Linking landscape patterns with ecological functions: A case study examining the interaction between landscape heterogeneity and carbon stock of urban forests in Xiamen, China

Yin Ren, Xiaohua Wei, Darui Wang, Yunjian Luo, Xiaodong Song, Yajun Wang, Yusheng Yang, Lizhong Hua

Abstract

The relationship between landscape patterns and functions is the central research theme of landscape ecology and forest management. This study assesses the interactive relationship of landscape heterogeneity with the carbon stock of urban forests in the city of Xiamen, Fujian Province, China, using spatial and statistical analyses. The objectives of this study are to explore the most appropriate scale for studying urban landscape patterns in Xiamen, analyze the dynamics of forested landscape heterogeneity at different scales, and identify suitable landscape metrics that are closely related to and can be used to describe vegetation carbon density. This study is based on data from 31,933 plots measured during the years 1972, 1996, and 2006 and collected as part of the Chinese National Forest Resource Planning and Inventory Program. A total of 12 landscape metrics were used to quantify spatial patterns and were subsequently related to vegetation carbon density. The results show that the most appropriate scale for landscape pattern analysis is 80 km². With urbanization advancing between 1972 and 1996, landscape heterogeneity at both class and landscape levels showed a significant increase and then remained stable from 1996 to 2006. Shannon’s diversity index was the most sensitive landscape metric among all selected landscape heterogeneity metrics, and its ability to explain the variation of carbon density was better than that of forest types. This study clearly shows that information on spatial patterns of landscape heterogeneity is important for urban forest landscape planning to achieve forest carbon objective.

Keywords:
- Landscape heterogeneity
- Landscape pattern
- Spatial scale
- Vegetation carbon stock
- Vegetation carbon density

1. Introduction

The study of interactions between landscape patterns, processes, and ecological functions at different spatial scales has always been the central and most difficult problem in landscape ecology and forest management (Wu, 2010). Increasing urbanization and associated pressures on the urban environment have caused urban forest landscapes to receive more attention in recent years (Batty, 2008; Zhao et al., 2010). Rapid urbanization and land use changes have increased landscape-scale heterogeneity of urban forests, which alters the structure, function, and processes of those forests (Walz, 2008).

Landscape metrics, which represent enriched information about landscape patterns, are simple quantitative metrics reflecting the composition of landscape structure and attributes of spatial land use allocation (Wu et al., 2002). Landscape metrics are useful for studying landscape patterns and are helpful in quantitative analysis of the spatial distribution of features and landscape composition. These metrics are also useful in the construction of relationships between landscape structures and ecological processes; a knowledge of the metrics helps researchers explain and better understand the interactions between the two (Fry et al., 2009). Using a broader range of landscape metrics related to ecological functions can enhance the validity of landscape analysis and allows data extrapolation to similar landscapes. In contrast, inappropriate use of landscape metrics can hamper the evaluation of the relationships between spatial patterns and processes. If landscape metrics are closely related to ecological functions and...
reflect important spatial distribution information, then the metrics can act as a connection between ecological processes and fundamental landscape structures (Li and Wu, 2004). Currently, numerous landscape metrics have been established and applied to the description of landscape patterns and processes. Although landscape metrics are of great interest in the design and management of urban forest landscapes, their true ecological significance in different landscape features at various spatial scales are still uncertain because most of the metrics are initially speculative and based on mathematical formulas. Therefore, there is a critical need to select landscape metrics that are closely related to ecological processes and functions and endow those metrics with true ecological significance.

Providing storage for vegetation carbon stock (t) and associated carbon density (t ha$^{-1}$) is an important ecological function of urban forests. These not only represent forest stand quality, but also reflect the degree of human interference (Trofymow et al., 2008). Much research has proven that tree species and age class composition cause most of the variation in vegetation carbon density in ecological systems (Fang et al., 2001; Ren et al., 2011a). Research also shows vegetation carbon density in heterogeneous forested landscapes is affected by a suite of interrelated changes (Laurance et al., 2006). Moreover, knowledge of carbon density is directly related to sustainable management of urban forest resources and assists land managers in improving the ecological functions of urban forests (Termorshuizen and Opdam, 2009). However, although an abundance of landscape metrics is available, they are seldom used in the study of interaction between landscape heterogeneity and vegetation carbon density. Therefore, research is needed to guide the selection of appropriate landscape metrics that can effectively quantify landscape patterns and vegetation carbon density.

Many researchers have attempted to clarify interactions between spatial and temporal heterogeneity of forest landscapes and to describe this ecological process through screening landscape metrics. For instance, Lee et al. (2009) conducted studies on interactions between the type of disturbance and vegetation distribution patterns in South Korea, and their results show that the heterogeneous forest landscape can greatly influence fire disturbance. Bartel et al. (2011) adopted a neutral landscape model to disclose the interaction between pattern and process in surface hydrology. The results show that use of landscape metrics to quantify landscape heterogeneity is valuable for basin comparison and classification in terms of the dominant processes and the correspondingly model requirements. However, little research has been conducted on the dynamic relationship between landscape pattern metrics and vegetation carbon density that is focused on landscape pattern and ecological functions. This makes it difficult to explore the driving mechanisms of spatial and temporal changes in vegetation carbon stock under the influence of human activities and to describe the interactive relationship between landscape heterogeneity and its ecological process. Demonstration of interactions and relationships between landscape patterns, processes and functions at various scales must be based on field observations over large areas. Unfortunately, few studies have focused on the relationships between urban forest carbon density and landscape heterogeneity based on large-scale field observations (Vogt et al., 2007). This is because the scale and spatial heterogeneity of a large study area does not lend itself well when using typical experimental designs. Also, landscape studies have not been improved on the basis of experiments and have not included ecological illustrations of relationships between landscape patterns, processes and functions (Walker, 2003).

Most past large- and mid-scale studies on urban forest landscapes have relied solely on remote sensing images, rather than on recognizing characteristics of each individual forest stand (Liang and Schwartz, 2009). Some studies even conclude that remote sensing images are the only visual materials that accurately reflect relationships between landscape patterns and processes (Li et al., 2011). Remote sensing has been used as an important tool for many years to examine forest canopy structure and has also been used indirectly to estimate the carbon stock of forests in many places around the world (Myeong et al., 2006). However, remote sensing images cannot supply detailed information about what is below the canopy (Rizkalla et al., 2009). Thus, it is difficult to estimate the age of trees. Furthermore, remote sensing errors caused by the level of resolution and by corrections during map drafting may affect the accuracy of mapping and landscape type designation, and can be seen in the form of landscape metrics (Nowak and Greenfield, 2012). Therefore, large-scale field observation data are needed and must be emphasized when trying to describe the dynamics of urban forest landscapes. This will allow researchers to establish links between urban forest processes and functions based on ecological significance of the landscape metrics used.

Forest attribute data from the forest management planning and inventory (FMPI) of China, collected every 10 years, are mainly used in forest resource planning and design. The FMPI data provide important information, such as biomass regression formulas related to tree species composition, plus forest age, planting density, volume and dominant tree species. We applied this major source of forest resource data to a wide variety of land types, including hills and patches, based on sub-compartment level samples. Sub-compartments are FMPI-designated sampling areas. These sample plots extend over a wide area and are at a large scale. We then used GIS with these data to construct feature and spatial data for each type of forest stand. These inventories use data from a large number of field measurements and are helpful in demonstrating the correlation between landscape patterns and ecological functions via the use of landscape metrics.

Urbanization can greatly transform the structure, function and processes of urban ecosystems and, thereby, influence the quality of the urban ecological environment (Ren et al., 2012). Globally, many countries are experiencing different stages and forms of urbanization caused by a combination of their various modes of economic development and by cultural traditions (Zhao et al., 2012). Coastal cities are key areas of global urbanization research. More than half of the global population, production and consumption are concentrated at or near coastlines, even though coastal areas make up only 10% of the global terrestrial land. During the past 30 years, the pace of urbanization in China has increased dramatically, especially in the eastern coastal areas. Xiamen was selected for this study because it reflects typical urbanization characteristics of Southeast Chinese cities. The results of this study will not only be useful in Xiamen, but may potentially be important in the management of urbanization in other Chinese cities. The objectives of this study are: (i) to explore the most appropriate scale for studying urban landscape patterns in Xiamen, (ii) to analyze dynamics of forest landscape heterogeneity at different scales in this area and (iii) to identify suitable landscape metrics that are closely related to and can be used to describe vegetation carbon density.

2. Materials and methods

2.1. Study area

The city of Xiamen (24°23′−24°54′N, 117°53′−118°26′E) in southeast Fujian Province on the southeast coast of China (Fig. 1) lies next to the Jiulong River estuary in the middle part of the western bank of the Taiwan Strait. The city boundary encompasses 1573 km$^2$. Xiamen lies within the south Asian tropical maritime monsoon climate zone with an annual average temperature of...
20.9 °C and average humidity of 76%. The majority of precipitation falls as rain between April and October, and averages 1143 mm annually. The major landforms are hills and terraces, with the terrain sloping generally from northwest to southeast. The major forest soils include laterites and red soil. The main tree species include *Acacia confusa*, *Pinus massoniana*, *Pinus elliottii*, *Eucalyptus* spp., *Cunninghamia lanceolata*, *Casuarina equisetifolia* and *Schima superba*. Urban forests consist of several types, including suburban forests, exurban forests, urban parks, botanical gardens and greenbelts.

The years 1972, 1996, 2006 were chosen to represent different stages of urbanization in Xiamen. At the initial stage of urbanization in 1972, land use change was minimal. Around 1996, urbanization accelerated and the degree of land use change increased rapidly, as sudden industrialization created jobs and resulted in dramatically increased population and associated urban sprawl. By 2006, much of Xiamen was urbanized, so land use changed modestly at this stage. Due to the implementation of forestry carbon regulation projects, forest area increased remarkably from 1972 to 2006 as land was converted from farmland to suburban or urbanized landscapes.

2.2. Data sources

We used three sets of Xiamen FMPI data, derived from 31,933 different sample plots measured in 1972, 1996, and 2006. Data include geographic distribution of forest resources, forest volume, tree species composition and age classes along with 1:10,000 scale topographic maps. Forest volumes were estimated with regression models using data from aerial photographs and from observed volumes based on FMPI data. Data from systematic sampling, stratified sampling, and cluster sampling field sample plots were used to measure the difference between growing stock volumes for each type of sampling, which was then compared with estimates of overall accuracy of the sampled volumes. These models and the FMPI data were applied to the study of both natural and artificial forests to estimate their biomass and net primary productivity (NPP) (Lei et al., 2009). Based on forest type, tree species, cultivation target and ages, forest age classes were categorized as young, middle-aged, premature, mature or post-mature. The FMPI forest compartment records contain detailed information related to tree species composition, and divided the stands into five forest categories including coniferous, broadleaved, mixed needle and broad-leaved, miscellaneous, and non-forest lands. Miscellaneous forest includes shrub forestland, bamboo forestland, nursery gardens, and recently clearcut forest. Non-forest land includes farmland, meadowland, land being used for construction, and open water. FMPI also classified mixed forests based on ratios of volume for different tree species. We generated a forest resource distribution map at an appropriate grid scale for the study area after converting graphics vectorization onto a grid map of 10 m x 10 m resolution.

2.3. Methods

2.3.1. Selection of analysis scale

The selection of appropriate scale in landscape analysis in a specific study area is critical because landscape metrics are sensitive to spatial range and granularity. Analysis through selection of appropriate scales may decrease differences of landscape metric values between different regions. We determined an appropriate scale by comparing various landscape metric values in sample plots at different scales. The three landscape metrics (Patch Density, Mean Euclidian Nearest Neighbor Distance, and Patch Cohesion Index) with weak relationships to each other at the class level, represent different attributes of landscape patterns. Therefore, these metrics can be screened as appropriate landscape metrics. Based on the above rules, square sample regions with areas of 1, 13, 30, 60, 80, and 115 km² were buffered from the sampled
points. Sample plot size is different for each scale, and corresponding landscape metrics can be calculated at each scale. As the scale increases, the curve of landscape metrics becomes stable and less volatile. As the metrics stabilize, we can identify the scale at which the value of square sample plot area is most appropriate for our analysis.

We first created a random sample of eight points scattered throughout the city area at intervals greater than 80 km². Two rules were used to choose the scales: (i) the scale should be large enough to cover different land-cover types, so heterogeneity characteristics can be displayed from the perspective of landscape and patch types; and (ii) the gap between these scales should not be too large, because otherwise it is difficult to determine trends in landscape metric change at different scales. We displayed the landscape metrics of the eight sample plots at six different scales. Values of the four metrics were plotted in six sampling regions, each with eight sample points, to validate the size at which most curves become asymptotic. We then compared the distribution of landscape values at various scales, observed their fluctuations and fluctuation range and selected the scale at which the landscape metric values remain stable (Pfister, 2004; Tian et al., 2011).

2.3.2. Calculation of forest carbon stock and carbon density
The biomass of different forest types can be calculated using the formula \( B = aV + b \) (Fang et al., 2001), where \( B \) is stand biomass (including all living trees and shrubs) \((\text{t ha}^{-1})\), \( V \) is standing volume \((\text{m}^3 \text{ha}^{-1})\), and parameters \( a \) and \( b \) are constants for a forest type (Table 1). A carbon fraction of 0.5 was used to convert stand biomass to carbon density \((\text{t ha}^{-1})\) (Fang et al., 2001; Ren et al., 2011b).

2.3.3. Calculation of importance values
Importance values (IV) were used to represent the dominance of different species within a community. This quantitative index was used to show the importance of each tree species to the composition of a forested community. The importance values for coniferous, broad-leaved, and mixed forests were calculated as follows, based on relative density, height, and basal area of each species:

- Relative density = number of plants of a species in a plot \( \times 100/\text{total number of plants of all species in the plot} \)
- Relative height = total height of all plants of a species in a plot \( \times 100/\text{total height of all plants in the plot} \)
- Relative basal area = total basal area of all plants of a species in a plot \( \times 100/\text{total basal area of all plants in the plot} \)
- Importance value (IV) = relative density + relative height + relative basal area

2.3.4. Analysis on landscape pattern dynamics
To analyze landscape pattern dynamics of Xiamen, landscape metrics quantifying landscape composition and configuration were calculated using raster data at three survey times (1972, 1996, and 2006) and the software FRAGSTATS version 3.3 (McGarigal et al., 2002). These metrics can be divided into three levels: patch, class and landscape. Patch-level metrics are used to calculate higher-level metrics and have little significance in landscape pattern analysis (Wu, 2000). In this study, we adopted landscape metrics at class and landscape levels only. We selected 12 frequently used metrics (their definitions are presented in Table A1 of the Appendix) including Largest Patch Index (LPI), Mean Patch Area (AREA_MN), Area-weighted Mean Shape Index (SHAPE_AM), Area-weighted Mean Contiguity Index (CONTIG_AM), Contagion (CONTAG), Interspersion & Juxtaposition Index (IJI), Landscape Shape Index (LSI), Patch Cohesion Index (COHESION), Patch Density (PD), Landscape Division Index (DIVISION), Mean Euclidian Nearest Neighbor Distance (ENN_MN), and Shannon’s Diversity Index (SHDI). According to the landscape patterns measured, these 12 metrics were divided into four groups: area and edge metrics (LPI and AREA_MN), shape metrics (SHAPE_AM and CONTIG_AM), aggregation metrics (CONTAG, IJI, LSI, COHESION, PD, DIVISION and ENN_MN), and diversity metrics (SHDI). Landscape composition and structure at class level were described using LPI, AREA_MN, CONTIG_AM, LSI, COHESION, PD, and ENN_MN, whereas landscape heterogeneity at landscape level was described using AREA_MN, SHAPE_AM, CONTAG, IJI, LSI, COHESION, PD, DIVISION, ENN_MN and SHDI.

2.3.5. Statistical analysis
Based on the appropriate spatial scales (80 km²) selected as described in Section 2.3.1, the entire study area was divided into 25 units. For each unit, carbon density, landscape metrics, and importance values of forest types were calculated at the time of each survey (1972, 1996, and 2006). Differences between categories were examined using the t-test for two categories, or by one-way analysis of variance followed by multiple comparison tests for comparison of more than two categories. When variances were homogeneous (Levene’s test), we used Tukey’s tests, otherwise, Games–Howell tests were used. To assess inter-correlations between variables, Spearman’s correlation between variables were analyzed. As a rule of thumb, if absolute values of correlation coefficients \( |r_{ij}| \) between variables are significant and greater than 0.80, they are considered to have high inter-correlation (i.e., the two variables can convey much of the same information) (Field, 2005). Thus, only one of them should be selected according to its ecological meaning for subsequent analyses. In addition, we performed stepwise linear regressions to compare effects of landscape heterogeneity on carbon density with forest types. The coefficient of determination (\( R^2 \)) was given for each model.

Statistical significance was determined at \( P < 0.05 \). All statistical analyses were carried out using SPSS version 16.0 software (SPSS Inc., Chicago, IL).

3. Results
3.1. Selection of appropriate spatial scales
The types of landscape elements studied could not be effectively analyzed at spatial scales of 1 km² and 13 km² (Fig. 2) because values of the landscape metrics vary dramatically at the scales below 80 km². The distribution of these values remains stable in the eight sample plots with the scales exceeding 80 km². Therefore, the scale of 80 km² was the most appropriate for division of landscape scale classes. After rasterizing 25 sample plots at this scale across the entire study area in Xiamen (Fig. 3), we calculated class- and landscape-level metrics for each sample plot, and then vegetation carbon stock and carbon density.

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**Table 1**

<table>
<thead>
<tr>
<th>Forest type</th>
<th>( a )</th>
<th>( b )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Casuarina equisetiformis</td>
<td>0.7441</td>
<td>3.2377</td>
</tr>
<tr>
<td>Cunninghamia lanceolata</td>
<td>0.3999</td>
<td>22.5410</td>
</tr>
<tr>
<td>Eucalyptus spp.</td>
<td>0.8873</td>
<td>4.5539</td>
</tr>
<tr>
<td>Schima superba</td>
<td>0.7564</td>
<td>8.3103</td>
</tr>
<tr>
<td>Pinus massoniana and Pinus elliottii</td>
<td>0.5101</td>
<td>1.0451</td>
</tr>
<tr>
<td>Acacia confusa</td>
<td>0.4754</td>
<td>22.5410</td>
</tr>
</tbody>
</table>

The biomass of different forest types can be calculated using the formula \( B = aV + b \) (Fang et al., 2001), where \( B \) is stand biomass (including all living trees and shrubs) \((\text{t ha}^{-1})\), \( V \) is standing volume \((\text{m}^3 \text{ha}^{-1})\), and parameters \( a \) and \( b \) are constants for a forest type (Table 1). A carbon fraction of 0.5 was used to convert stand biomass to carbon density \((\text{t ha}^{-1})\) (Fang et al., 2001; Ren et al., 2011b).
3.2. Dynamics of forest landscape heterogeneity

The spatial extent of the urban forests and the number of forest stands increased by 15,117 ha and 10,225 patches, respectively. At the class level, dynamics of forest heterogeneity were shown in Fig. 4. Because high correlations (generally $|r_s| > 0.80$) were found between LPI, AREA_MN, CONTIG_AM and COHESION (Table A3 of the Appendix), and COHESION has an advantage in quantifying habitat connectivity, we selected COHESION. Aggregation metrics (LSI, COHESION, PD and ENN_MN) can describe the dynamics of landscape composition and structure. Thus, only four forest heterogeneity metrics at the class level were chosen for describing their dynamics. Not all forest types and landscape metrics showed significant trends with urbanization stages. Four aggregation metrics of coniferous forests had no significant and consistent trends between 1976 and 2006. For broadleaved forests and mixed forests, LSI and PD significantly increased from 1972 to 1996 and then stabilized from 1996 to 2006 (Fig. 4a and c), while ENN_MN significantly decreased from 1972 to 1996 and then stabilized from 1996 to 2006 (Fig. 4d). However, COHESION of all forest types had no trends (Fig. 4b). Those results at the class level suggested that forest heterogeneity significantly increased from 1972 to 1996 and then remained stable from 1996 to 2006.

At the landscape level, forest heterogeneity metrics also varied (Fig. 5). We selected shape metric SHAPE_AM, aggregation metrics (IJL, LSI and ENN_MN) and diversity metric SHDI because they were relatively independent (generally $|r_s| < 0.80$) (Table A4 of the Appendix). SHAPE_AM, LSI and SHDI increased from 1972 to 1996, and stabilized from 1996 to 2006 (Fig. 5a, c, and e); ENN_MN decreased from 1972 to 1996 and then stabilized from 1996 to 2006 (Fig. 5d). However, IJL had no trends with urbanization stages (Fig. 5b). Those results at the landscape level suggested that forest heterogeneity significantly increased from 1972 to 1996 and then remained stable from 1996 to 2006.

Thus, our analysis clearly demonstrated that forest landscape heterogeneity significantly increased and then stabilized with urbanization stages (Figs. 4 and 5).

3.3. Dynamics of urban forest carbon stock

Carbon stock of the Xiamen urban forests in 1972 was 273,938 t, but increased by 865,589 t to reach a total of 1,139,527 t during
the 34-year study period. From 1972 to 2006, overall area, coverage, carbon stock and number of forest stands within the urban forests increased during the early stage (1972–1996) and decreased in the later stage (1996–2006), but the overall tendency was increasing. Carbon density of the urban forests in 1996 was significantly higher than that in 1972 (t-test, P < 0.05), while no significant difference in carbon density was detected between 1996 and 2006.

During urbanization, the changes of various tree species composition and age structures significantly influenced vegetation carbon density. The importance values of coniferous forests significantly increased from 1972 to 1996 and leveled off from 1996 to 2006, while those of mixed forests significantly decreased from 1972 to 1996 and leveled off from 1996 to 2006 (Fig. 6). The importance values of broadleaved forests showed no significant trends with urbanization stages (Fig. 6).

The percentage of carbon stock of young forests to total volume decreased by 61.57%, and more carbon stock was stored in mature forests. Carbon densities of broadleaved forests such as *Eucalyptus* spp., *Acacia confusa*, *Casuarina equisetifolia* and *Schima superba* were significantly higher than those of coniferous forests such as *Pinus massoniana* and *Cunninghamia lanceolata* (Games–Howell test, P < 0.05) (Table A2 and Fig. A2 in the Appendix). There were remarkable increases in the percentages of broadleaved and mixed forests (Table 2, Fig. A3 of the Appendix). The area ratios of coniferous to broadleaved forests decreased from 10.13:1 in 1972 to 0.85:1 in 2006. The area of coniferous forests decreased by 18,493 ha, while that of broadleaved forests increased by 21,970 ha.

### 3.4. Relative importance of landscape pattern metrics in carbon density

Correlation analyses were performed to identify robust landscape metrics that have significant relationships with carbon density across three survey times (1972, 1996 and 2006). At the class level, no robust landscape metrics had consistent correlations with carbon density across all three survey times (Table 3). However, landscape-level metric SHDI was significantly related to carbon density across all three survey times (P < 0.01) (Table 4). This indicated that SHDI is the most sensitive landscape index among all studied landscape metrics.

Stepwise regression was conducted to assess relative importance of landscape heterogeneity metric (SHDI) and forest types in carbon density. Table 5 showed SHDI played a dominant role in forest carbon density in 1972 and its importance was higher than those from importance values of forest types in the other
Fig. 4. Changes in landscape heterogeneity of main forest types at the class level in three survey times (1972, 1996, and 2006): (a) Landscape Shape Index (LSI), (b) Patch Cohesion Index (COHESION), (c) Patch Density (PD), and (d) Mean Euclidian Nearest Neighbor Distance (ENN_MN). Boxplots show the mean (black dot), median (black line inside the box), inter-quartile range (25–75% in the box), the range of 5–95% (the whisker) and outliers (the asteroids). Means sharing small different letters were statistically different ($P < 0.05$).

Fig. 5. Changes in landscape heterogeneity at the landscape level in three survey times (1972, 1996, and 2006): (a) Area-weighted Mean Shape Index (SHAPE_AM), (b) Interspersion and Juxtaposition Index (IJ), (c) Landscape Shape Index (LSI), (d) Mean Euclidian Nearest Neighbor Distance (ENN_MN), and (e) Shannon's Diversity Index (SHDI). Boxplots show the mean (black dot), median (black line in the box), inter-quartile range (25–75% in the box), the range of 5–95% (the whisker) and outliers (the asteroids). Means sharing small different letters were statistically different ($P < 0.05$).
two periods (1996 and 2006). In addition, the explanatory power of landscape heterogeneity (SHDI) in total variation of carbon density (increased from 55% in 1972 to 70% in 2006) was higher than those from importance values of forest types (increased from 0% in 1972 to 37% in 2006) (Table 5). Thus, landscape-level metric SHDI played a more important role in forest carbon density as compared with forest types.

4. Discussions

Our results showed that landscape metrics do not necessarily increase with the expansion of spatial scales because when the scale is less than 80 km², there is a threshold below which landscape metrics fluctuate dramatically. At the scales of 80 km² and above, the landscape metrics distribution in the eight sample plots tended to be stable. The above results agree with the study from Keitt et al. (1997) in coniferous forest and non-forest habitat patterns in Arizona, Colorado, New Mexico and Utah of the Southwest United States. Our finding of this threshold is also consistent with other studies at larger scales. For example, Griffith et al. (2003) found that changes of landscape metrics in five ecological zones in the Southeast United States remained stable with research scales in excess of 400 km². Uuemaa et al. (2005) proved that when landscape scale increases to 225 km², there is a remarkable correlation between water quality and landscape metrics. Although the ecosystem patterns at different scales vary, most studies emphasize that the scale effect has a significant impact upon landscape metrics (Crawley, 2001; Jones, 2011).

There was a significant and positive correlation between landscape-level metric SHDI and vegetation carbon density (P < 0.01) during all three survey times. We believe that three key factors may contribute to the significant relationship. The first factor is the increase of forest area. Local, provincial and national governments continued to promote afforestation and greening activities, and both forest area and carbon stock increased from 1972 to 2006. Second, there were changes to tree age structures. Large areas of young trees (diameter at breast height (DBH) < 8 cm) were planted to reforest barren hills during initial stages of urbanization in 1972. By 2006, the carbon densities of premature, mature, and post-mature forests increased by 13.21%, 11.39%, and 6.36% respectively between 1972 and 2006. Higher temperatures and increased exposure to sunlight in urban environments can increase tree growth relative to rural areas. Finally, tree species composition also changed. Large areas of coniferous forest were planted in 1972, and, as the forest grew and improved between 1972 and 1996, some areas of coniferous forest were converted to broad-leaved and mixed forest. The coniferous forest area decreased by 45.3%, with 19.27% of that area converted to the latter two forest types. Results of prior research have demonstrated that the annual carbon absorption of broad-leaved forests is remarkably higher than that of coniferous forests (Fig. A3). Thus, these combined effects produce higher carbon densities in urban forests, in spite of continuous heterogeneity. Specifically, SHDI becomes the most important and sensitive landscape metric affecting carbon density of urban forests across all urbanization stages.

Many studies have shown that screening of landscape heterogeneity metrics related to ecological functions is vital in efforts to show landscape patterns, processes, ecological functions, and interaction between scales (Li and Wu, 2004). However, landscape metrics that are screened in current studies are mainly based on relationships between landscape heterogeneity, forest wildlife habitat, forest fire and hydrologic processes (Murphy et al., 2010; Carey et al., 2011). To our knowledge, research on landscape heterogeneity metrics and carbon density has not been reported. Therefore, we do not compare similarities and differences in relationships between landscape heterogeneity metrics (SHDI) and carbon density with other studies. Nonetheless, we are certain that there are many biotic (e.g., forest types and forest growth phases) and abiotic factors (e.g. climate, geomorphology, soil, and interferences) that influence carbon density (Song and Woodcock,
than 100%. Individual influences of landscape heterogeneity and forest types were considered, so the sum of the explained percentages of total variation in carbon density may be greater than 100%.

In natural ecosystems, biotic factors are the dominant influences on carbon density (Mesquita et al., 1999; Laurance et al., 2006). In urban ecosystems, abiotic factors are the dominant influences on carbon density, and impacts of urban landscape change on carbon density are complicated. The resulting carbon density depends on the type of human transformation of the urban environment, as well as abiotic factors such as light, temperature, and soil condition (Nowak and Dwyer, 2007). The landscape heterogeneity shows the combined influences of multiple abiotic factors. Therefore, it is possible that the explanatory power of landscape heterogeneity in total variation of carbon density is higher than that from importance values of forest types as reported in our study.

As shown in Table 5, the importance of both landscape heterogeneity metric SHDI and vegetation types (represented by importance values of forest types) increased with urbanization stages from 1972 to 2006. In the early stage (1972), only SHDI played a dominant role, while forest types became important in later stages (broadleaved forest type in 1996; and mixed forest type in 2006). In spite of this, the importance of forest types was less than that of SHDI, mainly because the majority of broadleaved species are still relatively young in the study period and the carbon storage of big trees can be 1000 times greater than that of small trees (Nowak 1994; Ren et al., 2011a).

We make the following recommendations based on the present findings. First, quantitative analysis of spatial patterns is an important method within urban forest landscape planning. Patches should be categorized properly and appropriate landscape metrics selected, based on related ecological problems and study intensity during analysis of landscape patterns. Second, the size of urban forests should be increased to diversify forest structures and forest landscape patterns in subtropical areas. Finally, urban forests may also perform many other ecosystem services in urban ecosystems. There is at present an urgent need to learn how to select pertinent metrics for use in landscape analysis instead of continuing efforts to generate large numbers of landscape pattern metrics. Future efforts should place more emphasis on ecological processes and functions related to such landscape metrics (Wu, 2010).

### 5. Conclusions

This study assessed the influence of landscape heterogeneity and forest types on the carbon stock of urban forests in Xiamen, China. Using long-term and large-scale field observation data, we explored the most appropriate scale for studying urban landscape patterns in Xiamen. Integrating spatial and statistical analyses, landscape pattern dynamics analysis and biomass calculations, we identified suitable landscape metrics that were closely related to vegetation carbon density. We conclude that the most appropriate scale for landscape pattern analysis is 80 km². Urbanization in Xiamen has significantly increased landscape heterogeneity particularly in the early urbanization stage (from 1972 to 1996), which explained dynamics of carbon density over the study period. Among all selected landscape heterogeneity metrics, Shannon’s diversity index was the most sensitive index, and its ability to explain the variation of carbon density was better than that of forest types.

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**Table 5**

<table>
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<th>Year</th>
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<th>Final model</th>
<th>$R^2$</th>
<th>$F$</th>
<th>$P$</th>
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<td>1972</td>
<td>SHDI</td>
<td>CD = 2.76 (SHDI)−0.48</td>
<td>0.55</td>
<td>28.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>IV-C, IV-B and IV-M</td>
<td>CD = 2.08</td>
<td>0.00</td>
<td>0.00</td>
<td>1.000</td>
</tr>
<tr>
<td>1996</td>
<td>SHDI</td>
<td>CD = 10.97 (SHDI)−5.40</td>
<td>0.60</td>
<td>34.41</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>IV-C, IV-B and IV-M</td>
<td>CD = −10.10 (IV-B)+9.52</td>
<td>0.30</td>
<td>9.95</td>
<td>&lt;0.004</td>
</tr>
<tr>
<td>2006</td>
<td>SHDI</td>
<td>CD = 7.70 (SHDI)−1.97</td>
<td>0.70</td>
<td>53.88</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>IV-C, IV-B and IV-M</td>
<td>CD = 11.44 (IV-M)+3.62</td>
<td>0.37</td>
<td>13.24</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>SHDI, IV-C, IV-B and IV-M</td>
<td>CD = 8.9 (SHDI)−5.25 (IV-M)−1.32</td>
<td>0.80</td>
<td>44.69</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

**Abbreviations**: CD, carbon density (t/ha); SHDI, Shannon’s Diversity Index; IV-C, importance value of coniferous forests; IV-B, importance value of broadleaved forests; and IV-M, importance value of mixed forests.
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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2012.12.043.

References


