Impact of Green Space and Built Environment on Metabolic Syndrome: A Systematic Review with Meta-Analysis

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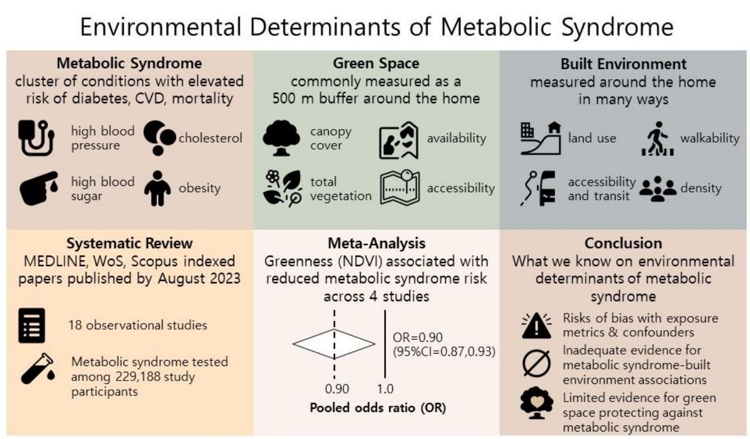
Abstract

Metabolic Syndrome presents a significant public health challenge associated with an increased risk of noncommunicable diseases such as cardiovascular conditions. Evidence shows that green spaces and the built environment may influence metabolic syndrome. We conducted a systematic review and meta-analysis of observational studies published through August 30, 2023, examining the association of green space and built environment with metabolic syndrome. A quality assessment of the included studies was conducted using the Office of Health Assessment and Translation (OHAT) tool. The Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) assessment was used to evaluate the overall quality of evidence. Our search retrieved 18 studies that met the inclusion criteria and were included in our review. Most were from China (n=5) and the U.S. (n=5), and most used a cross-sectional study design (n=8). Nine studies (50%) reported only green space exposures, seven (39%) reported only built environment exposures, and two (11%) reported both built environment and green space exposures. Studies reported diverse definitions of green space and the built environment, such as availability, accessibility, and quality, particularly around participants' homes. The outcomes focused on metabolic syndrome; however, studies applied different definitions of metabolic syndrome. Meta-analysis results showed that an increase in normalized difference vegetation index (NDVI) within a 500-m buffer was associated with a lower risk of metabolic syndrome (odds ratio [OR]=0.90, 95%CI=0.87−0.93, I^2=22.3%, n=4). A substantial number of studies detected bias for exposure classification and residual confounding. Overall, the extant literature shows a 'limited' strength of evidence for green space protecting against metabolic syndrome and an 'inadequate' strength of evidence for the built environment associated with metabolic syndrome. Studies with more robust study designs, better controlled confounding factors, and stronger exposure measures are needed to understand better what types of green spaces and built environment features influence metabolic syndrome.

Graphical Abstract



Highlights

- First review and meta-analysis of green space, built environment and Metabolic Syndrome.
- Meta-analysis found NDVI was negatively associated with Metabolic Syndrome.
- Most built environment studies did not show significant associations with Metabolic Syndrome.
- Most studies probably had high risks of bias for exposure classification detection.
- Evidence is 'limited' and 'inadequate' for green space and built environment, respectively.

1. Introduction

The global population is increasingly becoming urbanized, with more than half residing in urban areas by 2020, and this proportion is projected to rise to 68% by 2050 (Zhang et al., 2022; United Nations, 2018; World Health Organization, 2021). In some regions, this urban transition has coincided with lower physical activity, higher psychological stress, and unhealthy diet, contributing to a surge in noncommunicable diseases (NCDs) (World Health Organization, 2013; World Health Organization, 2018; Zhang et al., 2022). A substantial proportion of premature deaths can be attributed to NCDs, with a projected associated cost exceeding 5,000 USD for each affected individual (Allen et al., 2017; Chew et al., 2023).

Metabolic syndrome is a cluster of conditions including high blood pressure, abnormal blood sugar levels, lipid abnormalities, and abdominal obesity, all contributing to elevated risks of NCDs, in particular, type 2 diabetes, cardiovascular diseases (CVDs) and mortality (Day, 2007; O'Neill and O'Driscoll, 2015; Yang et al., 2020). Metabolic syndrome has emerged as a global public health concern, with 20-30% of adults affected by metabolic syndrome worldwide (Mohamed et al., 2023; Saklayen, 2018) and could be partly attributed to the resulting environmental changes and exposures (Leal and Chaix, 2011).

Green space encompasses vegetation, parks and associated natural elements (Frumkin, 2013; Taylor and Hochuli, 2017)). Increasing urbanization has led to a reduction in green spaces and natural elements that may limit opportunities for people's contact with nature (Connelly et al., 2020). Meanwhile, green space exposure is increasingly understood to improve human health (Yang et al., 2021), including metabolic syndrome (de Keijzer et al., 2019). Green space exposure may influence health (de Keijzer et al., 2019) through various mechanisms, including opportunities for physical activity and social engagement (Gong et al., 2014); reduced stress (Gong et al., 2016); and mitigated exposure to environmental hazards such as air pollution (Dadvand et al., 2012; Diener and Mudu, 2021), heat (Doick et al., 2014), and noise (Markevych et al., 2017). More specifically, studies have observed a protective association between residential greenness and the risk of metabolic syndrome (Chen et al., 2023; de Keijzer et al., 2019; Gong et al., 2014; Li et al., 2022).

The built environment encompasses human-made alterations to natural surroundings (e.g., residential structures, roadways, and public spaces) (Lawrence and Low, 1990; Roof and Oleru, 2008; Zhang et al., 2022). Previous studies have shown that the built environment can influence resident's metabolic health by influencing physical activity and sedentary behavior (Dengel et al., 2009; Edwardson et al., 2012; Frank et al., 2007; Saelens et al., 2003). For example, a study in China reported that higher walkability (accessibility to nearby amenities from residences or workplaces) was associated with a lower risk of metabolic syndrome incidence (Zhu et al., 2023). Perceived local land use mix was also negatively associated with metabolic syndrome (Baldock et al., 2012). Urban built environments, including pedestrian-friendly routes and public open spaces, are potential influencers of residents' lifestyle such as physical activity (e.g., walking, cycling) (Barnett et al., 2017; Colom et al., 2019; Van Cauwenberg et al., 2018) and sedentary behavior (e.g., car use, television watching) (Koohsari et al., 2015). Individuals having better access to recreational facilities tend to be more active (Cohen et al., 2006; Dengel et al., 2009; Gordon-Larsen et al., 2006; Jago et al., 2016), and prolonged sedentary time is associated with poor metabolic health (Carson et al., 2016).

Several previous systematic reviews have explored the connections between various aspects of the green space and built environment and cardiometabolic health outcomes. These reviews have covered topics such as the relationship between green space and cardiovascular mortality (Yuan et al., 2021), the impact of the built environment on cardio-metabolic health (Chandrabose et al., 2019), and cardiovascular disease outcomes (Malambo et al., 2016). We are unaware of a prior review that has systematically assessed metabolic syndrome in association with green space and the built environment. We sought to fill this gap by systematically and quantitatively assessing the association of green spaces and built environments with metabolic syndrome risk. We believe this approach will contribute valuable insights to the ongoing discourse surrounding the impact of green spaces and the built environment on cardiovascular health.

2. Methods

2.1. Study protocol registration

This systematic review and meta-analysis were conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021). The review protocol was preregistered on PROSPERO (CRD42023423940).

2.2. Study question

The research question addressed was as follows: "What are the associations of the green space and built environment with metabolic syndrome?

2.3. Eligibility criteria

Eligibility criteria were formulated using the Population, Exposure, Comparator, Outcome, and Study Design (PECOS) framework, a systematic approach that helped ensure the inclusion of relevant articles while minimizing potential bias in the review process (Hu et al., 2021; Ricciardi et al., 2022; Zare Sakhvidi et al., 2023). We included articles published by August 30, 2023, with full-texts available in English. The PECOS criteria applied are detailed in Table S1 and summarized below:

Population: The review considered studies involving human populations. We excluded non-human research and studies that evaluated the impact of green space through hypothetical scenarios.

Exposure: The review included studies with subjective (e.g., perceived distance) or objective exposure to green space (e.g., normalized difference vegetation index [NDVI]) in outdoor spaces (e.g., urban green spaces, parks, forests, and roadside trees). Studies assessing various aspects of the built environment, such as land use, transportation, walkability, population density, and relevant features, were also included. However, studies examining the impact of the food environment were excluded.

Comparator: The review considered studies that examined the risk or odds of metabolic syndrome across varying levels of exposure to the built environment or green space.

Outcome: The included studies focused on metabolic syndrome, adhering to established definitions. For instance, the National Cholesterol Education Program (NCEP) Adult Treatment Panel III (ATP III) delineated specific criteria for diagnosing metabolic syndrome: meeting three or more of the following conditions—waist circumference exceeding 40 inches (men) or 35 inches (women), blood pressure surpassing 130/85 mmHg, fasting triglyceride (TG) levels exceeding 150 mg/dL, fasting high-density lipoprotein (HDL) cholesterol levels falling below 40 mg/dL (men) or 50 mg/dL (women), and fasting blood sugar surpassing 100 mg/dL (Huang, 2009).

Study Design: The review encompassed observational studies utilizing cross-sectional, case-control, cohort, or ecological designs. Both quantitative and mixed-method designs were considered as inclusion criteria. Experimental studies and those with qualitative measurements were excluded.

2.4. Information sources and literature search

We performed a systematic keyword search across three databases - MEDLINE (through PubMed), Scopus, and Web of Science - using pre-defined PECOS. The searches were conducted on August 30, 2023. The search terms encompassed terms extracted from "Medical Subject Headings (MeSH)" in PubMed, along with title/abstract terms. Our search strategies involved combinations of keywords related to greens pace (e.g., greenness, green spaces, green area, and greenery), built environment (e.g., built environment, land use, and walkability) and metabolic syndrome (e.g., metabolic syndrome and cardio-metabolic syndrome). Language restrictions were applied, limiting the search to English. Additionally, we conducted a manual search through the reference lists of pertinent reviews to identify potential articles. Detailed search strategies and terms are in Supplementary Table S1.

2.5. Study selection

We used Rayyan (https://www.rayyan.ai/) for the management of retrieved articles through systematic searches. After duplicate removal, two reviewers (MMP and SA) independently assessed the titles and abstracts of all identified papers. Articles selected during the title and abstract screening were considered for full-text assessment. Throughout the screening process, studies were included only if they adhered to the predefined inclusion criteria. Any disagreements were resolved through discussion with a third reviewer (MHEMB, MJZS, or PD). The full texts of selected articles were examined according to the PECOS and entered the review if they fulfilled all the eligibility criteria.

2.6. Data extraction

Two researchers (MMP and SA) conducted data extraction. Both reviewers collected information pertaining to basic information (authors, publication year, country, study design, study population, and sample size), methodology (metabolic syndrome measurement, green space and built environment assessments, statistical analyses, and covariates), outcome measurement (odds ratio [OR] or relative risk [RR]) and hazard ratio [HR] along with their corresponding 95% confidence intervals [CIs] and effect coefficients [β] accompanied by standard errors [SE] considered in the analysis. In cases of any differences in the extracted data, consensus was reached through discussion between two co-authors (MMP and SA). In the case of any missing data, the reviewers contacted the corresponding authors.

2.7. Synthesis methods

Meta-analyses were performed for exposure-outcome pairs that had a minimum of three studies. For findings with a limited number of studies, we provided narrative descriptions instead of conducting meta-analyses. When studies reported multiple independent effect estimates for the same exposure-outcome pair, we selectively extracted the estimate from either the "fully adjusted" or the "main model." Based on the available data, we performed only one meta-analysis: NDVI at a 500-m buffer and metabolic syndrome. The following formula was employed to standardize the effect estimates (X. X. Liu et al., 2022):

Given the inherent heterogeneity in the study design and methodology and the small power of our heterogeneity tests, a conservative random-effects model was chosen for pooling risk estimates (Lin et al., 2017). The overall heterogeneity was evaluated using Cochran's Q statistic and I^2 statistic. Cochran's Q test determined the presence of statistically significant heterogeneity with a p-value < 0.05, indicating that the observed variation in effect sizes was unlikely to be due to chance alone (Higgins, 2008). Additionally, the I^2 statistic provided a measure of the proportion of total variation attributable to heterogeneity, with an I^2 value greater than 50% indicating substantial heterogeneity (Higgins and Thompson, 2002). The results of the pooled analysis were visually represented using forest plots.

To assess potential publication bias, we employed a funnel plot and conducted an Egger's regression test. In cases where we detected significant publication bias, indicated by funnel plot asymmetry or a p-value of < 0.05 in Egger's regression test, we applied the trim-and-fill method to correct the asymmetry. This resulted in an adjusted pooled estimate that accounted for the trimmed studies. To identify potentially influential studies, we conducted a sensitivity analysis by systematically removing one study at a time. This process allowed us to assess the impact of each specific study on the magnitude, direction, and significance of the pooled estimates. The meta-analysis was performed using the "metan" command in Stata 14 (StataCorp; College Station, TX, USA) (Harris et al., 2008).

2.8. Risk of bias assessment

We evaluated the potential biases in the reviewed studies using the Office of Health Assessment and Translation (OHAT) tool (Rooney et al., 2014). This tool has been previously employed in reviews of environmental exposures (including green spaces) and health outcomes (Buczyłowska et al., 2023; Cao et al., 2023). Adhering to the validated framework for observational human subject studies, our review focused on three critical elements (bias of exposure, outcome, and confounding) while also assessing five methodological criteria (selection bias, attrition/exclusion bias, selective reporting bias, conflict of interest and other). Each domain was categorized as "definitely low," "probably low," "probably high," or "definitely high" following established guidelines. Detailed guidelines for these adjusted OHAT criteria are in Table S2. To ensure consistency, two reviewers (MMP and SA) independently assessed the risk of bias for individual studies. In case of disagreements, a third reviewer (MHEMB) mediated the discussion to address the disparities in the data.

2.9. Overall quality of evidence assessment

We applied the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) tool to classify the overall quality of evidence (Cao et al., 2023; Haddad et al., 2023; Lam et al., 2021). According to the GRADE, the quality of evidence was classified into four categories: "high," "moderate," "low," and "very low." Initially, observational studies are given a moderate rating, which is then further evaluated with upgrades or downgrades according to GRADE criteria (Woodruff & Sutton, 2014). Downgrades are made based on factors such as risk of bias, indirectness, inconsistency, imprecision, and publication bias. Upgrades are made based on factors such as large effect size, dose response, and minimized confounding (Johnson et al., 2014). Here, 0 was considered for no change in ratings from the initial quality (i.e., moderate), while -1 or -2 were for downgrade ratings, and +1 or +2 were for upgrade ratings (Balshem et al., 2011). Two reviewers (MMP and SA) independently rated the evidence, and disagreements were resolved by a third reviewer (MHEMB). The assessment guidelines with rationale and judgments are presented in **Tables S3 and S4**.

2.10. Strength of evidence

Our assessment of the strength of the evidence used the Navigation Guide framework, a systematic approach for separately evaluating human and non-human studies before combining their overall strength (Lam et al., 2016). The strength of evidence across studies involved four factors: the quality of the body of evidence, direction of the effect, confidence in the effect, and other influential attributes of the data. The resulting ratings reflected the strength of evidence across studies and fell into categories such as sufficient evidence of benefits (a robust body of evidence supporting beneficial effects), limited evidence of benefits (the presence of evidence but with limitations), inadequate evidence of benefits (a lack of sufficient data to draw conclusions about benefits); and evidence of benefits absence (a lack of substantial evidence supporting benefits) (Uwak et al., 2021). The ratings reflect the strength and reliability of the evidence and support informed decision-making. Criteria for these adjustments are outlined in **Table S5**.

3. Results

3.1. Selection of studies

We identified a total of 1,374 articles through our database searches. After duplicate removal, title, and abstract screening, we reached 51 articles for full-text assessment. After full-text assessment, 18 articles were eligible and included in our review (Figure 1).

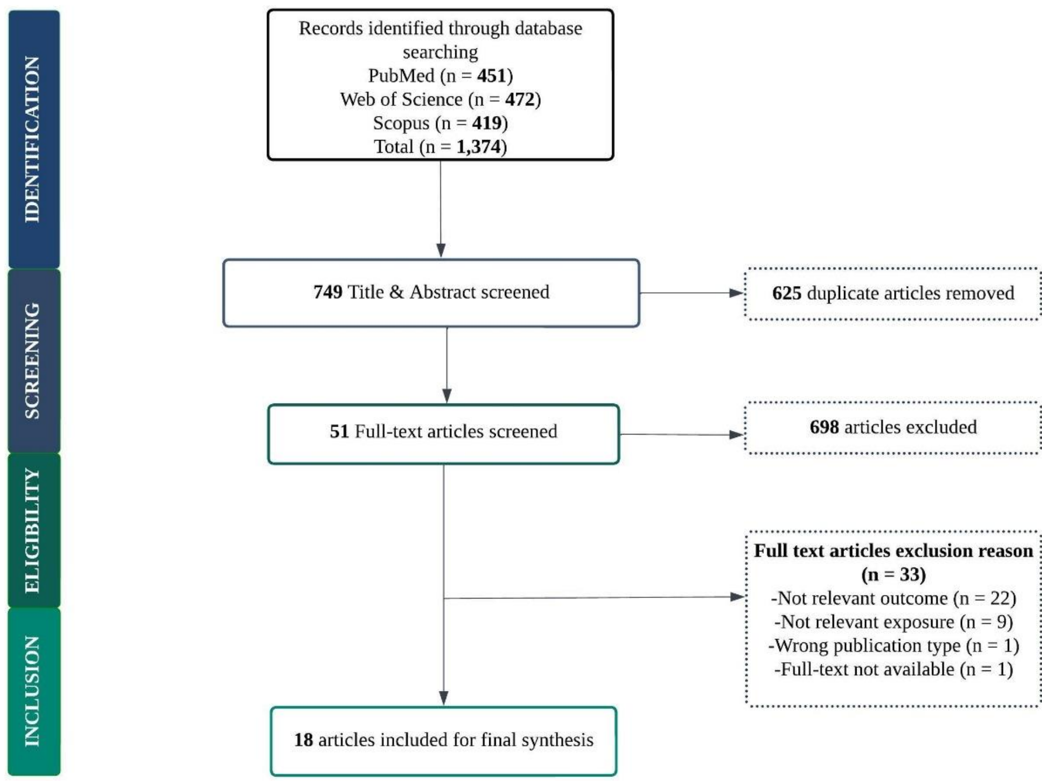


Figure 1. PRISMA flow chart for the study selection process.

3.2. Characteristics of included studies

Table 1 presents detailed characteristics of the included studies. Publication dates ranged from 2009 to 2023, with 60% (n = 11) published after 2020. The total sample size of the included studies was 156,820, with individual studies ranging from 75 (Joseph and Vega-lopez, 2020) to 49,893 (Ke et al., 2022) (Table 1). Of the total, 8 (44%) utilized a cross-sectional design, 7 (39%) used a cohort design and 3 (17%) were based on ecological study design (Figure 2). Most studies (n = 5, 28%) were conducted in China and the U.S. (n = 5, 28%) followed by Australia (n = 4, 22%). Most studies with a cross-sectional design were conducted in Australia (n = 4, 50%) and the U.S. (n = 3, 38%). The majority of studies with cohort design were conducted in China (n = 3, 43%). The ecological studies were conducted in the U.S. (n = 1, 33%), Greece (n = 1, 33%) and China (n = 1, 33%) (Figure 2). Most targeted adult populations (n = 11, 61%), followed by elderly individuals (n = 6, 33%) and adolescents (n = 1, 6%).

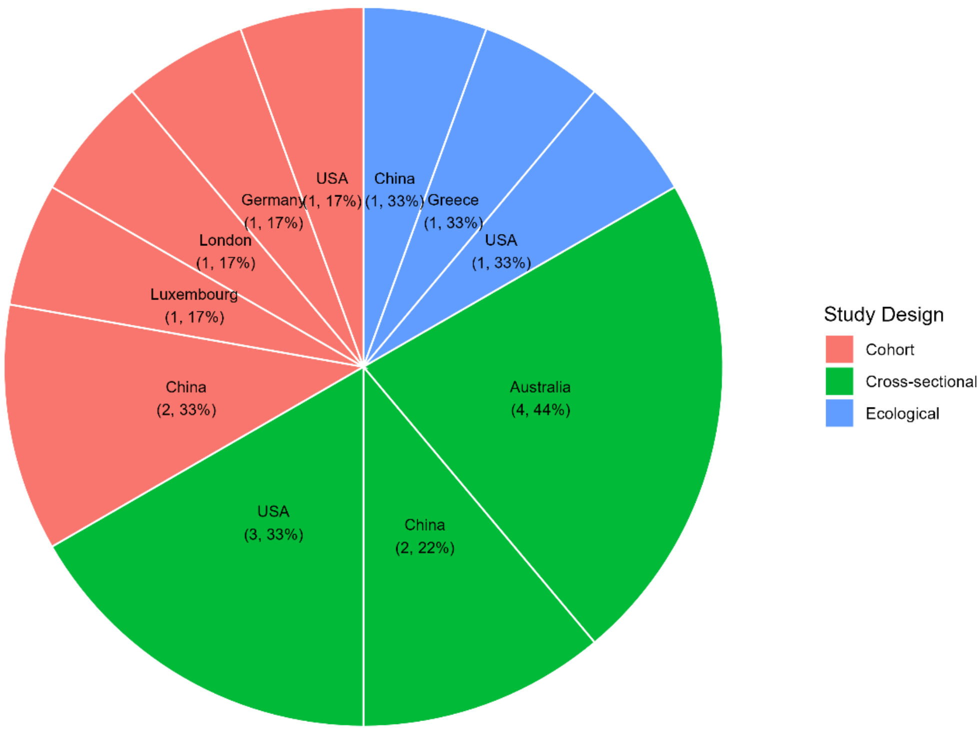


Figure 2. Distribution of studies by study design and country.

Thirteen studies identified metabolic syndrome outcomes in terms of the percentage of metabolic syndrome. Three more reported metabolic syndrome prevalence (Tsiampalis et al., 2021; Voss et al., 2021; Yang et al., 2019), while two reported a metabolic syndrome cluster score (Tharrey et al., 2023 Dengel et al., 2009). The majority used expert consensus and statements including the World Health Organization (WHO) (Barr et al., 2016; de Keijzer et al., 2020); Joint interim statement of the International Diabetes Federation Task Force on Epidemiology and Prevention, National Heart, Lung, and Blood Institute, American Heart Association, World Heart Federation, International Atherosclerosis Society, and International Association for the Study of Obesity (Barnett et al., 2022, Ke et al., 2022, Li et al., 2022, Tharrey et al., 2023, Voss et al., 2021, Yang et al., 2019); National Cholesterol Education Program Adult Treatment Panel III (NCEP ATP III) (Joseph and Vega-Lopez, 2020; Letellier et al., 2022; Liu et al., 2022; Tsiampalis et al., 2021); International Diabetes Federation criteria (Baldock et al. 2012, 2018); National Heart, Lung, and Blood Institute/American Heart Association (Braun et al., 2016); or criteria of the Metabolic Syndrome Study Cooperation Group of the Chinese Diabetes Society (CDS2004) (Zhu et al., 2023). Two studies did not report any source for their definition of metabolic syndrome (Aguilera et al., 2021; Dengel et al., 2009).

Table 1. Summary characteristics of included studies in the review (n = 18).

Author (s), Publication Year, Country	**Sample Size/Unit, Study Population, Study design**	**Type of exposure**	**Exposure matrices**	**Outcome definition**	**Outcome assessment source**	**Main findings**
Aguilera et al. 2021 USA	4,959 Adults Cross-sectional	Built environment	Distance to the nearest major arterial road; Street Length within 500 m; Distance nearest POE; Inverse of distance to nearest POE; Traffic VMT within 500 m	Metabolic syndrome (%)	Not Reported	The longer streets within the 500m impact zone were linked to a higher chance of developing metabolic syndrome (OR = 1.039, 95%CI= 1.016-1.062, p = 0.001)
Baldock et al. 2012 Australia	1,324 Adults Cross-sectional	Built environment	Local land-use mix	Metabolic syndrome (%)	IDF criteria	Local perceived land-use mix was found to have a lower risk of metabolic syndrome (OR = 0.87, 95% CI: 0.77-1.00, p = 0.04).
Baldock et al. 2018 Australia	1,491 Adults Cross-sectional	Green space	Objective distance, perceived distance, Overestimated distance to POS (parks, nature & sports field)	Metabolic syndrome (%)	IDF criteria	Objective distance (OR=0.92, 95% CI: 0.73-1.16, p=0.463), perceived distance (OR=1.08, 95% CI: 0.99-1.18, p=0.097), and overestimated distance (OR=1.22, 95% CI: 0.97-1.55, p=0.120) to POS were not associated with metabolic syndrome.
Barnett et al. 2022 Australia	3,681 Adults Cross-sectional	Built environment; Green space	Population density (person/ha), commercial land use (%), parkland (%), land-use mix (other), street intersection density (/km^2)	Metabolic syndrome (%)	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	A one-decile increase in either built environment and green space factors was not found to be significantly associated with metabolic syndrome (Population density (persons/ha): OR=0.997, 95%CI= (0.989, 1.006); Commercial land use (%): OR=0.998, 95%CI= (0.985, 1.011); Parkland (%): OR=1.002, 95%CI= (0.996, 1.009); Land use mix (other): OR=1.392, 95%CI= (0.734, 2.641); Street intersection density (/km2): OR=1.001, 95%CI= (0.998, 1.004).
Barr et al. 2016 Australia	5,241 Adults Cross-sectional	Built environment	Public transport accessibility	Metabolic syndrome (%)	WHO Definition	High public transport accessibility was not associated with the occurrence of metabolic syndrome (OR = 1.09, 95% CI = 0.91-1.31, p = 0.35).
Braun et al. 2016 USA	3,810 Elderly Cohort	Built environment	Street Smart Walk Score	Metabolic syndrome (%)	NHLBI/AHA Definition	Street Smart Walk Score was not associated with metabolic syndrome in both cross-sectional (OR (SE)=1.0022 (0.0185)) and

						longitudinal analysis (OR (SE)=0.9885 (0.0583)).
de Keijzer et al. 2019 London	6,076 Adults Cohort	Green space	NDVI 500m, NDVI 1000m & NDVI LSOA; VCF 500m, VCF 1000m & VCF LSOA	Metabolic syndrome (%)	WHO Definition	Higher residential greenness was associated with a decreased risk of metabolic syndrome: (NDVI 500m: HR(95%CI)=0.87 (0.77, 0.99); VCF 500m: HR(95%CI)=0.86 (0.78, 0.95); VCF 1000m: HR(95%CI)=0.85 (0.77, 0.94), VCF LSOA: HR(95%CI)= 0.83 (0.75, 0.92).
Dengel et al. 2009 USA	188 Adolescents Cross-sectional	Built environment; Green space	Residential Density, Distance to Transit, Density of Transit, Employment Density, Percent Land Use –residential, Percent Land Use –park and recreation, Percent Land Use –vacant, Median block size, Number of access points, Intersection density	Metabolic syndrome cluster score	Metabolic syndrome Z-score followed by (Kelly et al., 2008)	None of the features were significantly associated with metabolic syndrome, including residential density (rho=0.1016), distance to transit (rho=-0.0457), transit density (rho=0.0172), employment density (rho=0.0776), percent land use for residential (rho=0.0749), percent land use for park and recreation (rho=-0.1320, significant at p<0.10), percent land use for vacant (rho=-0.0804), median block size (rho=-0.0338), number of access points (rho=0.1160), and intersection density (rho=0.0953).
Joseph and Vega-lopez 2020 USA	75 Adults Cross-sectional	Built environment	Walking environment	Metabolic syndrome (%)	NCEP ATP III Definition	Walking environment was not associated with the presence of metabolic syndrome (OR = 0.64, 95%CI = 0.34-1.17).
Ke et al. 2022 China	49,893 Adults Cohort	Green space	NDVI 250m, NDVI 500m & NDVI 1250m	Metabolic syndrome (%)	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	Participants lived in the highest quartile of NDVI 250m, NDVI 500m, and NDVI 1250m had a 15% (OR = 0.85, 95% CI: 0.80–0.90), 12% (OR = 0.88, 95% CI: 0.83–0.93), and 11% (OR = 0.89, 95% CI: 0.85–0.95) lower risk of metabolic syndrome.
Letellier et al. 2022 USA	570 Adults Ecological	Built environment	Transportation	Metabolic syndrome (%)	NCEP ATP III Definition	Transportation (RR = 0.96, 95%CI = 0.89–1.04) did not show a significant association with metabolic syndrome.
Li et al. 2022 China	38,288 Adults Cross-sectional	Green space	NDVI 500m; EVI 500m	Metabolic syndrome (%)	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	Each IQR (0.62) increase in NDVI 500m and EVI 500m (IQR = 0.74) was associated with a 13% reduced risk of metabolic syndrome (NDVI 500m: OR = 0.87 [95% CI: 0.83, 0.92]; EVI 500m: OR = 0.87 [0.82, 0.91]), respectively.

Liu et al. 2022 China	38,288 Adults Cohort	Green space	NDVI 500m	Metabolic syndrome (%)	NCEP ATP III Definition	Higher greenness was not significantly associated with metabolic syndrome (OR (95%CI) = 0.93 (0.84, 1.04)).
Tharrey et al. 2023 Luxembourg	1,755 Elderly Cohort	Green space	SAVI 800m; TCD 800m	Metabolic syndrome score (%)	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	An increase in SAVI may significantly prevent the metabolic syndrome (change SAVI: β (95% CI) = − 0.05 (− 0.11, 0.00)).
Tsiampalis et al. 2021 Greece	2,749 Adults Ecological	Green space	Land covered by urban green spaces	Metabolic Syndrome prevalence	NCEP ATP III Definition	Areas with high coverage of urban green spaces were associated with a reduced prevalence of metabolic syndrome (IRR = 0.96, 95% CI = 0.95–0.96).
Voss et al. 2021 Germany	2,883 Elderly Cohort	Green space	NDVI 500m	Metabolic Syndrome prevalence & incidence	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	High greenness was not associated with prevalent and incident metabolic syndrome in both cross-sectional (NDVI 500m: (OR = 0.95, 95%CI = 0.84–1.06) and longitudinal analyses NDVI 500m : (OR = 0.86, 95%CI: 0.71–1.03).
Yang et al. 2019 China	15,477 Elderly Ecological	Green space	NDVI 500M, NDVI 1000m; SAVI 500m, SAVI 1000m; VCF 500m, VCF 1000m	Metabolic syndrome prevalence	Joint Interim Statement of the IDF, TFEP, NHLBI, AHA, WHF, IAS, IASO	Higher greenness (NDVI 500m: OR = 0.81, 95%CI = 0.70−0.93; NDVI 1000m: OR = 0.83, 95%CI = 0.72-0.95; SAVI 500m: OR = 0.80, 95% CI = 0.69 − 0.93); SAVI 1000m: OR = 0.82, 95%CI = 0.71− 0.94; VCF 500m: OR = 0.91, 95% CI = 0.83 − 1.00; VCF 1000m: OR = 0.95, 95%CI = 0.89−1.00) was associated with lower rate of metabolic syndrome.
Zhu et al. 2023 China	17,965 Elderly Cohort	Built environment	Walkability	Metabolic syndrome (%)	CDS 2004 criteria	Higher walkability was associated with lower hazards of metabolic syndrome (Q2:HR(95%CI) = 0.88(0.81,096) Q3: HR(95%CI) = 0.91(0.83,0.99) Q4: HR(95%CI)=0.88(0.80,0.96)).

Note: POE = Port of entry; VMT = Vehicle miles traveled; POS = Public open space; NDVI = Normalized Difference Vegetation Index; EVI = Enhanced Vegetation Index; SAVI = Soil-Adjusted Vegetation Index; VCF = Vegetation Continuous Field; LSOA = Lower Layer Super Output Area; TCD = Tree Canopy Density; HR = Hazard Ratio; OR = Odds Ratio; 95%CI = 95% Confidence Interval; IDF, International Diabetes Federation; CDS, Chinese Diabetes Society; TFEP, Task Force on Epidemiology and Prevention; NHLBI, National Heart, Lung, and Blood Institute; AHA, American Heart Association; WHF, World Heart Federation; IAS, International Atherosclerosis Society; IASO, International Association for the Study of Obesity; NCEP ATP III, National Cholesterol Education Program Adult Treatment Panel III;

3.3. Exposure assessment

Nine studies (50%) reported only green space (Baldock et al., 2018; de Keijzer et al., 2019; Ke et al., 2023; Li et al., 2022; L. Liu et al., 2022; Tharrey et al., 2023; Tsiampalis et al., 2021; Voss et al., 2021; Yang et al., 2020). Seven studies (39%) reported only built environment factors (Aguilera et al., 2021; Baldock et al., 2012; Braun et al., 2016; Dengel et al., 2009; Joseph and Vega-López, 2020; Letellier et al., 2022; Zhu et al., 2023). Two studies (11%) reported both built environment and green space exposures (Barnett et al., 2022; Dengel et al., 2009) **(Table 1).**

Exposure to green spaces was assessed through green space availability (n=10) using the NDVI, Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Vegetation Cover Fraction (VCF), Tree Canopy Density (TCD), or percentage of greenness coverage (Barnett et al., 2022; de keijzer et al., 2019; Dengel et al., 2009; Ke et al., 2022; Li et al., 2022; Liu et al., 2022; Tharrey et al., 2023; Tsiampalis et al., 2021; Voss et al., 2021; Yang et al., 2019). Accessibility (n=1) was assessed through distance to green space, gardens or park facilities (Baldock et al., 2018) **(Table 1, Table S9)**.

The built environment was characterized as traffic-related measures (n = 3), including distance nearest to major arterial roads (Majart), street length, distance nearest Port of Entry (POE), inverse of distance to nearest POE and traffic vehicle miles traveled (VMT) (Aguilera et al., 2021)**,** street intersection density (Barnett et al., 2022), or street pattern (Dengel et al., 2009). Other built environment measures were land-use mix (n = 3) (Baldock et al., 2012; Barnett et al., 2022; Dengel et al., 2009), walkability (n = 3) (Braun et al., 2016; Joseph and Vega-lopez, 2020; Zhu et al., 2023), transportations accessibility (n = 3) (Barr et al., 2016; Dengel et al., 2009; Letellier et al., 2022), population density (n = 1) (Barnett et al., 2022) and residential density (n = 1) (Dengel et al., 2009) **(Table 1, Table S9).**

Different data sources were used to estimate exposure, including satellite images**,** census data, government data repositories and questionnaires (i.e., perceived proximity and land use) **(Table S9).** Three studies used Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images with a 250 × 250 m spatial resolution (de keijzer et al., 2019; Ke et al., 2022; Liu et al., 2022) and four used Landsat satellite images with a 30 x 30 m resolution (Li et al., 2022; Tharrey et al., 2023; Voss et al., 2021; Yang et al., 2019) to estimate green space availability using remote sensing-based greenness indices (NDVI, EVI, SAVI, VCF, TCD). One study used a questionnaire to estimate the perceived distance to green space (Baldock et al., 2018). In terms of built environment data sources, two studies used government data repositories to estimate transportation accessibility (Barr et al., 2016) and street distance and density (Aguilera et al., 2021). Two studies estimated walkability in each participant's residential location using a free web-based tool available at https://www.walkscore.com/, an algorithm with scores ranging from 0 to 100 reflecting the degree of walkability. Studies used a walkability score (Braun et al., 2016; Zhu et al., 2023), and two used questionnaires to estimate the perceived local land-use mix (Baldock et al., 2012) and perceived walking environment (Joseph and Vega-lopez, 2020) **(Table S9).**

Eight studies applied buffers to estimated green space availability (Barnett et al., 2022; de Keijzer et al., 2019; Ke et al., 2022; Li et al., 2022; Liu et al., 2022; Tharrey et al., 2023; Voss et al., 2021; Yang et al., 2019) and one study used network buffer to estimate built environment features including transportation accessibility, percent land-use mix, and street pattern (Dengel et al., 2009). Buffer sizes ranged from 250m (Kee et al., 2022) to 3000m (Dengel et al., 2009), with the most commonly utilized buffer size being 500m.

In most such studies, circular buffers were employed, but one study used a network buffer (1600m) (Dengel et al., 2009) **(Table S9)**.

Of the reviewed studies, six reported temporality between exposure and outcome, ranging from 2 years (Tharrey et al., 2023) to 4 years (Liu et al., 2022). **(Table S10).**

Different levels of adjustment were applied in the studies, ranging from none (Aguilera et al., 2021; Dengel et al., 2009) to 14 variables (Barr et al., 2016). These adjustments encompassed various categories of covariates, including demographic factors, behavioral, environmental and area-level factors **(Table S8).** The most frequently accounted for variables were demographic (age, sex, income, education, occupation) and behavioral factors (smoking and alcohol consumption). Neighborhood socioeconomic status (SES) (Barnett et al., 2022; Barr et al., 2016; Barun et al., 2016; Tsiampalis et al., 2021), area-level income (Baldock et al., 2012; Baldock et al., 2018; de keijzer et al. 2019), population density (Barnett et al., 2022; Barr et al., 2016; Yang et al., 2019) and gross domestic product (GDP) (Liu et al., 2022; Yang et al., 2019) were included as area-level variables in some of the studies **(Table S8).**

Ten studies employed a mediation, effect modification, or moderation or interaction analysis (Baldock et al., 2012; Baldock et al., 2018; de Keijzer et al., 2019; Ke et al., 2022; Li et al., 2022; Liu et al., 2022; Tharrey et al., 2023; Voss et al., 2021; Yang et al., 2019; Zhu et al., 2023). The most frequently tested mediators were air pollution (de keijzer et al 2019; Li et al., 2022; Liu et al., 2022; Yang et al., 2019, Zhu et al. 2023) and physical activity (Baldock et al. 2018; de keijzer et al., 2019; Ke et al., 2022; Liu et al., 2022; Voss et al., 2021, Yang et al., 2019). Few studies reported that physical activity (de keijzer et al., 2019) and air pollution (de Keijzer et al., 2019; Li et al., 2022; Liu et al., 2022; Yang et al., 2019; Zhu et al., 2023), significantly mediated the association between greenness and metabolic syndrome, while walking time (Baldock et al., 2012) mediated the association between built environment and metabolic syndrome **(Table S8).**

3.4. Green space and metabolic syndrome associations

The studies that examined associations between green space and metabolic syndrome are summarized in Figure 3. Eleven studies, including four cross-sectional (Baldock et al., 2018; Barnett et al., 2022; Dengel et al., 2009; Li et al., 2022), two ecological (Tsiampalis et al., 2021; Yang et al., 2019) and five cohort studies (de Keijzer et al., 2019; Ke et al., 2022; Liu et al., 2022; Tharrey et al., 2023; Voss et al., 2021;) reported associations between green space and metabolic syndrome. Of these, one cross-sectional (Li et al., 2022), one ecological (Yang et al., 2019), and two cohort studies (de Keijzer et al., 2019; Ke et al., 2022) reported protective associations for green space in terms of NDVI or EVI with metabolic syndrome. One cohort study reported a protective association for SAVI with metabolic syndrome (Tharrey et al., 2023). Another ecological study found more urban green space cover was associated with a lower prevalence of metabolic syndrome (Tsiampalis et al., 2021). However, five studies did not find any significant associations between green space and metabolic syndrome (Baldock et al., 2018; Barnett et al., 2022; Dengel et al., 2009; Liu et al., 2022; Voss et al., 2021).

Green Space	Adjusted Association
NDVI	
de Keijzer et al., 2019	+
Ke et al., 2022	+
Li et al., 2022	+
Liu et al., 2022	0
Voss et al., 2021	0
Yang et al., 2019	+
EVI	
Li et al., 2022	+
SAVI	
Tharrey et al., 2023	+
Yang et al., 2019	+
VCF	
de Keijzer et al., 2019	+
Yang et al., 2019	+
TCD	
Tharrey et al., 2023	0
Percentage of Green Space	
Barnett et al., 2022	0
Tsiampalis et al., 2021	+
Green Space Accessibility	
Baldock et al., 2018	0

Built Environment	Adjusted Association
Land-use mix	
Baldock et al., 2012	+
Barnett et al., 2022	0
Dengel et al., 2009	0
Traffic related measures	
Aguilera et al., 2021	-
Barnett et al., 2022	0
Dengel et al., 2009	0
Walkability	
Braun et al., 2016	0
Joseph and Vega-lopez, 2020	0
Zhu et al., 2023	+
Transportation accessibility	
Barr et al., 2016	0
Dengel et al., 2009	0
Letellier et al., 2022	0
Population Density	
Barnett et al., 2022	0
Residential Density	
Dengel et al., 2009	0

"+" for significant protective association, **"0"** for no association, and **"-"** for significant deleterious association

Figure 3. Overview of studies examining green space and built environment exposure and their association with metabolic syndrome. NDVI, Normalized Difference Vegetation Index; EVI, Enhanced Vegetation Index; SAVI, Soil-Adjusted Vegetation Index; VCF, Vegetation Continuous Field; TCD, Tree Canopy Density.

We conducted a meta-analysis of the association between green space exposure, using NDVI at 500m buffer, and metabolic syndrome. The meta-analysis showed that an increase in mean NDVI at 500m buffer was associated with a lower risk of metabolic syndrome (combined OR = 0.90, 95%CI = 0.87-0.93, I^2 = 22.3%, n = 4) **(Figure 4).**

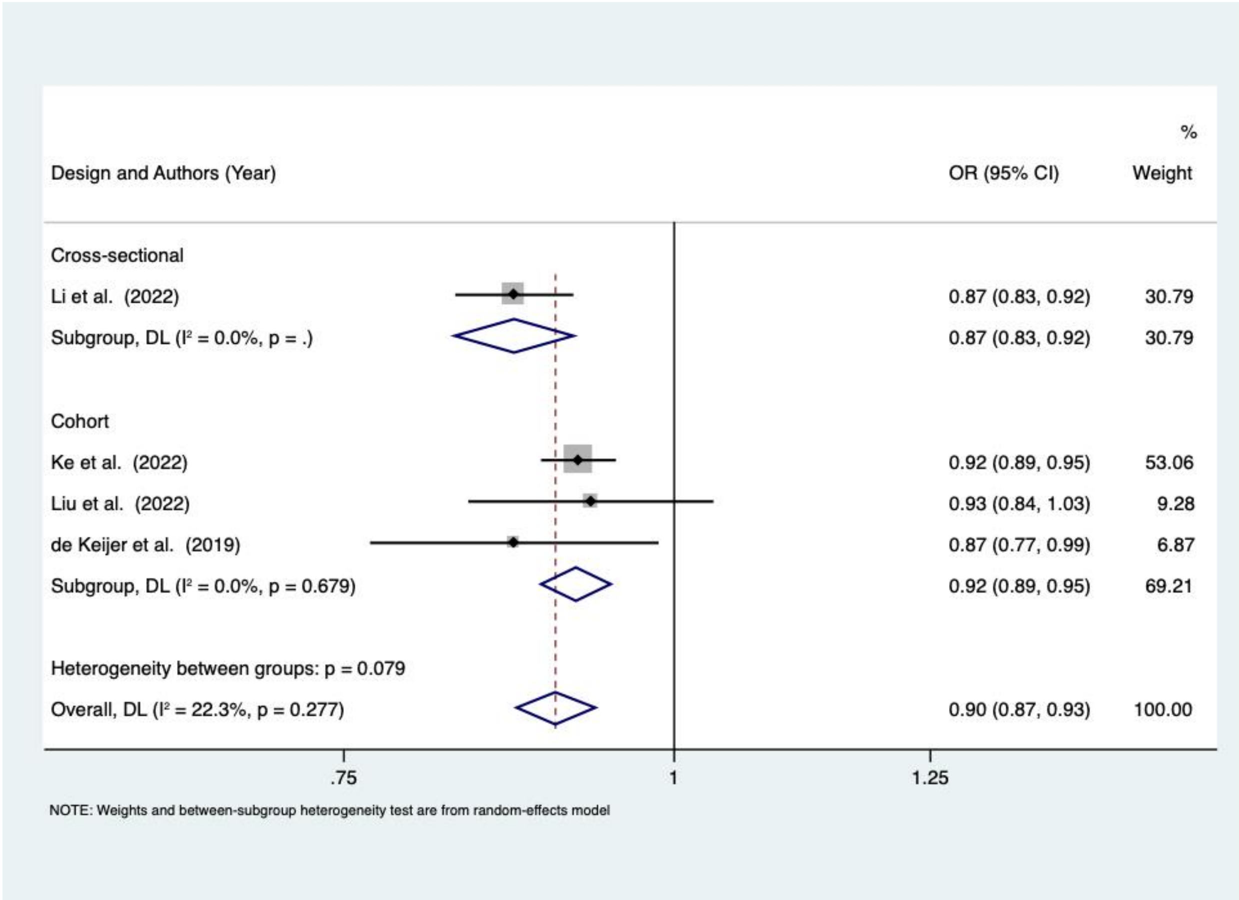


Figure 4. Meta-analysis of increase in mean NDVI with metabolic syndrome.

Sensitivity analyses using a leave-one-out method were not indicative of any influential study **(Table S11).** No evidence of publication bias for studies (Egger's test: p>0.05) with NDVI and metabolic syndrome outcome was observed **(Figure 5).**

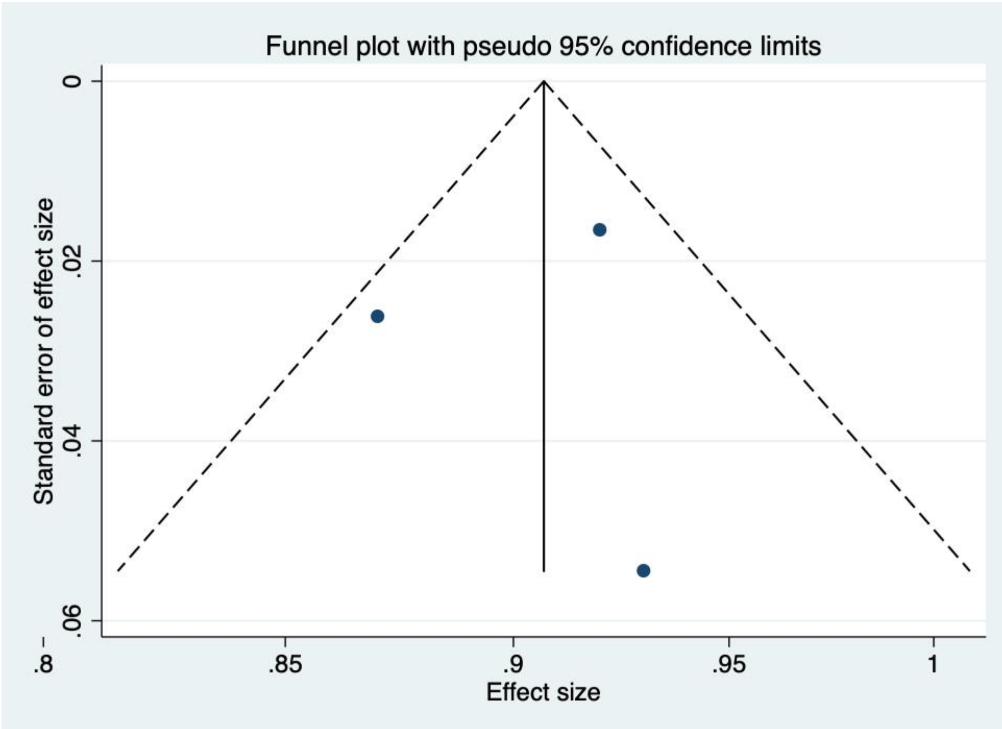


Figure 5. Funnel plot to estimate publication bias for green space and metabolic syndrome association.

3.5. Built environment and metabolic syndrome association

The summary of studies investigating the association between the built environment and metabolic syndrome is presented in **Figure 3** and **Table 1**. Nine studies, comprising six cross-sectional studies (Aguilera et al., 2021; Baldock et al., 2012; Barnett et al., 2022; Barr et al., 2016; Dengel et al., 2009; Joseph and Vega-lopez, 2020), one ecological (Letellier et al., 2022) and two cohort studies (Zhu et al., 2023; Braun et al., 2016), reported on the association between the built environment and metabolic syndrome. Due to high heterogeneity in exposure-outcome pairs, a meta-analysis was not possible.

Among the three cross-sectional studies examining local land-use mix (Baldock et al., 2012; Barnett et al., 2022; Dengel et al., 2009), one study (Baldock et al., 2012) reported that perceived local land-use mix protective against metabolic syndrome. However, the remaining two studies found no significant association between them (Barnett et al., 2022; Dengel et al., 2009).

Three cross-sectional studies investigated the association between traffic-related measures and metabolic syndrome (Aguilera et al., 2021; Barnett et al., 2022; Dengel et al., 2009). Among them, one study reported a harmful association between longer streets within the 500m impact zone and the risk of metabolic syndrome (Aguilera et al., 2021). However, the remaining two studies did not find any association between any type of traffic measures and metabolic syndrome (Barnett et al., 2022; Dengel et al., 2009).

Three studies, including two cross-sectional (Braun et al., 2016; Joseph and Vega-lopez, 2020) and one cohort study (Zhu et al., 2023), reported associations between walkability and metabolic syndrome. Among these, the cohort study found that higher walkability was associated with a lower risk of metabolic syndrome (Zhu et al., 2023). However, the remaining two studies did not identify any significant associations in this regard (Braun et al., 2016; Joseph and Vega-lopez, 2020).

Two cross-sectional studies (Barr et al., 2016; Dengel et al., 2009) and one ecological study (Letellier et al., 2022) investigated the association between public transportation accessibility and metabolic syndrome. None of these studies identified significant associations. Furthermore, two cross-sectional studies found no significant association between population density (Barnett et al., 2022) or residential density (Dengel et al., 2009) and metabolic syndrome.

3.6. Risk of bias assessment

The details of the risk of bias assessment for individual studies are illustrated in **Table S11**. The risk of bias varied dramatically across individual domains (Table 2). Bias in exposure classification reported a 33% 'Probably low' risk of bias. Only 6% showed a 'High' risk of bias, and the remaining showed a 'Definitely low' risk of bias for outcome measurements. Meanwhile, 17% of the articles reported a 'High' risk due to confounding. Higher shares of 'Definitely low' risk of bias were found for selection bias (83%), attrition/exclusion bias (89%), selective reporting bias (100%), conflict of interest (100%) and other bias (100%), respectively.

For green space, 54% of studies showed a 'Probably low' risk of bias for exposure classification. All studies showed a 'Definitely low' risk of bias in outcome classification, attrition bias, selective reporting bias, conflict of interest and other biases. Only 36% of studies reported 'Definitely low' risk bias due to confounding, while 92% of studies reported such risk for selection bias domain.

For the built environment, all studies showed a 'Probably high' risk of bias for exposure classification. All studies showed a 'Definitely low' risk of bias in selective reporting bias, conflict of interest and other biases. 9 out of 10 studies reported a 'Definitely low' risk of bias in outcome classification. Only 22% of studies reported 'Definitely low' risk bias due to confounding, while 67% of studies reported such risk for selection bias domain.

Table 2. Risk of bias rating for included studies determined by the OHAT tool.

Author (s), Year	Detection bias for exposure	Detection bias for outcome	Confounding bias	Selection bias	Attrition/exclusion bias	Selective reporting bias	Conflict of interest bias	Other bias
Aguilera et al., 2021	-	--	--	+	++	++	++	++
Baldock et al., 2012	-	++	++	++	++	++	++	++
Baldock et al., 2018	-	++	+	++	++	++	++	++
Barnett et al., 2022	-	++	+	-	++	++	++	++
Barr et al., 2016	-	++	+	++	++	++	++	++
Braun et al., 2016	-	++	++	++	-	++	++	++

de Keijzer et al., 2019	+	++	++	++	++	++	++	++
Dengel et al., 2009	-	++	--	++	++	++	++	++
Joseph and Vega-lopez 2020	-	++	-	+	+	++	++	++
Ke et al., 2022	+	++	+	++	++	++	++	++
Letellier et al., 2022	-	++	--	++	++	++	++	++
Li et al., 2022	+	++	++	++	++	++	++	++
Liu et al., 2022	+	++	++	++	++	++	++	++
Tharrey et al., 2023	+	++	+	++	++	++	++	++
Tsiampalis et al., 2021	-	++	-	++	++	++	++	++
Voss et al., 2021	+	++	+	++	++	++	++	++
Yang et al., 2019	-	++	++	++	++	++	++	++
Zhu et al., 2023	-	++	+	++	++	++	++	++
++ Definitely low	+	Probably low	-	Probably high	--	High		

3.7. Overall quality of evidence

Our assessments, guided by the criteria for evaluating evidence quality outlined in Table S12, yielded the following conclusions. For green space, a downgrade of one level was supported for ‘risk of bias’ as most studies in the review reported a ‘Probably high’ risk of bias in exposure classification detection. Similarly, a downgrade of one level was applied to the built environment for ‘risk of bias’ as most studies had a ‘Probably high’ risk of bias in exposure classification detection and several studies had a ‘Probably high’ risk bias for confounding variables adjustment. Consequently, the quality of evidence for both exposure-outcome pairs was low **(Table S13).**

3.8. Strength of evidence

Following the established criteria for evaluating the strength of evidence as outlined in Table S5, we conducted the following assessments. For green space-metabolic syndrome, the evidence was classified as "limited,” indicating that increased green space exposure is associated with a lower risk of metabolic syndrome. For the built environment-metabolic syndrome association, the evidence was graded as “inadequate” (Table S12).

4. Discussion

4.1. Summary of the key findings

We present the inaugural systematic review and meta-analysis of associations between green space and the built environment with metabolic syndrome. Most notably, our meta-analysis of NDVI and metabolic syndrome supports the potential benefits of green space in playing a protective role in the risk of metabolic syndrome. This finding is consistent with previous reviews and meta-analyses that indicate beneficial associations of green space on cardiovascular mortality (X.-X. Liu et al., 2022), blood pressure levels/hypertension (Zhao et al., 2022) and overweight and obesity status (Luo et al., 2020). However, the findings of our meta-analysis require cautious interpretation due to several factors. The overall low quality of evidence across studies, as per GRADE classification, could impact the reliability of the evidence. Thus, while suggesting potential associations, the evidence falls short of definitiveness.

In terms of the built environment, meta-analysis was not possible due to the high heterogeneity of exposure-outcome pairs. The reviewed studies presented a mixed view on the connection between the built environment and metabolic syndrome. Most studies in this domain did not find a significant association, indicating that traditional measurements of built environment features may not consistently relate to metabolic syndrome risk. Nevertheless, two studies suggested protective associations, emphasizing the positive impact of specific built environment aspects like local land-use mix (Baldock et al., 2012) and walkability (Zhu et al., 2023). This aligns with prior research indicating that areas with diverse land uses enhance walkability and reduce risks of noncommunicable diseases (Hamer and Chida, 2008). Walkable neighborhoods can promote physical activity, reduce sedentary behavior, and influence better dietary choices, potentially benefiting metabolic syndrome (Mackenbach et al., 2014). Furthermore, one study indicated that longer street distances may increase the risk of metabolic syndrome (Aguilera et al., 2021), possibly due to the discouragement of physical activity in environments where essential amenities are farther apart. However, findings should be approached cautiously, given the studies showing probably high risk of bias for exposure classification detection.

4.2. Potential mechanisms

The potential mechanisms through which green space and the built environment can influence metabolic syndrome are likely complex and multifaceted. While there is ongoing research in this area, several potential mechanisms and pathways have been suggested. One prominent mechanism is the positive impact of green space exposure on mental health. The stress reduction theory suggests that green spaces can induce a sense of emotional well-being and calming effects (Ulrich, 1983). Thus, exposure to green spaces can promote relaxation and stress reduction, which may indirectly affect metabolic health. A previous meta-analysis concluded that individuals with lower stress are less likely to have metabolic syndrome (Kuo et al., 2019). A second mechanism is the possibility of attention restoration (Kaplan, 1995) to reduce metabolic syndrome risk. Studies reported that there is a bidirectional association between mental health disorders and increases in metabolic syndrome risk (Nousen et al., 2014). Attention restoration in green space is associated with improved psychological well-being, including reduced symptoms of depression and anxiety (Lei, 2018). Thus, better mental health can lead to healthier lifestyle choices and behaviors that lower metabolic syndrome risk.

Encouraging physical activity in green spaces and the built environment is another potential pathway to reduce metabolic syndrome risk (Richardson et al., 2017). The availability of green spaces and recreational areas can promote activities like walking, jogging, and cycling (Feng et al., 2021). Accessible public transportation and pedestrian-friendly infrastructure further encourage walking and cycling for daily activities (Nieuwenhuijsen, 2020). Walkable neighborhoods with well-connected sidewalks and parks are associated with reduced metabolic syndrome risk (Wan Mohammad et al., 2021). In this review, one study found higher walkability to be associated with reduced metabolic syndrome risk (Zhu et al., 2023). Regular physical activity aids in controlling body weight, regulating glucose levels, and enhancing insulin sensitivity (Syeda et al., 2023). However, the mediating role of physical activity in the relationship between green space and health is inconsistent (Dzhambov et al., 2018) and may depend on factors like quality and safety (Klompmaker et al., 2018). Six studies used physical activity as a mediator, and only two mediated the association (Chen et al., 2023; de Keijzer et al., 2019).

Improving personal behaviors and lifestyle, such as avoiding smoking, reducing alcohol consumption, and eating a balanced diet, can also improve metabolic health (Choi et al., 2019). Studies suggest that green space may reduce unhealthy consumption behaviors, including smoking and alcohol consumption (Martin et al., 2019; Zhang et al., 2023). Moreover, sleep quality is a factor in metabolic syndrome risk (Che et al., 2021), and several studies suggest that green space exposure may improve sleep quality (Shin et al., 2020), which, in turn, can improve metabolic health.

Access to green spaces and recreational facilities offers alternatives to sedentary behaviors, reducing the risk of metabolic syndrome associated with prolonged television viewing or excessive screen time (Squillacioti et al., 2023; Edwardson et al., 2012). Natural settings and well-designed urban spaces can facilitate social interaction and community engagement (Astell-Burt et al., 2022). Social support and a sense of belonging can positively influence lifestyle choices, including diet and physical activity, which are key factors in metabolic syndrome prevention (Jennings and Bamkole, 2019; Joseph and Vega-López, 2020).

Addressing environmental hazards, such as air pollution (Mueller et al., 2020) and heat (Doick et al., 2014), and promoting a healthier microbiota (Mills et al., 2020) could also be potential mechanisms linking green space with reduced metabolic syndrome risk. Air pollution, a known contributor to chronic inflammation, has been linked to the development of metabolic syndrome (Wei et al., 2016). Four studies (Chen et al., 2023; de Keijzer et al., 2019; Li et al., 2022; Yang et al., 2019) found air pollution mediated the associations between green space and metabolic syndrome. One reported that lower walkability with high NO_2 was associated with increased metabolic syndrome risk (Zhu et al., 2023). Green spaces can enhance air quality and reduce heat, mitigating metabolic syndrome risk (Nowak et al., 2014).

4.3. Limitation of existing studies

Several exposure-related factors limit the prevailing literature's ability to examine green space and metabolic syndrome outcomes robustly. Temporality is a crucial consideration in epidemiological research as it helps establish the direction of causality and provides insights into whether exposure precedes or follows changes in health outcomes (Rothman & Greenland 2005). Most studies in this review were cross-sectional, limiting the opportunity to establish causality.

Studies in this review primarily focused on green space availability, overlooking essential aspects like accessibility, quality, and utilization. The limitation lies in the exclusive emphasis on quantity rather than factors like distance to green spaces or their usability (Sanders et al., 2015). Only one study in the review considered accessibility through distance to public green spaces (Baldock et al., 2018). None of the studies accounted for the quality of green space exposure, which is crucial for understanding its impact on health outcomes (Ye et al., 2022). Enhancing the measurement of green space and built environment exposure is vital for informed investment and decision-making. Similarly, while studies on built environment exposure addressed traffic-related measures, walkability, and transportation, they often overlooked neighborhood open spaces and quality that may play a significant role in physical activity and would translate into a benefit for metabolic health (Wang et al., 2019).

Exposure accuracy relies on factors like data sources, resolution, and greenspace categorization (Liao et al., 2021). Most reviewed studies used satellite data for greenspace assessment, though these data may not fully capture how individuals experience green space in urban areas. When assessing the built environment, studies predominantly used geospatial information systems (GIS) technology, but varied estimates hindered comparability. Limited use of perceived measures, such as land-use mix, walkability, and transportation, also posed exposure measurement risks. Most studies in this review measured green space and the built environment at the residence level, neglecting exposure at schools or workplaces where substantial time is spent and crucial for promoting healthy development (Gong et al., 2016). Additionally, the dynamic nature of the urban environment and individual influences on health outcomes were not addressed. The studies that measured green space availability within buffers around points of interest, such as homes, were constrained mainly to straight-line measures that might not effectively capture walking or commuting routes (Labib, Lindley and Huck, 2020; Ye et al., 2022). In contrast, built environment studies often didn't use buffer sizes, with some arguing that large buffers might overlook finer-scale variations. Street-network buffers, deemed more effective in capturing local accessibility (James et al., 2014), were employed in two of the reviewed studies (Barnett et al., 2022; Dengel et al., 2009).

Most studies of this review did not provide detailed explanations for mediation mechanisms. Studies using traditional statistical mediation analysis methods can have limitations, particularly in cases where multiple mediating pathways exist (Dzhambov et al., 2020). The requirement for a non-zero total effect larger than the direct effect can lead to incorrect conclusions. Further, inappropriate adjustment for intermediate behavioral variables when estimating the total effect of an exposure on an outcome can lead to over-adjustment and erroneous null findings. Studies did not consider sedentary behavior (e.g., TV viewing, car driving) as a mediator that might have an impact on metabolic health.

Future research can enhance existing literature by carefully examining multiple measures of SES (individual- and area-level income, educational achievement, home value) and urbanicity (population density, residential density) to address residual confounding and moderating effects (Browning et al., 2022; Browning and Rigolon, 2018; Rigolon et al., 2021). Prioritizing individual-level, quasi-experimental, and longitudinal designs is crucial, aligning with the need for implementation science in this research field (Marvier et al., 2023). Diverse green space exposure metrics, including objective (e.g., NDVI, MSAVI, street view metrics), subjective, and expert assessments of accessibility, availability, and visibility (Labib, Lindley and Huck, 2020) within network buffers or GPS trajectories, are crucial. Key focal points for future research should explore the dynamic nature of the built environment, incorporating factors like neighborhood open spaces and quality within network buffers to understand the built environment's multifaceted impact on health outcomes. Last, this review underscores the need for more advanced statistical methods, careful consideration of mediating mechanisms, and a broader exploration of behavioral factors, including sedentary behavior.

4.6. Limitations and future research needs

The heterogeneity among studies prevented us from conducting meta-analyses for the built environment and metabolic syndrome. Restricting our search to English keywords limited our ability to capture research conducted in non-English-speaking countries. This could affect the generalizability of our findings and overlook important cultural or geographical variations in the relationship between green space, health, and healthcare costs. Our review summarized information mainly from high-income countries rather than low- and middle-income countries (LMICs) with substantial healthcare burdens and inequities in access to green space (Rigolon et al., 2018). Tailoring research to local contexts, considering factors like climate and culture, would inform whether nature-based solutions can potentially reduce healthcare outcomes globally.

5. Conclusion

This systematic review examined 18 studies of associations between green space, built environment, and metabolic syndrome risk. While the available evidence is limited, our meta-analysis suggests a potential benefit of green space in reducing metabolic syndrome risk. Two studies on built environment features indicated that walkability and land-use mix were also associated with a reduced risk of metabolic syndrome; however, the strength of evidence for the built environment was inadequate. These findings underscore the need for more robust research methods, such as longitudinal studies with multiple exposure measurements and outcome assessments, to better understand these complex relationships. Our review also highlights a significant gap in scientific knowledge concerning the impact of environmental exposures on metabolic syndrome outcomes in LMICs. These regions have unique climates, economies and cultures. Study findings from other areas may not directly apply to LMIC contexts. Conducting well-designed longitudinal studies in diverse urban settings and thoroughly examining the underlying mechanisms can enhance our understanding of these relationships and their implications.

Author contributions

M.M.P., conceptualized the study, administered the project, developed methodology, conducted data curation & analysis, wrote the original draft, and created visualizations; M.J.Z.S., developed methodology, conducted analysis, contributed to reviewing & editing; S.A., conceptualized the study, conducted data curation, wrote the original draft; P.D., M.H.E.M.B., & M.A.A., conceptualized the study, developed methodology, contributed to reviewing & editing; M.L.B. & P.J., contributed to methodology development, contributed to reviewing & editing; T.A.B., contributed to reviewing and editing

All authors review and approve the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

References

Aguilera, J., Jeon, S., Chavez, M., Ibarra-Mejia, G., Ferreira-Pinto, J., Whigham, L.D., Li, W.W., 2021. Land-use regression of long-term transportation data on metabolic syndrome risk factors in low-income communities, in: Transportation Research Record. pp. 955–969. https://doi.org/10.1177/03611981211021853

Allen, L., Cobiac, L., Townsend, N., 2017. Quantifying the global distribution of premature mortality from non-communicable diseases. J. Public Heal. (United Kingdom) 39, 698–703. https://doi.org/10.1093/pubmed/fdx008

Astell-Burt, T., Hartig, T., Putra, I.G.N.E., Walsan, R., Dendup, T., Feng, X., 2022. Green space and loneliness: A systematic review with theoretical and methodological guidance for future research. Sci. Total Environ. 847, 157521. https://doi.org/10.1016/J.SCITOTENV.2022.157521

Baldock, K., Paquet, C., Howard, N., Coffee, N., Hugo, G., Taylor, A., Adams, R., Daniel, M., 2012. Associations between resident perceptions of the local residential environment and metabolic syndrome. J. Environ. Public Health 2012. https://doi.org/10.1155/2012/589409

Baldock, K., Paquet, C., Howard, N.J., Coffee, N.T., Taylor, A.W., Daniel, M., 2018. Are perceived and objective distances to fresh food and physical activity resources associated with cardiometabolic risk? Int. J. Environ. Res. Public Health 15. https://doi.org/10.3390/ijerph15020224

Balshem, H., Helfand, M., Schünemann, H.J., Oxman, A.D., Kunz, R., Brozek, J., Vist, G.E., Falck-Ytter, Y., Meerpohl, J., Norris, S., Guyatt, G.H., 2011. GRADE guidelines: 3. Rating the quality of evidence. J. Clin. Epidemiol. 64, 401–406. https://doi.org/10.1016/j.jclinepi.2010.07.015

Barnett, A., Martino, E., Knibbs, L.D., Shaw, J.E., Dunstan, D.W., Magliano, D.J., Donaire-Gonzalez, D., Cerin, E., 2022. The neighbourhood environment and profiles of the metabolic syndrome. Environ. Heal. A Glob. Access Sci. Source 21. https://doi.org/10.1186/s12940-022-00894-4

Barnett, D.W., Barnett, A., Nathan, A., Van Cauwenberg, J., Cerin, E., 2017. Built environmental correlates of older adults' total physical activity and walking: A systematic review and meta-analysis. Int. J. Behav. Nutr. Phys. Act. https://doi.org/10.1186/s12966-017-0558-z

Barr, A., Bentley, R., Simpson, J.A., Scheurer, J., Owen, N., Dunstan, D., Thornton, L., Krnjacki, L., Kavanagh, A., 2016. Associations of public transport accessibility with walking, obesity, metabolic syndrome and diabetes. J. Transp. Heal. 3, 141–153. https://doi.org/10.1016/j.jth.2016.01.006

Braun, L.M., Rodríguez, D.A., Evenson, K.R., Hirsch, J.A., Moore, K.A., Diez Roux, A. V., 2016. Walkability and cardiometabolic risk factors: Cross-sectional and longitudinal associations from the Multi-Ethnic Study of Atherosclerosis. Heal. Place 39, 9–17. https://doi.org/10.1016/j.healthplace.2016.02.006

Browning, M.H.E.M., Rigolon, A., 2018. Do Income, Race and Ethnicity, and Sprawl Influence the Greenspace-Human Health Link in City-Level Analyses? Findings from 496 Cities in the United States. Int. J. Environ. Res. Public Health 15, 1541. https://doi.org/10.3390/ijerph15071541

Browning, M.H.E.M., Rigolon, A., McAnirlin, O., Yoon, H. (Violet), 2022. Where greenspace matters most: A systematic review of urbanicity, greenspace, and physical health. Landsc. Urban Plan. https://doi.org/10.1016/j.landurbplan.2021.104233

Cao, N.-W., Zhou, H.-Y., Du, Y.-J., Li, X.-B., Chu, X.-J., Li, B.-Z., 2023. The effect of greenness on allergic rhinitis outcomes in children and adolescents: A systematic review and meta-analysis. Sci. Total Environ. 859, 160244. https://doi.org/10.1016/j.scitotenv.2022.160244

Carson, V., Tremblay, M.S., Chaput, J.P., Chastin, S.F.M., 2016. Associations between sleep duration, sedentary time, physical activity, and health indicators among Canadian children and youth using compositional analyses. Appl. Physiol. Nutr. Metab. 41, S294–S302. https://doi.org/10.1139/apnm-2016-0026

Chandrabose, M., Rachele, J.N., Gunn, L., Kavanagh, A., Owen, N., Turrell, G., Giles-Corti, B., Sugiyama, T., 2019. Built environment and cardio-metabolic health: systematic review and meta-analysis of longitudinal studies. Obes. Rev. https://doi.org/10.1111/obr.12759

Che, T., Yan, C., Tian, D., Zhang, X., Liu, X., Wu, Z., 2021. The Association Between Sleep and Metabolic Syndrome: A Systematic Review and Meta-Analysis. Front. Endocrinol. (Lausanne). 12. https://doi.org/10.3389/fendo.2021.773646

Chen, L., Jia, Y., Guo, Y., Chen, G., Ciren, Z., Chen, H., Duoji, Z., Xu, J., Yang, T., Xu, H., Feng, S., Jiang, Y., Guo, B., Meng, Q., Zhao, X., 2023. Residential greenness associated with decreased risk of metabolic- dysfunction-associated fatty liver disease: Evidence from a large population-based epidemiological study. Ecotoxicol. Environ. Saf. https://doi.org/10.1016/j.ecoenv.2022.114338

Chew, N.W.S., Ng, C.H., Tan, D.J.H., Kong, G., Lin, C., Chin, Y.H., Lim, W.H., Huang, D.Q., Quek, J., Fu, C.E., Xiao, J., Syn, N., Foo, R., Khoo, C.M., Wang, J.W., Dimitriadis, G.K., Young, D.Y., Siddiqui, M.S., Lam, C.S.P., Wang, Y., Figtree, G.A., Chan, M.Y., Cummings, D.E., Noureddin, M., Wong, V.W.S., Ma, R.C.W., Mantzoros, C.S., Sanyal, A., Muthiah, M.D., 2023. The global burden of metabolic disease: Data from 2000 to 2019. Cell Metab. 35, 414–428.e3. https://doi.org/10.1016/j.cmet.2023.02.003

Choi, S., Kim, K., Lee, J.K., Choi, J.Y., Shin, A., Park, S.K., Kang, D., Park, S.M., 2019. Association between change in alcohol consumption and metabolic syndrome: Analysis from the health examinees study. Diabetes Metab. J. 43, 615–626. https://doi.org/10.4093/dmj.2018.0128

Cohen, D.A., Ashwood, J.S., Scott, M.M., Overton, A., Evenson, K.R., Staten, L.K., Porter, D., McKenzie, T.L., Catellier, D., 2006. Public parks and physical activity among adolescent girls. Pediatrics. https://doi.org/10.1542/peds.2006-1226

Colom, A., Ruiz, M., Wärnberg, J., Compa, M., Muncunill, J., Barón-López, F.J., Benavente-Marín, J.C., Cabeza, E., Morey, M., Fitó, M., Salas-Salvadó, J., Romaguera, D., 2019. Mediterranean built environment and precipitation as modulator factors on physical activity in obese mid-age and old-age adults with metabolic syndrome: Cross-sectional study. Int. J. Environ. Res. Public Health. https://doi.org/10.3390/ijerph16050854

Connelly, F., Johnsson, R.D., Aulsebrook, A.E., Mulder, R.A., Hall, M.L., Vyssotski, A.L., Lesku, J.A., 2020. Urban noise restricts, fragments, and lightens sleep in Australian magpies. Environ. Pollut. 267. https://doi.org/10.1016/j.envpol.2020.115484

Dadvand, P., de Nazelle, A., Triguero-Mas, M., Schembari, A., Cirach, M., Amoly, E., Figueras, F., Basagaña, X., Ostro, B., Nieuwenhuijsen, M., 2012. Surrounding greenness and exposure to air pollution during pregnancy: An analysis of personal monitoring data. Environ. Health Perspect. 120, 1286–1290. https://doi.org/10.1289/ehp.1104609

Day, C., 2007. Metabolic syndrome, or What you will: Definitions and epidemiology. Diabetes Vasc. Dis. Res. https://doi.org/10.3132/dvdr.2007.003

de Keijzer, C., Basagaña, X., Tonne, C., Valentín, A., Alonso, J., Antó, J.M., Nieuwenhuijsen, M.J., Kivimäki, M., Singh-Manoux, A., Sunyer, J., Dadvand, P., 2019. Long-term exposure to greenspace and metabolic syndrome: A Whitehall II study. Environ. Pollut. 255. https://doi.org/10.1016/j.envpol.2019.113231

de Keijzer, C., Bauwelinck, M., Dadvand, P., 2020. Long-Term Exposure to Residential Greenspace and Healthy Ageing: a Systematic Review. Curr. Environ. Heal. Reports 7, 65–88. https://doi.org/10.1007/s40572-020-00264-7

Dengel, D.R., Hearst, M.O., Harmon, J.H., Forsyth, A., Lytle, L.A., 2009. Does the built environment relate to the metabolic syndrome in adolescents? Heal. Place. https://doi.org/10.1016/j.healthplace.2009.03.001

Diener, A., Mudu, P., 2021. How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective - with implications for urban planning. Sci. Total Environ. 796, 148605. https://doi.org/10.1016/J.SCITOTENV.2021.148605

Doick, K.J., Peace, A., Hutchings, T.R., 2014. The role of one large greenspace in mitigating London's nocturnal urban heat island. Sci. Total Environ. 493, 662–671. https://doi.org/10.1016/j.scitotenv.2014.06.048

Dzhambov, A.M., Browning, M.H.E.M., Markevych, I., Hartig, T., Lercher, P., 2020. Analytical approaches to testing pathways linking greenspace to health: A scoping review of the empirical literature. Environ. Res. 186. https://doi.org/10.1016/j.envres.2020.109613

Dzhambov, A.M., Markevych, I., Tilov, B., Arabadzhiev, Z., Stoyanov, D., Gatseva, P., Dimitrova, D.D., 2018. Lower Noise Annoyance Associated with GIS-Derived Greenspace: Pathways through Perceived Greenspace and Residential Noise. Int. J. Environ. Res. Public Health 15, 1533. https://doi.org/10.3390/ijerph15071533

Edwardson, C.L., Gorely, T., Davies, M.J., Gray, L.J., Khunti, K., Wilmot, E.G., Yates, T., Biddle, S.J.H., 2012. Association of sedentary behaviour with metabolic syndrome: A meta-analysis. PLoS One 7. https://doi.org/10.1371/journal.pone.0034916

Feng, X., Toms, R., Astell-Burt, T., 2021. Association between green space, outdoor leisure time and physical activity. Urban For. Urban Green. 66. https://doi.org/10.1016/j.ufug.2021.127349

Frank, L.D., Saelens, B.E., Powell, K.E., Chapman, J.E., 2007. Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? Soc. Sci. Med. https://doi.org/10.1016/j.socscimed.2007.05.053

Frumkin, H., 2013. The evidence of nature and the nature of evidence. Am. J. Prev. Med. https://doi.org/10.1016/j.amepre.2012.10.016

Gong, Y., Gallacher, J., Palmer, S., Fone, D., 2014. Neighbourhood green space, physical function and participation in physical activities among elderly men: The Caerphilly Prospective study. Int. J. Behav. Nutr. Phys. Act. https://doi.org/10.1186/1479-5868-11-40

Gong, Y., Palmer, S., Gallacher, J., Marsden, T., Fone, D., 2016. A systematic review of the relationship between objective measurements of the urban environment and psychological distress. Environ. Int. 96, 48–57. https://doi.org/10.1016/j.envint.2016.08.019

Gordon-Larsen, P., Nelson, M.C., Page, P., Popkin, B.M., 2006. Inequality in the built environment underlies key health disparities in physical activity and obesity. Pediatrics. https://doi.org/10.1542/peds.2005-0058

Haddad, P., Kutlar Joss, M., Weuve, J., Vienneau, D., Atkinson, R., Brook, J., Chang, H., Forastiere, F., Hoek, G., Kappeler, R., Lurmann, F., Sagiv, S., Samoli, E., Smargiassi, A., Szpiro, A., Patton, A.P., Boogaard, H., Hoffmann, B., 2023. Long-term exposure to traffic-related air pollution and stroke: A systematic review and meta-analysis. Int. J. Hyg. Environ. Health 247, 114079. https://doi.org/10.1016/j.ijheh.2022.114079

Hamer, M., Chida, Y., 2008. Active commuting and cardiovascular risk: A meta-analytic review. Prev. Med. (Baltim). https://doi.org/10.1016/j.ypmed.2007.03.006

Harris, R.J., Bradburn, M.J., Deeks, J.J., Altman, D.G., Harbord, R.M., Sterne, J.A.C., 2008. Metan: Fixed- and random-effects meta-analysis. Stata J. 8, 3–28. https://doi.org/10.1177/1536867x0800800102

Higgins, J.P.T., 2008. Commentary: Heterogeneity in meta-analysis should be expected and appropriately quantified. Int. J. Epidemiol. https://doi.org/10.1093/ije/dyn204

Higgins, J.P.T., Thompson, S.G., 2002. Quantifying heterogeneity in a meta-analysis. Stat. Med. 21, 1539–1558. https://doi.org/10.1002/SIM.1186

Hu, C.-Y., Yang, X.-J., Gui, S.-Y., Ding, K., Huang, K., Fang, Y., Jiang, Z.-X., Zhang, X.-J., 2021. Residential greenness and birth outcomes: A systematic review and meta-analysis of observational studies. Environ. Res. 193, 110599. https://doi.org/10.1016/j.envres.2020.110599

Huang, P.L., 2009. A comprehensive definition for metabolic syndrome. DMM Dis. Model. Mech. https://doi.org/10.1242/dmm.001180

Jago, R., Baranowski, T., Harris, M., 2016. Relationships Between GIS Environmental Features and Adolescent Male Physical Activity: GIS Coding Differences. J. Phys. Act. Heal. https://doi.org/10.1123/jpah.3.2.230

James, P., Berrigan, D., Hart, J.E., Aaron Hipp, J., Hoehner, C.M., Kerr, J., Major, J.M., Oka, M., Laden, F., 2014. Effects of buffer size and shape on associations between the built environment and energy balance. Heal. Place 27, 162–170. https://doi.org/10.1016/j.healthplace.2014.02.003

Jennings, V., Bamkole, O., 2019. The Relationship between Social Cohesion and Urban Green Space: An Avenue for Health Promotion. Int. J. Environ. Res. Public Health 16, 452. https://doi.org/10.3390/ijerph16030452

Joseph, R.P., Vega-López, S., 2020. Associations of perceived neighborhood environment and physical activity with metabolic syndrome among Mexican-Americans adults: A cross sectional examination. BMC Res. Notes 13. https://doi.org/10.1186/s13104-020-05143-w

Kaplan, S., 1995. The restorative benefits of nature: Toward an integrative framework. J. Environ. Psychol. 15, 169–182. https://doi.org/10.1016/0272-4944(95)90001-2

Ke, P., Xu, M., Xu, J., Yuan, X., Ni, W., Sun, Y., Zhang, H., Zhang, Y., Tian, Q., Dowling, R., Jiang, H., Zhao, Z., Lu, Z., 2023. Association of residential greenness with the risk of metabolic syndrome in Chinese older adults: a longitudinal cohort study. J. Endocrinol. Invest. 46, 327–335. https://doi.org/10.1007/s40618-022-01904-5

Kelly, A.S., Kaufman, C.L., Steinberger, J., Dengel, D.R., 2008. Body mass index and fasting insulin explain the association between the metabolic syndrome and measures of cardiovascular risk in overweight children [WWW Document]. Diabetes, 57 (Suppl. 1), p. A490. URL https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Body+mass+index+and+fasting+insulin+explain+the+association+between+the+metabolic+syndrome+and+measures+of+cardiovascular+risk+in+overweight+children&btnG= (accessed 9.2.23).

Klompmaker, J.O., Hoek, G., Bloemsma, L.D., Gehring, U., Strak, M., Wijga, A.H., van den Brink, C., Brunekreef, B., Lebret, E., Janssen, N.A.H., 2018. Green space definition affects associations of green space with overweight and physical activity. Environ. Res. 160, 531–540. https://doi.org/10.1016/j.envres.2017.10.027

Koohsari, M.J., Sugiyama, T., Sahlqvist, S., Mavoa, S., Hadgraft, N., Owen, N., 2015. Neighborhood environmental attributes and adults' sedentary behaviors: Review and research agenda. Prev. Med. (Baltim). https://doi.org/10.1016/j.ypmed.2015.05.027

Kuo, W. chin, Bratzke, L.C., Oakley, L.D., Kuo, F., Wang, H., Brown, R.L., 2019. The association between psychological stress and metabolic syndrome: A systematic review and meta-analysis. Obes. Rev. https://doi.org/10.1111/obr.12915

Lam, J., Koustas, E., Sutton, P., Padula, A.M., Cabana, M.D., Vesterinen, H., Griffiths, C., Dickie, M., Daniels, N., Whitaker, E., Woodruff, T.J., 2021. Exposure to formaldehyde and asthma outcomes: A systematic review, meta-analysis, and economic assessment. PLoS One 16, e0248258. https://doi.org/10.1371/journal.pone.0248258

Lam, J., Sutton, P., Kalkbrenner, A., Windham, G., Halladay, A., Koustas, E., Lawler, C., Davidson, L., Daniels, N., Newschaffer, C., Woodruff, T., 2016. A systematic review and meta-analysis of multiple airborne pollutants and autism spectrum disorder. PLoS One 11. https://doi.org/10.1371/journal.pone.0161851

Lawrence, D.L., Low, S.M., 1990. The Built Environment and Spatial Form. Annu. Rev. Anthropol. https://doi.org/10.1146/annurev.an.19.100190.002321

Leal, C., Chaix, B., 2011. The influence of geographic life environments on cardiometabolic risk factors: A systematic review, a methodological assessment and a research agenda. Obes. Rev. https://doi.org/10.1111/j.1467-789X.2010.00726.x

Lei, L., 2018. The effect of neighborhood context on children's academic achievement in China: Exploring mediating mechanisms. Soc. Sci. Res. 72, 240–257. https://doi.org/10.1016/j.ssresearch.2018.03.002

Letellier, N., Zamora, S., Yang, J.A., Sears, D.D., Jankowska, M.M., Benmarhnia, T., 2022. How do environmental characteristics jointly contribute to cardiometabolic health? A quantile g-computation mixture analysis. Prev. Med. Reports 30. https://doi.org/10.1016/j.pmedr.2022.102005

Li, X., Wang, Q., Feng, C., Yu, B., Lin, X., Fu, Y., Dong, S., Qiu, G., Jin Aik, D.H., Yin, Y., Xia, P., Huang, S., Liu, N., Lin, X., Zhang, Y., Fang, X., Zhong, W., Jia, P., Yang, S., 2022. Associations and pathways between residential greenness and metabolic syndromes in Fujian Province. Front. Public Heal. https://doi.org/10.3389/fpubh.2022.1014380

Lin, L., Chu, H., Hodges, J.S., 2017. Alternative measures of between-study heterogeneity in meta-analysis: Reducing the impact of outlying studies. Biometrics 73, 156–166. https://doi.org/10.1111/biom.12543

Liu, L., Yan, L.L., Lv, Y., Zhang, Y., Li, T., Huang, C., Kan, H., Zhang, J., Zeng, Y., Shi, X., Ji, J.S., 2022. Air pollution, residential greenness, and metabolic dysfunction biomarkers: analyses in the Chinese Longitudinal Healthy Longevity Survey. BMC Public Health 22. https://doi.org/10.1186/s12889-022-13126-8

Liu, X.-X., Ma, X.-L., Huang, W.-Z., Luo, Y.-N., He, C.-J., Zhong, X.-M., Dadvand, P., Browning, M.H.E.M., Li, L., Zou, X.-G., Dong, G.-H., Yang, B.-Y., 2022. Green space and cardiovascular disease: A systematic review with meta-analysis. Environ. Pollut. 301, 118990. https://doi.org/10.1016/j.envpol.2022.118990

Liu, X.X., Ma, X.L., Huang, W.Z., Luo, Y.N., He, C.J., Zhong, X.M., Dadvand, P., Browning, M.H.E.M., Li, L., Zou, X.G., Dong, G.H., Yang, B.Y., 2022. Green space and cardiovascular disease: A systematic review with meta-analysis. Environ. Pollut. https://doi.org/10.1016/j.envpol.2022.118990

Luo, Y.N., Huang, W.Z., Liu, X.X., Markevych, I., Bloom, M.S., Zhao, T., Heinrich, J., Yang, B.Y., Dong, G.H., 2020. Greenspace with overweight and obesity: A systematic review and meta-analysis of epidemiological studies up to 2020. Obes. Rev. https://doi.org/10.1111/obr.13078

Mackenbach, J.D., Rutter, H., Compernolle, S., Glonti, K., Oppert, J.M., Charreire, H., De Bourdeaudhuij, I., Brug, J., Nijpels, G., Lakerveld, J., 2014. Obesogenic environments: A systematic review of the association between the physical environment and adult weight status, the SPOTLIGHT project. BMC Public Health 14. https://doi.org/10.1186/1471-2458-14-233

Malambo, P., Kengne, A.P., De Villiers, A., Lambert, E. V., Puoane, T., 2016. Built environment, selected risk factors and major cardiovascular disease outcomes: A systematic review. PLoS One. https://doi.org/10.1371/journal.pone.0166846

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., Richardson, E.A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., Fuertes, E., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environ. Res. https://doi.org/10.1016/j.envres.2017.06.028

Martin, L., Pahl, S., White, M.P., May, J., 2019. Natural environments and craving: The mediating role of negative affect. Heal. Place 58. https://doi.org/10.1016/j.healthplace.2019.102160

Mills, J.G., Bissett, A., Gellie, N.J.C., Lowe, A.J., Selway, C.A., Thomas, T., Weinstein, P., Weyrich, L.S., Breed, M.F., 2020. Revegetation of urban green space rewilds soil microbiotas with implications for human health and urban design. Restor. Ecol. 28, S322–S334. https://doi.org/10.1111/rec.13175

Mohamed, S.M., Shalaby, M.A., El-Shiekh, R.A., El-Banna, H.A., Emam, S.R., Bakr, A.F., 2023. Metabolic syndrome: risk factors, diagnosis, pathogenesis, and management with natural approaches. Food Chem. Adv. https://doi.org/10.1016/j.focha.2023.100335

Mueller, W., Steinle, S., Pärkkä, J., Parmes, E., Liedes, H., Kuijpers, E., Pronk, A., Sarigiannis, D., Karakitsios, S., Chapizanis, D., Maggos, T., Stamatelopoulou, A., Wilkinson, P., Milner, J., Vardoulakis, S., Loh, M., 2020. Urban greenspace and the indoor environment: Pathways to health via indoor particulate matter, noise, and road noise annoyance. Environ. Res. 180, 108850. https://doi.org/10.1016/j.envres.2019.108850

Nieuwenhuijsen, M.J., 2020. Urban and transport planning pathways to carbon neutral, liveable and healthy cities; A review of the current evidence. Environ. Int. https://doi.org/10.1016/j.envint.2020.105661

Nousen, E.K., Franco, J.G., Sullivan, E.L., 2014. Unraveling the mechanisms responsible for the comorbidity between metabolic syndrome and mental health disorders. Neuroendocrinology 98, 254–266. https://doi.org/10.1159/000355632

Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. Environ. Pollut. 193, 119–129. https://doi.org/10.1016/j.envpol.2014.05.028

O'Neill, S., O'Driscoll, L., 2015. Metabolic syndrome: A closer look at the growing epidemic and its associated pathologies. Obes. Rev. https://doi.org/10.1111/obr.12229

Ricciardi, E., Spano, G., Lopez, A., Tinella, L., Clemente, C., Elia, G., Dadvand, P., Sanesi, G., Bosco, A., Caffò, A.O., 2022. Long-Term Exposure to Greenspace and Cognitive Function during the Lifespan: A Systematic Review. Int. J. Environ. Res. Public Health 19, 11700. https://doi.org/10.3390/ijerph191811700

Richardson, E.A., Pearce, J., Shortt, N.K., Mitchell, R., 2017. The role of public and private natural space in children's social, emotional and behavioural development in Scotland: A longitudinal study. Environ. Res. 158, 729–736. https://doi.org/10.1016/j.envres.2017.07.038

Rigolon, A., Browning, M., Lee, K., Shin, S., 2018. Access to Urban Green Space in Cities of the Global South: A Systematic Literature Review. Urban Sci. 2, 67. https://doi.org/10.3390/urbansci2030067

Rigolon, A., Browning, M.H.E.M., McAnirlin, O., Yoon, H., 2021. Green Space and Health Equity: A Systematic Review on the Potential of Green Space to Reduce Health Disparities. Int. J. Environ. Res. Public Heal. 2021, Vol. 18, Page 2563 18, 2563. https://doi.org/10.3390/IJERPH18052563

Roof, K., Oleru, N., 2008. Public health: Seattle and king county's push for the built environment, in: Journal of Environmental Health.

Rooney, A.A., Boyles, A.L., Wolfe, M.S., Bucher, J.R., Thayer, K.A., 2014. Systematic review and evidence integration for literature-based environmental health science assessments. Environ. Health Perspect. 122, 711–718. https://doi.org/10.1289/ehp.1307972

Saelens, B.E., Sallis, J.F., Frank, L.D., 2003. Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literatures. Ann. Behav. Med. https://doi.org/10.1207/S15324796ABM2502_03

Saklayen, M.G., 2018. The Global Epidemic of the Metabolic Syndrome. Curr. Hypertens. Rep. https://doi.org/10.1007/s11906-018-0812-z

Sanders, T., Feng, X., Fahey, P.P., Lonsdale, C., Astell-Burt, T., 2015. Greener neighbourhoods, slimmer children? Evidence from 4423 participants aged 6 to 13 years in the Longitudinal Study of Australian children. Int. J. Obes. 39, 1224–1229. https://doi.org/10.1038/ijo.2015.69

Shin, J.C., Parab, K.V., An, R., Grigsby-Toussaint, D.S., 2020. Greenspace exposure and sleep: A systematic review. Environ. Res. 182, 109081. https://doi.org/10.1016/j.envres.2019.109081

Squillacioti, G., De Petris, S., Bellisario, V., Borgogno Mondino, E.C., Bono, R., 2023. Urban environment and green spaces as factors influencing sedentary behaviour in school-aged children. Urban For. Urban Green. 88, 128081. https://doi.org/10.1016/J.UFUG.2023.128081

Syeda, U.S.A., Battillo, D., Visaria, A., Malin, S.K., 2023. The importance of exercise for glycemic control in type 2 diabetes. Am. J. Med. Open 9, 100031. https://doi.org/10.1016/j.ajmo.2023.100031

Taylor, L., Hochuli, D.F., 2017. Defining greenspace: Multiple uses across multiple disciplines. Landsc. Urban Plan. 158, 25–38. https://doi.org/10.1016/j.landurbplan.2016.09.024

Tharrey, M., Klein, O., Bohn, T., Malisoux, L., Perchoux, C., 2023. Nine-year exposure to residential greenness and the risk of metabolic syndrome among Luxembourgish adults: A longitudinal analysis of the ORISCAV-Lux cohort study. Heal. Place 81. https://doi.org/10.1016/j.healthplace.2023.103020

Tsiampalis, T., Faka, A., Psaltopoulou, T., Pitsavos, C., Chalkias, C., Panagiotakos, D.B., 2021. The relationship of the built and food environments with the metabolic syndrome in the Athens metropolitan area: a sex-stratified spatial analysis in the context of the ATTICA epidemiological study. Hormones. https://doi.org/10.1007/s42000-021-00293-3

Ulrich, R.S., 1983. Aesthetic and Affective Response to Natural Environment, in: Behavior and the Natural Environment. pp. 85–125. https://doi.org/10.1007/978-1-4613-3539-9_4

Uwak, I., Olson, N., Fuentes, A., Moriarty, M., Pulczinski, J., Lam, J., Xu, X., Taylor, B.D., Taiwo, S., Koehler, K., Foster, M., Chiu, W.A., Johnson, N.M., 2021. Application of the navigation guide systematic review methodology to evaluate prenatal exposure to particulate matter air pollution and infant birth weight. Environ. Int. 148, 106378. https://doi.org/10.1016/J.ENVINT.2021.106378

Van Cauwenberg, J., Nathan, A., Barnett, A., Barnett, D.W., Cerin, E., 2018. Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-Time Physical Activity: A Systematic Review and Meta-Analysis. Sport. Med. https://doi.org/10.1007/s40279-018-0917-1

Voss, S., Schneider, A., Huth, C., Wolf, K., Markevych, I., Schwettmann, L., Rathmann, W., Peters, A., Breitner, S., 2021. ENVINT-D-20-01309: Long-term exposure to air pollution, road traffic noise, residential greenness, and prevalent and incident metabolic syndrome: Results from the population-based KORA F4/FF4 cohort in Augsburg, Germany. Environ. Int. 147. https://doi.org/10.1016/j.envint.2020.106364

Wan Mohammad, W.S.N., Lokman, N.I.S., Hasan, R., Hassan, K., Ramlee, N., Mohd Nasir, M.R., Yeo, L.B., Gul, Y., Abu Bakar, K.A., 2021. The implication of street network design for walkability: A review, in: IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/881/1/012058

Wang, H., Dai, X., Wu, J., Wu, X., Nie, X., 2019. Influence of urban green open space on residents' physical activity in China. BMC Public Health 19. https://doi.org/10.1186/s12889-019-7416-7

Wei, Y., Zhang, J., Li, Z., Gow, A., Chung, K.F., Hu, M., Sun, Z., Zeng, L., Zhu, T., Jia, G., Li, X., Duarte, M., Tang, X., 2016. Chronic exposure to air pollution particles increases the risk of obesity and metabolic syndrome: Findings from a natural experiment in Beijing. FASEB J. 30, 2115–2122. https://doi.org/10.1096/fj.201500142

WHO, 2013. Global action plan for the prevention and control of noncommunicable diseases 2013-2020. World Heal. Organ. https://doi.org/978 92 4 1506236

World Health Organization, 2018. Noncommunicable diseases country profiles 2018. World Health Organization, World Health Organisation.

Yang, B.Y., Liu, K.K., Markevych, I., Knibbs, L.D., Bloom, M.S., Dharmage, S.C., Lin, S., Morawska, L., Heinrich, J., Jalaludin, B., Gao, M., Guo, Y., Zhou, Y., Huang, W.Z., Yu, H.Y., Zeng, X.W., Hu, L.W., Hu, Q., Dong, G.H., 2020. Association between residential greenness and metabolic syndrome in Chinese adults. Environ. Int. https://doi.org/10.1016/j.envint.2019.105388

Yang, B.Y., Zhao, T., Hu, L.X., Browning, M.H.E.M., Heinrich, J., Dharmage, S.C., Jalaludin, B., Knibbs, L.D., Liu, X.X., Luo, Y.N., James, P., Li, S., Huang, W.Z., Chen, G., Zeng, X.W., Hu, L.W., Yu, Y., Dong, G.H., 2021. Greenspace and human health: An umbrella review. Innovation. https://doi.org/10.1016/j.xinn.2021.100164

Ye, T., Yu, P., Wen, B., Yang, Z., Huang, W., Guo, Y., Abramson, M.J., Li, S., 2022. Greenspace and health outcomes in children and adolescents: A systematic review. Environ. Pollut. 314, 120193. https://doi.org/10.1016/j.envpol.2022.120193

Yuan, Y., Huang, F., Lin, F., Zhu, P., Zhu, P., 2021. Green space exposure on mortality and cardiovascular outcomes in older adults: a systematic review and meta-analysis of observational studies. Aging Clin. Exp. Res. https://doi.org/10.1007/s40520-020-01710-0

Zare Sakhvidi, M.J., Mehrparvar, A.H., Zare Sakhvidi, F., Dadvand, P., 2023. Greenspace and health, wellbeing, physical activity, and development in children and adolescents: An overview of the systematic reviews. Curr. Opin. Environ. Sci. Heal. 32, 100445. https://doi.org/10.1016/j.coesh.2023.100445

Zhang, T., Huang, B., Yan, Y., Lin, Y., Wong, H., Wong, S.Y. shan, Chung, R.Y.N., 2023. Associations of residential greenness with unhealthy consumption behaviors: Evidence from high-density Hong Kong using street-view and conventional exposure metrics. Int. J. Hyg. Environ. Health 249. https://doi.org/10.1016/j.ijheh.2023.114145

Zhang, Y., van Dijk, T., Wagenaar, C., 2022. How the Built Environment Promotes Residents' Physical Activity: The Importance of a Holistic People-Centered Perspective. Int. J. Environ. Res. Public Health. https://doi.org/10.3390/ijerph19095595

Zhao, Y., Bao, W.W., Yang, B.Y., Liang, J.H., Gui, Z.H., Huang, S., Chen, Y.C., Dong, G.H., Chen, Y.J., 2022. Association between greenspace and blood pressure: A systematic review and meta-analysis. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2021.152513

Zhu, Z., Yang, Z., Zhang, X., Yu, L., Yang, D., Guo, F., Meng, L., Xu, L., Wu, Y., Li, T., Lin, Y., Shen, P., Lin, H., Shui, L., Tang, M., Jin, M., Wang, J., Chen, K., 2023. Association of walkability and NO2 with metabolic syndrome: A cohort study in China. Environ. Int. 171. https://doi.org/10.1016/j.envint.2023.107731