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Research article

Health benefit contributions and differences of urban green spaces in the neighbourhood, a case study of Beijing, China

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ABSTRACT

Numerous studies demonstrate that urban green spaces enhance residents' health. However, limited clarity in green space classification and the complex interplay between green space attributes and other variables have constrained our comprehension of the nuanced relationships between specific green space attributes and health benefits. This study employs a case study in Beijing's central area, utilizing machine learning techniques (random forest modeling) combined with SHapley Additive exPlanations (SHAP) analysis to scrutinize the heterogeneous health impacts of various green space types. We examined 36 neighborhoods using multi-source data, including green space metrics, socioeconomic indicators, and health survey outcomes from 1116 residents. The results indicate that different types of green spaces contribute variably to health benefits. Park green spaces (PG) exhibited the most significant positive effect on residents' Physical type Summary (PCS) and Mental type Summary (MCS), surpassing the remaining green space types. Notably, residential green space with sampled communities (RG-I) exhibited a positive effect on residents' PCS, whereas residential green space with non-sampled communities (RG-O) was negatively associated with both the PCS and MCS. Street green space (SG) also showed a positive effect on PCS. Specifically, among all the green space metrics, Area_PG was the most critical determinant of PCS, followed by Proximity_PG and NDVI_PG. For MCS, Area_PG and Proximity_PG exhibited the most importance. Moreover, we delved into the interactions among predictors for health. In high-density neighborhoods, increasing the area of park green spaces significantly enhanced physical health benefits. While in neighborhoods with large area of park green spaces, positive social relationships more effectively boosted mental health benefits. These findings highlighted the distinct effects of various green space attributes in affecting health, especially the characteristics of land functions and utilization. Our study identifies the specific green space metrics in the neighbourhood that significantly impact residents' health, offering insights for more precise and effective urban green space regulation strategies aimed at improving human health.

1. Introduction

Rapid urbanization results in an escalating disconnection between urban dwellers and the natural environment (Zhang et al., 2017), and a continuing public health threat dominated by non-communicable diseases (NCDs) (Vos et al., 2015). Green space, as a vital natural resource in urban environments, is increasingly recognized as a crucial tool for addressing urbanization challenges and mitigating public health risks (Dimitrova and Dzhambov, 2017; Ma et al., 2022; Oosterbroek et al., 2023). Therefore, providing effective green space to urban dwellers is critical for environmental and social interventions in public health (World Health Organization, Regional Office for Europe, 2012).

Numerous studies have highlighted the beneficial effects of green space on human health (de Vries et al., 2003; Maas, 2006; Twohig-Bennett and Jones, 2018; Wu and Kim, 2021). However, the differences in the health benefits of green space, particularly the classification of green space according to land use and management in urban settings, have been largely overlooked (Feltynowski et al., 2018; Wang and Chang, 2023). Land use, as a reflection of policy and decision-making in urban land management (Masoudi et al., 2021), is crucial for urban green space planning and regulation (Biernacka and Kronenberg, 2018). Taking Chinese cities as an example, urban green spaces can be categorized into five types: park green space (PG), attached green space (e.g., residential green spaces [RG] and street

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green space [SG]), square green space, protective green space, and regional green space (Ministry of Housing and Urban-Rural Development, 2018). However, current researches that distinguish among the health benefits of various green spaces primarily rely on land cover classifications, such as woodlands, grasslands, and arable lands, among others (Li et al., 2015; Akpinar et al., 2016; Alcock et al., 2015; Bixby et al., 2015; Masoudi et al., 2021). These classifications fail to capture the actual health contribution of green space types in planning and management practices. Comprehensive comparisons of the health benefits of diverse green space types remain scarce (Wang and Chang, 2023). This discrepancy hinders our understanding of the complex relationships between different green space types and specific health benefits (Hartig et al., 2014), ultimately impeding the effective implementation of precise and effective green space-based strategies for public health (van den Bosch and Ode Sang, 2017). Urban green spaces in the neighbourhood, as the closest natural resource, are crucial to provide natural interactions and health benefits for urban residents (Weber and Schneider, 2021), such as RG (Feng and Astell-Burt, 2018; Xia et al., 2024; Orban et al., 2017), PG (Wu and Kim, 2021; Liu et al., 2017; Wang et al., 2024), and SG (de Vries et al., 2013; Wang et al., 2022a; Liu et al., 2023). However, there is still a lack of studies on the health benefit differences of these distinct green space types in the neighbourhood.

Moreover, current research focusing on the relationship between green space and health has employed a wide array of approaches and metrics to quantify green space characteristics (Dadvand and Nieuwenhuijsen, 2019; Nordbø et al., 2018; van den Berg et al., 2015). Common metrics of green space include the Normalized Difference Vegetation Index (NDVI) (Liu et al., 2023; Markevych et al., 2017; Huang et al., 2020), vegetation coverage or ratio (Feng and Astell-Burt, 2018; Dennis et al., 2015; Browning et al., 2019), proximity to green space (Reklaitiene et al., 2014; Song et al., 2024; Dennis et al., 2015), and the Green View Index (GVI) (Helbich et al., 2021; Wang et al., 2022a), among others. However, a significant limitation of current research lies in the metrics employed, which predominantly capture the attributes of total green space (Markevych et al., 2017), thereby neglecting to accurately portray the dimensional features of diverse green space types (Shahtahmassebi et al., 2021).

The influence of urban green spaces on residents' health is shaped by multiple interacting factors (James et al., 2015). However, the relationship between green spaces and health outcomes is not straightforward. Health disparities arise not only from green space presence but also from complex interactions between green space attributes, built environment characteristics, and individual factors (Lachowycz and Jones, 2013). These interactions add significant complexity, making it difficult to fully understand the impact of green space on health. Research evidence reveal that the health benefits of green spaces are often mediated by structural features of the built environment (Wang et al., 2022a; Chen et al., 2023; Yin et al., 2023). For instance, well-connected street networks or mixed land use patterns can amplify access to greenery, whereas fragmented urban forms may restrict utilization (Cervero and Duncan, 2003). Concurrently, individual-level traits further stratify health outcomes, as disadvantaged populations may experience limited green space access or reduced capacity to engage with available resources (Wolch et al., 2014). Critically, these relationships exhibit spatial heterogeneity, and contextual modifiers can reverse or strengthen associations (James et al., 2015). However, current research exhibits critical gaps in elucidating the interplay between natural environmental factors and socio-environmental factors. The precise interactive effects through which these factors influence health outcomes remain inadequately characterized, particularly in rapidly urbanizing regions. This knowledge deficit limits the capacity to comprehensively understand the multifactorial pathways through which green spaces mediate health effects, thereby constraining the development of targeted urban health interventions.

To address these challenges and enhance our understanding of the relationship between green space and health, this study integrates various dimensional features of diverse green space types into a unified analytical model. The main objectives are as follows: 1) to compare the health benefit contribution and differences of various green spaces in the neighbourhood. 2) to identify green space-related metrics and their interaction effects influencing residents' health. 3) to propose green space-based regulation strategies for promoting health benefits.

2. Literature review

Urban green spaces confer health benefits through their multidimensional features, including composition, structure, and ecological properties. Vegetation measured via NDVI or canopy cover correlates with reduced rates of depression, cardiovascular disease, and mortality (Twohig-Bennett and Jones, 2018; Huang et al., 2020). Vegetation-rich green spaces further enhance the microbial environment, improving the human immune function (Rook, 2013; Hanski et al., 2012). Higher levels of urban green space per capita are associated with improved mental and physical well-being, through ecological properties such as microclimate regulation, air purification, mitigating environmental hazards, and providing health-supportive ecosystem regulating services (Sæbø et al., 2012; Bowler et al., 2010). Additionally, the aesthetic and recreational value of green spaces encourages physical activity and social interaction among residents, aiding health recovery (Wang et al., 2024; Fan et al., 2011). Conversely, poorly maintained green spaces may diminish these benefits, exacerbating perceptions of insecurity or environmental stressors (Brindley et al., 2019). The spatial distribution of urban green spaces is crucial for ensuring equitable access to their benefits among residents (Rigolon et al., 2021). Uneven distribution can result in disparities in proximity to green spaces across different neighborhoods, thereby exacerbating health inequalities. For instance, low-income areas often have less access to high-quality green spaces (Mears et al., 2019). Addressing these distributional inequities is essential for advancing social equity and improving public health outcomes (Wolch et al., 2014). Different green space typologies, defined by land use, function, and management, yield distinct health outcomes. Parks, usually fully equipped and multifunctional, support social cohesion and stress reduction through activities and communal gatherings (Grilli et al., 2020). Private gardens and lawns provide daily micro-restorative experiences, improving mental health and cognitive function (Orban et al., 2017). Street trees, characterized by linear vegetation, primarily serve as pollution buffers, lowering exposure to PM2.5 and noise, thereby benefiting respiratory and cardiovascular health (Wang et al., 2019). Furthermore, there are still other informal urban green types that have been extensively studied (Kim et al., 2020). However, comparative studies remain limited, with most research focusing on aggregated green space metrics rather than disaggregated typologies (Wang and Chang, 2023). For example, NDVI captures overall vegetation but overlooks qualitative differences between a shaded urban park and a traffic-adjacent green belt. Different green space types may thus offer varying health benefits in terms of green space metrics (Hartig et al., 2014; Fan et al., 2011).

Neighbourhood green spaces are increasingly recognized as integral to public health (van Dillen et al., 2012; Jennings and Bamkole, 2019). Emerging research reveals that health outcomes depend on the synergistic interplay between green space attributes (e.g., quantity, proximity, quality), built environment features (e.g., road density, mixed land use), and individual determinants (e.g., age, socioeconomic status, physical activity levels) (Zhang et al., 2017; Yin et al., 2023; Maas, 2006). For instance, while green space proximity correlates with enhanced mental well-being (Dong and Qin, 2017), its efficacy is modulated by urban design, such as safe walking routes and individual behavioral patterns (Reyes-Riveros et al., 2021). Similarly, socioeconomic disparities may exacerbate inequities in green space access (Liu et al., 2021), amplifying health inequalities through mechanisms like environmental injustice (Rigolon et al., 2021). Understanding these multifaceted interactions necessitates interdisciplinary frameworks that integrate spatial geography, behavioral science, and epidemiology (Freymueller et al., 2024), ultimately informing equitable interventions to harness the health-promoting potential of green spaces (Wolch et al., 2014).

Effective health promotion requires green space strategies tailored to local ecological and sociodemographic contexts. Spatial equity is paramount, as marginalized neighborhoods often lack access to high-quality green infrastructure (Rigolon, 2016). In Beijing, rapid urbanization has intensified disparities in green space distribution, with central urban areas facing overcrowding and peripheral regions lacking accessible amenities (Zhang et al., 2022). Green spaces in the neighbourhood are crucial for providing daily opportunities for human-nature interaction and represent key units for achieving environmental spatial justice and implementing health intervention strategies (Ma et al., 2022). A comprehensive study on the features of green space types in neighbourhoods and their association with health benefits can fill critical evidence gaps and inform more precise and effective planning strategies for practical applications.

3. Methods

The research framework of this paper is shown in Fig. 1. Firstly, stratified random sampling was carried out according to the population of each subdistrict, and the community units were selected, and the corresponding buffers were generated as the sampled neighborhoods. Subsequently, various metrics of green space types were characterized, and the k-means clustering was used to classify the sampled neighborhoods according to the green space metrics. After that, the demographic and self-reported health information of residents in the sampled community units was collected through a questionnaire survey. Then, the random forest model and SHAP analysis were used to identify the key green space metrics affecting residents' health and their relative importance. Finally, based on the neighbourhood classifications and health-relevant green space metrics, adaptive green space strategies were proposed to improve health benefits.

3.1. Study area

Beijing, the capital city of China, is situated in the northern region of the North China Plain, encompassing a total area of approximately 16,410 km^2 and a population of 21.89 million individuals (Beijing Municipal Bureau of Statistics, 2023). The present study focuses specifically on the central urban region of Beijing, including 32 subdistricts as depicted in Fig. 2. It is characterized by its high level of urbanization and population density, and it confronts a typical contradiction between the intense development of urban areas and the uneven distribution of green space (Wu and Kim, 2021).

Based on the population of subdistricts in study areas (Beijing Municipal Bureau of Statistics, 2022), this study selected 64 communities from 32 subdistricts using a stratified random sampling method. Due to the admittance issue in gated communities, a total of 36 communities were ultimately included (Fig. 2). Here, we adopted a 1000-m buffer zone centered on the centroid of each community as its neighbourhood. This method is widely used in previous studies and facilitates comparative research (Zhang et al., 2022; Wang et al., 2019; Yin et al., 2023). Evidence suggests that a 1000-m buffer is optimal for predicting green space health benefits (Browning et al., 2019; Song et al., 2024; Schipperijn et al., 2017), and when the distance increased beyond 1000 m, the rate of residential visits to green space will drop sharply (Liu et al., 2017).

3.2. Data collection and calculation

3.2.1. Green space types and metrics

To identify specific type of green space in neighbourhood, the common datasets were used to determine the boundaries of each type of green space (Fig. 3c). Specifically, the boundaries of residential area were extracted using the Area of Interest (AOI) from Baidu Maps (https://map.baidu.com/) (accessed September in 2023). To account for differential access patterns and utilization behaviors, residential green spaces were operationally categorized into two distinct types: residential green space within sampled communities (RG-I) (located in the residence of the respondent), and residential green spaces within non-sampled communities (RG-O). The boundaries of parks were delineated from Baidu Maps by using the published park list (Beijing Municipal Forestry and Park Bureau, 2022). The road data was sourced from OpenStreetMap (https://www.openstreetmap.org/) (obtained in September 2023). Referring to previous studies (Wang and Chang, 2023), SG were defined as green spaces within a 30 m buffer along urban roads, which showed the most significant correlation with the eye-level GVI (Li et al., 2021). The green spaces beside roads located in parks, residential areas, and institutions were excluded from SG. The remaining green spaces were classified as other green space (OG). Then, the area, proximity, and NDVI metric for each type of green space were calculated, respectively.

To quantify the features of green space, we selected the most representative metrics from relevant research, including the NDVI, the area of vegetation cover, and proximity to green space (Rahimi-Ardabili et al., 2021; Dzhambov et al., 2020; Li et al., 2016). The calculation and data sources of the metrics were shown in Table S1.

By using the uncloudy Gaofen-2 remote sensing images (GF-2) obtained on September 8, 2022 with a spatial resolution of 1m by 1m, we calculate the overall NDVI of the study area through the ENVI 5.3 (Fig. 3a), employing the following formula:

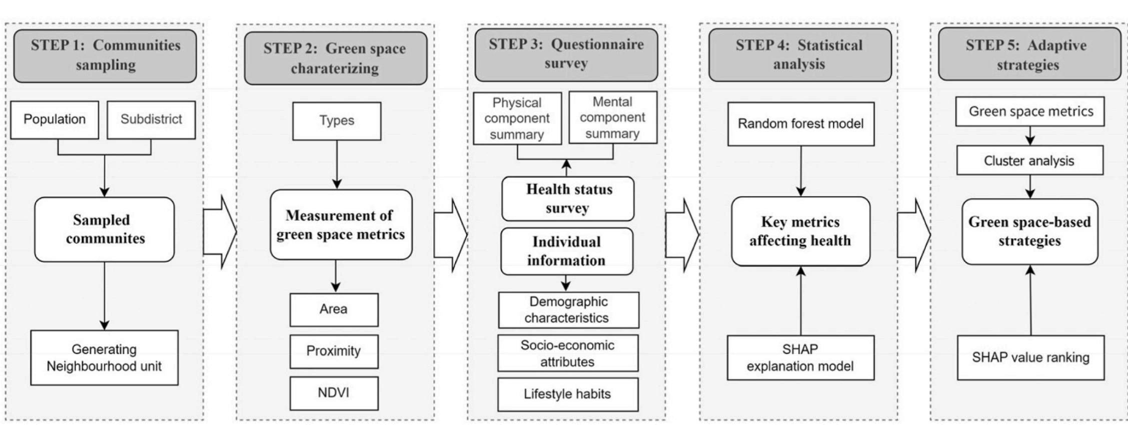

Fig. 1. Workflow for data collection and statistical analysis.

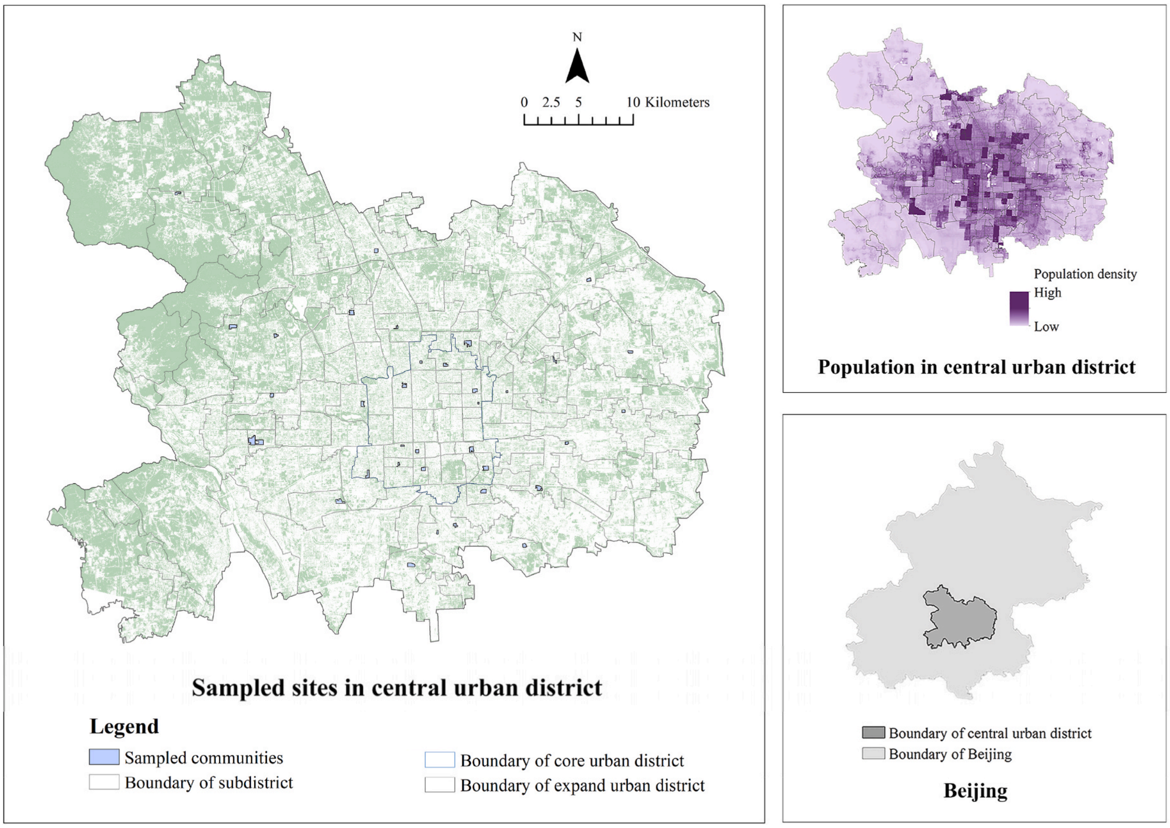

Fig. 2. Sampled communities in the central urban region of Beijing.

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

where NIR represents the Near-Infrared band and Red denotes the Red visible band. Subsequently, a sampling-based thresholding method was employed to extract green spaces (Nesbitt et al., 2019; Wang and Chang, 2023). We collected 100 visually distinguishable vegetation sample points from the study area's remote sensing image using ENVI 5.3 software. The mean NDVI of these points was calculated and adopted as the representative value for the vegetation in the study area. Then, all areas where the NDVI values exceed this mean were classified as green areas (Fig. 3b). After that, the GIS-based network analysis was applied to calculate the accessible area of the neighbourhood to evaluate the proximity of green space (Seifu and Stellmacher, 2021; Sister et al., 2010; Oh and Jeong, 2007). Lastly, the NDVI, the vegetation cover, and the proximity of green spaces were extracted for each neighbourhood through ArcMap 10.7 by zonal statistics.

For each type of green space, metrics including area, proximity, and NDVI were computed based on the extracted regions. The accuracy of various green spaces was validated by examining 360 randomly distributed points. The ground truth data for each sampling point was obtained using Google Earth images and field surveys. The overall accuracy was 90.28 %, meeting the accuracy requirements for the estimation.

3.2.2. *Health status of residents by questionnaire survey*

Between April and September 2023, six trained graduate students and ten recruited college volunteers conducted a questionnaire survey in the sampled communities. To ensure representation, households were selected based on equal distance between house numbers, and one respondent per household was randomly invited to participate in the survey. Before completing the questionnaire, respondents were thoroughly informed about the survey's content and asked for their consent. This study received approval from the Human Research Ethics Committee of China Agricultural University (CAUHR-2021002). Data collection was facilitated through the reputable questionnaire survey platform Wen Juan Xing (https://www.wjx.cn/). A total of 1309 samples were initially collected, but after excluding samples with incorrect residential addresses or missing personal information, the data set was reduced to 1184 questionnaires. Furthermore, respondents who most frequently visited green space outside the neighbourhood were excluded, leaving 1116 questionnaires that met the criteria for statistical analysis.

The physical and mental health of respondents was assessed using the Chinese version of the SF-12v2 scale, authorized by QualityMetric Incorporated (QUO-02573-B5Y0B8). The official scoring program PROCoRE 2.2 was employed to compute the final physical health score and mental health score. Since the SF-12v2 scale has a four-week recall period, we only surveyed residents who had resided in sampled communities for more than four weeks (Völker et al., 2018). The SF-12v2 scale comprises 12 questions, categorized into eight distinct health domains: Physical Functioning, Role Physical, Bodily Pain, General Health, Vitality, Social Functioning, Role Emotional, and Mental Health. These subscales can be synthesized into two types: the Physical Component Summary (PCS) and the Mental Component Summary (MCS). As a condensed version of the SF-36, a widely recognized tool for measuring health status (AI Omari et al., 2019; Ware et al., 1996), the SF-12v2 scale is particularly suited for large-scale health surveys requiring brief interview durations (Shou et al., 2016). Prior research has demonstrated the SF-12v2 scale's effectiveness, reliability, and sensitivity among Chinese populations (Lam et al., 2005, 2011).

3.2.3. *Covariates*

The individual level covariates were extracted from the questionnaire and encompassed personal lifestyle and habits that may impact residents' health, such as irregular daily routines, dietary status, sleep quality, chronic diseases, stress, and neighbourhood relationships

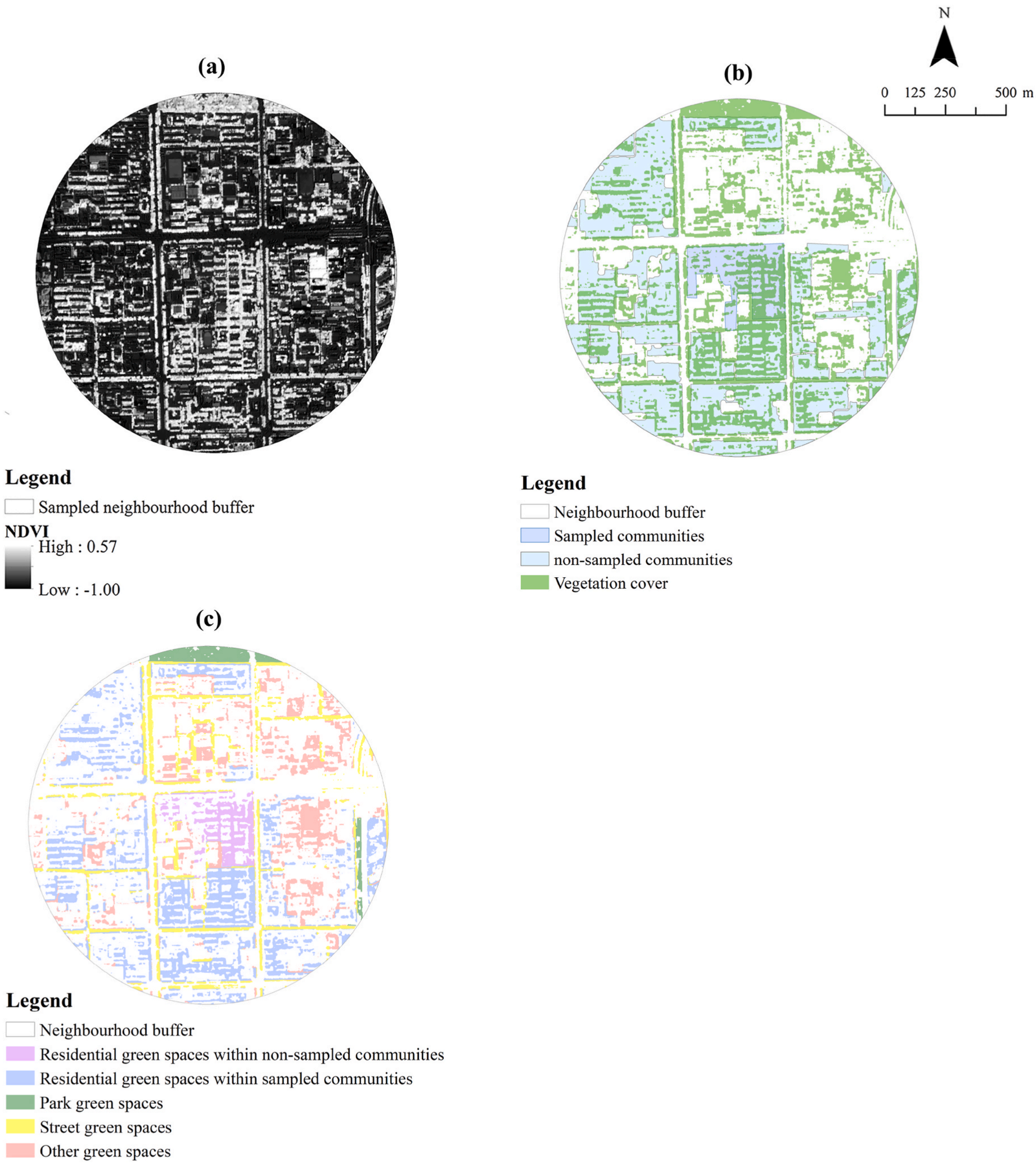

Fig. 3. Examples of different representations of green space metrics and types: (a) Normalized Differential Vegetation Index of neighbourhood; (b) Vegetation cover and accessible area of neighbourhood; (c) Various types of green spaces in neighbourhood.

(Rippe, 2018; Gascon et al., 2015; Astell-Burt et al., 2014). Additionally, demographic and socioeconomic factors were considered, including gender, age, employment status, years of education, marital status, living with minor children, income, housing, and household registration (Liu et al., 2022; Qin et al., 2021; Liu et al., 2022). Household registration (always named 'Hukou' in Chinese), It represents a person's situation of residence and migration, had been indicated health effect on residents (Jiang et al., 2022; Wang et al., 2019). Physical activities in green spaces, as the index of green space usage (GS_Usage), have increasingly garnered widespread attention in relevant studies (de Vries et al., 2013; Cox et al., 2018; Zhang et al., 2022). Thus, we obtained the duration and frequency of respondents' physical activities in green spaces over the past four weeks through the above questionnaire survey, which served as an individual variable for assessing GS_Usage.

Besides individual features, built environmental factors such as population density, road density, air quality (PM2.5), house price and mixed land use pattern were also recognized as covariates, with previous studies widely acknowledging their influence (Wang et al., 2019; Jiang et al., 2022; Wang and Tassinary, 2024; Zhang et al., 2024). Population density data was sourced from the WorldPop dataset, which provides high-resolution population distribution data at a spatial resolution of 100 m by 100 m. The PM2.5 concentration data in 2022 were obtained from the China High Air Pollutants (CHAP) database with a 1000 m by 1000 m spatial resolution (https://weijing-rs.github.io/product.html) (Wei et al., 2023). The road data was obtained from the OpenStreetMap platform (https://www.openstreetmap.org/), and the calculation was carried out by using the partition statistics function of ArcGIS 10.7. The average house price in the community is calculated by combining house price information from Anjuke (https://www.anjuke.com/) and China Housing Price Platform (https://www.creprice.cn/) (obtained in September 2023). To quantify mixed land use patterns, the entropy index was employed, as it is highly sensitive to changes in land use patterns and aligns well with the POI (Song et al., 2013). A higher entropy value indicates a higher level of land use balance and greater diversity in land use. The calculation method for the entropy index is detailed in the following equation:

$$Landmix_j = -\sum_{i=1}^{N} S_{ij} \times lnS_{ij} \Big/ lnN \tag{2}$$

Where $Landmix_j$ represents the mixed degree of land use in the neighbourhood j; S_{ij} represents the proportion of the number of POI class i to the total number of POI within the neighbourhood j. Here, POI data of the study area is collected from the open digital map platform provided by Baidu Maps (https://lbsyun.baidu.com/) (accessed in September 2023).

3.3. Statistical analysis

The random forest model was used to fit the prediction results of all metrics of green spaces and covariates on residents' PCS and MCS, respectively. The random forest model is a machine learning algorithm based on a decision tree ensemble. Compared with other machine learning models, the random forest model can effectively capture the complex relationships among variables, effectively reduce the risk of model overfitting, and has high robustness to noisy data and outliers (Breiman, 2001). Specifically, the random forest model was trained using 80 % of the data as the training set and the remaining 20 % as the test set. The performance of the model was evaluated using the mean square error (MSE), root-mean-squared error (RMSE), mean absolute error (MAE), and R^2. The performance of the model was evaluated using the mean square error (MSE), root-mean-squared error (RMSE), mean absolute error (MAE), and R^2. The lower the first three indicators are, the better the model performance is. The last indicator is approximately close to 1, indicating better performance.

Then, the SHAP analysis method was adopted to analyze the specific contributions of all the variables to health benefits. This interpretive model is based on cooperative game theory and quantifies the marginal contribution of each predictor to the model output by calculating the feature attribution value (Li et al., 2024). Based on the fairness allocation principle of Shapley values, it ensures the consistency of feature importance calculation (consistent with the model's changing trend), additivity (the sum of feature contributions is equal to the model's predicted value), and local accuracy (the feature contribution of a single prediction is precise), thereby breaking through the interpretability limitation of the "black box" of machine learning models (Lundberg and Lee, 2017).

This study implements the algorithm invocation RandomForestRegressor in Scikit-learn and SHAP analysis based on Python 3.1.1. Visualization tools such as Summary Plots, Beeswarm Plots, and Dependence Plots were utilized to systematically elucidate the direction and magnitude of effects exerted by green space metrics and covariates on health outcomes, as well as the interaction effects among variables.

3.4. Green space-based strategies for enhancing health benefits

By conducting k-means clustering on multi-dimensional metrics of green space in the neighbourhood (Pedregosa et al., 2011), the typical characteristics of urban green spaces in the neighbourhood of central Beijing are summarized. The Scikit-learn's Silhouette Coefficient is a method for measuring the quality of clustering. By finding the average silhouette coefficients of all samples in different numbers of clusters, it solves the problem of choosing the best value of k in k-means algorithms. Among them, the highest silhouette score represents the optimal number of clusters (Shahapure and Nicholas, 2020). By integrating the ranked importance and relative efficiency of green space metrics identified through random forest modeling and SHAP analysis, we developed neighbourhood-specific green space regulation strategies tailored to enhance health outcomes.

4. Results

4.1. Urban green space and built-environmental characteristics in the neighbourhood

The descriptive statistics of the urban green space metric in the neighbourhood of central Beijing are shown in Fig. 4 (detailed in Supplementary Data Table S2). Among the various green space types, OG had the largest mean area at 40.06 ± 26.76 ha, followed by SG at 19.36 ± 8.40 ha and RG-O at 18.45 ± 8.42 ha. In contrast, PG and RG-I were the smallest, with mean areas of 11.30 ± 10.46 ha and 2.31 ± 1.74 ha, respectively. In terms of proximity, each green space type displayed a similar trend to the area metrics. Regarding NDVI, PG showed the highest value at 0.27 ± 0.06, followed by OG at 0.22 ± 0.04 and SG at 0.21 ± 0.03. In contrast, RG-I and RG-O had the lowest NDVI values. Overall, each green space type in the neighbourhood exhibited distinct characteristics, potentially offering varied opportunities for residents to interact with nature. Detailed metrics for each specific neighbourhood were provided in Supplementary Data Tables S3, S4, and S5.

The sampled communities had an average population density of 15,504.33 ± 85.05 people per square kilometer and an average land use mix degree of 2.32, reflecting a high-density living environment and moderate land use complexity (Wang and Shaw, 2018). The annual average PM2.5 concentrations of sampled neighbourhoods was 50.85 μg/m^3, which highly exceeded the air quality guideline (10 μg/m^3 for annual mean) suggested by the World Health Organization and China's national ambient air quality standards (15 μg/m^3 and 35 μg/m^3 for Category I and II zones, respectively) (Ministry of Environmental Protection, 2012). The average road density in sampled neighbourhoods was 13.46 km/km^2, exceeding China's standard for central urban areas (8 km/km^2) in the "Standard for urban comprehensive transport system planning" of China (Ministry of Housing and Urban-Rural Development, 2018). The average residential property price was 87,245.67 CNY per square meter. These characteristics reflect the typical high-density development of Asian metropolises, providing a demonstration scenario for the research on the health benefits of urban green spaces in the context of localization.

4.2. Demographic characteristics and health status of residents

The overall sample characteristics are presented in Supplementary Data Table S6. The mean scores for the PCS and MCS were 48.73 and 46.26, respectively. These scores align with the ranges reported by AI Omari et al. (2019), where PCS scores ranged from 46.50 to 49.80 and MCS scores from 43.00 to 50.40. The SF-12v2 scale used in this study demonstrated satisfactory internal consistency with a Cronbach's α coefficient of 0.76, indicating reliable measurement of both physical and mental health for the residents.

Regarding the demographic characteristics of the sample, a slight majority of respondents were female (53.23 %), exceeding the proportion of male respondents (46.77 %). 57.17 % of respondents had full-time jobs, and a substantial proportion had completed 13–16 years of education, suggesting a high prevalence of college or university graduates. In terms of daily routines, 40.50 % reported irregular schedules, while 74.55 % and 60.04 % maintained balanced dietary status and good sleep quality, respectively. 68.46 % of residents expressed satisfaction with neighbourhood relations. Notably, 30.02 % of respondents had chronic diseases. 51.79 % reported low stress levels, 16.22 % average stress, and 31.99 % high stress. The data of GS_Usage was directly extracted from questionnaire data, showing an average usage of

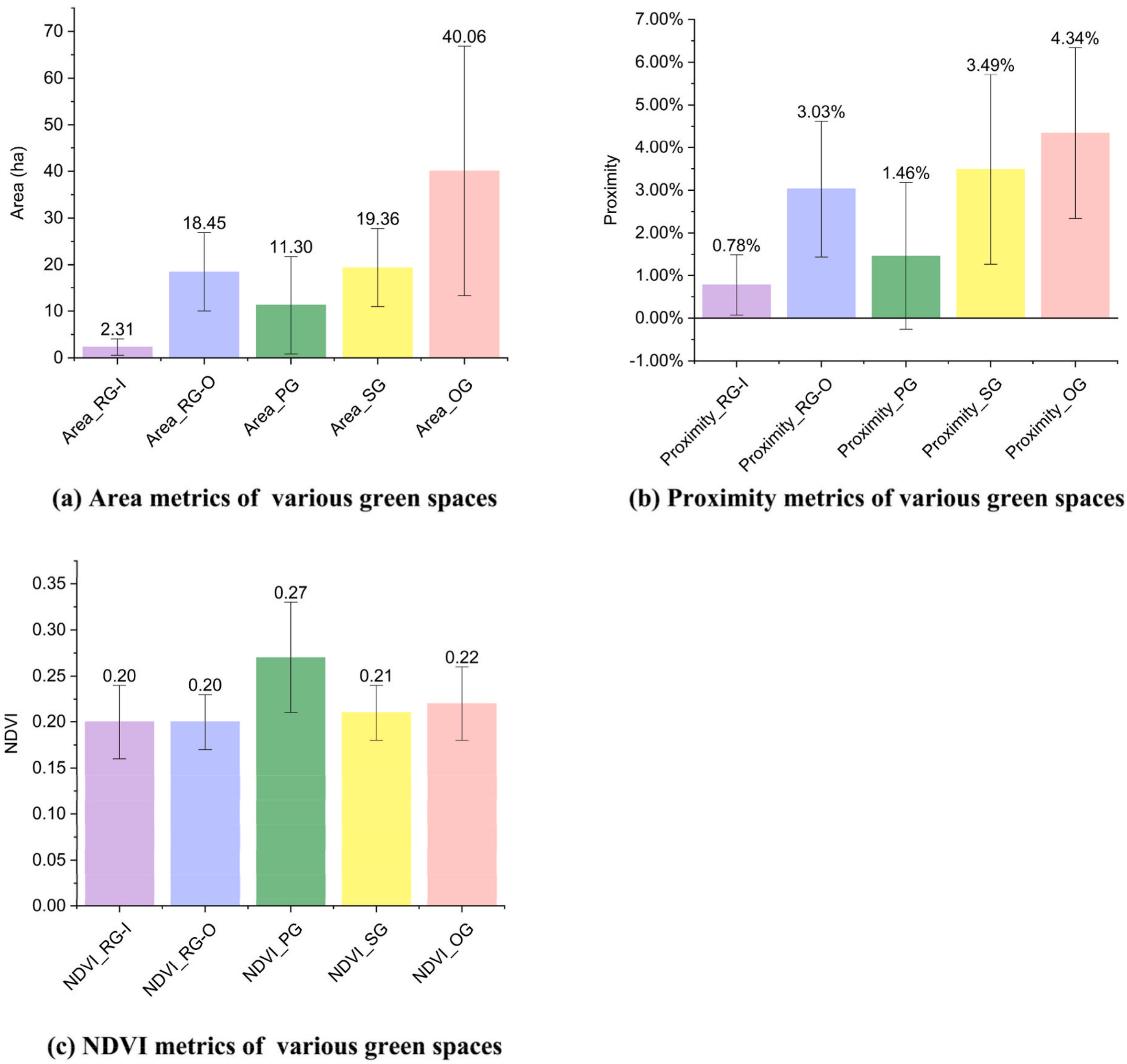

Fig. 4. Measurement metrics of various green space statistics: (a) Area; (b) Proximity; (c) NDVI.

4744.12 min over the past four weeks, approximately 2.82 h per day, indicating relatively high outdoor activity levels.

4.3. The relative importance of green spaces on residents' health

The bar charts (Fig. 5a and 7a) and pie charts (Fig. 5b and 7b) represent the SHAP values for data of different groups of indicators and various green space types, respectively. The SHAP summary plot (Fig. 6a and 8a) illustrates each indicator's importance to health, with indicators ranked in descending order of importance. Green space metrics and covariates are distinguished by different colors. The specific distribution of each indicator's SHAP value was illustrated using a swarm plot (Fig. 6b and 8b). The color gradient along the vertical axis indicates the magnitude of the values assigned to each point (sample) by each indicator. The horizontal axis shows SHAP values, with the same meaning as the vertical axis. Indicators farther from the origin have greater influence. Table 1 lists the top 20 potential predictors' importance values for residents' health outcomes.

As Fig. 5 shows, green space metrics account for 28.62 % of the relative importance in influencing residents' PCS. Among various green space types, PG is the most important (52.03 %), followed by RG-O (14.64 %), RG-I (12.65 %), and SG (10.83 %), with OG (9.85 %) the least important. This highlights the critical role of PG in affecting

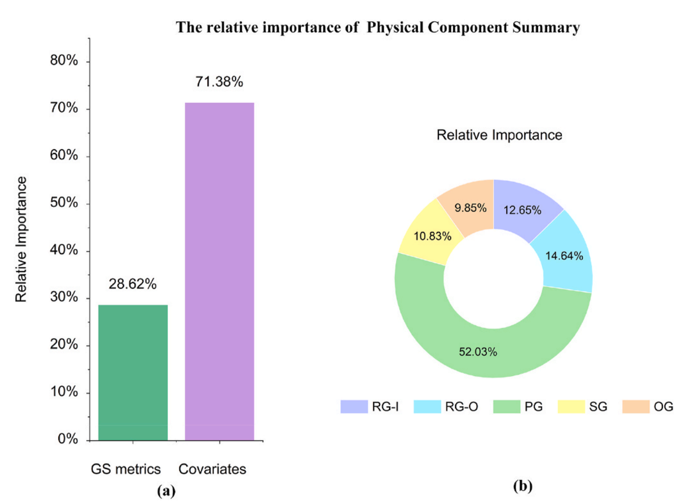

Fig. 5. Comparison of importance for PCS in groups of indicators based on SHAP value: (a) The relative importance of green space metrics and covariates for PCS; (b) The relative importance of each type of green space for PCS.

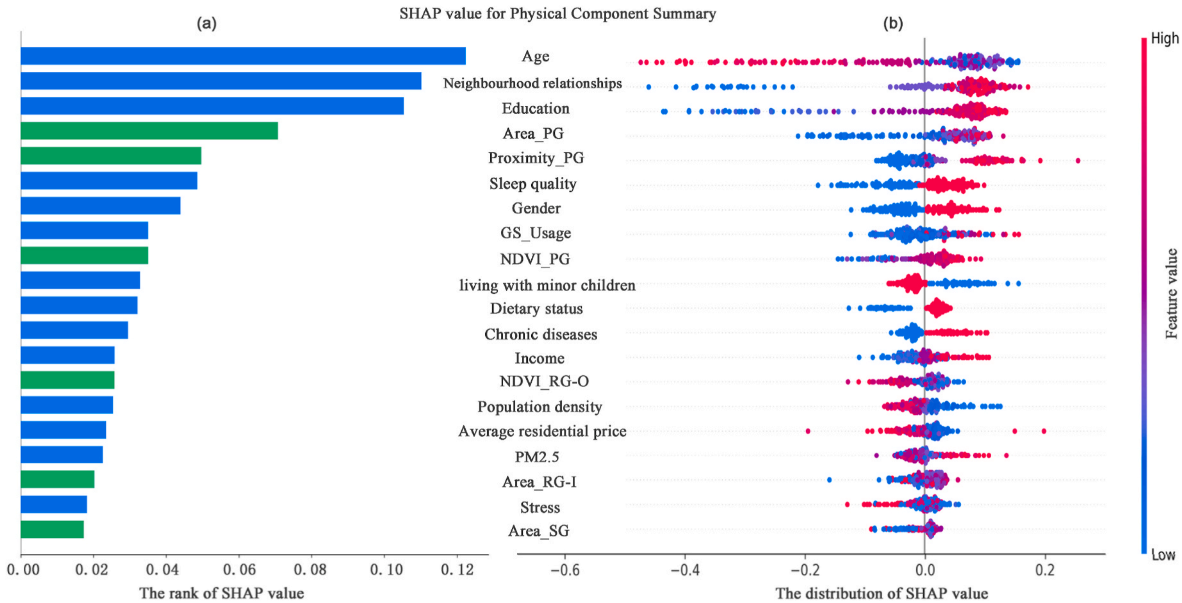

Fig. 6. Importance plot of the predictors based on SHAP value for PCS (Top 20): (a) The characteristic importance ranking based on SHAP value for PCS; (b) The characteristic importance distribution based on SHAP value for PCS.

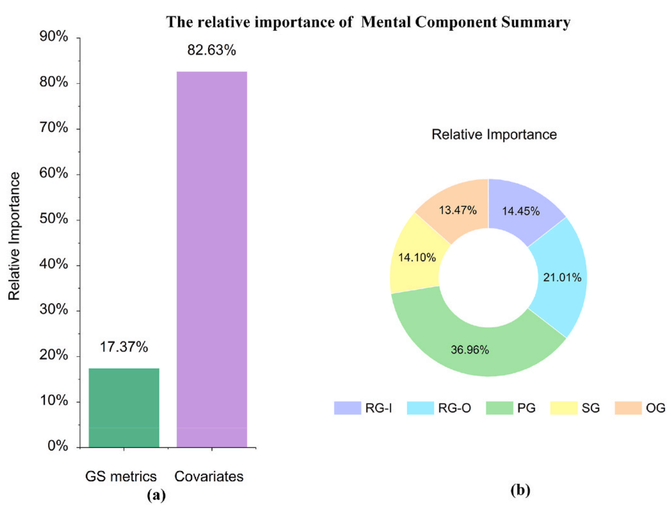

Fig. 7. Comparison of importance for MCS in groups of indicators based on SHAP value: (a) The relative importance of green space metrics and covariates for MCS; (b) The relative importance of each type of green space for MCS.

residents' PCS.

Specifically, from the indicators of each green space (Fig. 6), Area_PG (6.78 %) most strongly contributes to residents' physical health, followed by Proximity_PG (4.76 %) and NDVI_PG (3.36 %). All three dimensions of park green spaces have positive impacts. In contrast, NDVI_RG-O (2.47 %) shows a negative trend. Area_RG-I (1.94 %) and Area_SG (1.67 %) also have some positive effects. Additionally, GS_Usage (3.36 %) positively promotes residents' PCS. Among non-green space factors, age, neighbourhood relationships, and years of education are the most important in influencing PCS, underscoring the significance of individual-level factors.

In terms of residents' mental health, green space metrics have a relative importance of 17.37 %, which is lower than their influence on PCS (Fig. 7a). The trend in the importance of different neighbourhood green space types for MCS mirrors that observed for PCS. PG continues to have the highest importance ratio at 36.96 %, emphasizing its significant value in promoting health benefits. This is followed by RG-O (21.01 %), RG-I (14.45 %), and SG (14.0 %), while OG (13.47 %) contributes the least (Fig. 7b).

Fig. 8 illustrates the importance of each specific indicator to MCS. In terms of green space metrics, Area_PG (3.46 %) still contributes the most to residents' mental health, followed by NDVI_PG (2.25 %). Notably, both NDVI_RG-O (1.57 %) and Area_RG-O (1.35 %) showed a negative trend, indicating the negative impact of non-residential green space on health benefits. In addition, GS_Usage (4.07 %) is the most significant contributor to MCS among all green space indicators. Unlike the physical health benefits of air purification and climate regulation through green space, the mental health benefits derived from green spaces might depend more on direct use and exposure (Yang et al., 2025). Regarding non-green space factors, similar to their influence on PCS, neighbourhood relationships, sleep quality, dietary habits, and irregular schedules are the most important factors affecting MCS. This highlights the significant impact of individual-level factors, particularly lifestyle behaviors, on residents' health (Nijs and Reis, 2022; Firth et al., 2020).

4.4. *The interactive effect of green space-related features on residents' health*

Based on SHAP analysis, the Dependence Plot can further clarify the impact of variable interactions by identifying significant interacting variables and their trends. In this Plot, each data point represents a sample, with the horizontal axis indicating the value of variable X1, and the color of the points reflecting the value of variable X2. The vertical axis shows the SHAP interaction values, revealing how the interaction between X1 and X2 contributes to the model's predictions. We calculated the top 5 variable pairs for SHAP interaction effects on PCS and MCS (Table 2). Subsequently, we selected green space-related variable pairs for further analysis (Fig. 9).

Fig. 9a shows that among groups with more frequent GS_Usage (0.96 %), the positive impact of good neighbourhood relations on PCS is more pronounced. It suggests that the combination of good neighbourhood relations and frequent green space use may synergistically benefit PCS. Fig. 9b indicates that Area_PG (0.85 %) and population density jointly influence the importance of PCS. Low population density positively affects PCS, and this effect is enhanced by larger park areas. Conversely, high population density is generally linked to lower importance on PCS, but increasing park area in such regions can significantly boost

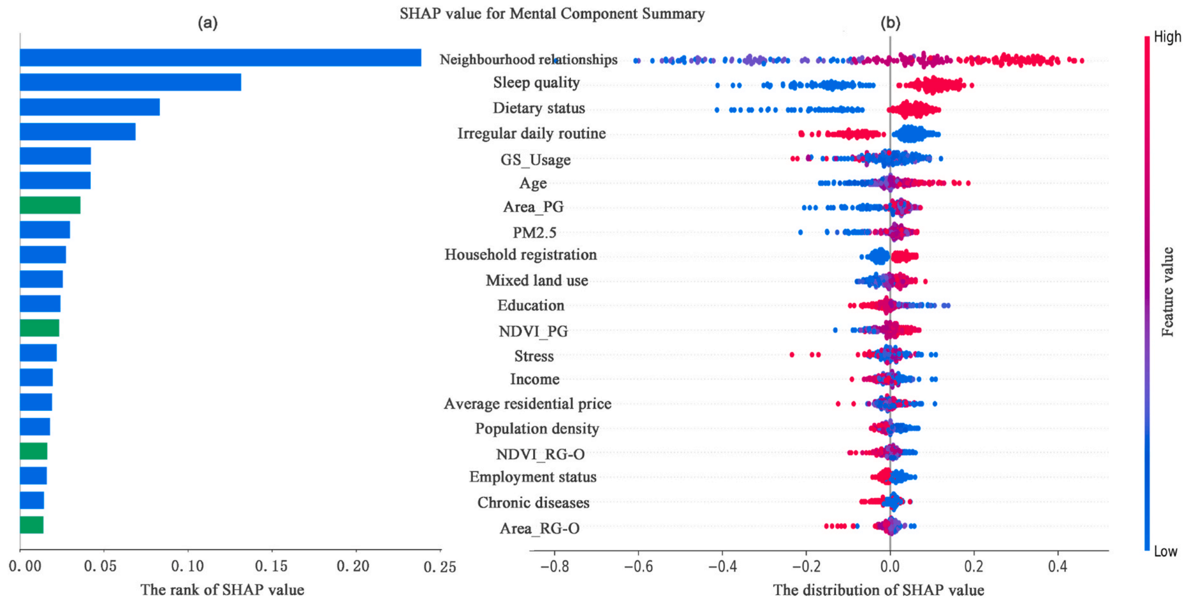

Fig. 8. Importance plot of the predictors based on SHAP value for MCS (Top 20): (a) The characteristic importance ranking based on SHAP value for MCS; (b) The characteristic importance distribution based on SHAP value for MCS.

Table 1
The importance value of predictors on residents' health(Top 20).

PCS		MCS	
Feature	Relative Importance	Feature	Relative Importance
Age	11.72 %	Neighbourhood relationships	23.00 %
Neighbourhood relationships	10.55 %	Sleep quality	12.68 %
Education	10.09 %	Dietary status	8.01 %
Area_PG	6.78 %	Irregular daily routine	6.63 %
Proximity_PG	4.76 %	GS_Usage	4.07 %
Sleep quality	4.65 %	Age	4.05 %
Gender	4.22 %	Area_PG	3.46 %
GS_Usage	3.36 %	PM2.5	2.87 %
NDVI_PG	3.36 %	Household registration	2.64 %
Living with minor children	3.15 %	Mixed land use	2.46 %
Dietary status	3.08 %	Education	2.34 %
Chronic diseases	2.84 %	NDVI_PG	2.25 %
Income	2.48 %	Stress	2.11 %
Area_RG-O	2.47 %	Income	1.89 %
Population density	2.44 %	Average residential price	1.84 %
Average residential price	2.25 %	Population density	1.73 %
PM2.5	2.17 %	NDVI_RG-O	1.57 %
Area_RG-I	1.94 %	Employment status	1.55 %
Stress	1.75 %	Chronic diseases	1.39 %
Area_SG	1.67 %	Area_RG-O	1.35 %
MSE	0.77	MSE	0.79
RMSE	0.87	RMSE	0.88
MAE	0.72	MAE	0.70
R^2	0.21	R^2	0.21

Table 2
The SHAP interaction value of the predictors on residents' health(Top 5 pairs).

PCS		MCS	
Feature	Interactive Strength	Feature	Interactive Strength
Age - Neighbourhood relationships	1.28 %	Neighbourhood relationships - Dietary status	2.51 %
Neighbourhood relationships - Education	1.26 %	GS_Usage - Neighbourhood relationships	2.32 %
GS_Usage - Neighbourhood relationships	0.96 %	Neighbourhood relationships - Sleep quality	1.84 %
Age - Sleep quality	0.93 %	Area_PG - Neighbourhood relationships	1.40 %
Area_PG - Population density	0.85 %	Age - Neighbourhood relationships	1.31 %

importance on PCS. Fig. 9c shows that GS_Usage (2.32 %) and neighbourhood relationships interactively affect MCS. Among those with higher usage of green spaces, positive neighbourhood relationships yield a greater positive impact on MCS. This highlights the significance of integrating social and natural elements for mental health benefits. Fig. 9d illustrates the interaction between the Area_PG (1.40 %) and neighbourhood relationships. In neighbourhoods with larger park areas, the positive impact of good neighbourhood relations on MCS is more pronounced. Conversely, in neighbourhoods with smaller park areas, the influence of neighbourhood relations on MCS is less significant.

4.5. The green space-based adaptive strategies for enhancing health benefits

4.5.1. The clustering result of sampled neighbourhoods

As shown in Fig. 10, all sampled neighborhoods were categorized into four classes via k-means cluster analysis. The optimal number of clusters was determined using the Silhouette Coefficient Method (detailed in Supplementary Data Table S7).

Class I encompassed the largest green space areas, predominantly for RG-I, RG-O, and PG. The proximity and NDVI for these green spaces aligned with their extensive areas. Class II was distinguished by large areas and high NDVI values for PG, while remaining green space types exhibited low metric values. Class III showed the largest SG areas and the highest SG proximity; however, the remaining green space types were relatively limited in areas. Notably, PG and RG-I in Class III also displayed high NDVI and proximity values, respectively. Class IV was characterized by the largest OG areas, coupled with the highest

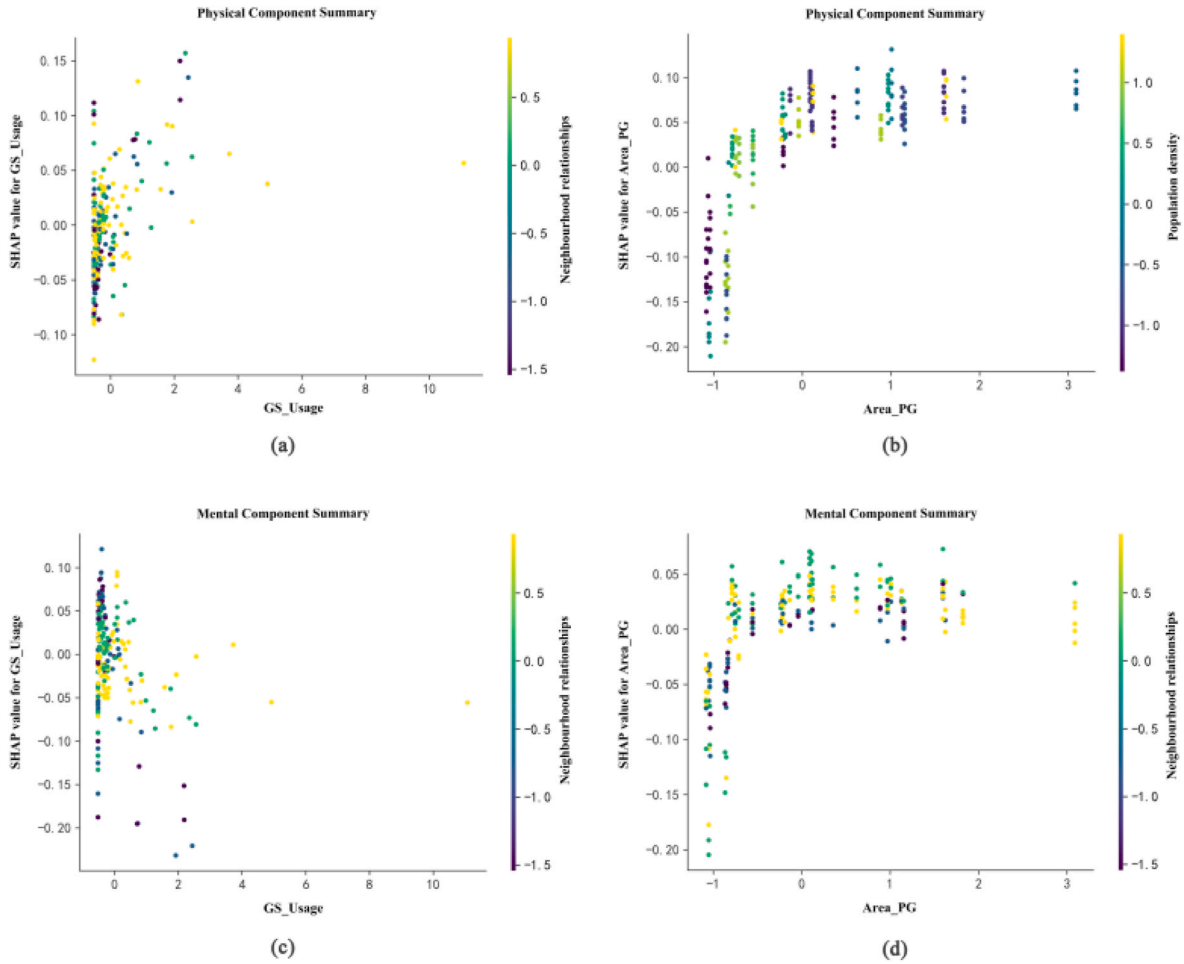

Fig. 9. The interaction effects of green space-related variable pairs on PCS and MCS: (a) The SHAP interaction value between GS_Usage - Neighbourhood relationships on PCS; (b) The SHAP interaction value between Area_PG - Population density on PCS; (c) The SHAP interaction value between GS_Usage - Neighbourhood relationships on MCS; (b) The SHAP interaction value between Area_PG - Neighbourhood relationships on MCS.

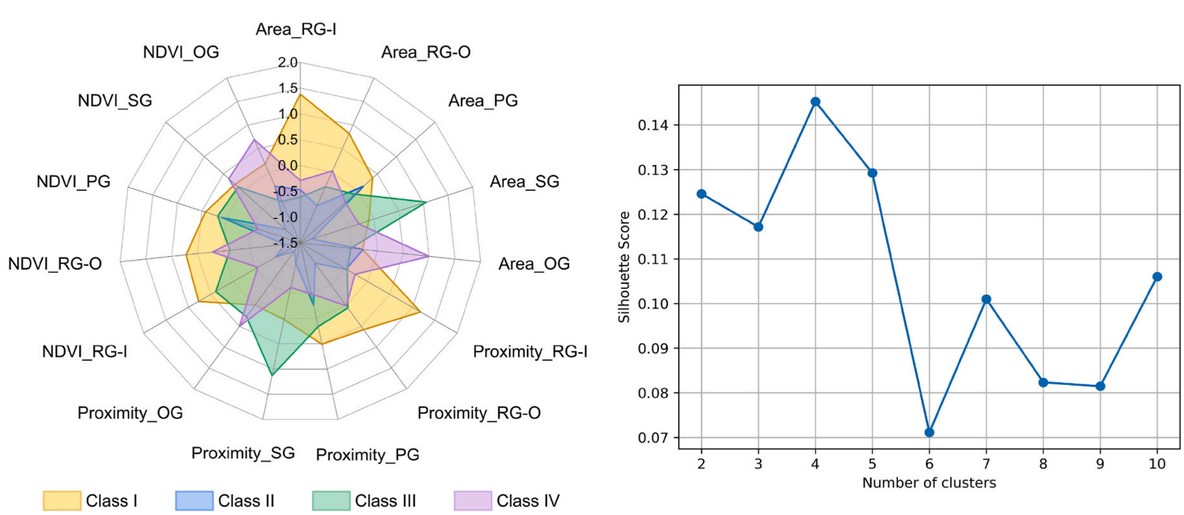

Fig. 10. The k-means cluster of green space metrics in sampled neighbourhoods.

proximity and NDVI values for OG, as well as the highest NDVI for SG. Additionally, Class IV exhibited large areas and elevated NDVI values for RG-O.

4.5.2. Green space strategies adapted to neighbourhood classes

Drawing upon the results of the identified key green space features and neighbourhood unit clustering, we proposed green space-based strategies aimed at enhancing health benefits (Fig. 11).

Neighborhoods in Class I exhibit excellent green space conditions. To

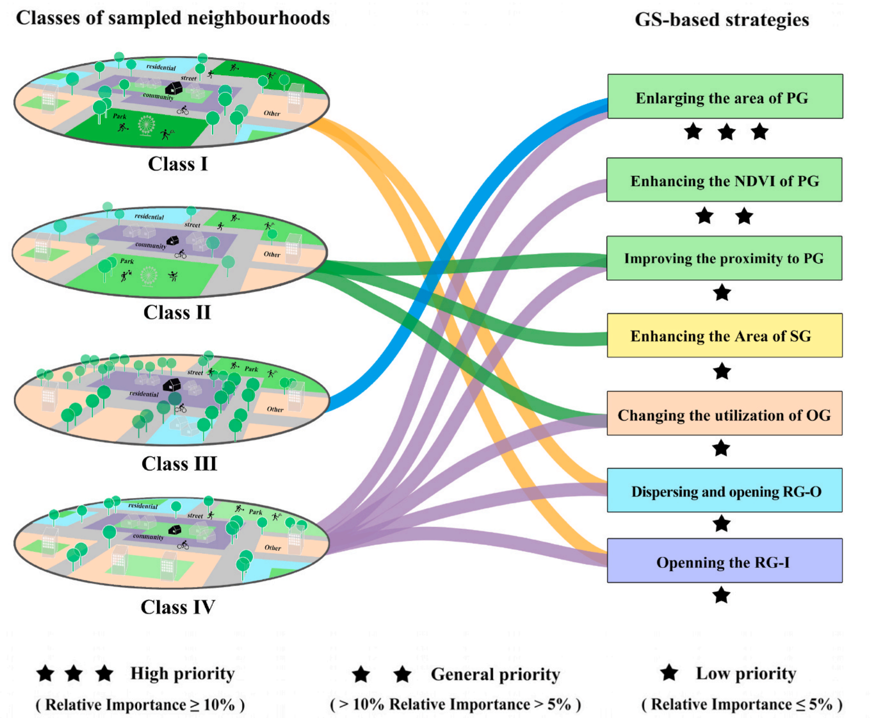

Fig. 11. Green space regulation strategies for enhancing health benefits.

further enhance their health benefits, strategies should center on optimizing RG-I and RG-O. This can be achieved by dispersing and opening RG-O to mitigate the negative effects and by opening up RG-I to better integrate them with surrounding areas. Class II neighborhoods, while having sufficient areas and good vegetation quality of PG, are limited in overall green resources. The primary strategy here is to enhance the proximity of PG. Additionally, expanding SG and constructing OG can contribute to improved health outcomes. Class III neighborhoods are characterized by superior metrics for SG and high NDVI values of both PG and RG-I. The recommended strategy is to moderately increase the area of PG to build on these strengths and enhance health benefits. Class IV neighborhoods stand out with prominent metrics for OG, high NDVI values for SG, and large areas of RG-I and RG-O. The corresponding regulatory strategy involves dispersing and opening RG-O while adjusting OG. These actions aim to convert underutilized areas into more accessible and functional green spaces, thereby maximizing their health benefits.

Finally, we set the priority for implementing green space strategies based on the combined importance values of PCS and MCS according to green space metrics. Metrics with a relative importance greater than or equal to 10 % are designated as high priority; those with a relative importance greater than 5 % but less than 10 % as general priority; and those with a relative importance of 5 % or less as low priority.

5. Discussion

5.1. The differences in health benefits based on green space classification

Previous studies have reported inconsistent findings regarding the health benefits of green spaces (Lee and Maheswaran, 2010; Kondo et al., 2018; de Keijzer et al., 2020), which may partly result from treating green space as a homogeneous entity in prior studies (Akpinar et al., 2016; Markevych et al., 2017). This study delineates the characteristics of various green space types in the neighbourhoods of central Beijing, revealing that different green space types exhibit distinct attributes and exert varying impacts on residents' health. For instance, PG typically provide high-quality green spaces and excellent facilities, offering residents superior natural contact and a diverse array of ecosystem services (Wang et al., 2022b). This underscores the critical role of PG in enhancing neighbourhood residents' health (Wang and Chang, 2003). Interestingly, RG-I and RG-O exhibited opposing effects on residents' health. Compared to PG, RG typically has a lower NDVI value. However, RG-I, located within the residents' own residential communities and offering superior accessibility and usage conditions, has positively impacted residents' health (Xia et al., 2024). Notably, our results indicate that RG-O negatively affected both PCS and MCS. This may stem from the unique environmental context of Chinese residential areas (Wu et al., 2021a). Most Chinese residential compounds are enclosed with security measures and walls, rendering green spaces and roads within these compounds largely inaccessible to the public (Miao, 2003). A higher proportion of RG-O within neighborhoods may thus signify fewer open public spaces. The inaccessibility of these non-open green spaces limits urban residents' ability to actively engage with them, thereby reducing their potential health benefits (Wu and Kim, 2021). Similar findings were reported in a recent study (Sun et al., 2024), but further research to verify the underlying mechanisms is warranted. In this context, opening up residential green spaces could be an effective strategy for enhancing neighbourhood green space health benefits. SG exhibit moderate metrics but are closely linked to residents' green space usage, significantly promoting leisure activities and active commuting (Vich et al., 2019). OG encompasses the largest greenery areas, mainly consisting of institution-affiliated green spaces, remnant woodlands, and wild grasslands (Masoudi et al., 2021; Li et al., 2015). However, much of OG lacks infrastructure and facilities, potentially hindering their active utilization (Li et al., 2023). Targeted regulatory strategies could significantly enhance OG's role in promoting health. These findings provide valuable insights into the distinct attributes of various green spaces, advancing our understanding of how diverse green space characteristics relate to health outcomes.

5.2. Interplay among health-related factors and green space interventions

Extensive research has established significant associations between health status and other factors, such as demographic attributes and lifestyle, as well as elements of the built environment (Diez-Roux, 2000; Cervero and Duncan, 2003; James et al., 2015; Firth et al., 2020; Nijs and Reis, 2022; Ziglio et al., 2004). In this study, age, years of education, neighbourhood relations, sleep quality, dietary status, and green space usage were found to be particularly influential in determining residents' health outcomes. Notably, neighbourhood relations emerged as the most critical factor for mental health and the second most important for physical health, underscoring the substantial impact of neighbourhood-related social factors on health (Eriksson and Emmelin, 2013). The study also revealed extensive interactions among these factors. Understanding these interactions enhances our comprehension of the complex relationships between green spaces and health, as well as the potential moderating effects of individual and built environment factors on the health benefits derived from green spaces. For instance, park areas exhibited significant interaction effects with population density on physical health and with neighbourhood relations on mental health. These findings suggest that the same green attributes can yield different health benefits depending on the interactions among conditions. Furthermore, objective green space features appeared to have a more substantial impact on physical health, while the usage of green space showed a greater importance for mental health. This may reflect the differential impacts of passive and active exposure to green spaces on health (Martinez-Juarez et al., 2015). From an ecosystem services perspective, green spaces can influence health through passive exposure, such as air purification and microclimate regulation, which provide physiological benefits without direct contact (Chiabai et al., 2018; James et al., 2016). In contrast, mental health benefits may depend more on active engagement with green spaces, such as through their aesthetic and recreational functions (Yang et al., 2025; Mitchell, 2013). Although individual-level factors may have a greater impact on health status, health interventions based on green spaces can not only produce direct positive effects on health availability but also effectively improve health through promoting healthy lifestyles and behaviors.

5.3. Limitations and prospects

In considering the current data sources and availability, several potential limitations of this study should be acknowledged for future research endeavors. This study did not include visual dimension metrics such as the GVI, which are typically derived from street view images (e.g., Google Street View). This metric primarily captures green space adjacent to streets and may overlook green space within parks and residential areas (Wang et al., 2019), therefore, the GVI metric was not included in this study. Consequently, this study did not delve into the mediating mechanisms through which green space metrics influence health. These unexamined areas could provide valuable insights into the relationships between various green space metrics and health outcomes (Markevych et al., 2017). Furthermore, the cross-sectional design of this study enables the establishment of correlations between green space and health benefits, but is insufficient for establishing causality (Lachowycz and Jones, 2013). Reverse causality cannot be ruled out, as healthier individuals may demonstrate a greater propensity for physical activity engagement (Zhang et al., 2024). Additionally, self-selection bias may confound these associations, as residents with higher health consciousness or socioeconomic advantages may disproportionately choose to live in neighborhoods with abundant green spaces (Wu et al., 2021b). Given that the SF-12v2 scale has a four-week standard recall period and is sensitive to short-term changes (Fong et al., 2010; Luo et al., 2003; Turner et al., 2013), we omitted the residents' length of residence as a covariate. However, the potential time-lag effect may introduce bias in health assessments. Precisely controlling respondents' residence could better improve the internal validity. Lastly, this study employed multi-source datasets; limitations in data acquisition and temporal resolution precluded achieving strict temporal alignment, which may have introduced bias. To mitigate this, the primary datasets were collected from April 2022 to September 2023, thereby minimizing potential bias. Moreover, the survey's implementation during April to September, potentially overlooking green space features in winter months, and inter-seasonal variability in green space functionality remains unaccounted (Zhang et al., 2024). Collecting and tracking longitudinal health data will enable a more precise evaluation of the health benefits of various green space attributes and facilitate the exploration of causal mechanisms (Dzhambov et al., 2020).

To maximize the health benefits of green spaces in neighbourhoods, it is crucial to identify the key green space metrics that influence residents' health. This study's comparison of health benefits across four major green space types, under three typical measurement dimensions, provides a foundational basis for developing healthier green spaces for residents. Each green space metric uniquely influenced the two health outcomes examined, emphasizing the necessity for nuanced differentiation of the green space types, measurement dimensions, and health outcomes. Further segmentation of green spaces by type and functional attributes remains crucial, such as categorizing them by hierarchical levels or access conditions. This approach can enhance the precision of green space intervention strategies for practical implementation. Additionally, future research should develop theoretical models that enhance health benefits and delve deeper into the pathways and mechanisms linking various green space metrics to specific health benefits (Kuo, 2015). The results suggest that neighbourhood relations contribute the magnificent importance to both the physical and mental health of residents and have a synergistic effect with numerous variable factors. This highlights the key role of social environmental factors at the humanistic level in residents' health. While numerous studies have explored the mechanisms by which green spaces affect health based on their natural environmental characteristics (Hartig et al., 2014; Markevych et al., 2017), fewer have examined health benefits within the context of the social and humanistic environment. This area deserves deeper exploration in future research. Moreover, current research remains fragmented, with limited investigation into cumulative risk pathways or temporal variability in interaction effects (Song et al., 2018). Future studies must integrate multilevel longitudinal data, dynamic spatial analytics, and equity-focused metrics to elucidate how the convergence of green space, built environment, and individual factors shapes health disparities. Such insights will inform the design of context-sensitive urban interventions that maximize health co-benefits across diverse populations.

6. Conclusion

This study aimed to evaluate the effects of various green space metrics on physical health and mental health by segmenting green space types under multiple measurement dimensions and identifying key green space metrics in the neighbourhood of central urban areas. This work provides a crucial foundation for promoting a healthier urban living environment. The findings revealed that different types of green spaces contribute variably to health benefits. PG demonstrated superior health benefits among all the green space types. Specifically, the Area_PG exhibited the most significant effects on both the PCS and MCS. It was worth noting, the health effects of RG-I and RG-O were differentiated, especially the potentially negative effects exerted by RG-O. In addition, the Area_PG showed a significant synergistic effect on PCS in areas with high population density and on MCS in areas with positive neighbourhood relations. These findings underscore the complexity of the relationship between green spaces and health, indicating that not all aspects of green space contribute equally to promoting residents' health. Nonetheless, by identifying key green space metrics that impact residents' health, this study offers insights for more precise and effective urban green space regulation strategies aimed at improving human health.

CRediT authorship contribution statement

Hailin Hong: Data curation, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Qing Chang:** Funding acquisition, Writing – review & editing, Supervision, Resources, Project administration, Conceptualization. **Kejun Cheng:** Investigation, Data curation. **Xiaohan Xie:** Data curation, Investigation.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126538.

Data availability

Data will be made available on request.

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