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RESEARCH ARTICLE

Geographical modeling of spatial interaction between human activity and forest connectivity in an urban landscape of southeast China

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Abstract Geographical detector models provide a quantitative approach for evaluating spatial correlations among ecological factors, population density and landscape connectivity. Here, we used a geographical model to assess the influence of different gradients of urbanization, human activities and various environmental factors on the connectivity of urban forest landscapes in Xiamen, China from 1996 to 2006. Our overarching hypothesis is that human activity has modified certain ecological factors in a way that has affected the connectivity of urban forest landscapes. Therefore, spatiotemporal distributions of landscape connectivity should be similar to those of ecological factors and can be represented quantitatively. Integral indices of connectivity and population density were employed to represent urban forest landscape connectivity and human activity, respectively. We then simulated the spatial relationship between forest patches and population density with Conefor 2.6 software. A geographical detector model was used to identify the dominant factors that affect urban forest landscape connectivity. The results showed that a distance of 600 m was the threshold of node importance. Mean annual temperature, mean annual precipitation, elevation, patch area, population density and dominant species had significant effects on the node importance. Mean annual temperature was more

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significant than population density in controlling the spatial pattern of the delta of the integral index of connectivity (dIIC). The spatial interaction between population density and various ecological factors as well as their linearly enhanced or nonlinearity enhanced urban forest landscape connectivity. In conclusion, a combination of graph theory and geographical detector models is effective for quantitatively evaluating interactive relationships among ecological factors, population density and landscape connectivity.

Keywords Geographical detector model · Graph theory analysis · Human activity · Landscape connectivity · Subtropical monsoon Asia · Urban forests

Introduction

Urban forest ecosystems are found in widespread areas ranging from urban cores to exurbs. Urban forest landscape connectivity has an important influence on urban ecosystem services and functions (e.g., seed migration and proliferation, animal migration, and gene flow) and interferes with water infiltration and soil erosion. Connectivity is directly related to the integrity, sustainability and stability of urban ecosystems (Urban et al. 2006). Maintaining landscape connectivity is a crucial part of the sustainable planning and management of urban forest landscapes (Wu 2013a).

Over the past decades, landscape connectivity research has focused mainly on the role of connectivity in the interplay among multiple landscape functions of natural ecological systems (*e.g.*, coastal plains, reefs, and forests) at different spatial scales (*e.g.*, patches, regions, and countries) (Gledhill et al. 2008; Garcia-Feced et al. 2011). Much research has been conducted on the mechanisms of the interaction between landscape connectivity and ecological processes of various communities using different landscape models, metrics and software packages (Urban and Keitt 2001; Galpern et al. 2011). Recent research has emphasized the application of landscape models combined with network analysis and landscape patterns of graph theory (Decout et al. 2012; Martin-Martin et al. 2013). Achievements have been made to better understand the relationships between human activity or landscape connectivity and urban species diversity (Luque et al. 2012). However, an integrated approach for quantifying human activities along different urbanization gradients and their effects on urban forest landscape connectivity, as well as the interactions among various environmental factors, has not yet been reported (Royle et al. 2013). Consequently, additional efforts are needed to reveal the mechanisms that explain how human activities influence changes in urban forest landscape connectivity (Martin-Queller and Saura 2013).

The distribution patterns of urban forest landscapes are associated with the mechanisms involved in forest patch formation and with environmental factors (e.g., climate, topography, and geomorphology) that are responsible for landscape patterns. As a result, the interactions between urban forest patches and human activity levels constantly shape urban forest landscape patterns. Additionally, human activity in urban areas is not only an important factor for driving urban ecological processes but also a key source of heterogeneity in urban forest landscapes. Thus, human activity can change the quality of resources, spatial positions and sizes of patches, and consequently the landscape patterns (Partel et al. 2007). Unfortunately, the interactions between human activity and urban forest landscape connectivity are poorly understood and evaluated. This shortcoming directly prevents an accurate assessment of the relationship between the levels of urban development and the conditions of urban forests (Ahern 2013; Wu 2013a). A quantitative analysis of this type of relationship represents a contemporary research direction in the field of ecological planning of urban forest landscapes (Wu 2013b).

Environmental variables affect the interactions between human activity and urban forest landscape connectivity and thus influence the overall evolution of urban ecological systems. Various environmental variables or factors with different coupling strengths not only define urban forest structures but also determine which ecological features and functions exist in multiple biological communities. These variables also affect urban forest landscape patterns and processes, where certain environmental factors may even dominate the connectivity of urban forest landscapes (Schweiger et al. 2005). However, the nonlinearity and complexity of urban forest ecosystems make it impossible to use a single method or model to conduct accurate and comprehensive assessments. Thus, it is necessary to integrate various methods when evaluating the effects of human activity on urban forest landscape connectivity (Urban et al. 2006).

The integration of a geographical detector model and graph theory provides a scientific basis for quantifying the driving mechanisms of the influence of human activities on urban forest landscape connectivity. A geographical detector model is a creative integration among various dominant ecological factors combined with logical reasoning and existing statistical techniques (Wang et al. 2010). This type of model not only addresses the spatial effects of explanatory variables on the explained variables but also helps reveal the interaction between the two types of variables (Li et al. 2013). Graph theory provides an explicit spatial description of landscape connectivity and associates graph structures with patch characteristics, ecological processes and thresholds. Graph theory can also be used to build a comprehensive index, such as the integral index of connectivity (IIC), which has practical applications. Graph theory is an important method for analyzing the structure and function of landscape connectivity (O'Brien et al. 2006). Thus, the integration of different methods and technologies can allow for a comprehensive consideration of environmental variables in landscape ecological planning and research. Environmental variables normally include biotic (such as area, tree species, forest age, and planting density) and abiotic factors (such as climate, topography, and soil conditions). Thus, an integrated approach can support more comprehensive and accurate assessments of human activity and landscape connectivity (Galpern et al. 2011).

The purpose of this study is to examine the effects of human activities along a gradient of urbanization and the effects of various environmental variables on the connectivity of urban forest landscapes in Xiamen City, China (Tang et al. 2013). The IIC and population density were selected to represent urban forest landscape connectivity and human activity, respectively. Conefor 2.6 software was combined with a geographical detector model to simulate spatial relationships between forest patches and population density and to identify the major factors that affect forest landscape connectivity. Our hypothesis is that human activity combined with certain ecological factors affect the connectivity of the urban forest landscape and that the spatiotemporal distribution of landscape connectivity is therefore similar to the distribution of these ecological factors. Our specific research questions were as follows: (1) What are the critical spatial thresholds at which urban forest landscapes are aggregated? (2) Where do the changes in the connectivity of urban forest landscapes occur? and (3) What environmental factors have a dominant influence on the connectivity of urban forest landscapes?

Materials and methods

The research methods of this study involved data, mapping, tools, metrics and landscape connectivity assessment outcomes (Fig. 1). The analysis procedure consisted of three steps: (1) mapping landscape units by integrating data from multiple sources, including weather records, forest management planning inventory (FMPI) data, elevation and population data; (2) selecting an appropriate threshold of distance using FMPI data to map forest habitat distribution and calculate the delta IIC (dIIC) values of forest classes using Conefor 2.6 software; and (3) clarifying the driving mechanisms in the geographical detector model by integrating multi-source data and dIIC.

Our study area is Xiamen (24°25′–24°54′N, 117°53′–118°25′E), a city in southeastern China that is characterized by a subtropical monsoon climate with maritime influences (Zhao et al. 2013; Yang et al. 2014). Xiamen has 165,036.3 ha of urban forest ecosystems consisting of suburban forest, exurban forest, city parks, botanical gardens and greenbelts that cover 45.60 % of the study area. Xiamen City consists of six administrative districts, including Siming, Huli, Jimei, Haicang, Tongan and Xiangan, which spread approximately 70 km from the center of the city northward. These six districts show a clear gradient of urbanization: the urban cores of Siming and Huli with a population density of 51 or more persons/ha, the suburbs of Jimei and Haicang with 8–50 persons/ha, and the exurbs of Tong'an and Xiangan with 8 or less persons/ha.

FMPI data obtained in 1996 and 2006 contained the attributes of tree species composition, age group, elevation, slope degree, direction, position, and site index, which were averaged for every subcompartment and georeferenced against topographic maps at a

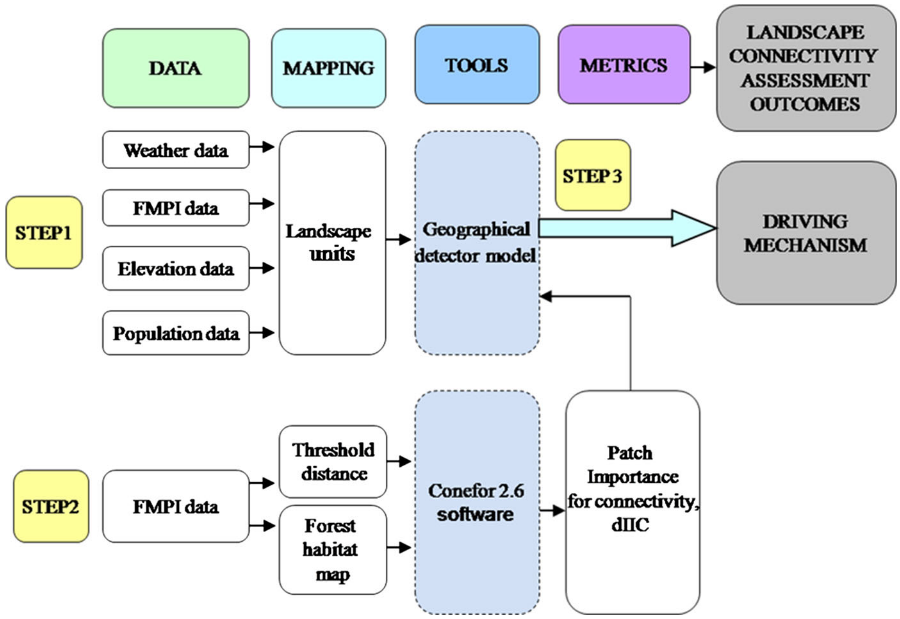


Fig. 1 Scheme of the proposed methodology. The data of three steps were processed using Conefor 2.6 software and a geographical detector model

scale of 1:10,000. Population density data were obtained from the governmental census database. Meteorological data were collected from 11 weather stations located in Xiamen metropolitan area. Digital elevation model data were downloaded from http://gdem.ersdac.jspacesystems.or.jp/ (see Table S1). The maps of mean annual temperature (MAT) and mean annual precipitation (MAP) in 1996 and 2006 were generated using the thin plate smoothing spline surface fitting technique in ANUSPLIN version 4.37. The maps of population density in 1996 and 2006 were generated with the kernel density model of ArcGIS software.

To conduct a connectivity analysis based on local urban forest conditions and previous studies, we selected the areas with a forest canopy density greater than 30 % and used 6 ha as the minimum patch size (Fu et al. 2010; Liu et al. 2014). The main forest types are *Pinus massoniana* Lamb, *P. elliottii* Engel, *Cunninghamia lanceolata* Hook., *Casuarina equisetifolia* Forst, *Acacia confusa* Merr., and *Eucalyptus robusta* Smith. The maximum dispersal distance of 1 km was used for the seeds of these tree species (Lü and Ni 2013).

We used Conefor 2.6 software (http://www.conefor.org) as a decision-making support tool (Saura and Torné 2009). This program uses the identification and prioritization of critical sites to analyze ecological connectivity (Saura et al. 2011) and is widely used in network connectivity analysis (Galpern et al. 2011; Decout et al. 2012; Luque et al. 2012). IIC was selected because it exhibits reliable properties that can be usedn to quantify inter- and intra-patch connectivity using values ranging from 0 to 1: larger IIC values indicate sites with better connectivity. IIC not only makes data acquisition easier but also is more sensitive to the presence of connecting elements. IIC was calculated as follows:

$$\mathrm{IIC} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{a_i a_j}{1+nl_{ij}}}{A_L^2} \tag{1}$$

where a_i is the area of forest patch i, a_j is the area of forest patch j, nl_{ij} is the number of links in the shortest paths between patches i and j within the threshold dispersal distance (also referred to as effective paths), n is the number of patches, and A_L is the total landscape area (including forest and non-forest areas) (Pascual-Hortal and Saura 2006).

The importance of a node can be expressed relatively as follows:

$$\mathrm{dIIC} = 100 \times \frac{I - I_{remove}}{I} \tag{2}$$

where I is the IIC value when all of the initially existing nodes are present and I_{remove} equals the IIC when any single node is removed (Saura and Pascual-Hortal 2007).

In this study, the rank of dI was used to represent the patch accounting for the proportion of the importance of the entire urban forest network in Xiamen.

In addition to IIC, the degree and betweenness centrality (*BC*) indices were used to identify crucial patches. The degree of a node measures the numbers of links for this node in a network, and *BC* is an index representing node centrality in the network. High *BC* nodes, which may have a low degree index value, are located at the convergence of paths and function as "bridges." *BC* is equal to the number of shortest paths from all vertices to all others that pass through that node. The *BC* for node *k* (BC_k) is defined as the sum of all the effective paths ($g_{ij(k)}$) between all pairs of patches ($i, j \neq k$) that go through *k* divided by the total number of effective paths (g_{ij}) between each pair of patches (i, $j \neq k$). The calculation of BC_k is as follows:

$$BC_k = \sum_i \sum_j \frac{g_{ij}(k)}{g_{ij}} \tag{3}$$

In addition to the complex connectivity indices, other simple binary indices were also used, such as the total number of links (*NL*), the number of components (*NC*), and the number of paths.

A geographical detector model detects various factors influencing the distribution of patches, the degree of influence of each factor and the interaction between factors based on spatial analysis of variance. Geographical detector models have been successfully used to explore determinants and their interaction with neural tube defects (Wang et al. 2010), mortality in children under 5 years old, and fluoroquinolone residues in the soil (Li et al. 2013). The software (www.sssampling.org/geogdetector) is based on the spatial consistency of variables, including a factor detector, an ecological detector, and an interaction detector. The factor detector is used to explore the impact of different factors on the research target; the ecological detector is used to explore the impacts of different levels of significance on those factors; and the interaction detector is used to explore the impacts of the combinations of different impact factors on the research target. We used a geographical detector model to analyze impact factors that result in the variations in dIIC in forest patches. We first classified the dIIC values and all the impact factors by using the equal interval classification. We then loaded the distribution layers of all the impact factors and dIIC into ArcGIS. We intersected all the layers including dIIC and all the impact factors into one layer to extract all the impact factors' attributes of the different layers. All the different impact factor values were input into the geographical detector model for runs. For additional details, please see Appendix Method 1.

Differences in dIIC among groups were examined using a *t* test for two groups or one-way analysis of variance followed by multiple comparison tests when more than two groups were compared. Games-Howell tests (paired comparisons when the variance had no homogeneity) were used when variances were heterogeneous (Levene's test), and Tukey's tests (paired comparisons among all the mean values of each group using the Student-Range statistical method) were used when variances were homogeneous. Statistical significance was determined at $p < 0.05$. Statistical analyses were conducted in SPSS version 16.0 (SPSS Inc., Chicago, IL, USA).

Results

Analysis of the optimal threshold distance

The number of components and the number of patches in the largest components were evaluated at different threshold distances (i.e., 50, 100, 200, 400, 600, 800, 1,000, 1,200, 2,000, 3,000, 4,000, 5,000, and 10,000 m) to determine the optimal threshold distance of connectivity. In 1996, at shorter threshold distances, NC decreased rapidly, and the number of patches of the largest component increased sharply with increases in threshold distance (Fig. 2). Specifically, when the interval was changed from 50 to 600 m, NC decreased from 224 to 43, and the number of patches of the largest component increased from 15 to 226. In addition, with the same changes in interval, the area of the largest component increased from 2,009 to 27,442 ha, and the proportion of the total area of the selected patches increased from 6.4 to 87.0 %. In 2006, similar dramatic trends were observed when the threshold distances increased from 50 to 600 m. While NC decreased from 160 to 35, the number of patches of the largest component increased from 29 to 156, and the area of the largest component increased from

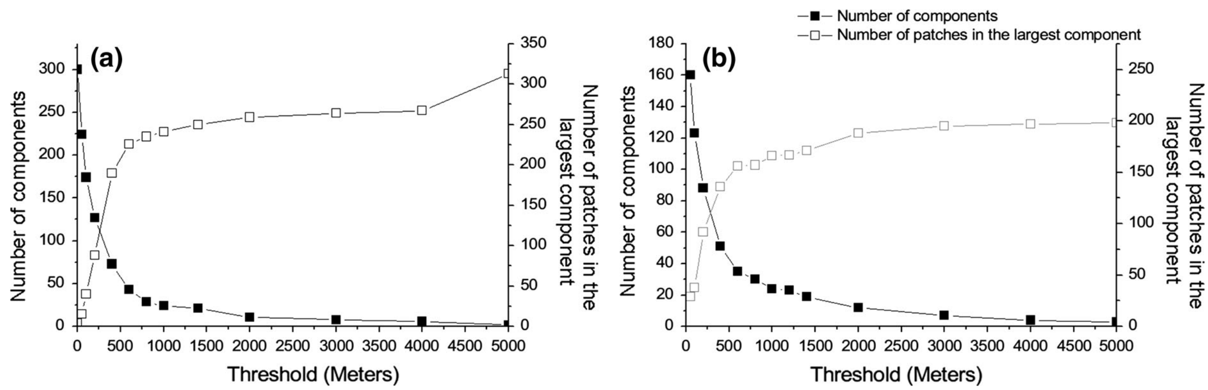


Fig. 2 Changes in the number of components and the number of patches of the largest component under different thresholds in 1996 (**a**) and 2006 (**b**)

6,146 ha (16.4 %) to 30,638 ha (81.5 %). However, only minor changes were observed beyond the 600-m threshold distance in both 1996 and 2006. This pattern implies that the landscape types were relatively homogeneous and that the landscape was consistently connected.

The contribution of different sizes of patches to connectivity at various threshold distances is represented by node importance. The optimal threshold indicates the importance of not only large nodes but also small and medium nodes. Small nodes clearly had lower importance than medium and large nodes at a 50 m threshold distance, after which small and medium nodes became more important before becoming less important again after a 600-m threshold (Fig. 3). Large nodes played a crucial role in landscape connectivity because patch area was the node attribute used to calculate IIC. The significance of small nodes proved difficult to determine. Consequently, small or medium nodes should be examined in addition to large nodes under the optimal threshold (Fig. 4).

Spatiotemporal distribution of the connectivity of forest patches

We defined A_{LC} as the area of the largest component and F^* as the ratio of A_{LC} to A_{TOT}, the total forest area from all patches (Ferrari et al. 2007). A total of 25,909.5 ha, accounting for 82.2 and 69.0 % of the vegetation patches in 1996 and 2006, respectively, remained unchanged between 1996 and 2006 (Fig. 5). Emerging patches accounted for 31.0 % of the area of the target patches in 2006. Approximately 17.8 % of the target patches in 1996 had vanished in 2006.

In 1996, 314 patches with areas of 6 ha or above covered a total area of 31,534.7 ha, and the mean patch area was 100.4 ha. The ten largest patches constituted 52.5 % of the total area. In 2006, Xiamen had 236 patches with a total area of 37,576.6 ha, and the mean patch area was 159.2 ha. The ten largest patches accounted for 64.7 % of the total area.

In both 1996 and 2006, the IIC values increased with threshold distance (Fig. 6). Under the optimal threshold distance of 600 m, the IIC values for urban cores decreased slightly from 1996 ($F^*_{1996} = 87.0$ %) to 2006 ($F^*_{2006} = 81.5$ %), whereas the IIC values for suburbs and exurbs increased. However, the connectivity of the entire urban landscape was improved by 66.0 % (Table 1).

The distribution of forest importance varied greatly from 1996 to 2006, and the landscape became more connected in 2006 (Fig. 7). Urban-core forest patches in 2006 essentially included the same physical areas as in 1996. However, suburban forest patches, which were loosely connected at the edges of administrative boundaries in 1996, were polarized into two large clusters in 2006. The isolation of these patches that occurred between 1996 and 2006 resulted in worsening connectivity. Nevertheless, the emergence of new patches led to a modest growth in connectivity. Exurban connectivity increased dramatically due to large emerging ecological patches, which connected these initially isolated small patches. As a result, overall connectivity increased significantly in Xiamen from 1996 to 2006.

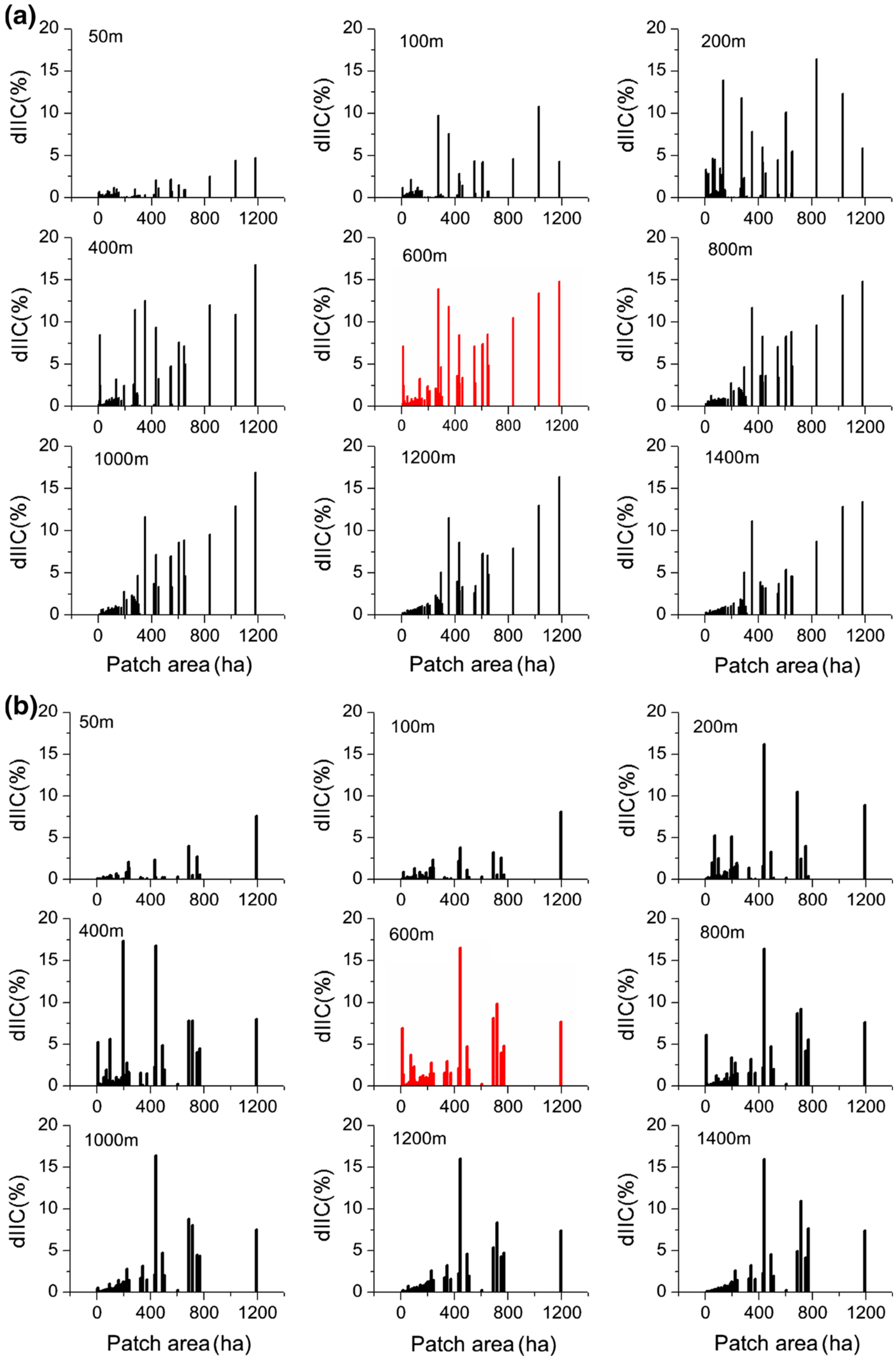


Fig. 3 Variations in the delta values of the integral index of connectivity (dIIC) for various sizes (ha) of the patches under different distance thresholds in 1996 (**a**) and 2006 (**b**). The *red* plots represent the selected threshold. (Color figure online)

Factors influencing dIIC

The downward trends in dIIC values in urban core and suburban areas contrast with the upward trend in dIIC values in exurbs (Fig. 8). The mean node importance increased from 10.96 (1996) to 15.80 (2006) in Xiamen (Table 2). However, patch importance in urban core and suburban areas experienced decreases over time (Fig. 8). An ascending trend with a change in dIIC values was observed for forest types and age classes (excluding over-mature forest) in exurbs (Fig. 8).

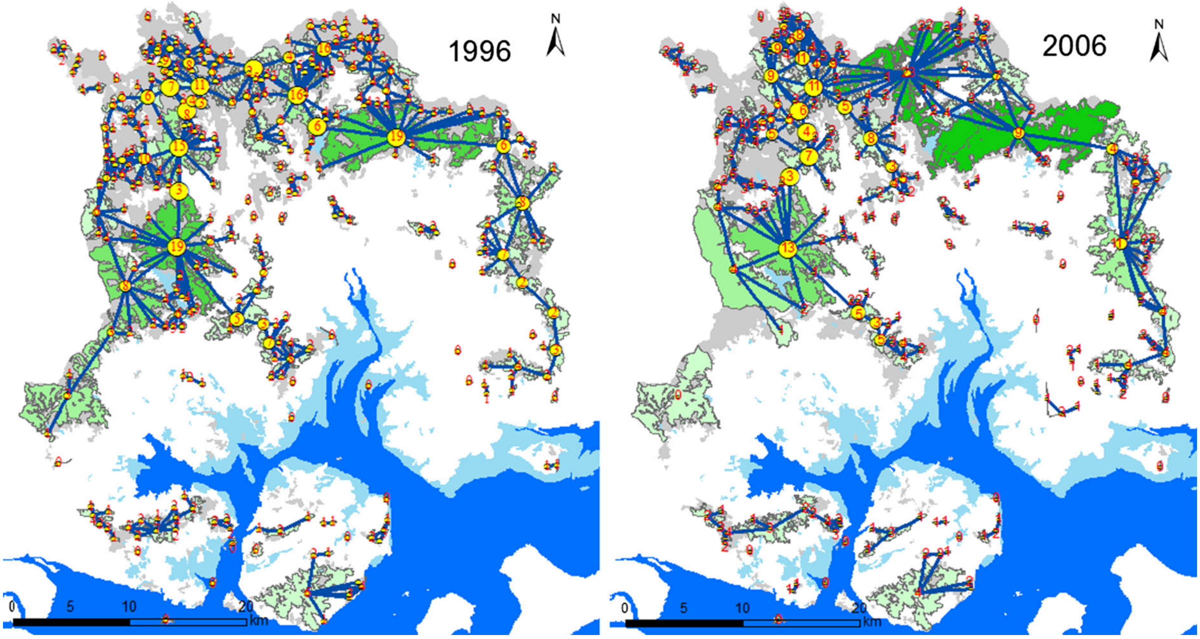


Fig. 4 Euclidean networks for Xiamen in 1996 and 2006. *Blue lines* represent links; *yellow circles* located at the centroid of the patch represent nodes; *red numbers* on the *circles* represent degrees. Circle diameters increase with the betweenness centrality score. (Color figure online)

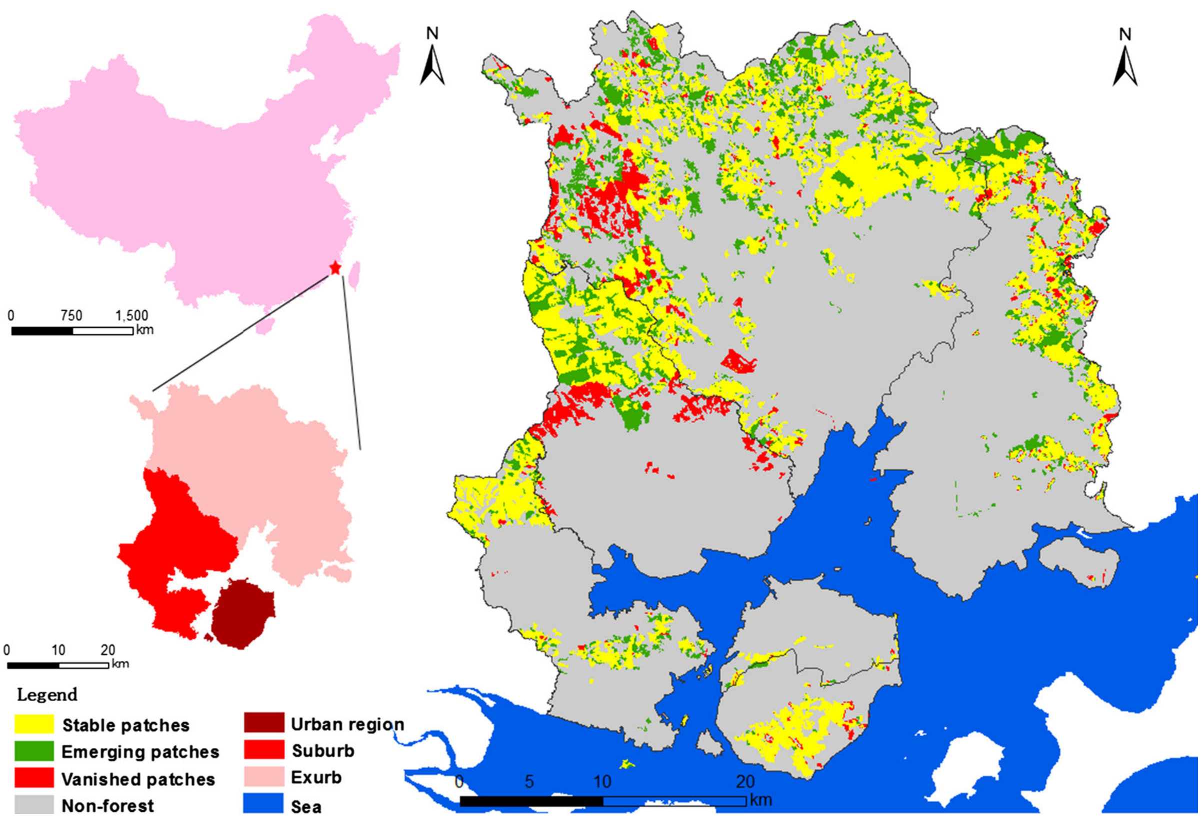


Fig. 5 Changes in the patches for Xiamen from 1996 to 2006

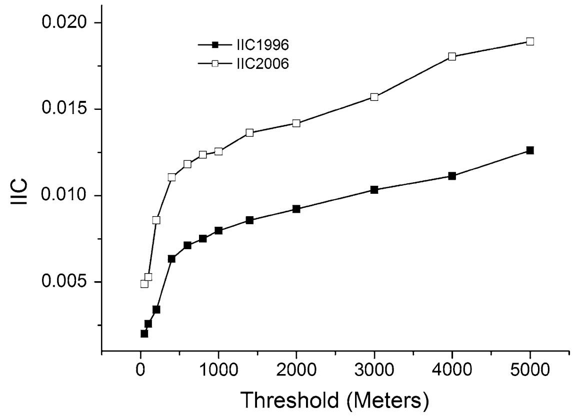


Fig. 6 Changes in the IIC under different thresholds in 1996 and 2006

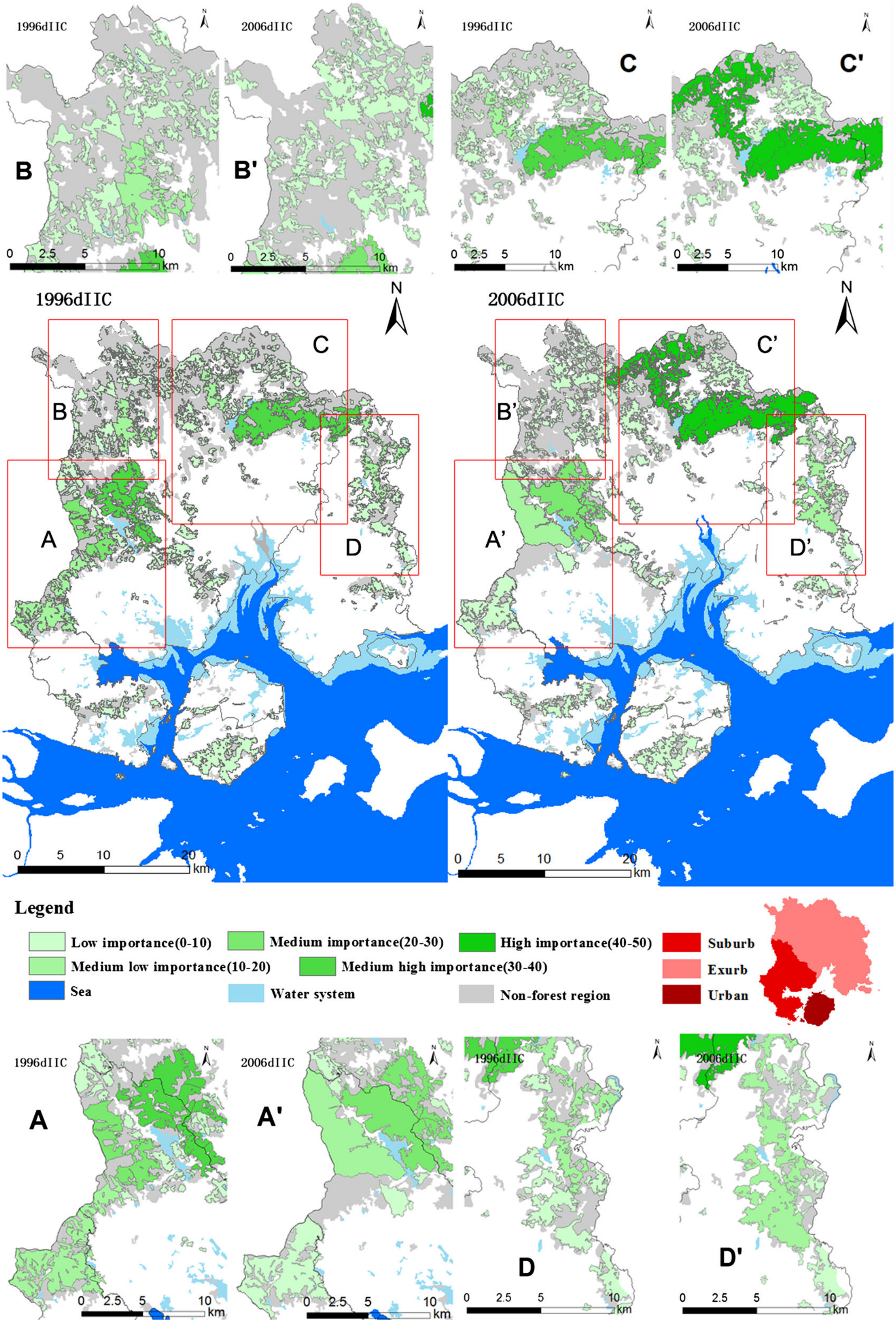
The population density in Xiamen increased from 565.0 ± 12.6 (mean ± standard error) people ha^{-1} in 1996 to 755.5 ± 11.9 people ha^{-1} in 2006 (*t*-test, $p < 0.01$) (Table 3). In both years, the population density was largest in urban cores and lowest in exurbs. The population density increased significantly ($p < 0.05$) from 2,085.6 ± 37.8 people ha^{-1} in 1996 to 2,789.0 ± 48.5 people ha^{-1} in 2006 in urban cores; from 503.6 ± 13.7 people ha^{-1} in 1996 to 673.4 ± 20.4 people ha^{-1} in 2006 in suburbs; and from 394.9 ± 8.1 people ha^{-1} in 1996 to 528.1 ± 6.2 people ha^{-1} in 2006 in exurbs (Table 3).

From 1996 to 2006, forest area in Xiamen decreased by 10.3 %, from 83,928 to 75,251 ha; meanwhile, stand density decreased from 2,106 stems ha^{-1} in 1996 to 1,932 stems ha^{-1} in 2006 ($p < 0.05$). The mean diameter at breast height (DBH) increased from 6.16 cm in 1996 to 11.26 cm in 2006, and mean tree height increased from 5.97 m in 1996 to 7.62 m in 2006) ($p < 0.01$). However, no significant change was found in the stand age between 1996 and 2006 ($p > 0.05$) (Table 2). In addition, topographical variables (e.g., slope angle, slope position and slope direction) did not change significantly between 1996 and 2006. A significant difference ($p < 0.01$) was observed among the ecological factors along the urbanization gradient. For details, see Ren et al. (2011a) (Table 2, Appendix Fig. S1).

Among the 12 selected factors, the major factors influencing node importance, listed in order of decreasing q value, were the MAT, MAP, elevation, patch area, population density and dominant species (Fig. 9). The MAT, MAP and elevation were more significant than population density in controlling the spatial pattern of the dIIC in 1996, whereas only the MAT was more significant than population density in 2006. However, under the different levels of urbanization, the influential factors varied (Table 3). Patch area (q values of 0.81 in 1996 and 0.69 in 2006) and population density (0.28 in 1996 and 0.18 in 2006) controlled the node importance in the urban core. Only elevation was more significant than population density in 2006. For the suburb, aside from patch area and population density, biological factors (dominant species and age class) and topographical factors (slope angle and slope direction) also exerted effects. Only slope direction was more significant than population density in 1996. Regarding the exurb, the influence of population density was absent. The node importance was dominated by abiotic factors (MAP, elevation and MAT), and biotic factors (patch area and dominant species) played a smaller role. MAT, MAP, elevation and dominant species were more significant than

Table 1 A comparison of various landscape measurements among urban cores, suburbs and exurbs, as well as the temporal changes in these measurements from 1996 and 2006

Year	Boundary	NL	NC	IIC	Patch number of the largest component	Total area of the patch components (ha)
1996	All regions	470	43	0.00712	226	31,431.5
	Urban core	18	9	0.01944	8	2,254.8
	Suburb	74	12	0.01439	26	8,220.7
	Exurb	380	24	0.00854	201	20,956.0
2006	All regions	341	35	0.01182	156	37,479.6
	Urban core	13	8	0.01819	6	2,232.5
	Suburb	26	8	0.01632	14	9,145.8
	Exurb	304	22	0.01824	154	26,101.3


1996dIIC
2006dIIC
B
B'
C
C'
A
A'
D
D'
D'
N
0
2.5
5
10
20
km
Legend
Low importance(0-10)
Medium low importance(10-20)
Medium importance(20-30)
Medium high importance(30-40)
High importance(40-50)
Sea
Water system
Non-forest region
Suburb
Exurb
Urban

◀**Fig. 7** Landscape connectivity (dIIC) in 1996 and 2006. Zones *A*, *B*, *C* and *D* are zoomed-in views of the regions with significant changes. There is polarization of the forest patches in zone *A*, partial fragmentation in zone *B*, the merging of initial isolated small patches in Zone *C* and the expansion of connected patches in Zone *D*

population density in controlling the spatial pattern of dIIC in 1996, whereas none of the 12 selected factors was more significant than population density in 2006. In addition, a linearly enhanced or nonlinearly enhanced interaction was observed for all relationships between population density and the 12 selected factors (Tables S3, S4, S5 and S6) (population density ∩ ecological factor) > (population density + ecological factor) or (population density ∩ ecological factor) > (population density, ecological factor) (Table 4).

Discussion

Construction of a comprehensive index of urban forest landscape connectivity

Recently, increasingly complex indices of landscape connectivity based only on mathematical statistics or topological calculations have been developed. However, these indices have failed to reveal the construction, composition and functional characteristics of landscapes (Table S2) (Devi et al. 2013). How should

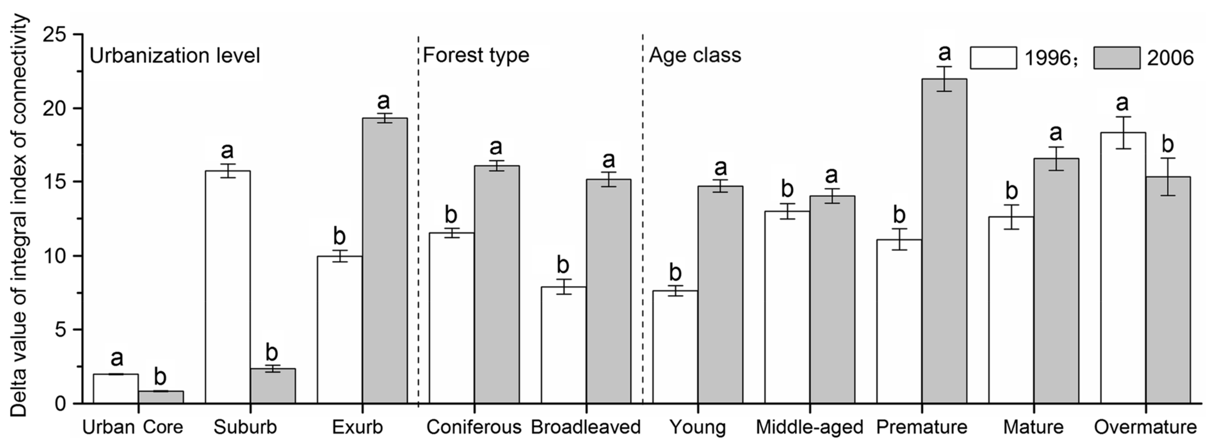


Fig. 8 Changes in the delta values of the integral index of connectivity (dIIC) among urbanization levels, forest types and age classes. Lowercase letters indicate significant differences between 1996 and 2006 ($P < 0.05$)

Table 2 A comparison of delta values of the integral index of connectivity (dIIC) and stand attributes among urban cores, suburbs and exurbs, as well as the temporal changes in these statistics from 1996 and 2006

Level	Year	dIIC	Stand age (year)	Mean DBH (cm)	Mean height (m)	Stand density (Stems ha^{-1})	Stand volume (m^3 ha^{-1})
All	1996	10.96 ± 0.27	24.20 ± 0.26	6.16 ± 0.14	5.97 ± 0.06	2,106 ± 25	52.55 ± 1.66
	2006	15.80 ± 0.28	23.77 ± 0.20	11.26 ± 0.09	7.62 ± 0.12	1,932 ± 15	53.06 ± 0.79
Urban core	1996	1.98 ± 0.02	33.59 ± 0.45	10.78 ± 0.19	6.88 ± 0.16	1,254 ± 46	50.26 ± 1.60
	2006	0.83 ± 0.03	36.63 ± 0.50	15.34 ± 0.30	10.22 ± 0.43	1,574 ± 23	52.62 ± 1.01
Suburb	1996	15.72 ± 0.45	29.81 ± 0.38	8.70 ± 0.23	6.99 ± 0.08	1,782 ± 35	87.63 ± 3.35
	2006	2.36 ± 0.23	29.95 ± 0.48	11.34 ± 0.40	9.06 ± 0.77	1,836 ± 35	69.08 ± 4.06
Exurb	1996	9.98 ± 0.38	24.77 ± 0.36	6.47 ± 0.20	6.34 ± 0.08	2,124 ± 33	53.02 ± 22.49
	2006	19.32 ± 0.32	21.68 ± 0.22	10.95 ± 0.08	7.18 ± 0.05	1,980 ± 17	50.31 ± 0.69

Data are presented as the mean ± SE (standard error)

Table 3 Relative importance of forest characteristics, climate, topography and population to the delta values of the integral index of connectivity (dIIC) for urban cores, suburbs and exurbs in 1996 and 2006

Factors	Urban core		Suburb		Exurb	
	1996	2006	1996	2006	1996	2006
Patch area	0.813	0.694	0.860	0.923	0.193	0.140
Dominant tree species	0.039	0.073	0.265	0.346	0.092	0.082
Canopy density	0.001	0.008	0.021	0.146	0.005	0.015
Age class	0.044	0.159	0.157	0.328	0.045	0.041
MAT	0.001	0.694	0.005	0.844	0.192	0.095
MAP	0.001	0.052	0.005	0.056	0.363	0.251
Elevation	0.001	0.005	0.005	0.017	0.264	0.310
Slope degree	0.031	0.078	0.197	0.372	0.016	0.003
Slope position	0.029	0.014	0.068	0.141	0.036	0.032
Slope direction	0.064	0.103	0.365	0.363	0.026	0.033
Site index	0.015	0.017	0.018	0.018	0.006	0.020
Population density	0.280	0.175	0.237	0.269	0.056	0.102

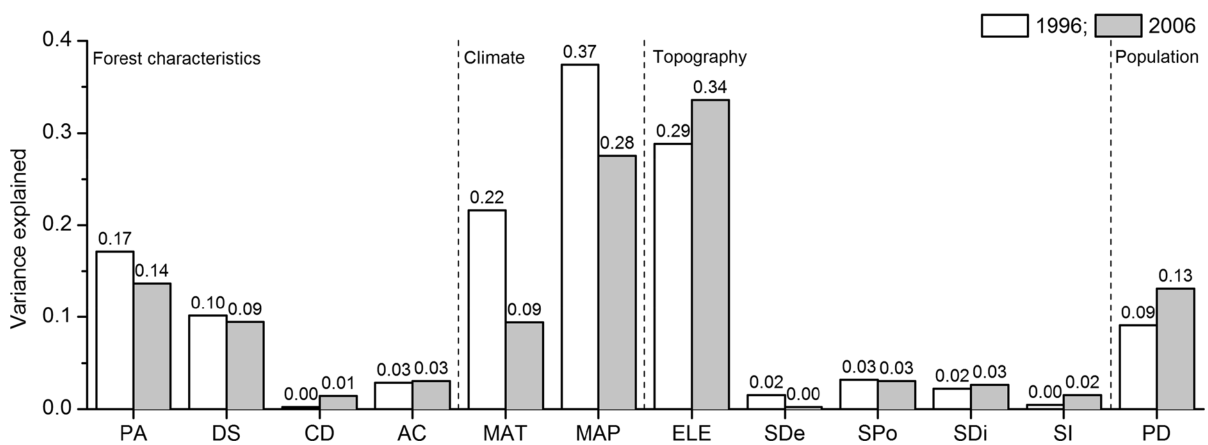


Fig. 9 Relative importance of forest characteristics, climate, topography and population to the delta values of the integral index of connectivity (dIIC). *PA* patch area, *DS* dominant species, *CD* canopy density, *AC* age class, *MAT* mean annual temperature, *MAP* mean annual precipitation, *ELE* elevation, *SDe* angle of slope, *SPo* slope position, *SDi* slope direction, *SI* site index, *PD* population density

metrics used to assess the connectivity in urban ecosystems be developed? (Goodwin 2003). IIC can quantify ecological connectivity and identify regions that have extensive ecological connectivity and enable the matching of all types of ecological factor information from multiple sources. Thus, IIC is considered the best index for estimating spatial variations of functional landscape connectivity. However, because the integration of human activities has not been considered with various types of ecological factors, IIC fails to explain the most valuable features and functions of urban forest landscape connectivity. Thus, this index is rarely used in landscape monitoring (Freudenberger et al. 2013). In the present study, we used graph theory analysis to integrate various types of ecological factors and used the geographical detector model to explore the impact of population density on IIC index. This approach provided a theoretical basis for the establishment of a more comprehensive and improved landscape connectivity index.

Urban forest landscape patterns and processes based on network analysis

Previous studies have often relied on remote sensing image interpretation and have not identified each

Table 4 Interaction effects between population density and other factors on the delta values of the integral index of connectivity (dIIC) for urban cores, suburbs and exurbs in 1996 and 2006

Level	Period	PA	DS	CD	AC	MAT	MAP	ELE	SDe	SPo	SDi	SI
All	1996	0.282↗↗	0.192↗↗	0.096↗↗	0.142↗↗	0.235*↑	0.394*↑	0.290*↑	0.100↑	0.112↑	0.115↗↗	0.095↑
	2006	0.261↑	0.197↑	0.143↑	0.163↗↗	0.189*↑	0.412↗↗	0.336↑	0.133↑	0.139↑	0.152↑	0.154↗↗
Urban core	1996	0.813↑	0.316↑	0.283↗↗	0.290↑	0.280↑	0.280↑	0.280↑	0.298↑	0.299↑	0.343↑	0.289↑
	2006	0.694↑	0.257↗↗	0.184↗↗	0.301↑	0.694↑	0.226↑	0.175*↑	0.251↑	0.188↑	0.279↗↗	0.191↑
Suburb	1996	0.899↑	0.331↑	0.248↑	0.363↑	0.237↑	0.237↑	0.237↑	0.361↑	0.256↑	0.482*↑	0.241↑
	2006	0.936↑	0.441↑	0.379↑	0.488↑	0.891↑	0.330↗↗	0.269↑	0.523↑	0.280↑	0.495↑	0.269↑
Exurb	1996	0.255↗↗	0.165*↗↗	0.061↗↗	0.111↗↗	0.199*↑	0.380*↑	0.265*↑	0.066↑	0.082↑	0.083↗↗	0.061↑
	2006	0.234↑	0.173↑	0.117↑	0.137↑	0.161↑	0.389↗↗	0.310↑	0.105↗↗	0.114↑	0.128↑	0.129↗↗

Notes: The symbol '*' denotes significant interactions ($P < 0.05$). The symbol "↑" denotes that factor A enhances factor B; i.e., $PD(A \cap B) > PD(A)$ and $PD(B)$. The symbol "↗↗" denotes the nonlinear enhancement of factor A and factor B; i.e., $PD(A \cap B) > PD(A) + PD(B)$

PA patch area, *DS* dominant species, *CD* canopy density, *AC* age class, *MAT* mean annual temperature, *MAP* mean annual precipitation, *ELE* elevation, *SDe* angle of slope, *SPo* slope position, *SDi* slope direction, *SI* site index, *PD* population density

independent block. Some scholars even believe that only remote sensing imagery can be effectively used to explain the relationship between landscape patterns and processes (Baggio et al. 2011; Cushman et al. 2011). The problem with remote sensing is that the images only depict changes in forest area but fail to reflect changes in structure and function. As a result, important information related to the block is missing. In addition, image resolution and mapping methods affect the accuracy of landscape modes. Therefore, considering an index of the sensitivity of measurement data and an index that changes with spatial resolution is necessary when using a landscape connectivity index to describe landscape patterns (Ren et al. 2011a; Ren et al. 2012). In the present study, we integrated a variety of ground-based observations and detailed survey data (i.e., census data, a forest inventory, and weather data). Based on the consistency of spatial and temporal scales, we used spatial interpolation techniques to generate spatial and temporal distribution diagrams of IIC landscape connectivity, population density and various ecological factors. This approach proved to be effective to study socially driven forces of urban forest landscape patterns to facilitate planning for urban forests with multiple ecological functions (Ahern 2013).

Development of quantitative measurement tools of landscape connectivity in the ecological planning of urban forest landscapes

A number of previous landscape connectivity models, such as the incidence function, neutral, and capture-recapture models, have made assumptions that clarify the interactions between urban population density and urban forest landscape connectivity, require direct observation and verification (Janin et al. 2009). In this study, we used the geographical detector model, which can detect dominant factors and interactions and extract implicit interactions among population density, ecological factors and landscape connectivity to quantify nominal data without any preconditions or limiting conditions (Wang and Hu 2012). Urban forest connectivity, as affected by the interactions between human activities and multiple ecological factors, has been combined with the design and analysis of ecological networks in a wide range of studies of forest landscape composition and the mechanisms that affect the spread of species (Richard and Armstrong 2010).

Continuous afforestation projects effectively select and use forest patches

Since the 1990s, a worldwide campaign encouraging reforestation and afforestation has increased the extent of tropical and subtropical forests by 2.8 Mha per year. Although previous studies evaluated a large area of forest connectivity, they did not apply ecological factors involved in the protection and planning of forest landscapes (Ren et al. 2011b). Current reforestation projects rarely consider spatial correlations of forest ecological factors and the role of multiple urban forest ecological functions in landscape planning (Garcia-Feced et al. 2011). Our study focused on both dynamic processes within the urban forest area and forest landscape connectivity during a reforestation or afforestation project. We also built multiple ecological services and functions of new forests from the perspective of forest network analysis. Our suggestions may apply to other forest regions in eastern Asia and have practical value in wildlife resource planning and landscape design. In addition, our approach can provide a useful diagnosis of urban landscape conditions and provide guidelines for afforestation projects that aim to improve urban forest landscapes.

Critical thresholds of connectivity in urban forest landscapes

Our results showed that in both 1996 and 2006, NC and the number of patches in the largest components changed only gradually beyond the 600-m threshold distance. Taking a graphical-theoretical approach, many researchers have examined the critical thresholds for resources, energy and organisms. These earlier studies failed to describe the general patterns of connectivity because different species respond differently to dispersal distances. Recently, the most common method employed has been to graphically compare many linking thresholds and analyze the tendency or the connection of study organism clusters. Our results for 13 threshold values, including the distance of the spread of the main species in urban forest areas, are consistent with the results of other published studies. For example, our results revealed a larger threshold of connectivity than the results of Andersson and Bodin (2009), who used a link threshold of 50 m for coal tits in an urban landscape of Sweden. Our threshold of connectivity is lower than that of Brooks (2006), who analyzed the pattern of hierarchical clustering for two populations, first among a fungal pathogen population at an extent of 1,000 m and second among the gene flow in a salamander species across a subcontinental range. Our results agree with those of O'Brien et al. (2006), who studied the distribution of woodland caribou in Manitoba, Canada. O'Brien et al. (2006) found that the range of scales (500 to 1,900 units) was associated with clusters that are larger than average for the landscape, revealing that caribou select larger areas of functionally connected habitat at these thresholds. Differences in the selection of the landscape connectivity threshold are mainly related to the distance that a species spreads, the enforceability of landscape connectivity, research purposes at different levels and the internal and external factors of landscapes. Therefore, a deep understanding of the threshold distance is important in the prioritization of landscape connectivity if the landscape elements are to be accurately measured (Lookingbill et al. 2010; Moilanen 2011).

Spatiotemporal heterogeneity of important values of connectivity in urban forest landscapes

The distribution of urban forest connectivity importance varied greatly in 1996 and 2006 along an urbanization gradient (Fig. 4). This finding shows that human activities have had both positive and negative effects on urban forest landscape connectivity during different stages of urbanization (Liu et al. 2006). In addition, the expansion of built-up land leads to a steady decline in forest landscape connectivity and forest area (Joshi et al. 2009). With increased intensive agricultural activity, afforestation projects may transform croplands into forest and steadily improve forest landscape connectivity and forest area (Tang et al. 2010). As a consequence of human activities and other ecological processes, the spatiotemporal heterogeneity of important values of urban forest landscape connectivity changes characteristically.

Zones A, B, C and D (Fig. 7) underwent substantial changes in exurban regions. The new ecological patches connected with initially isolated small patches led to a modest increase in connectivity. Numerous studies suggest that ecological habitat fragments that provide stepping stones for species from one habitat to another in a city have little impact on species that are easily dispersed (Urban and Keitt 2001). However, for most species that have a moderate ability to spread, a workable pattern can be achieved by linking large patches across the entire landscape and promoting the dynamic contact of urban blocks throughout the landscape; this approach plays an important role in the maintenance of ecological connectivity (Soga and Kaike 2013). The current results suggest that human activities have focused on high-value urban blocks in exurban areas and have enhanced the connectivity between blocks by building stepping stones. However, whether a stepping stone is efficient in maintaining connectivity between species must be further studied for specific species (Galpern et al. 2011).

Interactions between human activities and urban forest landscape connectivity

During rapid urbanization, MAT, MAP, elevation, patch area, population density and dominant species have strong effects on the importance of nodes. Although many studies have considered the ecological factors that affect landscape connectivity, the majority have focused on specific ecological factors. Research considering the effect of multiple ecological factors and human activities on landscape connectivity and confirming the dominant factors appears to be scarce. Saura et al. (2011) considered forest area to be an important factor affecting landscape connectivity and found the total amounts of energy and matter to be directly proportional to the area of a block. In other words, a larger block will have more ecological functions. A reduction in forest area and an increase in forest landscape fragmentation would lead to a reduction in landscape connectivity. Martín-Queller and Saura (2013) found that precipitation is the major determinant of species abundance. Changes in species abundance start with the complex interaction of environmental factors and then dissipate throughout the relevant habitat due to habitat loss and fragmentation. However, our study integrated a wide variety of ecological factors on the same GIS platform and performed a comprehensive comparison of these factors, which directly affect landscape connectivity.

MAT was more significant than population density in controlling the spatial pattern of dIIC in 1996 and 2006. This finding may be related to two factors. First, human activities dramatically affect both abiotic (e.g., light, temperature and humidity) and biological environments, which leads to forest growth. Second, the impact of human activities on urban forests is clearly related to location (Martin-Martin et al. 2013). Human activities severely affect locations that have convenient transportation, flat topography and a forested landscape around cities. However, human activities have little effect on distant, high-elevation forest landscapes. MAT is more significant than population density in controlling urban forest connectivity in Xiamen because the majority of urban forests are located in exurban areas.

The interaction between population density and ecological factors nonlinearly enhanced urban forest connectivity. Thus, in complex human-natural ecosystems, human activities together with complex ecological factors promote urban forest connectivity, and the interaction has a greater effect on urban forest landscape connectivity than any ecological factor alone. With increased urbanization, urban forest landscape connectivity will continue to increase. Previous research has mainly employed multivariate statistical analysis combined with graph theory to focus on the diversity of human activities, animals and plants as well as the interaction between animal and plant diversity with landscape connectivity (Martin-Martin et al. 2013). Little attention has been paid to the interactions between human activities and urban forest landscape connectivity. In fact, there is an indirect interaction between human activity and species diversity. Human activities profoundly change the connectivity of urban forest landscapes with species diversity through the construction of roads, the development of corridors and the establishment of protected areas (Schweiger et al. 2005). Although differences exist among different species in their response to continuous increases in connectivity, our study illustrated the driving mechanisms for the increase in urban forest landscape connectivity to aid in sustainable ecological landscape planning.

Recommendations and further study

We propose the following recommendations based on our results. First, software tools or models related to, and methods for analyzing, landscape connectivity must be developed. New theories should also be explored, and these methods and theories should be applied to urban forest management practices during landscape planning. Second, landscape patterns and population density should be combined to allow for dynamic networking observations. We should focus on population density and landscape connectivity to improve the diversity of urban forest landscapes and consider the direct and indirect effects of each ecological factor along the urban–rural gradient. Finally, policies that protect the landscape based on the changing trends and driving mechanisms of urban forest landscape connectivity are needed in urban zones with different gradients. Urban core management should focus on preventing a reduction in the forested area of urban areas. The analysis of suburbs should account for a wide variety of ecological factors affecting landscape connectivity, and exurbs should build interconnections between blocks with strong landscape connectivity.

Each landscape connectivity index has different ecological relevance. Additional studies are needed to compare relationships between multiple landscape connectivity indices and population density. These studies should use networked observations so that graphical and theoretical methods can be combined to establish a comprehensive index of urban forest landscape connectivity based on different importance values. In addition, differences in economic development and cultural traditions in different countries may create different interactions between human activities and urban forest landscape connectivity. As a result, the construction of an urban forest landscape connectivity index cannot simply be copied from one area to another and requires networking research at multiple spatial and temporal scales capable of addressing local needs. Further, several limitations still exist for geographical detector models. For example, we must apply a geographical detector model in a natural setting when selecting target species rather than limiting its application to research studies associated with human activities. In addition, we should explore various ways to validate the accuracy of model results, encourage the study of interdisciplinary coupling and develop potential applications of the geographical detector model to other analysis areas worldwide, including North America and Europe.

Conclusions

This study was supported by integrated field data from multiple sources, including forest resource planning and design survey data, population census data and meteorological records. Through the use of these data, interactive relationships among various factors were examined and related to the spatial distribution of ecological factors. New knowledge related to these factors was gained for the analysis of the mechanisms and influence of human activities on urban forest landscape connectivity in Xiamen City, China. This multi-source, data-based analysis using geographical detector models is an effective approach for quantitatively characterizing the interaction relationships among ecological factors, population density and landscape connectivity. This new method is particularly useful for urban landscape ecology research because it quantifies the impacts of human activity on landscape connectivity based on a complex set of factors.

The results of our analysis showed that the threshold of node importance was 600 m. MAT, MAP, elevation, patch area, population density and dominant species had strong effects on node importance. MAT was more significant than population density in controlling the spatial pattern of dIIC in 1996 and 2006. The interaction between population density and various ecological factors as well as their linearly or nonlinearity helped enhance urban forest landscape connectivity. Although field survey data that were collected and analyzed were directly applicable only to Xiamen City, our research methods and analysis procedures can be broadly applied in urbanized regions where different levels of human activity exist across landscapes.

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