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Neighborhood socioeconomic disadvantage and urban public green spaces availability: A localized modeling approach to inform land use policy

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ABSTRACT

Urban public green spaces (UPGSs) are rarely uniformly distributed across space. A subset of urban population is disproportionately well available of UPGSs, while other residents have considerably limited accessibility to UPGSs. Communicating and examining the spatial heterogeneity in UPGSs availability can formulate better land use policy. This paper applies the geographically weighted regression (GWR) to analyze the locality-specific relationships between neighborhood socioeconomic disadvantage and UPGSs availability at district level in Shanghai, China. In particular, we construct a neighborhood socioeconomic disadvantage index (NSDI) that incorporates elements from four dimensions including wealth, occupation, education and housing. Three domains of indicators (abundance, quality and accessibility) are developed to measure UPGSs. Results show that relationships between NSDI and UPGSs availability indicators present significant spatial non-stationarity. In general, UPGSs abundance and accessibility are lower in districts characterized by higher NSDI. However, converse trend is found in districts on the south-western urban edge. UPGSs quality is poorer in districts with higher socioeconomic disadvantage within the central city, while UPGSs in the socioeconomically disadvantaged exhibit better quality within the outskirts. Our results highlight the importance of considering the locality-specific neighborhood socioeconomic profiles of UPGSs availability. The applied GWR framework presents promising potential for better UPGSs planning in a policy context. In the future, two principles are required for urban greening policies: (1) a comprehensive perspective in UPGSs availability evaluation; (2) locality-specific target strategies. The principles are not only key for China but also relevant to other nations who wish to achieve successful urban greening.

1. Introduction

Urban public green spaces (UPGSs) refer to the non-private freely-accessible outdoor areas with amenities within urban limits (Wright Wendel et al., 2012). They are considered to be public goods and typically includes vegetated natural spaces (e.g., parks, small gardens, and urban forests) and human-modified places (e.g., plazas and squares, residential green spaces, institutional green spaces, and greenbelts) (de la Barrera et al., 2015; Shan, 2014; Wright Wendel et al., 2012). UPGSs deliver favorable places for recreation, relaxation, leisure, and health benefits, and foster urban community integration and social interaction. They also provide diverse ecosystem services (e.g., noise reduction, air filtration, climate regulation, and water conservation) and consequently positively contribute to life quality and urban sustainability. However, UPGSs management and planning nowadays face great challenges, considering the increasing and diversified demand associated with urbanization and society diversification (Shan, 2014). In this context, understanding the current status of UPGSs distribution and the variations across urban neighborhoods should provide essential knowledge for land use policy to optimize the benefits of UPGSs for urban residence.

Within city limits, UPGSs are rarely uniformly distributed across space (Barbosa et al., 2007; Kabisch and Haase, 2014; McConnachie and Shackleton, 2010). A subset of urban population is disproportionately well available of UPGSs, while other residents have considerably limited accessibility to UPGSs (Ernstson,

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2013; Kabisch and Haase, 2014; McConnachie and Shackleton, 2010). Previous studies on the UPGSs availability can be divided into two major categories: individual level and neighborhood level. At the individual level, researchers compare the profiles of UPGSs users through questionnaire survey or face-to-face interview. For example, the patterns of UPGSs usage are reported to vary significantly with users' occupation (Zhang and Gobster, 1998), education (Kemperman and Timmermans, 2006; Lo and Jim, 2010; Shan, 2014), marital status (Pincetl and Gearin, 2005; Sanesi and Chiarello, 2006), social hierarchy (Oguz, 2000; Shinew et al., 1995), race (Comber et al., 2008), and residential physical conditions (Peschardt et al., 2012; Sanesi and Chiarello, 2006; Shan, 2014). This category of studies receives the criticism that they incorporate bias in sampling and cannot fully capture the UPGSs availability patterns in space.

Some scholars attempt to associate UPGSs availability with neighborhood socioeconomic variables, since it can help identify the localities short of UPGSs supply for land use policy makers (Haaland and van den Bosch, 2015a,b). For example, Kabisch and Haase (2014) reported the considerable variations of UPGSs per capita in association with neighborhood immigrant percentage in Berlin, Germany. Neighborhood immigrant percentage is also indicative of limited UPGSs availability in UK (Barbosa et al., 2007), Canada (Pham et al., 2012), and US (Martin et al., 2004). In addition, UPGSs availability is found to be correlated with race (McConnachie and Shackleton, 2010; Dai, 2011; Pham et al., 2012), wealth (Martin et al., 2004; Mennis, 2006; Pham et al., 2012), education (Barbosa et al., 2007; Troy et al., 2007; Zhang et al., 2008), and housing tenure (Lowry et al., 2012; Perkins et al., 2004). Prior studies focus on the developed nations and only a few studies explore the UPGSs availability in developing countries, where UPGSs provision faces strong pressure competition from built-up land to accommodate huge population. In addition, past studies apply simple statistical method, the global ordinary least squares regression (OLS) in particular, to quantify the associations. It cannot adequately explain the associations, because (1) the homoscedasticity assumption of OLS may not be satisfied considering the great heterogeneity of UPGSs availability across space; (2) the OLS only considers the average conditions and therefore produces space-constant global relationships (Fotheringham and Brunsdon, 1999; Su et al., 2012, 2014a).

Neighborhood socioeconomic disadvantage (NSD) refers to the limits or shortage of wealth, capital, knowledge and resources to support sustainable well-being and quality of life (Jones-Webb and Wall, 2008). Sociological research demonstrates that residents in socioeconomically disadvantaged neighborhoods are more likely to encounter barriers to access services and job opportunity, experience social exclusion and crime, and be exposed to more pollution (Weng et al., 2016). As a multidimensional concept involving diverse elements (e.g., income, occupation, education and housing), NSD provides a complete picture of the neighborhood characteristics compared with the individual variables (Su et al., 2016; Weng et al., 2016). Geospatial tools, such as remote sensing, geographic information system (GIS) and landscape metrics, are efficient in describing natural resources patterns within cities (Su et al., 2011). They therefore show promising potential to characterize the UPGSs availability. Geographically weighted regression (GWR), the most popular local regression format, presents great superiority in characterizing spatial non-stationary relationships (Su et al., 2012; Wheeler and Páez, 2010). Numerous studies have evidenced the significant advantage of GWR over the OLS in land use studies (Jaimes et al., 2010; Su et al., 2012, 2014a; Xiao et al., 2013).

Against such backdrop, this paper applies multiple tools (remote sensing, landscape metrics, GIS, and GWR) to the case of Shanghai (China) and attempts to: (1) develop a neighborhood socioeconomic disadvantage index (ANSDI); (2) describe the UPGSs availability and the heterogeneity; (3) quantify the locality-specific relationships between UPGSs availability and NSD; and (4) discuss the implications for urban greening policy.

2. Materials and method

2.1. Study area

We select the Shanghai city as the study area, which is located in the central part of Chinese eastern coast (Fig. 1). Shanghai covers an area of 6300 km^2 and has a population of 24.3 million. It is the most densely populated city in China and one of the most populous cities around the world. As the leading core of Yangtze Delta Economic Zone, it has seen rapid population growth and economic development since the 1980s. The accelerating socioeconomic development has given rise to a conflict between built-up land and natural resources. More and more buildings have been constructed during the recent years (Su et al., 2014b). However, these buildings are in a disorganized manner (Su et al., 2014b), leaving little space for introducing UPGSs. In addition, neighborhood residential patterns and demographic profiles present polarization in space. These neighborhoods differ greatly in physical environment and public goods supply. Given this specific situation, Shanghai should be a good example to explore the issue under investigation.

In order to obtain the UPGSs information of Shanghai, we collected the Quickbird images in 2007 as data sources. Pre-processing involves the atmospheric correction, geometric correction, image mosaic and false color composite. Visual interpretation is employed to extract the UPGSs information (Fig. 2), since the machine-based classifications are limited in distinguishing fragmented land use types (Su et al., 2014b). In particular, the UPGSs in our study include the parks, gardens, greening forests, greenbelts along roads, greenbelt along rivers, greening squares, greening plazas, green spaces around residence, and green spaces around institutions. In total 160 referencing samples (80 from the original images and 80 from field trips) are used to access the accuracy. The producer's accuracy is 97.3%.

2.2. Neighborhood socioeconomic disadvantage index

Neighborhood is conceptualized to be a spatial scope within which elements are characterized by homogeneous characteristics (Gupta et al., 2012). As a relative concept, neighborhood can refer to community, district, walking distance scope in the literature (Su et al., 2016). In this study, neighborhood refers to district, the basic unit for official statistic data in Shanghai. Scholars have applied a great diversity of indicators to describe NSD. Jones-Webb and Wall (2008) used median household income, unemployment, female headship, and low educational attainment to indicate NSD. Kim (2010) applied poverty and female-headed households to measure NSD. Grow et al. (2010) employed adult female education level, median household income, race, and single parent households as NSD indicators. Turrell et al. (2010) measured NSD by considering the education, occupation, and household income. Presence of garbage/litter, vandalism, and poor/dilapidated housing were used to assess NSD in Singh and Ghandour (2012). Levels of poverty, educational attainment, unemployment, and residential mobility were utilized to measure NSD in Santiago et al. (2011). Hackman et al. (2012) described NSD by virtue of below poverty rate, unemployed rate, African–American proportion, and female-only household percentage. Brown et al. (2013) developed a composite of six variables representing employment, wealth, education, and income to measure NSD. Alvarado (2016) used proportion of managers and professionals, median income, not in labor force,