Spatial distribution of urban greenspace in response to urban development from a multi-scale perspective

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Abstract

Urban expansion and renewal are one of the major drivers affecting urban landscapes worldwide. Considerable research has been conducted to understand how urban greenspace (UG) changes in response to urbanization at various scales from individual patches to landscapes. However, most of these studies have been conducted at a single scale, and little is known from a multiple scale perspective. Here, we present a multi-scale analytical framework to quantify the spatial pattern of greenspace and its change by integrating rank-size distribution, urban–rural gradient analysis and hotspots analysis. We applied this framework to nine major Chinese cities using 2.5 m resolution Advanced Land Observation Satellite imagery captured in 2005 and 2010. We found the multi-scale assessment provides integrated and synthesized information about the dynamics of UG that would otherwise be missed. First, the hotspots analysis revealed dramatic change in UG for all the nine cities, and such change tended to be spatially clustered. Second, the spatial heterogeneity of UG decreased from 2005 to 2010 for all the cities as a result of the increase of UG in urban core areas and loss of UG in the urban periphery, resulting in landscape homogenization along the urban–rural gradient. Third, substantial loss of UG co-occurred with densification of urban land development, indicating potential adverse impacts of compact city on urban greenery. Infill development became dominant, with percentage ranging from 52.7% in Shanghai to 90.6% in Nanjing, resulting in more compact urban form. This study underscores the importance of a multi-scale perspective on understanding the spatial distribution of UG and its change, and its response to urban development.

1. Introduction

The number of urban dwellers exceeded that of the rural in 2007, and most of the population growth has been concentrated in urban areas since then, resulting in further expansion and/or densification of urban areas (Haaland and van den Bosch 2015, Gao et al 2019). Urban expansion and/or within-urban changes had diverse impacts on urban greenspace (UG) (Erener et al 2012, Zhao et al 2013, Yang et al 2014, Zhou et al 2018). For example, city densification can lead to the removal of greenspace for development on the one hand (Fuller and Gaston 2009, Brunner and Cozens 2013), but can also result in the generation of new greenspace simultaneously due to the high demand of UG in cities (Qian et al 2015, Yu et al 2017). Consequently, UG can be highly dynamic (Qian et al 2015, Zhou et al 2018). Such dynamic can influence its ecosystem services provisions on, for example, urban heat mitigation, air pollution reduction, and storm water runoff interception, which are central to human well-being and urban sustainability (Lo and Jim 2010, Sivam et al 2012, Wolch et al 2014, Zhou et al 2017b, 2018, 2019). Therefore, accurate quantification of the spatial distribution of UG and its change in response to urban development, has attracted...
increasing attention from ecologists and policy makers (He et al. 2019, Pregitzer et al. 2019).

Considerable research has emphasized UG dynamics with urbanization (Fuller and Gaston 2009, Byomkesh et al. 2011, Dallimer et al. 2011, Tang et al. 2012, Kabisch and Haase 2013, Zhao et al. 2013, Yang et al. 2014, Lu et al. 2017). For example, Nowak and Greenfield (2012) showed that tree cover in 17 out of 20 US cities had a decline between 2003 and 2009. Fuller and Gaston (2009) found urban compaction is likely to have a significant impact on UG provision based on their analysis on UG coverage across 386 European cities. Moving beyond the net change at the city scale, Qian et al. (2015) and Zhou et al. (2018) demonstrated high dynamics of UG in urban cores using high resolution imagery. Wang (2018) further identified the change types of UG at the patch level and revealed that almost all UG patches in Beijing experienced different types of changes between 2005 and 2009. These studies can capture where the fine-scale changes of UG occur, but typically do not further explore the spatiotemporal patterns of UG in response to urban development. Additionally, many studies have used landscape metrics along urban–rural gradients to investigate the spatiotemporal pattern of vegetation during urbanization (Kong and Nakagoshi 2006, Zhou et al. 2011, Salvati et al. 2014). These studies, however, mostly focused on a single scale.

Scholars have been increasingly recognized that it’s insufficient to understand ecological processes at one particular scale, due to the cross-scale drivers of change and its impacts (Cash et al. 2006, Mills et al. 2010, Scholes et al. 2013). This might be also true for understanding the spatiotemporal pattern of UG, and its response to urbanization. A multi-scale analysis includes two or more scales at which assessment is conducted simultaneously and relatively independently, but the results are integrated and synthesized to help understand the processes, effects and ecosystem services which operate at multiple scales (Scholes et al. 2013). For example, quantifying the distribution of patch size for UG at the landscape level could reveal the equitable distribution of UG linked to social justice (Watkins et al. 2016). This has the potential to understand the accessibility for local residents to UG. Meanwhile, the urban–rural gradient analysis could relate the spatial pattern of UG to urbanization and determine their influence on ecological attributes of the environment (Weng 2007). Moreover, identifying the hotspots of UG change could reveal the spatial heterogeneity of UG within a city, and further elucidate the effect of urban development on UG (Koprowska et al. 2020). Few studies, however, have attempted to integrate these approaches to provide a multi-scale, and thereby more holistic view on spatial pattern of UG and its change, even though the interaction between various services and benefits from UG in reality are manifold, and appear on different scales from city to specific sites (Demuzere et al. 2014).

Therefore, this study aims to combine different types of analysis at different scales to capture the spatiotemporal pattern of UG in nine Chinese cities, and its response to urban development. Here, we present a multi-scale framework that includes rank-size distribution, urban–rural gradient analysis and hotspots analysis to analyze the spatial pattern of UG. We conducted a comparison study in nine Chinese cities, using 2.5 m resolution Advanced Land Observation Satellite (ALOS) and Systeme Probatoire d’Observation de la Terre (SPOT) image data acquired in 2005 and 2010. Specifically, we first mapped all green patches and calculated the size distribution of UG patches using rank-size law. We then selected landscape metrics and calculated their changes along an urban–rural gradient using 1 km interval ring as the analytical unit. We further applied the hotspots analysis to map the spatial clusters of changes in greenspace within cities using a cell grid of 100 m by 100 m. The results from this study can enhance the understanding of the effects of urban development on greenspace dynamics within cities, and therefore provide insights on urban design and vegetation management.

2. Methods

2.1. Study area

This study focused on nine major Chinese cities, including three cities in the Beijing–Tianjin–Hebei (BTH) megaregion, i.e. Beijing and Tianjin—two municipalities directly under the Central government—and Tangshan; and six cities in the Yangtze River Delta (YRD) urban megaregion, i.e. the municipality of Shanghai, two capital cities of Nanjing and Hangzhou, and Suzhou, Wuxi, Changzhou (figure 1). These two megaregions are the most densely populated areas in China, and are located in the eastern part of North China and the lower reach of Yangtze River in the eastern and coastal part of China, respectively. The total areas of the two megaregions are approximately 215 800 and 103 960 km², with a total population of 111 million (8.07% of the total population of China), 98 million (7.13%) in 2015, respectively. The two megaregions have a total gross domestic product (GDP) of 20 453 billion RMB, accounted for 32.55% of the GDP in China (National Bureau of Statistics of China 2016).

The nine cities all experienced continuous and rapid population growth and economic development, and are facing the challenge of greenspace encroachment by more housing needs, meanwhile the opportunity to new greenspace redistribution for quality of life improvement. Rather than the entire administrative boundaries, the urban cores of nine cities which refer to the most well-developed areas in the city, where UG experienced high dynamics, were taken as study areas. The urban core was defined as the largest continuously developed region in the municipality where most human activities occurred, excluding satellite cities,
towns and villages (Hu et al 2017). The boundary of urban core for each city was delineated based on 30 m resolution land cover classification data. We generated a fishnet with a grid cell of 900 m × 900 m, then identified the grids with more than 50% developed land and dissolved these grids to one big polygon which represented the urban core of the city (Hu et al 2017).

Additionally, the cities in our study were classified to the 'big city' and 'medium-sized city' mainly based on the urban population and urban size. Specifically, the cities with the population >5 million and the size of well-developed area >350 km², including Beijing, Shanghai, Tianjin, Nanjing, Hangzhou, were defined as 'big city'. And the rest were defined as 'medium-sized city' (supplementary table 3 is available online at stacks.iop.org/ERL/15/064031/mmedia).

2.2. Mapping UG within cities based on high resolution imagery

Land cover data were devised from SPOT-5 and ALOS (supplementary table 4). We selected most of the imagery acquired on the dates when vegetation had leaf-on so that the impacts of seasonal difference in vegetation could be largely minimized. The SPOT and ALOS image data were pansharpened, and had a spatial resolution of 2.5 m and radiometric depth of 8 bits. We used an object-based approach to classify the land cover (Zhou and Troy 2008). We firstly segmented image into objects based on the multi-resolution segmentation algorithm, which is a bottom-up region merging technique. Then we classified the objects into four land cover types: vegetation (referred to as UG), impervious surface, water, and bare soil. The accuracies of the land cover classification were assessed by visually referencing to the 1 m spatial resolution imagery from Google Earth™. We generated 300 sample points by a stratified random sampling method in Erdas Imagine, with at least 30 samples for each class. The overall accuracies of the classifications ranged from 81.02% to 96.33%, and the class of greenspace has the user’s and producer’s accuracies ranging from 74.47% to 99.90% (Zhou et al 2018).

2.3. Methods for analysis of UG changes

2.3.1. Rank-size distribution of UG patches

We used ‘rank-size law’ to calculate the size distribution of UG patches, which can test evenness of UG at patch level within cities (Salat et al 2014):
2.3.2. The spatial variation across the urban–rural gradient

We integrated the urban–rural gradient approach with landscape metrics to quantify the spatiotemporal pattern of UG. We chose four landscape metrics, including percentage of UG (PLANDD), patch density (PD), edge density (ED) and landscape shape index (LSI). Landscape metrics were calculated within contiguous rings, at an 1 km interval, along the urban–rural gradient (Larondelle and Haase 2013) (figure 2). When calculating PD, ED and LSI, we excluded those patches that were only partly within a ring to avoid the overestimation of PD and ED. But we include all the green cover when calculating PLAND in each ring.

2.3.3. The hotspots analysis

We created cell grids of 100 m × 100 m for each city to quantify the spatial variation of UG. The change of percent cover of UG for each grid from 2005 to 2010 was (Wang et al 2019):

\[ p_i = \frac{P_{i(k)} - P_{j(k)}}{P_{j(k)}} \times 100, \]

where \( p_i \) is the change ratio for UG in the cell. \( P_{i(k)} \) and \( P_{j(k)} \) stand for the percentage of UG within the kth cell for times i and j, respectively.

We further used Getis-ord hotspots analysis to identify the spatial clusters of greenspace change within cities. Hotspots analysis utilizes a series of weighted features and identifies statistically significant hot spots and cold spots using Getis-Ord Gi* statistic, which calculates the GiszScore and GipValue for the selected parameters (Getis and Ord 1992). In general, hot spots and cold spots have very high or very low (negative) z-scores, with very small p-values, respectively (table 1). Here, we used the percentage of confidence level > 95% to identify hot/cold spots.

2.3.4. Typologies of urban expansion

We classified urban spatial change into three models, namely, leapfrogging, edge-expansion and infilling, and calculated the percentage of each model for each city to quantify the morphology of urban development. We first conducted an overlay operation between the 2005 and 2010 classification maps to identify the patches of newly developed land, and then classify them into one of the three spatial models, following the methods detailed in Xu et al (2007) and Li (2013):

\[ S = L_i / P, \]

where \( L_i \) presents the shared boundary between a newly developed patch and the previously developed patch, and \( P \) is the perimeter of the newly developed patch. The new patches were assigned as the type of ‘Leapfrogging’ when \( S = 0 \), ‘Edge-Expansion’ when \( 0 < S < 0.5 \), and ‘Infilling’ when \( 0.5 < S < 1 \).

Table 1. z-score and p-value in hotspot analysis.

| Gisz-score (standard deviation) | Gip-value (probability) | Confidence level |
|----------------------------------|-------------------------|-----------------|
| (−1.65 or + 1.65)                | <0.10                   | 90%             |
| (−1.96 or + 1.96)                | <0.05                   | 95%             |
| (−2.58 or + 2.58)                | <0.01                   | 99%             |

3. Results

3.1. The evenness of greenspace patches

Figure 3 shows the relative proportions of small and large UG patches. The slopes of the curves (b) for the nine cities were between 0.6671 and 0.8842 (table 2). In 2005, b value of Beijing is the highest (0.8517), followed by Tianjin (0.8316). In contrast, Tianjin has the highest value (0.8842) in 2010, with Wuxi (0.8583) and Suzhou (0.8512) ranking the second and third. The trends of size distribution for greenspace patches differed between big cities and medium-sized cities (figure 3 and table 2). The size distribution of UG patches for the five big cities (except for Tianjin) became more even with the decrease of b values, suggesting that more similar patches in size converged within cities. In medium-sized cities (i.e. Suzhou, Wuxi, Changzhou and Tangshan), however, the
increase of $b$ values revealed a more uneven distribution of UG patches. Meanwhile, the decrease of the large patches and increase of small patches for the four medium-sized cities in 2010 indicated increased fragmentation of UG (figure 3).

### 3.2. The spatial pattern of greenspace along the urban–rural gradient

The percent cover of UG gradually increased with the increase of distance from urban core for both 2005 and 2010. For all the nine cities except for Shanghai, the proportional cover of greenspace in each of the gradient ring became more similar in 2010 compared with 2005, suggesting UG became more evenly distributed along the urban–rural gradient (figure 4(a)). Surprisingly, changes in proportional cover of UG were greater in the urban core area (gradient rings 1–8) than the average change of the entire city for the five big cities (supplementary figure 10). In contrast to percent cover, PD was relatively high in urban core, and then decreased gradually with the increased distance from urban core in both years. It should be

### Table 2. Estimate of size distribution of UG for the nine cities in 2005 and 2010.

| Cities   | 2005          | 2010          |
|----------|---------------|---------------|
|          | $\text{Ln } a$ | $b$           | $R^2$ | Sig. | $\text{Ln } a$ | $b$           | $R^2$ | Sig. |
| Beijing  | 15.154        | 0.8517        | 0.9812 | 0.000 | 14.738 | 0.8022        | 0.9789 | 0.000 |
| Shanghai | 14.466        | 0.7445        | 0.9673 | 0.000 | 14.498 | 0.7365        | 0.9768 | 0.000 |
| Tianjin  | 14.734        | 0.8316        | 0.9826 | 0.000 | 15.273 | 0.8842        | 0.9517 | 0.000 |
| Nanjing  | 13.630        | 0.7179        | 0.9956 | 0.000 | 13.238 | 0.6671        | 0.9792 | 0.000 |
| Hangzhou | 14.011        | 0.7689        | 0.9620 | 0.000 | 13.490 | 0.7069        | 0.9843 | 0.000 |
| Suzhou   | 14.241        | 0.7936        | 0.9591 | 0.000 | 14.573 | 0.8512        | 0.9507 | 0.000 |
| Wuxi     | 13.619        | 0.7525        | 0.9858 | 0.000 | 14.424 | 0.8583        | 0.9573 | 0.000 |
| Changzhou| 13.681        | 0.7293        | 0.9612 | 0.000 | 14.337 | 0.8031        | 0.9784 | 0.000 |
| Tangshan | 12.738        | 0.7338        | 0.9906 | 0.000 | 13.112 | 0.8034        | 0.9561 | 0.000 |
noted that the difference of PD among different gradient rings decreased in 2010 (figure 4(b)). Similarly, ED decreased with the increase of distance from urban core for all the nine cities, suggesting higher degrees of fragmentation closer to urban core in both years (figure 4(c)). LSI exhibited a clear ‘inverse U-shape’ distribution with the urban core and urban periphery having lower values of LSI (figure 4(d)).

The changes of spatial pattern of UG along the urban–rural gradient differed among cities. The mean UG coverage increased in all the rings along the urban–rural gradient in the five big cities, but decreased in the other four medium-sized cities (supplementary figure 10). The PD, ED and LSI in each ring increased in the cities of the YRD megaregion from 2005 to 2010 (see the example of Shanghai in figures 5 and supplementary figure 11), suggesting increased greenspace fragmentation and shape complexity in these cities. But we found these metrics decreased in cities of the BTH megaregion (figure 5 for Beijing and supplementary figure 10), indicating reduced fragmentation and shape complexity of UG.
3.3. Hotspots of UG change within cities

UG coverage increased in over 60% of locations (i.e. grids) in the five big cities. In Beijing and Tianjin, increase in UG coverage had a range of 1%–20%, smaller than that of 1%–40% in Shanghai, Nanjing and Hangzhou. In contrast, the majority of grids (greater than 50%) decreased in the four medium-sized cities. Specifically, approximately 60% of grids decreased, with changes in percent cover ranging from 1% to 100% in Suzhou, Wuxi, and Changzhou, whereas more than 80% of grids in Tangshan decreased, with the magnitude mostly ranging from 1% to 20% (figure 6). Compared with the cities in the BTH megaregion, the cities in the YRD megaregion were more likely to undergo greater change of UG.

The hotspots analysis showed that in the nine cities, changes in UG tended to be clustered in space (figure 7). However, the distribution pattern of spatial clustering differed greatly by cities (figure 7). Specifically, hot spots of UG change in Beijing and Suzhou tended to occur in the urban periphery. In Shanghai, the clusters of increased UG were concentrated in the west of the city, and that of decrease mostly in the urban core and the east of the city. The hot spots of increase in Tianjin were mostly found in the old city center and the Binhai new district, while those in Changzhou was mostly in the urban periphery. Hot spots of UG increase were mostly located in the West Lake, and that of decrease mostly occurred in the east of the city, co-occurring with the eastward urban development. For Nanjing, Wuxi and Tangshan, the hot/cold spots spread out in all directions.

Figure 5. The comparison of the four landscape metrics in 2005 and 2010 for Beijing and Shanghai along the urban–rural gradient.
3.4. Spatial pattern of urban expansion typologies

The magnitude of urban expansion varied greatly by cities. The expansion rate of developed land ranged from 1.38% in Beijing to 11.57% in Changzhou from 2005 to 2010. The greatest increase occurred in the cities of Suzhou, Wuxi, and Changzhou, up to 9.70%, 9.28% and 11.57%, respectively. In contrast, big cities such Beijing and Tianjin had the least growth of developed land, with increase of 1.38% and 3.13%, respectively (figure 8).

All nine cities were dominated by the type of infill development during the study period (figure 9). The type of infill development contributed to 52.71% of the urban land growth in Shanghai, the least among all the cities, and to the maximum of 90.60% in Nanjing, showing the shift of the urban spatial model from edge-expansion and/or leapfrogging to infilling. For example, the type of edge-expansion only accounted for 9.08% in Nanjing, and the maximum of the percentage of the type of leapfrogging among all the cities was 4.33% in Shanghai. But it shall be noted that in cities such as Shanghai and Tianjin, there were still more than 40% of the newly developed urban land resulted from edge-expansion.

4. Discussion

4.1. The importance of multi-scale analysis for UG change

Results from this study show that the integration of approaches focusing different scales can provide a more holistic and comprehensive view on understanding the spatial pattern of UG and its change, and thereby may enhance our understanding on the social and ecological impacts of UG change. Results from rank-size distribution at the patch level showed different trends of changes in UG patches among cities. Big cities tended to have more newly established large patches, but in the four medium-sized cities, large patches were more likely to be fragmented into smaller ones. This is likely due to great effort that has been devoted to increasing the large greenspace patches in big cities such as Beijing and Hangzhou. Two remarkable examples are the Olympic Forest Park in Beijing and the Xixi National Wetland Park in
Hangzhou. It is increasingly recognized that larger patches can support more species and increase the biodiversity, and increase the supply of many other types of ecosystem services (Balvanera et al 2006, Joern and David 2007, Cardinale et al 2012, Mitchell et al 2015). However, the four medium-sized cities still experienced the loss of large patches. Such difference was likely due to the cities being in different phases of urban growth (Deng et al 2008, Yu and Zhou 2017).

Results from the urban–rural gradient approach indicated that UG became more evenly distributed, and the difference of the degree of fragmentation reduced along urban–rural gradient, resulting in homogenization of landscape structure. This result echoes the hypothesis that urban landscapes are becoming homogeneous (Jenerette and Potere 2010, Groffman et al 2014). It shall be noted that the urban–rural gradient analysis conducted in this study that used the 1 km interval buffer is most suitable to monocentric cities such as Beijing and Shanghai, but not for cities with multiple centers, such as the two cities, Hangzhou and Tianjin. Extending the urban–rural gradient approach to be better applicable to these types of cities would be highly desirable in future studies.

The hotspots analysis revealed the spatial clustering of UG, and its relation with urban land change (Ma and Xu 2010, Li et al 2017). Areas clustered with significant loss of UG tended to be where the new urban growth occurred. For example, the hotspots analysis for UG change in Shanghai showed that the decrease of UG were clustered in the east of city (figure 7)—the Pudong New Area where urban expansion mainly occurred (figure 8).

4.2. The implications of urban planning and management

The domain of infilling type of urban growth within cities suggested that the nine major Chinese cities became more compact in terms of spatial growth models. This result was consistent with findings from previous studies that some of the Chinese cities became more compact through infill development (Yu and Zhou 2017). In this study, we only focused on urban expansion in core areas of cities considering the consistency of ecosystem services provision in these densely populated zones. For example, infill development may establish new patches of UG, but unavoidably replace previously existing UG by buildings and pavement, resulting in high turn-over rate of UG (Zhou et al 2018). Although the same amount, or even more of new UG can be generated, which make more urban residents have access and proximity to green space, it does not mean that the same magnitude of ecological function obtained (Yang et al 2014, Sun and Chen 2017,
Wang et al. 2019). Therefore, urban plan and design shall consider the potential risks of losing UG due to infill development in addition to the social and ecological benefits brought about by more compact development (Artmann et al. 2019). Additionally, in terms of urban expansion, the urban forms and changes combining the macro level with micro dynamics should be further studied considering the spatiotemporal interdependences and global-local interactions.

Results of the spatial redistribution of UG associated with urban development indicated that cities are facing both opportunities and challenges for urban sustainability. On the one hand, UG became more evenly distributed along the urban–rural gradient, and thereby could potentially provide better access and more equal opportunities for urban dwellers to enjoy outdoor recreation (Niemelä 2014, Tsai et al. 2016, Balbi et al. 2019). On the other hand, there were greater change in percent cover of greenspace in locations closer to the urban core. Such high dynamism could potentially influence the quality of UG and thereby ecosystem services (Stagoll et al. 2012, Wolch et al. 2014).
Zhou et al. 2017a). For example, the newly created UG patches may have lower quality than the currently/ previously existing ones (Wang et al. 2019), and provide less ecosystem services (Sun and Chen 2017). This warrants further research in the future.

5. Conclusion

A multi-scale, and thereby more holistic view on spatial pattern of UG and its change is crucially important because the generation of such spatiotemporal pattern, and its social and ecological impacts are affected by processes at different scales from local sites to city and beyond. Here, we present a multi-scale framework that includes rank-size distribution, urban–rural gradient analysis and hotspots analysis to analyze the spatial pattern of UG using very high spatial resolution imagery. We found the multi-scale assessment provides integrated and synthesized information about the dynamics of UG that would otherwise be missed. First, the hotspots analysis revealed dramatic change in UG for all the nine cities, and such change tended to be spatially clustered. Second, the spatial heterogeneity of UG decreased from 2005 to 2010 for all the cities as a result of the increase of UG in urban core areas and loss of UG in the urban periphery, resulting in landscape homogenization along the urban–rural gradient. Third, substantial loss of UG co-occurred with densification of urban land development, indicating potential adverse impacts of compact city on urban greenery. This study underscores the importance of a multi-scale perspective on understanding the spatial distribution of UG and its change, and its response to urban development. Future studies that examine the social and ecological impacts of spatial patterns of UG at multiple scales are highly desirable.

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Data availability statements

Any data that support the finding of this study are included within the article.

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