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Review article

Modelling the effects of vegetation and urban form on air quality in real urban environments: A systematic review of measurements, methods, and predictions

Mengxue Yao [a], Michael Smith [b], Chengzhi Peng [a,*]

[a] School of Architecture and Landscape, The Arts Tower, University of Sheffield, S10 2TN, UK
[b] Department of Computer Science, Regent Court, University of Sheffield, S1 4DP, UK

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ABSTRACT

Air pollution poses a significant threat to public health and well-being. In recent decades, researchers have used direct measurements and predictive modelling to assess urban air quality. However, the impact of vegetation and urban form on air quality remains uncertain, particularly regarding their interconnected roles. This paper systematically reviews studies on real urban environments, focusing on how vegetation and urban form influence air quality assessment and prediction. It highlights key variables and their importance, as reported in the literature, and identifies areas needing further research to improve predictions of vegetation's effects on urban air quality in relation to urban morphology.

1. Introduction

1.1. Background and importance

Air pollution has long been a by-product of energy extraction from carbon-based combustion, driving production and consumption at scales that significantly threaten human and ecological health (Perera, 2018, Myers et al., 2013, Tong et al., 2022). As social-economic developments evolve, the sources and interactions of air pollutants have become more diverse and complex. For instance, the primary air pollutants commonly observed in Europe include particulate matter (PM), black carbon (BC), sulphur oxides (SOx), nitrogen oxides (NOx), ammonia (NH3), carbon monoxide (CO), methane (CH4), non-methane volatile organic compounds and certain metals and poly-cyclic aromatic hydrocarbons (EEA). The main known sources of air pollution are associated with human activities, including industrial emissions (Azarov et al., 2017), traffic emissions (Bai et al., 2022), agricultural fires (Khanal et al., 2022), and household emissions (Apte and Salvi, 2016). Natural processes, such as volcanic eruptions, dust storms, atmospheric inversions, can also cause or exacerbate air pollution (Burhan and Mukminin, 2020).

According to the "*State of Global Air 2020*" report (Hei, 2020), air pollution ranks as one of the leading causes of premature death and is closely linked to a variety of diseases. Exposure to air pollution has been strongly associated with specific health outcomes, including stroke, ischemic heart disease, chronic obstructive pulmonary disease, lung cancer, and pneumonia. Air quality has been a focus of global attention, and a number of air quality control standards, guidelines, laws, policies and agreements have been signed, such as the *WHO Global Air Quality Guidelines* (WHO, 2021), *the Clean Air Programme for Europe* (Amann et al., 2005), and *the UK Clean Air Act* (Act, 1970).

The relationship between urban form and air quality began to attract researchers' attention as early as the 1970s (Tolley and Cohen, 1976, Capannelli et al., 1977), including studies on urban vegetation (Nadel et al., 1977, Smith and Staskawicz, 1977). However, the relationships between vegetation and built urban form (i.e., urban morphological characteristics) affecting air quality are far from conclusive. In some studies, vegetation was considered a component of urban form, influencing aspects of vertical structures of an urban environment. On the other hand, vegetation was distinguished from urban form due to functional differences (e.g., natural vs. man-made and ecosystem services vs. structural functions) and the use of different metrics of measurement and analysis (e.g., biomass vs. construction density). Consequently, the impact of vegetation on air quality is often assessed under the influences of built urban form, intentionally or otherwise, making it challenging to isolate and quantify the effects of vegetation.

* Corresponding author.
E-mail address: c.peng@sheffield.ac.uk (C. Peng).

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Better understanding of the effects on air quality due to vegetation in real urban environments is required to inform urban greening planning and design decision-making.

1.2. Objectives and scope

This research aligns with the United Nations Sustainable Development Goals. Specifically, it supports Indicator 11.6.2 under Target 11.6, which specifies the annual mean levels of fine particulate matter (e.g. $PM_{2.5}$ and PM_{10}) in cities (population weighted) (Division, 2023). By addressing critical gaps in understanding the relationships between vegetation and air quality in real urban environments, this review contributes to actionable insights that can guide urban planning and policy development to achieve this target. We focus on the studies of urban air quality that examine the effects of vegetation in relation to (built) urban form characteristics. In Section 2, we first summarise the questions and findings from the previous review articles published during 2015–2023, to identify the areas for a new systematic review. In Section 3, we explain how the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) principles and protocol were applied to identify a set of 79 papers meeting the inclusion and exclusion criteria. Section 4 comprises five subsections that provide detailed analyses of the study methods and results under review: each corresponding to specific review questions. In Section 5, we discuss the key findings and implications of this systemic review in terms of the research transitions observed and the limitations of our review. We then conclude in Section 6 the significance of this review and the key pointers to further research.

2. Summary of previous reviews published in 2015–2023

We identified 23 review articles published during 2015–2023 that focused on vegetation, urban form and air quality. To inform our systematic review, we grouped and summarised these 23 review papers into four tables according to the keywords used by the authors (Appendix Tables A1a – A1d). The first set of eight reviews (listed in Appendix Table 1a) focused on vegetation's capacity to mitigate and remove air pollutants. The main questions discussed were the mitigation capacities of different vegetation strategies, such as green walls, green roofs, and green spaces/parks. Particulate matter (PM) was most discussed, along with O3, NO2, and poly-cyclic aromatic hydrocarbons (PAHs). These reviews also compared air cleaning effects according to vegetation species and traits.

The second set of six reviews in Appendix Table A1b shows a common interest in the processes and effects of vegetation on air pollution removal through deposition and dispersion. The deposition effect is considered an air pollutant capture mechanism via plant surfaces, while the dispersion effect involves transporting air pollutants through air flows, changing pollutants concentrations at different locations within the urban environment. This group of reviews discusses the deposition and aerodynamic dispersion models of green infrastructure at different scales, which include various research methods – on-site studies, wind tunnel research, and numerical simulations. Key parameters were discussed among different processes and models.

Appendix Table A1c contains seven reviews concerning the effects of vegetation in urban street canyons or open streets with or without buildings or other structures on both sides. Here, traffic emissions were the main source of air pollutants; trees and hedges planted in these urban spaces could function as porous obstacles. Other green infrastructure, such as green walls and green roofs, were of interest. Considering the combined effects of the built forms, emission patterns, there were noticeable characteristics in the concentration of air pollutants in urban streets (enclosed or open). Vegetation porosity was suggested as a parameter influencing whether barriers or obstacles reduce or increase air pollution concentrations in urban street spaces.

Finally, there are two review papers (Appendix Table A1d) summarising the studies that investigated the influence of vegetation not only on air pollution but also on other aspects of urban ecological systems, including runoff pollution removal and interactions with the intensity of urban heat and pollution islands. The reviews highlighted the increasingly multidisciplinary approaches to assessing urban vegetation as an ecosystem service.

In summary, the previous reviews have identified five focal areas of urban air quality research: (1) mitigation processes (deposition, dispersion); (2) models and parameters (numerical simulation, wind tunnel); (3) macro- and micro-structure of vegetation (e.g., leaf traits, porosity); (4) effects of plants in different urban forms and scales (street canyon, open road); and (5) ecological roles of plants in urban environments. However, these reviews also show some limitations. First, only five reviews were conducted following the PRISMA protocols (Diener and Mudu, 2021, Corada et al., 2021, Buccolieri et al., 2022, Chaudhuri and Kumar, 2022, Ernst et al., 2022). Second, the reviews reporting the effects of vegetation did not provide hierarchical correlation or regression accounts of the vegetation's effects on mitigating concentrations of air pollutants. Third, it is difficult to draw clear implications from reviews that mixed theoretical studies with studies of real urban environments. These limitations highlight key research gaps in previous reviews, including the limited focus on real urban environments and the lack of exploration into the hierarchical relationships between vegetation and air pollutants. To address these gaps, we have identified the following questions that necessitate a new systematic review:

1. What urban air quality indicators and data sources were used in the studies examining the effects of vegetation on urban air quality?
2. What metrics or indices were used to quantify the morphological characteristics of urban vegetation in studies on air quality?
3. What metrics or indices were used to quantify urban forms of real cities for air quality studies?
4. What data sources and methods were used for developing predictive models for assessing urban air quality of real urban environments?

3. Method and materials

Our systematic review follows the PRISMA framework, which provides a structured and transparent approach to reviewing the literature. This methodology addresses inconsistencies in prior reviews by ensuring that all included studies are systematically identified, screened, and evaluated based on predefined eligibility criteria. By focusing on quantitative studies conducted in real urban environments, we aim to overcome the lack of real-world validation highlighted in previous reviews. Additionally, the use of standardised metrics and comprehensive data extraction protocols ensures consistency across the studies analysed, facilitating more robust comparisons and actionable insights for urban planning and policy development.

We first explain how the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) were applied in this systematic review (Section 3.1). We then introduce the core materials that appeared in the articles identified by the search and selection criteria (Section 3.2).

3.1. Method: the PRISMA guidelines applied

The PRISMA guidelines were applied in three stages: (1) identification, (2) two-step selection – initial selection by abstract and title search, followed by selection via full-text search, and (3) grouping the identified articles into two main categories: Correlation/Regression Studies, and Prediction Models.

The following keywords were used in the initial search: 'air quality' OR 'air pollution' OR 'air pollutant' OR 'air pollutants', AND 'vegetation' OR 'green infrastructure' OR 'plant', AND 'urban' OR 'outdoor'. Publication dates were limited to 2012–2023. Scopus was selected as the database. The search focused on journal articles, including other relevant literature such as book chapters and conference papers. The initial search returned 3456 papers.

The first selection was conducted based on the search for abstracts, followed by a more detailed full-text reading and extraction. The criteria for the first selection were as follows:

Inclusion criteria:

1. Search for papers published only in English.
2. Include research articles published as open access full texts.
3. Include research articles focused on outdoor air quality and vegetation within urban areas.
4. Include research where air quality is the dependent variable and vegetation-related metrics or indices are part of the independent/explanatory variables.
5. Include studies that screen vegetation and air quality as interaction objects. For studies with additional objects, only review sections that address the influence of vegetation on air quality (e.g., interactions between vegetation, air pollution, and urban heat islands).
6. Focus on research examining the morphological characteristics of vegetation.
7. Include studies on air quality in real urban environments based on data-driven quantitative analyses or modeling.

Exclusion criteria:

1. Exclude studies on indoor air quality and indoor vegetation.
2. Exclude studies on vegetation in large non-urban environments (e.g., ecological forests, peri-urban farmlands).
3. Exclude studies related to plant adaptation or tolerance to air pollution; non-airborne pollutants (e.g., those in the rain); and vegetation effects such as ecological, economic, or social influences (e.g., effects on the thermal environment, economic benefits of greening, resident satisfaction with urban green spaces).
4. Exclude studies on the biological structures of plants (e.g., leaf traits such as wax or chlorophyll).
5. Exclude qualitative studies (e.g., guidelines, policy interpretations), numerical simulations (e.g., wind tunnels, CFD), laboratory based measurements (e.g., leaf deposition measurements), and studies of vegetation removal capacity based on biochemical processes (e.g., stomatal uptake).
6. Exclude articles primarily focused on population exposure, human health, and diseases.
7. Exclude all 23 previous review papers discussed in Section 2.

Our inclusion and exclusion criteria were intentionally designed to concentrate on specific research topics. To emphasize researches with real urban environments, we excluded numerical simulation studies. Furthermore, we did not categorise individual vegetation types—such as trees, hedges, green roofs, or green walls—because our primary objective was to summarise the vegetation indices employed in these studies. We assume that these indices are generally applicable to various types of vegetation.

Based on the above search and selection criteria, 301 papers were identified in the first round of the abstract search, of which 79 papers were retained after a more detailed extraction from the open access full texts. Fig. 1 shows the PRISMA process flowchart.

3.2. Materials: air quality, vegetation, urban morphology indicators/indices, and prediction models

Our initial summerisation of the core materials used in the 79 original research articles suggests five headings: (1) air quality indicators, (2) vegetation-related indices, (3) non-vegetation-related urban morphology indicators, (4) interrelations between vegetation and non-vegetation indices, and (5) predictive urban air quality models, as introduced below.

3.2.1. Air quality indicators

We identify nine groups of air quality indicators used in the reported urban air quality studies: particulate matter (PM), total suspended particulates (TSP), ultrafine particles (UFPs), nitrogen oxides (NOx), ozone (O3), carbon oxides (COx), sulphur dioxide (SO_2), black carbon (BC), and aerosol optical depth (AOD).

Particulate matter (PM) is a non-gaseous substance in the air composed of chemical compounds and materials. This review focuses on PM_{10}, $PM_{2.5}$, and PM_1, referring to particles smaller than 10, 2.5, and 1 micrometer in diameter, respectively.

Total suspended particulates (TSP) are airborne particulate matter

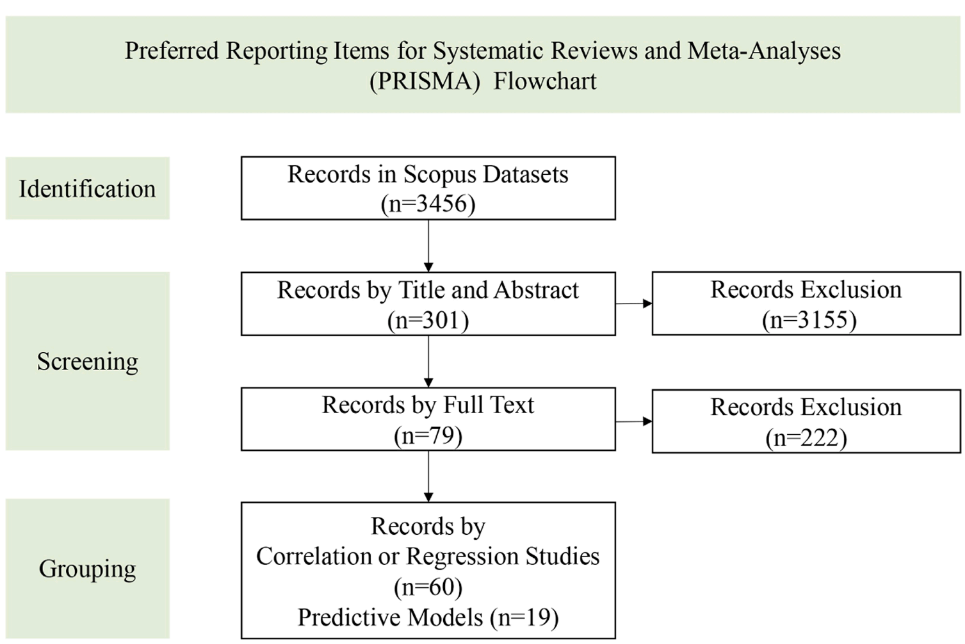

Fig. 1. Systematic literature review searching and retrieving flowchart (PRISMA).

(PM) with diameters of up to approximately 100 micrometers. These particulates originate from a variety of sources, encompassing both combustion and non-combustion activities. PM_{10}, $PM_{2.5}$, PM_1 are all components of TSP.

Ultrafine particles (UFPs) are particles characterized by an aerodynamic diameter of 0.1 μm (100 nm) or smaller. Due to their small size, UFPs can efficiently traverse the respiratory tract, reach and breach the alveolar-capillary barrier in the alveoli. Consequently, they can disseminate throughout the body via the circulatory system, posing a potential threat to human health (Kwon et al., 2020).

Nitrogen oxides (NOx) are gases produced from natural sources, motor vehicles and other fuel-burning processes. They are primarily composed of nitric oxide (NO) and nitrogen dioxide (NO_2).

Ozone (O_3) is present throughout the atmosphere. Stratospheric ozone, found in the upper atmosphere, forms a protective layer that shields life from the sun's harmful ultraviolet rays. However, ozone at ground level can be a harmful air pollutant and is the main ingredient in "smog." Ground-level ozone (O_3) does not originate directly from anthropogenic sources; rather, it is a secondary pollutant formed through a complex series of chemical reactions in the presence of sunlight.

Carbon oxides (COx). Carbon monoxide (CO) is a colourless, odourless gas released when something is burned. The primary contributors of CO to the atmosphere are automobiles, trucks, and other vehicles or machinery powered by the combustion of fossil fuels. Carbon dioxide (CO_2), another gas released from burning fossil fuels, is also colourless and non-flammable. While CO_2 is not typically considered an air pollutant, it is a significant heat-trapping (greenhouse) gas.

Sulphur dioxide (SO_2) is a corrosive, acidic gas. Approximately 99 % of atmospheric SO_2 comes from anthropogenic sources, primarily the combustion of fossil fuels such as coal, oil, and natural gas. SO_2 is a major air pollutant that is harmful to human lungs and can lead to serious respiratory diseases.

Black carbon (BC) is a component of $PM_{2.5}$, formed by the incomplete combustion of fossil fuels. BC can cause poor health and premature deaths, and it also warms the atmosphere by effectively absorbing sunlight.

Aerosol optical depth (AOD) is a dimensionless measurement that indicates how much sunlight is blocked due to the presence of fine solid particles or liquid droplets suspended in the air. As a measurement of the attenuation effects caused by atmospheric aerosols, AOD is increasingly used to evaluate the extent of ambient air pollution over large areas (Li et al., 2021a). AOD measurements can be obtained through satellite observations (Gupta et al., 2022), ground-based instruments (NOAA/ESRL, n.d.), or simulation and modelling (Boulisset et al., 2023).

3.2.2. Vegetation-related indices

Various vegetation-related indices have been defined at macro, meso, and micro scales. Based on remote sensing or aerial imaging data, macro indices (e.g., vegetation land use, landscape metrics) address large green spaces or landscape structures in cities. Meso indices (e.g., vegetation structures, green view index) focus on plant communities within city neighbourhoods or districts, where street-view images can be systematically captured and analysed. Micro indices, such as the leaf area index, deal with individual plant or vegetation characteristics.

3.2.3. Non-vegetation-related urban morphology indices

Non-vegetation-related factors and indices identified in this review include meteorological data (e.g., temperature, wind speed), urban form and structure (e.g., road length), land cover and surface (e.g., water bodies, industrial land cover), and socioeconomic factors (e.g., population density).

3.2.4. Interrelations of air quality indicators, vegetation and non-vegetation indices

We developed a novel data visualization scheme to highlight the interrelations of the air quality indicators, vegetation, and urban morphology indices (see Fig. 4). The frequency of studies on different air pollutants and their associated variables was also calculated (see **Section 4.4**).

3.2.5. Predictive modelling of urban air quality

Air quality prediction is an emerging and rapidly evolving research area, aiming to improve air quality prediction models. Combining multiple data sources, machine learning and artificial intelligence techniques are increasingly applied to enhance forecasting capabilities involving a large number of auxiliary variables.

In this review, 19 articles on air quality prediction were identified and summarised, including the modelling methods, the types of auxiliary variables used, and feature importance analysis.

4. Results

4.1. Air quality indicators and data sources

Based on the 79 papers reviewed, we identified three main sources of air quality data used in the studies: ground-level observations, satellite measurements, and online open datasets.

4.1.1. Ground-level observations

Ground-level observations are the most direct way to obtain data on air quality and various types of air pollution at the population level. The two most commonly used methods are ground-based station observations and on-site mobile measurements. The former typically involves an air quality monitoring network composed of fixed monitoring stations established or managed by government departments or specialised agencies. Generally, it features high temporal resolution but low spatial resolution, meaning the data often has temporal continuity but is geographically limited by the location and number of stations. In contrast, the latter method is more flexible, allowing researchers to use mobile tools to collect data with greater freedom in choosing sample locations. However, both are costly, requiring significant time, energy, equipment, and financial resources.

Among the 79 papers, 58 utilised ground-level observation data. Of these, 35 relied on ground-based station datasets, 22 employed on-site mobile measurement datasets, and one paper combined both methods. Appendix Table A2 summarises the sources of ground-level observation data.

4.1.2. Satellite measurements

Satellite measurement datasets are widely used as air quality data sources, employing remote sensing technologies to retrieve information via satellite imagery. This method is popular for obtaining global air quality grids due to its accessibility and availability, overcoming the location limitations of ground-based measurements and the time- and energy-intensive nature of mobile measurements. Commonly used satellite sensing instruments include Moderate Resolution Imaging Spectroradiometer (MODIS), Ozone Monitoring Instrument (OMI), Thermal Infrared Sensor (TIRS), and Visible Infrared Imaging Radiometer Suite (VIIRS). However, these datasets cannot directly distinguish concentrations of different components; instead, they retrieve target pollutant data based on the satellite's observation of aerosol optical depth (AOD). Additionally, tropospheric NO_2 can be measured through satellite images. Due to the limitations of satellite orbits, the resolution of these datasets is typically constrained. Appendix Table A3 summarises the satellite measurement datasets and their spatial resolutions.

4.1.3. Online open datasets

The retrieval process is essential for satellite measurement data to obtain target air pollution concentrations and achieve higher resolution. This typically involves using other data sources, such as ground-based observations, for calibration. By combining large amounts of data from multiple sources and undergoing rigorous screening, cleansing, computation, and validation processes, this method produces high-resolution predictions for specific areas. As a result, substantial data and computing resources are required. Consequently, some of these retrieved and validated target air pollution datasets are published online. These datasets are generally considered highly accurate and are widely used due to their high resolution and accessibility. Appendix Table A4 summarises the online public datasets used in the reviewed research articles.

For the air pollution data collected, pre-processing is essential due to issues like missing data and resolution inconsistencies. Appendix Table A5 summarises the data pre-processing methods used in the literature. Data interpolation methods, such as Inverse Distance Weighted (IDW) and Kriging, are commonly used to predict data distribution over larger areas based on a limited set of known data. Some research also uses linear regression to predict and fill in missing data. Additionally, resampling is often employed to achieve uniform dataset resolution. Ensuring data integrity is crucial for the smooth progression of subsequent studies.

4.2. Vegetation-related metrics and indices

Among these 79 papers, vegetation-related metrics and indices can be summarised into three categories: (1) Individual characteristics, (2) Satellite or street view sensing measurements, and (3) Landscape pattern metrics/indices. The vegetation type cluster primarily describes characteristics of macroscopic plant communities, including vertical and horizontal vegetation structures. Individual characteristics focus mainly on mesoscopic plant morphology traits, such as canopy and porosity. With advances in remote sensing technology and increased accessibility to open-source data, satellite and street view images have become convenient tools for quantifying vegetation characteristics in three dimensions. Landscape metrics include indices describing vegetation patch types and arrangements, widely used in landscape research. Additionally, morphological spatial pattern analysis (MSPA) is used to describe geometry and connectivity through geometric concepts, though it is not widely utilised in this research area. Table 1 presents selected vegetation-related metrics/indices in terms of definition, calculation, and unit of measurement.

Fig. 2 shows the number of articles that used various types of vegetation-related indices. Apart from the three main categories and MSPA, there is another set of metrics used in the studies, including vegetation structure (VS), and Land Use/Land Cover (LULC). NDVI is the most frequently used index, appearing in 36 papers, followed by various types of vegetation land types used in 27 papers. Landscape pattern indices constitute a broad category that includes several indices. Although different landscape pattern indices are sometimes combined in a single study, the total number of articles using them is relatively low. Overall, the application rate of indices in the macro-horizontal dimension is much higher than the usage rate of multi-dimensional indicators in the vertical dimension. For each of the vegetation-related indices/metrics used in the studies, a list of the literature reviewed is presented in Appendix Table A6.

4.3. Summary and classification of non-vegetation related indices

The non-vegetation related indicators or indices used in the literature can be classified into four clusters: (1) meteorological data, (2) urban form and structure, (3) non-vegetation land cover and surface, and (4) economic and social data. Fig. 3 shows the number of articles reviewed in terms of the non-vegetation-related indices used.

The meteorological data cluster contains 16 variables, with *wind speed*, *temperature*, and *humidity* being the top three used. The urban form and structure cluster includes 26 indicators or indices, consisting of the natural topographical characteristics of urban areas, such as *elevation* and *slope*, as well as the structural characteristics of the urban

Table 1
Summary of Vegetation-related metrics and indices.

Term	Definition	Calculator	Unit [Value range]
[1] Individual Characteristics			
Count	Vegetation/Trees Count: The total count of trees in certain areas.	$PVA = \frac{Vegetation\ Area}{Ground\ Area}$	Scalar [0, ∞]
LAI	Leaf Area Index: A dimensionless quantity characterizing plant canopies.	$LAI = \frac{Leaf\ Area}{Ground\ Area}$	Scalar [0,10]
CC/CD	Canopy Cover or Density: a ratio between the area covered by tree crowns and a total area within an area.	$Canopy\ Cover = \frac{Tree\ Crowns\ Covered\ Area}{Ground\ Area}$	Scalar [0, ∞]
DBH	Diameter at Breast Height: The tree diameter measured at 4.5 feet above the ground.	Direct measurement	Meter (m)
PS	Proportion of Species: Proportion of specific species in a green space.	$PS = \frac{The\ number\ of\ species}{The\ total\ number\ of\ vegetation}$	Scalar [0,1]
SR	Species Richness: The number of species in given samples.	$SR = \frac{The\ total\ number\ of\ species}{Area}$	Scalar [0, ∞]
Porosity	Tree Crowns/Belts Porosity: Ratio of area light penetrating trees in a planar or sectional area (*ha*).	Digital image processing	Scalar [0,1]
[2] Satellite sensing and street view scanning measurement			
Term	**Definition**	**Calculator**	**Unit [Value range]**
NDVI	Normalized Difference Vegetation Index: An index quantifies the vegetation by measuring the ratio of near-infrared (NIR) and visible red light (Red).	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$	Scalar [−1, 1]
SAVI	Soil Adjusted Vegetation Index: An index to correct NDVI for the influence of soil brightness in areas where vegetative cover (L [0,1]) is low.	$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)}*(1 + L)$	Scalar [−1, 1]
EVI	Enhanced Vegetation Index: An index to correct NDVI for atmospheric resistance (C), canopy background (L), and values from Blue band in areas with dense vegetation.	$EVI = G*\frac{(NIR - Red)}{(NIR + C1*Red - C2*Blue + L)}$	Scalar [−1, 1]
GTCT	Greenness Tasseled Cap Transformation: An index to convert	GIS-based digital image processing	% [0,100]

(*continued on next page*)

Table 1 (*continued*)

Term	Definition	Calculator	Unit [Value range]
[1] Individual Characteristics			
	satellite data into three spectral indicators with the Greenness indicator for vegetation growth cycles in particular.		
GVI	Green View Index: An objective measurement of urban green at the street level from a human-eye viewpoint.	$GVI = \frac{GreenPixelCount}{TotalPixelCount}$	% [0,100]
VGVI	Viewshed Greenness Visibility Index: In a GIS framework, $VGVI_j$ is the index value for the observer cell $_j$; G_j is the visible green cell, V_i is the visible non-green cell, and d_i is distance decay weight corresponding to visible cell *i*.	$VGVI_j = \frac{\sum_1^n G_i * d_i}{(\sum_1^n G_i * d_i) + (\sum_1^n V_i * d_i)}$ Where 0 = no green cells are visible, and 1 = all of the visible cells are green	Scalar [0,1]
[3] Landscape pattern metrics and indices			
Term	**Definition**	**Calculator**	**Unit [Value range]**
PLAND	Percentage of Landscape: Percentage of the total area of j_{th} patch of patch type *i* (a_{ij}) over the total area of the landscape (*A*).	$PLAND = \frac{\sum_{j=1}^{n} a_{ij}}{A} * 100$	% [0,100]
PD	Patch Density: Density of a certain patch in the landscape.	$PD = \frac{NP}{A}$	Patches/ km^2 [0, ∞]
MPS	Mean Patch Size is the area of all patches of patch type *i* (a_{ij}) divided by the number of the patch of type *i* (n_i), divided by 10,000 (to convert to hectare).	$MPS = \frac{\sum_{j=1}^{n} a_{ij}}{n_i} * \left(\frac{1}{10000}\right)$	Hectares
LSI	Landscape Shape Index: The ratio between the actual landscape edge length *(E)* and the hypothetical minimum edge length min E.	$LSI = \frac{E}{\min E}$ $LSI = \frac{0.25P_{ij}}{\sqrt{a_{ij}}}$	Scalar [1, ∞]
AI	Aggregation Index: The degree of aggregation or clumping.	$AI = \left[\frac{g_{ii}}{\max(g_{ii})}\right] * 100$	% [0,100]
ED	Edge Density: An landscape configuration description index which equals all edges in the landscape in relation to the landscape area.	$ED = \frac{E}{A}$	m/ha [0,∞]
AWMSI	Area-Weighted Mean Shape Index: Averaging the shape index value of all landscape patches, with the perimeter of patch (P_{ij}), the area of patch (a_{ij}), the total area of the landscape (*A*), weighted by the patch areas.	$AWMSI = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\frac{2\ln(0.25P_{ij})}{\ln(\sqrt{a_{ij}})} \left(\frac{a_{ij}}{A}\right)\right]$	Scalar [1, ∞]

environment, such *as road length* and *road density*. Among these, *elevation* and *DEM* were the most used variables. The non-vegetation land cover and surface cluster comprises variables that describe different land use types in 1- or 2-dimensional spaces. The economic and social data cluster covers population related, economic, traffic, social, and industrial activities.

4.4. Interrelations of vegetation, air quality indicators, and non-vegetation indices

The air quality indicators and associated variables of interest across the 79 papers were analysed. Among these variables, only data from more than two articles on the same air pollutant were retained. Fig. 4 shows the interrelations between air quality indicators, vegetation-related indices, and non-vegetation related indices, with the air quality indicators forming the central spine. The mapping shows that $PM_{2.5}$ is the pollutant of highest concern linked to most variables, followed by PM_{10} and NO_2. Among the vegetation related variables, those from satellite or street view imagery measurements and vegetation land type clusters were linked to more air quality indicators, while the landscape metrics cluster had a lower utilization rate. In contrast, the non-vegetation related variables/indices, as grouped in four sectors, were more evenly connected to air pollutants, with a slightly higher connection in the meteorological data.

4.5. Predictive modelling of urban air quality

Recently, identifying and evaluating variables for air quality prediction has become a focus of research. Of the 79 reviewed papers, 19 addressed urban air quality predictions. These studies outline a three-step process: (1) auxiliary variable selection, (2) predictive model development and validation, and (3) feature importance analysis. Step one involves data pre-processing, such as handling missing values and standardising dataset resolutions (see Appendix Table A5**).** Step two, the core stage, encompasses algorithm selection, parameter/hyper-parameter tuning, model training/testing, and validation (details in Appendix Table A7**)**. While the first two steps are essential, feature importance analysis is not always included. We identified at four types of prediction models and summarised their feature importance analyses.

4.5.1. Prediction methods and models

Predictive urban air quality models can be categorised into four types: (1) spatial estimation models, (2) traditional land use regression (LUR) models, (3) machine learning (ML) and deep learning (DL)

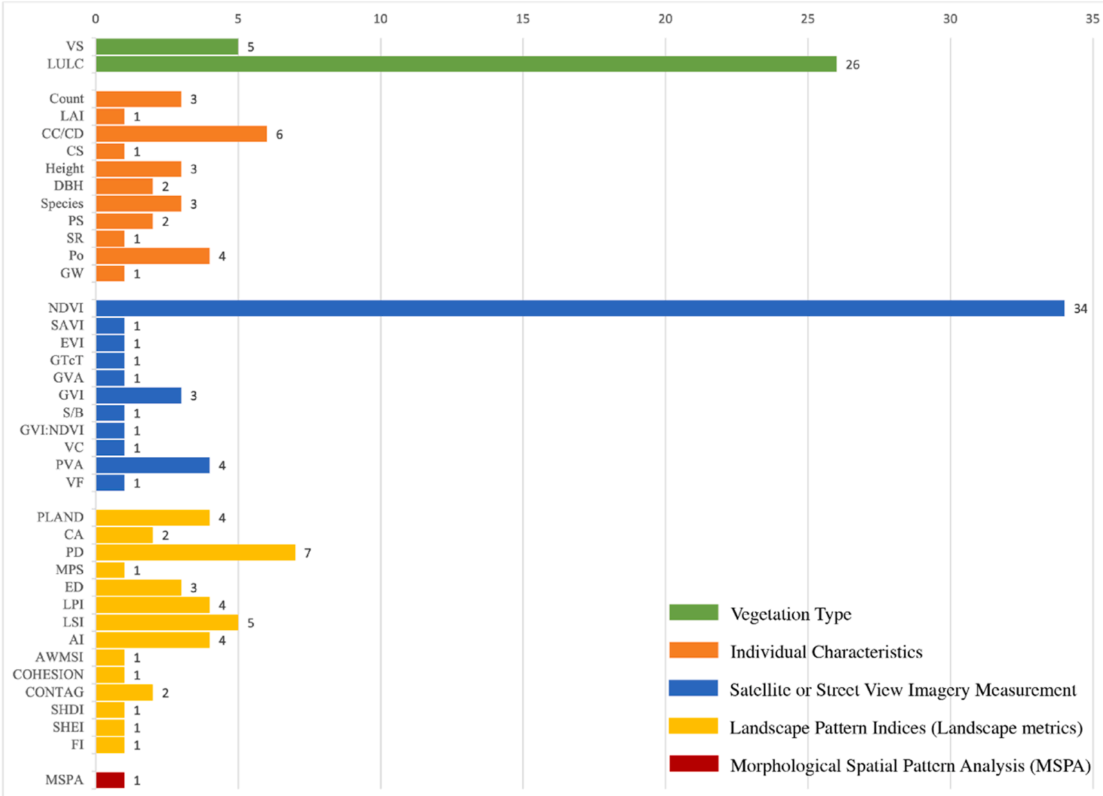

Fig. 2. Vegetation-related indices and numbers of associated research articles reviewed.

models, and (4) ML/DL LUR hybrid models.

4.5.1.1. Spatial estimation models. These are divided into two sub-types: interpolation methods and spatial regression models.

- Interpolation methods, such as Inverse Distance Weighting (IDW) and kriging (Ramos et al., 2016), estimate air quality in unmonitored areas using mathematical and geostatistical approaches. They rely on spatial relationships based on distances to known points, which often overlook other influential variables, leading to large margins of error. As a result, these methods are now primarily used for pre-processing, such as filling data gaps.
- Spatial regression models, particularly the Geographically Weighted Regression (GWR) model (Li et al., 2017), account for variable autocorrelation and heterogeneity, making them less dependent on ground-based stations.

4.5.1.2. Traditional land use regression (LUR) models. LUR models derive air quality (dependent variable) from station monitoring data and extract auxiliary variables (independent variables) are from buffer zones around the stations.

- Their accuracy is limited by station location and density, with most located in urban areas. Auxiliary variables extracted from multiple buffer zones can lead to data redundancy, collinearity and other issues, making variable selection critical. Common methods include correlation analysis and the Variance Inflation Factor (VIF).
- Although typically reliant on Multiple Linear Regression or stepwise (forward/backward) methods, LUR models struggle with non-linear relationships and handling large datasets effectively. Fig. 5 illustrates traditional LUR workflows (Han et al., 2022a; Kong and Tian, 2020; Guo et al., 2020; Van Ryswyk et al., 2019; Liu et al., 2019; Masri et al., 2019; Wu et al., 2017; Wu et al., 2015a; Meng et al., 2015; Rao et al., 2014).

4.5.1.3. Machine/deep learning prediction models. As machine learning (ML) and deep learning (DL) algorithms advance, ML/DL models are becoming as popular tools for predicting and analysing large, multidimensional datasets. These models excel at identifying non-linear relationships between air quality and auxiliary variables, surpassing traditional models by incorporating diverse data types (e.g., 3D variable indices) and sources (e.g., satellite AOD datasets) without reliance on ground monitoring stations. In the era of big data, this adaptability is invaluable. However, effective data cleaning and preprocessing are essential to address challenges like missing values and varying dataset resolutions. A key limitation of ML/DL models is their "black boxes" nature, which hinders interpretability. Techniques like feature important analysis are necessary to enhance understanding. Fig. 6 **(left)** summarises the ML/DL predictive modelling process (Tella and Balogun, 2021; Shogrkhodaei et al., 2021; Liu et al., 2020; Li et al., 2020b; Zhang and Hu, 2017).

4.5.1.4. ML/DL LUR hybrid models. To address the limitations of individual methods, a combined approach integrating LUR with ML/DL techniques has been developed. Based on ground monitoring data, LUR extracts buffer data, while ML/DL algorithms process large multidimensional datasets and analyse non-linear relationships. Fig. 6 **(right)** presents a flowchart of the mixed ML/DL LUR predictive air quality model (Qi et al., 2022; Babu Saheer et al., 2022; Han et al., 2022a).

4.5.2. Feature variable importance ranking

Across 19 reviewed articles on predictive air quality models, 55 feature variables were utilised. Five studies included feature variable importance analysis during model development. Table 2 summarises the results, with two studies focused on $PM_{2.5}$ prediction (Shogrkhodaei

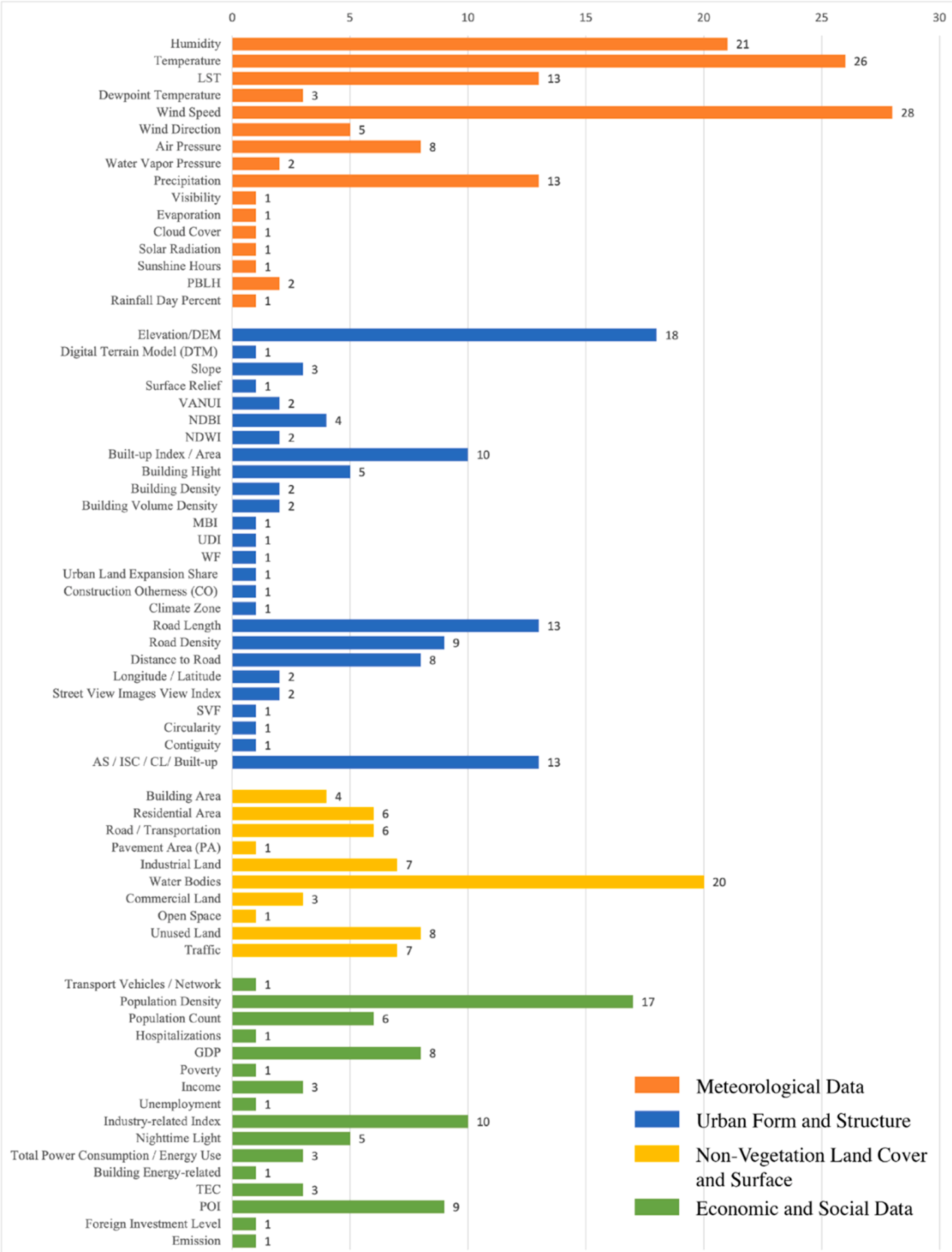

Fig. 3. Non-vegetation related indices and numbers of associated articles reviewed.

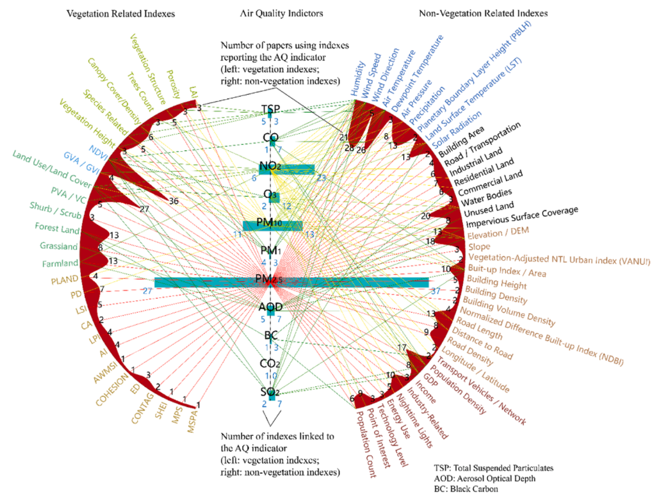

Fig. 4. Mapping the connections between Vegetation-Related Indices, Air Quality Indicators (Air Pollutants), and Non-Vegetation Related Indices used in the 79 original research articles reviewed.

et al., 2021; Li et al., 2020b) and three on NO_2, O_3, and PM_{10}, respectively (Qi et al., 2022; Han et al., 2022a; Tella and Balogun, 2021). Despite variations in feature selection and ranking, three common variables—humidity, maximum temperature, and elevation—were consistently used in modelling.

5. Discussion

5.1. Transition of the indices' measurements and prediction models

The initial search for this systemic review, conducted in early 2023, targeted studies from the past decade, a period marked by: (1) the proliferation of data sources through advancements in remote sensing and digital imaging, and (2) improved computational performance driven by machine learning and deep learning innovations.

5.1.1. The transition of air quality measurements and vegetation-related indices

Ground-based station monitoring (**Tables S.2–S.4**) remains widely used for direct and accurate air pollutant measurements. Since 2017, satellite sensing and online datasets have gained prominence, offering broader geographic coverage and higher resolution. Despite these advancements, ground-based monitoring remains essential for retrieving target air pollutant concentrations and validating satellite-derived data. Its role has evolved from a primary data source to a verification tool, improving research efficiency by addressing the spatial and cost limitations of ground monitoring networks and expanding air quality datasets.

Vegetation-related indices quantify horizontal and vertical characteristics. Horizontal indices, such as satellite-derived NDVI and land use metrics (e.g., PLAND), are preferred for their simplicity and ease of use, whereas vertical indices like Leaf Area Index (LAI) and porosity require specialised instruments and manual labour, resulting in smaller datasets. Landscape pattern metrics are less common due to their complexity.

Since 2020, street view images have provided an accessible, low-cost method for capturing vertical vegetation characteristics in urban areas. Advances in machine learning and deep learning have enhanced image analysis, significantly improving the efficiency and applicability of street-view images in urban greening research.

5.1.2. The evolution of air quality prediction models

Air quality prediction models have advanced from relatively simple spatial estimation techniques to land use regression (LUR) models using linear regression, and, after 2020, to machine learning and deep learning models. By 2022, hybrid models combining machine learning, deep learning, and LUR emerged, driven by high-performance computational algorithms capable of processing high-dimensional data and capturing complex non-linear relationships. Earlier methods like inverse distance weighting (IDW) and Kriging are now primarily used as pre-processing tool to fill missing data and harmonise dataset resolutions.

5.1.3. Some observations of the latest research trends (2023–24)

Since concluding our initial search for this systematic review, we have noted ongoing trends reported in recent research (post-2023). Traditional studies continue to focus on the impact of vegetation on air pollutants through localised sampling in specific areas such as schools,

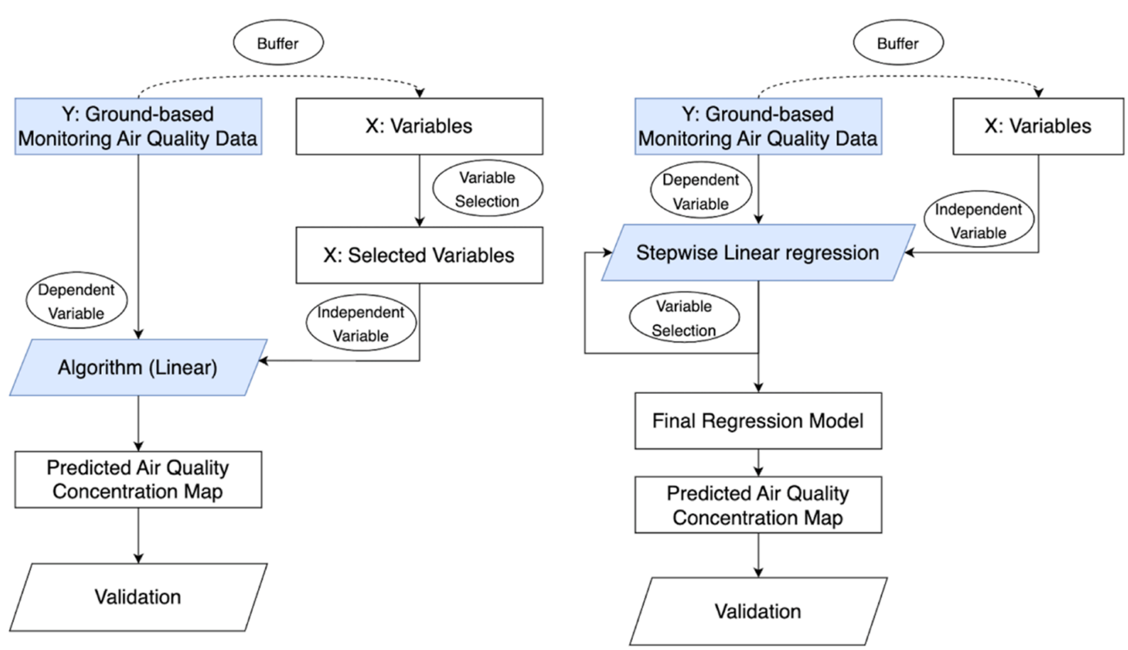

Fig. 5. Land use regression (LUR) based air quality models using multiple linear regression (left), stepwise (forward/backward) linear regression (right).

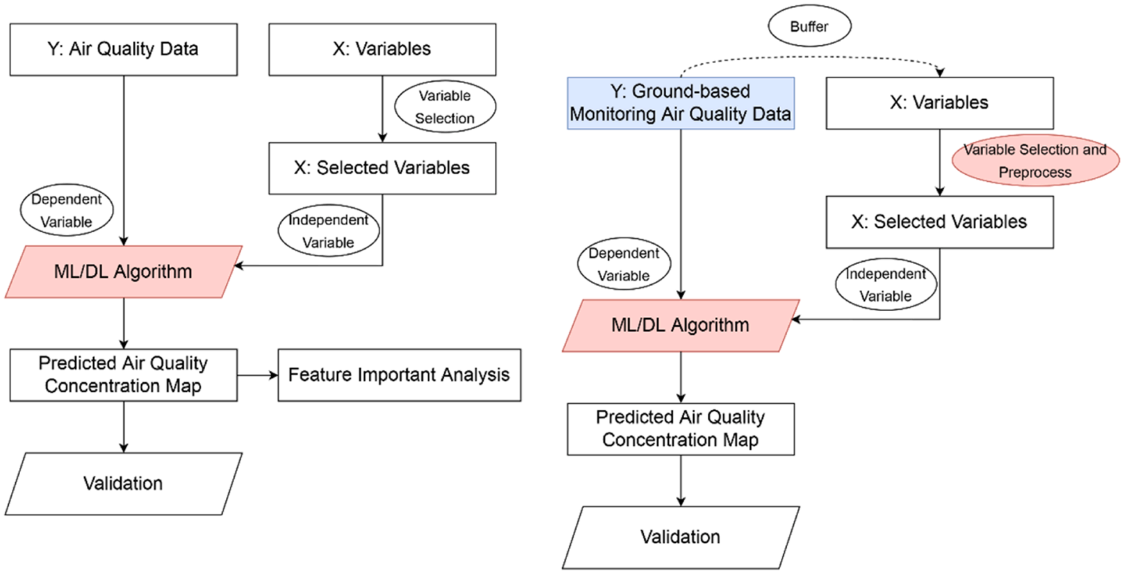

Fig. 6. ML/DL prediction modelling (left) and ML/DL LUR mixed modelling (right).

elderly care centres, and parks (Pan et al., 2024; Wang et al., 2024b; Wu et al., 2024; Ta and Promchan, 2024). Meanwhile, the growing availability of large datasets, including remote sensing data, has enabled broader-scale analyses of spatiotemporal air quality and vegetation distribution (Liu et al., 2024; Saha et al., 2024; Naboureh et al., 2024; Sheng et al., 2023; Kan et al., 2023; Mansourmoghaddam et al., 2023).

Recent advancements in remote sensing and street-view imaging have enhanced the quantification of urban vegetation. Machine learning (ML) and deep learning (DL) algorithms are increasingly applied to image-based tasks such as vegetation detection, canopy identification, and species classification. High-resolution datasets (e.g., WorldView-2/3 series, GeoEye-1, Planet Labs' SkySat, and Pleiades) enable detailed vegetation mapping (Guo et al., 2023; Sicard et al., 2023). Furthermore, integrating 3D vegetation analysis from street-view imagery marks a shift from traditional 2D studies. AI-driven computer vision now extracts 3D structural attributes, including vertical dimensions, offering deeper insights into urban greenery (Gupta et al., 2024; Xu et al., 2023). ML and DL algorithms are also pivotal in air quality prediction, improving analysis of high-dimensional datasets and assessing interactions among multiple variables (Wang et al., 2024a; Gündoğdu and Elbir, 2024). However, isolating the effects of individual factors remains a challenge, limiting the robustness of these analyses.

5.2. Limitations of this systematic review

We used the PRISMA framework to systematically review literature on the relationships between vegetation morphology, non-vegetation factors, and air quality in real urban environments. The inclusion and exclusion criteria defined the search and review scope, though some limitations remain.

5.2.1. Short of a meta-analysis

In reviewing prior research, we initially considered conducting a meta-analysis to evaluate the impact of vegetation on air quality improvement. However, significant variations in research scales, indices, methodologies, and metrics rendered a consistent meta-analysis infeasible. For instance, studies using the NDVI index employed different air quality indicators (e.g., AOD in Yang et al., 2022, and $PM_{2.5}$ in Llaguno-Munitxa et al., 2021) or distinct data processing methods (e.g., correlation analysis in Yang et al., 2022, and random forest modelling in Shogrkhodaei et al., 2021). As a result, we adopted a qualitative approach, organising findings into two methodological themes: correlation/regression studies and predictive models. This enabled us to map the range of air quality indicators, vegetation indices, urban form indices, and meteorological data, as well as the predictive models developed over the past decade.

While a meta-analysis in this field is feasible, it was not suitable at the time of this review. Future systematic reviews could enable meta-analyses by focusing on specific research questions addressed by multiple studies, ensuring consistency in metrics such as vegetation indices (e.g., NDVI) or types of green infrastructure (e.g., urban trees or green roofs/walls) within defined climatic regions and/or seasons. Such meta-analyses could adopt methodologies similar to those in evidence-based medicine, which is well developed and widely applied.

5.2.2. Limited green infrastructure types

Urban green infrastructure (GI) encompasses diverse forms beyond traditional plantings, including green walls and roofs, which play key roles in urban ecology. This review focuses on indices for quantifying vegetation characteristics, assuming their broad applicability across vegetation types. For example, NDVI captures horizontal greenery like green roofs, while GVI characterises vertical greenery such as street trees and green walls. Although, different GI types uniquely impact air quality—a topic warranting further review— recent studies (Vashishta et al., 2024; Barriuso and Urbano, 2021) highlight their potential to complement traditional urban vegetation.

5.2.3. Real urban environments and numerical simulations

This review focuses on studies conducted in real-world settings, excluding numerical simulations. Our aim is to summarise effective quantitative methods for complex environmental contexts in urban areas. While CFD-based numerical simulations can be isolate and quantify vegetation's effects on air quality by simplifying urban scenarios, they often depend on researcher-assumed parameters, potentially introducing biases. These assumptions may overlook the complexity of real-world processes involving numerous interacting variables. By concentrating on non-simulation research, we better capture insights from analysing large-scale high-resolution field measurements. However, validated simulations can contribute to enhanced ML/DL models where comprehensive and reliable field measurements are limited. In particular, these combined capabilities are essential for evaluating planning and design proposals which do not exist in reality. Comparing and combining empirical field studies with simulation-based findings offers a promising direction for future research.

Table 2
Feature variable importance ranking in predictive air quality modelling.

[1] NO2 prediction: LUR using street view imagery (SVI) and satellite sensing data (Qi et al., 2022)			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Built Environment (SVI)	3 [9]	Transport Vehicles (SVI)	1 [9]
People count (SVI)	8 [9]	Vegetation (SVI)	5 [9]
Natural scenery (SVI)	6 [9]	Water (SVI)	7 [9]
Ozone Monitoring Instrument (SVI)	4 [9]	Year	9 [9]
Transport Network (SVI)	2 [9]		
[2] O3 prediction: Ozone and UHI using a ML modified LUR method (Han et al., 2022a)			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Temperature	5 [20]	Industrial and Mining Land	13 [20]
Average Wind Speed	4 [20]	Major Road	12 [20]
Distance to Cultivated Land	9 [20]	Maximum Temperature	2 [20]
Distance to Major Road	18 [20]	Maximum Wind Speed	3 [20]
Distance to Printing Factory	10 [20]	PM10	16 [20]
Distance to Ridge Line	11 [20]	PM2.5	19 [20]
Elevation	6 [20]	Point of Interest (POI) - Factory	15 [20]
Green Space	8 [20]	POI - Gas Station	20 [20]
Gross Domestic Product (GDP)	7 [20]	Population	14 [20]
Humidity	1 [20]	Water Body (5000 m buffer)	17 [20]
[3] PM10 prediction: KNN, XGBoost, RF, and NB model (Tella and Balogun, 2021)			
K-Nearest Neighbor (KNN) model, Selangor State, Malaysia			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Wind Speed	2 [8]	Normalized Difference Vegetation Index (NDVI)	6 [8]
Build-up Index	7 [8]	Road Density	4 [8]
Elevation	1 [8]	Soil Adjusted Vegetation Index (SAVI)	5 [8]
Land Surface Temperature	3 [8]	Slope	8 [8]
XGBoost model, Selangor State, Malaysia			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Wind Speed	2 [8]	Normalized Difference Vegetation Index (NDVI)	6 [8]
Build-up Index	8 [8]	Road Density	4 [8]
Elevation	1 [8]	Soil Adjusted Vegetation Index (SAVI)	7 [8]
Land Surface Temperature	3 [8]	Slope	5 [8]
Random Forest (RF) model, Selangor State, Malaysia			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Wind Speed	2 [8]	Normalized Difference Vegetation Index (NDVI)	7 [8]
Build-up Index	8 [8]	Road Density	5 [8]
Elevation	1 [8]	Soil Adjusted Vegetation Index (SAVI)	6 [8]
Land Surface Temperature	3 [8]	Slope	4 [8]
Naive Bayes (NB) model, Selangor State, Malaysia			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Wind Speed	2 [8]	Normalized Difference Vegetation Index (NDVI)	7 [8]
Build-up Index	6 [8]	Road Density	4 [8]
Elevation	1 [8]	Soil Adjusted Vegetation Index (SAVI)	5 [8]
Land Surface Temperature	3 [8]	Slope	8 [8]
[4] PM2.5 prediction: Seasonal models using three ML algorithms (Shogrkhodaei et al., 2021)			
Spring model, Tehran metropolis			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Temperature	5 [10]	Maximum Wind Speed	6 [10]
Distance to Industrial	2 [10]	Normalized Difference Vegetation Index (NDVI)	1 [10]
Humidity	8 [10]	Population Density	4 [10]
Maximum Temperature	10 [10]	Rainfall	7 [10]
Minimum Temperature	9 [10]	Road Density	3 [10]
Summer model, Tehran metropolis			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**

Table 2 (*continued*)

[1] NO2 prediction: LUR using street view imagery (SVI) and satellite sensing data (Qi et al., 2022)			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Temperature	1 [10]	Maximum Wind Speed	10 [10]
Distance to Industrial	7 [10]	Normalized Difference Vegetation Index (NDVI)	6 [10]
Humidity	9 [10]	Population Density	8 [10]
Maximum Temperature	2 [10]	Rainfall	5 [10]
Minimum Temperature	4 [10]	Road Density	3 [10]
Autumn model, Tehran metropolis			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Temperature	6 [10]	Maximum Wind Speed	7 [10]
Distance to Industrial	4 [10]	Normalized Difference Vegetation Index (NDVI)	1 [10]
Humidity	5 [10]	Population Density	3 [10]
Maximum Temperature	9 [10]	Rainfall	8 [10]
Minimum Temperature	10 [10]	Road Density	2 [10]
Winter model, Tehran metropolis			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
Average Temperature	8 [10]	Maximum Wind Speed	7 [10]
Distance to Industrial	1 [10]	Normalized Difference Vegetation Index (NDVI)	2 [10]
Humidity	5 [10]	Population Density	3 [10]
Maximum Temperature	9 [10]	Rainfall	10 [10]
Minimum Temperature	6 [10]	Road Density	4 [10]
[5] PM2.5 prediction: Ensemble-based deep learning over California (Li et al., 2020b)			
Feature variable	**Ranking**	**Feature Variable**	**Ranking**
10-meter Northward Wind	20 [20]	Maximum Temperature	4 [20]
CO	1 [20]	Pressure	9 [20]
Daily Mean Downward Shortwave Radiation	15 [20]	Product of Latitude and Longitude	3 [20]
Dry Deposition of Ox	19 [20]	Sea Salt Concentrations in PM2.5	10 [20]
Elevation	18 [20]	Square of Latitude	7 [20]
Humidity	16 [20]	Square of Longitude	11 [20]
Impervious Layer	12 [20]	Temporal Basis Function 1	2 [20]
Latitude	5 [20]	Temporal Basis Function 2	14 [20]
Longitude	6 [20]	Temporal Basis Function 3	17 [20]
MAIAC AOD	8 [20]	Year	13 [20]

5.2.4. *Selection of searchable databases, languages, and accessibility*

We conducted a literature search on Scopus, a widely recognised database, yielding 3456 initial results. Scopus was chosen over alternatives like Web of Science due to its broader journal coverage across disciplines relevant to vegetation, urban form, and air quality, such as environmental sciences, urban studies, and engineering. Its robust citation metrics also facilitated the identification of influential studies and authors, enhancing the systematic review process. While articles not indexed in Scopus were excluded, its comprehensive coverage and alignment with PRISIMA guidelines supported transparent screening and selection. Limiting the review to English-language and open-access papers may have further excluded some relevant studies.

5.3. *Future research priorities*

Air quality significantly impacts human health and the environment, prompting global policy actions. Assessing and predicting air quality remains challenging due to the transient nature of urban air pollution (e.g., emission, dispersion, deposition, resuspension, interaction with urban lights). This review highlights the complexity of quantifying vegetation's effects on air quality in dynamic urban environments, where numerous variables interact. Advances in large-scale urban datasets from satellite and street-view imaging now enable the transition from 2D (planar) to 3D (volumetric) vegetation quantification. Integrating 3D vegetation indices with machine learning and deep learning shows new revenues for predictive air quality modelling. These technologies also enable automated plant species recognition, supporting evidence-based urban greening interventions to improve air quality.

However, a key challenge lies in the "black-box" nature of AI-based predictions, which obscures the interactions among variables affecting urban air quality. Enhancing the explainability of these models is crucial to inform urban planning and design decisions effectively.

5.4. Significant of this review

This review summarises advancements in vegetation-related indices, urban form, and their impact on urban air quality over the past decade, emphasizing their relevance to urban and landscape design. It also reviews air quality prediction models and algorithms, highlighting data-driven approaches and future research directions. These insights provide urban planners, designers, and policymakers with a foundation for informed science-based decisions for creating sustainable, air-purifying environments.

6. Conclusion

Informed by previous review articles, we set out a new systematic review to provide an up-to-date summary of 79 studies identified that focus on effects of vegetation and urban morphological characteristics on air quality. We identify four key questions to be addressed in the new systematic review concerning the range of air quality indicators and data sources used in the studies, the indices defined for quantifying vegetation morphology and urban form, and predictive models for assessing air quality of real urban environments.

There are nine groups of air quality indicators used ranging from particulate matter (PM) to aerosol optical depth (AOD) which is also increasingly used to derive air pollutant concentrations of various kinds covering large urban areas. Among them, $PM_{2.5}$ is the AQ indicator attracting the largest number of studies due to its significant impact on public health. In terms of data sources, we observe increasing utilisation of combined ground-based air quality monitoring measurements and satellite measurements to obtain the spatial-temporal resolutions required in the studies

In vegetation indices, two-dimensional indices are more commonly used to quantify vegetation morphological attributes. This is due to the fact that remote sensing technology has enabled quantification of top-view features over large areas, such as NDVI. In contrast, three-dimensional indices that capture vertical vegetation characteristics are less developed due to the technical challenge of semantic segmentation of vegetation in large volumes of urban scenes or street views.

Traditional on-site measurements can only provide small-scale vertical characteristics such as canopy features. With the advancement of large urban image datasets, including street view scans, advanced machine-learning techniques are being developed and applied in quantifying vertical dimension of urban vegetation in real cities. However, due to limited open-source urban image datasets and reliable image processing techniques, this remains a research topic to be further addressed in future research. More importantly, how vegetation indices defined and measured in both horizontal and vertical dimensions may be combined to form new three-dimensional vegetation indices remain to be further developed.

This systematic review identifies and summarises several air pollution prediction models. It shows that the traditional Land Use Regression (LUR) model is relatively well-established. LUR was frequently used pre-2020, but since then, the advancement of machine learning (ML) and deep learning (DL) algorithms has led to the rapid development of ML/DL models, which exhibited better prediction performance due to the computational power and intelligence unavailable before.

Finally, our attempt at summarising how vegetation and urban form variables may interact with different air pollutants can be explained to some extent by a feature importance analysis. We find that conducting a thorough meta-analysis of the effects of vegetation an urban form on air quality is not without substantial difficulties. There is a need for establishing a comprehensive air pollution research data repository, linking related studies to enable classifying and summarising data by pollutant types, research locations, spatial-temporal scales, and modelling methods. This could lead to identification of the key variables impacting specific air pollutants as the basis for bringing forward evidence-based guidelines applicable to cleaner air landscaping planning and urban design.

In conclusion, this systematic review offers a comprehensive summary of advancements in vegetation-related indices and other influencing factors, such as urban form, over the past decade, focusing on their impact on urban air quality. These elements are deeply intertwined with urban design, making our findings highly relevant for urban planners and designers aiming to create environments that promote nature-based solutions to air purification. Furthermore, we summarise the air quality prediction models and algorithms developed over the past ten years, prompting the emerging research trends of developing large-scale data-driven approaches. Advance in quantifying effects of vegetation on air quality in real urban environments can improve the proficiency of evidence-based planning and design decision-making.

Why is the paper significant?

This systematic review paper has been developed by first reviewing 23 review articles published during 2015–2022 focusing on vegetation, urban form and air quality. We address the limitations of the previous reviews by adopting the PRISMA protocols, identifying those studies carried out in real urban environments, and summarising the hierarchical correlation or regression accounts of the vegetation's effects on mitigating concentrations of air pollutants.

Based on the search and selection criteria, 301 papers were identified in the first round of the abstract search, of which 79 papers were retained after a more detailed extraction from the open access full texts. Our review answers four key questions:

- What urban air quality indicators and data sources were used in the studies examining the effects of vegetation on urban air quality?
- What metrics or indices were used to quantify the morphological characteristics of urban vegetation in studies on air quality?
- What metrics or indices were used to quantify urban form of real cities for air quality studies?
- What data sources and methods were used for developing predictive models for assessing urban air quality of real urban environments?

We present a novel data visualisation scheme to highlight the interrelations of the air quality indicators, vegetation, and urban morphology indices, showing frequency of studies on different air pollutants and their associated variables.

The outcome of our review shows clearly that $PM_{2.5}$ is most used among the nine groups of air quality indicators identified in the studies, highlighting its significance of public health impact. We draw out the interactions between air quality indicators, vegetation-related indices, and non-vegetation urban form indices. There are 19 studies (24 %) reporting predictive air quality models employing different methods and data sources. We summarise feature variable importance analyses of 55 variables through a ranking table. We conclude by pointing out that a new multi-view urban vegetation index scheme for quantifying the effects of inner urban greenery on the spatiotemporal distribution of PM2.5 concentrations can be developed on the basis of large-scale high-resolution air quality datasets, large open-source urban images repositories, and advance computational learning capabilities.

In preparing the manuscript, we have used ChatGPT for checking grammatical errors and stylistic issues. The authors bear full responsibilities of the entire content of the manuscript as written.

CRediT authorship contribution statement

Smith Michael: Supervision, Methodology, Conceptualization. **Peng Chengzhi:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Yao Mengxue:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation.

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.

Appendix

Table A1a
The previous eight reviews on mitigation and removal capacity of vegetation (Keywords: mitigation, phytoremediation, vegetation traits, air pollutants capture).

Article	Review Questions	Summary of Review Findings
(Hellebaut et al., 2022)	Current understanding and knowledge gaps in air quality and plants traits on green walls, evidence of knowledge application in design practice	Hairiness, roughness and leaf size are the traits that affect particulate matter (PM) capture. Review six green wall designs in Belgium & showing knowledge of plants traits and air pollutants removal in green wall design remained partial.
(Han et al., 2022b)	Phytoremediation of indoor air pollutants; removal efficiency of plants on different air pollutants under different environmental settings	Absorption and purification of different pollutants (formaldehyde, aromatic compounds and inorganic pollutants) are affected by different trait variables (leaf characteristics, planting patterns, species). The effectiveness of pollutant removal differs under different environmental settings (lab-scale studies, real-world site-specific indoor/outdoor conditions).
(Wróblewska and Jeong, 2021)	Effectiveness of plants on removing particulate matter (PM)	1) Deposition on leaf surfaces; 2) Factors affecting PM capture efficiency: leaf area index, morphological characteristics of leaf surfaces, environment (e.g., wind), and 3D geometry of city design; 3) different types of green infrastructure - green roofs, living walls, water reservoirs, urban farming; 4) PM removal capacity could be improved by species selection and increasing biodiversity.
(Diener and Mudu, 2021)	Effects and mechanisms of green spaces on reducing PM exposure to protect public health	1) Three mechanisms to reduce PM exposure: deposition, dispersion and modification; 2) Public health interventions to reduce PM exposure should consider sensitivity of green spaces in mitigating PM exposure: location of green spaces at a regional scale, porosity of green spaces at a local scale.
(Corada et al., 2021)	Effective leaf traits for enhancing PM capture	1) Coniferous needle leaves, 2) Small, rough and textured broad-leaves, 3) Extended oval shapes, 4) Waxy coatings and high-density trichomes; 5) Ancillary factors and the context of plantings should also be considered to improve PM removal, e.g., plant species, wind conditions, and locations.
(Sicard et al., 2018)	Quantification of O_3 removal capacity of trees, shrubs, and green roofs	For O_3 removal, urban trees are more efficient and cost effective than green roofs; broad-leaf tree species perform better than conifers, while evergreen are better than deciduous broadleaf.
(Gourdji, 2018)	Effects of green roofs on mitigating air pollution; plant species for PM, O_3, NO_2 reduction; effects of green roofs on air quality in the Montreal region, Canada	Air pollutants removal processes: 1) Deposition of PM, 2) Deposition of O_3 on plant or soil surfaces via stomatal conductance and non-stomatal uptake, 3) NO_2 removed by stomatal absorption; 4) Small Zone 5 hardiness tolerant plants on intensive green roofs was recommended for Montreal.
(Huang et al., 2018)	PAHs removal; PAHs accumulating capability of pine needles, Holm oak leaves, and moss	1) PAHs (Polycyclic aromatic hydrocarbons) uptake via absorption and adsorption; 2) Moss perform better in PAHs capture than oak leaves and pine needles; 3) Environment factors (temperature, seasonality, photolysis) could affect the transfer process of PHAs from atmosphere to vegetation.

Table A1b
The previous reviews of deposition and dispersion effects and processes of vegetation (Keywords: deposition, dispersion, aerodynamic, CFD, green walls, green infrastructure).

Article	Review Questions	Summary of Review Findings
(Li et al., 2022)	Removal of NO_2 by dry deposition of plants	Plant structure, chemical composition of leaves, nitrogen content of leaves, meteorological conditions, and other related factors affect the deposition mechanism and the efficiency of NO_2 removal.
(Ysebaert et al., 2021)	Effectiveness of green walls in removing PM	Species, pollution level and residence time affecting PM deposition on green walls. More field, wind tunnel and model validation studies are needed to eliminate discrepancies about the key parameters affecting PM capture by green walls.
(Badach et al., 2020)	Effects of urban greenery on mitigating air pollution in Polish cities	Urban greenery can have combined deposition and aerodynamic effects on air quality. Critical evaluation of local urban planning practice in Gdańsk, Warsaw, and Poznań found limited applicability of the known effects due to lack of accurate models and tools.
(Tiwari et al., 2019)	Green infrastructure (GI) impact on air pollution and health risk assessment	Ten studies that have quantified the linkage between GI, air pollution reduction and health benefits were identified and summarized. Simplified deposition schemes may lead to uncertainties in removal estimation. Future dispersion models need to account for wind speed based GI porosity as well as GI at different spatial scales (microscale and macroscale).

(continued on next page)

Table A1b (*continued*)

Article	Review Questions	Summary of Review Findings
(Buccolieri et al., 2019)	The effects of urban trees on air quality and thermal conditions learned from Computational Fluid Dynamics (CFD) studies	Parameterizations of urban vegetation (trees) are appropriate to account for aerodynamic and deposition effects; resuspension and thermal effects of different types of trees need more works in CFD; "the right tree in the right street" is a better approach.
(Janhäll, 2015)	Vegetation as ecosystem services for air quality improvements – effects of vegetation choice on air pollution from different sources and particle sizes	Urban vegetation effects on air quality summarised as 1) deposition process (particle properties and vegetation properties) at different scales (parks, regional); 2) dispersion effect of vegetation barriers. The studies reviewed include on-site measurements, wind tunnel studies and CFD modelling.

Table A1c
Previous reviews of the influence of vegetation in urban streets/roads (Keywords: barriers, obstacles, street canyons, open roads, street greening).

Article	Review Questions	Summary of Review Findings
(Buccolieri et al., 2022)	Influence of obstacles (porous & non-porous) on urban canyon ventilation including air pollutant dispersion	The isothermal flow dispersion effects of porous (trees, hedgerows) and non-porous obstacles (parked cars, low boundary walls or baffles, noise/roadside barriers, wind catchers, solar chimneys), and the efficacy, costs, as well as pros and cons.
(Chaudhuri and Kumar, 2022)	Strategic urban greening for long-term air pollution prevention and control measures	PRISMA-based review of global literature (post-2005) and a meta-analysis to be considered by air quality regulatory authorities with particular references to Indian cities to enhance tree species selection, removal strategies in street canyon and open road environment.
(Tomson et al., 2021)	Optimal form and arrangement of Green Infrastructure (GI) for air quality in street canyons	Deposition and dispersion are the main impact pathways for vegetation on air pollution. The effectiveness of different GI forms (trees, hedges, green roofs, green walls and green screens) in the street canyon environment and the methods for assessing effectiveness.
(Barwise and Kumar, 2020)	Vegetation barriers in open-road environment, optimal configuration as barriers between traffic emissions and adjacent spaces	Effective barriers design principles in different spatial scales (city scale, local scale) and plant selection recommendations (e.g., ecophysiological and morphological characteristics, species emissions) for open-road environment and street canyons in the UK.
(Mori et al., 2018)	The effect of air pollutants on human health, and the vegetation characteristics help to optimise air pollutants interception	Species selection and planting schemes (density of vegetation, disposition of plants, global dimensions of GI) should be considered according to different plating site characteristics (open areas vs. street canyons).
(Abhijith et al., 2017)	Aerodynamic effects and reduction potentials of vegetation in street canyon and open road; vegetation types and characteristics help air pollution reduction	1) In street canyons, hedges improve air quality while trees led to deterioration; 2) In open road, low porosity and tall vegetation helps to downwind pollutant reductions; 3) Green walls and roofs on building envelopes can be effective ways to improve air quality.
(Gallagher et al., 2015)	Passive methods for improving air quality and reducing personal exposure – porous and solid barriers	The strengths and limitations and modelling approaches of porous barriers (trees and vegetation) and solid barriers (noise barriers, low boundary walls, parked cars).

Table A1d
The previous reviews of plants as urban ecosystem services where air quality is a part (Keywords: urban ecosystems, nature-based, pollutants removal, urban greening, microclimate).

Article	Review Questions	Summary of Review Findings
(Biswal et al., 2022)	Nature-based systems for reducing pollutants in storm water, rainwater and urban air	1) Physico-chemical removal through filtration, adsorption, precipitation, and complexation; 2) Biological removal via air phytoremediation plants; 3) Roadside removal via vegetation characteristics of height, thickness, coverage, porosity.
(Ernst et al., 2022)	The relationships between urban greening, canopy layer urban heat island (UHI) and urban pollution island (UPI), air quality, and urban microclimate	1) The links between microclimate and air quality studies were weak; 2) tools for assessing greening's impacts on both microclimate and air quality with good accuracy at the city scale were not well developed; 3) interactions between plant functioning, microclimate and atmospheric composition may hold the key to modelling the links between urban greening, UHI, UPI.

Table A2
Summary of air quality indicators/indices and measurements from ground stations.

Article	Source/Agency	Air Pollutants	No. of Stations
(O'Regan et al., 2022)	Purple Air Network for Cork City, Ireland	$PM_{2.5}$, PM_{10}, PM_1	12

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Table A2 (*continued*)

Article	Source/Agency	Air Pollutants	No. of Stations
(Tella and Balogun, 2021, Halim et al., 2020, Shahrin et al., 2019)	the Malaysian Department of Environment (DOE)	PM_{10}, CO, O_3, NO, NO_2, NO_x, SO_2	8
(Wang et al., 2022b, Zhao et al., 2022, Li et al., 2021b,Wang et al., 2021, Han et al., 2020, Luan et al., 2020, Liu et al., 2019, Tian et al., 2019, Wang et al., 2018b, Zhang and Hu, 2017, Chen et al., 2016, Wu et al., 2015b, Wu et al., 2015a)	China Environmental Monitoring Station (http://www.cnemc.cn/)	$PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, CO, AQI,	1589
(Khan et al., 2022)	Environmental Protection Apartment, Punjab, Lahore	NOx, CO, SO_2, PM_{10}	20
(Zeng et al., 2022)	Shenzhen Municipal Ecological Environment Bureau, China (http://meeb.sz.gov.cn/)	$PM_{2.5}$	74
(Babu Saheer et al., 2022)	UK Air, Department for Environment Food & Rural Affairs (uk-air.defra.gov.uk/)	$PM_{2.5}$, PM_{10}, NO_2	1500+
(Han et al., 2022a)	Xi'an Air Quality Monitoring Stations, China	O_3	139
(Shogrkhodaei et al., 2021)	Tehran Air pollution control stations, Iran	$PM_{2.5}$	23
(Li et al., 2020c)	Shenyang Environment Monitoring Center, China	$PM_{2.5}$, PM_{10}, NO_2, SO_2	11
(Tian et al., 2020)	Georgia Department of Natural Resources, Environmental Protection Division (EPD)	$PM_{2.5}$	9
(Li et al., 2020a)	Weifang PM2.5 Monitoring Stations, China	$PM_{2.5}$	38
(Kong and Tian, 2020)	Beijing Municipal Environmental Monitoring Center, China (BMEMC 2018)	$PM_{2.5}$	35
(Guo et al., 2020)	Xi'an Air Quality Daily Reporting System, China (http://www.xianemc.gov.cn/)	$PM_{2.5}$	13
(Guo et al., 2019)	Tianjin air pollution monitoring stations, China	NO_2	23
(Li et al., 2017)	US Environmental Protection Agency (EPA)'s Air Quality System (AQS) (www.epa.gov/aqs)	$PM_{2.5}$	55
(Wu et al., 2017)	Taipei metropolis air pollutant monitoring database, Taiwan Air Quality Monitoring Network (airtw.moenv.gov.tw/eng/)	$PM_{2.5}$	17
(Ramos et al., 2016)	National Air Pollution Surveillance (NAPS) network of Environment Canada	$PM_{2.5}$	10
(Meng et al., 2015)	Shanghai Environmental Monitoring Centre (SEMC), China	NO_2	38

Table A3
Summary of satellite sensing air quality datasets.

Article	Dataset	Resolution
(Rahman and Haque, 2022)	Landsat data to retrieve AOD (earthexplorer.usgs.gov)	30m
(Islam et al., 2012)	Sentinel-5P Level-3 NO_2 Daily Product (V1)	0.01 arc-degree
(Qi et al., 2022)	OMI/Aura NO2 Tropospheric, Stratospheric & Total Columns MINDS Daily L3 Global Gridded (DOI: 10.5067/MEASURES/MINDS/DATA304)	$0.25^\circ \times 0.25^\circ$
(Sun et al., 2022, Xie and Sun, 2021, Li et al., 2020b)	MODIS MAIAC remote sensing AOD data (MCD19A2) (lpdaac.usgs.gov/products/mcd19a2v006)	1km
(Zhang and Hu, 2017)	MODIS Collection 6 Level 2 aerosol products (ladsweb.modaps.eosdis.nasa.gov/archive/allData/6)	3km
(Li et al., 2017)	MODIS AOD Level 2 product (Collection 5.1)	10km
(Li and Myint, 2021)	Landsat 5 satellite images to retrieve AOD	60m
(Syafei et al., 2019)	GOME-2 MetOP-A satellite datasets for NO_2	$80*40km^2$ or $80*10km^2$
(He et al., 2019)	Aqua and Terra MODIS Collection 6 Level 2 aerosol products	3km
(Wang ChengHao et al., 2017)	MODIS Terra Atmosphere Aerosol Level 2 Product	3km
(Ye et al., 2016)	HJ-1B satellite images for AOD retrieving	30m

Table A4
Summary of publicly available online datasets.

Article	Dataset	Resolution
(Hassan et al., 2022)	Socioeconomic Data and Applications Center (SEDAC) and Sentinel-5p data of the European Space Agency for the last 18 years (2002–2020)	1km
(Lin and Jiang, 2022)	Ground-level air pollutants for China (ChinaHighAirPollutants, CHAP) $PM_{2.5}$	1km
(Wei et al., 2021)	Socioeconomic Data and Applications Center (sedac.ciesin.columbia.edu/search/data?contains=PM2.5)	1km
(Li et al., 2021b)	Gridded global surface $PM_{2.5}$ concentration dataset	0.01°
(van Oorschot et al., 2021)	Annual mean PM_{10} concentrations Map, Hague (www.atlasleefomgeving.nl/kaarten)	25m
(Wang et al., 2019)	Open-Data Inventory for Anthropogenic Carbon dioxide (ODIAC) fossil fuel emission dataset from the Center for Global Environmental Research (db.cger.nies.go.jp/dataset/ODIAC/), National Institute for Environment Studies	1km
(Wang et al., 2020a, Lu et al., 2019)	The global annual average surface $PM_{2.5}$ concentrations grids provided by Atmospheric Composition Analysis Group (ACAG) at Dalhousie University	0.01°
(Bechle et al., 2017)	Publicly available global estimates of gridded annual surface NO_2 concentrations.	0.1° × 0.1°

Table A5
Summary of air quality data pre-processing methods.

Article	Method	Description
(Hassan et al., 2022, Sun et al., 2022, Halim et al., 2020, Arista et al., 2020, Li et al., 2020a, Shahrin et al., 2019, Cui et al., 2019, Chen et al., 2016, Ramos et al., 2016)	Inverse Distance Weighted (IDW)	IDW is one of the commonly used methods of spatial interpolation in air pollution prediction areas. It makes predictions on the concentration of unknown points based on a function of inverse distance from a known point, assuming that the closer they are to the known point, the greater the influence.
(Sun et al., 2022, Llaguno-Munitxa et al., 2021, Shogrkhodaei et al., 2021, Xie and Sun, 2021)	Kriging Interpolation	A set of geostatistical interpolation techniques wherein the value at an unobserved location is estimated through a linear combination of values from neighbouring locations. The weights assigned to these values are determined by a semivariogram which considers the spatial correlation. It has an effective performance in the data points having spatial autocorrelation. Ordinary Kriging and Universal kriging are wildly used in air pollution prediction areas.
(Li et al., 2020b, Zhang and Hu, 2017)	Linear Regression	A commonly employed technique for replacing missing values in a dataset. Typically, it involves predicting the missing data in the target dataset by establishing a linear relationship with a reference dataset.
(Qi et al., 2022, Yang et al., 2022, Hassan et al., 2022, Wei et al., 2021, Xie and Sun, 2021, Wang et al., 2019, Lu et al., 2019, Wang et al., 2018b, Wang ChengHao et al., 2017, Ye et al., 2016)	Resampling	Common data processing methods for uniform resolution of a different data set. It changes the dataset's spatial resolution by aggregating or interpolating values. Common types include Nearest Neighbor and Bilinear Interpolation.

Table A6
Summary of vegetation-related indices papers.

Vegetation-related indices	Articles
Vegetation Structure	(Niu et al., 2022, Jiang et al., 2021, Qiu et al., 2019, Qiu et al., 2018, Chen et al., 2015)
Land Use/Land Cover (LULC)	(Sun et al., 2022, Zeng et al., 2022, Han et al., 2022a, Llaguno-Munitxa et al., 2021, Li and Myint, 2021, Xie and Sun, 2021, Liu et al., 2020, Li et al., 2020b, Halim et al., 2020, Li et al., 2020c, Li et al., 2020a, Tian et al., 2020, Luan et al., 2020, Kong and Tian, 2020, Guo et al., 2020, Qiu et al., 2019, Van Ryswyk et al., 2019, Shahrin et al., 2019, Liu et al., 2019, Guo et al., 2019, Fan et al., 2019, Chen et al., 2016, Ye et al., 2016, Wu et al., 2015b, Wu et al., 2015a, Meng et al., 2015, Rao et al., 2014)
Count	(Babu Saheer et al., 2022, Llaguno-Munitxa et al., 2021, Yli-Pelkonen et al., 2017)
Leaf Area Index (LAI)	(Niu et al., 2022, van Oorschot et al., 2021, Wang et al., 2020b)
Canopy Cover/Density(CC/CD)	(Niu et al., 2022, Jiang et al., 2021, Wang et al., 2020b, Qiu et al., 2018, Chen et al., 2015, Islam et al., 2012)
Diameter at Breast Height (DBH)	(Niu et al., 2022, Yli-Pelkonen et al., 2017)
Vegetation Height (VH)	(Jiang et al., 2021, Wang et al., 2020b, Hart et al., 2020)
Species Related (Proportion of Species and Species Richness)	(Niu et al., 2022, Wang et al., 2020b, Grzędzicka, 2019, Desyana et al., 2017, Yli-Pelkonen et al., 2017)
Porosity	(Grzędzicka, 2019, Chen et al., 2015, Islam et al., 2012)
Percentage of Vegetation Area / Vegetation Coverage (PAV/VC)	(Grzędzicka, 2019, Masri et al., 2019, Lu et al., 2019, Syafei et al., 2019, Bechle et al., 2017)
NDVI (Normalized Difference Vegetation Index)	(Sun et al., 2022, Zeng et al., 2022, O'Regan et al., 2022, Yang et al., 2022, Hassan et al., 2022, Lin and Jiang, 2022, Zhao et al., 2022, Deb et al., 2022, Llaguno-Munitxa et al., 2021, Li and Myint, 2021, Tella and Balogun, 2021, Li et al., 2021b, Wang et al., 2021, Wei et al., 2021, Shogrkhodaei et al., 2021, Li et al., 2020b, Kong and Tian, 2020, Hart et al., 2020, Van Ryswyk et al., 2019,

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Table A6 (*continued*)

Vegetation-related indices	Articles
	Han et al., 2020, Wang et al., 2020a, Arista et al., 2020, Wang et al., 2019, Masri et al., 2019, Cui et al., 2019, Tian et al., 2019, He et al., 2019, Wang et al., 2018a, Wang et al., 2018b, Wang ChengHao et al., 2017, Zhang and Hu, 2017, Li et al., 2017, Wu et al., 2017, Farrell et al., 2015, Wu et al., 2015a, Dadvand et al., 2015)
SAVI (Soil Adjusted Vegetation Index)	(Tella and Balogun, 2021)
EVI (Enhanced Vegetation Index)	(Islam et al., 2022)
GTCT (Greenness Tasseled Cap Transformation)	(Ramos et al., 2016)
GVI/GVA (Green View Index / Green View Amount)	(Zeng et al., 2022, O'Regan et al., 2022, Wang et al., 2022b, Qi et al., 2022, Liu et al., 2020)
VGVI ()	(Labib et al., 2021)
Percentage of Landscape Types (PLAND)	(Wang et al., 2022a, Fan et al., 2019, Ye et al., 2016, Wu et al., 2015b)
Patch Density (PD)	(Wang et al., 2022a, Tian and Yao, 2022, Li et al., 2021b, Tian et al., 2020, Fan et al., 2019, Ye et al., 2016, Wu et al., 2015b)
Landscape Shape Index (LSI)	(Wang et al., 2022a, Tian and Yao, 2022, Li et al., 2021b, Tian et al., 2020, Ye et al., 2016)
Class Area (CA)	(Tian and Yao, 2022, Tian et al., 2020)
Largest Patch Index (LPI)	(Tian and Yao, 2022, Li et al., 2021b, Tian et al., 2020, Ye et al., 2016)
Aggregation Index (AI)	(Tian and Yao, 2022, Li et al., 2021b, Tian et al., 2020, Fan et al., 2019)
Area-Weighted MeanShape Index (AWMSI)	(Li et al., 2021b)
Patch Cohesion Index (COHESION)	(Li et al., 2021b)
Edge Density (ED)	(Tian et al., 2020, Ye et al., 2016, Wu et al., 2015b)
Contagion (CONTAG)	(Ye et al., 2016, Wu et al., 2015b)
Shannon's Evenness Index (SHEI)	(Wu et al., 2015b)
Mean Patch Size (MPS)	(Fan et al., 2019)
MSPA	(Li et al., 2021b)

Table A7
Types of air quality prediction models, algorithms, output resolutions, and validation.

Model	Article	Algorithm	Resolution	Model Validation and Prediction Accuracy
Spatial Estimation Models	(Liu et al., 2019)	OK; IDW	500m	LOOCV
	(Li et al., 2017)	GWR	10km	10-fold CV; RMSE/MAE/RRMSE/RMAE-
	(Ramos et al., 2016)	KED; IDW; KED-IDW	100m	LOOCV
	(Meng et al., 2015)	IDW; OK	1km	LOOCV; R^2/RMSE
Traditional Land Use Regression (LUR) Models	(Han et al., 2022a)	/	500m grid	Splitting 80% training and 20% test; R^2/MSE/RMSE/MAE
	(Kong and Tian, 2020)	SMR	10km grid	LOOCV
	(Guo et al., 2020)	SMR	100m grid	CV; R^2/RMSE/MPE
	(Van Ryswyk et al., 2019)	BFSR	10m grid	LOOCV
	(Liu et al., 2019)	/	500m grid	LOOCV
	(Masri et al., 2019)	BFSR	1km grid	LOOCV
	(Wu et al., 2017)	SLR	250m grid	10-fold CV; External Verification (out-of-sample observations from 2013)
	(Wu et al., 2015a)	SLR	30m grid	LOOCV; RMSE/NMSE
	(Meng et al., 2015)	SFR	1km grid	LOOCV; R^2/RMSE
	(Rao et al., 2014)	/	200m	CV
Machine/Deep Learning Prediction Models	(Tella and Balogun, 2021)	XGBoost; RF; KNN; NB	60m grid	Confusion matrix; Statistical Measures; ROC-AUC
	(Shogrkhodaei et al., 2021)	RF; AdaBoost; SGD	30m grid	Splitting 70% training and 30% test; RMSE/MAE; ROC-AUC
	(Liu et al., 2020)	RF; SVM; MLR	15 m distance along the route	10-fold CV (Splitting 70% training and 30% test); R^2/RMSE/MAE/IA
	(Li et al., 2020b)	Full Residual Deep Network	1km grid	63.3% samples for training and validation (80% training/20% validation), 36.7% for independent test; 4 monitoring sites for independent tests; R^2/RMSE

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Table A7 (*continued*)

Model	Article	Algorithm	Resolution	Model Validation and Prediction Accuracy
ML/DL LUR Models	(Zhang and Hu, 2017)	LEM	3km grid	10-fold CV; R^2/MPE/RMSE
	(Qi et al., 2022)	RF	100m grid (within 500m of each monitor)	10-fold CV (splitting training and testing set randomly, temporally, or spatially); R^2/MAE/RMSE
	(Babu Saheer et al., 2022)	LR; SVR; LSTM	Within 1km of monitor	MAE/MSE/RMSE/R^2/MAPE
	(Han et al., 2022a)	RF, MLR	500m grid	Splitting 80% training and 20% test; R^2/MSE/RMSE/MAE

OK: Ordinary Kriging, **IDW**: Inverse Distance Weighted, **KED**: Kriging with external drift, **KED-IDW**: A Hybridization of KED and IDW, **SMR**: Stepwise Multiple Regression, **BFSR**: Backwards and Forwards Stepwise Regression, **SLR**: Stepwise Linear Regression, **SFR**: Supervised Forward Regression, **LR**: Linear Regression, **MLR**: Multiple Linear Regression, **LEM**: Linear Mixed-effects Model, **XGBoost**: eXtreme Gradient Boosting algorithms, **RF**: Random Forest, **KNN**: K-Nearest Neighbour, **NB**: Naive Bayes, **SGD**: The Stochastic Gradient Descent algorithm, **SVR**: Support Vector Regression, **SVM**: Support Vector Machine, **LSTM**: Long Short Term Memory, **CV**: Cross-Validation, **LOOCV**: Leave-one-out cross-validation.

Statistical Measures includes Recall (REC), Precision (PREC), Specificity, Kappa Index (KI), F-measure, Accuracy, Fitting Index (IA). ROC-AUC: The area under the ROC curve, Error Metrics includes mean average error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), R^2score, mean percentage error (MPE), relative root mean squared error (RRMSE), relative mean absolute error (RMAE), normalized mean squared error (NMSE).

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