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Drivers of urban expansion over the past three decades: a comparative study of Beijing, Tianjin, and Shijiazhuang

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Abstract Urban expansion is influenced by various natural and anthropogenic factors. Understanding the driving forces of urban expansion is crucial for modeling the process of urban expansion as well as guiding urban planning and management. Here, we quantified and compared the effects of natural, socioeconomic, and neighboring factors on urban expansion and their temporal dynamics in three large cities in the Jing-Jin-Ji Urban Agglomeration: Beijing, Tianjin, and Shijiazhuang. We used remote sensing imagery from six epochs (circa 1980, 1990, 1995, 2000, 2005, and 2010) integrated with GIS techniques and analyzed using binary logistic regression. The relative importance of the three types of driving forces was further decomposed using variance partitioning. We found that the direction and/or magnitude of effects on the drivers of urban expansion varied with both epoch and city. Natural factors placed significant constraints at early stages of urban expansion, but this constraint relaxed over time. As precursor drivers of urbanization, socioeconomic factors significantly influenced urban growth in most epochs for each city. Non-urban lands near existing urban areas were more likely to be urbanized, due to easier access to existing transportation infrastructure and other facility resources. Furthermore, with urbanization, individual effects of drivers tended to be replaced by joint effects, especially for the neighboring factors. Similarities and differences in the individual and joint effects of drivers on urban expansion across cities and through time will provide valuable information for adaptive urban development strategies in the national capital region of China.

Keywords Remote sensing · Urban expansion · Driving forces · Logistic regression · Variance partitioning · Jing-Jin-Ji Urban Agglomeration

Introduction

Unprecedented urban land expansion has occurred globally over the last half century and is projected to be even more dramatic (Vitousek et al. 1997; Angel et al. 2005; Seto et al. 2011). As one of the most visible and irreversible forms of land transformation, urban land expansion has generated profound impacts on the Earth system from local to global scales, including loss and degradation of natural habitats (Litteral and Wu 2012); alterations of climate, atmospheric chemistry, and hydrology (Zhao et al. 2006; Kaye et al. 2006; Zhou et al. 2014); environmental pollution; and human health im-

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pacts (Gong et al. 2012). Many of the above-mentioned effects reach far beyond the city boundaries and are contributing to the most significant global environmental changes. At the same time, cities do provide a wide range of positive outcomes including lower infrastructure cost (Siedentop and Fina 2010) and higher production efficiency resulting from information spillover (Lucas 1988; Bettencourt 2013). Therefore, understanding the process of urban expansion and its causes and consequences has important implications for the long-term sustainability of dense human settlements (Lambin et al. 2001).

A considerable number of studies have been conducted on understanding spatiotemporal patterns of urban expansion. However, to date, in-depth analyses of the drivers of urban expansion are few. In fact, existing studies on urbanization drivers have mostly been confined to static qualitative analysis (Liu et al. 2005; Long et al. 2007; Long et al. 2008), and few have examined their temporal dynamics (Li et al. 2013; Schweizer and Matlack 2014), spatial disparities (Wang et al. 2016; Ju et al. 2016), and cross-city comparisons (Lu et al. 2013; Osman et al. 2016; Silva and Li 2017; Zhao et al. 2017). Little is known about the indivudual and joint effects of various driving forces, which are important for interpreting urban expansion mechanisms. A comprehensive understanding of urban expansion drivers and dynamic mechanisms is not only a prerequisite for comprehending the urbanization process and its ecological consequences but also the basis for supporting optimal urban planning and management strategies (Lu et al. 2013; Osman et al. 2016; Silva and Li 2017; Zhao et al. 2017).

China has experienced rapid urbanization over the past three decades (Zhao et al. 2015a, b). The Jing-Jin-Ji Urban Agglomeration (i.e., Beijing, Tian, and Hebei), encompassing the national capital region of China, has witnessed extensive urban growth (Wu et al. 2015), but has encountered problems such as economic disparities, water shortages, and severe air pollution events (Jiang et al. 2008). The Central Government of China has highlighted the integrated development of the Jing-Jin-Ji Urban Agglomeration since the beginning of 2014 and has been developing relevant plans to carry this national strategy forward. The designation of the state-level Xiongan New Economic Zone in 2017 to promote the formation of a world-class city cluster is a historical opportunity for the development of the Jing-Jin-Ji Urban Agglomeration. Consequently, a clear understanding of urban expansion and its driving forces in the Jing-Jin-Ji Urban Agglomeration is critically important not only for the capital region but also for China's sustainable growth in the future. For example, city planners need to know when to facilitate the transitions of urban expansion patterns (e.g., from infilling to leapfrogging or even building satellite towns to release space pressure in highly developed areas) and how socioeconomic factors interact with natural factors in urban development so that they can devise adaptive management and development options.

In an earlier study, we quantified and compared spatiotemporal patterns of urban expansion in three major cities (i.e., Beijing, Tianjin, and Shijiazhuang) in the Jing-Jin-Ji Urban Agglomeration over the past three decades (Wu et al. 2015). In this study, we delve further into a comparative study of the driving forces of urban expansion in Beijing, Tianjin, and Shijiazhuang from 1980 to 2010, covering five epochs (1980–1990, 1990–1995, 1995–2000, 2000–2005, and 2005–2010) and using multi-temporal Landsat remote-sensing data; natural, socioeconomic, and neighboring information integrated with geographic information system (GIS) techniques; and binary logistic regression modeling. Our objectives include (1) quantification of the driving forces of urban expansion in the three cities, (2) analysis of the similarities and differences among the cities through time, and (3) decomposition of the driving forces into independent and interactive effects.

Data and methods

Study area

The Jing-Jin-Ji Urban Agglomeration is the national capital region of China. It is located in the eastern part of the North China Plain along the Bohai Rim, and it is the largest urbanized region in northern China (Fig. 1a, b). Our study focuses on the three major cities of the Jing-Jin-Ji Urban Agglomeration: Beijing, Tianjin, and Shijiazhuang (Fig. 1c). Beijing and Tianjin are two municipalities under the direct administration of the Central Government, both surrounded by Hebei Province. Beijing is the capital of contemporary China as well as the political and cultural center of the nation. Tianjin, bordering Beijing to the northwest and Bohai Sea to the southeast, is the largest open port city and economic center in northern China. Shijiazhuang, as the political, economic, and cultural center of Hebei Province, is the provincial capital nearest to China's capital.

The average elevation of Tianjin is lower than that of Beijing and Shijiazhuang (Fig. 1c). The gross domestic product (GDP) of Beijing, Tianjin, and Shijiazhuang in 2010 was 1411.4, 922.4, and 340.1 billion RMB, respectively. The city populations in 2010 were 19.6, 12.9, and 10.2 million, respectively (NBSC 2011).

Extraction of urban land extent and urban expansion

Urban land extents were extracted from Landsat imagery for six epochs (circa 1980, 1990, 1995, 2000, 2005, and 2010) with the consideration of both science need (Liu et al. 2014; Homer et al. 2015) and availability of cloud-free images. Cloud-free Multispectral Scanner (MSS) satellite images before 1985 and cloud-free Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) satellite images after 1985 were used to calculate urban land expansion for three cities over the past three decades. Urban land was defined as all non-vegetative areas dominated by human-made surfaces, including roads and buildings. Detailed procedures on how urban land extents were derived can be found in our earlier study (Wu et al. 2015).

Figure 2 shows the complex patterns and rapid processes of urban expansion for the three cities during the past three decades. From 1980 to 2010, the average annual urban growth rates were 4.7%, 3.7%, and 3.2% for Tianjin, Beijing, and Shijiazhuang, respectively (Wu et al. 2015). The spatiotemporal patterns varied among the cities: Beijing exhibited a mononuclear polygon urbanization pattern; Tianjin formed a double-nucleated polygon-line urbanization pattern; and Shijiazhuang showed a point urbanization pattern.

Selection of driving forces and data processing

Spatiotemporal patterns of urban expansion resulted from complex interactions of natural, socioeconomic, and neighboring driving forces (Thapa and Murayama 2010; Seto et al. 2011; Yue et al. 2013; Li et al. 2013; Zhao et al. 2018). Based on their relationship with urban expansion, measurability, and data availability, a total of nine driving factors were chosen from these three major categories for our analysis (Table 1).

Natural factors

Elevation, slope, and distance to water, all affecting patterns of urban expansion (Thapa and Murayama 2010; Seto et al. 2011), are included in this study. Elevation and slope were derived from ASTER GDEM dataset (https://asterweb.jpl.nasa.gov/gdem.asp) and processed using ArcGIS 10.0. We extracted water data in the Landsat imagery and calculated the Euclidean distance to water of each pixel.

Socioeconomic factors

Socioeconomic factors are key forces driving urban expansion in China (Zhao et al. 2018). As nighttime lights (Doll et al. 2000) and road infrastructure (Danilina and Chebotarev 2017) are important socioeconomic features for urban systems, we included nightlight intensity and the distances to main roads, to main railways, to the city center, and to district centers in this study.

The road and railway dataset of 2009, approximately representing the year 2010, was obtained from the Natural Science Foundation of China (NSFC) program *The Influence of the High-Speed Rail on Regional Urban Spatial Structure*. Roads are subject to change over time due primarily to the establishment of new roads. The national-level trunk roads, major highways, and provincial-level trunk roads for the years 1990, 1995, 2000, and 2005 were extracted by visual interpretation of the Landsat imagery from corresponding time along with manual adjustment by comparing the imagery with the actual road data of 2009. Roads completed in the last year of one epoch could affect urbanization processes starting in the first year of this epoch as roads usually influence urban expansion since the initiation of road establishment planning. Therefore, we used road data from the last years of each epoch (1990, 1995, 2000, 2005, and 2010) to calculate the distance to main roads. As railways change little and are difficult to observe in the Landsat images, we considered the railways data of 1980–2010 as constant to derive the Euclidean distance to main railways.

The city and district centers were the locations of the municipal and district governments, respectively. The Euclidean distances to the city and district centers were calculated accordingly.

Human activities and economic development level are important drivers of urban expansion. However, to what extent they influence urban land transformation and what role they play jointly with other drivers are still unclear. To quantitatively map and model these drivers at the pixel level, we chose the Defense Meteorological Satellite Program/Operational Linescan

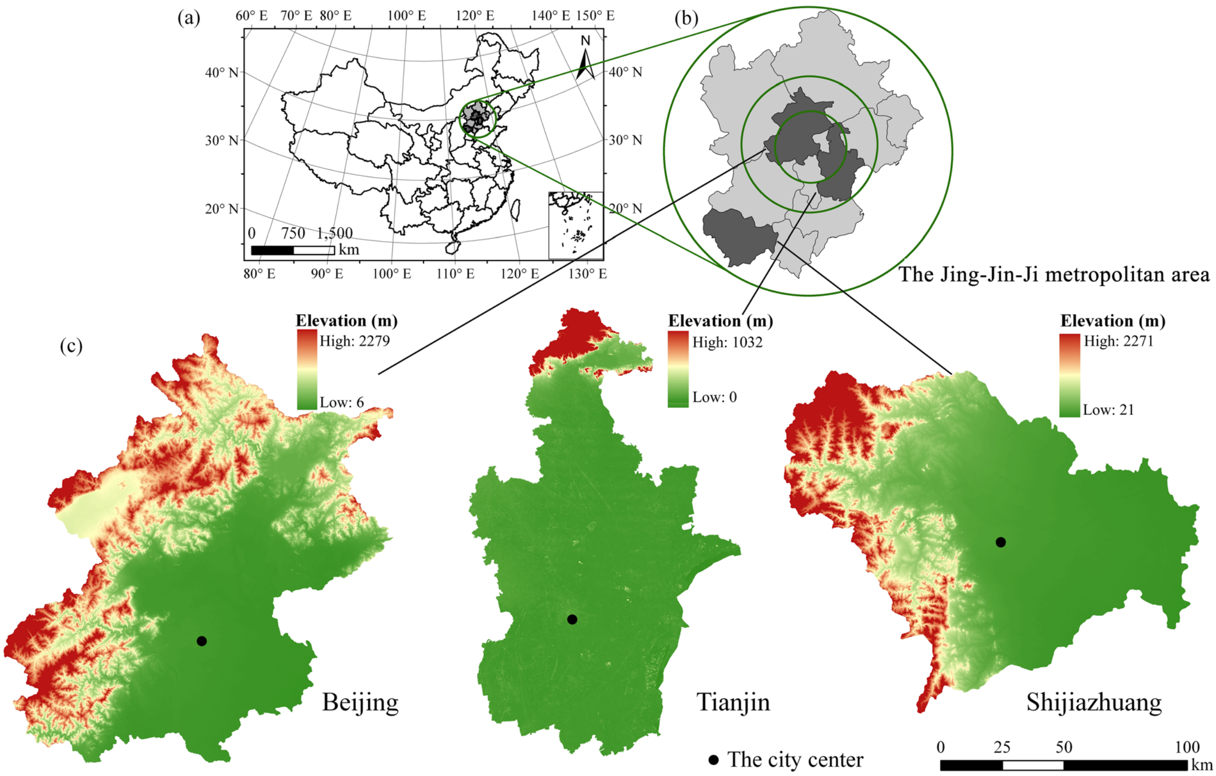

Fig. 1 The location and administrative divisions of the study area—Beijing, Tianjin, and Shijiazhuang: the study area in China (a), the study area in the Jing-Jin-Ji metropolitan area (b), and terrain and city centers (places of the municipal government) of Beijing, Tianjin, and Shijiazhuang (c)

System (DMSP/OLS) data, which used the visible and near-infrared light channel in dark background to record human footprints (Doll et al. 2006; Zhuo et al. 2009; Levin and Duke 2012; Wu et al. 2013). Stable-light

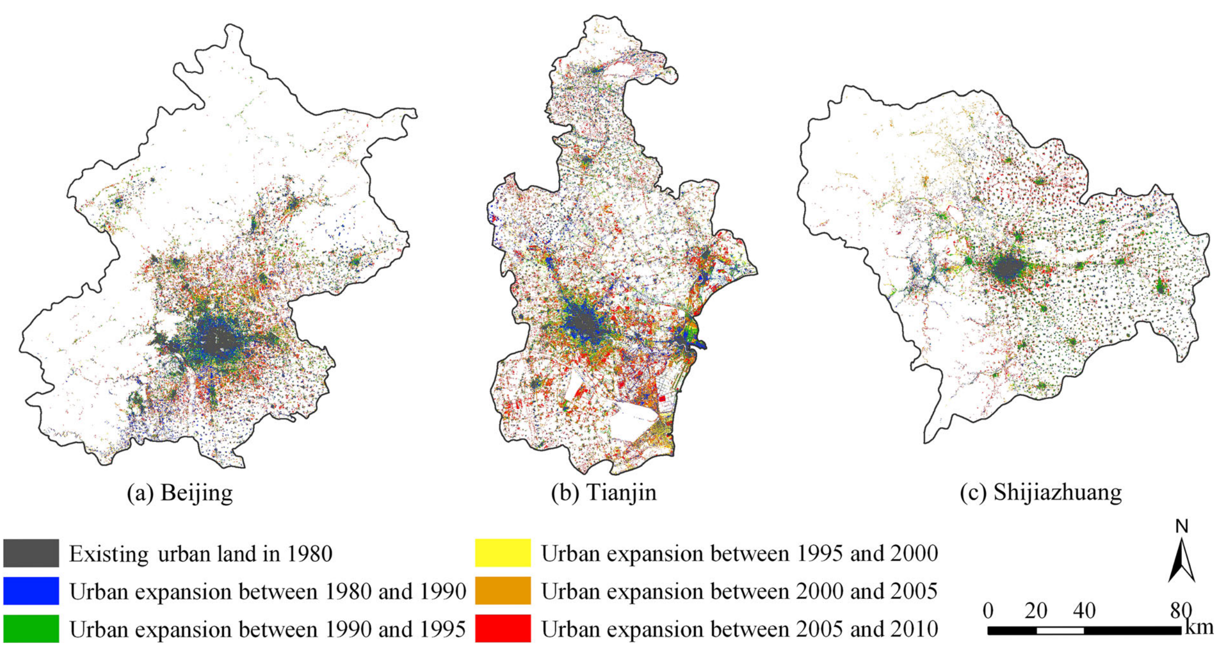

Fig. 2 Spatial extent of urban areas in Beijing (a), Tianjin (b), and Shijiazhuang (c) from 1980 to 2010

Table 1 Driving forces of urban expansion used in this study

Category	Variables	Static (S)/ dynamic (D)	Timeframes
Natural factors	Elevation	S	–
	Slope	S	–
	Distance to water	S	–
Socioeconomic factors	Distance to roads	D	End of epochs (1990, 1995, 2000, 2005, 2009)
	Distance to railways	S	–
	Distance to the city center	S	–
	Distance to district centers	S	–
	Nightlight intensity	D	2-year average prior to the beginning of epochs (average of 1978–1979, 1988–1989, 1993–1994, 1998–1999, 2003–2004)
Neighboring factors	Proportion of urban area within a 90-m window	D	Beginning of epochs (1980, 1990, 1995, 2000, 2005)

products with high brightness and long duration rather than ephemeral lights such as fires and other visual noise were used in our study to reflect socioeconomic activities. The stable-light dataset had a resolution of 1 km, and its values range from 0 to 63, containing the lights from cities, towns, and other sites with persistent lighting. From the NGDC website (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html), DMSP/OLS data for 1992–2013 can be obtained, which was obtained by six different satellites (F10, F12, F14, F15, F16, and F18). To reflect socioeconomic drivers of urban expansion, we used the nightlight intensity data prior to the beginning year of each period (1978, 1990, 1995, 2000, and 2005). Specifically, the 2-year averages of the nightlight intensity of 1978–1979, 1988–1989, 1993–1994, 1998–1999, and 2003–2004 were used for each epoch.

To reduce the uncertainty of the nighlight dataset and to extend the data range to 1978, we calibrated the nightlight data and built a model to simulate the trend of nightlight change with ArcGIS version 10.0 and R version 3.1.3 through the following steps (Elvidge et al. 2009). First, we selected Jixi City of Heilongjiang Province as the calibration area, because its high conformity of values over different years was suitable for calibration of DMSP/OLS data across China (Liu et al. 2012). Second, we chose data from satellite F16 in 2007 as the reference data for its highest cumulative value, which had been demonstrated by Liu et al. (2012). Then we built a quadratic regression model for original data and the reference data:

$$DN_{\text{correct}} = a \times DN^2 + b \times DN + c \tag{1}$$

where DN was the original value, DN_{correct} was the preliminary calibrated value, and a, b, and c were coefficients. For pixels with preliminary calibrated values higher than 63, we assigned their values as 63. Third, we averaged data from different satellites of the same year as the terminal calibrated value:

$$DN_C = \left(DN_i^a + DN_i^b\right)/2 \tag{2}$$

where DN_c was the terminal calibrated value and DN_i^a and DN_i^b were the preliminary calibrated values for two different satellites of the same year. Fourth, we simulated the value of 1978, 1979, 1988, and 1989 for each pixel using the artificial neural network. Finally, we used the average value of 2 years prior to the beginning of each period to depict the socioeconomic driver.

Neighboring factors

Neighboring factors were defined as the proportion of urban land in a surrounding area. We calculated the percent of urban land within a 3 × 3 pixel window to investigate the effects of local neighboring factors on urban expansion as a 100-m buffer (about 3 pixels of a 30-m-resolution urban map) is reported to be an effective distance to affect the possibility of urban development in Beijing (Liu and Zhou 2005).

All of the selected variables were compiled in raster files with a spatial resolution of 30 m and then normalized. To attenuate the effects of spatial autocorrelation, we randomly selected 500,000 sample points from each epoch, with the distance between each point greater than 30 m. The points that were urbanized during the period were coded as 1, and those not urbanized were coded as 0. The number of points coded as 0 was much larger than the number of points coded as 1. We then ran a random sampling procedure on points coded as 0 to obtain an equal number of samples of locations with change and no change (Cheng and Masser 2004).

Logistic regression and results evaluation

We applied binary logistic regression to analyze the influence of the selected variables on the probability of urban expansion. One logistic regression model was built for each epoch. The probability P was formulated as follows:

$$P = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}} \quad (3)$$

where x_k was the development factors of cell$_{ij}$, β_k were the weights of the development factors, and α was the intercept. The formulation above was usually transformed to a linear form:

$$Z = \ln\left(\frac{P}{1-P}\right) = \beta_0+\beta_1 x_1+\beta_2 x_x+\ldots+\beta_k x_k \quad (4)$$

The fits of the logistic regression models were evaluated with three complementary metrics. The first was Nagelkerke's R^2, which represents the proportion of dataset variance explained by the selected model (Nagelkerke 1991) and was calculated using the following equation:

$$R^2 = 1-\exp[-2/n(l_A-l_0)] \quad (5)$$

where n was the sample size, l_A was the log-likelihood of the selected model, and l_o was the log-likelihood of the null model with only the intercept as a predictor.

The second was the percentage of correctly predicted area under the curve (AUC) of the receiver operating characteristic (ROC) (Fawcett 2006). The ROC curve was built by plotting the sensitivity versus (1-specificity). The AUC can be interpreted as the probability of the model to achieve a higher predicted value of urbanization of a pixel that underwent urbanization than for those that did not. An AUC value approaching 1.0 indicates perfect performance, and a value of 0.5 indicates random discrimination.

The third metric of model fit was the percent of correct predictions (PCP), calculated as the number of correctly predicted cases divided by the total number of cases.

Variance partitioning

Variance partitioning is an effective method to quantify the relative effects of different determinants, which decomposes the variance of the dependent variables into individual shares and joint shares (Anderson and Gribble 1998; Heikkinen et al. 2005; Betts et al. 2006; Braimoh and Onishi 2007). In this study, we were interested in the relative importance of the natural, socioeconomic, and neighboring factors. The variation in the probability of urban expansion that was explained (Nagelkerke's R^2) was decomposed into seven fractions: individual effects of natural factors (*a*), individual effects of socioeconomic factors (*b*), individual effects of neighboring factors (*c*), joint effects of natural and socioeconomic factors (*d*), joint effects of natural and neighboring factors (*e*), joint effects of socioeconomic and neighboring factors (*f*), and joint effects of all three factors (*g*) (Fig. 3).

With different explanatory variables in logistic regression models, the following variance partitionings can be achieved: the probability of urban expansion that was explained by natural, socioeconomic, and neighboring factors (*A*), the probability of urban expansion that was explained by natural factors (*B*), the probability of urban expansion that was explained by socioeconomic factors (*C*), the probability of urban expansion that was explained by neighboring factors (*D*), the probability of urban expansion that was explained by natural and socioeconomic factors (*E*), the probability of urban expansion that was explained by natural and neighboring

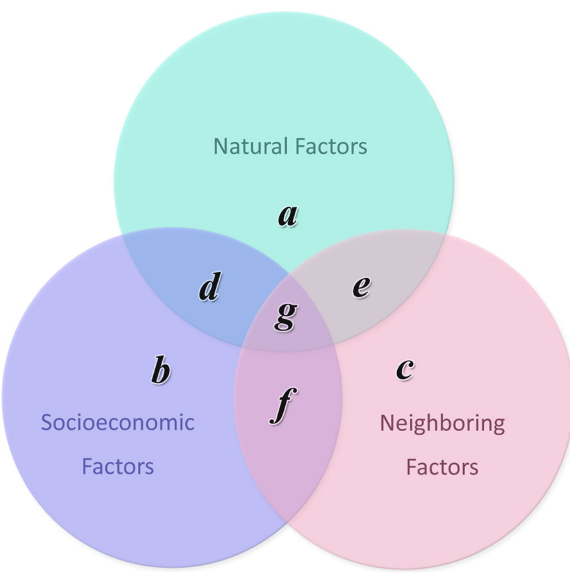

Fig. 3 Variance partitioning of factors driving urban expansion

factors (F), and the probability of urban expansion that was explained by socioeconomic and neighboring factors (G). Thereafter, fractions a, b, c, d, e, f, and g were calculated by the following equations:

$$A = a + b + c + d + e + f + g \tag{6}$$

$$B = a + d + e + g \tag{7}$$

$$C = b + d + f + g \tag{8}$$

$$D = c + e + f + g \tag{9}$$

$$E = a + b + d + e + f + g \tag{10}$$

$$F = a + c + d + e + f + g \tag{11}$$

$$G = b + c + d + e + f + g \tag{12}$$

Thus:

$$a = A - G \tag{13}$$

$$b = A - F \tag{14}$$

$$c = A - E \tag{15}$$

$$b + c + f = A - B \tag{16}$$

$$a + c + e = A - C \tag{17}$$

$$a + b + d = A - D \tag{18}$$

$$d = (A-D)-(A-G)-(A-F) = G + F - A - D \tag{19}$$

$$e = (A-C)-(A-G)-(A-E) = E + G - A - C \tag{20}$$

$$f = (A-B)-(A-E)-(A-F) = E + F - A - B \tag{21}$$

The procedures of factor selection, data sampling, logistic regression, results evaluation, and variance partitioning were all conducted using R software (Team 2013).

Results

Spatiotemporal distribution of driving forces

Normalized driving forces including natural, socioeconomic, and neighboring factors listed in Table 1 are illustrated as Fig. 4. Figure 4a shows spatial patterns of static factors for the three cities. The elevation and slope showed a descending trend from northwest to southeast for Beijing, a descending trend from west to east for Shijiazhuang, but a relatively low value for all of Tianjin. Distance to water was distributed more evenly in Tianjin than in Beijing or Shijiazhuang. Distance to railways showed an increasing trend from the city center to the suburbs for all three cities. Distances to city and district centers reflected the spatial distributions of centers and subcenters. Figure 4b illustrates the spatial and temporal patterns of dynamic factors. Spatially, the distance to roads represented a concentric pattern for Beijing and reticular patterns for Tianjin and Shijiazhuang. The nightlight intensity showed a mononuclear pattern for Beijing, a double-nucleated pattern for Tianjin, and a multi-point pattern for Shijiazhuang, corresponding to urban expansion patterns of the three cities identified in our earlier study (Wu et al. 2015). The distribution of neighboring factors depended on the spatial distribution of existing urban lands. Temporally, the spatial distributions of the three dynamic factors changed with increasing urbanization.

Modeling the driving forces of urban expansion

We ran logistic models with nine driving forces for the five epochs. The PCP values and the AUC values for all models were greater than 0.7, and Nagelkerke's R^2 values for all models ranged from 0.3 to 0.6, except a few cases. Thus, the logistic models in our study achieved relatively satisfactory fitting results according to existing findings (Rong et al. 2012).

The effects of natural factors, socioeconomic factors, and neighboring factors on urban expansion for the three cities are listed in Table 2. Elevation, slope, and distance to roads all showed negative effects on urban expansion. Nightlight intensity and neighboring factors had significant positive influences on urban expansion. The influence of distance to water, distance to railways, and distance to city and district centers varied by epoch and city. For example, distance to water showed positive effects in most epochs for Beijing, but negative effects in most epochs for Tianjin. For Shijiazhuang, distance to water affected urban expansion positively before 1995 but negatively after 1995. Distance to railways positively affected Tianjin, but negatively affected Beijing and Shijiazhuang in most epochs. For distance to city and district centers, Beijing showed negative effects in most epochs, and Tianjin and Shijiazhuang exhibited inconsistent trends.

From the perspective of the absolute values or magnitude, slope was the most significant natural factor influencing urban expansion, the distance to roads and nightlight intensity were the most significant socioeconomic factors, while neighboring factors we used significantly affected urban expansion of all the three cities for all periods.

Relative importance of driving forces

The selected nine factors presented different effects (Fig. 5). When compared among cities, neighboring factors were the most significant ones among the individual effects for the three cities, suggesting that urban expansion tended to occur near urbanized areas. Socioeconomic factors were the second most significant influence on urban expansion for Tianjin and Shijiazhuang, whereas natural factors had the second most significant influence for Beijing. Among the joint effects of two types of factors, the joint effects of natural factors and neighboring factors had the least impact.

When compared within cities, the magnitude of different factors and their joint effects presented different trends through time. For Beijing, joint effects of factors increased with the urbanization process, individual effects of natural factors decreased with the urbanization process, while individual effects of socioeconomic and neighboring factors fluctuated through time. For Tianjin, individual effects were larger than joint effects of factors. The individual effects of socioeconomic factors, neighboring factors, and their joint effects accounted for a large proportion of explained variance in various epochs. Through time, the individual effects of socioeconomic factors decreased with time while the individual effects of neighboring factors and their joints effects with natural or socioeconomic factors increased, but both with fluctuation. For Shijiazhuang, the individual effects of factors had the most significant influence. Individual effects of neighboring factors increased in the early epochs but later decreased.

Discussion

Natural factors, reflecting cities' internal physical attributes, provide the basic foundation and conditions for urban expansion. Urban settlements are generally built on flat lands proximate to water (Seto and Kaufmann 2003). Terrain, including elevation and slope, tends to constrain urban expansion, which has been observed for many cities around the world (Dubovyk et al. 2011; Li et al. 2013). Similarly, Beijing, Tianjin, and Shijiazhuang were all affected by elevation and slope negatively in the past three decades, although the magnitude of influence fluctuated. Among cities, the magnitude of topographic constraint to urban expansion was in a decreasing order from Beijing, Shijiazhuang to Tianjin because the Taihang Mountains and the Yanshan Mountains have restricted urban expansion in the northwest of Beijing and in the west of Shijiazhuang, whereas Tianjin is near the coast and generally flat (Wu et al. 2015). In particular, the expansion of Beijing to the northwest mountainous areas is prohibited because the vegetation in the mountains has been considered as the environmental protection belt, coinciding with its relatively high elevation and steep slope. Across the entire study period, the influence of terrain was most significant at the early stages of urban expansion and its constraint then became relaxed over time. This finding might be interpreted as either the flat lands had not been sufficient to accomodate rapid urban expansion or people preferred living in mountain areas rich in natural amenities or some combination of both influences. However, with further development of urbanization, the role of topographic constraint resumed in a degree whenever the leapfrogging urban growth form (i.e., a new urban patch is developed without spatial connection to the existing urban lands) increased. This interpretation can be supported by our earlier findings on the urban expansion process of these three cities (Wu et al. 2015).

Green development has been the current trend of human social development in the world. Suburban areas and as-yet-unexploited land with a good ecological environment play a more and more important role in future urban planning and construction, especially for big cities and urban agglomeration (Mertes et al. 2015; Mcdonnell and Macgregor-Fors 2016). With the advancement of technology and many people pursuing natural amenities and choosing to reconnect with nature, more natural landscapes, including remote mountain areas, will become the preferred alternative for the inevitable, accelerating rise of urban encroachment (Gude et al. 2006). This trend may have significant implications for urban planning and management strategies of the Jing-Jin-Ji Urban Agglomeration, and for Beijing and Shijiazhuang in particular. The mountains provide vital ecosystem functions and services, such as supplying humanity with clean water as "water towers"; harboring biodiversity as the "last refuge" for wildlife; and spiritual, scenic, cultural, and ethnological services (Körner and Ohsawa 2006). How to protect the ecological advantages

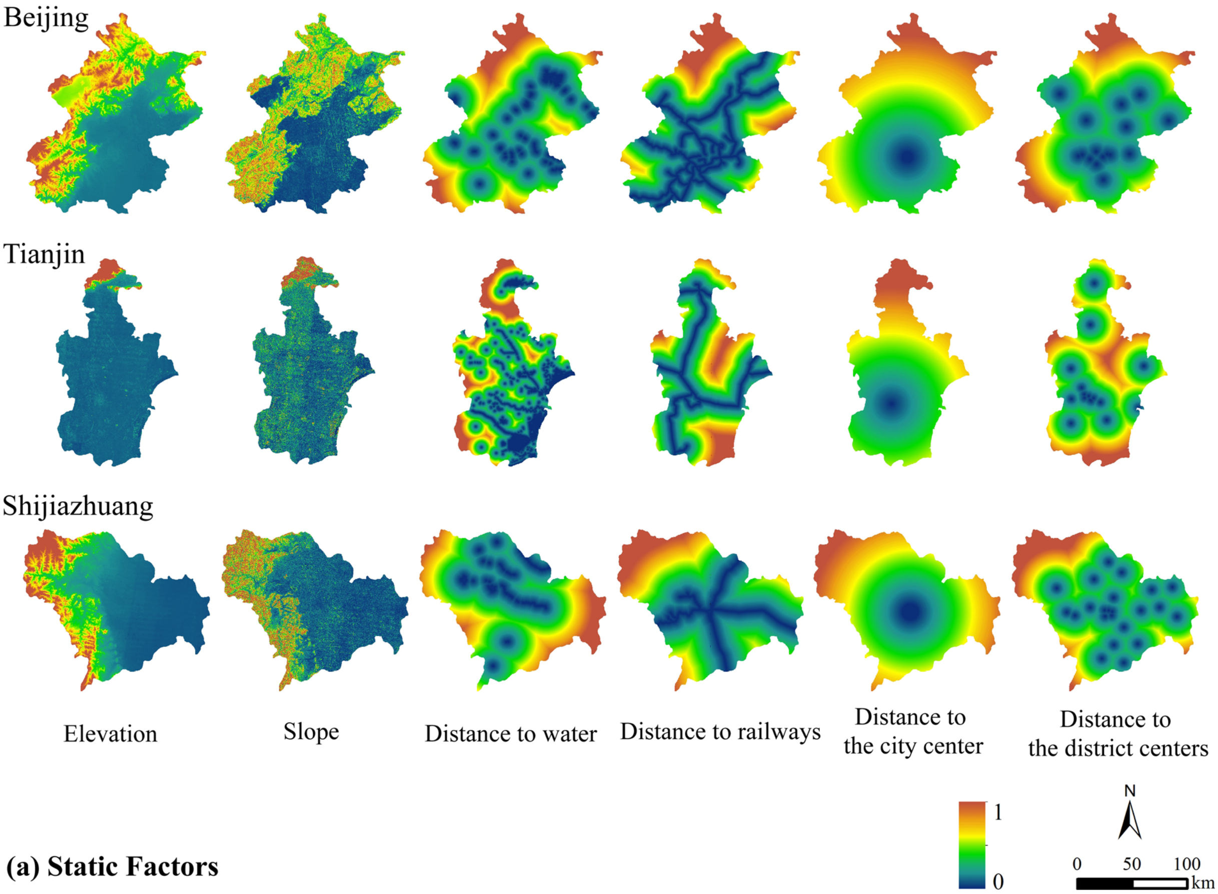

Fig. 4 Spatial distributions of normalized driving factors in Beijing, Tianjin, and Shijiazhuang including static factors (**a**) and dynamic factors (**b**)

brought about by natural terrain while preventing undesirable future urban development should be taken into account in urban planning and management in the region. Decomposition of the effects of natural drivers into individual and joint components might provide insightful information for balance between protection and development. The growth mode of polycentric and clustered arrangements of newly developed urban land in the mountain cities like Chongqing (Qu et al. 2014), which was associated with relatively high transportation efficiency and small ecological footprints, might offer some scientific knowledge for future urban planning decisions in the Jing-Jin-Ji Urban Agglomeration.

Socioeconomic factors offered external driving mechanisms for urban expansion. As these factors were dynamic, the influence they acted on urban expansion was unstable. The driving forces of road construction usually occurred before urban expansion. When a road was planned for construction, its potential convenience was predictable, leading to aggregation of new projects, such as residences, enterprises, public service facilities, commercial facilities, recreational facilities, and resulting urban expansion (Hills 1996). The influence of railway varied from city to city. For example, it had less influence than water on Tianjin, even sometimes presenting negative influence, because areas near railways experience more noise pollution. However, railways brought about positive effects to Beijing and Shijiazhuang facilitating urban expansion. The influence of the city and district centers was associated with the spatiotemporal patterns of urban expansion. For the mononuclear urban expansion of Beijing, the probability to be urbanized decreased with the distance to either the city or the district centers. For double-nucleated (Tianjin) or point (Shijiazhuang) urban expansion, the influence of distance to city or district centers was inconsistent. The nightlight intensity reflected economic development status. Economic development drove resource aggregation and provided financial support for city construction, thus resulting in urban expansion.

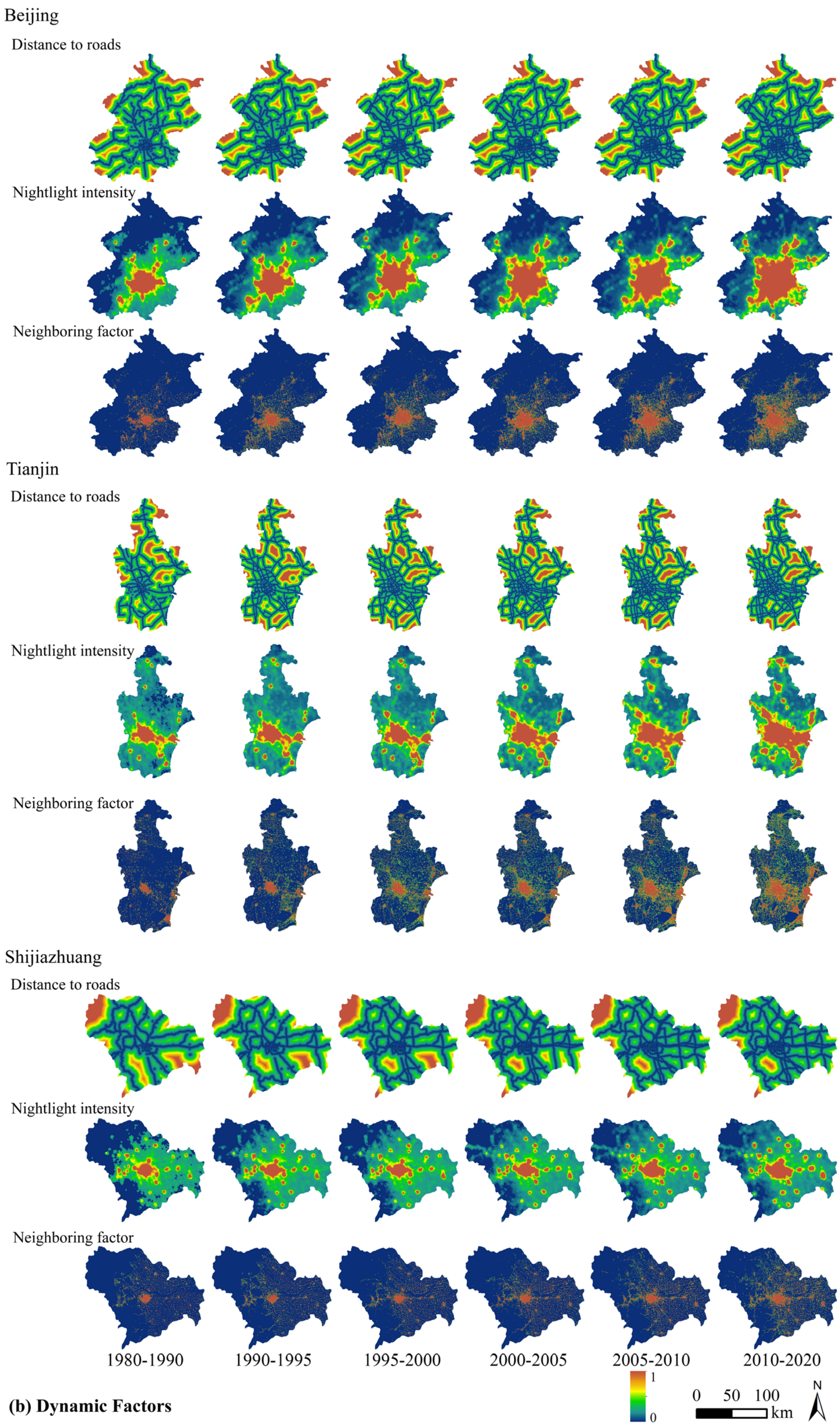

Fig. 4 (continued)

Table 2 Summary of driving forces of urban expansion for three cities between 1980 and 2010 from the logistic regression models

			1980–1990	1990–1995	1995–2000	2000–2005	2005–2010
Beijing							
Coefficient	Natural factors	Elevation	− 6.25***	− 1.35***	− 3.21***	− 4.37***	− 3.83***
		Slope	− 10.79***	− 9.16**	− 9.33***	− 7.25***	− 6.84***
		Distance to water	1.88***	− 0.51***	0.87***	0.41***	0.21**
	Socioeconomic factors	Distance to roads	− 1.71***	− 2.74***	− 1.34***	− 1.70***	− 1.75***
		Distance to railways	− 1.75***	0.85***	− 1.02***	− 1.30***	− 0.97***
		Distance to the city center	− 0.15*	0.12*	0.75***	− 0.16**	− 0.88***
		Distance to district centers	0.10*	− 1.83***	− 0.53***	− 0.59***	− 0.39***
		Nightlight intensity	1.96***	− 1.81***	1.63***	1.75***	1.38***
	Neighboring factors		4.41***	4.21***	3.87***	4.27***	3.42***
	Constant		0.48***	− 0.06***	− 0.28***	− 0.29***	0.51***
Model test	*n*		192,782	139,190	171,216	163,272	278,110
	PCP		0.72	0.77	0.84	0.74	0.79
	AUC		0.86	0.92	0.93	0.90	0.88
	R^2		0.53	0.58	0.57	0.60	0.52
Tianjin							
Coefficient	Natural factors	Elevation	− 7.15***	− 8.66***	− 5.39***	0.00	− 9.25***
		Slope	− 5.11***	− 3.55***	− 2.57***	− 2.94***	− 0.86***
		Distance to water	− 1.17***	− 0.66***	− 0.91***	− 1.06***	0.12***
	Socioeconomic factors	Distance to roads	− 1.35***	− 1.02***	− 0.93***	− 2.04***	− 0.65***
		Distance to railways	0.18***	− 1.94***	0.85***	0.91***	0.25***
		Distance to the city center	1.59**	0.04	0.84**	− 0.78***	0.48***
		Distance to district centers	− 0.44***	− 0.92***	0.26**	0.31***	− 0.41***
		Nightlight intensity	2.75***	1.17***	1.63***	1.55***	1.34***
	Neighboring factors		3.98***	4.22***	4.95***	4.97***	3.58***
	Constant		− 0.62***	0.33***	− 1.08***	− 0.61***	− 0.75***
Model test	*n*		233,148	176,648	193,968	310,870	477,038
	PCP		0.77	0.64	0.81	0.76	0.72
	AUC		0.80	0.79	0.82	0.80	0.74
	R^2		0.24	0.29	0.36	0.35	0.21
Shijiazhuang							
Coefficient	Natural factors	Elevation	− 0.76*	− 4.04***	− 1.85***	− 1.46***	− 1.87***
		Slope	− 7.95***	− 7.42***	− 0.83***	− 5.17***	− 3.42***
		Distance to water	1.80***	1.50***	− 0.67***	− 1.42***	− 0.90***
	Socioeconomic factors	Distance to roads	− 1.83***	− 3.00***	− 2.61***	− 3.45***	− 0.63***
		Distance to railways	− 1.03**	− 1.33***	− 2.42***	0.88***	− 0.96***
		Distance to the city center	− 1.46***	− 1.59***	− 0.88***	1.22***	0.47***
		Distance to district centers	− 2.13*	− 0.95***	− 0.76***	1.22***	− 2.35***
		Nightlight intensity	0.97***	3.06***	0.32***	2.98***	1.19***
	Neighboring factors		5.03***	5.78***	6.16***	5.21***	4.33***
	Constant		0.58***	0.32***	0.51***	− 1.13***	0.48***
Model test	*n*		70,640	147,086	99,302	100,258	210,868
	PCP		0.83	0.74	0.81	0.80	0.75
	AUC		0.88	0.76	0.87	0.83	0.80

Table 2 (continued)

	1980–1990	1990–1995	1995–2000	2000–2005	2005–2010
R^2	0.40	0.55	0.47	0.41	0.35

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Our results showed that socioeconomic factors, as the precursor drivers of urbanization, exerted a promoting influence on urban expansion most of the time. Urban planning is an instrument of government regulation aimed at optimizing urban functioning and spatial layout. Socioeconomic factors are important drivers of urban expansion that can be adjusted. As the key breakout from existing urban problems to a planning blueprint, socioeconomic factors should be deeply and explicitly considered in urban planning (Jantz et al. 2003). During the course of urban development, joint effects of socioeconomic drivers with other forces should be paid increasing attention in urban planning.

Neighboring factors have positive influences on various cities for various epochs, i.e., new urban growth points tend to appear near existing urban lands where more supporting facilities are available (Daniels 1999). A previous study, however, demonstrated that neighboring factors might induce a negative effect when leapfrogging expansion was dominant (Zhao 2010). Our results suggest that neighboring factors significantly enhance the possibility of urban expansion nearby across cities and over time and the magnitude of the effect varies with the composition of urban growth types. Neighboring factors usually act independently

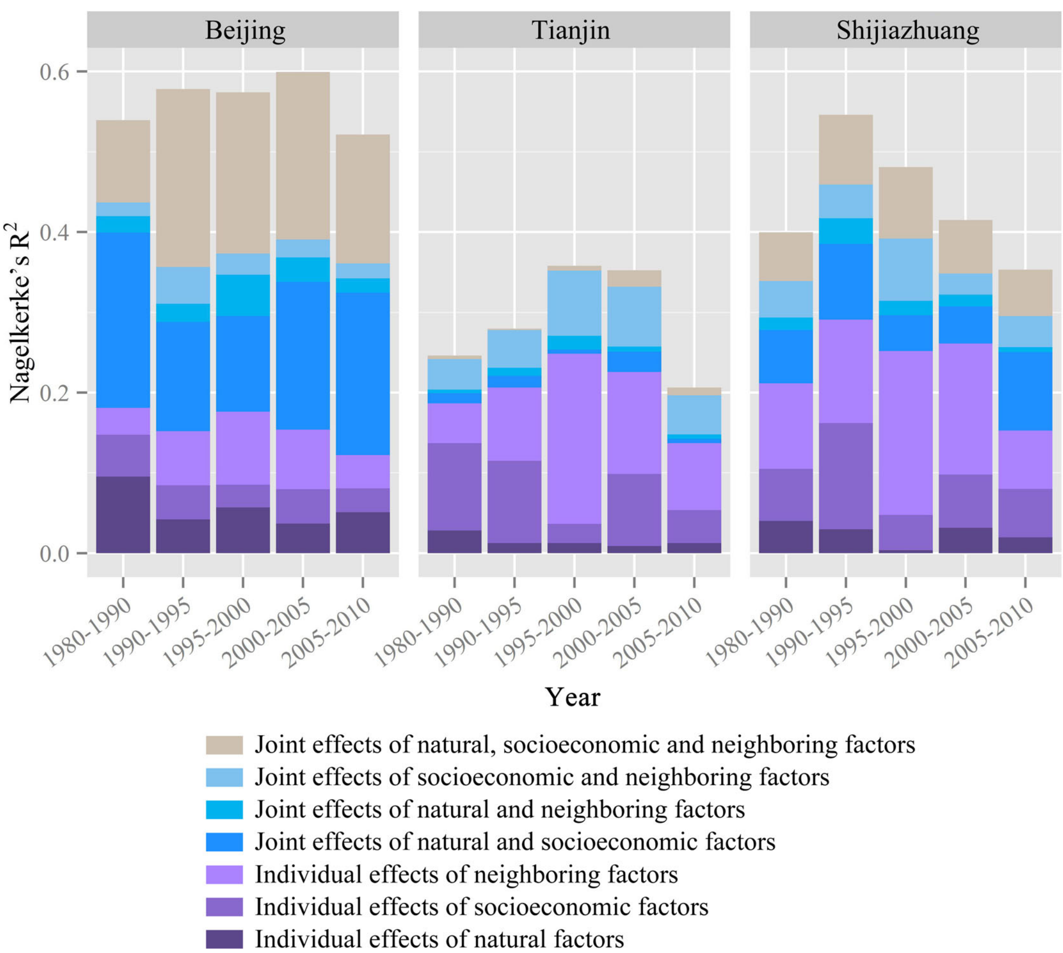

Fig. 5 Results of variance partitioning for driving factors in Beijing, Tianjin, and Shijiazhuang for the five epochs from 1980 to 2010

or interacted with socioeconomic factors. The joint effects of neighboring factors and natural factors were inconspicuous. Along with the urbanization process, the individual effects of neighboring factors tend to be replaced by joint effects with natural factors or socioeconomic factors, which can be explained by transportation costs associated with neighboring factors shown by Lu et al. (2013). In the early stage of urbanization, lower cost of living near existing transportation infrastructure attracts urban population aggregation. However, improvement of transportation infrastructure narrows disparities of transport costs for different areas and weakens the individual effects of neighboring factors. Therefore, to improve the transportation system and the accessibility of public utilities is an effective way to optimize urban expansion patterns. For big cities such as Beijing and Tianjin, little space remains in the neighborhood of existing urban land. Satellite towns and new areas aimed to disperse the space pressure of "the old town" become the focus of future urban construction. Accordingly, neighboring drivers should be replaced by efficient urban development strategies.

Using logistic modeling and variance partitioning techniques, we quantified the evolution of the relative importance of different drivers to the expansion of three major cities in China. The approaches presented here are generic and can be applied to other regions to illucidate the driving forces of urbanization. Our study covered three major cities with varying biophysical, socioeconomic, political, and cultural settings and significance, and the empirical results can certainly be used to facilitate the formulation of adaptive urban development strategies in the region. However, a broader comparative understanding of the driving forces across regions at the national and global scales is necessary to advance urban development theories and urban optimization skills (White et al. 2015; Zhao et al. 2018). In addition, the feedback between ecosystem services and urbanization (e.g., the valuable ecosystem services provided by the mountainous areas in the northwest of Beijing and Beijing expansion) may play an important role in urban development and management, which should be explicitly considered in future research.

Conclusions

Urban expansion has affected ecosystem functioning and services at local to global scales. It is necessary to analyze the driving forces of urban expansion and thus understand the mechanisms behind the urbanization process and provide scientific guidance for urban planning and management. However, temporally dynamic and comparative analyses on the driving forces of urban expansion over a relatively long timeframe are limited. In this study, we compared and decomposed the driving forces of urban expansion in the past three decades for Beijing, Tianjin, and Shijiazhuang using logistic regression and the variance partitioning method.

Spatiotemporal patterns of urban expansion for the three cities in the Jing-Jin-Ji Urban Agglomeration resulted from the combined effects of natural, socioeconomic, and neighboring factors. Urban expansion has been influenced by not only individual effects of factors but also joint effects. Joint effects, especially those of neighboring factors and other factors, shared a noticeable proportion of explained variance. The direction and magnitude of different driving forces varied with city and time.

In-depth analyses of the drivers of urban expansion in China and their dynamics have been lacking. As urban expansion continues to encroach into natural and seminatural ecosystems, it is important that the drivers behind spatiotemporal urban expansion be clearly understood and incorporated into urban planning and management decisions. This step is particularly important for the Jing-Jin-Ji Urban Agglomeration where a new blueprint for future urbanization and economic development has been rolled out recently. Quantifying, decomposing, and comparing drivers contribute to mechanistic understanding of urbanization in different stages for urban planners and managers. The scientific knowledge of urban expansion drivers and mechanisms from our study will provide direction, guidance, and support for adjusting and optimizing urban planning in the national capital region and other urban agglomerations of China.

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References

Anderson, M. J., & Gribble, N. A. (1998). Partitioning the variation among spatial, temporal and environmental components in a multivariate data set. *Australian Journal of Ecology, 23*, 158–167.

Angel, S., Sheppard, S. C., Civco, D. L., Buckley, R., Chabaeva, A., Gitlin, L., Kraley, A., Parent, J., & Perlin, M. (2005). *The dynamics of global urban expansion, transport and urban development department*. Washington D.C: The World Bank.

Bettencourt, L. M. (2013). The origins of scaling in cities. *Science, 340*, 1438–1441.

Betts, M. G., Diamond, A. W., Forbes, G. J., Villard, M., & Gunn, J. S. (2006). The importance of spatial autocorrelation, extent and resolution in predicting forest bird occurrence. *Ecological Modelling, 191*, 197–224.

Braimoh, A. K., & Onishi, T. (2007). Spatial determinants of urban land use change in Lagos, Nigeria. *Land Use Policy, 24*, 502–515.

Cheng, J. Q., & Masser, I. (2004). Understanding spatial and temporal processes of urban growth: cellular automata modelling. *Environment and Planning. B, Planning & Design, 31*, 167–194.

Danilina, E. I., & Chebotarev, V. E. (2017). Comprehensive assessment of road and communal infrastructure as an important tool for sustainable development of the urban economy. *Theoretical and Empirical Researches in Urban Management, 12*, 33–51.

Daniels, T. (1999). When city and country collide: managing growth in the metropolitan fringe. *Environmental Quality, 45*, 57–58.

Doll, C. H., Muller, J. P., & Elvidge, C. D. (2000). Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. *AMBIO, 29*, 157–162.

Doll, C. N. H., Muller, J. P., & Morley, J. G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics, 57*, 75–92.

Dubovyk, O., Sliuzas, R., & Flacke, J. (2011). Spatio-temporal modelling of informal settlement development in Sancaktepe district, Istanbul, Turkey. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*, 235–246.

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., Erwin, E. H., & Zhizhin, M. (2009). A fifteen year record of global natural gas flaring derived from satellite data. *Energies, 2*, 595–622.

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters, 27*, 861–874.

Gong, P., Liang, S., Carlton, E. J., Jiang, Q., Wu, J., Wang, L., & Remais, J. V. (2012). Urbanisation and health in China. *The Lancet, 379*, 843–852.

Gude, P. H., Hansen, A. J., Rasker, R., & Maxwell, B. (2006). Rates and drivers of rural residential development in the Greater Yellowstone. *Landscape and Urban Planning, 77*, 131–151.

Heikkinen, R. K., Luoto, M., Kuussaari, M., & Poyry, J. (2005). New insights into butterfly-environment relationships using partitioning methods. *Proceedings of the Royal Society B-Biological Sciences, 272*, 2203–2210.

Hills, P. J. (1996). What is induced traffic? *Transportation, 23*, 5–16.

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J., & Megown, K. (2015). Completion of the 2011 National Land Cover Database for the conterminous United States—representing a decade of land cover change information. *Photogrammetric Engineering & Remote Sensing, 81*, 345–354.

Jantz, C. A., Goetz, S. J., & Shelley, M. K. (2003). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropoliton area. *Environment and Planning. B, Planning & Design, 30*, 251–271.

Jiang, D., Zhuang, D. F., Xu, X. L., & Lei, Y. (2008). Integrated evaluation of urban development suitability based on remote sensing and GIS techniques—a case study in Jingjinji area, China. *Sensors, 8*, 5975–5986.

Ju, H., Zhang, Z., Zuo, L., Wang, J., Zhang, S., Wang, X., & Zhao, X. (2016). Driving forces and their interactions of built-up land expansion based on the geographical detector—a case study of Beijing, China. *International Journal of Geographical Information Science, 30*, 2188–2207.

Kaye, J. P., Groffman, P. M., Grimm, N. B., Baker, L. A., & Pouyat, R. V. (2006). A distinct urban biogeochemistry? *Trends in Ecology & Evolution, 21*, 192–199.

Körner, C., & Ohsawa, M. (2006). Mountain systems. In R. Scholes & N. Ash (Eds.), *Ecosystem and human well-being: current state and trends* (Millennium ecosystem assessment) (Vol. 1, pp. 681–716). Washington: Island Press.

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., & Folke, C. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change, 11*, 261–269.

Levin, N., & Duke, Y. (2012). High spatial resolution night-time light images for demographic and socio-economic studies. *Remote Sensing of Environment, 119*, 1–10.

Li, X. M., Zhou, W. Q., & Ouyang, Z. Y. (2013). Forty years of urban expansion in Beijing: what is the relative importance of physical, socioeconomic, and neighborhood factors? *Applied Geography, 38*, 1–10.

Litteral, J., & Wu, J. (2012). Urban landscape matrix affects avian diversity in remnant vegetation fragments: evidence from the Phoenix metropolitan region, USA. *Urban Ecosystems, 15*, 939–959.

Liu, H., & Zhou, Q. (2005). Developing urban growth predictions from spatial indicators based on multi-temporal images. *Computers, Environment and Urban Systems, 29*, 580–594.

Liu, J., Kuang, W., Zhang, Z., Xu, X., Qin, Y., Ning, J., Zhou, W., Zhang, S., Li, R., Yan, C., Wu, S., Shi, X., Jiang, N., Yu, D., Pan, X., & Chi, W. (2014). Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *Journal of Geographical Sciences, 24*, 195–210.

Liu, J. Y., Zhan, J. Y., & Deng, X. Z. (2005). Spatio-temporal patterns and driving forces of urban land expansion in China during the economic reform era. *AMBIO, 34*, 450–455.

Liu, Z. F., He, C. Y., Zhang, Q. F., Huang, Q. X., & Yang, Y. (2012). Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. *Landscape and Urban Planning, 106*, 62–72.

Long, H., Tang, G., Li, X., & Heilig, G. K. (2007). Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. *Journal of Environmental Management, 83*, 351–364.

Long, H., Wu, X., Wang, W., & Dong, G. (2008). Analysis of urban-rural land-use change during 1995-2006 and its policy dimensional driving forces in Chongqing, China. *Sensors, 8*, 681–699.

Lu, C., Wu, Y., Shen, Q., & Wang, H. (2013). Driving force of urban growth and regional planning: a case study of China's Guangdong Province. *Habitat International, 40*, 35–41.

Lucas, R. (1988). On the mechanics of economic-development. *Journal of Monetary Economics, 22*, 3–42.

Mcdonnell, M. J., & Macgregor-Fors, I. (2016). The ecological future of cities. *Science, 352*, 936–938.

Mertes, C. M., Schneider, A., Sulla-Menashe, D., Tatem, A. J., & Tan, B. (2015). Detecting change in urban areas at continental scales with MODIS data. *Remote Sensing of Environment, 158*, 331–347.

Nagelkerke, N. J. (1991). A note on a general definition of the coefficient of determination. *Biometrika, 78*, 691–692.

NBSC (National Bureau of Statistics of China). (2011). *China statistical yearbook*. Beijing: China Statistics Press.

Osman, T., Divigalpitiya, P., & Arima, T. (2016). Driving factors of urban sprawl in Giza Governorate of Greater Cairo Metropolitan Region using AHP method. *Land Use Policy, 58*, 21–31.

Qu, W., Zhao, S., & Sun, Y. (2014). Spatiotemporal patterns of urbanization over the past three decades: a comparison between two large cities in Southwest China. *Urban Ecosystems, 17*, 1–17.

Rong, Z. R., An-Qing, M. A., Wang, Z. K., & Zhou, K. (2012). Driving forces analysis of landscape pattern changes based on logistic regression model in wetland of Liaohe. *Environmental Science & Technology, 35*, 193–198.

Schweizer, P. E., & Matlack, G. R. (2014). Factors driving land use change and forest distribution on the coastal plain of Mississippi, USA. *Landscape and Urban Planning, 121*, 55–64.

Seto, K. C., Fragkias, M., Guneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PLoS One, 6*(8), e23777. https://doi.org/10.1371/journal.pone.0023777.

Seto, K. C., & Kaufmann, R. K. (2003). Modeling the drivers of urban land use change in the Pearl River Delta, China: integrating remote sensing with socioeconomic data. *Land Economics, 79*, 106–121.

Siedentop, S., & Fina, S. (2010). Urban sprawl beyond growth: the effect of demographic change on infrastructure costs. *Flux, 79–80*, 90–100.

Silva, P., & Li, L. (2017). Mapping urban expansion and exploring its driving forces in the city of Praia, Cape Verde, from 1969 to 2015. *Sustainability, 9*, 1434. https://doi.org/10.3390/su9081434.

Team, R. D. C. (2013). *R: a language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing ISBN 3-900051-07-0.

Thapa, R. B., & Murayama, Y. (2010). Drivers of urban growth in the Kathmandu valley, Nepal: examining the efficacy of the analytic hierarchy process. *Applied Geography, 30*, 70–83.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science, 277*, 494–499.

Wang, Q., Ren, Q., & Liu, J. (2016). Identification and apportionment of the drivers of land use change on a regional scale: unbiased recursive partitioning-based stochastic model application. *Agriculture, Ecosystems & Environment, 217*, 99–110.

White, R., Engelen, G., & Uljee, I. (2015). *Modeling cities and regions as complex systems: From theory to planning applications* (pp. 344). Cambridge, Massachusetts: MIT Press.

Wu, J., Wang, Z., Li, W., & Peng, J. (2013). Exploring factors affecting the relationship between light consumption and GDP based on DMSP/OLS nighttime satellite imagery. *Remote Sensing of Environment, 134*, 111–119.

Wu, W., Zhao, S., Zhu, C., & Jiang, J. (2015). A comparative study of urban expansion in Beijing, Tianjin and Shijiazhuang over the past three decades. *Landscape and Urban Planning, 134*, 93–106.

Yue, W. Z., Liu, Y., & Fan, P. L. (2013). Measuring urban sprawl and its drivers in large Chinese cities: the case of Hangzhou. *Land Use Policy, 31*, 358–370.

Zhao, C., Jensen, J., & Zhan, B. (2017). A comparison of urban growth and their influencing factors of two border cities: Laredo in the US and Nuevo Laredo in Mexico. *Applied Geography, 79*, 223–234.

Zhao, P. J. (2010). Sustainable urban expansion and transportation in a growing megacity: consequences of urban sprawl for mobility on the urban fringe of Beijing. *Habitat International, 34*, 236–243.

Zhao, S. Q., Da, L. J., Tang, Z. Y., Fang, H. J., Song, K., & Fang, J. Y. (2006). Ecological consequences of rapid urban expansion: Shanghai, China. *Frontiers in Ecology and the Environment, 4*, 341–346.

Zhao, S. Q., Zhou, D. C., Zhu, C., Qu, W. Y., Zhao, J. J., Sun, Y., Huang, D., Wu, W., & Liu, S. (2015a). Rates and patterns of urban expansion in China's 32 major cities over the past three decades. *Landscape Ecology, 30*, 1541–1559.

Zhao, S. Q., Zhou, D., Zhu, C., Sun, Y., Wu, W., & Liu, S. (2015b). Spatial and temporal dimensions of urban expansion in China. *Environmental Science & Technology, 49*, 9600–9609.

Zhao, S. Q., Liu, S., Xu, C., Yuan, W., Yan, W., Zhao, M., Sun, Y., Henebry, G. M., & Fang, J. Y. (2018). Contemporary evolution and scaling of 32 major cities in China. *Ecological Applications, 28*, 1655–1668.

Zhou, D. C., Zhao, S. Q., Liu, S. G., & Zhang, L. X. (2014). Spatiotemporal trends of terrestrial vegetation activity along the urban development intensity gradient in China's 32 major cities. *Science of the Total Environment, 488*, 136–145.

Zhuo, L., Ichinose, T., Zheng, J., Chen, J., Shi, P. J., & Li, X. (2009). Modelling the population density of China at the pixel level based on DMSP/OLS non-radiance-calibrated night-time light images. *International Journal of Remote Sensing, 30*, 1003–1018.