MODELING SPATIAL ACCESSIBILITY TO URBAN GREEN SPACES: A WORLDWIDE STUDY

A thesis for Applied Data Science master of the Graduate School of Natural Sciences

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Abstract:

Urban green spaces (UGSs) have been recognized as an essential role in urban ecosystem. Existing literature focused on the measurement of urban green space accessibility (UGSA) and inequity in a single city or cities in the same region. However, it is important to compare it on a global scale to raise the concern of policymakers and ensure the minimal UGSA standard and environmental justice for their citizens. By adopting the enhanced two-step floating catchment area (E2SFCA) method on 10 selected cities in North America, Asia, and Europe, we computed the normalized accessibility score for each population grid cell at a 250 × 250 m level. In addition, we measured the population-weighted average UGSA and the Gini coefficient to evaluate the overall accessibility and inequity for the selected cities. The result showed that in a single city, population grid cells with higher accessibility scores are concentrated near UGS with large size or dense distribution. However, the majority of the population only has a low accessibility level according to the criteria we set. When comparing UGSA among 10 cities, residents in North American cities have higher accessibility to UGS than European cities, and the Asian cities have the worst accessibility. Additionally, there is a severe inequity among people in all the cities, especially in Dublin, Shanghai, and Dhaka.

Keywords:

Urban green space, spatial accessibility, Two-Step floating catchment area method, distribution inequity

Table of Contents

1. Introduction

Urban green spaces (UGSs) have been recognized as an essential role in urban ecosystem. In addition to serving as places for leisure, sports, and socializing, UGSs function as homes for natural species, helping increase biodiversity (Nielsen et al., 2014). Numerous research has been conducted on the benefits UGSs could bring. The majority of the results showed they could reduce the mortality (Barboza et al., 2021; Gascon et al., 2016; Labib et al., 2021) and relieve noncommunicable diseases (World Health Organization, 2016), such as reduction of risk of cardiovascular disease (Tamosiunas et al., 2014), alleviation of diabetes mellitus conditions (De la Fuente et al., 2020), and respiratory conditions (Fuertes et al., 2020; Mueller et al., 2022), and more. In addition to physical health, it has been indicated that increasing exposure to UGS is associated with low mental illness (Beyer et al., 2014; Sugiyama et al., 2008), especially during the pandemic (Reid et al., 2022; Wortzel et al., 2021).

Therefore, research on accessibility to UGSs has raised concerns in the past few decades. Most of them could be divided into two broad categories, (a) the description of the urban green space accessibility (UGSA) and (b) the inequity of UGSA in a city (Nesbitt et al., 2019). Studies concerning the description of the UGSA mainly have two differences. The first is the data source of UGS. One of the major sources is government websites (Comber et al., 2008; Labib et al., 2021; Liu et al., 2021; Talen, 1997; Wu & He, 2018; Xiao et al., 2017). Another common source is the green space layer from GIS software such as open street map (OSM) (Wang et al., 2021), ESRI (Zhang et al., 2011), and Google Earth (Y. Chen et al., 2022). Derived data is another source, such as using supervised classification (Fan et al., 2017). The second is the models they used, from container approach (Abercrombie et al., 2008; De Chiara & Koppelman, 1975; Maroko et al., 2009; Timperio et al., 2007; Wang et al., 2021; Zhang et al., 2011), proximity approach (Maroko et al., 2009; Talen, 1997; Wang et al., 2021; Zhang et al., 2011), kernel density (Fan et al., 2017; Levine, 2010) in the early period to the interpolation methods such as gravity model (Hansen, 1959; Liu et al., 2021; Shen, 1998; Zhang et al., 2011), and 2SFCA (Luo & Qi, 2009; Luo & Wang, 2003; L. Shi et al., 2020; X. Shi et al., 2012; van Heerden et al., 2022; Ye et al., 2018) in recent studies.

Based on the measurement of UGSA, a large portion of studies focused on the inequity among different subgroups in a city, such as income-based (Comber et al., 2008; Liu et al., 2021; Wu & He, 2018) and racial/ethnic groups (Liu et al., 2021; Maroko et al., 2009; Talen, 1997). Some commonly used indices to measure the inequity of UGSA include Gini coefficient (Y. Chen et al., 2022) and Palma ratio (Liu et al., 2021). In addition, researchers used regression to discuss the relationship between UGSA and socioeconomic factors (Y. Chen et al., 2020; Nesbitt et al., 2019), such as education, ethnicity, income, and population density.

In addition to research on a single city, a few studies compared the UGSA for urban and rural areas within a country or region, such as the US (Zhang et al., 2011; Zhou & Kim, 2013), Europe (Wolff et al., 2020), China (Y. Chen et al., 2022), and Chile (Rojas et al., 2016). They showed that urban citizens enjoy a larger green space and accessibility than rural citizens (Y. Chen et al., 2022; Wolff et al., 2020; Zhang et al., 2011; Zhou & Kim, 2013). However, most of the existing literature focused on a single city or cities in the same region or country. Few studies made a comparison for UGSA or environmental justice on a global scale due to lack of consistent data, comparable and reproducible methods.

Therefore, this study aims to narrow down such gaps in the existing literature. It used a quantitative and replicable method to measure the UGSA in the selected cities of North America, Asia, and Europe, and evaluate the inequity of them. This study contributes to the research of UGSA in three ways. First, it is the first study to compare accessibility and inequity to UGS in global wide cities, not just in a single city or cities in the same region. Second, most of the existing literature focused on cities in high-income countries, and research on low or middle-income countries is limited. We selected 10 cities according to economic, demographic, and geographic dimensions, which could provide credible and robust results. Last but not least, we provided a modular model developed in python to make the computation of UGSA reproduceable for multiple cities at ease. In most studies, the common software used for the computation of UGSA is QGIS or ArcGIS. Nevertheless, they are inefficient when the number of cities as well as the spatial unit of analysis increase since the overall modelling approaches are often not replicable.

The following study is structured in five parts. Section 2 is a literature review of different approaches measuring the UGSA and inequity. Section 3 introduces data, study area, and methodology, then followed by the section presenting results, including the accessibility maps for 10 cities, the proportion of citizens with different accessibility levels, population-weighted average accessibility scores, and the Gini coefficient for those cities. In section 5, we compared the results with other studies and discussed limitations. At last, we summarized the whole study in section 6. The overall reproducible workflow of the methods can be found in the GitHub repository, https://github.com/qiuyixu/Green-space-accessibility-.

2. Literature review

2.1 Measurement of accessibility

The concept of accessibility describes the convenience (Alam et al., 2010) or potential to access spatially distributed opportunities (Páez et al., 2012) under various contexts. Approaches to measure accessibility have been evolving over the decades. Wang et al. (2021) and Zhang et al. (2011) both summarized the existing measurements of UGSA, which could be divided into three broad methodological approaches, namely container approach, travel cost approach, and spatial interaction method.

2.1.1 Container approach

In the early period, the "container approach" is one of the most common approaches. This method measures the total number or acreage of parks located within a typical geographic unit, such as zip code or census tract (De Chiara & Koppelman, 1975; Maroko et al., 2009). In light by the basic concept, many researchers created various indices, such as the percentage of the area used for UGS, and the area of UGS per capita within the geographic unit (Talen, 1997; Timperio et al., 2007; Wang et al., 2021). Though with advantages of computational convenience and suitability for regions that lack data, it could generate contradictory results to reality, especially for indices of normalized population (Abercrombie et al., 2008; Timperio et al., 2007). One of the reasons is the heterogeneous distribution of population within a geographic unit. Normalized population could not represent the real demand for a certain UGS (Maroko et al., 2009). Another reason is the famous Modifiable Areal Unit Problem (MAUP), which describes geographic measures or relationships of interest that could change because of the definition of spatial scales of the geographic unit of analysis (Zhang et al., 2011). As Wang et al. (2021) and Zhang et al. (2011) mentioned, this approach could lead to inconsistency if choosing a different distance threshold as the geographic container.

2.1.2 Travel cost approach

Travel cost approach measures the minimum travel time or distance (Euclidian or road network based) to UGS (Maroko et al., 2009). One of the advantages of this method is the measurement of distance or time is intuitive and interpretable. However, the assumption that people could only access the nearest UGS is unrealistic. Thus, a modified travel cost approach – proximity method, is used in many later studies. It measures the number of UGS a certain geographic unit could reach within a distance threshold or the average distance to all UGS within a certain distance (Zhang et al., 2011). Talen (1997) used this approach to compare equitability in facility distribution in Pueblo and Macon and revealed that the park distribution tends to benefit lower-income, non-White neighborhoods in Macon, but not Pueblo. Wang et al. (2021) compared the result of this method with the spatial interaction approach and found that the UGSA calculated under the two approaches are similar.

2.1.3 Spatial interaction method

2.1.3.1 Gravity model

Hansen-type measurement was first proposed by Hansen (1959) as the form of equation (1). In the context of UGSA, A_i is the cumulative accessibility of population location i, S_j is the number or area of UGS in location j, d_{ij} is the distance from location i to j, and f is the distance decay function between i and j.

$$A_i = \sum_j S_j f(d_{ij}) \tag{1}$$

Then Shen's model (Shen, 1998) modified the Hansen-type measurement by dividing a demand-related variable, which is shown in the equation (2) and (3). All the definitions of variables are the same as above, except P_k is the population at location k, and d_{kj} is the distance between k and j. Compared with Hansen-type, Shen's model breaks the assumption of uniformly spatially distributed demand. To be specific, uniformly distributed demand assumes people are evenly distributed at a location, which is not the case in most cities. The accessibility is more realistic if the demand potential (D_j) at each location is considered. In addition, this model avoids the MAUP problem in the container approach, because it doesn't need the geographic unit to compute the accessibility (Zhang et al., 2011). However, due to the assumption that each population location has access to all the UGS, the main drawback is it only considers the supply of green space but not the demand for them (Liu et al., 2021).

$$A_i = \sum_{j=1}^{n} \frac{S_j f(d_{ij})}{D_j} \tag{2}$$

$$D_j = \sum_{k=1}^{m} P_k f(d_{kj}) \tag{3}$$

2.1.3.2 Two-step floating catchment area

The 2SFCA analysis includes two steps which are shown in the equation (4) and (5). S_j is the area of UGS at location j, d_0 is catchment size, d_{kj} is the distance between location k and j, and P_k is the population within the catchment size. The first step is to compute the supply-demand ratio (R_i) of opportunities (UGS, job vacancy, physician, and more). The second step is to sum up the ratio of the opportunity each population location could reach within a certain distance (Luo & Qi, 2009). It is a special type of gravity model, as long as setting the distance decay function equals 1 in the catchment area and 0 outside (Luo & Qi, 2009). Compared with the gravity model, it uses catchment size to set catchment areas, which introduces the measurement of the supply-demand ratio of a UGS. Due to the advantage in interpretation, many UGSA research employed this approach in the past few decades (L. Shi et al., 2020; van Heerden et al., 2022; Ye et al., 2018). However, the main drawback is the assumption that people could not reach a UGS if the distance exceeds the catchment size. This is true for most situations because people probably go for a walk or exercise after a day of working just in the nearest park. However, it is also common that people would like to go to a wetland, zoo, or national park, which is far away from them in their free time. Under these situations, the accessibility could be distorted. Variants of this model have been proposed in recent decades, such as applying the distance decay function in the second step (X. Shi et al., 2012) or both steps (Enhancement 2FSCA) (Luo & Qi, 2009).

$$R_j = \frac{S_j}{\sum_{k\epsilon\{d_{kj}\leq d_0\}} P_k} \tag{4}$$

$$A_i^F = \sum_{j\epsilon\{d_{kj}\leq d_0\}} R_j = \sum_{j\epsilon\{d_{kj}\leq d_0\}} \frac{S_j}{\sum_{k\epsilon\{d_{ij}\leq d_0\}} P_k} \tag{5}$$

2.2 UGSA inequality

Based on the measurements of accessibility, many studies focused on the problems of environmental equity and equality. Not surprisingly, people with higher socioeconomic status and belong to major ethnics, or regions with higher housing prices indeed have higher accessibility to UGS in general (Comber et al., 2008; Liu et al., 2021; Maroko et al., 2009; Talen, 1997; Wu & He, 2018). In Beijing, Wu & He (2018) revealed that the higher-income residential zones have significantly higher access to UGS. In Chicago, Liu et al. (2021) found that the rank from highest accessibility to lowest is white-majority census tract, black-majority census tract, and Hispanic-majority census tract respectively, and the inequality inside the black-majority census tract based on income is the most severe one. In Pueblo, Talen (1997) demonstrated that regions with low housing value and high percentage of Hispanics have low access to UGS. In Leicester, Comber et al. (2008) showed that Christians have 44% more access to UGS than Hindus. More interestingly, Altmetric & Hamilton (2012) found that after realizing the UGS inequity, increasing UGS in the low-income area leads to the green space paradox, that is the low-income people would move to a lower green space.

Generally, two indices are used to measure the equity of UGSA, Gini coefficient and Palma ratio. Gini coefficient describes how inequal a situation departs from the perfect equality. It is defined based on the Lorenz curve, and the value equals the area between the line at 45 degrees and the Lorenz curve for accessibility (van Heerden et al., 2022). Another popular method is Palma ratio. It measures the inequity between the richest 10% and the poorest 10% of the population based on income. Compared with Gini coefficient, it is commonly used for income inequality measurement, and focuses more on polar groups (such as the richest and poorest).

3. Data and Methodology

3.1 Study area

We selected 10 world's major metropolitan cities from Asia, North America, and Europe. They are Amsterdam, The Netherlands; Dublin, Ireland; Ghent, Belgium; Dhaka, Bangladesh; Tel Aviv, Israel; Shanghai, China; Vancouver, Canada; Washington D.C., US; Philadelphia, US; Denver, US. We used the administration boundary of those cities to do the analysis, except Dhaka, Shanghai, and Amsterdam. For Dhaka, we chose the metropolitan area of the city since over 80% of the population is concentrated here. For Amsterdam, we used the bounding box for its urban area from OSM. For Shanghai, we selected the central area (Y. Chen et al., 2020), including Huangpu district, Xuhui district, Changning district, Jingan district, Putuo district, Hongkou district, Yangpu district, and Pudong.

As shown in table 1, the values of the UGS/total area ratio range from 42.99% to 0.81%. Three American cities have significantly higher UGS/total area ratios, which are 42.99% (Washington D.C.), 33.41% (Philadelphia), and 22.32% (Denver). Dublin has the highest UGS/total area ratio among the three European cities with a value of 6.33%. The ratio for Tel Aviv is 4.08%, which is much higher than the two other Asian cities. Dhaka has the lowest ratio among the 10 cities, with the value of 0.81%. As we can see, most of the cities meet the minimum UGS requirement of WHO (World Health Organization, 2017), which is 9 m^2 UGS per capita, except the three Asian cities. In addition, the population density varies, from 10600 (Dhaka, the world's most densely populated urban area) to 1700 (Ghent). As Nesbitt et al. (2019) revealed that economic factors are positively correlated to UGS, when selecting cities, we also considered different economic development levels as shown in table 1. Figure 1 is the spatial distribution of UGSs in 10 cities. The cities in North America have more huge green spaces, and the distributions are even, while UGS in Ghent and Dhaka are relatively concentrated.

Table 1: Description of 10 cities from economic, demographic, and geographic dimensions[1]

Continent	City	Urban Population	Urban Population $/km^2$	GDP per capita (\$)	UGS (km^2)	UGS/total area (%)	UGS/capita (m^2)
North America	Philadelphia	1603797	4612	68128.80	123.49	33.41	77.00
	Denver	715522	1805	58682.58	89.43	22.32	124.99
	Vancouver	662248	5750	40363.05	16.07	11.9	24.27
	Washington D.C.	689545	4361	98041.82	76.09	42.99	110.35
Europe	Ghent	260341	1700	39381.55	8.35	5.35	32.07
	Dublin	1173179	3689	83605.63	20.12	6.33	17.15
	Amsterdam	1558755	5214	38448.28	15.21	1.33	9.76
Asia	Tel Aviv	1388400	8058	67899.10	7.18	4.08	5.17
	Dhaka	21741090	10060	7655.50	17.58	0.81	0.81
	Shanghai	24890116	3925	89488.43	114.79	1.81	4.61

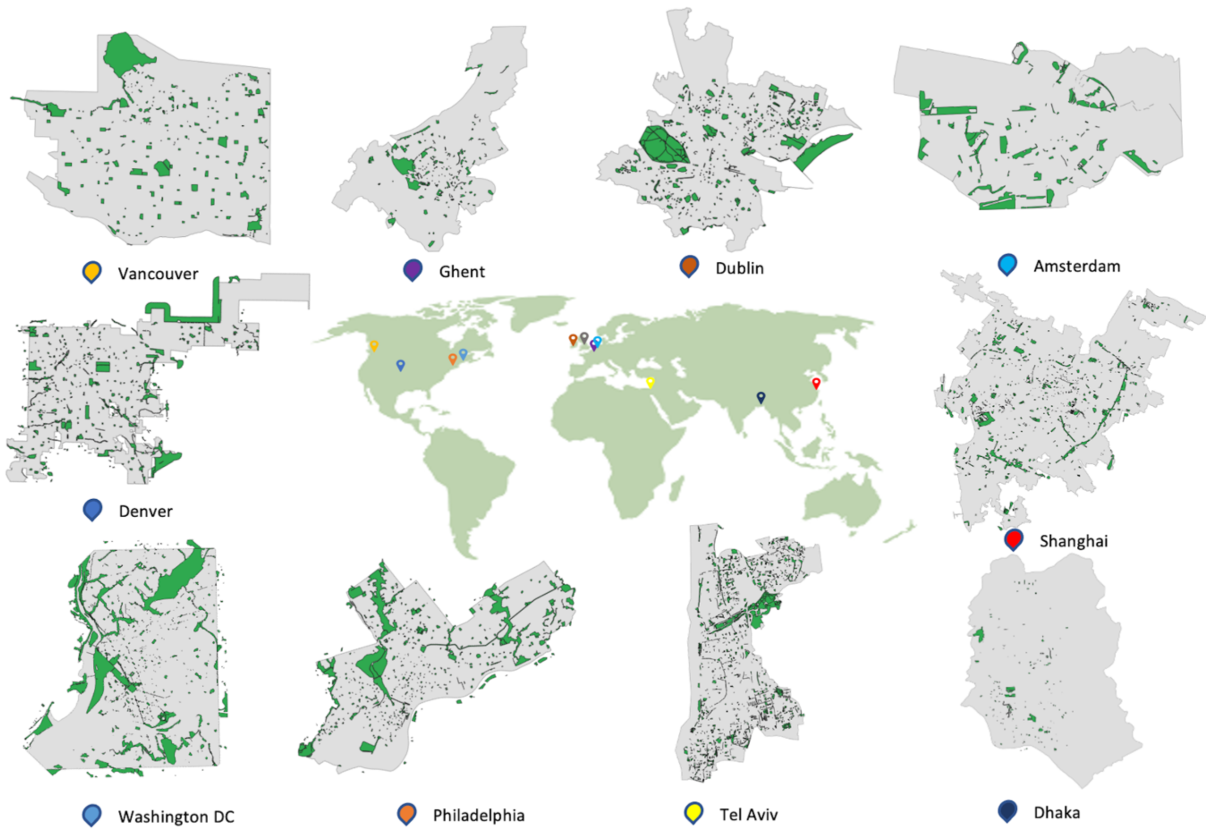

Figure 1: Spatial distribution of UGS in 10 cities

3.2 Data

We used UGS data from multiple sources. For US cities, UGS was extracted from Prior-Magee et al. (2020). For Dublin, we obtained the UGS dataset from the Smart Dublin website (Dublin City Council et al., 2022). For Amsterdam, we used UGS data from the City of Amsterdam (City of Amsterdam,

[1] Population, city area size, GDP per capita are all from Wikipedia in 2022, and UGS size see the data source in section 3.

2022). For Dhaka, we collected from City planning authority (2022) by RAJUK. For Ghent, we extracted data from Open Data Portaal (2022). For Tel Aviv-Yafo, we got the data from Municipality of Tel Aviv-Yafo (2022). For Vancouver, we collected the data from City of Vancouver (2022). For Shanghai, we sourced the data from Li et al. (2020). According to WHO guidelines, urban residents should be able to access UGS of at least 0.04 ha (400 m^2) within 300 m of their home (World Health Organization, 2017). As a result, we selected a size of UGS greater than 0.04 ha.

Road network data, city bounding boxes, and administrative boundaries were extracted from OSM using OSMnx package (Boeing, 2017). The grid population data for the year 2015 came from disaggregated census or administrative units to grid cells by CIESIN GPWv4.10. Here we chose a 250 × 250 m grid size.

3.3 Method

3.3.1 Catchment size and travel mode

Choosing the catchment size is essential for UGSA analysis. As suggested by WHO, citizens should live within 10 minutes' walk to a UGS nearby ("Environmental Sustainability in Metropolitan Areas", 2013). Accordingly, many studies set catchment sizes ranging from 300 m to 1000 m based on the walking speeds between 0.9 and 1.5 m/s (Nesbitt et al., 2019; Wang et al., 2021; Wu & He, 2018; Ye et al., 2018). In addition, other travel modes such as cycling and driving were also taken into account (Wang et al., 2021). However, because our research is based on cities worldwide, the main travel mode varies and is highly correlated with economic factors. Compared with other travel modes, walking is a more general one. In addition, walking and cycling are economic, environmentally friendly, and healthy traveling modes. Boone et al. (2009) revealed that people are likely to walk or cycle rather than driving if the distance is less than 1 mile. Ye et al. (2018) discovered that in Macau 80–90% of residents walk to UGSs. As a result, we selected walking as the travel mode, and the catchment sizes were 300 m, 600 m, and 1000m respectively.

3.3.2 Edge effect

Edge effect in the UGSA context refers to the situation that citizens who live near the borders of the urban area have access to UGSs outside the study area (Liu et al., 2021). If neglecting this situation, the UGSA for citizens who live near the boundary could be underestimated (X. Chen, 2017; Sadler et al., 2011). As a result, we set a buffer distance that equals the catchment size around the boundary of the study area to clip the green space data.

Meanwhile, citizens outside the borders could have access to UGSs near the borders of the urban area. If not taking this situation into account, UGSA for population grid cells around UGSs near the fringe of the urban area could be overestimated due to the underestimation of demand for those UGSs. Accordingly, we set a buffer distance that equals twice the catchment size around the boundary of the study area to clip the population data.

3.3.3 Definition of destination and origin

Most studies used geometric centroid of UGSs as the destination (Comber et al., 2008; Dai, 2010; Liu et al., 2021; Maroko et al., 2009; Wu & He, 2018; Zhang et al., 2011). However, in some situations such as UGSs with a large area, this measurement is oversimplified thus bringing inaccurate results. Therefore, some studies tried to simulate the realistic entrance of UGSs, which are defined as the intersection points of the road network and UGS with buffer (Labib et al., 2021; Wang et al., 2021). The buffer distance usually equals the width of the road network which extends the boundary of UGSs to connect with the road network.

We tested both destinations and found the simulation entrance method is more reasonable, which is consistent with (Wang et al., 2021). Thus, we chose the simulation entrances as the destinations in the rest of the article. As this study selected cities on a worldwide scale, we set a 20 m buffer distance considering wider roads in some cities (Wang et al., 2021).

Because we used a comprehensive road network, there could be multiple road lines along with each other (usually two walking roads) as shown in figure 2a. To solve this problem, if the distance between two intersection points that belong to the same UGS is less than 50m, we chose the first one. In figure 2a, the orange ones are all the intersection points between road networks and UGS boundary with buffer, and the green ones are the selected entrance gates, which seem more reasonable and could reduce the computationally intensive problem.

For origin, we used centroid of each population grid cell. The grid size of 250 × 250 m ensured that all UGS caught some population (Ye et al., 2018). Meanwhile, it could reduce the computationally intensive problem compared with a smaller one.

3.3.4 Measuring the UGSA

We used an enhanced two-step floating catchment area (E2SFCA) method to compute the UGSA in different cities at a 250× 250 m grid cell level. Figures 2a and 2b show the demand catchment area and supply catchment area respectively. The first step of this approach is to compute the supply-demand ratio of UGSs as is shown in equation (6). Where R_j is the supply-demand ratio of UGS j. S_j is the area size of UGS j. P_k is the population number in grid cell k. d_{kj} is the distance between the centroid of grid cell k and the nearest entrance of UGS j. d_0 is the catchment size (300m, 600m, 1000m), which determines the service area of UGS j. $G(d_{kj}, d_0)$ is the distance decay function of UGS j applying the Gaussian distribution equation in formulation (7). We assumed that grid cell k has no access to UGS j if d_{kj} is larger than the catchment size, that means $G(d_{kj}, d_0)$ equals 0. The nominator of equation (6) represents the supply of UGS j, and the denominator describes the demand for UGS j.

$$R_j = \frac{S_j}{\sum_{k \epsilon \{d_{kj} \leq d_0\}} G(d_{kj}, d_0)\, P_k} \tag{6}$$

$$G(d_{kj}, d_0) = \begin{cases} \frac{e^{-\frac{1}{2} \times \left(\frac{d_{kj}}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}}, & if\ d_{kj} < d_0 \\ 0, & if\ d_{kj} \geq d_0 \end{cases} \tag{7}$$

The second step is to compute the UGSA for each population grid cell. In equation (8), R_j is the supply-demand ratio calculated in the first step. If the nearest entrance of UGS j falls into the catchment area of grid cell i (use the centroid of grid cell i and add a d_0 buffer), then sum up all the supply-demand ratio of UGS multiple the accordingly distance decay function.

$$A_i = \sum_{j\epsilon\{d_{kj}\le d_0\}} G(d_{kj}, d_0)\, R_j = \sum_{j\epsilon\{d_{kj}\le d_0\}} G(d_{kj}, d_0)\, \frac{S_j}{\sum_{k\epsilon\{d_{ij}\le d_0\}} G(d_{kj}, d_0)\, P_k} \tag{8}$$

Next, we normalized the accessibility score for each population grid cell to make it comparable among different cities as equation (9).

$$A_n = \frac{A_i}{P_i} \tag{9}$$

A_i is the accessibility score of population grid cell i, P_i is the population of it. If the scores for population grid cells A and B are the same, but B has a larger population, then the above formula could generate different scores for them.

Except for normalizing the accessibility score for a single population grid cell, we further computed the population-weighted average accessibility score for the whole city using equation (10). A_i is the accessibility score for grid cell i; P_i is the population for grid cell i; $\bar{A}$ is the population-weighted average accessibility score of a city.

$$\bar{A} = \sum_{i=1}^{n} A_i * \frac{P_i}{\sum_{i=1}^{n} P_i} \tag{10}$$

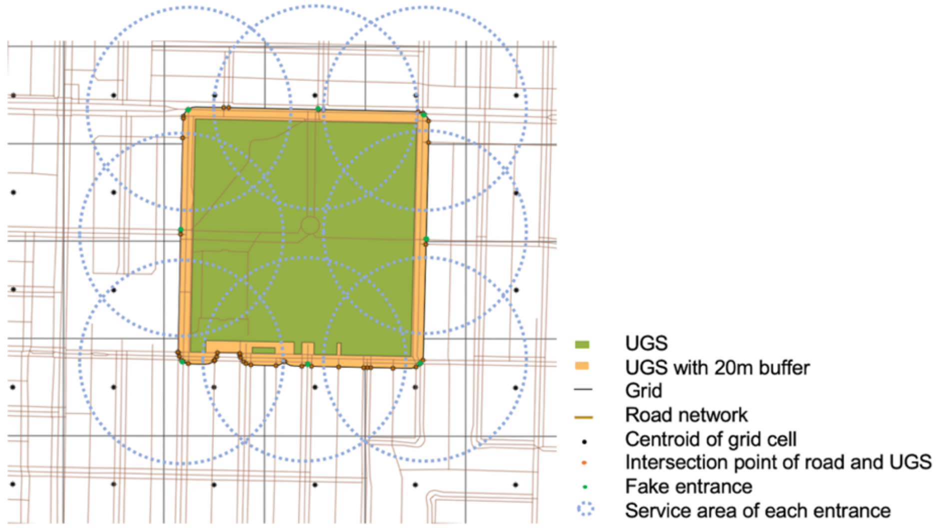

Figure 2a: Definition of supply catchment area

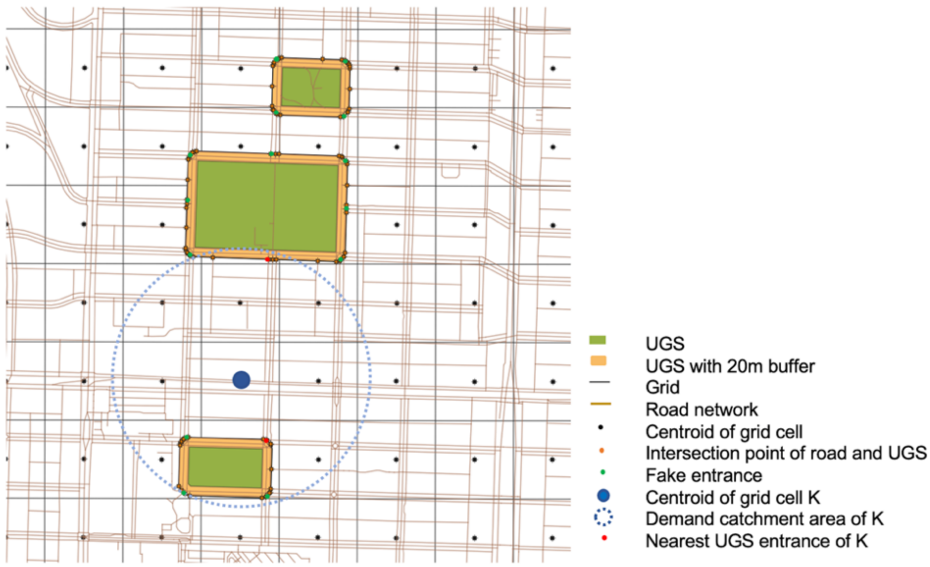

Figure 2b: Definition of demand catchment area

3.3.5 Measuring the inequity of UGSA

As discussed above, two indices are commonly used to measure the inequity of UGSA. We chose the Gini coefficient to represent the inequity of UGSA since Palma ratio is often used for comparison among different subgroups. In addition, Gini coefficient is more straightforward and interpretable (CEDLAS & World Bank, 2022). It is a ratio with a value between 0 and 1, and the higher the value the greater inequity. Before using formula (11) to calculate the value, we ranked the accessibility score in ascending order. l is the index of the population grid cell with the highest accessibility. A_i is the normalized UGSA in population grid cell i. n_i is the population of grid cell i.

$$G = 1 - 2\sum_{k=1}^{l}\left(\frac{\sum_k \sum_{i=1}^{k} A_i \times n_i}{\sum_{i=1}^{l} A_i \times n_i} \times \frac{n_i}{\sum_{i=1}^{l} n_i}\right) \tag{11}$$

3.3.6 Definition of UGSA levels

We set the standard of classifying 4 levels (No accessibility, Low accessibility, Middle accessibility, and High accessibility) of UGSA based on our hypothetical calculation. Then we can calculate the proportion of the population belonging to those levels in a city. We assumed that there are 1000 residents live near a UGS (UGS_K in figure 3) according to the standards set in the UK (Parry et al., 2016) and US (Handley et al., 2011). As WHO suggested, at least 9 m^2 of green per capita should be available (Russo & Cirella, 2018). Thus, the minimal size of UGS_K is 9000 m^2. No accessibility means people do not have any UGS within their catchment size. Then, the hypothetical maximum value for Low accessibility can be set as the score of population grid cell A under the worst situation of having access to UGS, which is assumed as (figure 3):

- Only one person is living in grid cell A, 999 people live in grid cell B.
- The person who lives in grid cell A could only reach UGS_K within a certain catchment size.
- Grid cell B is inside the UGS, which means distance between the centroid of grid cell B and the entrance of UGS_K is 0.
- Grid cell A is at the boundary of the catchment area of UGS_K, which means distance between the centroid of grid cell A and the entrance of UGS_K is catchment size.

The supply-demand ratio of UGS_K is the lowest under this condition, which is 6.5. Then, applying the E2SFCA model described above, we used supply-demand ratio of UGS_K to multiply the weight calculated by Gaussian distribution and got the score of 5.5. This accessibility score for A is the lowest under the situation of having access to UGS, and we set it as the maximum value for Low accessibility. Then, we assumed that the distance between the centroid of grid cell A and the entrance of UGS_K is half of the catchment size, and all other conditions remain unchanged. The score we got is 7.9, which is the maximum value for Middle accessibility.

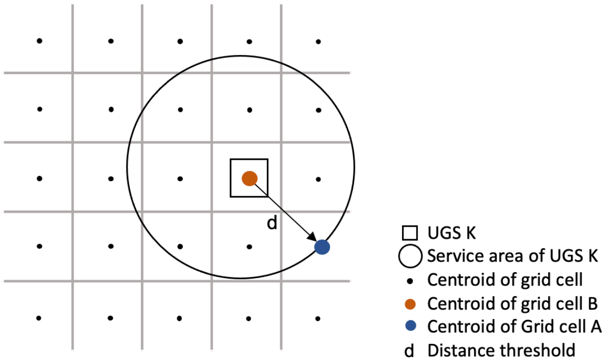

Figure 3: Definition of different UGSA levels

4. Results

4.1 Measurement and comparison of UGSA

Figure 4 is the spatial pattern of normalized accessibility scores for ten selected cities with catchment sizes of 300 m, 600 m, and 1000 m respectively. The results are classified based on the quantile classification method. To make the results in different cities and catchment sizes comparable, we averaged the upper limit of each quantile for 10 cities under the catchment size of 1000 m, and got the values of 0, 0.025, 0.065, 0.186 respectively[2]. In general, population grid cells with high accessibility scores are concentrated near UGSs. However, even though some grid cells have many UGSs around them, due to the high demand for those UGSs, the accessibility scores are not high. In addition, the accessibility scores are lower in the city center than in other areas in most cities, such as Washington D.C, Dublin, Amsterdam, Tel Aviv-Yafo, and Shanghai. This is understandable because most of the city centers are places for entertainment, commerce, and shopping. If separated by green spaces, the convenience could be weakened (Reimers & Clulow, 2000). In addition, higher population density in the city center leads to high demand for UGSs.

[2] The reason to choose 1000 m to get the averaged values is that the accessibility scores of 1000 m are wide enough to recognize the difference among quantiles.

In Vancouver, the western part has higher accessibility than the eastern due to the lower population density. In addition, West Vancouver is made up of affluent areas such as Kitsilano, while East Vancouver is for the working class traditionally. This reveals the inequity of UGSA to some extent and we discussed it in detail in the next section. In Denver, a lower population leads to higher accessibility scores in the southeast part. For Washington D.C., high accessibility scores appear on the border of the city, where huge parks are situated such as Rock Creek Park, and National Capital Parks. In Philadelphia, the large size of UGSs and less dense population contribute to extremely high scores in the Chestnut Hill district. It is also an affluent district known as the city's garden district, which indicated the existence of inequity. In Dublin, a dense population in the city centre leads to a higher demand for UGSs, thus the accessibility scores for this area are relatively low. For Amsterdam, there is a large and continuous area in Westpoort that has no accessibility since it is an industrial district and does not have UGS. In addition, the Centrum area has a relatively low accessibility score than other areas because of the large population and low supply of UGSs. For Ghent, due to the green space is concentrated in the middle part, the areas that have access to UGSs are concentrated accordingly. In Tel Aviv-Yafo, the low supply of UGSs and large population lead to the low accessibility scores in the city centre area. For the two cities from developing countries, Shanghai and Dhaka have distinctively low accessibility scores than other cities. This results from the low supply of UGSs (both size and number) in Dhaka. In Shanghai, the distribution of accessibility scores is consistent with the population distribution. As a result, the border area has a higher score than the inland area which is densely populated.

In addition, with the increase in catchment size, many population grid cells in different cities change to a higher accessibility score, especially from no accessibility to a low score (smaller than 0.025). This is consistent with common sense that with a larger catchment size people could have access to more UGSs. Meanwhile, in figure 4, we could find the scores for some population grid cells declined with increasing catchment size. This usually happened in population grid cells with scores greater than 0.186 and scores between 0.065 and 0.186. The reason is that increasing the service area of UGS leads to a lower supply-demand ratio of it.

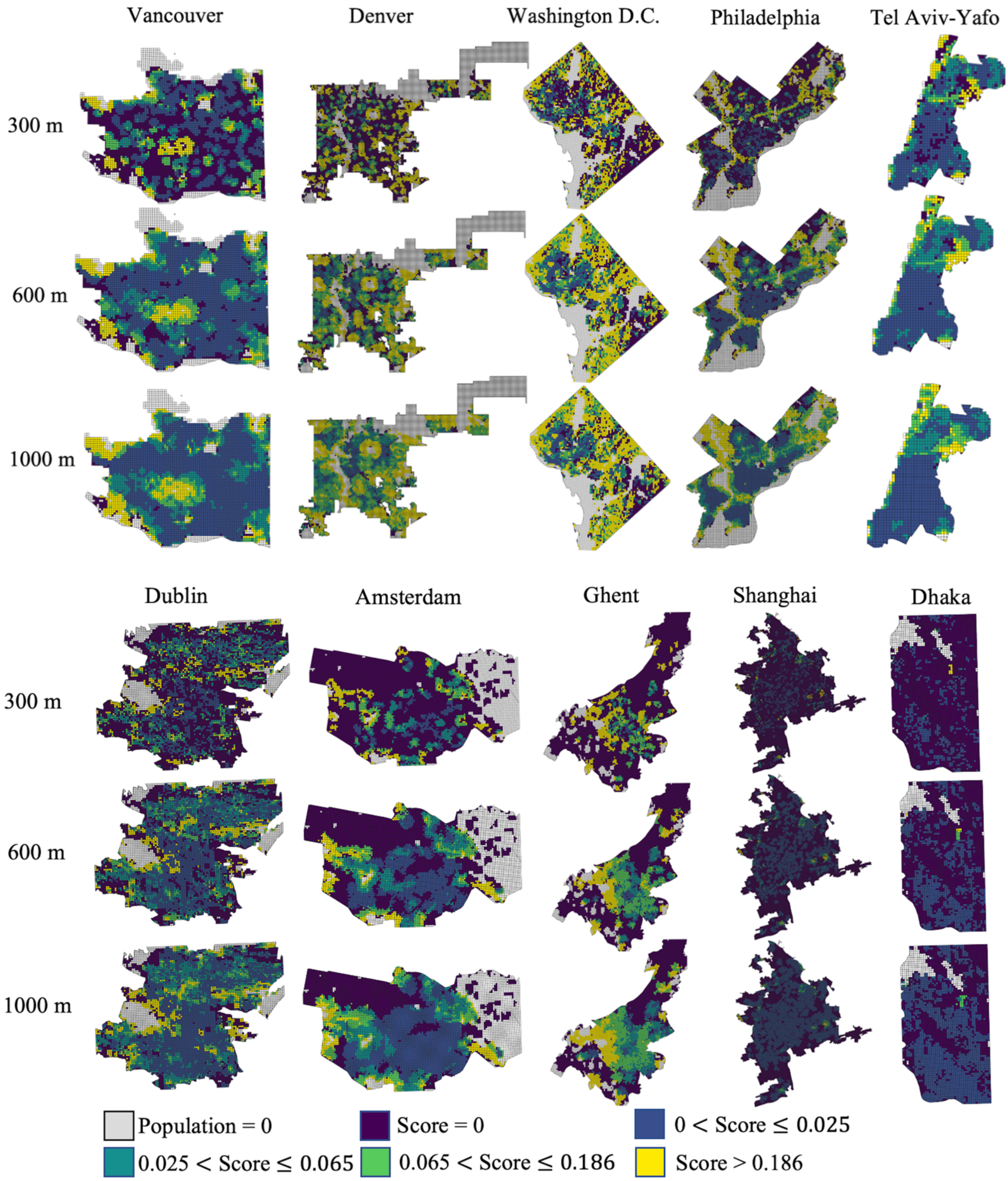

Figure 4: Spatial distribution of UGSA in 10 cities

Figure 5 illustrates the proportion of people who have no, low, middle, and high accessibility to UGSs in 10 cities according to the standard we set above. With a decreasing catchment size, the proportion of having no access to UGS increased which is consistent with the spatial distribution in figure 4. For residents who have access to UGS, their accessibility level is low, and the total percentage of the population with middle and high accessibility is less than 1% in each city. The four cities (Vancouver, Denver, Washington DC, and Philadelphia) in North America perform best. Larger than 97% of the population in those cities have access to UGS in 1000 m, and nearly half of their population have access in 300 m. In addition, proportions of high and middle accessibility to UGS in the four cities are higher than in other cities. Dublin performs best among the three European cities with 51.11% of its population having access to UGS under the 300 m distance threshold. The performances of those three Asian cities, especially the two from developing countries (Dhaka and Shanghai) are the worst. Under WHO standards, only 25.33% in Shanghai and 19.91% in Dhaka have low accessibility within 300 m.

Figure 5: Proportion of population of different levels: In each figure, from left to right is the proportion of four levels accordingly. If no number is shown for a certain level, it means 0%.

The comparison of population-weighted average UGSA of those cities is shown in table 2. The catchment size we choose is 300 m[3]. The ranking of scores is consistent with the conclusion above, that is the North American cities have higher accessibility to UGS than European cities, and the Asian cities have the worst accessibility among 10 selected cities. The ranking of Vancouver dropped due to its proportion of people who have high access to UGS is lower.

4.2 Measurement of inequity of UGSA

From the spatial pattern of UGSs in figure 4, we revealed that there exists inequity of UGSA in cities. As described in the methodology, we used Gini coefficient to represent the inequity of UGSA quantitatively. Table 2 is the result of Gini coefficient for 10 cities with a catchment size of 300 m. The values for 10 cities are all greater than 0.85, which indicates a severe inequity among people. The values for Shanghai, Dublin, and Dhaka are over 0.96, approximately maximal inequality (Gini coefficient equals 1). Combining factors of Gini coefficient and population-weighted average score, the three American cities, Denver, Washington D.C., and Philadelphia have a higher accessibility score and relatively better equity to UGSs among the selected cities. Meanwhile, though Dublin has a higher population-weighted average UGSA score, the distribution of UGSA is extremely inequal. The accessibility score for Dhaka and Shanghai are the lowest, and they also have the worst problem of extreme inequity in UGSA.

Table 2: Population-weighted average UGSA and Gini coefficient for 10 cities

	Population-weighted average UGSA	Gini Coefficient
Washington DC	65.96	0.920
Denver	39.85	0.906
Dublin	24.32	0.968
Philadelphia	19.50	0.923
Ghent	13.06	0.922
Vancouver	9.98	0.878
Amsterdam	7.69	0.919
Tel Aviv-Yafo	5.52	0.853
Shanghai	2.07	0.960
Dhaka	0.29	0.972

[3] We chose 300 m not only due to it is the suggested minimum distance from WHO, but also it is the strictest one.

5. Discussion

From the perspective of a single city, our results regarding the distribution of accessibility are consistent with some previous studies. Most people in the selected cities have access to UGS within 1000 m, but the accessibility level is low. (Liu et al., 2021; Wang et al., 2021; Wu & He, 2018; Ye et al., 2018) all showed that accessibility in their study areas was heavily skewed to low scores. In addition, a large portion of locations with high accessibility scores is located around huge natural UGS. This could give some suggestions to policymakers, in order to raise the accessibility for residents, more attention should be paid to artificially creating and maintaining UGSs since the natural green resource in a city is limited. In addition, for a catchment size of 1000 m, over 60% of citizens have access to UGS in all cities. However, with a stricter catchment size of 300 m, which is also the WHO recommended standard, nearly half of the population has no accessibility and the proportion in four cities (Shanghai, Dhaka, Ghent, Amsterdam) are even over 70%. This indicated that the measurement of UGSA is highly sensitive to the catchment sizes, which is consistent with Wang et al. (2021).

In our analysis, residents who live in the city center showed lower UGSA than non-center areas, which contradicted some existing research (Liu et al., 2021; Wang et al., 2021). One of the reasons is that we considered the edge effect in our study. The increased boundary leads to a higher UGSA for citizens who live near the boundary. In addition, the model used to measure the UGSA plays an important role. E2SFCA model used in our analysis took both supply and demand of a UGS into consideration, whereas the gravity model only considered the supply side of UGS (Wang et al., 2021). The UGSA calculated by E2SFCA tends to have a lower score than the gravity model due to the denser population in the city center in most cities. In addition, different cities have different structures and urban planning. City center in Vancouver, Dublin, Shanghai, Tel Aviv-Yafo, and Amsterdam is concentrated with places for entertainment and shopping. If they were segmented by green space, the convenience could be reduced.

Few studies compared UGSA in cities worldwide. According to our results, cities in North America have higher accessibility scores than the other two continents, and cities in Asia have the least accessibility scores in general. This could be explained by the uneven distribution of natural resources. To be specific, the total area of UGS in North American cities and the number of huge natural green spaces are larger than in other cities. Considering the economic factor, cities with higher GDP per capita have better accessibilities in general. Nevertheless, there still exist cities with higher GDP per capita, but a much lower UGSA, such as Tel Aviv-Yafo, and Shanghai. Moreover, we revealed that the relationship between UGSA and population density is weak. This can be observed from cities such as Philadelphia, Vancouver, Amsterdam, and Tel Aviv-Yafo. These places have dense population while achieved a higher accessibility score than other less densely populated cities. Additionally, we discovered severe inequity among people in all selected cities. This is consistent with Y. Chen et al. (2020, 2022), Comber et al. (2008), Liu et al. (2021), Timperio et al. (2007) and Wu & He (2018). The comparison of UGSA in cities with different socioeconomic factors and structures could raise the concern of policymakers to ensure the minimal UGSA standard and environmental justice for their citizens. For cities with similar structure, economic development level, or demographic but lower accessibility and severe inequity, urban planners could take the construction or maintenance of UGSs in cities with higher accessibility as a reference.

At last, we would like to mention that our research has several limitations. First, the proportion of selected cities in developing countries is low. As we compared the accessibility on a worldwide scale, including cities with various socioeconomic factors is beneficial. However, UGS data in some countries is not available due to low quality. Second, the E2FSCA model assumes that people cannot access UGS out of catchment size, which is not practical. In addition, the selection of catchment size and travel mode is subjective. Except for walking, many citizens prefer driving to UGS, especially families. Third, the simulation of fake entrances may not be accurate, which could impact the measurement of accessibility, especially for UGS with huge sizes. Lastly, we compared the accessibility and inequity of UGSA among cities with different characteristics in a qualitative way. Based on our study, more quantitative methods could be applied to analyze the relationship between UGSA and socioeconomic factors.

6. Conclusion

We selected 10 different cities according to economic, demographic, and geographic conditions, and computed the normalized UGSA based on the E2SFCA model. We considered the impact of the edge effect on both accessibility of citizens living near the boundary and the demand-supply ratio of UGS near the boundary, and selected intersection points between the road network and the boundary of UGS as fake entrances to ensure the credible and robust results. To better visualize the result of the comparison, we set the standard of four accessibility levels based on WHO suggestion and calculate the proportion of residents belonging to different levels accordingly. Based on the normalized accessibility score for each population grid cell, we compared the population-weighted average UGSA and evaluate the environmental justice in the selected cities using Gini coefficient.

For accessibility in a single city, population grid cells with high accessibility scores are concentrated near UGSs with large size or dense distribution. From the accessibility map, we also revealed that city center tends to have a lower score than other areas of that city. Nevertheless, for citizens who have access to UGSs in the selected cities, their accessibility level is low. With a decreasing catchment size, the proportion of having no access to UGSs substantially increased. When comparing UGSA in 10 cities, we found that based on population-weighted average scores and different levels of accessibility of residents, North American cities have higher accessibility to UGSs than European cities, and the Asian cities have the worst accessibility among 10 selected cities. However, there is a severe inequity among people in all the cities since all Gini coefficient values for 10 cities are larger than 0.8. Among all cities, Dublin, Shanghai, and Dhaka exist extreme inequity since Gini coefficient is all over 0.96.

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