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Dynamic greenspace exposure and residents' mental health in Guangzhou, China: From over-head to eye-level perspective, from quantity to quality

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ABSTRACT

Natural environments especially greenspace may play an important role in enhancing people's mental health. However, the existing literature mainly assesses greenspace exposure in people's residential neighbourhood ignoring the dynamic nature of daily movements and residential histories. Also, most research assesses greenspace from an 'over-head' perspective whereas an 'eye-level' perspective may better capture people's experiences of greenspace, including its quality. We examine the importance of capturing people's eye-level greenspace exposure across different places people occupy in their everyday lives. We construct four measures of greenspace capturing overhead (NDVI), eye-level quantity and quality (Street View Greenness (SVG)) and self-reported neighbourhood greenness exposure. First, we assessed greenspace exposure in residential neighbourhoods, workplaces, recreational places, mobility path and previous residential neighbourhood. The four greenspace indicators were not associated with each other, suggesting they capture different aspects of greenspace. Second, we examine the associations between dynamic greenspace exposure and residents' mental health using survey data collected from 26 neighbourhoods of Guangzhou, China. The results show that all measures in residential places are associated with mental health. However, only SVG-quality in recreational places is positively associated with mental health, while both SVG-quantity and SVG-quality in participant's mobility path are associated with mental health. Our findings demonstrate eye-level greenspace quality is more important in relation to mental health. Policymakers and planners should focus not only on residential neighbourhoods, but also consider the wider environments that people encounter in their everyday lives.

Keywords

Eye-level greenspace; Greenspace quality; Mental health; Activity places; Mobility path

1. Introduction

In many countries, including China, rapid urbanization and growing urban footprints, have often led to a rapid shrinkage of accessible greenspace (Li et al., 2017) with implications for urban residents' opportunities for interaction with the natural environment. Exposure to natural environments especially greenspace is important for residents, since evidence shows that they are important for urban residents' physical and mental health (Gascon et al., 2015; Groenewegen et al., 2012; Hartig et al., 2014; Markevych et al., 2017; Rosenberg, 2017). There are three potential main mechanisms through which greenspace influences people's mental health, including restoring capacities (restoration), building capacities (instoration) and reducing exposure to environmental stressors (Gascon et al., 2015; Hartig et al., 2014; Markevych et al., 2017). First, the restorative effects of greenspace can be explained by both stress reduction theory (SRT) and attention restoration theory (ART) which suggest that greenspace can mitigate mental stress (Kaplan, 1995; Ulrich et al., 1991). Second, instoration effect of greenspace indicates that greenspace can encourage residents to be more physically active and enhance the social cohesion within their neighbourhoods which are both beneficial for mental health (Liu et al., 2019; Liu et al., 2020; Ye et al., 2019; Wang et al., 2019). Last, greenspace can also reduce the negative effects of environmental hazards such as noise and air pollution on mental health (Dzhambov et al., 2018a; Dzhambov et al., 2018b). However, whilst some empirical work finds greenspace to be beneficial for mental health (Astellburt et al., 2012; Helbich et al., 2019; Liu et al., 2019; Sarkar et al., 2018; Triguero-Mas et al., 2015; Triguero-Mas et al., 2017; Wang et al., 2019), others have not found such an association (Alcock et al., 2015; Boers et al., 2018). In recent years, some scholars contend that the inconsistency of previous studies may be mainly due to two methodological reasons (Markevych et al., 2017): (a) techniques adopted to measure green space; and (b) capturing the full array of places where people are exposed to greenspace.

With respect to the techniques adopted to measure green space, in recent years, scholars are increasingly arguing that previous studies do not sufficiently integrate a human-centric approaches to greenspace measurement, including their eye-level experiences in, and perceptions of, such spaces (Guthman and Mansfield, 2013; Rosenberg, 2017; Senanayake and King, 2019). Two aspects of greenspace exposure assessment are particularly relevant here including measuring greenspace from an over-head perspective to an eye-level perspective and also capturing the quality of greenspaces, rather than relying on simplistic measures of the quantity of greenspace in a particular area. With regards to the first domain, natural environments exposure including greenspace, are normally measured using GIS (Geographic Information System) approaches (Groenewegen et al., 2012; Markevych et al., 2017), which may overlook people's actual ground-level environment exposure (Helbich et al., 2019; Ye et al., 2018). The over-head measures do not include for example detailed information about street plants, particularly smaller elements such as shrubs or lawns which are relevant to people's perception and experience of the environment. Helbich et al. (2019) demonstrate, this omission is important from a population health perspective. They found a positive association between greenspace assessed by street view images (i.e eye-level measures) and mental health, but no association between greenspace assessed by NDVI (Normalized Difference Vegetation Index) (i.e., an overhead measure) and mental health. Also, previous nature-exposure experiments indicate that a short-term eye-level greenspace interaction can help them mitigate psychological stress, restore energy, and thus may have beneficial effects on mental health (Bodin and Hartig, 2003; Browning et al., 2020; Hartig et al., 1991; Hartig et al., 2003; Jiang et al 2020). However, eye-level greenspace has received far less attention than overhead-view greenspace due to some key methodological limitations (Helbich et al., 2019; Markevych et al., 2017). Traditional ways for assessing people's eye-level natural environments exposure are either based on respondents' questionnaire (Takano et al., 2002) or field audit (de Vries et al., 2013; Van Dillen et al., 2012). Approaches using questionnaires usually asks respondents about their views of greenspaces

(Takano et al., 2002) while field audit method usually depends on experienced investigators who visit the neighbourhood and rate based on certain scale (de Vries et al., 2013; Van Dillen et al., 2012). Both methods have limitations including being subject to individual's biases, labour-intensive and time-consuming. Recently, with the development of geospatial big data and machine learning approaches, scholars have introduced a new approach assessing eye-level greenspace exposure based on street view images (Li et al. 2015). This shift from over-head perspective to human-centric perspective offers opportunities for enhanced assessments of exposure and therefore more robust studies of health-environment relations. As for the second domain, previous studies mainly focus on the effects of greenspace quantity (Groenewegen et al., 2012; Hartig et al., 2014; Rosenberg, 2017). However, some scholars have argued that research on neighbourhood greenspace and mental health should focus more on quality than quantity (Mitchell and Popham, 2007; Van Dillen et al., 2012). Greenspace quality provides an assessment of people's attitudes towards their surroundings, which may have different effects on people's mental health outcomes (Astell-Burt et al., 2014; Francis et al., 2012; Van Dillen et al., 2012). For example, van Dillen et al. (2012) found that residents' mental health is more clearly associated with greenspace quality than it is with quantity. Two main factors might influence the lack of attention on greenspace quality (Brindley et al., 2019). First, there are conceptual issues of greenspace quality, it is hard to find a universal definition (Brindley et al., 2019). Quality of greenspace refers to maintenance and qualities of a space including multi-dimensions of both physical and social components. For example, Van Dillen et al. (2012) measured quality by scoring levels of accessibility, maintenance, variation, naturalness, colourfulness, clear arrangement, shelter, absence of litter, safety and general impression, while Zhang et al. (2017) used six item scale related to facilities, amenities, natural features, incivilities, accessibility and maintenance. Second, the omission of quality may be also due to methodological limitations (Brindley et al., 2019). Similar to eye-level greenspace quantity, greenspace quality is usually assessed through two methods including questionnaires (Feng and Astell-Burt, 2017a, 2017b, 2018) and field audit (de Vries et al., 2013; Van Dillen et al., 2012). Both methods have obvious limits including being labor-intensive, time-consuming and cannot be applied to a large study area. The trend of paying more attention on greenspace quality than greenspace quantity also reflects the importance of human-centric perspective in health-environment studies.

In addition to concerns about whether greenspace measures sufficiently capture the human experience of such spaces, greenspace-health studies have also been critiqued for relying on measures based on people's residential neighbourhoods rather than attempting to capture people's daily activity places (working place and recreational place). This is a concern for epidemiological analyses as approaches relying on residential exposure assessments may misestimate peoples' greenspace exposure (Van Ham and Manley, 2012). The residential neighbourhood is usually defined by administrative units and people's exposure to greenspace is calculated by the total greenspace within this area (Helbich, 2018). This assessment of exposure can reflect people's most salient environmental exposure, since many people spend most of their time in residential area (Helbich, 2018). However, this exposure metric ignores people's daily mobility patterns (Kwan, 2012, 2018). Besides residential neighbourhood, people may spend much of their time in the work place and/or recreation space, so people's exposure to greenspace in these two places should also be considered (Schönfelder and Axhausen, 2003). Last, people's daily mobility paths connecting these activity places may also be considered for environment exposure since their daily commuting from place to place takes up a lot of time (Van Ham and Manley, 2012). People's most mobility-based environment exposure can be captured through their daily mobility paths. However, the information on work place, recreational place and travel routes can be collected using a travel diary or GPS (Global Position System) equipment (Li et al., 2018). The former method is relatively straightforward to implement, but it may cause potential bias since it is self-reported, while the latter method is often more accurate but is also time-consuming, costly and may cause potential ethical concerns.

Also, the association between greenspace exposure and mental health over people's residential history has attracted attention in recent years (Pearce et al., 2018; Pearce et al., 2016; Pearce, 2018). Since people may move from one residential neighbourhood to another over their life course and the nature of residential greenspaces may change significantly over time, analyses of the greenspace exposure based on current neighbourhood greenspace can underestimate the effect of greenspace (Wheeler et al., 2012). People's previous residential neighbourhood environment exposure may influence mental health later in life and previous residential neighbourhood environment exposure can interact with current residential neighbourhood environment exposure and have synergistic effects on mental health (Pearce et al., 2018; Pearce et al., 2016; Pearce, 2018). Therefore considering greenspace exposure in previous residential neighbourhoods is also important. This method can reflect the lag effect of environment exposure, since environment may not have influence on people's health immediately. The effects of the environment on people's health may be cumulative, so previous environment exposure also matters. However, it is usually challenging to obtain detailed information of people's previous environment exposure.

This study examines the association between dynamic greenspace exposure and residents' mental health among Chinese people using survey data collected from 26 neighbourhoods in Guangzhou (Fig 1). The study extends previous research in several aspects. First, it enhances our knowledge of the psychological benefits of greenspace exposure in China by considering both greenspace quantity and quality. Second, it takes into account of both over-head view greenspace exposure and eye-level greenspace exposure. Third, instead of only focusing on residential neighbourhood, this study further explores greenspace exposure through different exposure assessments including activity places, mobility path and previous residential neighbourhood.

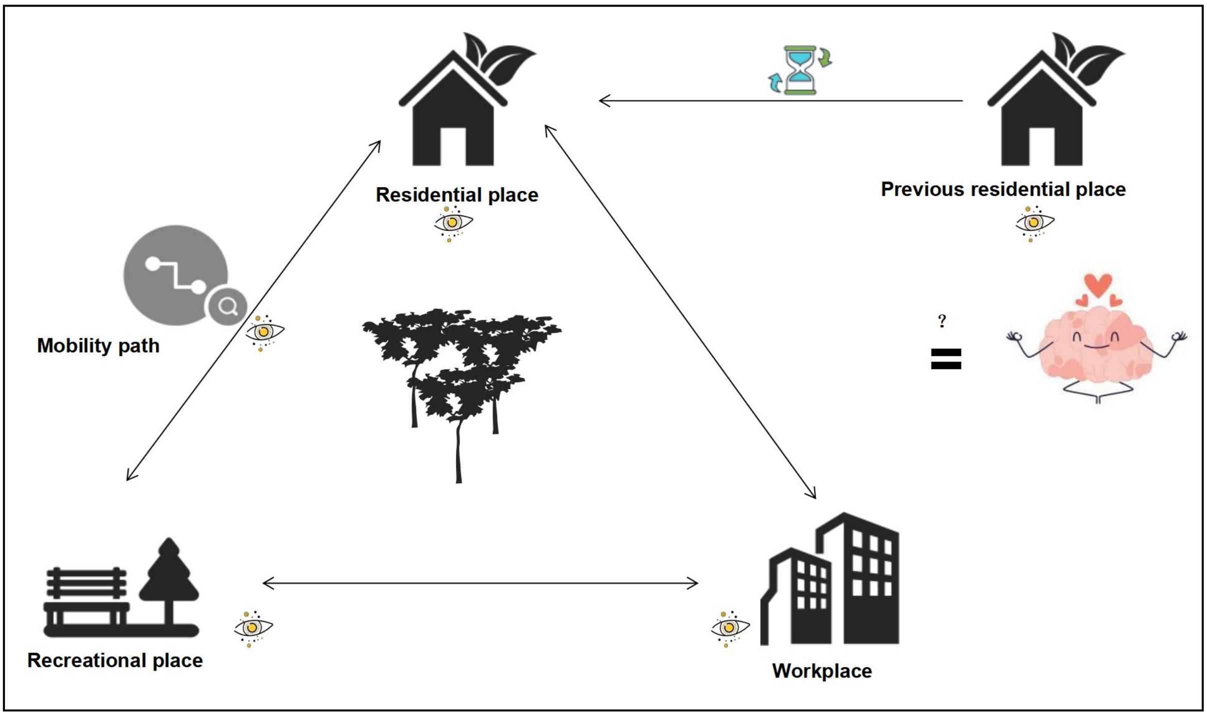

Fig. 1 The conceptual framework

2. Method

2.1. Survey data

A questionnaire survey collected basic information on residents' social communication, daily activities and health was administered in Guangzhou between March and August 2017. The survey aimed to reflect the challenges and ways to improve urban planning and community building among residents. Data were collected by 20 trained investigators. The 26 residential neighbourhoods (she qu) were selected from six inner-city districts of Guangzhou (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe, and Liwan) using a multi-stage stratified probability proportionate to population size (PPS) sampling technique. Investigators then randomly chose sampled households from each neighbourhood using the systematic sampling method. At the last stage, investigators chose one household member from each household using the Kish Grid method (Fig 2). The survey yielded a total of 1003 valid participants. The questionnaire survey was approved by Sun Yat-sen University (SYSU) and all participants gave informed consent. Individual-level data items solicited through the questionnaires includes personal characteristic (demographic and socioeconomic characteristics), residential and employment information, physical activity, self-reported health conditions, social interactions, and activity logs.

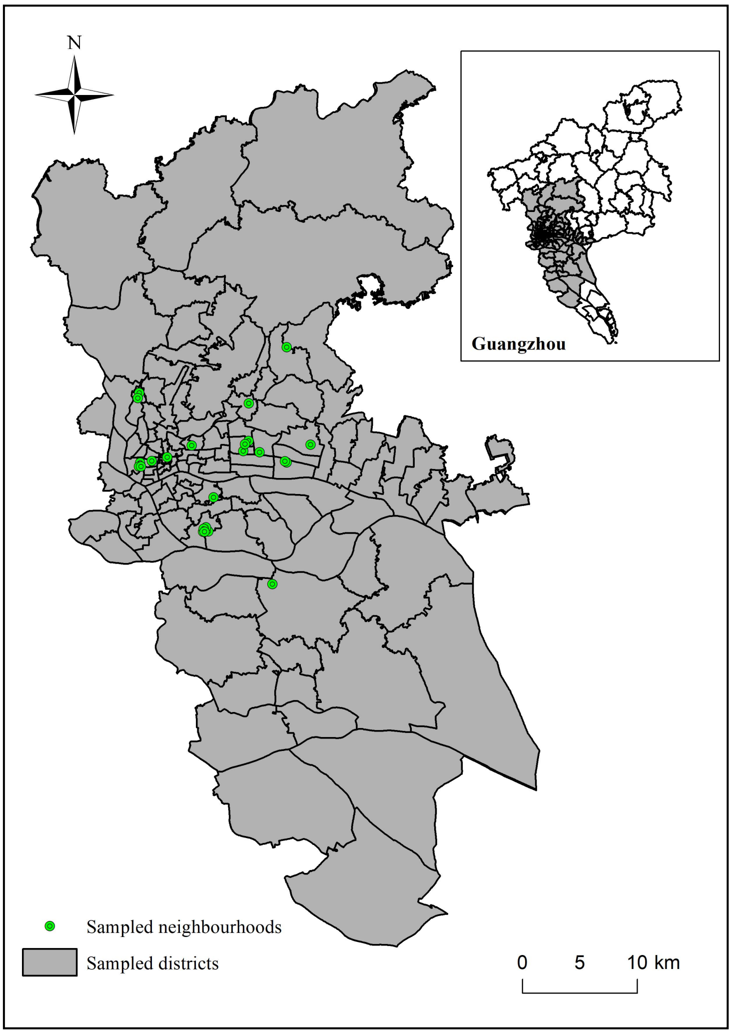

Fig. 2 The location of sampled neighborhoods.

2.2. Dependent Variables: Mental health

Mental wellbeing was measured using the five-item World Health Organization Well-Being Index (WHO-5) (Heun et al., 2001) and is one of the most widely used tools to assess mental wellbeing. The WHO-5 consists of five items, which are related to positive mood, vitality and general interests over the past two weeks (1. I have felt cheerful and in good spirits, 2. I have felt calm and relaxed, 3. I have felt active and vigorous, 4. I woke up feeling fresh and rested, 5. My daily life has been filled with things that interest me). Each item is scored on a six-point Likert scale, ranging from “never” to “every time.” We calculated the sum score of WHO-5, ranging from 0 to 25. The WHO-5 has been shown to have good validity and reliability across many countries (Guðmundsdóttir et al., 2014). Cronbach’s alpha indicated a high internal consistency among the five items (>0.82).

2.3. Independent Variables: Greenspace exposure

NDVI

In order to assess residents' over-head view greenspace exposure, we used the satellite-based NDVI (Tucker, 1979) as a surrogate of greenspace exposure. We used satellite images from Landsat8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) at a 30 m × 30 m spatial resolution to calculate the NDVI exposure. Data were obtained for 2016 from the USGS EarthExplorer (https://earthexplorer.usgs.gov/). We used cloud-free images in the greenest season (August) to avoid distortions, although Guangzhou is subtropical and so remains green year round. NDVI values vary between −1 and 1. A higher value indicates a higher density of healthy vegetation.

Street view greenness quantity

We use street view data to assess eye-level greenspace exposure. The images were extracted from Tencent Map [https://map.qq.com/] which is China's most comprehensive online map. It provides street view images taken from various positions and has been widely used in previous studies (Helbich et al., 2019; Wang et al., 2019). Based on OpenStreetMap (Haklay and Weber, 2008), we constructed street view sampling points along the road network. The sampling points were 100 metre apart. Following previous studies (Helbich et al., 2019; Wang et al., 2019), for each sampling point, we collected four images from four main cardinal directions (i.e., 0, 90,180, and 270 degrees). In total, 285,144 street view images were obtained for the study area.

Following previous studies (Helbich et al., 2019; Wang et al., 2019), to extract greenspace objects (e.g., grasses, trees) we used a fully convolutional neural network for semantic image segmentation (FCN-8s) (Long et al., 2015) based on the ADE20K dataset (Zhou et al., 2019) of annotated images for training purposes. The accuracy of the FCN-8s was with 0.814 for the training data and 0.811 for the test data. A flowchart for FCN-8s in this study can be found in Fig S1. Then, street view greenspace quantity per sampling point was determined as the ratio of the number of greenspace (e.g., trees and grasses) pixels per image summed over the four cardinal directions to the total number of pixels per image summed over the four cardinal directions. For each neighbourhood or exposure place, the street view greenspace quantity was calculated from the average score of all sampling point within the 1000-m buffer.

Street view greenness quality

First, we collected the training dataset from the set used in the SVG quantity assessment. Specifically, 2000 images were randomly selected. Then, the selected images were scored (0-10) based on greenspace quality attributes from previous studies (Van Dillen et al., 2012) including accessibility, maintenance, variation, naturalness, colourfulness, clear arrangement, shelter, absence of litter, safety and general impression (Cronbach's alpha=0.85). Then, a random forest model (Breiman, 2001) for automatic rating was trained by fitting each rating quality scores with the proportion of 151 elements from the image segmentations. Last, we used this automated scoring system to score all images on ten quality attributes.

In this way, we collected scores of ten attributes of greenspace quality for all images. Ten quality attributes for all images achieve high internal consistency (Cronbach's alpha>0.80). Following previous studies (Lu, 2019; Van Dillen et al., 2012), greenspace quality score for each image was calculated by the average score of all 10 attributes. For each neighbourhood or exposure place, the street view greenspace quality was calculated by the average score of all sampling point within the 1000-m buffer. More details of this approach can be found in supplement file..

Perceived greenspace quality

Following previous studies (Feng and Astell-Burt, 2017a, 2017b, 2018), we also evaluated neighbourhood greenspace quality through a self-reported question. Respondents were asked "Do you agree with the following statement about living in this neighbourhood: You feel comfortable in the greenspace or park in this neighbourhood". Responses to the statement were either "5=highly agreed" ,"4=agreed" ,"3=general", "2=disagreed" or "1=highly disagreed".

Covariates

We adjusted for a series of confounding demographic covariates: sex (males vs female), age (in years), education attainment (primary school or below; high school; college and above), marital status (single and not cohabiting, divorced, and widowed vs married vs cohabiting), hukou status (registered permanent residence vs registered temporary residence), average monthly household income, with chronic disease (yes vs no), current smoking (current smoker vs non-smoker) and alcohol consumption statuses (drinker vs non-drinker). At the neighbourhood level, following Frank et al. (2006), we chose three land use-related variables including population density (continuous in person/km^2), street intersection density (continuous in number of intersections/km^2) and land use mix (continuous variable which ranges from 0-1). Previous studies suggest that environmental contextual variables such as air pollution and noise may confound the association between greenspace and mental health (Dzhambov et al., 2018c; Markevych et al., 2017; Yuchi et al., 2020), so we also control for PM2.5 (fine particulate matter with a diameter of 2.5 μm or less) and perceived noise in our analysis. PM2.5 was derived from the 2016 Global Annual PM2.5 data grid, which uses MODIS, MISR and Sea WiFS Aerosol Optical Depth (AOD) data with geographically weighted regression, and available from the NASA Socioeconomic Data and Applications Center (SEDAC) at a 1k m × 1km spatial resolution (Van Donkelaar et al., 2016). Last, we used a self-reported scale to measure respondents' perceived noise pollution. Respondents were asked how the following noise pollution within their local neighbourhood influence their life (range from 'no such a problem=1' to 'very serious=5'): 'The noise of road traffic', 'The noise produced by subways, light rail, trains, etc.', 'The noise from the restaurant and so on', 'The noise of the house decoration' and 'The noise from construction sites, factories, etc'. (Cronbach's alpha>0.80). We averaged scores of the above items, and higher scores mean the higher level of perceived noise pollution.

Table 1. Descriptive statistics for the variables

Variables	Proportion/Mean (Standard Deviation)
Outcome	
WHO-5 (0-25)	15.27(3.60)
Predictors	
Residential neighbourhood (buffer size=1000m) n=1003	
NDVI [median (IQR)]	0.10(0.04)
SVG-quantity [median (IQR)]	0.19(0.08)
SVG-quality	5.64(0.39)
Self-reported greenspace quality	3.12(0.86)
Working place (buffer size=1000m) n=998	
NDVI [median (IQR)]	0.10(0.03)
SVG-quantity [median (IQR)]	0.19(0.08)
SVG-quality	5.42(0.38)
Recreational place (buffer size=1000m) n=809	
NDVI [median (IQR)]	0.09(0.04)
SVG-quantity [median (IQR)]	0.19(0.07)
SVG-quality	5.43(0.34)
Mobility path (buffer size=500m) n=994	
NDVI [median (IQR)]	0.09(0.02)
SVG-quantity [median (IQR)]	0.19(0.05)
SVG-quality	5.40(0.30)
Previous residential neighbourhood in 2012 (buffer size=1000m) n=862	
NDVI [median (IQR)]	0.09(0.03)
Individual covariates	
Gender (%)	
Male	49.95
Female	50.05
Age	36.41(9.68)
Marital status (%)	
Cohabiting	5.38
Married	80.06
Single and , divorced or widowed	14.56
Hukou status (%)	
Local hukou	80.96
Non-local hukou	19.04
Education (%)	
Junior high school or below	6.38
Senior high school	27.52
College or above	66.10
Gross monthly household income (Chinese Yuan)	15637.19(8488.45)

The presence of chronic disease (%)	
Yes	12.86
No	87.14
Current smoking status (%)	
Current smoker	39.38
Non-smoker	60.62
Current drinking status (%)	
Drinker	42.07
Non-drinker	57.93
Perceived noise (1-5)	2.25(0.69)
Built environment covariates	
Population density (person/km^2)	46687.33(30382.95)
Intersection density (number of intersections/km^2)	89.83(66.24)
Land use mix (0-1)	0.13(0.02)
$PM_{2.5}$ (μg/m3)	35.89(0.81)

2.4. Exposure assessments

People's daily activity places

We assessed greenspace exposure in three activity places including residential neighbourhood, working place and recreational place. The location of working place and recreational place (i.e place where they take physical activity) were reported by respondents. We evaluated environment exposure at working place and recreational place based on a 1000-m circular buffer of their geocoded location. For residential neighbourhood, we evaluated environment exposure based on 1000-m circular buffers of their centroids.

Mobility path

In the survey, participants were requested to recall all of their activities for the latest weekdays and weekend. These items include each of the activity locations or stay points (residences, workplaces, restaurants, shopping places, recreational places) and travel characteristics including origin, destination, transportation mode and duration. Based on these detailed activity log data, the path for each participant was delineated using individual trajectory recalled by participants and the trajectory was drawn based on the shortest path between each two reported location. A total of 14,439 items were recorded in their activity logs, so there are approximately 14.4 activities recorded for each participant. A 500-m road buffer was used for assessing greenspace exposure in travel routes.

Previous neighbourhood

We also considered greenspace exposure in respondents' previous housing address in 2012 (24% respondents changed their neighbourhood). We evaluated greenspace exposure at previous housing address based on NDVI with 1000-m circular buffers.

2.5. Multilevel analysis

To assess the linkage between greenness exposure and mental health, we fitted multilevel linear regressions (Raudenbush and Bryk, 2002). Multilevel models were preferable over single-level models due to the hierarchical structure of our data where individuals are nested in neighbourhood. The full multilevel model was specified as follows:

$$\mathrm{WHO}_{ij} = \beta_0 + \beta_1 \ \mathrm{Greenspace\ indicator}_j + \beta_2 \mathrm{Covariates}_{ij} + \beta_3 \mathrm{Covariates}_j + \mu_{ij} + \varphi_j$$

where i represents individuals and j represents neighbourhoods. $\mathrm{Greenspace\ indicator}_j$ represents a vector of neighbourhood-level variables of greenspace indicator (e.g. NDVI and SVG). $\mathrm{Covariates}_{ij}$ represents a vector of individual-level covariates. $\mathrm{Covariates}_j$ represents a vector of neighbourhood-level covariates. μ_{ij} and φ_j represent random errors at the individual level and the neighbourhood level, respectively. Variance inflation factors (VIF<3) suggested no severity of multicollinearity among predictors. ICC (Intra-class correlation coefficient) for the null model (0.39) confirmed the necessity of multilevel models, as living within the same neighbourhood accounted for 39 percent of the total variance in respondents' WHO-5 index.

First, we regressed WHO-5 index on covariates (Model 1). Second, we added residential neighbourhood greenspace indicators into model 1 (Model 2). Third, we added working place greenspace indicators into model 1 (Model 3). Fourth, we added recreational place greenspace indicators into model 1 (Model 4). Fourth, we added mobility path greenspace indicators into model 1 (Model 5). Fifth, we added previous residential neighbourhood greenspace indicators into model 1 (Model 6). For robustness test for the relationships between greenspace mental health based on different exposure assessments, we adjusted all greenspace indicators in a single model (Model 7). We repeated our analyses with different buffer sizes (place-based measures: 800-m and 1500-m; mobility-based measures: 300-m and 800-m). STATA v.15.1 was used for the statistical analysis (STATA, Inc. College Station, TX USA).

3. Results

3.1. Descriptive Statistics

The average WHO-5 scores for all respondents was 15.27 (SD: 3.60). In residential neighbourhoods, the median NDVI score was 0.104 (IQR:=0.041) and median SVG-quantity score was 0.19 (IQR:=0.08), while average SVG-quality and self-reported greenspace quality scores were 5.64 (SD:=0.39) and 3.12 (SD:=0.86), respectively. For the work place measures, the median NDVI score was 0.10 (IQR:=0.03) and median SVG-quantity score was 0.19 (IQR:=0.08), while the average SVG-quality scores was 5.42 (SD:=0.38). For the recreational place measures, the median NDVI score was 0.09 (IQR:=0.04) and median SVG-quantity score was 0.19 (IQR:=0.07), while the average SVG-quality scores was 5.43 (SD:=0.39). For the mobility path measures, the median NDVI score was 0.09 (IQR:=0.02) and median SVG-quantity score was 0.19 (IQR:=0.05), while the average SVG-quality scores was 5.40 (SD:=0.30). Also, the median NDVI score was 0.09 (IQR:=0.03) in respondents' previous residential neighbourhood in 2012.

The characteristics of the study population are summarized in Table 1. About half of participants were male (49.9%) and the average age was 38.4 years. Most respondents were married (80.06%) and were registered as temporary residents (80.96%). Approximately 27.52% of respondents had a high school education and 66.10% possessed a college level education. The average gross monthly household income was 15637.19 Chinese Yuan, while the average score of perceived noise was 2.25. Most respondents did not have chronic diseases (87.14%). About two thirds of respondents were either non-smoker (60.69%) or non-drinker (57.93%). The socio-economic characteristics of the study population is similar to general population based on census data in Guangzhou (Table S1), which indicates samples in this study are sufficiently representative. As for built environment covariates, the average population density, intersection density and land use mix index were respectively 46687.39 person/km^2, 89.83 intersections/km^2 and 0.13. The average concentration of PM2.5 was 35.89 μg/m3.

3.2. Correlation Analysis

The Spearman correlation coefficients were used to assess correlation between different greenspace measures. Using the residential neighbourhood measures, self-reported greenspace quality score was positively associated with SVG-quantity (rSp=0.04) and SVG-quality score (rSp=0.11). For the work place measures SVG-quantity score was positively associated with SVG-quality score(rSp=0.85). For the recreational place measures, NDVI score was negatively associated with NDVI in neighbourhood (rSp=-0.25), SVG-quantity (rSp=-0.10), SVG-quality (rSp=-0.14) and self-reported greenspace quality score (rSp=-0.11) in residential neighbourhood. For the mobility path measures, NDVI score was positively associated with NDVI score in residential neighbourhood (rSp=0.28). SVG-quantity core was also positively associated with SVG-quantity in residential neighbourhood (rSp=0.38). Also, SVG-quality score was positively associated with SVG-quality score (rSp=0.26) and self-reported greenspace quality score (rSp=0.04) in residential neighbourhood. Last NDVI score in previous residential neighbourhood was positively associated with NDVI score in current residential neighbourhood (rSp=0.15).

Table 2. Results of correlation tests: greenspace indicators in different exposure places.

	Residential neighbourhood				Working place			Recreational place			Mobility path			Previous residential neighbourhood
	NDVI	SVG-quantity	SVG-quality	Self-reported greenspace quality	NDVI	SVG-quantity	SVG-quality	NDVI	SVG-quantity	SVG-quality	NDVI	SVG-quantity	SVG-quality	NDVI
Residential neighbourhood NDVI	1													
Residential neighbourhood SVG-quantity	-0.35	1												
Residential neighbourhood SVG-quality	-0.16	0.58*	1											
Residential neighbourhood self-reported greenspace quality	-0.01	0.04**	0.61***	1										
Working place NDVI	0.04	-0.03	0.01	0.00	1									
Working place SVG-quantity	0.07	-0.10	0.08	0.03	0.29*	1								
Working place SVG-quality	0.09	-0.09	0.03	0.03	0.31	0.85**	1							
Recreational place NDVI	-0.25**	-0.10**	-0.14**	-0.11**	-0.07	-0.03	-0.07	1						
Recreational place SVG-quantity	-0.25*	-0.64	-0.28	-0.03	-0.02	0.05	0.06	-0.21	1					
Recreational place SVG-quality	-0.17*	-0.63	-0.18	-0.01	-0.00	-0.06	-0.07	0.08	-0.87	1				
Mobility path NDVI	0.28**	-0.33	-0.32	-0.16	0.19	0.07	0.10	0.31	0.23	0.19	1			
Mobility path SVG-quantity	0.09	0.32**	0.37*	0.06*	-0.01	0.04	0.04	-0.05	0.23	0.18	0.26*	1		
Mobility path SVG-quality	0.10	0.36*	0.29**	0.04**	0.02	0.05	0.10	-0.04	0.24	0.23	0.34*	0.69	1	
Previous residential neighbourhood NDVI	0.15**	-0.11	-0.05	-0.03	0.08	0.04	0.02	-0.06	0.12	0.10	0.06	0.01	0.04	1

Note: *p < 0.10, **p < 0.05, ***p < 0.01.

3.3. Multilevel Analysis

Table 3 illustrates the association between covariates and mental health. Married respondents had lower WHO scores than respondents who were cohabiting (Coef. = -1.43, SE=0.41). Respondents with senior high school education attainment had lower WHO scores than respondents with junior high school or below education attainment (Coef. = -0.85, SE=0.40). As for the built environment, population density was positively associated with WHO scores (Coef. = 4.34, SE=1.43) while intersection density was negatively associated with WHO scores (Coef. = -0.01, SE=0.00).

Table 3. The association between covariates and mental health (baseline model).

	Model 1 Coef. (SE)
Fixed part	
Individual covariates	
Male (referenced group= Female)	0.27(0.25)
Age	0.00(0.00)
Married (referenced group= Cohabiting)	-1.43***(0.41)
Single, divorced or widowed (referenced group= Cohabiting)	-0.49(0.45)
Local hukou (referenced group= Non-local hukou)	0.28(0.23)
Senior high school (referenced group= Junior high school or below)	-0.85**(0.40)
College or above (referenced group= Junior high school or below)	-0.13(0.38)
Gross monthly household income	-1.00*(0.53)
With chronic disease (referenced group= Without chronic disease)	-0.18(0.28)
Current smoker (referenced group= Non-smoker)	-0.43(0.29)
Drinker (referenced group= Non-drinker)	0.13(0.24)
Perceived noise	-0.28*(0.15)
Built environment covariates	
Population density	4.34**(1.73)
Intersection density	-0.01***(0.00)
Land use mix	39.80(29.41)
$PM_{2.5}$	-0.83(0.73)
Constant	27.05(22.29)
Random part	
Var (Neighbourhoods)	4.64**
Var (Individuals)	7.37**
Number of individuals	1003
Number of neighbourhoods	26
Log likelihood	-2460.38
AIC	4958.772

Note: Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *p < 0.10, **p

< 0.05, ***p < 0.01.

Table 4 illustrates the association between greenspace exposure and mental health based on different exposure assessments adjusted for individual and neighbourhood covariates. Model 2 shows greenspace-mental health association using the residential neighbourhood measures. NDVI (Coef. = 1.75, SE=0.83), SVG-quantity (Coef. = 2.60, SE=0.63), SVG-quality (Coef. = 2.54, SE=0.78) and self-reported greenspace quality score (Coef. = 0.41, SE=0.11) were all positively associated with WHO-5 scores. Model 3 shows greenspace-mental health association using working place measures. None of the greenspace indicators were significantly associated with WHO-5 scorese. Model 4 shows greenspace-mental health association using recreational place measures. Only SVG-quality was positively associated with WHO-5 scores (Coef. = 2.51, SE=0.69). Model 5 shows greenspace-mental health association using mobility place measures. Only SVG-quantity (Coef. = 0.59, SE=0.17) and SVG-quality (Coef. = 1.46, SE=0.49) was positively associated with WHO-5 scores. Model 6 shows greenspace-mental health association using the previous residential neighbourhood measures. No evidence can support NDVI in previous residential neighbourhood was related to current WHO-5 scores. In model 7 different greenspace indicators based on different exposure assessments were added simultaneously. Despite some differences in magnitude, the greenspace-WHO-5 scores associations found for different greenspace indicators based on different exposure assessments remained the same. To assess the robustness of our results we repeated our analyses using 800m and 1500m buffers to estimate greenspace exposure (300m and 800m buffers for mobility path). The results were not substantively altered (results available on request).

Table 4. The association between greenspace exposure and mental health in different exposure places.

	Model 2 Coef. (SE)	Model 3 Coef. (SE)	Model 4 Coef. (SE)	Model 5 Coef. (SE)	Model 6 Coef. (SE)	Model 7 Coef. (SE)
Variables						
Residential neighbourhood (buffer size=1000m) n=1003						
NDVI	1.75**(0.83)					0.69**(0.34)
SVG-quantity	2.60***(0.63)					2.23***(0.53)
SVG-quality	2.54***(0.78)					1.98***(0.54)
Self-reported greenspace quality	0.41***(0.11)					0.61***(0.13)
Working place (buffer size=1000m) n=998						
NDVI		0.04(0.08)				0.01(0.08)
SVG-quantity		0.05(0.23)				0.06(0.30)
SVG-quality		0.04(0.45)				0.02(0.51)
Recreational place (buffer size=1000m) n=809						
NDVI			0.02(0.14)			0.08(0.15)
SVG-quantity			0.64*(0.34)			0.33(0.34)
SVG-quality			2.51***(0.69)			1.88***(0.71)
Mobility path (buffer size=500m) n=994						
NDVI				-0.08(0.13)		-0.03(0.14)
SVG-quantity				0.59***(0.17)		0.53**(0.21)
SVG-quality				1.46***(0.49)		2.15***(0.55)
Previous residential neighbourhood in 2012 n=862						
NDVI					0.04(0.09)	0.00(0.10)

Note: Coef. = coefficient; SE = standard error. *p < 0.10, **p < 0.05, ***p < 0.01. Models are adjusted for all covariates.

4. Discussion

The novelty of this study is that this is the first study of the association of green space with mental health to use a greenspace quality assessment based on street view data and machine learning . Second, we included both over-head and eye-level greenspace exposures which bring human-centric perspective into greenspace-health association. Third, we also took into account exposure in different activity spaces including residential neighbourhood, activity places, mobility path and previous residential neighbourhood. This can help us further solve some of the limitation caused by Uncertain Geographic Context Problem (UGCoP) (Kwan, 2012). There are two main findings from this study. First, different measurements of greenspace (over-head vs eye-level perspective; quantity vs quality) may reflect different aspects of greenspace. Second, greenspace exposure assessments (activity places and mobility path) matters for greenspace-mental health association.

Although over-head greenspace has been shown to be important and related to health, eye-level greenspace may better represent people's actually perceived greenness on the ground compared to overhead-view assessments. Our findings provide empirical support to Wang et al. (2019) and Helbich et al. (2019), who both indicated the differences between two approaches when measuring greenspace exposures. Also, greenspace quantity and quality may also reflect different aspects of greenspace. Compared with greenspace quantity, quality is more subjective but reflective of people's actual attitude towards greenspace (Brindley et al., 2019). Our findings are consistent with van Dillen et al. (2012) and Feng et al. (2018) who both highlighted that greenspace quality is more related to people's subjective feelings. However, self-reported greenspace quality score was positively associated with SVG-quantity and SVG-quality in residential neighbourhood. This further indicates that eye-level greenspace is similar to self-reported greenspace and can reflect people's greenspace exposure on the ground. NDVI score in recreational place was negatively associated with greenspace indicators in residential neighbourhood. A possible explanation is that residents who live in neighbourhood with less greenspace are more eager for more greenspace in spare time, so they are more likely to seek for recreational places with more greenspace. Hence, in mobility path, greenspace indicators are positively associated with that in residential neighbourhood. This may be because residents living in greener neighbourhood are more likely to find a greener street at the point of origin (near residential neighbourhood). Also, residents will not choose a route mainly based on its greenness, but are more likely to choose the shortest path, so when begin with a greener street, people are more likely to be exposed to more greenspace in the route (Li et al., 2018; Mennis et al., 2018). Last NDVI score in previous residential neighbourhood was positively associated with NDVI score in current residential neighbourhood. The reason may be that residents have a certain dependence on the previous living environment, so living in greener neighbourhood previously may motivate residents to find a similar neighbourhood when they have to move to another neighbourhood.

Our results also suggest that residential neighbourhood greenspace may exert beneficial effects on psychological well-being in an urban population based on different indicators. This is consistent with cross-sectional studies (Dzhambov et al., 2018a; Dzhambov et al., 2018b; Groenewegen et al., 2012; Triguero-Mas et al., 2015; Triguero-Mas et al., 2017) that found positive association between neighbourhood NDVI and mental health. Similarly, our research confirms the two recent studies in China which showed that neighbourhood SVG-quantity benefits mental health for urban residents (Helbich et al., 2019; Wang et al., 2019). This is consistent with previous nature-exposure experiments which highlight the capacity-restoring effect of greenspace stimulus on mental wellbeing (Bodin and Hartig, 2003; Browning et al., 2020; Hartig et al., 1991; Hartig et al., 2003). Although based on field audit, previous studies also found that greenspace quality was positively related to mental health (de Vries et al., 2013; Van Dillen et al., 2012). Our study is the first using street view data to assess greenspace quality and provide further evidence that greenspace quality in residential neighbourhood is positively associated with mental health. The positive association of self-reported green space quality with mental health showed in our study is also supportive ofrecent studies in Australia (Feng and Astell-Burt, 2017a, 2017b, 2018) and in China (Zhang et al., 2019). All these findings suggest that greenspace in residential neighbourhood plays an important role in influencing people’s mental health and the reason may be that people are more likely to spend most of their time in or around residential neighbourhood than other places, so environment exposure within residential neighbourhood matters for their health-related behaviors and outcomes (Helbich, 2018).

As for activity places measures, our findings suggest that only SVG-quality in recreational place was positively associated with mental health while none of the workplace greenspace indicators was associated with mental health. Although focusing on schoolchildren two recent studies in Barcelona, Spain (Amoly et al., 2014; Dadvand et al., 2015) both found that NDVI around school is positively associated with mental health for children. However, we found no association between greenspace around the workplace and mental health for adults. Previous studies from China indicated that visible indoor greenspace is beneficial for mental heath in the workplace (Jia et al., 2018; Xue et al., 2016), while the visible outdoor greenspace around work places has no significant impact on mental health (Wu et al., 2021). Since most people work in indoor environments (e.g, high-rise buildings) in inner-city districts of Guangzhou (Zhou and Peng, 2020), one possible explanation for our findings relating to workplaces is that adults spend most of their time working indoors in China and thus are not influenced by the outdoor surrounding environment. Hence, previous studies indicated that visiting greenspace for leisure may encourage people to take physical activity which in turn reduces stress (Orsega-Smith et al., 2004; Wilhelm Stanis et al., 2009). One of the previous experiments also found that recreational running in a park provides people with psychologically restoration (Bodin and Hartig, 2003). Our results suggest that only SVG-quality in recreational place was positively associated with mental health and the reason may be that people go to recreational place mainly for taking physical activities and relax themselves, so they may have higher requirement for the surrounding greenspace such as its aesthetic value which is more related to quality than quantity.

As for mobility path measures, this study indicates that only SVG-quality and SVG-quantity were positively associated with mental health. Previous studies pointed out that both NDVI (Mennis et al., 2018) and SVG-quantity (Li et al., 2018) in mobility path were positively related to mental health for adolescents. The consistent finding for SVG-quantity indicates that exposure to green space during travelling is beneficial to mental health and this may be because most daily travelling includes walking behavior, and street greenery can provide shade protection, and offers restorative environment for pedestrians (Markevych et al., 2017). The inconsistent finding for NDVI may be mainly due to the greenery difference for study areas. Previous studies was conducted in Richmond, Virginia where total greenspace coverage is high (neighbourhood average NDVI=0.48), but our study was conducted in inner-city in Guangzhou, where greenspace coverage is low (neighbourhood average NDVI=0.10). With such low coverage of over-head green space, NDVI reflects only large green facilities such as parks (Ye et al., 2018). However, most active transport behaviors (i.e walking and cycling) occur on the street and pedestrians may not choose to go through the park, so NDVI in our study was not associated with mental health. Further, this study provided the first evidence for greenspace quality-mental health association in people’s mobility path. This result again is suggestive of the importance of greenspace quality for benefiting mental health. Our findings for mobility path measures support a previous simulated driving experiment which found that visible greenspace exposure on drivers’ mobility path (e.g., freeway) has positive impact on their mental status (Jiang et al., 2020).

Inconsistent with previous studies (Alcock et al., 2014; James et al., 2016; Pearce et al., 2018), we found no evidence to support greenspace exposure in previous neighbourhood is associated with current mental status. Pearce (2018) points out that early neighbourhood environment may affect people’s health outcomes in later life for two reasons. First, the effect of environmental exposure may accumulate over life and finally affect health. Second, people may be exposed to a certain kind of environment in critical periods during life and this may affect health later in life. Thus, the inconsistent finding in this study may also be explained by these two reasons. First, we only measure greenspace exposure in a single period before (2012) which is too close to the current period, so the long-term cumulative effect of greenspace can not be measured. Second, previous period (2012) may not be a critical period for any of the respondents in this study.

The following limitations of this study should be noted. First, our research was based on the analysis of cross-sectional data, which made it difficult to infer causation between greenspace exposure and mental health. Second, the activity places and mobility path were self-reported and subjective to recall errors. More objective measures such as journeys from GPS can be used in future studies. Third, we were not able to fully address selection bias. For example, people who had some unobserved attributes (e.g. route preference) which may be related to both greenspace exposure and mental health. Fourth, greenspace quality in this study may not include all dimensions, so this indicator may still be influenced by some potential bias. Fifth, the sample size in this study is relatively small and are only collected in a single city, so the results in this study may not be valid in other areas. Sixth, we do not have the information for respondents’ indoor working environment characteristics, which may have influence on our finding in workplace. Last, previous studies indicated that there is a dose-response relationship between greenspace and mental health (Jiang et al., 2014; White et al., 2019). Due to the difference in mobility patterns, people may have different doses of greenspace exposure in various activity places, which may explain the significant variations across the different measurements and assessments of greenspace exposure in this study. However, we do not have the information on participants’ duration and dose of greenspace exposure, which prevents inference of the dose-response relationship between greenspace and mental health in different contexts. In future research, portal devices like GPS and wearable cameras can be used to collect detailed data on dynamic greenspace exposure to analyse the dose-response effect of eye-level greenspace in future (Zhang et al 2021). This method can also help researcher record people's visible experience, details of exposure geography, context and elements, which is important for greenspace-health associations (Barnes et al., 2019).

5. Conclusion

This study is the first to systematically explore dynamic greenspace exposure and residents' mental health among people living in Chinese cities, using NDVI, SVG-quantity, SVG quality and self-reported greenspace quality as the surrogate of greenspace exposure. No evidence can support that different greenspace indicators are associated with each other, which suggests that they may reflect different aspects of greenspace. Respondents' greenspace exposure in residential neighbourhood are negatively associated with greenspace exposure in recreational place, but positively associated with greenspace exposure in mobility path. Results from statistical analyses show that all greenspace indicators in residential neighbourhood, are positively associated with mental health but none of exposures in work place are associated with mental health. Statistical results also show that only SVG-quality in recreational place is positively associated with mental health while only SVG-quantity and SVG-quality in mobility path are associated with mental health. No evidence is found to support that greenspace exposure in previous residential neighbourhood is associated with current mental health. In conclusion, among all spatial context measures for greenspace exposure, residential neighbourhood is still the most important one. To achieve the goal of promoting health and wellbeing through urban planning and design in Chinese urban settings, policymakers and planners are advised to take into account the attributes for greenspace quality such as the accessibility and safety of greenspace instead of developing interventions that seek solely to increase the quantity of available greenspace. Enhancing the various dimensions of greenspace quality in a Chinese urban context will require multi-sectoral action. For instance, transport sector could usefully consider on accessibility to greenspace (e.g.., increasing the provision of bus stops around greenspace), while urban designers may focus on naturalness and colourfulness (i.e., improving the design standard of greenspace). Also, to plan for a healthy city, policymakers and planners should not only focus on residential neighbourhood, but also develop interventions that account for residents' activity places and mobility path. For example, decision makers might consider increasing the investment in the provision of greenspace in populated and dense urban area which are frequented by large numbers of people as part of their daily routines.

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