



Chemical and Environmental Science Archives
(ISSN: 2583-1151)
An International Research Journal

DOI: <https://doi.org/10.47587/CESA.2026.6303>

Review Article

Air Quality Management in Urban Areas: A Review of Source Apportionment, Modeling, and Control Strategies

Ibiyemi Sesi Okelola¹ , Ibrahim Ayinla Mahmud¹ , Nathan Rimamsanati Yohanna^{2,3} , Moses Adondua Abah^{2,3}  and Micheal Oladosu Abimbola^{3,4} 

¹School of Engineering and Built Environment, University of Greater Manchester, Bolton, United Kingdom

²Department of Biochemistry, Faculty of Biosciences, Federal University Wukari, Taraba State, Nigeria

³ResearchHub Nexus Institute, Nigeria

⁴Department of Chemical Sciences, Faculty of Science, Anchor University, Ayobo, Lagos State, Nigeria

✉ Corresponding Author: Ibiyemi Sesi Okelola; io5aes@greatermanchester.ac.uk

Received: Aug 3, 2026/ Revised: Sept 18 2026/Accepted: Sept 19, 2026

Abstract

Urban air pollution presents a complex environmental and public health challenge driven by rapid population growth, expanding industrial activities, and increasing transportation demands. This review evaluates the integrated framework required for effective urban air quality management, focusing on source apportionment, atmospheric modeling, emission control strategies, and implementation challenges. Urban pollutants consist of primary emissions (e.g., road traffic, industrial activities, power generation, waste burning, and domestic fuel combustion) and secondary pollutants (e.g., ozone and secondary organic aerosols) formed via atmospheric oxidation and photochemical reactions. Because total pollutant mass does not reflect specific source toxicities or origins, source apportionment techniques including receptor models (Positive Matrix Factorization, Chemical Mass Balance), bottom-up emission inventories, and chemical tracer analyses are critical for quantifying specific source contributions. Furthermore, atmospheric prediction relies on Gaussian dispersion models for local street-canyon dynamics, chemical transport models for regional transboundary reactions, and emerging data-driven machine learning or satellite remote-sensing approaches to address spatial coverage gaps. Translating these technical insights into policy requires coordinated interventions across transportation, clean energy, waste management, and urban planning. However, persistent implementation bottlenecks remain, including sparse monitoring networks, weak emission inventories, technical constraints, and fragmented regulatory enforcement. Next-generation management must adopt an adaptive, evidence-based cycle integrating low-cost sensor networks, satellite observations, and artificial intelligence to refine exposure assessment and ensure sustained public health protection.

Keywords: Air Quality Management, , Receptor Modeling (PMF, CMB), Atmospheric Dispersion, Chemical Transport, Particulate Matter (PM_{2.5}), and Air Pollution

Introduction

Urban air pollution is a major environmental and public-health challenge because expanding cities concentrate populations, transportation, industry, energy consumption, and other emission-generating activities within limited areas (Chow, 2004; Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). This review argues that effective urban air-quality improvement requires the integration of source apportionment, atmospheric modeling, monitoring, and emission-control strategies

(Johnson *et al.*, 2011; Sokhi *et al.*, 2021; Krupnova *et al.*, 2022). The available literature links rapid urban development and economic activity with increasing pressure on urban and regional atmospheric environments (Chow, 2004; Fernando *et al.*, 2010). However, the supplied evidence consists mainly of reviews, methodological works, and regional assessments rather than one standardized global dataset (Chow, 2004; Colbeck *et al.*, 2010; Krupnova *et al.*, 2022).

Urbanization and population growth increase the scale of activities that generate air emissions (Chow, 2004; Colbeck *et al.*, 2010). Growing cities require more transportation, electricity, fuel, industrial production, construction, and domestic energy use (Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). Megacities concentrate people and economic activities in ways that create environmental effects at urban, regional, and global scales (Chow, 2004). Population growth also increases travel demand and the number of vehicles operating on urban roads (Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). Industrial facilities and transport are identified as major urban pollution sources, while domestic energy use and dispersed commercial activities add further emissions (Krupnova *et al.*, 2022; Akomolafe *et al.*, 2024). Maintaining acceptable urban air quality is therefore essential for protecting health, quality of life, and the surrounding environment (Chow, 2004; Colbeck *et al.*, 2010). Effective management requires reliable measurements, air-quality standards, emission inventories, source information, and policies suited to local conditions (Colbeck *et al.*, 2010; Johnson *et al.*, 2011).

Urban air pollution consists of primary pollutants emitted directly from sources and secondary pollutants formed through atmospheric chemical reactions (Arya, 1998; Krupnova *et al.*, 2022). Particulate matter, particularly PM_{2.5} and PM₁₀, is an important urban pollutant because its concentration, chemical composition, size distribution, and atmospheric persistence vary across locations and sources (Johnson *et al.*, 2011; Vu *et al.*, 2015). Fine particulate matter is emphasized as a major concern because of its association with serious adverse health effects (Johnson *et al.*, 2011). Particle number and size distributions can also provide information about emission sources and atmospheric processing (Vu *et al.*, 2015). Traffic, industrial emissions, biomass burning, cooking, transported aerosol, marine aerosol, and atmospheric nucleation all contribute to urban particle populations (Vu *et al.*, 2015). Traffic is identified as a particularly important source of particle numbers in urban environments (Vu *et al.*, 2015).

Nitrogen oxides, including nitrogen dioxide, are important combustion-related pollutants associated with traffic and other fuel-burning activities (Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). Sulfur dioxide is associated with sulfur-containing fuels and remains a significant concern in some developing-world cities (Chow, 2004; Colbeck *et al.*, 2010). Ozone is a secondary pollutant produced through photochemical processes involving precursor emissions such as nitrogen oxides and volatile organic compounds (Chow, 2004; Krupnova *et al.*, 2022). Carbon monoxide is produced by incomplete combustion, including combustion associated with vehicles and domestic fuel use (Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). Volatile organic compounds originate from industrial activities, solvents, fuel handling, traffic, and other anthropogenic sources (Longhurst & Brebbia, 2006; Akomolafe *et al.*, 2024). The behavior of these pollutants depends on emissions, sunlight, atmospheric chemistry, wind, turbulence, temperature, deposition, and

regional transport (Arya, 1998; Sokhi *et al.*, 2021; Krupnova *et al.*, 2022)

Urban air pollution produces consequences for human health, visibility, ecosystems, and climate-related processes (Chow, 2004; Sokhi *et al.*, 2021). Exposure to particulate matter and gaseous pollutants is associated with respiratory illness and cardiovascular effects in urban populations (Johnson *et al.*, 2011; Colbeck *et al.*, 2010; Akomolafe *et al.*, 2024). Particulate pollution is also linked in the supplied literature with premature mortality, particularly in highly polluted urban environments (Johnson *et al.*, 2011). Air pollution contributes to urban and regional haze, which reduces visibility and affects environmental quality (Chow, 2004). Ozone can damage vegetation and contribute to broader ecosystem impacts (Chow, 2004). Atmospheric particles and chemical processes can also interact with climate and regional atmospheric conditions (Chow, 2004; Sokhi *et al.*, 2021). These consequences demonstrate that air-quality management must address both short-term pollution episodes and long-term population exposure (Sokhi *et al.*, 2021).

Urban air-quality management is difficult because emissions originate from multiple sources with different chemical profiles, operating schedules, and spatial distributions (Johnson *et al.*, 2011; Krupnova *et al.*, 2022). Traffic emissions vary according to vehicle type, traffic volume, congestion, road location, and time of day (Krupnova *et al.*, 2022). Industrial emissions may vary with production processes, while domestic and commercial emissions may be widely dispersed and difficult to measure (Sokhi *et al.*, 2021; Akomolafe *et al.*, 2024). After release, pollutants are transported and diluted by wind and turbulence, deposited on surfaces, or transformed through chemical reactions (Arya, 1998; Fernando *et al.*, 2010). Buildings, street canyons, and urban structures further modify airflow and pollutant dispersion (Longhurst & Brebbia, 2006; Fernando *et al.*, 2010). Consequently, pollutant concentrations can differ between roads, neighborhoods, industrial zones, and background locations (Sokhi *et al.*, 2021; Krupnova *et al.*, 2022). Temporal variability also makes it difficult to identify dominant sources under changing meteorological and emission conditions (Krupnova *et al.*, 2022). Source apportionment is therefore important because it helps quantify the contributions of different pollution sources and supports more targeted control policies (Johnson *et al.*, 2011; Vu *et al.*, 2015).

This review evaluates how source-apportionment methods identify pollution sources, how atmospheric models predict pollutant transport and transformation, and how control strategies reduce emissions and exposure. It also considers implementation challenges involving limited monitoring capacity, uncertain emission inventories, spatial variability, atmospheric complexity, and long-range transport. Future progress will require integrated monitoring networks, improved source characterization, higher-resolution models,

cleaner technologies, effective public transportation, urban planning, and sustained policy engagement.

Sources and Characteristics of Urban Air Pollution

Urban air pollution is produced by a changing mixture of directly emitted pollutants and compounds formed after emission. The distinction matters because the pollutant measured at a monitoring site may not be the pollutant released by the original source: gases and particles can react, evaporate, condense, and move across administrative boundaries before exposure occurs. Fine particulate matter is especially important because its health and environmental effects depend not only on mass concentration but also on particle size, number, and chemical composition (Zhang *et al.*, 2015). A global review of 419 urban source-apportionment records from 51 countries estimated that traffic contributed about 25% of urban PM_{2.5}, industrial activities 15%, domestic fuel burning 20%, natural dust and salt 18%, and unspecified anthropogenic sources 22%, although the authors emphasized substantial regional heterogeneity and incomplete coverage (Karagulian *et al.*, 2015).

Major Primary Emission Sources

Road traffic: Road transport emits a mixture of exhaust and non-exhaust pollutants. Combustion in petrol and diesel engines releases nitrogen oxides (NO_x), carbon monoxide (CO), volatile organic compounds (VOCs), and primary particulate matter, while braking, tyre wear, and resuspended road dust add mineral and metal-rich particles. Traffic growth therefore affects both pollutant emissions and the number of people living or working close to emission corridors. A review of traffic-related pollution links increasing vehicle activity and fuel-combustion products with deteriorating urban air quality, with particulate matter and nitrogen dioxide among the routinely monitored traffic indicators (Khan, 2021). Traffic-related particles are also relevant to health because a systematic review and meta-analysis found that elemental carbon and organic carbon were among the PM_{2.5} constituents most consistently associated with adverse health outcomes, particularly for fossil-fuel combustion and traffic sources (Yoon *et al.*, 2023).

Industrial activities

Factories, refineries, metal processing, cement production, brick manufacture, and other industrial operations can release SO₂, NO_x, PM, VOCs, and trace metals through fuel combustion, high-temperature processing, material handling, and fugitive emissions. Industrial sources may be concentrated in particular districts, but their influence can extend beyond the industrial zone through stack emissions and regional transport. The global urban review identified industrial activity as a substantial contributor to ambient PM_{2.5}, while also showing that the size of the contribution varies markedly among cities and source-apportionment methods (Karagulian *et al.*, 2015).

Power generation

Fossil-fuel power plants emit SO₂, NO_x, particulate matter, and carbon-containing gases, with emission profiles depending on fuel type, combustion conditions, and control technology. Although tall stacks can reduce local ground-level concentrations near the facility, they can promote regional transport and secondary sulfate and nitrate formation downwind. Coal combustion is of particular health relevance because sulfate-containing PM_{2.5} has been repeatedly associated with adverse outcomes in the source- and composition-focused evidence synthesized by Yoon, Lim, and Thurston (Yoon *et al.*, 2023).

Construction and road dust

Excavation, demolition, earth moving, concrete handling, and vehicle movement over unpaved or dusty surfaces generate coarse particles and respirable fine particles. Road dust can also be repeatedly resuspended after it has accumulated, so concentrations may remain elevated even when direct construction activity is intermittent. The resulting PM₁₀ and PM_{2.5} are affected by surface moisture, wind, traffic speed, and the efficiency of dust-control practices; their contribution is therefore strongly site-specific rather than constant across an urban area (Karagulian *et al.*, 2015).

Waste burning

Open burning of municipal waste, agricultural residues, or mixed household refuse releases PM_{2.5}, CO, VOCs, and a chemically diverse mixture of organic compounds. Mixed waste can also generate toxic products when plastics and other synthetic materials burn under poorly controlled conditions. Beyond its direct emissions, waste burning supplies organic and nitrogen-containing precursors that can participate in secondary aerosol formation. The global source-apportionment review grouped biomass burning with source categories requiring urgent control because of its contribution to urban PM and associated disease burden (Karagulian *et al.*, 2015).

Residential fuel combustion

Cooking and heating with wood, coal, charcoal, kerosene, or other solid fuels can produce PM_{2.5}, CO, VOCs, and black carbon. Household emissions may affect indoor exposure directly and ambient air quality indirectly through building leakage, ventilation, and neighbourhood-scale dispersion. Domestic fuel burning represented approximately one-fifth of the globally averaged urban PM_{2.5} contribution in the reviewed source-apportionment database, although the estimate is not a universal city-level value (Karagulian *et al.*, 2015).

Small-scale commercial activities

Restaurants, bakeries, informal workshops, solvent use, small boilers, diesel generators, and repair activities can emit PM, VOCs, NO_x, and CO. These sources are often dispersed and may be poorly represented in conventional inventories, yet they can create localized exposure near markets, roadside

businesses, and dense mixed-use neighbourhoods. Their importance is amplified where many small emitters operate close to residences and pedestrian activity (Akomolafe *et al.*, 2024).

Table 1. Major urban air-pollution sources, pollutants, and environmental/health relevance

Source	Major Pollutants	Main Contributing Activities	Health / Environmental Relevance
Road traffic	PM _{2.5} , PM ₁₀ , NO _x , CO, VOCs, brake and tyre particles	Exhaust, braking, tyre wear, road-dust resuspension	Near-road exposure; respiratory and cardiovascular risks; ozone and secondary-PM precursors (Khan, 2021; Yoon <i>et al.</i> , 2023).
Industry	SO ₂ , PM, NO _x , VOCs, metals	Combustion, refining, metal, cement, and chemical processing	Local and regional particulate pollution; sulfate and metal-containing PM health relevance (Karagulian <i>et al.</i> , 2015; Yoon <i>et al.</i> , 2023).
Power generation	SO ₂ , NO _x , PM, CO ₂ , VOCs	Coal, oil, or gas combustion	Direct emissions and downwind secondary sulfate/nitrate formation (Yoon <i>et al.</i> , 2023; Fine <i>et al.</i> , 2008).
Waste burning	PM _{2.5} , CO, VOCs, organic compounds	Open burning of municipal or agricultural waste	Toxic direct exposure and precursor supply for secondary pollution (Karagulian <i>et al.</i> , 2015).
Construction and road dust	PM ₁₀ , PM _{2.5} , mineral dust, metals	Excavation, demolition, hauling, resuspension	Respiratory irritation and visibility reduction; strong dependence on wind and moisture (Karagulian <i>et al.</i> , 2015).
Domestic combustion	PM _{2.5} , CO, VOCs, black carbon	Solid-fuel cooking and heating	Household and ambient exposure; major urban PM source in some regions (Karagulian <i>et al.</i> , 2015).
Small-scale commercial activities	PM, VOCs, NO _x , CO	Restaurants, workshops, solvent use, small generators	Localized exposure in dense mixed-use areas and undercounting in inventories (Akomolafe <i>et al.</i> , 2024).

Secondary Pollutant Formation

Primary emissions do not remain chemically or physically unchanged. Atmospheric oxidation, photolysis, neutralization, condensation, and cloud processing convert precursor gases into secondary pollutants. Fine PM may be emitted directly, but it can also form through gas-to-particle conversion; both primary and secondary particles are subsequently transformed and transported before removal (Zhang *et al.*, 2015).

Secondary particulate matter includes sulfate, nitrate, ammonium, and secondary organic aerosol. These species can constitute a major fraction of PM_{2.5} across seasons and times of day, and their relative abundance changes with meteorology, precursor strength, thermodynamics, and

atmospheric processing (Fine *et al.*, 2008). Secondary organic aerosol remains particularly uncertain because ambient organic PM contains many oxidized compounds whose sources and formation mechanisms are not fully resolved; current estimates of the SOA fraction may carry uncertainty approaching 50% or more (Fine *et al.*, 2008).

Photochemical ozone forms when NO_x and VOCs react under sunlight through chains of atmospheric oxidation. The same precursor families can also contribute to secondary organic

aerosol and other gas-to-particle products, so reducing one pollutant does not always produce a proportional reduction in every secondary pollutant. Modeling work on ozone–particle coupling shows that control strategies must account for interactions among organic gases, NO_x, ozone chemistry, and aerosol formation rather than treating each pollutant independently (Meng *et al.*, 1997).

Spatial and Temporal Variability

Urban concentrations vary across minutes, seasons, neighbourhoods, and meteorological regimes. Traffic peaks can generate short-lived morning and evening enhancements, especially at roadside locations, while congestion can prolong emissions and reduce dispersion. The measured concentration is therefore determined by the balance between emissions and the atmospheric processes that transport and dilute them (Salmond & McKendry, 2009).

Seasonal variability reflects changes in heating demand, sunlight, boundary-layer depth, rainfall, wind, and atmospheric chemistry. Low wind and shallow mixing layers generally favour accumulation, whereas stronger horizontal and vertical dispersion tends to reduce concentrations; regional flows, sea breezes, and synoptic weather systems can also transport pollution into or out of a city (Salmond & McKendry, 2009).

Urban morphology adds another layer: building height, street-canyon geometry, road layout, and density alter airflow and pollutant residence time. Recent high-resolution modelling across four Italian cities found that wind speed and temperature reduced PM_{2.5}, while street-geometry effects were

non-linear and season-dependent (Metrangolo *et al.*, 2026). These interacting processes explain why two locations with similar emissions can have different exposure levels and why a city-wide average may conceal substantial neighbourhood-scale contrasts.

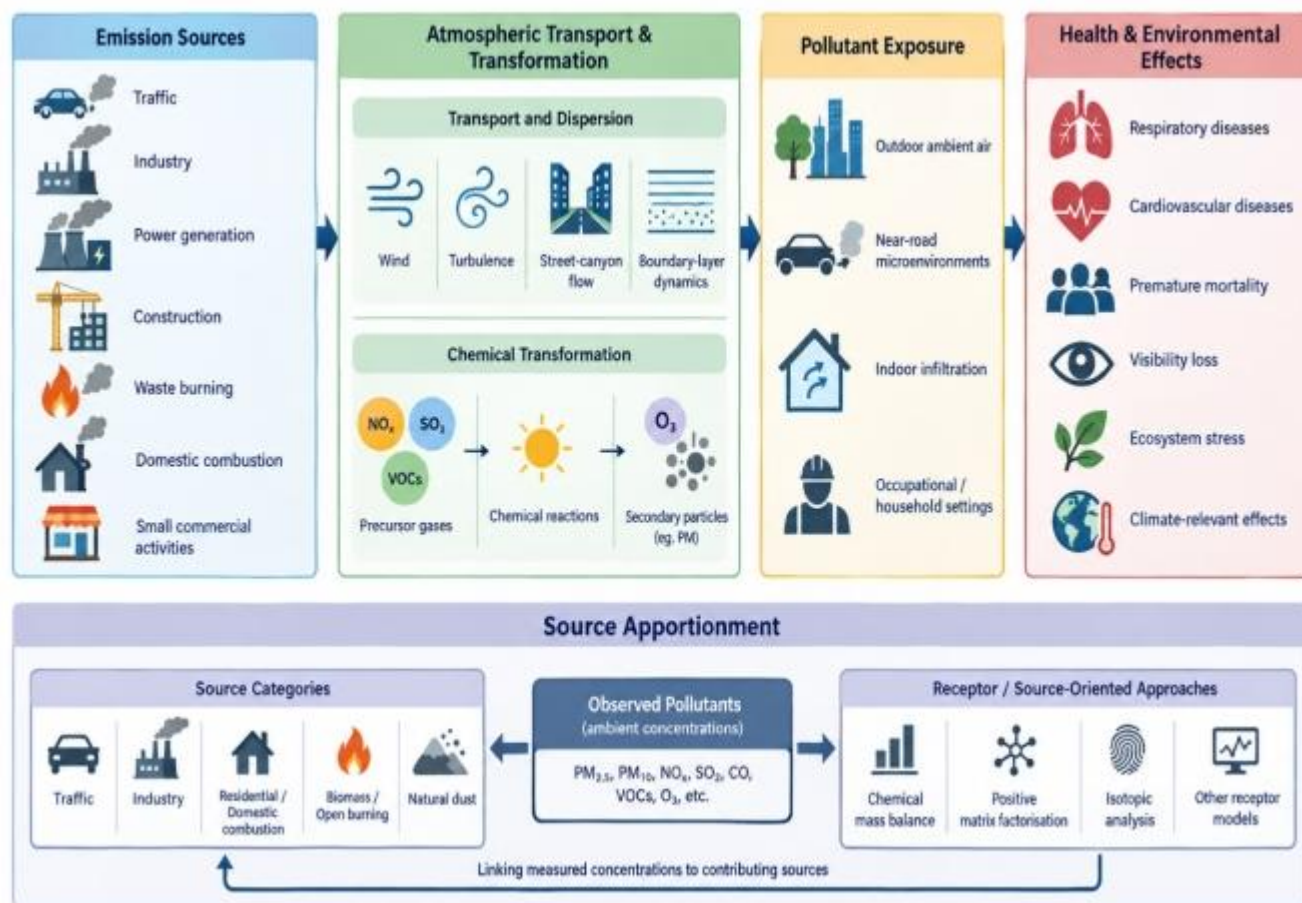


Figure 1. Major Sources and pathways of urban air pollution

Source: Kerkez *et al.* (2026)

Concept and Importance of Source Apportionment

Source apportionment identifies the pollutant sources contributing to concentrations measured at an urban receptor and estimates their relative contributions (Hopke, 2008). In receptor modelling, the receptor is typically a monitoring site or sample, while measured chemical composition is treated as a mixture of signatures from multiple sources (Srimuruganandam & Jose, 2016). This approach is particularly important for particulate matter (PM), because total PM mass does not indicate whether particles originate from traffic, combustion, industry, soil, sea salt, or secondary atmospheric formation (Moreno *et al.*, 2009).

Therefore, a high concentration at a single site cannot by itself identify the responsible source or determine which intervention would provide the greatest reduction (Hopke, 2008). Source-apportionment information links measured

concentrations to specific sources, supporting targeted control, exposure assessment, and evaluation of emission inventories (Choudhary, 2016).

Its policy value lies in distinguishing overall pollution levels from source-specific contributions (CHAPTER 5-Source Apportionment Measurement, 2012). Apportionment results can inform air-quality management plans, improve emission inventories, and provide source-specific exposure estimates for health studies (Hopke, 2008). This distinction is important because controls based solely on total PM mass may overlook chemical components or sources more strongly associated with adverse health effects (Moreno *et al.*, 2009). Source apportionment therefore supports prioritisation rather than simple ranking: the largest source is not necessarily the most toxic or the most controllable (Hopke, 2008).

Receptor-Based Approaches

Receptor models estimate source contributions from pollutant composition measured at a receptor using either known source profiles or statistically resolved source-related factors (Karagulian & Belis, 2012). Common approaches include Positive Matrix Factorization (PMF), Chemical Mass Balance (CMB), Principal Component Analysis (PCA), and related multivariate and trajectory-assisted methods.

PMF decomposes measured concentration data into source profiles and time-varying contributions while incorporating measurement uncertainty into the analysis (Belis *et al.*, 2015). Its major advantage is the ability to resolve factors without requiring complete predefined source profiles, which is useful where local emissions are poorly characterised (Srimuruganandam & Jose, 2016). However, statistical factors require chemical interpretation because they may represent mixed sources, atmospheric processes, or sources altered by ageing and condensation (Leea *et al.*, 2008). PMF reliability therefore depends on the measured species, uncertainty estimates, sampling design, factor number, and diagnostic evaluation of alternative solutions (Dutton *et al.*, 2010).

CMB estimates source contributions by combining measured receptor concentrations with chemically characterised source profiles (Karagulian & Belis, 2012). It is particularly useful when relevant source categories are known and representative local profiles are available (Srimuruganandam & Jose, 2016). Its main limitation is sensitivity to incomplete, outdated, regionally transferred, or atmospherically altered source profiles (Leea *et al.*, 2008). Molecular-marker CMB provides greater specificity by using distributions of selected organic compounds to associate ambient particles with source fingerprints (Schawer *et al.*, 1996).

PCA and related factor-analysis methods identify pollutants that vary together, providing an initial indication of common sources or shared atmospheric behaviour (CHAPTER 5-Source Apportionment Measurement, 2012). Although PCA is relatively simple and does not require a complete emission inventory, its components do not automatically represent physically defined sources or quantitative contributions (Choudhary, 2016). Other approaches include absolute principal component scores, constrained receptor models, conditional-probability functions, back-trajectory analysis, and hybrid receptor-chemical-transport models (CHAPTER 5-Source Apportionment Measurement, 2012). These methods can strengthen interpretation by linking statistical factors with wind direction, transport pathways, and regional chemical-transport information (Hopke, 2008).

PMF and CMB can identify major sources, but their agreement varies by source and receptor location (Leea *et al.*, 2008). Secondary inorganic aerosol estimates may show greater agreement, whereas primary-source estimates can differ because PMF reflects atmospheric processing while CMB relies on source profiles measured closer to emission

conditions (Leea *et al.*, 2008). Source identification should therefore rely on multiple lines of evidence, including model outputs, tracer behaviour, temporal patterns, meteorology, and knowledge of local activities (Watson *et al.*, 2016).

Emission Inventory Approaches

Emission inventories estimate pollutant releases from defined activities by combining activity data with emission factors and, where available, source-specific control efficiencies (Watson *et al.*, 2016). Bottom-up inventories estimate emissions from individual activities such as vehicle travel, fuel combustion, industrial production, construction, waste burning, and household energy use before aggregating them across a city or region (Sun *et al.*, 2020). These estimates can then be spatially and temporally allocated for air-quality management and chemical-transport modelling (Hopke, 2008). Activity data determine the scale and timing of an emission process, while emission factors convert activity into pollutant mass (Watson *et al.*, 2016). Transport inventories may require fleet composition, fuel use, road activity, and vehicle-specific factors, whereas residential-combustion inventories may require fuel type, appliance use, and seasonal demand (Sun *et al.*, 2020). Inventory reliability therefore depends on the quality of both the calculations and the underlying activity data, particularly for informal, diffuse, intermittent, or poorly regulated sources (Choudhary, 2016).

The main strength of emission inventories is their city-wide, source-oriented structure, which supports scenario testing and policy planning (Watson *et al.*, 2016). However, uncertain activity data and emission factors can bias source estimates, especially when local operating conditions differ from those used to derive the factors (Srimuruganandam & Jose, 2016). Inventories should therefore be evaluated against ambient measurements and receptor-model results rather than treated as complete representations of observed pollution (Watson *et al.*, 2016).

Tracer and Chemical-Fingerprint Approaches

Tracer approaches identify source categories using chemical species or compound groups that are enriched in particular emissions (Moreno *et al.*, 2009). Elemental tracers can help distinguish geological material, traffic, and industrial sources, although interpretation must account for shared sources and atmospheric transport (Moreno *et al.*, 2009). Because some toxic metals are concentrated in fine particles, elemental information may also help relate source contributions to potential health relevance (Moreno *et al.*, 2009).

Organic markers provide greater specificity for fine PM and have been used to distinguish emissions from gasoline and diesel vehicles, wood smoke, meat cooking, vegetative detritus, and cigarette smoke (Lin *et al.*, 2010). Molecular-marker distributions can be incorporated into CMB or used alongside PMF to improve interpretation of otherwise ambiguous source factors (Schawer *et al.*, 1996).

Volatile organic compound fingerprints demonstrate both the usefulness and limitations of tracer selection. Toluene-to-benzene and isopentane-to-n-pentane ratios have been used to distinguish traffic, biomass burning, garbage burning, and fossil-fuel-related emissions, although shared compounds require contextual interpretation (Kumar *et al.*, 2020). For example, propane may occur in crop-residue burning, meaning it should not automatically be interpreted as an LPG tracer in areas affected by biomass combustion (Kumar *et al.*, 2020).

Isotopic signatures provide another dimension of source discrimination because different source classes may have distinct isotopic compositions despite overlapping bulk chemistry (Moreno *et al.*, 2009). Their greatest value is achieved when isotope data are combined with elemental composition, organic markers, meteorology, and receptor modelling rather than treated as definitive fingerprints alone (Watson *et al.*, 2016).

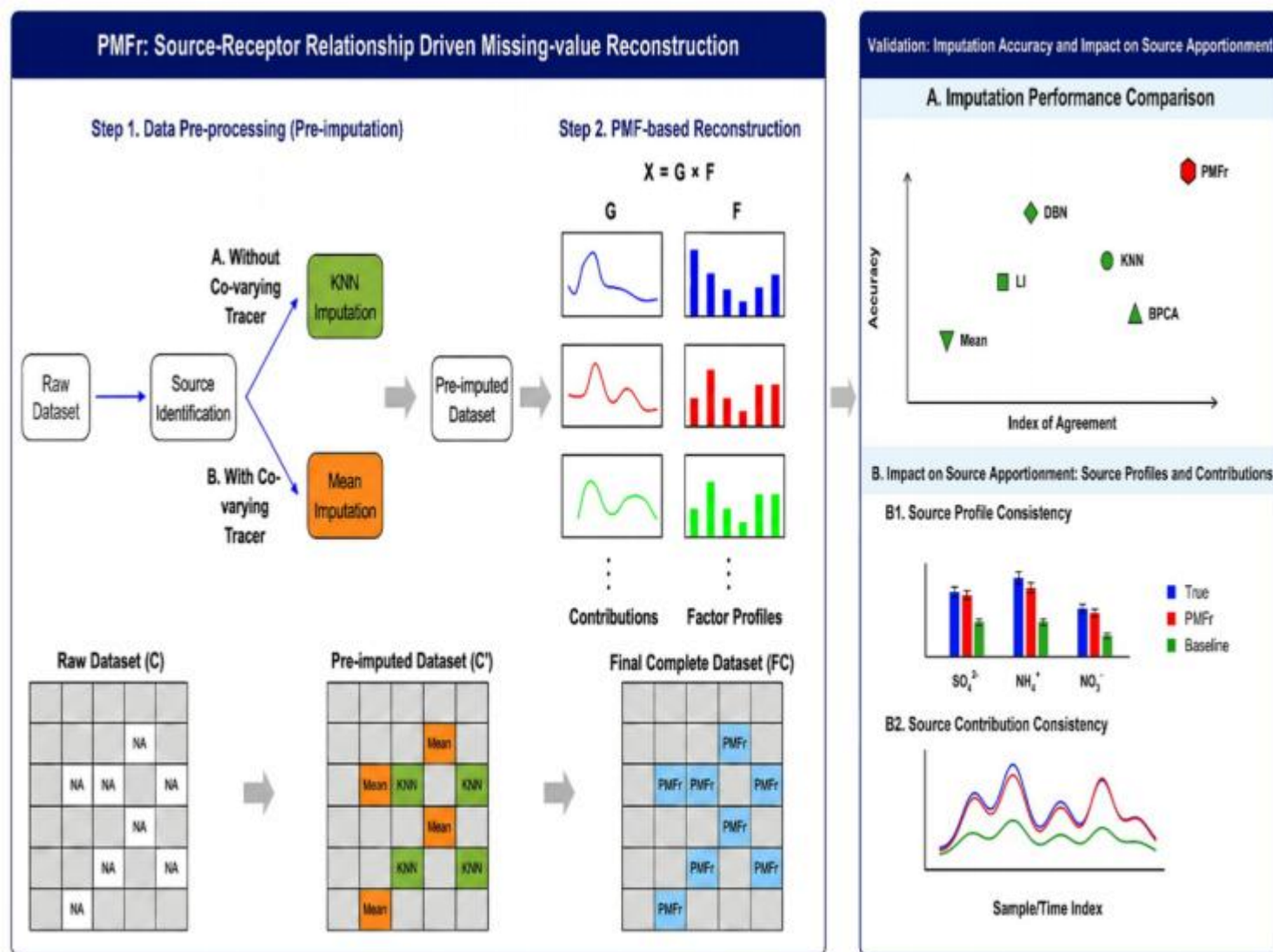


Figure 2. Integrated workflow for urban air-pollution source apportionment

Figure 2 represents source apportionment as an integrated evidence chain rather than a single model run (Karagulian & Belis, 2012). Emission measurements and activity data define candidate source processes, while chemical characterization supplies the elemental, ionic, carbonaceous, organic, or isotopic variables needed to distinguish them (Watson *et al.*, 2016). Statistical and receptor models then resolve source-

related patterns, which are checked against source profiles, tracers, meteorology, time trends, and chemical-transport information (Hopke, 2008). The final contribution estimates should be interpreted with uncertainty bounds and translated into control priorities only after considering source magnitude, controllability, exposure relevance, and local policy feasibility (Hopke, 2008).

Table 2. Major source-apportionment methods used in urban air-quality studies

Method	Principle	Main application	Strength	Major limitation
PMF	Decomposes speciated concentration data into source profiles and time-varying contributions while using measurement uncertainties (Belis <i>et al.</i> , 2015).	Identifying and estimating contributions from major source factors (Dutton <i>et al.</i> , 2010).	Does not always require predefined local source profiles (Srimuruganandam & Jose, 2016).	Sensitive to input quality, factor selection, rotational ambiguity, and source mixing (Dutton <i>et al.</i> , 2010).
CMB	Solves a chemical mass-balance equation using measured receptor concentrations and source profiles (Karagulian & Belis, 2012).	Quantifying known sources with available chemical profiles (Srimuruganandam & Jose, 2016).	Provides relatively direct source-specific interpretation (Schawer <i>et al.</i> , 1996).	Requires reliable, representative source profiles and appropriate markers (Leea <i>et al.</i> , 2008).
PCA	Identifies pollutant groups that covary and may reflect common sources or processes (CHAPTER 5-Source Apportionment Measurement, 2012).	Preliminary source identification and data exploration (Choudhary, 2016).	Relatively simple and does not require a complete prior inventory (CHAPTER 5-Source Apportionment Measurement, 2012).	Usually provides limited quantitative source attribution and can be difficult to interpret physically (Choudhary, 2016).
Emission inventory	Estimates emissions from activity data, emission factors, and control information (Watson <i>et al.</i> , 2016).	City-wide source estimation, scenario testing, and policy planning (Hopke, 2008).	Directly links source sectors to management interventions and chemical-transport modelling (Watson <i>et al.</i> , 2016).	Informal, diffuse, intermittent, and poorly characterised activities may be underrepresented (Choudhary, 2016).
Tracer/fingerprint analysis	Uses diagnostic elements, organic markers, isotopes, or compound ratios to distinguish source categories (Moreno <i>et al.</i> , 2009).	Confirming source identity and strengthening receptor-model interpretation (Lin <i>et al.</i> , 2010).	Can provide high source specificity when markers are truly source-selective (Schawer <i>et al.</i> , 1996).	Markers can be shared between sources, altered during atmospheric processing, or misinterpreted without local context (Kumar <i>et al.</i> , 2020).

Atmospheric Modeling and Prediction of Urban Air Quality

Urban air-quality modelling integrates emissions, meteorology, atmospheric chemistry, observations, and exposure-relevant concentrations across spatial and temporal scales. Dispersion and chemical-transport models provide

mechanistic representations of pollutant movement and transformation, while statistical and machine-learning models

derive relationships from historical observations and satellite products extend coverage where monitoring is sparse (Chudnovsky, 2021; Ballesteros Peinado *et al.*, 2025). No single approach is sufficient for all urban applications because street-canyon processes, regional transport, chemical ageing,

data availability, and computational requirements vary among cities (Fallahshorshani et al., 2012; Lolli, 2025).

Dispersion Modelling

Gaussian dispersion models remain a foundation for estimating near-source pollutant concentrations from specified emissions and meteorological conditions (Turner, 1979; Hanna, 2014). They assume that plume concentrations follow approximately Gaussian distributions in the crosswind and vertical directions, with wind speed, atmospheric stability, mixing height, source characteristics, and receptor location influencing predicted concentrations (Yang, 2004). In urban environments, however, buildings, surface roughness, mechanical turbulence, and recirculation can violate these assumptions, requiring modifications that account for enhanced mixing and turbulence in built-up areas (Hanna, 2014).

Urban dispersion models can represent point, line, and area sources according to their spatial characteristics. Point sources include stacks and other localized releases, line sources represent elongated emitters such as roads, and area sources describe distributed emissions from neighbourhoods, industrial zones, construction activities, and other diffuse surfaces (Thistle & Londergan, 1991; Middleton, 1995). Road traffic is commonly represented using line-source formulations, although complex road networks and interacting plumes may require more advanced plume-in-grid approaches (Wang & Rote, 1975; Briant & Seigneur, 2014). Line-source models can represent concentration changes away from roadways more explicitly, whereas area-source formulations may be more appropriate for diffuse neighbourhood emissions (Yang, 2004). Traffic applications therefore require consistent coupling of traffic activity, emission factors, dispersion processes, and meteorological data (Fallahshorshani et al., 2012).

At the local scale, predicted concentrations are particularly sensitive to wind direction, atmospheric stability, mixing height, street orientation, building-induced turbulence, and variations in near-road emissions (Middleton, 1995; Hanna, 2014). Model evaluation should therefore use observations that correspond to the modelled spatial and temporal scales rather than relying only on citywide averages (Turner, 1979; Fallahshorshani et al., 2012).

Chemical Transport Models

Chemical transport models (CTMs) extend dispersion modelling by representing the emission, transport, chemical transformation, and removal of multiple atmospheric species (Turner, 1979; Middleton, 1995). They are particularly important for pollutants formed or substantially modified in the atmosphere, including ozone, secondary particulate matter, sulfate, and nitrate (Laskarzewska et al., 2004; Barone et al., 1999; Fisher, 1983). Precursors such as nitrogen oxides,

volatile organic compounds, sulfur compounds, and ammonia can therefore contribute to pollutant formation away from their original emission sources (Middleton, 1995; Barone et al., 1999).

CTMs represent processes such as advection, mixing, chemical reactions, deposition, and aerosol transformation across gridded or trajectory-based domains (Middleton, 1995). Deposition removes pollutants from the atmosphere and transfers contaminants to surfaces including soil, vegetation, buildings, and water (Middleton, 1995; Fisher, 1983). Model performance consequently depends on the quality of emission inventories, meteorological fields, chemical mechanisms, boundary conditions, and parameterisations of unresolved processes (Turner, 1979; Fisher, 1983). Urban concentrations may also reflect pollution transported from neighbouring cities, industrial regions, wildfire and biomass-burning areas, and longer-range regional pathways. Regional CTMs are therefore valuable for assessing transboundary pollution, regional haze, acid deposition, and the relative contributions of local and transported emissions (Middleton, 1995).

Secondary pollutant formation distinguishes chemistry-resolving models from approaches focused mainly on primary emissions (Laskarzewska et al., 2004; Barone et al., 1999). Models that omit atmospheric ageing and precursor interactions may underestimate ozone and secondary aerosol formation (Middleton, 1995). CTMs consequently support emission-control scenarios by evaluating both changes at the source and their downstream chemical effects (Fisher, 1983).

Data-Driven and Statistical Models

Statistical and machine-learning models provide complementary approaches for estimating and forecasting pollutant concentrations from historical observations and predictors such as meteorology, traffic, season, time of day, land use, and neighbouring-monitor measurements (Sharma et al., 2022; Ballesteros Peinado et al., 2025). Linear and multivariable regression, autoregressive models, ARIMA, and related time-series methods remain useful because they are relatively transparent and can perform well where relationships are stable (Ballesteros Peinado et al., 2025). ARIMAX, for example, has shown strong short-term forecasting performance by combining autoregressive structure with external predictors (Deshmukh, 2017).

Machine-learning methods can capture nonlinear relationships among pollution, meteorology, traffic, land use, and remote-sensing variables that are difficult to represent mechanistically (Rybarczyk & Zalakeviciute, 2018; Masih, 2019). Ensemble and regression methods are commonly applied to concentration estimation, while neural-network and support-vector approaches are frequently used for forecasting (Rybarczyk & Zalakeviciute, 2018; Masih, 2019). Deep-learning and hybrid models can further represent temporal dependence and complex interactions, although careful validation and interpretability assessment remain necessary (Ballesteros Peinado et al., 2025). Short-term forecasting can

support alerts, exposure reduction, traffic management, and responses to episodic pollution, but performance depends on training-period length, missing-data treatment, station representativeness, meteorological forecasts, and adequate representation of extreme pollution events (Sharma *et al.*, 2022; Deshmukh, 2017; Rybarczyk & Zalakeviciute, 2018; Ballesteros Peinado *et al.*, 2025).

Satellite and Remote-Sensing Applications

Satellite remote sensing provides spatially extensive observations that complement the point measurements of ground stations (Tulloch & Li, 2004; Chudnovsky, 2021). For particulate matter, aerosol optical depth (AOD) is commonly used as an intermediate indicator that must be related to ground-level PM using statistical, chemical-transport, or hybrid models (Shin *et al.*, 2019; Chudnovsky, 2021). Satellite observations do not directly measure ground-level exposure because the relationship between AOD and surface concentrations depends on vertical pollutant profiles, meteorology, aerosol composition, and cloud conditions (Shin *et al.*, 2019; Chudnovsky, 2021).

The major advantage of satellite observations is their spatial coverage across areas lacking dense monitoring networks (Chudnovsky, 2021; Dubey, 2011). Their operational use is nevertheless constrained by spatial resolution, revisit time, cloud cover, missing retrievals, and differences between satellite overpass times and ground observations (Shin *et al.*, 2019; Lolli, 2025). Stronger applications therefore integrate satellite retrievals with ground measurements, meteorological variables, land-use information, and model outputs rather than treating any single data stream as complete (Engel-Cox *et al.*, 2004; Chudnovsky, 2021). Sentinel-2 AOD combined with meteorological variables has, for example, demonstrated agreement between estimated PM_{2.5} and ground observations while supporting higher-resolution urban mapping (Gitahi & Hahn, 2020). Such integrated systems can improve exposure mapping and fill monitoring gaps, although uncertainties from retrieval, calibration, meteorology, and ground observations must be propagated through the resulting estimates (Shin *et al.*, 2019; Lolli, 2025).

Table 3. Modeling approaches for urban air-quality assessment and prediction

Modeling approach	Main purpose	Data requirements	Typical application	Limitation
Dispersion models	Local pollutant distribution from specified sources and meteorology (Middleton, 1995).	Emissions, source geometry, terrain, land use, and meteorological data (Middleton, 1995).	Roads, industrial stacks, point, line, and area sources (Turner, 1979; Middleton, 1995).	Sensitive to source characterization, stability assumptions, urban turbulence, and model scale (Hanna, 2014; Turner, 1979).
Chemical transport models	Atmospheric chemistry, transport, deposition, and regional concentration fields (Turner, 1979; Middleton, 1995).	Emissions, meteorology, chemical mechanisms, boundary conditions, and deposition parameters (Turner, 1979; Fisher, 1983).	Regional pollution movement, ozone, secondary aerosol, sulfate, nitrate, and transboundary pollution (Laskarzewska <i>et al.</i> , 2004; Fisher, 1983).	Computationally demanding and sensitive to emissions and meteorological uncertainty (Turner, 1979; Lolli, 2025).
Statistical models	Estimate relationships and short-term pollution levels from historical observations (Ballesteros Peinado <i>et al.</i> , 2025).	Historical pollutant observations, meteorology, time-series structure, and covariates (Ballesteros Peinado <i>et al.</i> , 2025; Deshmukh, 2017).	Exposure assessment, interpolation, trend analysis, and forecasting (Ballesteros Peinado <i>et al.</i> , 2025; Sharma <i>et al.</i> , 2022).	May have limited mechanistic interpretation and can fail when relationships change (Rybarczyk & Zalakeviciute, 2018; Ballesteros Peinado <i>et al.</i> , 2025).
Machine learning	Nonlinear prediction,	Large, representative datasets with pollutant, meteorological, traffic,	Short-term forecasting,	Dependent on training data, validation design, feature quality,

	estimation, downscaling, and forecasting (Rybarczyk & Zalakeviciute, 2018; Masih, 2019).	land-use, or satellite predictors (Sharma <i>et al.</i> , 2022; Ballesteros Peinado <i>et al.</i> , 2025).	peak prediction, and integration of heterogeneous data (Rybarczyk & Zalakeviciute, 2018; Lolli, 2025).	and interpretability (Ballesteros Peinado <i>et al.</i> , 2025; Masih, 2019).
Satellite-based models	Spatial estimation and monitoring where ground stations are sparse (Chudnovsky, 2021; Shin <i>et al.</i> , 2019).	AOD or other remote-sensing products, ground calibration, meteorology, and often land-use or CTM predictors (Shin <i>et al.</i> , 2019; Chudnovsky, 2021).	Citywide PM mapping, spatial exposure estimation, and monitoring-network extension (Tulloch & Li, 2004; Engel-Cox <i>et al.</i> , 2004).	Requires calibration and is affected by clouds, missing values, temporal mismatch, and retrieval uncertainty (Shin <i>et al.</i> , 2019; Gitahi & Hahn, 2020).

Urban Air-Pollution Control and Management Strategies

Urban air-quality management should link source identification, atmospheric modelling, intervention, exposure

reduction, and health protection. Source-apportionment evidence helps identify major contributors and direct controls toward priority sources (Coelho, 2023; Jafari *et al.*, 2021).

Transportation-Based Control

Vehicle-emission standards, inspection programmes, cleaner fuels, and fleet renewal can reduce traffic emissions when effectively enforced. Public transport, walking, cycling, low-emission zones, and traffic-management measures can further reduce traffic activity and exposure when implemented as coordinated strategies (Khreis, 2022). Electric vehicles reduce tailpipe emissions, although tyre wear, brake particles, and road dust remain important non-exhaust sources. Transport models can help assess how fleet changes, traffic restrictions, and street design influence neighbourhood-scale pollution (Khreis, 2022).

Industrial and Energy-Sector Controls

Industrial pollution control should combine emission limits, cleaner production, fuel switching, energy efficiency, and end-of-pipe technologies. Flue-gas desulfurisation, particulate filtration, and nitrogen-oxide controls can reduce emissions when supported by monitoring and maintenance. Replacing high-emitting fuels with cleaner or renewable energy can provide air-quality and climate benefits, although cost and energy reliability remain important considerations (Integrated Strategies for Improving Urban Air Quality, 2026).

Household and Commercial Energy Interventions

Clean cooking fuels, electrification, and improved combustion technologies can reduce household particulate and combustion-related emissions. Energy-efficiency measures can further reduce fuel consumption when they do not shift pollution to another fuel or location. Effective interventions should consider affordability, fuel availability, user preferences, and appliance performance rather than assuming that a cleaner fuel automatically produces clean indoor air.

Dust and Waste Management

Construction controls should include material covering, wet suppression, wheel washing, speed control, and rapid site restoration to reduce PM₁₀ and PM_{2.5} emissions. Road-dust management should combine street cleaning, surface maintenance, and reduced vehicle speeds because resuspended dust is influenced by both road conditions and traffic activity. Reliable waste collection and restrictions on open burning are also necessary to reduce particulate matter, carbon monoxide, and volatile organic compound emissions.

Urban Planning and Nature-Based Approaches

Land-use planning can separate sensitive populations from major roads and industrial sources while improving access to public transport (Alabi, 2026). Green infrastructure can intercept pollutants, modify local microclimates, and provide environmental co-benefits, although its effectiveness depends on vegetation type, canopy structure, street geometry, and maintenance (Kumar, 2024; Ravindra, 2026). Vegetation should therefore be strategically placed because poorly designed planting in street canyons may restrict pollutant dispersion.

Monitoring and Regulatory Enforcement

Continuous monitoring, emission reporting, enforceable standards, and public disclosure are essential for accountability. Low-cost sensors can expand monitoring

coverage, but calibration, siting, uncertainty, and data quality require careful control (World Meteorological Organization [WMO], 2024). Regulatory monitors, satellites, low-cost sensors, and atmospheric models should therefore be integrated rather than treated as interchangeable measurements.

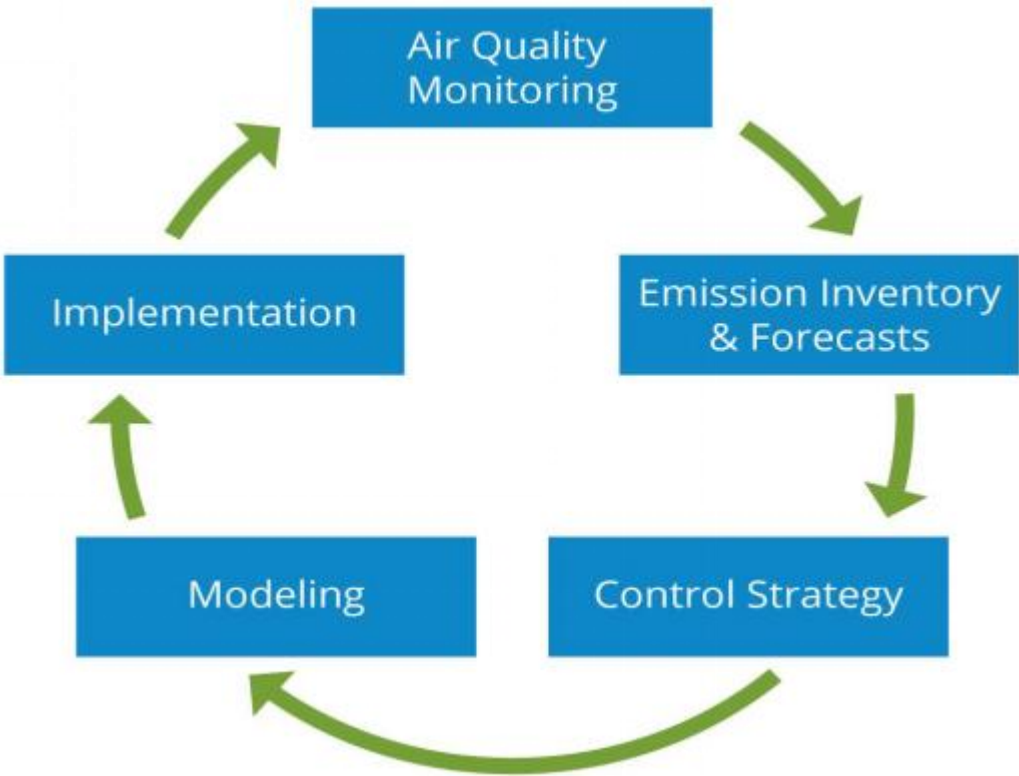


Figure 3. Source-to-control framework for urban air-quality management
Source: Coelho, (2023)

The framework shown in figure 3 ensures that interventions are supported by measured or modelled source evidence rather than applied generically. Post-intervention monitoring then determines whether the expected reduction occurred.

Challenges in Implementing Effective Urban Air-Quality Management

Effective urban air-quality management is constrained by weak monitoring, technical limitations, fragmented governance, inadequate financing, and unequal exposure. Sparse monitoring networks can miss neighbourhood-level pollution, while low-cost sensors require calibration, co-location, quality control, and uncertainty reporting (World Meteorological Organization [WMO], 2024; Bagkis et al., 2025). Short monitoring campaigns and incomplete emission inventories can obscure seasonal effects and informal, industrial, dust, and traffic sources. Atmospheric models must

integrate emissions, chemistry, meteorology, transport, and boundary conditions across different spatial and temporal scales, making independent validation and uncertainty assessment essential (Dai et al., 2026). Fragmented institutional responsibilities and weak enforcement can also reduce the effectiveness of otherwise adequate air-quality standards and policies (Jafari et al., 2021). Monitoring infrastructure, calibration, maintenance, training, and data systems further require sustained institutional financing rather than short-term investment (WMO, 2024). Finally,

interventions may widen existing inequalities if highly exposed communities are excluded from monitoring and decision-making, whereas community participation can improve sensor placement, data interpretation, and mitigation strategies. Appropriate privacy and data-governance safeguards are also necessary when personal exposure information is collected (Bagkis et al., 2025).

Major Challenge	Consequence	Potential Solution
Sparse monitoring networks	Poor characterization of spatial and temporal pollution patterns	Deployment of calibrated and quality-controlled low-cost sensor networks
Weak emission inventories	Uncertain source attribution and emission estimates	Regularly updated emission inventories combined with source-oriented atmospheric models.
Limited funding	Delayed implementation of monitoring and	Long-term institutional financing for monitoring, modelling,

	pollution-control interventions	and control programmes
Weak enforcement	Poor compliance with air-quality standards and emission regulations	Transparent standards supported by continuous monitoring, enforcement, and public reporting
Limited technical capacity	Poor application and interpretation of air-quality models and monitoring data	Capacity building through technical training, instrument co-location, calibration, and quality-assurance programmes

Sources: Coelho, (2023); Dai et al. (2026)

Emerging Technologies and Future Directions

According to the World Meteorological Organization [WMO] (2024), emerging technologies are expanding the capacity of urban air-quality monitoring, prediction, and management. Low-cost and distributed sensors can provide local, near-real-time pollution information where regulatory networks are sparse and can support source detection, mitigation assessment, and community monitoring. However, their affordability does not eliminate the need for calibration, co-location, quality control, maintenance, and uncertainty assessment (World Meteorological Organization [WMO], 2024; Bagkis et al., 2025). Artificial intelligence and machine learning can combine sensor, meteorological, land-use, and

satellite data to improve pollution mapping and forecasting, but these approaches should complement rather than replace emission inventories, atmospheric models, and expert interpretation because data limitations and model uncertainty can produce unreliable predictions (Uzhinskiy, 2025; Dai et al., 2026). Satellite observations provide broad spatial coverage and can identify urban and regional pollution patterns that ground networks may miss. Their value increases when combined with ground observations and machine-learning models, although satellite measurements should not be treated as direct substitutes for ground-level exposure because meteorology, vertical pollutant profiles, clouds, and retrieval uncertainty affect the relationship between satellite observations and surface concentrations (Uzhinskiy, 2025).

Table 6. Emerging technologies for next-generation urban air-quality management

Technology	Application	Major Advantage	Current Limitation	Future Potential
Low-cost sensors	Local monitoring	Affordable spatial coverage	Calibration, maintenance, and uncertainty	Dense community monitoring networks (World Meteorological Organization [WMO], 2024; Bagkis et al., 2025)
Artificial intelligence and machine learning	Forecasting and mapping	Rapid multi-source prediction	Data dependence and model uncertainty	Decision-support systems (Uzhinskiy, 2025; Dai et al., 2026)
Satellite sensing	Regional and urban mapping	Broad spatial coverage	Limited direct representation of surface exposure	Integrated exposure maps (Uzhinskiy, 2025)
Digital twins	Scenario testing	Dynamic intervention planning	High data and computational requirements	Smart-city air-quality management (Dai et al., 2026; WMO, 2024)

Digital-twin systems represent a further development by integrating real-time sensors, satellite observations, emission inventories, and atmospheric models to test potential interventions before implementation. Their effectiveness will depend on reliable data streams, interoperable infrastructure, transparent assumptions, computational capacity, and institutional support (WMO, 2024; Dai et al., 2026). Integrated climate and air-pollution policies can also align decarbonisation, clean energy, active mobility, and urban greening so that climate actions produce additional air-quality benefits. Future urban air-quality management should therefore follow an adaptive cycle of measuring pollution, identifying sources, modelling outcomes, implementing targeted controls, evaluating results, and revising interventions based on new evidence (WMO, 2024; Dai et al., 2026).

Conclusion

Urban air pollution arises from interacting transport, industrial, household, waste, dust, and land-use sources, so isolated controls rarely address the complete exposure pattern. Source apportionment helps identify priority contributors, while atmospheric modelling explains pollutant dispersion, chemical transformation, and potential responses to intervention. Effective management should therefore combine monitoring, source evidence, modelling, enforceable regulation, targeted controls, and post-intervention evaluation. No single measure is sufficient for complex urban environments, and implementation must consider cost, enforcement, community participation, and unequal exposure. Future systems should integrate low-cost sensors, satellite observations, artificial intelligence, emission inventories, and atmospheric models while maintaining calibration, uncertainty reporting, and human oversight.

Authors' Contributions

The authors of this research have significantly contributed to the study's conception, data collection, and manuscript development. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accept full responsibility for the content and integrity of the work.

Acknowledgement

We thank all the researchers who contributed to the success of this research work.

Conflict of Interest

The authors declared that there are no conflicts of interest.

Funding

No funding was received for this research work.

References

- Akomolafe, O. O., Olorunsogo, T., Anyanwu, E. C., Osasona, F., Ogugua, J. O., & Daraojimba, O. H. (2024). Air quality and public health: A review of urban pollution sources and mitigation measures. *Engineering Science & Technology Journal*. <https://doi.org/10.51594/estj.v5i2.751>
- Arya, S. (1998). Air pollution meteorology and dispersion. [Publisher information not supplied.]
- Bagkis, E., Hassani, A., Schneider, P., DeSouza, P., Shetty, S., Kassandros, T., Salamalikis, V., Castell, N., Karatzas, K., Ahlawat, A., & Khan, J. (2025). Evolving trends in application of low-cost air quality sensor networks: Challenges and future directions. *npj Climate and Atmospheric Science*, 8, 335. <https://doi.org/10.1038/s41612-025-01216-4>
- Belis, C., Karagulian, F., Amato, F., & et al. (2015). A new methodology to assess the performance and uncertainty of source apportionment models II: The results of two European intercomparison exercises. *Atmospheric Environment*. <https://doi.org/10.1016/J.ATMOSENV.2015.10.068>
- Choudhary, A. (2016). Potential of receptor models in source apportionment of atmospheric aerosols: A review.
- Chow, J. (2004). Introduction to the A&WMA 2004 critical review: Megacities and atmospheric pollution. *Journal of the Air & Waste Management Association*.
- Coelho, S., Ferreira, J., & Lopes, M. (2023). Source apportionment of air pollution in urban areas: A review of the most suitable source-oriented models. *Air Quality, Atmosphere & Health*. <https://doi.org/10.1007/s11869-023-01334-z>
- Colbeck, I., Nasir, Z. A., & Ali, Z. (2010). The state of ambient air quality in Pakistan—A review. *Environmental Science and Pollution Research*, 17(1), 49–63.
- Dai, Y., Qian, J., Zhong, J., Cai, X., & MacKenzie, A. R. (2026). Recent progress, bottlenecks, and outlook of multiscale air quality modelling: A review. *Atmospheric Environment*: X, 29, 100435. <https://doi.org/10.1016/j.aeaoa.2026.100435>
- Derwent, R. G., Middleton, D. R., Field, R. A., Goldstone, M. E., Lester, J. N., & Perry, R. (1995). Analysis and interpretation of air quality data from an urban roadside location in central London over the period from July 1991 to July 1992. *Atmospheric Environment*, 29(8), 923–946.
- Dutton, S., Vedal, S., Piedrahita, R., & et al. (2010). Source apportionment using positive matrix factorization on daily measurements of inorganic and organic speciated PM_{2.5}. *Atmospheric Environment*. <https://doi.org/10.1016/J.ATMOSENV.2010.04.038>
- Fallah Shorshani, M., André, M., Bonhomme, C., & Seigneur, C. (2012). Coupling traffic, pollutant emission, air and water quality models: Technical review and perspectives. *Procedia—Social and Behavioral Sciences*, 48, 1794–1804.
- Fernando, H., Zajic, D., Sabatino, S., Dimitrova, R., Hedquist, B., & Dallman, A. (2010). Flow, turbulence, and pollutant dispersion in urban atmospheres. *Physics of Fluids*.
- Fine, P., Sioutas, C., & Solomon, P. (2008). Secondary particulate matter in the United States: Insights from the Particulate Matter Supersites Program and related studies. *Journal of the Air & Waste Management Association*. <https://doi.org/10.3155/1047-3289.58.2.234>
- Hanna, S. R. (2014). A 40-year history of a simple urban dispersion model and its evaluation. In D. Steyn & R. Mathur (Eds.), *Air pollution modeling and its application XXIII* (pp. 329–339). Springer.
- Hopke, P. (2008). The use of source apportionment for air quality management and health assessments. *Journal of Toxicology and Environmental Health, Part A*. <https://doi.org/10.1080/15287390801997500>
- Jafari, A. J., Charkhloo, E., & Pasalari, H. (2021). Urban air pollution control policies and strategies: A systematic review. *Journal of Environmental Health Science and Engineering*, 19(2), 1911–1940. <https://doi.org/10.1007/s40201-021-00744-4>
- Johnson, T., Guttikunda, S., Wells, G. J., Artaxo, P., Bond, T., Russell, A., Watson, J., & West, J. (2011). Tools for improving air quality management: A review of top-down source apportionment techniques and their application in developing countries. [Publication details not supplied.]
- Karagulian, F., & Belis, C. (2012). Enhancing source apportionment with receptor models to foster the air quality directive implementation. *International Journal of Environment and Pollution*. <https://doi.org/10.1504/IJEP.2012.051192>
- Karagulian, F., Belis, C., Dora, C., et al. (2015). Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric Environment*. <https://doi.org/10.1016/J.ATMOSENV.2015.08.087>
- Khan, M. (2021). A review of traffic-related air pollution. *International Journal of Engineering Works*. <https://doi.org/10.34259/IJEW.21.806175179>
- Krupnova, T., Bulanova, A., Makarovskikh, T., & Herreinstein, A. V. (2022). Urban air pollution modeling: A critical review. *Theoretical and Applied Ecology*.
- Kumar, A., Sinha, V., Shabin, M., & et al. (2020). Non-methane hydrocarbon (NMHC) fingerprints of major urban and agricultural emission sources for use in source apportionment studies. *Atmospheric Chemistry and Physics*. <https://doi.org/10.5194/acp-20-12133-2020>
- Leea, S., Liua, W., Wanga, Y., & et al. (2008). Source apportionment of PM_{2.5}: Comparing PMF and CMB results for four ambient monitoring sites in the southeastern United States.
- Lin, L., Lee, M. L., & Eatough, D. (2010). Review of recent advances in detection of organic markers in fine particulate matter

- and their use for source apportionment. *Journal of the Air & Waste Management Association*. <https://doi.org/10.3155/1047-3289.60.1.3>
- Lolli, S., Garzelli, A., & Salcedo Bosch, A. (2025). Hotter cities, hazier skies: Exploring aerosol feedback to urban heat using satellite data. In *Remote sensing of clouds and the atmosphere XXX*. SPIE.
- Longhurst, J., & Brebbia, C. (Eds.). (2006). *Air pollution XIV*. [Publisher information not supplied.]
- Meng, Z., Dabdub, D., & Seinfeld, J. (1997). Chemical coupling between atmospheric ozone and particulate matter. *Science*. <https://doi.org/10.1126/SCIENCE.277.5322.116>
- Metrangolo, C., Dinoi, A., Pappacogli, G., et al. (2026). Influence of urban morphology on traffic-related air pollution dispersion in urban environments. *Atmosphere*. <https://doi.org/10.3390/atmos17030234>
- Moreno, T., Querol, X., Alastuey, A., & Gibbons, W. (2009). Identification of chemical tracers in the characterisation and source apportionment of inhalable inorganic airborne particles: An overview. *Biomarkers*. <https://doi.org/10.1080/13547500902965435>
- Salmond, J., & McKendry, I. (2009). Chapter 2: Influences of meteorology on air pollution concentrations and processes in urban areas. <https://doi.org/10.1039/9781847559654-00023>
- Schawer, J., Cass, G., Rogg, W. F., & Mazurek. (1996). Source apportionment based on molecular markers present in airborne fine particles.
- Sokhi, R., Moussiopoulos, N., Baklanov, A., et al. (2021). Advances in air quality research—Current and emerging challenges. *Atmospheric Chemistry and Physics*.
- Srimuruganandam, B., & Jose, J. (2016). Air quality management through receptor modelling. *Indian Journal of Science and Technology*. <https://doi.org/10.17485/IJST/2016/V9I32/99170>
- Sun, X., Wang, H., Guo, Z., & et al. (2020). Positive matrix factorization on source apportionment for typical pollutants in different environmental media: A review. *Environmental Science: Processes & Impacts*. <https://doi.org/10.1039/c9em00529c>
- Turner, D. B. (1979). Atmospheric dispersion modeling: A critical review. *Journal of the Air Pollution Control Association*, 29(5), 502–519.
- Vu, T., Delgado-Saborit, J., & Harrison, R. (2015). Particle number size distributions from seven major sources and implications for source apportionment studies. *Atmospheric Environment*.
- Watson, J., Chow, J., Chen, L., & et al. (2016). Source apportionment: Principles and methods. <https://doi.org/10.1039/9781782626589-00072>
- World Meteorological Organization. (2024). Integrating low-cost sensor systems and networks to enhance air quality applications. WMO.
- Yoon, J., Lim, C. C., & Thurston, G. D. (2023). Associations between fine particulate matter composition and sources with adverse health effects: A systematic review and meta-analysis. *ISEE Conference Abstracts*. <https://doi.org/10.1289/isee.2023.fp-103>
- Zhang, R., Wang, G., Guo, S., et al. (2015). Formation of urban fine particulate matter. *Chemical Reviews*. <https://doi.org/10.1021/acs.chemrev.5b00067>

How to cite this article

Okolosi, I. S., Mahmud, I. A., Yohanna, N. R., Abah, M. A., & Abimbola, M. O. (2026). Air quality management in urban areas: A review of source apportionment, modeling, and control strategies. *Chemical and Environmental Science Archives*, 6(3), 50–64. <https://doi.org/10.47587/CESA.2026.6303>

This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/)

