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Are greenspace quantity and quality associated with mental health through different mechanisms in Guangzhou, China: A comparison study using street view data

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Abstract

Residential greenspace quality may be more important for people's mental health than the quantity of greenspace. Existing literature mainly focuses on greenspace quantity and is limited to exposure metrics based on an over-head perspective (i.e., remote sensing data). Thus, whether greenspace quantity and quality influence mental health through different mechanisms remains unclear. To compare the mechanisms through which greenspace quantity and quality influence mental health, we used both remote sensing and street view data. Questionnaire data from 1003 participants in Guangzhou, China were analysed cross-sectionally. Mental health was assessed through the World Health Organization Well-Being Index (WHO-5). Greenspace quantity was measured by both remote sensing-based Normalized Difference Vegetation Index (NDVI) and Street View Greenness-quantity (SVG-quantity). Greenspace quality was measured by both Street View Greenness-quality (SVG-quality) and questionnaire-based self-reported greenspace quality. Structural equation models were used to assess mechanisms through which neighbourhood greenspace exposure has an influence on mental health. Stress, social cohesion, physical activity and life satisfaction were found to mediate both SVG-quality - WHO-5 scores and self-reported greenspace quality - WHO-5 scores associations. However, only NO_2 (nitrogen dioxide) mediated the association between NDVI and WHO-5 scores, while NO_2, perceived pollution and social cohesion mediated the association between SVG-quantity and WHO-5 scores. The mechanisms through which neighbourhood greenspace exposure influences mental health may vary across different exposure assessment strategies. Greenspace quantity influences mental health through reducing harm from pollution, while greenspace quality influences mental health through restoring and building capacities.

Keywords

Residential greenspace; Quantity and Quality; Mental health; Mechanisms; Street view data

Highlights

- Deep learning and street view images were used to measure greenspace quantity and quality.
- Greenspace quantity influences mental health mainly by reducing pollution harm.
- Greenspace quality influences mental health mainly by restoring capacities and building capacities.

1. Introduction

1.1 Mechanisms linking greenspace to mental health

Environmental epidemiologists and population health scientists have identified three pathways through which greenspace exposure may influence mental health (Dzhambov et al., 2020; Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017). The first pathway implies reducing environmental harms such as air pollution and noise, which are harmful for people's mental health (Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017). Vegetation such as grasses and trees can mitigate the detrimental effect of air pollution by directly reducing pollutants such as fine particulate matters in the air and adsorbing solid particles (Eisenman et al., 2019; Wang et al., 2019b; Klompmaker et al., 2019; Vieira et al., 2018; Yli-Pelkonen et al., 2018). The second pathway is restoring capacities (restoration) which includes reducing mental stress and improving restorative quality (Markevych et al., 2017). Both stress reduction theory (Ulrich et al., 1991) and attention restoration theory highlight the effect of greenspace on reducing mental stress and restoring attention (Kaplan, 1995; Ulrich et al., 1991). The last pathway is associated with building capacities (instoration) such as encouraging physical activity and improving social cohesion within the neighbourhood (Markevych et al., 2017). A large body of literature has noted greenspace can motivate residents to take more outdoor activities such as walking, because they can also benefit from natural scenery when doing exercise, benefiting residents' mental health as result (Cohen-Cline et al., 2015; Dzhambov et al., 2018a; Dzhambov et al., 2018b; Liu et al., 2019; Picavet et al., 2016; Wang et al., 2019a). Also, previous studies noted that social cohesion is a mechanism through which green space's influences on residents' mental health, because greenspace provides residents with more opportunities to meet with each other and enhances social cohesion within the neighbourhood (de Vries et al., 2013; Hunter et al., 2015; Sugiyama et al., 2008).

1.2 The omission of the quality and eye-level perspective of greenspace exposure

The existing literature on the connections between greenspace and mental health is mostly concerned with the effects of greenspace quantity rather than greenspace quality (Knobel et al., 2019; Knobel et al., 2021; Kruize et al., 2020; Mitchell and Popham, 2008; Van Dillen et al., 2012). Although a few studies have highlighted the importance of greenspace quality for mental health in developed countries, scarce attention has been paid to developing countries (Feng and Astell-Burt, 2018; Knobel et al., 2020; Knobel et al., 2021; Mitchell and Popham, 2008; Van Dillen et al., 2012; Zhang et al., 2017). Importantly, the small body of existing work suggests that green space quality may be more important for mental health than greenspace quantity (Feng et al., 2018; Van Dillen et al., 2012). For instance, Feng and Astell-Burt. (2018) found that residential greenspace quality but not quantity was associated with symptoms of psychological distress for women in postpartum. These findings might be explained by greenspace-related behaviours (Knobel et al., 2021). Neighbourhoods with low quality greenspace may be less frequently visited by local residents which undermines the potential mental health benefits of green space exposure (Van Dillen et al., 2012).

Two main and related reasons might explain the general lack of attention to greenspace quality (Brindley et al., 2019). First, there is a lack of consistency in how greenspace quality is defined, with different studies prioritizing alternative dimensions of greenspace quality with different approaches to operationalization (Knobel et al, 2021). Compared to objective items (e.g., absence of litter), subjective items (e.g.., safety) are more challenging to measure, and internal consistency tests are necessary for the rating procedure (Knobel et al, 2021). Second, the omission of quality may be also due to methodological limitations (Brindley et al., 2019). Greenspace quality is usually assessed through either questionnaires (Feng and Astell-Burt, 2017) or field audit (de Vries et al., 2013; Van Dillen et al., 2012) However, both approaches are labor-intensive and time-consuming, leading to calls for new and efficient approaches to assessing greenspace quality such as those based on street view data (Lu, 2018). Street view data can be advantageous because they capture – at scale - important information such as street-level visible vegetation including trees and grasses (Wang et al., 2021). With the help of machine learning approach, street-level visible vegetation can be automatically extracted from street view data, so using street view data to assess greenspace quality is more efficient than traditional methods (Wang et al., 2021).

Also, as shown in several studies, greenspace can be measured from overhead and eye-level perspectives which can have different health effects on residents since overhead-view greenspace does not capture important aspects of these environments including small ground objects such as street trees (Helbich et al., 2019; Wang et al., 2019a). Therefore, the mechanisms through which overhead-view and eye-level greenspace influence mental health may also be different (Wang et al., 2019a). However, eye-level greenspace has received less attention than overhead-view green space mainly due to methodological limitations (Lachowycz and Jones, 2013; Markevych et al., 2017). Light Detection and Ranging (LiDAR) data which provide detailed assessments of vegetation and other land cover characteristics can also be used to assess street-level greenspace exposure (Bork and Su, 2007; Chen et al., 2015; Labib et al., 2021; Van Berkel et al., 2018). For example, Labib et al. (2021) used LiDAR imagery to create a fine spatial resolution greenness index in Manchester, UK. However, fine-scale LiDAR is not always available in developing countries, so in recent years some scholars has begun to use street view data to assess street-level visible greenspace exposure in these places (Helbich et al., 2019; Wang et al., 2019a).

1.3 Research gaps and objectives

In summary, through an assessment of the previous research on how greenspace influences mental health, it is apparent that there are several research gaps. First, studies focusing on greenspace quality - mental health associations remain scarce. Also, the pathways linking greenspace quality to mental health are uncertain. Second, previous studies mainly focus on remote sensing data which measures greenspace exposure from over-head view; less attention is paid to eye-level greenspace exposure. Third, while much scholarly attention has been paid to the beneficial effect of residential greenspace on mental health in developed countries, there is surprisingly little empirical research on the benefits of residential greenspace in other parts of the world, including China. Recent review indicates that the greenspace-health association may vary across different regions (Zhang et al., 2020), so further identifying the effect of greenspace quantity and quality on health in the Chinese context will contribute to existing literature.

With these research needs in mind, this study examines the biopsychosocial pathways linking residential greenspace quantity and quality to mental health among a population from China based on street view data and machine learning approach as well as traditional remote sensing data. It particularly focuses on the extent to which the mechanisms of reducing harm, restoring capacities and building capacities mediate the association between residential greenspace quantity, quality and mental health (Fig 1). The study extends previous research in several respects. First, it enhances our knowledge of the different mechanisms through which greenspace quantity and quality influence mental health. Second, it also explores the different mechanisms through which eye-level greenspace and over-head view greenspace influence mental health.

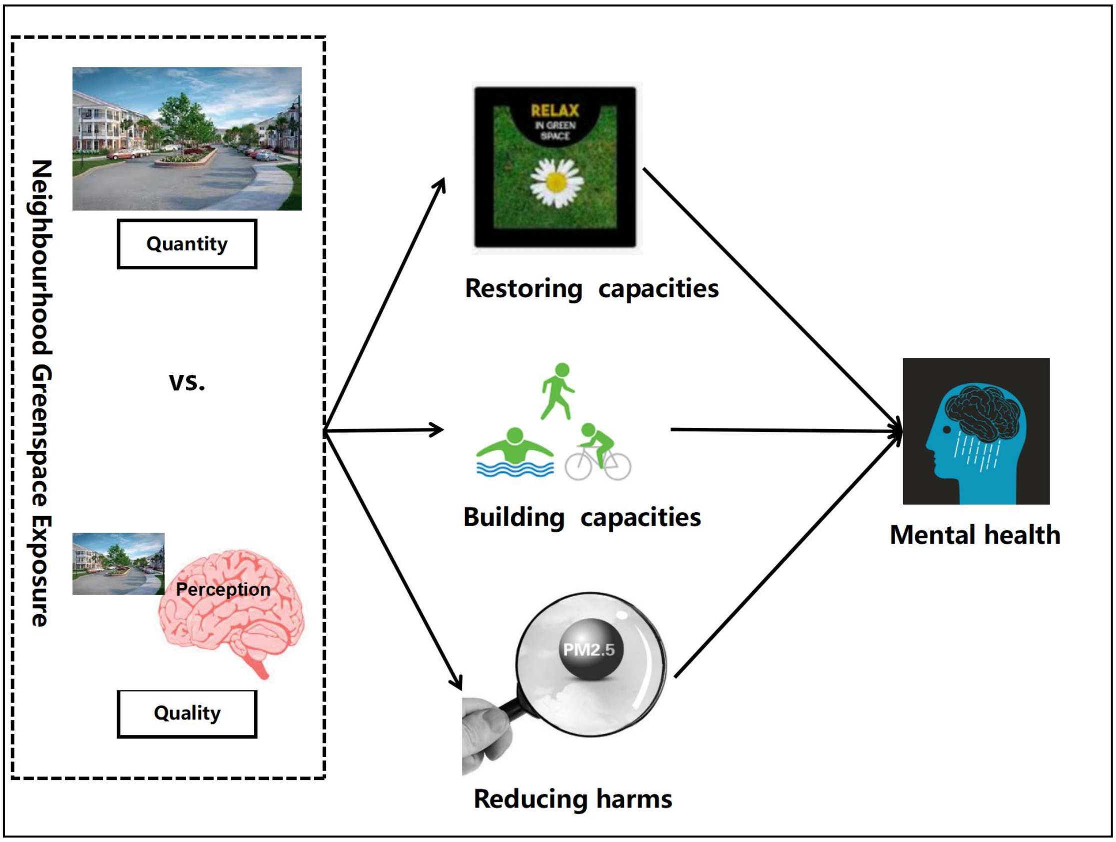

Fig 1. The theoretical framework of this study

2. Materials and methods

2.1 Study population

In order to assess the relationship between greenspace exposure and mental health outcome, we used questionnaire data, and integrated these with street view and remote sensing data. A questionnaire survey was carried out in Guangzhou between March and August 2017. The survey aimed to reflect the challenges and ways to improve urban planning and community building from the perspective of residents. All questionnaires were collected in-person by 20 trained investigators. The investigators selected 26 inner-city residential neighbourhoods (*juzhuxiaoqu*) 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 (Fig S1). Residential neighbourhood (*juzhuxiaoqu*) is the primary residential unit in the Chinese context, which is similar to residential block. Investigators then randomly chose sampled households from each neighbourhood using the systematic sampling method (Black, 2019). This method ensures that the number of households selected from each neighbourhood is consistent. In the final stage, investigators chose one household member from each household using the Kish Grid method (Kish, 1949). To qualify for the survey, respondents had to be aged above 18 and not to be students. The survey yielded a total of 1003 valid participants. Authorization of the study was consented by Sun Yat-Sen University Research ethics committee. All the subjects were informed and consented to the protocol of study. The result of comparison of demographic information between survey data and census data. (Table S3) indicated that our sample is representative for the general population in our research area.

2.2 Exposure assessment

The main objective of this study is to compare the effects of different greenspace indicators (quantity v.s quality; eye-level v.s over-head view) on mental health (Fig 1). Therefore, we chose four indicators in our analysis including Normalized Difference Vegetation Index (NDVI), Street View Greenness-quantity (SVG-quantity), Street View Greenness-quality (SVG-quality) and questionnaire-based self-reported greenspace quality.

Greenspace quantity

Street view data

In order to assess residents' eye-level greenspace exposure, we use street view images. The images were extracted from Tencent Map in 2016 (June to August) [https://map.qq.com/] which is the most comprehensive online map in China. It provides street view images taken from various positions and has been used for previous studies (Helbich et al., 2019; Wang et al., 2019a; Wang et al., 2019b). Based on OpenStreetMap (Haklay and Weber, 2008), we constructed street view sampling point along the road network. The sampling points were 100 metres apart. Following previous studies (Helbich et al., 2019; Wang et al., 2019a), 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.

Following previous studies (Helbich et al., 2019; Wang et al., 2019a), to use street view data for extracting greenspace objects (e.g., street-level 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 (details can be found in supplement file). The accuracy of the FCN-8s was with 0.815 for the training data and 0.810 for the test data reasonably high. Then, street view greenness-quantity (SVG-quantity) per sampling point was determined as the ratio of the number of greenspace 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, the street view greenspace quantity was calculated by the mean score of all sampling points within the 1000-m buffer. Based on existing literature

(Browning and Lee, 2017; Frank et al., 2007; Labib et al., 2020; Nordbø et al., 2018), 1000m buffer is usually used to measure 10-15 min walking distance from residential location, which reflects residents daily activity range. Also, using a single buffer facilitates the analysis, since the inclusion of multiple buffers for a single exposure may lead to multicollinearity.

Remote sensing data

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 was calculated from the following formula: (Red − VIS)/(Red + VIS), where NIR stood for reflectance in the near-infrared band and Red stands for the spectral reflectance measurements acquired in the red (visible). NDVI values vary between −1 and 1. A higher value indicates a higher density of healthy vegetation (i.e., parkland and grassland). NDVI will capture large greenspace objects such as public parks and large gardens while SVG would add street trees, mowed grasses. We omitted pixels with a negative NDVI value before averaging across each study neighbourhood, following previous studies (Markevych et al., 2017). For each neighbourhood, the NDVI was calculated by the mean score of all pixels within the 1000 m buffer. Following previous studies (de Keijzer et al., 2019; Triguero-Mas et al., 2017), median NDVI and SVG-quantity was expressed per interquartile range (IQR) increase in exposure.

Greenspace quality

Street view data

We also used street view data to assess greenspace quality. First 2000 images were randomly chosen for the training and testing dataset. The selected images were scored (0-10) based on ten greenspace quality attributes including accessibility, maintenance, variation, naturalness, colourfulness, clear arrangement, shelter, absence of litter, safety and general impression (Cronbach's alpha=0.85) (Van Dillen et al., 2012). Then, we trained a random forest model (Breiman, 2001) for automatic rating. It was trained by fitting each quality attribute score with the proportion of 151 elements from the image segmentations. Last, after the random forest was trained, we used it to score ten attributes of greenspace quality for all images. In order to assess feasibility of aggregating ten attributes into a single index, we evaluated its internal consistency by calculating the Cronbach's alpha (Cronbach, 1947). Ten quality attributes for all images achieve high internal consistency (Cronbach's alpha>0.80). Following previous studies (Van Dillen et al., 2012), the greenspace quality score for each image was calculated by the mean score of all ten attributes. For each neighbourhood, the street view greenspace quality was calculated by the mean score of all sampling points within the 1000-m buffer. More details of this approach can be found in supplement file.

Questionnaire data

Following Feng and Astell-Burt (2017), we also evaluated neighbourhood green space 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 range from “1=highly disagreed” to “5=highly agreed”.

2.3 Outcome assessment

Mental health was measured by the five-item World Health Organization Well-Being Index (WHO-5) (Heun et al., 2001). The WHO-5 is one of the most widely used tools for assessing mental health. The five items relate to general interests, vitality and positive mood over the past two weeks. Each item is rated based on a six-point Likert scale, ranging from “never” to “every time”. We used the sum score of WHO-5, ranging from 0 to 25. The WHO-5 has been proven to achieve good validity and reliability in the Chinese context (Kong et al., 2016). Cronbach’s alpha indicated a high internal consistency among all the items (>0.80).

2.4 Mediators

2.4.1 Mitigation indicators

$PM_{2.5}$

Previous studies pointed out that greenspace benefit mental health by mitigating exposure to environmental stressors especially air pollution (Markevych et al., 2017). $PM_{2.5}$ (fine particulate matter with a diameter of 2.5 μm or less) and NO_2 (Nitrogen dioxide) are usually treated as mitigation indicators in epidemiology studies (Dzhambov et al., 2018b; Wang et al., 2019b). We used the 2016 Global Annual $PM_{2.5}$ data grid, generated using 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). We calculated the annual average $PM_{2.5}$ concentration using the average pixel value within the 1000 m circular buffer around the centroid of each study neighbourhood in 2016.

NO_2

NO_2 concentrations were extracted from a globally available land use model with a spatial resolution of 100 m (Larkin et al., 2017). We calculated the annual average NO_2 concentration using the average pixel value within the 1000 m circular buffer around the centroid of each study neighbourhood in 2016.

Perceived pollution

Besides objective measurement of air pollution ($PM_{2.5}$ and NO_2), subjective perceived pollution should be considered as a mitigation indicator (Dzhambov et al., 2018b; Wang et al., 2019a).

Following previous studies (Liu et al., 2019; Wang et al., 2019a), we used an eight-item scale to measure respondents' subjective perception of air and noise pollution. Specifically, respondents were asked the extent to which the following air or noise pollution within the neighbourhood influence their life (range from "no such a problem=1" to "very serious=5"): "Air pollution from car exhaust", "Air pollution such as dust from construction sites", "Air pollution from industry", "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 "Noise from construction sites, factories, etc". (Cronbach's alpha>0.80). We used the mean score of the above eight items to measure the level of perceived pollution. Higher scores mean the higher level of perceived pollution.

2.4.2 Restoration indicators

Stress

Stress was assessed by a self-reported question: "How often have you felt stressed over the past year" (range from "never=1" to "always=5"). This variable was treated as a continuous variable, since the path coefficient of a continuous variable is more easily to calculate in mediation analysis (MacKinnon et al., 2007). Also treating it as binary variable in a Gaussian framework may cause bias. Higher scores indicates the more stressful feeling.

Life satisfaction

Life satisfaction was measured by the Satisfaction With Life Scale (SWLS) (Pavot and Diener, 2009). SWLS includes five questions including "In most ways, my life is close to my ideal", "The conditions of my life are excellent", "I am satisfied with my life", "So far I have gotten the important things I want in life" and "If I could live my life over again, I would change almost nothing". Respondents were asked to indicate the extent to which they agree or disagree with each of the above statements. A seven-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (7) was used. We used the mean score of the above five items to measure the level of life satisfaction (Cronbach's alpha>0.85) Higher scores mean the higher level of life satisfaction.

2.4.3 Instoration indicators

Physical activity

Respondents' physical activity was quantified by their weekly physical exercise time in hours base on International Physical Activity Questionnaire (Craig et al., 2004). They reported their last week's vigorous-intensity, moderate-intensity and mild-intensity exercise time respectively. Respondents' physical activity was calculated by their last week's total exercise time.

Social cohesion

Following previous studies (de Vries et al., 2013; Sugiyama et al., 2008), we used a five-item scale to measure respondents' perception of social cohesion. Specifically, respondents were asked the extent to which they agreed with the following statements (range from "strongly disagree=1" to "strongly agree=5"): "I am familiar with my neighbors", "I think my neighbors have similar views and ideas", "I think the neighbors in the neighbourhood trust each other", "When in trouble, I can find my neighbor to help" and "I think the neighborhood is very harmonious". (Cronbach's alpha>0.80). We used the mean score of the above five items to measure the level of neighbourhood social cohesion. Higher scores mean the perception of stronger neighbourhood social cohesion.

2.5 Covariates

Respondents' sociodemographic information were also collected in our questionnaire survey. Following previous studies (Dzhambov et al., 2018a; Dzhambov et al., 2018b; Wang et al., 2019a), we adjusted for a series of confounding sociodemographic covariates: sex (males vs female), age (in years), marital status (single and not cohabiting, divorced, and widowed vs married vs cohabiting), hukou status (registered permanent residence vs registered temporary residence), educational attainment (junior high school or below; senior high school; college and above), gross monthly household income (in Chinese Yuan), the presence of chronic disease (yes vs no). housing satisfaction (range from "very unsatisfied=1" to "very satisfied=5"). At the neighbourhood level following Frank et al. (2006), we adjusted for a series of built environment covariates, including population density (continuous variable in person/km^2), street intersection density (continuous variable in number of intersections/km^2) and land use mix (continuous variable which ranges from 0-1). We calculated the built environment covariates within the 1000 m circular buffer around the centroid of each study neighbourhood. Also, following previous studies (de Keijzer et al., 2019; Dzhambov et al., 2018a; Triguero-Mas et al., 2017), neighbourhood deprivation index (NDI) was included to measure neighbourhood-level socioeconomic status (supplement file).

2.6 Statistical analyses

We used a structural equation models to compare mechanisms through which neighbourhood greenspace exposure quantity and quality have influence on mental health while accounting for clustered study outcomes within neighbourhood (Lee, 1990). Respondents were clustered within each neighbourhood, so the confidence interval (standard error) was adjusted based on the cluster structure of individuals. (Buzas, 1990). The models in this study did not suffer from multicollinearity based on variance inflation factor (< 3) values. Results of correlation tests for greenspace indicators (Table S1) indicated that they are not highly correlated with each other (Pearson correlation $r < 0.6$).

We used parallel mediation mode to model pathways linking greenspace to mental health and to evaluate the mediating effect of presuming no interaction between the greenspace exposures and mediators. We fitted the parallel mediation model (Fig 2) with seven parallel mediators for three major mechanisms (Mitigation, restoration and instoration effects). Also, we used different measures of greenspace exposure as described above. Then, we calculated the direct and indirect effects in the parallel mediation models based on the approach proposed by Preacher and Hayes (2008). We obtain 95% CIs of for each paths using cluster confidence interval (Buzas, 1990). Goodness of fit was assessed by standardized root mean square residual (SRMSR), root mean square error of approximation (RMSEA), and comparative fit index (CFI). We calculated these based on the method proposed by Hu and Bentler (1999). For sensitivity tests, we repeated our analyses using 600m and 800m neighbourhood buffers instead of 1000m buffers for residential greenspace exposure and the substantive results were unaltered (Table S4 and S5). Second, we controlled for greenspace exposure in respondents' workplace accordingly and results remained to be stable (Table S6).

For all analyses, we defined statistical significance as $P < 0.05$ for a 2-tailed test. STATA v.15.1 was used for the statistical analysis (STATA, Inc. College Station, TX USA).

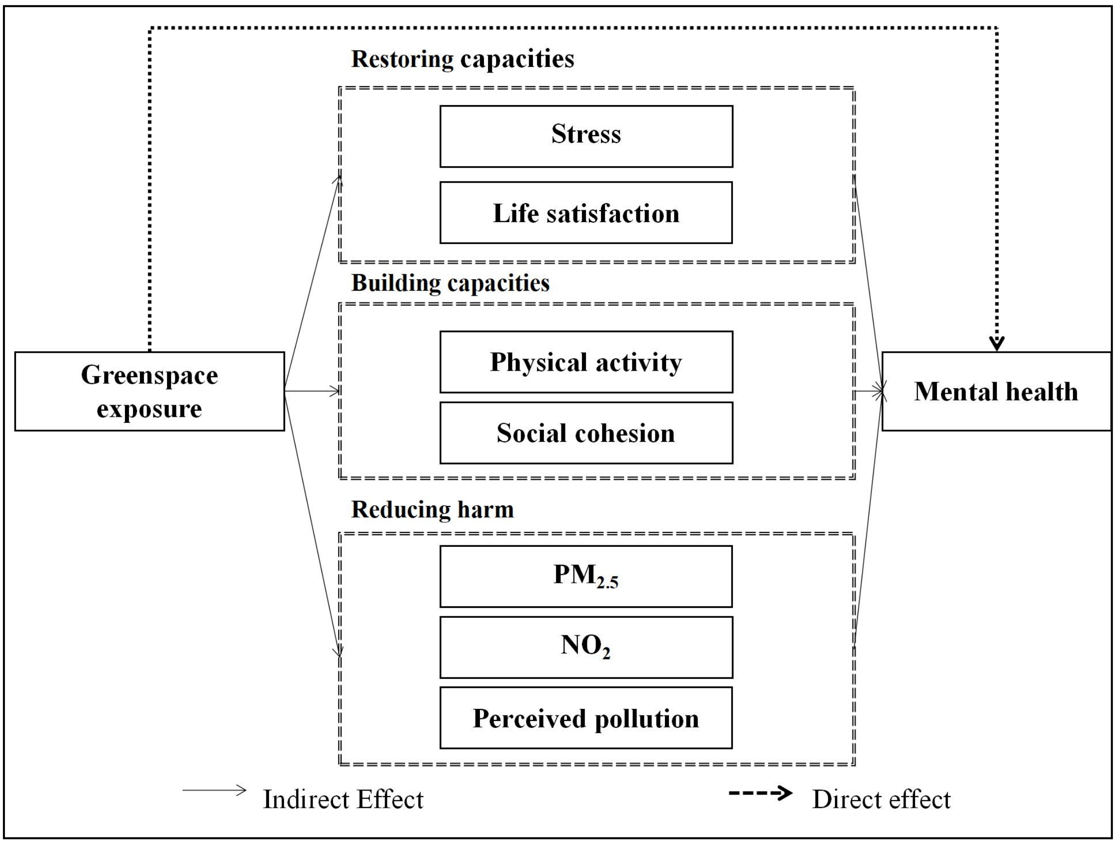

Fig 2. The parallel mediation models of this study

3. Results

3.1 Characteristics of the study population

Table 1 summarizes the characteristics of the study population. The average WHO-5 score of the total respondents was 15.27, with a SD of 3.60. The median score of NDVI and SVG-quantity were 0.10 (IQR=0.04) and 0.19 (IQR=0.08) while the average score of SVG-quality and self-reported greenspace quality were 5.64(SD=0.39) and 3.12(SD=0.86). The mean age was 38.36 years and 50.05% were male. Most of the respondents were local residents (80.96%) and married (80.06%). About 6.38% of the respondents attended junior high school, 27.52% had a senior high school degree, and 66.10 % had a college degree or a higher qualification. Only 12.86% had chronic disease. The average gross monthly household income was 15637.19 Chinese Yuan, while the average housing satisfaction score was 4.02. As for built environment characteristics, the average population density of the sampled neighbourhood was 46687.33 persons per km^2, the intersection density was 282.20 intersections per km2, and the average land use mix score was 0.13. The average distance to the nearest park was 0.664 km and the average NDI was 0.21.

Table 1. Summary statistics for all variables.

Variables	Proportion/Mean (Standard Deviation)
Outcome	
WHO-5 (0-25)	15.27(3.60)
Predictors	
Residential neighbourhood (buffer size=1000m)	
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)
Mediators	
Perceived level of stress (1-5)	2.54(1.02)
Neighbourhood social cohesion (1-5)	3.43(0.57)
Time spent on physical activity (min/week)	131.32(111.19)
Life satisfaction (1-7)	4.57(1.04)
The concentration of $PM_{2.5}$ ($\mu g/m^3$)	35.89(0.81)
The concentration of NO_2 ($\mu g/m^3$)	27.69(5.22)
Perceived level of air/noise pollution (1-5)	2.22(0.69)
Individual covariates	
Gender (%)	
Male	49.95

Female	50.05
Age	36.41(9.68)
Marital status (%)	
Cohabiting	5.38
Married	80.06
Single and not cohabiting, 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)	15637.18(8488.45)
The presence of chronic disease (%)	
Yes	12.86
No	87.14
Housing satisfaction (1-5)	4.02(0.60)
Built environment covariates	
Population density (person/km^2)	46687.32(30382.95)
Intersection density (number of intersections/km^2)	89.83(66.24)
Land use mix (0-1)	0.13(0.02)
Distance to the nearest park (km)	0.66(0.44)
Social environment covariate	
NDI	0.21(0.17)

3.2 Structural Equation Models

We obtained reasonably well-fitting final parallel mediation models across all greenspace indicators (Fig 2-4): SRMSR < 0.035, RMSEA < 0.035, CFI > 0.900. Fig. 3 reports path coefficients and 95% confidence intervals (CI) for the parallel mediation model in the SEM for NDVI. NDVI was negatively associated with $PM_{2.5}$, and NO_2. However, no evidence supported that NDVI was also associated with stress, social cohesion, physical activity, life satisfaction or perceived pollution. Table 2 indicates that a 1-IQR greater NDVI was significantly and indirectly associated with a 0.082-unit higher WHO-5 scores through NO_2 concentration. There was no evidence to suggest that NDVI could directly influence WHO-5 scores.

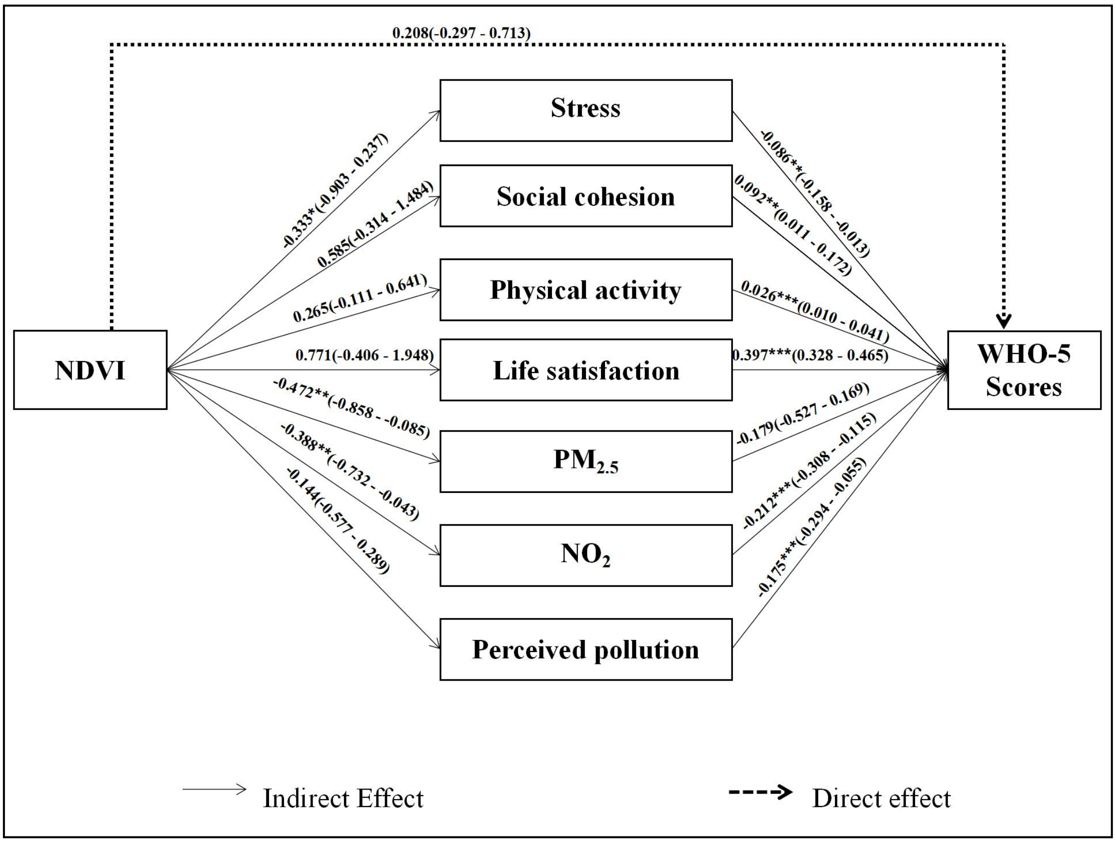

Fig 3. Standardized coefficients of the structural equation model for the association between NDVI, mediators and WHO-5 scores. Coefficients (cluster 95% CI) of the SEM. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Models are fully adjusted for covariates.

Fig. 4 shows that SVG-quantity was positively and directly associated with WHO-5 scores. Also, SVG-quantity was negatively associated with NO_2 concentration and perceived pollution, which were both negatively associated with WHO-5 scores. SVG-quantity was positively associated with social cohesion which was positively associated with WHO-5 scores. However, there was no evidence to suggest that SVG-quantity was also associated with stress, physical activity or life satisfaction. Table 2 indicates that a 1-IQR greater SVG-quantity was significantly and indirectly associated with a 0.032-unit higher WHO-5 scores through social cohesion, a 0.050-unit higher WHO-5 scores through NO_2 concentration and a 0.011-unit higher WHO-5 scores through perceived pollution. Also, a 1-IQR greater SVG-quantity was significantly and directly associated with a 0.072-unit higher WHO-5 scores.

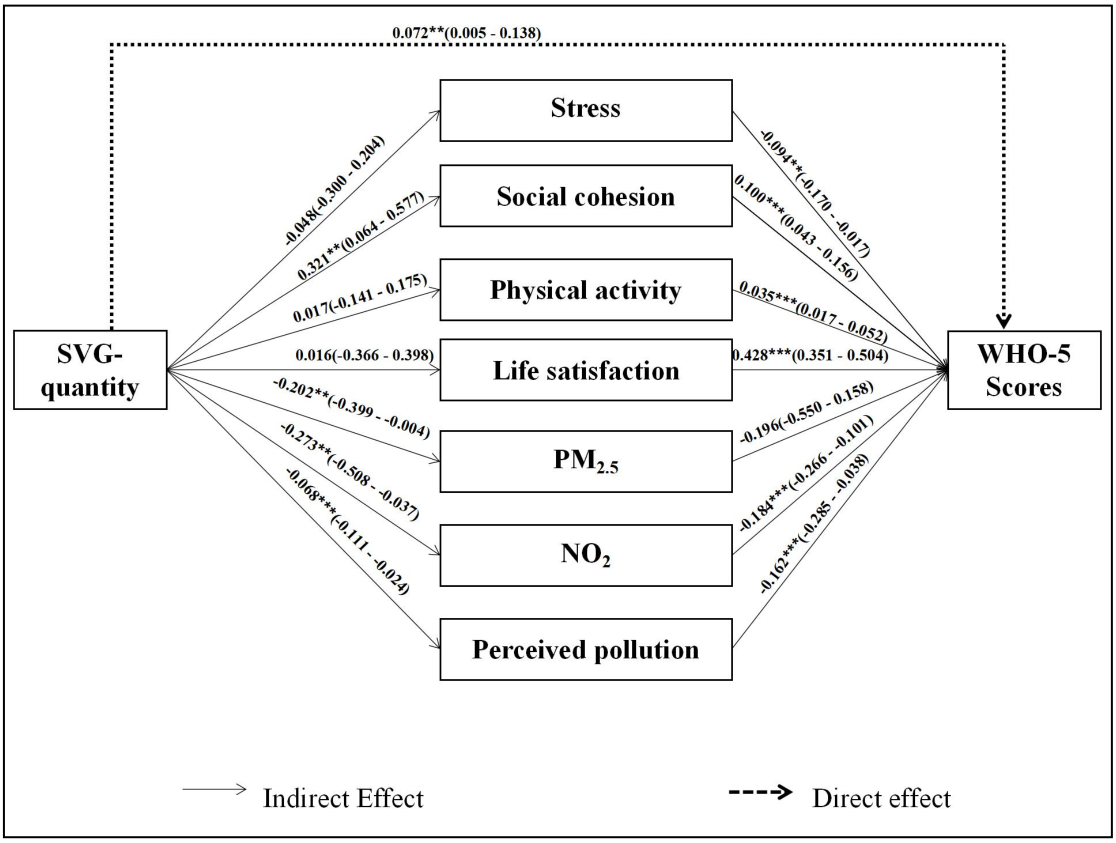

Fig 4. Standardized coefficients of the multilevel structural equation model for the association between SVG-quantity, mediators and WHO-5 scores. Coefficients (cluster 95% CI) of the SEM. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Models are fully adjusted for covariates.

Fig. 5 shows that SVG-quality did seem to be related to WHO-5 scores, but only through indirect pathways of social cohesion, physical activity and life satisfaction which were all positively associated with WHO-5 scores. Hence, SVG-quality was negatively associated with stress which was also negatively associated with WHO-5 scores. However, no evidence can support that SVG-quality was also associated with $PM_{2.5}$, NO_2 or perceived pollution. Table 2 indicates that a 1-unit greater SVG-quality was significantly and indirectly associated with a 0.034-unit higher WHO-5 scores through stress, a 0.002-unit higher WHO-5 scores through social cohesion, a 0.004-unit higher WHO-5 scores through physical activity and a 0.162-unit higher WHO-5 scores through life satisfaction.

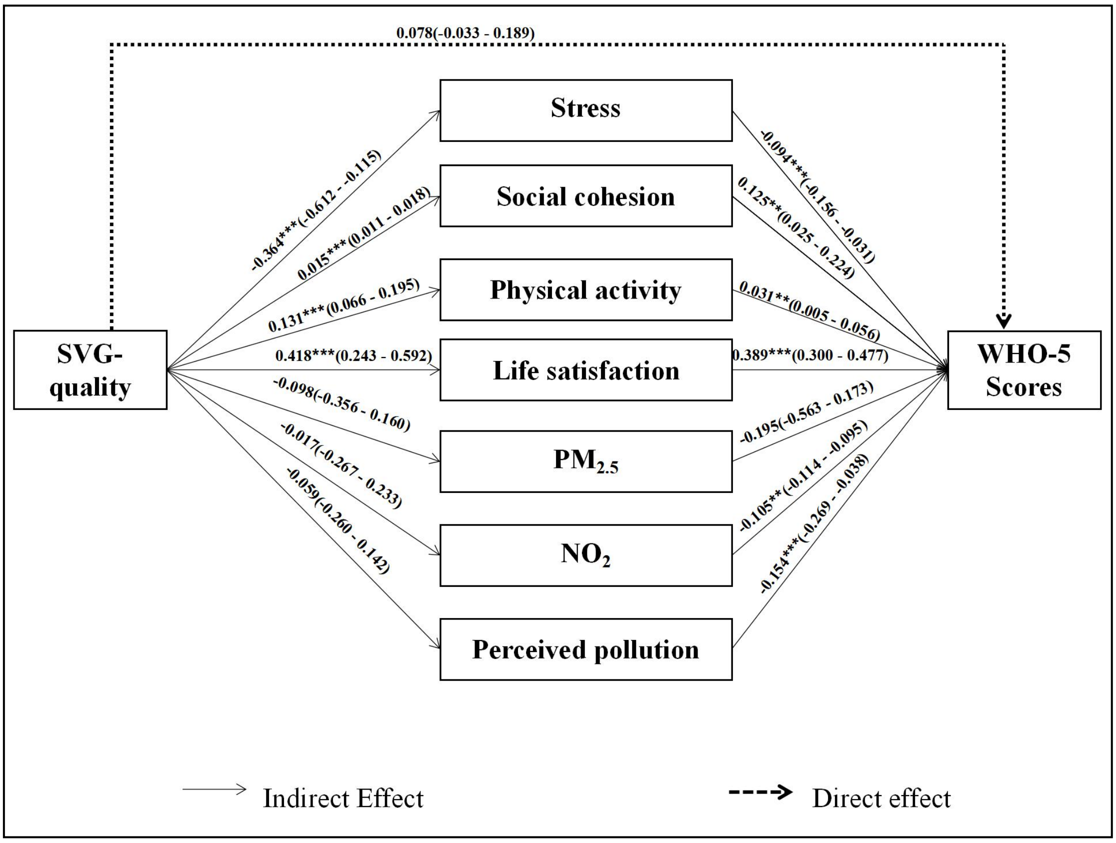

Fig 5. Standardized coefficients of the multilevel structural equation model for the association between SVG-quality, mediators and WHO-5 scores. Coefficients (cluster 95% CI) of the SEM. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Models are fully adjusted for covariates.

Fig. 6 shows that self-perceived greenspace quality seem to be related to WHO-5 scores through both direct pathway and indirect pathways of social cohesion, physical activity and life satisfaction, which all were positively associated with WHO-5 scores. Also, self-perceived greenspace quality was associated with WHO-5 scores through indirect pathways of stress which was negatively associated with WHO-5 scores. However, there was no evidence to suggest that self-perceived greenspace was also associated with $PM_{2.5}$, NO_2 or perceived pollution. Table 2 indicates that a 1-unit greater self-perceived greenspace quality was significantly and indirectly associated with a 0.009-unit higher WHO-5 scores through stress, a 0.018-unit higher WHO-5 scores through social cohesion, and a 0.064-unit higher WHO-5 scores through life satisfaction. Also, a 1-unit greater self-perceived greenspace quality was significantly and directly associated with a 0.091-unit higher WHO-5 scores.

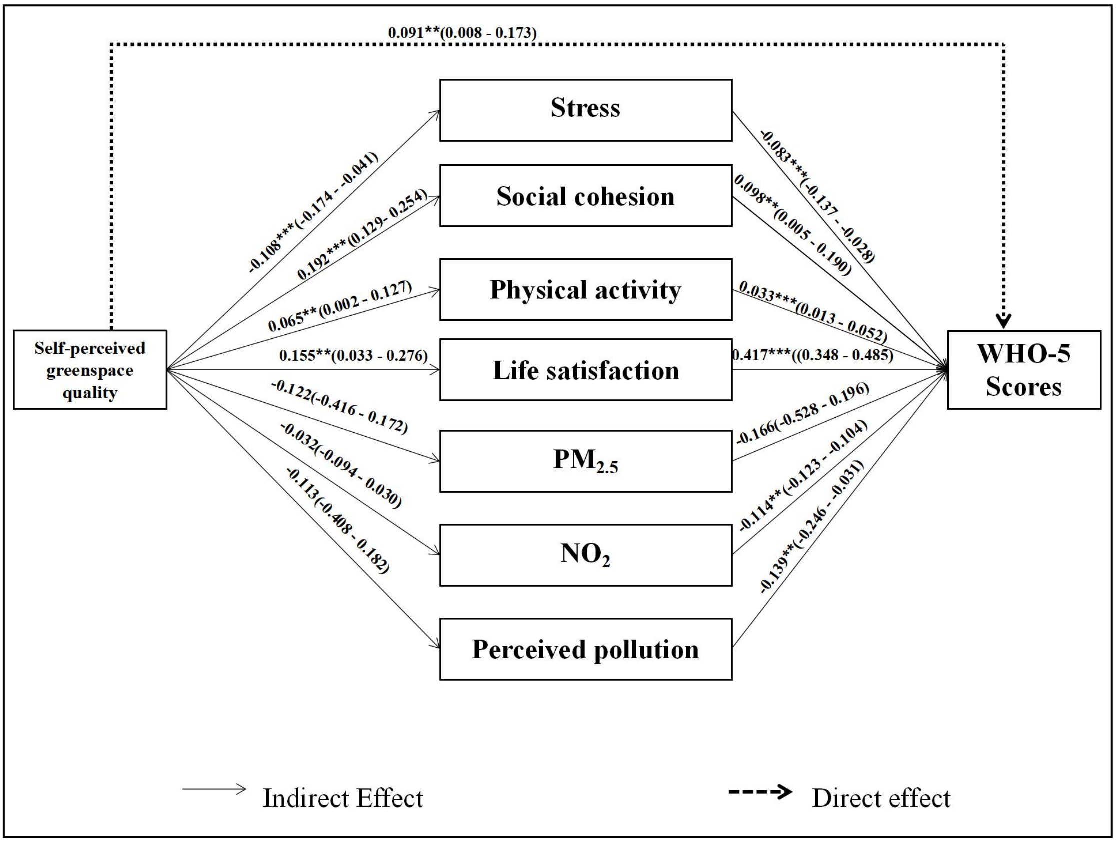

Fig 6. Standardized coefficients of the multilevel structural equation model for the association between self-perceived greenspace quality, mediators and WHO-5 scores. Coefficients (cluster 95% CI) of the SEM. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Models are fully adjusted for covariates.

Table 2. Direct and indirect effects of associations between greenness exposure and mental well-being.

	Indirect effect							Direct effect
	Greenspace-Stress	Greenspace-Social cohesion	Greenspace-Physical activity	Greenspace-Life satisfaction	Greenspace-$PM_{2.5}$	Greenspace-NO_2	Greenspace-Perceived pollution	Greenspace-WHO scores
	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)	Coeff. (95% CI)
NDVI	0.028(-0.024 - 0.081)	0.053(-0.040 - 0.147)	0.006(-0.002 - 0.016)	0.306(-0.164 - 0.776)	0.084(-0.093 - 0.262)	**0.082**(0.001 - 0.162)**	0.025(-0.051 - 0.101)	0.208(-0.297 - 0.713)
SVG-quantity	0.004(-0.019 - 0.028)	**0.032**(0.001 - 0.063)**	0.001(-0.003 - 0.004)	0.006(-0.155 - 0.169)	0.039(-0.040 - 0.119)	**0.050**(0.003 - 0.097)**	**0.011**(0.001 - 0.021)**	**0.072**(0.005 - 0.138)**
SVG-quality	**0.034**(0.002 - 0.065)**	**0.002**(0.000 - 0.003)**	**0.004***(0.002 - 0.006)**	**0.162***(0.086 - 0.239)**	0.019(-0.041 - 0.079)	0.002(-0.023 - 0.027)	0.009(-0.022 - 0.040)	0.078(-0.033 - 0.189)
Self-perceived greenspace quality	**0.009**(0.001 - 0.036)**	**0.018**(0.001 - 0.016)**	0.002(-0.000 - 0.004)	**0.064**(0.013 - 0.115)**	0.020(-0.044 - 0.084)	0.003(-0.002 - 0.009)	0.015(-0.025 - 0.056)	**0.091**(0.009 - 0.173)**

Note: Models adjusted for individual level covariates; *p < 0.10, **p < 0.05, ***p < 0.01.

CI= cluster confidence interval calculated based on robust cluster standard error; NDVI=Normalized Difference Vegetation Index; NO_2= nitrogen dioxide; $PM_{2.5}$= fine particulate matter with a diameter of 2.5 μm or less; SVG-quantity= street view images-based greenness quantity; SVG-quality= street view images-based greenness quality.

4. Discussion

4.1 Interpretation of the findings in the context of available evidence

This study extends previous research on the association between residential greenspace exposure and mental health in several respects. Specifically, it enhances our knowledge of the different mechanisms through which greenspace quantity and quality influence mental health. All the four metrics in this study reflect different aspects of greenspace. NDVI reflects over-head perspective of the greenspace quantity, while SVG-quantity is its counterpart from the eye-level perspective. Also, SVG-quality measures eye-level perspective of the greenspace quality, while self-perceived greenspace quality reflects individuals' general impression of the surrounding greenspace. The inverse correlation between SVG and NDVI may be explained by the lack of large green infrastructures (i.e., urban parks) in the research area (Wang et al., 2021). Our research area is in inner-city area of Guangzhou, where the population density is high and the dominant land use type is commercial sites (Gong et al., 2014). Therefore, there is not enough land for developing large green infrastructures, and the majority of vegetation is the street-level vegetation (i.e., trees and grasses) in such area. The key finding in this study is that stress, social cohesion, physical activity and life satisfaction mediated both SVG-quality - WHO-5 scores and self-reported greenspace quality - WHO-5 scores association. However, only NO_2 (nitrogen dioxide) mediated the association between NDVI and WHO-5 scores while NO_2, perceived pollution and social cohesion mediated the association between SVG-quantity and WHO-5 scores.

As for greenspace quantity and quality, most previous studies focused on greenspace quantity and found that it can influence mental health by reducing harms, restore capacities and build capacities (de Vries et al., 2013; Dzhambov et al., 2018a; Dzhambov et al., 2019; Dzhambov et al., 2018b; Sugiyama et al., 2008; Triguero-Mas et al., 2015; Triguero-Mas et al., 2017). This study showed that greenspace quantity (NDVI and SVG-quantity) has influence on mental health mainly by reducing harms (NO_2 and perceived pollution). A growing body of literature describes negative associations between neighbourhood greenspace quantity and surrounding pollution levels (Dadvand et al., 2015; James et al., 2016; Wang et al., 2019b). Greenspace quantity reflects the presence of vegetation and its extent which may absorb air pollutants, mitigate airborne pollutant concentrations or prevent traffic-related air-pollutants from getting into residential neighbourhood (Dadvand et al., 2015; de Keijzer et al., 2019; Markevych et al., 2019). However, inconsistent with most previous studies (de Vries et al., 2013; Dzhambov et al., 2018a; Dzhambov et al., 2019; Dzhambov et al., 2018b; Sugiyama et al., 2008; Triguero-Mas et al., 2015; Triguero-Mas et al., 2017), this study did not find evidence to support that greenspace quantity influences mental health by restoring capacities (stress and life satisfaction) and building capacities (physical activity and social cohesion). The restoration and instoration effects of greenspace mainly depend on the actual usage of greenspace, but greenspace quantity may not be directly related to the visit of greenspace from local residents (Xiao et al., 2017). Greenspace may not be used or visited frequently by people if it is perceived to be low quality such as being unsafe or not maintained well (Fermino et al., 2013). Some studies even reported that with low quality such as being unsafe, the quantity of greenspace may even be negative to people's mental health, since they may feel scared that it may be a shelter for gangs or criminal and avoid taking physical activity or meeting with friend there (Fleming et al., 2016).

As for greenspace quality (SVG-quality and self-perceived greenspace quality), this study found that it has influence on mental health mainly by restoring capacities (stress and life satisfaction) and building capacities (physical activity and social cohesion). This study was one of the first study to test the mitigation effect of greenspace quality, but we did not find evidence to support that greenspace quality is associated with reducing harms. The finding may be explained by that fact that greenspace quality mainly depends on how people subjectively evaluate greenspace, but it may not reflect the presence of vegetation which is important for its biological functional of reducing harms. For instance, Brindley et al. (2018) pointed out that greenspace quality is associated with its naturalness such as the presence of flowers and animals around it, but these characters of greenspace is not related to its ability of reducing pollution. Hence, greenspace with high quality is usually in a small scale (i.e., private gardens) since the maintenance is usually expensive (Richardson et al., 2017), so its vegetation may not be dense enough to absorb or block out pollutants. Similar to the findings from de Vries et al. (2013), the restoration and instoration effects of greenspace quality were once confirmed by this study. First, the restorative quality of greenspace depends on people's willingness of staying in that environment (Dzhambov et al., 2019; Liu et al., 2017) and greenspace quality directly reflect people's evaluation of greenspace which is associated with their willingness of use it (Brindley et al., 2019), so people are more likely to visit and stay in greenspace with higher quality which may help them reduce stress and improve positive emotions. Second, in order to build capacities within the greenspace, people need to take physical activity or interact with neighbours in it (Markevych et al., 2017). Previous studies indicated that people are more willing to chooses a pleasing environment to take physical activity and greenspace with higher quality can provide a more enjoyable and accessible setting for physical activity, so it may be more related to physical activity than quantity (de Vries et al., 2013; Lu, 2018; Van Dillen et al., 2012). Also, greenspace with higher quality provides a more pleasing meeting place for residents to socialize with their neighbours (Vries et al., 2013). The increasing of social cohesion requires long-term social interactions instead of a nodding acquaintance (Kawachi and Berkman, 2000), and people may stay longer and chat with their neighbours in greenspace with higher quality (de Vries et al., 2013), so quality more be more important than quantity in building social cohesion.

Another finding in this study is that consistent with previous studies (Helbich et al., 2019; Wang et al., 2019a), this study finds that eye-level greenspace exposure (SVG and self-perceived greenspace quality) and over-head view greenspace exposure (NDVI) may influence people's mental health through different mechanisms. For over-head view greenspace exposure (NDVI), similar to previous work from Barcelona (Gascon et al., 2018), we found that that objective measurement of air pollution (NO_2) mediated the association between NDVI and mental health. In contrast, Dzhambov et al. (2018a) did not find such an association for NDVI, objective measurement of air pollution and mental health in Bulgaria. The inconsistent finding may be explained by the limitation of NDVI (Helbich et al., 2019; Wang et al., 2019a). Consistent with the findings from Dzhambov et al. (2018b) and Wang et al. (2019b), we did not find that perceived pollution mediated the association between NDVI and mental health which may because NDVI may not reflect people's actual perceived greenspace exposure which may be more relevant to their perceived environmental stressors (Wang et al., 2019b). Also, we did not find evidence to support that NDVI can have influence on mental health by restoring capacities (stress and life satisfaction) and building capacities (physical activity and social cohesion) which is inconsistent with previous studies (Dzhambov et al., 2018a; Dzhambov et al., 2019; Dzhambov et al., 2018b; Triguero-Mas et al., 2015; Triguero-Mas et al., 2017). The reason may be that our study area is in an area with high population density, so NDVI may not reflect the presence of available or visible vegetation accurately (Song et al. 2019; Ye et al., 2018). Also, many physical activities and social interactions occur on the street, but the resolution of NDVI is too coarse in this study to reflect street-level vegetation (Lu, 2018; Wang et al., 2019a).

As for eye-level greenspace exposure (SVG and self-perceived greenspace quality), similar to existing literature (de Vries et al., 2013; Sugiyama et al., 2008; Wang et al., 2019a), it has influence on people's mental health through not only reducing harms (noise and air pollution), but also through restoring capacities (stress and life satisfaction) and building capacities (physical activity and social cohesion). First, eye-level greenspace exposure measures greenspace from an individual perspective and angle of view perpendicular to the horizontal plane, so it may reflect the presence of street-level vegetation such as trees more accurately which may be more effective in mitigating pollution (Wang et al., 2019b). Second, eye-level greenspace exposure is more related to people's actual perceived greenness, which is important for attracting people's attention, improve their positive feelings and reduce perceived environmental stressors (Liu et al., 2019; Wang et al., 2019a). Third, eye-level greenspace exposure can reflect visible and available greenspace which are more likely to be visited by residents and be taken as a public open space for physical activities and social interactions (Wang et al., 2019a).

4.2 Strengths and limitations

Numerous strengths need to be emphasized. First, we investigated both the effect of greenspace quantity and greenspace quality on mental health which contributes to the existing knowledge of greenspace - mental health associations. Second, we also assessed both the influence of both eye-level greenspace exposure and over-head view greenspace exposure on mental health. Last, we not only explored the direct effect of greenspace, but also the mechanisms through which greenspace has influence on mental health.

Our study was limited in several ways, however. First, our research was based on cross-sectional data, which prevents us from inferring causation between greenspace exposure and mental health. We cannot rule out the reverse causation and using longitudinal data is required to confirm causal direction. Second, several mediators used in the present study were based on self-reported questions. Self-reported measures are potentially unreliable and suffer from self-reporting bias. Nonetheless, self-reported data can offer a broader range of responses than many other data collection instruments, and can be advantageous in obtaining subjects' perspectives, views, and opinions. More objective measures (i.e. wearable devices) should be used in future studies. Also, we did not have respondents' information of actual use or actual visual exposure to green spaces, which means there may be a difference between our exposure assessment and respondents actual greenspace exposure. Third, the street view data were collected in 2016, while survey data was collected in 2017, which may cause some bias due to a temporal misalignment. Also, street view data cannot capture season changes which may cause bias. Nevertheless, Guangzhou is in the subtropical zone, where there are limited changes in greenspace across the seasons, so temporal discordance is unlikely to affect substantively the main findings. Fourth, there is an inconsistency in the spatial resolution of PM2.5, NO2 and NDVI (ranging from 30m to 1km grid squares), which may lead to imprecision in the exposure assessment for some environmental variables and result in potential bias in the final results. Hence, the 1000-m buffer size of greenspace exposure may benefit some exposure-mediator pairs (i.e, air pollution), but lead to bias for other pairs (i.e., social cohesion). This is because a larger buffer is sufficient in measuring air pollution exposure due to its smooth variation over space, while social contacts may occur within a smaller buffer around neighbourhood. Fifth, we did not measure respondents' indoor greenspace exposure or (green) window views. Also, we did not have respondents' attitudes towards greenspace or their childhood experience of contacting greenspace. The above four limitations are either related to measuring error or omitted variable bias, which may influence the estimation of coefficients of our models. Sixth, we presume no interaction between exposure and mediators to simplify the setting of model, but this may cause bias if there are actual interactions between these factors. Such limitation is related to model setting and may also impact the coefficient of the model. Last, daily exposure to greenness is not limited to residential neighbourhood, so future studies should also consider greenspace exposure in other activity places or even across people's mobility spaces that they encounter in their everyday lives (Helbich, 2018).

5. Conclusion

Our results suggest that the mechanisms through which neighbourhood greenspace exposure influences mental health may vary with different exposure assessments. Greenspace quantity (NDVI and SVG-quantity) has influence on mental health mainly by reducing harm while greenspace quality (SVG-quality and self-reported greenspace quality) has influence on mental health mainly by restoring capacities and building capacities. To our knowledge, this study is the first to explore associations between neighbourhood greenspace exposure and mental health in a large Chinese city using different exposure assessment strategies. A more definitive study is necessary to confirm our results.

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Declaration of Competing Interest

The authors declare that there are no conflicts of interest.

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