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RESEARCH ARTICLE

Thresholds of landscape change: a new tool to manage green infrastructure and social–economic development

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Abstract An understanding of how and where a landscape can be improved with green infrastructure is important for the development of land-use policies. However, it is still a big challenge to manage landscapes due to a lack of condition-based diagnosis and consistent conflicts with social–economic interests. The purpose of this study is to identify the thresholds of landscape change and to explore new reference lines of policy decision-making for balancing social–economic development and green infrastructure management. Five different landscape types and their thresholds of landscape change were identified using parametric and piecewise linear models in the district of Haidian, Beijing, PR China, and their changes and social–economic drivers were analyzed with principal component analysis and a stepwise linear regression model for the time period 1991–2010. It is shown that different thresholds of different landscapes do exist and can be identified by the area of their key elements of green infrastructure. Integrating these thresholds into a social–economic context, it is shown where and how social–economic variables can be manipulated quantitatively to achieve development targets with respect to green infrastructure in individual towns and the entire district. Green infrastructure can be managed by changing just a small proportion of social–economic investment. This paper provides a useful tool to achieve a sustainable development by balancing green infrastructure with social–economic interests.

Keywords Threshold · Landscape change · Social–economic development · Green infrastructure · Sustainable development · China

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Introduction

A landscape is characterized by the presence of a distinct and recognizable pattern of elements or properties (Swanwick 2002). An important part of most landscapes is their green infrastructure (GI), which are natural and man-made green landscape elements such as forests, arable fields, parks and trees (Weber et al. 2006). These elements are usually scattered throughout a landscape and form a heterogeneous mosaic of patches. The structure and function of a landscape is largely affected by the spatial

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arrangement of these heterogeneous patches (Byomkesh et al. 2012), and mainly dominated by key GI elements, which have a high correlation to landscape function and structure and occupy a certain area of the landscape (Li et al. 2006). GI plays an important role in promoting ecosystem and human health (Tzoulas et al. 2007), and is essential for life-quality and the cultural anchoring of society (Fry et al. 2004; Kim and Pauleit 2007). The ongoing urbanization rapidly changes existing GI and causes ecological and landscape problems, e.g. through the loss of woodlands (Penas et al. 2011), increasing the risks of floods (Nedkov and Burkhard 2012) and the disappearance of the "sense of place" (Soini et al. 2012). Most of these changes appear to be irreversible (Davis et al. 2010), and changing social–economic developments change the GI composition of landscapes (van Eetvelde and Antrop 2009). For example, the traditional late commons and outfields landscape occupied 55 % of the area between the cities of Ghent and Bruges in 1755, but is entirely lost since 1910 (van Eetvelde and Antrop 2009). Even today, the structural change in European agriculture threatens the identity of historically grown, small-scale rural landscapes with hedges, small forests and interspersed trees, and generates new types of large-scale landscapes without such GI types (de Aranzabal et al. 2008).

Ongoing social–economic development changes GI often so profoundly that cultural anchoring, biodiversity and life quality are lost. To avoid such negative impacts of development, the analysis and management of landscape change has received great attention. Landscapes are commonly described by identifying, classifying, mapping and assessing of different landscape features (Swanwick 2002; Jellema et al. 2009; Brown and Brabyn 2012). The description of landscape features and their values only does, however, not provide enough information about the location, extent and possible management of ongoing landscape change (Kim and Pauleit 2007). Recent studies suggested that thresholds can be applied in ecosystem management (Huggett 2005; Lindenmayer and Luck 2005). A threshold is a point or zone, where a small change will cause a sudden, significant change in the current state (Muradian 2001; Kato and Ahern 2011). It is a quantitative measure to manage ecosystem to a desired state and an important tool for sustainable development (Bestelmeyer 2006; Price et al. 2009; West et al. 2009; McClanahan et al. 2011; Seddon et al. 2011). However, it is still a big challenge for policy makers to enhance ecosystem resilience, since GI is affected by rapidly changing social–economic contexts (Bateman et al. 2011; Horan et al. 2011). An increasing number of studies tried to link social–economic decision making with ecological thresholds (Walker et al. 2004; Renaud et al. 2010; Horan et al. 2011; Chen et al. 2012). These studies made progress in balancing ecosystem conservation and social–economic development, but the realism of such models is still unclear due to the complexity and dynamics of interactions. The challenge of defining thresholds quantitatively remains one of the major obstacles to manage landscapes in reality.

In China, the speed of ongoing GI change is remarkable. Beijing lost 1,857 km^2 of its green space between 1992 and 2004, including farmland, grassland and water bodies (Xu et al. 2011). This corresponds to 11.3 % of the total area of Beijing and to an annual loss of 155 km^2 of GI. Under these circumstances, a better understanding of how and where landscape change can occur and the identification of objectively determinable parameters for landscape management are urgently needed.

The high visibility of GI makes it an important factor for the formation of a particular landscape character and very suitable to analyze landscape change. We hypothesized that thresholds of landscape change are most visibly expressed by the area percentage of key landscape elements which mainly refer to land-use types, because a change of other natural landscape properties like soil properties and topography is unlikely to occur over a few years. The objectives of this study were a) to identify the thresholds of landscape change based on key landscape elements in different landscapes of the Haidian District, Beijing, China, and b) to test how social–economic development can be manipulated to maintain or manage the current green infrastructure.

Materials and methods

Study area and datasets

The study area was the district of Haidian (39°53′–40°9′N, 116°2′–116°23′E), which is located in the northwestern part of Beijing, PR China (Fig. 1). It covers an area of 431 km^2 and lays between 4 and

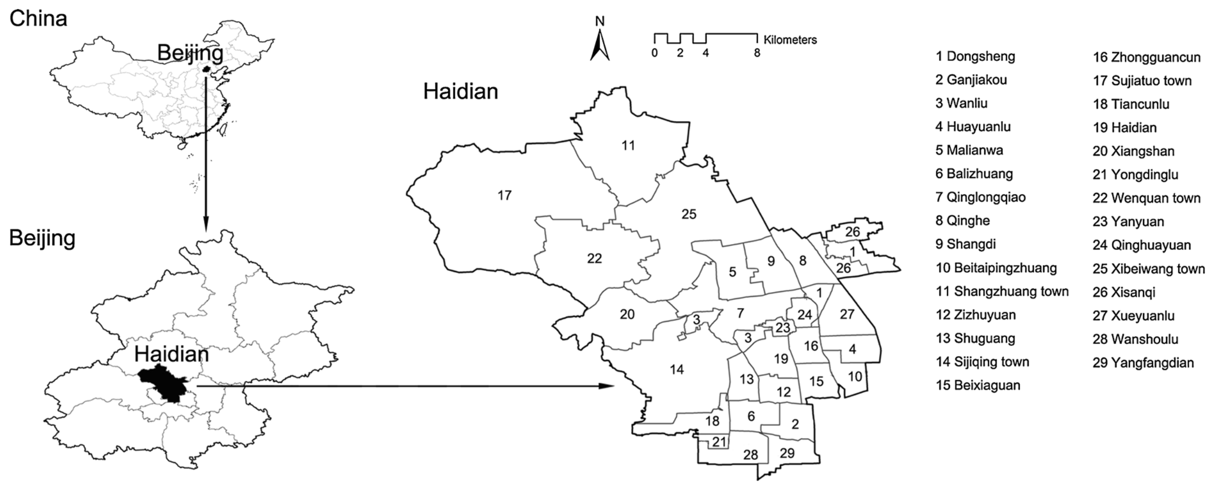

Fig. 1 Location of the Haidian district and its subdivisions

1,261 m asl. Land-use maps of different years (1991, 2001, 2004, 2006, 2008, and 2010; scale 1:10,000) from the Haidian Bureau of the Land Consolidation Center of China were transformed to identify the major landscapes of Haidian. These maps depict six GI types, including public green space, forest, farmland, orchard, water bodies, other green infrastructure, and one category non-GI which is characterized by the absence or an extremely low density of green features (Table 1). These types were selected, because they can be easily identified in the real landscape and closely match human perception. Topographic data like altitude and slope as well as soil data was attributed to these GI types (Table 1). Altitude data was obtained from the digital elevation model with a 30 × 30 m resolution (DEM 2010), while slope data was derived from the DEM by using ArcGIS 9.3. Data of eight social–economic variables of different towns in Haidian were collected from the Haidian Statistical Yearbooks (2004–2011) and analyzed to identify the potential driving forces of landscape change (Table 1).

Characterization and classification of landscapes

A landscape is characterized by the presence of a distinct and recognizable pattern of elements or properties (Swanwick 2002). Here, land-use, topographic and soil data were mapped as separate layers and overlaid in ArcGIS 9.3 to generate landscape patches of different properties (Fig. 2 step a). The similarity of individual patches was assessed and patches were grouped into five distinct landscapes (Fig. 2 step b). This number is considered acceptable for the classification on district level (Peng et al. 2007). Similarity was calculated based on patch properties, the spatial distribution of patches in the investigated region and on their boundaries with other patches (Martin et al. 2006; Ruiz and Domon 2009). Two landscape metrics, the mean proximity index distribution (PROX) and the mean euclidean nearest neighbor distance (ENN), were calculated using FRAGSTATS 3.3 (McGarigal et al. 2002) at the patch-level to describe the degree of isolation of individual patches within a landscape and the fragmentation of the landscape. The raster version of FRAGSTATS was used with a grid resolution of 30 m. Three matrices, including patches × landscape elements (land-use types, soil, slope, altitude), patches × landscape pattern indices (PROX, ENN) and patches × frequency of boundaries, were set-up for each year and each matrix was subjected to a detrended correspondence analysis (DCA). All obtained DCA-axes from each year were clustered using a k-means clustering method (Martin et al. 2006). In order to compare the landscapes between years, a special matrix was designed, in which the rows corresponded to the area of the different landscapes in the investigated years, while the columns contained the percentage area of the different land-use types of each landscape. The matrix was clustered using Euclidian distance as measure of similarity and

Table 1 Natural and social–economic data of the study area

Name	Type	Scale	Year of data
Types of green infrastructure	Public green space	1:10,000	1991,
	Farmland		2001,
	Orchard		2004,
	Forest		2006,
	Water body		2008,
	Other green space		2010
	Non-GI		
Soil parent materials	Basic rocks	1:50,000	2005
	River alluvium		
	Mud rocks		
	Diluvia alluvium		
	Lake deposits		
	Siliceous rocks		
	Acidic rocks		
	Calcareous rocks		
	Loess-like diluvia alluvial		
	Loess-like deposits		
	Loess-like sediment		
	Loess silty sand		
	Others		
Altitude	4–102 m	30 m	2010
	102–1261 m		
Slope	0°–2°	1:10,000	2010
	2°–6°		
	6°–15°		
	15°–25°		
	25°–45°		
	≥45°		
Social–economic variables	Income catering & accommodation	Town-level	2004, 2006, 2008, 2010
	People in science & technology		
	People in water & environmental management		
	People in educational sector		
	People in social organizations		
	Registered population		
	Migrant workers		
	Rental income		

the hierarchical cluster as the grouping method. Landscapes were considered to be equivalent between years, if they were clustered into the same group.

Identification of thresholds of landscape change

In order to identify those patches which changed landscapes between years, the landscape map of Haidian of a preceding year was subtracted from the landscape map of the following year using ArcGIS (Fig. 2 step c). As a result, two groups of patches were obtained for each landscape: newly appeared patches and disappeared patches. In total, five groups of disappeared patches and five groups of newly appeared patches were obtained by comparing the six available landscape maps from the years 1991 to 2010. For each changed patch, the percentage of its land-use composition was measured to identify key landscape elements (Fig. 2 step d). A land-use type was defined as a key landscape element, if it had a positive correlation with its landscape and an area percentage of >5 %. If one patch contained more than one key landscape element, the percentages of these key landscape elements were summed up. The calculated percentages of key landscape elements were classified into 20 groups with a range of 5 % (from 0 to 100 %), and the frequency of each group was calculated. Thresholds of landscape change were tested by analyzing the frequency with a piecewise linear model (Fig. 2 step e).

Relationships between social–economic factors and GI types

To understand the relationships between social–economic variables and GI types, a stepwise linear regression analysis was applied. Prior regression analysis, town-level data of social–economic variables was analyzed with a principal component analysis (PCA) to eliminate multi-collinearity effects (Fig. 2 step f). 116 datasets from the time period 2004 to 2010 were used for analysis (29 towns × 4 years), because social–economic data were not available for the years 1991 and 2001 (Fig. 2, step g). Principal component (PC) scores were put in the regression models as independent variables (x_i), while the summed areas of different GI types of each town were treated as

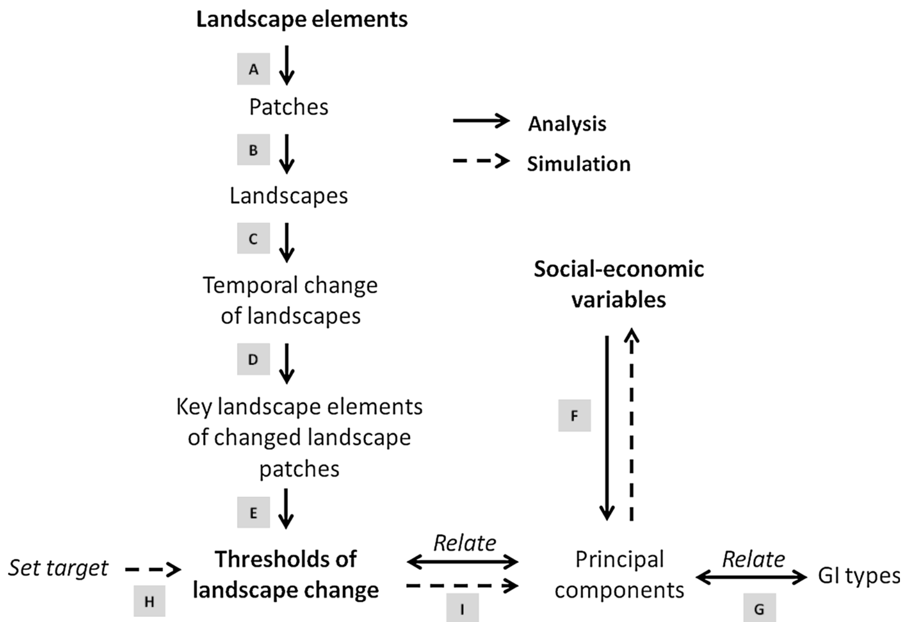

Fig. 2 Methodological framework of thresholds and their application in social–economic management. (*a*) Formation of landscape patches; (*b*) Characterization and classification of landscapes; (*c*) Identification of temporal change of landscapes; (*d*) Identification of key landscape elements of changed landscape patches; (*e*) Identification of thresholds of landscape changes; (*f*) PCA for social–economic variables; (*g*) Quantification of relationships between social–economic factors and GI types; (*h*) Identification of scenario targets of GI management; (*i*) Identification of reference lines of social–economic development for GI management

dependent variable (Y). Variables in the models were selected according to a significant proportion of residual variation explained after all other variables were included ($p < 0.01$). The coefficient of determination (R^2) was used to judge the quality of the regression models. A regression model was accepted if the variance explained by the model was higher than 50 % at a significance level of $p < 0.05$. Regressions were estimated through the linear model:

$$\mathrm{Y_{GI}} = B_0 + \sum_{i=1}^{n} \mathrm{b_i x_i} \tag{1}$$

where $\mathrm{Y_{GI}}$ is the area percentage of the GI type, x is the score of PCs obtained from PCA, b is the regression coefficient, n is the number of components and B_0 is a constant. From this model, a change of PC scores can be calculated from the area percentage of GI requiring management.

Another product of PCA is a set of "component score coefficient matrix", which describes the relationships between each original variable and the principal components through a coefficient (Chen and Wang 2001). This relationship can be expressed as follows:

$$\mathrm{Y_{sc}} = \sum_{i=1}^{n} \mathrm{c} \times \mathrm{x_i} \tag{2}$$

where $\mathrm{Y_{sc}}$ is the value of a social–economic variable, c is the coefficient of component score obtained from "component score coefficient matrix", x is the PC score, n is the number of components. Therefore, we can quantify changes of the original variables based on PC scores which were calculated by formula (1). All statistical analyses were performed using IBM SPSS Statistics 20.

Reference of social–economic decision-making for GI management

The average size of patches, which changed between 1991 and 2010, was determined (320 × 320 m) and used as grid size for calculating the percentage area of key landscape elements of all landscapes in Haidian for the year 2010. Based on the area percentages of these key landscape elements, it was analyzed where and which patches were below, within or above the thresholds for landscape change. In order to determine which and to what extent social–economic variables should be changed to protect and manage different GI, two adaptation scenarios were chosen: (a) the area of key landscape elements of different landscapes dominated by GI covers was increased to lower boundary of the threshold zone, while (b) the area of key landscape elements was increased to the upper boundary of the threshold zone (Fig. 2 step h). The area of those GI types, which required changes to achieve these two targets, were summarized for each town, and were then put in the regression equations (Eq. 1) to analyze the change of PC scores (Fig. 2, step I) and thus, of social–economic variables. All calculations of socio-economic data for each town were summarized to obtain the changes of socio-economic data at the district scale.

Results

Changes of landscapes

Five landscapes were identified in Haidian, which were present in all investigated years: mountain woodlands, urban settlements, rural settlements, recreation areas and agricultural and forest lands (Fig. 3). Mountain woodlands were located in the west of Haidian and occupied 15 % of the whole district area. Its area remained relatively stable between 1991 and 2010. Urban settlements comprised residential areas and commercial estates and were located in the southern part of the study area. Urban settlements increased significantly from 4 to 25 % between 1991 and 2010, to the disadvantage of rural settlements and agricultural and forest lands. Rural settlements consisted of traditional settlements with little public green space and were scattered throughout the northern and central areas of Haidian. Their area increased slowly from 18 to 22 % between 1991 and 2001, remained almost stable at 26–27 % until 2008, and decreased to 23 % until 2010. Recreation areas covered the smallest area of Haidian (5–6 %) and consisted of public parks or gardens. Recreation areas were stable between 1991 and 2008, but increased sharply to 12 % by 2010. Agricultural and forest lands consisted of farmland, orchards and forests. Their area decreased rapidly from 57 to 25 % between 1991 and 2010, mainly in favor of rural settlements.

Green infrastructure composition of landscapes

Mountain woodlands were dominated by two GI-types: forests (82.9 %) and public green space (8.8 %) (Fig. 4a). The increase in area of this landscape over

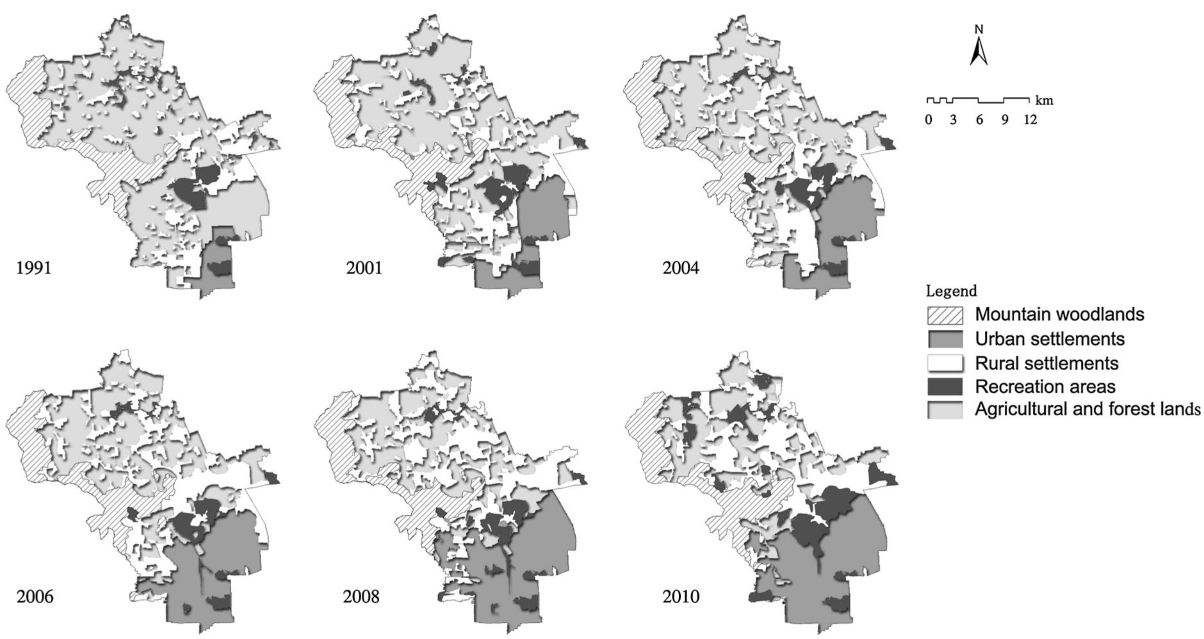

Fig. 3 Dominant landscapes of Haidian between 1991 and 2010

the observation period was related to these two GI types, but mainly the result of an increase in public green space. Urban settlements were dominated by non-GI (80.9 %) and public green space (6.7 %) (Fig. 4b), and their area increase was the result of expanding areas of both land-use types between 1991 and 2010. A large proportion of rural settlements was occupied by non-GI (68.1 %) and forest (12.5 %) (Fig. 4c), whereas the area of public green space was minor (less than 5 %). The key landscape elements of recreation areas were public green space (65.9 %), non-GI (10.0 %) and forest (6.9 %) (Fig. 4d). Agricultural and forest lands were dominated by farmland (24.4 %), orchard (16.7 %) and forest (26.3 %) and the area increase between 1991 and 2010 was related to the expansion of all three land-use types (Fig. 4e). All given percentages are average values for the time period between 1991 and 2010.

Thresholds of landscape change

Thresholds were identified for all five landscapes, above or below which the likelihood for a landscape change increased or decreased (Fig. 5). Landscape changes usually occurred when the key landscape elements of each landscape covered an area of 40–60 % of the respective landscape. There were, however, slight differences in thresholds between the individual landscapes. Mountain woodlands increasingly disappeared, if the area share of the key landscape elements dropped below 46 %, and expanded above 52 % (Fig. 5a). This landscape is unstable within this range, and most likely transformed to another landscape below this range. For the remaining landscapes, these threshold zones were at 43–60 % (urban settlements), 45–60 % (rural settlements), 49–62 % (recreation areas) and 37–50 % (agricultural and forest lands) of the total landscape area, respectively (Fig. 5b–e).

In the year 2010, only a very small proportion (4 %) of the area of mountain woodlands was below and within the threshold zone of this landscape (Fig. 6). The area below and within the threshold zone was 8.5 % for urban settlements. 13.1 and 8 % of rural settlements area were below and within the threshold zone of this landscape. In recreation areas, there was a large area (20 %) below the threshold zone of this landscape, while only 3.4 % within the threshold zone. A large area (31.2 %) was below the threshold zone of agricultural and forest lands, while only 5.5 % was within the threshold zone.

Relationships between social and economic factors and GI types

Four principal components were identified with PCA, which represent different combinations of social–economic factors which drive landscape change. These components explained together 84.1 % of the

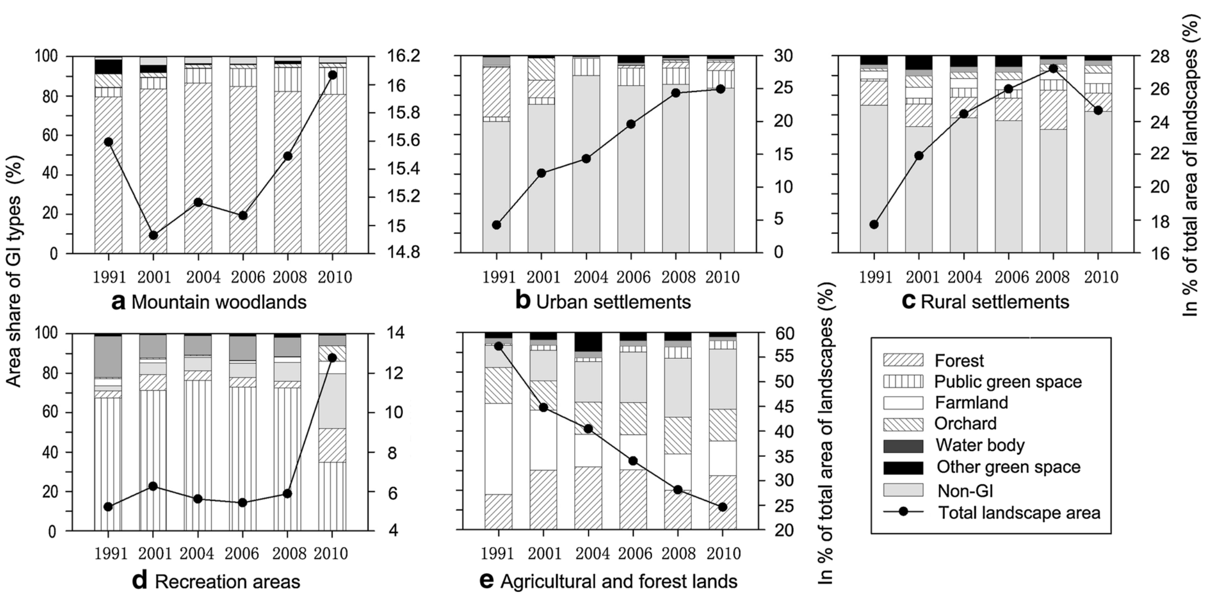

Fig. 4 Composition of green infrastructure of different landscapes in Haidian

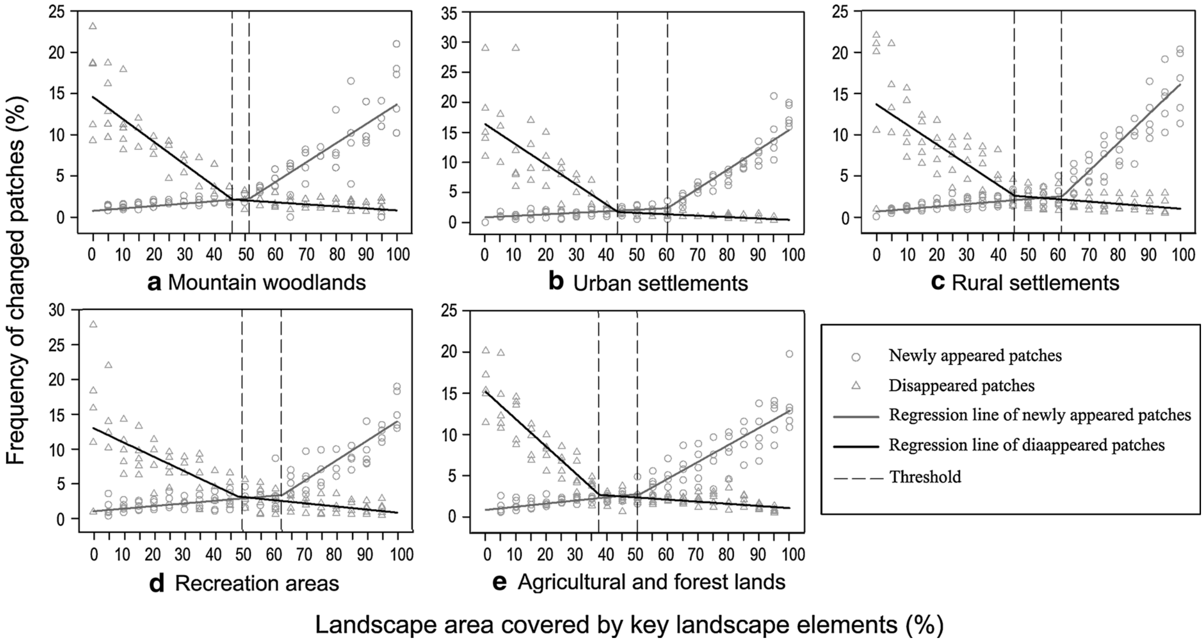

Fig. 5 Thresholds for landscape change. *Grey lines* represent the best-fit models for the regression of newly appeared patches, and *black lines* represent the best-fit models for the regression of disappeared patches. *Dotted black lines* indicate the thresholds for landscape change

cumulative variance (Table 2). The first component (PC1) mainly comprised three different types of indicators: permanent population, economic income (tenancy, catering and accommodation) and investment in scientific research. These indicators were associated with positive PC1 scores, and were highly correlated to each other. The second component (PC2) was interpreted as a level of social organization (number of employed persons in social organizations) and was associated with negative PC2 scores. The third component (PC3) was related to the level of education. The number of employed persons in education was positively, while the number of migrant workers was negatively related to PC3. The fourth component (PC4) was interpreted as investment in environmental management, since indicators for the management of water and environment was linked to positive PC4 values.

Regression equations for each GI type differed from each other (Table 3). The results showed that social–economic variables explained 79–87 % of the variance of GI types, and the regression models were highly significant. PC1 had a negative correlation with all GI types, but especially with forest. The area of public green space was positively correlated with PC2 and PC4. The area of farmland was correlated with PC1 and PC4, but not with the other two components. The area of farmland was negatively related to PC1, but positively to PC4. The area of orchards was positively related to PC3.

Formulas (Table 4) obtained from the component score coefficient matrix of the PCA (see Appendix—Supplementary Table 1) show the relationships between each original variable and the principal components.

Reference of social–economic decision-making for GI management

The results for the whole district of Haidian showed that social–economic variables had to change between −0.14 and 0.32 % to achieve the lower threshold (Scenario A), and between −0.19 and 0.46 % for the upper threshold (Scenario B) (Fig. 7a). The directions of change of all social–economic variables were consistent for both thresholds. The development of water and environmental facilities should be largely improved while the development of social organization and tenancy should be strictly limited. For the individual towns of Haidian, the ranges of required socio-economic changes for

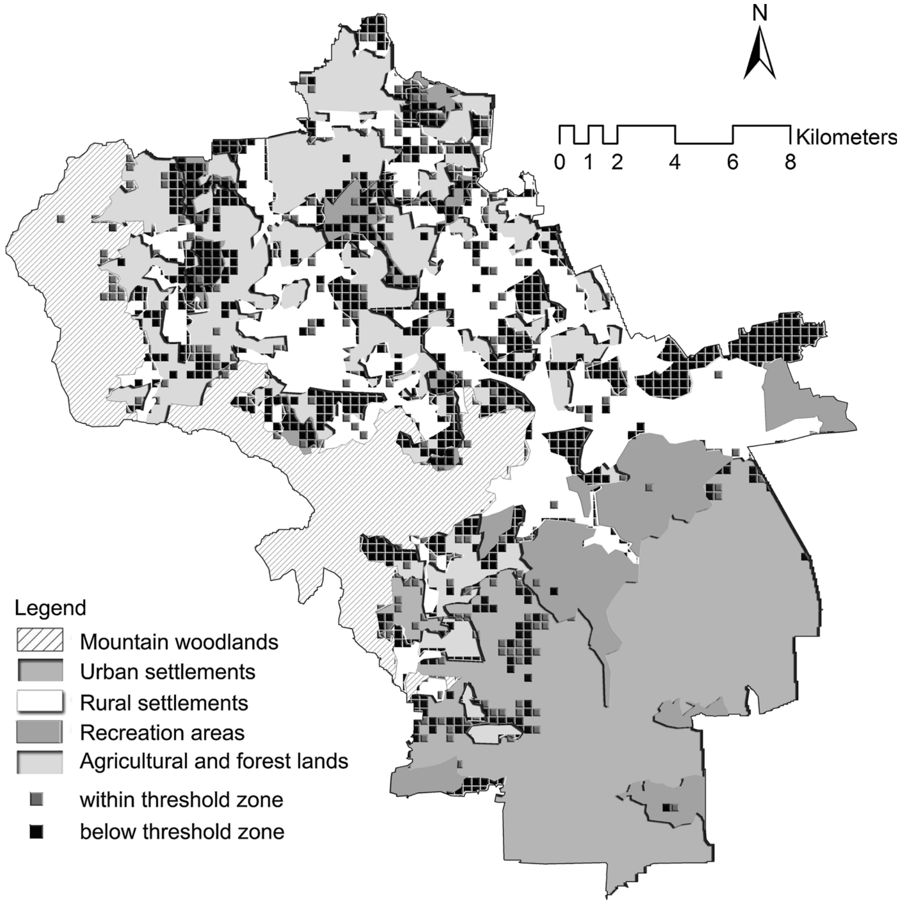

Fig. 6 Landscape conditions based on threshold zones of different landscapes for the year 2010

Table 2 Summary of the principal components analysis of social–economic variables

Variable	PC 1	PC 2	PC 3	PC 4
Income catering & accommodation	0.835	−0.01	0.082	0.305
People in science & technology	0.813	0.002	0.027	−0.189
People in water & environmental management	0.289	0.445	0.305	0.764
People in educational sector	0.501	0.220	0.642	−0.420
People in social organizations	0.555	−0.662	−0.108	0.197
Registered population	0.856	0.295	−0.088	−0.284
Migrant workers	0.389	0.495	−0.738	−0.023
Rental income	0.742	−0.417	−0.105	0.042
Initial eigenvalues	3.436	1.19	1.088	1.011
% of variance	42.95	14.88	13.60	12.64

Table 3 Regression analysis of different GI types and PCs obtained from PCA

Regression models	*n*	R^2	Sig.
Y(public green space) = $0.659-0.24\ X_1 + 0.82\ X_2 + 0.764\ X_4$	116	0.802	0.000
Y (farmland) = $0.539-2.17\ X_1 + 3.686\ X_4$	32	0.796	0.000
Y (orchard) = $1.747-1.349\ X_1 + 4.604\ X_3$	45	0.786	0.000
Y (forest) = $7.175-10.439\ X_1 + 1.943\ X_2$	70	0.87	0.000

Y area percentage of different GI types, X_1–X_4 principal component (PC1–PC4) scores obtained from PCA, *n* number of observations, R^2 coefficient of determination

landscape improvement were larger. Social–economic variables ranged between −0.86 and 1.24 % around the lower threshold, and between −1.11 and 1.65 % around the upper threshold (Fig. 7b).

Table 4 Relationships between social and economic variables and PCs obtained from PCA

Variable	Equation
Income catering & accommodation	$Y = 0.243X_1 - 0.009X_2 + 0.075X_3 + 0.302X_4$
People in science & technology	$Y = 0.237X_1 + 0.002X_2 + 0.025X_3 - 0.187X_4$
People in water & environmental management	$Y = 0.084X_1 + 0.374X_2 + 0.28X_3 + 0.756X_4$
People in educational sector	$Y = 0.146X_1 + 0.185X_2 + 0.59X_3 - 0.415X_4$
People in social organizations	$Y = 0.162X_1 - 0.556X_2 - 0.099X_3 + 0.195X_4$
Registered population	$Y = 0.249X_1 + 0.248X_2 - 0.081X_3 - 0.281X_4$
Migrant workers	$Y = 0.113X_1 + 0.416X_2 - 0.678X_3 - 0.023X_4$
Rental income	$Y = 0.216X_1 - 0.35X_2 - 0.097X_3 + 0.042X_4$

Y percentage of different variables which need to be managed, *X_1–X_4* principal component (PC1–PC4) scores obtained from the regression analysis

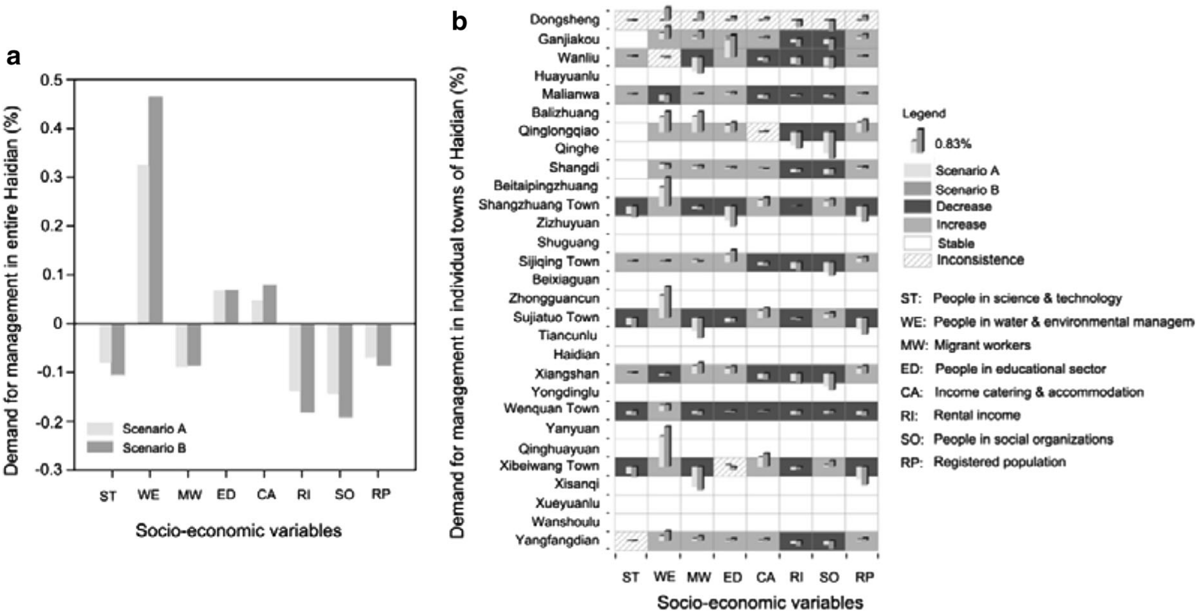

Fig. 7 Reference targets of social–economic development for (**a**) the entire district of Haidian and (**b**) its individual towns. Scenario A suggests to develop a social–economic factor to the lower boundary of the threshold zone, whereas scenario B indicates a need for development towards the upper boundary of the threshold zone. For further explanation see text

There were three different ways of adapting social–economic variables to prevent a change of landscape: to decrease, to increase or to maintain the current level of importance. The way of adaptation of a social–economic variable was usually similar for both thresholds, but in some cases social–economic variables required to be managed in opposite directions to achieve the lower or upper threshold, respectively. In 16 out of 29 towns in Haidian, most variables required no additional management to prevent landscape change (e.g. in Huayuanlu and Balizhuang; Fig. 7b). In 12 towns, most social–economic variables were in a state that increased the susceptibility to landscape change (e.g. in Sujiatuo, Dongsheng) and required additional management to enhance landscape resilience.

Discussion

Thresholds of landscape change

The results of this study show that the susceptibility of existing landscapes to change can be determined spatially and quantitatively based on measurable threshold zones, which are related to social–economic factors. This allows policy makers to set quantitative targets for the social–economic development of a certain region, while present landscapes and landscape characters are conserved and managed. Threshold zones involve a more gradual transition between two states (Muradian 2001; Lindenmayer and Luck 2005) and are very different from point-type thresholds, beyond which rapid shifts of state or regime occur (Kato and Ahern 2011). A landscape is usually a mixture of natural and human elements (Tasser et al. 2009). Natural attributes of landscapes, such as soil properties, elevation and slope, usually change gradually and with a low speed, especially if vegetation cover is present (Schoorl and Veldkamp 2001). Although human elements of landscapes, e.g. land use, may change very sudden, their spatial distribution can also change gradually (Bel et al. 2012; Wagner and Fortin 2013). This may partly explain why there exist threshold zones for landscape change.

Our results show that different landscapes have different thresholds. A number of studies found that the width of the threshold zone is related to the resilience of a system (Tilman and Downing 1994; Thrush et al. 2009). Resilience is the capacity of a system to return to its previous state (Briske et al. 2008) and related to its ability for self-regulation (Ruben Lopez et al. 2013). In this study, landscape resilience was mainly affected by the recoverability of GI elements. Once natural GI like woodlands is destroyed, it is difficult to re-establish it again (van Eetvelde and Antrop 2009). In contrast, non-GI is more easily re-established (Hamre et al. 2007). The recoverability of artificial and semi-natural GI, such as public green space and farmland, is between those of natural GI and non-GI types, because artificial and semi-natural GI can be recovered through careful management (Hall et al. 2003). Therefore, the threshold zone of mountain woodlands in Haidian had the smallest range, while urban and rural settlements had the largest widths.

Although there is no consensus yet, most studies indicate that the upper and lower boundaries of threshold zones are controlled by landscape sensitivity (Betts et al. 2007). Landscape sensitivity is the susceptibility of a landscape to the change of a landscape component that has the potential to alter the entire landscape (Usher 2001). The sensitivity of a landscape is related to complexity of its components (Usher 2001, Betts et al. 2007). Landscapes with complex components have a high sensitivity to landscape change (Betts et al. 2007), which means that the key characteristics of a landscape are easily altered, and small changes of landscape components may change its composition. The threshold zone of agricultural and forest lands had the smallest lower and upper boundaries, indicating a low sensitivity for landscape change due to few natural (forest) and semi-natural GI types (farmland and orchards). In contrast, the threshold zone of recreation areas had the highest lower and upper boundaries of all investigated landscapes. Its complex composition, consisting of natural (forest), artificial (public green space) and non-GI types, resulted in a high sensitivity for landscape change.

Landscape management

When the thresholds of key landscape elements are crossed, the ecosystem services of a GI-dominated landscape can be decreased in a way that feedback mechanisms prevent their short-term recovery (McClanaha et al. 2011). It is suggested here that landscape areas of a landscape dominated by GI covers below and within the threshold zone are in need of an active management, but should be conserved if they are above the threshold zone. Therefore, the boundaries of the threshold zones can be considered as a quantitative target for the management of individual landscape areas and provide useful information about the location, type and extent of needed management to policy makers. In practice, different goals or desired states of ecosystem conservation will lead to different reference lines for social–economic development (Samhouri et al. 2010). Here, two different targets for landscape management of the whole district and individual towns were proposed based on threshold zones. For example, the investment in the education sector in Xibeiwang should be increased when the goal is at the lower boundary of the threshold zone, while it should be reduced when the goal is at the upper boundary of the threshold zone. The results of this study are in line with some threshold-based ecosystem management studies, which suggested the use of thresholds for setting management targets (Jansson and Angelstam 1999; Bestelmeyer 2006; McClanahan et al. 2011). However, several studies contended that these thresholds should not be the target of management (Rompré et al. 2010). Instead, policymakers should base a management decision on a more conservative point than the actual threshold in order to reduce risk (Samhouri et al. 2010; Jr. Hunter ML et al. 2009). Radford et al. (2005) suggested that a goal well in excess of 10 % tree cover is required to prevent the collapse of the woodland-dependent avifauna in landscapes of Victoria, Australia. The actual distance of the decision point from the threshold depends on the management targets and the local conditions of different systems. On the other hand, small changes in ecosystem management may result in significant changes in social–economic management of the system (Pacini et al. 2004). Thus, the implementation of any safe minimum-standard strategy will be controversial (Bateman et al. 2011). The only objectively tangible points for decision making are the boundaries of the threshold zones, but policy makers must understand the relationships between thresholds and objectives when using these points as a minimum goal for management.

Social–economic demand for GI management

This study shows how social–economic variables change in response to different GI management goals. In individual towns and the whole district of Haidian, the management of water and environment requires support to meet the increasing demand of ecosystem services. According to our results, the demand for public green space and farmland is especially high. This indicated that an increasing investment in environmental protection is one of the most important ways to enhance ecosystem services. In contrast, a booming economy and the influx of people have a great negative influence on GI covers, especially on forest. Our results indicate that rental income needs to be decreased by 0.18 %, if GI is managed to achieve scenario B in the whole district. This equals only 0.06 % of Haidian's gross domestic product (BHSY 2011). However, not all economic variables should be limited to achieve scenario B. The development of catering and accommodation should be supported in several towns (e.g. Wanliu and Xiangshan), because it has likely a positive effect on the development of public green spaces (Tables 2, 3). The control of population growth may also improve GI, e.g. in Sujiatuo and Xibeiwang. This is consistent with most research studies, which indicated that an increasing population will lead to an increase in non-GI (Hasan 2010). For the entire district of Handan, the current population needs to decline by only 0.08 % to reach the target of scenario B, which is a small as compared to the current population of Haidian (BHSY 2011). Our results show some positive relationships between the investment in education and the presence of orchards in the landscape (Tables 2, 3). However, the number of school-age children decreased in rural villages recent years (Xue-Jun and Wu 2008), which resulted in a reduction of funds for rural towns, such as Shangzhuang and Sujiatuo town. In this context, it is necessary to improve the level of education for local adults, but current investment in education needs to be increased by only 0.07 % to reach scenario B. Social organization had negative correlations with GI covers in this study. This is consistent with the research of Foster (1999) who argues that social organization gives local residents the increasing opportunity to consume resources indirectly. The investment in social organization needs to be decreased by 0.19 % to reach scenario B for the whole district, which implies that the number of persons in social organizations should be reduced by 72. The investment into scientific research should be reduced by only 0.1 % in most towns of Haidian to achieve scenario B. From the above perspective, GI can be managed only by changing a small proportion of social–economic development.

Benefits and challenges of threshold-based social–economic decision-making

Threshold-based social–economic decision-making takes advantage of mathematical relationships between recognizable landscape elements and human-induced pressures from social–economic development. Thresholds provide a quantitative basis for the understanding of how to manage a social–economic system for GI improvement. This approach connects social–economic development and resource management better than sole threshold-based resource management and adaptive management, which attempt to maintain or enhance ecological resilience without considering social–economic effects (Roe and van Eeten 2001). In contrast to resilience-based management, this approach emphasizes the social–economic conditions and dynamics that determine the probability of thresholds being crossed, rather than attributes and management actions that affect state vulnerability and proximity to thresholds (Briske et al. 2008). Policy makers might decide to set decision criteria based on this reference to avoid conflicts between landscape conservation and social–economic development.

Although landscape thresholds were determined by testing the frequencies of relative area shares of key landscape elements in this study, it is still necessary to consider the effect of landscape pattern. This is another important aspect of landscape change (Ruiz and Domon 2009) and difficult to assess, because landscape patterns vary along different scales of space (Lindenmayer and Luck 2005). Moreover, stable landscape patterns can change abruptly without any obvious reason (Swetnam 2007). Although a target reference for social–economic policy decision-making was proposed here, policy makers still face very complex decisions, because trade-offs between thresholds and social–economic development targets were not investigated. The accounting of potential trade-offs is particularly challenging, when interactions between different goals are considered. Given the conflicting demands of landscape conservation and social–economic development, it is up to policymakers to determine whether to breach a particular utility threshold in favor of some other objectives or not. These gaps should receive more attention in future research.

Conclusion

Thresholds of landscape change do exist in the real landscape of Haidian. These thresholds are a useful tool to provide quantitative targets for GI management. Since a landscape is inevitably linked to the ongoing social–economic development of an area, the establishment of threshold-based targets for social–economic development has a great potential to balance conflicts between development and GI conservation. Improvements in the management of water and environment are necessary to improve GI in Haidian, while population, tenancy and social organization should be limited in the whole district and most individual towns. GI can be managed by changing a small proportion of social–economic development.

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