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Spatiotemporal patterns and inequity of urban green space accessibility and its relationship with urban spatial expansion in China during rapid urbanization period

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Abstract

Equitable access to urban green spaces (UGS) is an important component of social justice and can be quantified using indices such as urban green space accessibility (UGSA). However, the spatiotemporal patterns and inequity of UGSA among cities with different developments during rapid urbanization are unclear, especially lack evidence at a macroscopic national scale during rapid urbanization. Therefore, we evaluated the UGSA in 366 cities of China during 1990-2015 by the Gaussian-based two-step floating catchment area method (Gaussian-based 2SFCA). Then, the inequity pattern of UGSA among cities with different economic developments was analyzed by the concentration curve and concentration index. Finally, the relationship between UGSA and urban spatial expansion was explored quantitatively by the spatial econometric model. The results showed that: (1) The overall UGSA in China declined significantly by nearly 57.23 % during 1990-2015. From the regional perspective, the UGSA in the southeastern region was always lower than that in the northwestern region, the Eastern zone presented a downward trend. From the perspective of different sizes cities, the UGSA of the megacities kept decreasing during 1990-2015, while UGSA of the large, medium, and small cities had turned to increase since 2010. (2) During rapid urbanization, the equity of UGSA among the cities gradually improved, while the cities with low economic developments tended to have higher UGSA. (3) Urban spatial expansion led to the decrease of UGSA during 1990-2015, while the impact had spatiotemporal heterogeneity, and UGSA had a positive spatial spillover effect. Our research provides a comparative baseline for the improvement of UGSA from a macroscopic perspective for China's urbanization policy in the future and novel insights into the green justice issue. The results can be compared with the development of UGS in other countries at different urbanization stages to promote UGS design and policy.

Keywords: Urban green space accessibility; Urbanization; Spatiotemporal patterns; Inequity; Gaussian-based 2SFCA; Spatial econometric model

1. Introduction

Urban green spaces (UGS) are the artificial, semi-natural, and natural ecosystems dominated by vegetation in urban areas, and include parks, gardens, forests, grasslands, natural reserves (Dai, 2011; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2019). The definition also includes blue spaces such as river corridors and wetlands (Wolch et al., 2014). In this paper, we only considered the formally designated UGS which are well-recognized, clearly demarcated, managed, and maintained (e.g., green squares, parks, forest, and large water bodies) rather than informal green spaces which are often smaller, less obvious, more dispersed, and unintentional formations with an uncertain legal, socio-economic, and ecological status. UGS provide a large number of ecosystem services including provisioning, regulating, and cultural services. First, UGS can provide raw materials (e.g. timber and leaf litter), and replenish water sources to provide drinking water (Wolch et al., 2014). Second, UGS reduce air and water pollution, regulate microclimate, prevent flood damage (Wuestemann et al., 2017; Chen et al., 2019b; Li et al., 2020; Yu et al., 2020; Heo et al., 2021b). Third, UGS provide urban residents with areas for recreation and sporting activities, which promotes outdoor physical exercises and social interactions, and contributes to physical and psychological health and human wellbeing (De Ridder et al., 2004; Macintyre et al., 2019; Zhang et al., 2020b; Pearsall et al., 2020). As a public service facility, fair and rational access to UGS contributes to social justice (Wolch et al., 2014; Biernacka et al., 2018). Existing studies have found that UGS can reduce health disparities between the wealthy residents and vulnerable groups by relieving the psychosocial stress of poor households (Hunter et al., 2019; Li et al., 2016), mitigating environmental hazards in lower socioeconomic communities (Bhatnagar, 2017; Myers et al., 2013), and improving the health status of vulnerable groups (Alderton et al., 2019; Demoury et al., 2017; Yeager et al., 2018). Therefore, the opportunities for people to access UGS should be equitable. The spatiotemporal patterns and inequity of people's access to UGS services are receiving increased attention.

The world's population increasingly lives in cities, and rapid urbanization has been an important feature of land use and population change in Asia and Latin America in the last few decades (Wang et al., 2020; Kanbur et al., 2013). This has resulted in a large expansion of urban land and an explosion in urban populations, which will continue in the future (United Nations, 2005; United Nations, 2014). The rapid urban land expansion has led to landscape fragmentation and reduction of green spaces (Kong et al., 2007; Nations et al., 2014; Sun et al., 2019; Lin et al., 2016), and has initiated a series of ecological and environmental problems (Guo et al., 2019; Kuang et al., 2017; Zhang et al., 2018). Urbanization tends to decrease access to UGS, which causes an impact on the health and well-being of urban residents, which in turn may further exacerbate social inequity (Wuestemann et al., 2017; Tzoulas et al., 2007). Access to UGS in this paper refers to residents entry into the UGS on the premise that we assume all of UGS can be freely reached and safely used for recreational purposes at any time, without any restrictions (Biernacka et al., 2018). As the largest developing country in the world, China has experienced rapid urban transformation in the last 30 years (Zhao et al., 2013). China has been under the uniform leadership of the central government in the past decades, and there has been tremendous government-led investment in urban green spaces planning combined with supporting greening policies to mitigate the adverse effects of urbanization on the human living environment (Zhao et al., 2013; Wu et al., 2021). The greening policies and urbanization which are two seemingly conflicting effects make the relationship between urban residents' access to UGS and urbanization more complicated. There is an urgent need to explore how access to UGS and their inequity changes in China during periods of rapid urbanization.

Urban green space accessibility (UGSA) can effectively evaluate both the potential and the inequity of UGS access for residents (Dai, 2011; Kabisch et al., 2016; Wolch et al., 2014). UGSA can be defined as the degree of difficulty for people to access UGS. Previous studies commonly measure UGSA by the distance or travel time for residents to access UGS (Comber et al., 2008), and the more sophisticated studies take into consideration the area and quality of green space, transportation cost, population density, and other factors (Dai, 2011; Norman et al., 2006; Zakarian et al., 1994). Over the past few decades, multiple methods have been developed to assess the UGSA. The following methods are the main UGSA evaluation approaches: 1) cover method (Coombes et al., 2010); 2) container method (Haase et al., 2014); 3) gravity model (McCormack et al., 2010). The cover method and container method both assume that residents only choose the nearest UGS, while they usually have more options, and they even tend to choose farther UGS. The gravity model considers the possibility of multiple choices, but ignores the supply-demand relationship between the UGS and population (Wu et al., 2020a). As a special form of the gravity model (Chen et al., 2019c), the two-step floating catchment area method (2SFCA) not only has most of the advantages of the gravity model but also takes into account resource supplies and population demands and their interactions for measuring potential UGSA (Dai, 2011). Of all the above methods, the 2SFCA and their improved models are most commonly used as 2SFCA have obvious advantages, and have been widely used in studies on UGSA (Chen, 2019; Hu et al., 2020; Ji et al., 2020; Wu et al., 2020a). The current applications of 2SFCA are mainly focused on a small scale (e.g., communities or single cities), while there is a rare application in long-term UGSA research at a national scale.

Most research on UGSA has focused on existing patterns of greenspace and current levels of access at the city scale (Rigolon et al., 2014; Cetin, 2015; Engelberg et al., 2016; Wu et al., 2020a; Chen et al., 2020; Pearsall et al., 2020; Liu et al., 2021). Some research works have explored the spatiotemporal patterns of UGSA in a single city (Xing et al., 2018; Ye et al., 2018). Some studies have looked at the temporal component at the national or regional scale, for example comparing cities diverging under different political regimes in Eastern Europe (Kabisch et al., 2013), or comparing city development patterns on either side of a national border (Inostroza et al., 2019), but few have looked at long-term spatiotemporal patterns of UGSA at national scale in developing country with rapid urbanization.

The majority of studies on urban social justice focus on the inequity of UGSA among groups with different socio-economic status, racial characteristics, age, income, gender, and other demographic factors, which restrict their analysis to a particular city (Dai, 2011; Cetin, 2015; Iraegui et al., 2020; Chen et al., 2020; Heo et al., 2021b). However, due to the differences in the definition and scale of UGS, accessibility indicator, characteristics of cities (e.g., politics, economics, and culture) (Wu et al., 2021; Zhang et al., 2020a), the results are remarkably inconsistent. Having realized these gaps, scholars begin to carry out investigations across multiple cities in a region or a nation. Although there is a successive emergence of studies in Canada (Tooke et al., 2010), Europe (Kabisch et al., 2016; Zepp et al., 2020), Germany (Wuestemann et al., 2017), the United States (Nesbitt et al., 2019), and China (Wu et al., 2021), the comparative objects are mostly within the urban environment, the analyses are usually based on existing patterns of UGS, and there are few studies on the dynamics of UGS equity between cities with different development levels at the national or regional scale. The capacity of urban planning and greening policy implementation is varied in cities with different development levels. Rapid urbanization will have varying effects on UGSA in different cities. It remains to be explored how the urbanization changes the UGS equity between cities.

Therefore, this paper aims to explore spatiotemporal patterns and inequity of UGSA and its relationship with urban spatial expansion in China during the rapid urbanization period. Our research objectives are: (1) to calculate the UGSA and analyze its spatiotemporal patterns of 366 cities in China from 1990 to 2015. (2) to analyze the dynamic inequity patterns of UGSA among the cities at the different development stages. (3) to explore the impacts of urban spatial expansion on UGSA through the spatial econometric models. The study result can provide a comparative baseline for the improvement of UGSA from a regional and national scale. Meanwhile, it is also an innovative large-scale application attempt of the 2SFCA method.

2. Study area and data source

2.1. Study area

In this study, all 366 cities in the Chinese mainland were covered for analysis, containing cities at three administrative levels: 4 provincial cities (Beijing, Shanghai, Tianjin, and Chongqing), 21 province directly administrating county cities (‘Sheng_zhi_xia_xian’), and all prefecture-level administrative unit cities in the Chinese mainland. The prefecture-level administrative units in China contain the prefecture-level city (‘Di_ji_shi’), autonomous prefecture (‘Zi_zhi_zhou’), prefecture (‘Di_qu’), and league (‘Meng’). Some cities had administrative division adjustments during the period 1990-2015, therefore we applied the 2015 administrative division boundary in all analyses for ease of comparison.

For comparative purposes, cities within China were allocated into four economic zones according to China's Economic Geographical Zoning Scheme (National Bureau of Statistics, 2011; Dou et al., 2020) (Fig. 1) (Table 1). Meanwhile, according to the 2010 sixth national population census data of China and (Dou et al., 2020), 294 cities (only prefecture-level cities) were divided into 4 population-based city size classes (Table 2). The Hu Huanyong Line is an important division line of population density and socioeconomic development in China (Chen et al., 2019a; Chen et al., 2016) (see Fig. 1), which divides the Chinese mainland into southeastern and northwestern regions.

Table 1 Economic zones division in China

Zone	Provincial-level administrative units

Northeastern zone	Heilongjiang, Jilin, and Liaoning
Eastern zone	Beijing, Shanghai, Tianjin, Shandong, Guangdong, Jiangsu, Hebei, Zhejiang, Hainan, and Fujian.
Central zone	Shanxi, Henan, Anhui, Jiangxi, Hubei, and Hunan
Western zone	Chongqing, Sichuan, Yunnan, Guizhou, Gansu, Shannxi, Qinghai, Ningxia, Guangxi, Xinjiang, Tibet, and Inner Mongolia

Table 2 Population-based city size classes in China

City size	Criterion
megacities	> 5 million population
large cities	1 to 5 million population
medium cities	0.5 to 1 million population
small cities	< 0.5 million population

From 1990 to 2015, China's economy developed rapidly, with an increasing population and substantial urbanization (Fig. 2). Statistics (National Bureau of Statistics, 2016) show that China's GDP has increased by a factor of 35 in 15 years, with an average annual growth of 235.48 %. Although the population growth rate was relatively low, about 20.23 %, the total population has increased by 23.19 million. Urban built-up area (UBUA) increased by 39,975.80 km^2, nearly 3.44 times.

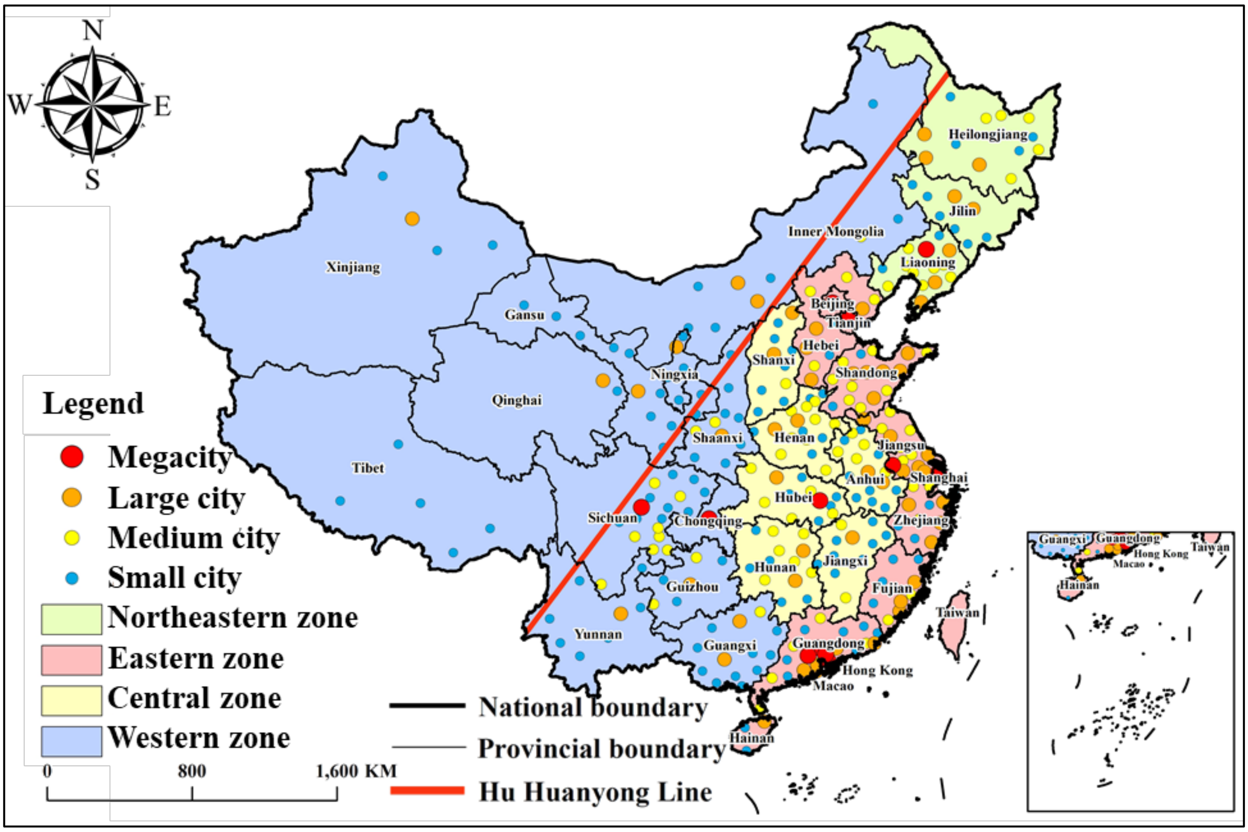


Fig. 1. Locations of provinces and cities investigated in China, and economic zones.

Redline shows division along the Hu Huanyong line.

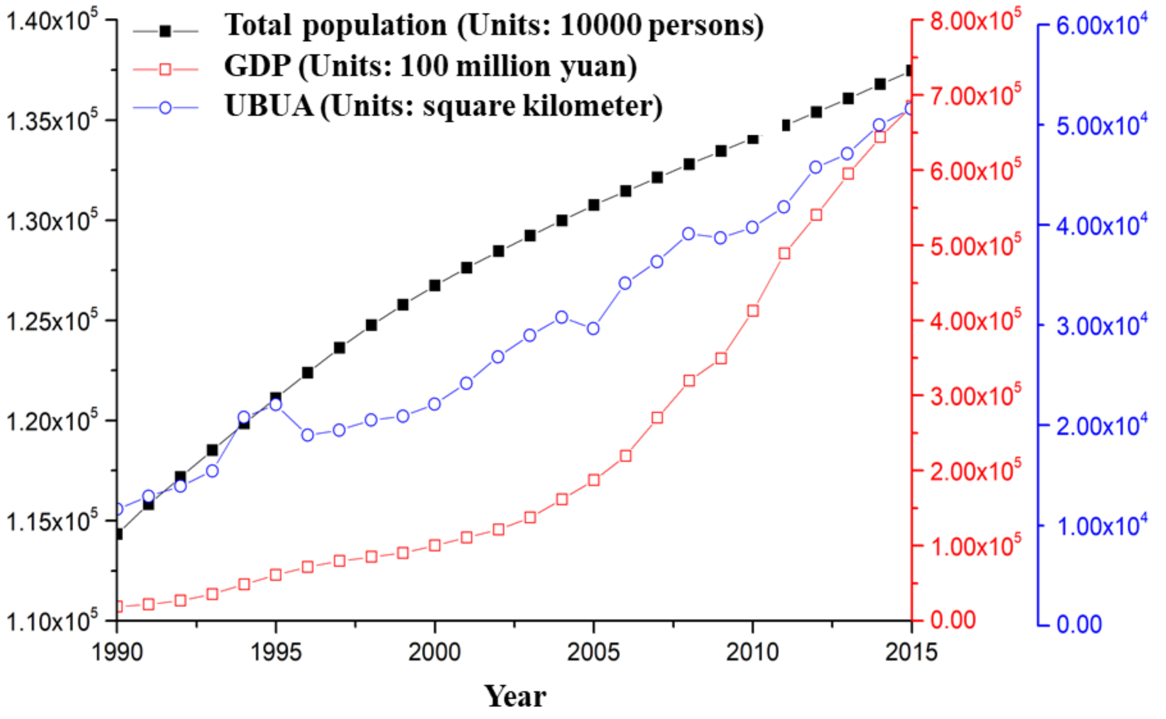


Fig. 2. Temporal trend of the total population, GDP, and UBUA in China from 1990 to

2015.

2.2. Data source

The UGS and UBUA data were extracted from land use and cover change (LUCC) data. The LUCC datasets for 1990, 2000, 2010, and 2015 were downloaded from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). Population and GDP datasets for 1990, 2000, 2010, and 2015 were obtained from RESDC. The spatial resolution of LUCC, population, and GDP dataset was 1 × 1 km. DEM data were downloaded from RESDC with a resolution of 90 × 90 m. Administrative unit boundaries for all 366 cities in 2015 were obtained from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn) at a spatial scale of 1:4,000,000.

3. Methods

A detailed description of each step is introduced in this section. Fig. 3 presents the work flow of this study.

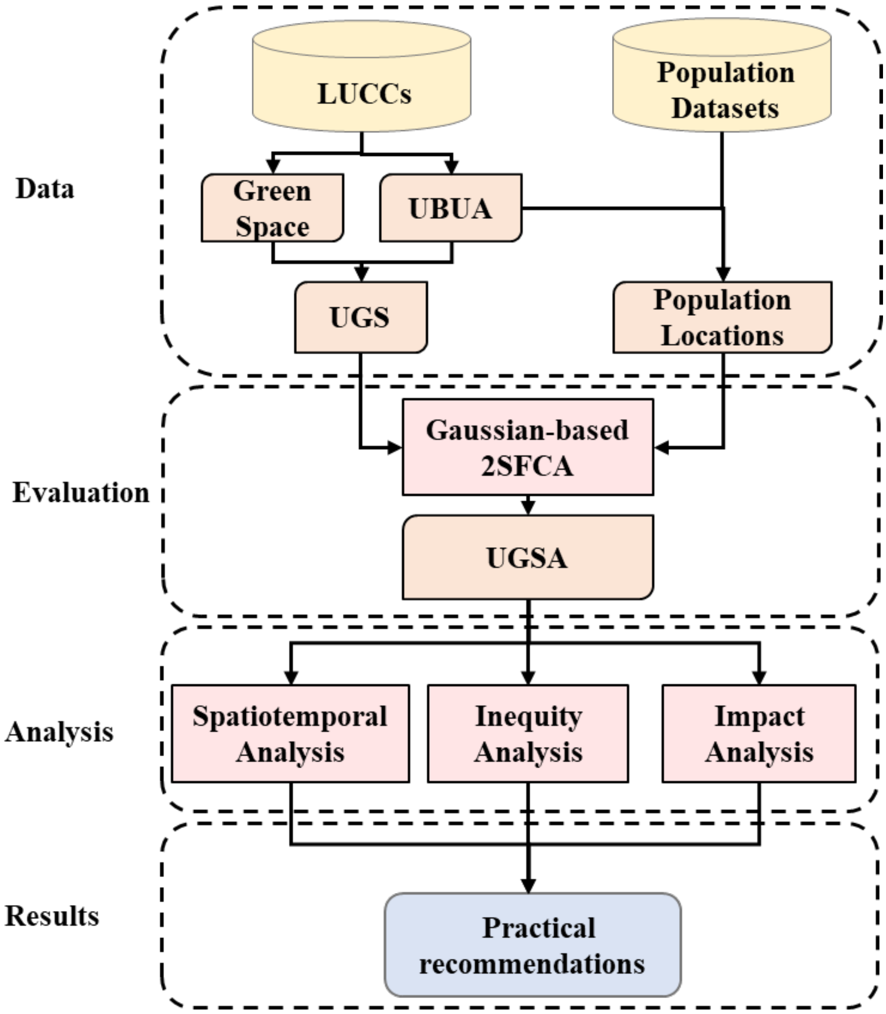


Fig. 3. Work flow chart of this study. Acronyms denote the following meanings: LUCCs (Land use and cover change datasets), UBUA (Urban built-up area), UGS (Urban green spaces), Gaussian-based 2SFCA (Gaussian-based two-step floating catchment area method), UGSA (Urban green space accessibility).

3.1. UGSA evaluation

We defined the green spaces in the UBUA or within a certain distance as UGS. In addition to agricultural land and unused land, all classes of ecological land were regarded as UGS containing forest, grassland, river /canal, reservoir, lake, beach land, and tidal flats (Wolch et al., 2014; Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2019). Assessment of accessible green spaces included all UGS within a 2500 m buffer of the UBUA boundary. This buffer radius was selected for the following reasons: previous research has shown that regardless of the modes of transportation, the psychological limit of daily travel is 30min (Wang et al., 2013). Walking is the most common modes of daily transportation, and walking for 30 minutes can be regarded as the limit of walking accessibility. Generally, humans can walk 2500 m in 30 minutes at normal walking speed (5 km/h). 2500 m buffer zone was taken to extract all UGS that people can reach on daily walking. At the same time, UGS within 2500 m is also suitable for the daily visit of citizens by public transportation and cycling. Catchments which is larger than 30 min travel distance will over-smooth the accessibility, thus concealing the variation in accessibility (Dai, 2011). Based on this buffer, we calculated the UGS data for China's 366 cities for four periods: 1990, 2000, 2010, and 2015. As an example to visualize the calculations, the spatial distributions of UGS in Beijing city from 1990 to 2015 are shown in Fig. 4.

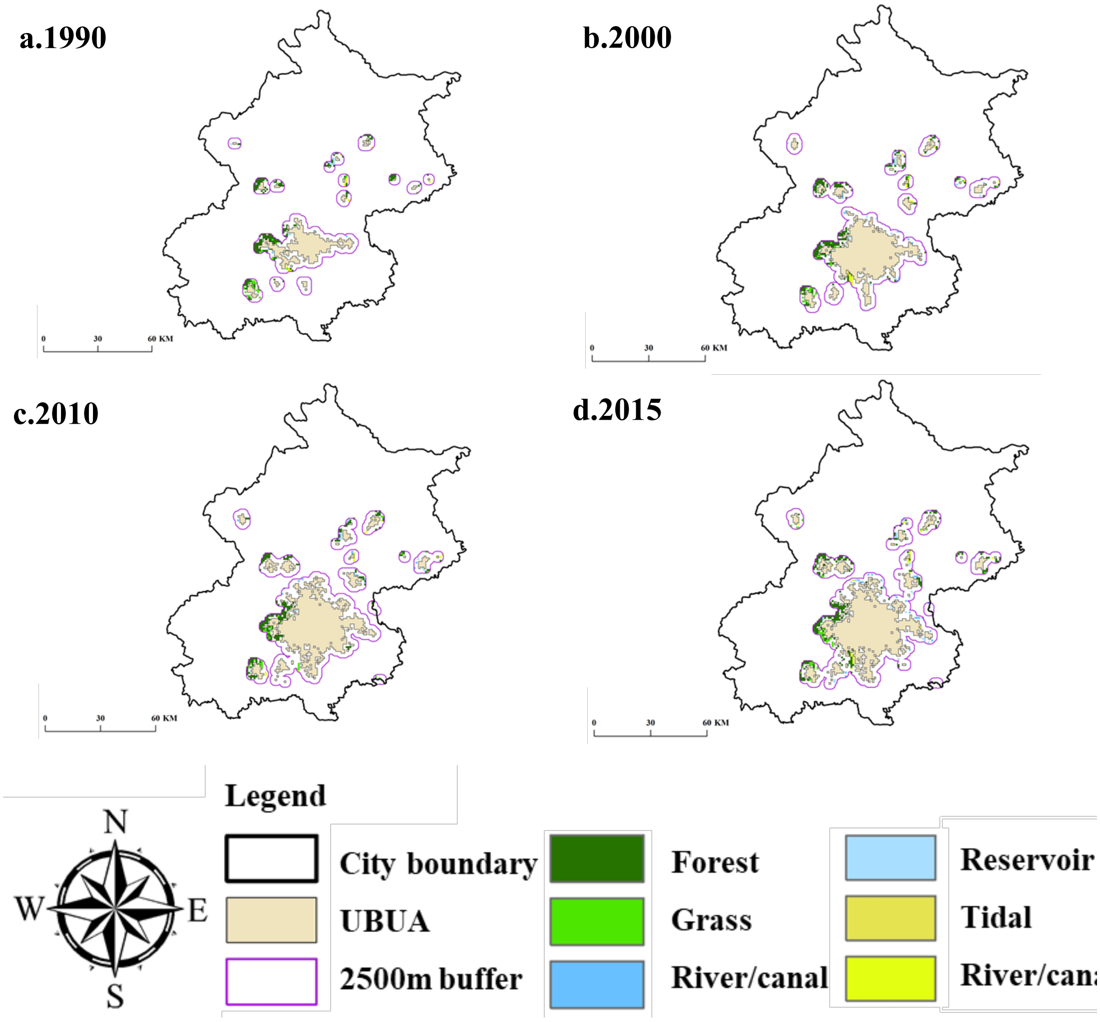


Fig. 4. Spatial distribution of urban green spaces in Beijing city from 1990 to 2015.

Second, population numbers for 1990, 2000, 2010, and 2015 were calculated for the areas defined by the UBUA boundaries, and transformed into a points data layer in ArcGIS. Gaussian-based 2SFCA was performed as follows (Dai, 2011).

Step 1. For each green space *j*, all population locations (*k*) within the threshold travel distance d_0 starting from *j* were identified, to calculate the catchment area of green space *j* (Fig. A1). The population at *k* is weighted using a Gaussian function (*G*), which characterizes friction-of-distance as follows:

$$G(d_{kj}, d_0) = \begin{cases} \frac{e^{-0.5\times\left(\frac{d_{kj}}{d_0}\right)^2} - e^{-0.5}}{1 - e^{(-0.5)}}, & d_{kj} \leq \ d_0 \\ 0, & d_{kj} > \ \ d_0 \end{cases} \quad (1)$$

where d_{kj} is the travel distance from the populations at k to the green space j. The weighted population within the catchment of j is summed up as potential users of green space j. The ratio of green space to populations (R_j) is expressed as follows:

$$R_j = \frac{S_j}{\sum_{k\in\{d_{kj}\leq d_0\}} G(d_{kj}, d_0) P_k} \quad (2)$$

where P_k is the population at location k whose centroid lies in the catchment ($d_{kj} \leqslant d_0$) from green space j; S_j is the capacity (i.e., area) of green space at j. The value of R_j represents the per capita green area that the potential users of green space j can obtain.

Step 2. For each population location i, search all green spaces l within the threshold travel distance d_0 from i, thus establishing the catchment for the population at i (Fig. A2). R_l is weighted using a Gaussian function (G). Sum up weighted R_l within the catchment area of green spaces i to obtain the spatial accessibility at population location i as follows:

$$A\mathrm{i} = \sum\nolimits_{l\in\{d_{il}\leq d_0\}} G(d_{il}, d_0) R_l \quad (3)$$

where l denotes all green spaces within the catchment of population location i. A_i is the accessibility score, which represents the amount of green spaces every nearby resident can obtain. A larger R_j value denoted that each potential resident can access more green space.

3.2. Spatiotemporal patterns of UGSA

Hot spot analysis (Getis-Ord Gi*) is a spatial statistical method proposed by Getis and Ord (Giles-Corti et al., 2005) that can effectively identify cold and hot spots with statistical significance in space. In hot spot analysis, the Gi* value of each spatial object was calculated to delimit the high and low clustering. Both Z-score and p-value are used to measure the statistical significance and to judge whether to reject the null hypothesis. For a statistically significant positive Z-score, as the Z-score increases, the clustering of high values becomes closer (hot spots). For a statistically significant negative Z-score, as the Z-score decreases, the clustering of low values becomes closer (cold spots).

The Natural Breaks method is a data classification method designed to determine the best arrangement of values into different classes, which is also called the Jenks natural breaks classification method (Jenks, 1967). The main idea of the method is reducing the variance within classes and maximizing the variance between classes. Specifically, this method is done by seeking to minimize each class' average deviation from the class mean, while maximizing each class' deviation from the means of the other groups (Stefanidis et al., 2013). The Natural Breaks method was applied to group the UGSA in China during 1990-2015.

Global Moran's I is a classic spatial autocorrelation statistic. The statistic can measure and analyze the degree of dependency among observations in geographic space. Global Moran's $I > 0$ indicates that spatial autocorrelation is postive, and the greater its value, the more obvious the spatial autocorrelation. Global Moran's $I < 0$ indicates that spatial autocorrelation is negative, and the smaller its value, the greater the spatial difference. Otherwise, Global Moran's $I = 0$ indicates that the space distribution is random.

To further analyze the spatiotemporal dynamics of UGSA, we constructed three indices, containing overall change of urban green space accessibility (OC_{UGSA}), annual change of urban green space accessibility (AC_{UGSA}) and annual change percent of urban green space accessibility (ACP_{UGSA}), to capture the changes in UGSA in different size cities and different zones. OC_{UGSA} and AC_{UGSA} can measure changes of UGSA and are effective tools for comparison of variation of UGSA over different periods. ACP_{UGSA} was selected for comparison of variation of UGSA for various size cities in the same period, because it eliminates the effect of city size. The formulae are as follows:

$$OC_{UGSA} = UGSA_j - UGSA_i \tag{4}$$

$$AC_{UGSA} = \frac{UGSA_j - UGSA_i}{Year} \tag{5}$$

$$ACP_{UGSA} = \frac{\left(UGSA_j - UGSA_i\right)/UGSA_i}{Year} \tag{6}$$

where $UGSA_i$ and $UGSA_j$ represent the UGSA at the start of year *j* and end of year *i*, respectively. Year is the time span from year *j* to year *i*. OC_{UGSA} and AC_{UGSA} refer to the total and annual changes of UGSA, respectively.ACP_{UGSA} represents the annual change rate of the UGSA from year *j* to year *i*.

3.3. Inequity of UGSA among cities

Concentration curves are commonly used to capture inequalities of public services among different socioeconomic groups (Wagstaff et al., 2003; Doherty et al., 2014). In Fig. A3, X-axis represents the cumulative percentage of residents' incomes, Y-axis represents the cumulative percentage of resource utilization, curve C is the concentration curve, and M is the line of perfect equality. When curve C is on the left side of M, it indicates that resources are mainly concentrated in poorer socioeconomic groups. When curve C is on the right side of line m, people with higher economic status possess more resources. The closer the distance between curve C and M, the resource allocation is more perfect, and vice versa (Fig. A3). In this study, GDP was used to reflect the level of urban economic development level, and UGSA was the public service. In order to compare the inequality of UGSA among different years, we drew the concentration curve of UGSA from 1990 to 2015 based on the total GDP of the administrative unit in 2015.

The Concentration Index (CI) can also be used for quantifying socioeconomic inequality (Wagstaff et al., 2003; Doherty et al., 2014). In this study, CI was used to explore the temporal variation of inequalities of UGSA. The range of CI is between -1 and 1, with zero representing perfect equality. When the CI is positive, it indicates that the more developed areas have higher UGSA; when the CI is negative, it means that the higher UGSA is occupied by the less developed areas. The CI can be calculated by the covariance method, using the following formula:

$$CI = \frac{2}{\mu} COV(UGSA, r) \tag{7}$$

where r is the order of city ranking by 2015 GDP, μ is the mean of UGSA.

3.4. Impact of urban spatial expansion on UGSA

Studies that ignore spatial factors may produce estimation errors, which are caused by a significant spatial spillover effect (Liu et al., 2017; Wu et al., 2020b). Considering potential spatial autocorrelation, we applied spatial econometric models to explore the impact of urban spatial expansion on UGSA. The dependent variable in this study was UGSA in logarithmic form (lnUGSA), the independent variable was the proportion of

UBUA in logarithmic form (lnPUBUA). The control variables contained the proportion of green space area (PGSA), DEM in logarithmic form (lnDEM), GDP in logarithmic form (lnGDP), and population in logarithmic form (lnPOP). Logarithms were used to reduce the influence of large values.

lnUGSA: UGSA is an effective index to measure the inequity of urban residents in accessing UGS. In this study, the logarithm of the average UGSA of each prefecture-level unit was regarded as the UGSA of the unit.

lnPUBUA: The spread of UBUA will make the land use around the built-up area change rapidly, thus affecting UGSA. The proportion of UBUA of each prefecture-level administrative unit was calculated, and the proportion was logarithmic to measure the speed of urban spatial expansion, representing the speed of urbanization.

PGSA: People living in a city with rich green space resources often have more opportunities to access green space. We calculated the proportion of green space area of each administrative unit to represent the number of green space resources

lnDEM: Topography is a common impact factor of the regional economy, population, and green space resources. In this study, the logarithmic mean value of DEM of prefecture-level administrative units was calculated to represent the topography features.

lnGDP: Urban planning in developed regions usually gets more financial support, considering green space protection and infrastructure construction (Zhao et al., 2013), which may improve the UGSA to a certain extent. However, there may be a phenomenon of paying attention to economic development and ignoring green space protection, which reduces the UGSA. In this study, the level of economic development was represented by GDP in logarithmic form.

lnPOP: In cities with a large population will have more social activities and the per capita green space resources may be less. This study used the logarithm of the total population of each prefecture-level administrative unit to represent social development levels.

We constructed three spatial models in this analysis: The Spatial Lagged Model (SLM) considers the possible spatial spillover effects between dependent variables. The Spatial Error Model (SEM) considers the influence of random error terms of neighbor units on the random errors in the focal unit. Lastly, the Spatial Durbin Model (SDM) considers the influence of independent variables and dependent variables of neighbor units on dependent variables in the focal unit. The formulae of the three models are as follows:

SLM:

$$lnUGSA_{it} = \alpha + \gamma \ln PUBUA_{it} + \beta C_{it} + \rho \sum_{j}^{n} W_{ij}\, ln\, UGSA_{jt} + u_i + \varepsilon_{it} \quad (8)$$

SEM:

$$lnUGSA_{it} = \alpha + \gamma \ln PUBUA_{it} + \beta C_{it} + \varphi \sum_{j}^{n} W_{ij} e_{it} + u_i + \varepsilon_{it} \quad (9)$$

SDM:

$$lnUGSA_{it} = \alpha + \gamma \ln PUBUA_{it} + \beta C_{it} + \rho \sum_{j}^{n} W_{ij}\, lnUGSA_{jt} + \theta \sum_{j}^{n} W_{ij}\, ln\, PUBUA_{jt} + \sigma \sum_{j}^{n} W_{ij}\, C_{jt} + u_i + \varepsilon_{it} \quad (10)$$

（i,j=1,2,…,n; t=1990,2000,2010,2015）

where i and j denote prefecture-level administrative units, n is the total number of prefecture-level administrative units and *t* indicates time. $lnUGSA_{it}$ is the UGSA vector of the *i*th province at time *t*. $lnPUBUA_{it}$ is the vector of the main independent variable, the proportion of the built-up area. C_{it} is the matrix of control variables, containing PGSA, lnDEM, lnGDP, and lnPOP. u_i is the cross-sectional intercept term. ε_{it} is the random error term. W_{ij} denotes the element of the *i*th row and the *j*th column of the spatial weight matrix. $W_{ij}\, ln\, UGSA_{jt}$ in equation (1) is the W_{ij} interacts with the spatially lagged dependent variable. $W_{ij}e_{it}$ in equation (9) is the W_{ij} interacts with the spatially dependent random error term. $W_{ij} ln\, PUBUA_{jt}$ and $\sum_j^n W_{ij}\, C_{jt}$ in equation (10) denote the W_{ij} interacts with the spatially lagged independent variables, containing the main independent variable (*lnPUBUA*) and control variables.

The inverse-distance matrix was used for spatial weighting within the spatial econometric model. This is based on the reciprocal distance between the geometric center points of cities.

There are five effects for each model: ordinary least squares (OLS), random effect, spatial fixed effect, temporal fixed effect, and spatiotemporal fixed effect. Because the data for control variables selected in this analysis are invariable, only the OLS, random effects, and time fixed effects were considered.

The method is based on LeSage and Pace (LeSage et al., 2009). First, Lagrange Multiplier test (LM test) statistics (LMLag, LMError) and Robust Lagrange Multiplier test (Robust-LM test) statistics (R-LMLag、R-LMError) are constructed to determine whether the variables show spatial correlation, and whether SLM and SEM models are suitable for our data. Second, Wald test Statistics (Wald test lag, Wald test error) and Likelihood Ratio test (LR test) statistics (LR test lag, LR test error) were used to test hypothesis 1 and hypothesis 2 of spatial econometric models respectively, to determine whether SDM can be simplified into SLM and SEM models. The SDM was a more suitable model than the SLM if Hypothesis 1 was rejected, while the SDM was more suitable than the SEM if Hypothesis 2 was rejected. Third, the Hausman test was used to determine whether the fixed effects (FE) or random effect (RE) panel model should be selected.

Hypotheses 1: H_0: $\theta=\sigma_1=\sigma_2=\ldots=\sigma_5=0$

Hypotheses 2: H_0: $\theta=-\rho\gamma$, $\sigma_1=-\rho\beta_1$, $\sigma_2=-\rho\beta_2,\ldots,\ \sigma_5=-\rho\beta_5$

In this study, we use the following rules to determine the applicable model: if the null hypotheses of Wald test and LR test are rejected, SDM should be selected; if the null hypotheses of Wald test are not rejected, and Robust-LM test supports SLM, we choose the SLM; if the null hypotheses of LR test cannot be rejected, and Robust-LM test supports SEM, SEM should be selected; If the result of LM, Wald or LR statistics is inconsistent, SDM should be chosen.

Further, we calculated the marginal effects of urban spatial expansion on UGSA based on the method proposed by Lesage and Pace (LeSage et al., 2009), including direct, indirect, and overall average marginal effects. The direct marginal effects indicate the influence of the local independent variable on the dependent variable. Indirect effects can be used to measure the impact of an independent variable in the neighbor area on the local dependent variable. Overall average marginal effects, namely total effects, represents the overall influence of the independent variable on the dependent variable.

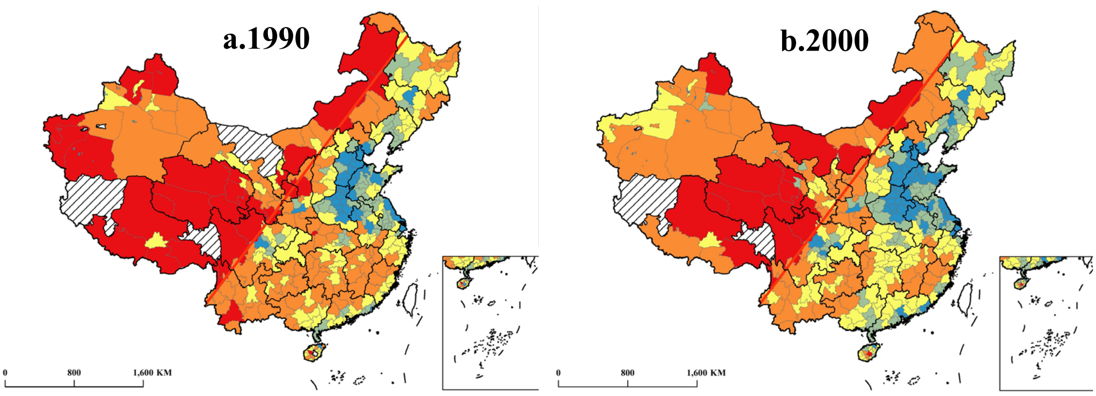
4. Results

4.1. Spatiotemporal patterns of UGSA in China

4.1.1. Overall spatiotemporal patterns of UGSA in China

From 1990 to 2015, UGSA in China decreased rapidly (Table 3). The results showed that the overall UGSA in all cities decreased by more than half (57.23%) during the study period, from 48,491.48 m^2/person in 1990 to 20,739.11 m^2/person in 2015, decreased by 27,752.3 m^2/person, with an annual reduction of 2.29 %. In particular, the reduction percentage for overall UGSA was the highest during 1990-2000, with an annual reduction of 5.91 %. The overall UGSA showed a trend of rapid reduction from 1990 to 2000, a slow increase from 2000 to 2010, and then a renewed but slow reduction from 2010 to 2015.

In this study, lnUGSA were grouped by the Natural Breaks method (Fig. 5), Hotspot Analysis (Getis-Ord Gi*) was used to identify hot and cold spots with statistical significance (Fig. 6), and we applied global Moran's I to determine the global spatial autocorrelation of UGSA. Our results showed that there was no significant change in the overall spatial patterns of UGSA in China from 1990 to 2015. High UGSA areas were mainly concentrated northwestern region indicated by the Hu Huanyong Line, appearing in Qinghai, Tibet, central and western Inner Mongolia, Yunnan, and Guizhou. There were hot spots in these areas. The regions with low UGSA were mainly concentrated southeastern region indicated by the Hu Huanyong Line, including Henan, Hebei, Shandong, Jiangsu, and Anhui where there were significant cold spots in these provinces. The patterns of UGSA presented spatial autocorrelation on a regional scale. The global Moran's I of lnUGSA were 0.064 (1990), 0.065 (2000), 0.013 (2010) and 0.024 (2015), respectively. The global Moran's I were all positive and extremely significant (P<0.01), suggesting that the spatial patterns of UGSA had a significant and positive spatial autocorrelation, and the global spatial autocorrelation of UGSA first decreased (1990-2010) and then increased (2010-2015).



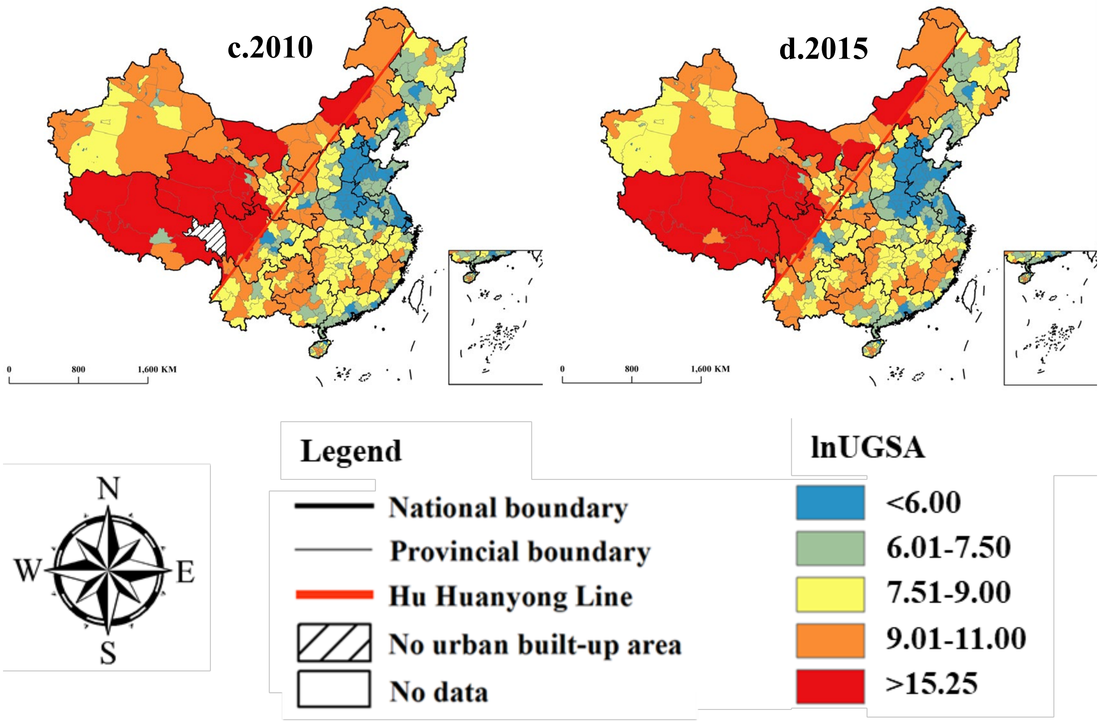
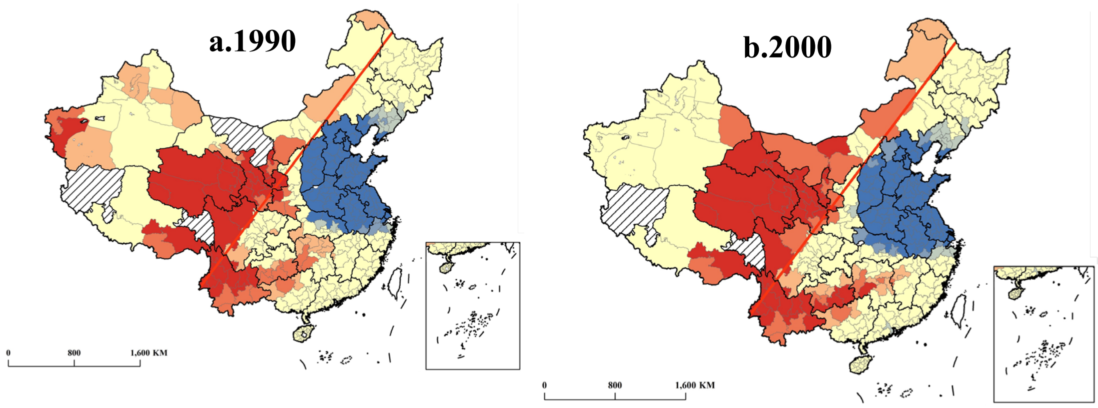


Fig. 5. Overall spatiotemporal patterns of urban green space accessibility in China from 1990 to 2015.



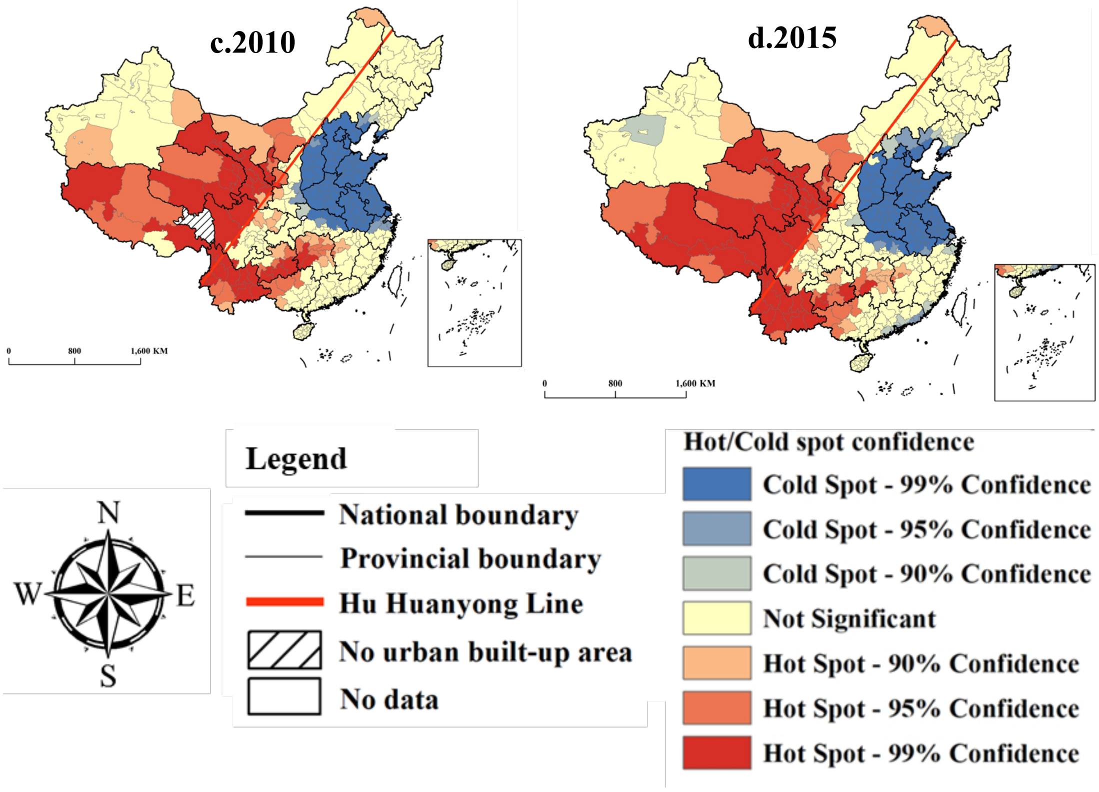


Fig. 6. Hot spot analysis of urban green space accessibility in China from 1990 to 2015.

4.1.2. Dynamic analysis of UGSA in the different zone in China

The UGSA in the different zones all showed a decreasing trend from 1990 to 2015. The UGSA decreased the fastest in the Western zone (2.32 % annually) and the slowest in the Northeast zone (1.26 % annually). Despite the UGSA in the Western zone decreasing rapidly, the UGSA in this zone was still the highest in 2015, reaching 49,791.23 m^2/person. In 2015, the UGSA in the Eastern zone was the lowest, only 2,989.10 m^2/person.

The UGSA in the Western zone showed a similar trend to the overall UGSA in China. The ACP_{UGSA} in the Western zone increased from - 6.08 % (1990-2000) to 2.00 % (2000-2010), and the ACP_{UGSA} in China increased from - 5.91 % to 1.55 %. When the ACP_{UGSA} in the Western zone decreased from 2.00 % (2000-2010) to - 2.15 % (2010-

2015), the ACP_{UGSA} in China decreased from 1.55 % to - 1.90 %.

During the study period, the UGSA in the Eastern zone always showed a downward trend, but the downward trend was gradually contained (Table 3). The UGSA in the Eastern zone decreased from 4.06 % (1990-2000) to 2.38 % (2000-2010), and further decreased to 0.12 % in 2010-2015.

4.1.3. Dynamic analysis of UGSA in cities of different sizes in China

From 1990 to 2015, the overall UGSA in cities of different sizes decreased significantly. OC_{UGSA} of all selected cities was -7,592.49 m^2/person and ACP_{UGSA} was -1.93 % (Table 4). ACP_{UGSA} increased from -5.00 % (1990-2010) to 7.46 % (2010-2015).

The UGSA varies significantly among cities of different sizes. The UGSA in megacities always decreased during the study period, while the UGSA in large, medium, and small cities had been increasing since 2010, and the growth rate of small cities was as high as 8.59 %. With the increase of urban scale, the UGSA gradually decreased. In 2015, the UGSA in megacities was only 390.72 m^2/person, while UGSA in small cities was 14,731.48 m^2/person, the UGSA in small cities was almost 38 times of that in megacities. We found that UGSA was always in inverse proportion to the size of the city during the study period.

Table 3 Urban green space accessibility in different zones in China during 1990–2015.

Zone	1990-2000			2000-2010			2010-2015			1990-2015			2015
	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	UGSA (m^2/Person)
Eastern zone	-2702.08	-270.21	-4.06	-940.08	-94.01	-2.38	-17.50	-3.50	-0.12	-3659.66	-146.39	-2.20	2989.10
Central zone	-3067.22	-306.72	-4.27	-624.99	-62.50	-1.52	155.53	31.11	0.89	-3536.68	-141.47	-1.97	3643.27
Western zone	-71975.87	-7197.59	-6.08	9300.39	930.04	2.00	-6006.37	-1201.27	-2.15	-68681.85	-2747.27	-2.32	49791.23
Northeastern zone	-2295.38	-229.54	-4.05	128.44	12.84	0.38	389.23	77.85	2.23	-1777.71	-71.11	-1.26	3885.38
Overall	-28652.61	-2865.26	-5.91	3074.06	307.41	1.55	-2173.82	-434.76	-1.90	-27752.37	-1110.09	-2.29	20739.11

Table 4 Urban green space accessibility in various size cities in China during 1990–2015

City size	1990-2000			2000-2010			2010-2015			1990-2015			2015
	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	OC_{UGSA} (m^2/Person)	AC_{UGSA} (m^2/Person)	ACP_{UGSA} (%)	UGSA (m^2/Person)
Megacity	-807.41	-80.74	-6.33	-71.52	-7.15	-1.53	-5.61	-1.12	-0.28	-884.54	-35.38	-2.77	390.72
Large city	-990.63	-99.06	-3.74	-383.36	-38.34	-2.31	106.09	21.22	1.67	-1267.90	-50.72	-1.92	1379.18
Medium city	-1976.52	-197.65	-4.17	-286.87	-28.69	-1.04	213.86	42.77	1.72	-2049.53	-81.98	-1.73	2693.44
Small city	-14737.43	-1473.74	-5.12	-3715.54	-371.55	-2.65	4425.11	885.02	8.59	-14027.86	-561.11	-1.95	14731.48
Overall	-7854.33	-785.43	-5.00	-1941.48	-194.15	-2.47	2203.32	440.66	7.46	-7592.49	-303.70	-1.93	8113.52

Overall change of urban green space accessibility (OC_{UGSA})

Annual change of urban green space accessibility (AC_{UGSA})

Annual change percent of urban green space accessibility (ACP_{UGSA})

4.2. Inequity pattern of UGSA in China

Fig. 7 shows the dynamic inequity patterns of UGSA between cities with different economic development levels during 1990-2015. The concentration curves of UGSA in the four phases are all on the left side of the perfect equity line, and the CI indexes are all negative, which indicates that less-developed cities always had more UGSA than developed cities during the study period.

The inequity of UGSA in cities with different development levels gradually decreased during 1990-2015. The absolute value of CI reduced gradually, the CI value of UGSA was -0.73 in 1990 and -0.60 in 2015. The proportion of UGSA occupied by less developed cities was gradually decreasing. In 1990, the poorest 20 % of the cities occupied nearly 80 % of the UGSA, while the poorest 40 % of the cities had approximately 80 % of the UGSA in 2015.

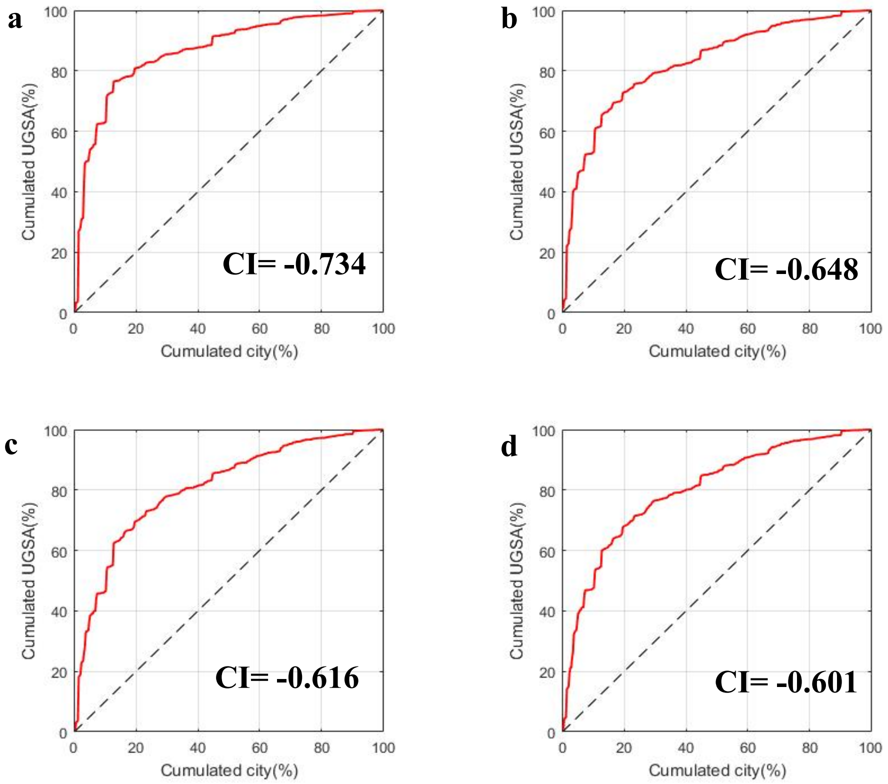


Fig. 7. Concentration curves for urban green space accessibility. Fig a, b, c, and d represent four phases containing 1990, 2000, 2010, and 2015 respectively.

4.3. Impact of urban spatial expansion on UGSA in China

The estimation results of the nine models, including All sample model, different size city models (Mega city, Large city, Medium city, and Small city), and different zone models (Northeastern zone, Eastern zone, Central zone, and Western zone) are presented in Table 5. The LM test or Robust-LM test statistics of all models were significant, which demonstrated spatial correlation effects. The Hausmann test showed that all Hausmann estimators were significant at the 10 % level, so the fixed effect model was suitable for our estimation. Most of the models rejected the null hypothesis of the Wald test and LR test, suggesting that SLM and SEM were not suitable for our data, and so the SDM was applied in our analysis. Therefore, the nine models we constructed were spatial Durbin model with fixed time effect (SDM-TFE).

4.3.1. All sample model

First of all, the results of All sample model showed that there is a significant negative correlation between urban spatial expansion and UGSA (P<0.01), indicating that the expansion of UBUA led to the decline of UGSA. Then, $W_{ij}\ln PUBUA_{jt}$ had a significant positive impact on $lnUGSA_{it}$, suggesting that UBUA had a positive spatial spillover effect. Finally, we also found that the $W_{ij}lnUGSA_{jt}$ had a significant positive impact on $lnUGSA_{it}$, which demonstrated that there was a positive spillover effect of UGSA.

Further, we calculated the marginal effects of urban spatial expansion on UGSA including direct, indirect, and overall average marginal effects (Table 6). The direct effect coefficient of urban spatial expansion was -0.49 (significant at the 1 % significance level), which demonstrated that a 1 % increase in the average local PUBUA would decrease UGSA by 0.49 %. The indirect effect of urban spatial expansion was positive (0.48) and significant at 1 % significance level. The overall impact was negative, but not significant.

As for the influence of control variables, the results also showed that the PGSA had a positive effect on UGSA, a 1 % increase in the PGSA increased the UGSA by 0.04 %, which was significant at the level of 1 %. Then, population and GDP had significant negative effects on the UGSA. Population had the largest impact (-0.62), followed by GDP. When the population and GDP increase by 1 %, the UGSA decreased by 0.62 % and 0.29 %, respectively. Finally, DEM also had a significant negative impact on UGSA, which indicated that the UGSA is poorer in higher elevation areas.

4.3.2. Different size city models

There were differences in the impact of urban spatial expansion on UGSA in different size cities. Except for the Mega city model, the coefficients of urban spatial expansion in the remaining three models were negative. The $W_{ij}\ln PUBUA_{jt}$ only in the Mega city and the Small city model had a significant impact on the UGSA, which was -0.37 and 0.25, respectively, demonstrating that there were negative and positive spatial spillover effects in the urban spatial expansion in these cities respectively. The $W_{ij}lnUGSA_{jt}$ in the Mega city, Medium city and Small city models had a significant positive impact on UGSA, which indicated that there was a positive spillover effect of UGSA in these cities. The direct effects of urban spatial expansion in the Large city, Medium city, and Small city models were all negative, and significant at the level of 1 %. The direct effect of urban spatial expansion in the Medium city model was the highest, followed by Small city model, and the direct effect in Large city model was the weakest. Only the Medium city model's indirect effect of urban spatial expansion was a significant negative. For the overall effect, every 1 % increase in the urban spatial expansion in medium cities reduced the UGSA by 1.06 %, and the impacts on small cities, large cities, and megacities were not significant. Urban spatial expansion in medium cities had the strongest impact on UGSA.

The control variables have different effects on the UGSA in different size cities. Our results showed that the direct effects of the PGSA on the UGSA were significantly positive. Most of the indirect effects in the models were not significant, only the

Medium city model had significant positive effects. For the overall effect, except for megacities, the PGSA had a significant positive impact on the UGSA in the other three sizes of cities, with the strongest impact on medium cities, followed by small cities, and the weakest impact on large cities. Secondly, the influence of DEM on the UGSA was also different. Only in the Small city model, DEM had a significant negative direct effect on UGSA, which meant that the UGSA in small cities was possibly more affected by the local topographical conditions. However, the overall effect of DEM on the UGSA in the Small city model was significantly positive, because the indirect effect was positive and offsets part of the direct effect. Compared with small cities, the UGSA in medium cities was much more affected by DEM, and the overall effect was -0.43 ($P < 0.01$). The direct effect of population on the UGSA in different sized cities was significant and negative, which meant that more local population lead to less UGSA. The indirect effects of the population were mostly positive and significant. However, only in the Small city model, the overall effect was significantly negative. The direct effect of GDP on Mega city and Large city models were - 0.57 and 0.23 respectively. For cities of different sizes, the indirect and overall effects of GDP were not significant.

4.3.3. Different zone models

The impacts of urban spatial expansion on UGSA varied among the different zones in China. In the Northeastern zone, Eastern zone, Middle zone, and Western zone models, the coefficients of urban expansion were all negative and passed the significance test. Only the spatial lag terms of the PUBUA in the Eastern and Central zone models had a significant positive impact on the UGSA, indicating that there were positive spatial spillover effects in the urban spatial expansion of the two zones. The spatial lag term of UGSA in the Eastern, Central, and Western zone models had significant positive impacts on UGSA, indicating there were positive spillover effects of UGSA in these three zones. In the four zone models, the direct effect of PUBUA was all significant negative, and the order of effect was Central zone model > Northeastern zone model > Eastern zone model > Western zone model. Only the indirect effect of the Eastern zone model passed the significance test and is positive. For the overall effect of the four zone models, the impacts of urban spatial expansion on UGSA were all non-significant.

The effects of control variables on UGSA in four zones were also different. Firstly, the PGSA in the four zone models had significant positive effects on UGSA ($P < 0.01$). As for the indirect effect, PGSA only had significant positive effects in the Central and Western zones models. From the overall effect, the PGSA had significant positive impacts on UGSA in the Eastern, Middle, and Western zone models, with the strongest impact in the Central zone, followed by the Eastern zone, and the weakest in the Western zone. Secondly, the impact of DEM on the UGSA was also different between zones. From the perspective of direct effect, only Northeastern and Western zone models passed the significance test. There were positive and negative direct effects in Northeastern and Western zone models, respectively. The indirect and overall effects of DEM on UGSA in the Central and Western zones models passed the significance test, and the overall effects on the Central and Western zones models were -0.64 and 0.21, respectively. The direct effect of population on UGSA in different zones models were significant and negative. The overall effect was negative, and the overall effect of Eastern, Central, and Western zone models are significant, the order of overall effect was Central zone model > Eastern zone model > Western zone model. Finally, besides the Central zone model, GDP had significant direct effects on UGSA in the other three zone models, which were positive for the Northeastern and the Eastern zone models, and negative for the Western zone model. The indirect and overall effects of GDP were not significant.

Table 5 Estimation results of the spatial panel models (Note: ***, and ** indicate $p < 0.01$ and $p < 0.05$ respectively)

Dependent variable	lnUGSA								
		City				Zone			
	All samples	Mega	Large	Medium	Small	Northeastern	Eastern	Central	Western
lnPUBUA	-0.52***	0.26	-0.31***	-0.47***	-0.36***	-0.25	-0.26***	-0.36***	-0.19***
PGSA	0.03***	1.58**	2.65***	2.28***	3.23***	1.28***	3.05***	1.86***	3.40***
lnDEM	0.09**	-0.16	-0.07	0.08	-0.16**	0.15	0.03	-0.06	-0.49***
lnPOP	-0.43***	-1.31***	-1.13***	-0.93***	-0.79***	-1.06***	-1.05***	-0.80***	-0.77***
lnGDP	0.05	-0.61***	0.22**	0.10	-0.02	0.22**	0.20***	-0.08	-0.16***
W*lnPUBUA	0.51***	-0.37	-0.60	-0.14	0.25**	-0.84	0.44***	0.37***	0.09
W*PGSA	-0.005**	0.61	-0.43	0.17	-2.01***	-0.19	-1.10***	0.51	-2.19***
W*lnDEM	-0.17***	0.07	-0.06	-0.33***	0.25***	-0.01	-0.06	-0.21**	0.62***
W*lnPOP	0.10	1.09***	1.09**	0.98***	0.64***	0.71	0.27	0.14	0.59***
W*lnGDP	-0.20***	0.37	0.22	-0.003	0.09	0.38	-0.05	0.02	0.08
W*lnUGSA	0.46***	0.23**	-0.16	0.43***	0.66***	-0.14	0.49***	0.58***	0.37***
R-squared	0.87	0.87	0.74	0.85	0.87	0.79	0.88	0.93	0.81
Hausman test	24.25**	17.48	41.01***	42.39***	42.89***	24.12**	36.78***	26.99***	56.06***
LMLag	126.20***	3.21	1.28	13.28***	15.69***	0.55	11.94***	100.21***	0.25
R-LMLag	5.38**	8.86***	6.71**	0.28***	32.40***	4.40**	8.52***	38.89***	55.57***
LMError	546.16***	0.16	1.58	54.29***	308.47***	1.47	90.88***	75.46***	126.17***
R-LMError	425.34***	5.80**	7.01***	41.29***	325.17***	5.31**	87.47***	14.15***	181.49***
Wald test Lag	227.74***	35.57***	13.43**	96.98***	218.90***	6.45	156.86***	53.99***	139.54***
LR test Lag	171.60***	25.13***	14.11**	76.15***	186.97***	6.94	100.33***	37.82***	121.81***
Wald test Error	88.64***	25.55***	19.53***	33.68***	16.05***	11.79**	32.840***	48.15***	51.97***
LR test Error	-127.73	23.82***	19.94***	34.35***	13.92**	12.60**	33.24***	42.80**	46.99**
Model	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE	SDM-TFE

Table 6 Marginal effects (Note: ***, and ** indicate $p < 0.01$ and $p < 0.05$ respectively)

Effect	Variables	All samples	City				Zone			
			Mega	Large	Medium	Small	Northeastern	Eastern	Central	Western
Direct	lnPUBUA	-0.49***	0.22	-0.31**	-0.51***	-0.36***	-0.25	-0.22***	-0.33***	-0.19***
	PGSA	0.03***	1.72	2.67***	2.41***	3.24***	1.30***	3.11***	2.18***	3.34***
	lnDEM	0.08**	-0.16	-0.08	0.05	-0.13**	0.15	0.03	-0.11	-0.47***
	lnPOP	-0.45***	-1.19***	-1.14***	-0.86***	-0.78***	-1.08***	-1.08***	-0.86***	-0.75***
	lnGDP	0.03	-0.57**	0.23**	0.11	-0.02	0.22	0.20***	-0.08	-0.16***
Indirect	lnPUBUA	0.48***	-0.37	-0.48	-0.55***	0.05	-0.72	0.58***	0.34	0.03
	PGSA	0.01***	1.13	-0.78	1.87***	0.39	-0.42	0.74	3.52***	-1.42***
	lnDEM	-0.23***	0.04	-0.03	-0.48***	0.41**	-0.02	-0.07	-0.54***	0.68***
	lnPOP	-0.17**	0.90**	1.11**	0.94***	0.34	0.76	-0.47	-0.72	0.46***
	lnGDP	-0.32***	0.28	0.17	0.07	0.20	0.32	0.09	-0.06	0.04
Total	lnPUBUA	-0.01	-0.15	-0.79	-1.06***	-0.31	-0.97	0.36	0.01	-0.16
	PGSA	0.04***	2.84	1.88***	4.28***	3.62***	0.88	3.85***	5.69***	1.92***
	lnDEM	-0.15***	-0.12	-0.11	-0.43***	0.28	0.12	-0.05	-0.64***	0.21**
	lnPOP	-0.62***	-0.29	-0.02	0.07	-0.44	-0.32	-1.55***	-1.58***	-0.29**
	lnGDP	-0.29***	-0.31	0.39	0.18	0.18	0.54	0.29	-0.14	-0.12

5. Discussion

5.1. Change of UGSA varied among the cities of different sizes during China's urbanization

The overall UGSA decreased seriously during the study period, and our spatial econometric model confirmed that the decline of local UGSA was the result of urban spatial expansion. In the early stage of urbanization in China, the spatial expansion of UBUA occupies the UGS and reduces the UGSA directly (Lin et al., 2013; Cao et al., 2017; Deng et al., 2009). Meanwhile, the increase of UBUA is often accompanied by the aggregation of the urban population leading to a further decline in the per capita green space occupancy. Since the reform and opening-up policy in 1978, megacities and large cities in the east coastal zone were prioritized for urbanization and socioeconomic developments, and the UBUA rapidly expanded (Fang, 2009; Liu et al., 2014). With the rapid development of eastern cities, cities in other zones began to enter the stage of rapid urbanization from 1990 to 2000. The UGSA in cities of different sizes showed a trend of rapid decline in that period. In particular, UGSA in megacities declined significantly, with an average annual decline of 6.33%. Due to the China Western Development Plan in 1999 and the Rise of the Central China Plan in 2004, the UBUA of China's medium and small cities in west and central zones began to grow significantly (Dou et al., 2020; Kuang et al., 2016). It explains to some extent the general decline of UGSA in cities of different sizes from 2000 to 2010.

It is worth mentioning that the decline rate of the UGSA in cities with different size in China from 2000 to 2010 was significantly lower than that from 1990 to 2000, and in addition to the slight decline of UGSA in megacities, the UGSA in cities of other sizes had turned to an increase from 2010 to 2015. It suggests that although urban spatial expansion led to the decline of UGSA during the rapid urbanization, the impact of urbanization on UGSA in China has a clear spatiotemporal heterogeneity. The decline of UGSA caused by urban spatial expansion only can be considered as a phenomenon in a specific period or region.

China's greening policies may also have played an important role in the subsequent change of UGSA. In 1992, the State Council issued the Urban Greening Regulations which made clear the importance of UGS but lacked specific urban greening objectives (State Council of the PRC, 2011). The circular of the State Council on Strengthening Urban Greening Construction in 2001 further defined the objectives and tasks of urban greening: by 2010, the green space rate of urban planning built-up areas should reach more than 35%, and the green coverage rate should reach more than 40 % (State Council of the PRC, 2001). To a certain extent, it curbed the decline of UGSA from 2000 to 2010, and made the UGSA of the large, medium, and small cities show an upward trend from 2010 to 2015.

The results of our spatial econometric model indicated that there was a positive spatial spillover effect of UGSA in China. Local city governments in China are sensitive to the central government's greening policies and there is often a competitive relationship between local governments. They usually refer to the UGS development of neighboring cities to determine the UGS supply of their cities, which leads to positive spillover effects as a result of UGS construction (Xu et al., 2018). Thus, positive greening policy and planning can not only promote the UGS supply level of the local city, but also indirectly improve the UGS supply level of the surrounding cities. The declining trend of UGSA in cities of different sizes slowed down from 2000 to 2010, and the general increase of UGSA from 2010 to 2015 may benefit from the spatial spillover effect of local government greening policy.

In a few cases, decreases in the urban population could also explain improvements in the UGSA for local and surrounding cities. A decrease in population does not automatically lead to a decline in residential areas and a subsequent increase in urban green space on a large scale (Kabisch et al., 2013)， but increases the per capita green space occupancy. For example, in the Sichuan, Chongqing, and Guizhou continuous area, which is the most densely populated area in the Western zone, cities experienced a significant outflow of permanent residents during 2000-2010 (Mao et al., 2015), the middle period of our analysis, when the regional UGSA values slightly improved.

The spatiotemporal changes of UGSA are highly related to the UGS. In Ethiopia, the UGS in its rapid urbanization areas also showed a declining trend from 1975 to 2015 (Molla et al., 2018). However, things are different in the developed areas in Europe and U.S.A. There was nearly no change in UGS between 1990 and 2000 but increased in UGS from 2000 to 2006 in Europe (Kabisch et al., 2013). Meanwhile, UGS were relatively constant from 2000 to 2016 in the 40 U.S. Northeastern urban counties (Heo et al., 2021a). Countries and cities of different sizes or development stages may have different abilities to maintain UGS. As the Chinese cities always have been under a uniform regime during the rapid urbanization in the past three decades, the change of UGSA in China has unique characteristics and can be used as a broad reference. UGSA based on Gaussian-based 2SFCA mainly depends on the LUCC data and can be easily applied to the cities in other developing countries or developed areas, which are under multiple regimes or at different stages of urbanization.

5.2. The improvement of UGSA equity comes at the expense of the cities in the Western zone

During the period of rapid urbanization, cities with lower economic development levels always had more UGSA in China. Ranked by GDP in 2015, 85 % of the poorest 20% cities were located in the Western zone and had about 65 - 80 % of UGSA during the study period. According to LUCC data, China's Western zone was rich in natural green space resources, accounting for about 74 % of the total green space in China in 2015. The UGSA of the Western zone was 4.07-6.08 times the sum of the other zones. However, urbanization in the Western zone is largely behind other regions and the UBUA occupied less green space (Maimaitiming et al., 2013; Du et al., 2019). In addition, the Western zone is sparsely populated and it is easier for residents to access UGS in the Western zone than in the other zones.

The equity of UGSA among cities in China had improved gradually over time. However, the improvement of UGSA equity has come at the expense of the Western zone cities' UGSA. The initial average UGSA in the Western zone in 1990 was the highest but their decline rate was the fastest during the last 30 years. Although the initial UGSA of the other three zones was low in 1990, the decline rate was slow, and the total decline was only 13.07 % of that in the Western zone. Thus, the difference in UGSA decline rates between the four zones leads to the gradual improvement of UGSA equity in China overall. It is noteworthy that the downward trend of UGSA in cities of the Eastern zone had been curbed in recent years. The high level of urbanization in the Eastern zone may be close to a turning point on the Kuznets curve (Yang et al., 2013), and urbanization will increase the demand for green space and ecosystem services. At the same time, the Eastern zone may benefit from the central government's greening policy and the spillover effect of UGSA. We believe that the cities in the Eastern zone will optimize urban spatial planning in the near future and the UGSA will increase further.

The pattern of improved equity across China’s cities is mainly a function of the rapid decline of UGSA in cities of the Western zone, where UGSA is facing a severe challenge from urbanization, rather than an improvement in cities of the other zones. UGSA of cities in the Western zone decreased by 68,681.85 m^2/person, with an average annual decrease of 2.51 % from 1990 to 2015. Especially after 2010, UGSA in the Central and Northeast zones had shown an upward trend, and the ACP_{UGSA} of the Eastern zone was only -0.12 %, while the ACP_{UGSA} of the Western zone was as high as -2.15 %. The Western zone had a great impact on the overall UGSA level of China as its vast territory. The improvement of UGSA in the Western zone deserves urgent attention. The previous study also found similar results that the UGS coverage of cities in the Western zone showed a declining trend from 2002 to 2012, and spatial disparity of UGS coverage also declined across 288 cities in China (Wang et al., 2019). It is worth noting that the UGSA of prefecture-level cities in the Western zone had been on the rise since 2010, with an average annual growth rate of 9.93 %, according to analysis on data. However, the UGSA in the cities of the Western zone declined seriously with an average annual decrease of 2.51 % after 2010. This is because the calculation of UGSA in the cities of the Western zone also took into account the UGSA in the province directly administrating county, autonomous prefecture, league, and prefecture (See section 2.1, it introduces the classification of cities that we analyzed). Our results showed that after 2010, the ACP_{UGSA} of the autonomous prefecture, league, and prefecture was -1.44 %, -6.74 %, and -4.20 %, respectively. In China， the changing pattern of green space was a response to the combined effects of rapid urbanization and greening policies, and green space coverage may increase with urbanization level (Gan et al., 2014). Greening policy plays an important role in the growth of UGS in China (Wang et al., 2019). As autonomous prefectures, leagues, and prefectures in the Western zone are in the middle and early stages of urbanization. There is not enough financial support for local UGS development and the implementation of the central government's greening policy is insufficient. Therefore, in the future, urbanization policies that suit local conditions need to be designed in different zones. Meanwhile, more attention should be paid to the urban planning and construction of cities in the Western zone, especially the urban construction of autonomous prefectures, leagues, and prefectures.

5.3. Limitations and future work

There are still some limitations in our research. First, due to the spatial resolution of land use data, small patches of green space inside UBUA may be overlooked to some extent. It could potentially have introduced calculation errors, which may underestimate the UGSA in some cities, and affect more localized dynamics within the megacities and large cities. In the future, high-resolution remote sensing data can be considered as auxiliary data to calculate UGSA. Second, we only consider the size of available UGS to evaluate accessibility and future studies should consider the quantitative features of UGS such as tree coverage, vegetation species, tree canopy coverage, trail density and number of supporting facilities (Dai, 2011; Zhang et al., 2020a). The qualitative features of UGS should also be taken into account, including quietness, spaciousness, maintenance, safety, cleanliness, aesthetics, and others (Wende et al., 2012; Stessens et al., 2020; Huang et al., 2021). At the same time, whether UGS is admitted or not is also a crucial qualitative feature, which is highly related to whether UGSA can be evaluated more accurately. Research on qualitative features often provides valuable insight, which can explain in greater depth how aspects of the environmental impact on target groups' lives, and contribute to determining the pertinent target for intervention (Macintyre et al., 2019; Burton et al., 2015). Third, we only consider the large-scale formal UGS, but not the informal green space. In future research, we should use a wider classification of UGS including informal spaces (e.g., pocket parks, green walls or roofs, residential green spaces, and others). UGS of a smaller size close to the place of residence need to be fully considered, as they are the most easily available areas for the citizens. Fourth, we chose a Gaussian function to reflect the travel friction between urban residents and UGS over realistic distances in urban settings, which assumes travel friction is uniform with distance. It may not fully capture the actual travel friction within individual cities in which the travel distance will vary depending on city morphology, natural barriers such as rivers, road networks, and public transport networks (Dai, 2011). But using the same travel mode is more convenient to compare the UGSA between a large number of different cities. Fourth, buffer analysis was applied to simplify the calculation, but this may overestimate the UGSA. The combination of road network data can bring more accurate results, which is worth considering in the next work. Fifth, we only took into account the location of the residents, the results can be used to reflect static justice but not dynamic justice. In the next work, we can look at the availability and accessibility of UGS during e.g., commute to work to produce the result reflecting dynamic justice. Sixth, our methodology focused on walking, the most common mode of daily transportation for residents to access UGS. However, it is possible in the future to calculate accessibility using a range of traffic modes including biking, taking public transit, and driving a private vehicle. In the end, the method of this study is applicable to the global scale. In future work, our method of the UGSA can be applied for the cities around the world can be calculated in combination with the data set of global scale (e.g., remote sensing data, population, statistical yearbook), to compare the UGSA and its spatial inequity among the different regions in the world.

6. Conclusion

We found that the UGSA in China declined significantly during the rapid urbanization and the overall decline was nearly 57.23 %. The UGSA in the southeastern region indicated by the Hu Huanyong Line was always lower than that in the northwestern region. Cities with low economic development levels had more UGSA in China. Urban spatial expansion leads to the decline of UGSA on the whole during the study period, and UGSA had a positive spatial spillover effect. The equality of UGSA between cities had improved gradually over time.

However, the improvement in the equity relationship comes at the expense of the rapid decline of UGSA in cities of the Western zone. The UGSA in the Western zone is facing a severe challenge from urbanization, and cities in the Western zone had a large number of UGS resources but they did not pay much attention to the protection and planning of UGS, which caused a significant UGSA decline in recent decades. More attention should be paid to the UGS planning and protection of autonomous prefectures, leagues, and prefectures, because there was a significant UGSA decline in recent years. While the impact of urbanization on UGSA in China has a clear spatiotemporal heterogeneity and the urban spatial expansion decline UGSA only can be regarded as a regional or specific period phenomenon. The change of UGSA in different zones was affected by population migration and the greening policies of central or local governments. UGSA in China had a positive spatial spillover effect, which indicates that where the local government improves the UGSA of the city this may also indirectly improve the UGSA of surrounding cities as local city authorities follow trends set by their neighbors. The greening policies of the central government are effective and the city's greening policies have a demonstration effect. It is still necessary to continue to implement greening policies to curb the decline of UGSA.

Our study provides new evidence from a macroscopic perspective for the study of dynamic inequity of UGS among cities, spatiotemporal patterns, and its relationship with urban expansion during the period of rapid urbanization. It provides a baseline for the future development of China's UGS development strategies and scientific samples for other countries' UGS policies. The UGSA calculated by 2SFCA in this study can be easily applied in a large-scale comparative study for other regions in the world in the future.

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