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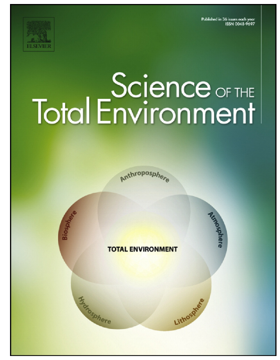

Measuring spatio-temporal heterogeneity and interior characteristics of green spaces in urban neighborhoods: A new approach using gray level co-occurrence matrix

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Title: Measuring spatio-temporal heterogeneity and interior characteristics of green spaces in urban neighborhoods: A new approach using gray level co-occurrence matrix

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Abstract

Urban green space (UGS) is a complex and highly dynamic interface between people and nature. The existing methods of quantifying and evaluating UGS are mainly implemented on the surface features at a landscape scale, and most of them are insufficient to thoroughly reflect the spatial-temporal relationships, especially the internal characteristics changes at a small scale and the neighborhood spatial relationship of UGS. This paper thus proposes a method to evaluate the internal dynamics and neighborhood heterogeneity of different types of UGS in Leipzig using the grey level co-occurrence matrix (GLCM) index. We choose GLCM variance, contrast, and entropy to analyze five main types of UGS through a holistic description of their vegetation growth, spatial heterogeneity, and internal orderliness. The results show that different types of UGS have distinct characteristics due to the changes of surrounding buildings and the distance to the built-up area. Within a one-year period, seasonal changes in UGS far away from built-up areas are more obvious. As for the larger and dense urban forests, they have the lowest spatial heterogeneity and internal order. On the contrary, the garden areas present the highest heterogeneity. In this study, the GLCM index depicts the seasonal alternation of UGS on the temporal scale and shows the spatial form of each UGS, being in line with local urban planning contexts. The correlation analysis of indices also proves that each type of UGS has its distinct temporal and spatial characteristics. The GLCM is valid in assessing the internal characteristics and relationships of various UGS at the neighborhood scales, and using the methodology developed in our study, more studies

and field experiments could be fulfilled to investigate the assessment accuracy of our GLCM index approach and to further enhance the scientific understanding on the internal features and ecological functions of UGS.

Keywords: Urban green space; urban planning; spatial heterogeneity; internal orderliness; RapidEye data, vegetation management

Highlights (4-5)

- The exploration of internal dynamics and heterogeneity in UGSs at a fine scale is limited.
- GLCM index quantifies the vegetation growth, heterogeneity and textural regularity of UGSs.
- Gardens show the greatest spatial heterogeneity, while urban forests have the lowest.
- Each type of UGS has unique and distinctive spatio-temporal characteristics.
- The spatial and texture analysis of UGSs provide evidence for their fine-scale management.

1. Introduction

Urban green space (UGS) refers to the sum of the land and open space covered by vegetation in the urban planning area, including urban forests, parks, residential green spaces, and other open spaces (Kabisch et al., 2016). UGS plays an extremely important role in maintaining, improving the urban environments and the quality of human settlements and cities' livability. UGS can provide multiple benefits to nature and people (Wang et al., 2022), including air purification (Parsa et al., 2019; Xu et al., 2020;), climate change adaptation and mitigation (Gage and Cooper, 2017; Zhou and Cao, 2020), water quality improvement (Decina et al., 2020), stormwater runoff reduction (Kuehler et al., 2017; Machado et al., 2019), biodiversity conservation (Sandström et al., 2006), the removal of air pollution (Selmi et al., 2016) andnoise abatement (Gidlöf-Gunnarsson and Öhrström, 2007), as well as contributing to the social and psychological well-being of residents throughreducing in the possibilities ofdepression, anxiety, and body mass(Soga et al., 2017). ,The production of these benefits is affected by the growth and physiological functions of the plants in the urban ecosystem, as well as by the social-ecological environment that exists in the UGS (Lin et al., 2019; Sonti, 2019). Therefore, the study of UGS is of practical value for the prediction and intervention of these benefits (Li et al., 2019). However, as a dynamic social ecosystem (Johnson et al., 2020; Ogden et al., 2019), the complexity of UGS increases the difficulty of understanding and modeling the relationships between landscape structure and ecological functions. Therefore, an accurate and effective method to discover the spatio-temporal landscape characteristics of

UGS is crucial to solving the unique characteristics and scale requirements of the urban environment (McDonnell and MacGregor-Fors, 2016).

In recent years, many studies based on hyperspectral remote sensing have developed methods to quantify and evaluate UGS (Liu et al., 2021; Qian et al., 2015; Shekhar and Aryal, 2019). Vegetation has always been the focus of UGS evaluation (Wania and Weber, 2007), in addition, a series of UGS characteristics such as size, shape, connectivity, composition, and configuration have also been discussed extensively (Grafius et al., 2018; Harris et al., 2018; Jaganmohan et al., 2016; Rudd et al., 2002; Schipperijn et al., 2010; Yu et al., 2020). However, in addition to the quantification of surface features, process characteristics should be used as the basis for quantitative analysis of landscapes, especially time and scale (Lausch et al., 2015). On the one hand, the current research on UGS at the landscape scale mainly focused on vegetation structure and composition (Templeton et al., 2019), although the connectivity (Pirnat and Hladnik, 2016) and fragmentation (Gong et al., 2013) have been widely discussed, there is still a lack of continuous landscape patterns measurements (Park and Guldmann, 2020), such as spatial heterogeneity measurement (Fan and Myint, 2014; Lausch et al., 2015), especially mosaic gradient landscapes composed of heterogeneous land cover in cities and suburbs (Van de Voorde et al., 2011), such continuous or discontinuous forest patches generally exist in cities and even national regions(Salvati et al., 2017). Relying on broad and common methods and indicators to conceptualize the ecological significance of urban characters may oversimplify the relationship between urban ecosystem functions and landscape structure (Park and Guldmann, 2020). On the other hand, the existing studies on the time scale of UGS are more like a reflection of the construction and decline of green space (Derkzen et al., 2015; Liu et al., 2021; Wang et al., 2019). They usually evaluate the land use of UGS, rather than the interference and management of human activities on green spaces. Although the concept of neighborhood interaction between adjacent land use types is well-known (Fujita et al., 1999), most of the public managers, policymakers or scientists and their UGS evaluation still relies on land use size and vegetation richness (Annerstedt van den Bosch et al., 2016; Kabisch et al., 2016; Wu et al., 2019), overlooking the fact that the same land-use type could show a variety of spatial and temporal characteristics within different surrounding environments. For example, UGS presents a diversity green index for different building types and for the same land use such as forests, the green index substantially varies (Gupta et al., 2012; Liu et al., 2016). With the development of the sustainable city, green space provision is a dauting challenge particularly in compact cities (Haaland and van den Bosch, 2015). Although UGS assessment has been mostly carried out at the landscape level rather than at the local site scale (Daniels et al., 2018), the research on different types of green space, especially on a small scale, can better reflect the diversity of ecosystem services (Kondo et al., 2018; Pueffel et al., 2018; Xiao et al., 2018) and differentiation of human management (Aronson et al., 2017). At present, there is little research on these small patches (Wang et al., 2021), which necessitates more detailed analysis with abundant data sources

(Feltynowski et al., 2018). From this perspective, a method that can reflect the spatial heterogeneity of UGS and simultaneously demonstrate the intensity of human activities on a small scale is significant

Successful management of UGS to ensure they sustainably provide ecosystem services requires timely, accurate, and abundant information to understand the ecological processes and neighbors relationships of forest patches on different temporal and spatial scales (Bartesaghi-Koc et al., 2019; Shive et al., 2018). In urban ecosystemsmapping, many popular vegetation indices have been used to extract the spatial information of urban greenery, including Normalized difference vegetation index (NDVI) proposed by Tucker (1979), Leaf area index (LAI) proposed by Chen and Black (1992), Green normalized difference vegetation index (gNDVI) proposed by Gitelson et al., (1996), and the GLCM (Haralick et al., 1973). Among them, GLCM has fewer applications, despite some studies show it may have better performance in spatial heterogeneity (Wellmann et al., 2018) and boundary recognition. As a widely used method for extracting second-order statistical texture features, GLCM constructs a combination of variables by analyzing a large number of variables and fitting training samples and plays an important role in image analysis and recognition (Hall-Beyer, 2017a; Haralick et al., 1973; Srivastava et al., 2020). It has been applied in high-precision feature classification (Dhumal et al., 2019), landscape patterns (Park and Guldmann, 2020), crowd retrieval (Alazawi et al., 2019; Hao et al., 2017), and medical imaging detection (Parvez and

Phadke, 2017; Xian, 2010). Although it is often used as a classification tool based on its advantages in boundary recognition (Hall-Beyer, 2017a), especially for confusing patches (Numbisi et al., 2019). It also has efficient applications in quantifying landscape features. First, it can predict landscape interior composition, aggregation, dispersion, and heterogeneity. For example, Park and Guldmann (2020) found that GLCM as a landscape spatial index can provide a more detailed explanation in urban canopy landscapes. Second, it can measure the heterogeneity of similar patches. Ozdemir et al., (2018) using GLCM homogeneity predicted birds species richness and using GLCM correlation predicted micro-habitat diversity. Furthermore, Ismail et al., (2018) quantified spatial heterogeneity in submarine canyons using GLCM entropy and evaluated the metric as a proxy for biodiversity. Blanco et al., (2020) used the GLCM feature combination of relatively homogeneous regions to describe the land surface temperature. Overall, since the GLCM map shows the status of texture features at a specific time, it can be used as an effective evaluation method to quantify the intensity of land use for specific temporal scales (Wellmann et al., 2018). However, the functionality of GLCM has not yet been fully utilized, considering most of the investigations are conducted on the category-level landscape indicators, and there is a lack of exploration and measurement of landscape-level models involving multiple land cover categories (Park and Guldmann, 2020). Thus, applying GLCM to complex urban ecological environments will give a full picture of its richness in providing texture information, and its application for playing as a reference for the planning and protection of various UGS.

This study proposes a method for using GLCM as a spatial landscape index to evaluate the UGS spatiotemporal characteristics on a small scale. Taking the urban areas of Leipzig, Germany as a case, the aim of this study is to find out the temporal and spatial changes of different types of UGS using GLCM index. The advantages, potential applications, and limitations of the GLCM index for spatio-temporal heterogenous analysis have been discussed to give an insight on future work, regarding the way to employ the GLCM index as an informative spatial landscape metric for spatial planning.

2. Study area and data used for sample analysis

2.1 Study area

Our study area is the City of Leipzig (Figure 1), a fast-growing and compact city located in eastern Germany with around 580,000 inhabitants. Leipzig has extensive urban forests, with trees covering 30% of the total area (Banzhaf et al., 2020). In the process of urban development in Leipzig, due to the economic crisis and political changes, the city lost a large amount of population from 1930 to 2010; however, since 2012, with the economic recovery, the demand for UGS has intensified due to urban population increase. To support the development and biodiversity of the city, Leipzig has supplemented numerous parks, public green spaces, and allotment gardens (Wilke and Fibich, 2017), resulting in almost 121 m^2 of green space per capita (Banzhaf and Kollai, 2015). The wide alluvial forest belt from south to northwest forms a strong green backbone near the city center

(Jingxia Wang et al., 2019a). Furthermore, many parks, cemeteries, allotment gardens, and open green spaces interweave into a diverse green network. So far, as one of the leading cities in East Germany, it is a home for the continuous distribution of communities and open space in the neighborhood that represents the characteristics of urban configuration. Therefore, this study chooses its five most important UGS, including urban forests, parks, residential green spaces, allotment and community gardens, and fragmented green spaces. We explore their spatial-temporal characteristics in-depth to reveal the internal dynamics and neighbor heterogeneity to guide their sustainable development and efficient management in the future.

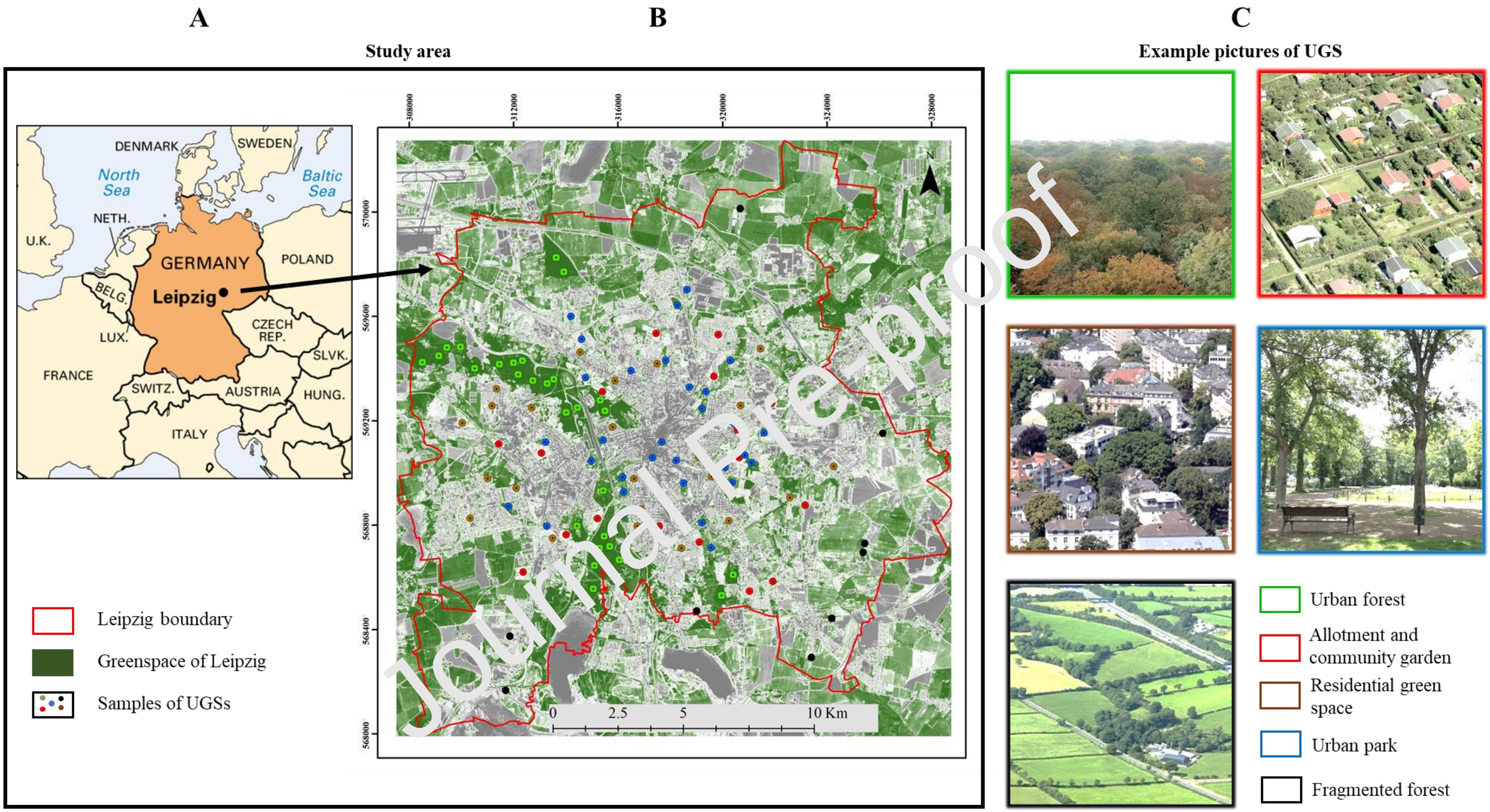


Figure 1. (A) The location of Leipzig city in Germany; (B) greenspace map of Leipzig (including agricultural areas), and the samples of UGS; (C) the example pictures of 5 types of UGSs, including urban forest (green points and square), allotment and community garden (red points and square), residential green space (brown points and square), urban park (blue points and square) and fragmented green spaces (black points and square)

2.2 The inventory dataset

In our study, we determined the four seasons from 2011 to 2012 based on the day of the year (DOY) and the European standard season division (Table 1). In this way, we generated an intra-year time series with 12 images per tile (Table 2). The RapidEye sensor contains five spectral bands ranging from 400 to 850nm: blue band (440~510nm); green band (520~590nm); red band (630~685nm); red edge band (690~730nm); near-infrared band (760~850nm) with a spatial resolution of 5 m, an orbital height of 630 km, and synchronized with the solar orbit. Since its first launch in August 2008, it has been widely used in the fields of land, agriculture, forestry, resources, and environment (Adam et al., 2014; Kafy et al., 2021; Krischke et al., 2000; Tigges et al., 2013; Zhang et al., 2021), because of its abundant spatial and spectral information. Its distinct red edge band is sensitive to changes of chlorophyll content (Ozkan et al., 2017) and thereby greatly assists our investigations in species separation. To accurately recognize the type of green spaces and surrounding environment, as ground truth data, a biotope map from the Saxony in 2014 was used, given the fact that it has a long tradition of more than 45 years (Schulte and Sukopp, 1993). Based on aerial photography and ground surveys of individual habitats, it has mapped diverse locations and biomes in different regions and conducted long-term monitoring. It provides a basis for further spatial analysis of ecological conditions on landscape-level (Löfvenhaft et al., 2002), it is widely used for policymaking in landscape planning and management (Jingxia Wang et al., 2019b;

Werner and Zahner, 2010).

Table 1. The remote sensing and inventory dataset

<table>
<tr><th>Datasets</th><th>Masked out areas</th><th>Date</th><th>Source</th></tr>
<tr><td>Satellite images</td><td>Full region of Leipzig</td><td>2011-2012</td><td>RapidEye (RapidEye, 2016)</td></tr>
<tr><td>City border</td><td>Rural surrounding</td><td rowspan="5">2014</td><td rowspan="5">The free state of Saxony (Schulte and Sukopp, 1993; Jingxia Wang et al., 2019b)</td></tr>
<tr><td rowspan="4">Biotope map</td><td>Forests</td></tr>
<tr><td>green and blue infrastructure</td></tr>
<tr><td>Green and open spaces</td></tr>
<tr><td>Built-up areas, traffic facilities, and special areas</td></tr>
</table>

Table 2. Image acquisition dates of the RapidEye remote sensing data.

Acquisition date	Season	Month	DOY (Day of year)
26.01.2012	Winter	January	26
01.03.2011	Winter	March	60
22.03.2011	Spring	March	91
21.04.2011	Spring	April	111
14.05.2012	Spring	May	135
03.06.2011	Spring	June	154
27.06.2011	Summer	June	178

24.07.2012	Summer	July	206
20.08.2011	Summer	August	232
25.09.2011	Autumn	September	265
31.10.2012	Autumn	October	305
21.11.2012	Autumn	November	326

2.3 Sample selection

UGS is an area for greening the environment in addition to urban built-up land, which has positive effects on urban ecology, and residents' recreation. To reflect the impact and ecological function support of UGSs on the surrounding environment, a combination of different natural forms and management methods such as city central parks, residential parks, gardens, and urban forests has been formed. Considering the resolution of images and the green space composition status of Leipzig, we mainly discussed 5 types of urban green spaces, including urban forests, urban parks, residential green spaces, allotments and community gardens, and fragmented green spaces. Leipzig has about 2,160 hectares of forest area (Wilke and Fibich, 2017). The Leipzig alluvial forest in the lowlands of the Luppe, Pleiße, and Weißer Elster rivers is the most important and largest urban forest corridor. Similar green corridors are also distributed in Parthe and Rietzschkeaue in the north, as well as Grünzug Südost to Störmthaler See, and Anne-Crottendorfer railway lane (Stadt Leipzig 2013). Except for green corridors, there are is a large number of urban public green spaces, including parks and gardens. Hasse (2019) had surveyed and mapped the distribution of residential green spaces, allotments and community gardens, forests, and parks in Leipzig. Based on these data, we adopted a stratified random sampling method to have a total of 110 samples from four types of urban forest patches (Table 3), including 27 in forest areas, 32 in parks, 24 in residential areas, 17 in gardens. As for the fragmented green spaces, we had 10 samples for them for our comparison considering Leipzig has some fragmented green spaces located near farmland and outside residential areas that separate the city and suburbs (The distribution of sample points is shown in Figure 1).

Table 3. Selected samples of each UGSs type.

Type of UGSs	Area(ha)	Proportion	Number of samples
Urban forests	2160	27%	27
Parks	2608	32%	32
Residential green spaces	1990	24%	24
Allotment and community garden	1364	17%	17
Fragmented green spaces	-	-	10
In total	8122	100%	110

3. Methods and data analysis

3.1 Workflow

In this study, based on remote sensing data and ground truth data, the temporal and spatial characteristics of 5 types of UGS in Leipzig were quantitatively identified and evaluated. The workflow is shown in Figure 2. In the first step, after performing radiometric and atmospheric corrections on the acquired remote sensing images using the Erdas imagine ACTOR 2 (Richter and Schläpfer, 2019), we extracted NDVI, and the first 3 components in principal component analysis (PCA), proposed by Wold et al., (1987). We found that NDVI was more stable and was able to provide greater contrast, whereas principal components from PCA did not contribute to recognizable results. Thus, in the second step, we calculated the GLCM based on the gray image of NDVI and got 8 indices (Table 4). Before sample selection, we randomly collected 500 circular samples with a radius of 10 m in the study area. Then, combined with the Biotope map, the UGS was divided into 5 categories, and a total of 110 sampling points (Table 3) were selected as our final sampling points using the stratified random sampling method. In the last step, the GLCM variance, GLCM contrast, and GLCM entropy were selected as the main indices to quantitatively analyze the vegetation growth, contrast, and potential human interference of the 5 types of UGSs. In order to further explore whether the vegetation growth, heterogeneity and regularity of urban green space affect each other, we discussed their correlation using Pairwise Pearson's correlation coefficient that calculated in SPSS software (*SPSS Correlation Analysis Tutorial*).

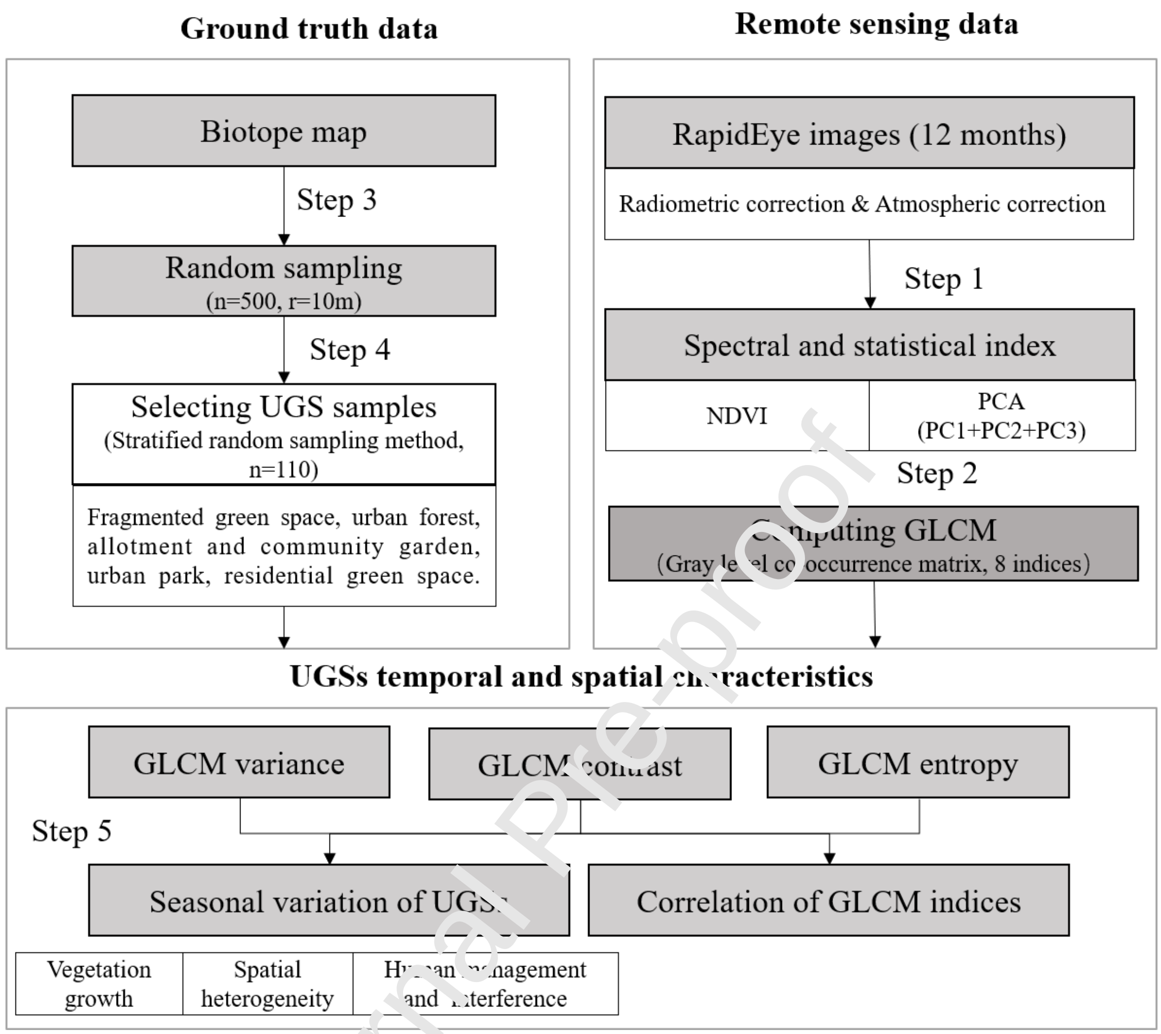


Figure 2. Flowchart of the methodology for GLCM computing, UGS samples selecting and the UGS temporal and spatial characteristics assessing

3.2 GLCM computing

GLCM is a texture extraction method that measures comprehensive information about the distance, direction, interval, and change range of the image, it has high accuracy in identifying the texture and regularity of the images (Srivastava et al., 2020). When describing the landscape patterns, it performs better than the landscape metrics, which can be used as a reliable index for the spatial configuration (Park and Guldmann, 2020). As for texture statistics, the GLCM index includes variance, mean, homogeneity, contrast, dissimilarity, entropy, angular second moment (ASM), and correlation within a given window size and offset (Haralick et al., 1973). These texture statistics are defined as 3 main categories in general research applications: 1) statistical group, which describes the basic statistical variables of the gray value in the texture, such as mean, variance, and correlation; 2) contrast group, which measures local changes within the patch and the difference with surrounding pixels, such as contrast, homogeneity, and dissimilarity; 3) orderliness group that reflects the regularity and disorder of the pixel values, such as ASM and entropy.

The calculation of GLCM is based on gray level images and the common methods for gray level conversion include using an index (e.g. NDVI or Normalized difference building index (NDBI) (Hall-Beyer, 2017a). Considering our study objects, as well as more accurate comparative information between vegetation and buildings in the city (Kuffer et al., 2016; Zhong et al., 2017), we used NDVI as the original information channel. The second step is to choose a moving window size and it is an important means to balance the amount of information extracted from texture features and the amount of noise. In our study, due to the high resolution of the RapidEye image and low heterogeneity inside the UGS (Chen et al., 2004), we chose a 5×5 window size which is the same spatial resolution of our data source.

The texture is a descriptive statistic that will differ under distinct contexts. It can be different due to the change of study scales and window size. . (Hall-Beyer, 2017b). Therefore, we applied a regional GLCM calculation in Leipzig on R-4.2.0 (R core team, 2020) to undertake a comparative analysis of UGSs in different regions,. At the same time, the 8 indices obtained were according to their categories.

Table 4. The category of GLCM indices.

Group	GLCM index	Equation	Description
Stats group	Mean	$\sum_{i,j=0}^{n-1} i(P_{i,j})$	The average of gray level values in an image
	Variance	$\sum_{i,j=0}^{n-1} P_{i,j}(i - MEAN)^2$	It increases when the gray level values differ from their mean
	Correlation	$\sum_{i,j=0}^{n-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$	Returns a measurement of how correlated a pixel is to its neighbor over the whole image
Contrast group	Homogeneity	$\sum_{i,j=0}^{n-1} \frac{P_{i,j}}{1+(i-j)^2}$	Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal
	Contrast	$\sum_{i,j=0}^{n-1} P_{i,j}(i-j)^2$	Returns a measurement of the intensity contrast between a pixel and its neighbor over the whole image
	Dissimilarity	$\sum_{i,j=0}^{n-1} P_{i,j}\lvert i-j\rvert$	Similar to Contrast
Orderliness group	Entropy	$\sum_{i,j=0}^{n-1} P_{i,j}(-\ln P_{i,j})$	Returns the summation of squared elements in the GLCM
	Angular second moment	$\sum_{i,j=0}^{n-1} {P_{i,j}}^2$	Returns the sum of squared elements in the GLCM

3.3 Indices selection

We have identified 8 GLCM indices that can be divided into 3 groups. Indices belonging to the same group have similar descriptive information regarding the landscape texture. Among these 8 indices, contrast, dissimilarity, entropy, and variance are the most widespread that can be associated with visual edges of land-cover patches (Hall-Beyer, 2017a). They have excellent edge recognition ability in reflecting the spatial relationships and resources exchange between diverse UGSs and their respective surroundings. GLCM variance is suitable for different urban environments with sharp contrasts between buildings and their surroundings (Kuffer et al., 2016). In the application of information science, entropy often means more information, and higher entropy indicates more complex variability, it is important to the textures of particular landscape metrics (Hall-Beyer, 2017), and it is verified that it is the most relevant parameter to the landscape index (Ozdemir et al., 2012). Contrast and dissimilarity have a high degree of positive correlations in the description of texture features, and they all change significantly with displacement (Gebejea and Huertas, 2013). But GLCM contrast is related to the average gray level difference between adjacent pixels, which is similar to variance, and its unique visual evaluation can distinguish different texture patterns (Hall-Beyer, 2017a). Therefore, we choose variance, contrast, and entropy as the main indicators for the next analysis. In our experiment, the variance can well describe the vegetation coverage and the visual boundary between the vegetation and the built-up area; the contrast will be used to supplement the contrast between the vegetation and the built-up area boundary, and reflect the spatial heterogeneity in the patch at the same time. As a measure of information richness, entropy can supplement contrast in expressing the heterogeneity within the patch, reflecting the regularity of the patch. In other words, its changes can reflect the interference between human activities and UGS.

4. Results

4.1 Texture features of UGS

By executing GLCM extraction and calculation in Leipzig, we got the converted GLCM variance, contrast, and entropy map (Figure 3). According to the landscape and texture characteristics of the GLCM index, we found that the GLCM variance value is lower in waters and built-up areas, while the vegetation area is higher. It has an excellent ability to distinguish vegetation and building areas. In addition, due to its value range, different vegetation areas (such as forests, grasslands, gardens) and different vegetation coverage (inside or edge of the forest) can be well displayed on the map, so GLCM variance has great potential in UGS when evaluating vegetation growth and coverage; It can be seen from the GLCM contrast map that Leipzig’s urban patches present a sprawling unstructed trend gradient of spatial heterogeneity. The wide alluvial forest belt from south to northwest divides the city into east and west urban areas, and the construction area spreads outward in fragments. The urban sprawl trajectory and the transitional edge between urban and rural areas can be reflected in the map, especially the fragmentation and density changes of urban patches; GLCM entropy, as the most informative index in the ordered group, reflects the regularity of the texture in the image. The closer to the dense or continuous building area, the higher the index value in Leipzig. It shows that the areas with denser human activities have higher entropy.

From the visual map of the UGS patches (Figure 4), GLCM variance has better boundary recognition capabilities, especially in the boundary between vegetation and buildings. However, it performs poorly in the garden area. GLCM contrast reflects the spatial difference between patches in texture, it shows strong contrast in parks and residential areas, while the contrast in fragmented green space is not obvious. GLCM entropy is an index that reflects the richness of texture information. It has great potential in expressing the internal texture characteristics of patches. For example, urban forest patches with uniform variance and contrast, displays mottled graphics, which may because of the differences in tree species. This means that it has finer resolution capabilities on small scales.

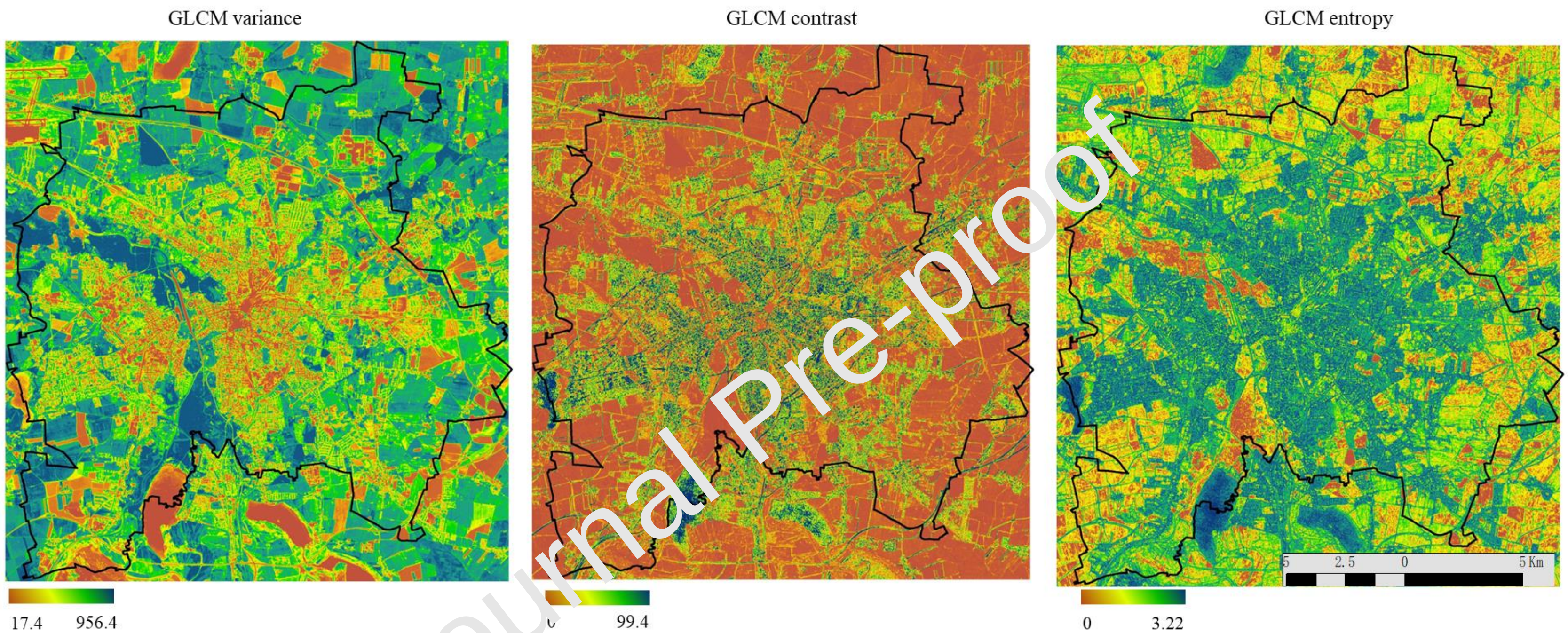


Figure 3. The GLCM variance, contrast, and entropy map of Leipzig, the value from low to high displayed in color brown, green and blue.

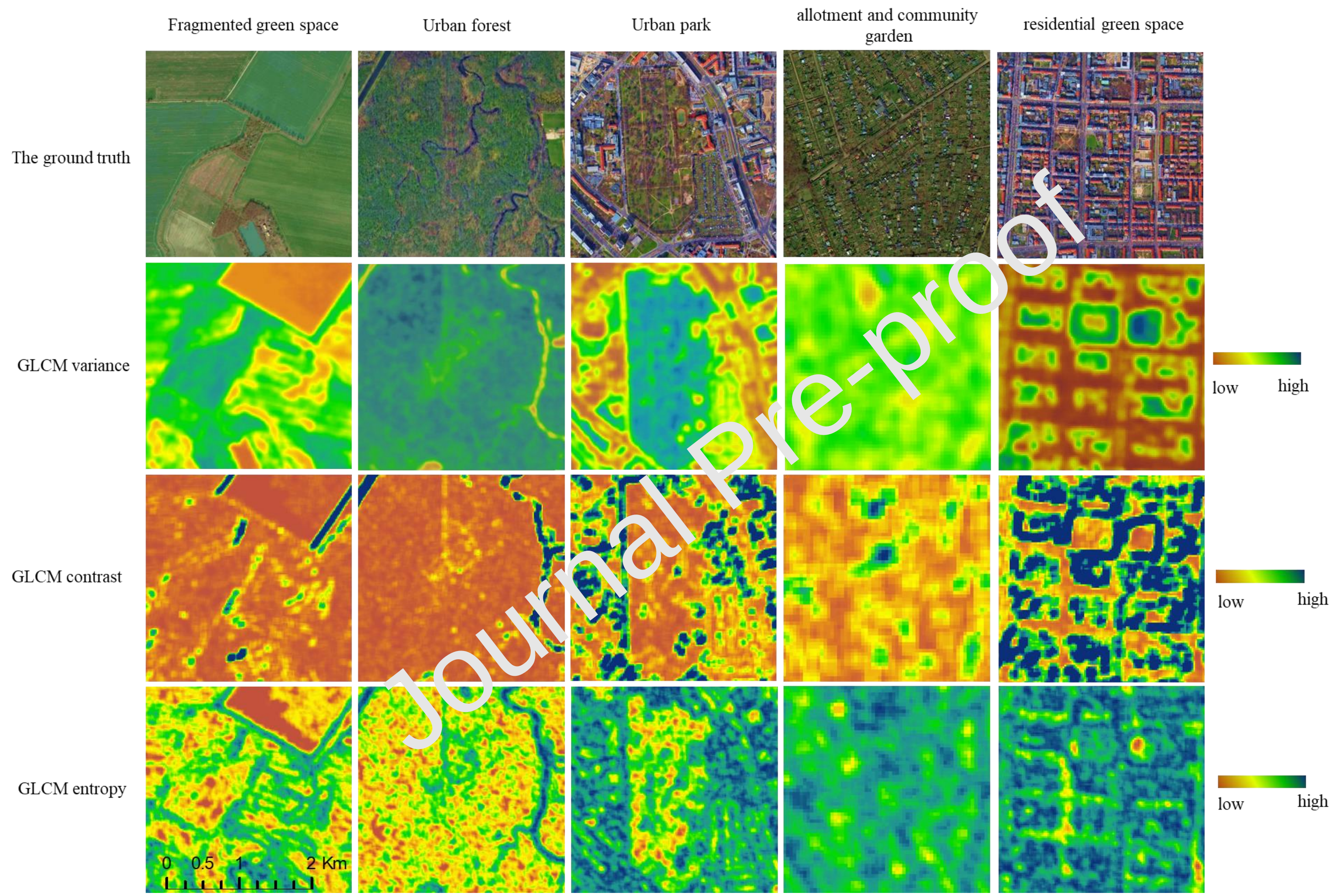


Figure 4. The GLCM variance, contrast, and entropy map of 5 types UGS in Leipzig, the value from low to high displayed in the color brown, green and blue.

4.2 The seasonal variation of UGS

4.2.1 The seasonal vegetation growth of UGS

As shown in Figure 5, the GLCM sample variance map for each type of UGS shows diverse discrepancies in four seasons. It can be observed that the GLCM variance had better boundary recognition when the vegetation grew well in summer and autumn. The right part of Figure 5 demonstrates the values of GLCM variance change from spring to winter. The values of the 5 types of UGS are highest in summer, especially in the urban forest with the densest canopy in summer. Compared between seasons, we found that vegetation growth in urban forest areas shows almost the same variation as the seasonal change. Compared with other UGS, the garden had the lowest variance, and the annual change was relatively stable. Residential green space also has a low variance, and its value is the lowest among all UGS in autumn and winter. It tends to have a lower amount of vegetation, which is scattered and small, and it is often surrounded by a large number of buildings. The fall of leaves and snow cover contribute to the similarity of the GLCM variance values for all 5 UGSs. Overall, GLCM variance shows obvious seasonal characteristics when it is used to describe vegetation growth and shows good visual boundary recognition ability in built-up areas.

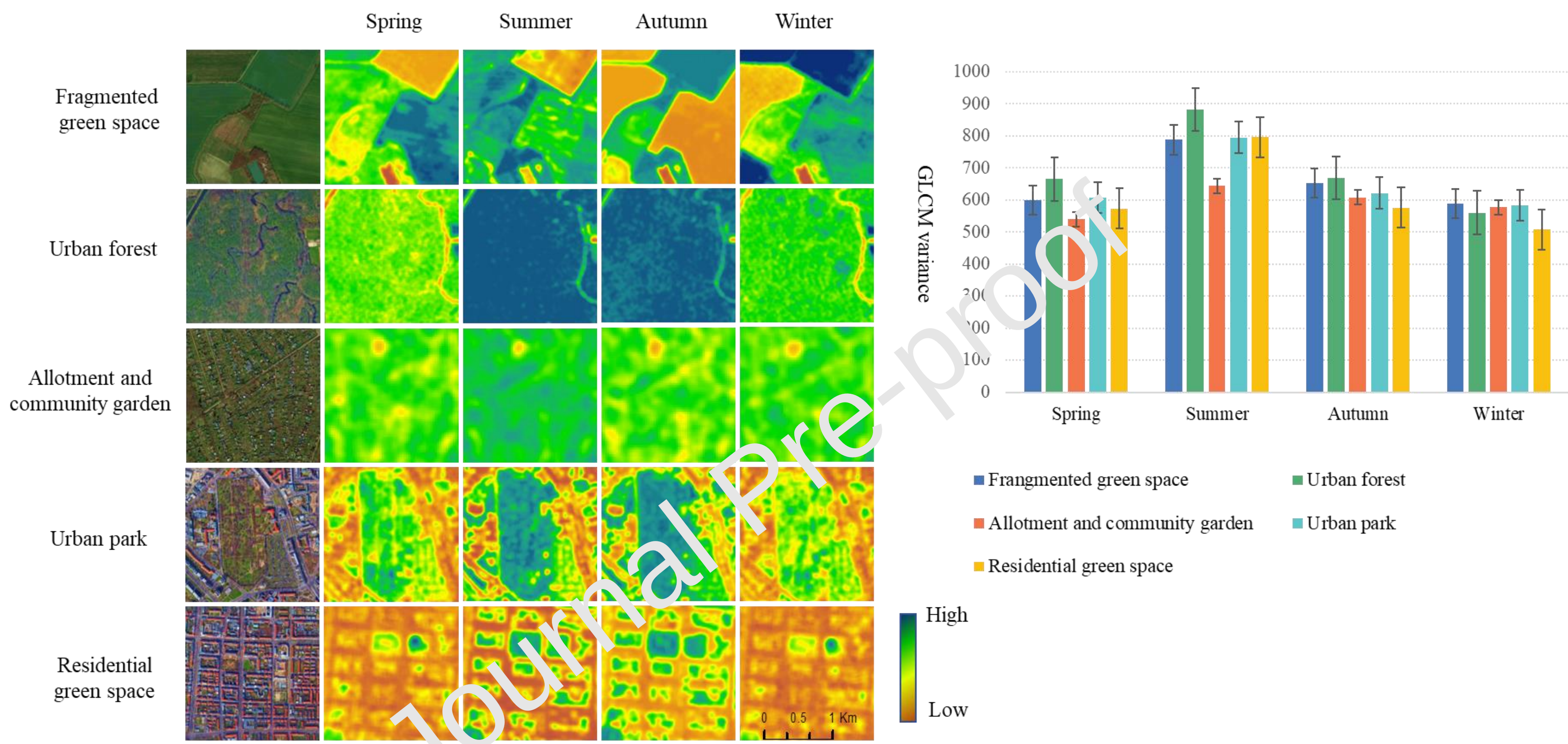


Figure 5. The GLCM variance of 5 UGSs in four seasons (left: GLCM variance sample map. Right: GLCM variance values and standard error graph of samples)

4.2.2 The seasonal heterogeneity of UGS

GLCM contrast represents the contrast of local gray values, the larger the value, the stronger the heterogeneity. As shown in Figure 6, the closer to the built-up area, the higher the contrast of each UGP type. Among all five UGP types, the boundary recognition ability of residential green spaces performs best, especially those areas within high-density of buildings and continuous built-up areas. However, the forest areas have lower contrast values due to their high homogeneity in essence.

The statistical analysis result on the right of Figure 6 shows that the heterogeneity of the 5 UGSs has significant differences within the four seasons. The heterogeneity of urban forest areas and fragmented green spaces areas were relatively stable throughout the year, but the value is lowest in summer. Both residential areas and gardens belong to densely built-up areas, and their textural heterogeneity remained at a high level throughout the year. However, the vegetation composition of gardens was more complex and there was more evergreen vegetation, the heterogeneity of gardens maintained a high level although the leaves fall in autumn. In winter, the heterogeneity of UGS increased compared to autumn. However, the heterogeneity of the gardens was at the lowest level in the whole year in winter. Overall, in cold winter, the withering or death of the vegetation leads to the reduction of heterogeneity.

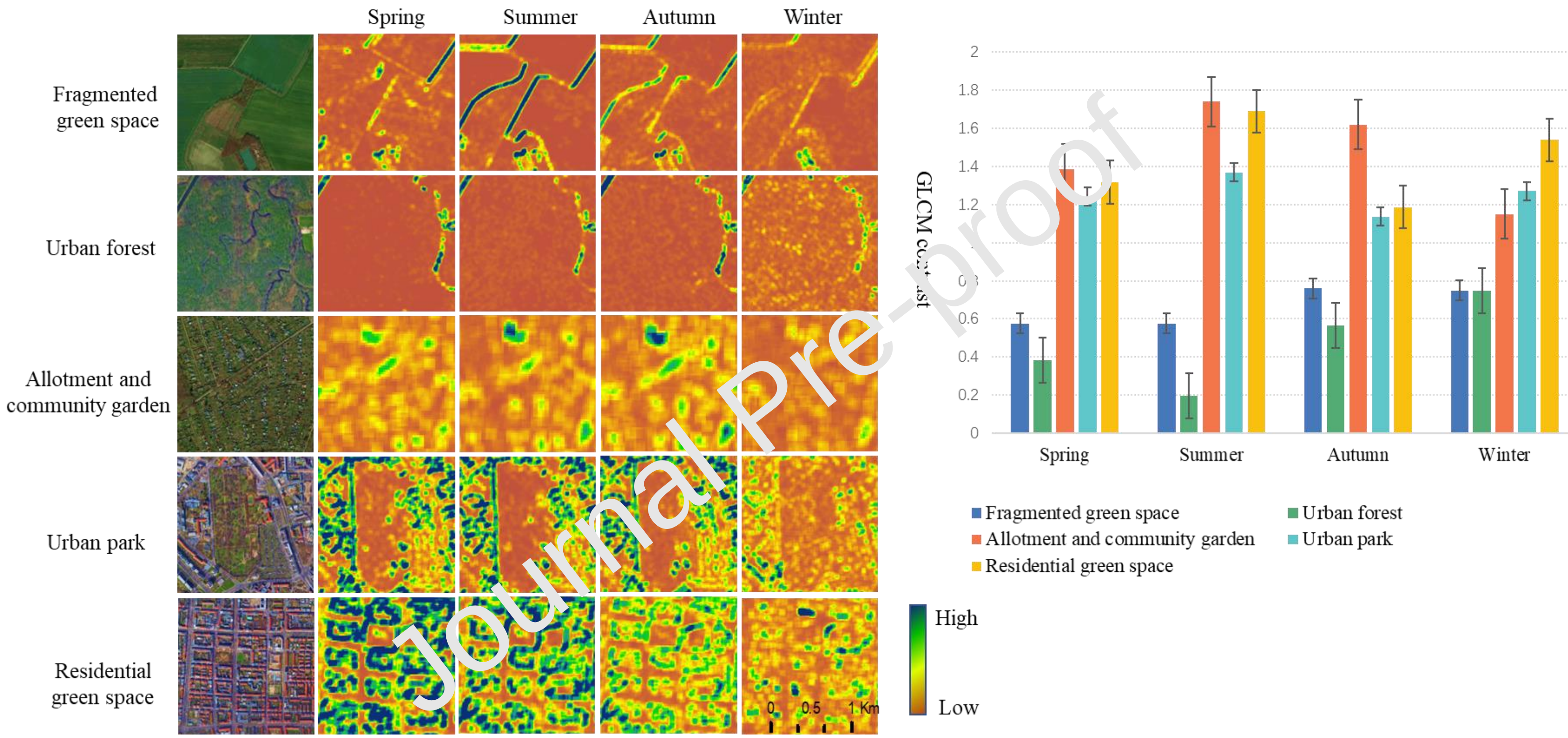


Figure 6. The GLCM contrast of 5 UGSs in seasons (left: GLCM contrast sample map. Right: GLCM contrast values and standard error graph of samples).

4.2.3 The seasonal GLCM entropy of UGS

In Figure 7, we found that the closer to the built-up area, the higher the entropy value (the color tends to green-blue). The GLCM entropy in the patch shows obvious mottled pixels, and there were strong gray contrasts, such as in the interior of urban forests, bare ground, and different tree species created mottled patterns. The numerical analysis indicated that the garden area has the highest entropy and maintains a stable range of changes throughout the year. GLCM entropy in urban forests is the lowest, followed by fragmented green spaces, considering most of the fragmented green spaces are located at the edge of farmland, roads, or rivers. Although no strong human interference was observed, the GLCM entropy of fragmented green spaces could attribute to their surrounding environment (e.g. rivers diverged by green spaces or roads) and on-site activities (e.g. agricultural plantation and grain harvest). In general, the GLCM entropy is a manifestation of the complexity of information within the patch, it does not change with seasons.

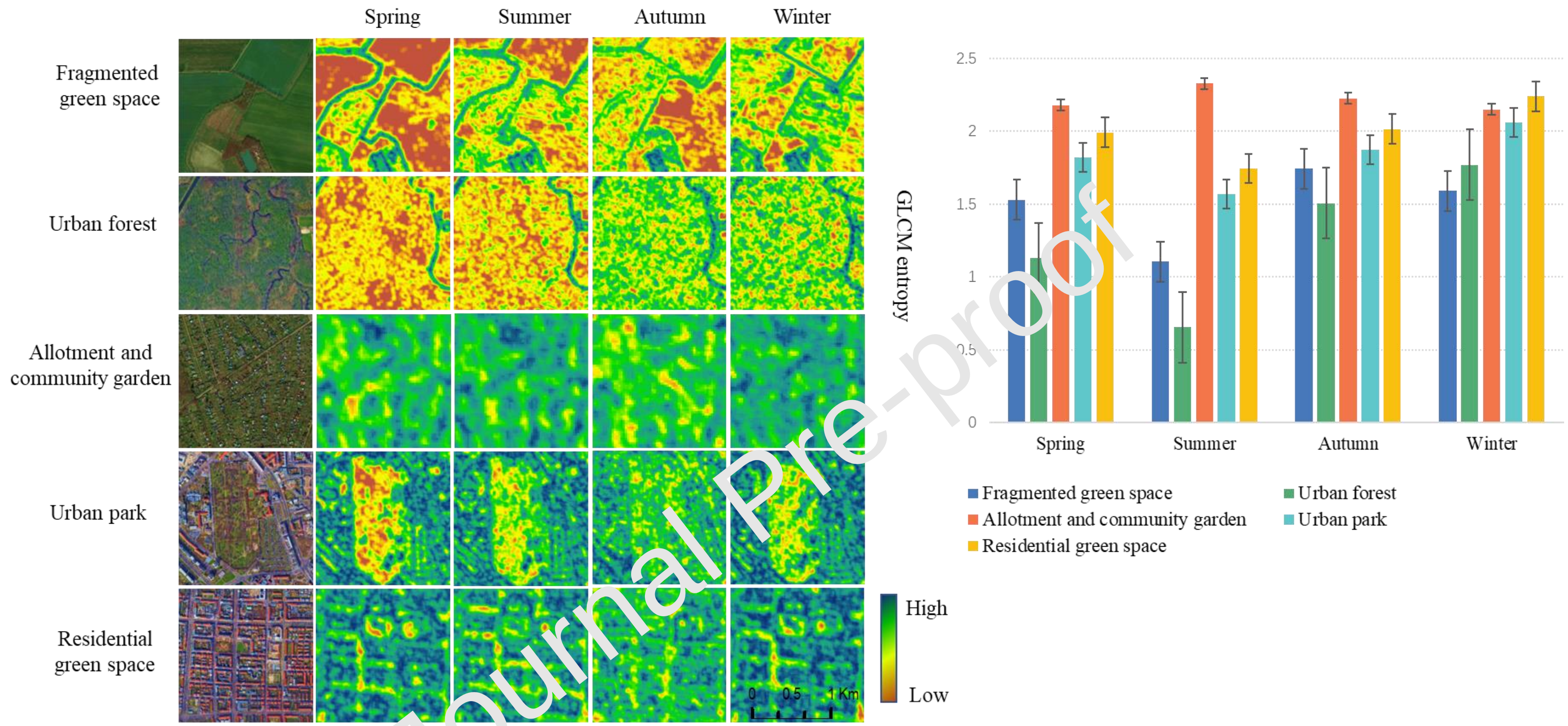
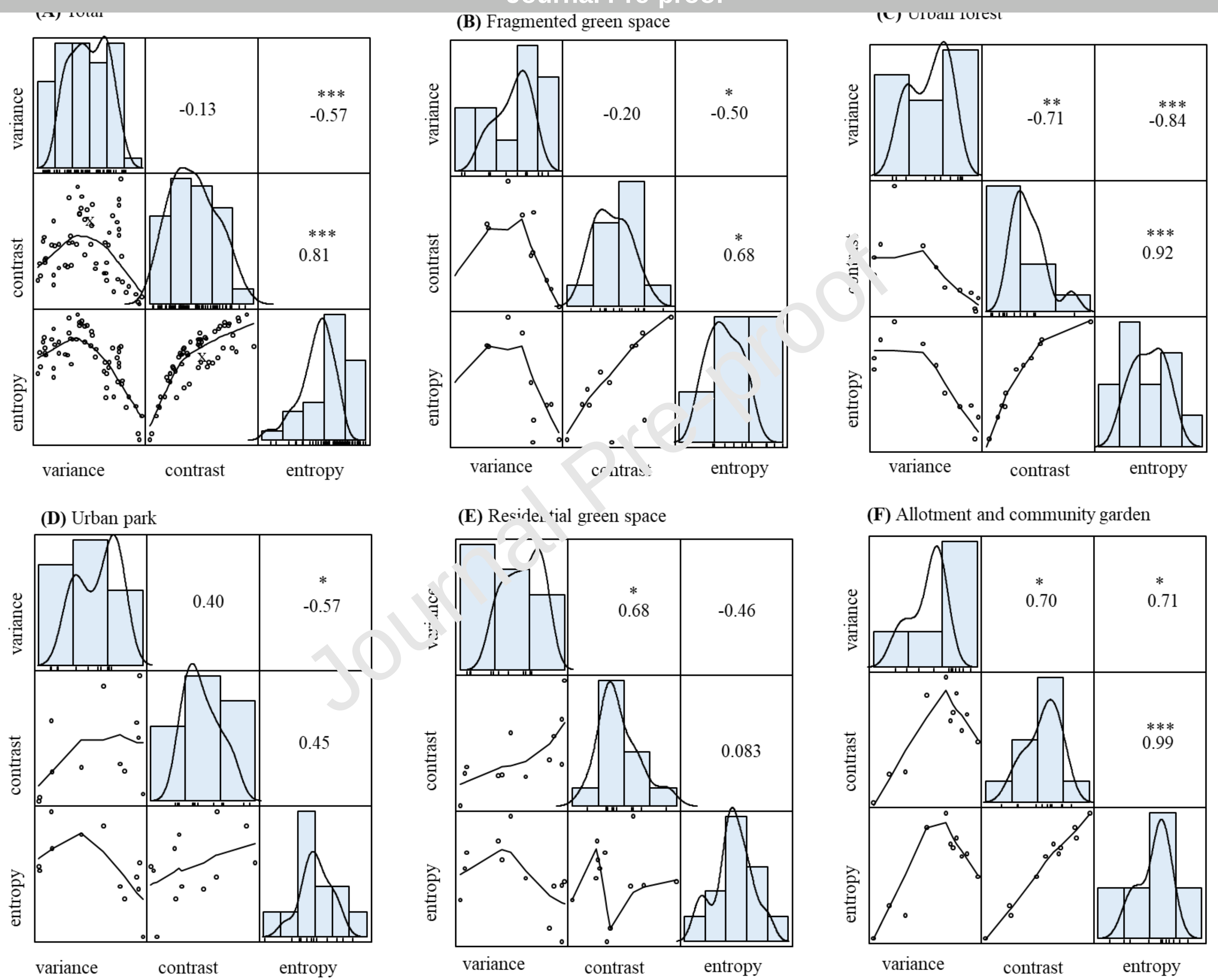


Figure 7. The GLCM entropy of 5 UGSs in seasons (left: GLCM entropy sample map. Right: GLCM entropy values and standard error graph of samples).

4.3 Correlation among GLCM indices

Through the results above we found that the influence of seasonal changes on UGSs is mainly reflected in vegetation growth, and the changes in spatial heterogeneity are mainly reflected in fallen leaves and winter snow, but the impact of seasons on the regular and orderliness of green spaces is relatively small.

To investigate the relationships between our derived GLCM indices, we conducted a correlation analysis on the GLCM indices of the 5 types of UGS. As Figure 8 shown, overall, the three indices of GLCM had an obvious correlation with each other in urban forest patches. First, GLCM variance has a strong negative correlation with GLCM entropy and the results can be interpreted as the stronger the human management and interference of UGS patches, the lower the green space naturality. As for the GLCM contrast and GLCM entropy, they have a strong positive correlation, which means that the stronger the human management and interference of UGS patches, the higher the spatial heterogeneity. However, the correlation between GLCM contrast and GLCM variance is not statistically significant. Allotment gardens and urban forests had the most significant correlation on GLCM indices, both indicate a positive correlation between GLCM contrast and GLCM entropy. But the correlation was opposite between GLCM variance and GLCM contrast, as well as between GLCM contrast and GLCM entropy. It means for urban forests, the better the trees grow and the lusher the canopy cover, the contrast observed through texture features will decrease and lose the information richness of texture features at the same time. While in allotment gardens, due to the diversity of species and frequent manual management, the trees grow very well and show high contrast and information richness. The correlation of the indices is not significant in other types of UGSs, UGSs have similar performances in built-up and non-built-up areas respectively. But the correlation between GLCM variance and GLCM entropy is negative in parks and residential areas, as shown in the overall correlation chart, generally the stronger the human management and interference, the worse the vegetation growth; However, due to mostly frequent human management, the GLCM variance and GLCM entropy of garden areas change smoothly throughout the year (see Figure 4 and Figure 6) and they also present strong positive correlation.



(B) Fragmented green space
(D) Urban park
(E) Residential green space
(F) Allotment and community garden
variance
contrast
entropy
-0.13
*** -0.57
*** 0.81
-0.20
* -0.50
* 0.68
** -0.71
*** -0.84
*** 0.92
0.40
* -0.57
0.45
* 0.68
-0.46
0.083
* 0.70
* 0.71
*** 0.99

Figure 8. Pairwise pearson`s correlation coefficient among the GLCM variance, GLCM contrast, and GLCM entropy of 5 types of UGSs. (Note: Scatter plots indicating the degree of correlation between variables (below diagonal) and pairwise pearson`s correlation *r* values (above diagonal). Statistical significant correlation coefficients are indicated as following: * $p<0.05$, ** $p<0.01$ and *** $p<0.00$

5 Discussion

5.1 The landscape description using GLCM indices

We evaluated the temporal and spatial characteristics of UGSs through three indices of GLCM. The results show that, first, the variation of texture features can describe the spatial relationship of the interior of a patch and between patches, such as the complexity of the internal components of the patches (Kuplich et al., 2005) (i.e. the complexity in an urban forest in Figure 7); the spatial heterogeneity between patches (Numbisi et al., 2019) (e.g. the built-up area in Figure 6); the potential influence of human interference and management on the patches (Wellmann et al., 2018) (in Figure 6 and 7, the garden area maintains stable temporal and spatial changes). Second, both the GLCM contrast and entropy, there is a clear distinction between built-up areas and non-built areas, namely the denser the buildings the stronger the heterogeneity and human interference and management (Grimm et al., 2000). Third, on the time scale, the effect of seasonal change on UGS is mainly reflected in the vegetation growth (Figure 5), and the change in heterogeneity is mainly reflected in the fall of leaves and snow cover (Wang et al., 2014) (Figure 6), but the impact on human interference and management is relatively small. As shown in Figure 7, most of the UGS annual changes are not significant, except for forest areas. It might be resulted from that the GLCM entropy is an index describing the regularity of internal textures, and the natural changes of forests have caused this change (Wang and Zhao, 2018).

Using the GLCM index as a landscape metric is an attempt to study the spatial characteristics of ecological landscapes. Although we have not analyzed all of the GLCM indices, we have selected representative indices from the three categories of the GLCM index, considering the indices of the same category have strong correlations and usually reflect similar spatial variation information (Hall-Beyer, 2017b). GLCM is not only a tool for extracting information, but its spatio-temporal performance still has a broader development space. For example, predicting biodiversity (Ozdemir et al., 2018), assessing and quantifying land-use intensity (Wellmann et al., 2018). But it has still some gaps, such as the choice of the research object scale, the confusion of the index function and so on. In the future, the uses of higher resolution remote sensors and deep learning methods will assist in accurately quantifying its dynamics (Huerta et al., 2021). Therefore, we aware that using GLCM as a landscape metric requires more comprehensive and systematic research, although it is beyond the scope of this study.

5.2 The computation of GLCM indices

In general, the calculation of GLCM is highly dependent on the scale range (Josselin and Louvet, 2019), and it is impossible to apply from one scale to another (Hall-Beyer, 2017b). For example, when extracting texture features in a forest range and a city range separately, the GLCM variance value of the same forest is totally different and cannot be compared. Therefore, in this study, we extracted texture features of the entire urban area (at the same spatial scale) to compare the landscape spatial attributes of different green spaces. Our study results proved that: 1) In terms of boundary recognition, GLCM variance can better show the boundary of vegetation area and the built-up area in summer and autumn. 2) GLCM entropy can not only reflect the amount of information inside the patch, such as open spaces and species biodiversity but also express human management and interference by the orderliness of texture distribution. 3) GLCM contrast can express the spatial heterogeneity of urban landscape, especially the transition zone of different land-use types. From the GLCM map of the green space (Figure 3), we can find that even for the same land cover type, the patch has a mottled pattern. At the forest patch scale, we infer that it can distinguish between deciduous trees and evergreen trees, it is a promising method for detecting species diversity(Zhao and Wang, 2020). Therefore, GLCM can be used to reflect the heterogeneity within the patch, the diversity of species, and the edge effect of the ecosystem in future studies.

5.3 The limitations of this study

According to our statistical results, the spatial characteristics of the garden area change little in a year due to frequent human management. This is because the vegetation of the garden has a higher biodiversity than other types of urban green spaces (Dixon, 2022), and at the same time, these vegetations are managed and protected by the owner more carefully as a luxury (Cameron et al., 2012). Throughout the year, the vegetation maintained a consistent morphology, such as lawns that were regularly mowed, thus reflected little change in the annual remote sensing imageries. In addition, using older imagery in our study may be detrimental to predicting future trends in UGS, because alien plant species are currently naturalized (Pysek et al., 2017), especially in gardens

(Haeuser et al., 2018), this may give a different result with seasonal variation. Although our study revealed the spatial characteristics of the interior and neighborhoods of urban green space patches, it cannot perform a unified quantitative analysis of the time series of multiple satellites images in the study area.

We are aware of the methodological limitation due to GCLM computation merely based on NDVI. Although NDVI has excellent identification and description capabilities (Defries and Townshend, 1994), it causes confusion when depicting the water area (Szabó et al., 2016). As shown in Figure 3, the value of the water area in the variance map is close to large continuous buildings and bare fallow land. Besides, the exploration of temporal and spatial characteristics of GLCM is different from land use classification, and there is still a lack of verification of accuracy. When evaluating the heterogeneity of a green space, a detailed field investigation is necessary, otherwise it can only be compared amongst different types of green space. As shown in Figure 6, we can find from the GLCM contrast map and statistical chart that the garden has a particularly high heterogeneity, but unsure about how many species it has indeed.

5.4 The implications and challenges for urban green infrastructure planning

Our study is a one-year analysis for the purpose of disclosing the seasonal vegetation growth and heterogeneous changes in the UGSs of Leipzig. It has verified the possibility of GLCM indices being used for the landscape description,, excluding the reflection of urban expansion or renewal over a long term. In urban green infrastructure planning, we should pay attention to the urban challenges caused by the interior heterogeneity of UGSs to people and nature (Haaland and van den Bosch, 2015), apart from the increase and loss of UGS coverage. These challenges ought to be addressed in urban green infrastructure planning, include but are not limited to, the impact of UGS on residents' health and well-being (Bertram and Rehdanz, 2015), social equity (Kimpton, 2017), biodiversity loss (Ikin et al., 2013), and the lack of recreation areas. In the process of urban expansion, while more or the same amount of new green spaces can be created, it does not mean that urban residents are close to green space and thereby can obtain corresponding quality ecological functions (Feltynowski et al., 2018; Wang et al., 2019b). Therefore, from methodological perspective, our research may contribute to further studies in quantifying internal quality of various urban green spaces such as residential green spaces, allotments, and urban forests.

Many cities are currently exploring more comprehensive UGS management and planning strategies in the context of urban growth (e.g., Wang et al., 2022) and regeneration. It is important to include the measurement of small-scale green space characteristics (Haaland and van den Bosch, 2015), particularly considering the internal textual distinction and the interactions between UGS and their surrounding environments (Wang et al., 2020). Given that the spatiotemporal features of UGSs are crucial for dealing with the challenges of climate change adaptation and mitigation (Demuzere et al., 2014), biodiversity conservation (Aronson et al., 2017), and human health (Wolch et al., 2014), our method may help better understand the spatial functions and driving forces of UGSs. In urban green infrastructure planning, green and blue spaces with lower GLCM variance could be firstly considered, as they would likely provide less ecological function (Semeraro et al., 2021) such as uneven land surface temperature (Masoudi and Tan, 2019). Moreover, green and blue spaces with high GLCM contrast need to be focused since high heterogeneity areas are oftentimes related to high biodiversity hotspots (Lepczyk et al., 2017; Sodoudi et al., 2018). The areas with high GLCM entropy reflect frequent human activities and high potentials of planning activities, and the stability of their ecosystems is deserved to be attention, such as the demise and fragmentation of green spaces (Colding et al., 2020; Huang et al., 2021). An in-depth analysis considering GLCM changes across years, with many on-site investigations, and respectively for each green infrastructure type will be insightful to further validate the value of the GLCM index for urban green infrastructure planning. Although it is out of scope of this study, our study can still provide a basis (i.e. the detailed interior characteristics of UGSs) for addressing urban challenges in green infrastructure planning, in particular in climate change adaptation and biodiversity conservation (Wang, 2020).

5 Conclusion

In this study, we combined remote sensing technology and texture feature extraction methods and employed the GLCM index to evaluate the spatio-temporal characteristics of UGSs in Leipzig. We unveiled the internal dynamics and neighborhood heterogeneity of different types of UGS (e.g. residential green spaces, allotment areas). We selected

GLCM variance, contrast, and entropy to analyze different types of UGSs based on the description of vegetation growth, spatial heterogeneity, and interior orderliness. The results show that different types of UGS have conspicuous characteristics considering their surrounded buildings and the distance from the built-up area. Notably, within one year, UGS far away from built-up areas has more pronounced seasonal variations; however, large and dense urban forests have the lowest spatial heterogeneity and interior orderliness. According to the correlation analysis, it is found that, in general, the variance and entropy are significantly negatively correlated amongst varied UGSs, while GLCM contrast and entropy are significantly positively correlated. It is worth noting that the correlation between variance and contrast of green space in built-up areas and vegetation areas is opposite.

Conclusively, it is reasonable to use the GLCM index as a landscape metric to evaluate UGS, especially for measuring landscape heterogeneity at very fine scale. This method based on "form-structure" provides a better understanding on the spatial variation and and spatio-temporal relationships of different UGS. The insightful information demonstrated in this study could contribute to spatially explicit urban green infrastructure planning and support fine-scale UGS management with site-specificity.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Graphical abstract