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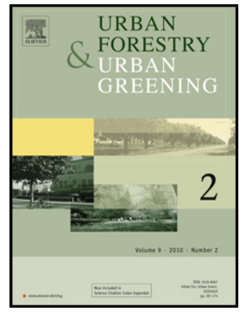

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ABSTRACT

Sensing urban greenness from street view data offers a new and alternative way of measuring the association between greenness exposure and subjective wellbeing in developing countries where traditional census data are poor. This paper focuses on the association between life satisfaction and street-level visible greenness exposure at residential and work locations, using a combination of sensor data and individual cross-sectional survey data (4619 employed respondents) in Beijing, China. We use a single self-reported question (““how well are you satisfied with your life as a whole”’) to measure life satisfaction. Street View Greenness (SVG) is taken as a surrogate for street-level visible greenness exposure at residential and work locations. The results suggest that street-level visible greenness exposure in residential locations is positively associated with perceived satisfaction, though such effects are less significant after considering greenness exposure at work locations. The stratified analysis provides the insight that the associations between street-level visible greenness exposure and life satisfaction vary with individual demographic and socioeconomic characteristics such as sex, age educational attainment and income. Males, young adults, people with low income and educational attainment may benefit more from SVG exposure than other groups. Findings of this study suggest that urban greenness in residential and work environments should simultaneously be taken into the design of land use and public policies aiming to improve people's subjective wellbeing.

Keywords: Greespace; Well-being; Neighbourhood; Workplace; Street view data

1. Introduction

Megacities from the developing world have been pursuing public investments to support the maintenance and development of urban greenness for the transformation of people's quality of life (del Pulgar et al., 2020; Liu et al., 2019; Xiao et al., 2017). Promoting urban greenness has often been touted as a useful and effective way to support people's subjective wellbeing (Douglas et al., 2017; Hartig et al., 2014; Markevych et al., 2017). Life satisfaction can reflect people's overall levels of subjective well-being and is relatively stable across many years (Pavot 2008; Schimmack 2009). Therefore, exploring the association between urban greenness and life satisfaction is important for further understanding the long-term health benefits of greenness. Sensing urban greenness signifies one's subjective wellbeing through reducing disamenities derived from air pollution, noise and heat, restoring from stress and building capacities in terms of physical activity and social cohesion (Hartig et al., 2014; Liu et al., 2019; Markevych et al., 2017; Wang et al., 2019a). This is particularly the case for China, where public awareness of urban greenness has risen dramatically over the past decade (Liu et al., 2019; Wang et al., 2019a). In this context, precise measurement of urban greenness exposure has become increasingly important, since it supports subjective wellbeing implications.

The mainstream empirical literature on well-being and urban greenness has largely focused on evidence for the benefits of green space from Western countries (Adhikari et al., 2020; Markevych et al., 2017). Most existing research evaluating the subjective wellbeing implications of urban greenness assesses the effects of urban green space through geographical measurements of residential proximity to green spaces (i.e urban parks) (Ambrey and Fleming, 2011; Ambrey and Fleming, 2014; Fleming et al., 2016; Tsurumi and Managi, 2015) or overall amount of green spaces (i.e vegetation coverage) (Dzhambov et al., 2020). Typically, existing studies suggest that satisfaction levels are positively associated with proximity to urban green space (Ambrey and Fleming, 2011; Ambrey and Fleming, 2014; Fleming et al., 2016; Stigsdotter et al., 2010; Tsurumi and Managi, 2015). Other recent work suggests negative or no significant association between urban green space and satisfaction outcomes after controlling for individual and neighbourhood characteristics (Brown et al., 2016; Ma et al., 2018). More recent work has shifted traditional proximity methods towards the machine learning and big data approaches by using street view images to predict street-level visible greenness at the local area level (Wang et al., 2019a). Recent studies have also shifted their focus away from the average or independent effect of urban green space on individuals' satisfaction to reveal that individuals' perceived satisfaction may respond differently to greenness amenities depending on individuals' heterogeneous demographic characteristics (Li et al., 2015, 2016; Tabrizian et al., 2018, 2020; Wu et al., 2019b).

This study explores the relationship between potential exposure to street-level visible urban greenness and life satisfaction at residential and employment locations using a combination of street view data and individual survey data collected from Beijing, China. We conducted our research in China, where people have fewer opportunities to visit large areas of natural environment due to the high speed of urbanization. Thus, the planning for street-level visible urban greenness, which is small greenspace, becomes an important issue, especially in big cities such as Beijing. This study extends previous research in three ways. First, our greenness data allows us to illustrate the important role of street-level visible greenness measures in affecting life satisfaction, after controlling for the traditional measure of proximity to urban parks. Second, our robustness check further sheds lights on the heterogeneous effects of street-level visible greenness exposure on life satisfaction across social groups, which is important for examining the effect of greenspace on promoting social equity, especially in developing countries. Third, there is a substantial empirical literature that investigates various aspects of urban greenness. Much of it is concerned with variations in urban green space accessibility or greenness levels in residential areas. Only a small number of studies look at the relationship between urban greenness at workplaces and wellbeing or health outcomes (Colley et al., 2017; Dravigne et al., 2008; Gilchrist et al., 2015; Lottrup et al., 2013; Xue et al., 2016). However, these studies either focused on indoor vegetation or assessed greenness exposure in workplace through self-reported questions. For example, Dravigne et al. (2008) found that greenspace exposure in workplaces could be positively associated with life satisfaction, though they measured greenspace exposure based on self-reported questions. Gilchrist et al. (2015) found that people's mental wellbeing is associated with window views of greenspace. Put differently, our investigation presents the evidence for combining sensored street view data with traditional survey data to shed light on the contextualized association between greenness and subjective wellbeing. We also improve on the previous work by simultaneously considering the joint effects of greenspace exposure in both residential and work locations.

2. Literature review

The literature that analyses the association between urban greenness and life satisfaction has developed rapidly over the past decades. Most studies have suggested that limited access to green space may adversely affect subjective well-being and other health outcomes (Fleming et al., 2016; Stigsdotter et al., 2010; Tsurumi and Managi, 2015), while others have reported no significant associations (Brown et al., 2016; Ma et al., 2018). Several mechanisms, including restoring capacities, building capacities and reducing exposure to environmental stressors, may explain the linkage between urban greenness exposure and life satisfaction (Markevych et al., 2017). First, stress reduction theory (SRT) and attention restoration theory (ART) suggest that urban greenness may benefit people's wellbeing by reducing stress and restoring attention (Kaplan, 1995; Ulrich et al., 1991). Second, greenness exposure is associated with encouraging physical activity and facilitating social cohesion within residential neighbourhoods (Liu et al., 2019; Wang et al., 2019a). Third, greenness amenities can also reduce people's exposure to environmental hazards, including air pollution, noise and heatwaves (Markevych et al., 2017; Wang et al., 2019a; Wu et al., 2020), and contribute to better perceived living experiences of residents.

Some studies, however, have realized the important role of different ways of measuring urban greenness in influencing implications for subjective health and wellbeing (Lu et al., 2019; Wang et al., 2019a). Traditional measures include using the geographical distance to parks and green space to assess the proximity effects of urban green space, whereas more recent work has shifted towards using satellite-sensored data such as remote sensing data and street-level visible data such as online street view information to assess urban greenness exposure (Lu et al., 2019; Ye et al., 2019). In comparison with street-level visible street view data, remote sensing data may ignore street-level vegetation that can be perceived by residents. The observed vegetation can reflect residents' actual greenness exposure levels and are therefore expected to play a critical role for residents' lived experiences (Wang et al., 2019a). It is important to acknowledge that for some pathways underlying health effects of greenness (i.e reducing environmental hazards), remote sensing-based greenness may be more relevant to health than street view greenness (SVG) because they capture overall vegetation quantity, while street view greenness may be more related to perceptual and behavioral pathways grounded in actual interaction (Dzhambov et al., 2020).

While most previous studies have assessed greenspace exposure in residential neighbourhoods (Markevych et al., 2017), the empirical literature on urban greenness has paid increasing attention to workplaces, where people spend considerable time engaging with the local environment (Dravigne et al., 2008; Gilchrist et al., 2015). The omission of greenness exposure in non-residential activity sites may lead to biased estimation of the beneficial effects of greenness. Indeed, it is possible that people who are less exposed to greenness amenities within their own neighbourhoods may be exposed to greenness in workplaces and other activity sites (Helbich, 2018). This study advances the investigation by hypothesizing that the association between life satisfaction and urban greenness is not only influenced by residential locations, but also by work locations.

Following the "equigenesis" theoretical framework, people of different socioeconomic status (SES) may not benefit equally from exposure to greenness (Feng and Astell-Burt, 2017; Mitchell et al., 2015; Pearce et al., 2016). On the one hand, people with high SES are more likely to have higher life satisfaction, since they can afford better health-related services (Barger et al., 2009). On the other hand, previous studies have indicated that people with lower SES may benefit more from greenspace than those with higher SES. For example, Mitchell et al. (2015) found that people with lower SES benefit more in terms of subjective wellbeing from having good access to green/recreational facilities. One reasonable explanation is that most greenspace, such as street vegetation and parks, are public facilities provided by local government and can be used free of charge (Mitchell et al., 2015; Pearce et al., 2016; Xiao et al., 2017). There has been some evidence to support the notion that the association between greenness and life satisfaction may vary by demographic characteristics such as gender and age (Ambrey and Fleming, 2014; Astell-Burt et al., 2014), which can be defined as culturally mediated gender roles in greenspace exposure. Bos et al. (2016) find that males can benefit more from greenness exposure in residential neighbourhoods because they undertake more physical activities in their neighbourhoods and therefore are better exposed to urban greenness. However, De Vries et al. (2003) find that females are more likely to benefit from greenspace exposure within their neighbourhoods, since they spend more time close to home due to their household work duties. As for the age difference, Ambrey and Fleming (2014) suggest that compared with older adults, younger and middle-aged adults benefit less from greenness exposure. In contrast, some studies have reported that the association between greenness exposure and wellbeing in residential neighbourhoods is less significant for older adults because they are more likely to spend more time at home and have a sedentary behaviour (Astell-Burt et al., 2014). Clearly, there are mixed results in the western literature, but findings are largely supportive of the importance of considering heterogeneity in the influence of greenness on life satisfaction across social groups. However, existing studies from the developing world have yet to pay much attention to decomposing the perceived effects by individual demographic characteristics such as income, age, and gender in the street-level visible greenness context.

3. Methodology

3.1. Individual-level survey data

This study used data collected through the Chinese Livable Survey (Ma et al., 2018; Wu et al., 2019a) conducted in 2013 (Fig. 1). The research team selected survey respondents based on a stratified proportional-to-population size sampling technique in metropolitan Beijing areas. In the first step, districts were chosen from the whole city. Second, neighbourhoods were selected from the sampled districts. Last, respondents were selected from each neighbourhood. Recent studies have shown that the respondents in this survey are representative for the population in Beijing based on the demographics derived from 2010 population census data (Wu et al., 2019a). All selected respondents had lived in Beijing for more than six months. Both residents with local *hukou* (registered permanent residence) and without local *hukou* (registered temporary residence) were included. All respondents were invited to give their written consent. The overall response rate was 85.71%. The survey yielded a total of 4619 valid employed respondents (1381 invalid respondents).

<Figure 1 about here>

3.2. Dependent variable

Following previous studies (Ma et al., 2018; Wu et al., 2019b), life satisfaction is this study was measured a single question. The respondents were asked “how well are you satisfied with your life as a whole”. In the survey questionnaire the answered item was scored using a five-point scale ranging from “very dissatisfied” to “very satisfied”. In order to avoid sparse data bias (Greenland et al., 2016), we dichotomized the dependent variable. We regarded “very dissatisfied” and “dissatisfied” as low life satisfaction while “general”, “satisfied” and “very satisfied” were regarded as high life satisfaction.

3.3. Independent variable

SVG was calculated through street view images which were collected in 2012 by street view vehicles from Tencent, one of the largest online map services in China. We gained access to Tencent Street view images with API following previous studies (Wang et al., 2019a). We constructed sampling points for collecting street view images along the road network based on OpenStreetMap (Haklay and Weber, 2008). Sampling points were 100 metres apart. For each sampling point, we collected four street view images from different points of the compass (0, 90, 180, and 270 degrees). In total, we gathered 125,324 street view images.

Following Wang et al. (2019a), we used a machine learning approach based on semantic image segmentation techniques to extract different kinds of streetscape objects. We used a fully convolutional neural network for semantic image segmentation (FCN-8s), which has been proved to be capable of identifying 150 kinds of ground objects (i.e. trees and grasses) accurately (Long et al., 2015). Our training model was based on the online annotated images dataset called ADE20K (Zhou et al., 2019). Following Wang et al. (2019a), SVG per sampling point was determined as the proportion of pixels representing greenspace in the four street view images. For neighbourhood, we calculated the SVG by averaging the SVG scores for all sampling points within 500-metre circular buffers following previous studies (Nordbø et al., 2018), which were created based on the centre of gravity for each residential neighbourhood (*juzhuxiaoqu*). Last, we calculated the SVG for respondents' workplaces by averaging the SVG scores for all sampling points within 500-metre circular buffers, which were created based on the location of each respondent's workplace.

Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) was also used as the surrogate of greenness exposure in sensitivity analysis. NDVI was calculated by reflectance in the near-infrared band (NIR) and reflectance in the visible region (VIS) from satellite images. Its values range between −1 and 1. A higher value indicates a higher quantity of vegetation. We used NDVI raster product provided by Resource and Environment Science and Data Center (http://www.resdc.cn/data.aspx?DATAID=257).

3.4. Covariates

We controlled for some individual-level demographic variables, including homeownership, sector of employer, occupational status, household income, sex, age, educational attainment, *hukou* status, marital status. Based on Tencent location-based social media, we also controlled for population density (persons/km^2) in both residential neighbourhood and working following previous studies (Liu et al., 2020). All of the descriptive statistics are presented in Table 1.

3.5. Statistical analysis

As our data had a hierarchical structure, multilevel logistic regressions (Raudenbush and Bryk, 2002) were used to examine the associations between SVG and the likelihood of reporting low life satisfaction. In the models, individuals at Level 1 were nested within neighbourhoods at Level 2. We used moderation analysis to explore the interaction term between SVG in residential neighbourhood and working place. The intraclass correlation coefficient (ICC) for the null model was 0.132. Normally, ICC above 0.10 indicates the need to compensate for nesting, so our result indicates that life satisfaction within the same neighbourhood and same individual were correlated, confirming that the application of multilevel models is appropriate. In this study, we used a random intercept multilevel model, which means that the intercept term contained mixed effects (both random and fixed effects). We employed a stepwise approach to test the effect of SVG on respondents' life satisfaction. First, we estimated the association between covariates and respondents' life satisfaction (Model 1a). Second, we regressed respondents' life satisfaction on the SVG in the residential neighbourhood (Model 1b). Third, we regressed respondents' life satisfaction on the SVG in the workplace (Models 1c). Fourth, we regressed respondents' life satisfaction on both SVG in the residential neighbourhood and SVG in the workplace at the same time (Model 1d). Last, previous studies indicate that greenspace has a dose-dependent effect on wellbeing (Helbich et al., 2018), so the effect of greenspace exposure in one place may be influenced by the greenspace exposure in another place. Based on the above evidence, we hypothesized that greenspace exposure in the neighbourhood may be influenced by the greenspace exposure in the workplace, so the interaction term between SVG in the residential neighbourhood and the workplace was added into Model 1d (Model 1e). The variance inflation factor (<3) indicates that collinearity of different variables is acceptable in this study. In the next step, we conducted four robustness tests (Model 2a-2d) to test the sensitivity of the relationship between SVG and respondents' life satisfaction. Since the buffer size may affect the effect of greenspace exposure (Su et al., 2019), we changed the buffer size to 800 metres and re-ran the fully adjusted model (Model 2a). We also changed the independent variable to NDVI (normalized difference vegetation index) in Model 2b, since the effect of greenspace exposure may also influenced by the measurement of greenspace (Wang et al., 2019a). NDVI is a remote-sensing based measurement of greenspace that measures greenspace from an overhead perspective. Thus, it provides a different measurement of greenspace which is comparable with SVG (Wang et al., 2019a). Last, since older adults may have a different perception of natural environments (Wang et al., 2019b), we excluded them from the sample and re-ran the fully adjusted model (Model 2c). Also, in the last step, we performed several stratified analyses to test the heterogeneous effects of SVG on respondents' life satisfaction (Model 3-6). The analyses were performed using Stata 15.1 (StataCorp., College Station, TX, USA) using the 'meologit' commands.

4. Results

4.1. Characteristics of the study population

Table 1 summarizes the characteristics of the study population. 85.7% of the respondents reported low life satisfaction, while 14.3% reported high life satisfaction. The average SVG was 0.130 in residential neighbourhood and 0.125 in working place. Hence, the average population density was 15274 persons/km^2 in residential neighbourhood and 24312 persons/km^2 in working place. Overall, about half of the respondents were homeowner, 20.3% worked in state sector and 26.9% were highly skilled workers. About 28.1% of the respondents had income below 4999 RMB per month, 55.3% had a income between 5000 and 14999 RMB per month, and 16.6% had income over 15000 RMB per month. Nearly half of the respondents were female, while about two third had a degree above high school. About 76.5% of the respondents aged below 39, 23.1% aged between 39 and 60, and only 0.4% aged above 60. 62.7% of the respondents had local hukou, and 58.5%

were married.

<Table 1 about here>

4.2. Baseline results

Table 2 illustrates the baseline model for the results of SVG on respondents' life satisfaction. Model 1a shows the relationship between covariates and respondents' life satisfaction. Homeowners were less likely to report low life satisfaction compared with non-homeowners (OR = 0.612, 95% CI: 0.485-0.772). Compared to respondents with household income less than 4999 RMB per month, respondents with higher household income were less likely to report low life satisfaction (>5000 and <14999 RMB per month: OR = 0.629, 95% CI: 0.510-0.775); >15000 RMB per month: OR = 0.360, 95% CI: 0.256-0.506).

Model 1b shows the relationship between SVG in residential neighbourhood and respondents' life satisfaction, while Model 1c shows the relationship between SVG in the workplace and respondents' life satisfaction. Respondents' odds of reporting low life satisfaction was negatively associated with SVG in the residential neighbourhood (OR = 0.473, 95% CI: 0.136-0.639), but life satisfaction was not associated with SVG in the workplace. Model 1d shows the joint effect of both SVG in the residential neighbourhood and SVG in the workplace on respondents' life satisfaction. Despite some differences in the coefficient for odds, the neighbourhood SVG - life satisfaction associations remained significant (OR = 0.634, 95% CI: 0.160-0.948), but life satisfaction was still not associated with SVG in the workplace. We further examined whether the effect of SVG in the residential neighbourhood on respondents' life satisfaction was moderated by SVG in the workplace in Model 1e (Table 2). The results indicated that the effect of SVG in the residential neighbourhood on respondents' life satisfaction was not moderated by SVG in the workplace.

<Table 2 about here>

4.3. Robustness and heterogeneity of effects

Table 3 summarizes the results of robustness tests on the correlation between SVG and the respondents' life satisfaction. Despite some differences in the coefficient for odds, the neighbourhood SVG - life satisfaction associations remained significant and the signs of their coefficients remained the same across all models for robustness tests.
<Table 3 about here>

We performed several stratified analyses to test the heterogeneous effects of SVG on respondents' life satisfaction. Table S1 shows the heterogeneous effects between men and women. Model 3a shows that SVG in the residential neighbourhood was negatively associated with males' odds of reporting low life satisfaction (OR = 0.218, 95% CI: 0.128-0.694), but males' life satisfaction was not associated with SVG in the workplace. Model 3b suggests that the effect of SVG in the residential neighbourhood on males' life satisfaction was not moderated by SVG in the workplace. Model 3c indicates that neither SVG in the residential neighbourhood nor SVG in the workplace was associated with females' life satisfaction. Model 3d suggests that the effect of SVG in the residential neighbourhood on females' life satisfaction was also not moderated by SVG in the workplace.

Results (Table S2) show the heterogeneous effects by age groups. Model 4a indicates that SVG in the residential neighbourhood was negatively associated with the odds of reporting low life satisfaction for respondents under 39 years old (OR = 0.278, 95% CI: 0.052-0.479), but life satisfaction was not associated with SVG in the workplace for respondents under 39 years old. Model 4c and 4e indicate that neither SVG in the residential neighbourhood nor SVG in the workplace was associated with life satisfaction for respondents above 39. As for the interaction effect, Model 4b, 4d and 4f suggests that the effect of SVG in the residential neighbourhood on respondents' life satisfaction was also not moderated by SVG in the workplace.

Results (Table S3) show the heterogeneous effects by income levels. Model 5a indicates that that SVG in the residential neighbourhood was negatively associated with odds of reporting low life satisfaction for respondents with household income less than 4999 RMB per month (OR = 0.597, 95% CI: 0.298-0.965), but life satisfaction was not associated with SVG in the workplace for these respondents. Model 5c indicates that SVG in the residential neighbourhood was also negatively associated with odds of reporting low life satisfaction for respondents with household income between 5000 and 14999 RMB per month (OR = 0.679, 95% CI: 0.220-0.935), but life satisfaction was not associated with SVG in the workplace for these respondents. Model 5e indicates that neither SVG in the residential neighbourhood nor SVG in the workplace was associated with life satisfaction for respondents earning over 15000 RMB per month. As for the interaction effect, Model 5b, 5d and 5f suggests that the effect of SVG in the residential neighbourhood on respondents' life satisfaction was not moderated by SVG in the workplace.

Results (Table S4) shows the heterogeneous effects by educational attainment levels. Model 6a shows that the SVG in the residential neighbourhood was negatively associated with the odds of reporting low life satisfaction for respondents with educational attainment of high school level and below (OR = 0.505, 95% CI: 0.222-0.896), but life satisfaction was not associated with SVG in the workplace for these respondents. Model 6b suggests that the effect of SVG in the residential neighbourhood on life satisfaction was not moderated by SVG in the workplace for respondents with educational attainment of high school level and below. Model 6c indicates that neither SVG in the residential neighbourhood nor SVG in the workplace was associated with life satisfaction for respondents with educational attainment of above high school level. Model 6d suggests that the effect of SVG in the residential neighbourhood on life satisfaction was also not moderated by SVG in the workplace for respondents with educational attainment of above high school level.

5. Discussion

This study was the first to systematically explore the association between street-level visible greenness exposure and life satisfaction in both residential and work locations. We identified the street-level visible greenness exposure by using street view data and a machine learning approach. Our results suggested that residential greenness exposure is positively associated with residents' life satisfaction, after controlling for population density and individual sociodemographic characteristics. This finding confirmed those of previous studies that have only used traditional proximity measures in the US (Kearney, 2006; Kweon et al., 2010) and other developed countries (Fleming et al., 2016; Stigsdotter et al., 2010; Tsurumi and Managi, 2015; Zhang et al., 2017).

The results suggested there is no significant association between greenness exposure in work locations and life satisfaction. Importantly, we did not find the significant interaction effect between greenness exposure in residential and work locations on the respondents' life satisfaction, but the results showed that the association between greenness exposure in residential neighbourhoods and life satisfaction is less significant after considering greenness exposure at work locations. One important implication from this is the importance of simultaneously considering the joint effects of greenness exposure in residential areas and workplaces on life satisfaction. There are several further detailed implications for planning and public policy. First, people who live and work in high-rise office buildings in a city with high density may not perceive the greenery at ground level. Also, the long indoor working hours for Beijing residents may prevent people from paying too much attention to outdoor vegetation, which may explain the insignificance of the direct effect of greenness exposure in work locations. Second, existing literature has indicated that the restorative effects of the natural environment depend on actual engagement at different activity sites (Hartig et al., 1991). The joint effect highlights the importance of considering the workplace for greenness exposure. The decrease in the effect of greenness exposure in the residential neighbourhood after considering greenness exposure at work locations indicates that greenness exposure in one place may share health benefits in other places and the effect of greenness from place to place should be considered as a whole. People may have interactive chances to engage with greenness in both residential areas and workplaces during their daily work-life schedules, so greenness in both residential and work areas should be considered as a whole in the planning process. Third, our results provide suggestive evidence to support Dravigne et al.'s (2008) argument that greenness exposure through window views in workplaces matters for life satisfaction through a joint effect. Therefore, planning programs that delineate the exposure to urban greenness are important for enhancing people's lived experiences.

Previous studies indicate that the effect of greenspace on people's wellbeing may vary by sex, age educational attainment and income (Maas et al., 2006; Richardson and Mitchell, 2010). Our stratified and moderation analysis also suggested that the association between greenness exposure and life satisfaction tends to vary with individual socio-demographic characteristics. Consistent with previous studies (Astell-Burt et al., 2014; Richardson and Mitchell, 2010), we found that males can benefit more from street-level visible greenness exposure than females. One possible explanation for this is that males spend more time on outdoor physical activity than females in China (Muntner et al., 2005), so they are more likely to be exposed to and influenced by greenness when conducting outdoor physical activity. Greenness exposure was positively associated with young adults' life satisfaction, but such association is not significant for older adults. This is consistent with the western evidence and suggests that young adults who may spend more time in outdoor activities are likely to be better engaged with urban greenness and public services (Astell-Burt, 2014). We also identified important ways in which life satisfaction implications of greenness exposure vary with income and educational attainment levels. The "equigenic" effect indicates that people with lower SES benefit more from greenspace, because people with higher SES have more health-related resources, and greenspace is only one of them, but those with lower SES may rely more on greenspace which is provided by the government as public facilities (Pearce et al., 2016). Thus, an important implication from these findings is that it is necessary for urban greenspace planning policy to focus more on socio-demographically disadvantaged groups.

Our study has several limitations due to data constraints. First, our cross-sectional data setting makes it difficult to infer causation between street-level visible greenness exposure and life satisfaction. It is also not possible to assess the dynamic seasonal effects of changes in urban greenness on subjective wellbeing. Second, respondents' work and residential places are geographically coded by using self-reported locations, which may not be precisely accurate in comparison to locations tracked using the Global Positioning System (GPS). Hence, without GPS, we do not know respondents' duration of greenspace exposure, which prevents us from identifying more reliable relationship between street-level visible greenness exposure and life satisfaction. Third, although we have used different buffer sizes for robustness tests, the Modifiable Areal Unit Problem (MAUP) may still exist and cause potential bias (Fotheringham and Wong, 1991). Fourth, we did not have respondents' home addresses due to privacy protection rules, so we can only assess greenspace exposure at neighbourhood level. Fifth, sampling points in this study were 100 metres apart, but this resolution for sampling points may not be high enough, since greenspace in Beijing can be highly localized. Sixth, street visible greenness is still important for people living or working in high-rise buildings, because they can view street greenness from buildings and when they take outdoor activity they will also be influenced by street greenness. However, our approach cannot accurately reflect visible greenspace exposure from high-rise residential flats or high-rise workplaces which may cause bias to our results. Seventh, the seasonal fluctuation of street view images may cause potential bias of the calculation of SVG. Last, some important built environment covariates related to density, diversity and design are not included in this study.

6. Conclusion

This study explores the association between life satisfaction and street-level visible greenness exposure at residential and work locations among people living in Beijing, China using SVG as the surrogate of street-level visible greenness exposure. Results from statistical analyses show that street-level visible greenness exposure in residential locations is positively associated with life satisfaction, though such effects are less significant after considering greenness exposure at work locations. The stratified and moderation analysis provides the insight that the associations between street-level visible greenness exposure and life satisfaction vary with individual demographic and socioeconomic characteristics such as sex, age educational attainment and income. To achieve the goal of promoting life satisfaction through urban planning in China, policymakers should pay attention to urban greenness in residential and work environments simultaneously.

Author statement

Wenjie Wu: Conceptualization, Writing - Review & Editing. Yao Yao: Visualization. Yimeng Song: Methodology. Dongsheng He: Visualization. Ruoyu Wang: Conceptualization, Methodology, Software, Writing Original draft preparation, Writing - Review & Editing.

Declaration of Competing Interests

The authors declare that there are no conflicts of interest.

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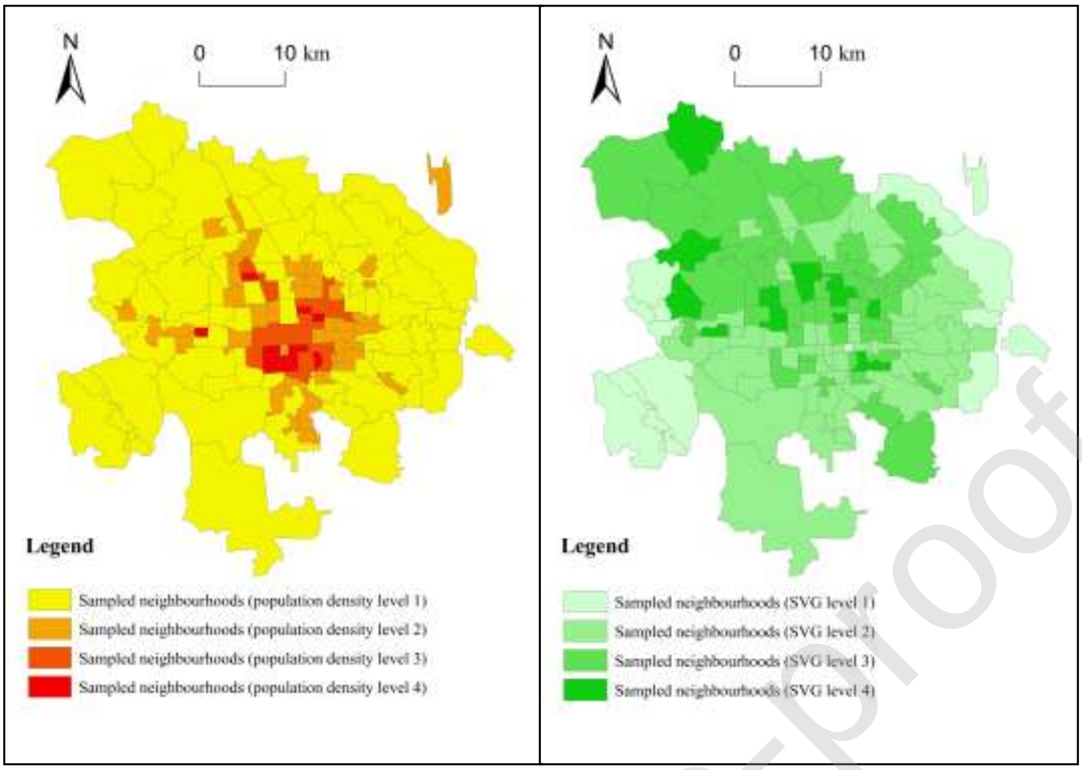

(a) (b)

Fig. 1 Research area and the distribution of the SVG value (a) and population density (b) for sampled neighbourhoods in Beijing, China (value was classified based on natural break rule)

Table 1 Descriptive statistics.

Variables	Proportion (numbers)/mean (SD)
Dependent variables	
Life satisfaction (%)	
High	85.668 (3957)
Low	14.332 (662)
Independent variables	
SVG in residential neighbourhood (0-1)	0.130(0.082)
SVG in working place (0-1)	0.125(0.072)
Covariates	
Homeownership (%)	
Homeowner	49.773 (2299)
Non-homeowner	50.227 (2320)
Sector of employer (%)	
State sector	20.351 (940)
Others	79.649 (3679)

Occupational status (%)	
Highly skilled	26.976 (1246)
Others	73.024 (3373)
Income level (%)	
<4999 RMB per month	28.101 (1298)
>5000 and <14999 RMB per month	55.293 (2554)
>15000 RMB per month	16.606 (767)
Sex (%)	
Male	52.630 (2431)
Female	47.370 (2188)
Age (%)	
< 39 years old	76.510 (3534)
> 39 and < 60 years old	23.079 (1066)
> 60 years old	0.411 (19)
Educational attainment level (%)	
High school level and below	33.622 (1553)
Above high school level	66.378 (3066)
Hukou status (%)	
Local hukou	62.741 (2898)
None-local hukou	37.259 (1721)
Marital status (%)	
Married	58.519 (2703)
Others	41.481 (1916)
Population density in residential neighbourhood (persons/km^2)	15274.214(8630.954)
Population density in working place (persons/km^2)	24311.515(15340.609)

SD = standard deviation

Table 2 Baseline model predicting life satisfaction.

	Model 1a OR. (95% CI)	Model 1b OR. (95% CI)	Model 1c OR. (95% CI)	Model 1d OR. (95% CI)	Model 1e OR. (95% CI)
Fixed part					
Independent variables					
SVG in residential neighbourhood		0.473**(0.136-0.639)		0.634**(0.160-0.948)	0.624**(0.093-0.924)
SVG in working place			0.704(0.160-2.094)	0.902(0.198-2.673)	0.906(0.196-2.697)
SVG in residential neighbourhood × SVG in working place					1.080(0.414-2.373)
Covariates					
Age(ref: < 39 years old)					
> 39 and < 60 years old	1.190(0.929-1.524)	1.196(0.934-1.533)	1.206(0.908-1.602)	1.213(0.913-1.611)	1.210(0.910-1.607)
> 60 years old	0.741(0.398-1.379)	0.747(0.401-1.390)	0.749(0.244-2.298)	0.755(0.246-2.312)	0.743(0.242-2.276)
Homeowner (ref: Non-homeowner)	0.612***(0.485-0.772)	0.610***(0.483-0.769)	0.616***(0.471-.805)	0.614***(0.469-0.803)	0.615***(0.470-0.804)
Local hukou (ref: non-local hukou)	0.838(0.666-1.053)	0.841(0.669-1.057)	0.797*(0.614-1.035)	0.799*(0.616-1.037)	0.799*(0.615-1.037)
State sector (ref: Others)	0.982(0.757-1.273)	0.983(0.758-1.274)	0.871(0.649-1.168)	0.870(0.648-1.166)	0.869(0.648-1.166)
Highly skilled (ref: Others)	1.040(0.820-1.320)	1.040(0.820-1.319)	1.214(0.935-1.576)	1.213(0.935-1.575)	1.219(0.938-1.583)
Income level (ref: <4999 RMB per month)					
>5000 and <14999 RMB per month	0.629***(0.510-0.775)	0.630***(0.511-0.776)	0.602***(0.473-0.766)	0.604***(0.475-0.769)	0.607***(0.477-0.772)
>15000 RMB per month	0.360***(0.256-0.506)	0.359***(0.256-0.505)	0.351***(0.239-0.517)	0.352***(0.239-0.518)	0.354***(0.240-0.521)
Male (ref: female)	1.040(0.905-1.309)	1.088(0.905-1.308)	0.962(0.779-1.188)	0.962(0.779-1.188)	0.961(0.778-1.187)
Above high school level (ref: High school level and below)	0.850*(0.687-1.003)	0.856*(0.691-1.009)	0.778**(0.610-0.993)	0.781**(0.613-0.993)	0.783**(0.614-0.999)
Married (ref.= Others)	1.133(0.912-1.407)	1.137(0.915-1.412)	1.123(0.880-1.434)	1.126(0.882-1.434)	1.122(0.879-1.432)
Population density in residential neighbourhood	1.001(0.999-1.001)	1.001(0.999-1.001)	1.004(0.999-1.014)	1.004(0.999-1.014)	1.004(0.999-1.015)
Population density in working place			1.001(.999-1.008)	1.001(0.999-1.008)	1.002(0.999-1.009)
Constant	0.384***(0.252-0.587)	0.418***(0.268-0.652)	0.383***(0.198-0.739)	0.404***(0.198-0.739)	0.382***(0.196-0.746)

Random part					
Var(Neighbourhoods)	1.307**	1.297**	1.168**	1.157**	1.167**
Number of individuals	4,619	4,619	3,687	3,687	3,687
Number of neighbourhoods	2370	2370	2,034	2,034	2,034
Log likelihood	-2038.572	-2032.873	-1526.927	-1522.331	-1525.550
AIC	4107.146	4102.746	3087.854	3083.663	3085.100

OR = odds ratio; CI = confidence interval; AIC = Akaike information criterion. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 3 Robustness tests

	Model 2a OR. (95% CI) Buffer size=800m	Model 2b OR. (95% CI) Buffer size=800m	Model 2c OR. (95% CI) Independent variables=NDVI	Model 2d OR. (95% CI) Independent variables=NDVI	Model 2e OR. (95% CI) Excluding respondents>60 years old	Model 2f OR. (95% CI) Excluding respondents>60 years old
SVG in residential neighbourhood	0.402**(0.225-0.805)	0.415**(0.256-0.823)	0.631**(0.265-0.955)	0.622**(0.293-0.934)	0.628**(0.256-0.919)	0.616**(0.279-0.964)
SVG in working place	0.886(0.234-2.122)	0.827(0.181-2.108)	0.933(0.190-2.156)	0.931(0.189-2.292)	0.937(0.191-2.196)	0.912(0.140-2.433)
SVG in residential neighbourhood × SVG in working place		1.562(0.286-2.253)				1.096(0.279-1.714)
NDVI in residential neighbourhood			0.978**(0.586-0.998)	0.948**(0.578-0.995)		
NDVI in working place			0.729(0.405-2.276)	0.759(0.393-2.279)		
NDVI in residential neighbourhood × NDVI in working place				1.344(0.403-1.758)		
Log likelihood	-1524.595	-1523.875	-1526.254	-1525.477	-1511.417	-1507.066
AIC	3085.190	3085.752	3092.508	3092.954	3056.834	3052.133

Models were fully adjusted.

OR = odds ratio; CI = confidence interval; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01.