Residential greenness, air pollution and psychological well-being among urban residents in Guangzhou, China

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Abstract: China's rapid urbanization has led to an increasing level of exposure to air pollution and a decreasing level of exposure to vegetation among urban populations. Both trends may pose threats to psychological well-being. Previous studies on the interrelationships among greenness, air pollution and psychological well-being rely on exposure measures from remote sensing data, which may fail to accurately capture how people perceive vegetation on the ground. To address this research gap, this study aimed to explore relationships among neighbourhood greenness, air pollution exposure and psychological well-being, using survey data on 1029 adults residing in 35 neighbourhoods in Guangzhou, China. We used the Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG) to assess greenery exposure at the neighbourhood level, and we distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics. We used two objective (PM2.5 and NO2 concentrations) measures and one subjective (perceived air pollution) measure to quantify air pollution exposure. We quantified psychological well-being using the World Health Organization Well-Being Index (WHO-5). Results from multilevel structural equation models (SEM) showed that, for parallel mediation models, while the association between SVG-grass and psychological well-being was completely mediated by perceived air pollution and NO2, the relationship between SVG-tree and psychological well-being was completely mediated by ambient PM2.5, NO2 and perceived air pollution. None of three air pollution indicators mediated the association between psychological well-being and NDVI. For serial mediation models, measures of air pollution did not mediate the relationship between NDVI and psychological well-being. While the linkage between SVG-grass and psychological well-being scores was partially mediated by NO2-perceived air pollution, SVG-tree was partially mediated by both ambient PM2.5-perceived air pollution and NO2-perceived air pollution. Our results suggest that street trees may be more related to lower air pollution levels and better mental health than grasses are.

Response to Reviewers: Responses to Reviewer #1

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Research Data Related to this Submission

There are no linked research data sets for this submission. The following reason is given:
The authors do not have permission to share data

*Title Page

Running title: Greenness, air pollution and psychological well-being

Residential greenness, air pollution and psychological well-being among urban residents in Guangzhou, China

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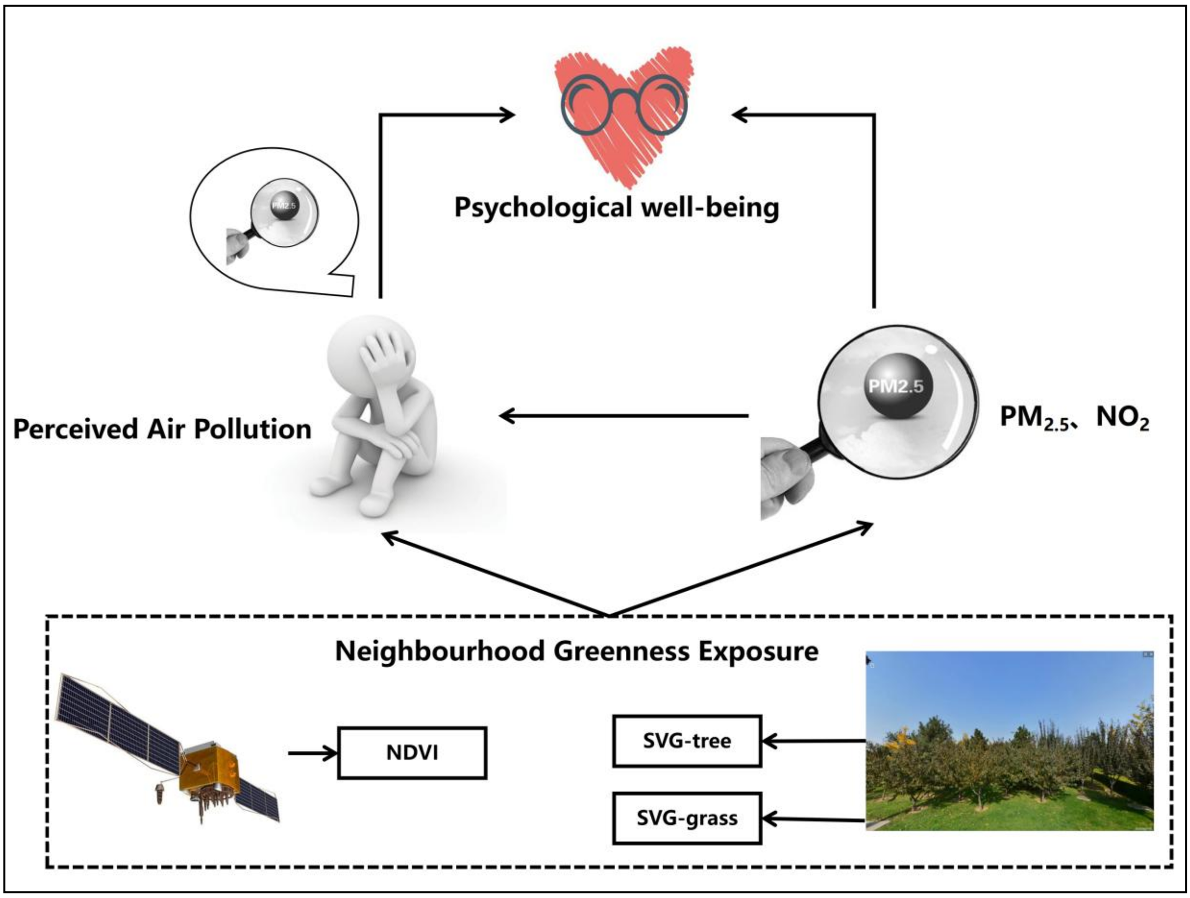
Abstract

China’s rapid urbanization has led to an increasing level of exposure to air pollution and a decreasing level of exposure to vegetation among urban populations. Both trends may pose threats to psychological well-being. Previous studies on the interrelationships among greenness, air pollution and psychological well-being rely on exposure measures from remote sensing data, which may fail to accurately capture how people perceive vegetation on the ground. To address this research gap, this study aimed to explore relationships among neighbourhood greenness, air pollution exposure and psychological well-being, using survey data on 1029 adults residing in 35 neighbourhoods in Guangzhou, China. We used the Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG) to assess greenery exposure at the neighbourhood level, and we distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics. We used two objective (PM2.5 and NO2 concentrations) measures and one subjective (perceived air pollution) measure to quantify air pollution exposure. We quantified psychological well-being using the World Health Organization Well-Being Index (WHO-5). Results from multilevel structural equation models (SEM) showed that, for parallel mediation models, while the association between SVG-grass and psychological well-being was completely mediated by perceived air pollution and NO2, the relationship between SVG-tree and psychological well-being was completely mediated by ambient PM2.5, NO2 and perceived air pollution. None of three air pollution indicators mediated the association between psychological well-being and NDVI. For serial mediation models, measures of air pollution did not mediate the relationship between NDVI and psychological well-being. While the linkage between

SVG-grass and psychological well-being scores was partially mediated by NO2-perceived air pollution, SVG-tree was partially mediated by both ambient PM2.5-perceived air pollution and NO2-perceived air pollution. Our results suggest that street trees may be more related to lower air pollution levels and better mental health than grasses are.

Keywords: Air pollution; Psychological well-being; Residential greenness; Street view data,

Graphical abstract



Capsule: Neighbourhood greenness may benefit mental health by decreasing air pollution.

Highlights

- Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG) were used to assess greenness exposure, and trees (SVG-tree) and grasses (SVG-grass) were distinguished when generating streetscape greenery exposure metrics.
- Both objective ($PM_{2.5}$ and NO_2 concentrations) and subjective (perceived air pollution) measures were used to quantify air pollution exposure.
- NDVI, SVG-tree and SVG-grass were positively associated with psychological well-being.
- The streetscape greenery-mental health association was mediated by ambient $PM_{2.5}$, NO_2 and perceived air pollution in parallel mediation models.
- The streetscape greenery-mental health association was mediated by ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution in serial mediation models
- Neither measures of air pollution mediated the association between NDVI and psychological well-being.

Abbreviations: CI= confidence interval; NDVI, normalized difference vegetation index; NO_2= nitrogen dioxide; $PM_{2.5}$, particles $\leqslant$2.5 μm in aerodynamic diameter; q25, first quartile; q75, third quartile; SVG-grass, street view images-based greenness assessed in density of grasses; SVG-tree, street view images-based greenness assessed in density of trees; WHO-5, World Health Organization Well-Being Index; .

1. Introduction

China urbanized very rapidly over the past 40 years, with the proportion of urban residents having grown from approximately 18% in 1978 to 56% in 2015 (NBSC, 2016). While development has brought economic benefits, it has diminished opportunities for contact with nearby vegetation, limiting exposure to “greenness” (Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017), and increased the risk of exposure to air pollution (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).

Multiple cross-sectional (Banay et al., 2019; Hystad et al., 2019; Lee et al., 2019; Sarkar et al., 2018; Song et al., 2019) and longitudinal (Alcock et al., 2014; Astell-Burt et al., 2014; Feng and Astell-Burt, 2017, 2018) epidemiologic investigations have reported positive associations between greenness and psychological well-being. Neighbourhood greenness may benefit psychological well-being by mitigating pathophysiologic processes that lead to neuroinflammation, cerebrovascular damage and neurodegeneration (Kioumourtzoglou et al., 2017; Buoli et al., 2018). Greenness surrounding residential areas is found to encourage physical activities (Maas et al., 2008; Richardson et al., 2013; Sugiyama et al., 2008; van den Berg et al., 2019) and social contact among neighbours, thereby benefitting psychological well-being (de Vries et al., 2013; Maas et al., 2009; Sugiyama et al., 2008). In addition, greenspace has been shown to be a resource for psychological restoration, which indicates it can reduce psychological stress (Kaplan, 1995; Hartig, 2008; Hartig et al., 2014; Ulrich et al., 1991).

Scholars have increasingly become concerned about the adverse effects of air pollution on psychological well-being (Buoli et al., 2018; Kampa and Castanas, 2008; Lim et al., 2012; Wang et al., 2019a; Wang et al., 2018; Wang et al., 2014). Rapid urbanization and industrialization is normally accompanied by an increased risk of exposure to air pollution (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019). Previous studies showed that air pollution may discourage physical activities and decrease people's willingness to socialize with their neighbours in outdoor settings (An and Xiang, 2015; Roberts et al., 2014; Wang et al., 2019a). Thus, less exposure to greenness and greater exposure to air pollution may threaten the psychological well-being of urban populations (Chen and Nakagawa, 2018).

Recent reviews suggest that neighbourhood greenery may protect psychological well-being by mitigating environmental stressors such as air pollution (Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017). Some studies have reported a significant role for air pollution in mediating associations between greenness exposure and health (Gascon et al., 2018; James et al., 2016; Thiering et al., 2016; Yang et al., 2019), whereas others have found no solid evidence (Dzhambov et al., 2018a, b; Vienneau et al., 2017; Yitshak-Sade et al., 2017). Yet, previous studies on the interrelationships among neighbourhood greenness, air pollution and psychological well-being rely on exposure measures from remote sensing (i.e., satellite) data, which may fail to accurately capture how people perceive vegetation on the ground (Dzhambov et al., 2018a, b; Gascon et al., 2018; Liu et al., 2019a, b; Wang et al., 2019b). There has been little research on the association between greenspace and mental health in China to date, and, studies have mainly focused on the direct effect of greenspace on health (Liu et al., 2019a, b; Wang et al., 2019b).

To address the above-mentioned knowledge gaps, we explored relationships among neighbourhood greenness, air pollution and psychological well-being in an urban Chinese population. We focused on the extent to which air pollution mediated the association between residential greenness and psychological well-being. We used the Normalized Difference Vegetation Index (NDVI) and streetscape greenery measures to assess greenery exposure at the neighbourhood level. We also distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics, to identify whether the relationship among neighbourhood greenness, air pollution and psychological well-being varied due to different measures of neighbourhood greenness and air pollution (Fig. 1).

(Fig 1 about here)

2. Data and methods

2.1. Study population

We enrolled 1029 study participants between June and August 2016. We first selected 35 residential neighbourhoods (with mean $\pm_{SD}$ area =1.91 km^2 ± 574.691 m^2. Total area= 66.85km^2) from six districts in Guangzhou city (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe and Liwan), using a multi-stage stratified sampling method with probabilities proportionate to population sizes. We then randomly chose 30 households from each neighbourhood. Finally, we randomly enrolled one adult from each household using the Kish Grid method (Kish, 1949). Thus, 35 neighourhoods x 30 household x 1 person/household = 1050 participants. However, 21 potential participants did not complete the study questionnaire, so the final sample size in this study was 1029 (98% participation rate). The study protocol was approved by the Sun Yat-sen University Research Ethics Committee, and all participants completed informed consent prior to enrollment.

2.2 Psychological well-being assessment

Study participants were invited to complete the World Health Organization five-item Well-Being Index (WHO-5) (Heun et al., 2001). The WHO-5 questions evaluate respondents' psychological feelings over the previous two weeks, including: "I have felt cheerful and in good spirits", "I have felt calm and relaxed", "I have felt active and vigorous", "I woke up feeling fresh and rested" and "My daily life has been filled with things that interest me". Each item is scored on a 6-point Likert scale, ranging from "never" to "every time", and the total score ranges from 0 to 25. Greater values indicate better psychological well-being. The WHO-5 has been shown to have good validity and reliability in many countries (Krieger et al., 2014) and has been validated in China. In our sample, the questionnaire had good reliability (test-retest reliability=0.995, $p<0.01$), and the Cronbach's alpha (0.815) indicated high internal consistency.

2.3 Residential greenness assessment

2.3.1 NDVI

We used the satellite-based NDVI (Tucker, 1979) as a surrogate of neighbourhood greenness 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 in 1000 m buffers around the centroid of each study neighbourhood. Remote sensing data were obtained for the year 2016 from the USGS EarthExplorer (https://earthexplorer.usgs.gov/). We used cloud-free images in the greenest month of the year (August) to avoid distortions. Guangzhou has a subtropical climate, so most of its vegetation stays green year round. We omitted pixels with a negative NDVI value before averaging across each study neighbourhood, following the approach employed in previous studies (Markevych et al., 2017).

2.3.2 SVG-tree and SVG-grass

We also used street-view imagery-based greenness indices as surrogates of neighbourhood greenness exposure. We calculated the SVG using street-view imagery from Tencent (Lu et al., 2018; Lu, 2019; Helbich et al., 2019; Wang et al., 2019b, c). First, we collected a series of street view images from Tencent Online Map [https://map.qq.com], the most comprehensive online street view image database in China, as described previously (Helbich et al., 2019; Wang et al., 2019b, c). Street view sampling points were identified 100 m apart along the local road network, which was obtained from OpenStreetMap (Haklay and Weber, 2008). For each sampling point, we collected street view images from 0, 90, 180 and 270 degrees (Helbich et al., 2019; Wang et al., 2019b, c). We collected 125,656 street view images from 31,414 sampling points in this study.

We distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics, using a machine learning approach based on semantic image segmentation techniques. We employed a fully convolutional neural network for semantic image segmentation (FCN-8s), which has been shown to be capable of identifying 150 types of ground objects (e.g., trees and grasses) accurately (Kang and Wang, 2014; Long et al., 2015). Our training model was based on the online ADE20K annotated images data set (Zhou et al., 2019). The accuracy of the FCN-8s was 81% for the training data and 80% for the test data. Following previous studies (Helbich et al., 2019; Wang et al., 2019b, c), SVG-tree and SVG-grass at each sampling point were determined as the proportion of tree or grass pixels per image summed over the four cardinal directions (i.e., 0, 90, 180 and 270 degrees) relative to the total number of pixels per image summed over the four cardinal directions. We calculated the SVG-tree and SVG-grass for each neighbourhood by averaging the SVG-tree and SVG-grass scores for all sampling points within 1000 m circular buffers around the centroid of each study neighbourhood.

2.4 Air pollution assessment

2.4.1 $PM_{2.5}$ and NO_2 concentrations

We assessed exposure to air pollution using predicted $PM_{2.5}$ and NO_2 concentrations within a 1000 m circular buffer around the geographic centroid of study neighbourhoods. We used the 2016Global Annual $PM_{2.5}$ data grid, generated using MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) data with geographically weighted regression, and available from the

NASA Socioeconomic Data and Applications Center (SEDAC) at a 1000 m × 1000 m spatial resolution (van Donkelaar et al., 2016; 2018). Nitrogen dioxide (NO_2) concentrations were also extracted from a globally available land use regression model with a spatial resolution of 100 m (Larkin et al., 2017). We calculated the annual average $PM_{2.5}$ and NO_2 concentrations using the average pixel value within the 1000 m circular buffer around the centroid of each study neighbourhood.

2.4.2 Perceived air pollution

Participants' perceived air pollution was measured with the following question: "Are you satisfied with the air quality within your residential neighbourhood (very dissatisfied=1; dissatisfied=2; neither satisfied nor dissatisfied=3; satisfied=4; very satisfied=5)". We reverse-coded perceived air pollution, so that higher values indicated less satisfaction with air quality and higher air pollution levels.

2.5 Covariates

Following previous studies (Helbich et al., 2019; Yang et al., 2019), we adjusted for a series of confounding sociodemographic covariates: sex (males vs female), age (in years), educational attainment (primary school or below; high school; college and above), marital status (single, divorced, and widowed vs married or cohabited), hukou status (registered permanent residence vs registered temporary residence), annual household income (< 2999 Chinese Yuan; 3000-6999 Chinese Yuan; 7000-12000 Chinese Yuan; > 12000 Chinese Yuan), and medical insurance participation (yes vs no).

2.6 Statistical analysis

Spearman's correlations were estimated to examine relationships among the greenness and air pollution exposure measures. We used a multilevel structural equation models to assess associations between neighbourhood greenness exposure, air pollution and psychological well-being while accounting for clustered study outcomes within neighbourhood (Lee, 2002). Participants were clustered by neighbourhood, so individual effects were captured by level 1 and neighbourhood effects were captured by level 2. Multivariate models did not suffer from multicollinearity based on the tolerance (> 0.25) and variance inflation factor (< 3) values.

We used two approaches to model pathways linking greenspace to psychological well-being and to evaluate the mediating effect of air pollution, presuming no interaction between the exposures and mediators. We used parallel mediation models, in which the mediators were assumed to act independently, and serial mediation models, in which objective air pollution measures were assumed to have an influence on subjective measures of air pollution and in turn, on psychological well-being. First, we fitted the parallel mediation model (Fig 2 A) with three parallel mediators ($PM_{2.5}$, NO_2 and perceived air pollution). Also, we used different measures of greenness as described above. Second, we fitted the serial mediation model (Fig 2 B), which assumed that residential greenness could affect mental wellbeing through actual exposure to air pollution (PM2.5 and NO2) and the perception of air pollution. Again, we used different measures of greenspace. Third, we calculated the direct and indirect effects in the parallel mediation model and in the serial mediation model based on the approach proposed by Hayes (2013) and Zhao et al. (2010). We used bootstrapping (5000 samples) to obtain bias-corrected 95% CIs of for each paths (Hayes,2013; Zhao et al., 2010). Goodness of fit was assessed by standardized root mean square residual (SRMSR), root mean square error of approximation (RMSEA), and comparative fit index (CFI). Hu and Bentler (1999) suggested that the acceptable model fit should be as follows: RMSEA (⩽0.06,90% CI⩽ 0.06), SRMSR (⩽0.08), and CFI (⩾0.95). The detailed information for SEM was shown in Fig S1.

(Fig 2 about here)

To assess the robustness of our results, we repeated our analyses using 800m and 1500m neighbourhood buffers instead of 1000m buffers when measuring exposure to residential greenness and air pollution (results available on request). 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).

3. Results

3.1 Descriptive statistics

The characteristics of the study population are summarized in Table 1; there was no missing data. About half of participants were male (50.2%) and the average age was 41.2 years. Most respondents were married (78.3%) and were registered as temporary residents (77.8%). Approximately 50.0% of respondents had a high school education and 47.4% possessed a college level education. Most respondents earned 3000-6999 Chinese Yuan per year (70.7%), and had medical insurance (97.1%).

The average WHO-5 scores for all respondents was 12.08 (SD: 3.71). The median score for NDVI was 0.10 (IQR=0.04), while median scores for SVG-tree and SVG-grass were 0.24 (IQR=0.07) and 0.01 (IQR=0.02), respectively. There were no statistically significant correlations between NDVI and SVG-tree score (r_{Sp}=-0.16, p=0.23), or SVG-grass score (r_{Sp}=-0.45, p=0.15), or between SVG-grass score and SVG-tree score (r_{Sp}=0.56, p=0.09). Average neighbourhood $PM_{2.5}$ and NO_2 concentrations and perceived air pollution scores were 35.97 and 28.21 μg/m^3 and 3.06, respectively, although the values were uncorrelated (p>0.05).

(Table 1 about here)

3.2 Associations between greenness exposure, air pollution and psychological well-being: Parallel mediation model

We obtained a reasonably well-fitting final parallel mediation model: SRMSR = 0.035, RMSEA = 0.034 (90% CI: 0.022, 0.041), CFI = 0.949. Fig. 3 (A) reports path coefficients and 95% confidence intervals (CI) for the parallel mediation model in the multilevel SEM. NDVI was positively and directly associated with WHO-5 scores, but there was no evidence that NDVI was also associated with $PM_{2.5}$, NO_2 or perceived air pollution. WHO-5 score was negatively associated with the $PM_{2.5}$, NO_2 and perceived air pollution. Table 2 indicates that a

1-IQR greater NDVI was significantly and directly associated with 0.44-unit higher WHO-5 score. There was no evidence to suggest that NDVI could influence WHO-5 scores through an indirect effect.

(Fig 3 about here)

(Table 2 about here)

Fig. 3 (B) also shows that SVG-grass was negatively associated with NO_2 concentration and perceived air pollution, which all were negatively associated with WHO-5 scores. However, there was no evidence to suggest that SVG-grass was also associated with $PM_{2.5}$ or directly associated with WHO-5 score. Table 2 indicates that a 1-IQR greater SVG-grass was significantly and indirectly associated with a 0.06-unit higher WHO-5 score through perceived air pollution and a 0.23-unit higher WHO-5 score through NO_2 concentration. There was no evidence to suggest that SVG-grass could directly influence WHO-5 score.

Fig. 3 (C) shows that SVG-tree was negatively associated with PM2.5, NO2 and perceived air pollution, which all were negatively associated with WHO-5 score. However, there was no evidence that SVG-tree was directly associated with WHO-5 score. Table 2 indicated that a 1-IQR greater SVG-tree was significantly and indirectly associated with 0.03-unit higher (95% CI: 0.002-0.07) WHO-5 score through perceived air pollution, a 0.04-unit higher (95% CI: 0.003-0.07) WHO-5 score through PM2.5, and a 0.14-unit higher (95% CI 0.01-0.26) WHO-5 score through NO2. There was no evidence of a direct SVG-tree effect on WHO-5 scores.

3.3 Associations between greenness exposure, air pollution and psychological well-being: Serial mediation model

We obtained a reasonably well-fitting final serial mediation model: SRMSR = 0.031, RMSEA = 0.029 (90% CI: 0.020, 0.045), CFI = 0.966. Fig. 4 (A) reports path coefficients and 95% CI for serial mediation model in the multi-level SEM. NDVI was positively and directly associated with WHO-5 score. Although, $PM_{2.5}$ and NO_2 were both significant positively associated with perceived air pollution, which was negatively associated with WHO-5 scores, there was no evidence that NDVI was correlated to $PM_{2.5}$ or NO_2. Table 3 also shows that each IQR greater NDVI was significantly and directly associated with 0.41-unit higher (95% CI: 0.06-0.77) WHO-5 score in the serial mediation model. There was no evidence of an indirect NDVI effect on WHO-5 scores.

(Fig 4 about here)

(Table 3 about here)

Fig. 4 (B) shows that SVG-grass was positively and directly associated with WHO-5 score. SVG-grass was negatively associated with NO_2, which was positively associated with perceived air pollution. However, there was no association of SVG-grass with $PM_{2.5}$. Table 3 indicates that a 1-IQR greater SVG-grass was significantly and directly associated with a 1.89-unit higher WHO-5 score. A 1-IQR greater SVG-grass was also significantly and indirectly associated with a 0.04-unit higher WHO-5 score through the serial NO_2-perceived air pollution pathway. Yet, there was no evidence that SVG-grass could influence WHO-5 score through the serial $PM_{2.5}$-perceived air pollution pathway.

Fig. 4 (C) shows that SVG-tree was negatively associated with $PM_{2.5}$ and NO_2 concentrations, which were positively associated with perceived air pollution. However, there was no evidence for a direct association between SVG-tree and WHO-5 score. Table 3 indicates that each IQR greater SVG-tree was significantly and indirectly associated with 0.01-unit higher WHO-5 score through both the NO_2-perceived air pollution and the $PM_{2.5}$-perceived air pollution serial pathways. Still, there was no evidence supporting that SVG-tree directly influenced WHO-5 score

Last, we combined parallel and serial mediation model. The detailed information for combined SEM was shown in Fig S1 (C). Despite some differences in magnitude, the signs of their coefficients remained the same across all models (Fig S2).

4. Discussion

4.1 Key findings

We found that greenness exposure was positively associated with psychological well-being and that air pollution exposure in part mediated the association in this cross-sectional investigation of an urban Chinese study population. More specifically, we found that NDVI, SVG-tree score and SVG-grass score correlated with WHO-5 score. For parallel mediation models, while the association between SVG-grass and WHO-5 scores was completely mediated by perceived air pollution and NO_2, the relationship between SVG-tree and WHO-5 scores was completely mediated by ambient $PM_{2.5}$, NO_2 and perceived air pollution. In addition, none of three air pollution indicators mediated the association between WHO-5 scores and NDVI. For serial mediation models, measures of air pollution did not mediate the relationship between NDVI and WHO-5 scores. While the linkage between SVG-grass and WHO-5 scores was partially mediated by NO_2-perceived air pollution, the relationship for SVG-tree was partially mediated by both ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution. To the best of our knowledge, this is the first report of parallel and serial mediating effects for reported associations between greenness exposure and psychological well-being which distinguishes exposure to SVG-grass from exposure to SVG-tree.

4.2 Greenness and psychological well-being

Our results suggest that residential greenness may exert beneficial effects on psychological well-being in an urban population. Previous cross-sectional studies conducted in Bulgaria (Dzhambov et al., 2018a, b) and in four European cities (Triguero-Mas et al., 2017), including Barcelona (Spain), Stoke-on-Trent (United Kingdom), Doetinchem (The Netherlands) and Kaunas (Lithuania), also found that neighbourhood greenness exposure (NDVI) was positively related to psychological well-being. Similarly, cross-sectional studies from the UK (Sarkar et al., 2018), US (Banay et al., 2019) and Spain (Gascon et al., 2018;

Triguero-Mas et al., 2015) reported negative associations between neighbourhood greenness exposure measured as NDVI and the odds of reporting a history of doctor-diagnosed depressive disorder. The association between greenness exposure and psychological well-being as measured with WHO-5 was strongest in our results for SVG-tree, weakest for NDVI, and with moderate effect estimates for SVG-grass. Our satellite-based NDVI and street view images-based SVG were uncorrelated. This finding is consistent with previous findings from China (Helbich et al., 2019) and the U.S. (Larkin and Hystad, 2018), which also reported weak correlations between satellite-based and street view images-based measures of greenness, as well as an inverse association for greenness exposure and geriatric depression (Helbich et al., 2019). Though less widely employed than satellite-based approaches, street view images may be a useful tool for greenness assessments, as they capture different aspects of neighbourhood environments (Villeneuve et al, 2018; Weichenthal et al., 2019). Epidemiological studies of greenness and human health frequently employed the NDVI (Banay et al., 2019; Markevych et al., 2014a, 2016), presence of greenspace (Triguero-Mas et al., 2015; 2017), greenspace availability (Triguero-Mas et al., 2015; 2017), access to greenspace (Markevych et al., 2014b) or proximity to the nearest park (Fan et al., 2011) to assess neighbourhood greenness. However, these approaches are limited by an inability to differentiate types of vegetation, an issue that we addressed by measuring SVG-tree and SVG-grass.

4.3 Air pollution and psychological well-being

Our results also suggest that poorer air quality may exert a pejorative effect on psychological well-being. These results are consistent with previous reports originating both from developed (Kim et al., 2016b; Lim et al., 2012; Pun et al., 2016) and developing nations (Wang et al., 2018, 2019a). For example, greater concentrations of ambient $PM_{2.5}$ were cross-sectionally associated with more severe symptoms of anxiety and depression in a nationally representative sample of the U.S. population 57-85 years of age (Pun et al., 2016). Greater $PM_{2.5}$ exposure was also associated with more severe depressive symptoms in a Chinese study population (Wang et al., 2018; 2019a). This association might be explained in part by the "constrained restoration" hypothesis, indicating that air pollution may influence psychological well-being by undermining residents' perception of greenness's restorative quality (von Lindern et al., 2016). We also found associations between greater ambient $PM_{2.5}$ and poor psychological well-being captured with WHO-5. Prior evidence suggested negative associations between psychological health and perceived air pollution in Bulgaria (Dzhambov et al., 2018a; 2018b). Rather than offering an accurate surrogate for airborne hazards, perceived air pollution may be interpreted aesthetically, as adverse odors for example, affecting psychological well-being through annoyance rather than pathophysiology (Claeson et al., 2013). Yet, objective (i.e., ambient NO_2 monitoring) and subjective measures of air quality were similar in Lyon, France in all but the elderly subpopulation (Deguen et al., 2017).

4.4 Air pollution as mediator of greenness-psychological well-being associations

A growing literature describes negative relationships between neighbourhood greenness and surrounding air pollution levels (Dadvand et al., 2015; James et al., 2016; Pacifico et al., 2009; Su et al., 2011). Improved air quality may result from diminished traffic-related air-pollutants in greener areas due to the absence of motor vehicle traffic (Dadvand et al., 2015; Su et al., 2011). Green vegetation, such as tall and dense trees, may also absorb air pollutants, mitigating airborne pollutant concentrations (Eisenman et al., 2019; Pugh et al., 2012; Yli-Pelkonen et al., 2018). However, different types of vegetation (e.g., trees and grasses) have different effects on air pollutants and on air purification. For example, trees adsorb airborne particulate and gaseous pollutants, which helps to mitigate air pollutant concentrations (Hirayabashi Nowak, 2016; Niinemets et al., 2014; Nowak et al., 2014), but analogous effects are not described for grasses in the literature.

Several observational investigations have reported statistically significant mediating effects for air pollution in associations between greenness and blood lipids (Yang et al., 2019), insulin resistance (Thiering et al., 2016) and mortality (James et al., 2016), although others did not (Vienneau et al., 2017; Yitshak-Sade et al., 2017). Still, few previous studies have evaluated air pollution as an intervening variable between greenness and psychological health to date (Markevych et al., 2017). Air pollutants mediated 0.8% ($PM_{2.5}$) to 4.1% (NO_2) of the inverse associations between neighbourhood greenness and self-reported use of prescription benzodiazepines by 958 Spanish adults (Gascon et al., 2018). However, studies in Bulgaria, employing NO_2 and perceived air pollution measures (Dzhambov et al., 2018a; 2018b), and in Switzerland (Vienneau et al., 2017) did not identify air pollution as a significant mediator of greenness-psychological well-being associations.

Similar to previous work from Bulgaria (Dzhambov et al., 2018a; Dzhambov et al., 2018b), we did not detect mediating effects for air quality on associations between psychological well-being using a satellite-based greenness index (i.e., NDVI). In contrast, Gascon and colleagues (Gascon et al., 2018) reported mediation effects for NO_2, a gaseous air pollutant, which is inconsistent with our results. The reason may be that our study area is in the inner city with a high population density, so NDVI cannot accurately measure the presence of vegetation (Ye et al., 2018). Also, another reason may be that the resolution of NDVI is relatively coarse in this study which does not measure greenspace exposure in respondents exact household addresses. However, we detected mediating effects for associations of psychological well-being with street view image-based greenness indices (i.e., SVG-tree and SVG-grass). Whereas the association of WHO-5 with SVG-tree was mediated by objectively predicted $PM_{2.5}$ and NO_2 concentrations, and by subjectively perceived air pollution, the association of WHO-5 with SVG-grass was mediated only by NO_2 and perceived air pollution. As traffic emissions are the primary source of air pollutants in urban areas like Guangzhou (Li et al., 2014;Wang et al., 2006), grasses may not be tall and dense enough to block and absorb all air pollutants (Tong et al., 2015; Vos et al., 2013). Yet, street-level grasses may still shift residents' attention and reduce stress (de Vries et al., 2013), improving the perceived environment. Rotko et al. (2002) and Egondi et al. (2013) pointed out that when people focus less on environment stressors they may perceive less pollution even when actual air pollution is severe. Thus, it is tempting to speculate that the impact of perceived air pollution was attributable to aesthetic factors in mediating the association between SVG-grass score and psychological well-being in our study. Another important finding from our serial mediation models is that objectively predicted $PM_{2.5}$ and NO_2 may have influenced perceived air pollution and subsequently affected psychological well-being. Consistent with our findings, Rotko et al. (2002) found that perceived air pollution was positively associated with $PM_{2.5}$ and NO_2 concentrations. Dzhambov et al. (2018a,b) used serial mediation models to find a statistically significant serial mediating role for NO_2-annoyance and perceived air pollution-restorative quality between greenspace and psychological well-being. Yet, the serial mediating effects of NO_2-perceived air pollution and $PM_{2.5}$-perceived air pollution have not received much attention to date. Thus, the relationship among greenspace, objective air pollution, perceived air pollution and psychological well-being need more attention in future studies.

4.5 Strengths and limitations

The current study has several strengths. First, our random sampling strategy provided a representative sample of adults in Guangzhou city, enhancing generalizability and minimizing selection bias. Second, we used several measures to capture various aspects of greenness exposure, including a satellite-based vegetation index (i.e., NDVI) and street view image-based greenness indices (i.e., SVG-tree and SVG-grass). Compared with previous studies, SVG-tree and SVG-grass measured eye-level greenspace exposure in this study, which may more accurately reflect residents' actual exposure to and perception of greenspace than satellite-based measures. This allowed us to compare associations for different types and contexts of greenness exposure. Third, we evaluated air pollution using satellite based $PM_{2.5}$ and NO_2 estimates as well as perceived air pollution. This allowed us to compare the mediating effects of both objective and subjective measures of air pollution. Fourth, we used a validated and reliable psychological assessment tool (i.e. WHO-5) to collect individual level study outcomes from participants. Finally, we captured and adjusted the study results for a comprehensive panel of potential confounding variables to enhance the validity of our results.

However, our study also has several limitations, and results from our analysis should be considered as preliminary. First, the cross-sectional study design prevented us from clearly establishing a temporal relationship between greenness and psychological well-being. Thus, we cannot rule out reverse causality, in which poorer psychological well-being may have led to residence in a less green neighbourhood. Second, we did not have participants' home addresses and so we measured greenness and air pollution exposures at the residential neighbourhood level, which may have misclassified some participants. Furthermore, we measured only the quantity of greenspace, whereas the quality of greenspace is also important (Van Dillen et al., 2012). We also did not measure perceived greenspace exposure in this study. Street view and remote sensing-based greenness measures were unrelated in our study, consistent with the results of previous studies (Larkin and Hystad, 2018; Helbich et al., 2019) and studies in high population density urban areas (Ye et al., 2018). The discrepancy may be due to local eye-level exposure captured by SVG while remote sensing-based greenness represents more generalized exposure. Third, our limited sample size may have provided insufficient statistical power to detect modest associations. Fourth, street view images were taken at different time points throughout 2016, so they may not reflect participants' actual street-level greenspace exposure during the entire year. Fifth, we assessed only two objective measure of air pollution (i.e., $PM_{2.5}$ and NO_2) and one measure of subjective air pollution (i.e., perceived air pollution), and we thus are unable to draw inference on mediating effects beyond this limited profile. Sixth, we demarcated the exposure based on circular buffers, which may have led to a modifiable areal unit problem (Fotheringham and Wong, 1991). However, we found similar results when using various buffer sizes in a sensitivity analysis. Hence we did not have respondents' actual household address, so we have to measure environment exposure in neighbourhood level. Seventh, we did not consider noise, blue space and neighbourhood-level socioeconomic status data in this study, which may also be related to residents' psychological well-being (Dzhambov et al., 2018b). Eighth, NDVI is one of the predictors in the LUR (land used regression) used to generate NO_2 estimates, so this may have somewhat inflated the correlation with greenness measures. Last, daily exposure to greenspace was not limited to the residential environment, and the duration spent in residential neighbourhoods was not taken into account in this study (Helbich, 2008).

5. Conclusions

Predicted $PM_{2.5}$ and NO_2 concentrations and perceived air pollution mediated (in both parallel and serial mediation models) associations between street view image-based measures of neighbourhood greenness and psychological well-being, although the effects differed between SVG-tree and SVG-grass. Yet, these factors were not important mediators of a satellite-based measure of neighbourhood greenness and psychological well-being. Our results suggest that the relationships among neighbourhood greenness, air pollution and psychological well-being may vary with different exposure assessment strategies. To our knowledge, this study is the first to explore associations among neighbourhood greenness, air pollution and psychological well-being in a large Chinese city. A more definitive study is necessary to confirm our results.

Declaration of interests

None

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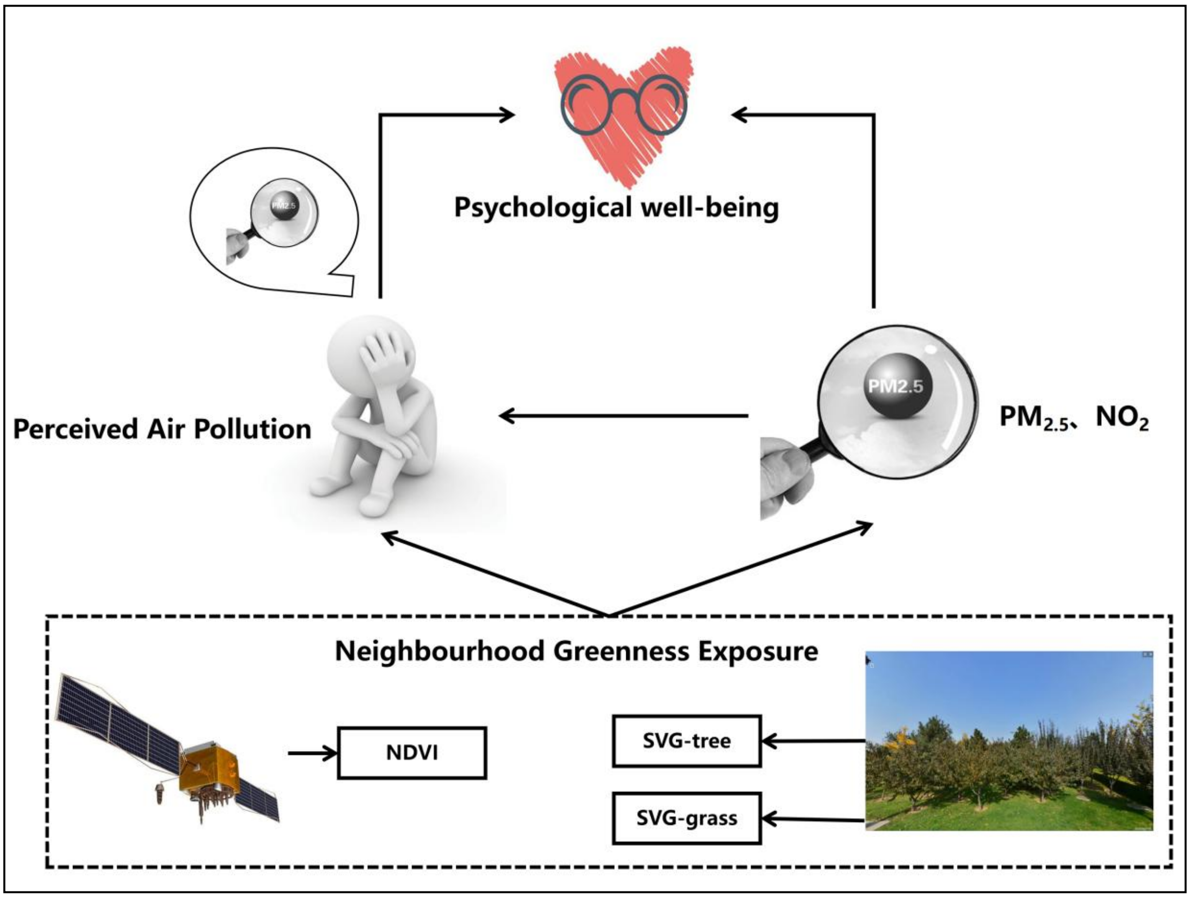
*Graphical Abstract

Graphical abstract



***Highlights (for review : 3 to 5 bullet points (maximum 85 characters including spaces per bullet point)**

Highlights

- Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG) were used to assess greenness exposure, and trees (SVG-tree) and grasses (SVG-grass) were distinguished when generating streetscape greenery exposure metrics.
- Both objective ($PM_{2.5}$ and NO_2 concentrations) and subjective (perceived air pollution) measures were used to quantify air pollution exposure.
- NDVI, SVG-tree and SVG-grass were positively associated with psychological well-being.
- The streetscape greenery-mental health association was mediated by ambient $PM_{2.5}$, NO_2 and perceived air pollution in parallel mediation models.
- The streetscape greenery-mental health association was mediated by ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution in serial mediation models
- Neither measures of air pollution mediated the association between NDVI and psychological well-being.

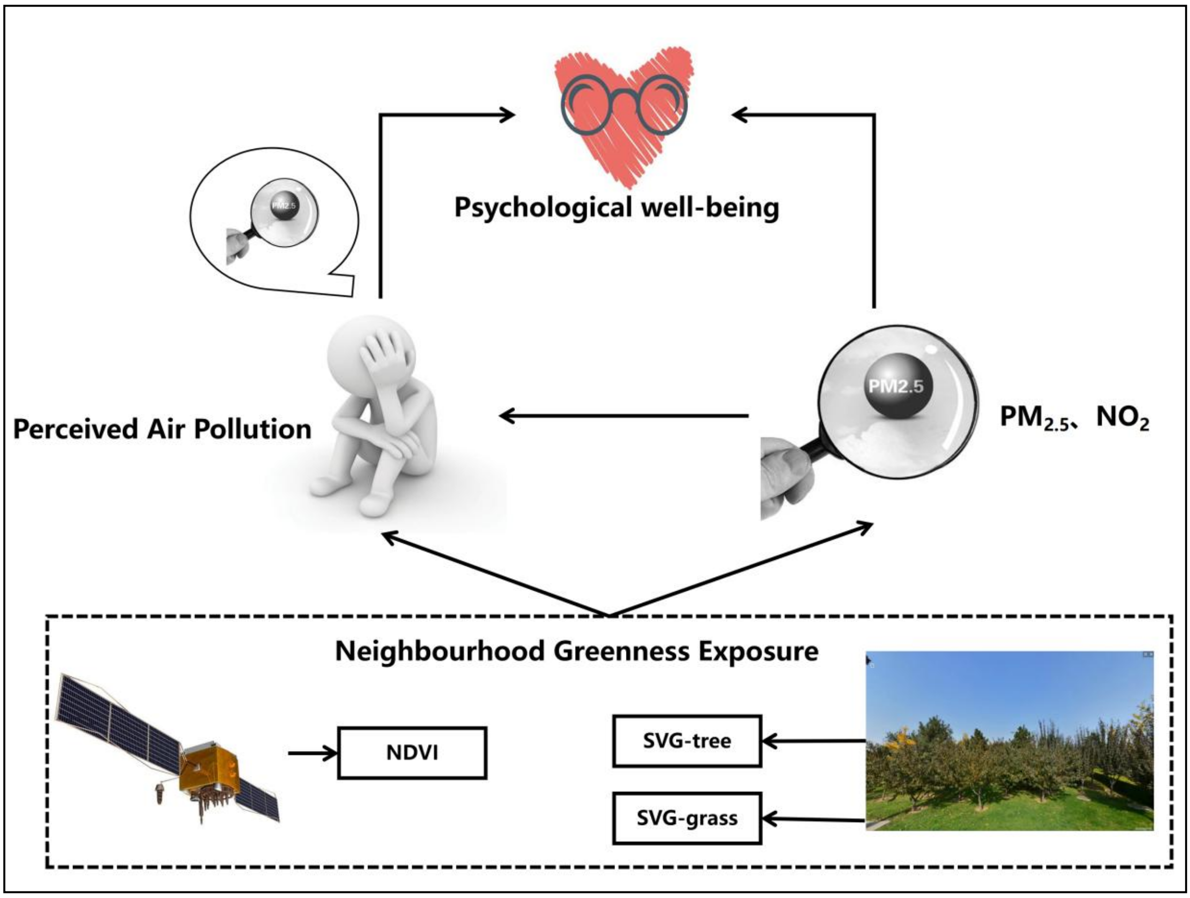
Abstract

China's rapid urbanization has led to an increasing level of exposure to air pollution and a decreasing level of exposure to vegetation among urban populations. Both trends may pose threats to psychological well-being. Previous studies on the interrelationships among greenness, air pollution and psychological well-being rely on exposure measures from remote sensing data, which may fail to accurately capture how people perceive vegetation on the ground. To address this research gap, this study aimed to explore relationships among neighbourhood greenness, air pollution exposure and psychological well-being, using survey data on 1029 adults residing in 35 neighbourhoods in Guangzhou, China. We used the Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG) to assess greenery exposure at the neighbourhood level, and we distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics. We used two objective ($PM_{2.5}$ and NO_2 concentrations) measures and one subjective (perceived air pollution) measure to quantify air pollution exposure. We quantified psychological well-being using the World Health Organization Well-Being Index (WHO-5). Results from multilevel structural equation models (SEM) showed that, for parallel mediation models, while the association between SVG-grass and psychological well-being was completely mediated by perceived air pollution and NO_2, the relationship between SVG-tree and psychological well-being was completely mediated by ambient $PM_{2.5}$, NO_2 and perceived air pollution. None of three air pollution indicators mediated the association between psychological well-being and NDVI. For serial mediation models, measures of air pollution did not mediate the relationship between NDVI and psychological well-being. While the linkage between

SVG-grass and psychological well-being scores was partially mediated by NO_2-perceived air pollution, SVG-tree was partially mediated by both ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution. Our results suggest that street trees may be more related to lower air pollution levels and better mental health than grasses are.

Keywords: Air pollution; Psychological well-being; Residential greenness; Street view data,

Graphical abstract



Capsule: Neighbourhood greenness may benefit mental health by decreasing air pollution.

Highlights

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- The streetscape greenery-mental health association was mediated by ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution in serial mediation models
- Neither measures of air pollution mediated the association between NDVI and psychological well-being.

Abbreviations: CI= confidence interval; NDVI, normalized difference vegetation index; NO_2= nitrogen dioxide; $PM_{2.5}$, particles ≤2.5 μm in aerodynamic diameter; q25, first quartile; q75, third quartile; SVG-grass, street view images-based greenness assessed in density of grasses; SVG-tree, street view images-based greenness assessed in density of trees; WHO-5, World Health Organization Well-Being Index; .

1. Introduction

China urbanized very rapidly over the past 40 years, with the proportion of urban residents having grown from approximately 18% in 1978 to 56% in 2015 (NBSC, 2016). While development has brought economic benefits, it has diminished opportunities for contact with nearby vegetation, limiting exposure to “greenness” (Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017), and increased the risk of exposure to air pollution (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).

Multiple cross-sectional (Banay et al., 2019; Hystad et al., 2019; Lee et al., 2019; Sarkar et al., 2018; Song et al., 2019) and longitudinal (Alcock et al., 2014; Astell-Burt et al., 2014; Feng and Astell-Burt, 2017, 2018) epidemiologic investigations have reported positive associations between greenness and psychological well-being. Neighbourhood greenness may benefit psychological well-being by mitigating pathophysiologic processes that lead to neuroinflammation, cerebrovascular damage and neurodegeneration (Kioumourtzoglou et al., 2017; Buoli et al., 2018). Greenness surrounding residential areas is found to encourage physical activities (Maas et al., 2008; Richardson et al., 2013; Sugiyama et al., 2008; van den Berg et al., 2019) and social contact among neighbours, thereby benefitting psychological well-being (de Vries et al., 2013; Maas et al., 2009; Sugiyama et al., 2008). In addition, greenspace has been shown to be a resource for psychological restoration, which indicates it can reduce psychological stress (Kaplan, 1995; Hartig, 2008; Hartig et al., 2014; Ulrich et al., 1991).

Scholars have increasingly become concerned about the adverse effects of air pollution on psychological well-being (Buoli et al., 2018; Kampa and Castanas, 2008; Lim et al., 2012; Wang et al., 2019a; Wang et al., 2018; Wang et al., 2014). Rapid urbanization and industrialization is normally accompanied by an increased risk of exposure to air pollution (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019). Previous studies showed that air pollution may discourage physical activities and decrease people's willingness to socialize with their neighbours in outdoor settings (An and Xiang, 2015; Roberts et al., 2014; Wang et al., 2019a). Thus, less exposure to greenness and greater exposure to air pollution may threaten the psychological well-being of urban populations (Chen and Nakagawa, 2018).

Recent reviews suggest that neighbourhood greenery may protect psychological well-being by mitigating environmental stressors such as air pollution (Hartig et al., 2014; Markevych et al., 2017; Nieuwenhuijsen et al., 2017). Some studies have reported a significant role for air pollution in mediating associations between greenness exposure and health (Gascon et al., 2018; James et al., 2016; Thiering et al., 2016; Yang et al., 2019), whereas others have found no solid evidence (Dzhambov et al., 2018a, b; Vienneau et al., 2017; Yitshak-Sade et al., 2017). Yet, previous studies on the interrelationships among neighbourhood greenness, air pollution and psychological well-being rely on exposure measures from remote sensing (i.e., satellite) data, which may fail to accurately capture how people perceive vegetation on the ground (Dzhambov et al., 2018a, b; Gascon et al., 2018; Liu et al., 2019a, b; Wang et al., 2019b). There has been little research on the association between greenspace and mental health in China to date, and, studies have mainly focused on the direct effect of greenspace on health (Liu et al., 2019a, b; Wang et al., 2019b).

To address the above-mentioned knowledge gaps, we explored relationships among neighbourhood greenness, air pollution and psychological well-being in an urban Chinese population. We focused on the extent to which air pollution mediated the association between residential greenness and psychological well-being. We used the Normalized Difference Vegetation Index (NDVI) and streetscape greenery measures to assess greenery exposure at the neighbourhood level. We also distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics, to identify whether the relationship among neighbourhood greenness, air pollution and psychological well-being varied due to different measures of neighbourhood greenness and air pollution (Fig. 1).

(Fig 1 about here)

2. Data and methods

2.1. Study population

We enrolled 1029 study participants between June and August 2016. We first selected 35 residential neighbourhoods (with mean ± $_{SD}$ area =1.91 km^2 ± 574.691 m^2. Total area= 66.85km^2) from six districts in Guangzhou city (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe and Liwan), using a multi-stage stratified sampling method with probabilities proportionate to population sizes. We then randomly chose 30 households from each neighbourhood. Finally, we randomly enrolled one adult from each household using the Kish Grid method (Kish, 1949). Thus, 35 neighourhoods x 30 household x 1 person/household = 1050 participants. However, 21 potential participants did not complete the study questionnaire, so the final sample size in this study was 1029 (98% participation rate). The study protocol was approved by the Sun Yat-sen University Research Ethics Committee, and all participants completed informed consent prior to enrollment.

2.2 Psychological well-being assessment

Study participants were invited to complete the World Health Organization five-item Well-Being Index (WHO-5) (Heun et al., 2001). The WHO-5 questions evaluate respondents' psychological feelings over the previous two weeks, including: "I have felt cheerful and in good spirits", "I have felt calm and relaxed", "I have felt active and vigorous", "I woke up feeling fresh and rested" and "My daily life has been filled with things that interest me". Each item is scored on a 6-point Likert scale, ranging from "never" to "every time", and the total score ranges from 0 to 25. Greater values indicate better psychological well-being. The WHO-5 has been shown to have good validity and reliability in many countries (Krieger et al., 2014) and has been validated in China. In our sample, the questionnaire had good reliability (test-retest reliability=0.995, p<0.01), and the Cronbach's alpha (0.815) indicated high internal consistency.

2.3 Residential greenness assessment

2.3.1 NDVI

We used the satellite-based NDVI (Tucker, 1979) as a surrogate of neighbourhood greenness 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 in 1000 m buffers around the centroid of each study neighbourhood. Remote sensing data were obtained for the year 2016 from the USGS EarthExplorer (https://earthexplorer.usgs.gov/). We used cloud-free images in the greenest month of the year (August) to avoid distortions. Guangzhou has a subtropical climate, so most of its vegetation stays green year round. We omitted pixels with a negative NDVI value before averaging across each study neighbourhood, following the approach employed in previous studies (Markevych et al., 2017).

2.3.2 SVG-tree and SVG-grass

We also used street-view imagery-based greenness indices as surrogates of neighbourhood greenness exposure. We calculated the SVG using street-view imagery from Tencent (Lu et al., 2018; Lu, 2019; Helbich et al., 2019; Wang et al., 2019b, c). First, we collected a series of street view images from Tencent Online Map [https://map.qq.com], the most comprehensive online street view image database in China, as described previously (Helbich et al., 2019; Wang et al., 2019b, c). Street view sampling points were identified 100 m apart along the local road network, which was obtained from OpenStreetMap (Haklay and Weber, 2008). For each sampling point, we collected street view images from 0, 90, 180 and 270 degrees (Helbich et al., 2019; Wang et al., 2019b, c). We collected 125,656 street view images from 31,414 sampling points in this study.

We distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating streetscape greenery exposure metrics, using a machine learning approach based on semantic image segmentation techniques. We employed a fully convolutional neural network for semantic image segmentation (FCN-8s), which has been shown to be capable of identifying 150 types of ground objects (e.g., trees and grasses) accurately (Kang and Wang, 2014; Long et al., 2015). Our training model was based on the online ADE20K annotated images data set (Zhou et al., 2019). The accuracy of the FCN-8s was 81% for the training data and 80% for the test data. Following previous studies (Helbich et al., 2019; Wang et al., 2019b, c), SVG-tree and SVG-grass at each sampling point were determined as the proportion of tree or grass pixels per image summed over the four cardinal directions (i.e., 0, 90, 180 and 270 degrees) relative to the total number of pixels per image summed over the four cardinal directions. We calculated the SVG-tree and SVG-grass for each neighbourhood by averaging the SVG-tree and SVG-grass scores for all sampling points within 1000 m circular buffers around the centroid of each study neighbourhood.

2.4 Air pollution assessment

2.4.1 $PM_{2.5}$ and NO_2 concentrations

We assessed exposure to air pollution using predicted $PM_{2.5}$ and NO_2 concentrations within a 1000 m circular buffer around the geographic centroid of study neighbourhoods. We used the 2016Global Annual $PM_{2.5}$ data grid, generated using MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) data with geographically weighted regression, and available from the

NASA Socioeconomic Data and Applications Center (SEDAC) at a 1000 m × 1000 m spatial resolution (van Donkelaar et al., 2016; 2018). Nitrogen dioxide (NO_2) concentrations were also extracted from a globally available land use regression model with a spatial resolution of 100 m (Larkin et al., 2017). We calculated the annual average $PM_{2.5}$ and NO_2 concentrations using the average pixel value within the 1000 m circular buffer around the centroid of each study neighbourhood.

2.4.2 Perceived air pollution

Participants' perceived air pollution was measured with the following question: "Are you satisfied with the air quality within your residential neighbourhood (very dissatisfied=1; dissatisfied=2; neither satisfied nor dissatisfied=3; satisfied=4; very satisfied=5)". We reverse-coded perceived air pollution, so that higher values indicated less satisfaction with air quality and higher air pollution levels.

2.5 Covariates

Following previous studies (Helbich et al., 2019; Yang et al., 2019), we adjusted for a series of confounding sociodemographic covariates: sex (males vs female), age (in years), educational attainment (primary school or below; high school; college and above), marital status (single, divorced, and widowed vs married or cohabited), hukou status (registered permanent residence vs registered temporary residence), annual household income (< 2999 Chinese Yuan; 3000-6999 Chinese Yuan; 7000-12000 Chinese Yuan; > 12000 Chinese Yuan), and medical insurance participation (yes vs no).

2.6 Statistical analysis

Spearman's correlations were estimated to examine relationships among the greenness and air pollution exposure measures. We used a multilevel structural equation models to assess associations between neighbourhood greenness exposure, air pollution and psychological well-being while accounting for clustered study outcomes within neighbourhood (Lee, 2002). Participants were clustered by neighbourhood, so individual effects were captured by level 1 and neighbourhood effects were captured by level 2. Multivariate models did not suffer from multicollinearity based on the tolerance (> 0.25) and variance inflation factor (< 3) values.

We used two approaches to model pathways linking greenspace to psychological well-being and to evaluate the mediating effect of air pollution, presuming no interaction between the exposures and mediators. We used parallel mediation models, in which the mediators were assumed to act independently, and serial mediation models, in which objective air pollution measures were assumed to have an influence on subjective measures of air pollution and in turn, on psychological well-being. First, we fitted the parallel mediation model (Fig 2 A) with three parallel mediators ($PM_{2.5}$, NO_2 and perceived air pollution). Also, we used different measures of greenness as described above. Second, we fitted the serial mediation model (Fig 2 B), which assumed that residential greenness could affect mental wellbeing through actual exposure to air pollution (PM2.5 and NO2) and the perception of air pollution. Again, we used different measures of greenspace. Third, we calculated the direct and indirect effects in the parallel mediation model and in the serial mediation model based on the approach proposed by Hayes (2013) and Zhao et al. (2010). We used bootstrapping (5000 samples) to obtain bias-corrected 95% CIs of for each paths (Hayes,2013; Zhao et al., 2010). Goodness of fit was assessed by standardized root mean square residual (SRMSR), root mean square error of approximation (RMSEA), and comparative fit index (CFI). Hu and Bentler (1999) suggested that the acceptable model fit should be as follows: RMSEA (⩽0.06,90% CI⩽ 0.06), SRMSR (⩽0.08), and CFI (⩾0.95). The detailed information for SEM was shown in Fig S1.

(Fig 2 about here)

To assess the robustness of our results, we repeated our analyses using 800m and 1500m neighbourhood buffers instead of 1000m buffers when measuring exposure to residential greenness and air pollution (results available on request). 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).

3. Results

3.1 Descriptive statistics

The characteristics of the study population are summarized in Table 1; there was no missing data. About half of participants were male (50.2%) and the average age was 41.2 years. Most respondents were married (78.3%) and were registered as temporary residents (77.8%). Approximately 50.0% of respondents had a high school education and 47.4% possessed a college level education. Most respondents earned 3000-6999 Chinese Yuan per year (70.7%), and had medical insurance (97.1%).

The average WHO-5 scores for all respondents was 12.08 (SD: 3.71). The median score for NDVI was 0.10 (IQR=0.04), while median scores for SVG-tree and SVG-grass were 0.24 (IQR=0.07) and 0.01 (IQR=0.02), respectively. There were no statistically significant correlations between NDVI and SVG-tree score (r_{Sp}=-0.16, p=0.23), or SVG-grass score (r_{Sp}=-0.45, p=0.15), or between SVG-grass score and SVG-tree score (r_{Sp}=0.56, p=0.09). Average neighbourhood $PM_{2.5}$ and NO_2 concentrations and perceived air pollution scores were 35.97 and 28.21 μg/m^3 and 3.06, respectively, although the values were uncorrelated (p>0.05).

(Table 1 about here)

3.2 Associations between greenness exposure, air pollution and psychological well-being: Parallel mediation model

We obtained a reasonably well-fitting final parallel mediation model: SRMSR = 0.035, RMSEA = 0.034 (90% CI: 0.022, 0.041), CFI = 0.949. Fig. 3 (A) reports path coefficients and 95% confidence intervals (CI) for the parallel mediation model in the multilevel SEM. NDVI was positively and directly associated with WHO-5 scores, but there was no evidence that NDVI was also associated with $PM_{2.5}$, NO_2 or perceived air pollution. WHO-5 score was negatively associated with the $PM_{2.5}$, NO_2 and perceived air pollution. Table 2 indicates that a

1-IQR greater NDVI was significantly and directly associated with 0.44-unit higher WHO-5 score. There was no evidence to suggest that NDVI could influence WHO-5 scores through an indirect effect.

(Fig 3 about here)

(Table 2 about here)

Fig. 3 (B) also shows that SVG-grass was negatively associated with NO_2 concentration and perceived air pollution, which all were negatively associated with WHO-5 scores. However, there was no evidence to suggest that SVG-grass was also associated with $PM_{2.5}$ or directly associated with WHO-5 score. Table 2 indicates that a 1-IQR greater SVG-grass was significantly and indirectly associated with a 0.06-unit higher WHO-5 score through perceived air pollution and a 0.23-unit higher WHO-5 score through NO_2 concentration. There was no evidence to suggest that SVG-grass could directly influence WHO-5 score.

Fig. 3 (C) shows that SVG-tree was negatively associated with PM2.5, NO2 and perceived air pollution, which all were negatively associated with WHO-5 score. However, there was no evidence that SVG-tree was directly associated with WHO-5 score. Table 2 indicated that a 1-IQR greater SVG-tree was significantly and indirectly associated with 0.03-unit higher (95% CI: 0.002-0.07) WHO-5 score through perceived air pollution, a 0.04-unit higher (95% CI: 0.003-0.07) WHO-5 score through PM2.5, and a 0.14-unit higher (95% CI 0.01-0.26) WHO-5 score through NO2. There was no evidence of a direct SVG-tree effect on WHO-5 scores.

3.3 Associations between greenness exposure, air pollution and psychological well-being: Serial mediation model

We obtained a reasonably well-fitting final serial mediation model: SRMSR = 0.031, RMSEA = 0.029 (90% CI: 0.020, 0.045), CFI = 0.966. Fig. 4 (A) reports path coefficients and 95% CI for serial mediation model in the multi-level SEM. NDVI was positively and directly associated with WHO-5 score. Although, $PM_{2.5}$ and NO_2 were both significant positively associated with perceived air pollution, which was negatively associated with WHO-5 scores, there was no evidence that NDVI was correlated to $PM_{2.5}$ or NO_2. Table 3 also shows that each IQR greater NDVI was significantly and directly associated with 0.41-unit higher (95% CI: 0.06-0.77) WHO-5 score in the serial mediation model. There was no evidence of an indirect NDVI effect on WHO-5 scores.

(Fig 4 about here)

(Table 3 about here)

Fig. 4 (B) shows that SVG-grass was positively and directly associated with WHO-5 score. SVG-grass was negatively associated with NO_2, which was positively associated with perceived air pollution. However, there was no association of SVG-grass with $PM_{2.5}$. Table 3 indicates that a 1-IQR greater SVG-grass was significantly and directly associated with a 1.89-unit higher WHO-5 score. A 1-IQR greater SVG-grass was also significantly and indirectly associated with a 0.04-unit higher WHO-5 score through the serial NO_2-perceived air pollution pathway. Yet, there was no evidence that SVG-grass could influence WHO-5 score through the serial $PM_{2.5}$-perceived air pollution pathway.

Fig. 4 (C) shows that SVG-tree was negatively associated with $PM_{2.5}$ and NO_2 concentrations, which were positively associated with perceived air pollution. However, there was no evidence for a direct association between SVG-tree and WHO-5 score. Table 3 indicates that each IQR greater SVG-tree was significantly and indirectly associated with 0.01-unit higher WHO-5 score through both the NO_2-perceived air pollution and the $PM_{2.5}$-perceived air pollution serial pathways. Still, there was no evidence supporting that SVG-tree directly influenced WHO-5 score

Last, we combined parallel and serial mediation model. The detailed information for combined SEM was shown in Fig S1 (C). Despite some differences in magnitude, the signs of their coefficients remained the same across all models (Fig S2).

4. Discussion

4.1 Key findings

We found that greenness exposure was positively associated with psychological well-being and that air pollution exposure in part mediated the association in this cross-sectional investigation of an urban Chinese study population. More specifically, we found that NDVI, SVG-tree score and SVG-grass score correlated with WHO-5 score. For parallel mediation models, while the association between SVG-grass and WHO-5 scores was completely mediated by perceived air pollution and NO_2, the relationship between SVG-tree and WHO-5 scores was completely mediated by ambient $PM_{2.5}$, NO_2 and perceived air pollution. In addition, none of three air pollution indicators mediated the association between WHO-5 scores and NDVI. For serial mediation models, measures of air pollution did not mediate the relationship between NDVI and WHO-5 scores. While the linkage between SVG-grass and WHO-5 scores was partially mediated by NO_2-perceived air pollution, the relationship for SVG-tree was partially mediated by both ambient $PM_{2.5}$-perceived air pollution and NO_2-perceived air pollution. To the best of our knowledge, this is the first report of parallel and serial mediating effects for reported associations between greenness exposure and psychological well-being which distinguishes exposure to SVG-grass from exposure to SVG-tree.

4.2 Greenness and psychological well-being

Our results suggest that residential greenness may exert beneficial effects on psychological well-being in an urban population. Previous cross-sectional studies conducted in Bulgaria (Dzhambov et al., 2018a, b) and in four European cities (Triguero-Mas et al., 2017), including Barcelona (Spain), Stoke-on-Trent (United Kingdom), Doetinchem (The Netherlands) and Kaunas (Lithuania), also found that neighbourhood greenness exposure (NDVI) was positively related to psychological well-being. Similarly, cross-sectional studies from the UK (Sarkar et al., 2018), US (Banay et al., 2019) and Spain (Gascon et al., 2018;

Triguero-Mas et al., 2015) reported negative associations between neighbourhood greenness exposure measured as NDVI and the odds of reporting a history of doctor-diagnosed depressive disorder. The association between greenness exposure and psychological well-being as measured with WHO-5 was strongest in our results for SVG-tree, weakest for NDVI, and with moderate effect estimates for SVG-grass. Our satellite-based NDVI and street view images-based SVG were uncorrelated. This finding is consistent with previous findings from China (Helbich et al., 2019) and the U.S. (Larkin and Hystad, 2018), which also reported weak correlations between satellite-based and street view images-based measures of greenness, as well as an inverse association for greenness exposure and geriatric depression (Helbich et al., 2019). Though less widely employed than satellite-based approaches, street view images may be a useful tool for greenness assessments, as they capture different aspects of neighbourhood environments (Villeneuve et al, 2018; Weichenthal et al., 2019). Epidemiological studies of greenness and human health frequently employed the NDVI (Banay et al., 2019; Markevych et al., 2014a, 2016), presence of greenspace (Triguero-Mas et al., 2015; 2017), greenspace availability (Triguero-Mas et al., 2015; 2017), access to greenspace (Markevych et al., 2014b) or proximity to the nearest park (Fan et al., 2011) to assess neighbourhood greenness. However, these approaches are limited by an inability to differentiate types of vegetation, an issue that we addressed by measuring SVG-tree and SVG-grass.

4.3 Air pollution and psychological well-being

Our results also suggest that poorer air quality may exert a pejorative effect on psychological well-being. These results are consistent with previous reports originating both from developed (Kim et al., 2016b; Lim et al., 2012; Pun et al., 2016) and developing nations (Wang et al., 2018, 2019a). For example, greater concentrations of ambient $PM_{2.5}$ were cross-sectionally associated with more severe symptoms of anxiety and depression in a nationally representative sample of the U.S. population 57-85 years of age (Pun et al., 2016). Greater $PM_{2.5}$ exposure was also associated with more severe depressive symptoms in a Chinese study population (Wang et al., 2018; 2019a). This association might be explained in part by the "constrained restoration" hypothesis, indicating that air pollution may influence psychological well-being by undermining residents' perception of greenness's restorative quality (von Lindern et al., 2016). We also found associations between greater ambient $PM_{2.5}$ and poor psychological well-being captured with WHO-5. Prior evidence suggested negative associations between psychological health and perceived air pollution in Bulgaria (Dzhambov et al., 2018a; 2018b). Rather than offering an accurate surrogate for airborne hazards, perceived air pollution may be interpreted aesthetically, as adverse odors for example, affecting psychological well-being through annoyance rather than pathophysiology (Claeson et al., 2013). Yet, objective (i.e., ambient NO_2 monitoring) and subjective measures of air quality were similar in Lyon, France in all but the elderly subpopulation (Deguen et al., 2017).

4.4 Air pollution as mediator of greenness-psychological well-being associations

A growing literature describes negative relationships between neighbourhood greenness and surrounding air pollution levels (Dadvand et al., 2015; James et al., 2016; Pacifico et al., 2009; Su et al., 2011). Improved air quality may result from diminished traffic-related air-pollutants in greener areas due to the absence of motor vehicle traffic (Dadvand et al., 2015; Su et al., 2011). Green vegetation, such as tall and dense trees, may also absorb air pollutants, mitigating airborne pollutant concentrations (Eisenman et al., 2019; Pugh et al., 2012; Yli-Pelkonen et al., 2018). However, different types of vegetation (e.g., trees and grasses) have different effects on air pollutants and on air purification. For example, trees adsorb airborne particulate and gaseous pollutants, which helps to mitigate air pollutant concentrations (Hirayabashi Nowak, 2016; Niinemets et al., 2014; Nowak et al., 2014), but analogous effects are not described for grasses in the literature.

Several observational investigations have reported statistically significant mediating effects for air pollution in associations between greenness and blood lipids (Yang et al., 2019), insulin resistance (Thiering et al., 2016) and mortality (James et al., 2016), although others did not (Vienneau et al., 2017; Yitshak-Sade et al., 2017). Still, few previous studies have evaluated air pollution as an intervening variable between greenness and psychological health to date (Markevych et al., 2017). Air pollutants mediated 0.8% ($PM_{2.5}$) to 4.1% (NO_2) of the inverse associations between neighbourhood greenness and self-reported use of prescription benzodiazepines by 958 Spanish adults (Gascon et al., 2018). However, studies in Bulgaria, employing NO_2 and perceived air pollution measures (Dzhambov et al., 2018a; 2018b), and in Switzerland (Vienneau et al., 2017) did not identify air pollution as a significant mediator of greenness-psychological well-being associations.

Similar to previous work from Bulgaria (Dzhambov et al., 2018a; Dzhambov et al., 2018b), we did not detect mediating effects for air quality on associations between psychological well-being using a satellite-based greenness index (i.e., NDVI). In contrast, Gascon and colleagues (Gascon et al., 2018) reported mediation effects for NO_2, a gaseous air pollutant, which is inconsistent with our results. The reason may be that our study area is in the inner city with a high population density, so NDVI cannot accurately measure the presence of vegetation (Ye et al., 2018). Also, another reason may be that the resolution of NDVI is relatively coarse in this study which does not measure greenspace exposure in respondents exact household addresses. However, we detected mediating effects for associations of psychological well-being with street view image-based greenness indices (i.e., SVG-tree and SVG-grass). Whereas the association of WHO-5 with SVG-tree was mediated by objectively predicted $PM_{2.5}$ and NO_2 concentrations, and by subjectively perceived air pollution, the association of WHO-5 with SVG-grass was mediated only by NO_2 and perceived air pollution. As traffic emissions are the primary source of air pollutants in urban areas like Guangzhou (Li et al., 2014;Wang et al., 2006), grasses may not be tall and dense enough to block and absorb all air pollutants (Tong et al., 2015; Vos et al., 2013). Yet, street-level grasses may still shift residents' attention and reduce stress (de Vries et al., 2013), improving the perceived environment. Rotko et al. (2002) and Egondi et al. (2013) pointed out that when people focus less on environment stressors they may perceive less pollution even when actual air pollution is severe. Thus, it is tempting to speculate that the impact of perceived air pollution was attributable to aesthetic factors in mediating the association between SVG-grass score and psychological well-being in our study. Another important finding from our serial mediation models is that objectively predicted $PM_{2.5}$ and NO_2 may have influenced perceived air pollution and subsequently affected psychological well-being. Consistent with our findings, Rotko et al. (2002) found that perceived air pollution was positively associated with $PM_{2.5}$ and NO_2 concentrations. Dzhambov et al. (2018a,b) used serial mediation models to find a statistically significant serial mediating role for NO_2-annoyance and perceived air pollution-restorative quality between greenspace and psychological well-being. Yet, the serial mediating effects of NO_2-perceived air pollution and $PM_{2.5}$-perceived air pollution have not received much attention to date. Thus, the relationship among greenspace, objective air pollution, perceived air pollution and psychological well-being need more attention in future studies.

4.5 Strengths and limitations

The current study has several strengths. First, our random sampling strategy provided a representative sample of adults in Guangzhou city, enhancing generalizability and minimizing selection bias. Second, we used several measures to capture various aspects of greenness exposure, including a satellite-based vegetation index (i.e., NDVI) and street view image-based greenness indices (i.e., SVG-tree and SVG-grass). Compared with previous studies, SVG-tree and SVG-grass measured eye-level greenspace exposure in this study, which may more accurately reflect residents' actual exposure to and perception of greenspace than satellite-based measures. This allowed us to compare associations for different types and contexts of greenness exposure. Third, we evaluated air pollution using satellite based $PM_{2.5}$ and NO_2 estimates as well as perceived air pollution. This allowed us to compare the mediating effects of both objective and subjective measures of air pollution. Fourth, we used a validated and reliable psychological assessment tool (i.e. WHO-5) to collect individual level study outcomes from participants. Finally, we captured and adjusted the study results for a comprehensive panel of potential confounding variables to enhance the validity of our results.

However, our study also has several limitations, and results from our analysis should be considered as preliminary. First, the cross-sectional study design prevented us from clearly establishing a temporal relationship between greenness and psychological well-being. Thus, we cannot rule out reverse causality, in which poorer psychological well-being may have led to residence in a less green neighbourhood. Second, we did not have participants' home addresses and so we measured greenness and air pollution exposures at the residential neighbourhood level, which may have misclassified some participants. Furthermore, we measured only the quantity of greenspace, whereas the quality of greenspace is also important (Van Dillen et al., 2012). We also did not measure perceived greenspace exposure in this study. Street view and remote sensing-based greenness measures were unrelated in our study, consistent with the results of previous studies (Larkin and Hystad, 2018; Helbich et al., 2019) and studies in high population density urban areas (Ye et al., 2018). The discrepancy may be due to local eye-level exposure captured by SVG while remote sensing-based greenness represents more generalized exposure. Third, our limited sample size may have provided insufficient statistical power to detect modest associations. Fourth, street view images were taken at different time points throughout 2016, so they may not reflect participants' actual street-level greenspace exposure during the entire year. Fifth, we assessed only two objective measure of air pollution (i.e., $PM_{2.5}$ and NO_2) and one measure of subjective air pollution (i.e., perceived air pollution), and we thus are unable to draw inference on mediating effects beyond this limited profile. Sixth, we demarcated the exposure based on circular buffers, which may have led to a modifiable areal unit problem (Fotheringham and Wong, 1991). However, we found similar results when using various buffer sizes in a sensitivity analysis. Hence we did not have respondents' actual household address, so we have to measure environment exposure in neighbourhood level. Seventh, we did not consider noise, blue space and neighbourhood-level socioeconomic status data in this study, which may also be related to residents' psychological well-being (Dzhambov et al., 2018b). Eighth, NDVI is one of the predictors in the LUR (land used regression) used to generate NO_2 estimates, so this may have somewhat inflated the correlation with greenness measures. Last, daily exposure to greenspace was not limited to the residential environment, and the duration spent in residential neighbourhoods was not taken into account in this study (Helbich, 2008).

5. Conclusions

Predicted $PM_{2.5}$ and NO_2 concentrations and perceived air pollution mediated (in both parallel and serial mediation models) associations between street view image-based measures of neighbourhood greenness and psychological well-being, although the effects differed between SVG-tree and SVG-grass. Yet, these factors were not important mediators of a satellite-based measure of neighbourhood greenness and psychological well-being. Our results suggest that the relationships among neighbourhood greenness, air pollution and psychological well-being may vary with different exposure assessment strategies. To our knowledge, this study is the first to explore associations among neighbourhood greenness, air pollution and psychological well-being in a large Chinese city. A more definitive study is necessary to confirm our results.

Declaration of interests

None

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Table
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Table 1. Summary statistics of variables among study participants (n=1029).

Variables	Mean (SD)/Median (q25-q75)
WHO-5 Score, mean (SD)	12.08 (3.71)
Greenness measures:	
NDVI, median (q25-q75)	0.10 (0.07-0.12)
SVG-tree, median (q25-q75)	0.24 (0.20-0.26)
SVG-grass, median (q25-q75)	0.01 (0.003-0.02)
Air pollution measures:	
Perceived air pollution score, mean (SD)	1.94(1.21)
$PM_{2.5}$ ($\mu g/m^3$), mean (SD)	35.97 (0.46)
NO_2 ($\mu g/m^3$), mean (SD)	28.21(4.86)
Demographic factors	
Sex, n (%)	
Male	516 (50.15)
Female	513 (49.85)
Age (years), mean (SD)	41.19 (13.58)
Marital status, n (%)	
Single, divorced, and widowed	223 (21.67)
Married or living as married	806 (78.33)
Hukou status, n (%)	
Registered permanent residence	800 (77.75)
Registered temporary residence	229 (22.25)
Educational attainment, n (%)	
Primary school or below	25 (2.53)
High school	515 (50.05)
College and above	489 (47.42)
Annual household income, n (%)	
< 2999 Chinese Yuan	74 (7.19)
3000-6999 Chinese Yuan	726 (70.65)
7000-12000 Chinese Yuan	157 (15.26)
> 12000 Chinese Yuan	72 (6.90)
Medical insurance, n (%)	
Having medical insurance	999 (97.09)
No medical insurance	30 (2.91)

NDVI=Normalized Difference Vegetation Index; NO_2= nitrogen dioxide; $PM_{2.5}$= fine particulate matter with an airborne diameter of 2.5 μm or less; SVG-grass= street view images-based greenness assessed by density of grasses; SVG-tree=street view images-based greenness assessed by density of trees; WHO-5 score=World Health Organization Five-item Well-Being Index

Table 2. Air pollution as mediators of associations between greenness exposure and psychological well-being: Parallel mediation models

	Indirect effect									Direct effect		
	Greenspace-Perceived air pollution β. (95% CI)			Greenspace-$PM_{2.5}$ β. (95% CI)			Greenspace-NO_2 β. (95% CI)			Greenspace-WHO scores β. (95% CI)		
NDVI	0.01 (-0.003-0.02)	-	-	0.02 (-0.01-0.06)	-	-	0.06 (-0.03-0.15)	-	-	0.44*** (0.11 - 0.77)	-	
SVG-grass	-	0.06** (0.01-0.12)	-	-	0.06 (-0.12-0.25)	-	-	0.23** (0.00-0.47)	-	-	1.79 (-1.06-4.65)	-
SVG-tree	-		0.03** (0.002-0.07)	-	-	0.04** (0.003-0.07)	-	-	0.14** (0.01-0.26)	-	-	0.55 (-0.71-1.82)

Note: Models adjusted for individual level covariates: sex, age, education attainment, marital status, hukou status, annual household income and medical insurance participation.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

CI= confidence interval; 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-grass= street view images-based greenness assessed by density of grasses; SVG-tree= street view images-based greenness assessed by density of trees.

Table 3. Air pollution as mediators of associations between greenness exposure and psychological well-being: Serial mediation models

	Indirect effect						Direct effect		
	Greenspace-$PM_{2.5}$-Perceived air pollution β. (95% CI)			Greenspace-NO_2-Perceived air pollution β. (95% CI)			Greenspace-WHO scores β. (95% CI)		
NDVI	0.00 (-0.003-0.01)	-	-	0.00 (-0.002-0.01)	-	-	0.41** (0.06 -0.77)	-	
SVG-grass	-	0.03 (-0.01-0.07)	-	-	0.04*** (0.01-0.07)	-	-	1.89** (0.20-3.57)	-
SVG-tree	-	-	0.01** (0.003-0.02)	-	-	0.01** (0.002-0.03)	-	-	0.58 (-0.67-1.82)

Note: Models adjusted for individual level covariates: : sex, age, education attainment, marital status, hukou status, annual household income and medical insurance participation.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

CI= confidence interval; 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-grass= street view images-based greenness assessed by density of grasses; SVG-tree= street view images-based greenness assessed by density of tree.

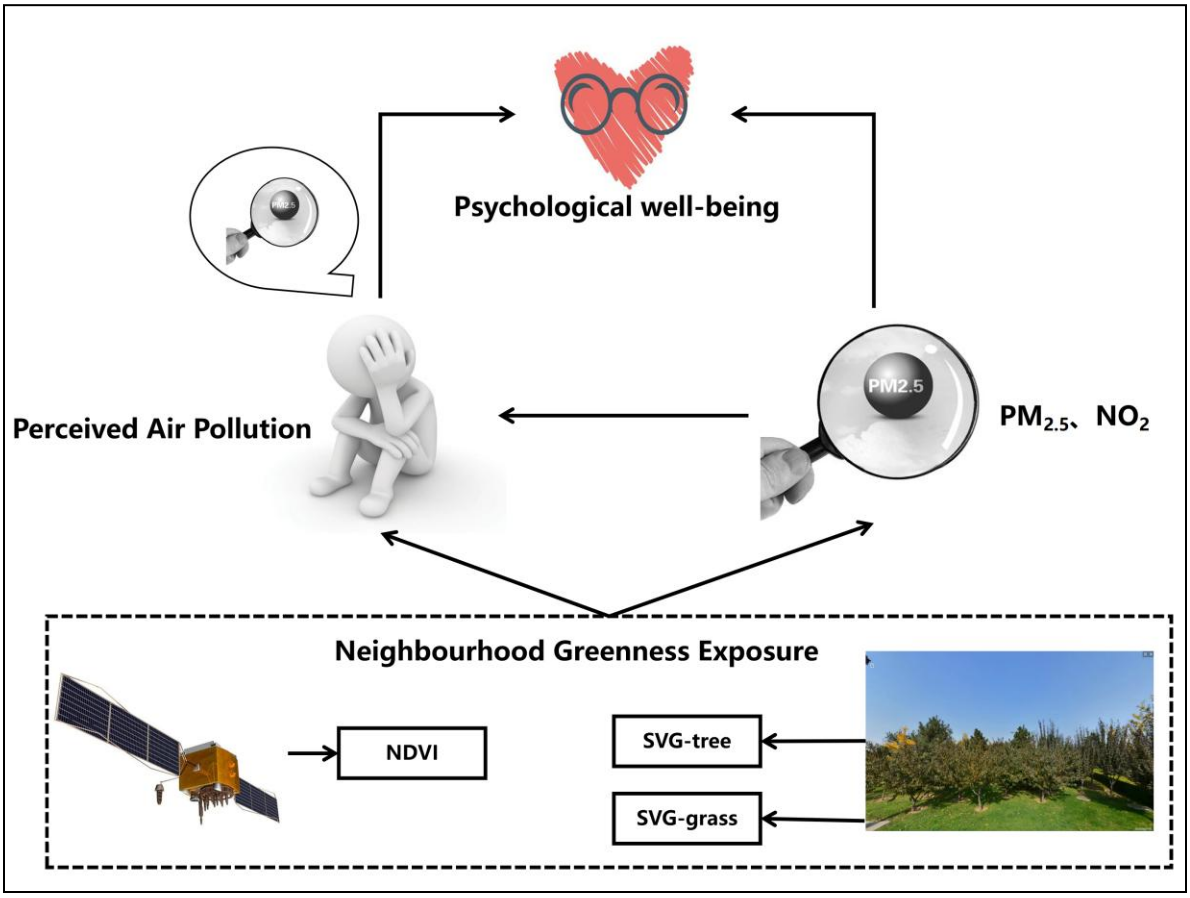
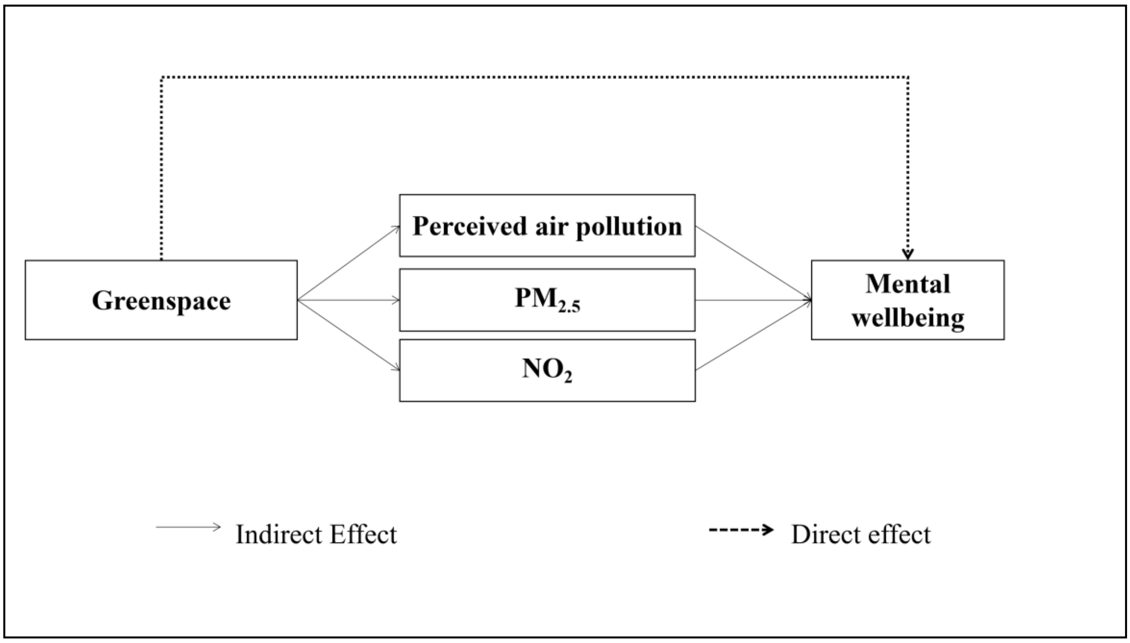
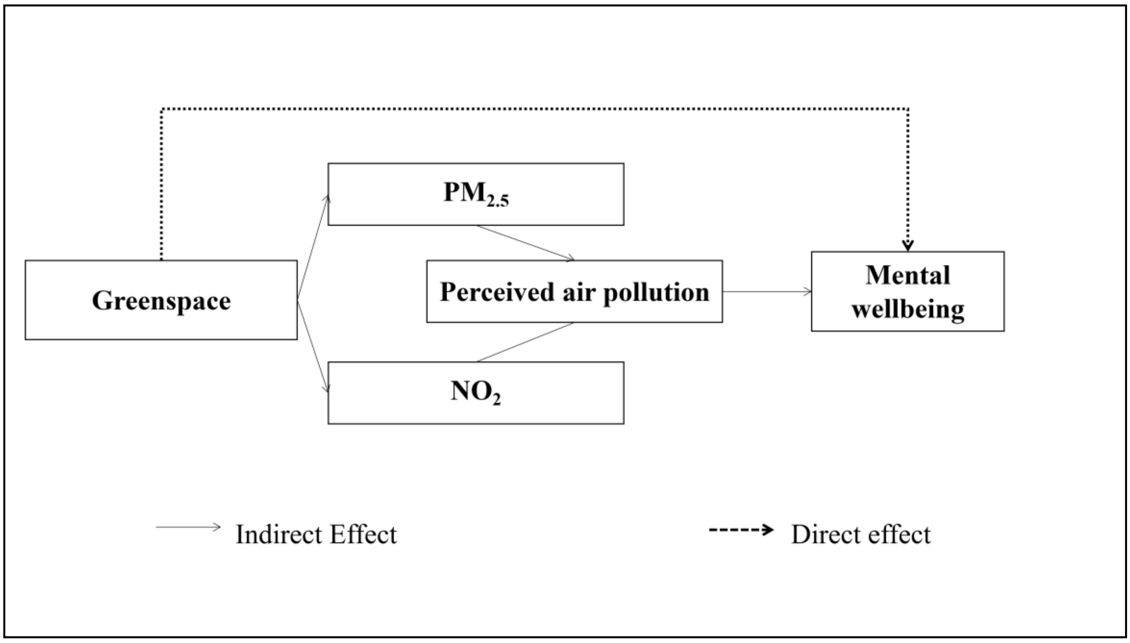


Fig 1. Theoretical framework describing the nature of associations among psychological well-being, air quality and neighbourhood greenness

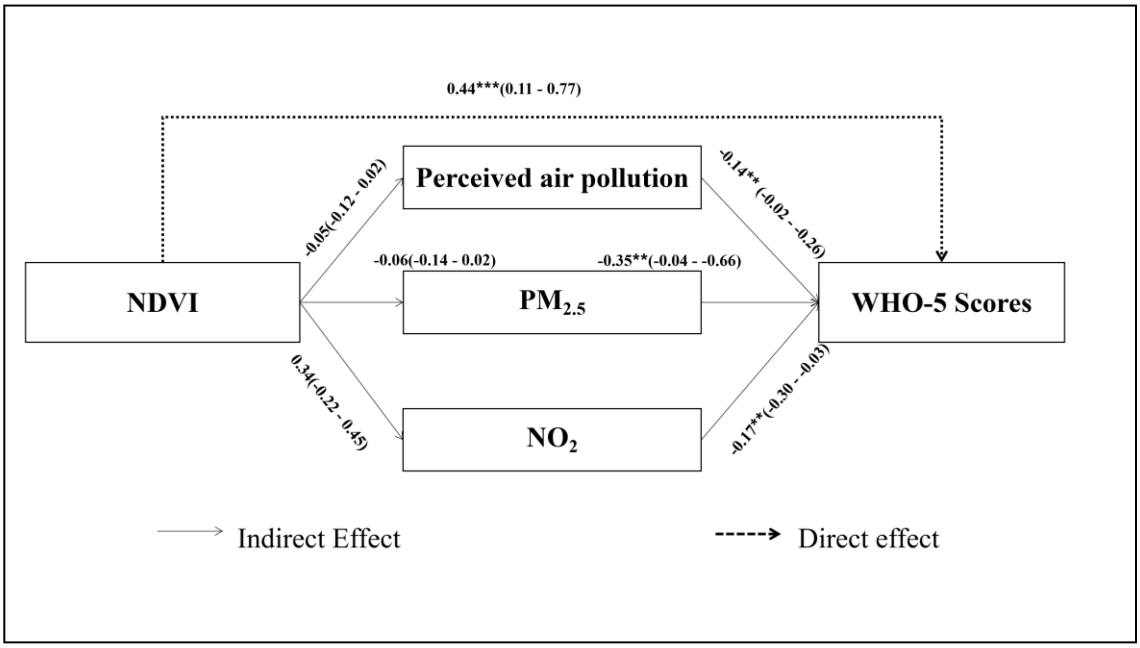


(A)

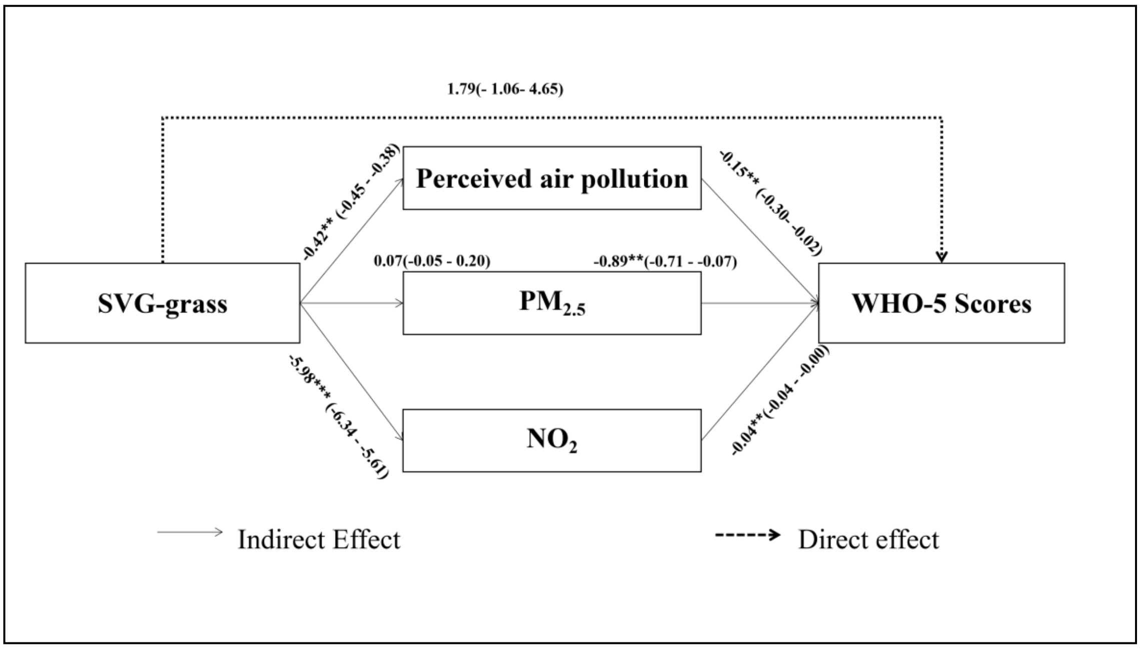


(B)

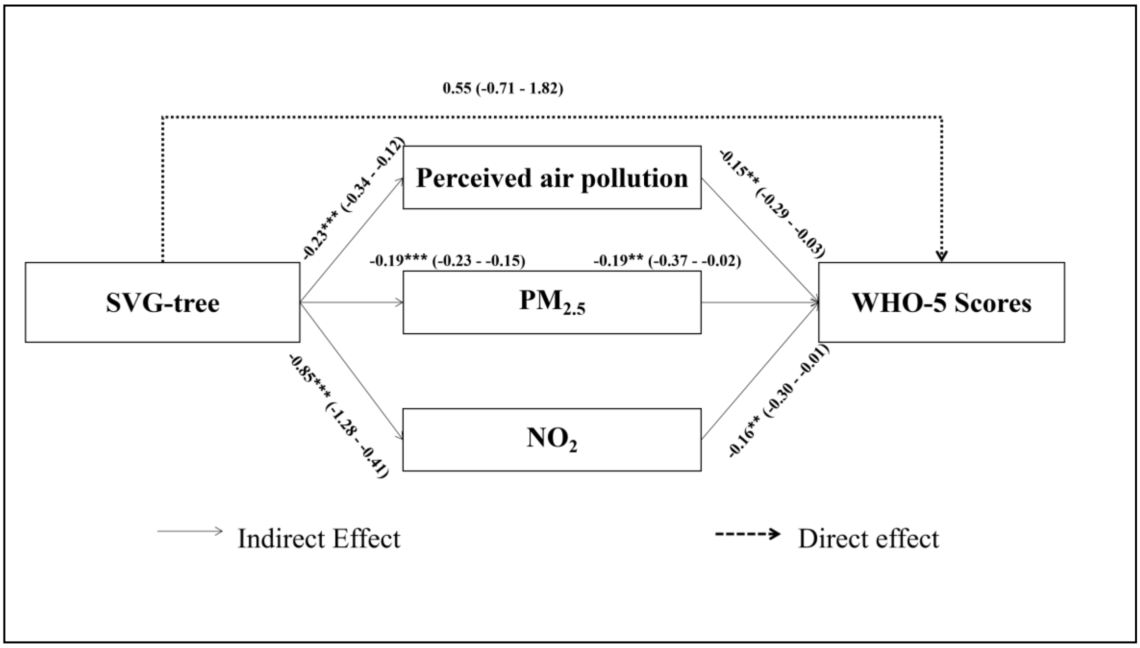
Fig 2. Conceptual diagrams of two approaches for modelling pathways linking greenspace to psychological wellbeing. A- parallel mediation model, for which the mediators were assumed to act independently. B- serial mediation models, for which objective air pollution measures were assumed to influence subjective air pollution measurement.


0.44***(0.11 - 0.77)
Perceived air pollution
-0.05(-0.12 - 0.02)
-0.14** (-0.02 - -0.26)
-0.06(-0.14 - 0.02)
-0.35**(-0.04 - -0.66)
NDVI
PM2.5
WHO-5 Scores
0.34(-0.22 - 0.45)
-0.17**(-0.30 - -0.03)
NO2
Indirect Effect
Direct effect

(A)

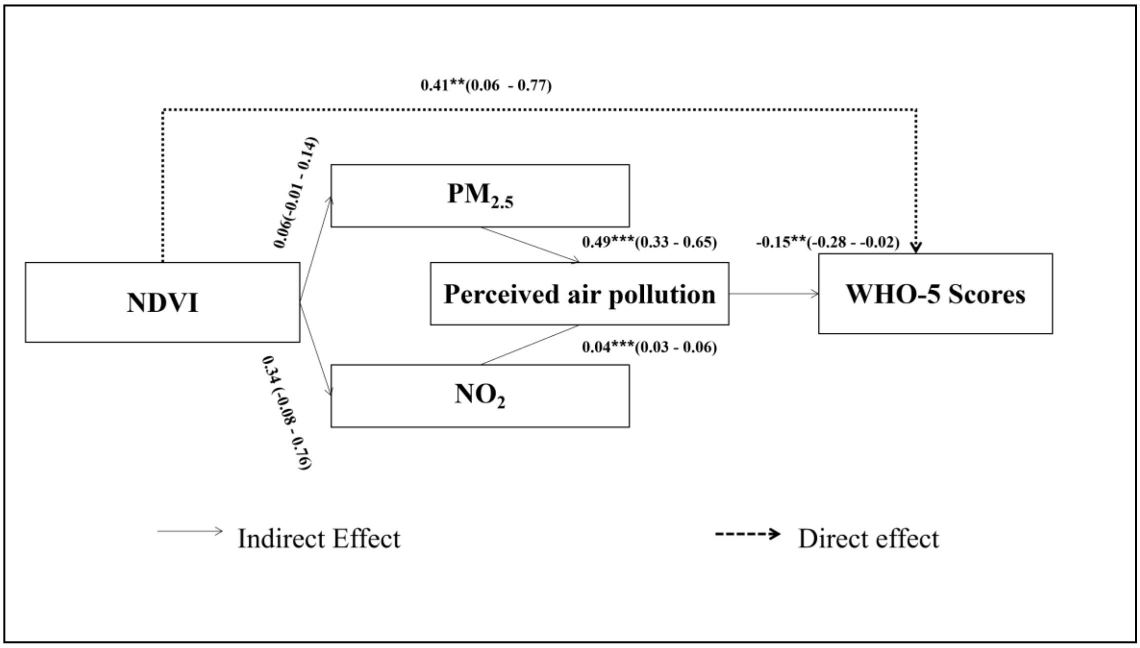

1.79(- 1.06- 4.65)
Perceived air pollution
-0.42** (-0.45 - -0.38)
-0.15** (-0.30- -0.02)
0.07(-0.05 - 0.20)
-0.89**(-0.71 - -0.07)
SVG-grass
PM2.5
WHO-5 Scores
-5.98*** (-6.34 - -5.61)
-0.04**(-0.04 - -0.00)
NO2
Indirect Effect
Direct effect

(B)

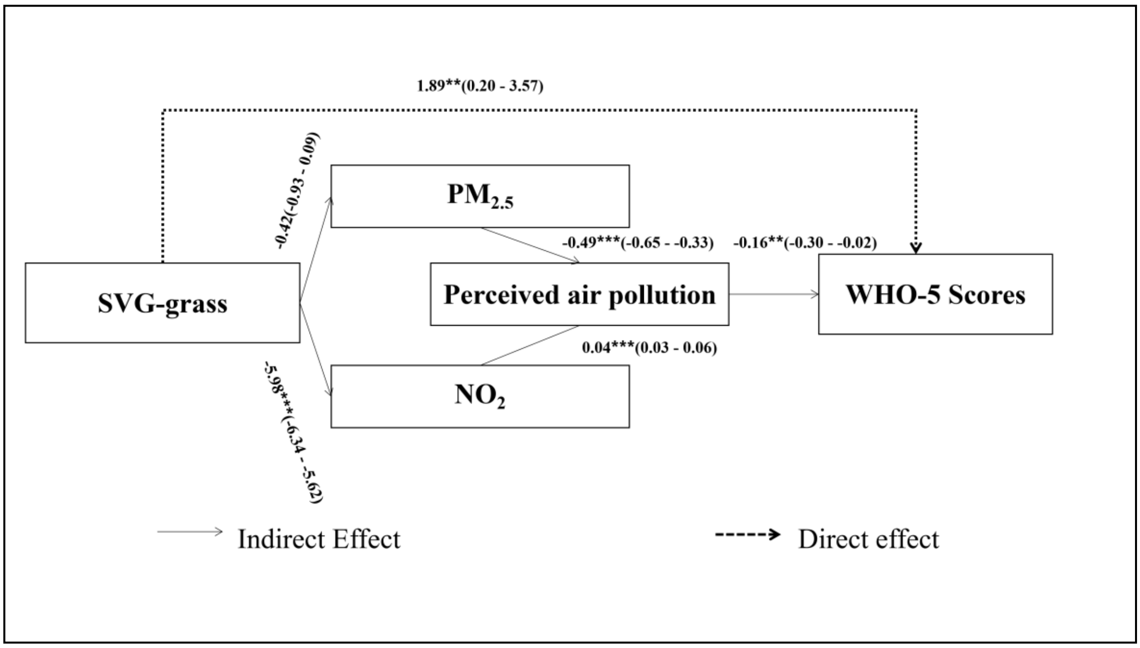


(C)

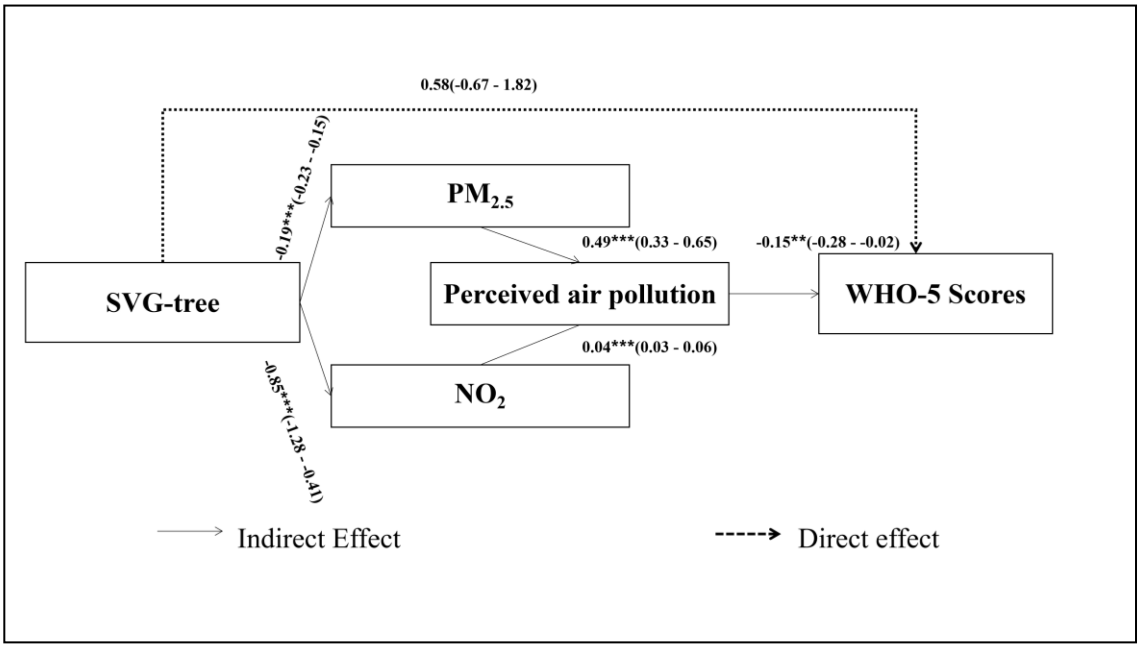
Fig 3. Coefficients of the multilevel structural equation model for parallel mediation, for which the mediators were assumed to act independently. A- NDVI as the greenspace indicator. B- SVG-grass as the greenspace indicator. C- SVG-tree as the greenspace indicator. Coefficients (with robust standard errors) of the SEM. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.


0.41**(0.06 - 0.77)
0.06(-0.01 - 0.14)
PM2.5
0.49***(0.33 - 0.65)
-0.15**(-0.28 - -0.02)
NDVI
Perceived air pollution
WHO-5 Scores
0.04***(0.03 - 0.06)
0.34 (-0.08 - 0.76)
NO2
Indirect Effect
Direct effect

(A)


1.89**(0.20 - 3.57)
-0.42(-0.93 - 0.09)
PM2.5
-0.49***(-0.65 - -0.33)
-0.16**(-0.30 - -0.02)
SVG-grass
Perceived air pollution
WHO-5 Scores
0.04***(0.03 - 0.06)
-5.98***(-6.34 - -5.62)
NO2
Indirect Effect
Direct effect

(B)



(C)

Fig 4. Coefficients of the multilevel structural equation model for serial mediation, for which the objective air pollution measures were assumed to influence subjective air pollution measurement. A- NDVI as the greenspace indicator. B- SVG-grass as the greenspace indicator. C- SVG-tree as the greenspace indicator. Coefficients (with robust standard errors) of the SEM. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Declaration of interests

None