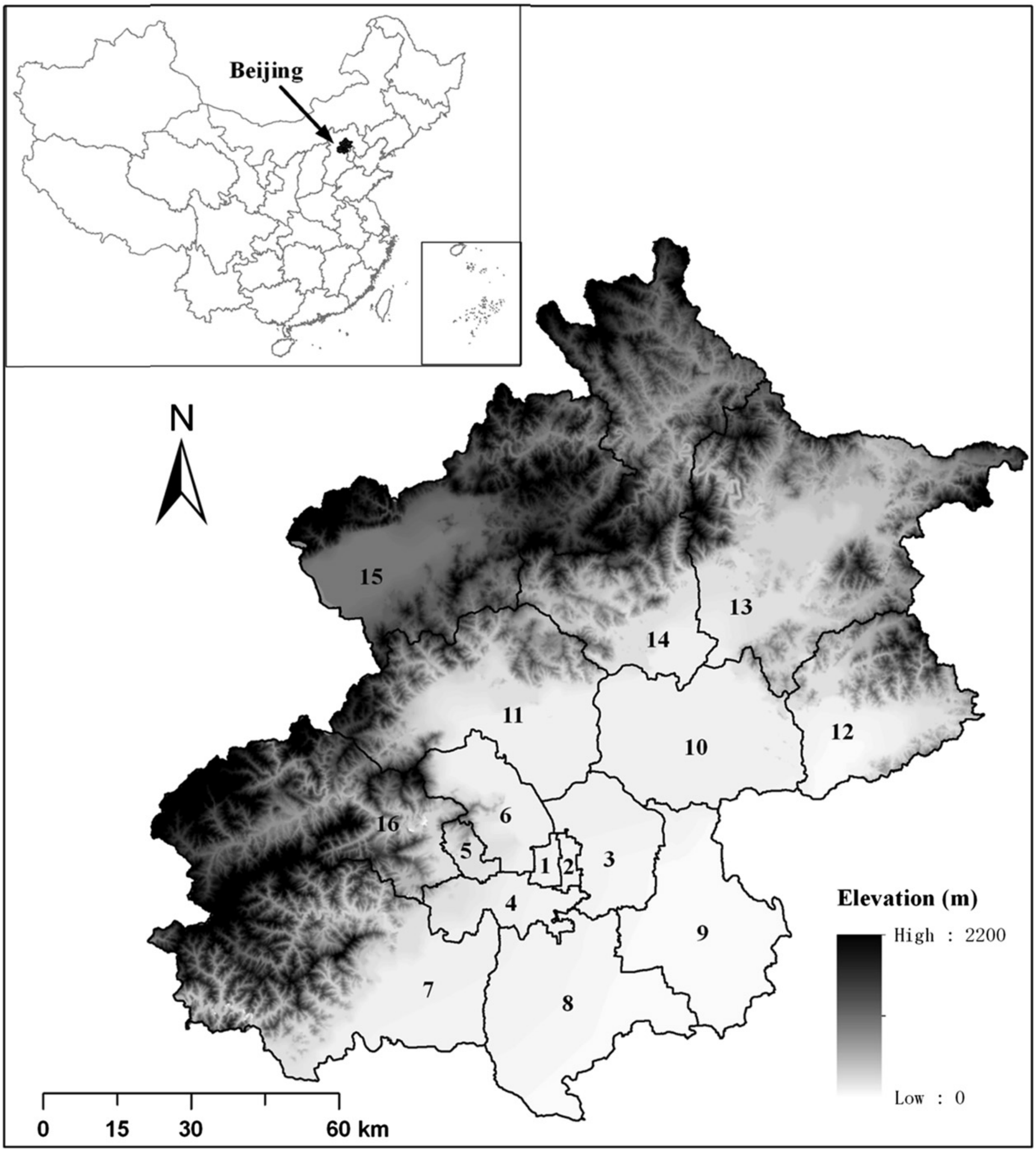

Fig. 1. Location of the studied area and its topography. (1: Xicheng, 2: Dongcheng, 3: Chaoyang, 4: Fengtai, 5: Shijingshan, 6: Haidian, 7: Fangshan, 8: Daxing, 9: Tongzhou, 10: Shunyi, 11: Changping, 12: Pinggu, 13: Miyun, 14: Huairou, 15: Yanqing; 16: Mentougou).

Beijing city increased 558% from 183.84 km^2 in 1973 to 1209.97 km^2 in 2005 (Mu et al., 2007).

Beijing is composed of fourteen districts (Xicheng, Dongcheng, Haidian, Shijingshan, Fengtai, Chaoyang, Mentougou, Fangshan, Daxing, Tongzhou, Shunyi, Changping, Pinggu, and Huairou), and two counties (Yanqing and Miyun) (Fig. 1). Forest is the major land use type, which covered an area of 6870.8 km^2 (42% of the total area) in 2008 and is distributed mainly in the mountainous areas. Urban land took up 21% of Beijing in 2008, located on the plains area surrounding the city center. There were 2316.86 km^2 of farmland (14% of the total area) in 2008, mainly located in the periphery of the city on the plains areas (Beijing Municipal Bureau of Land and Resources, 2009).

Quantifying the extent and rate of urban expansion

Multi-temporal satellite images were used to detect urban expansion in Beijing from 1972 to 2010 (Table 2). The data from 1972 were Corona (KH-4B) panchromatic images that were taken by the Central Intelligence Agency (CIA) and the U.S. Air Force and declassified on February 24, 1995 (Dashora, Lohani, & Malik, 2007). These images were acquired from the U.S. Geological Survey's Earth Resources Observation and Science (USGS/EROS) and had a spatial resolution of 1.8 m. The Corona images were georeferenced to orthorectified SPOT images collected in 2007 using second-order polynomial transformation with the nearest neighbor resampling method. The root mean square error (RMSE) of the geometric

Table 2
The description of images used for mapping urban expansion from 1972 to 2010.

Date (y/m/d)	Satellite (sensor)	Spatial resolution (m)	Spectral resolution
1972/05/29	Corona (KH-4B)	1.8	Panchromatic
1984/10/03	Landsat 5 (TM)	30	Multispectral
1992/09/07	Landsat 5 (TM)	30	Multispectral
2000/08/20	Landsat 7 (ETM+)	30	Multispectral
2010/08/08	Landsat 5 (TM)	30	Multispectral

correction was smaller than 1 pixel (1.8 m). For the years 1984, 1992, 2000, and 2010, Landsat 5 TM and Landsat 7 ETM+ images with a spatial resolution of 30 m were used (Table 2). These Landsat images were also georeferenced to the SPOT images with an RMSE of less than 0.5 pixels (15 m). The Corona images have a much higher spatial resolution than the TM images. A possible way to address this inconsistency is to decrease the spatial resolution of the Corona images to that of TM (Bhatta, Saraswati, & Bandyopadhyay, 2010). However, downscaling the Corona images to a 30 m resolution would make it more difficult to differentiate between urban and non-urban land, as the Corona images have only one band. Thus, we interpreted the images directly and then resampled the classified map to a 30 m resolution to address the inconsistencies in spatial resolution between the different images.

Urban land in this study was defined as developed land covered by an impervious surface (e.g., residential land, commercial land, industrial land, roads) (Bhatta et al., 2010; Müller et al., 2010). We used the post-classification method to detect urban expansion by overlaying multi-temporal LULC maps. The most common method for generating a series of multi-temporal LULC maps to detect LULC change is to classify the remote sensing images of each time independently (e.g., Bhatta et al. (2010) and Wu and Zhang (2012)). However, this method can lead to the detection of spurious changes because of spatial misalignment (Linke et al., 2009; Zhou, Troy, & Grove, 2008). These spurious changes can be reduced by using a backdating method (Feranec, Hazeu, Christensen, & Jaffrain, 2007; Linke et al., 2009). Using a backdating method, the detection of urban expansion from 1972 to 2010 involves the following two steps: 1) generating the LULC map in 2010, and 2) using the 2010 LULC data as the base map, creating LULC maps for the years 2000, 1992, 1984, and 1972, and then detecting urban expansion.

Generating a base map: An objected-based classification method was applied to the 2010 Landsat TM images to separate developed land (i.e., urban land) from non-urban land using Definiens Developer 7.0. This method was chosen as it produces higher classification accuracy than the pixel-based classification method (Bhaskaran, Paramananda, & Ramnarayan, 2010; Zhou et al., 2008). A slope map derived from a digital elevation model (DEM) of 30 m resolution and a land use map from 2007 acquired from the Beijing Municipal Bureau of Land and Resources were used as auxiliary maps during the classification. The image was first segmented into different objects (polygons) using a multi-resolution segmentation approach (Zhou & Troy, 2008). Urban land was then recognized based on object characteristics such as spectral features, spatial relations, statistical indices, and the information of the auxiliary maps. Consequently, a map with two land use types (i.e., urban and non-urban) was generated. We selected 200 randomly generated points to assess the accuracy of the map. High-resolution images from Google Earth acquired in 2010 were used as reference data. The accuracy of this map was estimated at a Kappa value of 0.9.

Creating LULC maps for other years and detecting urban expansion: A backdating method was then applied to map urban expansion during the four time periods. For example, to map the changes (i.e., urban expansion) from 2000 to 2010, we overlaid the 2010 map, the base map, on the images acquired in 2000 and detected the changes through visual interpretation. We marked the polygons that showed changes. For polygons where changes only occurred in a part of them, we split these polygons and marked the part with the change. Urban expansion during other three periods was mapped using the same procedure. As a result, we generated five LULC maps with binary classes (i.e., urban and non-urban) (Fig. 2) and four maps showing urban expansion for the four time periods in the past forty years (Fig. 3). All these maps were converted to raster files with a 30 m resolution using the maximum area algorithm in ArcGIS 9.3.

Potential driving factors of urban expansion

We did a comprehensive literature review and found that four types of driving factors have been typically considered in studies of urban expansion (Table 1). In this study, we selected seven variables representing physical, socioeconomic, and neighborhood factors (Table 3). We did not include factors of land use policy and spatial planning because of the lack of long-term data on these aspects.

Physical factors

Physical factors (e.g., climate and topography) are the fundamental determinants of the extent, the spatial distribution, and the spatial expansion of urban land. Precipitation and topography affect the potential extent of a city by restricting the water supply and the land provisions at the city level (He, Okada, Zhang, Shi, & Zhang, 2006; Liu & Zhou, 2005). Topography also determines the location of urban expansion within a city because urban development generally prefers flat areas (Aspinall, 2004; Müller et al., 2010). As we wanted to identify the driving factors that determine the location of urban expansion in this study, two topographic variables (elevation and slope) were selected. Both elevation and slope were derived from the 30 m resolution DEM. The slope was calculated as a percentage, namely, the rise divided by the run, multiplied by 100.

Socioeconomic factors

Socioeconomic development is one of the most important driving factors of urban expansion. Census-based socioeconomic variables (e.g., population and GDP) have shown significant positive effects on urban expansion at various scales (Seto et al., 2011; Wu & Zhang, 2012). Other than census-based socioeconomic variables, proximity variables, such as distance to socioeconomic centers and distance to roads, also significantly affect urban expansion (Luo & Wei, 2009; Müller et al., 2010; Reilly et al., 2009). In this study, we selected two types of proximity variables (i.e., distance to socioeconomic centers and distance to roads) to represent socioeconomic factors, as detailed below. We did not include GDP or population because access to these data for the entire time period was denied and the spatial resolution of the data for these two variables is much coarser than that of the variables used in the logistic regression.

(1) Distance to socioeconomic center. The socioeconomic center was usually represented as the city center, the central business district (CBD), the suburban (county) center, etc. The greater the proximity to these centers, the higher the probability of being urbanized (Braimoh & Onishi, 2007; He et al., 2006). In this study, two types of socioeconomic centers were selected: the city center and the county (or district) center. The former may explain the spatial pattern of concentric urban expansion, while the latter can better explain the urban expansion of satellite cities. Proximity to the city center and the county center was calculated as the Euclidean nearest distance using Spatial Analyst in ArcGIS™ 9.3.
(2) Distance to roads. Roads play an indispensable role in urban expansion because they not only decrease the cost of

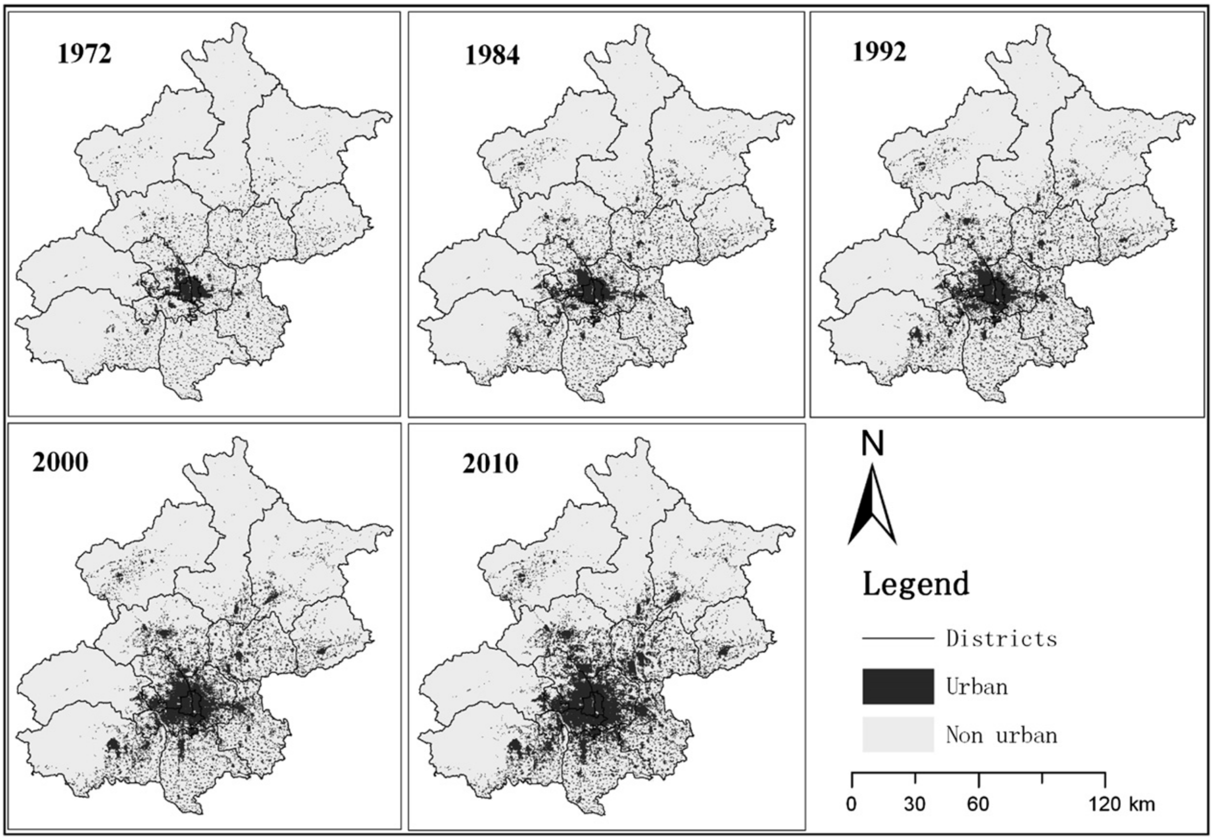

Fig. 2. Spatial distribution of urban land in five years.

construction but also facilitate residents' daily lives. Therefore, areas closer to roads might have a higher probability of urban expansion (Liu & Zhou, 2005; Reilly et al., 2009; Ye, Zhang, Liu, & Wu, 2011). Roads of different types are usually designed for different purposes and may have varied effects on urban expansion. In this study, we considered highways (national-level roads connecting Beijing and other cities) and major roads (province-level roads connecting socioeconomic centers in Beijing). As roads are usually temporally dynamic, a single dataset of roads could not effectively represent road conditions for such a long time period (1972–2010) in this study. We applied the backdating procedure to map the road network for each year. We first developed the road dataset for 2010 based on the map of road network planning from the Master Plan of Beijing City (2004–2020) and the TM image of 2010. Then, we constructed the road dataset for 2000 by eliminating the roads that did not exist on the images from 2000. Similar procedures were used to obtain the roads layer for 1990, 1984, and 1972. The Euclidean distances to the two types of roads were calculated using Spatial Analyst in ArcGIS 9.3. During the logistical regression analysis that was performed later, distance to the roads during the final year of the time period was used. For example, distance to the roads in 2010 was used to analyze the effects of the proximity to roads on urban expansion from 2000 to 2010. The distance to roads in 2010 was used because the roads completed in 2010 would affect urban expansion during the period of 2000–2010.

Neighborhood factors

Neighborhood factors in this study are defined as the proportion of different land uses (e.g., urban, agriculture, forest) in a surrounding area. The proportion of land that is urban is the most frequently considered variable. A large number of articles have consistently reported that locations are more likely to be developed if they are surrounded by more urban land (Liu & Zhou, 2005; Luo & Wei, 2009; Müller et al., 2010). We calculated the percent of urban land in each pixel within a 7 × 7 pixel window (approximately 100 m radius) to investigate the effects of local neighborhood factors on urban expansion. We used a 7 × 7 window because a previous study in Beijing found that built-up areas within a 100 m buffer are most likely to affect the possibility of a location being developed (Liu & Zhou, 2005).

All of the selected variables were compiled in raster files with a spatial resolution of 30 m, equal to that of urban expansion map.

Statistical analysis

Data sampling

There were a very large number of pixels (3378 × 3690) with a 30 m resolution for the dependent and explanatory variables in this study. It was not efficient, if not impossible, to handle such data in the later statistical analysis. In addition, both dependent and explanatory variables may have been spatially autocorrelated, which may have biased the results of the later regression analysis (Cheng & Masser, 2003; Crk, Uriarte, Corsi, & Flynn, 2009; Luo & Wei, 2009). These two issues can be addressed through a data sampling approach that integrates systematic and random sampling (Cheng & Masser, 2003; Crk et al., 2009; Luo & Wei, 2009). We followed this approach in our study. For each period, we first randomly selected 20,000 sample points with the distance between each point greater than 400 m to minimize spatial autocorrelation. We then coded the points that were urbanized during the period as 1 and the points that were not urbanized as 0. The resultant number of points with no change (i.e., coded as 0) was

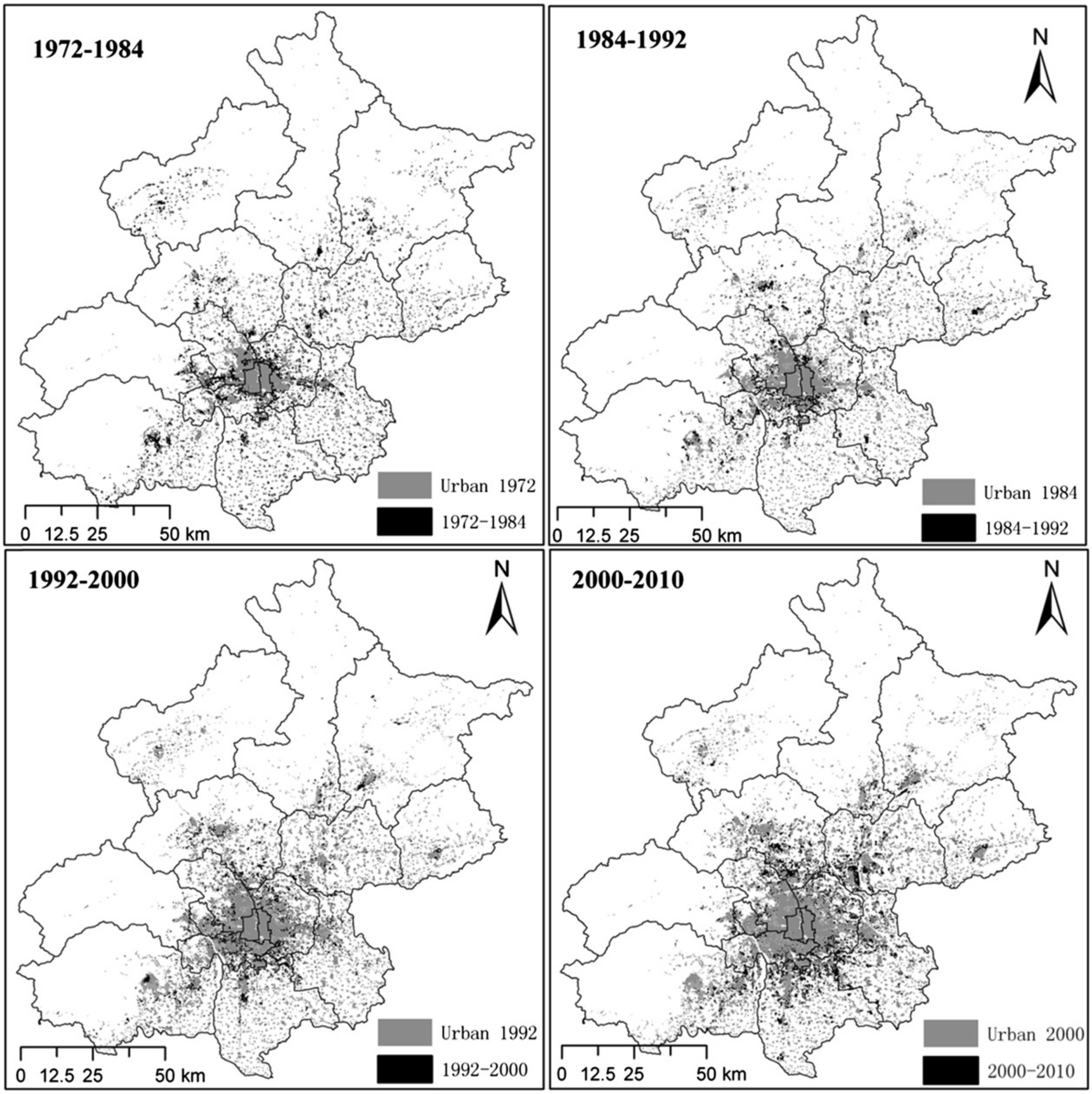

Fig. 3. Urban expansion in Beijing from 1972 to 2010.

much larger than the number of points with change (i.e., coded as 1). Therefore, to obtain an equal number of samples of locations with change and no change, we ran another random sampling procedure on points coded as 0 (Cheng & Masser, 2003; Monteiro, Fava, Hiltbrunner, Della Marianna, & Bocchi, 2011). Consequently, the numbers of sample points used in the later logistical regression were 1106, 650, 968, and 1244 for the periods of 1972–1984, 1984–1992, 1992–2000, and 2000–2010, respectively.

Table 3
List of the selected drivers of urban expansion.

Category	Variables	Description
Physical factor	Elevation (m)	Elevation
	Slope	Slope
Socioeconomic factor	Dis2City (km)	Distance to city center
	Dis2County (km)	Distance to county center
	Dis2Hiway (km)	Distance to highway
	Dis2Maroad(km)	Distance to major road
Neighborhood factor	PropUrban	Proportion of urban area within a 210 m window

Binary logistic regression

Binary logistic regression was applied to investigate the effects of the selected variables on the probability of urban expansion. The logistical regression model was formed as:

$$\text{logit}(y) - \log\left(\frac{y}{1-y}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \quad (1)$$

where y is the probability of urbanization, β_0 is the intercept, β is a vector of estimated parameters, x is a vector of driving factors, and ε is a randomly distributed residual error.

One logistic regression model was built for each time period. The dependent variable was a binary vector coded as 1 (changed) or 0 (no change). The explanatory variables were the seven factors described in Section 2.3.

The Percent Correct Predictions (PCP) was calculated to evaluate the performance of the logistic regression model. The samples were classified into predicted 0s and 1s based on the built model, and then they were compared to the actual 0s and 1s. Finally, the (total) PCP was calculated as the number of correctly predicted cases divided by the total number of cases. In addition, the percentage of correctly predicted area under the curve (AUC) of the relative operating characteristic (ROC) was calculated (Crk et al., 2009). The ROC curve was plotted with the sensitivity (true positive rate) versus 1-the specificity (false positive rate) for every possible cutoff that could be chosen to convert the predicted probability of urban expansion into the actual degree of urbanization. The AUC was then calculated as a measure of the probability of the model to render a higher predicted value of urbanization for a pixel that underwent urbanization than for those that did not. An AUC value approaching 1 indicates perfect performance of the model.

Nagelkerke's R^2 was used to evaluate the model's fit (Betts, Diamond, Forbes, Villard, & Gunn, 2006; Nagelkerke, 1991). Nagelkerke's R^2 was calculated using the following equation:

$$R^2 = 1 - \exp[-2/n(l_A - l_0)] \tag{2}$$

where n is the sample size, l_A is the log-likelihood of the focused model, and l_0 is the log-likelihood of the null model with only the intercept as a predictor. The calculated R^2 is consistent with the classical R^2 and can be interpreted as the proportion of explained variation (Betts et al., 2006; Nagelkerke, 1991).

In addition, Moran's I of the residual of the models was calculated to check the spatial autocorrelation of the residuals of the models using GeoDa (Anselin, 2005).

Variance partitioning

Researchers and decision-makers not only engage in the identification of the driving factors of urban expansion but are also interested in the relative importance of these factors (Braimoh & Onishi, 2007; Long et al., 2012; Thapa & Murayama, 2010). Variance partitioning is recognized as an effective method to address this question by decomposing the variance of the dependent variable into different parts that are explained by the explanatory variables (or groups of variables) independently or jointly (Anderson & Gribble, 1998; Betts et al., 2006; Heikkinen, Luoto, Kuussaari, & Pöyry, 2005). We conducted variance partitioning for each logistic regression model to examine the relative importance of the physical factors, the socioeconomic factors, and the neighborhood factors in determining urban expansion. The variation in the probability of urban expansion that was explained, namely, Nagelkerke's R^2, was decomposed into seven fractions: (*1*) unique effects of physical factors, (*2*) unique effects of socioeconomic factors, (*3*) unique effects of neighborhood factors, (*4*) joint effects of physical and socioeconomic factors, (*5*) joint effects of socioeconomic and neighborhood factors, (*6*) joint effects of physical and neighborhood factors, and (*7*) joint effects of physical, socioeconomic, and neighborhood factors. The calculation of each fraction followed the procedure detailed in Anderson and Gribble (1998) and Heikkinen et al. (2005).

Results

Spatial patterns of urban expansion

In the past forty years, Beijing experienced considerable urban expansion. The area of urban land in 1972 was 861 km^2, accounting for 5.26% of the total area. In 2010, urban land increased to 2666 km^2 and comprised 16.28% of the total area (Table 4). More than 1800 km^2 land was urbanized during the period from 1972 to 2010. The period from 1992 to 2000 had the highest annual expansion rate (58.91 km^2/yr), followed by the periods from 2000 to 2010 (56.78 km^2/yr), 1972 to 1984 (40.51 km^2/yr), and 1984 to 1992 (35.02 km^2/yr) (Table 4).

Table 4
Urban land and urban expansion in Beijing from 1972 to 2010.

Year	Area (km^2)	Percent (%)	Time period	Annual expansion (km^2/yr)
1972	861.04	5.26		
1984	1347.19	8.22	1972–1984	40.51
1992	1627.34	9.93	1984–1992	35.02
2000	2098.64	12.81	1992–2000	58.91
2010	2666.40	16.28	2000–2010	56.78

Spatial modeling of urban expansion

Logistic regression models including the selected seven variables effectively explained the variance in urban expansion for all four periods. The values of PCP from high to low were 88.6, 84.3, 81.5, and 78 for the periods of 1992–2000, 2000–2010, 1984–1992, and 1972–1984, respectively (Table 5). The areas under the ROC curves were 0.88, 0.90, 0.87, and 0.92 for the four consecutive periods, respectively (Table 5), indicating a high degree of spatial consistency between the model predictions and actual urban expansion. Similar to the AUC, the explained variance of the probability of urban expansion for the period of 2000–2010 was the highest (49%), followed by the periods of 1984–1992, 1992–2000, and 1972–1984, which had values of 44%, 43%, and 42%, respectively (Table 5). The residuals of the models for the periods of 1972–1984 and 1992–2000 showed significant but very weak spatial autocorrelations (Table 5).

The variables of physical, socioeconomic, and neighborhood factors together significantly affected the urban expansion in Beijing (Table 5). Elevation and slope showed consistently negative effects on urban expansion in the past forty years, except for elevation during the period of 1984–1992. The percentage of urban areas within a 210 m window had consistently positive effects on urban expansion for all of the four periods. The socioeconomic factors also showed significant influences on urban expansion, but their effects varied over time. The distances to the city center and the county center showed consistently negative relationships with urban expansion, while the effects of the distance to roads on urban expansion varied over time. The distance to the highways negatively affected urban expansion after 1992, and the distance to major roads only had effects on urban expansion in the period of 1992–2000 (Table 5).

Table 5
Summary of the logistic regression models.

Variables	1972–1984	1984–1992	1992–2000	2000–2010
Constant	1.94**	2.04**	2.54**	2.74**
Elevation (m)	−0.002**	−0.001	−0.003**	−0.003**
Slope	−0.057**	−0.078**	−0.036**	−0.034**
Dis2City (km)	−0.014**	−0.033**	−0.019**	−0.028**
Dis2County (km)	−0.053**	−0.069**	−0.044**	−0.042**
Dis2Hiway (km)	−0.009	0.028	−0.030*	−0.13**
Dis2Maroad (km)	−0.041	0.005	−0.11**	2.25E-38
PropUrban	8.02**	5.58**	3.13**	3.97**
n	*1106*	*650*	*968*	*1244*
PCP	*78*	*81.5*	*88.6*	*84.3*
AUC	*0.88*	*0.90*	*0.87*	*0.92*
R^2	*0.42*	*0.44*	*0.43*	*0.49*
Moran's I	*0.05***	*0.01*	*0.02**	*0*

*$P < 0.05$, **$P < 0.01$.

With the selected seven variables, we found that the unique effects of the three groups of variables on urban expansion varied with time (Fig. 4). The unique effects of physical factors and neighborhood factors both decreased, while the effect of socioeconomic factors increased along with the urbanization process (Fig. 4). During the period of 1972–1984, the unique effects of the physical factors were the highest, followed by socioeconomic factors and neighborhood factors. After that, the socioeconomic factors independently explained the most variance in urban expansion (Fig. 4).

Discussion

We examined the driving factors of urban expansion in Beijing over a period of nearly 40 years (1972–2010). Using binary logistic regression, we found that physical, socioeconomic, and neighborhood factors simultaneously affected urban expansion. In addition, we found that the effects of these factors changed along with the urbanization process. The findings of this study have important theoretical, methodological and management implications.

Theoretical implications

Physical factors: Elevation and slope both showed significantly negative effects on urban expansion in Beijing, indicating that the steep and elevated areas were less likely to be developed. The negative effects of slope on urban expansion have been observed all over the world (Dubovyk et al., 2011; Ye et al., 2011). The reason for this negative effect may be that the development cost in these areas is higher than that in flat areas. In contrast, the effects of elevation on urban expansion depend on the topography of the studied area. Higher elevation usually restricts urban expansion because the development of areas at higher elevations may be more costly. However, positive effects of elevation on urban expansion have observed in Lagos, Nigeria because drainage is needed in areas with low elevation, which may increase the cost of land development (Braimoh & Onishi, 2007; Dewan & Yamaguchi, 2009).

The two physical factors (i.e., slope and elevation) showed consistent negative effects on urban expansion for all four periods, except elevation in the period of 1984–1992. However, the magnitude of the unique effects of the physical factors decreased along with the urbanization process. The physical factors were the

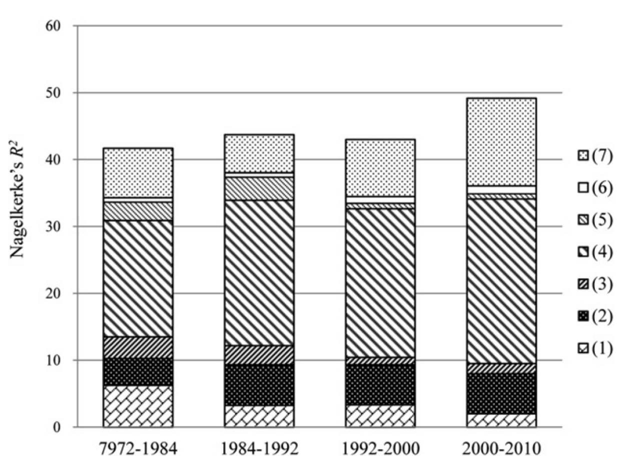

Fig. 4. Results of variance partitioning. (*1*) unique effects of physical factors, (*2*) unique effects of socioeconomic factors, (*3*) unique effects of neighborhood factors, (*4*) joint effects of physical and socioeconomic factors, (*5*) joint effects of socioeconomic and neighborhood factors, (*6*) joint effects of physical and neighborhood factors, and (*7*) joint effects of physical, socioeconomic, and neighborhood factors.

most important variable to affect urban expansion in the early stages (1972–1984), but they became less important than socioeconomic factors in the following years. The decrease in the effects of physical factors on urban expansion may be due to the following: 1) with the urbanization process, the previously less-suitable areas, such as mountainous areas with high elevations and slopes, started to be urbanized because of the shortage of land for construction (Ye et al., 2011); 2) the advancement of technology decreased the construction cost for locations with high elevations and steep slopes and thus increased the likelihood of urban expansion in the mountainous areas (Ye et al., 2011); and 3) along with improvements in the standard of living, wealthy people could afford the high development costs in the mountainous areas to access better environmental quality. This change in lifestyle further reduced the magnitude of the effects of elevation and slope on urban expansion.

Socioeconomic factors: Significant negative relationships between the probability of urban expansion and the distance to socioeconomic centers (the city center or the county center) and the distance to roads were found in this study, suggesting that the closer an area is to the socioeconomic centers and roads, the higher its likelihood of urban development. These results were consistent with previous findings (Dubovyk et al., 2011; Luo & Wei, 2009; Poelmans & Van Rompaey, 2009). This finding may be due to locations closer to the socioeconomic centers offering more opportunities to access socioeconomic resources (e.g., employment, urban infrastructure).

In addition, our results showed that the effects of socioeconomic factors on urban expansion varied over time. Distance to the city center and the county center showed consistently negative effects on urban expansion in the past forty years. The effects of the distance to roads, however, varied over time. The effects of the distance to roads on urban expansion became significant after 1992. This change may have been due to the implementation of the land leasing policy, which started in 1992 and allows the paid transfer of land use rights. Before 1992, land use rights, and thus the locations of urban expansion, were controlled entirely by the government. With the implementation of the land leasing policy, however, decisions about land use were also greatly affected by the market. Consequently, locations closer to roads were more likely to be developed.

Neighborhood factors: Neighborhood factors, represented as the proportion of urban land within a 210 m window in this study, positively affected urban expansion, indicating that urban expansion tended to take place in locations near developed areas. This finding was consistent with previous studies (Braimoh & Onishi, 2007; Hu & Lo, 2007; Huang, Zhang, & Wu, 2009; Luo & Wei, 2009). This result may have been found because locations close to developed areas have lower costs for development and better accessibility to the urban infrastructure (e.g., parks, supermarkets). However, negative effects of surrounding developed land on urban expansion were found in Silicon Valley in the U.S. because of the residents' desires for more private space and the avoidance of social and visual interaction (Reilly et al., 2009).

The magnitude of unique effects of neighborhood factors on the likelihood of urban expansion decreased with the urbanization process. This result was similar to that found in Silicon Valley (Reilly et al., 2009). The effects of the percentage of urban land in the neighborhood on urban expansion were positive in the early stages (1940–1984) but changed to negative later on (Reilly et al., 2009). The decreasing effects of neighborhood factors on urban expansion indicated that, more and more, newly added urban land was located further away from the existing urban land, and the spatial pattern of urban expansion became increasingly dispersed in Beijing (Zhao, 2010).

Methodological implications

This study analyzed the relative importance and temporal dynamics of the driving factors of urban expansion in Beijing, China for the past forty years, which extended studies on the driving factors of urban expansion. Similar to most studies that analyze landscape history, the models we built in this study were incomplete, that is, the models did not include all possible variables that may affect urban expansion because of a lack of data, variables that could not be measured, and the presence of unknown driving factors (Hietel et al., 2007; Marcucci, 2000). For example, we did not consider the factor of urban planning because such a dataset was not available for the entire study period. Urban planning can greatly affect urban expansion (Long et al., 2012; Tavares et al., 2012). A previous study in Beijing, however, indicated that while urban planning (i.e., Master Plans) had some effects on urban expansion, its relative importance was not comparable to other factors, such as distance to the city center, distance to roads, and the percentage of urban land within a window (Long et al., 2012). Therefore, it was assumed that not including the factor of urban planning did not affect our results significantly.

In this analysis, we did not include census-based socioeconomic variables such as population and GDP, which may be important driving factors of urban expansion (Liu & Zhou, 2005; Seto et al., 2011; Wu & Zhang, 2012). We did not include these variables for two main reasons. First, data for these variables were not available for the entire study time period. Second, the spatial resolution of the datasets for these variables was much coarser than that of the variables used in the logistic regressions. In addition, as these variables were potentially correlated with the variables included in the logistic regression models used in this study (Hietel et al., 2007), not including these variables (i.e., population and GDP) seemed that it would not greatly affect the model's performance. In fact, the values of both the PCPs and the AUCs, indicators of model performance, were high and very close to those from studies that included many more variables (Cheng & Masser, 2003; Dubovyk et al., 2011), suggesting that the main driving factors were included in our models. It should be noted that the values of Nagelkerke's R^2 were moderate. This may be because we used presence and absence data as dependent variable in the regression analysis.

Management implications

In this study, we found a decreasing role of physical factors (elevation and slope) in restricting urban expansion in Beijing, suggesting an increase of development pressure in the mountainous areas. The mountainous areas in Beijing provide crucial ecosystem services, such as water conservation, biodiversity conservation and recreation provision for the city (Li, Wang, Paulussen, & Liu, 2005; Zhang, Li, Xie, & Xiao, 2010). Therefore, policies and measures should be implemented to protect these ecologically important zones.

The decreasing positive effects of neighborhood factors on urban expansion in Beijing indicated that, more and more, urban expansion came in the form of leapfrogging and the spatial pattern of urban expansion became increasingly dispersed (Zhao, 2010). As dispersed urban expansion may cause much more ecological and environmental problems than a more compact pattern (Stone, Mednick, Holloway, & Spak, 2007; Zhao, 2010), special efforts should be devoted to controlling urban sprawl in Beijing.

Summary and conclusions

Based on multi-temporal remote sensing images, we observed a rapid urban expansion in Beijing during the period of 1972–2010. The urban land increased by 209% from 861 km^2 to 2666 km^2. Physical, socioeconomic, and neighborhood factors significantly affected urban expansion, among which socioeconomic factors were the most important driving factors, except for during the period of 1972–1984. The relative importance of the driving factors varied over time along with the urbanization process. The magnitude of the unique effects of physical factors and neighborhood factors declined while that of socioeconomic factors increased along with the urbanization process. This study extended our understanding of urban expansion in that the effects of the driving factors on urban expansion change along with the urbanization process. In addition, based on the findings in this study, we suggest that effective urban planning and management should be implemented to prevent the mountainous areas from being urbanized and to control urban sprawl in Beijing.

In this study, we only included seven variables for several reasons that we discussed above. The inclusion of more potential driving factors in a future study would be worthwhile. In addition, while we investigated the temporal dynamics of the effects of driving factors on urban expansion, we did not examine the spatial heterogeneity of the driving factors. Empirical studies have shown that the effects of the driving factors on urban expansion may vary spatially (Luo & Wei, 2009; Müller et al., 2010). Therefore, future work on the spatial heterogeneity of the effects of the driving factors on urban expansion is recommended.

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