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Supply and demand assessment of urban recreation service and its implication for greenspace planning-A case study on Guangzhou

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ABSTRACT

Nature-based recreation in urban areas is important for the well-being of citizens. Spatial quantification of recreation service supply and demand can support urban greenspace (UGS) planning by revealing if supply meets demand. This research proposes a comprehensive framework to assess urban recreation service supply (characterized by available UGS area within a certain radius around a residence) and demand (characterized by UGS area required by the population for recreation) in the context of UGS planning. This framework contains three elements: (a) multi-scale spatial quantification of the supply–demand balance; (b) spatial match of supply and demand; (c) spatial clustering analysis of the supply–demand balance. We present a case study for the city of Guangzhou, China, and discuss its implications for UGS management. We found that although there is a high supply of UGS in Guangzhou, between 88% and 96% of inhabitants have a recreation service deficit, depending on the demand criteria. Recreation service supply–demand balance showed a strong clustering pattern. The top 10% of deficit clustering area accounted for 47% of the under supplied population and 57% of the UGS deficit. Our study indicates that the demand for recreational UGS must be considered to adequately represent recreation benefits in urban areas, and illustrates how hotspot analyses can be used to target prioritized area for UGS management. We discuss the limitations of the framework and possible improvements for future studies.

1. Introduction

The well-being of city-dwellers relies on a sustained supply of ecosystem services in cities (Keeler et al., 2019). Nature-based recreation (hereafter *recreation services*) represents an important service since it benefits people in many ways such as increasing aesthetic experience (Church et al., 2014), enhancing mental health (Bratman et al., 2019), and increasing social cohesion (Hernández-Morcillo, Plieninger, & Bieling, 2013). Urban greenspace (UGS) provides major opportunities for recreation. Thus, integrating recreation services into UGS planning is crucial to secure such experiences for future city-dwellers. For example, in China, which is undergoing rapid urbanization, UGS development is emphasized to secure recreation services alongside other ecological benefits by national regulations such as the *New type of urbanization planning of China (2014–2020)* (SCPRC, 2014) and the *National forestry city development planning (2018–2025)* (NFGA, 2018).

Spatially explicit assessments of supply and demand for recreation services can be used to effectively plan UGS development that improves recreational opportunities where it is needed (Burkhard, Kroll, Nedkov, & Müller, 2012; Castillo-Eguskitza, Martín-López, & Onaindia, 2018). Here, we define supply and demand for recreation services in quantitative, non-monetary terms, in line with the ecosystem service literature. Within this body of literature supply has been defined as the potential of ecosystems, including their processes and functions, to provide an ecosystem service, without consideration of actual human recognition or use of the service (Tallis et al., 2012). For example, the percentage of 17 land cover types is used as a proxy for cultural ecosystem service supply in the UK's national ecosystem assessment (Church et al., 2014). Two general perspectives on ecosystem service demand exist (Wolff, Schulp, & Verburg, 2015). The first perspective defines demand as the actual use or consumption of a service, in line with the general economic definition (Champ, Boyle, & Brown, 2017; Tardieu & Tuffry, 2019). This demand can be assessed by environmental economic methods such as travel cost method (Bertram & Larondelle, 2017; Tardieu & Tuffry, 2019; Termansen, McClean, & Jensen, 2013). The second perspective uses preferences, desires and

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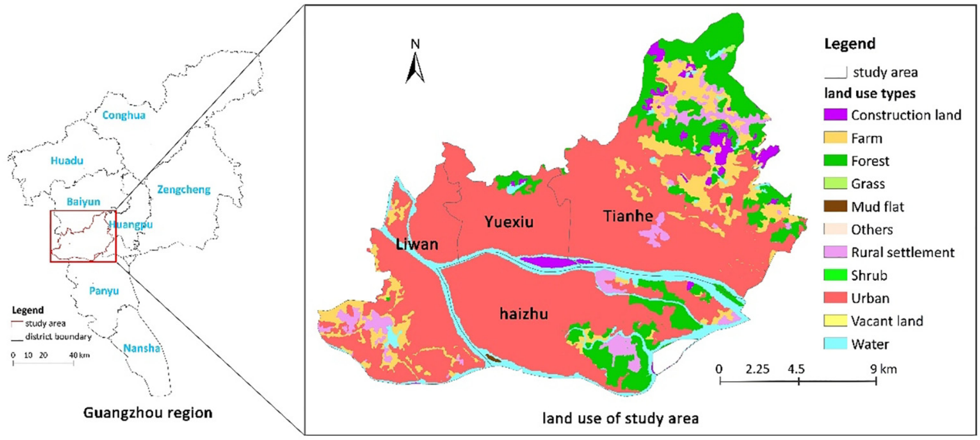

Fig. 1. Land use map of study area in 2015.

socio-economic characteristics to define demand for ecosystem services, sometimes can be assessed through choice experiments (Artti, Anna-Kaisa, & Ville, 2014; Binner et al., 2017; Champ et al., 2017; Hanley, Wright, & Koop, 2002).

To quantify recreation services, we apply a generalizable ecosystem service approach that uses comparable biophysical metrics (i.e., non-monetary) for supply and demand (Tratalos, Haines-Young, Potschin, Fish, & Church, 2016). In this study we characterize supply using "available UGS area within a certain radius around a residence" which is specified by land cover. This is in line with the above-mentioned definition of supply (Tallis et al., 2012). We characterize demand as "UGS area required by the population for recreation" defined by population and per capita UGS area, which is in accordance with second perspective on recreation demand (Hegetschweiler et al., 2017; Wolff et al., 2015). It is best to parameterize demand with local preference obtained from surveys. However, quantified UGS availability goals in urban planning policy can be used to calibrate demand if survey data is not available. In this way, the supply and demand are directly comparable in quantitative terms (i.e., UGS area). Also, the supply and demand indicators can be produced rapidly and cost-effectively.

Spatial configuration between supply and demand is especially important for recreation services, which depends on people physically being in a given space and interacting with nature (Hernández-Morcillo et al., 2013). UGS located in distant suburban areas is less visited, even when highly attractive (Žlender & Thompson, 2017). In many cities, large UGS patches are often located in the outskirts of cities and densely populated inner-city areas have much less UGS. Thus, in addition to increasing the total recreation service supply, an assessment of the spatial configuration of supply and demand is important in order to ensure access to recreation opportunities where it is currently lacking. Methods that overlay areas of supply and demand have been used to visually reveal the spatial match between supply and demand, however, quantitative indicators are still lacking (Hirons, Comberti, & Dunford, 2016).

In the context of UGS planning, given that investment budgets are limited, wisely targeting investments that benefit as many people as possible is an important issue (Cai, Gibbs, Zhang, Ferrier, & Cai, 2017). "Hotspots" are widely used in ecosystem service assessments with the purpose of guiding investment priorities. The hotspots concept has been used to describe the areas that provide large proportions or values of a particular service or areas that provide multiple ecosystem services (Egoh et al., 2008; Schröter & Remme, 2016). Schröter and Remme (2016) argued that integrating demand will help to set quantitative ecosystem service targets within hotspot areas. However, most studies mainly focus on supply hotspots without sufficiently considering demand (Cai et al., 2017). Thus, there is a clear need to include demand into hotspot analyses, especially for ecosystem services where addressing demand is crucial, such as recreation.

In this paper, we present a modelling framework to quantify and compare supply and demand of recreation services in cities. The framework facilitates UGS planning by quantifying multiple dimensions of recreation service supply and demand: (1) multi-scale spatial quantification of the supply–demand balance, (2) the degree of spatial match between supply and demand, and (3) a spatial clustering analysis of the supply–demand balance. We designed the framework so that it can be used with parameters derived from policy goals, or, for more relevant results, with local preference data obtained from surveys. We apply the framework to the Chinese city of Guangzhou. We use a survey and a review of policy documents to parameterize the model, and to demonstrate its use for Guangzhou's UGS planning.

2. Methods

2.1. Case study: Guangzhou—a typical city in South China

Guangzhou is located in South China (E112°57′–E114°3′, N22°26′–N23°56″) and is the third largest metropolitan city with the earliest history of urbanization. UGS accounts for 42.5% of the city area and per capita parkland is 17.1 m^2, which is high compared with the average parkland of other Chinese cities which is 13.1 m^2/cap (BFLGZM, 2017a). However, like many other cities, the population is concentrated in inner-city areas while large UGS areas are located in *peri*-urban areas. *Enhancement of national forestry city planning* identified that providing accessible UGS for recreation is the key task of UGS planning and the city government of Guangzhou is investing 830 million USD to optimize the UGS configuration to increase recreation opportunities (BFLGZM, 2017b). Our study area consists of the four most developed urban districts: Tianhe, Yuexiu, Haizhu, and Liwan (Fig. 1). The area is about 329.2 km^2 and the population was 5,046,955 in the sixth population census (GZSB, 2013). We chose this area because these four districts constitute the built-up area according to Guangzhou's master planning and represent a typical urban landscape. The outskirts are dominated by rural landscape.

2.2. A general overview of the study

The framework proposed in this study is schematized in Fig. 2. First, we mapped supply and demand. Supply was modelled using spatial data for UGS (further detailed in Section 2.5.1) and information from the survey we conducted (further detailed in Section 2.5.3) to set the influence radius of UGS. Demand was quantified using two methods: (1) survey responses quantifying people's comfort regarding different levels of crowding of UGS (see Section 2.5.4), and (2) a per capita UGS area goal (i.e., policy goal for UGS availability) as detailed by policy

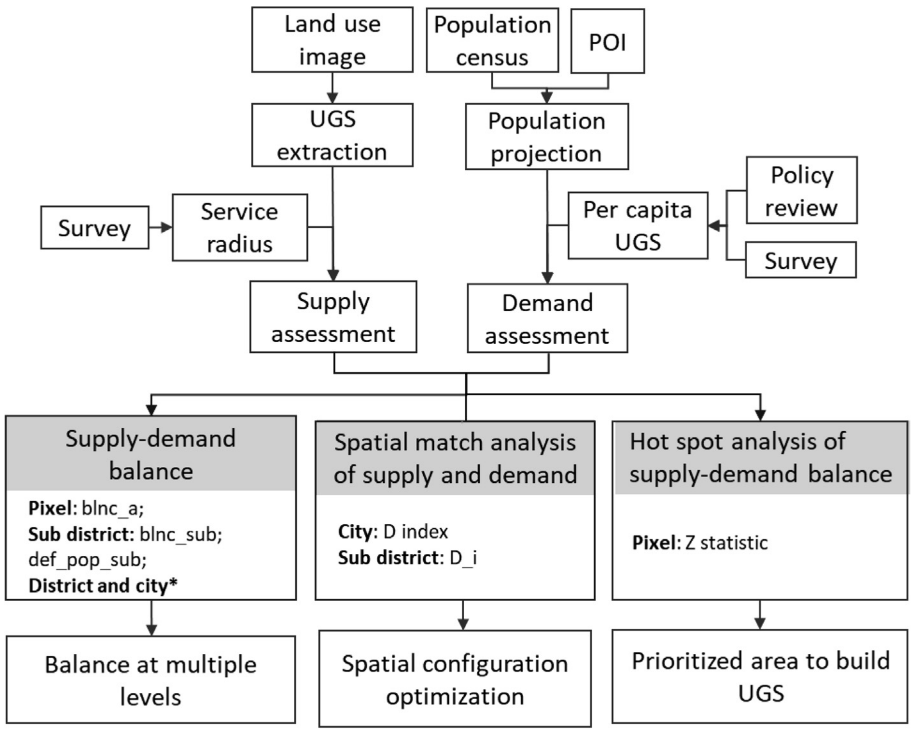

Fig. 2. Methodological framework to assess the supply and demand of recreation services.

documents (see Section 2.5.4). Based on the assessments of supply and demand, three methods were used to analyze their relationships.

First, we assessed the supply–demand balance at the pixel level (blnc_*a*). Based on this balance at the pixel level we calculated supply–demand balance and population with a UGS deficit within different administrative units, namely sub-districts (blnc_*sub*, def_pop_*sub*), districts, and at city level. Second, the degree of spatial match (disparity index, D) between supply and demand was assessed at the city scale, indicating the overall supply and demand configuration. A disparity index was analyzed at the sub-district level (D_*i*) to reveal the contribution of each sub-district to overall disparity. Third, we assessed the spatial clustering pattern (hotspot analysis) of the supply–demand balance.

2.3. Recreation service supply and demand assessment

2.3.1. Recreation service supply model

To calculate recreation service supply, for each pixel the amount of UGS within the radius of *d*_max is summed, as shown in Eq. (1).

$$sup\_a = \begin{cases} \frac{1}{n}\sum S_i & if \;\; d \le d\_max \\ 0 & if \;\; d > d\_max \end{cases} \tag{1}$$

where sup_*a* is recreation service supply to pixel *a* (m^2); S_i is area of UGS in pixel *i*; *d* is the Euclidean distance between pixel *a* and pixel *i*; *d*_*max* is the maximum radius within which UGS can provide recreation services. *d*_*max* can be calibrated using an empirical survey of people's preferences to determine how far they are willing to travel to visit UGS. Alternatively, this parameter can be calibrated using a UGS planning goal, which defines the service radius of UGS or the accessibility requirement of UGS.

In previous studies kernel, Gaussian, dicotomy and power functions have been used to describe the decay of a service against distance (Giles-Corti & Donovan 2002; Wang, 2012). However, few studies test the form of the function with empirical data (Lee & Hong, 2013; Zulian, Paracchini, Maes & Liquete 2013). We adopted a dichotomy approach since other function forms are challenging to apply to raster dataset. Since each UGS pixel is accounted for n times (*n* is the number of pixels within *d*_max), pixel-level supply is divided by *n*. As a result, the sum of pixel-level supply values over an area amounts to the actual area of UGS within this area (see Appendix A). Note that UGS supply is distributed to all surrounding pixels. Alternatively, the service could be distributed only to populated pixels, with more populated pixels getting more service supply.

2.3.2. Recreation service demand model

We propose a demand model that can be calibrated using an empirical survey as well as with easily accessible data (e.g., policy goals) when a survey is not available. We calculated demand as per capita UGS multiplied by population (Eq. (2), adopted from Lee & Hong, 2013). Per capita UGS area is people's preferences for UGS area to secure their recreation opportunity. Mathematically, the demand metric is calculated as:

$$dmd\_a = pop * gcap \tag{2}$$

where dmd_a is recreation service demand in pixel *a* (m^2); *pop* is population in pixel *a; gcap*is the UGS area required per person for recreation (m^2 /cap). It is best to parameterize *gcap* by using local survey data on people's preferences, but a policy goal that is often represented as per capita UGS or the presence of UGS within a certain distance from residents' home, can also be applied. For Guangzhou, we apply both the survey and policy goals to parameterize *gcap* (Section 2.5.4).

2.4. Comparing supply and demand

2.4.1. Recreation service supply and demand balance

First, pixel level supply–demand balance is calculated as Eq. (3).

$$blnc\_\ a = sup\_\ a - dmd\_a \tag{3}$$

where blnc_*a* is the recreational UGS supply–demand balance in pixel *a* (m^2); sup_*a* is the supply of UGS in pixel *a* (m^2); dmd_*a* is the demand for UGS in pixel *a* (m^2). If blnc_*a* $<$ 0, we define pixel *a* as UGS deficit compared with the predefined demand criterion. If blnc_*a* $>$ 0, pixel *a* has a UGS surplus.

Then, based on the pixel level result (blnc_*a*), two balance measurements can be calculated at the aggregated scales that the user is interested in. Here we present an example for the sub-district scale.

First, the recreational UGS supply–demand balance. This refers to the amount of UGS in surplus or deficit in relation to the population of the sub-district and the predefined UGS demand criterion:

$$\mathrm{blnc\_}sub = \sum_{1}^{n} \mathrm{blnc\_}a \tag{4}$$

where blnc_*sub* is the recreational UGS supply–demand balance in a sub-district (m^2); *n* is the number of pixels in the sub-district.

Second, the population under deficit. This indicates the population that has less UGS than the defined demand criterion:

$$\mathrm{def\_pop\_}sub = \sum \mathrm{pop}_a \ \text{if} \quad \mathrm{blnc\_}a < 0 \tag{5}$$

where pop_*a* is population at pixel *a*; def_pop_*sub* is the population under deficit relative to the predefined UGS criterion in a sub-district.

2.4.2. Spatial match between recreation service supply and demand

Ideally, areas with larger populations should be allocated more UGS. However, very often, a large proportion of UGS is located in *peri*-urban areas while a large proportion of the population is located in inner-city areas. Even if there is a lot of UGS at city level, there may still be people in the city with insufficient UGS. This spatial mismatch can be detected by the disparity index. The disparity index provides additional information alongside the supply–demand balance, because the balance cannot reflect how supply and demand are related spatially. There are several metrics such as Local Moran's I, Location Quotient or modified disparity index depicting disparity (Brown & Chung, 2006). The differences between these metrics are related to (1) whether they are measured globally or locally and (2) whether they address the spatial effect of disparity of adjacent analysis units. We adopted the disparity index (D) to assess the global spatial disparity of the recreation service supply and demand over the city. This indicator is most widely used in demographic studies to represent the mix of population of different ethnic groups or social-economic status (Duncan & Duncan, 1955; Lee & Hong, 2013). To capture local spatial disparity, we further developed an additional indicator (D_i) which assesses the contribution of each analysis unit to the overall disparity. D can be calculated as:

$$\mathrm{D} = \frac{1}{2}\sum_{1}^{n}\left|\frac{\mathrm{dmd\_}a}{\mathrm{dmd\_}city} - \frac{\mathrm{sup\_}a}{\mathrm{sup\_}city}\right| \quad \mathrm{D} \sim (0,\, 1) \tag{6}$$

where D is disparity index at city scale; dmd_*a* is demand for UGS in pixel *a*; dmd_*city* is demand for UGS over the city; sup_*a* is supply of UGS to pixel *a*; sup_*city* is supply of UGS over the city; *n* is the number of pixels in the city. And D_i can be calculated as:

$$D\_i = \frac{\frac{\mathrm{sup\_}i}{\mathrm{sup\_city}} - \frac{\mathrm{dmd\_}i}{\mathrm{dmd\_}city}}{2\mathrm{D}} \qquad \sum_{1}^{n} D\_i = 1 \tag{7}$$

where $D_{\_i}$ is the contribution of the sub-district *i* to the overall disparity (%); sup_*i* is the supply of UGS in a sub-district; dmd_*i* is the demand of UGS in a sub-district; Negative values indicate that the proportion of UGS supply is smaller than the proportion of UGS demand; Positive values mean the opposite. A conceptual example can be found in Appendix A.

2.4.3. Spatial clustering of supply–demand balance

The methods for spatial clustering pattern analysis influence the outcome (Schröter & Remme, 2016). Of the available clustering pattern analysis methods to assess ecosystem service hot and coldspots, the Getis-Ord G_i* method (Eq. (8)) is the most suitable for our study as it indicates clustered hotspots, i.e., larger areas and not single cells that happen to have high or low values (Schröter & Remme, 2016). Building a new UGS in coldspot areas (clustered high deficit values) will change both the supply–demand balance of the pixel but also change the balance of the surrounding deficit neighborhoods. The Getis-Ord Gi* equation is as follows:

$$G_i^* = \frac{\sum_{a=1}^{n} w_{i,a}\mathrm{blnc\_}a - blnc\sum_{a=1}^{n} w_{i,a}}{s\sqrt{\frac{\left[n\sum_{a=1}^{n} w_{i,a}^2 - (\sum_{a=1}^{n} w_{i,a})^2\right]}{n-1}}}$$

$$\mathrm{X} = \frac{\sum_{a=1}^{n} blnc\_a}{n}, \quad s = \sqrt{\frac{\sum_{a=1}^{n} bnlc\_a^2}{n} - bnlc^2} \tag{8}$$

where G_i* is the spatial statistic; blnc_*a* is UGS balance of pixel *a*, which is the variable to be conducted spatial analysis; blnc is the mean value of blnc_*a*; $\omega_{i,a}$ is the spatial weight of pixel *i* and pixel *a*; *n* is the number of pixels. The Getis-Ord Gi* analysis results in a Z-value. If $Z < -1.96$, it indicates a coldspot which means clustering of low values; If $Z > 1.96$, it is a hotspot which means clustering of high values; Values $-1.96 < Z < 1.96$ indicate no significant clustering pattern (Esri, 2018).

Spatial clustering analysis of supply–demand balance is conducted in ArcGIS 10.6. We classified the study area into 10 categories according to quantiles of the Z statistics. Deficit UGS area and population with a UGS deficit in each quantile category were calculated.

2.5. Data source and processing

2.5.1. Greenspace extraction

Although satellite data with moderate spatial resolution (e.g., Landsat) has been widely used in UGS detection, small and fragmented UGS, which is common in high-density cities and important for recreation, is often over- or underestimated (Gariazzo, Pelliccioni, & Bolignano, 2016). Therefore, we followed the method proposed by Song, Huang, Cai, and Chen (2018) to extract UGS from Google Images (17 grades, 1.2 m resolution), Open Street Map (OSM, 2018) and 30 m land use data interpreted from Landsat 8 images (GDC, 2018). Since the images are composited with R-G-B bands with digital values ranging from 0 to 255, the Normalized Difference Greenness Index (NDGI) (Uto, Takabayashi, Kosugi, & Ogata, 2008), combined with the blue band are used to extract UGS. For technical details, see Song et al., (2018). The image was converted from 1.2 m to 30 m using the "sum" aggregation type in the ArcGIS 10.6 Aggregation tool to generate an acceptable computation load. Farmland was removed using the 30 m land use map, as we were only interested in recreation-related UGS. Water bodies were removed using Open Street Map. An example of UGS extraction results can be found in SFig 1 in Appendix B. While we include street trees in the analysis, we should note that this may overestimate the amount of UGS available, as recreation is not the dominant function of tree-lined streets.

2.5.2. Population projection

We used China's sixth population census data (GZSB, 2013) and Gaode POIs (points of interest, i.e., all geographic entities, such as hospitals, schools, shops, especially those closely related with daily life) to project population. Gaode POIs are collected from multiple sources including Gaode map, Siweituxin, and internet user tagging, and are used for navigation (https://www.navinfo.com/). Gaode POIs are highly accurate, comprehensive and frequently updated. They have been used in urban function zone identification, resource allocation, and urban area boundary determination (Chen, Liu, & Liang, 2016). There are 870 types of POIs in the latest classification code of Gaode map. We extracted the commercial and residential category using Gaode API with Python. There are 11 sub-categories in the commercial and residential category, from which we kept dormitories, villas, residential communities, and residential areas. In total, 5482 residential locations were defined. Then we used the ArcGIS 10.6 Kernel Density tool to convert residence points to population density. The area of

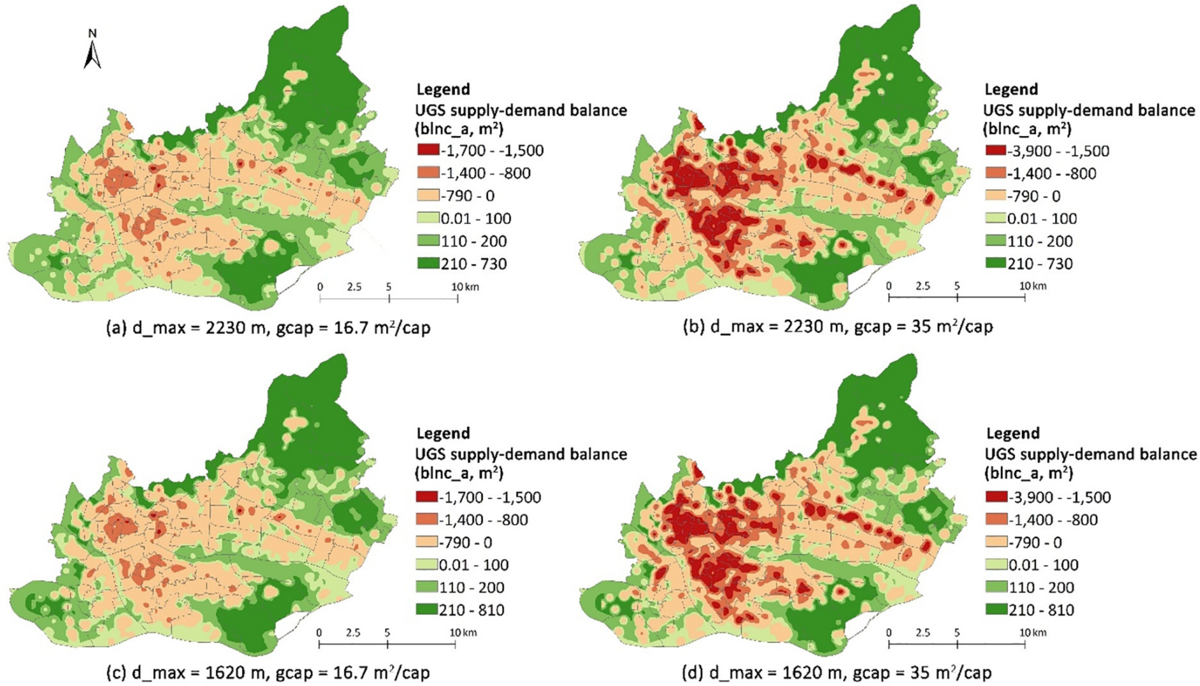

Fig. 3. Pixel level recreation service supply–demand balance (m^2) using different parameters (stated under each map).

Guangzhou's residential community ranges from 0.5 to 73 ha, which is equal to a 40–482 m circular radius (www.fangtianxia.com). We assumed the residential community is circular and we chose 500 m as a search radius in the Kernel Density analysis.

2.5.3. Recreation survey

The survey was conducted in July 2018 by online survey company "Wenjuanxing" to investigate general preferences for recreation in UGS. The company sent emails to a panel of existing "Wenjuanxing" users and invited them to fill in the survey for financial compensation. The following quality control was applied: (1) stratified sampling was used to improve the representativeness of the sample; (2) only questionnaires that are finished within a certain time are valid; (3) the questionnaire is invalid if there were logical contradictions. The questionnaire is included in Appendix D. In the survey, we showed respondents some pictures of UGS with various visitor density and asked "According to the pictures, what visitor density makes you feel an area is too crowded to visit?". Then the average of the minimum area for recreation of all respondents was calculated to calibrate *gcap*. We asked two questions: "What do you think is the maximum travel distance from home to the UGS for daily recreation on foot" and "What do you think is the most comfortable distance from home to the UGS for daily recreation on foot". The average of the maximum distance and the average of the most comfortable travel distance were used to calibrate *d*_max. We collected 766 valid questionnaires (a response rate of 23%). Males accounted for 47.4% of the sample and 31.9% of the respondents attained college and graduate degree. Respondents less than 20, between 20 and 60 and above 60 accounted for 27%, 65.8%, 7.2% of the sample respectively. The sample is representative of the population.

2.5.4. gcap calibration

We calibrated *gcap* using survey responses and policy goals. Based on the survey, the average minimum demanded area for recreation was 16.7 m^2/cap which was used to calibrate *gcap*. We reviewed all related policy documents to collect parameters on UGS demand, including the *Master plan of Guangzhou City* (GZMPNRB, 2019), *Greenspace system planning of Guangzhou City* (BFLGZM, 2017c), *Enhancement of national forestry city planning* (BFLGZM, 2017b), *National code for park planning and design (GB51192–2016)* (hereafter *national code*, MOHURD, 2016), *Local code for city park planning and design in Guangzhou (DBJ440100/T 23–2009)* (hereafter *local code*, BFLGZM, 2009), *Special planning of park construction and protection in Guangzhou (2017–2035)* (BFLGZM, 2018). The latter document states that per capita UGS should reach 18 m^2/cap in 2020, and no less than 18 m^2/cap to 2035 considering population growth. The *national code* and the *local code* state that to ensure the outdoor recreation quality, 45 m^2/cap of large park and 25 m^2/cap of community park should be available for each visitor. An average of 35 m^2 UGS per visitor should be ensured to improve recreation experience. We applied the lowest (16.7 m^2/cap from the survey) and highest value (35 m^2/cap from the national and local code) to calibrate per capita UGS demand. To save space, in the disparity index and spatial clustering pattern analyses, we only report the results with 16.7 m^2/cap as demand criterion, since it provides similar result using 35 m^2/cap, and one criterion can serve the purpose of demonstrating the method.

2.5.5. d_max calibration

We used two search radii collected in the survey: the mean value of maximum travel distance and most comfortable travel distance of the respondents. The maximum and most comfortable travel distances are 21.6 and 29.7 min, respectively. Assuming the average walking speed is 4.5 km/h (Ji, Sun, & Jia, 2018), we obtained 1620 m and 2230 m to calibrate *d*_max. These parameter values are comparable with travel distances from studies in other Chinese cites (Tong, 2016; Xing, Liu, & Liu, 2018). A limitation of our approach is that it did not differentiate between travel distances of population groups with different characteristics (e.g., age, car ownership, income) or vary search radii of UGS according to their quality. We further address this in the discussion section.

3. Results

3.1. Recreation service supply–demand balance at different scales

The pixel-level recreation service supply–demand balance results (bnlc_*a*) using different parameter combinations are shown in Fig. 3.

Table 1
Recreation service supply–demand balance at district and city scale.

Districts	Supply-demand balance (km^2)		Percent of population under deficit (%)	
	16.7 m^2/cap criterion	35 m^2/cap criterion	16.7 m^2/cap criterion	35 m^2/cap criterion
Haizhu	−9.2	−37.69	93%	97%
Liwan	−4.03	−20.46	89%	96%
Tianhe	18.03	−8.09	77%	91%
Yuexiu	−11.46	–32.18	96%	99%
City	−6.65	−98.41	88%	96%

Note: d_max = 2230 m; total population: 5.01 million

The spatial pattern of the results exhibits strong correlation with the lowest pixel-level Pearson Correlation being 0.98 (P less than 0.0001, n = 365048). There is no obvious difference between using 1620 m and 2230 m as the service radius (d_max), however, deficit pixels increase significantly with per capita UGS demand (*gcap*) increasing from 16.7 to 35 m^2/cap. Since the two d_max values did not impact the results much, we only present the supply–demand balance results for a d_max of 2230 m at sub-district and district scales. Recreation service supply and demand assessments are shown in SFig 2, SFig 3, SFig 4, SFig 5 in Appendix B.

District and city-scale supply–demand balances are shown in Table 1. The total UGS area balance over the study area is −6.65 km^2 and −98.41 km^2 with 16.7 m^2/cap and 35 m^2/cap as demand criteria respectively. Between 4.42 and 4.79 million people do not have access to sufficient UGS, accounting for between 88% and 96% of the total population. All four studied districts have a high proportion of the population with a UGS deficit while Haizhu and Yuexiu have higher deficits in terms of UGS area.

The sub-district level supply–demand balance is shown in Fig. 4. The recreational UGS balance (blnc_*sub*) ranges from −1.91 to 11.06 km^2 and from −4.88 to 10.71 km^2 with 16.7 and 35 m^2/cap as demand criteria, respectively (Fig. 4a, Fig. 4b). Most sub-districts with a UGS deficit are located in Guangzhou's inner-city area while sub-districts with a UGS surplus are at the fringe of the study area. There are 34 out of 79 sub-districts where 95%–100% of the population has less than 16.7 m^2/cap UGS and 53 sub-districts where 95%–100% of the population has less than 35 m^2/cap UGS (Fig. 4c, Fig. 4d, Table 2).

Table 2
Number of sub-districts in different deficit rate classes.

Deficit rate*	# of sub-districts associated with the deficit rate (16.7 m^2/cap demand criterion)	# of sub-districts associated with the deficit rate (35 m^2/cap demand criterion)
0–50%	7	1
51%–70%	8	3
71%–85%	11	7
86%–95%	19	15
96%–100%	34	53
Total	79	79

Note: *Deficit rate is defined by percent of population with a UGS deficit in a sub-district.

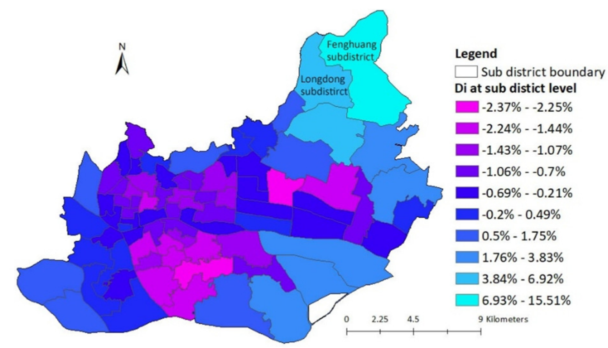

Fig. 5. The contribution of each sub-district to overall disparity of the study area.

3.2. Spatial match between recreation service supply and demand

The D index of the study area is 0.6 using pixel level as analysis unit. Fig. 5 shows the contribution of each sub-district to the disparity across the city. Longdong and Fenghuang sub-districts show very high contributions, indicating high proportion of UGS distributed in the area with low proportion of population. Sub-districts in the inner-city area also have a high contribution to overall disparity indicating high

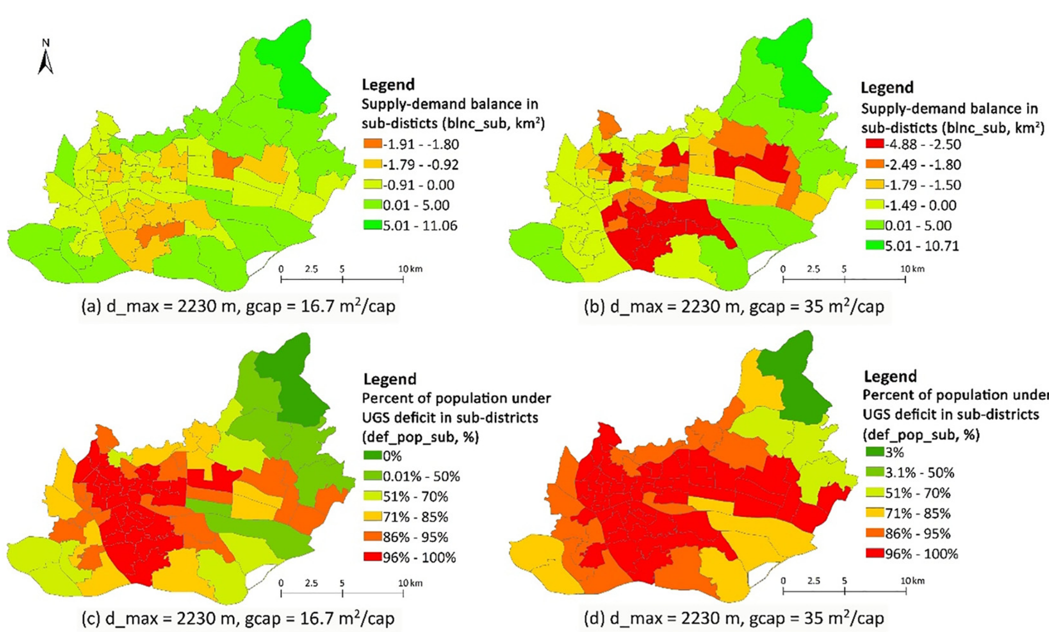

Fig. 4. Sub-district level supply–demand balance and percentage of population with less than the defined UGS demand criteria.

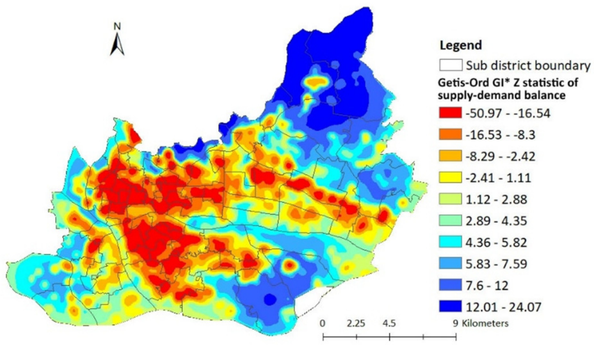

Fig. 6. Recreation service supply–demand balance hotspot analysis.

proportion of population but low proportion of UGS (purple areas in Fig. 5).

3.3. Recreation service supply–demand cluster analysis

The hotspot analysis of the supply–demand balance shows an obvious clustering pattern (Fig. 6). The deficit UGS area and the population with a UGS deficit in each quantile class of the Z-value are provided in Table 3. The area of lowest 10% of Z-value (supply–demand balance coldspots) accounted for 47% of the population with insufficient recreational UGS relative to the defined criterion and 57% of the area with a UGS deficit. The area of lowest 20% of Z-value accounted for 74% of population with insufficient recreational UGS relative to the defined criterion and 85% of the area with a UGS deficit.

4. Discussion

A key finding of our case study is the high proportion of people who do not meet the defined criteria for UGS: 88% and 96% of the population is in UGS deficit, with the demand criterion set to 16.7 m^2/cap or 35 m^2/cap, respectively. This result shows that the vast majority of people lack accessible UGS even if the UGS deficit at the city level is not large (-6.65 km^2 for the 16.7 m^2/cap demand criterion, about 2% of the surface area included in this study). Guangzhou has been recognized as the "National Forestry City" and its UGS is high compared to other Chinese cities (CSSN, 2016). However, there is still a vast majority of people that lack sufficient UGS for recreation. The entire population in 19 out of 79 sub-districts has less UGS than the 16.7 m^2/cap criterion (STable 1 in Appendix C). It is not unusual for urban populations to have a UGS deficit. A review of 104 UGS studies showed that only 20% of papers found adequate UGS provision compared with policy goals, which varied among cities. The cities that do meet the criteria often have a low UGS goal (e.g., 2 m^2/person in Hong Kong) (Boulton, Dedekorkut-Howes, & Byrne, 2018). Thus, there is an urgent need for increasing the accessible UGS for recreation in cities.

Table 3
Deficit UGS area and population with a UGS deficit in hotspot classes (Z quantiles).

Z quantile	Deficit UGS area (km^2)	Ratio	Deficit population (millions)	Ratio
10%	29.10	57%	2.09	47%
20%	14.05	28%	1.20	27%
30%	6.50	13%	0.76	17%
40%	1.35	3%	0.38	9%
50%	0	0	0	0
60%	0	0	0	0
70%	0	0	0	0
80%	0	0	0	0
90%	0	0	0	0
100%	0	0	0	0
Total	51.00	100%	4.42	100%

Note: UGS: urban greenspace; Categories are made according to the quantile of Z statistic generated from Getis-Ord Gi* analysis; Ratio is calculated using deficit UGS area and population with a UGS deficit in each Z quantile zone divided the total value.

In Chinese cities, indicators such as UGS per capita, proportion of land area covered by parkland service shed (i.e., areas from which parks are assumed to be accessible, usually a fixed radius around a park) are used as planning instruments. These indicators are monitored and reported at the city and district level every year. For example, the Guangzhou Municipal Forestry Bureau reported that residents have 17.1 m^2 UGS per inhabitant at city level (BFLGZM, 2017a). However, a large proportion of people did not even meet the 16.7 m^2/cap criterion in this study. We further compared indicators used in this study (UGS area balance and population with UGS deficit) with the matrix used in government documents (UGS per capita) for each sub-district. We found that in several sub-districts that meet the required UGS criterion measured by "UGS per capita", a large part of the population still does not have the demand criterion (16.7 m^2/cap) at their disposal (STable 1 in Appendix C). For example, in Dengfeng, Xinhua and Shamian sub-districts, > 80% of the population are with UGS deficit, although the sub-district per capita UGS is above 16.7 m^2. When comparing these indicators, the "population with a UGS deficit compared with the defined demand criterion" indicator we proposed can better assess recreational UGS supply–demand balance. Also, it is straightforward and easy to communicate with policy makers, planners and public. Thus, we recommend UGS planners to assess the population with a UGS deficit to improve recreation opportunities within cities.

Previous research on the disparity index defines values under 0.4 as low segmentation, above 0.5 as segmentation, and above 0.6 as high segmentation (Sun, Shi, & Gu, 2017), meaning that Guangzhou has high segmentation (D index = 0.6). The local disparity index D_i showed that the Fenghuang and Longdong sub-districts that are located in the *peri*-urban area contributed most to overall disparity. We further tested the index's sensitivity by removing these two sub-districts from the analysis. The D index reduced significantly, becoming 0.5 at the city level. This showed that the outer city sub-districts have a disproportionately high effect on the disparity of supply and demand, namely a large proportion of UGS is in *peri*-urban sub-districts, while only a small proportion of the population lives there. When only looking at inner-city sub-districts, UGS and population are not segmented.

In China, the finest administrative unit is the sub-district, which is too coarse to target priority areas for UGS planning. Our study provided spatial units independent of administrative boundaries with the cluster analysis. Clustering of low supply–demand balance values (coldspots) can help target new UGS investments. For example, the area with the lowest 10% Z-values (i.e., 10% of the study area) encompasses 42% of population with less UGS than 16.7 m^2/cap criterion and 57% of deficit UGS area. These areas could be prioritized for building new UGS and would greatly contribute to reducing the deficit population.

Our study shows that assessing the balance and spatial match between supply and demand of recreational UGS from multiple perspectives is feasible with both data that are widely available (i.e., land cover, population, UGS per capita goal) and by using survey data. However, many aspects of individual's preferences were included in a limited way in the case study. For example, people may travel longer than the predefined distance to more attractive UGS; different age groups, or different traffic modes vary in distances travelled for recreation (Hernández-Morcillo et al., 2013). Literature in the environmental economics has developed many assessment methods that are specifically relevant for quantifying demands and preferences (Champ et al., 2017) which could be combined with framework we presented to provide more accurate results. For example, in a choice experiment method, if UGS attributes such as types (e.g., forest or park), presence of water, and travel distance (e.g., 1000 m, 3000 m) are assessed, the willingness to accept travel distance could be calculated based on the UGS types and the presence of water feature. We could then assign different search radii to UGS accordingly. If population characteristics such as age or income are collected in the choice experiment, the willingness to accept travel distance of a specific population group can be estimated. Then the supply–demand balance of different subgroups can be assessed.

There are several potential measures that can be taken to improve the balance between recreation service supply and demand in cities. In Guangzhou, it is important to optimize the pattern of UGS by carefully selecting locations to build new UGS that reduce the spatial separation between supply and demand. Accessible small-scale UGS such as pocket parks should be promoted to meet people's demands regarding travel distance for recreation activities, since large vacant places are generally unavailable in inner-city areas. Local scale urban renewal and restoration programs (such as brown field restorations, residential renovation etc.) bring an opportunity to increase accessible UGS in cities, which will change the supply–demand balance (Beames et al., 2018; Rall & Haase, 2011). Another set of measures would be to improve street greenery or other walkability measures (e.g., more sidewalks and crosswalks) or public transport to increase people's willingness to travel for recreation (Giles-Corti et al., 2013; Sarkar et al., 2015). This would also change the supply–demand balance, especially given the fact that areas of high UGS supply are not fully accessible by residents in high demand areas.

5. Conclusion

Integrating recreation services into UGS planning is of great importance to secure nature-based recreation in urban areas. The Chinese government has realized the importance of recreation services and is making a commitment to make huge investments. In this paper we proposed a comprehensive framework of recreation service supply and demand assessment and conducted a case study on Guangzhou to demonstrate its usefulness in facilitating UGS planning.

Based on our study we have three main conclusions. First, measuring the population with a UGS deficit is a better representation of the actual recreation services. In Guangzhou's case, although the total amount of UGS at the city level is high, between 88% and 96% of people have a recreation service deficit because of the spatial distribution of population and UGS. Second, combining the disparity indices (D and D_i) can capture both global and local disparity. Supply and demand are segmented in Guangzhou, which is because a large proportion of UGS is located in *peri*-urban sub-districts with relatively small proportion of population. Third, hotspot analyses can be used to target priority areas for UGS management, and this type of analysis should consider recreation demand. The recreation service supply–demand balance of Guangzhou showed a strong clustering pattern. Therefore, adding UGS in the highest supply–demand balance coldspots (i.e., the 10% surface area in the lowest Z quantile which indicates clustered high deficit) would be a highly effective way to alleviate the UGS deficit of up to 47% of the population with less UGS than the defined criterion.

CRediT authorship contribution statement

Hongxiao Liu: Conceptualization, Methodology, Writing - original draft, Formal analysis, Writing - review & editing. **Roy P. Remme:** Conceptualization, Methodology, Writing - review & editing. **Perrine Hamel:** Conceptualization, Methodology, Writing - review & editing. **Huifu Nong:** Formal analysis, Resources, Software. **Hai Ren:** Conceptualization, Methodology, Funding acquisition, Supervision.

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Appendix A. Supplementary data

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