ASSESSING URBAN GREEN SPACE DISTRIBUTION IN A COMPACT MEGACITY BY LANDSCAPE METRICS

Huilin LIANG[a], Di CHEN[b], Qingping ZHANG[a]

*aCollege of Landscape Architecture, Nanjing Forestry University, No. 159, Longpan Road,
Nanjing, Jiangsu, China*
bCollege of Architecture and Urban Planning, Tongji University, No. 1239, Siping Road, Shanghai, China

Abstract. The pattern and structure of urban green space (UGS) plays a significant role in the landscape and ecological quality (LEQ) of UGS, especially in a compact city with limited space. Based on landscape metrics, this study proposes an innovative method to quantify the effects of UGS pattern and structure on LEQ. Taking Shanghai, China as the study area, we calculated all landscape-level spatial metrics in FRAGSTATS, used correlation analysis in SPSS for data reduction, and adopted factor analysis and cluster analysis to statistically analyze the metrics and assesse the LEQ of UGS. These methods bridge the research gap of UGS distribution assessment for LEQ value by landscape metrics. Results showed that new districts usually have higher LEQ of UGS than old towns. Of the 17 districts in Shanghai, Chongming has the highest LEQ of UGS and Hongkou has the lowest. For the UGS pattern and structure, the eight old towns are similar, in contrast to the new districts of Chongming and Pudong, which are more dissimilar than the other districts for LEQ of UGS. The findings could help compact cities having limited UGS to develop and achieve better LEQ.

Keywords: urban green space (UGS), landscape and ecological quality (LEQ), landscape pattern, compact city, landscape metric, environmental sustainability.

Introduction

Urban green space (UGS) is important for urban sustainability (Haq 2011), and provides cities a wide range of ecosystem services (Wolch *et al.* 2014). These spaces may support urban ecological integrity (Andersson 2006), provide food (Groenewegen *et al.* 2006), improve micro-climate regulation (Neuenschwander *et al.* 2014), control pollution (Escobedo *et al.* 2011), filter air (Gill *et al.* 2007), clean water, attenuate noise, and replenish groundwater (Thompson 2002; Sherer 2003; James *et al.* 2009). Considering cities are becoming increasingly hotter, congested, crowded, and polluted (Blanco *et al.* 2009), which could be migrated by UGS, the environment benefits of UGS need more concern and attention for urban sustainability.

Most landscapes provide a multitude of functions (i.e., regulation, habitat, production, information and carrier functions), which have been divided into three types of values: ecological, social-cultural and economic value (de Groot 2006). Urban green space is a spatial structure that is related to various ecological processes (McGarigal,

McComb 1995), and has spatial ecological effects of its landscape patterns and functions within its boundaries and beyond (Chang *et al.* 2011). As remnants of a cultural landscape with rich biodiverse habitats (Barthel *et al.* 2005), UGS provides significant contribution to ecosystem services (Goddard *et al.* 2010). UGS structure is crucial for biodiversity maintenance (Antrop 2005). Moreover, the spatial configuration of UGS significantly affects the magnitude of land surface temperature (Kong *et al.* 2014) and has been used frequently to assess the urban heat island effect (Chen *et al.* 2014). Due to accelerating urbanization in compact cities, urban planners have an imperative to make limited UGS address the deteriorating environmental quality and to provide greater ecological benefits by optimizing UGS distribution. To encourage sensible choices that promote sustainable development, information on the spatial distributions of landscape functions and services is needed (Hermann *et al.* 2014). The ecological value of UGS is determined by the integrity of habitat and regulation functions of UGS according to ecological metrics, such as diversity, complexity and rarity (de Groot *et al.*

Corresponding author: Qingping Zhang
E-mail: Zhangqingping2015@163.com

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2003). Thus assessing UGS structure for landscape and ecological value using relative landscape metrics could promote better urban planning and improve development decision making for landscape protection and improvement (Buyantuyev *et al.* 2010; Wu *et al.* 2011).

A large body of research has tried to analyze and assess UGS structure and pattern based on spatial metrics. Some studies focused on the effects of UGS spatial pattern on land surface temperature by using landscape metrics (Li *et al.* 2012; Hamada *et al.* 2013; Li *et al.* 2013; Kong *et al.* 2014). Some studies focused on the correlation between biodiversity and UGS spatial character based on landscape metrics (Schindler *et al.* 2008; Kong *et al.* 2010; La Rosa *et al.* 2013; Walz 2015). Some studies focused on analyses of specific landscape patterns by using landscape metrics, such as UGS fragmentation (Tian *et al.* 2011; Fan, Myint 2014) and heterogeneity (Plexida *et al.* 2014). Some studies focused on the dynamics of UGS in urbanization using spatial metrics (Zhou, Wang 2011; Byomkesh *et al.* 2012; Qian *et al.* 2015). Compared with other softwares such as Patch Analyst (Rempel *et al.* 1999), APACK (Saura, Torne 2009) and QRULE (Gardner 1999), FRAGSTATS (McGarigal *et al.* 2002) is comprehensive, powerful, easy to use, and is the most widely used package for landscape pattern analysis (McGarigal, McComb 1995; Turner *et al.* 2001). Most of the relevant research used numerous landscape indicators to quantify UGS pattern and structure. However, few studies quantify the effects of UGS pattern and structure on landscape and ecological quality (LEQ); an exception is the research of Tian *et al.* (Tian *et al.* 2014) who selected some landscape indices to analyze the ecological quality of UGS landscape patterns in the compact city of Hong Kong.

To rectify the shortcomings of currently available assessment techniques of UGS landscape and ecological quality, we used multiple software to study the contribution that UGS pattern and structure makes to the LEQ of UGS. The study was conducted on Shanghai, a compact megacity. Our study had three objectives: (1) introduce a new approach for evaluating the contribution of spatial pattern and structure to LEQ of UGS; (2) use the new approach to analyze the structure and distribution of UGS in the compact city of Shanghai; (3) account for the correlation between UGS pattern and distribution and its influences, thereby assisting policy makers and planners to develop intervention programs in UGS planning and development.

1. Materials and methods

1.1. Study area

Shanghai (121°50′E, 31°40′N) is located at the mouth of the Yangtze River (Chang Jiang) (Fig. 1) and is one of the largest and most densely populated cities in China. The
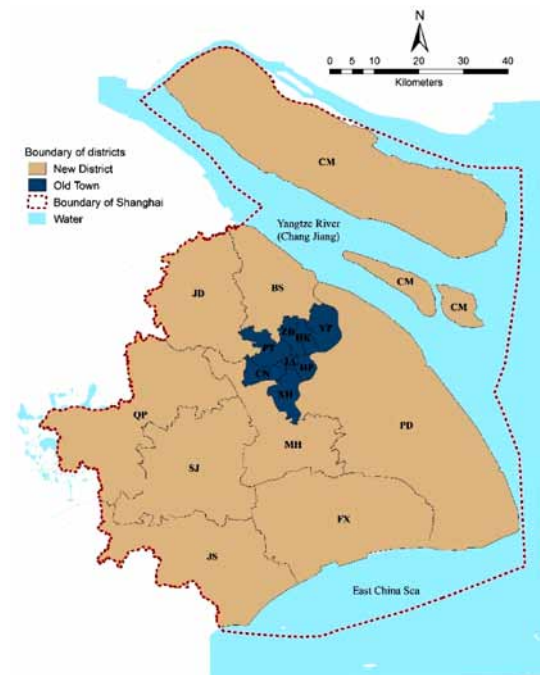
Abbreviation: Huangpu (HP); Xuhui (XH); Changning (CN); Jiang'an (JA); Putuo (PT); Zhabei (ZB); Hongkou (HK); Yangpu (YP); Pudong (PD); Minhang (MH); Baosha (BS); Jiading (JD); Jinshan (JS); Songjiang (SJ); Qingpu (QP); Fengxian (FX); Chongming (CM)

Fig. 1. Study area

city covers an area of 634,050 ha, has a registered population of 18.6 million and consists of 17 districts, including eight old towns and nine new districts (Fig. 1). Belonging to the subtropical moist marine climate zone, the city experiences four distinct seasons and receives sufficient rainfall and large amounts of sunshine. Compared with the cities with more than 300 m² per capita green cover (Fuller, Gaston 2009), such as Liège (Belgium), Oulu (Finland) and Valenciennes (France), the quantity of UGS in Shanghai is really scarce, as its per capita green cover was only 13.38 m² in 2014. Shanghai is a congested and compact megacity with meager ground UGS, and is in great need of enhancing the efficiency with which UGS provides environmental benefits.

1.2. Data preparation

The detailed methodology of this study is shown in Figure 2. The data used in this study were purchased from the Chinese government (http://ngcc.sbsm.gov.cn/). These data included satellite images acquired in 2014 (resolution of 0.5×0.5 m), high quality land-use maps (resolution of 0.5×0.5 m, compiled in 2014), land survey data, and district boundary maps. The UGS in this study included four categories: public green land, forest, garden and agriculture. The boundaries of different land uses (the four UGS categories, as well as water and built-up land) were manually digitized from the high quality land-use
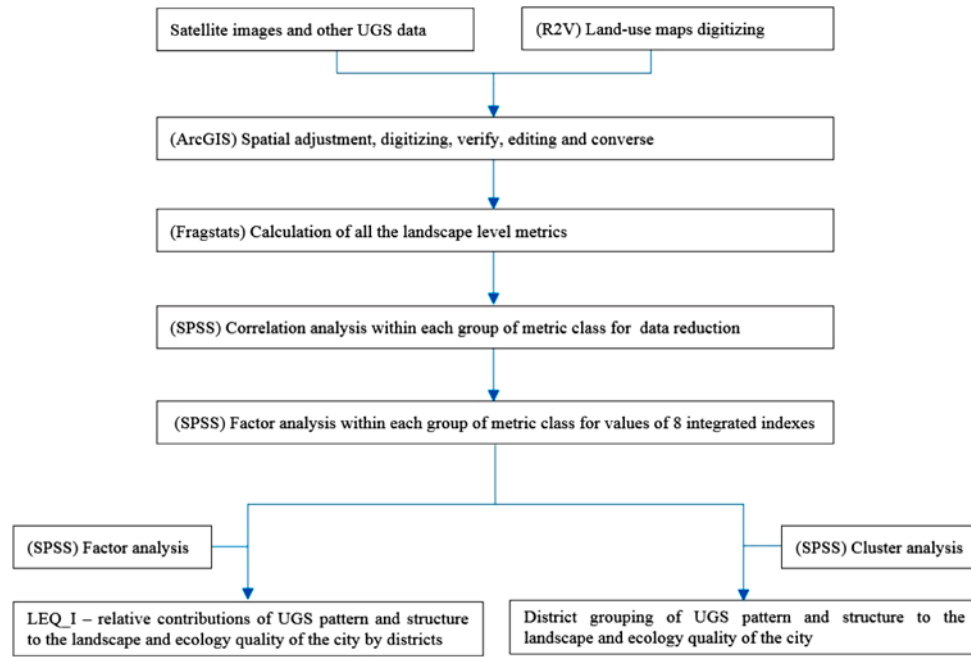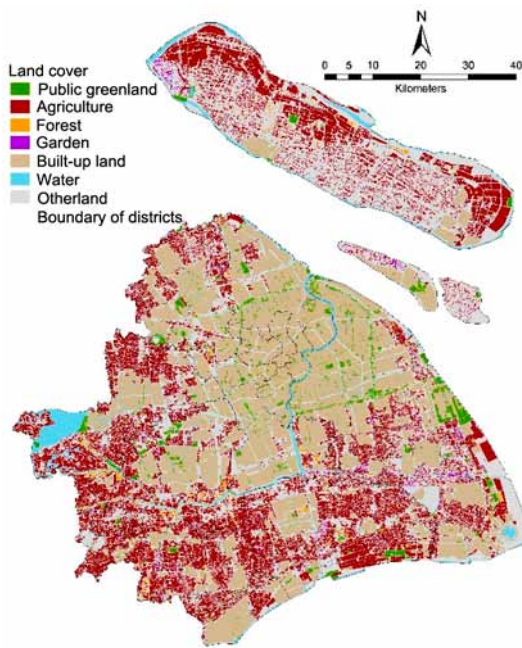
Fig. 2. Methodology chart

Fig. 3. Land use distribution in Shanghai

maps and labeled piece by piece using the software R2V for Microsoft Windows (version 5.5, Able Software Corp., Lexington, MA, USA) to output area feature files (shape-file). These area feature files were input to ArcGIS (version 10.2, ESRI, Redlands, CA, USA) software for spatial adjustment with reference to the satellite images. The satellite images were also visually interpreted and field trips were performed to check, modify, refine and verify the land use data digitized using R2V. All land use data digitized in ArcGIS were assigned a feature property of land use

type (public green land, forest, garden, agriculture, water, built-up land or other land) and a corresponding type ID (Fig. 3). The combined "layer" with all seven land use data and different type IDs was converted from a feature to a raster format in ArcGIS and output as TIFF files of 17 districts with a cell size of 5 m, which was suitable for processing using the FRAGSTATS software.

1.3. Landscape metric calculation

For greater number of indices, the software of FRAG-STATS (version 4.2) was used in this research for landscape metric calculation. To quantify the landscape pattern and green structure of the city, all the 116 landscape metrics at the landscape level in FRAGSTATS were chosen to analyze the land use pattern of UGS by district. The metrics calculated include eight categories, e.g. area, shape, edge and contrast, core area, proximity, subdivision, contagion, and diversity (Table 1). Detailed information for the calculated metrics can be found elsewhere (McGarigal *et al.* 2012).

Table 1. Landscape metrics calculated in Fragststs (McGarigal *et al.* 2012)

Class	Acronym	Metric name
Area	TA	Total area
	LPI	Large patch index
	AREA	Mean patch area
	GYRATE	Radius of gyration
Shape	PAFRAC	Perimeter-area fractal dimension

End of Table 1

Class	Acronym	Metric name
	PARA	Perimeter-area ratio
	SHAPE	Shape index
	FRAC	Fractal dimension index
	CIRCLE	Related circumscribing circle
	CONTIG	Contiguity index
Edge & Contrast	TE	Total edge
	ED	Edge density
	CWED	Contrast-weighted edge density
	TECI	Total edge contrast index
	ECON	Edge contrast index
Core area	TCA	Total core area
	NDCA	Number of disjunct core area
	DCAD	Disjunct core area density
	CORE	Core area
	DCORE	Disjunct core area
	CAI	Core area index
Proximity	ENN	Euclidean nearest neighbor distance
	PROX	Proximity index
	SIMI	Similarity index
	CONNECT	Connectance index
Subdivision	NP	Number of patches
	PD	Patch density
	DIVISION	Landscape division index
	SPLIT	Splitting index
	MESH	Effective mesh size
Contagion/ Interspersion	CONTAG	Contagion
	IJI	Interspersion juxtaposition index
	PLADJ	Proportion of like adjacencies
	AI	Aggregation index
	LSI	Landscape shape index
	COHESION	Patch cohesion index
Diversity	PR	Patch richness
	PRD	Patch richness density
	RPR	Relative patch richness
	SHDI	Shannon's diversity index
	SIDI	Simpson's diversity index
	MSIDI	Modified Simpson's diversity index
	SHEI	Shannon's evenness Index
	SIEI	Simpson's evenness index
	MSIEI	Modified Simpson's evenness index

1.4. Statistical analysis

Using the FRAGSTATS calculations of all 116 landscape-level UGS metrics for each of 17 districts as a basis, statistical analyses were conducted using the software SPSS (version 22, IBM Corp., Armonk, NY, USA) for the assessment of UGS pattern and structure. Correlation analysis was used within each class of landscape metrics for data reduction. Spearman's rank correlation coefficient (r_s) was calculated for all pairwise correlations among the variables (i.e., the metrics in this study) in each class of the pairs of metrics having a rank correlation coefficient equal to or higher than 0.9 ($|r_s| \geq 0.9$), only one metric was retained (Griffith *et al.* 2000; Torras *et al.* 2008). For the pairs of highly correlated metrics, the metrics commonly used in greenspace pattern analysis literature were selected.

After data reduction, factor analysis (Riitters *et al.* 1995) was performed for the remaining metrics within each group for different metric classes. By using the extraction method of principal component analysis, the varimax rotation method with Kaiser normalization, and the factor-score calculation method of regression, additional variances, non-correlated factors, component score coefficients, and regression factor scores were obtained. Then the integrated index value of each metric class by district was formulated as Eqs (1)–(8).

$$ARE\_I_d = \sum_{i=1}^{n} \left(ARE\_E_{di} \times ARE\_FS_{di} \right). \tag{1}$$

Equation (1) yields the index value for area (*ARE*) in a given district *d*; I_d is the integrated index value of each metric class; E_{di} is the eigenvalue of each component; and FS_{di} is the regression factor score of each factor. Eqs (2)–(8) yield index values for edge and contrast (*EDG*), shape (*SHA*), core area (*COR*), proximity (*PRO*), subdivision (*SUB*), contagion (*CON*) and division (*DIV*).

$$EDG\_I_d = \sum_{i=1}^{n} \left(EDG\_E_{di} \times EDG\_FS_{di} \right); \tag{2}$$

$$SHA\_I_d = \sum_{i=1}^{n} \left(SHA\_E_{di} \times SHA\_FS_{di} \right); \tag{3}$$

$$COR\_I_d = \sum_{i=1}^{n} \left(COR\_E_{di} \times COR\_FS_{di} \right); \tag{4}$$

$$PRO\_I_d = \sum_{i=1}^{n} \left(PRO\_E_{di} \times PRO\_FS_{di} \right); \tag{5}$$

$$SUB\_I_d = \sum_{i=1}^{n} \left(SUB\_E_{di} \times SUB\_FS_{di} \right); \tag{6}$$

$$CON\_I_d = \sum_{i=1}^{n} \left(CON\_E_{di} \times CON\_FS_{di} \right); \tag{7}$$

$$DIV\_I_d = \sum_{i=1}^{n} \left(DIV\_E_{di} \times DIV\_FS_{di} \right). \tag{8}$$

Table 2. Landscape metrics selected after data reduction

Class (number of metrics)	Landscape metric (acronym)
Area (8)	Total area (TA); Large patch index (LPI); Mean patch area (AREA_MN); Area-weighted mean patch area (AREA_ AM); Median patch area (AREA_MD); Mean radius of gyration (GYRATE_MN); Standard deviation in radius of gyration (GYRATE_SD); Coefficient of variation in radius of gyration (GYRATE_CV)
Shape (19)	Perimeter-area fractal dimension (PAFRAC); Area-weighted mean perimeter area ratio (PARA_AM); Median perimeter area ratio (PARA_MD); Range in perimeter area ratio (PARA_RA); Mean shape index (SHAPE_MN); Area-weighted mean shape index (SHAPE_AM); Median shape index (SHAPE_MD); Range in shape index (SHAPE_RA); Standard deviation shape index (SHAPE_SD); Mean fractal dimension index (FRAC_MN); Area-weighted mean fractal dimension index (FRAC_AM); Median fractal dimension index (FRAC_MD); Range in fractal dimension index (FRAC_RA); Standard deviation in fractal dimension index (FRAC_SD); Area-weighted mean related circumscribing circle (CIRCLE_AM); Median related circumscribing circle (CIRCLE_MD); Standard deviation in related circumscribing circle (CIRCLE_SD); Coefficient of variation in related circumscribing circle (CIRCLE_CV); Area-weighted mean contiguity index (CONTIG_AM)
Edge & Contrast (3)	Edge density (ED); Range in edge contrast index (ECON_RA); Coefficient of variation in edge contrast index (ECON_CV)
Core area (9)	Total core area (TCA); Disjunct core area density (DCAD); Mean core area (CORE_MN); Median core area (CORE_MD); Standard deviation in core area (CORE_SD); Coefficient of variation in core area (CORE_CV); Median disjunct core area (DCORE_MD); Range in core area index (CAI_RA); Standard deviation in core area index (CAI_SD)
Proximity (10)	Mean Euclidean nearest neighbor distance (ENN_MN); Median Euclidean nearest neighbor distance (ENN_MD); Range in Euclidean nearest neighbor distance (ENN_RA); Standard deviation in Euclidean nearest neighbor distance (ENN_SD); Coefficient of variation in Euclidean nearest neighbor distance (ENN_CV); Mean proximity index (PROX_MN); Area-weighted mean proximity index (PROX_AM); Median proximity index (PROX_ MD); Coefficient of variation in proximity index (PROX_ CV); Connectance index (CONNECT)
Subdivision (4)	Number of patches (NP); Patch density (PD); Splitting index (SPLIT); Effective mesh size (MESH)
Contagion/ Interspersion (4)	Contagion (CONTAG); Aggregation index (AI); Landscape shape index (LSI); Patch cohesion index (COHESION)
Diversity (2)	Patch richness (PR); Patch richness density (PRD)

With the eight integrated index values of each metric class by district obtained above, factor analysis was performed again to get the integrated index value of all metric classes by district for *UGS* pattern and structure analysis among the 17 districts. The integrated index value of *UGS* was formulated as Eq. (9):

$$LEQ\_I_d = \sum_{i=1}^{n}\left(UGS\_E_{di} \times UGS\_FS_{di}\right), \qquad (9)$$

where in a given district d, LEQ_I_d is the integrated index value of all metric classes.

To further analyze and compare the UGS pattern and structure of different districts, hierarchical cluster analysis of all the integrated index values of different metric classes by district was performed. In the analysis, centroid clustering and squared Euclidean distance were used to group the districts for which integrated index values were related and similar.

2. Results

2.1. UGS distribution by district

The area of different types of UGS by districts was shown in Figure 3, which presents the general characteristics of UGS distribution for different types in different districts in Shanghai. Areas of the four types of UGS in new districts of the city are all significantly larger than that in old towns. Pudong has a larger area of public green land, forest and garden than most of the other districts. Chongming has a larger area of forest, garden and agriculture than most of the other districts. Baoshan and Minhang have less forest, garden and agriculture area than the other new districts.

2.2. UGS pattern and structure characteristics by metric class

Using the correlation analysis procedure within each metric class, 1029 metric correlations were examined for all pairs of metrics within all groups, of which 143 were found to be significant ($|r_s| \geq 0.9$). Through data reduction, the original set of landscape-level metrics was reduced from 116 to 59 (Table 2). The integrated scores of each landscape metric class by district, obtained through factor analyses of the 59 selected metrics within eight groups, are given in Figure 4, which shows the relative contributions of different aspects of UGS pattern and structure to the LEQ of UGS in different districts.

The new districts usually have higher LEQ of UGS subdivision, core area, and patch edge and contrast than the old towns (Fig. 4). Of the 17 districts, Fengxian and Jinshan have the highest LEQ of UGS patch edge and contrast and the eight old towns all have the lowest quality. Pudong has the highest LEQ of UGS subdivision and Changning has the lowest. Chongming has the highest LEQ of UGS core area and Jing'an has the lowest. Thus,

the relative contributions of UGS patch subdivision, core area and edge to LEQ of UGS in new districts has been improved through district development. Furthermore, the characteristics of UGS patch edge in old towns are exactly the same.

In contrast, the new districts usually have lower LEQ of UGS diversity than the old towns (Fig. 4). Of the 17 districts, Jing'an has the highest LEQ of UGS diversity and the nine new districts all have much lower values, which are similar to each other. Although new districts generally have higher patch richness (PR) of UGS than the old towns, the patch richness density (PRD) of UGS in districts is much lower than in the old towns. Thus, the relative contributions of UGS diversity to LEQ of UGS have been lowered due to district development; the mono-distribution of UGS type might be the primary cause.

There were no significant difference of LEQ of UGS area, shape, proximity and contagion metrics between new districts and old towns. Of the 17 districts, Chongming has the highest LEQ of UGS area and Minhang has the lowest. Changning has the highest LEQ of UGS shape and Jing'an has the lowest. Jing'an has the highest LEQ of UGS proximity and Fengxian has the lowest. Chongming has the highest LEQ of UGS contagion and Huangpu has the lowest. Thus, the relative contributions of UGS area, shape, proximity and contagion metrics to LEQ of UGS are not directly related to district development, although some indexes of these four groups are related to district development.

2.3. LEQ of UGS by district

Tables 3 and 4 show results of factor analysis of the eight integrated indexes for the 17 districts. Three notable components were extracted, with the first contributing 45.38% variance of initial eigenvalues, the second contributing 26.03%, and the third contributing 18.66%. The first component was characterized by a high negative loading of DIV_I and high positive loading of EDG_I and SUB_I. Thus, the first component represents the LEQ of UGS in new districts. The second component was characterized
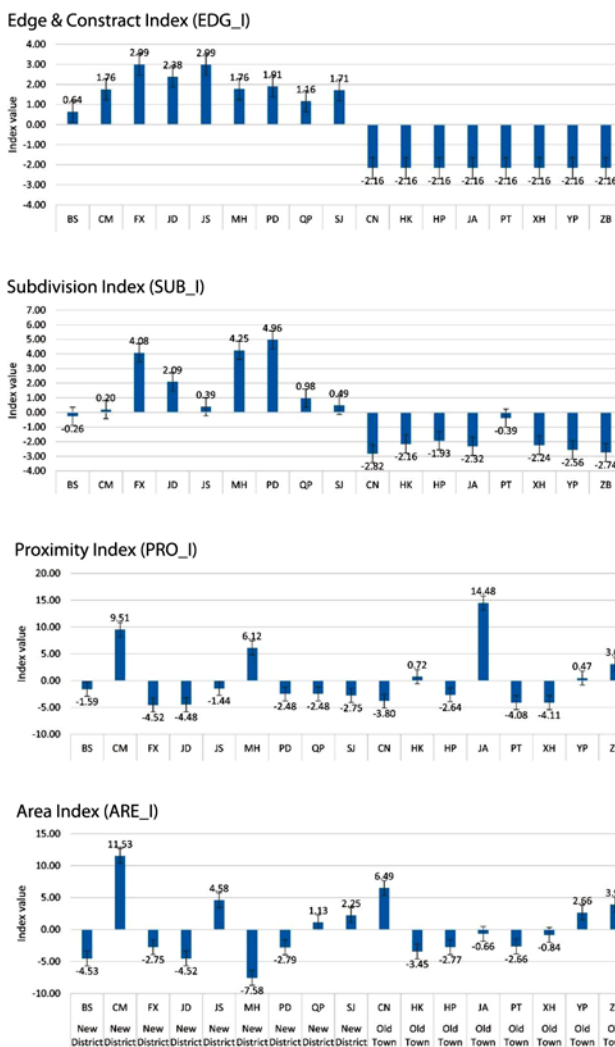
Note. The abbreviations of districts are explained in Figure 1.

Fig. 4. Index value of each metric class by district

by a high positive loading of ARE_I, CON_I and COR_I. Thus, the second component represents the UGS having large area in old towns. The third component was characterized by a high positive loading of PRO_I and high negative loading of SHA_I, and was correlated to UGS with small area in old towns.

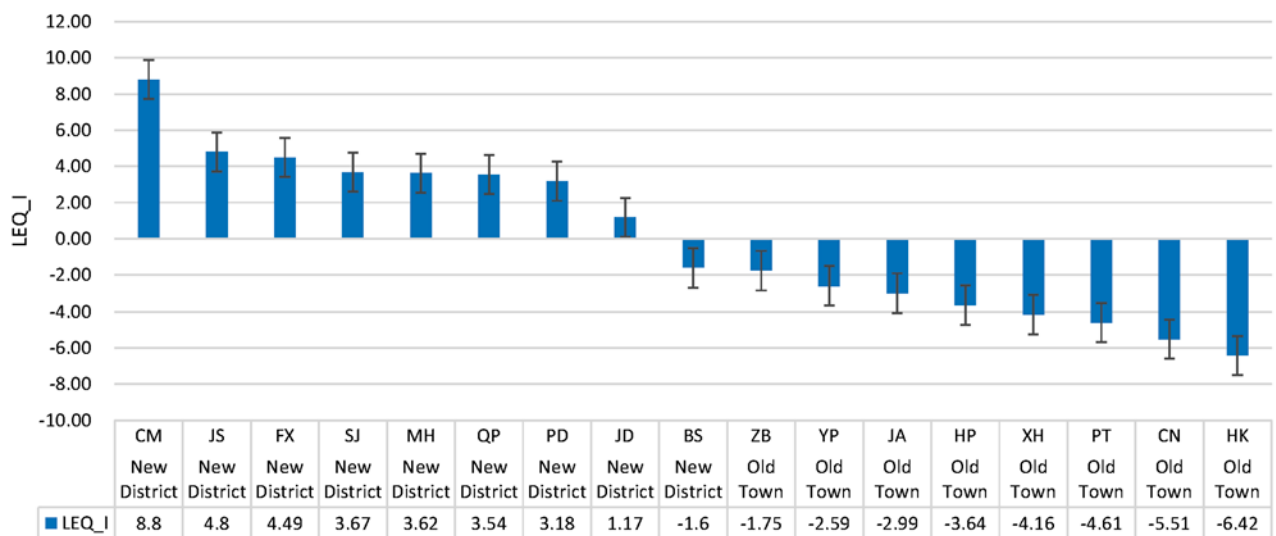Figure 5 shows the relative contributions of UGS pattern and structure to the LEQ of the city by district.

Table 3. Factor loadings in factor analysis with varimax method

Com-ponent	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Va-riance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.630	45.376	45.376	3.630	45.376	45.376	2.951	36.889	36.889
2	2.082	26.028	71.405	2.082	26.028	71.405	2.551	31.892	68.781
3	1.493	18.664	90.069	1.493	18.664	90.069	1.703	21.288	90.069
4	0.457	5.712	95.780	–	–	–	–	–	–
5	0.171	2.141	97.921	–	–	–	–	–	–
6	0.110	1.374	99.295	–	–	–	–	–	–
7	0.039	0.481	99.776	–	–	–	–	–	–
8	0.018	0.224	100.000	–	–	–	–	–	–

Table 4. Rotated component matrix and variance explained for UGS pattern and structure characteristics for 17 districts in Shanghai

Integrated index for each metric category	Component		
	1	2	3
ARE_I	−0.282	0.919	0.186
CON_I	0.285	0.921	−0.017
COR_I	0.454	0.808	−0.252
DIV_I	−0.873	−0.338	0.286
EDG_I	0.939	0.243	0.007
PRO_I	−0.173	0.017	0.869
SHA_I	−0.042	0.014	−0.876
SUB_I	0.953	−0.181	0.001

Note. Italic numbers indicate component loadings >|0.8|. Components are characterized by the corresponding integrated indexes with bold number. The metrics class abbreviations are explained in methods part.

	CM New District	JS New District	FX New District	SJ New District	MH New District	QP New District	PD New District	JD New District	BS New District	ZB Old Town	YP Old Town	JA Old Town	HP Old Town	XH Old Town	PT Old Town	CN Old Town	HK Old Town
LEQ_I	8.8	4.8	4.49	3.67	3.62	3.54	3.18	1.17	-1.6	-1.75	-2.59	-2.99	-3.64	-4.16	-4.61	-5.51	-6.42

Note. The abbreviations of districts are explained in Figure 1. "LEQ_I" is explained in methods part.

Fig. 5. Landscape ecological quality index values for districts in Shanghai

The new districts usually have higher LEQ of UGS than the old towns. Of the 17 districts, Chongming has the highest LEQ of UGS and Hongkou has the lowest. The contribution of UGS pattern and structure to the LEQ of the city has been improved due to district development.

The district group results from cluster analysis of selected metrics are shown in Figure 6. Rescaled distance equal to "5" was considered suitable for grouping the districts into clusters. Three clusters were identified that represented different characteristic UGS patterns and structures of districts. The first cluster is related to the eight old towns in Shanghai. The third cluster is related to the new districts of Chongming and Pudong. The second cluster is related to the remaining seven new districts. Thus, the eight old towns are similar in their UGS pattern and structure, as are most of the new districts (except Chongming and Pudong). The new districts of Chongming and Pudong are dissimilar from all other districts (new and old) for LEQ of UGS.

2.4. LEQ of UGS and per capita green cover

Figure 7 shows the paradoxical relationships between LEQ_I and per capita green cover. Green cover in the figure refers to public green land and forest. It seems a positive relationship between LEQ_I and per capita green cover, as new districts have both higher green cover per capita and better UGS LEQ than old towns. This phenomenon seems conceivable and reasonable. However, the relationship between LEQ_I and per capita green cover within the group of new districts or old towns pretended to be negative. For new districts, as green cover per capita increases, LEQ_I decreases. For old towns except Hongkou, as green cover per capita increases, LEQ_I decreases. This phenomenon might be counterintuitive. It showed that
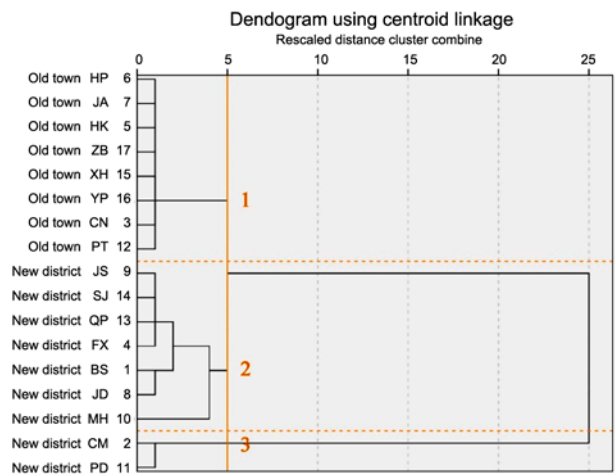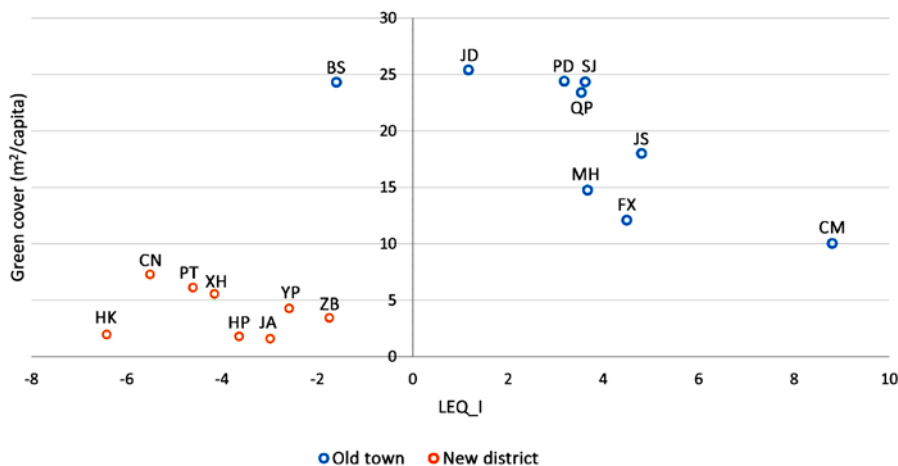

Note. The abbreviations of districts are explained in Figure 1.
Fig. 6. Cluster analysis of selected metrics

districts of the same development with lower green cover per capita usually have better UGS LEQ.

3. Discussion

In the calculation of integrated landscape metrics, because of agriculture, forest and garden UGS types, the new districts usually have more types of UGS, especially for agriculture. Agricultural and forested lands usually occur as discrete, large areas distributed within districts. Thus, although new districts have more UGS types than old towns, the new districts also have lower patch richness density (PRD) and lower LEQ of UGS diversity.

In the pattern characteristic grouping of the districts, the fact that the eight old towns have similar character in integrated landscape metrics might be because they underwent a similar complex development process that resulted in a similar UGS quantity and distribution pattern.

Note. The abbreviations of districts are explained in Figure 1. "LEQ_I" is explained in methods part.
Fig. 7. UGS LEQ and per capita green cover

That the seven new districts (except Chongming and Pudong) have similar character in integrated landscape metrics might be because they are similar in area (which is larger than other districts), with fewer restrictions posed by constructed buildings and with more agricultural and forested land. Chongming and Pudong are distinctive in UGS character, but for different reasons. Chongming is the least developed district in Shanghai and has a large area and the most agriculture. Conversely, Pudong is the most developed district, encompassing a large area with the most public green land in Shanghai.

The fact that the new districts have higher LEQ_I and per capita green cover than the old towns indicates that the causes of UGS in new districts with higher LEQ include both quantity and distribution of UGS. The negative relationship between LEQ_I and per capita green cover among both new districts and old towns indicates that the distribution of UGS largely determines its LEQ in these districts without a significant difference in quantity of UGS. Of the new districts, Chongming has the highest LEQ_I for UGS but lowest per capita green cover. This relationship might arise because per capita green cover is defined by per capita public green land cover and excludes agricultural land; Chongming has much more agriculture than the other districts. Of the old towns, Hongkou has lower LEQ_I and per capita green cover than the other districts indicating that both quantity and distribution of UGS are the causes of its lower LEQ. Thus, Hongkou not only needs to increase UGS (especially public green land) but also needs to optimize the distribution and structure of UGS.

This study provides some important contributions to the assessment of UGS. It fills a gap in the scientific literature by assessing the LEQ of UGS by qualification of UGS pattern on the basis of spatial metrics. Because a single landscape metric is inadequate, indices are related; thus, redundant information in multiple indices must be abridged for effective UGS pattern measurement, and selection of appropriate metrics is crucial. Previous studies identified some important landscape metrics for calculation by subjective factors (Zhou, Wang 2011; Tian *et al.* 2014). In contrast, this study calculated all indices using the FRAGSTATS software and selected appropriate metrics objectively through correlation analysis. This procedure not only ensures data integrity, but also avoids data redundancy using objective criteria. By employing factor analyses twice, this improved procedure reduced the data dimension of landscape indices to quantify UGS pattern and structure for each district. Therefore, this method provides a direct comparison of UGS LEQ among 17 districts. Moreover, by cluster analysis of all the integrated indexes of metric classes, the grouping analysis of UGS pattern and structure of the 17 districts also avoided the use of subjective factors.

However, this study has some limitations. It focused on one point in time instead of several times. Thus, the results can be used to reflect and analyze only the present situation, not the evolution of UGS pattern over time. For a time-evolution analysis, the statistical changes of UGS landscape metrics over a number of years are needed, requiring UGS measurements at multiple points in time. Thus, future studies should include data from multiple time points to obtain a more comprehensive understanding of UGS evolution over time in a compact city.

Conclusions

In summary, this research developed an improved method for UGS LEQ assessment and used the method to analyze UGS distribution, pattern and structure for the megacity of Shanghai. In addition, the study provides valuable insights for policy makers and planners striving to develop an ecological and sustainable city with limited UGS. Results from the research justify the following conclusions. The relative contributions of UGS area, shape, proximity and contagion metrics to LEQ of UGS are not directly related to district development. New districts usually have higher LEQ of UGS than the old towns. However, for new districts and old towns respectively, districts with lower green cover per capita have better UGS LEQ. These results of the study in the compact city (e.g., Shanghai) not only assist in identifying the strengths and weaknesses of UGS distribution, pattern and structure, but also in optimizing UGS pattern and distribution to improve LEQ of UGS.

Author contributions

Conceived and designed the experiments: HL. Performed the experiments: HL DC. Analyzed the data: HL. Contributed materials/analysis tools: QZ. Contributed to the writing of the manuscript: HL. Revised and approved the final version of the paper: HL QZ.

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Huilin LIANG. Affiliation: College of Landscape Architecture, Nanjing Forestry University, Nanjing, Jiangsu, China. Scientific degree: Master's degree. Research interests: Environmental sustainability; Landscape management; Landscape planning. Number of publications: 3. Number of attended conferences: 2.

Di CHEN. Affiliation: College of Architecture and Urban Planning, Tongji University, Shanghai, China. Scientific degree: Master's degree. Research interests: Landscape management; Landscape planning. Number of publications: 5. Number of attended conferences: 2.

Qingping ZHANG. Affiliation: College of Landscape Architecture, Nanjing Forestry University, Nanjing, Jiangsu, China. Scientific degree: PhD. Research interests: Environmental sustainability; Landscape management; Landscape planning. Number of publications: 23. Number of attended conferences: 16.