Science of the Total Environment 627 (2018) 1572–1584

Contents lists available at ScienceDirect

Science of the Total Environment

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

The rapid but “invisible” changes in urban greenspace: A comparative study of nine Chinese cities

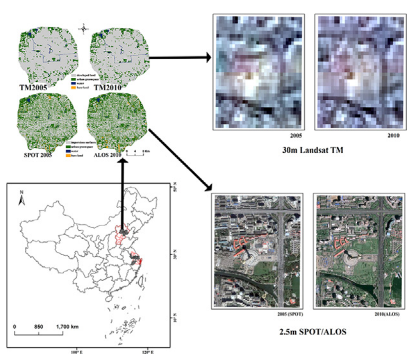
Weiqi Zhou [a,b,*], Jing Wang [a,b], Yuguo Qian [a], Steward T.A. Pickett [c], Weifeng Li [a], Lijian Han [a]

[a] State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China
[b] University of Chinese Academy of Sciences, Beijing 100049, China
[c] Cary Institute of Ecosystem Studies, Box AB, Millbrook, NY 12545, USA

HIGHLIGHTS

- Urban greenspace (UGS) is highly fragmented, heterogeneous, and dynamic.
- UGS has high turnover rates, but changes often occur as small patches.
- Only can high resolution image reveal such change, but not medium resolution data.
- Cross-city comparison reveals different spatial patterns and change among cities.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 9 December 2017
Received in revised form 31 January 2018
Accepted 31 January 2018
Available online 9 February 2018

Editor: D. Barcelo

Keywords:
Greenspace
Spatial resolution
Spatial pattern
Patch dynamic
Ecosystem services
China

ABSTRACT

Quantifying the spatial pattern and change of urban greenspace is a prerequisite to understanding the myriad ecosystem services provided by urban greenspace. Previous studies have largely focused on loss of greenspace due to urban expansion, using medium resolution imagery. This paper presents a comparison study on the spatiotemporal patterns of urban greenspace in nine major cities in China, using 2.5 m resolution ALOS and SPOT image data collected in 2005 and 2010, respectively. The changes in urban greenspace were further compared with those based on the commonly used 30 m Landsat TM data. The results show: 1) Urban greenspace was highly fragmented and heterogeneous, characterized by a mix of a large number of small-sized patches (smaller than 0.1 ha) with relatively few dispersed large patches in nine cities. 2) In contrast to findings from previous research that greenspace in inner cities tends to remain largely unchanged, urban greenspace in all nine cities was highly dynamic, experiencing both gain and loss, with net change ranging from 0.51% to 11.26% over five years. Most of the changes in urban greenspace, however, tended to occur as small patches, and could only be revealed by high spatial resolution imagery. 3) Spatial patterns of greenspace varied greatly across cities in terms of patch size, patch and edge density, and shape. Urban greenspace became increasingly fragmented and complex in the southern cities, but the opposite in the northern cities. The high turnover dynamics of urban greenspace in cities proper provide opportunities for better design and planning to achieve urban sustainability, but also call for better protection of small-sized urban greenspaces in Chinese cities.

* Corresponding author at: State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China.
E-mail address: wzhou@rcees.ac.cn (W. Zhou).

https://doi.org/10.1016/j.scitotenv.2018.01.335

1. Introduction

Urban greenspace refers to any vegetation found in the urban environment, including woodland, grassland, wetland, garden and other vegetated areas (Kabisch and Haase, 2013; Taylor and Hochuli, 2017). Greenspace in urban areas provides myriad ecosystem services (ES) that are central to human well-being and urban sustainability (Groenewegen et al., 2006; Ouyang et al., 2016; Pathak et al., 2011; Thompson et al., 2012; Wu, 2013; Wolf and Housley, 2014; Zhou et al., 2014; Yan et al., 2016). Ecosystem services provided by urban greenspace play a vital role in counteracting environmental problems caused by increasing urban density or by climate change (Kabisch, 2015). These include regulating services such as urban heat island mitigation, air pollution reduction, storm water runoff interception (Huang and Cadenasso, 2016; Park et al., 2017; Yao et al., 2015; Yan et al., 2016; Zhou et al., 2011, 2017b), biodiversity conservation (Ziter, 2016), and health benefits such as relieving stress and anxiety (Coutts and Hahn, 2015). The combination of environmental and social values has motivated many cities to maintain and expand urban greenspace, both within and surrounding the cities. However, the spatial pattern and change of urban greenspace can significantly affect the ES provided by the greenspace. For example, numerous studies that focus on effects of spatial pattern of greenspace on land surface temperature have shown that the composition and configuration of greenspace had significant effects on regulating services on microclimate (e.g., Chen et al., 2014; Maimaitiyiming et al., 2014; Zhou et al., 2017a, 2017b). In addition, the spatial pattern of greenspace is strongly related to adequacy of greenspace in cities, and thereby influences the cultural ecosystem services provided by greenspace (Lo and Jim, 2010). Therefore, to evaluate the efficacy of their efforts, and fully understand the ES provided by urban greenspace, it is crucial to first accurately characterize and quantify the spatial pattern and change of urban greenspace (Lovell and Taylor, 2013; Wu, 2014; Pickett et al., 2017; Qian et al., 2015b; Zhou et al., 2017a).

Quantifying spatiotemporal pattern of urban greenspace frequently relies on remote sensing. Numerous studies have been conducted on urban greenspace mapping and change analysis. These studies have used a variety of remotely sensed image data having different spatial resolutions, ranging from sub-meter to 1000 m (e.g., Stefanov et al., 2001; Zhang et al., 2003; Zhou et al., 2008; Wang et al., 2018). While changes in urban greenspace have been an important research topic, most previous studies focused on loss of greenspace associated with urban expansion (Hurd et al., 2001; Kong and Nakagoshi, 2006; Miller, 2012; Portillo-Quintero et al., 2012; Seto et al., 2002; Yuan et al., 2005; Zhou and Wang, 2011; Yang et al., 2014). These studies usually found that changes in greenspace occurred in the urban-rural periphery, coincident with urban expansion (Peng et al., 2016b; Portillo-Quintero et al., 2012; Seto et al., 2002; Yuan et al., 2005; Miller, 2012). Greenspace in cities proper, or urban core areas, however, remained largely unchanged (Li et al., 2011; Xu et al., 2011; Zhou and Wang, 2011). These results are somewhat contradictory to the perceptions in many cities. On the one hand, there are still great pressures from development on conversion of greenspace to buildings and infrastructures, particularly in cities in developing countries (Qian et al., 2015a). On the other hand, many cities have devoted great efforts to increasing urban greenspace (Beijing Landscape Bureau, 2007; Van Den Hoek et al., 2014). Consequently, urban greenspace may be dynamic, even in highly urbanized areas.

These contradictory results may be due to the data used to quantify the dynamics of urban greenspace (Qian et al., 2015b). Most of the previous studies of urban greenspace dynamics have used data derived from medium-resolution remotely sensed imagery. While these data are very useful for quantifying the coarse-scale loss of greenspace associated with urban expansion, they may be inadequate in characterizing changes of urban greenspace in built areas, where most of the changes in urban greenspace may involve small areas (Qian et al., 2015b). However, these small patches of greenspace, similar to large greenspaces such as parks and urban forests, can provide important ecological functions and ecosystem services (Pickett, 2010; Niemelä, 2014; Wu, 2014). Considering the "invisible" greenspace patches, which can only be revealed by high spatial resolution remote sensing data, can help better understand and assess ecosystem services provided by urban greenspace (Qian et al., 2015b).

Recognizing the importance of accurate quantification of the spatial pattern and change of urban greenspace at fine scales, high spatial resolution image data, such as SPOT, IKONOS, QUICKBIRD, WorldView, and aerial imagery, have been increasingly used for fine-resolution urban greenspace mapping and change analysis (e.g., Zhou et al., 2008; MacFaden et al., 2012; Ramos-Gonzalez, 2014; Qian et al., 2015a). In addition to large greenspaces, patches of small-sized urban green cover can be accurately mapped from high spatial resolution imagery (Mathieu et al., 2007; Zhou and Troy, 2008; Zhou et al., 2008; MacFaden et al., 2012). Using multitemporal high spatial resolution image data, fine-scale changes in urban greenspace can also be detected (e.g., Zhou et al., 2008; Qian et al., 2015a). These studies have mostly focused on a single city. However, Nowak and Greenfield (2012) compared the change in tree and impervious cover in 20 U.S. cities. They used a random sampling approach focusing on changes in direction and rate of coverage but not the spatial pattern. Few studies, however, have examined the fine-scale spatial pattern of urban greenspace and its change for cross-city comparisons. Consequently, a quantitative understanding of the fine-scale spatiotemporal pattern of urban greenspace across different cities remains elusive.

This paper presents a comparison study of the spatiotemporal patterns of urban greenspace in nine major cities in China, using high spatial resolution image data collected in 2005 and 2010. The study cities are located in the Beijing-Tianjin-Hebei (BTH) and Yangtze River Delta (YRD) urban megaregions, described in details below. It tests the hypothesis that urban greenspace in well-developed city regions may be experiencing great changes, due to the combination of pressure for development and renewal, as well as the increasing efforts to increase urban greenspace in many cities (United Nations, 2014; Locke et al., 2010; Pataki, 2013). The changes in urban greenspace based on high resolution image data were further compared and contrasted with those from the most commonly used 30 m resolution Landsat Thematic Mapper (TM) data. Specially, the aims of this study are: 1) to quantify the spatiotemporal patterns of urban greenspace in urban core areas, and examine how they varied within and across different cities; and 2) to investigate and compare the efficacy of data with different spatial resolution on detecting such patterns. Results from this study have important implications for urban greenspace management and planning.

2. Data and methods

2.1. Study area

This research focuses on nine cities in China, including the three largest cities, Beijing (BJ), Tianjin (TJ) and Tangshan (TS) in the Beijing-Tianjin-Hebei (BTH) urban megaregion, and the six largest cities, Shanghai (SH), Nanjing (NJ), Hangzhou (HZ), Suzhou (SZ), Wuxi (WX), Changzhou (CZ)in the Yangtze River Delta (YRD) urban megaregion (Fig. 1). The BTH urban megaregion is located in the eastern part of North China, with a total population of 10.53 million, and gross domestic product (GDP) of 6647.90 billion RMB (10.45% of the total GDP of China) in 2014. The YRD urban megaregion is located at the lower reach of Yangtze River in the eastern and coastal part of China. It is one of the most densely populated and rapidly developing regions in China, with a total population of 150.47 million and GDP of 13,804.73 billion, accounting for approximately 11% and 22% of China's total population and GDP, respectively (Appendix, Table A1). The nine cities vary in socioeconomic characteristics. Beijing and Shanghai, the two largest cities in China, are the political and cultural center, and financial and economic center, respectively. Tianjin is the largest open port city, and an economic center in northern China. Nanjing and Hangzhou, as the capitals of Jiangsu and Zhejiang Provinces, respectively,

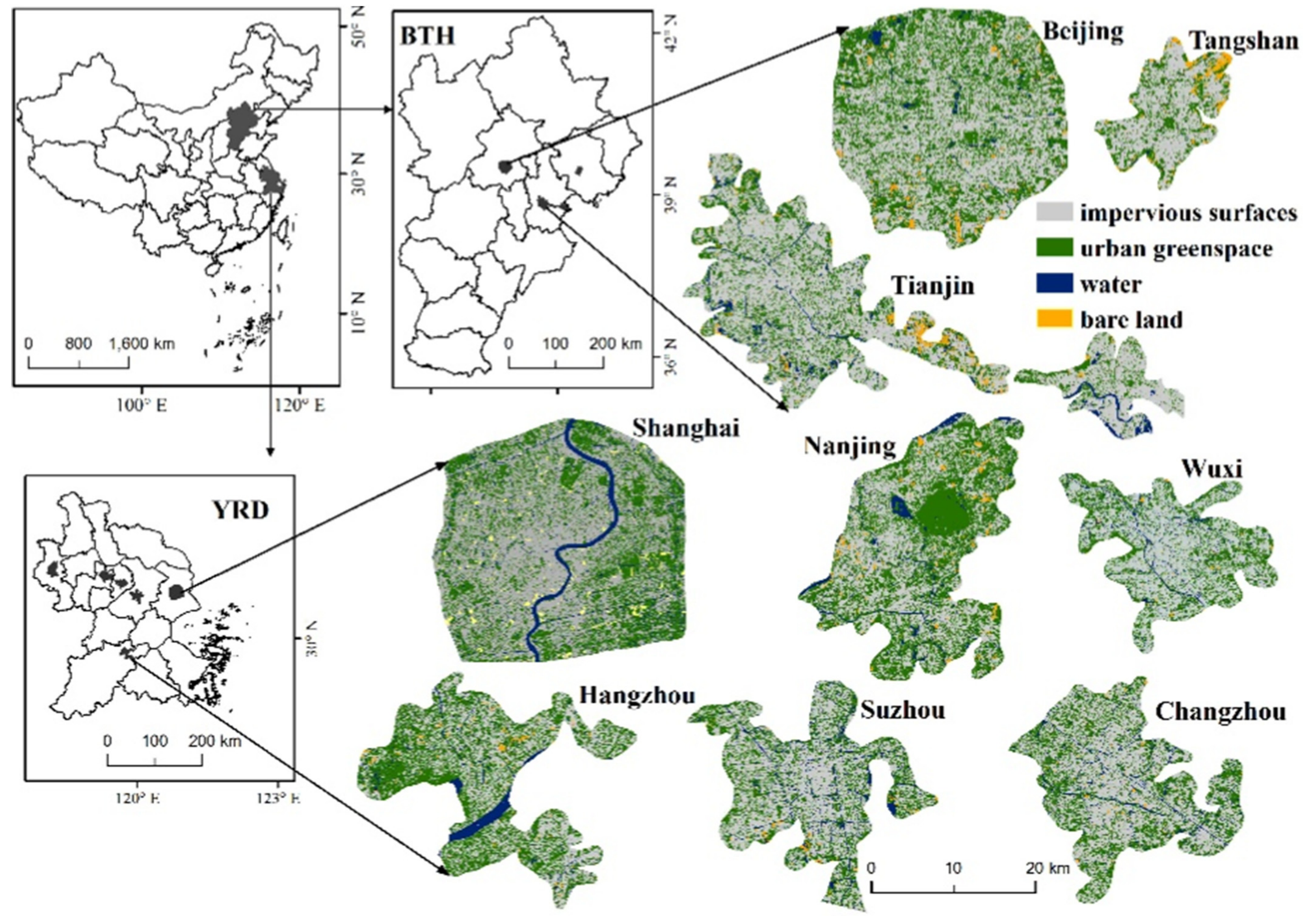


Fig. 1. The spatial distribution of the two urban megaregions, and the nine cities.

are regional political, economic, cultural, and transportation centers. Suzhou, Wuxi, Changzhou, and Tangshan represent medium-sized cities. For all nine cities, the continuous population growth and economic development frequently resulted in loss of vegetation on construction, and thus reduction in ES provision (Zhang et al., 2017). On the other hand, the great efforts on greening led to increase of urban greenspace (Qian et al., 2015a), which is vital to provision of multiple ES.

Our analysis is restricted to the most well-developed areas, or the urban cores of the nine cities, instead of encompassing the entire city administrative boundaries, which would include a large proportion of undeveloped lands (Fig. 1). The core area for each city was defined as the largest continuously developed region within the municipality of each city, excluding satellite cities, towns and villages within the municipality (Hu et al., 2017). The boundary of the core area for each city was delineated based on the 30 m resolution land cover classification data, following the approach detailed in Hu et al. (2017).

The study chose the time period of 2005–2010 for comparisons because changes in urban greenspace were expected in these cities during this time period. From 2005 to 2010, many of the selected cities experienced great pressure on the urban expansion or renewal, but meanwhile, were also implementing many green strategies and campaigns (Du et al., 2014; Jiang et al., 2016; Wu and Zhang, 2012; Yu et al., 2017).

2.2. Mapping urban greenspace based on high and medium spatial resolution data

Two types of remotely sensed images were used to map urban greenspace. Specifically, this study used high spatial resolution image data from SPOT-5 (Systeme Probatoire d'Observation de la Terre) and ALOS (Advanced Land Observation Satellite), and the most commonly used 30 m Landsat-5 TM imagery (Table 1). The SPOT imagery has one 2.5 m panchromatic band and four multispectral bands including three 10 m bands (green, red and near-infrared) and one 20 m resolution shortwave infrared band. Similarly, the ALOS imagery has one 2.5 m panchromatic band and four 10 m multispectral bands (green, blue, red, and near-infrared). The multispectral bands were first pan-sharpened into 2.5 m spatial resolution using the panchromatic band with the principal components algorithm. Geometric registration was then conducted using imagery from Google Earth™ as the reference. A polynomial model and the

Table 1
The data and their acquisition dates for the analysis.

Sensor	SPOT-5	ALOS	TM
Beijing	2005-10-08	2009-10-22	Summer leaf-on
Shanghai	2005-6-12 2005-9-30	2010-01-14	Summer leaf-on
Tianjin	2006-09-11	2009-05-03 2009-10-17	Summer leaf-on
Nanjing	2004-08-10 2004-11-15	2009-05-22 2010-05-25	Summer leaf-on
Hangzhou	2005-9-19 2005-10-30	2010-10-05	Summer leaf-on
Suzhou_Wuxi_ChangZhou Area	2005-06-12 2005-09-29 2006-05-27	2010-05-03 2010-08-20 2010-12-07	Summer leaf-on
Tangshan	2005-10-14	2009-06-30 2009-10-17	Summer leaf-on

nearest neighborhood resampling approach were used for spatial rectification. The root mean square error was less than 0.5 pixel.

An object-based approach was used for land cover classification with the high spatial resolution imagery (Qian et al., 2015a; Qian et al., 2015b; Zhou et al., 2008). Using an object-based approach, required the image to be first segmented into objects. Subsequently, rulesets were developed to classify the objects into different land cover types (Zhou and Troy, 2008; Qian et al., 2015a). The multi-resolution segmentation algorithm is a bottom-up region merging technique that is embedded in eCognition software (version 9.0). Four land cover classes were included: (1) vegetation (referred to as urban greenspace), (2) impervious surface (or developed land), (3) water, and (4) bare soil. The accuracy assessment was conducted by visually referring to the 1-meter spatial resolution imagery available from Google Earth™. A stratified random sampling method in Erdas Imagine (version 9.1) was used to generate 300 sample points, with at least 30 samples for each class. The overall accuracies of the classifications based on high spatial resolution imagery ranged from 81.02% to 96.33%, with the user's and producer's accuracies for greenspace ranging from 84.78% to 99.90% (Table 2).

An object-based backdating approach was used for land cover classification from Landsat TM imagery (Yu et al., 2017). The LULC map of 2010 was first generated by an object-based classification approach. Three levels of objects were created with the scale parameters setting as 10 (Level 1), 30 (Level 2), and 50 (Level 3) by testing different parameter values. Objects at Level 1 were used for classification of water, grass and barren land. Objects at Level 2 were used for identifying farmland and developed land, and those at Level 3 were used for forested land. The 2010 LULC map was then used as a reference map to generate the map in 2005 using an object-based backdating approach. Extensive manual editing was conducted for classification refinement to further improve the accuracies of the maps by referring to high spatial resolution data such as 2.4 m QuickBird and 2.5 m SPOT 5 imagery. Consequently, the overall accuracies based on TM data ranged from 90.25% to 96.69%, and the user's and producer's accuracies for greenspace ranged from 88.00% to 98.67% (Table 2).

2.3. Quantifying the spatial pattern of urban greenspace and its change

For each city, the percent cover of urban greenspace (PLAND) was first calculated for both 2005 and 2010. The calculation was done separately using the high and medium spatial resolution data of urban greenspace, and the results from the two datasets were compared. As the results showed that for all the nine cities, medium resolution TM data greatly underestimated the percent cover of urban greenspace, as well as the change, the analysis focuses on urban greenspace mapped from the high spatial resolution image data hereafter.

To better understand the gain and loss of greenspace, the land cover transfer matrix was calculated to quantify the conversions between urban greenspace and other land cover types. Four frequently used metrics were selected to quantify the spatial pattern of urban greenspace and its change (McGarigal et al., 2002; Peng et al., 2010; Peng et al., 2016a). These included landscape shape index (LSI) that measures landscape complexity, mean patch size (MPS), patch density (PD), and edge density (ED) to quantify fragmentation of urban greenspace (Appendix, Table A2). To better understand the distribution and changes of urban greenspace patches of different sizes, and thus the fragmentation process of urban greenspace, the distributions of patch size of greenspace and their changes were further investigated from 2005 to 2010. Specifically, the urban greenspace patches were divided into five size classes: (1) less than 0.1 ha, (2) 0.1–1 ha, (3) 1–10 ha, (4) 10–100 ha, and (5) more than 100 ha (Fig. 2). The frequency distribution of urban greenspace was calculated according to the five classes in terms of total area and number of patches for each city in 2005 and 2010. Box-plots were used to measure the dispersion and range of the patch sizes. By comparing the box-plots from different years for each city, the characteristics of transformations of patches in different sizes were examined.

Following the comparison based on individual landscape metrics, principal component analysis (PCA) were conducted using a combination of the five metrics, to reveal the difference and similarity of spatial pattern of urban greenspace and the change among the nine cities. In contrast to previous studies that mostly focused on analysis of stand-alone metrics (Gan et al., 2014; Qian et al., 2015b; Zhou et al., 2011; Zhou and Wang, 2011), the PCA integrated the characteristics of five metrics, and transformed a set of observations of potentially correlated landscape indices into a set of values of linearly uncorrelated variables called principal components (Wold et al., 1987). This transformation allows for a better understanding of a combination of multiple indices, and could identify potential clusters of cities having similar spatial patterns of urban greenspace in given year, or having similar patterns in changes.

3. Results

3.1. Medium resolution TM data greatly underestimated the cover of greenspace

The results showed that the percent cover of urban greenspace mapped from the two datasets with different spatial resolution was very different. According to the TM data, the percent cover of urban greenspace ranged from 9.90% in Shanghai to 28.64% in Nanjing for 2005, with a mean of 20.44%, and from 9.85% in Tianjin to 20.52% in Nanjing for 2010, with a mean of 15.94% (Table 3). In contrast, percent cover of urban greenspace derived from the 2.5 m high resolution image data was much higher than that revealed by the 30 m resolution TM data for all the nine cities (Fig. 3, Table 3). The average percent cover of urban greenspace was 34.48% in 2005, ranging from 26.06% in Tianjin to 41.30% in Changzhou. In 2010, the average percent cover of urban greenspace was 35.11%, ranging from 24.50% in Tangshan to 48.99% in Nanjing (Table 3).

Changes in percent cover of greenspace revealed by TM data were also very different from those from high resolution data, and the difference varied by cities. The high resolution data showed that urban greenspace increased in five cities, including Beijing, Shanghai, Tianjin, Nanjing, and Hangzhou. TM data, however, indicated that percent cover of greenspace decreased in seven out of the nine cities (the exceptions were Beijing and Shanghai). The magnitudes in the change of percent cover revealed by the two datasets, were also different. For example, in Beijing, the percent cover of urban greenspace remained largely unchanged, with a slight increase of 0.42% from 13.27% to

Table 2
Accuracies of the classifications of urban greenspace for the nine cities.

	SPOT-5			ALOS			TM		
	Producer's accuracy	User's accuracy	Kappa	Producer's accuracy	User's accuracy	Kappa	Producer's accuracy	User's accuracy	Kappa
Beijing	95.10%	90.78%	0.89	90.24%	97.37%	0.92	94.87%	98.67%	0.97
Shanghai	97.33%	92.41%	0.90	77.78%	74.47%	0.64	87.50%	96.97%	0.95
Tianjin	90.48%	84.78%	0.78	88.57%	88.57%	0.83	91.67%	93.22%	0.93
Nanjing	94.58%	96.91%	0.93	89.45%	93.68%	0.85	95.42%	96.51%	0.94
Hangzhou	91.46%	99.90%	1.00	92.68%	84.44%	0.70	90.51%	94.13%	0.92
Suzhou_Wuxi_Changzhou	96.08%	96.08%	0.92	95.12%	98.73%	0.98	88.00%	97.06%	0.95
Tangshan	90.25%	84.93%	0.87	92.73%	83.61%	0.89	91.65%	93.22%	0.93

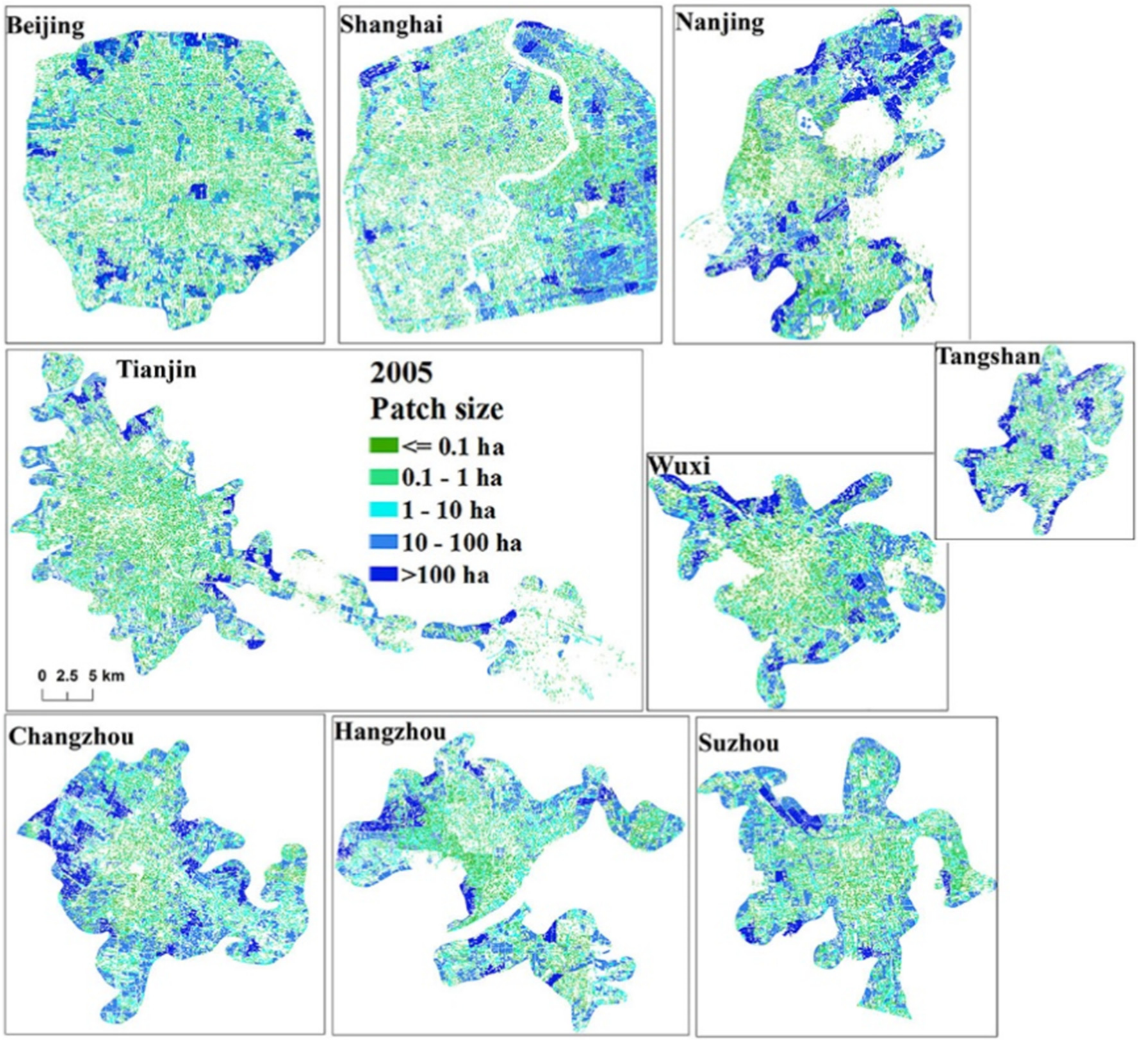


Fig. 2. The spatial distribution of patches with different sizes for nine cities.

13.69%, as suggested by TM data. However, the high resolution data showed that the percent cover increased from 28.01% to 32.22%, an increase of 4.21%, or approximately 30 km^2 in total area.

Our results showed that while the 30 m resolution TM data could generally extract relatively large patches of urban greenspace (e.g., forest remnants, large parks, and large golf courses), they neither detected most of the small patches, nor their changes (see example in Fig. 4). Consequently, the results from the TM data greatly underestimated the percent cover of greenspace and its change in core cities. This result was consistent with those from previous studies (e.g., Zhou et al., 2008; Ramos-Gonzalez, 2014; Qian et al., 2015a, 2015b). Therefore, we will hereafter focus on the results from the high resolution data.

3.2. Urban greenspace was highly dynamic

The results based on the high spatial resolution data showed that urban greenspace was highly dynamic for all the nine cities. Proportional cover of urban greenspace increased in all the five more populous cities (i.e., Beijing, Shanghai, Tianjin, Nanjing and Hangzhou). Percent cover of urban greenspace, however, greatly decreased in the four medium-sized cities. Specifically, the percent cover of greenspace increased by 11.26%, or a total of 4384 ha for Hangzhou, 6.45%, or 5074.66 ha for Shanghai, 4.54%, or 2348.35 ha for Nanjing, 4.21%, or 2812.67 ha for Beijing, and 0.51%, or 296.08 ha for Tianjin. Meanwhile, there were a net decrease of 9.52% (or 1509.23 ha), 9.07% (or 2618.43 ha), 6.40% (or 2438.81 ha), and 5.30% (or 1908.17 ha) in Tangshan, Wuxi, Changzhou and Suzhou, respectively.

Results from the transfer matrices indicated that changes in urban greenspace were much more dramatic than the net increase or decrease would suggest (Table 4). The absolute values in net change of percent cover of urban greenspace ranged from 0.51% to 11.26%, or from 296.08 ha to 5074.66 ha (Table 4). However, when considering both the gain and loss of greenspace, the percent cover involved was much more dynamic (Table 4). For example, there was slight increase of 0.51% in urban greenspace for Tianjin City. However, this relatively small net

Table 3
The percent cover of urban greenspace based on TM and SPOT/ALOS for nine cities in 2005 and 2010.

	TM		SPOT/ALOS	
	2005	2010	2005	2010
Beijing	13.27%	13.69%	28.00%	32.22%
Shanghai	9.90%	19.40%	29.45%	35.92%
Tianjin	11.76%	9.85%	26.06%	26.56%
Nanjing	28.64%	20.52%	44.40%	48.99%
Hangzhou	18.66%	14.78%	36.39%	47.58%
Suzhou	25.27%	17.42%	39.60%	34.27%
Wuxi	25.67%	16.31%	31.06%	31.06%
Changzhou	26.89%	15.61%	41.30%	34.88%
Tangshan	23.94%	15.84%	34.02%	24.50%

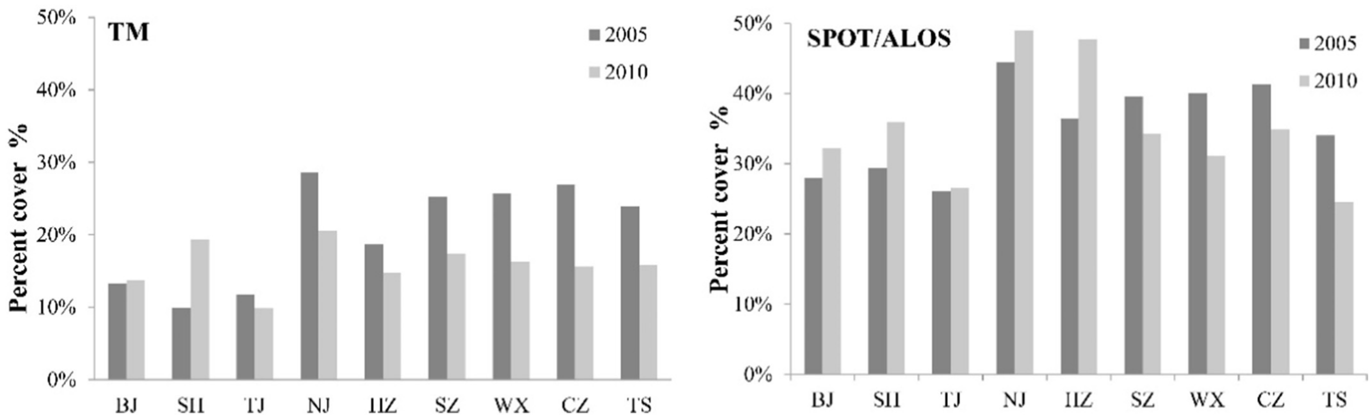


Fig. 3. The percent cover of urban greenspace and change mapped from SPOT/ALOS (left) and TM (right) for the nine cities. Notes, BJ = Beijing, SH = Shanghai, TJ = Tianjin, NJ = Nanjing, HZ = Hangzhou, WX = Wuxi, CZ = Changzhou, TS = Tangshan.

increase resulted from an approximately 18% (or 10,525.28 ha) gross land cover change related to greenspace: There was 9.19% (or 5410.68 ha) of greenspace gained and 8.68% (or 5114.60 ha) of greenspace lost. For cities such as Hangzhou, the changes related to urban greenspace were even greater. From the relatively short period between 2005 and 2010, 8875.57 ha of new urban greenspace were generated from other land cover types (mainly impervious surfaces), but over the same time, 4491.57 ha of urban greenspace were lost, resulting in a net increase of 4384 ha (or 11.26%) greenspace in Hangzhou (Table 4). Overall, the three largest cities, Shanghai, Beijing, and Tianjin, had less change in greenspace than the other six cities. This is likely due to the greater efforts dedicated to greening in these large cities (Zhao et al., 2013).

3.3. Spatial patterns of urban greenspace and their changes

There were similarities and differences in the spatial patterns of urban greenspace among cities, according to the selected landscape metrics (Fig. 5). For example, the mean patch size of urban greenspace was

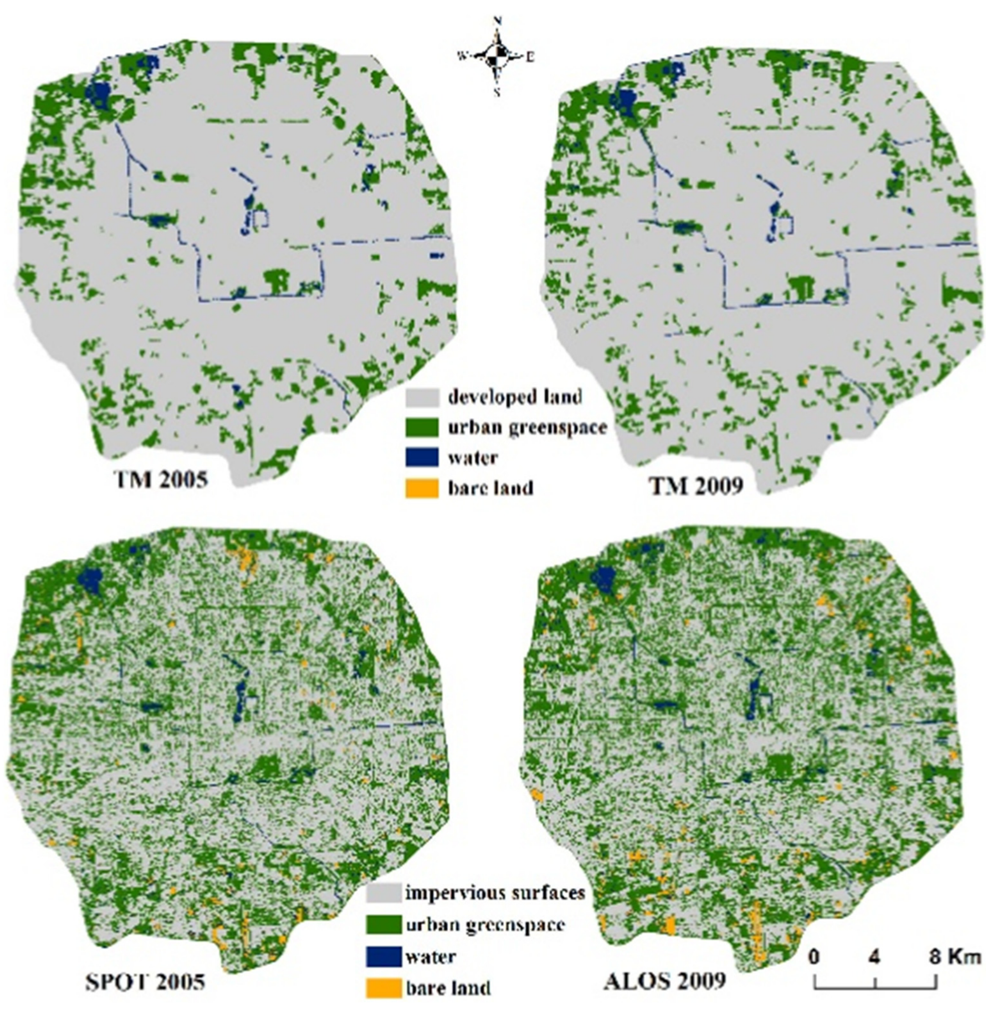


Fig. 4. Classification results for Beijing from TM data and the high resolution SPOT/ALOS data.

Table 4
Greenspace change from 2005 to 2010, based on the 2.5 m high resolution SPOT/ALOS data.

Change of greenspace	Gained greenspace		Lost greenspace		Net change	
	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)
Beijing	7010.97	10.50%	4198.30	6.29%	2812.67	4.21%
Shanghai	12,306.38	15.65%	7231.72	9.21%	5074.66	6.45%
Tianjin	5410.68	9.19%	5114.60	8.68%	296.08	0.51%
Nanjing	9460.25	18.27%	7111.90	13.74%	2348.35	4.54%
Hangzhou	8875.57	22.80%	4491.57	11.54%	4384.00	11.26%
Suzhou	5034.81	13.99%	6942.97	19.30%	−1908.17	−5.30%
Wuxi	2771.35	9.60%	5389.78	18.67%	−2618.43	−9.07%
Changzhou	4646.73	12.19%	7085.53	18.58%	−2438.81	−6.40%
Tangshan	735.65	4.64%	5544.88	14.15%	−1509.23	−9.52%

small for all the cities, almost all amounting to less than 1 ha. Patch density, edge density and landscape shape index differed greatly among the nine cities. Even for cities in the same megaregion, spatial patterns of urban greenspace varied greatly. Changes in spatial patterns of urban greenspace, however, were more similar among cities in the same urban megaregion than for cities in other regions. For example, PD and ED decreased, but MPS increased in all three cities of the BTH urban megaregion (i.e., Beijing, Tianjin and Tangshan), suggesting urban greenspace became more aggregated instead of fragmented in these cities. In contrast, both PD and ED increased, while MPS declined in all the six cities except for Nanjing in the YRD urban megaregion, indicating increasingly fragmented urban greenspace in these cities. Similarly, in contrast to the decrease of LSI in Beijing, Tianjin, and Tangshan, LSI increased in all of the six cities in the YRD urban megaregion, suggesting the shape of urban greenspace became more complicated from 2005 to 2010 in these six cities.

The proportional distribution of patches based on patch size showed that the majority of the patches were small (Fig. 6). For all nine cities, approximately 60% of the greenspace patches were smaller than 0.1 ha. These small patches, however, generally accounted for less than 10% of the total area of the urban greenspace. Large patches, while much fewer in number, contributed to the majority of the total area of urban greenspace. In contrast, fewer than 10% of the patches ranged in size from 1 to 100 ha. These patches, however, accounted for more than 50% of the total area of urban greenspace. The number of patches greater than 100 ha was less than 1%, but accounted for more than 10% of the total area of greenspace.

The accumulated probability of patches in terms of the number and size of patches showed that the proportional distributions of patches changed greatly from 2005 to 2010, but with large variations in magnitude among cities (Figs. 6, 7). First, the proportion of small patches greatly increased in all the six cities of the YRD urban megaregion, suggesting increased degree of fragmentation in urban greenspace. In contrast, patch sizes of urban greenspace in the three cities of the BTH urban megaregion, tended to increase (Fig. 7a). Second, the trends of greenspace patch size varied among cities. The patch size of urban greenspace in Beijing, Shanghai, Hangzhou and Suzhou revealed a trend of polarization. That is, the small patches tended to be smaller, while large patches became even larger. However, in Tianjin, Nanjing and Tangshan, the proportion of medium-sized patches increased, most likely resulting from the expansion of some of the small patches, combined with a loss of some of the large patches (Fig. 7b–f).

By combining of the landscape metrics and their changes, the PCA showed how the structure of greenspace and the fragmentation

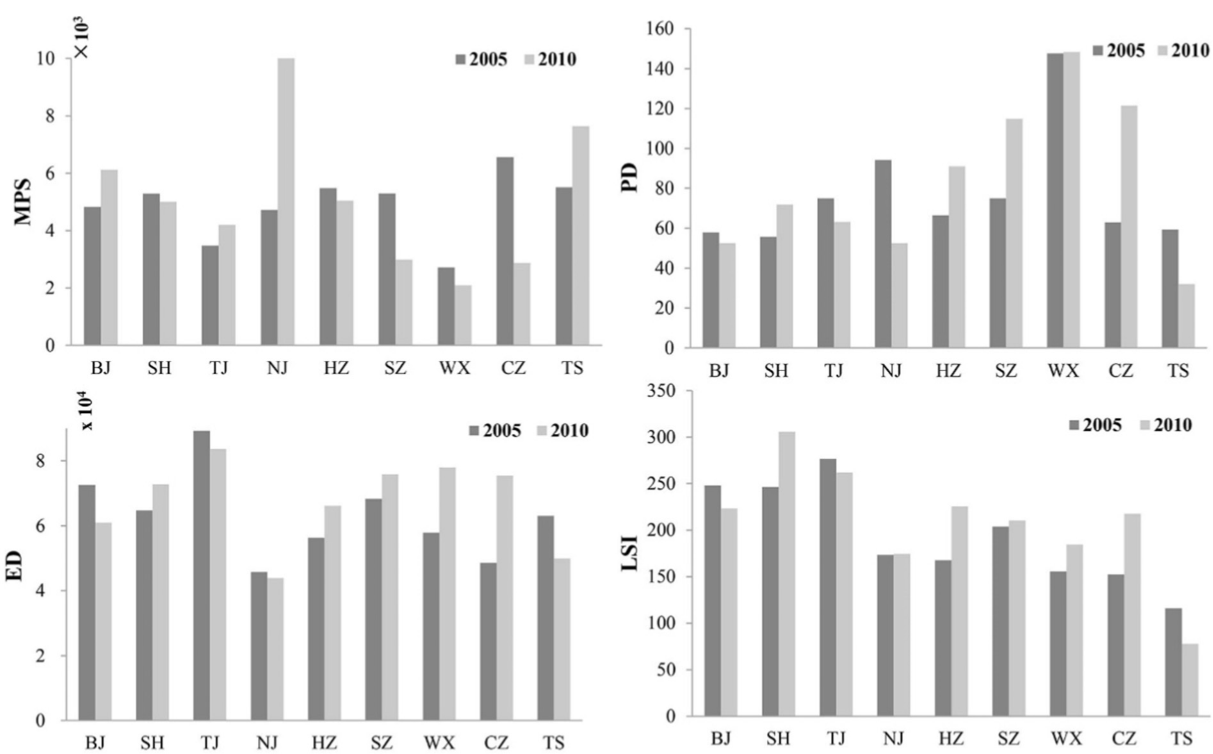


Fig. 5. The four spatial configuration metrics for greenspace of the nine cities in 2005 and 2010 based on SPOT/ALOS data.

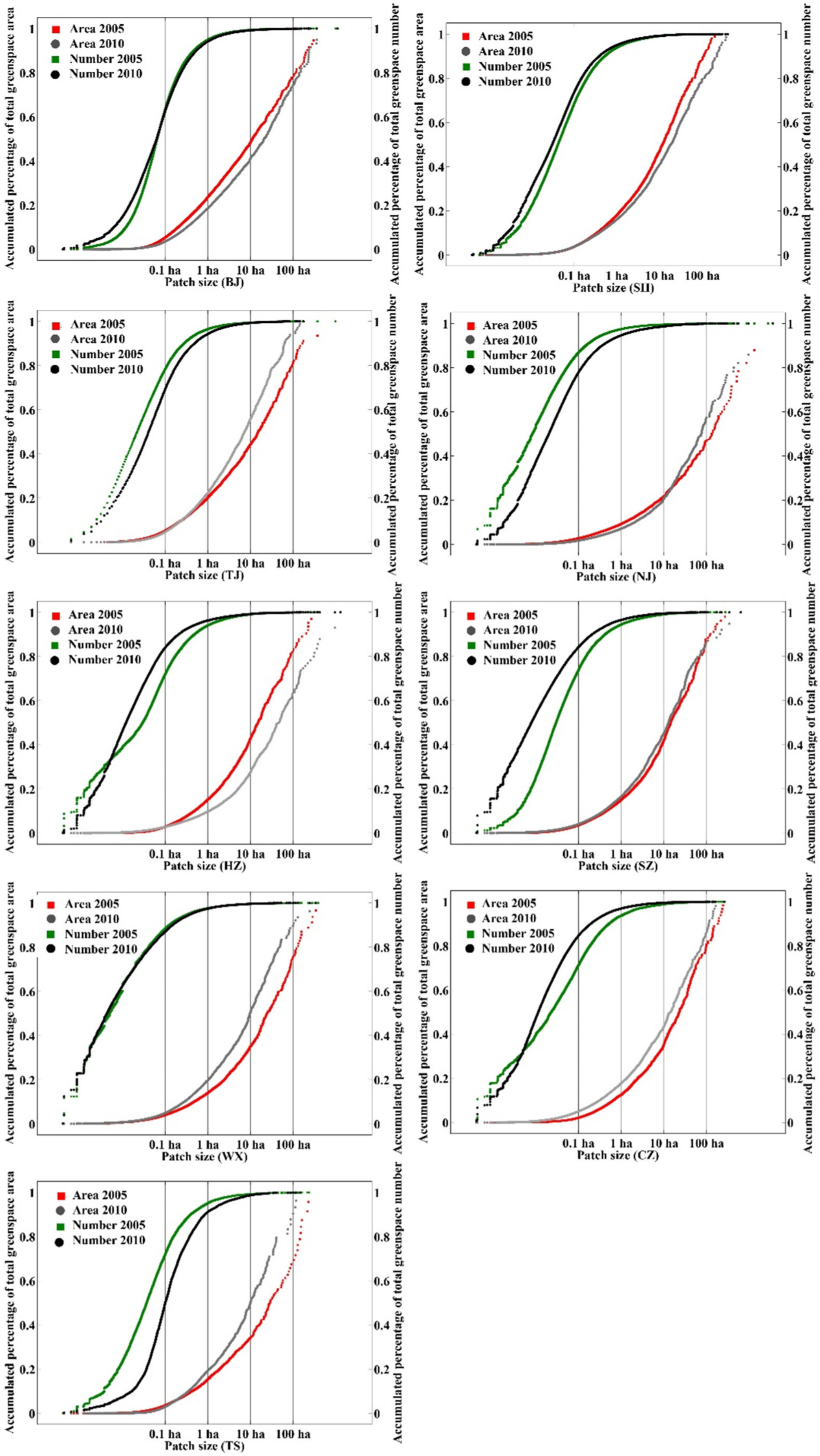


Fig. 6. Accumulated probability of patches in terms of patch size in the nine cities between 2005 and 2010.

processes in these cities were clustered (Fig. 8; Appendix, Table A3). The spatial patterns of urban greenspace in the nine cities were clearly distinguished by PCA in 2005 and 2010 (Fig. 8a, b). In 2005, about 90.71% of the total variance was explained by the first two principal components (i.e., $PCA1_{2005}$ and $PCA2_{2005}$). Based on the loadings of $PCA1_{2005}$, the three megacities, Beijing, Shanghai and Tianjin, were well separated from the other six relatively small cities (Appendix, Table A3). It showed that these three megacities had positive loadings on $PCA1_{2005}$, while cities such as Hangzhou, Suzhou, Wuxi, and Changzhou were more compactly clustered on the negative range of that axis (Fig. 8a). In 2010, the first PC ($PCA1_{2010}$) accounted for 58.44% of the total variance, and represented the variations in the two fragmentation metrics (i.e., MPS and ED), while $PCA2_{2010}$ accounted for 24.11% of the total variance and mainly represented the variation of percent cover of urban greenspace. Similarly, the nine cities were divided into two groups: the first group, including Suzhou, Wuxi, Changzhou, and Tianjin, was closer to the $PCA2_{2010}$ axis and gathered together at the negative range of $PCA1_{2010}$. And the second group, including Beijing, Shanghai and Hangzhou, clustered around the origin (Fig. 8b).

As for the changes from 2005 to 2010, the first two principal components accounted for 89.59% of the total variance, with the first axis contributing 65.46% of the variance of initial eigenvalues, and the second 24.13% (Fig. 8c). The first component consisted of ED, PD and LSI, representing the variation of patch fragmentation and shape complexity. The results showed that PCA1 clearly differentiated cities in the north from those in the south (except for Nanjing). Shanghai, Hangzhou,

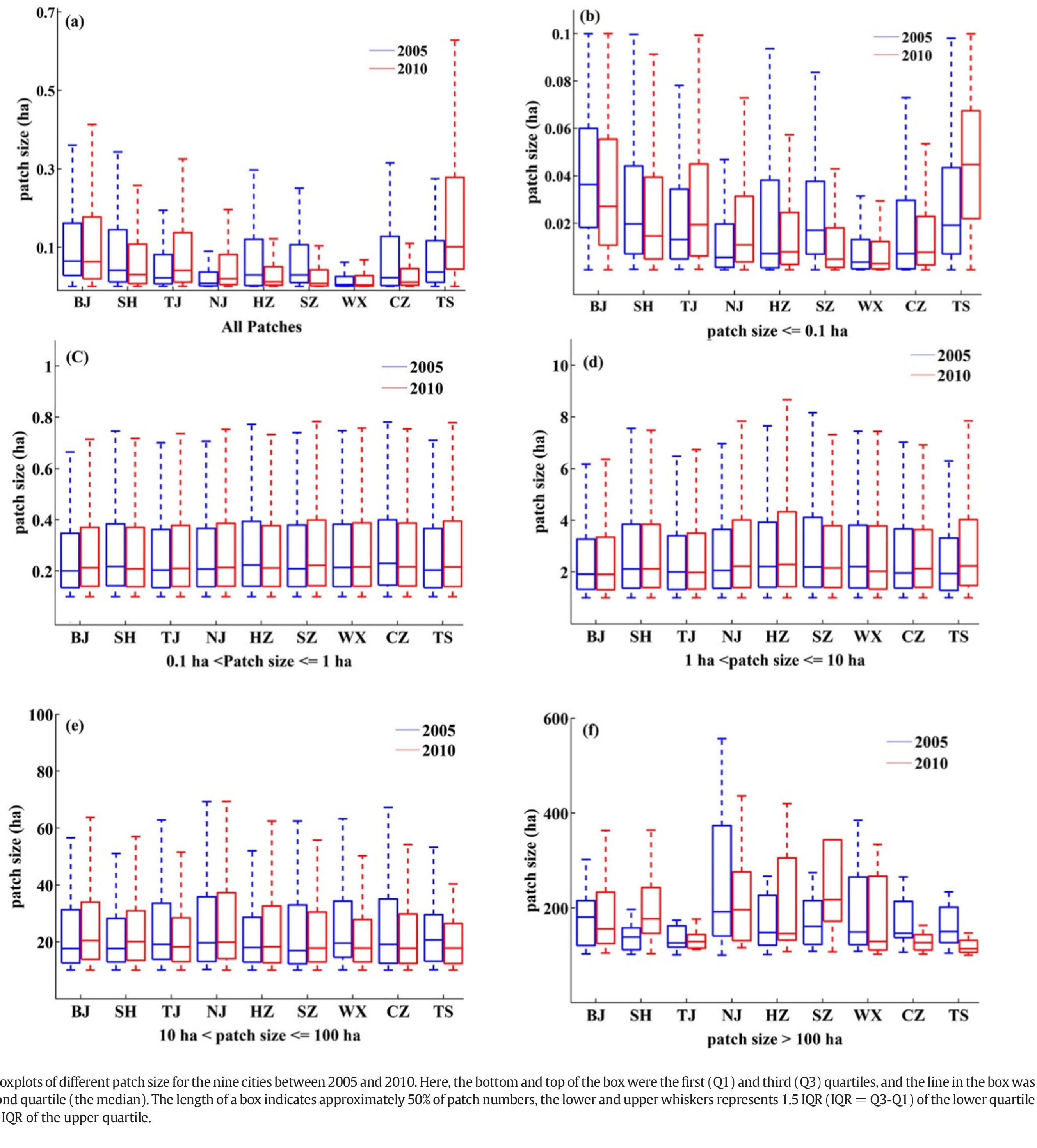


Fig. 7. Boxplots of different patch size for the nine cities between 2005 and 2010. Here, the bottom and top of the box were the first (Q1) and third (Q3) quartiles, and the line in the box was the second quartile (the median). The length of a box indicates approximately 50% of patch numbers, the lower and upper whiskers represents 1.5 IQR (IQR = Q3-Q1) of the lower quartile and 1.5 IQR of the upper quartile.

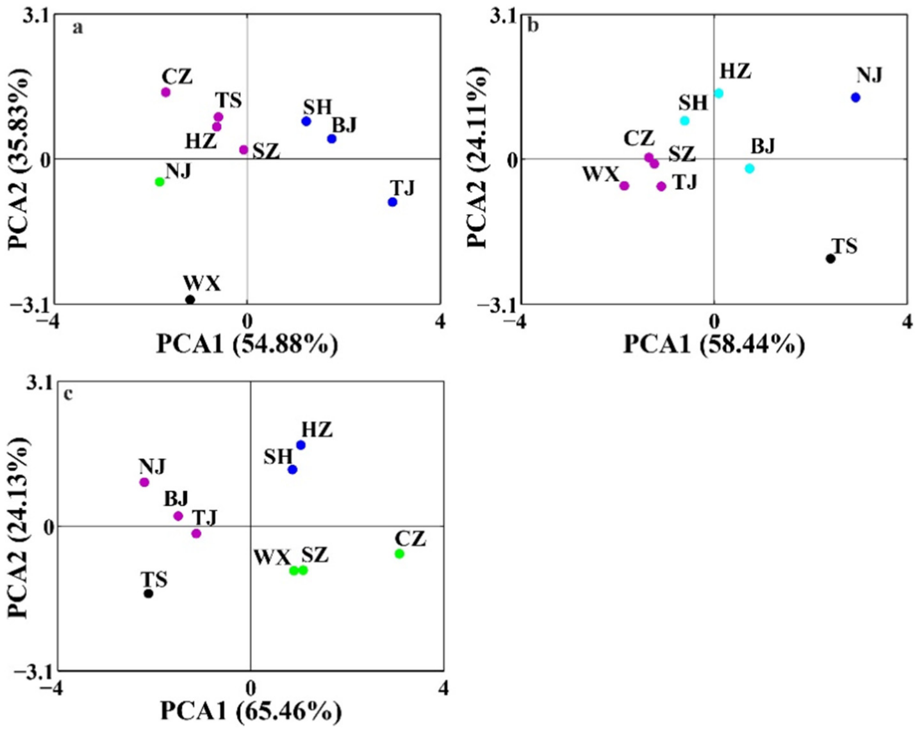


Fig. 8. Principal Components Analysis of the nine cities with different greenspace patch metrics mapped from SPOT/ALOS data. The dots of the same color were grouped together into a category. Pane A: 2005, panel B: 2010, and panel C: the change from 2005 to 2010.

Suzhou, Wuxi, and Changzhou were located on the positive section of PCA1, but Beijing, Tianjin and Tangshan occupied the negative range. This suggested increased greenspace fragmentation and complexity in the southern cities, but reduced fragmentation in northern cities from 2005 to 2010 (Fig. 8c). This type of regional difference may result from geographical and climatic factors. Compared to northern cities, cities in the south have more favorable climate for vegetation growth, and therefore are more likely to create more discrete, and small-sized green spaces (Zhao et al., 2013).

4. Discussion

4.1. The highly dynamic urban greenspace in Chinese cities

Relatively few studies have been conducted to examine the within-city urban greenspace dynamics for Chinese cities, especially using high spatial resolution imagery (Qian et al., 2015b). Our results based on high spatial resolution image data indicated that urban greenspace in all the nine cities was highly dynamic. Within a relatively short five-year time period, all of the nine cities experienced tremendous absolute changes in gain or loss of urban greenspace, even though the net change might appear small in some of the cities. These results were contradictory to most of the previous studies that used medium resolution image data (typically 30 m TM data), which found that urban greenspace within urban cores remained largely unchanged (e.g., Xu et al., 2011; Zhou and Wang, 2011). It should also be noted that most of these studies, however, focused on changes of urban greenspace in the urban fringes caused by urban expansion. The current study focused on the formally defined core areas of the nine cities. Focus on core areas of cities is justified by the need to consider demand and provision of ecosystem services in these densely populated zones (Haase et al., 2014).

Studies have also been conducted to investigate within-city urban greenspace change in other U.S. and European cities (e.g., Fuller and Gaston, 2009; Kabisch and Haase, 2013; Nowak and Greenfield, 2012; Szymanska et al., 2015; Zhou et al., 2008). These studies, however, generally found much lower degrees of urban greenspace dynamics within cities. For example, the study by Nowak and Greenfield (2012) on 20 U.S. cities showed that from 2005 to 2009 tree cover increased by an average of 2.1%, and an average of 2.3% loss, resulting in an average net change of 0.2% during the four years of their study. Additionally, in contrast to the general trends of decreasing tree cover in many U.S. cities (Nowak and Greenfield, 2012), urban greenspace in five out of the nine Chinese cities increased. Because there are few assessments of urban greenspace change within cities, further investigation is required, especially the inclusion of more cities globally. Such future studies can test whether the very high degree of greenspace change within cities only occurs in developing countries such as China, or also occurs in developed countries. In addition, it would be important to include cities representing a larger range of sizes, from large cities as in this study, to medium- and small-sized cities. The United Nations (2014) has estimated that in fact the majority of urban conversion globally will take place in small to medium sized cities. The complexity of urban change in cities representing different sizes throughout the world may reveal a variety of greenspace dynamics (McHale et al., 2015).

The high dynamism of urban greenspace in the nine cities seems to be the result of the combined influences of two major factors – efforts on greening such as tree planning programs, and great pressures from development. On the one hand, because of the very high value of land in the core city, urban development and increased economic activity have caused many changes to the existing urban green space (Qian et al., 2015a; Li et al., 2016). Infill development even caused clearance of those small patches that are not well protected (Brunner and Cozens, 2013). On the other hand, many of the Chinese cities have devoted substantial efforts to increasing urban greenspace, aiming to improve residents' living environments. Due to the limited land resources in city cores that are available for greening, it is impossible to depend upon plentiful large-sized greenspace patches. The 'filling in' approaches, therefore, are frequently conducted, and thus lead to numerous small-sized urban greenspace. For example, establishing the Olympic Forest Park and implementing the "Plant Where Possible" policy in Beijing have successfully led to the creation of much new, and mostly small urban greenspace (Qian et al., 2015a; Wang, 2009). Similarly, Hangzhou has created a program to establish a green network system, along with a series of greening projects. The nine cities in this study are relatively well-developed and wealthy, and thus have more resources for city greening (Zhao et al., 2013). Future studies that include a larger number of cities with a broad range of social and economic conditions would be highly desirable.

The finding that greenspace is highly dynamic within cities has important implications for urban greenspace management and planning. This high degree of dynamism provides both opportunity and challenge for better urban greenspace management and planning. On the one hand, the creation of a large amount of new urban greenspace provides opportunities for better design and planning to improve the accessibility, equity of spatial distribution, and quality of urban greenspace, and therefore to achieve an improved urban sustainability (Beatley and Manning, 1997; Wu, 2008; Niemelä, 2014; Qian et al., 2015b). On the other hand, such a high degree of dynamism may threaten the quality or persistence of existing greenspace, and resulting in substitution of greenspace having low quality. Such degradation of greenspace can lead to lower quality of life in well-developed parts of cities, due to loss of biodiversity, worsened recreation possibilities, and reduced provision of ecosystem services (Haaland and van den Bosch, 2015; Lo and Jim, 2010).

In addition, such frequent changes of urban greenspace may lead to inconsistent provision of ecosystem services over time, with implications for urban sustainability (Lo and Jim, 2010; Wolch et al., 2014; Zhou et al., 2017). This is because not only the spatial pattern of urban greenspace influences its provision services (Li et al., 2011; Chen et al., 2014; Maimaitiyiming et al., 2014), but also where and how greenspace has changed (Lo and Jim, 2010; Sivam et al., 2012). For example, the high turnover rate of urban greenspace associated with shrinking, or even disappearing of existing greenspace in old core areas may decrease the local availability of greenspace, and thereby damage the ecosystem services provided by greenspace (Lo and Jim, 2010). Provision of new greenspace on urban fringes is not likely to compensate residents of old core areas. Future research that focuses on the effects of different types of changes in greenspace –disappearing, new creation, expansion, fragmentation or shrinking– on the provision of ecosystem services would be highly desirable. Meanwhile, in addition to protecting the large patches of urban greenspace such as parks and remnant forests, policy-makers and natural resource managers should pay more attention to the protection of small patches of urban greenspace (Pickett, 2010), which are frequently ignored, and therefore become the targets of development (Brunner and Cozens, 2013). These small urban greenspaces, similar to larger ones, play crucial roles in providing regulating and cultural ES, as well as enhancing human health and well-being. In fact, recent studies have suggested that the roles of small greenspaces for urban conservation may be more important than previously assumed (Rupprecht and Byrne, 2014).

4.2. Quantifying within-city urban greenspace and change needs high spatial resolution image data

Our results showed that for all the nine cities, urban greenspace was highly dynamic. However, such dynamics, can only be revealed by high spatial resolution imagery, but not by the medium resolution data such as the most commonly used 30 m resolution TM data. Indeed, our results showed that the majority of the patches of urban greenspace were too small to be detectable by medium resolution imagery. In addition, medium resolution imagery was not able to detect most of the changes in urban greenspace, which tend to be small due to the very limited land available for greening within cities (Qian et al., 2015b). Consequently, medium resolution data such as 30 m TM imagery tend to underestimate the percent coverage of urban greenspace, as well as their changes. Similarly, Smith et al. (2010) found that the 30-m National Land Cover Database (NLCD) in the U.S. poorly discerned small or patchy tree cover and under-reported canopy cover in urbanized areas. Urban greenspace is highly fragmented and heterogeneous, characterized by a mix of very many small patches with relatively few dispersed large patches (Figs. 6 & 7) only visible to high resolution imagery.

These small patches of urban greenspace, unlike large greenspaces that are relatively rare and typically not within walking distance of the majority of urban residents (Wolch et al., 2014), are widely distributed and embedded in built-up areas where people live, work, and play. Therefore, these greenspaces are considered as "nature nearby" (Nilon, 2011), and thus can play crucial roles in providing cultural ecosystem services (Niemelä, 2014), and enhancing human health and well-being (Coutts and Hahn, 2015). Additionally, these small patches of green cover can contribute to biodiversity, stormwater management, microclimate mitigation and other services, similar to large greenspaces (Bolund and Hunhammar, 1999; Strohbach et al., 2013; Wu, 2014; Zhou et al., 2014). In fact, recent studies suggested that the roles of these "informal" urban greenspace for urban conservation may be more important than previously assumed (Rupprecht and Byrne, 2014). Consequently, to fully understand ecosystem services provided by urban greenspace, it is important and necessity to use high spatial resolution image data to quantify the fine-scale spatial patterns of urban greenspace and change.

5. Conclusion

Previous studies have largely focused on loss of greenspace due to urban expansion, using medium resolution imagery and focusing on the growing urban fringes. This study presents a comparison study of the spatiotemporal patterns of urban greenspace in nine major cities in China, using 2.5 m high spatial resolution ALOS and SPOT image data collected in 2005 and 2010, respectively. The changes in urban greenspace were further compared and contrasted with those based on the most commonly used 30 m Landsat TM data. The results showed: 1) Urban greenspace was highly fragmented and heterogeneous, characterized by a mix of a large number of small-sized patches with relatively few dispersed large patches in all nine cities. 2) In contrast to findings from previous research that greenspace in inner cities tends to remain largely unchanged, urban greenspace in all nine cities was highly dynamic, experiencing dramatic gain and loss during the five years. Changes in percent cover of urban greenspace ranged from a reduction of 9.52% (or 1509.23 ha) in Tangshan to an increase of 11.26% (or 4383.0 ha) for Hangzhou. Most of changes in urban greenspace, however, tended to occur as patches that were small in size, which could only be revealed by high spatial resolution imagery. 3) Spatial patterns of greenspace varied greatly across cities in terms of patch size, patch and edge density and shape. Urban greenspace became increasingly fragmented and complex in the southern cities, but the opposite in the northern cities. Our results highlight the necessity of using high spatial resolution data to adequately quantify the spatial distribution of urban greenspace and its change, and therefore to fully understand the myriad ecosystem services provided by urban greenspace. The high dynamics of urban greenspace in core cities provide opportunities for better design and planning to achieve an improved urban sustainability, but also call for better protection of small urban greenspace in Chinese cities.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (Grant No. 41422104, 4177011341 and 41590841), the project "Developing key technologies for establishing ecological security patterns at the Beijing-Tianjin-Hebei urban megaregion" of the National key research and development program (2016YFC0503004), the Key Research Program of Frontier Sciences, CAS (QYZDB-SSW-DQC034), and the China Ecosystem Survey (2000−2010) (grant no. STSN-12-00). The support of the Urban Sustainability Research Coordination Network (RCN 1140070) is also gratefully acknowledged.

Table A1
Quick fact of the nine cities.

	Size of well-developed area (km^2)*	Climatic types	Mean annual temperature (°C)	Mean annual precipitation (mm)	Population (million)	GDP (billion RMB)
Beijing	667.8	Temperate continental monsoon climate	10.0–12.0	626.0	19.6	1411.4
Tianjin	617.5		13.0	650.0	12.9	922.4
Tangshan	158.6		10.6	644.2	7.4	446.9
Shanghai	786.3	Subtropical monsoon climate	16.0	1200.0	23.0	1716.6
Nanjing	517.7		15.4	1106.0	80.0	501.0
Hangzhou	389.5		17.5	1139.0	87.0	594.6
Suzhou	359.8		16.2	1500.0	6.4	922.9
Wuxi	288.8		15.5	1000.0	4.7	575.8
Changzhou	381.5		15.4	1071.0	3.6	297.7

From NBSN (2010).
* Sizes of the well-developed proportion of the city, but population and GDP statistics from the whole city.

Table A2
Landscape metrics used in this study.

Metrics	Description	Unit	Range
Percentage of landscape (PLAND)	The proportion of the area of certain land use class to the entire landscape area	%	[0,100]
Mean patch size (MPS)	The area occupied by particular patch type divided by the number of patches of that type	m^2	[0, ∞]
Patch density (PD)	The number of patches per 100 ha	Number per 100 ha	[0, ∞]
Edge density (ED)	The total perimeter of particular patch type divided by the total area of patches of that type	m^{-1}	[0, ∞]
Landscape shape index (LSI)	A modified perimeter-area ration of the form that measures the shape complexity of the whole landscape or a specific patch type	None	[1, ∞]

Table A3
Loading on each metric in the PCA.

Metric	2015		2010		Change from 2005 to 2010	
	Component 1	Component 2	Component 1	Component 2	Component 1	Component 2
PLAND	**−0.5651**	−0.099	0.1627	**0.8314**	−0.067	**0.8811**
MPS	−0.1824	**0.7062**	**0.5686**	0.1267	**−0.501**	0.2360
PD	−0.2185	**−0.6927**	−0.4666	0.1324	**0.5184**	−0.0308
ED	**0.5652**	−0.1006	**−0.5672**	−0.047	**0.5060**	0.0027
LSI	**0.5294**	−0.0408	−0.3329	0.5218	0.4693	0.4087
Eigenvalue	2.74	1.79	2.92	1.21	3.27	1.21
%Variance explained	54.88%	35.83%	58.44%	24.11%	65.46%	24.13%
%Cumulative variance	54.88%	90.71%	58.44%	82.55%	65.46%	89.59%

Note: the bold values represent the main explanatory variables of corresponding principle component axes.

References

Beatley, T., Manning, K., 1997. The Ecology of Place: Planning for Environment, Economy, and Community. Island Press.

Beijing Landscape Bureau, 2007. Beijing green space planning Beijing (in Chinese).

Bolund, P., Hunhammar, S., 1999. Ecosystem services in urban areas. Ecol. Econ. 29, 293–301.

Brunner, J., Cozens, P., 2013. 'Where have all the trees gone?' Urban consolidation and the demise of urban vegetation: a case study from Western Australia. Plan. Pract. Res. 28, 231–255.

Chen, A., Yao, X.A., Sun, R., Chen, L., 2014. Effect of urban green patterns on surface urban cool islands and its seasonal variations. Urban For. Urban Green. 13 (4), 46–654.

Coutts, C., Hahn, M., 2015. Green infrastructure, ecosystem services, and human health. Int. J. Environ. Res. Public Health 12, 9768–9798.

Du, J., Thill, J.C., Peiser, R.B., Feng, C., 2014. Urban land market and land-use changes in post-reform China: a case study of Beijing. Landsc. Urban Plan. 124, 118–128.

Fuller, R.A., Gaston, K.J., 2009. The scaling of green space coverage in European cities. Biol. Lett. 5, 352–355.

Gan, M., Deng, J., Zheng, X., Hong, Y., Wang, K., 2014. Monitoring urban greenness dynamics using multiple endmember spectral mixture analysis. PLoS One 9, e112202.

Groenewegen, P.P., den Berg, A.E., de Vries, S., Verheij, R.A., 2006. Vitamin G: effects of green space on health, well-being, and social safety. BMC Public Health 6, 149.

Haaland, C., van den Bosch, C.K., 2015. Challenges and strategies for urban green-space planning in cities undergoing densification: a review. Urban For. Urban Green. 14, 760–771.

Haase, D., Frantzeskaki, N., Elmqvist, T., 2014. Ecosystem services in urban landscapes: practical applications and governance implications. Ambio 43, 407–412.

Hu, X., Zhou, W., Qian, Y., Yu, W., 2017. Urban expansion and local land-cover change both significantly contribute to urban warming, but their relative importance changes over time. Landsc. Ecol. 32, 763–780.

Huang, G., Cadenasso, M.L., 2016. People, landscape, and urban heat island: dynamics among neighborhood social conditions, land cover and surface temperatures. Landsc. Ecol. 31, 2507–2515.

Hurd, J.D., Wilson, E.H., Lammey, S.G., Civco, D.L., 2001. Characterization of forest fragmentation and urban sprawl using time sequential Landsat imagery. ASPRS 2001 Annual Convention, St. Louis, MO.

Jiang, G., Ma, W., Qu, Y., Zhang, R., Zhou, D., 2016. How does sprawl differ across urban built-up land types in China? A spatial-temporal analysis of the Beijing metropolitan area using granted land parcel data. Cities 58, 1–9.

Kabisch, N., 2015. Ecosystem service implementation and governance challenges in urban green space planning—the case of Berlin, Germany. Land Use Policy 42, 557–567.

Kabisch, N., Haase, D., 2013. Green spaces of European cities revisited for 1990–2006. Landsc. Urban Plan. 110, 113–122.

Kong, F.H., Nakagoshi, N., 2006. Spatial-temporal gradient analysis of urban green spaces in Jinan, China. Landsc. Urban Plan. 78, 147–164.

Li, M.S., Zhu, Z.L., Vogelmann, J.E., Xu, D., Wen, W.S., Liu, A.X., 2011. Characterizing fragmentation of the collective forests in southern China from multitemporal Landsat imagery: a case study from Kecheng district of Zhejiang province. Appl. Geogr. 31, 1026–1035.

Li, F., Sun, Y., Li, X., Hao, X., Li, W., Qian, Y., Liu, H., Sun, H., 2016. Research on the sustainable development of green-space in Beijing using the dynamic systems model. Sustain. For. 8, 965.

Lo, A.Y.H., Jim, C.Y., 2010. Differential community effects on perception and use of urban greenspaces. Cities 27, 430–442.

Locke, D.H., Grove, J.M., Lu, J.W.T., Troy, A., O'Neil-Dunne, J.P.M., Beck, B.D., 2010. Prioritizing preferable locations for increasing urban tree canopy in New York City. Cities Environ. 3 (Article 4).

Lovell, S.T., Taylor, J.R., 2013. Supplying urban ecosystem services through multifunctional green infrastructure in the United States. Landsc. Ecol. 28, 1447–1463.

MacFaden, S.W., O'Neil-Dunne, J.P.M., Royar, A.R., Lu, J.W.T., Rundle, A.G., 2012. High-resolution tree canopy mapping for new York City using LIDAR and object-based image analysis. J. Appl. Remote. Sens. 6, 23.

Maimaitiyiming, M., Ghulam, A., Tiyip, T., Pla, F., Latorre-Carmona, P., Halik, Ü., Sawut, M., Caetano, M., 2014. Effects of green space spatial pattern on land surface temperature: implications for sustainable urban planning and climate change adaptation. ISPRS J. Photogramm. Remote Sens. 89, 59–66.

Mathieu, R., Freeman, C., Aryal, J., 2007. Mapping private gardens in urban areas using object-oriented techniques and very high-resolution satellite imagery. Landsc. Urban Plan. 81, 179–192.
McGarigal, K., Cushman, S., Neel, M., & Ene, E. (2002). FRAGSTATS: spatial pattern analysis program for categorical maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst. http://www.umass.edu/landeco/research/fragstats/frag-stats.html.
McHale, M.R., Pickett, S.T.A., Barbosa, O., Bunn, D.N., Cadenasso, M.L., Childers, D.L., Gartin, M., Hess, G.R., Iwaniec, D.M., McPhearson, T., Peterson, M.N., Poole, A.K., Rivers, L., Shutters, S.T., Zhou, W.Q., 2015. The new global urban realm: complex, connected, diffuse, and diverse social-ecological systems. Sustain. For. 7, 5211–5240.
Miller, M.D., 2012. The impacts of Atlanta's urban sprawl on forest cover and fragmentation. Appl. Geogr. 34, 171–179.
Niemelä, J., 2014. Ecology of urban green spaces: the way forward in answering major research questions. Landsc. Urban Plan. 125, 298–303.
Nilon, C.H., 2011. Urban biodiversity and the importance of management and conservation. Landsc. Ecol. Eng. 7, 45–52.
Nowak, D.J., Greenfield, E.J., 2012. Tree and impervious cover change in U.S. cities. Urban For. Urban Green. 11, 21–30.
Ouyang, Z., Zheng, H., Xiao, Y., Polasky, S., Liu, J., Xu, W., Wang, Q., Zhang, L., Xiao, Y., Rao, E.M., Jiang, L., Lu, F., Wang, X.K., Yang, G.B., Gong, S.H., Wu, B.F., Zeng, Y., Yang, W., Daily, G.C., 2016. Improvements in ecosystem services from investments in natural capital. Science 352, 1455–1459.
Park, J., Kim, J.H., Lee, D.K., Park, C.Y., Jeong, S.G., 2017. The influence of small green space type and structure at the street level on urban heat island mitigation. Urban For. Urban Green. 21, 203–212.
Pataki, D.E., 2013. Urban greening needs better data. Nature 502, 624.
Pathak, V., Tripathi, B.D., Mishra, V.K., 2011. Evaluation of anticipated performance index of some tree species for green belt development to mitigate traffic generated noise. Urban For. Urban Green. 10, 61–66.
Peng, J., Wang, Y., Zhang, Y., Wu, J., Li, W., Li, Y., 2010. Evaluating the effectiveness of landscape metrics in quantifying spatial patterns. Ecol. Indic. 10, 217–223.
Peng, J., Xie, P., Liu, Y., Ma, J., 2016a. Urban thermal environment dynamics and associated landscape pattern factors: a case study in the Beijing metropolitan region. Remote Sens. Environ. 173, 145–155.
Peng, J., Zhao, S., Liu, Y., Tian, L., 2016b. Identifying the urban-rural fringe using wavelet transform and kernel density estimation: a case study in Beijing City, China. Environ. Model. Softw. 83, 286–302.
Pickett, S.T.A., 2010. The wild and the city. In: Redford, K.H., Fearn, E. (Eds.), State of the Wild: a Global Portrait 2010. Island Press, Washington DC, pp. 153–159.
Pickett, S.T.A., Cadenasso, M.L., Rosi-Marshall, E.J., Belt, K.T., Groffman, P.M., Grove, J.M., Irwin, E.G., Kaushal, S.S., LaDeau, S.L., Nilon, C.H., Swan, C.M., Warren, P.S., 2017. Dynamic heterogeneity: a framework to promote ecological integration and hypothesis generation in urban systems. Urban Ecosystems 20, 1–14.
Portillo-Quintero, C.A., Sanchez, A.M., Valbuena, C.A., Gonzalez, Y.Y., Larreal, J.T., 2012. Forest cover and deforestation patterns in the Northern Andes (Lake Maracaibo Basin): a synoptic assessment using MODIS and Landsat imagery. Appl. Geogr. 35, 152–163.
Qian, Y.G., Zhou, W.Q., Li, W.F., Han, L.J., 2015a. Understanding the dynamic of greenspace in the urbanized area of Beijing based on high resolution satellite images. Urban For. Urban Green. 14, 39–47.
Qian, Y.G., Zhou, W.Q., Yu, W.J., Pickett, S.T.A., 2015b. Quantifying spatiotemporal pattern of urban greenspace: new insights from high resolution data. Landsc. Ecol. 30, 1165–1173.
Ramos-Gonzalez, O.M., 2014. The green areas of San Juan, Puerto Rico. Ecol. Soc. 19, 7.
Rupprecht, C.D., Byrne, J.A., 2014. Informal urban green-space: comparison of quantity and characteristics in Brisbane, Australia and Sapporo, Japan. PLoS One 9, e99784.
Seto, K.C., Woodcock, C.E., Song, C., Huang, X., Lu, J., Kaufmann, R.K., 2002. Monitoring land-use change in the Pearl River Delta using Landsat TM. Int. J. Remote Sens. 23, 1985–2004.
Sivam, A., Karuppannan, S., Mobbs, M., 2012. How "open" are open spaces: evaluating transformation of open space at residential level in Adelaide – a case study. Local Environ. 17, 815–836.
Smith, M.L., Zhou, W.Q., Cadenasso, M., Grove, M., Band, L.E., 2010. Evaluation of the national land cover database for hydrologic applications in urban and suburban Baltimore, Maryland. J. Am. Water Resour. Assoc. 46, 429–442.
Stefanov, W.L., Ramsey, M.S., Christensen, P.R., 2001. Monitoring urban land cover change: an expert system approach to land cover classification of semiarid to arid urban centers. Remote Sens. Environ. 77, 173–185.
Strohbach, M.W., Lerman, S.B., Warren, P.S., 2013. Are small greening areas enhancing bird diversity? Insights from community-driven greening projects in Boston. Landsc. Urban Plan. 114, 69–79.
Szymanska, D., Lewandowska, A., Rogatka, K., 2015. Temporal trend of green areas in Poland between 2004 and 2012. Urban For. Urban Green. 14, 1009–1016.
Taylor, L., Hochuli, D.F., 2017. Defining greenspace: multiple uses across multiple disciplines. Landsc. Urban Plan. 158, 25–38.
Thompson, C.W., Roe, J., Aspinall, P., Mitchell, R., Clow, A., Miller, D., 2012. More green space is linked to less stress in deprived communities: evidence from salivary cortisol patterns. Landsc. Urban Plan. 105, 221–229.
United Nations. (2014). World urbanization prospects: the 2014 revision highlights. United Nations, New York. https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf United States Conference of Mayors. Protecting and Developing the Urban Tree Canopy: a 135 City Survey. (Washington DC).
Van Den Hoek, J., Ozdogan, M., Burnicki, A., Zhu, A.X., 2014. Evaluating forest policy implementation effectiveness with a cross-scale remote sensing analysis in a priority conservation area of Southwest China. Appl. Geogr. 47, 177–189.
Wang, X.J., 2009. Analysis of problems in urban green space system planning in China. J. For. Res. 20, 79–82.
Wang, J., Zhou, W., Qian, Y., Li, W., Han, L., 2018. Quantifying and characterizing the dynamics of urban greenspace at the patch level: a new approach using object-based image analysis. Remote Sens. Environ. 204, 94–108.
Wolch, J.R., Byrne, J., Newell, J.P., 2014. Urban green space, public health, and environmental justice: the challenge of making cities 'just green enough'. Landsc. Urban Plan. 125, 234–244.
Wold, S., Esbensen, K., Geladi, P., 1987. Principal component analysis. Chemom. Intell. Lab. Syst. 2, 37–52.
Wolf, K.L., Housley, E., 2014. Environmental Equality: Providing Nearby Nature for Everyone. TKF Foundation, Annapolis.
Wu, J.G., 2008. Toward a landscape ecology of cities: beyond buildings, trees, and urban forests. In: Carreiro, M.M., Song, Y.C., Wu, J.G. (Eds.), Ecology, Planning and Management of Urban Forests: International Perspectives. Springer, New York, pp. 10–28.
Wu, J.G., 2013. Landscape sustainability science: ecosystem services and human well-being in changing landscapes. Landsc. Ecol. 28, 999–1023.
Wu, J.G., 2014. Urban ecology and sustainability: the state-of-the-science and future directions. Landsc. Urban Plan. 125, 209–221.
Wu, K.Y., Zhang, H., 2012. Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978–2008). Appl. Geogr. 34, 137–145.
Xu, X., Duan, X., Sun, H., Sun, Q., 2011. Green space changes and planning in the capital region of China. Environ. Manag. 47, 456–467.
Yan, J., Lin, L., Zhou, W., Ma, K., Pickett, S.T.A., 2016. A novel approach for quantifying particulate matter distribution on leaf surface by combining SEM and object-based image analysis. Remote Sens. Environ. 173, 156–161.
Yang, J., Huang, C.H., Zhang, Z.Y., Wang, L., 2014. The temporal trend of urban green coverage in major Chinese cities between 1990 and 2010. Urban For. Urban Green. 13, 19–27.
Yao, L., Chen, L., Wei, W., Sun, R., 2015. Potential reduction in urban runoff by green spaces in Beijing: a scenario analysis. Urban For. Urban Green. 14, 300–308.
Yu, Z., Wang, Y., Deng, J., Shen, Z., Wang, K., Zhu, J., Gan, M., 2017. Dynamics of hierarchical urban green space patches and implications for management policy. Sensors (Basel) 17.
Yuan, F., Sawaya, K.E., Loeffelholz, B.C., Bauer, M.E., 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sens. Environ. 98, 317–328.
Zhang, X.Y., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sens. Environ. 84, 471–475.
Zhang, D., Huang, Q., He, C., Wu, J., 2017. Impacts of urban expansion on ecosystem services in the Beijing-Tianjin-Hebei urban agglomeration, China: a scenario analysis based on the shared socioeconomic pathways. Resour. Conserv. Recycl. 125, 115–130.
Zhao, J., Chen, S., Jiang, B., Ren, Y., Wang, H., Vause, J., Yu, H., 2013. Temporal trend of green space coverage in China and its relationship with urbanization over the last two decades. Sci. Total Environ. 442, 455–465.
Zhou, W.Q., Troy, A., 2008. An object-oriented approach for analysing and characterizing urban landscape at the parcel level. Int. J. Remote Sens. 29, 3119–3135.
Zhou, X., Wang, Y.C., 2011. Spatial–temporal dynamics of urban green space in response to rapid urbanization and greening policies. Landsc. Urban Plan. 100, 268–277.
Zhou, W.Q., Troy, A., Grove, M., 2008. Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data. Sensors 8, 1613–1636.
Zhou, W.Q., Huang, G.L., Pickett, S.T.A., Cadenasso, M.L., 2011. 90 years of forest cover change in an urbanizing watershed: spatial and temporal dynamics. Landsc. Ecol. 26, 645–659.
Zhou, W.Q., Qian, Y.G., Li, X.M., Li, W.F., Han, L.J., 2014. Relationships between land cover and the surface urban heat island: seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. Landsc. Ecol. 29, 153–167.
Zhou, W., Pickett, S.T.A., Cadenasso, M.L., 2017a. Shifting concepts of urban spatial heterogeneity and their implications for sustainability. Landsc. Ecol. 32, 15–30.
Zhou, W., Wang, J., Cadenasso, M.L., 2017b. Effects of the spatial configuration of trees on urban heat mitigation: a comparative study. Remote Sens. Environ. 195, 1–12.
Ziter, C., 2016. The biodiversity-ecosystem service relationship in urban areas: a quantitative review. Oikos 125, 761–768.