Ecological Indicators 60 (2016) 921–929

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

A multivariate analysis integrating ecological, socioeconomic and physical characteristics to investigate urban forest cover and plant diversity in Beijing, China

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ARTICLE INFO

Article history:
Received 3 April 2015
Received in revised form 30 June 2015
Accepted 9 August 2015
Available online 11 September 2015

Keywords:
Urbanization
Urban ecosystems
Socio-ecological complexities
Urban ecology
Landscape ecology

ABSTRACT

Understanding the factors driving the variation in urban green space and plant communities in heterogeneous urban landscapes is crucial for maintaining biodiversity and important ecosystem services. In this study, we used a combination of field surveys, remote sensing, census data and spatial analysis to investigate the interrelationships among geographical and social-economic variables across 328 different urban structural units (USUs) and how they may influence the distributions of urban forest cover, plant diversity and abundance, within the central urban area of Beijing, China. We found that the urban green space coverage varied substantially across different types of USUs, with higher in agricultural lands ($N=15$), parks ($N=46$) and lowest in utility zones ($N=36$). The amount of urban green space within USUs declines exponentially with the distance to urban center. Our study suggested that geographical, social and economic factors were closely related with each other in urban ecological systems, and have important impacts on urban forest coverage and abundance. The percentage of forest as well as high and low density urban areas were mainly responsible for variations in the data across all USUs and all land use/land cover types, and thus are important constituents and ecological indicators for understanding and modeling urban environment. Herb richness is more strongly correlated with tree and shrub density than with tree and shrub richness ($r=-0.472$, $p<0.05$). However, other geographic and socioeconomic factors showed no significant relationships with urban plant diversity or abundance.

1. Introduction

The existence of urban plants and their associated ecological processes play an important role in the structure, function and dynamics in urban ecosystems (Pickett and Cadenasso, 2008). Urban socioeconomic system means a set of critical resources (natural, socioeconomic, and cultural) whose flow and use is regulated by a combination of ecological and social systems (Berkes et al., 2003). The urban forest, along with buildings and surfaces, is a principal element of urban structure (Ridd, 1995). Plants contribute to the spatial structure of urban systems not only through their presence in parks and reserves, but also throughout the entire urban mosaic. The urban forest, which includes individual trees along streets and in backyards as well as stands of remnant forest (Nowak et al., 2001), has become one of the most extensively researched topics in urban ecology because of its environmental, social and economic benefits (Peckham et al., 2013). Specifically, environmental benefits include urban heat island effect mitigation

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http://dx.doi.org/10.1016/j.ecolind.2015.08.015
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(Yuan and Bauer, 2007), carbon sequestration (Jo and McPherson, 1995; Nowak and Crane, 2002), air purification (Nowak et al., 2006), habitat provision (Young, 2010), and an increase in local biodiversity (Kong et al., 2010). Social benefits include, for example, esthetic pleasure (Smardon, 1988), improved human health (Maas et al., 2006, 2009; Qureshi and Breuste, 2010), faster recovery from illness through establishment of a tranquil and healthy environment (Kuo and Sullivan, 2001), and reduction of crimes and fear of crime (Troy et al., 2012). In terms of economic benefits, urban forest could help increase real estate values (Anderson and Cordelland, 1988), and also stimulate higher economic activity (e.g., tourism and direct provision of timber) in tree-covered areas (Baines, 2000).

Many researchers have studied urban forest and plant diversity changes as well as the driving forces behind these changes in different cities around the world. However, the driving force has not been found to be the same everywhere. For example, in many U.S. cities, plant diversity and the proportion of vegetation cover is closely related to residents' income (Iverson and Cook, 2000; Martin et al., 2004; Clarke et al., 2013), the proportion of immigrants (Troy et al., 2007; Szantoi et al., 2012), and the geographic slope (Kim and Zhou, 2012). Other studies in different regions of the world suggested that policy or governance-related factors played a leading role. For example, rapid urbanization and greening policies accounted for the process of green space change in Kunming, China in Zhou and Wang (2011). Kendal et al. (2012) found that 'top down' political factors in Ballarat, Australia were more important than individual behaviors in determining tree cover, and physical rather than socio-economic factors were better predictors of species richness across all land uses. In Bloomington, Indiana, USA, urban land use as governed by municipal zoning policies plays a role in the abundance, distribution, and potential future location of urban trees independent of policies meant specifically to manage canopy (Mincey et al., 2013). Therefore, comparative studies in varying cultural, political and geographic contexts are required to improve our understanding of how socio-economic conditions may drive patterns of urban vegetation.

Beijing, as one of the fastest growing cities in China, harbors 618 plant species belonging to 349 genera, 103 families, and 14 different chorological spectra (Zhao et al., 2010). The area dedicated to public green space reached 15.7 m^2 per capita in 2013 (BD, 2014). Urbanization results in homogenization of the landscape, and is often the main cause for the loss of overall biodiversity and native species in modified landscapes (McDonnell, 2011; Pauleit et al., 2010). For example, 53% of the plant species in Beijing are aliens (Zhao et al., 2010; Wang et al., 2011). Urban structural unit is a good model to explore urban vegetation cover and plant diversity changes in complex urban ecosystem. Urban structural units (USUs) are work (or similar) units in urbanized areas, such as parks, areas of commerce, and areas for transportation (Wang et al., 2013). Wang et al. (2013) examined single linear relationships between forest cover and the construction period/housing price in three USUs (i.e., universities/colleges, parks and residential areas). However, the urban ecosystem is highly heterogeneous, having biotic and abiotic components, and the relationships among these components are not simple linear relationships between pairs (Pickett and Cadenasso, 2008).

Recently, some studies (e.g. Egoh et al., 2008; Naidoo and Ricketts, 2006; Nelson et al., 2009) explore the spatial patterns of provision of multiple services across landscapes, and these studies focused on spatial concordance among services as evidence of win–win opportunities for conservation of multiple ecosystem services and biodiversity. However, it is scarce to explore more types of USUs with PCA and multivariate regression in urban ecosystem, while understanding the driving factors of urban green space and plant diversity in highly heterogeneous landscapes of Beijing is crucial for deciding how to best maintain biodiversity and the provision of ecosystem services.

We focused on three questions in this study. Firstly, how does the urban green space vary by urban structural unit (USU)? Secondly, how do the geographical, social and economic factors interrelate with each and to what extent can they explain the variations of urban green space at the USU level? Thirdly, at the USU level, how do plant species richness and density vary by USUs, and what factors may influence the urban plant communities? We intended to identify key indicators that could predict patterns across all land use cover types. We also explored the driving force(s) behind forest cover and plant diversity in Beijing, which would provide important implications for better incorporating biodiversity and the provision of ecosystem services in future urban planning and design.

2. Method

2.1. Study area

Beijing is located at the northwestern border of the North China Plain. The city has an annual average temperature of 11.7 °C and annual average precipitation of 595 mm, with most of this precipitation occurring in the summer. Beijing has a nearly 3000-year history as China's political and cultural center, 800 of which Beijing has been the capital city in China following the Yuan dynasty (1271–1368, AD). The central urban area is confined within the fifth ring road (Fig. 1) and covers an area of 650 km^2 (BISM, 2005). In 2009, Beijing's population reached 21.14 million, and the permanent resident population density is of 1311 persons/km^2 (GD, 2014). Its urban greening percentage is up to 46.8% (BMBS, 2012). The economy experienced fast growth following the implementation of a market-oriented reform policy in late 1970s. For the past several decades, Beijing has also undergone a rapid urbanization, with urban areas increasing from 64 km^2 in 1978 to 16 thousand km^2 in 2009; the area within the fifth ring road as of 2009 is 650 km^2 in BMBS (2009).

2.2. Sampling design

An even grid based stratified sampling method was developed for this study. First, we obtained two scenes of cloud-free SPOT 5 (Satellite Pour l'Observation de la Terre) images with spatial resolution of 10 m and acquisition dates of 30 August and 25 October 2002, respectively. Both images were geometrically rectified by ground control points from orthorectified images and then mosaiced using ERDAS Imagine™ software. The images within the fifth ring road of Beijing were extracted and tilted into 160 2 km × 2 km grids. Then, one to four USUs within each grid were selected randomly in each grid cell. The boundary of each USU was determined on the printed photo by referring to Google Earth (accessed from June to July in 2010), Beijing City Atlas (BISM, 2005, scale 1:50,000) and in situ surveys (including interviewing local people for a given USU's boundaries). Finally, referring to the SPOT 5 images, the boundaries were drawn by on-screen digitization of the images with ArcGIS 10 (Fig. 1).

In this study, we did not adopt a completely random sampling approach mainly because we did not know a priori where the sampling sites would be. Furthermore, the urban vegetation and socio-economic data of sampling plots could not be accessed if they fell on water-covered areas (e.g., Kunming Lake of the Summer Palace) or impermeable surfaces (such as Tian'anmen Square). Our sampling method had the likelihood to introduce some sampling bias; therefore, we increased the sampling size (number of samples) for each USU type in order to minimize the bias as much as possible.

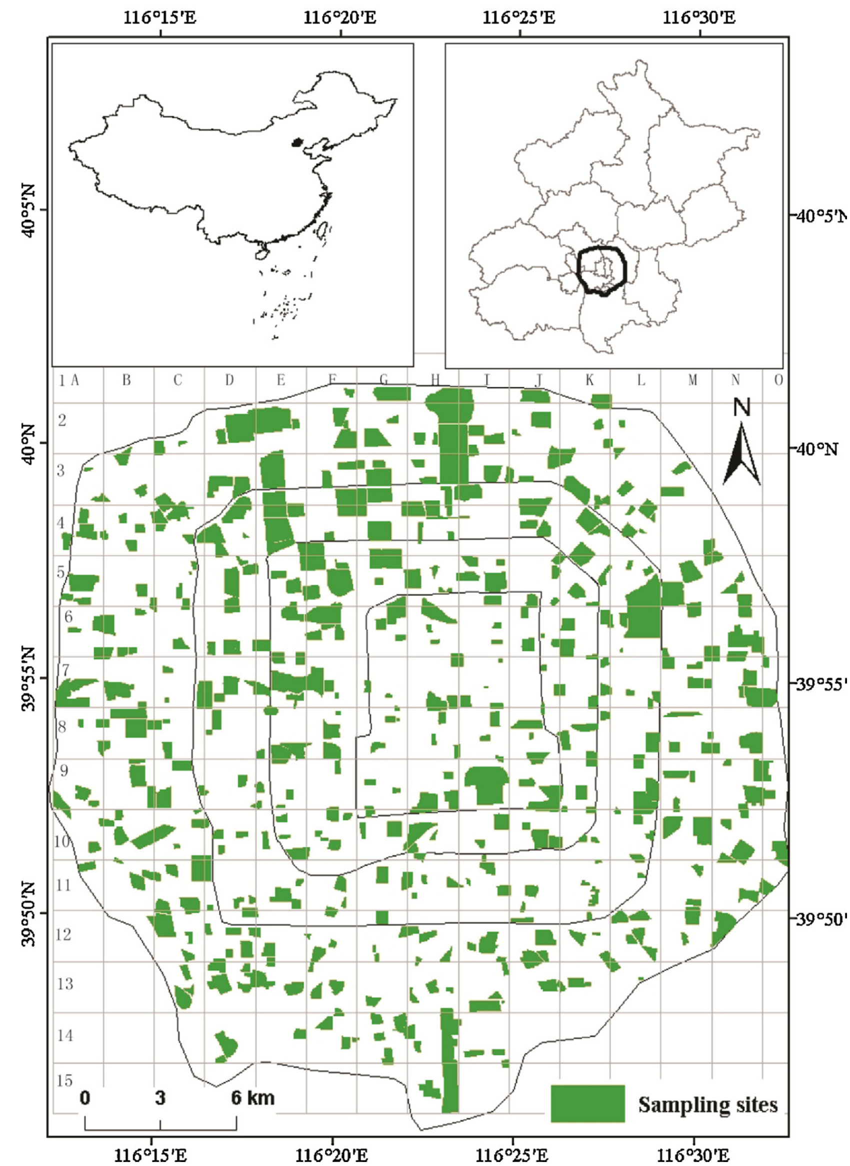

Fig. 1. Study area and sampling sites. A–O represent the column name from left to right, and 1–14 represent the row name from the top to bottom; therefore, F3a represents the first USU in the grid F3.

2.3. Land use/land cover classification

An appropriate land cover classification system developed by Cadenasso et al. (2007) was adapted to identify land cover classes from the SPOT 5 image. A land use/land cover map for the study area was derived using an object-based image analysis (OBIA) approach. Two scenes of SPOT imagery (4 color banded; 10 m resolution) acquired on 30 August and 25 October 2002 were used as the main sources for Land Use and Land Cover (LULC) classification. Three main steps were used for the classification. First, we performed a multi-resolution image segmentation to generate image objects on which the classification algorithm could be applied. For this segmentation, we used a 'scale parameter' of 20, which was determined by visual interpretation of the segmentation results. The important outcome of the segmentation process is to identify objects that were homogeneous and included the features (i.e., spectral values, shape, texture, etc.) that can be used for classification (Walker and Blaschke, 2008). Second, once the segmentation was achieved, we utilized a combination of fuzzy rules and standard nearest neighbor (SNN) algorithm to classify each image object. A total of 200 training samples were selected and referenced with the auxiliary data (including digital topographic maps, field survey data, high spatial resolution imagery (Quick Bird) (QB), and Google Earth) to identify their representative classes. Based on the spectral and spatial information of these samples, we created the SNN feature space and fuzzy rule algorithms that were collectively used for classification. Each image object was assigned a probability of which LULC class it belonged, and the final class of image objects was decided on the basis of which class has the highest probability. Finally, we refined the classification with manual adjustment to improve the overall quality of classification. As a result, six categories were identified: exposed land, open water, forest, high-density urban, low density urban, and farmland. The classification was performed using Definiens 7.0 software. Classification accuracy was assessed by comparing the reference collection with classified imagery (Congalton, 1991). Based on the confusion matrix, the overall accuracy of land cover classification was 92.56%, and the Kappa coefficient was 0.92 (ca. Wang et al., 2013). Based on the derived LULC map, we further calculated the percentage for each LULC type within every USU in ArcGIS 9.3 (ESRI).

The classification scheme of the USUs in this study was modified from the Urban Forest Effects (UFORE) Model: Field Data

Collection Manual (UFORE, 2011). For our study, 'Agriculture' (A) includes farmland and orchards. 'Commerce' (C) includes hotels, businesses, and logistics centers. 'Institutional' (I) includes museums, colleges/universities, research institutions, places of historic interest and scenic beauty, general institutions, primary and middle schools. 'Park' (P) is parklands. 'Residential' (R) includes urban villages, low and high-density residential areas, and Siheyuan (Courtyards). 'Transportation' (T) includes overpasses, bridges, roads, expressways, bus stops, train stations, airports, and bus stations; T also includes limited access roadways (usually fenced), train tracks, airports, shipyards, etc. 'Utility' (U) includes public squares, refuse processing plants, sports centers sewage treatment plants, entertainment plazas, hospitals, government organs and government offices. Finally, 'water/wetland' (W) includes rivers, canal, and lakes.

2.4. Socioeconomic variables

Based on prior information, data for the construction period, housing price, and population density for each USU were collected and used as representative socioeconomic indicators (variables). These were considered as the most relevant indicators by which to address the question and objective of this study. To determine the construction period (years), first, the year when the USU was established or brought into service/function was accessed by referring city portal website or through interviews with the local people in each USU. Then, using 2011 minus the year of establishment, we obtained the construction period that reflected the total length of the USU's existence. Housing price (Yuan/m^2) was accessed from the Beijing Aifang website (http://beijing.aifang.com/) from April 1 to June 1 in 2011. The average second-hand housing price for each nearby USU was accessed from that website. Only a few USUs had no house price information, and for those cases, we referred to the local housing value evaluation center (i.e., http://www.zplh.net/) and interviewed more than 30 local people to calculate the average and avoid bias as much as possible. We counted the number of buildings (B), storeys of each building (S) and apartments of each storey (A) (if any) within each USU via visiting each USU or referring Google Earth (http://earth.google.com/). We get the average number of each family member (M) via referring to the Beijing Statistics Yearbook (BMBS, 2009), and the population (P) of each USU was determined as the following formula: $P = B \times S \times A \times M$. Permanent population density (person/km^2) = P/A. A is the area of each USU.

Besides, a questionnaire including average income, average age, percentage of alien people, percentage of house rent, number of each family member, average education level and main professional was performed in Beijing via interviewing local people of each residential areas.

A central/median point within each USU was determined to represent the geographical position of each USU within Beijing. Then the area, longitude, latitude and the distance from urban center (Tian'anmen square) were accessed in ArcGIS 9.3. Ramalho and Hobbs (2011) pointed out that categorical or quantitative measures of geographical linear distance in urban ecological studies can be ambiguous and misleading. In Beijing, however, more people prefer to live in the urban center, as it provides better resources for education and medical treatment (Time Architecture, 2007). In addition, the urban sprawl in Beijing occurs from the second to fifth ring road (Ding, 2005), and readily manifests along urban–rural gradient in Beijing.

2.5. Vegetation survey

The vegetation survey was conducted with a stratified sampling method for each USU. Each USU was divided into tree, shrub and herb layers; each sampling site was selected randomly in each layer. A woody plant was considered a tree if its trunk diameter were larger than 2 cm; otherwise, it was classed as a shrub. We had at least three 10 m × 10 m tree sampling plots within each USU, with five 2 m × 2 m shrub sampling plots and 1 m × 1 m herb sampling plots nested within each tree plot. However, if the USU was highly heterogeneous (such as a park) or was larger than 30 km^2, more than three tree sampling plots were investigated. We recorded the species name, diameter at breast height (DBH), height, and crown width for each tree; the species name, crown width, and height for each shrub; and the species name, height and number of individuals for each herb. Four plant richness and density variables are calculated as follows:

Tree and shrub richness = The total number of tree and shrub species in three 10 m × 10 m tree/shrub plots for each USU;
Herb richness = The number of herb species in each 1 m × 1 m herb plot;
Tree and shrub density = The total number of tree and shrub species individuals/300 m^2, three 10 m × 10 m tree and shrub plot in each USU;
Herb density = The total number of herb species individuals/$N \times 1$ m^2 plot, N = the number of herb plots in each USU.

2.6. Data analysis

The multivariate analytical technique of Principal Component Analysis (PCA) was used in this study. The statistical software of Minitab16® was used to perform all the multivariate analysis. PCA was used both for the sake of dimension reduction and for examining/describing the pattern(s) of collective variation in the multivariate data set. For preliminarily exploratory analysis, no rotations were used. The principal components (PC) obtained by the analysis are regarded as the linear combinations of the variables under study, and thus hold and summarize optimum information in the data.

PCA with Varimax method of orthogonal rotation was then used at the secondary stage of the analysis. Each sampling site comprised subset-areas, categorized by the dominant land cover. The land cover types were classified as forest land, exposed (barren) land, water, high density, low density or farmland in this study. For PCA, more general and meaningful variables of %forest land, %Exp, %water, %hidensity, %low dens and %farmland were derived for each sample by multiplying the area of each of the subset by 100 and dividing by the total sampling area.

The sum of the variables for forest land, exposed areas, water-covered areas, high density, low density and farmland was compared with the total area of the sampling site for each sample, and values showing a difference of more than 5% were removed. The data was then z-score standardized for the multivariate analyses. Standardization helped to eliminate the errors and to manage any issues that could arise due to large differences among means and variances and the different units of variables. A preliminary exploratory PCA was first carried out to refine the data and it was noticed that the data contained some extreme values, as shown in the score plot of the first two components, which dominated the overall correlation model of the PCA. The contribution of a variable in a PC depends upon its "loading", the coefficient of the variable in the linear equation connecting variables with the PC.

We further performed multiple regression analyses to evaluate the relative importance of each variable for urban forest. We used hierarchical partitioning to evaluate the relative importance of each model term on urban green space. The most parsimonious model was selected using Akaike's Information Criterion, AIC (Burnham and Anderson, 1998). We also examined the bivariate relationships using a scatterplot, which was fit with appropriate functions as needed. Model assumptions were checked and

Table 1
Eigenvalues and loadings for each of the five chosen PCs obtained by the PCA. %hidensity = percentage of high density urban area; %low dens = percentage of high density urban area; % farm = percentage of farmland area; %water = percentage of water-covered land; %Exp = percentage of exposed land area; %forest = percentage of forestland area; %green = percentage of greening land area.

Variable	PC1	PC2	PC3	PC4	PC5
Eigenvalue	2.8855	2.0037	1.6315	1.2135	1.1425
%Proportion	19.2	13.4	10.9	8.1	0.076
%Cumulative	19.2	32.6	43.5	51.6	59.2
The distance from urban center	0.465	−0.068	−0.058	−0.197	−0.06
Construction period	−0.266	−0.11	0.177	0.34	0.098
Housing price	−0.321	−0.023	0.134	0.25	0.251
Population density	−0.433	−0.071	0.063	0.18	0.198
Richness of trees and shrubs	−0.11	−0.383	−0.463	0.066	−0.133
Density of trees and shrubs	−0.048	−0.095	−0.418	0.116	0.28
Richness of Herbs	0.025	−0.257	−0.521	−0.059	−0.065
Density of Herbs	−0.053	−0.415	−0.109	0.21	−0.072
%Exp	0.305	−0.06	0.085	0.161	0.462
%forest	0.143	−0.425	0.318	−0.174	0.025
%water	0.02	−0.329	0.171	−0.065	−0.031
%high density	−0.447	0.163	−0.137	−0.428	−0.091
%low dens	0.261	0.251	−0.135	0.65	−0.265
%farm	0.15	0.011	−0.16	−0.127	0.685
%green	0.015	−0.448	0.266	0.06	−0.129

Variance inflation Factor (VIF) (1.8) suggested no violation of multicollinearity. We also examined all pairwise comparisons among concentrations using a Tukey's honestly significant difference multiple comparison test.

3. Results

Table 1 contains the eigenvalues for the first five PCs obtained by the PCA. These five PCs account for 59.2% of the cumulative variation in the data. Table 1 also lists the proportion of the total variation for which each of these PCs is exclusively responsible. Each of these PCs can be defined as a linear combination of the variables present in the real data. Table 1 lists all loadings for each of the five chosen PCs. The variables contributing the most to PC1 (±loading more than 0.300) are the distance from urban center, %Exp, housing price, population density and %hidensity, while PC2 is mainly governed by variables including: richness of herbs, %water, richness of trees and shrubs, density of herbs, %forest and %green, as these have extreme loadings (Fig. 2). Using the same argument, Table 1 shows that PC3 is mainly influenced by %forest, %green, density of trees and shrubs, richness of trees and shrubs and richness of herbs, PC4 by %low dens, construction period and %hidensity, and PC5 by %farmland and %Exp.

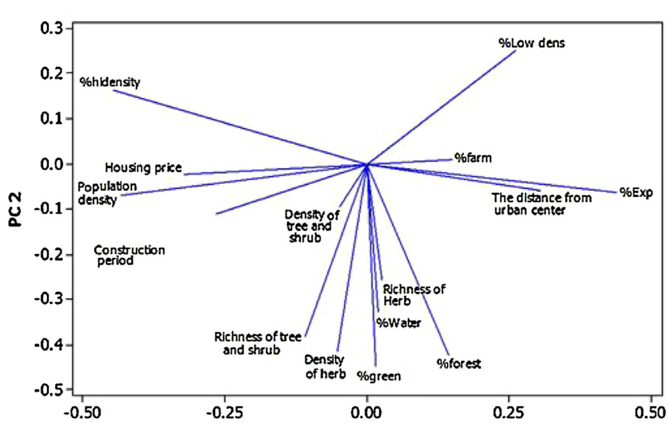

Fig. 2. Loading plot of the first two-factor analysis (PCs) showing the contribution of variables in the factor analysis (PCs). %hidensity = percentage of high density urban area; %low dens = percentage of low density urban area; %farm = percentage of farmland area; %water = percentage of water-covered land; %Exp = percentage of exposed land area; %forest = percentage of forestland area; %green = percentage of greening land area.

The PC accounting for the most variation (19.2%) in the data, i.e., PC1, is mainly influenced by variables including distance from the urban center, %Exp, housing price, population density and %hidensity (±loading more than 0.300). Therefore, the heterogeneity of the studied urban regional samples mainly derives from socioeconomic variability and corresponding changes in use of sparsely landscaped land. Furthermore, PC4 (8.1% of the total variance) had high loadings for the variables of low-density urban area, high-density urban area, and construction period. This PC clearly quantified the socioeconomic history and the land cover of the sampled regions. PC5 (7.6% of the total variance) has significant contribution by the variables %farmland and %Exp areas. As farmland is not correlated to any socioeconomic factor, land cover type, or plant diversity parameter, and as exposed land is weakly correlated only with the distance from the urban center, PC5 accounts for the abundance and influence of farmland and barren lands in the studied urban area.

An obvious clustering of the variables is also evident from the loading plot (Fig. 2). This clustering can be accounted by the correlation coefficients of these variables, which are listed in the Appendix. Among the LULC types, only %hidensity shows significant correlation with the distance from urban center and with population density ($r = -0.433$ and 0.315, $p < 0.05$), which are both strongly correlated ($r = -0.613$, $p < 0.05$) with each other. Therefore, these variables clearly form a cluster in the loading plot; the variables housing price and construction period join this cluster because of their correlation ($r = 0.37$ and 0.33, $p < 0.05$) with population density. The variable %hidensity is moderately to weakly correlated with %forest and %low dens (with a negative r). Distance from the urban center, %Exp, and %farmland are all weakly correlated; therefore, the latter two form a cluster showing an association with the first.

The variables %forest, %low dens, %hidensity and %Exp were the four main variables in our loading plot of the first two rotated components, which indicated that these four variables could contribute to most common variances in our study (Fig. 2). The variables %forest, %low dens, %hidensity and %Exp were thus likely mainly responsible for the variation in the data in all USUs and across all land use types. Other variables only caused variation in certain USUs. Therefore, these three variables can be used as indicators/predictors for every type of land use in this study (Fig. 2).

Multiple regression analyses were applied to evaluate the relative importance of each variable to the urban forest, and

Table 2
Summary of the total number of samples and average unit size (with standard deviation) for each USU type.

Urban structural unit (USU)	Number of samples	Area (±SD) (ha)
Agriculture	15	25.9 (±20.6)
Commerce	35	20.7 (±16.5)
Institution	85	24.8 (±27.3)
Park	46	36.8 (±43.8)
Residential	135	22.1 (±15.2)
Transportation	18	33.8 (±63.0)
Utility	36	21.6 (±20.2)
Water/wetland	10	56.6 (±75.6)

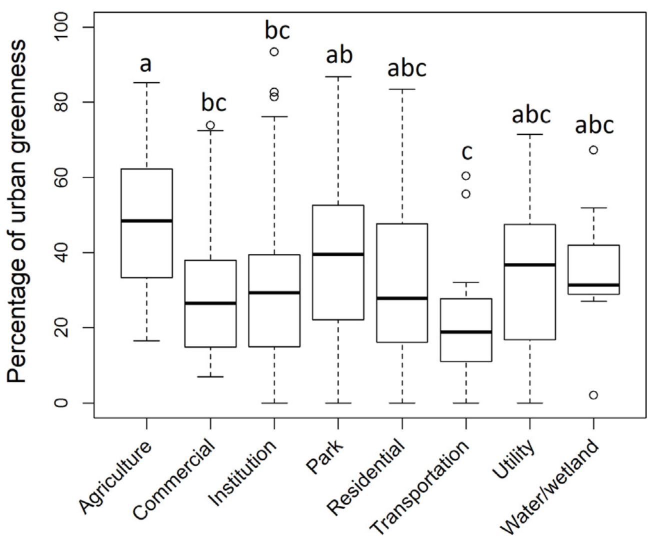

Fig. 3. Variations in percentage of urban greenness among urban structural units (USUs). Groups with different letters indicate significant difference as determined from Tukey's multiple comparison test. Refer to Table 1 for the number of samples for each USU.

hierarchical partitioning was used to evaluate the relative importance of each model term on urban green space. We found that urban green space exhibited great variability across all USU types. Highest green space coverage was found in Agriculture ($N = 15$), Park ($N = 46$) and Utility ($N = 36$), and lowest was found in Transportation ($N = 18$) with Tukey's multiple comparison tests (Table 2 and Fig. 3). The best AIC model accounted for 16% of the

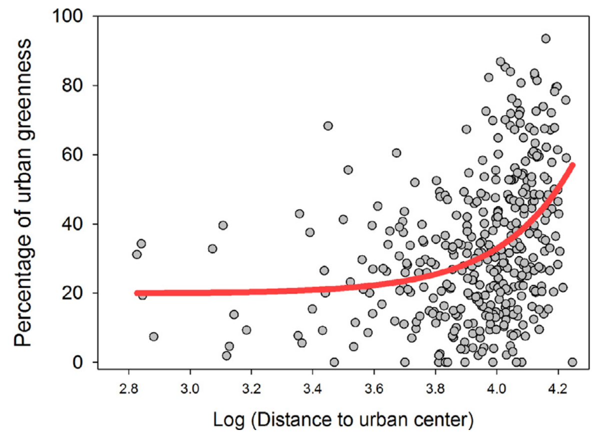

Fig. 5. Scatterplot of percentage of urban greenness and log-transformed distance to urban center, indicating that the amount of urban green space declines exponentially as USU is closer to urban center.

variation of percentage of urban greenness. The amount of urban green space declines exponentially the closer a USU is to the urban center (Figs. 4 and 5).

No significant relationships were found between urban plant diversity and abundance with other geographic and socioeconomic factors. Only housing price was correlated to tree/shrub species richness (negative correlation), but housing price only explained a very small proportion of the variation (Fig. 6).

4. Discussion

4.1. Relationships among different components of urban ecosystem

In our study, we exclude variation in the indicators and correlations depending on seasons (e.g., water availability in the summer, etc.), the distance from urban center, construction period, housing price, and population density have expected correlations with each other (Table 1). The distance from urban center is negatively correlated with housing price ($r = -0.43$) and population density ($r = -0.61$), indicating that the price of houses and population density are lower in areas further away from the urban center. In addition, population density is also positively correlated with construction period ($r = 0.33$) and housing price ($r = 0.37$), suggesting

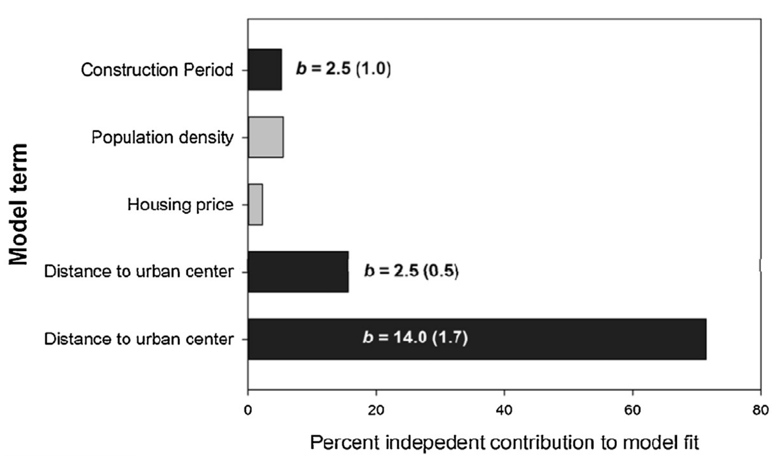

Fig. 4. Hierarchical partitioning result illustrates the independent effects of model terms for urban greenness (i.e., predictor variables). Dark bars indicate variables in the AIC-best model, and text gives their slopes and standard errors. All predictor variables were log-transformed because of the right-skewed distribution, and standardized prior to analyses. The best AIC-model accounted for 16% of the variation of percentage of urban greenness. Model assumptions were met and VIF (1.8) suggested no violation of multicollinearity.

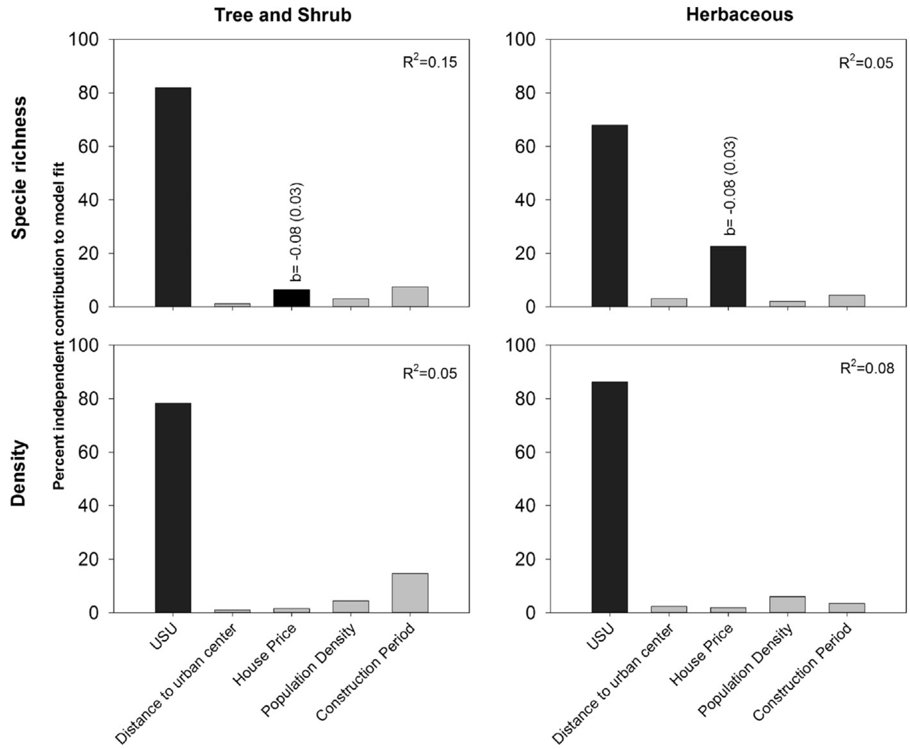

Fig. 6. Hierarchical partitioning result illustration the independent effects of model terms (i.e., predictor variables) for species richness and density. Dark bars indicate variables retained in the AIC-best model, and text gives their slopes and standard errors. Column indicates tree/shrub and herbaceous layer, and row indicates species richness and density. All responses were log-transformed to satisfy the model assumption.

that more densely populated areas are more likely to have existed longer and have higher property values. The amount of urban green space declines exponentially the closer the USU is to the urban center. This reflects how it becomes more feasible to develop green space alongside a lower population density where the housing prices are also lower (Fig. 5).

Beijing shows a pattern of urban sprawl: older houses/buildings are usually located near the urban center, where people are concentrated and the houses are expensive. This pattern is consistent with the development pattern and life style in most Chinese cities: unlike those living in western cities (i.e., cities in Europe and the USA), people in China prefer to live close to downtown or central business regions, rather than suburban areas, so that the individuals can access convenient transportation and municipal infrastructure and facilities such as hospital and education (Time Architecture, 2007). On the contrary, wealthy or middle-class families in western countries prefer to live in the suburban or exurban areas. For example, while the total population of Atlanta, Georgia, USA only increased by 22,000 in the past 10 years, 2,100,000 people are crowded in its suburban regions, with these crowds surging to areas even further afield (SCD, 2004). This phenomenon of urban sprawl over time occurs mainly because of life style, values and perspectives; e.g., the wealthier people in the west prefer to choose suburbs, as these have a better environment and more convenient transportation.

As indicated by earlier studies (Grove et al., 2006; Luck et al., 2009; Boone et al., 2010), population is one of the important socioeconomic variables affecting the urban green space variation; therefore, we included population density in this study, and expected that population density would play a role in determining urban green space. However, population density was not significantly correlated to urban green space variation. This result, though, might due to the mismatch between the scale at which population density data were accumulated (i.e., district-level) and the scale (i.e., USUs level) at which they may exert the influences. Unfortunately, district-level population density is the finest available data; the results might change if finer-level population data would be made available. The population data for each USU in Chinese cities are deemed confidential by official agencies, unlike USA cities, in which the data could be more readily obtained (Grove et al., 2006). Therefore, in our study, we used the population data for each district from local published Statistical Yearbooks; i.e., the population density for each USU is represented by the average population density of each district in which the USU falls. Given the heterogeneity of urban ecosystem, the population for parks and residential areas are not the same, a discrepancy that might have contributed to the non-significant relationship between population density and urban green space coverage.

4.2. Plant species richness and density vary by USUs

The urban ecosystem is a highly heterogeneous and complex system in which human activities, such as those related to socio-economic or urban management factors, determine the greenness coverage; in other words, human activities play a greater role in determining the green space coverage in urban systems than natural processes do (Martin et al., 2004; Troy et al., 2007; Kendal et al., 2012; Szantoi et al., 2012; Mincey et al., 2013). In our study, the loadings of PC2 (responsible for 13.4% of the total variance; Table 1) show that richness of herbs, richness of trees and shrubs, density of herbs, and urban green space may respond in the same direction to external environmental drivers, even though no land cover area was weakly correlated with any of the plant diversity parameters. This suggests that increase in urban green space can still help conserve urban plant communities, albeit such an effect is limited. The richness and density of herbs refer to the species composition and population density of all types of herbs, respectively. Therefore, this PC explains the herb species composition rather than that of the trees or shrubs. We also found that richness of herbs is more strongly correlated to the density of trees and shrubs than to the richness of trees and shrubs (Table 1). Perhaps this correlation between herb richness and tree/shrub density arises because a greater number of trees and shrubs provide a microclimate (e.g., moisture, temperature) that is more suitable for herbs, and thus generates a beneficial habitat for more herb species.

Some studies (Grove et al., 2006; Luck et al., 2009; Boone et al., 2010) indicated that householders' income was an important factor affecting the plant richness for each USU, therefore, in this study we also intended to include householders' income as one of the variables. Our hierarchical partitioning results indicated that no significant relationships were found between urban plant diversity and abundance with other geographic and socioeconomic factors; only housing price was weakly negatively correlated with tree/shrub species richness, and only explained a very small proportion of the variation (Fig. 6). This result is different from "luxury effect" proposed by Hope et al. (2003), i.e. more wealthier, more plant diversity in their residential areas. There are three reasons that might explain the weak relationships: first, while Grove et al. (2006) were able to obtain USA city householders' income, we were not able to acquire those same data for Beijing residents. The questionnaire for our study, designed and performed in some residential areas of Beijing by Wang, asked about income and education level, but the primary results were not ideal, because Chinese city dwellers are very reluctant to answer such private questions; Americans tend to provide relatively complete socioeconomic data (Grove et al., 2006; Troy et al., 2007; Boone et al., 2010). Even though we could not get the householders' income precisely as Grove et al. (2006), housing price reflects the income level of its residents (Guo et al., 2007), and as housing price has been used as one of the socioeconomic variables in Wang et al. (2013), we also used the average housing price as one of the socioeconomic variables in this study. Second, the housing price in Beijing has increased very rapidly in recent years alongside the rapid urbanization, therefore, it is inaccurate to consider housing price in and of itself as a socioeconomic factor driving plant richness in Beijing. For example, the housing price in Beijing increased eight times in the past eight years (from 2003 to 2011) and is highly influenced by multiple factors, such as the annual income of residents, price indices of investment in fixed assets, and the consumer price index, etc. Lastly, in China, urban greening is primarily managed by the government. In the USA, 60–70% of land in a city is privately owned and landscaped. So the housing price in the USA can have strong relationship with the plant diversity, to some extent, China city dwellers did not involve in their yards plant species choosing and planting like USA cities, China urban residents often entrust their yard greening to outside company and the greening species could be changed frequently because of different owners' preference, while the companies implement the greening policy according to trend and bid money to arrange the greening area and plant species.

To manage biodiversity, the existing diversity in older neighborhoods should be maintained, and the introduction of new species to newer neighborhoods should be encouraged (Clarke et al., 2013). In this study, we found that the plant diversity variables exhibited only moderate/weak to even negligible correlation with each other. The richness of trees, shrubs and herbs are moderately correlated ($r = -0.472$, $p < 0.05$). The richness of herbs is also weakly correlated with their density. The remaining plant diversity measures show no correlation with one another. One possible explanation for the lack of relationship is that urban vegetation, which is highly influenced by purposeful planning and design, is likely to be determined by decisions from local agencies and thus might not be captured by socioeconomic conditions. Each habitat patch may serve as a source or a sink for individuals of the human population (Pulliam, 1988). In this study, PC3 (10.9% of the total variance) is mainly influenced by forest cover, greening area, density of trees and shrubs, richness of trees and shrubs, and richness of herbs. Unlike PC2, this PC does include richness of both trees and shrubs. Thus, this PC takes into account both the tree and shrub species composition and human population. In addition, the variables %green, %water and density of herbs, which clustered together, do not correlate with any of the other variables. This is likely because areas of green space, supported by water, are mainly used to support grass-like herbs rather than trees or shrubs (e.g., such as golf courses).

5. Conclusion

Socioeconomic factors (i.e., construction period, housing price and population density) have strong correlations with distance to urban center. The urban green space coverage is highest in Agriculture and Park, and lowest in Utility. The amount of urban green space within USUs declines exponentially with the distance to urban center. Geographical, social and economic factors were closely related with each other in urban ecological systems. The percentage of forest as well as high and low density urban areas were mainly responsible for variations in the data across all USUs and all land use/land cover types. However, other geographic and socioeconomic factors showed no significant relationships with urban plant diversity or density.

The richness of herbs was more strongly correlated to the density of trees and shrubs than to the richness of trees and shrubs. To some extent, a higher density of trees and shrubs would create a more suitable habitat for more understory herb species. Hence, we could establish trees, shrubs and herbs in a multi-layered community to make full use of the ecological resources spatially. In turn, using the ecological resources to their full potential would increase the habitat diversity and make the ecological space more heterogeneous, enriching species diversity.

Acknowledgements

The authors thank Xiao-Ma Li for creating Fig. 1 and Hai-Lei Zhao for entering some raw data. This study was funded by the National Natural Science Foundation of China (41201049). The authors sincerely thank the anonymous reviewers for their constructive comments to the initial manuscript.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2015.08.015.

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