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

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

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

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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 (PM<sub>2.5</sub> and NO<sub>2</sub> 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<sub>2</sub>, the relationship between SVG-tree and psychological well-being was completely mediated by ambient PM<sub>2.5</sub>, NO<sub>2</sub> 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<sub>2</sub>-perceived air pollution, SVG-tree was partially mediated by both ambient PM<sub>2.5</sub>-perceived air pollution and NO<sub>2</sub>-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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Response: As suggested, we added the combination model in supplement file. Also, the results were reported in the text. "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)." (page 18 line 348)

Reviewer comment 2: Finally, the gSEM graphs - I would really add the random intercept to NO<sub>2</sub> and PM<sub>2.5</sub> as well, but we can live with the model as it is.

Response: Thanks for your comments. However, NO<sub>2</sub> and PM<sub>2.5</sub> were measured in neighbourhood, so they did not have variance within neighbourhood which prevents us from adding random intercept term.

### Research Data Related to this Submission

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There are no linked research data sets for this submission. The following reason is given:

The authors do not have permission to share data

1 Running title: Greenness, air pollution and psychological well-being  
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6 **Residential greenness, air pollution and psychological well-being among urban**  
7 **residents in Guangzhou, China**  
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1 **Abstract**

2 China' s rapid urbanization has led to an increasing level of exposure to air pollution and a  
3 decreasing level of exposure to vegetation among urban populations. Both trends may pose  
4 threats to psychological well-being. Previous studies on the interrelationships among  
5 greenness, air pollution and psychological well-being rely on exposure measures from remote  
6 sensing data, which may fail to accurately capture how people perceive vegetation on the  
7 ground. To address this research gap, this study aimed to explore relationships among  
8 neighbourhood greenness, air pollution exposure and psychological well-being, using survey  
9 data on 1029 adults residing in 35 neighbourhoods in Guangzhou, China. We used the  
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12 and grasses (SVG-grass) when generating streetscape greenery exposure metrics. We used  
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14 pollution) measure to quantify air pollution exposure. We quantified psychological well-being  
15 using the World Health Organization Well-Being Index (WHO-5). Results from multilevel  
16 structural equation models (SEM) showed that, for parallel mediation models, while the  
17 association between SVG-grass and psychological well-being was completely mediated by  
18 perceived air pollution and NO2, the relationship between SVG-tree and psychological  
19 well-being was completely mediated by ambient PM2.5, NO2 and perceived air pollution.  
20 None of three air pollution indicators mediated the association between psychological  
21 well-being and NDVI. For serial mediation models, measures of air pollution did not mediate  
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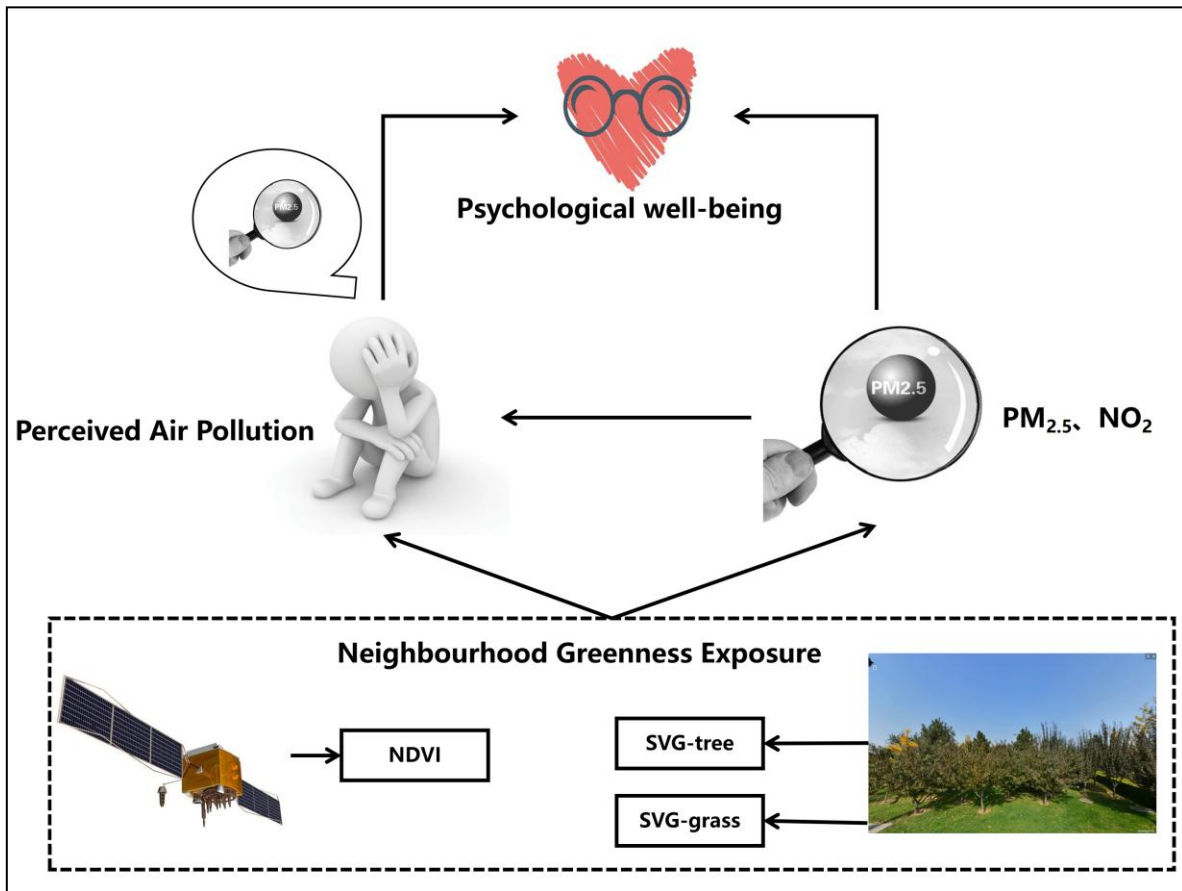
23 SVG-grass and psychological well-being scores was partially mediated by NO<sub>2</sub>-perceived air  
24 pollution, SVG-tree was partially mediated by both ambient PM<sub>2.5</sub>-perceived air pollution  
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26 lower air pollution levels and better mental health than grasses are.

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

28



29 Graphical abstract



30

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33

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

35

36 Highlights

37

38 • Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG)  
39 were used to assess greenness exposure, and trees (SVG-tree) and grasses (SVG-grass)  
40 were distinguished when generating streetscape greenery exposure metrics.

41 • Both objective (PM<sub>2.5</sub> and NO<sub>2</sub> concentrations) and subjective (perceived air pollution)  
42 measures were used to quantify air pollution exposure.

43 • NDVI, SVG-tree and SVG-grass were positively associated with psychological  
44 well-being.

45 • The streetscape greenery-mental health association was mediated by ambient PM<sub>2.5</sub>,  
46 NO<sub>2</sub> and perceived air pollution in parallel mediation models.

47 • The streetscape greenery-mental health association was mediated by ambient  
48 PM<sub>2.5</sub>-perceived air pollution and NO<sub>2</sub>-perceived air pollution in serial mediation  
49 models

50 • Neither measures of air pollution mediated the association between NDVI and  
51 psychological well-being.

52

53 **Abbreviations:** CI= confidence interval; NDVI, normalized difference vegetation index;  
54 NO<sub>2</sub>= nitrogen dioxide; PM<sub>2.5</sub>, particles  $\leq 2.5$   $\mu\text{m}$  in aerodynamic diameter; q25, first  
55 quartile; q75, third quartile; SVG-grass, street view images-based greenness assessed in  
56 density of grasses; SVG-tree, street view images-based greenness assessed in density of trees;  
57 WHO-5, World Health Organization Well-Being Index; .

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## 75 **1. Introduction**

76 China urbanized very rapidly over the past 40 years, with the proportion of urban residents  
77 having grown from approximately 18% in 1978 to 56% in 2015 (NBSC, 2016). While  
78 development has brought economic benefits, it has diminished opportunities for contact with  
79 nearby vegetation, limiting exposure to “greenness” (Hartig et al., 2014; Markevych et al.,  
80 2017; Nieuwenhuijsen et al., 2017), and increased the risk of exposure to air pollution (Chen  
81 et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).

82

83 Multiple cross-sectional (Banay et al., 2019; Hystad et al., 2019; Lee et al., 2019; Sarkar et  
84 al., 2018; Song et al., 2019) and longitudinal (Alcock et al., 2014; Astell-Burt et al., 2014;  
85 Feng and Astell-Burt, 2017, 2018) epidemiologic investigations have reported positive  
86 associations between greenness and psychological well-being. Neighbourhood greenness may  
87 benefit psychological well-being by mitigating pathophysiologic processes that lead to  
88 neuroinflammation, cerebrovascular damage and neurodegeneration (Kioumourtzoglou et al.,  
89 2017; Buoli et al., 2018). Greenness surrounding residential areas is found to encourage  
90 physical activities (Maas et al., 2008; Richardson et al., 2013; Sugiyama et al., 2008; van den  
91 Berg et al., 2019) and social contact among neighbours, thereby benefitting psychological  
92 well-being (de Vries et al., 2013; Maas et al., 2009; Sugiyama et al., 2008). In addition,  
93 greenspace has been shown to be a resource for psychological restoration, which indicates it  
94 can reduce psychological stress (Kaplan, 1995; Hartig, 2008; Hartig et al., 2014; Ulrich et al.,  
95 1991).

96

97 Scholars have increasingly become concerned about the adverse effects of air pollution on  
98 psychological well-being (Buoli et al., 2018; Kampa and Castanas, 2008; Lim et al., 2012;  
99 Wang et al., 2019a; Wang et al., 2018; Wang et al., 2014). Rapid urbanization and  
100 industrialization is normally accompanied by an increased risk of exposure to air pollution  
101 (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).  
102 Previous studies showed that air pollution may discourage physical activities and decrease  
103 people's willingness to socialize with their neighbours in outdoor settings (An and Xiang,  
104 2015; Roberts et al., 2014; Wang et al., 2019a). Thus, less exposure to greenness and greater  
105 exposure to air pollution may threaten the psychological well-being of urban populations  
106 (Chen and Nakagawa, 2018).

107

108 Recent reviews suggest that neighbourhood greenery may protect psychological well-being  
109 by mitigating environmental stressors such as air pollution (Hartig et al., 2014; Markevych et  
110 al., 2017; Nieuwenhuijsen et al., 2017). Some studies have reported a significant role for air  
111 pollution in mediating associations between greenness exposure and health (Gascon et al.,  
112 2018; James et al., 2016; Thiering et al., 2016; Yang et al., 2019), whereas others have found  
113 no solid evidence (Dzhambov et al., 2018a, b; Vienneau et al., 2017; Yitshak-Sade et al.,  
114 2017). Yet, previous studies on the interrelationships among neighbourhood greenness, air  
115 pollution and psychological well-being rely on exposure measures from remote sensing (i.e.,  
116 satellite) data, which may fail to accurately capture how people perceive vegetation on the  
117 ground (Dzhambov et al., 2018a, b; Gascon et al., 2018; Liu et al., 2019a, b; Wang et al.,  
118 2019b). There has been little research on the association between greenspace and mental

119 health in China to date, and, studies have mainly focused on the direct effect of greenspace on  
120 health (Liu et al., 2019a, b; Wang et al., 2019b).

121

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

131

(Fig 1 about here)

132

## 134 **2. Data and methods**

### 135 ***2.1. Study population***

136 We enrolled 1029 study participants between June and August 2016. We first selected 35  
137 residential neighbourhoods (with mean  $\pm$  SD area =1.91 km<sup>2</sup>  $\pm$  574.691 m<sup>2</sup>. Total area=  
138 66.85km<sup>2</sup>) from six districts in Guangzhou city (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe and  
139 Liwan), using a multi-stage stratified sampling method with probabilities proportionate to  
140 population sizes. We then randomly chose 30 households from each neighbourhood. Finally,

141 we randomly enrolled one adult from each household using the Kish Grid method (Kish,  
142 1949). Thus, 35 neighbourhoods x 30 household x 1 person/household = 1050 participants.  
143 However, 21 potential participants did not complete the study questionnaire, so the final  
144 sample size in this study was 1029 (98% participation rate). The study protocol was approved  
145 by the Sun Yat-sen University Research Ethics Committee, and all participants completed  
146 informed consent prior to enrollment.

147

## 148 ***2.2 Psychological well-being assessment***

149 Study participants were invited to complete the World Health Organization five-item  
150 Well-Being Index (WHO-5) (Heun et al., 2001). The WHO-5 questions evaluate respondents'  
151 psychological feelings over the previous two weeks, including: "I have felt cheerful and in  
152 good spirits", "I have felt calm and relaxed", "I have felt active and vigorous", "I woke up  
153 feeling fresh and rested" and "My daily life has been filled with things that interest me". Each  
154 item is scored on a 6-point Likert scale, ranging from "never" to "every time", and the total  
155 score ranges from 0 to 25. Greater values indicate better psychological well-being. The  
156 WHO-5 has been shown to have good validity and reliability in many countries (Krieger et al.,  
157 2014) and has been validated in China. In our sample, the questionnaire had good reliability  
158 (test-retest reliability=0.995,  $p<0.01$ ), and the Cronbach's alpha (0.815) indicated high  
159 internal consistency.

160

## 161 ***2.3 Residential greenness assessment***

### 162 ***2.3.1 NDVI***

163 We used the satellite-based NDVI (Tucker, 1979) as a surrogate of neighbourhood greenness  
164 exposure. We used satellite images from Landsat8 OLI (Operational Land Imager) and TIRS  
165 (Thermal Infrared Sensor) at a 30 m × 30 m spatial resolution to calculate the NDVI in 1000  
166 m buffers around the centroid of each study neighbourhood. Remote sensing data were  
167 obtained for the year 2016 from the USGS EarthExplorer (<https://earthexplorer.usgs.gov/>).  
168 We used cloud-free images in the greenest month of the year (August) to avoid distortions.  
169 Guangzhou has a subtropical climate, so most of its vegetation stays green year round. We  
170 omitted pixels with a negative NDVI value before averaging across each study  
171 neighbourhood, following the approach employed in previous studies (Markevych et al.,  
172 2017).

173

### 174 2.3.2 SVG-tree and SVG-grass

175 We also used street-view imagery-based greenness indices as surrogates of neighbourhood  
176 greenness exposure. We calculated the SVG using street-view imagery from Tencent (Lu et  
177 al., 2018; Lu, 2019; Helbich et al., 2019; Wang et al., 2019b, c). First, we collected a series of  
178 street view images from Tencent Online Map [<https://map.qq.com>], the most comprehensive  
179 online street view image database in China, as described previously (Helbich et al., 2019;  
180 Wang et al., 2019b, c). Street view sampling points were identified 100 m apart along the  
181 local road network, which was obtained from OpenStreetMap (Haklay and Weber, 2008). For  
182 each sampling point, we collected street view images from 0, 90, 180 and 270 degrees  
183 (Helbich et al., 2019; Wang et al., 2019b, c). We collected 125,656 street view images from  
184 31,414 sampling points in this study.



185

186 We distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating  
187 streetscape greenery exposure metrics, using a machine learning approach based on semantic  
188 image segmentation techniques. We employed a fully convolutional neural network for  
189 semantic image segmentation (FCN-8s), which has been shown to be capable of identifying  
190 150 types of ground objects (e.g., trees and grasses) accurately (Kang and Wang, 2014; Long  
191 et al., 2015). Our training model was based on the online ADE20K annotated images data set  
192 (Zhou et al., 2019). The accuracy of the FCN-8s was 81% for the training data and 80% for  
193 the test data. Following previous studies (Helbich et al., 2019; Wang et al., 2019b, c),  
194 SVG-tree and SVG-grass at each sampling point were determined as the proportion of tree or  
195 grass pixels per image summed over the four cardinal directions (i.e., 0, 90, 180 and 270  
196 degrees) relative to the total number of pixels per image summed over the four cardinal  
197 directions. We calculated the SVG-tree and SVG-grass for each neighbourhood by averaging  
198 the SVG-tree and SVG-grass scores for all sampling points within 1000 m circular buffers  
199 around the centroid of each study neighbourhood.

200

## 201 ***2.4 Air pollution assessment***

### 202 *2.4.1 PM<sub>2.5</sub> and NO<sub>2</sub> concentrations*

203 We assessed exposure to air pollution using predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations within a  
204 1000 m circular buffer around the geographic centroid of study neighbourhoods. We used the  
205 2016Global Annual PM<sub>2.5</sub> data grid, generated using MODIS, MISR and SeaWiFS Aerosol  
206 Optical Depth (AOD) data with geographically weighted regression, and available from the

207 NASA Socioeconomic Data and Applications Center (SEDAC) at a 1000 m × 1000 m spatial  
208 resolution (van Donkelaar et al., 2016; 2018). Nitrogen dioxide (NO<sub>2</sub>) concentrations were  
209 also extracted from a globally available land use regression model with a spatial resolution of  
210 100 m (Larkin et al., 2017). We calculated the annual average PM<sub>2.5</sub> and NO<sub>2</sub> concentrations  
211 using the average pixel value within the 1000 m circular buffer around the centroid of each  
212 study neighbourhood.

213

#### 214 *2.4.2 Perceived air pollution*

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

220

#### 221 *2.5 Covariates*

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

229

## 230 *2.6 Statistical analysis*

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

238

239 We used two approaches to model pathways linking greenspace to psychological well-being  
240 and to evaluate the mediating effect of air pollution, presuming no interaction between the  
241 exposures and mediators. We used parallel mediation models, in which the mediators were  
242 assumed to act independently, and serial mediation models, in which objective air pollution  
243 measures were assumed to have an influence on subjective measures of air pollution and in  
244 turn, on psychological well-being. First, we fitted the parallel mediation model (Fig 2 A) with  
245 three parallel mediators (PM<sub>2.5</sub>, NO<sub>2</sub> and perceived air pollution). Also, we used different  
246 measures of greenness as described above. Second, we fitted the serial mediation model (Fig  
247 2 B), which assumed that residential greenness could affect mental wellbeing through actual  
248 exposure to air pollution (PM<sub>2.5</sub> and NO<sub>2</sub>) and the perception of air pollution. Again, we  
249 used different measures of greenspace. Third, we calculated the direct and indirect effects in  
250 the parallel mediation model and in the serial mediation model based on the approach

251 proposed by Hayes (2013) and Zhao et al. (2010). We used bootstrapping (5000 samples) to  
252 obtain bias-corrected 95% CIs of for each paths (Hayes,2013; Zhao et al., 2010). Goodness of  
253 fit was assessed by standardized root mean square residual (SRMSR), root mean square error  
254 of approximation (RMSEA), and comparative fit index (CFI). Hu and Bentler (1999)  
255 suggested that the acceptable model fit should be as follows: RMSEA ( $\leq 0.06$ , 90% CI  $\leq$   
256 0.06), SRMSR ( $\leq 0.08$ ), and CFI ( $\geq 0.95$ ). The detailed information for SEM was shown in  
257 Fig S1.

258

259 (Fig 2 about here)

260

261 To assess the robustness of our results, we repeated our analyses using 800m and 1500m  
262 neighbourhood buffers instead of 1000m buffers when measuring exposure to residential  
263 greenness and air pollution (results available on request). For all analyses, we defined  
264 statistical significance as  $P < 0.05$  for a 2-tailed test. STATA v.15.1 was used for the statistical  
265 analysis (STATA, Inc. College Station, TX USA).

266

## 267 **3. Results**

### 268 *3.1 Descriptive statistics*

269 The characteristics of the study population are summarized in Table 1; there was no missing  
270 data. About half of participants were male (50.2%) and the average age was 41.2 years. Most  
271 respondents were married (78.3%) and were registered as temporary residents (77.8%).  
272 Approximately 50.0% of respondents had a high school education and 47.4% possessed a

273 college level education. Most respondents earned 3000-6999 Chinese Yuan per year (70.7%),  
274 and had medical insurance (97.1%).

275

276 The average WHO-5 scores for all respondents was 12.08 (SD: 3.71). The median score for  
277 NDVI was 0.10 (IQR=0.04), while median scores for SVG-tree and SVG-grass were 0.24  
278 (IQR=0.07) and 0.01 (IQR=0.02), respectively. There were no statistically significant  
279 correlations between NDVI and SVG-tree score ( $r_{sp}=-0.16$ ,  $p=0.23$ ), or SVG-grass score  
280 ( $r_{sp}=-0.45$ ,  $p=0.15$ ), or between SVG-grass score and SVG-tree score ( $r_{sp}=0.56$ ,  $p=0.09$ ).

281 Average neighbourhood  $PM_{2.5}$  and  $NO_2$  concentrations and perceived air pollution scores  
282 were 35.97 and 28.21  $\mu g/m^3$  and 3.06, respectively, although the values were uncorrelated  
283 ( $p>0.05$ ).

284

285 (Table 1 about here)

286

### 287 ***3.2 Associations between greenness exposure, air pollution and psychological well-being:***

#### 288 ***Parallel mediation model***

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

295 1-IQR greater NDVI was significantly and directly associated with 0.44-unit higher WHO-5  
296 score. There was no evidence to suggest that NDVI could influence WHO-5 scores through  
297 an indirect effect.

298

299 (Fig 3 about here)

300 (Table 2 about here)

301

302 Fig. 3 (B) also shows that SVG-grass was negatively associated with NO<sub>2</sub> concentration and  
303 perceived air pollution, which all were negatively associated with WHO-5 scores. However,  
304 there was no evidence to suggest that SVG-grass was also associated with PM<sub>2.5</sub> or directly  
305 associated with WHO-5 score. Table 2 indicates that a 1-IQR greater SVG-grass was  
306 significantly and indirectly associated with a 0.06-unit higher WHO-5 score through  
307 perceived air pollution and a 0.23-unit higher WHO-5 score through NO<sub>2</sub> concentration.  
308 There was no evidence to suggest that SVG-grass could directly influence WHO-5 score.

309

310 Fig. 3 (C) shows that SVG-tree was negatively associated with PM<sub>2.5</sub>, NO<sub>2</sub> and perceived  
311 air pollution, which all were negatively associated with WHO-5 score. However, there was no  
312 evidence that SVG-tree was directly associated with WHO-5 score. Table 2 indicated that a  
313 1-IQR greater SVG-tree was significantly and indirectly associated with 0.03-unit higher  
314 (95% CI: 0.002-0.07) WHO-5 score through perceived air pollution, a 0.04-unit higher (95%  
315 CI: 0.003-0.07) WHO-5 score through PM<sub>2.5</sub>, and a 0.14-unit higher (95% CI 0.01-0.26)  
316 WHO-5 score through NO<sub>2</sub>. There was no evidence of a direct SVG-tree effect on WHO-5

317 scores.

318

### 319 ***3.3 Associations between greenness exposure, air pollution and psychological well-being:***

#### 320 ***Serial mediation model***

321 We obtained a reasonably well-fitting final serial mediation model: SRMSR = 0.031, RMSEA  
322 = 0.029 (90% CI: 0.020, 0.045), CFI = 0.966. Fig. 4 (A) reports path coefficients and 95% CI  
323 for serial mediation model in the multi-level SEM. NDVI was positively and directly  
324 associated with WHO-5 score. Although, PM<sub>2.5</sub> and NO<sub>2</sub> were both significant positively  
325 associated with perceived air pollution, which was negatively associated with WHO-5 scores,  
326 there was no evidence that NDVI was correlated to PM<sub>2.5</sub> or NO<sub>2</sub>. Table 3 also shows that  
327 each IQR greater NDVI was significantly and directly associated with 0.41-unit higher (95%  
328 CI: 0.06-0.77) WHO-5 score in the serial mediation model. There was no evidence of an  
329 indirect NDVI effect on WHO-5 scores.

330

331 (Fig 4 about here)

332 (Table 3 about here)

333

334 Fig. 4 (B) shows that SVG-grass was positively and directly associated with WHO-5 score.  
335 SVG-grass was negatively associated with NO<sub>2</sub>, which was positively associated with  
336 perceived air pollution. However, there was no association of SVG-grass with PM<sub>2.5</sub>. Table 3  
337 indicates that a 1-IQR greater SVG-grass was significantly and directly associated with a  
338 1.89-unit higher WHO-5 score. A 1-IQR greater SVG-grass was also significantly and

339 indirectly associated with a 0.04-unit higher WHO-5 score through the serial NO<sub>2</sub>-perceived  
340 air pollution pathway. Yet, there was no evidence that SVG-grass could influence WHO-5  
341 score through the serial PM<sub>2.5</sub>-perceived air pollution pathway.

342

343 Fig. 4 (C) shows that SVG-tree was negatively associated with PM<sub>2.5</sub> and NO<sub>2</sub> concentrations,  
344 which were positively associated with perceived air pollution. However, there was no  
345 evidence for a direct association between SVG-tree and WHO-5 score. Table 3 indicates that  
346 each IQR greater SVG-tree was significantly and indirectly associated with 0.01-unit higher  
347 WHO-5 score through both the NO<sub>2</sub>-perceived air pollution and the PM<sub>2.5</sub>-perceived air  
348 pollution serial pathways. Still, there was no evidence supporting that SVG-tree directly  
349 influenced WHO-5 score

350

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

354

## 355 **4. Discussion**

### 356 ***4.1 Key findings***

357

358 We found that greenness exposure was positively associated with psychological well-being  
359 and that air pollution exposure in part mediated the association in this cross-sectional  
360 investigation of an urban Chinese study population. More specifically, we found that NDVI,



361 SVG-tree score and SVG-grass score correlated with WHO-5 score. For parallel mediation  
362 models, while the association between SVG-grass and WHO-5 scores was completely  
363 mediated by perceived air pollution and NO<sub>2</sub>, the relationship between SVG-tree and WHO-5  
364 scores was completely mediated by ambient PM<sub>2.5</sub>, NO<sub>2</sub> and perceived air pollution. In  
365 addition, none of three air pollution indicators mediated the association between WHO-5  
366 scores and NDVI. For serial mediation models, measures of air pollution did not mediate the  
367 relationship between NDVI and WHO-5 scores. While the linkage between SVG-grass and  
368 WHO-5 scores was partially mediated by NO<sub>2</sub>-perceived air pollution, the relationship for  
369 SVG-tree was partially mediated by both ambient PM<sub>2.5</sub>-perceived air pollution and  
370 NO<sub>2</sub>-perceived air pollution. To the best of our knowledge, this is the first report of parallel  
371 and serial mediating effects for reported associations between greenness exposure and  
372 psychological well-being which distinguishes exposure to SVG-grass from exposure to  
373 SVG-tree.

374

#### 375 ***4.2 Greenness and psychological well-being***

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

383 Triguero-Mas et al., 2015) reported negative associations between neighbourhood greenness  
384 exposure measured as NDVI and the odds of reporting a history of doctor-diagnosed  
385 depressive disorder. The association between greenness exposure and psychological  
386 well-being as measured with WHO-5 was strongest in our results for SVG-tree, weakest for  
387 NDVI, and with moderate effect estimates for SVG-grass. Our satellite-based NDVI and  
388 street view images-based SVG were uncorrelated. This finding is consistent with previous  
389 findings from China (Helbich et al., 2019) and the U.S. (Larkin and Hystad, 2018), which  
390 also reported weak correlations between satellite-based and street view images-based  
391 measures of greenness, as well as an inverse association for greenness exposure and geriatric  
392 depression (Helbich et al., 2019). Though less widely employed than satellite-based  
393 approaches, street view images may be a useful tool for greenness assessments, as they  
394 capture different aspects of neighbourhood environments (Villeneuve et al, 2018;  
395 Weichenthal et al., 2019). Epidemiological studies of greenness and human health frequently  
396 employed the NDVI (Banay et al., 2019; Markevych et al., 2014a, 2016), presence of  
397 greenspace (Triguero-Mas et al., 2015; 2017), greenspace availability (Triguero-Mas et al.,  
398 2015; 2017), access to greenspace (Markevych et al., 2014b) or proximity to the nearest park  
399 (Fan et al., 2011) to assess neighbourhood greenness. However, these approaches are limited  
400 by an inability to differentiate types of vegetation, an issue that we addressed by measuring  
401 SVG-tree and SVG-grass.

402

### 403 ***4.3 Air pollution and psychological well-being***

404 Our results also suggest that poorer air quality may exert a pejorative effect on psychological

405 well-being. These results are consistent with previous reports originating both from  
406 developed (Kim et al., 2016b; Lim et al., 2012; Pun et al., 2016) and developing nations  
407 (Wang et al., 2018, 2019a). For example, greater concentrations of ambient PM<sub>2.5</sub> were  
408 cross-sectionally associated with more severe symptoms of anxiety and depression in a  
409 nationally representative sample of the U.S. population 57-85 years of age (Pun et al., 2016).  
410 Greater PM<sub>2.5</sub> exposure was also associated with more severe depressive symptoms in a  
411 Chinese study population (Wang et al., 2018; 2019a). This association might be explained in  
412 part by the “constrained restoration” hypothesis, indicating that air pollution may influence  
413 psychological well-being by undermining residents’ perception of greenness’s restorative  
414 quality (von Lindern et al., 2016). We also found associations between greater ambient PM<sub>2.5</sub>  
415 and poor psychological well-being captured with WHO-5. Prior evidence suggested negative  
416 associations between psychological health and perceived air pollution in Bulgaria (Dzhambov  
417 et al., 2018a; 2018b). Rather than offering an accurate surrogate for airborne hazards,  
418 perceived air pollution may be interpreted aesthetically, as adverse odors for example,  
419 affecting psychological well-being through annoyance rather than pathophysiology (Claeson  
420 et al., 2013). Yet, objective (i.e., ambient NO<sub>2</sub> monitoring) and subjective measures of air  
421 quality were similar in Lyon, France in all but the elderly subpopulation (Deguen et al.,  
422 2017).

423

#### 424 ***4.4 Air pollution as mediator of greenness-psychological well-being associations***

425 A growing literature describes negative relationships between neighbourhood greenness and  
426 surrounding air pollution levels (Dadvand et al., 2015; James et al., 2016; Pacifico et al.,

427 2009; Su et al., 2011). Improved air quality may result from diminished traffic-related  
428 air-pollutants in greener areas due to the absence of motor vehicle traffic (Dadvand et al.,  
429 2015; Su et al., 2011). Green vegetation, such as tall and dense trees, may also absorb air  
430 pollutants, mitigating airborne pollutant concentrations (Eisenman et al., 2019; Pugh et al.,  
431 2012; Yli-Pelkonen et al., 2018). However, different types of vegetation (e.g., trees and  
432 grasses) have different effects on air pollutants and on air purification. For example, trees  
433 adsorb airborne particulate and gaseous pollutants, which helps to mitigate air pollutant  
434 concentrations (Hirayabashi Nowak, 2016; Niinemets et al., 2014; Nowak et al., 2014), but  
435 analogous effects are not described for grasses in the literature.

436

437 Several observational investigations have reported statistically significant mediating effects  
438 for air pollution in associations between greenness and blood lipids (Yang et al., 2019),  
439 insulin resistance (Thiering et al., 2016) and mortality (James et al., 2016), although others  
440 did not (Vienneau et al., 2017; Yitshak-Sade et al., 2017). Still, few previous studies have  
441 evaluated air pollution as an intervening variable between greenness and psychological health  
442 to date (Markevych et al., 2017). Air pollutants mediated 0.8% (PM<sub>2.5</sub>) to 4.1% (NO<sub>2</sub>) of the  
443 inverse associations between neighbourhood greenness and self-reported use of prescription  
444 benzodiazepines by 958 Spanish adults (Gascon et al., 2018). However, studies in Bulgaria,  
445 employing NO<sub>2</sub> and perceived air pollution measures (Dzhambov et al., 2018a; 2018b), and  
446 in Switzerland (Vienneau et al., 2017) did not identify air pollution as a significant mediator  
447 of greenness-psychological well-being associations.

448

449 Similar to previous work from Bulgaria (Dzhambov et al., 2018a; Dzhambov et al., 2018b),  
450 we did not detect mediating effects for air quality on associations between psychological  
451 well-being using a satellite-based greenness index (i.e., NDVI). In contrast, Gascon and  
452 colleagues (Gascon et al., 2018) reported mediation effects for NO<sub>2</sub>, a gaseous air pollutant,  
453 which is inconsistent with our results. The reason may be that our study area is in the inner  
454 city with a high population density, so NDVI cannot accurately measure the presence of  
455 vegetation (Ye et al., 2018). Also, another reason may be that the resolution of NDVI is  
456 relatively coarse in this study which does not measure greenspace exposure in respondents  
457 exact household addresses. However, we detected mediating effects for associations of  
458 psychological well-being with street view image-based greenness indices (i.e., SVG-tree and  
459 SVG-grass). Whereas the association of WHO-5 with SVG-tree was mediated by objectively  
460 predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations, and by subjectively perceived air pollution, the  
461 association of WHO-5 with SVG-grass was mediated only by NO<sub>2</sub> and perceived air pollution.  
462 As traffic emissions are the primary source of air pollutants in urban areas like Guangzhou  
463 (Li et al., 2014; Wang et al., 2006), grasses may not be tall and dense enough to block and  
464 absorb all air pollutants (Tong et al., 2015; Vos et al., 2013). Yet, street-level grasses may still  
465 shift residents' attention and reduce stress (de Vries et al., 2013), improving the perceived  
466 environment. Rotko et al. (2002) and Egondi et al. (2013) pointed out that when people focus  
467 less on environment stressors they may perceive less pollution even when actual air pollution  
468 is severe. Thus, it is tempting to speculate that the impact of perceived air pollution was  
469 attributable to aesthetic factors in mediating the association between SVG-grass score and  
470 psychological well-being in our study. Another important finding from our serial mediation

471 models is that objectively predicted PM<sub>2.5</sub> and NO<sub>2</sub> may have influenced perceived air  
472 pollution and subsequently affected psychological well-being. Consistent with our findings,  
473 Rotko et al. (2002) found that perceived air pollution was positively associated with PM<sub>2.5</sub>  
474 and NO<sub>2</sub> concentrations. Dzhambov et al. (2018a,b) used serial mediation models to find a  
475 statistically significant serial mediating role for NO<sub>2</sub>-annoyance and perceived air  
476 pollution-restorative quality between greenspace and psychological well-being. Yet, the serial  
477 mediating effects of NO<sub>2</sub>-perceived air pollution and PM<sub>2.5</sub>-perceived air pollution have not  
478 received much attention to date. Thus, the relationship among greenspace, objective air  
479 pollution, perceived air pollution and psychological well-being need more attention in future  
480 studies.

481

#### 482 *4.5 Strengths and limitations*

483 The current study has several strengths. First, our random sampling strategy provided a  
484 representative sample of adults in Guangzhou city, enhancing generalizability and  
485 minimizing selection bias. Second, we used several measures to capture various aspects of  
486 greenness exposure, including a satellite-based vegetation index (i.e., NDVI) and street view  
487 image-based greenness indices (i.e., SVG-tree and SVG-grass). Compared with previous  
488 studies, SVG-tree and SVG-grass measured eye-level greenspace exposure in this study,  
489 which may more accurately reflect residents' actual exposure to and perception of greenspace  
490 than satellite-based measures. This allowed us to compare associations for different types and  
491 contexts of greenness exposure. Third, we evaluated air pollution using satellite based PM<sub>2.5</sub>  
492 and NO<sub>2</sub> estimates as well as perceived air pollution. This allowed us to compare the

493 mediating effects of both objective and subjective measures of air pollution. Fourth, we used  
494 a validated and reliable psychological assessment tool (i.e. WHO-5) to collect individual  
495 level study outcomes from participants. Finally, we captured and adjusted the study results  
496 for a comprehensive panel of potential confounding variables to enhance the validity of our  
497 results.

498

499 However, our study also has several limitations, and results from our analysis should be  
500 considered as preliminary. First, the cross-sectional study design prevented us from clearly  
501 establishing a temporal relationship between greenness and psychological well-being. Thus,  
502 we cannot rule out reverse causality, in which poorer psychological well-being may have led  
503 to residence in a less green neighbourhood. Second, we did not have participants' home  
504 addresses and so we measured greenness and air pollution exposures at the residential  
505 neighbourhood level, which may have misclassified some participants. Furthermore, we  
506 measured only the quantity of greenspace, whereas the quality of greenspace is also important  
507 (Van Dillen et al., 2012). We also did not measure perceived greenspace exposure in this  
508 study. Street view and remote sensing-based greenness measures were unrelated in our study,  
509 consistent with the results of previous studies (Larkin and Hystad, 2018; Helbich et al., 2019)  
510 and studies in high population density urban areas (Ye et al., 2018). The discrepancy may be  
511 due to local eye-level exposure captured by SVG while remote sensing-based greenness  
512 represents more generalized exposure. Third, our limited sample size may have provided  
513 insufficient statistical power to detect modest associations. Fourth, street view images were  
514 taken at different time points throughout 2016, so they may not reflect participants' actual

515 street-level greenspace exposure during the entire year. Fifth, we assessed only two objective  
516 measure of air pollution (i.e., PM<sub>2.5</sub> and NO<sub>2</sub>) and one measure of subjective air pollution (i.e.,  
517 perceived air pollution), and we thus are unable to draw inference on mediating effects  
518 beyond this limited profile. Sixth, we demarcated the exposure based on circular buffers,  
519 which may have led to a modifiable areal unit problem (Fotheringham and Wong, 1991).  
520 However, we found similar results when using various buffer sizes in a sensitivity analysis.  
521 Hence we did not have respondents' actual household address, so we have to measure  
522 environment exposure in neighbourhood level. Seventh, we did not consider noise, blue space  
523 and neighbourhood-level socioeconomic status data in this study, which may also be related  
524 to residents' psychological well-being (Dzhambov et al., 2018b). Eighth, NDVI is one of the  
525 predictors in the LUR (land used regression) used to generate NO<sub>2</sub> estimates, so this may  
526 have somewhat inflated the correlation with greenness measures. Last, daily exposure to  
527 greenspace was not limited to the residential environment, and the duration spent in  
528 residential neighbourhoods was not taken into account in this study (Helbich, 2008).

529

## 530 **5. Conclusions**

531 Predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations and perceived air pollution mediated (in both  
532 parallel and serial mediation models) associations between street view image-based measures  
533 of neighbourhood greenness and psychological well-being, although the effects differed  
534 between SVG-tree and SVG-grass. Yet, these factors were not important mediators of a  
535 satellite-based measure of neighbourhood greenness and psychological well-being. Our  
536 results suggest that the relationships among neighbourhood greenness, air pollution and



537 psychological well-being may vary with different exposure assessment strategies. To our  
538 knowledge, this study is the first to explore associations among neighbourhood greenness, air  
539 pollution and psychological well-being in a large Chinese city. A more definitive study is  
540 necessary to confirm our results.

541

#### 542 **Declaration of interests**

543 None

544

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547

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557

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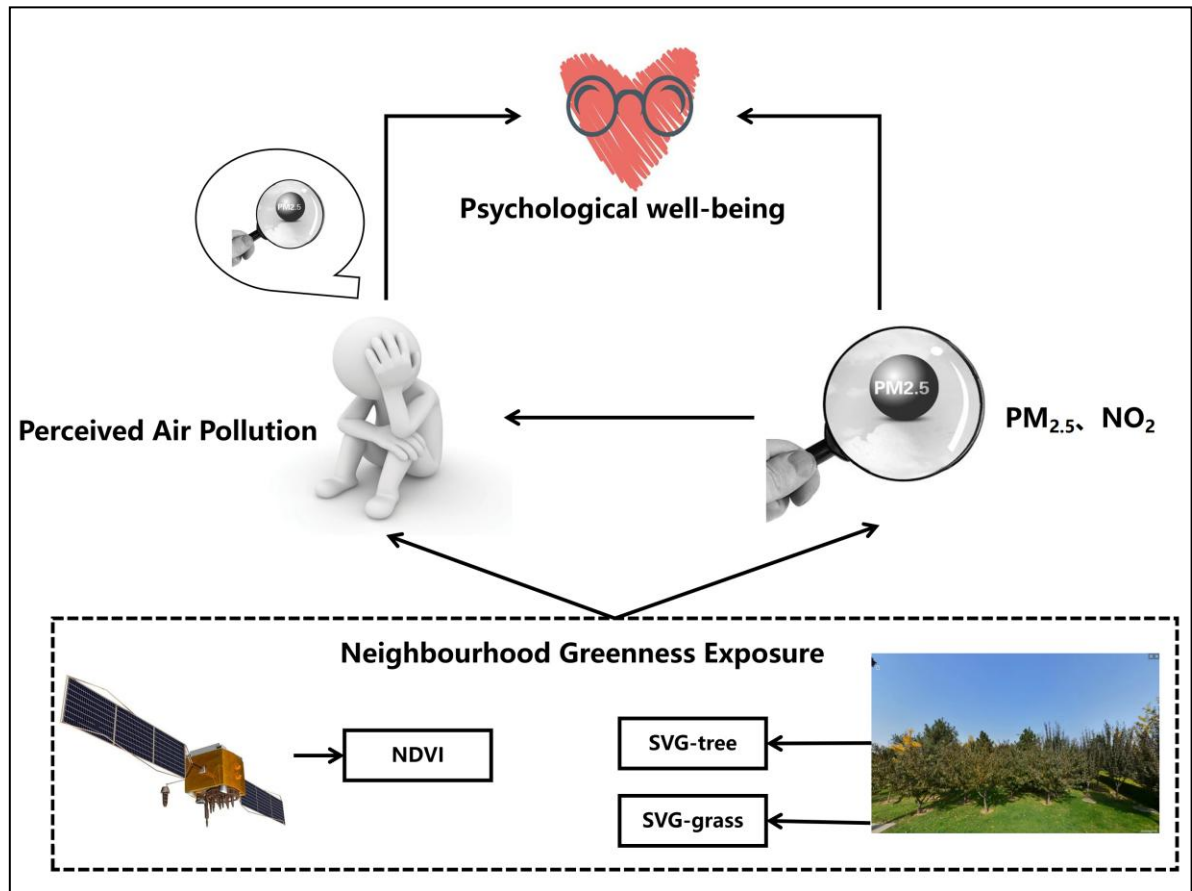
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Graphical abstract



## 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<sub>2.5</sub> and NO<sub>2</sub> 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<sub>2.5</sub>, NO<sub>2</sub> and perceived air pollution in parallel mediation models.
- The streetscape greenery-mental health association was mediated by ambient PM<sub>2.5</sub>-perceived air pollution and NO<sub>2</sub>-perceived air pollution in serial mediation models
- Neither measures of air pollution mediated the association between NDVI and psychological well-being.

1 **Abstract**

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

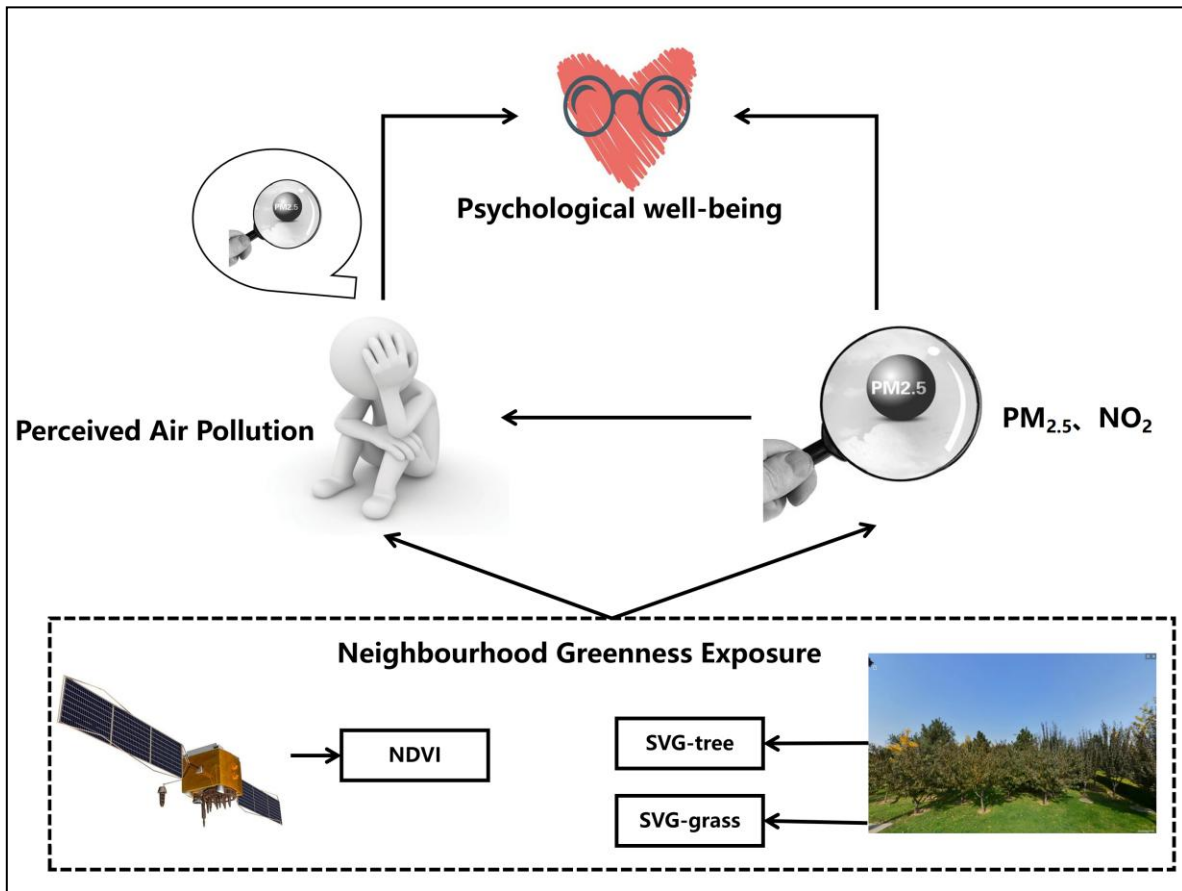
23 SVG-grass and psychological well-being scores was partially mediated by NO<sub>2</sub>-perceived air  
24 pollution, SVG-tree was partially mediated by both ambient PM<sub>2.5</sub>-perceived air pollution and  
25 NO<sub>2</sub>-perceived air pollution. Our results suggest that street trees may be more related to  
26 lower air pollution levels and better mental health than grasses are.

27

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

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30 Graphical abstract



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

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37 Highlights

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39 • Normalized Difference Vegetation Index (NDVI) and streetscape greenery (SVG)  
40 were used to assess greenness exposure, and trees (SVG-tree) and grasses (SVG-grass)  
41 were distinguished when generating streetscape greenery exposure metrics.

42 • Both objective (PM<sub>2.5</sub> and NO<sub>2</sub> concentrations) and subjective (perceived air pollution)  
43 measures were used to quantify air pollution exposure.

44 • NDVI, SVG-tree and SVG-grass were positively associated with psychological  
45 well-being.

46 • The streetscape greenery-mental health association was mediated by ambient PM<sub>2.5</sub>,  
47 NO<sub>2</sub> and perceived air pollution in parallel mediation models.

48 • The streetscape greenery-mental health association was mediated by ambient  
49 PM<sub>2.5</sub>-perceived air pollution and NO<sub>2</sub>-perceived air pollution in serial mediation  
50 models

51 • Neither measures of air pollution mediated the association between NDVI and  
52 psychological well-being.

53

54 **Abbreviations:** CI= confidence interval; NDVI, normalized difference vegetation index;  
55 NO<sub>2</sub>= nitrogen dioxide; PM<sub>2.5</sub>, particles  $\leq 2.5$   $\mu\text{m}$  in aerodynamic diameter; q25, first  
56 quartile; q75, third quartile; SVG-grass, street view images-based greenness assessed in  
57 density of grasses; SVG-tree, street view images-based greenness assessed in density of trees;  
58 WHO-5, World Health Organization Well-Being Index; .

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## 76 **1. Introduction**

77 China urbanized very rapidly over the past 40 years, with the proportion of urban residents  
78 having grown from approximately 18% in 1978 to 56% in 2015 (NBSC, 2016). While  
79 development has brought economic benefits, it has diminished opportunities for contact with  
80 nearby vegetation, limiting exposure to “greenness” (Hartig et al., 2014; Markevych et al.,  
81 2017; Nieuwenhuijsen et al., 2017), and increased the risk of exposure to air pollution (Chen  
82 et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).

83

84 Multiple cross-sectional (Banay et al., 2019; Hystad et al., 2019; Lee et al., 2019; Sarkar et  
85 al., 2018; Song et al., 2019) and longitudinal (Alcock et al., 2014; Astell-Burt et al., 2014;  
86 Feng and Astell-Burt, 2017, 2018) epidemiologic investigations have reported positive  
87 associations between greenness and psychological well-being. Neighbourhood greenness may  
88 benefit psychological well-being by mitigating pathophysiologic processes that lead to  
89 neuroinflammation, cerebrovascular damage and neurodegeneration (Kioumourtzoglou et al.,  
90 2017; Buoli et al., 2018). Greenness surrounding residential areas is found to encourage  
91 physical activities (Maas et al., 2008; Richardson et al., 2013; Sugiyama et al., 2008; van den  
92 Berg et al., 2019) and social contact among neighbours, thereby benefitting psychological  
93 well-being (de Vries et al., 2013; Maas et al., 2009; Sugiyama et al., 2008). In addition,  
94 greenspace has been shown to be a resource for psychological restoration, which indicates it  
95 can reduce psychological stress (Kaplan, 1995; Hartig, 2008; Hartig et al., 2014; Ulrich et al.,  
96 1991).

97



98 Scholars have increasingly become concerned about the adverse effects of air pollution on  
99 psychological well-being (Buoli et al., 2018; Kampa and Castanas, 2008; Lim et al., 2012;  
100 Wang et al., 2019a; Wang et al., 2018; Wang et al., 2014). Rapid urbanization and  
101 industrialization is normally accompanied by an increased risk of exposure to air pollution  
102 (Chen et al., 2017; Han et al., 2014; Li et al., 2016; Song et al., 2018; Wang et al., 2019).  
103 Previous studies showed that air pollution may discourage physical activities and decrease  
104 people's willingness to socialize with their neighbours in outdoor settings (An and Xiang,  
105 2015; Roberts et al., 2014; Wang et al., 2019a). Thus, less exposure to greenness and greater  
106 exposure to air pollution may threaten the psychological well-being of urban populations  
107 (Chen and Nakagawa, 2018).

108

109 Recent reviews suggest that neighbourhood greenery may protect psychological well-being  
110 by mitigating environmental stressors such as air pollution (Hartig et al., 2014; Markevych et  
111 al., 2017; Nieuwenhuijsen et al., 2017). Some studies have reported a significant role for air  
112 pollution in mediating associations between greenness exposure and health (Gascon et al.,  
113 2018; James et al., 2016; Thiering et al., 2016; Yang et al., 2019), whereas others have found  
114 no solid evidence (Dzhambov et al., 2018a, b; Vienneau et al., 2017; Yitshak-Sade et al.,  
115 2017). Yet, previous studies on the interrelationships among neighbourhood greenness, air  
116 pollution and psychological well-being rely on exposure measures from remote sensing (i.e.,  
117 satellite) data, which may fail to accurately capture how people perceive vegetation on the  
118 ground (Dzhambov et al., 2018a, b; Gascon et al., 2018; Liu et al., 2019a, b; Wang et al.,  
119 2019b). There has been little research on the association between greenspace and mental

120 health in China to date, and, studies have mainly focused on the direct effect of greenspace on  
121 health (Liu et al., 2019a, b; Wang et al., 2019b).

122

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

132

(Fig 1 about here)

134

## 135 **2. Data and methods**

### 136 *2.1. Study population*

137 We enrolled 1029 study participants between June and August 2016. We first selected 35  
138 residential neighbourhoods (with mean  $\pm$  SD area =1.91 km<sup>2</sup>  $\pm$  574.691 m<sup>2</sup>. Total area=  
139 66.85km<sup>2</sup>) from six districts in Guangzhou city (Yuexiu, Haizhu, Panyu, Baiyun, Tianhe and  
140 Liwan), using a multi-stage stratified sampling method with probabilities proportionate to  
141 population sizes. We then randomly chose 30 households from each neighbourhood. Finally,

142 we randomly enrolled one adult from each household using the Kish Grid method (Kish,  
143 1949). Thus, 35 neighbourhoods x 30 household x 1 person/household = 1050 participants.  
144 However, 21 potential participants did not complete the study questionnaire, so the final  
145 sample size in this study was 1029 (98% participation rate). The study protocol was approved  
146 by the Sun Yat-sen University Research Ethics Committee, and all participants completed  
147 informed consent prior to enrollment.

148

## 149 ***2.2 Psychological well-being assessment***

150 Study participants were invited to complete the World Health Organization five-item  
151 Well-Being Index (WHO-5) (Heun et al., 2001). The WHO-5 questions evaluate respondents'  
152 psychological feelings over the previous two weeks, including: "I have felt cheerful and in  
153 good spirits", "I have felt calm and relaxed", "I have felt active and vigorous", "I woke up  
154 feeling fresh and rested" and "My daily life has been filled with things that interest me". Each  
155 item is scored on a 6-point Likert scale, ranging from "never" to "every time", and the total  
156 score ranges from 0 to 25. Greater values indicate better psychological well-being. The  
157 WHO-5 has been shown to have good validity and reliability in many countries (Krieger et al.,  
158 2014) and has been validated in China. In our sample, the questionnaire had good reliability  
159 (test-retest reliability=0.995,  $p<0.01$ ), and the Cronbach's alpha (0.815) indicated high  
160 internal consistency.

161

## 162 ***2.3 Residential greenness assessment***

### 163 ***2.3.1 NDVI***

164 We used the satellite-based NDVI (Tucker, 1979) as a surrogate of neighbourhood greenness  
165 exposure. We used satellite images from Landsat8 OLI (Operational Land Imager) and TIRS  
166 (Thermal Infrared Sensor) at a 30 m × 30 m spatial resolution to calculate the NDVI in 1000  
167 m buffers around the centroid of each study neighbourhood. Remote sensing data were  
168 obtained for the year 2016 from the USGS EarthExplorer (<https://earthexplorer.usgs.gov/>).  
169 We used cloud-free images in the greenest month of the year (August) to avoid distortions.  
170 Guangzhou has a subtropical climate, so most of its vegetation stays green year round. We  
171 omitted pixels with a negative NDVI value before averaging across each study  
172 neighbourhood, following the approach employed in previous studies (Markevych et al.,  
173 2017).

174

### 175 *2.3.2 SVG-tree and SVG-grass*

176 We also used street-view imagery-based greenness indices as surrogates of neighbourhood  
177 greenness exposure. We calculated the SVG using street-view imagery from Tencent (Lu et  
178 al., 2018; Lu, 2019; Helbich et al., 2019; Wang et al., 2019b, c). First, we collected a series of  
179 street view images from Tencent Online Map [<https://map.qq.com>], the most comprehensive  
180 online street view image database in China, as described previously (Helbich et al., 2019;  
181 Wang et al., 2019b, c). Street view sampling points were identified 100 m apart along the  
182 local road network, which was obtained from OpenStreetMap (Haklay and Weber, 2008). For  
183 each sampling point, we collected street view images from 0, 90, 180 and 270 degrees  
184 (Helbich et al., 2019; Wang et al., 2019b, c). We collected 125,656 street view images from  
185 31,414 sampling points in this study.

186

187 We distinguished between trees (SVG-tree) and grasses (SVG-grass) when generating  
188 streetscape greenery exposure metrics, using a machine learning approach based on semantic  
189 image segmentation techniques. We employed a fully convolutional neural network for  
190 semantic image segmentation (FCN-8s), which has been shown to be capable of identifying  
191 150 types of ground objects (e.g., trees and grasses) accurately (Kang and Wang, 2014; Long  
192 et al., 2015). Our training model was based on the online ADE20K annotated images data set  
193 (Zhou et al., 2019). The accuracy of the FCN-8s was 81% for the training data and 80% for  
194 the test data. Following previous studies (Helbich et al., 2019; Wang et al., 2019b, c),  
195 SVG-tree and SVG-grass at each sampling point were determined as the proportion of tree or  
196 grass pixels per image summed over the four cardinal directions (i.e., 0, 90, 180 and 270  
197 degrees) relative to the total number of pixels per image summed over the four cardinal  
198 directions. We calculated the SVG-tree and SVG-grass for each neighbourhood by averaging  
199 the SVG-tree and SVG-grass scores for all sampling points within 1000 m circular buffers  
200 around the centroid of each study neighbourhood.

201

## 202 ***2.4 Air pollution assessment***

### 203 *2.4.1 PM<sub>2.5</sub> and NO<sub>2</sub> concentrations*

204 We assessed exposure to air pollution using predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations within a  
205 1000 m circular buffer around the geographic centroid of study neighbourhoods. We used the  
206 2016Global Annual PM<sub>2.5</sub> data grid, generated using MODIS, MISR and SeaWiFS Aerosol  
207 Optical Depth (AOD) data with geographically weighted regression, and available from the

208 NASA Socioeconomic Data and Applications Center (SEDAC) at a 1000 m × 1000 m spatial  
209 resolution (van Donkelaar et al., 2016; 2018). Nitrogen dioxide (NO<sub>2</sub>) concentrations were  
210 also extracted from a globally available land use regression model with a spatial resolution of  
211 100 m (Larkin et al., 2017). We calculated the annual average PM<sub>2.5</sub> and NO<sub>2</sub> concentrations  
212 using the average pixel value within the 1000 m circular buffer around the centroid of each  
213 study neighbourhood.

214

#### 215 *2.4.2 Perceived air pollution*

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

221

#### 222 *2.5 Covariates*

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

230

## 231 *2.6 Statistical analysis*

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

239

240 We used two approaches to model pathways linking greenspace to psychological well-being  
241 and to evaluate the mediating effect of air pollution, presuming no interaction between the  
242 exposures and mediators. We used parallel mediation models, in which the mediators were  
243 assumed to act independently, and serial mediation models, in which objective air pollution  
244 measures were assumed to have an influence on subjective measures of air pollution and in  
245 turn, on psychological well-being. First, we fitted the parallel mediation model (Fig 2 A) with  
246 three parallel mediators (PM<sub>2.5</sub>, NO<sub>2</sub> and perceived air pollution). Also, we used different  
247 measures of greenness as described above. Second, we fitted the serial mediation model (Fig  
248 2 B), which assumed that residential greenness could affect mental wellbeing through actual  
249 exposure to air pollution (PM<sub>2.5</sub> and NO<sub>2</sub>) and the perception of air pollution. Again, we  
250 used different measures of greenspace. Third, we calculated the direct and indirect effects in  
251 the parallel mediation model and in the serial mediation model based on the approach

252 proposed by Hayes (2013) and Zhao et al. (2010). We used bootstrapping (5000 samples) to  
253 obtain bias-corrected 95% CIs of for each paths (Hayes,2013; Zhao et al., 2010). Goodness of  
254 fit was assessed by standardized root mean square residual (SRMSR), root mean square error  
255 of approximation (RMSEA), and comparative fit index (CFI). Hu and Bentler (1999)  
256 suggested that the acceptable model fit should be as follows: RMSEA ( $\leq 0.06$ , 90% CI  $\leq$   
257 0.06), SRMSR ( $\leq 0.08$ ), and CFI ( $\geq 0.95$ ). The detailed information for SEM was shown in  
258 Fig S1.

259

260

(Fig 2 about here)

261

262 To assess the robustness of our results, we repeated our analyses using 800m and 1500m  
263 neighbourhood buffers instead of 1000m buffers when measuring exposure to residential  
264 greenness and air pollution (results available on request). For all analyses, we defined  
265 statistical significance as  $P < 0.05$  for a 2-tailed test. STATA v.15.1 was used for the statistical  
266 analysis (STATA, Inc. College Station, TX USA).

267

### 268 **3. Results**

#### 269 *3.1 Descriptive statistics*

270 The characteristics of the study population are summarized in Table 1; there was no missing  
271 data. About half of participants were male (50.2%) and the average age was 41.2 years. Most  
272 respondents were married (78.3%) and were registered as temporary residents (77.8%).  
273 Approximately 50.0% of respondents had a high school education and 47.4% possessed a



274 college level education. Most respondents earned 3000-6999 Chinese Yuan per year (70.7%),  
275 and had medical insurance (97.1%).

276

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

285

286 (Table 1 about here)

287

### 288 ***3.2 Associations between greenness exposure, air pollution and psychological well-being:***

#### 289 ***Parallel mediation model***

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

296 1-IQR greater NDVI was significantly and directly associated with 0.44-unit higher WHO-5  
297 score. There was no evidence to suggest that NDVI could influence WHO-5 scores through  
298 an indirect effect.

299

300 (Fig 3 about here)

301 (Table 2 about here)

302

303 Fig. 3 (B) also shows that SVG-grass was negatively associated with NO<sub>2</sub> concentration and  
304 perceived air pollution, which all were negatively associated with WHO-5 scores. However,  
305 there was no evidence to suggest that SVG-grass was also associated with PM<sub>2.5</sub> or directly  
306 associated with WHO-5 score. Table 2 indicates that a 1-IQR greater SVG-grass was  
307 significantly and indirectly associated with a 0.06-unit higher WHO-5 score through  
308 perceived air pollution and a 0.23-unit higher WHO-5 score through NO<sub>2</sub> concentration.  
309 There was no evidence to suggest that SVG-grass could directly influence WHO-5 score.

310

311 Fig. 3 (C) shows that SVG-tree was negatively associated with PM<sub>2.5</sub>, NO<sub>2</sub> and perceived  
312 air pollution, which all were negatively associated with WHO-5 score. However, there was no  
313 evidence that SVG-tree was directly associated with WHO-5 score. Table 2 indicated that a  
314 1-IQR greater SVG-tree was significantly and indirectly associated with 0.03-unit higher  
315 (95% CI: 0.002-0.07) WHO-5 score through perceived air pollution, a 0.04-unit higher (95%  
316 CI: 0.003-0.07) WHO-5 score through PM<sub>2.5</sub>, and a 0.14-unit higher (95% CI 0.01-0.26)  
317 WHO-5 score through NO<sub>2</sub>. There was no evidence of a direct SVG-tree effect on WHO-5

318 scores.

319

### 320 *3.3 Associations between greenness exposure, air pollution and psychological well-being:*

#### 321 *Serial mediation model*

322 We obtained a reasonably well-fitting final serial mediation model: SRMSR = 0.031, RMSEA  
323 = 0.029 (90% CI: 0.020, 0.045), CFI = 0.966. Fig. 4 (A) reports path coefficients and 95% CI  
324 for serial mediation model in the multi-level SEM. NDVI was positively and directly  
325 associated with WHO-5 score. Although, PM<sub>2.5</sub> and NO<sub>2</sub> were both significant positively  
326 associated with perceived air pollution, which was negatively associated with WHO-5 scores,  
327 there was no evidence that NDVI was correlated to PM<sub>2.5</sub> or NO<sub>2</sub>. Table 3 also shows that  
328 each IQR greater NDVI was significantly and directly associated with 0.41-unit higher (95%  
329 CI: 0.06-0.77) WHO-5 score in the serial mediation model. There was no evidence of an  
330 indirect NDVI effect on WHO-5 scores.

331

332 (Fig 4 about here)

333 (Table 3 about here)

334

335 Fig. 4 (B) shows that SVG-grass was positively and directly associated with WHO-5 score.  
336 SVG-grass was negatively associated with NO<sub>2</sub>, which was positively associated with  
337 perceived air pollution. However, there was no association of SVG-grass with PM<sub>2.5</sub>. Table 3  
338 indicates that a 1-IQR greater SVG-grass was significantly and directly associated with a  
339 1.89-unit higher WHO-5 score. A 1-IQR greater SVG-grass was also significantly and

340 indirectly associated with a 0.04-unit higher WHO-5 score through the serial NO<sub>2</sub>-perceived  
341 air pollution pathway. Yet, there was no evidence that SVG-grass could influence WHO-5  
342 score through the serial PM<sub>2.5</sub>-perceived air pollution pathway.

343

344 Fig. 4 (C) shows that SVG-tree was negatively associated with PM<sub>2.5</sub> and NO<sub>2</sub> concentrations,  
345 which were positively associated with perceived air pollution. However, there was no  
346 evidence for a direct association between SVG-tree and WHO-5 score. Table 3 indicates that  
347 each IQR greater SVG-tree was significantly and indirectly associated with 0.01-unit higher  
348 WHO-5 score through both the NO<sub>2</sub>-perceived air pollution and the PM<sub>2.5</sub>-perceived air  
349 pollution serial pathways. Still, there was no evidence supporting that SVG-tree directly  
350 influenced WHO-5 score

351

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

355

## 356 **4. Discussion**

### 357 ***4.1 Key findings***

358

359 We found that greenness exposure was positively associated with psychological well-being  
360 and that air pollution exposure in part mediated the association in this cross-sectional  
361 investigation of an urban Chinese study population. More specifically, we found that NDVI,

362 SVG-tree score and SVG-grass score correlated with WHO-5 score. For parallel mediation  
363 models, while the association between SVG-grass and WHO-5 scores was completely  
364 mediated by perceived air pollution and NO<sub>2</sub>, the relationship between SVG-tree and WHO-5  
365 scores was completely mediated by ambient PM<sub>2.5</sub>, NO<sub>2</sub> and perceived air pollution. In  
366 addition, none of three air pollution indicators mediated the association between WHO-5  
367 scores and NDVI. For serial mediation models, measures of air pollution did not mediate the  
368 relationship between NDVI and WHO-5 scores. While the linkage between SVG-grass and  
369 WHO-5 scores was partially mediated by NO<sub>2</sub>-perceived air pollution, the relationship for  
370 SVG-tree was partially mediated by both ambient PM<sub>2.5</sub>-perceived air pollution and  
371 NO<sub>2</sub>-perceived air pollution. To the best of our knowledge, this is the first report of parallel  
372 and serial mediating effects for reported associations between greenness exposure and  
373 psychological well-being which distinguishes exposure to SVG-grass from exposure to  
374 SVG-tree.

375

#### 376 ***4.2 Greenness and psychological well-being***

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

384 Triguero-Mas et al., 2015) reported negative associations between neighbourhood greenness  
385 exposure measured as NDVI and the odds of reporting a history of doctor-diagnosed  
386 depressive disorder. The association between greenness exposure and psychological  
387 well-being as measured with WHO-5 was strongest in our results for SVG-tree, weakest for  
388 NDVI, and with moderate effect estimates for SVG-grass. Our satellite-based NDVI and  
389 street view images-based SVG were uncorrelated. This finding is consistent with previous  
390 findings from China (Helbich et al., 2019) and the U.S. (Larkin and Hystad, 2018), which  
391 also reported weak correlations between satellite-based and street view images-based  
392 measures of greenness, as well as an inverse association for greenness exposure and geriatric  
393 depression (Helbich et al., 2019). Though less widely employed than satellite-based  
394 approaches, street view images may be a useful tool for greenness assessments, as they  
395 capture different aspects of neighbourhood environments (Villeneuve et al, 2018;  
396 Weichenthal et al., 2019). Epidemiological studies of greenness and human health frequently  
397 employed the NDVI (Banay et al., 2019; Markevych et al., 2014a, 2016), presence of  
398 greenspace (Triguero-Mas et al., 2015; 2017), greenspace availability (Triguero-Mas et al.,  
399 2015; 2017), access to greenspace (Markevych et al., 2014b) or proximity to the nearest park  
400 (Fan et al., 2011) to assess neighbourhood greenness. However, these approaches are limited  
401 by an inability to differentiate types of vegetation, an issue that we addressed by measuring  
402 SVG-tree and SVG-grass.

403

#### 404 ***4.3 Air pollution and psychological well-being***

405 Our results also suggest that poorer air quality may exert a pejorative effect on psychological

406 well-being. These results are consistent with previous reports originating both from  
407 developed (Kim et al., 2016b; Lim et al., 2012; Pun et al., 2016) and developing nations  
408 (Wang et al., 2018, 2019a). For example, greater concentrations of ambient PM<sub>2.5</sub> were  
409 cross-sectionally associated with more severe symptoms of anxiety and depression in a  
410 nationally representative sample of the U.S. population 57-85 years of age (Pun et al., 2016).  
411 Greater PM<sub>2.5</sub> exposure was also associated with more severe depressive symptoms in a  
412 Chinese study population (Wang et al., 2018; 2019a). This association might be explained in  
413 part by the “constrained restoration” hypothesis, indicating that air pollution may influence  
414 psychological well-being by undermining residents’ perception of greenness’s restorative  
415 quality (von Lindern et al., 2016). We also found associations between greater ambient PM<sub>2.5</sub>  
416 and poor psychological well-being captured with WHO-5. Prior evidence suggested negative  
417 associations between psychological health and perceived air pollution in Bulgaria (Dzhambov  
418 et al., 2018a; 2018b). Rather than offering an accurate surrogate for airborne hazards,  
419 perceived air pollution may be interpreted aesthetically, as adverse odors for example,  
420 affecting psychological well-being through annoyance rather than pathophysiology (Claeson  
421 et al., 2013). Yet, objective (i.e., ambient NO<sub>2</sub> monitoring) and subjective measures of air  
422 quality were similar in Lyon, France in all but the elderly subpopulation (Deguen et al.,  
423 2017).

424

#### 425 ***4.4 Air pollution as mediator of greenness-psychological well-being associations***

426 A growing literature describes negative relationships between neighbourhood greenness and  
427 surrounding air pollution levels (Dadvand et al., 2015; James et al., 2016; Pacifico et al.,

428 2009; Su et al., 2011). Improved air quality may result from diminished traffic-related  
429 air-pollutants in greener areas due to the absence of motor vehicle traffic (Dadvand et al.,  
430 2015; Su et al., 2011). Green vegetation, such as tall and dense trees, may also absorb air  
431 pollutants, mitigating airborne pollutant concentrations (Eisenman et al., 2019; Pugh et al.,  
432 2012; Yli-Pelkonen et al., 2018). However, different types of vegetation (e.g., trees and  
433 grasses) have different effects on air pollutants and on air purification. For example, trees  
434 adsorb airborne particulate and gaseous pollutants, which helps to mitigate air pollutant  
435 concentrations (Hirayabashi Nowak, 2016; Niinemets et al., 2014; Nowak et al., 2014), but  
436 analogous effects are not described for grasses in the literature.

437

438 Several observational investigations have reported statistically significant mediating effects  
439 for air pollution in associations between greenness and blood lipids (Yang et al., 2019),  
440 insulin resistance (Thiering et al., 2016) and mortality (James et al., 2016), although others  
441 did not (Vienneau et al., 2017; Yitshak-Sade et al., 2017). Still, few previous studies have  
442 evaluated air pollution as an intervening variable between greenness and psychological health  
443 to date (Markevych et al., 2017). Air pollutants mediated 0.8% (PM<sub>2.5</sub>) to 4.1% (NO<sub>2</sub>) of the  
444 inverse associations between neighbourhood greenness and self-reported use of prescription  
445 benzodiazepines by 958 Spanish adults (Gascon et al., 2018). However, studies in Bulgaria,  
446 employing NO<sub>2</sub> and perceived air pollution measures (Dzhambov et al., 2018a; 2018b), and  
447 in Switzerland (Vienneau et al., 2017) did not identify air pollution as a significant mediator  
448 of greenness-psychological well-being associations.

449



450 Similar to previous work from Bulgaria (Dzhambov et al., 2018a; Dzhambov et al., 2018b),  
451 we did not detect mediating effects for air quality on associations between psychological  
452 well-being using a satellite-based greenness index (i.e., NDVI). In contrast, Gascon and  
453 colleagues (Gascon et al., 2018) reported mediation effects for NO<sub>2</sub>, a gaseous air pollutant,  
454 which is inconsistent with our results. The reason may be that our study area is in the inner  
455 city with a high population density, so NDVI cannot accurately measure the presence of  
456 vegetation (Ye et al., 2018). Also, another reason may be that the resolution of NDVI is  
457 relatively coarse in this study which does not measure greenspace exposure in respondents  
458 exact household addresses. However, we detected mediating effects for associations of  
459 psychological well-being with street view image-based greenness indices (i.e., SVG-tree and  
460 SVG-grass). Whereas the association of WHO-5 with SVG-tree was mediated by objectively  
461 predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations, and by subjectively perceived air pollution, the  
462 association of WHO-5 with SVG-grass was mediated only by NO<sub>2</sub> and perceived air pollution.  
463 As traffic emissions are the primary source of air pollutants in urban areas like Guangzhou  
464 (Li et al., 2014; Wang et al., 2006), grasses may not be tall and dense enough to block and  
465 absorb all air pollutants (Tong et al., 2015; Vos et al., 2013). Yet, street-level grasses may still  
466 shift residents' attention and reduce stress (de Vries et al., 2013), improving the perceived  
467 environment. Rotko et al. (2002) and Egondi et al. (2013) pointed out that when people focus  
468 less on environment stressors they may perceive less pollution even when actual air pollution  
469 is severe. Thus, it is tempting to speculate that the impact of perceived air pollution was  
470 attributable to aesthetic factors in mediating the association between SVG-grass score and  
471 psychological well-being in our study. Another important finding from our serial mediation

472 models is that objectively predicted PM<sub>2.5</sub> and NO<sub>2</sub> may have influenced perceived air  
473 pollution and subsequently affected psychological well-being. Consistent with our findings,  
474 Rotko et al. (2002) found that perceived air pollution was positively associated with PM<sub>2.5</sub>  
475 and NO<sub>2</sub> concentrations. Dzhambov et al. (2018a,b) used serial mediation models to find a  
476 statistically significant serial mediating role for NO<sub>2</sub>-annoyance and perceived air  
477 pollution-restorative quality between greenspace and psychological well-being. Yet, the serial  
478 mediating effects of NO<sub>2</sub>-perceived air pollution and PM<sub>2.5</sub>-perceived air pollution have not  
479 received much attention to date. Thus, the relationship among greenspace, objective air  
480 pollution, perceived air pollution and psychological well-being need more attention in future  
481 studies.

482

#### 483 ***4.5 Strengths and limitations***

484 The current study has several strengths. First, our random sampling strategy provided a  
485 representative sample of adults in Guangzhou city, enhancing generalizability and  
486 minimizing selection bias. Second, we used several measures to capture various aspects of  
487 greenness exposure, including a satellite-based vegetation index (i.e., NDVI) and street view  
488 image-based greenness indices (i.e., SVG-tree and SVG-grass). Compared with previous  
489 studies, SVG-tree and SVG-grass measured eye-level greenspace exposure in this study,  
490 which may more accurately reflect residents' actual exposure to and perception of greenspace  
491 than satellite-based measures. This allowed us to compare associations for different types and  
492 contexts of greenness exposure. Third, we evaluated air pollution using satellite based PM<sub>2.5</sub>  
493 and NO<sub>2</sub> estimates as well as perceived air pollution. This allowed us to compare the

494 mediating effects of both objective and subjective measures of air pollution. Fourth, we used  
495 a validated and reliable psychological assessment tool (i.e. WHO-5) to collect individual  
496 level study outcomes from participants. Finally, we captured and adjusted the study results  
497 for a comprehensive panel of potential confounding variables to enhance the validity of our  
498 results.

499

500 However, our study also has several limitations, and results from our analysis should be  
501 considered as preliminary. First, the cross-sectional study design prevented us from clearly  
502 establishing a temporal relationship between greenness and psychological well-being. Thus,  
503 we cannot rule out reverse causality, in which poorer psychological well-being may have led  
504 to residence in a less green neighbourhood. Second, we did not have participants' home  
505 addresses and so we measured greenness and air pollution exposures at the residential  
506 neighbourhood level, which may have misclassified some participants. Furthermore, we  
507 measured only the quantity of greenspace, whereas the quality of greenspace is also important  
508 (Van Dillen et al., 2012). We also did not measure perceived greenspace exposure in this  
509 study. Street view and remote sensing-based greenness measures were unrelated in our study,  
510 consistent with the results of previous studies (Larkin and Hystad, 2018; Helbich et al., 2019)  
511 and studies in high population density urban areas (Ye et al., 2018). The discrepancy may be  
512 due to local eye-level exposure captured by SVG while remote sensing-based greenness  
513 represents more generalized exposure. Third, our limited sample size may have provided  
514 insufficient statistical power to detect modest associations. Fourth, street view images were  
515 taken at different time points throughout 2016, so they may not reflect participants' actual

516 street-level greenspace exposure during the entire year. Fifth, we assessed only two objective  
517 measure of air pollution (i.e., PM<sub>2.5</sub> and NO<sub>2</sub>) and one measure of subjective air pollution (i.e.,  
518 perceived air pollution), and we thus are unable to draw inference on mediating effects  
519 beyond this limited profile. Sixth, we demarcated the exposure based on circular buffers,  
520 which may have led to a modifiable areal unit problem (Fotheringham and Wong, 1991).  
521 However, we found similar results when using various buffer sizes in a sensitivity analysis.  
522 Hence we did not have respondents' actual household address, so we have to measure  
523 environment exposure in neighbourhood level. Seventh, we did not consider noise, blue space  
524 and neighbourhood-level socioeconomic status data in this study, which may also be related  
525 to residents' psychological well-being (Dzhambov et al., 2018b). Eighth, NDVI is one of the  
526 predictors in the LUR (land used regression) used to generate NO<sub>2</sub> estimates, so this may  
527 have somewhat inflated the correlation with greenness measures. Last, daily exposure to  
528 greenspace was not limited to the residential environment, and the duration spent in  
529 residential neighbourhoods was not taken into account in this study (Helbich, 2008).

530

## 531 **5. Conclusions**

532 Predicted PM<sub>2.5</sub> and NO<sub>2</sub> concentrations and perceived air pollution mediated (in both  
533 parallel and serial mediation models) associations between street view image-based measures  
534 of neighbourhood greenness and psychological well-being, although the effects differed  
535 between SVG-tree and SVG-grass. Yet, these factors were not important mediators of a  
536 satellite-based measure of neighbourhood greenness and psychological well-being. Our  
537 results suggest that the relationships among neighbourhood greenness, air pollution and

538 psychological well-being may vary with different exposure assessment strategies. To our  
539 knowledge, this study is the first to explore associations among neighbourhood greenness, air  
540 pollution and psychological well-being in a large Chinese city. A more definitive study is  
541 necessary to confirm our results.

542

### 543 **Declaration of interests**

544 None

545

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548

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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 <sub>2.5</sub> (µg/m <sup>3</sup> ), mean (SD)	35.97 (0.46)
NO <sub>2</sub> (µg/m <sup>3</sup> ), 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<sub>2</sub>= nitrogen dioxide; PM<sub>2.5</sub>= 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			Greenspace-PM <sub>2.5</sub>			Greenspace-NO <sub>2</sub>			Greenspace-WHO scores	
	β. (95% CI)			β. (95% CI)			β. (95% CI)			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<sub>2</sub>= nitrogen dioxide; PM<sub>2.5</sub>= 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 <sub>2.5</sub> -Perceived air pollution			Greenspace-NO <sub>2</sub> -Perceived air pollution			Greenspace-WHO scores	
	β. (95% CI)			β. (95% CI)			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<sub>2</sub>= nitrogen dioxide; PM<sub>2.5</sub>= 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.

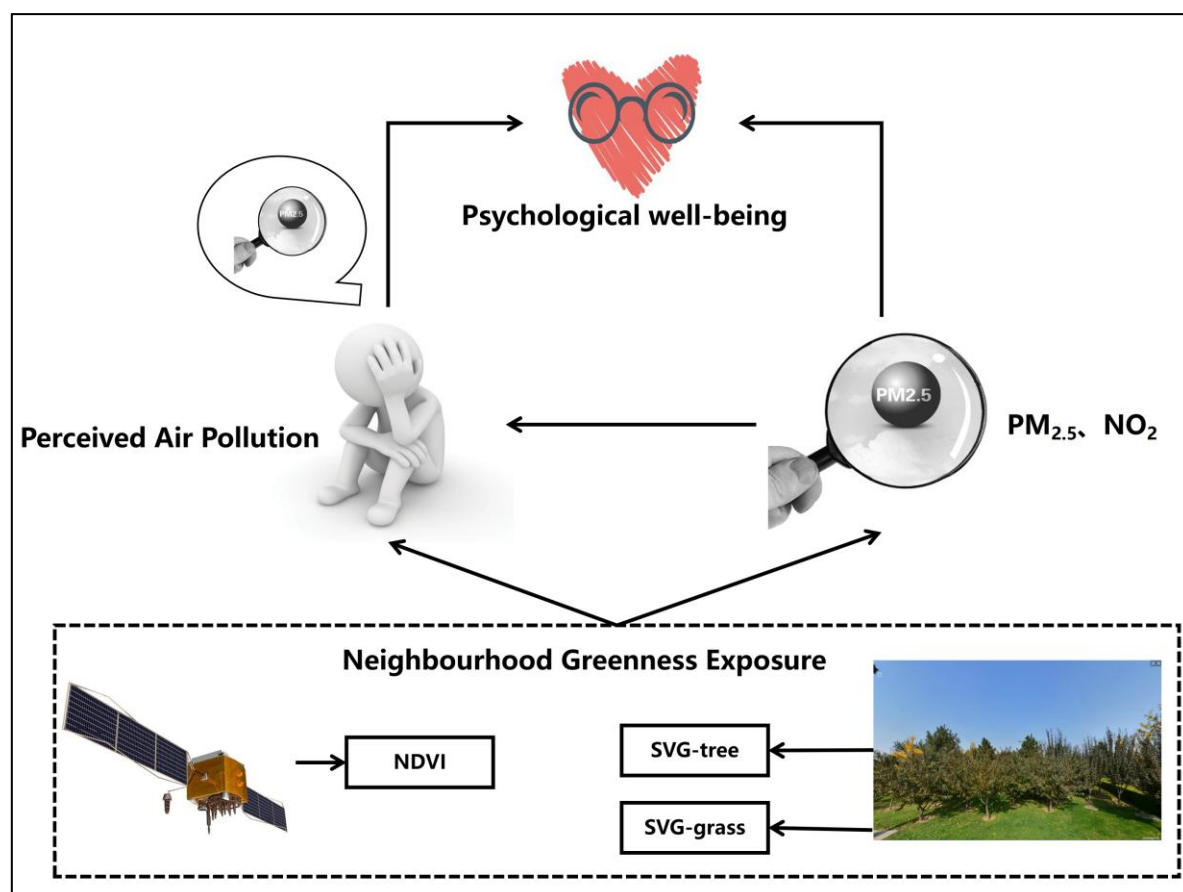
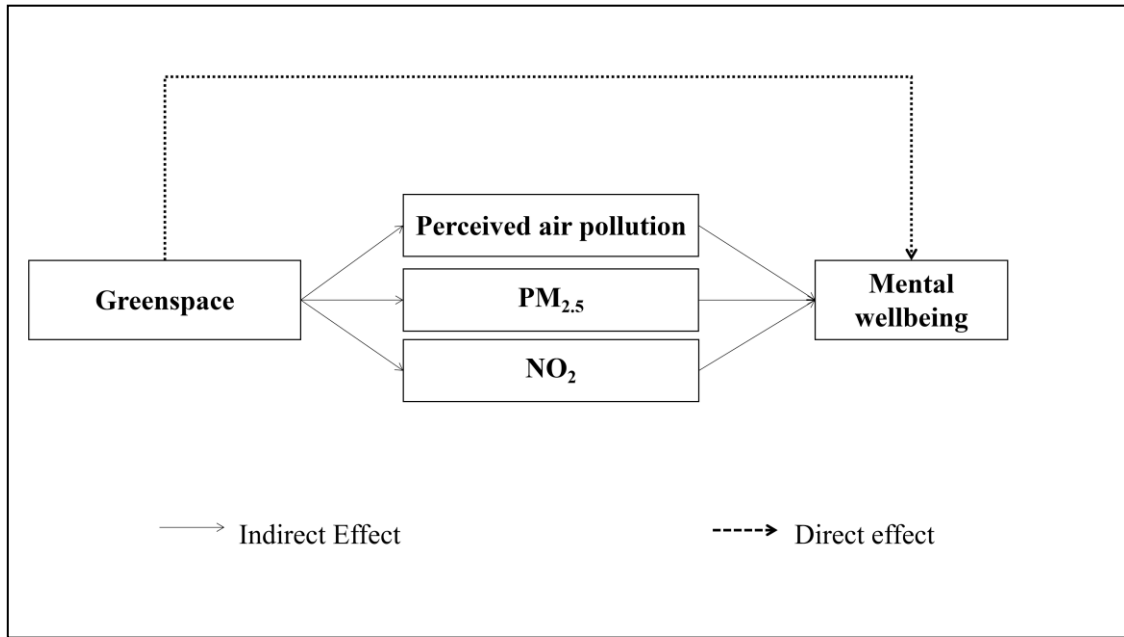
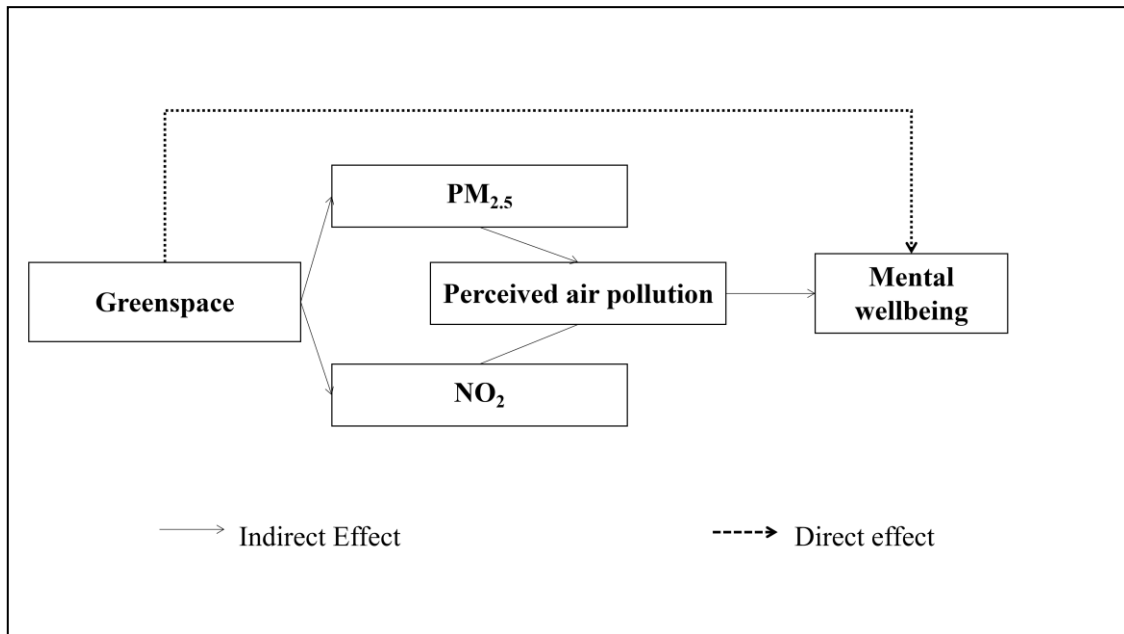


Fig 1. Theoretical framework describing the nature of associations among psychological well-being, air quality and neighbourhood greenness



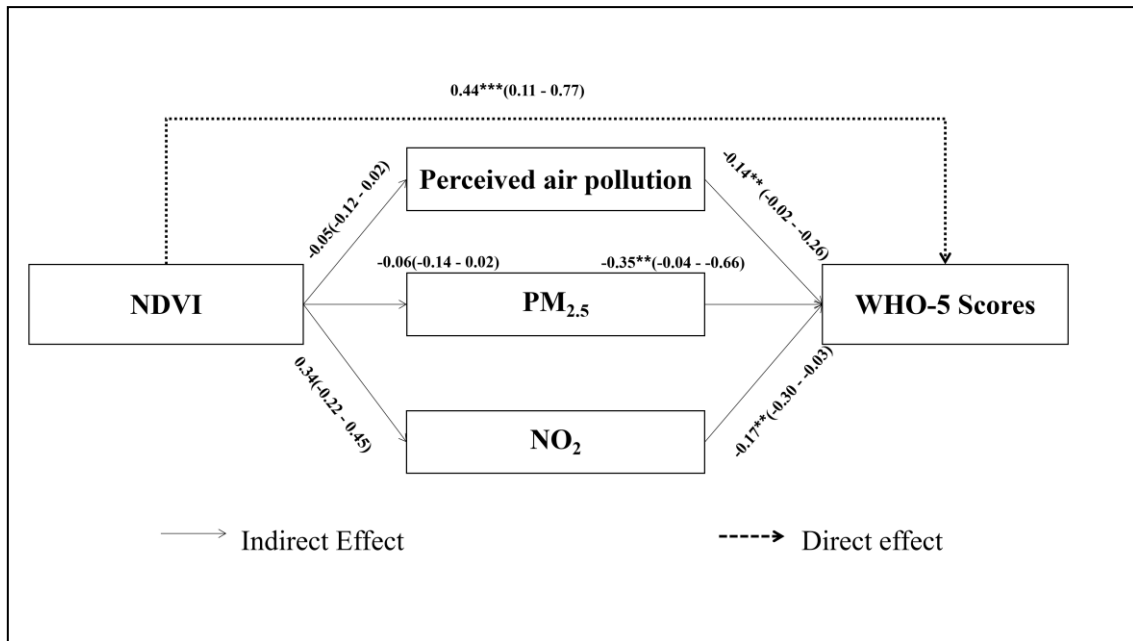


(A)

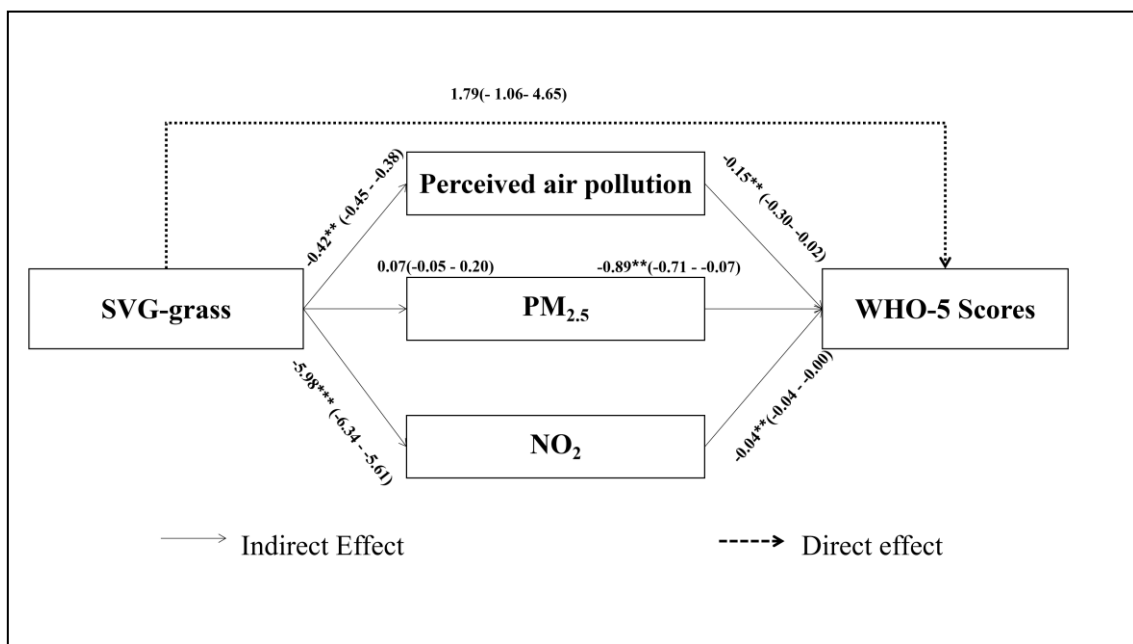


(B)

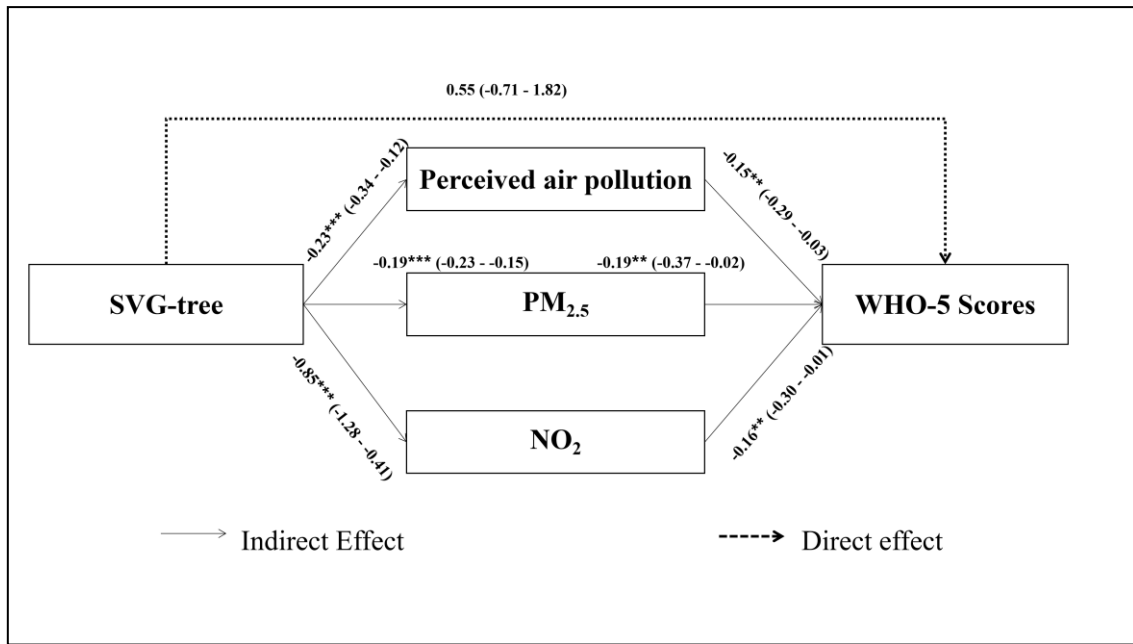
Fig 2. Conceptual diagrams of two approaches for modelling pathways linking greenspace to psychological wellbeing. A- parallel mediation model, for which the mediators were assumed to act independently. B- serial mediation models, for which objective air pollution measures were assumed to influence subjective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



(A)

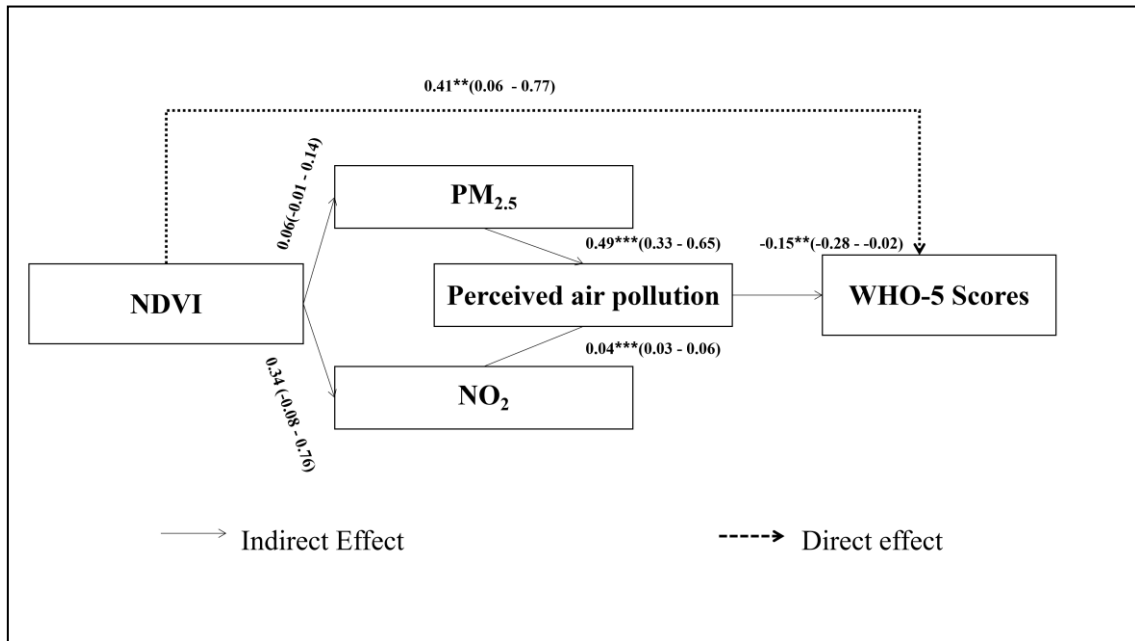


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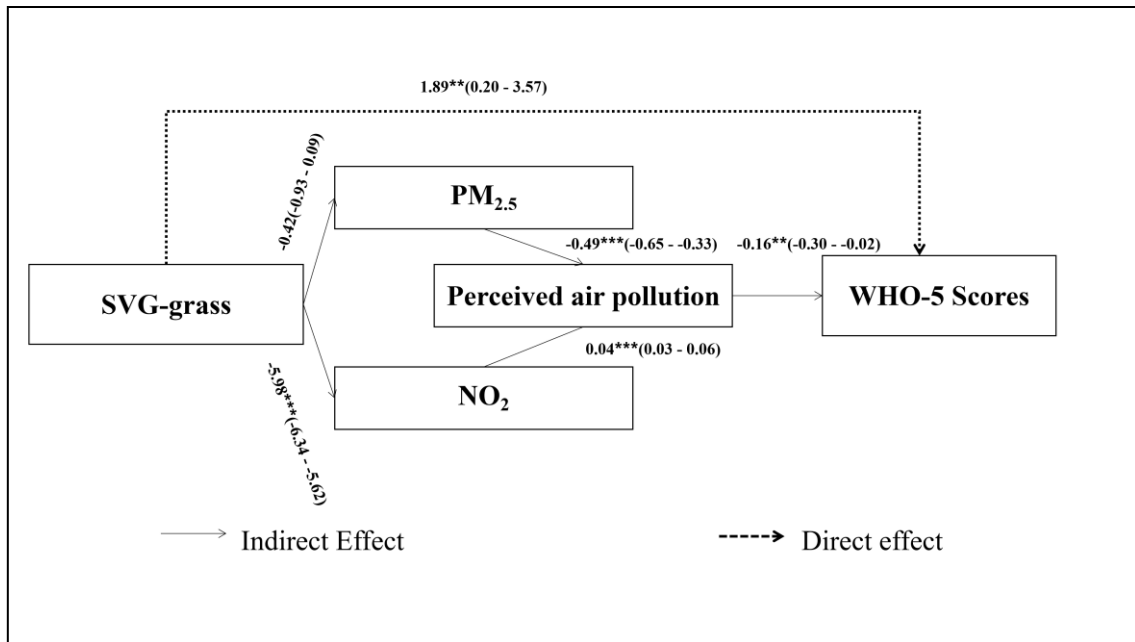


(C)

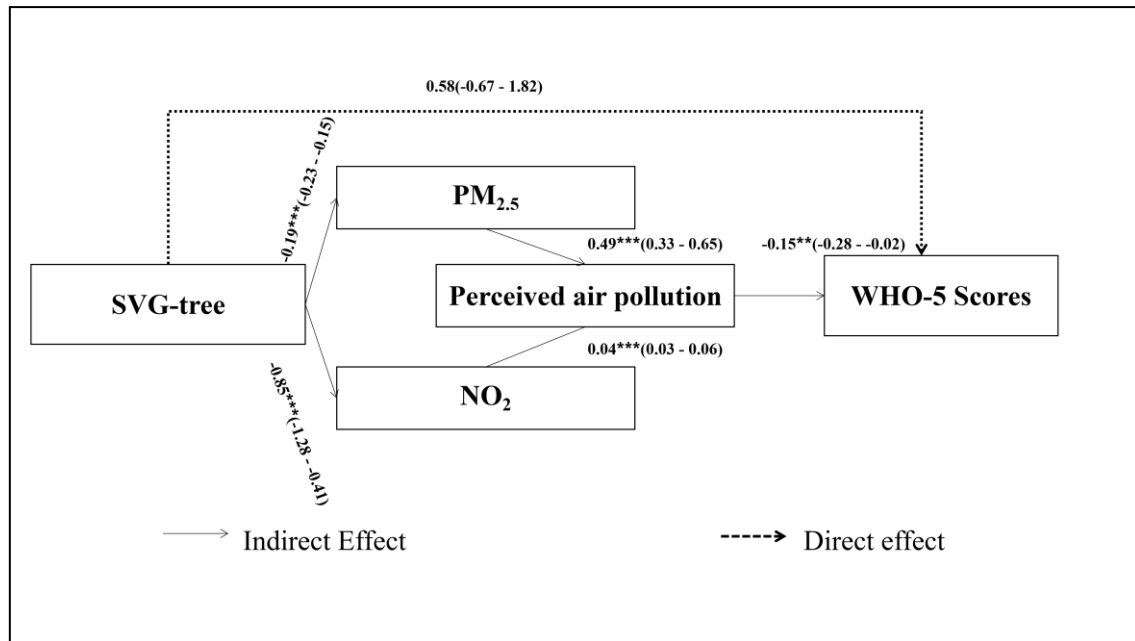
Fig 3. Coefficients of the multilevel structural equation model for parallel mediation, for which the mediators were assumed to act independently. A- NDVI as the greenspace indicator. B- SVG-grass as the greenspace indicator. C- SVG-tree as the greenspace indicator. Coefficients (with robust standard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



(A)



(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: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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**Declaration of interests**

None