Landscape and Urban Planning 240 (2023) 104881

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Urban overall and visible greenness and diabetes among older adults in China

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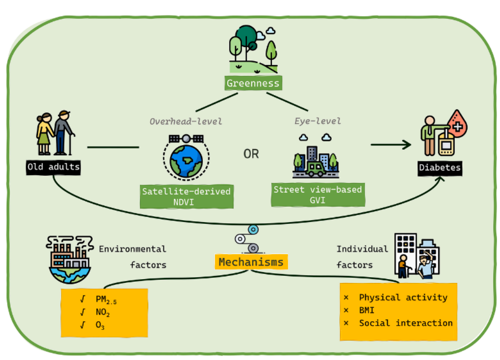
HIGHLIGHTS

- Overall but not visible greenness was beneficially associated with diabetes in older adults.
- The association was more pronounced among the old adults with higher level of education or household income.
- The association was partially mediated by environmental factors of air pollution, but not by individual physical activity, BMI, and social interaction.
- Increasing overall greenness is a potential means to lower the diabetes risk for the older urban residents.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Greenness
Green space

ABSTRACT

Neighborhood greenness has been shown to reduce diabetes risk, however, no studies have compared the effects of overall greenness with visible greenness, which is crucial for understanding how greenness influences diabetes risk. Our study aims to explore the associations between greenness matrix and diabetes, as well as the potential

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https://doi.org/10.1016/j.landurbplan.2023.104881
Received 5 December 2022; Received in revised form 8 June 2023; Accepted 2 September 2023
Available online 6 September 2023
0169-2046/

Greenery
NDVI
Street view
Diabetes

effect modifications and mediating factors. We used logistic regressions to examine the cross-sectional associations of the satellite-based Normalized Difference Vegetation Index (NDVI) and street view-based Green View Index (GVI) with diabetes in 3,924 urban older adults enrolled in the 2017–2018 wave of Chinese Longitudinal Healthy Longevity Survey (CLHLS). We conducted the stratified analyses by age, sex, household income and education. Mediation analyses were also performed to see whether physical activity, BMI, air pollution, and social interaction mediate the associations. Significant associations with diabetes were only observed for NDVI but not for GVI. Participants in the highest quartile of NDVI and GVI had 52% (95 % CI: 48%, 63%) and 14% (-10%, 44%) lower odds of reporting having diabetes diagnosed by a doctor. The protective effects of NDVI were more pronounced in the young old (≥75–95 years) and high-education or high-income groups. No difference between males and females were observed. Air pollution (e.g., $PM_{2.5}$, NO_2 and O_3) partially mediated the associations, but physical activity, BMI, and social interaction may not mediate the associations. Our findings indicate beneficial associations between overall greenness but not visible greenness surrounding residences with diabetes in older urban residents in China, especially for old adults with higher education or household income levels. Environmental factors (e.g., air pollution) but not individual behavioural characteristics are the potential underlying mechanisms.

1. Introduction

Diabetes is among the most challenging health issues of the 21st Century (Saeedi, Petersohn, Salpea, Malanda, Karuranga, Unwin, Colagiuri, Guariguata, Motala, Ogurtsova, Shaw, Bright, & Williams, 2019; Tremblay & Hamet, 2019; Zimmet, Magliano, Herman, & Shaw, 2014). China has the largest population with diabetes worldwide (Yang et al., 2010). With rapid aging and changes in environment and lifestyle, diabetes prevalence in China increased from<1% in the 1980s to 12.4% in 2018 (Pan, X.-R., Yang, W.-Y., Li, G.-W., Liu, J., Prevention, N. D., Group, C. C., 1994; Wang et al., 2021a). In 2018, 1 in 4 people aged over 70 years in China lived with diabetes (Wang et al., 2021a). Diabetes greatly increases the economic burden and causes the loss of productivity and early mortality (Guo et al., 2021). Effective prevention and intervention approaches are needed to stem the rising tide of diabetes in China. Diabetes has a complex etiology involving genetic, environmental and behavioral origins (Tremblay & Hamet, 2019). From a practical point of view, the identification of environmental factors is essential since many factors can be modified by changes in policy or behaviors.

To date, whether greenness produces a beneficial effect on diabetes, especially in old adults, remains an open question. Although growing evidence shows that neighborhood greenness protects against diabetes (Bodicoat et al., 2014; Khan, Sultana, Islam, & Biswas, 2021; Müller, Harhoff, Rahe, & Berger, 2018), there is also research reported no associations (Patino et al., 2021). Most research focuses on Europe and the US, while the Asian context has remained oblivious. A challenge for these studies is the characterization of people's exposure to trees and plants (Donovan et al., 2022). A common approach is to use the satellite-derived Normalized Difference Vegetation Index (NDVI) or the land use map to measure the individual exposure around the residence. But these indices only reflect the overall greenness but cannot distinguish the types of green space. Moreover, such indices only represent a bird's eye (i.e., overhead-level) perspective but do not necessarily reflect the people's eye-level perspective on greenness (Yue, Yang, & Van Dyck, 2022). Recently, the geo-tagged Street View images combined with machine learning techniques provided the opportunity for capturing the visible green space by Green View Index (GVI) (Li et al., 2015). Some epidemiological studies utilized GVI for individual exposure assessment of visible greenness (Helbich, Poppe, Oberski, Zeylmans van Emmichoven, & Schram, 2021; Miron-Celis et al., 2023; Wang et al., 2022; Yu et al., 2021a), but the existing comparisons with traditional satellite-derived assessments are still mixed and need further investigations (Helbich et al., 2019; Larkin & Hystad, 2019; Sun, Song, & Lu, 2022b; Yu et al., 2021b; Zhang, Liu, Zhou, Cheng, & Zhao, 2022).

The mechanisms that mediate the associations between greenness and health outcomes are only partially known. However, certain pathways are likely important for the intervention from a built environment perspective. These causal pathways may include increased physical activity, less stress, enhanced immune function, better social connectedness, less noise, and improved air quality (Dalton et al., 2016; Yang et al., 2019). Some of them, such as stress reduction, may be mediated visually and aesthetically (Donovan et al., 2022). Compared with the satellite-derived index, the street-view greenness index may have a better ability to detect the relationship with the improved health explained by aesthetic or visual cues from the environment. Hence, the comparison of NDVI and GVI would help understand the underlying mechanisms linking greenness and diabetes.

In light of the above-mentioned knowledge gaps, we leverage NDVI, GVI, and diabetes data from nationwide representative survey data of Chinese older populations to investigate the relation between residential greenness exposure metrics (i.e., overall greenness and visible greenness) and diabetes. In order to identify the effect modifications of demographic and socio-economic factors, we explored whether the associations with overall greenness and visible greenness differed by age group, sex, household income, and education. We also investigated whether these associations were mediated by air pollution ($PM_{2.5}$, NO_2, and O_3), physical activity, social interaction, and body mass index (BMI) to explore the potential mechanisms linking greenness and diabetes.

2. Methods

2.1. Study population

Our study used a nationally representative sample from the 2017–2018 wave of the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The CLHLS is a prospective cohort aiming to understand the social, behavioral, and biological determinants of healthy aging and longevity among the older adults in China. Interviews were conducted in randomly selected half of the counties and cities in 22/31 provinces in China (Fig. 1), representing>80% of China's total population. Well-trained interviewers administered the surveys and collected their data on basic demographic characteristics, cognitive function, nutrition and lifestyle, history of diseases, psychological status, and physical capacity following a structured questionnaire. The details on the sampling design, ethics approval, and data quality of the CLHLS were previously published by Yao et al. (2022).

Because the street view images are generally unavailable in rural China, we only keep the urban participants in the 2017–2018 wave of CLHLS in the statistical analysis. The participants aged ≥65 years and lived in cities or towns for >6 months were included. The exclusion criteria of our sampling were those with unavailable information on GVI or NDVI due to no geoinformation or no available street view images, or with missing information on diabetes. Eventually, 3,924 participants were included (Figure A1).

2.2. Assessment of diabetes

In the CLHLS, participants were asked whether they had ever been diagnosed by a doctor that they had diabetes. The CLHLS survey did not distinguish the types of diabetes, since>99% of the diabetics in China are known to be type 2 diabetes mellitus (T2DM) (Li, Guo, & Cao, 2021).

2.3. Greenness exposure metrics

We used the NDVI to assess the satellite-derived overall greenness exposure. NDVI is computed as the ratio of the difference between the near-infrared region (NIR) and red reflectance (RED) to their sum (Weier & Herring, 2000). The range of NDVI is from −1 to 1, with higher NDVI indicating more greenness. We downloaded all available images at a spatial resolution of 30 m from Landsat 8 Collection Tier 1 from June 1st to August 31st 2018 through the Google Earth Engine. To minimize cloud contamination and consider the seasonal variations in vegetation status across different regions in China, Maximum value compositing (MVC) technique has been employed by preserving the maximum NDVI value by each 30 m grid cell of all satellite images during one year (Viovy, Arino, & Belward, 1992). The individual residential address was converted to the latitude and longitude coordinates. It remains unknown which size of the buffer zone around the residence is the most appropriate to explore the environmental impacts on human behaviors and their health outcomes, and buffers with radii ranging from 300 m to 1.0 km have been widely used. Considering that smaller buffers may be more appropriate for older populations due to their reduced physical capacity (Yue et al., 2022), in this study, individual-level NDVI exposure was assessed and computed as the averaged NDVI in a 500 m buffer around the coordinate of participant's residential location. NDVI exposure were converted into 4 quartiles: quartile 1 (Q1: ≤0.14), quartile 2 (Q2: >0.14–0.17), quartile 3 (Q3: >0.17–0.21), and quartile 4 (Q4: >0.21). Effect estimates for the NDVI in 100 m, 300 m, 1 km, and 2 km buffers were reported in sensitivity analyses.

GVI was used to assess the street view-based visible greenness exposure. We first obtained the OpenStreetMap road network within a circular buffer of 500 m around each participant's residence location using ArcGIS, and then randomly selected 20 sampling points in the road network within each buffer using Grasshopper (Fig. 2). We chose the random sampling approach instead of the commonly used method of sampling at an equal distance due to that the equal-distance way cannot capture the images on winding roads. We downloaded the closest Baidu street view images in the horizontal direction of each sampling point from different angles (0°, 90°, 180°, and 270°) from the survey year 2017–2018. Baidu map is the Chinese equivalent of Google Maps. If no street view images were available during the year 2017–2018, we carried forward images from the year prior and up to 2 years before if needed. Most street view images were captured in summer when the trees and plants are the greenest. In total, 313,920 street view images were obtained for the included 3,924 participants.

GVI was extracted from the street view images by semantic segmentation using the DeepLab V3+, which is the third generation improvement version of the DeepLab convolutional neural network series proposed by Google (Chen, Zhu, Papandreou, Schroff, & Adam, 2018). DeepLab V3 + was trained using the CityScapes dataset, and the xception71_dpc_cityscapes_trainval model (https://download.tensorflow.org/models/deeplab_cityscapes_xception71_trainvalfine_2018_09_08.tar.gz) of DeepLab V3 + was used. GVI for each sampling point was calculated as the mean proportion of the trees and plants in four matched images. GVI for each participant is the average GVI of all sampling points in circular buffers of 500 m around each participant's residential location. Therefore, GVI ranges from 0 to 1, with a higher value indicating a greener street greenness. To ensure the random sampling did not induce biased exposure, we repeated the random sampling and found the two sets of GVIs were highly correlated (correlation coefficient = 0.93, P < 0.001). Thus, the random sampling would not cause exposure misclassification. GVI exposure were converted into 4 quartiles: quartile 1 (Q1: ≤0.18), quartile 2 (Q2:

Fig. 1. Residential locations of the study participants and NDVI from Landsat 8 and GVI for each participant in a buffer size of 500 m.

Fig. 2. (a) An example of NDVI surface from Landsat 8 in buffer size of 500 m around a participant's residential location, sampling points of street view images, and (b) examples of using street view images to assess the visible greenness.

>0.18–0.23), quartile 3 (Q3: >0.23–0.30), and quartile 4 (Q4: >0.30).

2.4. Covariates

To minimize the bias induced by confounders, we reviewed the published paper in recent 20 years to identify the common predictors of diabetes as covariates (Chien et al., 2009; Xie, Nikolayeva, Luo, & Li, 2019). Covariates in our analyses included age, sex, marital status (married or not married), years of education (0, ≥1–5, or ≥6 years of schooling), household income level (<30000 or ≥30000 RMB Yuan per year), smoking status (smoke at present, smoked in the past but not at present, or never smoked), drinking status (drink at present, drank in the past but not at present, or never drank). We imputed missing data of covariates using multivariate imputation by chained equations (van Buuren & Groothuis-Oudshoorn, 2011), which allows for building up an imputation model with mixed-type covariates.

2.5. Mediating variables

To understand the pathways linking greenness and diabetes, we considered the individual-level physical activity (exercise at present, exercised in the past but not at present, or never exercised), BMI [underweight (<18.5), normal weight (≥18.5–24.0), overweight (≥24.0–28.0), or obesity (≥28.0), unit: kg/m^2], and social interaction, as well as air pollution ($PM_{2.5}$, O_3, and NO_2) at the environmental level as potential mediators. Information on regular physical activity was collected using two questions (1) "Do you do exercises regularly at present?" and recoded as yes (Y-1) or no (N-1); (2) "Did you do exercises regularly in the past?" and recoded as yes (Y-2) or no (N-2). We combined the answers to these two questions to three levels of physical activity: (1) exercise at present (Y-1), (2) exercised in the past but not at present (N-1 and Y-2), or (3) never exercised (N-1 and N-2). Social interaction was measured based on the frequencies of participating in three kinds of activities: the group leisure activities (e.g., play cards, chess or mah-jongg, square dances), informal interaction (e.g., visit people, and socialize with friends), and other organized social activities (e.g., did volunteer or charity work). A 1–5 score was given to each activity based on five levels of frequency: never (1 score), sometimes but not monthly (2 score), at least once in a month but not weekly (3 score), once for a week but not daily (4 score), and almost every day (5 score). And the final score of the individual's social interaction was defined as the highest frequency of the three kinds of activities. Annual gridded concentrations of $PM_{2.5}$ (1 km × 1 km), NO_2 (10 km × 10 km), and O_3 (10 km × 10 km) were obtained from the ChinaHighAirPollutants (CHAP, https://weijing-rs.github.io/product.html). Briefly, the CHAP dataset integrated big data including remote sensing products (e.g., aerosol optical depth), atmospheric reanalysis, ground-based measurements, pollutant emissions and population distribution using artificial intelligence (Wei et al., 2020; Wei et al., 2021). This air pollution dataset is a series of long-term, high-resolution and high-data quality ground-level air pollutant products for China, for instance, the R^2 and RMSE for the cross-validation of $PM_{2.5}$ is 0.92 (10.76) μg/m^3 on a daily basis (Wei et al., 2022a; Wei et al., 2022b). The averaged concentrations of 4-year annually averaged $PM_{2.5}$, NO_2, and O_3 from 2014 to 2017 in 500 m circle buffers were calculated as the air pollution exposure.

2.6. Statistical analyses

The unavailability of historical street view images in China before 2015 prevented us to use the longitudinal study design, thus a cross-sectional research design was utilized in our study. In statistical analyses, we used logistic regression models to evaluate the association between greenness and diabetes. First, we developed a crude model as model 1 for regression. Second, model 2 included the covariates of age and sex. Third, a fully adjusted model was developed as model 3 to further adjust for education, income, marital status, drinking status, and smoking status. We introduced diabetes as a dummy variable in the models. Considering the associations between greenness and diabetes may be non-linear, we categorized NDVI and GVI as quartiles and set the lowest quartile (Q1) as the reference. The results were presented as the estimates of odds ratios (OR) and their 95% confidence intervals (CI). The *P*-trend values were also calculated by using continuous variables (i.e., 1, 2, 3, 4) for quartiles of greenness exposures to test the significance of the linear trend of the associations between NDVI or GVI levels and diabetes.

Effect modifications by age, sex, income, and education was evaluated by stratified analyses. In the stratified analyses, we categorized age into four groups (>95, >85–95, >75–85, and ≥ 65–75 years), and household income levels into two groups [high-income group (≥30,000 RMB Yuan) and low-income group (<30,000 RMB Yuan)], and years of education into three groups [high-education group (≥6 years of schooling), median education group (≥1–5 years of schooling), and low education group (0 years of schooling)], using the cut-off points referred by previous studies (Fu, Sherris, & Xu, 2022; Hou et al., 2019; Hu et al., 2022).

To shed light on the hypothetical mechanisms that air pollution, weight status, and human behaviors may mediate the associations between NDVI and diabetes, multi-stage mediation analyses considering the potential mediators of BMI, physical activity, social interaction, and air pollutants (O_3, $PM_{2.5}$, and NO_2) were carried out (Baron & Kenny, 1986). This mediation analysis divided the total effect of greenness on diabetes into a direct and an indirect component. The percentage of mediation was calculated as the mediation (i.e., the indirect effect) divided by the total effect using 1000 Monte Carlo simulations to estimate the confidence intervals. Sobel tests were performed to test the significance of the mediation effects (Sobel and Leinhart, 1982).

All statistical analyses were performed in R 4.1.2 using the packages of "psych", "mediation" and "gmodels". A two-tailed *P* value<0.05 was considered statistically significant.

2.7. Sensitivity analyses

In order to test the robustness of our results, we also conducted the sensitivity analyses for both NDVI and GVI by including the covariates of the distance between the main road with a width of>100 m and the participant' s home, the province, and population density and land use mixture at the city level in the logistic regression models, since prior studies demonstrated that noise, population density, living region, and land use mixture may influence the diabetes risks (Liu et al., 2019; Pasala, Rao, & Sridhar, 2010; Sakhvidi, Sakhvidi, Mehrparvar, Foraster, & Dadvand, 2018). Population density was computed as the total population in 2020 of one city divided by the area of this city, with population data collected from the China Seventh National Census (https://www.stats.gov.cn/tjsj/pcsj/). The national land use data in 2018 based on Landsat remote sensing images was obtained from the Chinese Academy of Sciences Resource and Environmental Science Data Center (https://www.resdc.cn), and this land use map comprises 32 land use types at a 30 m spatial resolution (Xia et al., 2022). The Shannon's diversity index (SHDI) based on all land use types was used to measure the city-level land use mixture (Nagendra, 2002). SHDI was computed as $-\Sigma prop_i * \ln(prop_i)$, with $prop_i$ refers to the proportion of grids belonging to the land use type i.

3. Results

3.1. Descriptive statistics

The descriptive characteristics of the study participants are summarized in Table 1. The 3,924 participants had a mean age of 84.6 years (standard deviation (SD) ± 11.6); nearly half of them (46.5%) were males. Most of the participants never smoke (71.0%) and drank (75.2%). There were 43.7% of the participants currently engaged in exercises, while 44% of the participants never did any exercise. The prevalence of diabetes among the study population was 17.6%. Participants with diabetes were younger and more likely to have current exercise, high household income, and high BMI, as well as never smoke or drank, than participants without diabetes (Table 1). The spearman's correlation coefficient of NDVI and GVI was 0.12 (P<0.001, Figure A2).

3.2. Greenness metrics and diabetes

Crude (model 1), adjusted (model 2), and fully adjusted (model 3) ORs and their 95% CIs for diabetes in relation between NDVI and GVI are given in Table 2. Overall, the likelihood of participants with diabetes significantly decreased with higher NDVI levels (Table 2, *Ps* for trend<0.001) in the crude, adjusted, and fully adjusted models. Further adjustment for covariates in model 2 and model 3 attenuated slightly the associations. Individuals exposed to the highest level of NDVI presented around half the likelihood (OR: 0.48, 95% CI: 0.37–0.62 in model 3) of reporting having diabetes diagnosed by a doctor compared to individuals exposed to the lowest NDVI level. In contrast, higher GVI exposure seemed to be associated with higher odds of reporting having diabetes diagnosed by a doctor, although none of the associations was

Table 1
Descriptive statistics of diabetes, non-diabetes, and all study participants. *P* value for the chi-square test for comparing the characteristics between diabetes and non-diabetes groups.

	Diabetes (n = 693)	Non-diabetes (n = 3,231)	*P* value	Total (n = 3,924)
Age [a]	80.18 ± 9.67	85.56 ± 11.73	<0.001	84.61 ± 11.58
Sex			0.628	
Male	322 (46.5%)	1,534 (47.5%)		1,856 (47.3%)
Female	371 (53.5%)	1,697 (52.5%)		2,068 (52.7%)
Household income			<0.001	
<30000	101 (14.6%)	789 (24.4%)		890 (22.7%)
≥30000	592 (85.4%)	2,442 (75.6%)		3,034 (77.3%)
Marital status			<0.001	
Married	395 (57.0%)	1,381 (42.7%)		1,776 (45.3%)
Not married	298 (43.0%)	1,850 (57.3%)		2,148 (54.7%)
Years of education			<0.001	
0	139 (20.1%)	1,163 (36.0%)		1,302 (33.2%)
1–5	131 (18.9%)	652 (20.2%)		783 (20.0%)
≥6	423 (61.0%)	1,416 (43.8%)		1,839 (46.9%)
Smoking status			<0.01	
Current	59 (8.5%)	415 (12.8%)		474 (12.1%)
Ever	124 (17.9%)	539 (16.7%)		663 (16.9%)
Never	510 (73.6%)	2,277 (70.5%)		2,787 (71.0%)
Drinking status			<0.01	
Current	70 (10.1%)	476 (14.7%)		546 (13.9%)
Ever	78 (11.3%)	351 (10.9%)		429 (10.9%)
Never	545 (78.6%)	2,404 (74.4%)		2,949 (75.2%)
Physical activity			<0.001	
Current	352 (50.8%)	1,363 (42.2%)		1,715 (43.7%)
Ever	81 (11.7%)	403 (12.5%)		484 (12.3%)
Never	260 (37.5%)	1,465 (45.3%)		1,725 (44.0%)
BMI			<0.001	
<18.5 kg/m^2	31 (4.5%)	493 (15.3%)		524 (13.4%)
18.5–24 kg/m^2	309 (44.6%)	1,574 (48.7%)		1,883 (48.0%)
24–28 kg/m^2	264 (38.1%)	866 (26.8%)		1,130 (28.8%)
≥28 kg/m^2	89 (12.8%)	298 (9.2%)		387 (9.9%)
NDVI [a]	0.17 ± 0.05	0.18 ± 0.05	<0.001	0.18 ± 0.05
GVI [a]	0.25 ± 0.09	0.24 ± 0.09	<0.01	0.24 ± 0.09

Note: [a] Mean ± standard deviation with *t*-test.

Table 2
Associations between NDVI and GVI and diabetes in the 2017–2018 CLHLS.

		Model 1		Model 2		Model 3	
		OR, 95 %CI	*P* for trend	OR, 95 %CI	*P* for trend	OR, 95 %CI	*P* for trend
NDVI	Lowest	Reference	<0.001	Reference	<0.001	Reference	<0.001
	2nd	0.78 (0.63, 0.97) *		0.83 (0.66, 1.03)		0.87 (0.69, 1.08)	
	3rd	0.65 (0.52, 0.81) ***		0.70 (0.56, 0.88) **		0.80 (0.63, 1.00)	
	Highest	0.46 (0.36, 0.59) ***		0.48 (0.38, 0.62) **		0.55 (0.43, 0.71) ***	
GVI	Lowest	Reference	0.136	Reference	0.054	Reference	0.214
	2nd	0.86 (0.68, 1.09)		0.87 (0.68, 1.11)		0.88 (0.69, 1.12)	
	3rd	0.99 (0.78, 1.25)		0.99 (0.78, 1.25)		0.95 (0.74, 1.20)	
	Highest	1.14 (0.91, 1.44)		1.22 (0.97, 1.54)		1.14 (0.90, 1.44)	

Model 1 was a crude model.
Model 2 included covariates of age and sex.
Model 3 included covariates from model 2 plus marital status, education level, household income level, smoking status, and drinking status.
Significance levels: *$P<0.05$, **$P<0.01$, ***$P<0.001$.
Note: NDVI: Lowest (Q1: >0.05–0.14), 2nd (Q2: >0.14–0.17), 3rd (Q3: >0.17–0.21), Highest (Q4: >0.21–0.42);
GVI: Lowest (Q1: >0–0.18), 2nd (Q2: >0.18–0.23), 3rd (Q3: >0.23–0.30), Highest (Q4: >0.30–0.60).

significant (*Ps* for trend>0.05).

3.3. Subgroup analysis

Fig. 3 and Table A1–A4 shows the ORs and their 95% CIs in the age-, sex-, education-, and income-stratified analyses. Subgroup analyses showed that NDVI level was beneficially associated with the likelihood of participants with diabetes only in age groups of≥75–85 years and ≥85–95 years (*P* for trend<0.001). For the old adults aged 75–85 years and ≥85–95 years, those in the highest NDVI level had 53% (95% CI: 27–70%, model 3) and 49% (95% CI: 14–70%, model 3) lower odds for having diabetes compared with those in the lowest NDVI level, respectively. But we did not observe a statistically significant association for older adults aged ≥65–75 and ≥95 years (*P* for trend=0.06 and 0.53, respectively).

Gender-stratified results showed that higher NDVI level was associated with the lower likelihood of diabetes in both males significantly (NDVI Q4 vs. Q1 in model 3: OR=0.44 [95% CI: 0.30–0.63]) and females (NDVI Q4 vs. Q1 in model 3: OR=0.70 [95% CI: 0.49–0.98]) (Table A2). Point estimates show stronger protective effects for males than females but the gender differences in the ORs were not statistically significant.

In the stratified analysis by education or household income, the satellite-derived greenness's effects on diabetes were more pronounced in older participants with higher education or income level (Fig. 2). The trend by household income level shows that being exposed to green spaces is equally beneficial for high-income groups, regardless of the quantity of greenspace exposure; whereas for low-income individuals the protective associations were non-significant for all levels of greenness (Table A3). In addition, results by educational level do not show a trend; although the strongest associations are found for individuals with higher education (NDVI Q4 vs. Q1 in model 3, OR=0.47 [95% CI: 0.34–0.66], *P* for trend<0.001, Table A4), the effect seems to be stronger for individuals with low education level compared to individuals with medium education level.

In line with the results from all included participants, we did not find any significant exposure–response associations between GVI and

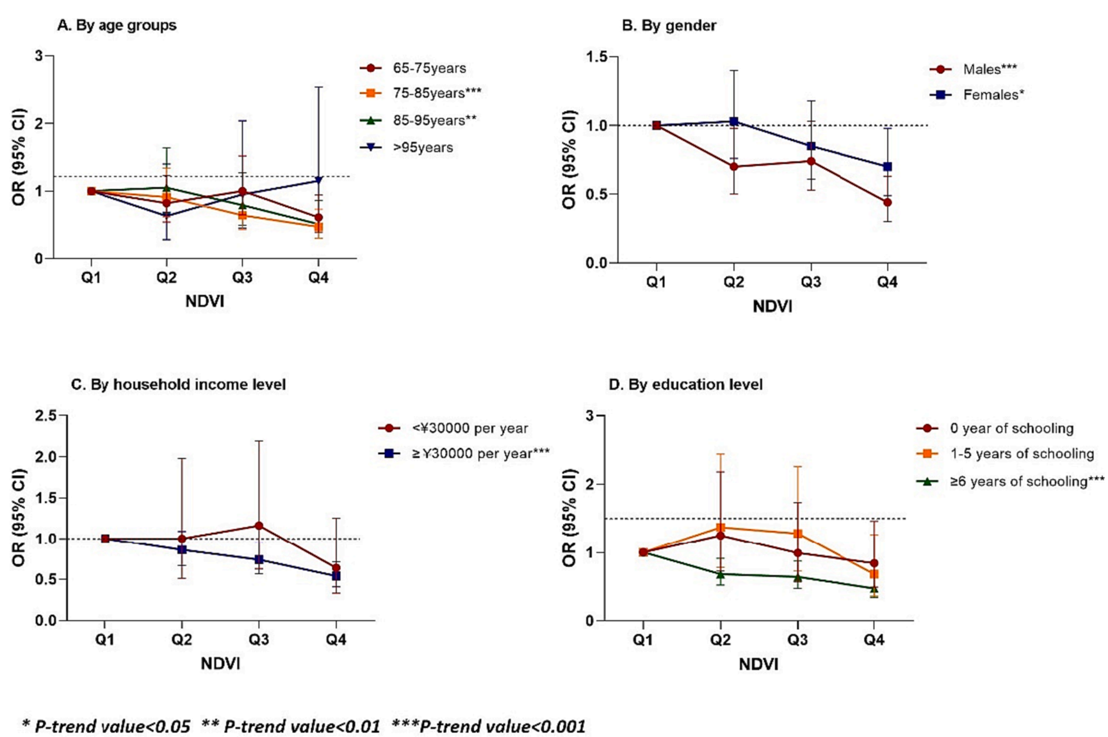

Fig. 3. Multivariable-adjusted association between NDVI and diabetes by age groups (A), gender groups (B), household income levels (C), and education levels (D).

diabetes in the stratified analyses (results now shown).

3.4. Mediating analyses

Mediation analysis suggested that, after full adjustment, $PM_{2.5}$, NO_2 and O_3 significantly mediated 5.0% (95 %CI: 0.6, 12%), 41.0% (95 %CI: 26.4, 76.0%) and 10.7% (95 %CI: 3.7, 23.0%) of the estimated associations between NDVI and diabetes, respectively (Table 3 and Figure A2). However, Table 3 revealed no evidence of the mediation effect of physical activity, BMI, and social interaction.

3.5. Sensitivity analyses

We found that additionally including each of the distance between the main road and resident's location, the living province, the population density, or the land use mixture in the logistic regressions did not alter the results for both NDVI and GVI (Table A5–A8, and Table A13–A16). The choice of a larger or smaller radius of buffer (100 m, 300 m, 1 km, or 2 km) also did not change the beneficial associations between NDVI and diabetes (Table A9–A12). Therefore, our results passed robustness tests.

4. Discussion

To our best knowledge, this study is among the first nationwide investigation to date, to compare the associations between the overall or visible greenness and diabetes from a large sample of old adults. Our population-based study indicates that higher overall greenness but not visible greenness level was significantly associated with diabetes for old adults in China. The associations between overall greenness and diabetes were robust by changing the buffer radius and controlling for the potential confounders. The potential protective effect was more pronounced for old residents with higher education or income level. These associations were partially mediated by the environmental factors of air pollution ($PM_{2.5}$, NO_2 and O_3), rather than individual characteristics of physical activity, BMI, and social interaction.

Our principal finding adds to the growing evidence that vegetation could be beneficial to multiple health outcomes including diabetes (Fong, Hart, & James, 2018; Kang, Zhang, Gao, Lin, & Liu, 2020). For example, a US study found that each 0.1-unit increase in NDVI is associated with an 8% (95 %CI: 6, 10%) lower risk of diabetes (Brown et al., 2016); a cross-sectional study based on the data from 33 Chinese communities showed that a 0.1-unit increase in NDVI was significantly associated with 12% (95 %CI: 6, 18%) lower odds of diabetes (Yang et al., 2019); and recently, two cohort studies in Taiwan province and Ningbo city in China also found that higher long-term exposure of NDVI is associated with a lower risk of diabetes (Tsai et al., 2021; Yu et al., 2022). Although it's difficult to compare the estimates due to different NDVI settings (as a continuous variable or a categorical variable) and study designs (as an ecological, cross-sectional, or longitudinal study), we searched the literature regarding NDVI and diabetes in recent 10 years in PubMed and Web of Science and found the majority of existing literature (10/11) provided consistent evidence that the neighborhood vegetation may lower the diabetes risk, while one ecological study has no such evidence (Patino et al., 2021).

Table 3
Proportions of the associations between NDVI and diabetes mediated by physical activity, BMI, social interaction, $PM_{2.5}$, NO_2, and O_3.

	Proportion mediated (%, 95% CI)	*P* value
Physical activity	−0.81 (−4.13, 2.00)	0.47
BMI	2.47 (-0.72, 7.00)	0.13
Social interaction	−0.03 (−1.36, 1.00)	0.90
$PM_{2.5}$	5.04 (0.57, 12.00)	<0.05*
NO_2	41.02 (26.37, 76.00)	<0.001***
O_3	10.71 (3.66, 23.00)	<0.001***

Note: Significance levels: **P*<0.05, ***P*<0.01, ****P*<0.001.

Very few studies have examined the link between visible greenness and diabetes. Only one study based on the survey data of 4,155 adults aged 20–98 in Harbin, China, concurred with our study reporting no significant association between neighborhood GVI and diabetes (Leng, Li, Yan, & An, 2020). Our findings support the evidence from Yang et al. (2020b) and Helbich et al. (2019) that the associations with health outcomes (e.g., mental health) or human behaviors (e.g., mobility) vary by greenness measures. Researchers speculated that it was because the greenness matrix represents different aspects (e.g., types, quantity, and quality) of green spaces, considering the correlations among various greenness measures are often weak (Wang et al., 2021b). For example, satellite-derived greenness reflects the overall quantity of the greenness surrounding the residence, but street view-based greenness almost exclusively reflects the quantity of visible greenery in and around the streets.

The effects of greenness on individual health were described as a function of the types, quantity, and quality of greenness, the actual contact or use of the greenness, and the psychological and physiological characteristics of individuals. The diversity of lifestyles affects the heterogeneity in the contact with greenness, for example, some people often do physical exercise in the park but others do not. Other behavior factors also play roles in the actual greenness exposure, for instance, old populations often spend most of their time at home, hence, the actual contact with green space is limited. From this behavior pattern, the impacts of greenness on the broad environment, such as reducing air pollution or increasing negative air ions, may be a causal factor for the protective effects, considering green space was found to mitigate the air pollution-related inflammatory response (Elten, Benchimol, Fell, & Lavigne, 2019). Importantly, it suggests we consider the roles of the widespread green-related environmental effects in the health benefits of greenness. In addition, modifications of the types and quality of green space exist, since greenness acts on health by a complex mechanism involving multiple pathways (Donovan et al., 2022). For example, the visible greenness was reported to reduce short-term markers of stress, with much of the effect mediated aesthetically (James, Banay, Hart, & Laden, 2015; Li & Sullivan, 2016).

Although the biological mechanism of greenness–diabetic outcomes is still unclear, previous research has proposed several environmental and biopsychosocial pathways (Fong et al., 2018; James et al., 2015). First, green space may lower the diabetes risk by reducing air pollution (Hirabayashi & Nowak, 2016), considering that numerous studies have demonstrated the adverse effect of air pollution on metabolic health and the incidence of diabetes (Eze et al., 2015; Yang et al., 2020a; Ye, Li, Han, Wu, & Fang, 2022). The mediating analysis in our study also reveals that the overall reduced $PM_{2.5}$, NO_2 and O_3 by higher greenness could partly mediate the association (proportions = 5.0%, 41.0% and 10.7%, respectively, *Ps* < 0.05). Other potential pathways include reduced noise, decreased stress, higher social interaction, and higher physical activity (Shen et al., 2021; Yue et al., 2022). For example, urban parks, gardens, and forests could increase people's physical activities, which is an important protective factor against diabetes (Sigal, Kenny, Wasserman, Castaneda-Sceppa, & White, 2006). However, our study provided no evidence that the individual characteristics of physical activity, BMI, and social interaction mediated the relation, which implies that the benefits were mainly credited to a healthier environment, but not to the individual behavior through directly contacting or using green spaces.

Previous literature suggested that greenness-related health benefits may differ by socioeconomic status (Son et al., 2021). For diabetes, we did not find beneficial associations with greenness for participants with lower levels of education or household income. Although the reason for this result is unascertained, it indicates that improving the socioeconomic status of low-income or low-education old adults in China may provide greater equity in access to the protective effects of greenness for better health. In contrast, one study in the Netherlands reported contrary findings that green space alleviates the effects of air pollution on the prevalence of diabetes only in low socioeconomic status (SES) areas (Groenewegen et al., 2018). The inconsistent results indicate a considerable heterogeneity of the differences in beneficial effects of greenness between high-SES and low-SES populations globally and regionally, however, this issue thus far received very little attention. Intersectionality between SES and greenness exposure may contribute to health disparities through multiple pathways (e.g., the inequality in the quality of greenness), which is worth exploring in more detail.

A strength of our study was our ability to compare the satellite-derived overall greenness and street view-based visible greenness within participants' neighborhoods with diabetes at a national level. Together with the comparison, the comprehensive investigations of modifications and intermediate factors enabled our study to examine the potential underlying mechanisms linking greenness and diabetes. This overcomes past limitations of previous greenness–diabetes analyses that have been published. This study also has several limitations. First, the assessment of diabetes was self-reported and did not distinguish type 1 and type 2 diabetes, which may bias the risk estimates and mediating effects. Second, the cross-sectional design limited our capability to establish causality. Further longitudinal studies are needed to explore the long-term effect of greenness and determine the underlying mechanisms by including other personal, environmental, and family information. Third, although we used multiple buffer sizes to assess the neighborhood vegetation, we did not consider the types, quality, and actual use of vegetation, which may induce exposure measurement error. Incorporating time-activity patterns to estimate the actual exposure and use of greenness should be an important focus of future interdisciplinary studies. Fourth, though the majority of the street view images were taken during the clear summer months, a small portion (<20%) of the sampled street view images in our study were collected during other seasons. The convolutional neural network model has a partial solution by predicting the canopy based on the trunks and branches, this problem may still lead to exposure misclassification considering the amount of street greenery is seasonally dependent. Fifth, since the Baidu street view images are only available in inner-city areas in China, excluding participants with missing information on GVI may eliminate samples in suburban areas of cities and small and middle-sized towns and thus cause bias for risk estimates, as those living in these areas may have a lower risk of diabetes (Zhao et al., 2023).

From 2021 to 2045, it is projected that the number of adults with diabetes would increase from 140 million to 174 million in China (Sun et al., 2022a). Policy approaches through shaping the built environment to reduce diabetes risk are promising. Despite China being one of the leading countries in the greening of the world through land-use management (Chen et al., 2019), a number of regions in China are experiencing vegetation decreasing under the pressure of both climate warming and population increase (Lü et al., 2015). The results of our study recommended the importance of urban greening strategies, including maintaining diverse types of green space (e.g., urban parks) beyond the street greenery and improving their quality and use. The incorporation of dense patches of vegetation and more vegetation complexity in the planning and management of urban green spaces is recommended because people prefer to visit green spaces with more dense or complex vegetation (Harris, Kendal, Hahs, & Threlfall, 2018). Certainly, while the protective effect of the current street view-based greenness on diabetes was not found, it doesn't mean that there is no role for visible greenness in human health. Our results can inform the government to reconsider the health effects of the increased visible greenery, particularly the street greenery. Considering we observed that vegetation may lower the diabetes risk by reducing the air pollution level, future work should examine the impacts of the design and choice of neighborhood visible vegetation on the health effects, such as tall or short trees, and dense or sparse vegetation. It may aid in the detailed explanation of the differences between the effects of overall and visible greenness on diabetes.

5. Conclusions

Our findings indicate the protective effect of neighborhood overall greenness but not visible greenness on diabetes for urban old residents in China, especially for those with higher education or household income levels. Our findings imply that the benefits of greenness on diabetes may be partially credited to a healthier environment by greening (e.g., reduced air pollution), but not to the BMI, enhanced physical activity, or social interaction through directly contacting or using green spaces. Increasing the diverse types of greenness but not only street greenery in the neighborhoods would be worth considering the approach against diabetes, however, the government should be cautious about the SES disparity in the benefits.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgements

The study was supported by the National Natural Science Foundation of China (42001013, 72061137004), the U.S. National Institute of Aging/ National Institute of Health (P01AG031719), the National Key R&D Program of China (2018YFC2000400), the Zhejiang Provincial Natural Science Foundation of China (Y23D050006), the Key Laboratory of Intelligent Preventive Medicine of Zhejiang Province, China (2020E10004), the Leading Innovative and Entrepreneur Team Introduction Program of Zhejiang (2019R01007).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104881.

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