# Urban greenspace and mental health in Chinese older adults: associations across different greenspace measures and mediating effects of environmental perceptions

Yafei Yue [a,b], Dongfeng Yang [a], Delfien Van Dyck [b,*]

[a] *Department of Urban Planning, School of Architecture and Fine Art, Dalian University of Technology, Dalian, China*

[b] *Department of Movement and Sports Sciences, Faculty of Medicine and Health Sciences, Ghent University, Ghent, Belgium*

## Abstract

This study aimed to contrast the associations of street view-, land use- and satellite-derived greenspace measures with older adults' mental health and to examine the mediating effects of neighborhood environmental perceptions (i.e., noise, aesthetics and satisfaction with recreational opportunities) to explain potential heterogeneity in the associations. Data of 879 respondents aged 60 or older in Dalian, China were used, and multilevel regression models were conducted in Stata. Results indicated that the Normalized Difference Vegetation Index (NDVI), vegetation coverage, park coverage and streetscape grasses were positively correlated with older adults' mental health. The associations of exposure metrics measured by overhead view were stronger than those measured by the street view. Streetscape grasses had a stronger association with older adults' mental health than streetscape trees. Noise, aesthetics and satisfaction with recreational opportunities mediated these associations, but the strength of the mediating effects differed across the greenspace measures. Our findings confirm the necessity of multi-measures assessment for greenspace to examine associations with older adults' mental health in Chinese settings and can contribute to the realization of health benefits of urban greenspace.

**Keywords:** NDVI, Streetscape Greenness, Older Adults, Mental Health, Multilevel Regression Model

## 1 Introduction

Urban greenspace, including urban parks, nature reserves and walking greenways, is a critical environmental resource that benefits mental health (Gascon et al., 2018; Giannico et al., 2021; Lai et al., 2020). A growing body of research has shown that greenspace can relieve stress (Hazer et al., 2018; Tyrväinen et al., 2014), restore concentration (Li et al., 2018; Wang et al., 2020), improve cognitive ability (Besser et al., 2017; Liu et al., 2019a), regulate negative psychology such as anger, anxiety and depression (Barnett et al., 2018; Gascon et al., 2018; Helbich et al., 2019), and reduce mental disorders (Markevych et al., 2017). However, the associations between greenspace exposure metrics and mental health seem to vary depending on the type of greenspace exposure metric used (Dzhambov et al., 2018; Reid et al., 2017; Wang et al., 2021). For instance, Feng and Astell-Burt (2018) found that residential greenspace quality but not quantity was associated with symptoms of psychological distress in adolescents (Feng and Astell-Burt, 2017). It was streetscape greenness rather than greenery cover that was inversely associated with depressive symptoms among older people (Helbich et al., 2019). Different methods to operationalize greenspace may be one of the reasons for the diverse conclusions in studies focusing on the greenspace-mental health association

(Houlden et al., 2018; Labib et al., 2020a; Reid et al., 2018). Therefore, it is necessary to examine relationships between different greenspace exposure metrics and mental health systematically, in order to provide a basis for the selection of greenspace planning indicators.

Remote sensing is one of the most common methods to generate objective greenspace indicators (Helbich et al., 2021; Jiang et al., 2017; Labib et al., 2020). It either uses derivates of vegetation indices (Markevych et al., 2017), such as the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), or classifies images as surrogate measures into land use and land cover categories (e.g., forests and parks) (Helbich et al., 2018; Zock et al., 2018). NDVI can quantify the density of vegetation and reflect vegetational health (Helbich et al., 2019; Tucker, 1979). To define vegetation cover, cultivated land, forest and grassland are usually aggregated. NDVI or vegetation cover, derived from remote sensing with downward-facing satellites, is usually selected as a greenspace indicator for research and urban planning purposes. Such downward-facing satellites however, conceptually represent an overhead perspective but do not always reflect the eye-level perspective that people have on greenspace (Dong et al., 2018; Lu et al., 2018). The Attention Restoration Theory posits that the presence of visible outdoor greenery can have therapeutic influences and fosters restoration from anxiety (Lega et al., 2021; Ulrich, 1984). The Stress Recovery theory also indicates that visible natural environments offer a concrete and available means of reducing suffering and enhancing effectiveness (Kaplan and Kaplan, 1989; Li et al., 2018). So, eye-level measurements are desired when studying the relationship between greenspace exposure and mental health. Recently, a few studies discovered that street view data could capture eye-level visible vegetation such as trees and grasses (Rzotkiewicz et al., 2018; Wang et al., 2021). Such eye-level vegetation can be extracted automatically using a machine learning approach, while simultaneously being effective and accurate (Dong et al., 2018; Li et al., 2018; Weichenthal et al., 2019). The bulk acquisition of street view data has broadened the scope of studies and increased possibilities for research. For example, Wang et al. (2021) found that streetscape greenspace quantity and quality were associated with mental health through different mechanisms.

The mechanisms through which greenspace derived from overhead and eye-level view is associated with mental health may differ (Wang et al., 2019a), because overhead view does not identify smaller and/or vertical areas of perceived greenspace (e.g., street trees, lawns, green walls), which are especially important in cities (Helbich et al., 2019; Wang et al., 2019a). However, due to methodological limitations, eye-level greenspace has received less attention in research than overhead-view greenspace (Lachowycz and Jones, 2013; Markevych et al., 2017). Only a few studies previously compared associations of greenspace metrics using overhead and street view with mental health. Helbich et al. (2019) found that street-view greenspace was inversely associated with geriatric depression in Beijing and achieved a better model goodness-of-fit than NDVI using multilevel regressions. In another study, streetscape greenery and NDVI were each positively associated with adults' wellbeing in Guangzhou (Zhou et al., 2020). The available evidence is insufficient to draw firm conclusions and in addition, it is unclear which mechanisms may explain the differences in associations between different types of greenspace metrics and mental health indicators in older adults. Specific mediation effects may be present here, but these are underexplored.

It is essential to examine mediating effects as they may better capture specific pathways through which greenspace measures influence mental health. Several mediators may be important in the associations of greenspace and mental health indicators (Markevych et al., 2017; Zhang et al., 2021b). For instance, park coverage measured in overhead view has indirect associations with mental health indicators through residents' perceptions of opportunities for recreational activities provided by public parks (Liu et al., 2017a; Tyrväinen et al., 2014). Streetscape greenness, representing visual exposures experienced during day-to-day activities, may better reflect residents' perceptions of aesthetics than vegetation cover or NDVI, so mediating effects of aesthetical perceptions may be stronger when using street-view measures instead of overhead-view measures (Kothencz et al., 2017). Furthermore, tree cover may better reflect potential air pollution filtration, noise reduction and heat perception compared with other types of vegetation (Klingberg et al., 2017; Signoretta et al., 2019).

Previous studies proposed that restorative effects of urban greenspace environments can be achieved by fully accounting for visual perceptions, auditory perceptions and human activity (Chen et al., 2009; Marselle et al., 2016). Restorative value and preference were positively predicted by visual factors (arbors, shrubs, and grass), auditory factors (flowing water sounds, wind-induced vegetation sounds, birdsong), and recreational opportunities (attractions and leisure activities) (Lai et al., 2020; Marselle et al., 2016). Exposure to natural environments can improve human mental health and wellbeing by auditory-visual-cognitive combinations (Liu et al., 2019a; Pheasant et al., 2010). As a result, perceptions of noise, aesthetics and recreational opportunities seem to be important mediating variables to investigate when examining the pathway of greenspace to mental health. These perceptions correspond to auditory, visual, and cognitive factors, respectively.

To our knowledge, no studies systematically and simultaneously examined the associations of greenspace metrics derived from street view, remote sensing, land use and vegetation type with older adults' mental health, nor did they examine the potential mediating effects of neighborhood environmental perceptions like noise, aesthetics and satisfaction with recreational opportunities in those associations (Gascon et al., 2015; Zhang et al., 2021b). However, examining the strength of these specific associations is important to give advice to urban planners regarding the selection of appropriate greenspace exposure metrics. Furthermore, greenspace and mental health indicators can vary greatly between and within cities. Cities are distinct in terms of a variety of factors (e.g., population sociodemographic characteristics, land use patterns, transportation, historical and cultural context, climate) as well as their spatial patterning (Cusack et al., 2017; Giannico et al., 2021), which may influence how greenspace influences mental health. To fully understand how greenspace is related to mental health indicators, research in different continents covering the full range in green environments and in mental health indicators is necessary. Although some studies on the associations of greenspace with mental health have been conducted in China (Dong et al., 2018; Liu et al., 2019b; Liu et al., 2019c; Wang et al., 2019a; Yao et al., 2019), previous studies have primarily been conducted in megacities such as Beijing and Guangzhou. There is currently a scarcity of research in second-tier Chinese cities, which have distinct environmental characteristics (Zhang et al., 2021b).

To overcome these shortcomings, the main aim of this study was to examine the associations of multi-dimensional quantitative greenspace indicators, containing NDVI, vegetation coverage, park coverage, streetscape greenness, streetscape trees and streetscape grasses, with older adults' mental wellbeing. This paper contributes to the literature in the following three ways. First, greenspace metrics were derived from street view, remote sensing, land use and vegetation type (He et al., 2022). Second, we explored the mediating effects of individuals' perceptions of noise, aesthetics and their satisfaction with recreational opportunities on the associations between greenspace with older adults' mental wellbeing to explain potential inconsistent results. Third, it is one of the first studies on associations of diverse greenspace metrics with older adults' mental health in a typical second-tier aging city in China. In Dalian, the prevalence of mental diseases in older adults is considerably high (25%) (Sun and Lu, 2022). These findings are helpful for evidence-based planning strategies and can provide guidelines for designing greenspace in similar Chinese second-tier cities.

Two hypotheses were generated, namely that the strength of the associations of the greenspace exposure metrics with mental wellbeing varies depending on greenspace measures, and that specific mediating pathways would be present, depending on the greenspace metric examined. This study contributes to the literature by providing an empirical exploration for the realization of the health benefits of urban greenspace.

## 2 Materials and methods

### 2.1 Procedure and study design

This is an observational study, conducted in residential areas in Dalian, China (Fig. 1). Residential neighborhoods range from 0.03 to 1.12 $km^2$ (mean=0.28 $km^2$; SD±0.24). The recruitment procedure was based on a two-stage stratified sampling design. In the first stage, 61 residential neighborhoods (neighborhoods) were randomly selected from the main urban area of Dalian. Then, in each residential neighborhood, 12-18 older adults who were over 60 and had been living at their current address for more than 10 years were randomly selected as respondents. We selected individuals living at their current address for at least ten years in order to exclude newly arrived older immigrants. Mental health outcomes of short-term migrants are not the result of the current surrounding environments to a large extent, considering that mental health outcomes are related to the cumulative effect of the environment (Dzhambov et al., 2020; Labib et al., 2020a; Wang et al., 2021).

Preliminary home interviews were conducted to determine whether the selected older adults were willing to participate in the survey. Among the total of 986 randomly selected older adults (conformity with criteria), 900 of them from different households finally participated in the interview (response rate 91.3%). Interviews were conducted face-to-face at respondents' homes. All the interviewers participated in a training course before conducting survey data collection. The questionnaire data was collected from May to October 2019. Questionnaires with incomplete answers, apparently contradictory answers, and regular answers (e.g., all the same options) were deleted. 879 participants with valid data were included in further data analyses. Through detailed individual interviews, participants' mental wellbeing, environmental perceptions and socio-economic attributes were assessed. The study protocol was approved by the Dalian University of Technology Research Ethics Committee, and all participants completed informed consent before enrollment.

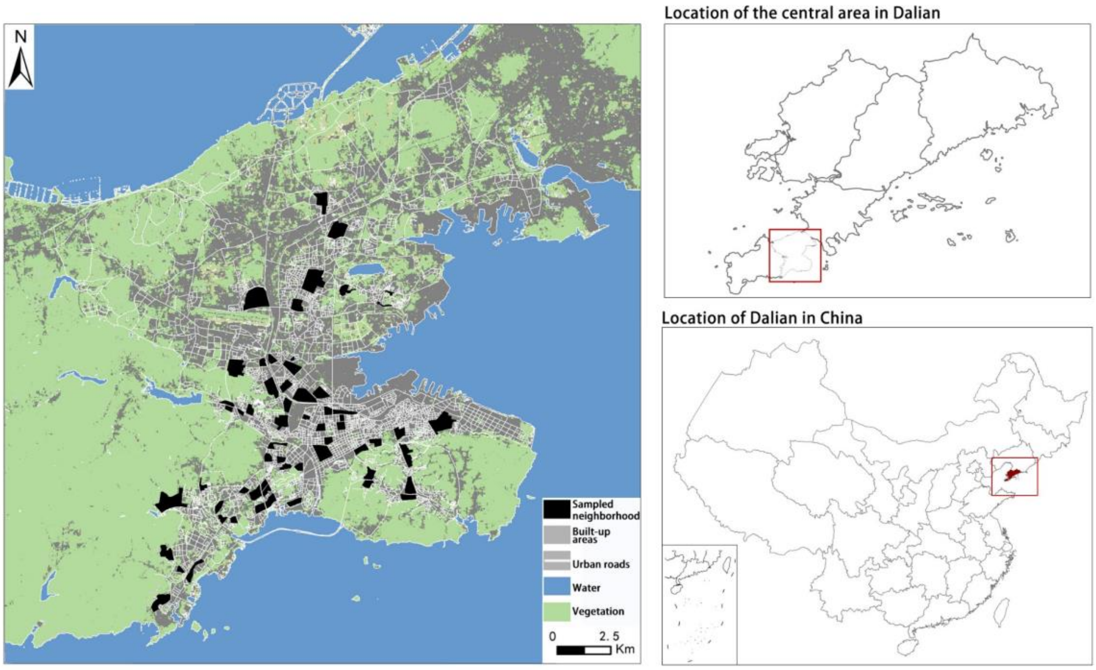


Fig. 1 Location of the study area and neighborhoods

## 2.2 Mental wellbeing

The questions used to assess mental health originate from the WAVE 1' dataset, which is a survey designed by the World Health Organization (WHO). The WAVE survey is a longitudinal study of aging and health with nationally representative samples of adults from 6 low- and middle-income countries including China (Arokiasamy et al., 2017). We selected questions to assess older adults' mental wellbeing from the Chinese version of the questionnaire (SAGE team, 2013). Three aspects of mental wellbeing were assessed: place-related emotional wellbeing (Burton et al., 2011); emotional wellbeing (Liu et al., 2017b; Steptoe et al., 2015) and evaluative wellbeing (Steptoe et al., 2015). Place-related emotional wellbeing was assessed with two items (I have been satisfied with the neighborhood as a place to live in the past 30 days; I have been attracted by trips in the local neighborhood in the past 30 days). Emotional wellbeing was assessed with two items (I have felt sad, down or depressed in the past 30 days; I had a period lasting several days feeling worried or anxiety in the past year), and evaluative wellbeing with one item (I have been satisfied with my life as a whole in the past year). A composite scale for mental wellbeing was constructed by summing the scores on the separate items. Each item was scored on a 5-point Likert scale, ranging from "never" (= 0) to "always" (= 4), and the total score ranged from 0 to 20. Greater values indicate better mental wellbeing. The reliability of the questionnaire was checked using a Cronbach's Alpha coefficient. Factor analysis was used to test the construct validity of the questionnaire. In our study, Cronbach's Alpha value was 0.791 ($\geqslant$0.700), which means that these five items have good reliability. Kaiser-Meyer-Olkin (KMO) was 0.806 (>0.700), which means that these five items have high construct validity.

## 2.3 Greenspace exposure metrics

It remains unclear which definition of neighborhood size is most appropriate when studying environmental influences on mental health and related behaviors. Buffers with radii ranging from 0.4 km to 1.0 km have been frequently used, with some evidence suggesting that smaller buffers may be more appropriate for older adults given their reduced physical capacity (Barnett et al., 2018; Cerin et al., 2014). Depending on the study focus (e.g., whether related to physical or mental health responses to greenspace) different buffer distances seem to be used. For example, studies focusing on mental health were more likely to select buffer distances less than or equal to 300 m (Labib et al., 2020b). The 300 m radius was derived from an estimate of the average distance older people would be able to walk comfortably from their homes, based on 10 minutes' walking time and findings that older people walk more slowly than the average fit male adult (Burton et al., 2011). Also, in line with the uncertain geographic context problem, epidemiological findings could be affected by how the neighborhood size and shape were defined before abstracting greenspace information (Kwan, 2012; Markevych et al., 2017). So, we selected 300 m, 500 m buffers and residential neighborhood boundaries to measure the greenspace exposure metrics.

Multiple greenspace measures were derived for each neighborhood, including NDVI (Landsat 8, 30 m resolution), vegetation coverage, park coverage, streetscape greenness, streetscape trees and streetscape grasses. They were calculated for each neighborhood separately by averaging the scores for all sampling points within a 300 m and 500m circular buffer around the geographic centroid of each study neighborhood and within the residential neighborhood boundary. Each of these measures is described in more detail below. Table 1 shows the calculation method and data source of the greenspace characteristics.

Table 1 Design and calculation method of urban greenspace metrics

| Characteristics | Calculation Method | Data Sources | Data Dates |
|---|---|---|---|
| NDVI | Extracted from remote sensing images by software ENVI | Landsat-8 images | 2019 |
| Vegetation coverage | Extracted from globe land cover data by software ArcGIS | Global 30-m land-cover classification with a fine classification system in 2020 (GLC_FCS30-2020) | 2020 |
| Park coverage | Calculating coverage rate of parks in neighborhoods by software ArcGIS | The location and shape of parks in Dalian | 2019 |
| Streetscape greenness/trees/grasses | Extracted from Tencent Street View data by a fully convolutional neural network | Tencent Street View data | 2016 |

### 2.3.1 NDVI

To calculate annual NDVI, we used Landsat-8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) satellite images at a resolution of 30 m. NDVI is an indicator of overall greenness based on land surface reflectance of visible (RED) and near infrared (NIR) parts of the spectrum, calculated as (NIR-RED)/(NIR + RED) (Tucker, 1979). The scale runs from -1 to 1, with higher numbers indicating more greenness. Annual values are the mean NDVI from all images taken during 2019 after screening each image for water, snow, shadows, and cloud cover using the cloud mask band derived from the Fmask algorithm (Zhu and Woodcock, 2012). The final NDVI estimates were then averaged in each study neighborhood (Barnett et al., 2018). Negative values represent water, ice, and non-vegetated soil. We converted all negative NDVI values to zero, such that negative values (which indicates subsets of non-green space) would not offset positive (green) values in calculating areal averages (Markevych et al., 2017; Reid et al., 2018).

### 2.3.2 Vegetation coverage and park coverage

Percentage vegetation coverage was based on the land cover data derived from the global 30-m land-cover product with fine classification system in 2020 (GLC_FCS30-2020), which is publicly available (http://hdl.pid21.cn/21.86109/casearth.5fbc7904819aec1ea2dd7061). GLC_FCS30-2020 product is divided into 30 categories at a spatial resolution of 30 m (Zhang et al., 2021c), including trees, grass, impervious surfaces, water and barren land, etc. Vegetation coverage was estimated by dividing the total area of all vegetation (i.e., tree, grass, shrub, forest, etc.) in the buffer or residential neighborhood by the total area of the buffer or residential neighborhood. The map regarding the location and shape of various parks in 2019 in Dalian was provided by the Dalian Institute of Planning and Design. Park coverage was determined by dividing the total area of parks in the buffer or residential neighborhood by the total area of the buffer or residential neighborhood.

### 2.3.3 Streetscape greenness

To extract street view greenspace from downloaded images, a machine learning approach was implemented. We utilized a semantic segmentation technique to overcome the limitations of pixel-wise classifications based on an image's additive colors (e.g., natural and manmade green objects are indistinguishable) (Larkin and Hystad, 2019; Long et al., 2015). We used a fully convolutional neural network for semantic segmentation (i.e., the FCN-8s) (Long et al., 2015) to segment the street view images into common ground objects since deep learning performed well for pattern recognition tasks (Rawat and Wang, 2017). Fig. 2 depicts the network structure of FCN-8. For a technical detailed description, see Long et al. (2015), and Rawat et al. (2017). We used annotated images from the ADE20K scene parsing and segmentation database5 to train the network (Zhou et al., 2019). The proportion of greenspace (e.g., trees, grass, plants) was determined after obtaining image segmentations by feeding the street view images into the trained network.

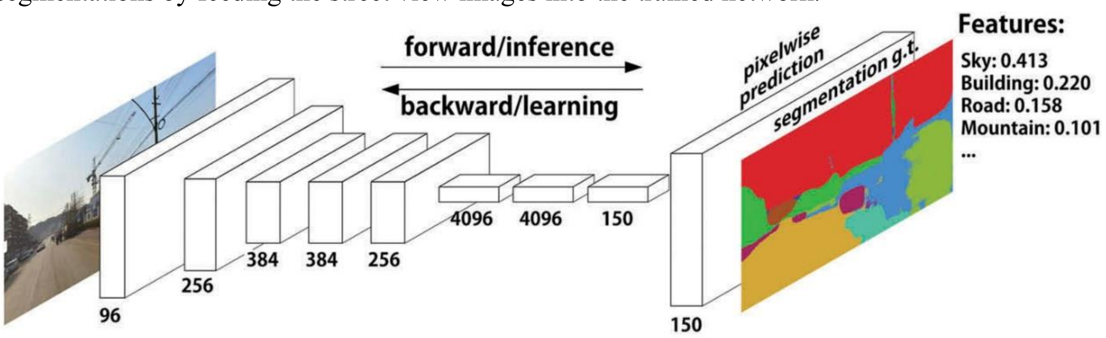


Fig. 2 Architecture of the fully convolutional network (Long et al., 2015). The attached numbers refer to a layer's convolution kernel size.

All streetscape indicators were computed using Tencent Street View images extracted from Tencent Online Map, which were mainly collected in May and June 2016 (Sun & Lu, 2022). Sampling points were extracted at 50-meter intervals on roads covering the street view image in Dalian's main urban area. Streetscape greenness per sampling point represents the rate of the number of greenness pixels per image summed over the four cardinal directions (90°, 180°, 270°, 360°) to the total number of pixels per image summed over the four cardinal directions (Dong et al., 2018). The methods used to calculate streetscape trees and grasses are the same as those used to calculate streetscape greenness. Finally, averages per circular buffers and residential neighborhoods were determined (Li and Ghosh, 2018).

## 2.4 Environmental perceptions

The potential mediators (i.e., perceptions of noise and aesthetics, satisfaction with recreational opportunities) were assessed through a questionnaire. The questions were informed by relevant literature (Kothencz et al., 2017; Krajter Ostoić et al., 2017). Perception of noise was assessed with one item (How quiet is the neighborhood in terms of traffic noise) (Irvine et al., 2009; Szeremeta and Zannin, 2009), perception of aesthetics with one item (How beautiful is the neighborhood in terms of visual aesthetics) (Chen et al., 2009; Mansor et al., 2012), and satisfaction with recreational opportunities with one item (How much does the neighborhood satisfy the function 'recreational opportunities in terms of leisure and exercise activities') (Jim and Chen, 2006; Nasution and Zahrah, 2014). Each environmental perception was scored on a 5-point Likert scale.

## 2.5 Socio-demographics

Socio-demographic characteristics can affect residents' mental health (Dong and Qin, 2017; Triguero-Mas et al., 2015), so multiple covariates data on an individual level were obtained through the survey. We controlled for the factors suggested by previous studies, including age, gender, educational level, monthly income level, and years of living at the current address (Besser et al., 2017). Moreover, pre-retirement occupation and homeownership are important (Zock et al., 2018); lacking the latter was found a risk factor for mental disorders in the Chinese context (Liu et al., 2017a). We also considered the number of co-occupants in a household, as single older adults are high-risk groups for mental health problems (Tsai et al., 2016). Given that physical health affects mental health (Steptoe et al., 2015), we controlled for the respondent's rating of their physical functional ability, which was scored on a 5-point Likert scale, ranging from "completely unable to move by myself" to "able to perform activities completely unrestricted". Homeownership was coded into three categories: own, kinsfolks and others. This is to describe who owns the property residents live in currently. The pre-retirement occupation was coded into three categories: manual work, intellectual work and other. Manual work is characterized as more closely related to, or dependent on, physical labor or skills, such as personnel of commerce, catering and service, and producers of farming, etc. Intellectual work is characterized as more closely related to, or dependent on the mind or brain, such as employed position at desk, general and middle management and university professors, etc. Gender, pre-retirement occupation, number of co-occupants, education level and homeownership were included as dummy variables in the models.

## 2.6 Statistical analyses

We estimated the relationship between residential greenspace exposure and mental health using multilevel linear regression models. Since single-level regressions treat the health outcomes of respondents as independent observations and ignore bias of the hierarchical structure in model estimates, they will overestimate the statistical significance (Raudenbush and Bryk, 2002). To examine whether the association of greenspace with mental health could be partially explained by the perceived environmental factors, we conducted a multi-step mediation analysis (Baron and Kenny, 1986). Mediation analysis decomposes the effect of greenspace on mental health into a direct and a mediation (indirect) component as well as a total effect. Fig. 3 shows the analysis framework. The percentage of mediation was determined by dividing the mediation by the total effect.

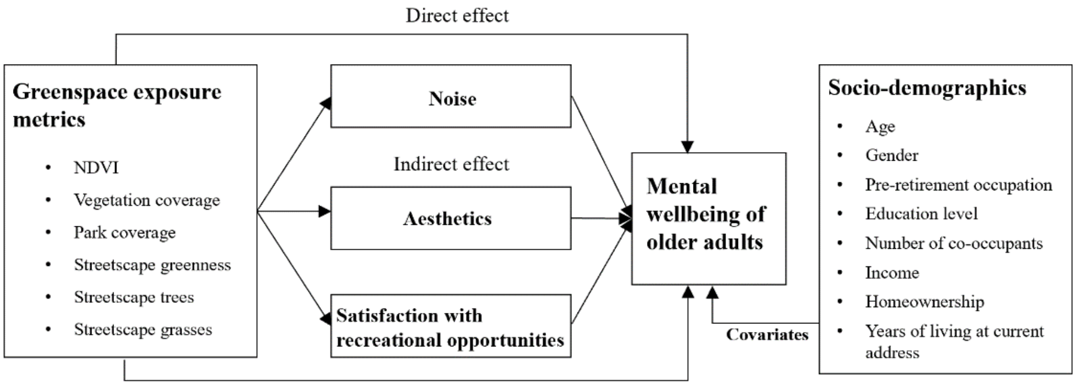


Fig. 3 Analytical framework of this study

The following steps were conducted. First, we identified a direct link between greenspace and older adults' wellbeing scores. Model 1a included socio-demographics. Models 1b-1h further contained NDVI, vegetation coverage, park coverage, streetscape greenness, streetscape trees and streetscape grasses separately. We developed multilevel linear regression models fully adjusted for socio-demographic variables (Gelman and Hill, 2006) with mental wellbeing scores as the continuous outcome (Raudenbush and Bryk, 2002). A random intercept was applied to take into account correlations that arise as a result of respondents being nested in neighborhoods with similar exposures. Model performance was assessed by the Akaike Information Criterion (AIC). A lower AIC value indicates better goodness-of-fit (Burnham and Anderson, 2002). An AIC difference of 2 indicates a significant difference between the models (Helbich et al., 2019). Second, we regressed NDVI on each potential mediator in Model 2a. Similarly, the other greenspace measures were regressed on each potential mediator separately in Models 2b-2f. Third, models 3a-3d respectively assessed the associations of the greenspace exposure metrics with mental wellbeing scores, considering the significant mediators identified in the second step. Sobel tests were conducted to test the significance of the mediation effect (Sobel, 1982).

We first conducted specific analyses using 500 m buffers. Then, we repeated our analyses using 300 m buffers and residential neighborhood boundaries instead of 500 m buffers when measuring exposure to greenspace as the robustness test. Statistical analyses were carried out in STATA 15.1.

## 3 Results

### 3.1 Characteristics description

Table 2 shows the individual socio-demographic variables and greenspace exposure metrics. At individual level, slightly more females than males participated in the study and the average age was 73.2 years. 34.7% of the respondents had a high school education or higher and approximately 12.9% possessed a college-level education. 27.5% of the participants had a monthly income of RMB 2000-3000 (USD 314.70-472.05). In total, 61.8% of the respondents had been living at their current address for more than 20 years. The average mental wellbeing score of the 879 respondents was 12.75 and the standard deviation was 2.92. In our sample, 72.1% of the older adults were aged 65 and over, compared to 68.3% in Dalian census data. Furthermore, 46.2% of our sample was male, compared to 47.6% in the census data (Dalian Municipal Bureau of Statistics, 2021). This indicates that regarding age and gender, our study sample is representative for the older population in Dalian.

At environmental level in Table 2, all the greenspace metrics were between 0 and 1. The highest average in all metrics was streetscape greenness score, which was 0.18 (SD±0.06). The average NDVI score was 0.07 (SD ± 0.01), while the park coverage score was 0.06 (SD ± 0.06). The standard deviation of vegetation coverage is 0.12, indicating a large difference in greening level between neighborhoods. Fig. 4 shows the various characteristics of the greenspace exposure metrics.

Table 2 Descriptive statistics for individual- and environmental-level variables

| | **Mean (SD) / N (%)** |
|---|---|
| **Individual-level variables (n=879)** | |
| Age (years) | |
| 60-70 | 394(44.82%) |
| 71-80 | 293(33.33%) |
| 81+ | 192(21.84%) |
| Gender | |
| Male | 406(46.19%) |
| Female | 473(53.81%) |
| Pre-retirement occupation | |
| Intellectual work | 314(35.72%) |
| Manual work | 505(57.45%) |
| Other | 60(6.83%) |
| Education level | |
| Primary school or lower | 300(34.13%) |
| Middle school | 274(31.17%) |
| High school | 192(21.84%) |
| College/university | 113(12.86%) |
| Number of co-occupants | |
| 1 | 116(13.20%) |
| 2 | 388(44.14%) |
| 3 and more | 375(42.66%) |
| Monthly income level | |
| RMB 0-1000 (USD 0-157.35) | 116(13.20%) |
| RMB1001-2000 (USD 157.51-314.70) | 63(7.17%) |
| RMB2001-3000 (USD 314.86-472.05) | 242(27.53%) |
| RMB3001-4000 (USD 472.21-629.41) | 242(27.53%) |
| RMB4000+ (USD 629.41+) | 216(24.57%) |
| Homeownership | |
| Own | 571(64.96%) |
| Kinsfolks | 261(29.69%) |
| others | 47(5.35%) |
| Years of living at current address | |
| 10 - 15 | 169(19.23%) |
| 16 - 20 | 167(19.00%) |
| 20+ | 543(61.77%) |
| Physical function (range=0-4) | 2.54(0.98) |
| Environmental perceptions | |

| | |
|---|---|
| Noise (range=0-4) | 2.45(1.00) |
| Aesthetics (range=0-4) | 2.37(1.02) |
| Satisfaction with recreational opportunities (range=0-4) | 2.32(0.85) |
| Mental wellbeing (range=0-20) | 12.75(2.92) |
| **Environmental-level variables (n =61)** | |
| NDVI (range=0.05-0.11) | 0.07(0.01) |
| Vegetation coverage (range=0.01-0.60) | 0.12(0.12) |
| Park coverage(range=0.00-0.26) | 0.06(0.06) |
| Streetscape greenness(range=0.09-0.39) | 0.18(0.06) |
| Streetscape trees(range=0.06-0.32) | 0.16(0.05) |
| Streetscape grasses(range=0.00-0.03) | 0.01(0.01) |

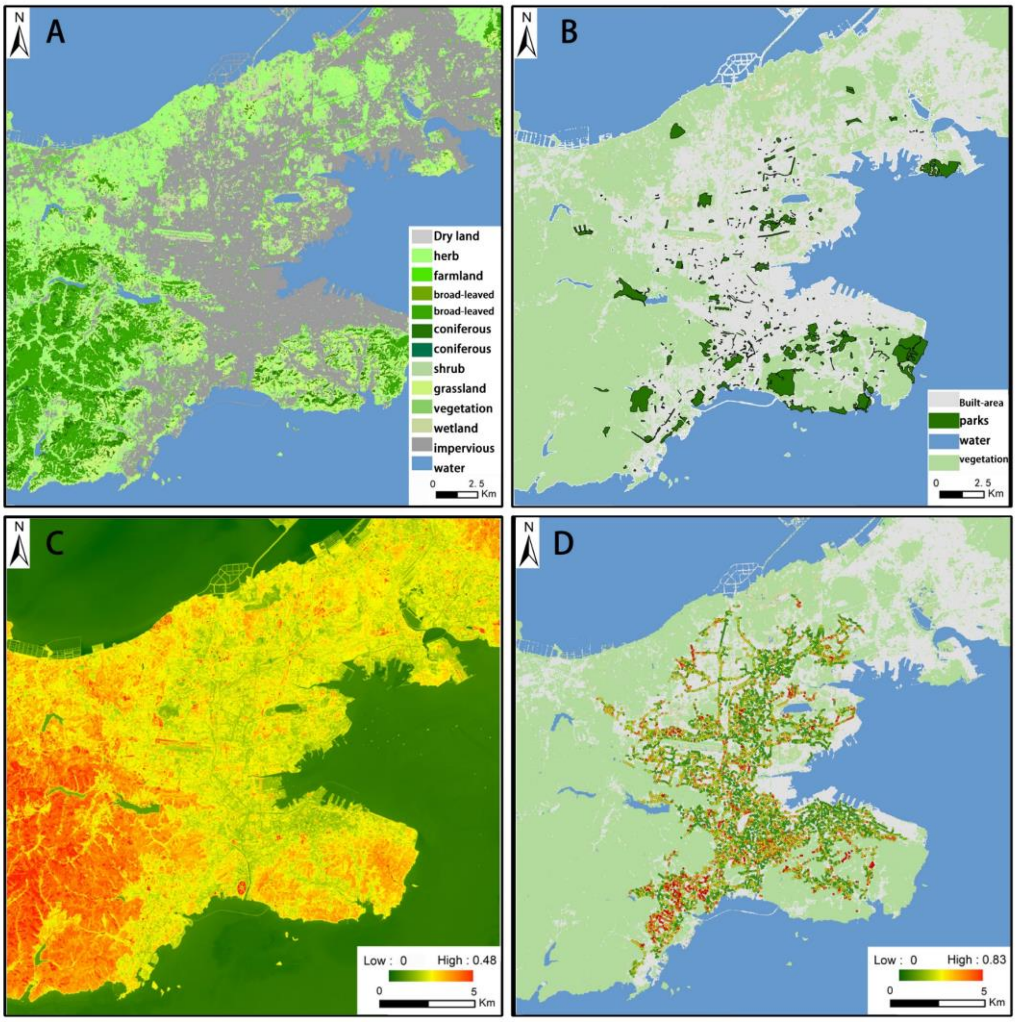


Fig. 4: Greenspace exposure metrics in Dalian: (A) 2020 land coverage with 30-meter resolution (GLC_FCS30-2020) (B) Parks distribution in Dalian (C) NDVI (D) Streetscape greenness

Table 3 shows the correlations between greenspace assessments. While most of the correlations were positive, some patterns were noticeable. Streetscape greenness and streetscape trees had the highest correlation (β=0.97) because trees are a major part of streetscape greenness. Also, between NDVI and vegetation coverage a high correlation was present (β=0.73). Park coverage was not significantly correlated with streetscape greenness and streetscape trees.

Table 3 Correlation matrix of greenspace measures

| | NDVI | Vegetation coverage | Park coverage | Streetscape greenness | Streetscape trees | Streetscape grasses |
|---|---|---|---|---|---|---|
| NDVI | 1.00 | | | | | |
| Vegetation coverage | $0.73^{***}$ | 1.00 | | | | |
| Park coverage | $0.20^{***}$ | $0.18^{***}$ | 1.00 | | | |
| Streetscape greenness | $0.40^{***}$ | $0.19^{***}$ | -0.03 | 1.00 | | |
| Streetscape trees | $0.27^{***}$ | $0.11^{***}$ | -0.09 | $0.97^{***}$ | 1.00 | |
| Streetscape grasses | $0.49^{***}$ | $0.16^{***}$ | $0.27^{***}$ | $0.35^{***}$ | $0.19^{***}$ | 1.00 |

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

## 3.2 Multilevel regression models

The neighborhood-level intra-class correlation of the null model was 0.17. This indicates that wellbeing scores are moderately clustered within the neighborhood, which demonstrates the validity of the multilevel approach. Table 4 displays the results of multilevel regression models. Adding variables of greenspace exposure metrics (Model 1b-1h) respectively to Model 1a led to a decrease in AIC scores and thus an improvement in model goodness-of-fit. The adjusted model with NDVI (Model 1b) had the lowest AIC score, followed by the models with vegetation coverage, streetscape grasses and park coverage. The refitted models with variables derived from street view data performed worse than with the NDVI (Models 1b) and vegetation coverage from GlobeLand30 remote sensing data (Models 1c) as indicated by notable AIC differences. Remarkably, the adjusted model with streetscape grasses (Model 1h) had a lower AIC score (and thus a better model fit) than the models with streetscape greenness (Models 1e) and streetscape trees (Models 1f).

Table 4 Results of multilevel regression models

| Variable | Null model | Model 1a | Model 1b | Model 1c | Model 1d | Model 1e | Model 1f | Model 1h |
|---|---|---|---|---|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| **Fixed effects** | | | | | | | | |
| **Socio-economic characteristics（individual level）** | | | | | | | | |
| Age | | $0.03^{***}$ (0.01) | $0.03^{***}$ (0.01) | $0.03^{***}$(0.01) | $0.03^{***}$ (0.01) | $0.03^{***}$ (0.01) | $0.03^{***}$ (0.01) | $0.03^{***}$ (0.01) |
| Gender (ref: male) | | 0.10 (0.14) | 0.10 (0.14) | 0.11 (0.14) | 0.11 (0.14) | 0.10 (0.14) | 0.10 (0.14) | 0.11 (0.14) |
| Pre-retirement occupation (ref: head work) | | -0.12 (0.19) | -0.11 (0.19) | -0.11 (0.19) | -0.12 (0.19) | -0.12 (0.19) | -0.12 (0.19) | -0.13(0.19) |
| Education level (ref: primary school or lower) | | | | | | | | |
| Middle and high school | | -0.03 (0.25) | -0.04 (0.25) | -0.03 (0.25) | -0.02 (0.25) | -0.03 (0.25) | -0.03 (0.25) | -0.04 (0.25) |
| College/university | | 0.16 (0.23) | 0.15 (0.23) | 0.15 (0.23) | 0.17 (0.23) | 0.16 (0.23) | 0.16 (0.23) | 0.15 (0.23) |
| Number of co-occupants (ref: 1) | | | | | | | | |
| 2 | | 0.21 (0.18) | 0.19 (0.18) | 0.22 (0.18) | 0.21 (0.18) | 0.21 (0.18) | 0.21(0.18) | 0.20 (0.18) |
| 3 + | | $0.55^{***}$(0.19) | $0.52^{***}$(0.19) | $0.55^{***}$ (0.19) | $0.55^{***}$(0.19) | $0.55^{***}$(0.19) | $0.55^{***}$(0.19) | $0.54^{***}$(0.19) |
| Monthly income level | | 0.06 (0.08) | 0.05 (0.08) | 0.06 (0.08) | 0.06 (0.08) | 0.06 (0.08) | 0.06 (0.08) | 0.06 (0.08) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Homeownership (ref: not own) | | 0.27$^{*}$ (0.16) | 0.30$^{*}$ (0.16) | 0.28$^{*}$ (0.16) | 0.28$^{*}$ (0.16) | 0.28$^{*}$ (0.16) | 0.28$^{*}$ (0.16) | 0.29$^{*}$ (0.16) |
| Years of living at current address | | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) | -0.02$^{***}$ (0.01) |
| Physical function | | 0.16$^{***}$ (0.04) | 0.17$^{***}$ (0.04) | 0.16$^{***}$ (0.04) | 0.17$^{***}$ (0.04) | 0.17$^{***}$ (0.04) | 0.17$^{***}$ (0.04) | 0.16$^{***}$ (0.04) |
| **Characteristics of greenspace （neighborhood level）** | | | | | | | | |
| NDVI | | | 2.28$^{**}$ (1.02) | | | | | |
| Vegetation coverage | | | | 1.06$^{**}$ (0.45) | | | | |
| Park coverage | | | | | 0.73$^{*}$ (0.43) | | | |
| Streetscape greenness | | | | | | 0.25 (0.84) | | |
| Streetscape trees | | | | | | | 0.16 (0.78) | |
| Streetscape grasses | | | | | | | | 1.02$^{*}$ (0.61) |
| Constant | 10.56$^{***}$(0.13) | 7.18$^{***}$ (0.95) | 5.65$^{***}$ (1.05) | 6.92$^{***}$ (0.92) | 7.08$^{***}$ (0.96) | 7.05$^{***}$ (0.97) | 7.09$^{***}$ (0.98) | 6.99$^{***}$ (0.94) |
| **Random effects** | | | | | | | | |
| ICC | 16.87% | 14.10% | 12.53% | 13.21% | 13.88% | 14.32% | 14.32% | 13.70% |
| Var (Neighborhood-level constant) | 0.70 | 0.55 | 0.48 | 0.51 | 0.54 | 0.56 | 0.56 | 0.53 |
| Var（individual level） | 3.44 | 3.35 | 3.35 | 3.35 | 3.35 | 3.35 | 3.35 | 3.34 |
| AIC | 3232.20 | 3229.43 | 3219.79 | 3223.55 | 3225.36 | 3226.03 | 3226.24 | 3223.76 |

Note: *p < 0.10; **p < 0.05; ***p < 0.01; ref = reference category; The specific model (the explanatory variable at the neighborhood level corresponding to the model): Model 1b (NDVI), Model 1c (Vegetation coverage), Model 1d (Park coverage), Model 1e (Streetscape greenness), Model 1f (Streetscape trees), Model 1g (Streetscape grasses).

We observed a statistically significant and positive association of NDVI and vegetation coverage with mental wellbeing ($p < 0.05$) (Model 1b and 1c), and a marginally significant positive association of park coverage and streetscape grasses with wellbeing ($p < 0.10$) (Model 1d and 1h). In contrast, streetscape greenness and streetscape trees had no significant correlation with mental wellbeing, although AIC scores of the model improved compared to the null model.

Adding variables of exposure to greenspace did not alter the significance levels of the covariates (Model 1a-1h), although the coefficients changed slightly. Some of the covariates were statistically significant (model 1a). Older age was positively associated with wellbeing ($p < 0.01$). Longer duration of living at the current address was negatively correlated with wellbeing ($p < 0.01$). Living with 2 or more people was positively correlated with wellbeing, compared with living alone ($p < 0.01$). Having higher physical functional ability was associated with higher wellbeing scores among the older adults ($p < 0.01$). We found no evidence that gender, personal income, pre-retirement occupation, and education level were significantly related to older adults' mental wellbeing.

## 3.3 Mediating effects of environmental perceptions

Table 5 shows the results of regressing greenspace metrics on the mediators. In models 2a, 2b, 2c, 2f, greenspace metrics were positively related to all environmental perceptions (potential mediators). Streetscape greenness and streetscape trees had no association with most potential mediators. We observed that NDVI and vegetation coverage were positively associated with noise ($p<0.01$), while park coverage was only marginally significantly associated with noise ($p<0.10$). Although both streetscape trees and streetscape grasses were derived from street-view images, large differences in the associations with the environmental perceptions were found.

Table 5 Results of regressing greenspace metrics on potential mediators

| Greenspace metrics | Noise | Aesthetics | Satisfaction with recreational opportunities |
|---|---|---|---|
| | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| Model 2a (NDVI) | 2.17*** (0.25) | 1.64*** (0.26) | 0.75*** (0.22) |
| Model 2b (Vegetation coverage) | 1.22*** (0.15) | 1.17*** (0.16) | 0.34** (0.13) |
| Model 2c (Park coverage) | 0.34* (0.19) | 0.63*** (0.20) | 0.30** (0.15) |
| Model 2d (Streetscape greenness) | 0.46* (0.27) | 0.39 (0.27) | -0.01 (0.23) |
| Model 2e (Streetscape trees) | 0.12 (0.24) | 0.21 (0.25) | 0.03 (0.20) |
| Model 2f (Streetscape grasses) | 0.79*** (0.18) | 0.60*** (0.19) | 0.36** (0.15) |

Note: *p < 0.1; **p < 0.05; ***p < 0.01; Model 2a (NDVI), Model 2b (Vegetation coverage), Model 2c (Park coverage), Model 2d (Streetscape greenness), Model 2e (Streetscape trees), and Model 2f (Streetscape grasses) means regressing respective greenspace metrics as explanatory variables on potential mediators.

Table 6 presents the unstandardized direct, indirect, and total effects of greenspace exposure metrics on wellbeing scores. As streetscape greenness and streetscape trees had no association with wellbeing scores and most mediators (Table 4 and 5), no further examination of potential mediating effects was done. The indirect effects of NDVI, vegetation coverage and streetscape grasses on mental wellbeing scores through noise, aesthetics and satisfaction with recreational opportunities were all significant. This indicates that these three mediators mediated the associations of NDVI, vegetation coverage and streetscape grasses with wellbeing scores. However, only aesthetics and satisfaction with recreational opportunities mediated the association between park coverage and mental wellbeing scores. Through comparing the differences between parallel mediating pathways in the association of NDVI with older adults' mental health, we observed that the mediating effect of satisfaction with recreational opportunities (β=1.32) was significantly stronger than the mediating effect of noise (β=0.61) and aesthetics (β=0.39). Also, in the association of streetscape grasses with mental wellbeing scores, the mediating effect of satisfaction with recreational opportunities (β=0.63) was significantly stronger than that of aesthetics (β=0.14). Satisfaction with recreational opportunities was the most crucial mediating variable in all models and this pathway accounted for respectively 56.9%, 48.8%, 67.9% and 63.6% of the total indirect effects in Models 3a, 3b, 3c, 3d.

Table 6 Results of mediating effects models

| Greenspace measures | Total effect | Specific indirect effects (mediators tested all-at-a-time) | | | Direct effect |
|---|---|---|---|---|---|
| | | Noise | Aesthetics | Satisfaction with recreational opportunities | |
| | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) | Coef. (SE) |
| Model 3a (NDVI) | 2.42*** (0.51) | 0.61*** (0.13) | 0.39*** (0.10) | 1.32*** (0.37) | 0.11 (0.28) |
| Model 3b (Vegetation coverage) | 1.23*** (0.32) | 0.35*** (0.08) | 0.28*** (0.06) | 0.60*** (0.22) | -0.01 (0.18) |
| Model 3c (Park coverage) | 0.60* (0.39) | 0.10 (0.07) | 0.15** (0.05) | 0.53* (0.28) | -0.19 (0.20) |
| Model 3d (Streetscape grasses) | 1.22*** (0.37) | 0.22*** (0.06) | 0.14** (0.05) | 0.63** (0.26) | 0.23 (0.19) |

Note: *p < 0.1; **p < 0.05; ***p < 0.01; Model 3a (NDVI), Model 3b (Vegetation coverage), Model 3c (Park coverage), and Model 3d (Streetscape grasses) means putting respective greenspace metrics into mediating analysis with three mediators.

## 3.4 Robustness checks

The results of the robustness check were overall consistent with what is displayed in Table 4-6 (results available in the supplementary document). The only difference was that park coverage within the residential neighborhood boundaries had no positive association with older adults' mental wellbeing. We speculate that considerable portions of the parks were within the circular buffers but not within residential neighborhood boundaries, which may contribute to the discrepancies in results. The associations of other greenspace metrics with mental wellbeing were consistent with previous models and the order of AIC scores did not change when excluding park coverage within residential neighborhood boundaries. The above shows that overall, our observed results were robust.

# 4. Discussion

We investigated the associations of multiple greenspace exposure metrics derived from street view, land use and satellite data with older adults' mental health using a cohort from Dalian. Our finding showed that greenery in the overhead view, including NDVI, vegetation coverage and park coverage, correlates positively with older adults' mental wellbeing to varying degrees, which corresponds with findings reported elsewhere (Triguero-Mas et al., 2015; Wang et al., 2021; Zhang et al., 2021b). Although the application of street view data is gaining attention (Middel et al., 2019; Rzotkiewicz et al., 2018), only a few studies assessed associations between streetscape greenness and mental health indicators (Helbich et al., 2019; Wang et al., 2021; Wang et al., 2019b; Zhou et al., 2020), and results have not been consistent (Helbich et al., 2021; Wang et al., 2020). Therefore, we investigated the effect of streetscape greenery on older adults' mental wellbeing in a Chinese second-tier city, emphasizing the distinction of street vegetation types. A novel finding that emerged from this study, is the following: streetscape grasses were positively associated with mental wellbeing in older adults but streetscape trees were not. Notably, greenspace exposure metrics in overhead view had a stronger association with older adults' mental wellbeing than street view exposure metrics in our study. Furthermore, the second aim of this paper was to examine the mediating role of perceptions of noise, aesthetics, and satisfaction with recreational opportunities in the association of greenspace measures with mental health. The results showed that these mechanisms can explain the associations of multiple greenspace measurements with older adults' mental health to a certain extent, and satisfaction with recreational opportunities was the strongest mediator.

Below, we discuss and compare three sets two similar indicators assessed from a different perspective: Vegetation coverage and park coverage; greenness in overhead view and street view; streetscape trees and streetscape grasses. Furthermore, we discuss the contribution of the three examined mediators to provide empirical evidence for the selection and prioritization of greenspace planning indicators in Chinese second-tier cities.

Although both park coverage and vegetation coverage were derived from overhead view images, park coverage was less strongly associated with mental health than vegetation coverage. This is not in line with previous studies, showing that park quantity and usage can have significant positive effects on mental health (Esther H.K et al., 2017; Lai et al., 2020). Vegetation coverage in the neighborhood was also found to be associated with mental health in previous studies (Su et al., 2019; Zhang et al., 2021a). Regarding the comparison of the two metrics, a similar conclusion is reflected in another study (Zhang et al., 2021a). Zhang et al. (2021) found that canopy coverage showed a stronger association with mental health than park area at the adjacent spatial scale (a 100 m buffer zone surrounding residence) in adults because the sum of visual greenness around the residence played a more important role in promoting mental health. Conversely, Yang et al. (2021) found distance to parks to be more strongly related to mental health than vegetation quantity (Liu et al., 2017a; Yang et al., 2021).

The mediation analyses showed that perceptions of noise and aesthetics, as well as satisfaction with recreational opportunities, mediated the association of vegetation coverage with mental wellbeing, while only aesthetics and satisfaction with recreational opportunities mediated the association between park coverage and wellbeing scores. Park coverage may mainly reflect opportunities for social gathering and activities and may not be directly related to noise perceptions compared with overall greenery in the neighborhood (Zhang et al., 2021a), so this may explain why the mediating effect of noise was not significant. Preliminary evidence shows that greenspace exposure is related to the improvement of mental wellbeing through noise reduction (Wang et al., 2020). Therefore, the absence of the mediation pathway of noise abatement may be part of the reason for the discrepancy in the strength of associations of vegetation coverage and park coverage with mental wellbeing.

Moreover, the weak association of park coverage with mental wellbeing could also be attributed to the low-level actual visitation of parks. Existing research indicated that the restorative effects of greenspace are dependent on actual engagement at various activity sites (Dzhambov et al., 2018; Tyrväinen et al., 2014). Yang et al. (2021) found that mainly the quality of greenery in the park had a strong association with the total number of park visitors. It seems that the mere ‘presence’ of parks is not sufficient to attract residents to visit them. Due to physical conditions and retirement, older adults often have a limited travel range (Barnett et al., 2018; Burton et al., 2011). Many of them are reluctant to travel long distances to reach the park (Byrne and Wolch, 2009; Žlender and Ward Thompson, 2017), resulting in low numbers of older adult visitors in some parks. In our interviews with older adults, we learned that many older adults preferred to communicate, play cards and play chess with familiar neighbors in the small leisure places with vegetation around the residence. That may explain the stronger correlation between vegetation coverage and mental wellbeing.

In this study, greenspace exposure metrics in overhead view derived from satellite data had a stronger association with older adults’ mental wellbeing than those derived from street view images. The association of greenspace measured in overhead view such as NDVI and vegetation coverage with mental health has been confirmed in most previous studies (Liu et al., 2019c; Reid et al., 2018; Wang et al., 2021). However, evidence regarding the association of streetscape greenness with mental health outcomes is not uniform. Our findings showing no association between streetscape greenness and mental wellbeing contrast with those of a study in adults in Guangzhou (Wang et al., 2019a) and one among older adults in Beijing (Helbich et al., 2019), China where the association between streetscape greenness and depression was statistically significant in a few larger administrative areas. Similar to our findings, a previous study in the Netherlands found no association between streetscape greenness and adults’ mental health (Helbich et al., 2021).

Possible explanations for the absence of an association between streetscape greenness and mental wellbeing, and the contradicting findings compared to the studies conducted in larger cities in China, are the following: First, we speculate that the species, age and number of street trees varies limitedly between neighborhoods in Dalian. The absence of an association with mental wellbeing could be due to a tiny difference in streetscape greenness between buffers, which implies that statistical power may be insufficient to detect associations (Kothencz et al., 2017). Second, this disparity in associations could also be attributed to differences in the size and shape of the geographical context (Helbich et al., 2021; Reid et al., 2018). The average neighborhood size in the study conducted in Beijing was 2.1 $km^2$ which is much larger than our study neighborhoods (mean=0.28 $km^2$). Third, the target group in the Guangzhou study were adults rather than older adults which may result in the discrepancy in conclusions, as older adults differ significantly from adults in terms of travelling tracks, psychological state and environmental exposure (Kerr et al., 2012). Fourth, the discrepancy in questionnaires used to assess mental health indicators may also contribute to the contrasting conclusions between studies. We assessed mental health originating from the WAVE 1' dataset designed by WHO (SAGE team, 2013). However, mental health was measured by the five-item WHO Wellbeing Index (WHO-5) (Heun et al., 2001) in the study in Guangzhou. The assessment of mental health in the study in Beijing was carried out with the self-rated Geriatric Depression Scale (GDS-15) (Sheikh and Yesavage, 1986).

Streetscape trees were not associated with older adults' mental health in our study. Previous studies on the association between greenspace and mental health that distinguish vegetation types have focused on overhead view, missing investigations regarding street view images. Several studies focused exclusively on exposure to trees and documented associations with a lower prevalence of depression and stress among adults (Beyer et al., 2014; Taylor et al., 2015). The reasons for the discrepancy in conclusions might be similar to the reasons elaborated on when explaining the lack of associations detected for streetscape greenness, as streetscape trees account for the majority of streetscape greenness, which is visible in the high correlation between the two measures. Besides, trees may also have different psychological effects depending on the area where they are located. Taylor et al. (2017) found that trees in parks were more strongly associated with health outcomes than trees on the road, whereas we only focused on trees on streets.

Nonetheless, streetscape grasses had a significant association with older adults' mental health in this study. It was also verified that streetscape grasses were related to mental health by pathways of noise, aesthetics and satisfaction with recreational opportunities in the mediating analysis. Tsai et al. (2016) revealed that grasses along the roads could provide places and opportunities for recreational activities, which validates the potential positive association of streetscape grasses with mental health indicators. Meanwhile, we speculate that more streetscape grasses often entail the presence of a fairly decent greenery environment with lawns or squares. Such environments are often environments where residents with a high income live. It has been verified in previous studies that residents with relatively higher household incomes are more likely to be satisfied with life and have higher levels of mental wellbeing (Vemuri et al., 2009; Wu et al., 2019).

Satisfaction with recreational opportunities had stronger mediating effects than perceptions of noise and aesthetics in the associations of greenspace exposure metrics with older adults' mental health. There are some possible explanations for these observations. More recreational opportunities in greenspace can encourage health-enhancing behaviours which can improve negative psychological status (e.g., anxiety, depression) and alleviate stress and tension (Casado-Arzuaga et al., 2013). Visitors to greenspace can directly experience psychological benefits through relaxation and physical activity (Tyrväinen et al., 2007). Although noise abatement and aesthetics services are usually correlated with restorative function, they appeared to be not apparent and directly "tangible" for enhancing older adults' pleasurable experience and mental wellbeing (Kothencz et al., 2017). That leaves older adults unaware of the mental benefits of greenspace through noise abatement and increased aesthetics. Furthermore, the greenspace in the study area was mainly scattered rather than concentratedly arranged which also weakens the function of noise abatement and aesthetics services (Klingberg et al., 2017), while greenspace with a scattered layout probably less strongly suppress recreational activities.

The current findings have practical implications. First, the different associations of diverse greenspace exposure metrics with older adults' mental wellbeing provide evidence for the use and prioritization of greenspace planning indicators in a local area or specific city. Specifically, at the quantitative indicator levels, NDVI and vegetation coverage still are the most reliable indicators when creating psychological health-friendly greenspace in Dalian according to our conclusions. This also provides evidence for similar Chinese second-tier cities. One of the reasons why NDVI may be a better metric is that NDVI takes into account all vegetation types and their health, whereas the other metrics only account for a sub-set of vegetation or do not reflect vegetation health. Second, during neighborhood planning and construction phase, local government, policymakers, and relevant personnel should fully recognize the inadequacy of a single greenspace indicator for greenspace planning. A multi-dimensional greenspace indicator system needs to be developed, covering overhead view, eye-level view and vegetation types, and considering the health benefits of different perspectives and different types of greenspace. Third, professionals should avoid directly adopting the experience of other cities and need to tailor the approach to the local context and the city combined with specific study results. For instance, selecting streetscape greenness as a greenspace exposure metric to assess associations with mental health is not applicable in all cities, due to discrepancies in geography and size. Forth, given the strongest mediating role of satisfaction with recreational opportunities, community or neighborhood administrators should highlight the importance of recreational opportunities when greenspace in residential areas is designed, and the emphasis should not solely be put on improving greenspace quantity. These findings are helpful for evidence-based planning strategies and can provide guidelines for designing greenspace and neighborhood landscapes which can further contribute to ageing in place policies.

## 4.1 Strengths and limitations

We attempted to systematically compare associations of different objective greenspace metrics with older adults' mental wellbeing. The first strength of our study was that greenspace was measured from street view images (streetscape trees and streetscape grasses) and land use classification (park coverage) besides remote sensing (NDVI and vegetation coverage). The use of diverse measures is an advancement compared to previous studies, which were often restricted to earth observation data that was frequently of limited resolution (Gascon et al., 2018; Reid et al., 2018). Instead of labor-intensive and time-consuming neighborhood audits, a large volume of street view images combined with an efficient segmentation algorithm allowed us to identify greenspace and vegetation types more efficiently and accurately. Second, instead of focusing on Chinese metropolises, a critical aspect is the selection of a Chinese second-tier and highly ageing city. However, transferring and generalizing our conclusions to other areas needs further verification. Third, our random sampling strategy provided a representative sample of older adults in Dalian, improving generalizability and reducing selection bias.

However, our study still had several limitations. First, the method we have chosen to calculate streetscape greenspace has some drawbacks. First, the methodology is inadequate for capturing eye-level greenness visibility exposure at high spatial resolutions for observers located on the ground (Zhu et al., 2021). Second, as streetscape greenspace is a point-based estimation, and when aggregated at an area level by mean or median, it is sensitive to the location of sampled sites, overweighing the values of densely located sites (Kumakoshi et al., 2020). Third, street-only greenness visibility values are not fully representative of total neighborhood visibility due to the under-representation of visible greenness in locations such as backyards and community parks (Labib et al., 2021). A second limitation of the study is the fact that the season in which the street view images are taken impacts the performance of the streetscape greenspace measures (Xia et al., 2021). However, street view images are not updated frequently. Our images did not match exactly with the questionnaire survey data which may cause some bias in the conclusions. Third, although we chose multiple neighborhood sizes and shapes based on the elderly's daily travel scope (Liu et al., 2019b; Su et al., 2019), they still cannot accurately reflect actual exposures along with residents' daily mobility (Helbich, 2018) because of the lack of physical activity and travel data and limitations of the neighborhood calculation method (without using residential address). Better estimates of actual greenspace exposures and greenspace use that incorporate time-activity patterns will be an important focus of future studies. Fourth, self-selection continues to be an issue due to a lack of information on older adults' attitudes toward and motivations for choosing a residential neighborhood (Zhang, 2014). Fifth, we were unable to determine causation between greenspace exposure and mental health because of cross-sectional data. Sixth, accessibility to greenspace was not included in this study. Accessibility measures can capture important aspects of public availability and access to greenspace for recreation and physical activity (Jarvis et al., 2020a; Jarvis et al., 2020b; Labib et al., 2021). Seventh, potential pathways linking greenspace to mental health also include reducing exposure to air pollution and heat, attention restoration, physiological stress recovery, encouraging physical activity and facilitating social cohesion, which were not included in our analysis (Dzhambov et al., 2018; Markevych et al., 2017).

## 5 Conclusions

This study provides empirical evidence regarding the association and pathways linking greenspace to the mental health of older adults in a Chinese second-tier city. When combined with deep learning, street view data provides a valuable tool for automated environmental assessments of physical streetscapes. Results from multilevel models and mediation analysis show that greenspace exposure metrics in overhead view and street view partly are, to varying degrees, positively associated with older adults' mental wellbeing. In these associations, satisfaction with recreational opportunities had a stronger mediating effect than noise and aesthetics. Our findings support the development of a multi-dimensional greenspace indicator system covering overhead view data, eye-level view data, and different vegetation types when creating psychological health-friendly environments. It is also important to acknowledge that associations with mental health vary within and between cities and attention should be paid to the provision of recreational opportunities when making greenspace planning.


## Acknowledgement

This work was supported by National Natural Science Foundation of China (Grant Nos. 52078095 and 51638003), by China Scholarship Council (Grant Nos. 202006060186).


## References


Arokiasamy, P., Uttamacharya, Kowal, P., Capistrant, B.D., Gildner, T.E., Thiele, E., et al., 2017. Chronic Noncommunicable Diseases in 6 Low- and Middle-Income Countries: Findings From Wave 1 of the World

Health Organization's Study on Global Ageing and Adult Health (SAGE). American Journal of Epidemiology, 185, 414-428.

Barnett, A., Zhang, C.J.P., Johnston, J.M., Cerin, E., 2018. Relationships between the neighborhood environment and depression in older adults: a systematic review and meta-analysis. International Psychogeriatrics 30, 1153-1176.

Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of personality and social psychology 51, 1173.

Besser, L.M., McDonald, N.C., Song, Y., Kukull, W.A., Rodriguez, D.A., 2017. Neighborhood Environment and Cognition in Older Adults: A Systematic Review. Am J Prev Med 53, 241-251.

Beyer, K.M.M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F.J., Malecki, K.M., 2014. Exposure to Neighborhood Green Space and Mental Health: Evidence from the Survey of the Health of Wisconsin. International Journal of Environmental Research and Public Health 11, 3453-3472.

Burnham, K.P., Anderson, D.R., 2002. A practical information-theoretic approach. Model selection and multimodel inference 2.

Burton, E.J., Mitchell, L., Stride, C.B., 2011. Good places for ageing in place: development of objective built environment measures for investigating links with older people's wellbeing. BMC Public Health 11, 839.

Byrne, J., Wolch, J., 2009. Nature, race, and parks: past research and future directions for geographic research. Progress in Human Geography 33, 743-765.

Casado-Arzuaga, I., Madariaga, I., Onaindia, M., 2013. Perception, demand and user contribution to ecosystem services in the Bilbao Metropolitan Greenbelt. Journal of Environmental Management 129, 33-43.

Cerin, E., Cain, K.L., Conway, T.L., Van Dyck, D., Hinckson, E.S., Jasper, De Bourdeaudhuij, I., et al., 2014. Neighborhood Environments and Objectively Measured Physical Activity in 11 Countries. Medicine & Science in Sports & Exercise, 46, 2253-2264.

Chen, B., Adimo, O.A., Bao, Z., 2009. Assessment of aesthetic quality and multiple functions of urban green space from the users' perspective: The case of Hangzhou Flower Garden, China. Landscape and Urban Planning 93, 76-82.

Cusack, L., Larkin, A., Carozza, S.E., Hystad, P., 2017. Associations between multiple green space measures and birth weight across two US cities. Health Place 47, 36-43.

Dalian Municipal Bureau of Statistics. Communiqué of the 7th National Population Census of Dalian. 2021. [2022-02-12]. Available from: https://stats.dl.gov.cn/art/2021/6/11/art_3812_700674.html.

Dong, H., Qin, B., 2017. Exploring the link between neighborhood environment and mental wellbeing: A case study in Beijing, China. Landscape and Urban Planning 164, 71-80.

Dong, R., Zhang, Y., Zhao, J., 2018. How Green Are the Streets Within the Sixth Ring Road of Beijing? An Analysis Based on Tencent Street View Pictures and the Green View Index. International Journal of Environmental Research and Public Health 15, 1367.

Dzhambov, A.M., Browning, M., Markevych, I., Hartig, T., & Lercher, P., 2020. Analytical approaches to testing pathways linking greenspace to health: A scoping review of the empirical literature. Environ Res, 186, 109613.

Dzhambov, A., Hartig, T., Markevych, I., Tilov, B., Dimitrova, D., 2018. Urban residential greenspace and mental health in youth: Different approaches to testing multiple pathways yield different conclusions. Environmental Research 160, 47-59.

Esther H.K, Y., Winky K.O, H., Edwin H.W, C., 2017. Elderly satisfaction with planning and design of public parks in high density old districts: An ordered logit model. Landscape and Urban Planning 165, 39-53.

Feng, X., Astell-Burt, T., 2017. The Relationship between Neighbourhood Green Space and Child Mental Wellbeing Depends upon Whom You Ask: Multilevel Evidence from 3083 Children Aged 12–13 Years. International

Journal of Environmental Research and Public Health 14, 235.

Gascon, M., Sanchez-Benavides, G., Dadvand, P., Martinez, D., Gramunt, N., Gotsens, X., Cirach, M., Vert, C., Molinuevo, J.L., Crous-Bou, M., Nieuwenhuijsen, M., 2018. Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study. Environ Res 162, 231-239.

Gascon, M., Triguero-Mas, M., Martinez, D., Dadvand, P., Forns, J., Plasencia, A., Nieuwenhuijsen, M.J., 2015. Mental health benefits of long-term exposure to residential green and blue spaces: a systematic review. Int J Environ Res Public Health 12, 4354-4379.

Gelman, A., Hill, J., 2006. Data analysis using regression and multilevel/hierarchical models. Cambridge university press.

Giannico, V., Spano, G., Elia, M., D'Este, M., Sanesi, G., Lafortezza, R., 2021. Green spaces, quality of life, and citizen perception in European cities. Environ Res 196, 110922.

Hazer, M., Formica, M.K., Dieterlen, S., Morley, C.P., 2018. The relationship between self-reported exposure to greenspace and human stress in Baltimore, MD. Landscape and Urban Planning 169, 47-56.

He, D., Miao, J., Lu, Y., Song, Y., Chen, L., Liu, Y., 2022. Urban greenery mitigates the negative effect of urban density on older adults' life satisfaction: Evidence from Shanghai, China. Cities, 124, 103607.

Helbich, M., 2018. Toward dynamic urban environmental exposure assessments in mental health research. Environ Res 161, 129-135.

Helbich, M., Klein, N., Roberts, H., Hagedoorn, P., Groenewegen, P.P., 2018. More green space is related to less antidepressant prescription rates in the Netherlands: A Bayesian geoadditive quantile regression approach. Environmental Research 166, 290-297.

Helbich, M., Poppe, R., Oberski, D., Zeylmans van Emmichoven, M., Schram, R., 2021. Can’t see the wood for the trees? An assessment of street view- and satellite-derived greenness measures in relation to mental health. Landscape and Urban Planning 214.

Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., Wang, R., 2019. Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. Environ Int 126, 107-117.

Heun, R., Bonsignore, M., Barkow, K., Jessen, F., 2001. Validity of the five-item WHO Well-Being Index (WHO-5) in an elderly population. European Archives of Psychiatry and Clinical Neuroscience 251, 27-31.

Houlden, V., Weich, S., Porto de Albuquerque, J., Jarvis, S., Rees, K., 2018. The relationship between greenspace and the mental wellbeing of adults: A systematic review. PLoS One 13, e0203000.

Irvine, K.N., Devine-Wright, P., Payne, S.R., Fuller, R.A., Painter, B., Gaston, K.J., 2009. Green space, soundscape and urban sustainability: an interdisciplinary, empirical study. Local Environment 14, 155-172.

Jarvis, I., Gergel, S., Koehoorn, M., van den Bosch, M., 2020a. Greenspace access does not correspond to nature exposure: Measures of urban natural space with implications for health research. Landscape and Urban Planning 194, 103686.

Jarvis, I., Koehoorn, M., Gergel, S.E., van den Bosch, M., 2020b. Different types of urban natural environments influence various dimensions of self-reported health. Environmental Research 186, 109614.

Jiang, B., Deal, B., Pan, H., Larsen, L., Hsieh, C.-H., Chang, C.-Y., Sullivan, W.C., 2017. Remotely-sensed imagery vs. eye-level photography: Evaluating associations among measurements of tree cover density. Landscape and Urban Planning 157, 270-281.

Jim, C.Y., Chen, W.Y., 2006. Perception and Attitude of Residents Toward Urban Green Spaces in Guangzhou (China). Environmental Management 38, 338-349.

Kaplan, R., Kaplan, S., 1989. The experience of nature: A psychological perspective. Cambridge university press.

Kerr, J., Rosenberg, D., Frank, L., 2012. The Role of the Built Environment in Healthy Aging:Community Design, Physical Activity, and Health among Older Adults. Journal of Planning Literature 27, 43-60.

Klingberg, J., Broberg, M., Strandberg, B., Thorsson, P., Pleijel, H., 2017. Influence of urban vegetation on air pollution and noise exposure – A case study in Gothenburg, Sweden. Science of The Total Environment 599-600, 1728-1739.

Kothencz, G., Kolcsar, R., Cabrera-Barona, P., Szilassi, P., 2017. Urban Green Space Perception and Its Contribution to Well-Being. Int J Environ Res Public Health 14.

Krajter Ostoić, S., Konijnendijk van den Bosch, C.C., Vuletić, D., Stevanov, M., Živojinović, I., Mutabdžija-Bećirović, S., Lazarević, J., Stojanova, B., Blagojević, D., Stojanovska, M., Nevenić, R., Pezdevšek Malovrh, Š., 2017. Citizens' perception of and satisfaction with urban forests and green space: Results from selected Southeast European cities. Urban Forestry & Urban Greening 23, 93-103.

Kumakoshi, Y., Chan, S.Y., Koizumi, H., Li, X., Yoshimura, Y., 2020. Standardized Green View Index and Quantification of Different Metrics of Urban Green Vegetation. Sustainability 12, 7434.

Kwan, M.-P., 2012. How GIS can help address the uncertain geographic context problem in social science research. Annals of GIS 18, 245-255.

Labib, S.M., Lindley, S., Huck, J.J., 2020a. Scale effects in remotely sensed greenspace metrics and how to mitigate them for environmental health exposure assessment. Computers, Environment and Urban Systems 82.

Labib, S.M., Lindley, S., Huck, J.J., 2020b. Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. Environmental Research 180, 108869.

Labib, S.M., Lindley, S., Huck, J.J., 2021. Estimating multiple greenspace exposure types and their associations with neighbourhood premature mortality: A socioecological study. Science of The Total Environment 789, 147919.

Lachowycz, K., Jones, A.P., 2013. Towards a better understanding of the relationship between greenspace and health: Development of a theoretical framework. Landscape and Urban Planning 118, 62-69.

Lai, K.Y., Sarkar, C., Sun, Z., Scott, I., 2020. Are greenspace attributes associated with perceived restorativeness? A comparative study of urban cemeteries and parks in Edinburgh, Scotland. Urban Forestry & Urban Greening 53.

Larkin, A., Hystad, P., 2019. Evaluating street view exposure measures of visible green space for health research. Journal of Exposure Science & Environmental Epidemiology 29, 447-456.

Lega, C., Gidlow, C., Jones, M., Ellis, N., Hurst, G., 2021. The relationship between surrounding greenness, stress and memory. Urban Forestry & Urban Greening 59.

Li, D., Deal, B., Zhou, X., Slavenas, M., Sullivan, W.C., 2018. Moving beyond the neighborhood: Daily exposure to nature and adolescents' mood. Landscape and Urban Planning 173, 33-43.

Li, X., Ghosh, D., 2018. Associations between Body Mass Index and Urban "Green" Streetscape in Cleveland, Ohio, USA. International Journal of Environmental Research and Public Health 15, 2186.

Liu, H., Li, F., Li, J., Zhang, Y., 2017a. The relationships between urban parks, residents' physical activity, and mental health benefits: A case study from Beijing, China. J Environ Manage 190, 223-230.

Liu, Y., Dijst, M., Faber, J., Geertman, S., Cui, C., 2017b. Healthy urban living: Residential environment and health of older adults in Shanghai. Health Place 47, 80-89.

Liu, Y., Hu, M., Zhao, B., 2019a. Audio-visual interactive evaluation of the forest landscape based on eye-tracking experiments. Urban Forestry & Urban Greening 46, 126476.

Liu, Y., Wang, R., Grekousis, G., Liu, Y., Yuan, Y., Li, Z., 2019b. Neighbourhood greenness and mental wellbeing in Guangzhou, China: What are the pathways? Landscape and Urban Planning 190.

Liu, Y., Wang, R., Xiao, Y., Huang, B., Chen, H., Li, Z., 2019c. Exploring the linkage between greenness exposure and depression among Chinese people: Mediating roles of physical activity, stress and social cohesion and moderating role of urbanicity. Health Place 58, 102168.

Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation, 2015 IEEE

Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3431-3440.
Lu, Y., Sarkar, C., Xiao, Y., 2018. The effect of street-level greenery on walking behavior: Evidence from Hong Kong. Soc Sci Med 208, 41-49.
Mansor, M., Said, I., Mohamad, I., 2012. Experiential Contacts with Green Infrastructure's Diversity and Well-being of Urban Community. Procedia - Social and Behavioral Sciences 49, 257-267.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., Richardson, E.A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., Fuertes, E., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ Res 158, 301-317.
Marselle, M.R., Irvine, K.N., Lorenzo-Arribas, A., Warber, S.L., 2016. Does perceived restorativeness mediate the effects of perceived biodiversity and perceived naturalness on emotional well-being following group walks in nature? Journal of Environmental Psychology 46, 217-232.
Middel, A., Lukasczyk, J., Zakrzewski, S., Arnold, M., Maciejewski, R., 2019. Urban form and composition of street canyons: A human-centric big data and deep learning approach. Landscape and Urban Planning 183, 122-132.
Nasution, A.D., Zahrah, W., 2014. Community Perception on Public Open Space and Quality of Life in Medan, Indonesia. Procedia - Social and Behavioral Sciences 153, 585-594.
Pheasant, R.J., Fisher, M.N., Watts, G.R., Whitaker, D.J., Horoshenkov, K.V., 2010. The importance of auditory-visual interaction in the construction of 'tranquil space'. Journal of Environmental Psychology 30, 501-509.
Raudenbush, S.W., Bryk, A.S., 2002. Hierarchical linear models: Applications and data analysis methods. sage.
Rawat, W., Wang, Z., 2017. Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review. Neural Computation 29, 2352-2449.
Reid, C.E., Clougherty, J.E., Shmool, J.L.C., Kubzansky, L.D., 2017. Is All Urban Green Space the Same? A Comparison of the Health Benefits of Trees and Grass in New York City. International Journal of Environmental Research and Public Health 14, 1411.
Reid, C.E., Kubzansky, L.D., Li, J., Shmool, J.L., Clougherty, J.E., 2018. It's not easy assessing greenness: A comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York City. Health & Place 54, 92-101.
Rzotkiewicz, A., Pearson, A.L., Dougherty, B.V., Shortridge, A., Wilson, N., 2018. Systematic review of the use of Google Street View in health research: Major themes, strengths, weaknesses and possibilities for future research. Health & Place 52, 240-246.
SAGE team, 2013. China - Study on Global Ageing and Adult Health-2007/10, WAVE 1. 2014.
Sheikh, J.I., Yesavage, J.A., 1986. Geriatric Depression Scale (GDS): Recent Evidence and Development of a Shorter Version, 165-173.
Signoretta, P.E., Buffel, V., Bracke, P., 2019. Mental wellbeing, air pollution and the ecological state. Health & Place 57, 82-91.
Sobel, M.E., 1982. Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. Sociological Methodology 13, 290-312.
Steptoe, A., Deaton, A., Stone, A.A., 2015. Subjective wellbeing, health, and ageing. The Lancet 385, 640-648.
Su, J.G., Dadvand, P., Nieuwenhuijsen, M.J., Bartoll, X., Jerrett, M., 2019. Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. Environment International 126, 162-170.
Sun, P., Lu, W., 2022. Environmental inequity in hilly neighborhood using multi-source data from a health promotion view. Environ Res 204, 111983.
Szeremeta, B., Zannin, P.H.T., 2009. Analysis and evaluation of soundscapes in public parks through interviews and

measurement of noise. Science of The Total Environment 407, 6143-6149.

Taylor, M.S., Wheeler, B.W., White, M.P., Economou, T., Osborne, N.J., 2015. Research note: Urban street tree density and antidepressant prescription rates—A cross-sectional study in London, UK. Landscape and Urban Planning 136, 174-179.

Triguero-Mas, M., Dadvand, P., Cirach, M., Martínez, D., Medina, A., Mompart, A., Basagaña, X., Gražulevičienė, R., Nieuwenhuijsen, M.J., 2015. Natural outdoor environments and mental and physical health: Relationships and mechanisms. Environment International 77, 35-41.

Tsai, W.-L., Floyd, M.F., Leung, Y.-F., McHale, M.R., Reich, B.J., 2016. Urban Vegetative Cover Fragmentation in the U.S.: Associations With Physical Activity and BMI. American Journal of Preventive Medicine 50, 509-517.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8, 127-150.

Tyrväinen, L., Mäkinen, K., Schipperijn, J., 2007. Tools for mapping social values of urban woodlands and other green areas. Landscape and Urban Planning 79, 5-19.

Tyrväinen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., Kagawa, T., 2014. The influence of urban green environments on stress relief measures: A field experiment. Journal of Environmental Psychology 38, 1-9.

Ulrich, R.S., 1984. View through a window may influence recovery from surgery. Science 224, 420-421.

Vemuri, A.W., Morgan Grove, J., Wilson, M.A., Burch, W.R., 2009. A Tale of Two Scales: Evaluating the Relationship Among Life Satisfaction, Social Capital, Income, and the Natural Environment at Individual and Neighborhood Levels in Metropolitan Baltimore. Environment and Behavior 43, 3-25.

Wang, R., Feng, Z., Pearce, J., Liu, Y., Dong, G., 2021. Are greenspace quantity and quality associated with mental health through different mechanisms in Guangzhou, China: A comparison study using street view data. Environ Pollut 290, 117976.

Wang, R., Feng, Z., Pearce, J., Zhou, S., Zhang, L., Liu, Y., 2021. Dynamic greenspace exposure and residents' mental health in Guangzhou, China: From over-head to eye-level perspective, from quantity to quality. Landscape and Urban Planning 215, 104230.

Wang, R., Helbich, M., Yao, Y., Zhang, J., Liu, P., Yuan, Y., Liu, Y., 2019a. Urban greenery and mental wellbeing in adults: Cross-sectional mediation analyses on multiple pathways across different greenery measures. Environ Res 176, 108535.

Wang, R., Yang, B., Yao, Y., Bloom, M.S., Feng, Z., Yuan, Y., Zhang, J., Liu, P., Wu, W., Lu, Y., Baranyi, G., Wu, R., Liu, Y., Dong, G., 2020. Residential greenness, air pollution and psychological well-being among urban residents in Guangzhou, China. Sci Total Environ 711, 134843.

Wang, R., Yuan, Y., Liu, Y., Zhang, J., Liu, P., Lu, Y., Yao, Y., 2019b. Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. Health Place 59, 102186.

Weichenthal, S., Hatzopoulou, M., Brauer, M., 2019. A picture tells a thousand…exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology. Environment International 122, 3-10.

Wu, W., Wang, M., Zhu, N., Zhang, W., Sun, H., 2019. Residential satisfaction about urban greenness: Heterogeneous effects across social and spatial gradients. Urban Forestry & Urban Greening 38, 133-144.

Xia, Y., Yabuki, N., Fukuda, T., 2021. Development of a system for assessing the quality of urban street-level greenery using street view images and deep learning. Urban Forestry & Urban Greening 59, 126995.

Yang, Y., Lu, Y., Yang, H., Yang, L., Gou, Z., 2021. Impact of the quality and quantity of eye-level greenery on park usage. Urban Forestry & Urban Greening 60.

Yao, Y., Liang, Z., Yuan, Z., Liu, P., Bie, Y., Zhang, J., Wang, R., Wang, J., Guan, Q., 2019. A human-machine adversarial scoring framework for urban perception assessment using street-view images. International Journal of Geographical Information Science 33, 2363-2384.

Zhang, J., 2014. Revisiting residential self-selection issues: A life-oriented approach. Journal of Transport and Land Use 7, 29-45.

Zhang, L., Tan, P.Y., Richards, D., 2021a. Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health. Landscape and Urban Planning 213, 104131.

Zhang, R., Zhang, C.Q., Rhodes, R.E., 2021b. The pathways linking objectively-measured greenspace exposure and mental health: A systematic review of observational studies. Environ Res 198, 111233.

Zhang, X., Liu, L., Chen, X., Gao, Y., Xie, S., Mi, J., 2021c. GLC_FCS30: global land-cover product with fine classification system at 30 m using time-series Landsat imagery. Earth Syst. Sci. Data 13, 2753-2776.

Zhou, B., Zhao, H., Puig, X., Xiao, T., Fidler, S., Barriuso, A., Torralba, A., 2019. Semantic understanding of scenes through the ade20k dataset. International Journal of Computer Vision 127, 302-321.

Zhou, Y., Yuan, Y., Chen, Y., Lai, S., 2020. Association Pathways Between Neighborhood Greenspaces and the Physical and Mental Health of Older Adults-A Cross-Sectional Study in Guangzhou, China. Front Public Health 8, 551453.

Zhu, W., Wang, J., Qin, B., 2021. Quantity or quality? Exploring the association between public open space and mental health in urban China. Landscape and Urban Planning 213.

Zhu, Z., Woodcock, C.E., 2012. Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sensing of Environment 118, 83-94.

Žlender, V., Ward Thompson, C., 2017. Accessibility and use of peri-urban green space for inner-city dwellers: A comparative study. Landscape and Urban Planning 165, 193-205.

Zock, J.-P., Verheij, R., Helbich, M., Volker, B., Spreeuwenberg, P., Strak, M., Janssen, N.A.H., Dijst, M., Groenewegen, P., 2018. The impact of social capital, land use, air pollution and noise on individual morbidity in Dutch neighbourhoods. Environment International 121, 453-460.