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Tree abundance, species richness, or species mix? Exploring the relationship between features of urban street trees and pedestrian volume in Jinan, China

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ABSTRACT

Accumulating evidence has confirmed that urban greenery, especially street trees, is beneficial to walking behaviors. Existing street greenery exposure-walking behavior studies have focused on the quantity of greenery, which is often measured by normalized difference vegetation index (NDVI) or green view index (GVI). However, some important qualities of street trees, the dominant component of urban greenery, were often overlooked, due to the labor-intensive and expensive nature of on-site surveys. To address this issue, we proposed a cutting-edge deep learning technique to identify street tree species at the individual tree level. We established a citywide dataset of all street trees with species information via 185,831 Baidu Street View images (BSV) in Jinan, China. Population-level walking intensity, measured by pedestrian volume, was retrieved from BSV images using Baidu AI. We further adopted spatial regression models to investigate the association between pedestrian volume and street tree characteristics, including street tree abundance (number of street trees), species richness (number of unique tree species) and species mix (the degree of diversity of tree species). The built environment and urban greenery covariates were adjusted in the models. The results indicate that the street tree abundance and species mix are positively associated with pedestrian volume. Species richness is not associated with it. Besides, spatial mismatch is identified between abundance and species mix of street trees in the study area. Hence, to facilitate walking behavior and deliver related health benefits, it is necessary to develop fine-grained measures of street greenery features.

1. Introduction

Street trees have long been recognized for their vital role in urban sustainability, providing a range of ecosystem services that enhance environmental quality and human well-being (Davies and Lafortezza, 2017). From improving air and water quality to mitigating urban heat islands, from fostering social cohesion and improving mental health, the benefits of urban street trees are diverse and substantial (Donovan and Butry, 2010). While the belief that "trees are beneficial" has been challenged due to concerns over ecological disturbances (Roy et al., 2012), infrastructure conflicts (Conway and Yip, 2016), and cost management (Lara A. Roman et al., 2021), the multitude of advantages offered by street trees within urban contexts remains unassailable.

Street trees, an essential element of urban greenery, significantly influence the urban micro-climate, air quality, and serve as a catalyst for physical activity, thereby impacting public health positively (Lee et al., 2016; Markevych et al., 2017). The allure of tree-canopied streets often positions them as the preferred locale for a myriad of physical activities, such as walking, cycling, and jogging, emphasizing their accessibility and the pleasant ambiance they offer (Ki and Lee, 2021; Yi Lu, 2019; L. Yang et al., 2024). Besides, exposure to street trees improves individuals' aesthetic enjoyment of urban spaces (Camacho-Cervantes et al., 2014) and increases both the likelihood and duration of active transportation (Yi Lu, 2019; L. Yang et al., 2020), which in turn reduces

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long-term stress (D. Li and Sullivan, 2016) and the risk of many chronic diseases (Mitchell and Popham, 2008; Wei et al., 2023).

In a nutshell, street greenery has positive effects on physical activity and walking behavior (Cambra and Moura, 2020; L. Yang et al., 2021). As demonstrated in previous reviews, researchers often measure overall level or quantity of urban greenery through remote sensing imagery or street view images (B. Jiang et al., 2017; Ye et al., 2019). Due to methodological limitations, citywide tree-species information at the individual tree level is hard to assess. Such limitation may lead to potential neglect of the aesthetic effect of diverse street trees, which may also affect walking and physical activity (Akpinar, 2016; Tsai et al., 2019). For instance, greenspaces with diverse tree species (e.g., urban park) may create a better aesthetic experience for pedestrians than woodland with a single tree species (e.g., forest nursery). Therefore, constructing a citywide street tree inventory with tree species information and exploring the association between street tree features and pedestrian volume is a necessary and novel research front.

While there are existing studies that utilize LiDAR data for tree species identification (Michałowska and Rapiński, 2021), various challenges in methodology, budgeting, and human resource allocation render most of the current approaches largely ineffective when it comes to creating a comprehensive citywide tree inventory. Only a handful of cities have succeeded in constructing detailed street tree databases (Nielsen et al., 2014; Lara A Roman et al., 2017). To address the above gaps, we employed a novel deep learning approach to detect and classify street trees via street view images (SVIs) to build citywide tree inventory. We further investigated the association between street tree characteristics and pedestrian volume in Jinan, China after adjusting for other potential walk-promoting urban greenery and built environment covariates. In the light of prior evidence, we hypothesized positive effects of street tree density, species richness and species mix upon pedestrian volume.

2. Literature review

2.1. Fine-grained measurement of greenery exposure

To measure urban greenery at a large scale, there are two main approaches, namely top-down and human-eye level greenery assessment (B. Jiang et al., 2017; Ye et al., 2019). Top-down indices, e.g., tree cover density and normalized difference vegetation index (NDVI) (B. Jiang et al., 2017), were mainly calculated by the high-resolution remote sensing images and widely applied to assess urban greenery from national to neighborhood scale (Klemm et al., 2015). The top-down approach has been widely adopted by forestry departments and urban planners to measure the local greenness level due to the accessibility of remotely-sensed images and the efficiency of such measurement (He et al., 2022; L. Jiang et al., 2021). However, it is uncertain whether such greenery is physically or visually accessible by the public. Indeed, the overhead view of greenery is different from the street landscape perceived by pedestrians (X. Li et al., 2015). For example, the vegetation under tree canopies and in urban vertical greening systems might be overlooked (Yi Lu, 2019).

To address the limitations of the overhead-view greenery assessment, scholars have adopted street view images to assess eye-level greenery in recent years (X. Li et al., 2015). By retrieving panoramic images with geolocation information along streets, previous studies have calculated Green View Index (GVI) to simulate the perception of street greenery (Yi Lu, 2019; Ye et al., 2019). Some studies reported that street view images were more accurate than remote sensing images in measuring exposure to green spaces for pedestrians (Leslie et al., 2010; Ye et al., 2019). As the primary metric for assessing eye-level greenery, GVI evaluated the proportion of green pixels in a street view image, i.e., the number of green exposures (Klemm et al., 2015; X. Li et al., 2015). However, it could not measure the specific vegetation information represented by the green pixels, such as the species, number, and species diversity of street trees (D. Liu et al., 2023).

Inequality in street greening represents another critical dimension warranting attention. In some U.S. cities, the forestry department's primary consideration in allocating street trees was to provide shade and ecological services (Ketcham, 2015), As a result, spatial inequality of street trees, both in terms of quantity and quality, might exist across geographic areas and social groups (Lin et al., 2021). According to previous findings, street tree distribution was linked to income and race, with affluent communities tending to have more street trees, while low-income and minority neighborhoods having less (Apparicio et al., 2012; Gerrish and Watkins, 2018). In addition to the quantity inequality, street tree quality inequality existed among different neighborhoods and streets (Avolio et al., 2018). For two streets with the same GVI value, the quality of street trees could be vastly different. For example, tree species of a car-oriented road tended to be homogeneous (Ferrer, Ruiz, and Mars, 2015), while a walking-oriented street generally provided a plentiful and diverse combination of tree species to enhance walking experience (Hegetschweiler et al., 2017). Therefore, it is beneficial to obtain detailed street tree information to expand our understanding of the link between street trees and walking behaviors.

2.2. Methods to assess detailed street tree information

There are mainly three methods to acquire detailed street tree information: field audit, surveys, and sensors (including both remote and local sensors, e.g., RGB camera). Researchers choose different methods based on the availability of funding, time, and labor, as well as the required precision of the data (Fassnacht et al., 2016). Field audit refers to the direct examination of a tree or other vegetation conducted by botanists or other professionals (Wäldchen and Mäder, 2018). This method could obtain accurate and complete information about each individual tree, but it is laborious and time-consuming. Hence, field audit is often suitable for small-scale examination. Survey approach gathered data from authorities or citizens by questionnaires (Schaminée et al., 2009), which is less costly but also less precise compared with field study. With the development of big data technology and machine learning, extracting information from pictures obtained from cutting-edge sensors has been widely applied in assessing tree information. Light Detection and Ranging (LiDAR) sensors (Bauwens et al., 2016; Sankey et al., 2017), hyperspectral cameras (Sankey et al., 2017), multi-spectral cameras (Amiri et al., 2018) and normal RGB imaging cameras (Schiefer et al., 2020), loaded on satellite (Pu et al., 2018), aircraft (Sankey et al., 2017; Schiefer et al., 2020), terrestrial vehicles (Bauwens et al., 2016) are used in different tasks. As a kind of terrestrial-based RGB images, Street View Image is emerging in urban greenery studies and gaining traction due to its wide coverage and open access (Berland and Lange, 2017; Yi Lu, 2019).

To classify plants, traditional studies often focused on one or multiple significant features such as the shape of the leaf or the color of the flower (Caglayan et al., 2013; Ren et al., 2012). With the development of computer technology, researchers have employed metrics of these features extracted by humans or computer vision algorithms to automatically classify plants with machine learning algorithms such as support vector machine (SVM) (Kazmi et al., 2015), k-nearest neighbors (K-NN) (Yigit et al., 2019) and random forest (RF) (Immitzer et al., 2012). The emergence of convolutional neural network (CNN) has markedly enhanced the capability of computer vision (O'Shea And Nash, 2015). Recently, CNN has been extensively utilized for plant identification and classification (Alzubaidi et al., 2021; Mochida et al., 2018).

2.3. Collective walking behavior

The evolving methods for street tree assessment reflect a growing scholarly interest in the broader dimensions of benefits of street trees (Zhang et al., 2017). Green spaces are not merely beneficial for biodiversity and environmental quality; they also play a pivotal role in enhancing the social and physical well-being of urban communities (Reyes-Riveros et al., 2021). This is particularly significant in light of the fast-paced lifestyle caused by global urbanization, which has not only led to a general lack of sufficient physical activity but also precipitated a series of public health issues for urban residents (Y. Jiang et al., 2022; World Health Organization, 2020). Walking is an accessible form of physical activity because it causes minimal injury risk and therefore is suitable for people with different physical or socioeconomic conditions (Litman, 2003). Previous studies have often assessed individual-level walking behavior (i.e., duration or frequency of walking) via questionnaires or surveys, because these studies focused on the potential health benefits of walking for individual person (Y. Jiang et al., 2021; Y. Yang et al., 2019).

Some studies focused on collective walking behavior defined as population-scale walking patterns such as pedestrian volume on streets (Chen et al., 2022; Y. Jiang et al., 2021). This behavior has been shown to enhance urban vibrancy (Chen et al., 2022), boost residents' well-being (Wolf and Wohlfart, 2014) and promote social sustainability (Herrmann-Lunecke et al., 2020). Collective walking behavior could create lively urban spaces, and encourage social interaction and economic activities (Y. Jiang et al., 2021). Additionally, collective walking could reduce the incidence of chronic diseases (e.g., depression, obesity and cardiovascular diseases) at the population scale and thus improve the overall well-being of urban residents (Y. Jiang et al., 2022; Wolf and Wohlfart, 2014). Collective walking behavior also contributes to social sustainability by promoting sustainable transportation and reducing air pollution and greenhouse gas emissions (Kahn and Morris, 2009; Woodcock et al., 2009).

Furthermore, some scholars argued that collective walking behavior is more susceptible to planning interventions as it reflects the general walking intensity in an area, irrespective of potential variations of individual walking behavior in this area (Foster et al., 2018). Recent studies show that pedestrian count is an appropriate indicator for measuring collective walking behavior (Chen et al., 2022). Traditional pedestrian volume surveys were conducted mainly through field audits, i.e., counting the pedestrian on street or within community based on on-site observations, which was time-consuming and labor-intensive (Y. Jiang et al., 2021). To effectively acquire pedestrian counts at city scale, researchers had recently introduced machine learning techniques to automatically detect pedestrians via street view images (Chen et al., 2020; D. Liu et al., 2023; Yin et al., 2015). A recent validation study in Tianjin, China found that the pedestrian volume identified using street view images was highly consistent with the results of a field audit in terms of general trends (Chen et al., 2020).

2.4. Greenery exposure and walking behavior

Urban greenery has attracted increasing attention from walking-related studies for its population-scale effects (Y. Lu et al., 2018; Y. Yang et al., 2019). Previous studies have shown inconsistency in the relationship between top-down greenery and walking time (Persson et al., 2019; Z. Wang et al., 2021). The inconsistent findings were related to the walking purpose (i.e., recreational and utilitarian walking) (Z. Wang et al., 2021; Y. Yang et al., 2019) and different greenery definitions (Klompmaker et al., 2018).

Substantial evidence suggested that eye-level greenery showed positive impacts on walking behavior by promoting pedestrian volume (Chen et al., 2022) and enhancing walking duration (Ki and Lee, 2021; Y. Lu et al., 2018; Wu et al., 2023). For instance, a study of 90,445 Hong Kong residents denoted that street greenery was positively associated with odds of walking and walking duration (Y. Lu et al., 2018). A study conducted in Seoul also indicated that street greenery was significantly associated with both utilitarian and recreational walking time (Ki and Lee, 2021). Another study conducted in Shanghai, China, also revealed the positive association between eye-level greenery and pedestrian volume (Chen et al., 2022).

However, there was less evidence on the association between walking behavior and street tree features, partly due to the difficulty to assess street tree information (Sarkar et al., 2015; Vich et al., 2019). Previous studies mainly focused on improving pedestrian microclimate, such as radiant temperature, humidity, air pollution etc., in order to enhance pedestrian comfort (Coutts et al., 2016; Estacio et al., 2022). Only a handful of studies have demonstrated significant relationship between street tree density and walking behavior. For example, two studies from London, UK, and Barcelona, Spain, revealed that street tree density had positive impacts on walking frequency and walking time, respectively (Sarkar et al., 2015; Vich et al., 2019).

Apart from the quantity of street trees, street-tree quality, including species richness and species diversity, might play a crucial role in enhancing walkability. Each tree species has unique biological characteristics, including the type of vegetation (e.g., evergreen coniferous or deciduous broadleaf) (Galán Díaz et al., 2023), canopy types (Niinemets, 2010), leaf-on seasons (Miao et al., 2021). A high species diversity of street trees not only provided aesthetic value to the streetscape (Nagendra and Gopal, 2010) but also increased pedestrian appeal and ensured a good walking experience across different seasons, ultimately making walking more attractive (Hartig and Kahn, 2016; Voigt et al., 2014). However, evidence linking pedestrian volume to the quality of street trees was still limited (Lin et al., 2021).

3. Methods

3.1. Study area

Jinan is the capital city of Shandong Province and one of the fourteen megalopolises in China with a size of 10,224.45 km^2 and a population of 9.20 million in 2020 (National Bureau of Statistics of China, 2020). The study was conducted in the core area of Jinan (approximately 258.27 km^2) (Fig. 1), which was considered as the most densely populated and urbanized part in the city. Jinan has a temperate continental monsoon climate, and the street trees are mainly broad-leaved deciduous trees. For its outstanding achievements in urban green space construction, Jinan was awarded as an international garden city in 2019 (LivCom Committee, 2019).

Previous evidence indicated that street trees were often dominated by one or a limited number of species (J. Liu and Slik, 2022; Shams et al., 2020). According to statistics, 90% of the street tree inventory in Jinan consisted of seven indigenous common taxa of species, i.e., oriental plane (*Platanus* spp.), poplar (*Populus* spp.), willow (*Salix* spp.), locust (*Robinia* spp.), cypress (*Platycladus* spp.), wax tree (*Ligustrum* spp.) and pine (*Pinus* spp.) (Jinan Landscape Bureau, 2007), which were selected as the test trees in this study.

We generated an 800 × 800 m grid which served as the statistical and analytical unit over the study area, considering the area covered by a 15-minute walking radius (Y. Lu et al., 2018; Y. Yang et al., 2019) (Fig. 1). Grids with no detected pedestrians and no sampling points of street view images (mostly in mountainous areas and farmlands) were discarded, leaving 395 grids for the final analysis. Pedestrian volume, tree species characteristics and all other covariates (i.e., urban greenery and built environment variables) were measured for each grid.

3.2. Street tree species recognition

3.2.1. Image sources and dataset

In this study, we chose Baidu Street View (BSV) as the image source. Compared with other SVI platforms in mainland China such as Tencent Map and Gaode Map, BSV is the only one that provides SVIs at multiple seasons. Therefore, we selected BSV images taken between March and August for the tree species classification because the street trees tend to lush and distinguishable.

In order to collect BSV images of the study area, we utilized a Python script to automatically retrieve data through the Baidu Map API (https:

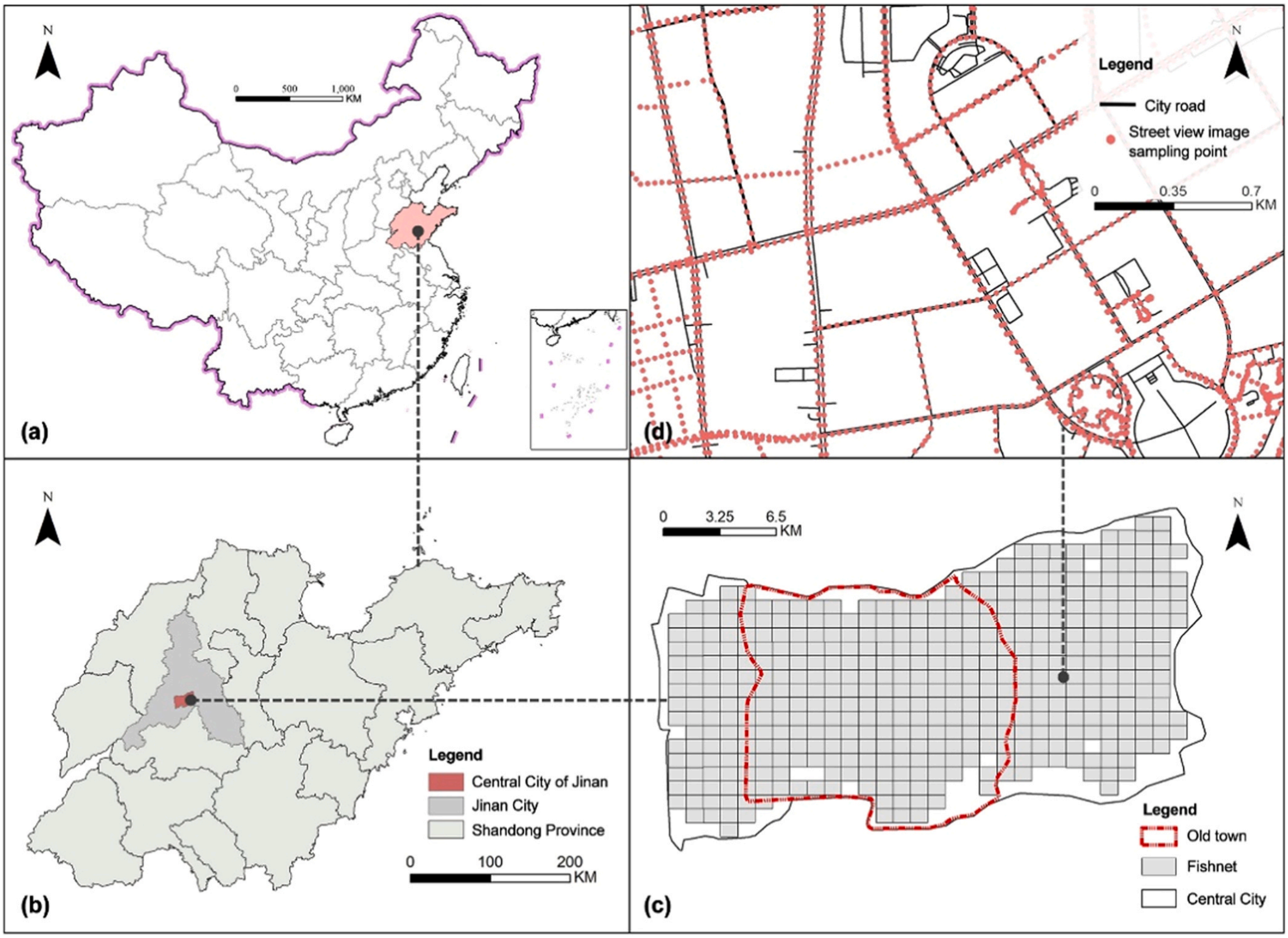

Fig. 1. Study area: (a) Location of Shandong Province in China; (b) Location of Jinan City in Shandong Province; c) the 800 × 800 m grids of Central Jinan, China; d) an example of street segments and street view image sampling points in the study area.

//lbsyun.baidu.com/) at 50-meter intervals along the street network. For each sampling point, we collected BSV images from four different directions using the heading parameters of 0°, 90°, 180°, and 270°, corresponding to the front, right, back, and left sides of the camera mounted on the vehicle.

Finally, 185,831 BSV images were retrieved from the study area. To guarantee a sufficient number of street view images for identifying each tree species, we ensured a minimum of 1000 images per species. The training dataset was composed of 2700 randomly selected images for further analysis. These images were labeled and randomly divided into training, validation, and testing sets with proportions of 70%, 20%, and 10%. The dataset covered various aspects such as context, vegetation density, weather, and lighting conditions. The study focused on the seven major local species in Jinan city, with any other identified species labeled as "other trees." Two trained research assistants labeled the nine classes of street trees in the training dataset, ensuring accurate identification of the local species.

3.2.2. Model of street tree species recognition

To achieve optimal efficiency and accuracy in our object detection task, we followed the latest study (D. Liu et al., 2023) and employed the You Only Look Once (YOLO) series, specifically utilizing YOLO v5 as our model of choice. This one-step object detection model has gained significant popularity due to its robust ability to detect objects of varied scales and those that overlap, both of which are common characteristics found within the environment of urban street trees (Fig. 2).

In the BSV training dataset, the number of samples for different species were severely imbalanced which could undermine the performance of the model. To cope with this issue, we replaced the original loss function with a class-balanced loss function. The Cross-Entropy (*CE*) loss function is the original classification loss function used in YOLOv5:

$$CE_{softmax}(z,y) = -\log\left(\frac{\exp(z_y)}{\sum_{j=1}^{C}\exp(z_j)}\right) \tag{1}$$

where z_y represents the anticipated likelihood for a specific species *y*, and *C* denotes the overall species count.

According to Cui (2019), the species-weighted loss function utilized a weighting method that varied in an inverse relationship with the number of valid samples for each species. This approach resulted in an increased probability for smaller classes, a decreased probability for larger classes, and ultimately generated predicted results that more closely aligned with actual outcomes. If species *y* has *Ny* training samples and the overall amount of training samples is *N*, the equation for the SB cross-entropy loss is expressed as follows:

$$SB_{softmax}(z,y) = -\frac{\left(1-\frac{(N-1)}{N}\right)}{\left(1-\frac{N_y-1}{N_y}\right)}\log\left(\frac{\exp(z_y)}{\sum_{j=1}^{C}\exp(z_j)}\right) \tag{2}$$

3.2.3. Street tree characteristics

To measure the street tree features of each geographic unit and evaluate its association with walking behavior, we employed three

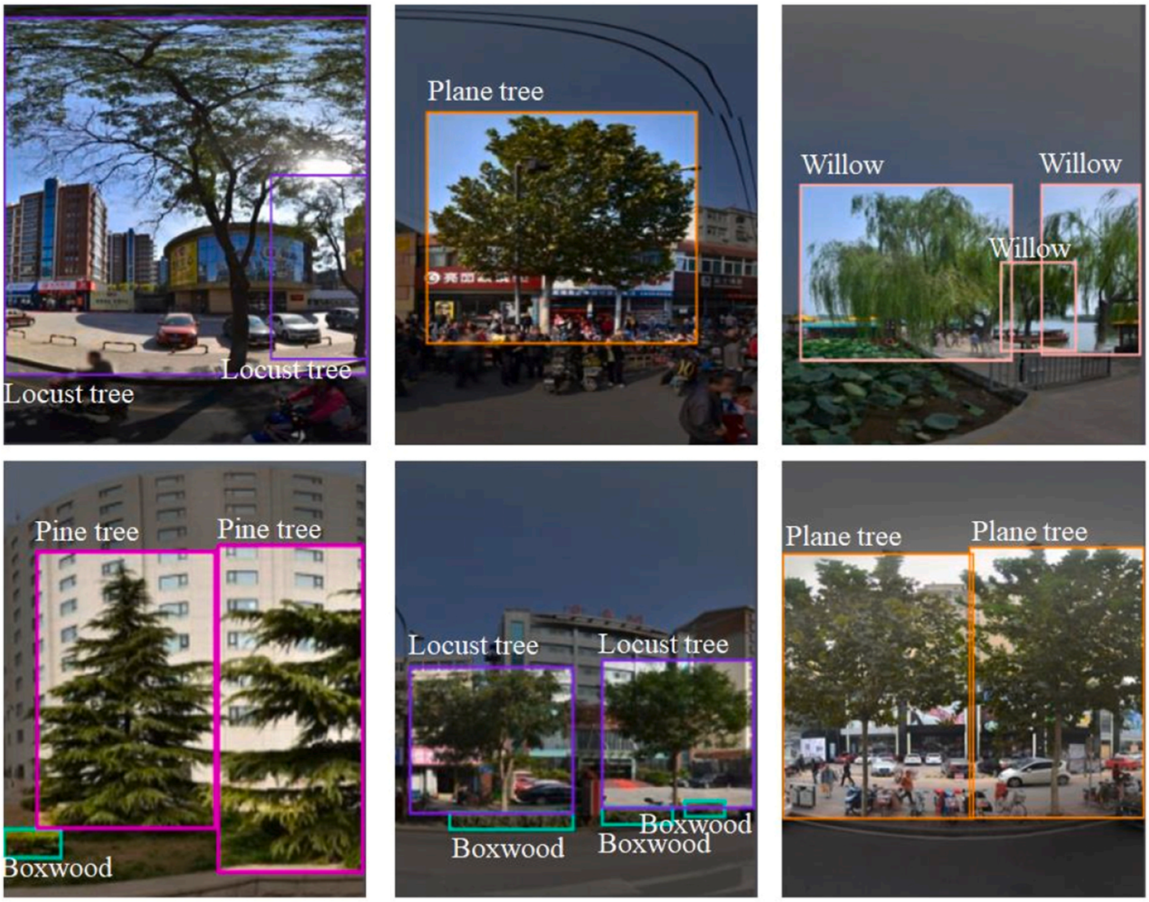

Fig. 2. Examples of labeled Baidu Street View images in which the frame colors correspond to various tree species.

indices i.e., trees abundance of, tree species richness and species mix. The trees abundance was the number of street trees in each grid. The precision and recall of the tree identification in our study reached over 90%. The results indicated that our method exhibited a relatively high degree of accuracy when compared with previously findings (Choi et al., 2022).

Diverse tree species has long been recognized as a vital feature to enhance landscape aesthetics (Gerstenberg and Hofmann, 2016). We used two measures to assess the level of tree species diversity: species richness and species mix. The species richness was the number of tree species in each grid. Considering that tree species identification mainly includes seven major local species and "other species", there were eight tree species types in total included in this study. Therefore, for each grid, the value of species richness ranged between 0 and 8. However, the species richness might be inadequate to describe the level of diversity. If a space has a large number of species but dominated by one of them, it is not biodiverse. For example, both of two identical grids have two tree species, willow and pine. One grid has 50 willow trees and 50 pine trees, while the other has 99 willow trees and one pine tree. The tree diversity is higher in the former grid than in the latter, despite the species richness is identical. Therefore, we also employed the species mix (i.e., Shannon's diversity index) as follows (Shannon, 1948).

$$H' = -\sum_{i=1}^{s} p_i \ln p_i \tag{3}$$

p_i is the proportion of the number of species i to number of all detected plants in a geographic unit. S is the whole number of species in the unit. The Shannon index is a widely used measure of biological diversity, with higher values indicating greater species richness and evenness within a unit.

3.3. Collective walking behavior

Collective walking behavior was measured by pedestrian volume retrieved from the aforementioned BSV images (N = 185,831) over the study area. We used Baidu pedestrian detection AI (https://ai.baidu.com/tech/body/num) to obtain pedestrian counts in the BSV images (Fig. 3), which was validated by comparing with field audit data (Chen et al., 2022; Y. Jiang et al., 2021). The sum of four directionally detected pedestrian counts in a sampling point was considered as the pedestrian volume of that sampling point. In a manual audit of 100 randomly chosen pictures, Baidu AI achieved a highly consistent result with the expert judgement (Pearson's r = 0.92). Therefore, pedestrian flow for each grid was determined by calculating the median number of pedestrians of all the sample points in a grid.

3.4. Covariates

3.4.1. Urban Greenery

In the present study, we calculated urban greenery from eye-level view and top-down view, i.e., green view index (GVI) and Normalized Difference Vegetation Index (NDVI). GVI was usually regarded as a measure for the street greenery perceived by pedestrians, and it was extracted from the 185,831 BSV images using PSPNet, an effective machine learning technique (Zhao et al., 2017). We employed PSPNet pretrained by Cityscape dataset which comprised more than 5000 streetscape images with state-of-the-art pixel-level annotations across 50 cities (Cordts et al., 2016) (Fig. 3). The GVI in each sampling point was measured as the average ratio of vegetation pixel of four BSV images in that sampling point. After a manual validation of 100 random BSV images using Adobe Photoshop, the automated GVI calculation

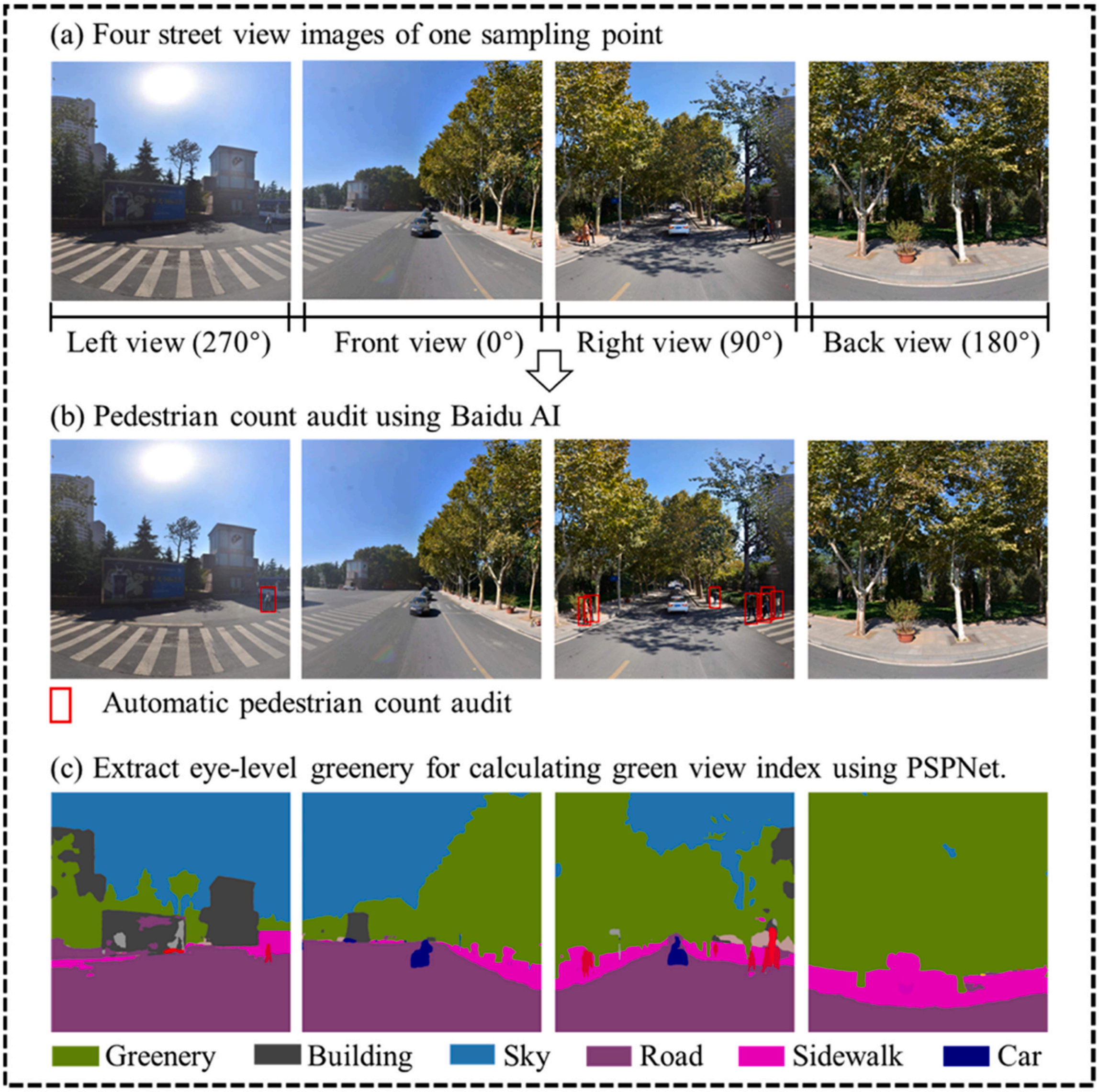

Fig. 3. Using Baidu Street View (BSV) to process pedestrian count audit and to extract eye-level greenery (a) For each sampling point, there are four BSV images collected from front (0°), right (90°), back (180°) and left (270°) directions. (b) Automatic pedestrian volume detection via the pedestrian counting function of Baidu AI. (c) Using PSPNet algorithm to extract street greenery pixels for calculating green view index (GVI).

demonstrated a high degree of accuracy and reliability (Pearson's r = 0.94). Finally, we calculated the average GVI value of all sampling point within each grid as the eye-level GVI of that grid.

NDVI was measured by the Landsat 8 remote-sensing imagery acquired from June 2019 (Xu, 2014). The equation of NDVI is shown as: *NDVI = (NIR - Red) / (NIR + Red)*, where NIR and Red are spectral reflectance measurements acquired using near-infrared and red light, respectively. The range of NDVI value is from −1.0–1.0; The closer the NDVI value reaches to 1.0 indicates a higher level of top-down urban greenery.

3.4.2. Built environment features

We measured potential walking-influencing built environment variables based on 5D framework, including density, diversity, destination accessibility, distance to transit and design (Y. Jiang et al., 2021). Density was calculated by building floor area and population density in each grid (Y. Yang et al., 2019). Population density data was obtained from Worldpop in 2018 (https://www.worldpop.org/), with a 100 × 100 m resolution. Land-use mix was used to quantify land-use diversity (Y. Jiang et al., 2021). We calculated the entropy score of three land-use categories retrieved from Jinan municipal natural resources and planning bureau (http://nrp.jinan.gov.cn/), including residence, commerce, and public service (Shannon, 1948). The equation of land-use mix is shown as: $\text{Land use mix} = (-1)\sum_i (d_i \ln(d_i))/\ln(3)$, where d_i denotes the ratio of specify land use category of total land use. Distance to transit was measured as the quantity of bus stations within each grid (J. Wang and Cao, 2017). Destination accessibility was defined as the number of five types of POIs (i.e., public service POI, company POI, residential POI, commercial POI, and recreational POIs) in each grid (Chen et al., 2022). The POI data was retrieved from Gaode Map Service (http://lbs.amap.com). Design was measured by the number of street crossings (three streets and above), as well as the total road length in each grid (Cerin et al., 2017). Building floor area, road density, street intersections and bus stops were acquired from the OpenStreetMap in 2019 (https://www.openstreetmap.org/). We calculated all built environment factors using ArcGIS 10.6.

3.5. Statistical analysis

Before conducting our analysis, we performed a Variance Inflation Factor (VIF) analysis among all independent variables to avoid collinearity. The result demonstrated that all VIFs were less than 4, indicating that there was no serious multicollinearity issue in the model.

First, we adopted ordinary least square (OLS) regression model to investigate the independent associations between pedestrian volume and street tree characteristics after controlling for the urban greenery and built environment covariates. The OLS model is defined as follows:

$$y = X\beta + \varepsilon \tag{4}$$

where y is the dependent variable, X is the independent variable(s), β is the coefficient associated with each independent variable., and ε is a vector of random error terms.

To account for potential spatial autocorrelation among neighboring grids, we conducted a test on the residuals of the OLS model using the global Moran's I (Fischer and Getis, 2010). The result indicated a significant spatial autocorrelation in pedestrian volume, with a Moran's I value of 0.588. Therefore, two major spatial regression models, i.e., spatial lag model (SLM) and spatial error model (SEM), were considered (Anselin and Rey, 1991). SLM assumes that spatial dependence may be caused by the autocorrelation of the dependent variable, while SEM suggests that it is caused by the autocorrelation of the residuals (Anselin and Rey, 1991).

A Lagrange multiplier (LM) pre-test was performed to determine the most suitable spatial regression model for pedestrian volume data (Anselin et al., 2010). The result of the LM pre-test was presented in Table 1. Lagrange Multiplier (lag), Robust LM (lag), and Lagrange Multiplier (error) were statistically significant. However, Robust LM (error) had a p-value of 0.860, indicating that it was not significant. Hence, SLM was more suitable than SEM in this study. SLM can be calculated as follows:

$$y = \rho \mathrm{W_y} + \mathrm{X}\beta + \varepsilon \tag{5}$$

where ρ denotes the parameter for spatial autocorrelation, and Wy represents a spatial weight matrix that accounts for the spatial lags of the dependent variables in neighboring units. The matrix was constructed using the Queen's contiguity criterion, and the spatial regression analysis was conducted using Geoda v.1.2 software. To fulfill the normality assumption and improve the distribution of pedestrian volume, a natural logarithmic transformation was applied to the dependent variable prior to conducting the statistical analysis.

4. Results

4.1. Tree species classification

In the field of computer vision, object detection performance is often evaluated using the Average Precision (AP) metric. This metric assessed the agreement between the predicted and actual boundaries of objects, normalized by their combined area, thereby providing an equitable evaluation of precision and recall. In particular, our study employed the average AP score at a 0.5 Intersection over Union (IoU) threshold (mAP0.5) as the main performance measure, where IoU threshold pertains to the degree of overlap between predicted and actual objects.

We compared the efficacy of all current models which employed SVIs as the sole dataset to process tree species classification (Table 2). Our model achieved a higher mAP0.5 value of 0.587 than the models of Branson et al. (2018) and Choi et al. (2022), which attained mAP0.5 values of 0.581 and 0.564, respectively. The results indicated that our model exhibited superior performance in the tree species classification task.

We detected 144,596 street trees from a dataset of 185,831 Baidu Street View (BSV) images in Jinan, China. To validate the accuracy of our automatic detection method, we compared the findings to the 2007 field survey conducted by the local landscape department (Jinan Landscape Bureau, 2007). Fig. 4 demonstrates that the amount of eight species in the present study aligned with the findings of the 2007 field audit. Locust tree, poplar and oriental plane dominated both tree classification result and the field study in 2007. Besides, a number of pine trees and cypresses were detected in our study while there was no relevant data of these trees in 2007 field audit. Three main street tree indicators (i.e., tree abundance, species richness, and species mix) and urban greenery covariates (i.e., NDVI and green view index) were aggregated within the 800 m grid, and the results are presented in Fig. A1.

4.2. Relationships between pedestrian volume and street trees indicators

4.2.1. Descriptive statistics

The descriptive statistics and correlation matrix of all variables (i.e., street tree characteristics and covariates) in a grid are shown in Table 3 and Fig. A2. The average ratio of species richness, tree abundance and species mix for all grids were 6.13 (SD = 1.94), 167.17 (SD = 181.64) and 0.78 (SD = 0.38), respectively. Regarding the urban greenery characteristics, the average of GVI for all grids was 0.14 (SD = 0.07) and that of NDVI was 0.16 (SD = 0.04).

In terms of built environment variables, the study area exhibited high population density (M = 691.84 /km^2, SD = 436.73), with a large building floor area (M = 554124.41 m^2, SD = 323571.84), a mixed land use (M = 0.72, SD = 0.32). Public transportation was also easily accessible (M = 3.06, SD = 2.79). Each grid had average of 5.49 street intersections (SD = 6.76) and 79017.69 m of average road length (SD = 26792.12), indicating a well-connected street network. In terms of accessibility of pedestrian facilities, there are more public service, company and commercial POIs than residence and recreational POI.

The results of two multivariate models associating pedestrian volume and street tree characteristics were shown in Table 4. SLM had a better model goodness-of-fit (i.e., higher Log likelihood (LL) and R-squared, lower Akaike info criterion (AIC) and Schwarz criterion (SC)) than OLS model, thus we primarily followed the SLM results. For street tree characteristics, street trees abundance and species mix had positive association with pedestrian volume. Species richness, however, had not.

For the urban greenery variables, the eye-level greenery, GVI, was positively associated with pedestrian volume. The overhead level greenery (i.e., NDVI), however, was negatively associated with pedestrian volume. Among the built environment covariates, population density, land-use mix, public service POI, and commercial POI were positively associated with pedestrian volume. The SLM model achieved an R^2 value of 0.774, demonstrating that it can explain 77.4% of the

Table 1
Lagrange multiplier (LM) diagnostics for spatial dependence.

Dependent variable	Statistic	DF	Value	p-value
Pedestrian volume	Lagrange Multiplier (lag)	1	84.375	< 0.001***
	Robust LM (lag)	1	45.498	< 0.001***
	Lagrange Multiplier (error)	1	38.908	< 0.001***
	Robust LM (error)	1	0.031	0.860

Note: DF = Degrees of freedom; LM = Lagrange multiplier; *p < 0.05. **p < 0.01. ***p < 0.001.

Table 2
Performance evaluation of all existing tree classification models employing SVIs as sole dataset.

Study	Model performance (mAP0.5)	Study area
Choi et al., 2022	0.564	Seoul, South Korea
Branson et al., 2018	0.581	Pasadena, United States
Our model	0.587	Jinan, China

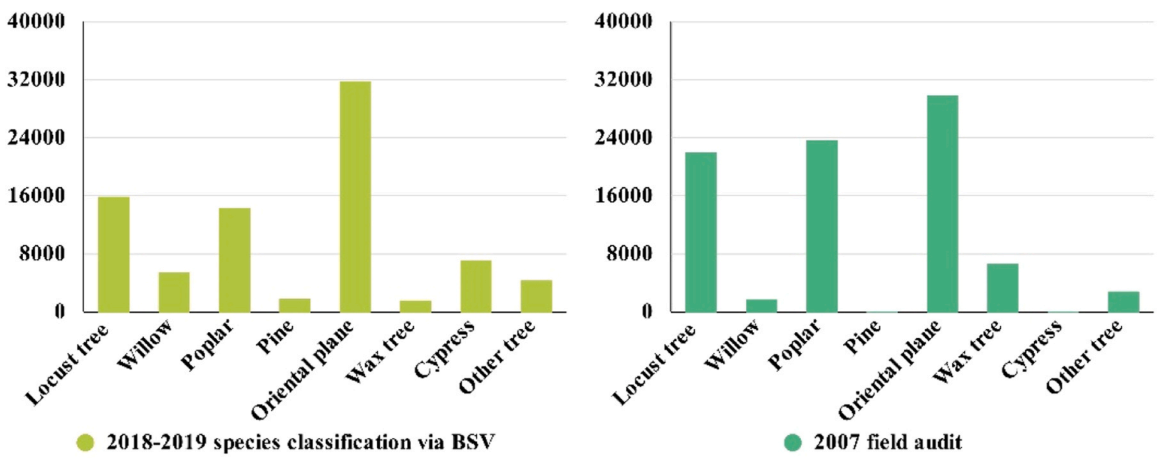

Fig. 4. The street tree detection result of our study vs. 2007 field audit of street tree distribution.

Table 3
Descriptive statistics for all indicators within Central Jinan, China, sampled in 2018–2019 (Fishnet = 800 × 800 m, N =395).

Variables (unit)	Mean	SD
Street tree characteristics		
Species richness (*N*)	6.13	1.94
Tree abundance (*N*)	167.17	181.64
Species mix	0.78	0.38
Urban greenery characteristics		
Greenery view index (GVI)	0.14	0.07
Normalized Difference Vegetation Index (NDVI)	0.16	0.04
Built environment characteristics		
Population density (*N* /km^2)	691.84	436.73
Building floor area (m^2)	554124.41	323571.84
Land-use mix	0.72	0.32
Number of bus stops (*N*)	3.06	2.79
Street intersection (*N*)	5.49	6.76
Road density (m)	79017.69	26792.12
Public service POI (*N*)	51.56	56.78
Company POI (*N*)	56.02	63.44
Residential POI (*N*)	9.82	9.40
Commercial POI (*N*)	43.37	48.32
Recreational POI (*N*)	8.80	10.39

variation in pedestrian flow within the study area.

4.3. Comparison between abundance and species mix of street trees

According to the results of SLM (Section 4.2), both street tree numbers and species mix had positive associations with pedestrian volume. Therefore, it is advisable to consider both numbers and species mix of street tree during urban street-tree layout planning. Hence, we try to find out the spatial distribution of both street trees abundance and species mix. We divided the grids into high/low tree abundance and high/low species mix based on the corresponding median values (Fig. 5). All grids were divided into four categories (Fig. 6), i.e., grids with high tree abundance and high species mix (H/H); grids with high tree abundance and low species mix (H/L); grids with low tree abundance and high species mix (L/H) and grids with low tree abundance and low species mix (L/L).

As seen in Fig. 6, spatial disparities existed in the four categories of grids. The H/H grids was mainly located in the central old town and the core area of the new town in the southeast. H/L grids was mainly distributed in the northwestern and northeastern urban sub-centers; L/H grids was located in the northeastern towns and villages, while small part of the L/H grids was distributed on the fringes of H/H areas. The grids for L/L were situated in the suburban areas, mainly in the southwest of the study area. In general, apart from H/H areas, the other areas were lacking in the abundance of street trees or in the species mix, or both.

5. Discussion

Previous studies have demonstrated the positive impact of street greenery, especially street trees, on physical activity among urban residents. Optimizing the design of street trees to facilitate an active lifestyle, could yield significant public health benefits. However, most existing studies have primarily focused on the quantity rather than the quality of street greenery. There is an urgent need to assess the quality of street trees, because previous studies also confirm its role on physical activity and human perception. To address such research gap, we innovatively assessed both the abundance and species diversity of street trees from freely available Street View images. Using 185,831 Baidu Street View images from Jinan, China, we further examined the association between pedestrian volume and street tree characteristics. In general, this study extended prior studies in two respects.

First, at the methodological front, the present study provides a cost-effective method to assess fine-grained street tree information at any spatial scale. Both quantitative (i.e., tree abundance) and qualitative (i.e., species richness and diversity mix) features of street trees of any place with Street View image coverage can be obtained. The present method offered the merits of high precision, cost-effectiveness and large geographic reach over the traditional field audit. It can collect citywide data of street tree species with geographic information in a rapid manner. Such a method can advance the research field in urban tree management, healthy cities, and urban ecology.

Second, our study pinpoints the positive effects of both abundance and species mix of street trees on pedestrian volume after adjusting other covariates. To the best of our knowledge, it is the first study confirming the positive link between species diversity of street trees and collective walking behavior at a citywide scale. The large spatial coverage ensures that our results are reliable and generalizable to the entire Jinan population.

5.1. Major Findings

This study yielded three major findings. First, street-trees abundance was positively associated with pedestrian volume, which supplemented previous findings that the level of street greenery can promote active travel (Y. Lu et al., 2018; Sarkar et al., 2015). Street tree abundance could reflect the potential quantity of street greenery, since more street trees could furnish pedestrians with a pleasant walking environment (Lee et al., 2016). The positive effects of high GVI on population-level walking have also been reported in both our study and prior evidence

Table 4
Results of regression models of pedestrian volume, street tree characteristics, and other covariates (Fishnet = 800 × 800 m, N =395).

Model predictors	OLS		SLM	
	Coef. (SE)	*p*-value	Coef. (SE)	*p*-value
Street tree characteristics				
Species richness	-0.041 (0.019)	0.037*	-0.025 (0.017)	0.142
Tree abundance	0.000 (0.000)	< 0.001***	0.001 (0.000)	< 0.001***
Species mix	0.286 (0.089)	0.001**	0.180 (0.077)	0.019*
Urban greenery				
GVI	0.852 (0.320)	0.008**	0.549 (0.287)	0.048*
NDVI	-1.445 (0.551)	0.009**	-1.107 (0.477)	0.020*
Built environment				
Population density	0.002 (0.000)	< 0.001***	0.001 (0.000)	0.001**
Building floor area	-0.000 (0.000)	0.952	-0.000 (0.000)	0.477
Land-use mix	0.201 (0.072)	0.006**	0.147 (0.062)	0.018*
Street intersection	0.007 (0.004)	0.067	0.000 (0.003)	0.847
Road density	0.000 (0.000)	0.029	0.000 (0.000)	0.932
Number of bus stops	0.009 (0.008)	0.248	0.006 (0.007)	0.364
Public service POI	0.003 (0.001)	< 0.001***	0.002 (0.001)	< 0.001***
Company POI	0.000 (0.000)	0.257	0.000 (0.000)	0.424
Residential POI	0.008 (0.003)	0.033*	-0.000 (0.003)	0.975
Commercial POI	0.003 (0.001)	0.004**	0.003 (0.001)	0.001**
Recreational POI	-0.002 (0.003)	0.439	-0.002 (0.003)	0.346
Log likelihood (LL)	-151.925		-111.796	
Akaike info criterion (AIC)	337.85		259.593	
Schwarz criterion (SC)	405.448		331.167	
R-squared	**0.711**		**0.774**	

Note: Coef. = Coefficient; SE = Standard error; GVI = green view index; NDVI = Normalized Difference Vegetation Index; POI = point of interest; *p < 0.05; **p < 0.01; ***p < 0.001.

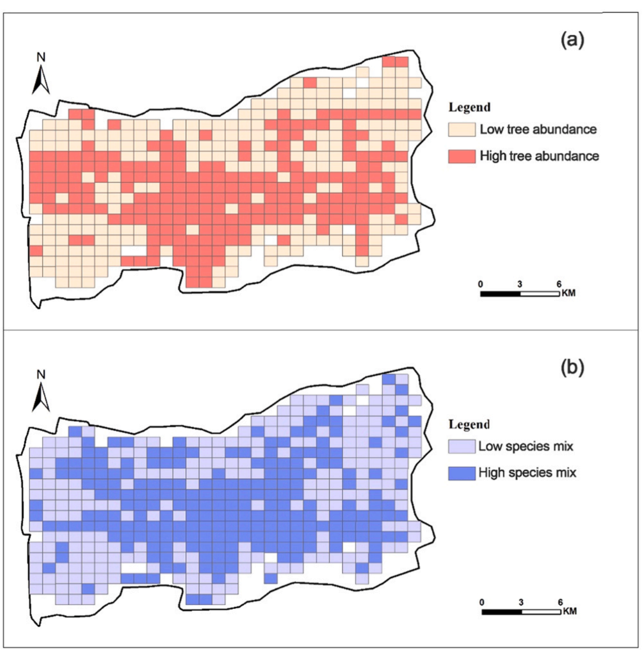

Fig. 5. Grids with a) high/low street tree abundance, and b) high/low species mix.

(Yi Lu, 2019; Y. Yang et al., 2019). Besides, street trees effectively create a comfortable walking microclimate (e.g., reducing noise, enhancing air quality and improving heat perception) to achieve a pleasant walking experience (Coutts et al., 2016).

Second, tree species mix instead of species richness had a positive association with pedestrian volume, demonstrating an independent effect of the greenery quality on collective walking behavior. A community with diverse tree species could provide various ecosystem services such as esthetics, biodiversity, and microclimate (Clarke et al., 2013; Coutts et al., 2016). The species mix of street trees might facilitate collective walking behavior via three mechanisms: (a) by providing aesthetic appeal, enhancing street quality perception (Y. Lu et al., 2018; Weber, 2014), (b) by improving noise reduction, air purification, and other ecological services (Amini Parsa et al., 2019; H. N. Li et al., 2010) (c) by creating a more natural ecological environment, reducing stress and improving mental health (Łaszkiewicz and Sikorska, 2020; Wei et al., 2023). Specifically, prior evidence indicated that highly diverse tree species efficaciously enhanced the overall perceived aesthetics and street built environment quality, which has been considered as an indispensable element of walkability and urban vibrancy (Saelens and Handy, 2008). High species mix on streets can also lead to better biodiversity (Leidinger et al., 2021), which benefits the ecological environment of the street, such as better air quality and lower noise levels. Numerous studies have shown that a positive correlation existed between the street eco-environmental level and the duration of residents' daily physical activity (An et al., 2019; Foraster et al., 2016). By providing a more ecologically sustainable street landscape, the overall walking experience of the street can be effectively enhanced. Furthermore, urban greenery, especially diverse green spaces was proven to be related to reducing physiological stress (Remme et al., 2021) and recovering from attention fatigue (Engemann et al., 2019); for example, individuals tend to immerse themselves in a leisurely stroll through a green space replete with a variety of flora to reinvigorate their senses (S. Liu and Wang, 2021; Wu et al., 2023).

Third, we noticed that some urban greenery and built environment covariates played vital roles in pedestrian volume. GVI had a positive association with pedestrian volume, while NDVI had a negative association. The results are inconsistent with prior evidence (Y. Jiang et al., 2021; Mouratidis and Poortinga, 2020). Such inconsistency might relate to the spatial mismatch of two greenery measures. The top-down greenery cover assessed by NDVI is not equal to the eye-level greenery assessed by GVI, and the latter may better present what pedestrians can perceive when walking on streets (Ye et al., 2019). Regarding the built environment covariates, population density had a positive association with pedestrian volume. An area with a high population density might stimulate more street activities at population level, because of the potential high pedestrian supply. Our study confirmed that mixed land-use can lead to an increase in pedestrian flow (Chen et al., 2022; Yi Lu et al., 2017). Diverse land use was proven to have beneficial effects in

Fig. 6. Classification of the study area into four categories, according to the tree abundance and species mix outcomes.

lessening travel distance and encouraging both leisure and utilitarian walking behaviors (Chen et al., 2022; Saelens and Handy, 2008).

Fourth, our study revealed significant spatial disparities of street trees in urban areas. We observed that areas with a higher tree abundance do not necessarily have a high level of species mix, and vice versa. To better understand these disparities, we classified all grids into four distinct clusters based on a combination of street tree abundance and species mix. These clusters offered unique insights into the urban development and street tree planting characteristics of different areas. For example, the H/H cluster, located in old town areas, boasted a well-established street tree system with both high tree abundance and tree species mix. In contrast, the H/L cluster, situated in new towns or urban renewal areas, prioritized tree abundance over quality to achieve a desirable level of street greenery. The L/H cluster, primarily comprising urban peripheral areas, struggled with a lack of street trees despite a diverse natural environment. Furthermore, the L/L cluster, consisting of farming and industrial areas, had poor street greenery in terms of both tree quality and quantity. Our study highlights the importance of considering the unique characteristics of each cluster when undertaking any urban renewal efforts. Simply increasing tree abundance may not be the most effective way to promote biodiversity or collective walking. Instead, we recommend a more nuanced approach that considers the specific needs and challenges of each cluster to achieve optimal street greenery and sustainable urban development. In addition, the above-mentioned spatial disparities could identify the spatial inequalities of street trees in a high urban density context in Asia, which supplement previous evidence found in the low or medium urban density context of North America (Lin et al., 2021).

5.2. Planning implications

Our findings have several planning and tree management implications. Firstly, a pedestrian-friendly greening environment requires not only abundant trees, but also diverse tree species (Tsai et al., 2019). Hence, urban forestry sectors and landscape architects might establish tailored strategies to enhance street greening for the four clusters listed in Section 4.3 respectively (Morgenroth et al., 2016). These strategies should account for the varying levels of tree abundance and species diversity within each cluster, aiming to enhance street greening in a manner that addresses the specific needs of each area.

Secondly, it may be beneficial to broaden the focus beyond global parameters of urban greenness (e.g., NDVI) and individual greenness visibility (e.g., GVI) to include more detailed aspects of street tree exposures, including species diversity and tree counts (Morgenroth et al., 2016). Our advice is by switching appropriate attention to the latter, we can not only enhance urban forest biodiversity but also improve street walkability, and thus help create a healthy and vibrant urban environment.

Thirdly, by focusing on the detailed aspects of street tree exposures, urban forestry plans can greatly promote biodiversity within urban ecosystems (J. Liu and Slik, 2022). Relevant policies should encourage the planting of a diverse array of street tree species, especially in areas with high resident exposure to greenery. This diversity can not only enhance the aesthetic and ecological value of urban areas but also support a variety of ecosystem services that benefit urban residents.

Furthermore, the implementation of the abovementioned planning implications requires the collaboration of multiple stakeholders, including urban planners, landscape architects, environmental scientists, public health professionals, and the community. Engaging local residents in the planning and management of urban greenery can ensure that initiatives are responsive to the needs and values of the community, thereby enhancing the success and sustainability of urban forestry efforts. In summary, by adopting a holistic and nuanced approach to urban greening, cities can foster environments that support active lifestyles, ecological resilience, and community well-being.

6. Limitations

This study has some limitations. First, the cross-sectional study design could not establish the causal relationship between pedestrian volume and street tree characteristics. Future studies should adopt the natural experimental or quasi-natural experimental methods to acquire more robust findings.

Second, although the pedestrian volume and street tree characteristics were measured at a street segment level, we aggregated these parameters as well as other covariates at an 800 m grid level. This aggregation, to some degree, may lead to two limitations, i.e., ecological fallacy and omitted individual factors such as a pedestrian's age, gender, and income (Kwan, 2018). However, our decision to conduct our analysis at the grid level is based on two considerations. Firstly, grid-level analysis enabled more effective integration of existing data resources, considering their availability and accuracy. Secondly, grid-level analysis also helped mitigate the small-scale variability and noise in street segment level data, thereby enhancing the robustness of our research results. For example, the pedestrian volume of a street segment can fluctuate significantly over time. By aggregating the pedestrian volume of multiple street segments in a grid, we were able to provide a reliable and standardized method for analyzing pedestrian volume.

Third, as the primary data source of this study, the BSV images were collected at different time periods (peak hours vs. off-peak hours), different days (weekdays vs. weekends), and different seasons, which may affect the results of pedestrian detection and tree species classification (Chen et al., 2022; D. Liu et al., 2023). We selected all BSV images collected in spring and summer to achieve optimal species identification accuracy. Further studies are needed to mitigate the bias arising from temporal fluctuation.

Furthermore, this study prioritized the identification of street trees within street view imagery. However, it is important to acknowledge that our study did not extend to other forms of urban greenery such as shrubs, grasslands, and vertical green structures. These elements have been shown to impact physical activity as well (Spano et al., 2021). Future research could focus on these elements to provide a more comprehensive assessment of urban greening.

7. Conclusion

This study has offered new insights into the relationship between street tree characteristics and pedestrian volume at a city scale. All street tree characteristics were retrieved using a novel deep learning method in conjunction with street view images. The spatial lag model denoted that pedestrian volume was positively associated with both abundance and species mix of street trees. The finding sheds new light on our knowledge of the interaction between walking behavior and street trees. Furthermore, we highlighted the citywide spatial mismatch between the abundance and species mix of street trees, which will assist the relevant authorities in developing tailored street tree planting strategies.

Appendix

CRediT authorship contribution statement

Yi LU: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition. **Dongwei LIU:** Writing – original draft, Validation, Formal analysis, Data curation. **Lijian REN:** Writing – review & editing, Supervision, Funding acquisition. **George GREKOUSIS:** Writing – review & editing, Supervision. **Yuxiao JIANG:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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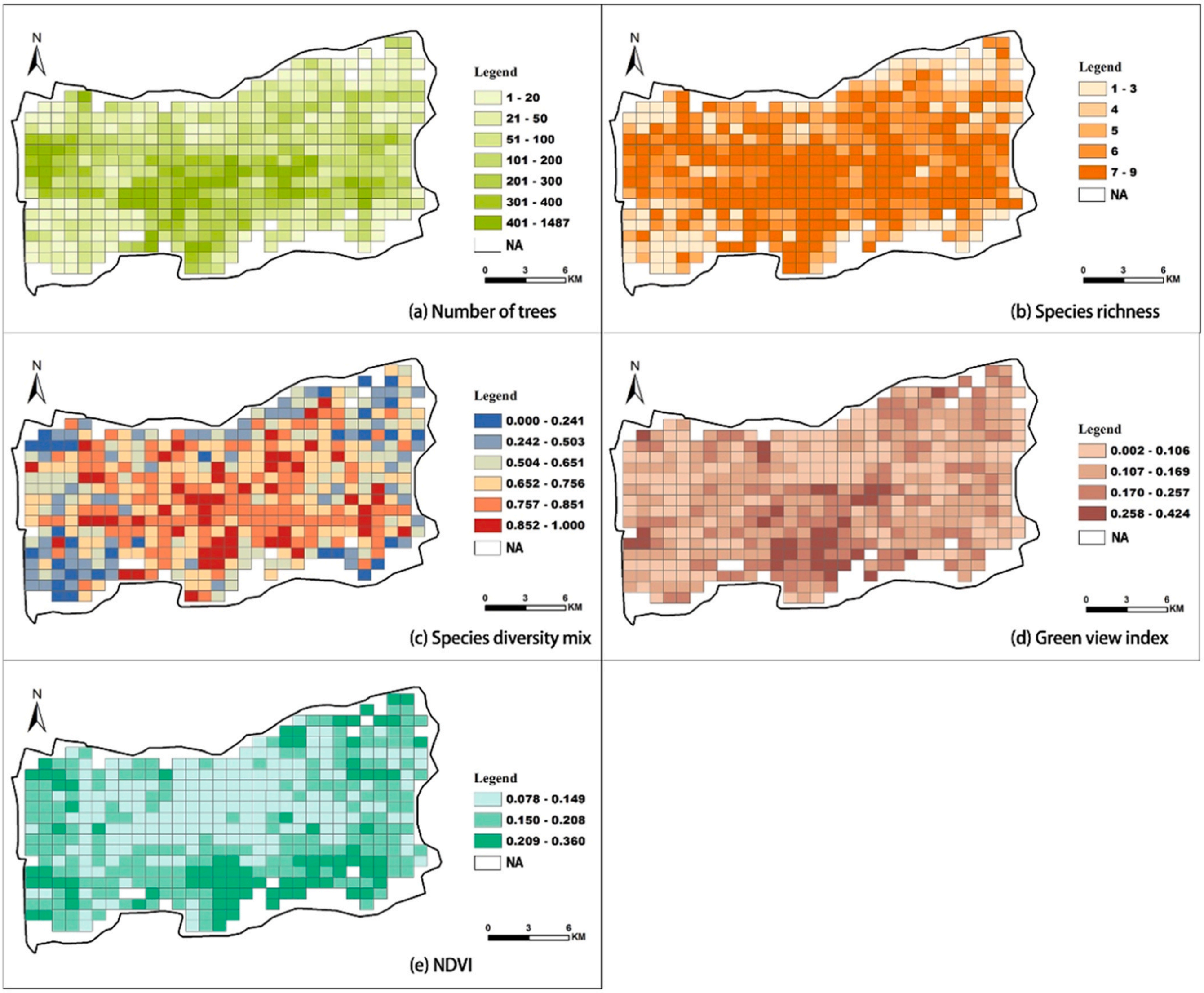

Fig. A1. The results of street tree indicators and urban greenery covariate aggregated by the 800 m grid in Central Jinan, China (Fishnet = 800 × 800 m, N = 395); (a) street-trees abundance; (b) species richness of street tree; (c) street-trees species mix; (d) green view index; (e) NDVI.

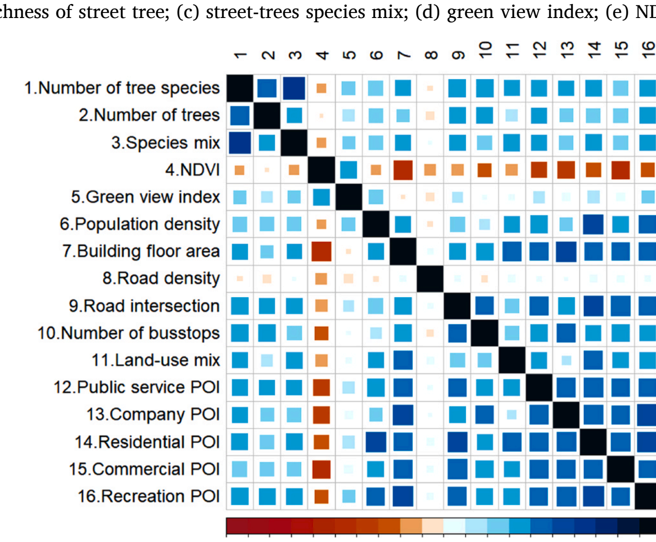

Fig. A2. Correlation of all variables including street tree indices, urban greenery covariates and built environment covariates aggregated by 800 m grid in Central Jinan, China (Fishnet = 800 × 800 m, N = 395).

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