Indian Journal of Engineering & Materials Sciences
Vol. 33, April 2026, pp. 143-159
DOI: 10.56042/ijems.v33i02.24343

Review Article

Evaluating line source emission models for Indian urban environments

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Received: 29 September 2025; accepted: 21 January 2026

Vehicular emissions have constituted a primary source of urban air pollution, with profound implications for public health and environmental quality, especially in rapidly developing countries like India. This review has chronicled the progression of mobile source emission inventory methodologies, which have transitioned from simplified Excel-based bottom-up approaches to sophisticated tools such as MOBILE, MOVES, COPERT, and IVE. Early methods have primarily utilized static emission factors combined with limited vehicle activity and road length data, resulting in poor spatial and temporal resolution and inconsistent emission estimates. Advanced inventory models have improved accuracy by incorporating modal driving cycles, vehicle-specific power calculations, and detailed fleet characteristics; however, their efficacy in developing country contexts has often been hampered by the unavailability of comprehensive local inputs, including fuel composition, vehicle kilometres travelled, and fleet age distributions. This review has highlighted significant deficiencies in model validation, emission factor localization, and integration of real-world traffic dynamics within existing emission inventories. Current inventories have largely neglected to disaggregate vehicle kilometres travelled by road type or to capture heterogeneous traffic behaviour, leading to biased spatial emission distributions and compromised policy relevance. The review has identified the Indian Vehicle Emission (IVE) model as a promising example that has improved context specificity through detailed driving cycle and terrain sensitivity, complementing established models like MOVES and COPERT. To enhance emission inventory reliability for rapidly urbanizing Indian cities, the adoption of a modular, India-specific emission framework has become essential. Such a framework should incorporate real-time vehicle counts, stratified vehicle activity by road classification, and heterogeneous traffic patterns. Implementing an India-tailored emission inventory model will greatly support urban air quality management and policy formulation, aligning with national objectives such as the National Clean Air Programme (NCAP). It will provide policymakers with precise, actionable insights to target emission hotspots, design effective interventions, and ultimately safeguard urban environmental health.

Keywords: Bottom-up emission inventory, Indian urban air pollution, National clean air programme (NCAP), Vehicle kilometre travelled (VKT)

1 Introduction

Air pollution constitutes a critical environmental challenge of global significance, particularly in rapidly growing economies such as India. The World Health Organization (WHO) reported millions of premature mortalities annually caused by ambient air pollution and predominantly attributable to cardiovascular and respiratory diseases[1]. Among the diverse sources of air pollution, vehicular emissions, categorised as mobile emissions, have become a prominent contributor to the degradation of urban air quality. These emissions arise from fuel combustion in both on-road and off-road vehicles, leading to the release of pollutants including particulate matter (PM), nitrogen oxides (NO_2), carbon monoxide (CO), and hydrocarbons (HC)[2]. To quantify these emissions and inform targeted mitigation strategies, emission inventories are developed. These inventories constitute comprehensive databases that estimate the pollutant emission load released into the atmosphere from various sources within a specified temporal and geographic scope. Emission sources are broadly categorized into stationary sources (such as industries and power plants), area sources (including open biomass burning and construction activities), and mobile sources (primarily vehicular traffic), as depicted in Fig. 1[3].

A line source emission inventory represents a specific subset of mobile emission inventories that concentrates on emissions occurring along linear

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pathways, such as roads and highways. Unlike area or point sources, line sources are distinguished by their elongated emission patterns, which are influenced by factors including traffic volume, vehicle type, driving behaviour, road gradient, and meteorological conditions. In urban environments, line source emissions from densely trafficked corridors constitute a critical factor affecting air quality, with significant implications for environmental health and urban planning[4]. The relationship between air pollution and line source emission inventories is direct and critically important. Empirical studies have demonstrated that areas with heavy traffic congestion exhibit elevated emissions, particularly of particulate matter (PM2.5) and nitrogen oxides (NOx)[5]. Accurate estimation of line source emission loads enables researchers and policymakers to identify pollution hotspots, assess exposure risks, and develop targeted interventions such as traffic management measures or vehicular technology improvements. The importance of emission inventories has increased owing to their direct influence on public health, urban air quality, and climate action planning. Moreover, these inventories are essential for dispersion modelling, health risk assessment, and the formulation of city-level emission reduction strategies[6].

In urban centres characterized by complex traffic dynamics and heterogeneous vehicle fleets, such as Delhi and Mumbai, localized emission estimates can exhibit considerable variability depending on the employed inventory methodology. For example, two studies conducted within the same city using distinct emission inventory models (e.g., MOBILE and COPERT) and varying assumptions regarding vehicle kilometres travelled (VKT), fleet age, and fuel type have produced divergent emission estimates. This disparity underscores the critical need for standardized, locally adapted emission inventory frameworks to ensure accuracy and comparability[7]. To address the complexities associated with vehicular emissions and enhance estimation accuracy, several computational models have been developed internationally. Notable examples include MOBILE, developed by the U.S. Environmental Protection Agency (EPA); the Motor Vehicle Emission Simulator (MOVES); and COPERT, developed by the European Environment Agency. These models enable estimation of emissions from diverse vehicle categories across varying operational conditions. By integrating emission factors, activity data, and vehicle fleet characteristics, they provide a systematic framework for the generation of emission inventories[8]. These models are particularly valuable in contexts lacking real-time monitoring data, as they facilitate predictive analysis and support the evaluation of policy interventions.

This review study seeks to critically evaluate the methodologies, strengths, limitations, and applicability of mobile emission inventory models, with a focused emphasis on their implementation within the Indian context. A comprehensive understanding of the operational frameworks of these models and their adaptability to local conditions is essential for enhancing the accuracy and reliability of emission inventories. Such insight is pivotal for supporting evidence-based environmental governance and facilitating informed decision-making in urban air quality management.

2 Materials and Methods

A comprehensive literature review was conducted to examine the current state of research in mobile emission inventory modelling and vehicular emissions assessment. An illustration in Fig. 2 explicitly reveals that the systematic collection encompassed 60 publications spanning the period from 1987 to 2025, demonstrating the evolution and increasing prominence of this research domain over nearly four decades.

An illustration in Fig. 2 explicitly reveals that the systematic collection encompassed 60 publications spanning the period from 1987 to 2025, demonstrating the evolution and increasing prominence of this research domain over nearly four decades. The chronological analysis reveals a marked intensification in research activity, particularly from 2008 onwards, with notable peaks in publication frequency during 2016 (4 publications), 2023 (5 publications), and 2024 (7 publications). Furthermore, the keyword analysis reveals ten

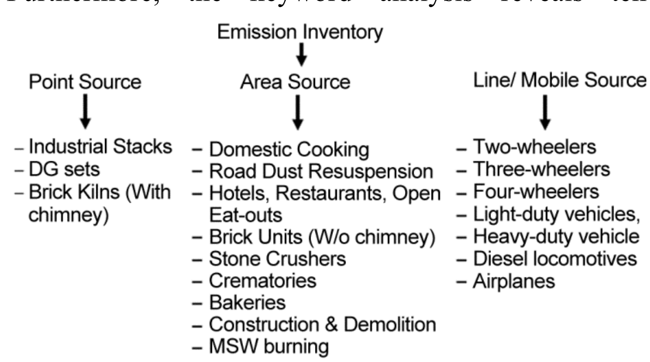

Fig. 1 — Emission inventory and its types with example.

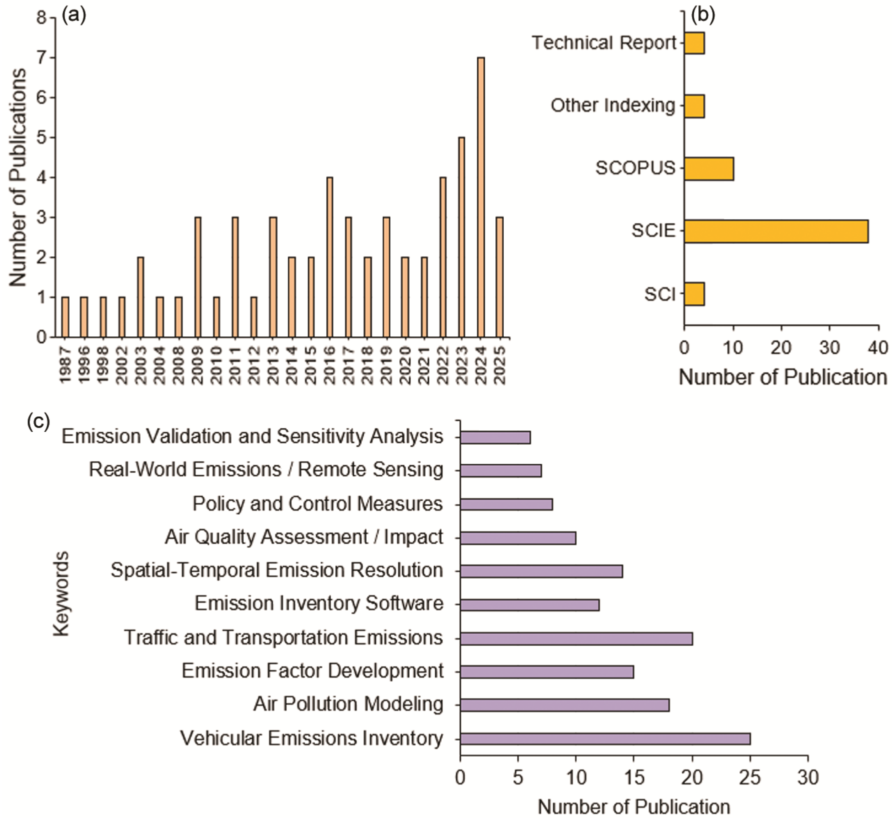

Fig. 2 — Number of publications based on (a) Published year, (b) Article indexing and (c) Keyword.

primary research themes, with vehicular emissions inventory (25 publications) and air pollution modelling (20 publications) representing the most extensively studied areas. Other significant themes include traffic and transportation emissions (18 publications), emission factor development (15 publications), and spatial-temporal emission resolution (12 publications), collectively demonstrating the multidisciplinary approach required for comprehensive emission inventory development. This temporal pattern reflects the growing global concern regarding urban air quality and the corresponding emphasis on developing robust emission quantification methodologies. The literature collection comprises 45 peer-reviewed journal articles (75%), 9 books/conference proceedings (15%), and 6 technical reports/software guides (10%) (Table 1).

This distribution ensures comprehensive coverage of both theoretical developments and practical implementation aspects of emission inventory modelling. Among the journal articles, Elsevier emerges as the predominant publisher with 20 publications, followed by MDPI (5 publications) and Springer Nature (9 publications). Key journals include Transportation Research Part D: Transport and Environment (6 publications) and Atmospheric Environment (7 publications), indicating the interdisciplinary nature of this research field spanning atmospheric sciences, environmental engineering, and transportation studies. The inclusion of technical reports from authoritative agencies such as the US Environmental Protection Agency (EPA), World Health Organization (WHO), and European Environment Agency provides essential regulatory and methodological context, ensuring the review encompasses both academic research and operational guidance documents. This literature collection provides a robust foundation for examining the methodological evolution, technological advances, and regional applications of mobile emission inventory models, particularly in the context of developing nations, where urbanization and motorization present unique challenges for air quality management.

2.1 Overview of mobile emission models

Mobile emission inventory models constitute computational frameworks designed to quantify

Table 1 — Number of publications chosen from different articles types i.e. journal articles, conference proceedings, and technical reports.

Publisher Name	Journal Name / Source	Number of Publications
	Journal Articles (45)	
American Geophysical Union	Journal of Geophysical Research	2
Copernicus Publications	Atmospheric Chemistry and Physics (Copernicus Publications)	1
Copernicus Publications	Earth System Science Data	2
Current Science Association	Current Science	1
Elsevier	Atmospheric Environment	7
Elsevier	Atmospheric Pollution Research	1
Elsevier	Atmospheric Pollution Research	1
Elsevier	Energy Policy	1
Elsevier	Journal of Environmental Sciences	1
Elsevier	Science of the Total Environment	2
Elsevier	Transportation Research Part D: Transport and Environment	6
Elsevier	Urban Climate	1
MDPI	Atmosphere	4
MDPI	Energies	1
Springer	Environmental Science and Engineering	1
Springer Nature	Environmental Monitoring and Assessment	1
Springer Nature	Environmental Science and Pollution Research	3
Springer Nature	International Journal of Environmental Science and Technology	1
Springer Nature	SN Applied Sciences	2
Springer Nature	Springer Plus	2
Taylor & Francis	Journal of Air & Waste Management Association	3
Thai Society of Higher Education	Environment Asia	1
	Books/Conference Proceedings (09)	
IEEE	IEEE Forums and Conferences	2
WIT Press	WIT Transactions on the Built Environment	1
Intech Open	Book Chapter (Air Pollution Dispersion & Inventory)	1
Polish Association of Logistics	Logistics and Transport	1
Progressive Sustainable Developers Nepal (PSD-Nepal)	International Journal of Environment	1
African Journal of Environmental Sci & Tech	African Journal of Environmental Science and Technology	1
CNKI (Online)	MOVES Emission Sensitivity (Online Publication)	1
IOP Publishing	IOP Conference Series: Earth and Environmental Science	1
	Technical Reports/Software Guides (06)	
US EPA	US EPA Emission Inventory Improvement Program / MOVES / MOBILE6	4
WHO	WHO Report	1
European Environment Agency	COPERT Model Documentation	1

emissions from vehicular sources through the integration of traffic activity data, vehicle fleet composition, roadway characteristics, and pollutant-specific emission factors. These models serve as fundamental components within comprehensive air quality management systems, providing essential tools for policymakers, researchers, and urban planners to systematically assess emissions of key atmospheric pollutants, including particulate matter (PM), nitrogen oxides (NOx), carbon monoxide (CO), and hydrocarbons (HC)[9,10] The development of these models has been motivated by the imperative to comprehensively understand and mitigate the environmental and public health impacts of vehicular emissions, particularly within urban environments where traffic congestion and heterogeneous fleet compositions preclude direct measurement methodologies. Mobile emission models fulfil multiple critical functions, encompassing regulatory compliance assessment, emission forecasting, urban transportation planning, and comprehensive environmental impact evaluation[8,9].

Internationally, several well-established modelling frameworks have been developed to estimate emissions from road transport, including MOBILE, MOVES (Motor Vehicle Emission Simulator), COPERT (Computer Programme to calculate Emissions from Road Transport), and IVE (International Vehicle Emissions), among others, a detailed description given in Table 2. These models exhibit considerable variation in their underlying methodologies, computational complexity, geographic applicability, data requirements, and scope of implementation, reflecting diverse regional approaches to vehicular emission quantification.

The selection of an appropriate emission inventory model is contingent upon the availability and granularity of input data, the spatial and temporal scale of analysis, the geographic context, and the target pollutant species. For example, although MOVES delivers high-resolution spatial and temporal emission estimates, its reliance on detailed activity data and U.S.–specific fleet characteristics necessitates substantial localization efforts to ensure applicability in contexts such as India[2,7].

In recent years, there has been increasing focus on the adaptation of mobile emission inventory models for developing nations, where heterogeneous vehicle fleets, variable fuel types, and suboptimal road infrastructure introduce significant uncertainties. To address these challenges, researchers are investigating customized and hybrid methodologies, including the incorporation of real-time vehicle telematics, to enhance the precision of emission estimates. A thorough comprehension of model capabilities and limitations is therefore indispensable for selecting the most suitable framework for emission inventory development and for underpinning robust air quality management strategies in diverse urban environments.

This review is organized into five interrelated sections to facilitate a coherent and thorough discourse. Section 1 introduces the challenge of vehicular emissions and their role in urban air pollution, underscoring the imperative for robust mobile emission inventories. Section 2 provides a detailed overview of established inventory frameworks MOBILE, MOVES, COPERT, and spreadsheet-based approaches outlining their genesis, structural components, and prospective applications. The third section synthesizes critical insights from the extant literature, pinpointing methodological deficiencies, challenges in accurately representing heterogeneous vehicle fleets, and limitations in emission load estimation. The fourth section undertakes a comparative analysis of emission outputs generated by different models for identical urban areas, elucidating the influence of divergent model assumptions, data resolutions, and input constraints on inventory results. The fifth and final section

Table 2 — A detailed description of globally renowned emission inventory model.

Model	Developer	Description	Application	Level of Detail
MOBILE [10]	United States Environmental Protection Agency (U.S. EPA)	One of the earliest vehicular emission models, serving as a foundation for subsequent frameworks. Employed for regulatory and planning purposes in the U.S. before being phased out in favor of more advanced models.	Regulatory compliance and transportation planning in the United States	Macroscopic: aggregated regional and national emission estimates
MOVES [9]	United States Environmental Protection Agency (U.S. EPA)	A dynamic, activity-based model that simulates emissions during different driving modes (e.g., idling, cruising, acceleration). Supports analyses from project to national scale, enabling high-resolution spatial and temporal emission inventories.	Regulatory tool for high-resolution emission forecasting and transportation impact assessment in the U.S.	Mesoscopic and microscopic: detailed, location-specific, time-resolved emission inventories
COPERT [8]	European Environment Agency (EEA)	A Europe-focused model used for national and regional inventories under UNFCCC and EMEP obligations. Calculates emissions based on vehicle and fuel types, technology classes, and driving conditions. Regularly updated to reflect evolving vehicle technologies and policies.	National and regional emission inventory reporting in Europe under UNFCCC and EMEP frameworks	Macroscopic: aggregated emission estimates at national and regional scales

presents overarching conclusions and formulates recommendations for future model development, with particular emphasis on the incorporation of localized input parameters, road-type-specific vehicle-kilometres-travelled (VKT) estimations, and the integration of real-time vehicular activity data.

2.2 General estimation approach

Line-source emissions denote pollutants discharged along linear infrastructure most prominently roadways in urban settings where vehicular traffic constitutes the principal contributor to the emission inventory. In numerous metropolitan areas, emissions from road networks represent in excess of 70% of total pollutant load. Emissions per road segment are computed and aggregated across the network using:

$$EL = \sum_{i=1}^{n}(V_i \times EF_i \times L_i) \quad \ldots(1)$$

where,

EL : Emission Load (kg day^{-1}),
V_i : Daily Vehicle Count for Vehicle Category.
EF_i : Emission Factor (kg $vehicle^{-1}$ km^{-1}),
L_i : Road Segment Length (km).

Line-source emission inventories are constructed via methodologies that differ in data intensity, temporal resolution, and intended application, broadly classified into static bottom-up, dynamic/mesoscale, and model-integrated/microscale approaches. The static bottom-up method commonly applied for regional or long-term inventories employs average daily traffic volumes and fixed emission factors by vehicle category to generate segment-level annual or seasonal emissions. While this approach supports regulatory compliance, trend analysis, and policy planning, its lack of temporal granularity limits its applicability for short-term air quality modelling and exposure assessment. Dynamic or mesoscale techniques introduce temporal variability by integrating hourly or daily traffic flow, congestion levels, and speed profiles, producing time-resolved emission estimates suited to street-scale forecasting, gridded action planning, dispersion modelling, and health impact studies. These methods require detailed traffic data and often employ spatiotemporal interpolation or traffic simulation. Microscale or model-integrated approaches couple high-resolution traffic simulators with sophisticated emission models (e.g., MOVES, COPERT), capturing emissions from transient vehicle operations idling, acceleration, and deceleration. The resulting granular inventories are particularly valuable for evaluating traffic management scenarios and localized mitigation strategies.

2.3 Static bottom-up approach

Static bottom-up emission inventories form the foundational methodology for estimating vehicular pollution in urban settings by aggregating emissions calculated at the road-segment level using average traffic activity and fixed emission factors. In this approach, the daily vehicle count for each category is multiplied by a representative emission factor and the segment length, and summed across the network to yield annual or seasonal totals (Table 3).

Biswal *et al.*[11] employed high-resolution traffic data calibrated with in situ measurements to generate hourly COPERT-based estimates for 127 vehicle categories, producing gridded maps and temporal profiles for Delhi's Road links[12] demonstrated adaptability in Manizales by integrating SATURN traffic assignments with COPERT factors, adjusting European parameters to local fleet characteristics to overcome limited local emission testing data. Li *et al.* [13] extended the bottom-up framework to non-exhaust sources, mapping 1 km^2 road-dust re-suspension emissions in Harbin by incorporating silt loading and meteorological inputs, thereby broadening static inventories beyond tailpipe contributions. Singh *et al.*[14] pioneered IVE-based inventories for Delhi (2008–09), coupling traffic surveys and fleet profiles with AERMOD dispersion to validate CO, NO_x, and PM estimates against observed concentrations. Badiya *et al.*[15] aligned bottom-up outputs with national fuel statistics to quantify CO_2 and criteria pollutants in India for 2020, enabling post-facto policy impact assessment. Baidya and Borken-Kleefeld's[16] multi-city study (1980–2005) underscored the sensitivity of emissions to fleet age, technology layers, and reconciling VKT with fuel data to minimize uncertainty advanced spatial precision in Mumbai by using a 400 m grid to represent exhaust and non-exhaust sources, identifying transport sector hotspots for PM under India's NCAP. Saberiyansani and Hashemi's[17] comparative analysis in Iran highlighted COPERT's robustness with detailed datasets and IVE's flexibility under sparse data conditions, guiding model selection in emerging regions. Shrestha *et al.*[18] adapted bottom-up methods for Kathmandu's high-altitude context by applying altitude-adjusted, speed-specific

Table 3 — A detailed description of Static Bottom-Up approach for emission inventory of line source.

Reference	Year	Pollutants	Model / Tools	Advantages	Limitations	Novelty
Biswal *et al.*[11]	2023	CO, NO_x, PM	COPERT + Google API traffic data	High temporal (hourly) and spatial resolution; 127 vehicle categories; local EF calibration	Requires high-resolution traffic inputs; intensive calibration against measurements	Integration of real-time API data with bottom-up EF framework for megacity road-link inventories
Villalobos *et al.*[12]	2021	CO, NO_x, HC, PM	COPERT + SATURN	Adaptable for data-limited small cities; scalable; spatially explicit	Reliance on European emission factors; limited local emission test data	Coupling traffic assignment with COPERT for small urban centres in developing countries
Li *et al.*[13]	2020	$PM_{2.5}$ (road dust)	Static bottom-up	Incorporates non-exhaust emissions; seasonal EF adjustment; gridded 1 km^2 output	Focus on road dust only; requires field silt loading measurements and meteorological data	Extension of bottom-up method to road dust re-suspension emissions
Sharma *et al.*[14]	2013	CO, NO_x, PM	IVE + AERMOD	Validated with dispersion modeling; applicability in data-scarce environments	IVE parameters may not fully reflect local fleet heterogeneity; limited to 2008–09 data	Early IVE application in Delhi with integration into AERMOD for validation
Badiya *et al.*[15]	2022	CO_2, CO, NO_x, PM	Static bottom-up	Alignment with national fuel statistics; post-facto policy impact assessment	National statistics may mask local variability; static EF cannot resolve temporal fluctuations	Coupling emission inventory with retrospective policy evaluation
Borken-Kleefeld's[15]	2009	CO, NO_x, HC, PM, CO_2, others	Static bottom-up	Long-term (1980–2005) multi-city coverage; uncertainty minimization via VKT–fuel reconciliation	High data requirements for fleet age and technology lifetimes; potential data gaps for older periods	Reconciliation of VKT estimates with actual fuel consumption to reduce uncertainty
Mangaraj P, *et al.*[16]	2024	$PM_{2.5}$	Static bottom-up (400 m grid)	Fine spatial resolution; includes organized and informal transport; hotspot mapping	Grid-based approach may require significant GIS processing; non-exhaust segmentation complexity	Ultra-fine grid representation and integration of informal transport sector under NCAP framework
Saberiyansani and Hashemi's[17]	2025	CO, NO_x, PM, HC	COPERT vs. IVE	Comparative sensitivity analysis; guidance on model selection for emerging regions	Findings transferable but region-specific validation needed; dependent on input data availability	Systematic comparative evaluation of two models under varying data scenarios
Ghimire K, *et al.*[18]	2014	CO, NO_x, PM	Static bottom-up	Altitude-adjusted EF; local surveys; covers high-altitude impacts	Limited pollutant scope; survey-based fleet estimates may introduce subjective bias	Incorporation of altitude correction in emission factors for high-elevation urban inventory
Laura Gallardo *et al.*[19]	2012	CO, NO_x, HCs, PM	Static bottom-up	Incorporates ethanol-blended fuels; local regulatory EF database; sectoral attribution	Regional fuel mix complexity; alternative fuel EF uncertainties	Inclusion of fuel diversity and fuel-switching policy considerations in bottom-up framework for Latin American city

factors to local survey data, quantifying CO, NO_x, and PM daily loads. Laura Gallardo *et al.*[19] illustrated the importance of alternative fuel inclusion in São Paulo by leveraging CETESB emission factors to reveal differential sectoral contributions to CO, NO_x, HCs, and PM.

2.4 Top-down approach

Top-down emission inventory methods represent an alternative framework that estimates vehicular emissions by starting with aggregated regional or national data such as fuel consumption statistics and spatially disaggregating these totals based on proxies or activity patterns. This approach circumvents the intensive data requirements of bottom-up methods while providing robust regional totals for policy analysis and cross-validation of regulatory estimates (Table 4).

Harley (1996)[20] pioneered fuel-based top-down emission inventories by combining regional fuel sales data with real-world, fleet-weighted emission factors derived from remote sensing measurements in California's South Coast Air Basin. Their methodology minimized uncertainties associated with traffic activity estimates while revealing significant discrepancies when compared to model-based inventories, thereby establishing the diagnostic value of fuel-based approaches in validating regulatory emission estimates. Linsey *et al.* (2002)[21] extended this framework by integrating fuel consumption data, remote sensing observations, and ambient air quality measurements to refine photochemical modeling inputs for Central California. Their analysis demonstrated that top-down estimates for non-methane volatile organic compounds (NMVOCs) exceeded EMFAC model predictions by 40–100%, while NO_x and CO estimates exhibited substantial variability, underscoring how neglecting real-world fleet behaviour in bottom-up models can introduce bias in air quality simulations.

For developing countries, Singh *et al.* (2022)[14] constructed a national-scale inventory for India using fuel consumption records, registration-based fleet statistics, and broad activity multipliers to estimate CO_2 and criteria pollutants. While their aggregated framework successfully captured state-level emission variability and enabled policy impact assessment, it lacked the spatial resolution necessary for urban hotspot identification. Similarly, Goyal *et al.*[6] employed a vehicle-kilometre-based approach to estimate trace gas emissions from Indian road transport between 2001 and 2013, revealing annual growth rates of 8–9% driven by rapid motorization. Both studies highlight the policy relevance of top-down methods for national reporting and trend analysis in data-limited environments.

In the United Kingdom, large-scale remote sensing datasets have been employed to verify the National Atmospheric Emissions Inventory (NAEI) against real-world fleet emission rates. These top-down adjustments revealed systematic underreporting of NO_x and other pollutants for specific vehicle classes, with national passenger car and light-duty van NO_x emissions underestimated by 24–32%, and up to 47% in urban areas, reinforcing the critical importance of observational constraints in inventory validation processes. Doumbia *et al.* (2018)[22] evaluated fuel-based top-down models for West African cities, finding that reliance on national fuel sales statistics introduces significant uncertainty due to inconsistent reporting and prevalent informal fuel markets, leading

Table 4 — A detailed description of Top-Down approach for emission inventory of line source.

Reference	Year	Pollutants	Model/Tools	Advantages	Limitations	Novelty
Harley[20]	1996	CO, NO_x, HC	Fuel-based + Remote sensing	Minimizes traffic activity uncertainty; robust regional totals; real-world emission factors	Limited spatial resolution; requires extensive remote sensing data	First fuel-based top-down inventory with remote sensing validation
Linsey *et al.*[21]	2002	NO_x, CO, NMVOCs	Fuel-based + Air quality data	Integrates ambient observations; improves photochemical modeling inputs	Model-measurement discrepancies; regional transferability constraints	Integration of fuel, remote sensing, and ambient air quality data
Singh *et al.*[14]	2022	CO_2, CO, NO_x, PM	National fuel statistics	Captures state-level variability; policy impact assessment capability	Lacks spatial resolution for urban hotspots; static temporal resolution	Alignment with national fuel consumption for policy evaluation
Goyal *et al.*[6]	2013	CO, NO_x, HC, PM	VKT-based scaling	National trend analysis; captures motorization impacts	Limited validation against measurements; coarse spatial allocation	Long-term trend assessment for rapidly motorizing economy
UK Studies	2021	NO_x, CO, NH_3	Remote sensing validation	Large-scale fleet coverage; identifies inventory biases	Equipment costs; measurement conditions constraints	Systematic national inventory verification using remote sensing
Doumbia *et al.*[22]	2018	CO_2, CO, NO_x, PM	Fuel-based	Applicable in data-scarce regions; leverages existing fuel statistics	Informal fuel market uncertainties; 30-50% discrepancies with bottom-up	Assessment of fuel-based method limitations in West African context

to potential underestimation of actual fuel consumption and emissions. Comparisons with limited bottom-up surveys revealed discrepancies exceeding 30–50%, indicating that hybrid approaches combining fuel-based data with localized traffic and fleet activity surveys are essential for improving accuracy in data-scarce settings.

2.5 Dynamic or mesoscale estimation approach

Dynamic or mesoscale emission inventory methodologies introduce temporal and spatial variability by integrating time-resolved traffic information such as speeds, accelerations, and congestion patterns into emission calculations. These approaches leverage traffic simulation outputs, GPS or floating car data, and link-level activity profiles to generate hourly or sub-hourly emission estimates, thereby capturing peak-period dynamics and localized hotspots that static bottom-up methods overlook (Table 5).

Shan *et al.* (2019)[23] developed a GPS-integrated dynamic inventory for Shanghai by coupling real-time speed data with the MOVES model, demonstrating that static methods under-estimated peak-hour emissions by 15–25%. Although this framework achieved high spatial and temporal fidelity, incomplete GPS coverage on minor roadways and significant computational demands limited its applicability in data-sparse regions. He *et al.* (2016)[24] constructed an hourly inventory for Nanjing by combining traffic simulation outputs with COPERT emission functions, revealing that neglecting temporal fluctuations induces substantial exposure biases along major corridors. Their analysis underscored the necessity of time-specific emission inputs for evaluating traffic management policies, though generalized fleet assumptions and omission of seasonal activity cycles constrained accuracy. Yao *et al.* (2015)[25] employed floating car data within a GIS-based model for Shanghai, using COPERT speed-emission curves to quantify diurnal NO_x peaks over 40% of daily totals thereby highlighting the pollution impact of congestion. However, the model's lack of real-world acceleration/deceleration profiles resulted in underestimation under stop-and-go conditions. Zhang *et al.* (2016)[26] developed a mesoscale inventory for Los Angeles by integrating link-level traffic microsimulation with MOVES in a GIS environment, finding that accounting for signalized intersections and stop-and-go behaviour increased CO and NO_x estimates by 30% compared to static approaches. Despite improvements in health impact assessment accuracy, the method's intensive data requirements and computational burden pose challenges for full metropolitan deployment.

2.6 Microscale or model integrated estimation approach

Microscale emission inventory approaches provide the highest fidelity by estimating emissions at the intersection, corridor, or link level through the coupling of traffic simulation outputs with detailed emission models. By capturing vehicle operating modes acceleration, deceleration, idling, and stop-and-go dynamics these frameworks deliver fine-scale temporal and spatial resolution crucial for localized policy analysis and health impact studies (Table 6). Key models employed in microscale approaches include MOBILE, MOVES, COPERT, and IVE:

(i) MOBILE: Introduced by the U.S. EPA in 1970, MOBILE estimates emissions of NO_x, CO,

Table 5 — A detailed description of Dynamic or mesoscale estimation approach.

Reference	Year	Pollutants	Model/Tools	Advantages	Limitations	Novelty
Shan *et al.*[23]	2019	CO, NO_x, PM	MOVES + GPS speed data	Captures real-time speed variations; high spatiotemporal resolution	Incomplete GPS coverage on minor roads; high computational demand	First integration of GPS-derived speeds with MOVES for dynamic urban emissions inventory
He *et al.*[24]	2016	CO, NO_x, HC, PM	COPERT + Traffic simulation	Hourly emissions; supports policy evaluation for traffic measures	Generalized fleet composition; lacks seasonal activity profiles	Combines NRT traffic simulation with COPERT to assess spatial resolution impacts on emissions
Yao *et al.*[25]	2015	NO_x	COPERT + Floating car data	Identifies congestion-driven peaks; GIS-based spatial mapping	Does not incorporate acceleration/deceleration profiles; underestimates stop-and-go emissions	Utilizes floating car data for diurnal emission estimation
Zhang *et al.*[26]	2016	CO, NO_x	MOVES + Microsimulation + GIS	Accounts for intersections and stop-and-go dynamics; enhances health impact modeling	Highly data-intensive; computationally heavy for full-scale city applications	Integrates microscopic traffic simulation into mesoscale emission inventory framework

Table 6 — Description of microscale or model integrated estimation approach.

Reference	Year	Pollutants	Model	Advantages	Limitations	Novelty
USEPA [10]	2003	NO_x, CO, VOCs, PM	MOBILE6.2	Captures diverse driving scenarios (cold starts, idling); regulatory acceptance; urban planning	Limited to U.S. fleet and fuel standards; coarse spatial resolution	First comprehensive link-level emissions estimation incorporating cold starts
USEPA [9]	2014	CO_2, CO, NO_x, PM, HC, CH_4	MOVES	Wide pollutant scope including GHGs; customizable local inputs; detailed driving mode simulation	High data requirements (VKT, fleet age, control programs); computationally intensive	Introduced real-world g/km emission factors with high temporal resolution
European Environment Agency [8]	2018	CO_2, NO_x, CO, PM, VOCs	COPERT5	Empirical factors for varied road types; supports EU/UN reporting; adaptable to tech updates	Based on European vehicle classes; requires localization of emission factors	Integrates correction for congestion, road gradients, and weather conditions
Goyal *et al.*[6]	2013	CO_2, NO_x, PM, CO, HC	IVE	Minimal local data inputs; global technology database; suitable for developing regions	Relies on generalized emission factors; limited representation of local driving cycles	Enables rapid bottom-up inventory in data-scarce urban environments

VOCs, and PM based on fleet composition, traffic activity, fuel type, and meteorology. It accommodates diverse driving scenarios including cold starts and idling making it indispensable for urban air quality planning [10].

(ii) MOVES: Launched by the U.S. EPA in 2004, MOVES replaced MOBILE, expanding pollutant scope to include CO_2 and greenhouse gases, and classifying vehicles into light- and heavy-duty categories. It integrates local inputs vehicle population, VKT, fuel usage, and control programs and simulates driving modes to derive real-world emission factors (g/km) across criteria pollutants [9].

(iii) COPERT: Developed by the European Environment Agency, COPERT computes emissions of CO_2, NO_x, CO, PM, VOCs, CH_4, and other species using empirical emission factors stratified by vehicle class, fuel type, and driving conditions (urban/rural/highway). It supports national and subnational reporting under EU directives and UNFCCC protocols and adapts to local technologies and road types [8].

(iv) IVE: The International Vehicle Emissions model created by UCR and ISSRC with USEPA and World Bank support targets data-scarce regions by using global vehicle and fuel databases with minimal local inputs. It generates estimates for CO_2, NO_x, PM, CO, and HC, emphasizing flexibility and rapid deployment for developing countries [14].

Furthermore, a detailed comparative analysis is presented in the Table 7.

2.7 Model based case studies

Lei *et al.*[27] present a localized methodology to adapt the MOVES model for estimating truck emissions at the road-segment level, addressing significant gaps in heavy-duty vehicle emission inventories in developing countries. The study introduces an innovative protocol that converts engine torque and rotational speed data into second-by-second vehicle speed, enabling seamless integration between local driving cycles and the MOVES framework. A notable advancement is the "match year" method, which aligns U.S.-based MOVES emission outputs with Chinese emission standards by comparing emission outcomes rather than direct emission factors. Incorporating detailed local truck fleet data including vehicle age distribution and emission standard compliance allowed for the derivation of weighted emission factors across various pollutants, road types, and speed ranges. Findings indicate the highest emission factors occur at low speeds (~5 mph) due to congestion, with marked reductions up to 20 mph, beyond which declines are less pronounced. Interestingly, NOx emissions increase at higher speeds, underlining the necessity for balanced speed management strategies. Spatiotemporal analysis revealed that emissions are concentrated along major freight corridors and outer ring roads, displaying distinctive district-level patterns for freight traffic. The study concludes that mitigating congestion and optimizing truck movement can substantially reduce emissions, offering a practical and transferable framework for policymakers and environmental

Table 7 — Comparative analysis of MOBILE6.2, MOVES, COPERT5, and IVE emission inventory models.

Description	MOBILE6.2	MOVES	COPERT5	IVE
Developer	U.S. EPA	U.S. EPA	European Environment Agency	UC Riverside & ISSRC
Year Introduced	2003	2004	Version 5 in 2018	2013
Pollutants Covered	NO_x, CO, VOCs, PM	CO_2, CO, NO_x, PM, HC, CH_4	CO_2, NO_x, CO, PM, VOCs, CH_4	CO_2, NO_x, PM, CO, HC
Geographic Applicability	Primarily U.S. fleet and standards	Primarily U.S., customizable	European countries primarily; adaptable elsewhere	Global applicability, especially for developing countries
Spatial Resolution	Link/intersection level	Link/intersection level	Local to national scale	Urban/regional level
Temporal Resolution	Hourly, supports cold start and idling	Hourly and sub-hourly; real-world driving modes	Hourly to annual scales	Hourly to daily; simplified driving behavior
Input Data Requirements	Fleet composition, VKT, fuel type, meteorology	Vehicle population, VKT, driving cycles, fuel consumption, inspection/maintenance programs	Fleet composition, fuel types, driving conditions, road types, tech characteristics	Vehicle type, fuel characteristics, global tech databases, simplified driving cycles
Emission Factor Basis	Empirical, U.S.-specific emission factors	Real-world emission factors based on modal activities	Empirical emission factors based on European data	Mixed global and generalized emission factors
Driving Condition Modeling	Includes cold starts, idling, acceleration, deceleration	Detailed driving mode simulation (idle, accelerate, cruise, decelerate)	Urban, rural, highway; congestion, gradients, weather corrections	Simplified driving modes; limited acceleration/ deceleration detail
Regulatory Applications	Widely used for environmental assessment and regulatory compliance in U.S.	Primary emission model for U.S. EPA regulatory and planning purposes	Support EU reporting, climate change protocols, air quality regulations	Designed for rapid deployment in developing countries with limited data
Computational Complexity	Moderate; less computationally demanding than MOVES	High; computationally intensive due to modal simulations and detail	Moderate; less detailed traffic modeling but complex EF adjustments	Low to moderate; simpler inputs but less granular outputs
Advantages	Well-established with historical continuity; good for scenario extremes (cold start)	High accuracy from real-world driving data; flexible; detailed pollutant and mode-specific estimates	Adaptability to multiple European vehicle classes; detailed fleet and fuel type stratification	Ease of use in data-poor regions; flexible; reasonable estimates with minimal local data
Limitations	U.S.-centric assumptions; outdated for new technologies; limited spatial detail	High data needs; requires detailed local inputs and calibration; significant computational cost	Primarily European fleet and fuel data; requires regional calibration for accuracy outside Europe	Generalized emission factors may reduce accuracy; limited representation of local driving cycles
Novel Features / Novelty	Cold-start and extreme scenario modelling; early comprehensive inventory model integrating diverse emission scenarios	Real-world g/km emission factors; modal activity integration; incorporates modal emission factors; adaptable to diverse pollutants and vehicle categories	Correction factors for congestion, gradients, and weather; enables regulatory reporting with correction factors for traffic and environmental conditions	Simplified bottom-up model with a global database enabling use in data-scarce contexts; focus on global applicability and developing country adaptability balancing complexity and data availability

agencies, particularly in urban areas lacking comprehensive emission assessment tools.

Perugu's[28] study focuses on the localization and customization of the U.S. EPA's MOVES emission model to better reflect conditions prevailing in Indian urban environments, specifically targeting light-duty vehicles in Hyderabad. The research replaces the default Federal Test Procedure (FTP-75) driving cycle embedded within MOVES with the Modified Indian Driving Cycle (MIDC) alongside locally collected driving cycle data to more accurately represent real-world traffic characteristics. The study reports emission rates for carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NOx) that are approximately 9.54, 8.37, and 9.45 times higher, respectively, than those in the default U.S.-centric MOVES inventory. These elevated emissions are primarily attributed to factors such as severe traffic congestion, slower vehicle speeds, and suboptimal road conditions frequently encountered in Indian cities. In addition, the vehicle deterioration rates were recalculated, revealing a significantly accelerated degradation of emissions performance relative to U.S. standards. Validation of the modified emission factors was achieved through project-level dispersion modeling utilizing an operational street pollution model, which demonstrated satisfactory agreement with observed near-road pollutant concentrations (R^2 = 0.656 for CO and 0.648 for NOx). This work represents the first comprehensive effort to recalibrate the VSP-based MOVES model for Indian contexts, establishing a detailed methodological framework that leverages real-time traffic activity and GPS-derived driving data. The findings underscore the critical importance of incorporating localized driving cycles and traffic conditions when applying international emission models in developing countries to enhance the accuracy and relevance of vehicular emission estimates.

Vallamsundar[29] provide a comparative evaluation of the MOVES and MOBILE emission inventory models, highlighting the advanced capabilities of MOVES relative to the older MOBILE framework. MOVES employs a modal-based approach that facilitates second-by-second emission estimations grounded in detailed vehicle operating conditions such as acceleration, deceleration, and idling. Coupled with its graphical user interface and relational database framework, MOVES offers enhanced flexibility, superior data management, and a more accurate representation of modern vehicular technologies. These attributes render MOVES particularly suitable for regional and project-level emission inventories that support transportation conformity analyses under federal air quality regulations. Their case study in Cook County, Illinois, reveals that MOBILE significantly underestimates emissions of carbon monoxide (CO) and nitrogen oxides (NOx) compared to MOVES2010, with MOVES predicting[17] 10% higher NOx and 16% higher CO_2 emission loads. Discrepancies primarily arise from fundamental differences in emission factor derivation: MOBILE relies on aggregated rates, whereas MOVES utilizes a detailed vehicle activity-based structure. The authors emphasize that MOVES' advancement leads to more realistic emission inventories with direct implications for air quality management and transportation planning. However, transitioning from MOBILE to MOVES involves technical and institutional challenges, including the necessity for updated regional datasets and specialized practitioner training, underscoring the complexity of model evolution despite its benefits.

Lin *et al.*[30] developed an integrated modelling framework that couples the MOVES emission model with dynamic traffic assignment to improve emission estimation accuracy for project-scale transportation policy evaluations. This integration automates data exchange processes and substantially enhances the representation of traffic dynamics and vehicle-specific operating modes. The authors emphasize that the precise characterization of vehicle operating mode distributions is vital for generating reliable emission estimates. The study highlights the importance of incorporating realistic, activity-based traffic data in project-level emission analyses, as relying solely on default model parameters may produce significant inaccuracies. This coupled framework offers a more robust and behaviourally accurate tool for assessing transportation emission impacts at fine spatial and temporal scales.

Ntziachristos *et al.*[31] presented a case study reveals that passenger cars are the predominant contributors to carbon monoxide (CO) and carbon dioxide (CO_2) emissions, accounting for nearly half of the total fuel consumption and CO_2 output. Conversely, heavy-duty trucks and buses, despite their comparatively smaller numbers, dominate nitrogen oxides (NOx) and particulate matter (PM) emissions. Two-wheelers, prevalent in urban settings, are identified as the highest emitters of volatile organic compounds (VOCs). Officially adopted by 22 EU member states, COPERT is recognized for its versatility in addressing multiple vehicle categories. The model's robust methodology and user-friendly interface facilitate accurate estimation of road transport emissions, enabling effective evaluation of policy interventions. Prospective enhancements recommended for COPERT include regular updates of emission factors to incorporate emerging technologies, improved modelling of non-exhaust emissions such as tire and brake wear, integration with real-world driving and traffic data to enhance precision, and inclusion of advanced fuels and vehicle technologies like hybrids and electric vehicles.

Ekstrom *et al.*[32] conducted a rigorous evaluation of the COPERT emission inventory model by comparing its output against real-world emission measurements obtained through optical remote sensing of on-road vehicles under actual driving conditions. The study revealed that COPERT consistently underestimates emissions, particularly for nitrogen oxides (NOx) and carbon monoxide (CO), relative to remote sensing data. This underestimation is attributed to COPERT's dependence on average speed driving cycles, which fail to capture emission spikes associated with urban driving characterized by frequent stop-and-go traffic, idling, and acceleration/deceleration events. Additionally, vehicle-specific attributes such as engine type, age, and maintenance status were found to significantly influence emission levels, with older vehicles lacking advanced emission control technologies exhibiting substantially higher emissions than those predicted by the model. The findings suggest that COPERT's assumptions regarding fuel quality, traffic conditions, and vehicle performance inadequately reflect the complexity and variability of real-world urban traffic, leading to inaccuracies in emission inventories. The authors advocate for localized calibration of COPERT's emission factors using empirical data from regions with high traffic congestion and heterogeneous vehicle fleets to improve predictive performance. Enhancing the model's representation of real-world driving conditions and aging vehicle stock is crucial for generating more accurate urban emission assessments.

López *et al.*[33] conducted a comparative analysis of particulate matter (PM), hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NOx) emissions from urban buses operating in Madrid, utilizing on-board measurement systems under real driving conditions. The study revealed significant discrepancies between measured emissions and COPERT model estimates, particularly for NOx and CO, where the model substantially underestimated actual emission levels. Variability in the degree of underestimation was observed based on fuel type diesel versus compressed natural gas (CNG) and Euro emission standards. These results highlight the limitations of the COPERT model in accurately representing real-world emission dynamics of urban bus fleets, especially in traffic conditions dominated by frequent stop-and-go patterns and intensive acceleration events. The findings emphasize the need for incorporating real-world operational data in emission models to enhance their predictive reliability in urban fleet assessments.

Perdikopoulos *et al.*[34] present a detailed investigation of vehicular emissions in Delhi, a city grappling with severe air quality issues. The study develops a comprehensive emission inventory for criteria pollutants, namely particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NOx), and volatile organic compounds (VOCs), using the COPERT model integrated with vehicle activity data and emission factors sourced from both Indian and international studies. The methodology assesses the contributions of various vehicle categories to Delhi's overall pollution burden. Findings indicate that road transport is the principal source of NOx, CO, and PM emissions, with two-wheelers accounting for the majority of CO emissions due to their extensive fleet, while light-duty and heavy-duty vehicles dominate NOx and PM emissions. The study further highlights the disproportionately high emissions from older vehicles lacking modern emission control technologies, particularly for PM and NOx. However, the model's reliance on generalized traffic assumptions and average speed profiles leads to underestimation of emissions in congested, stop-and-go traffic characteristic of Indian urban environments. The discrepancies between COPERT estimates and on-road measurements are attributed to the model's insufficient representation of heterogeneous driving behaviours, traffic jams, and peak-hour conditions. The authors advocate for the incorporation of localized driving cycle data and real-world emission measurements to improve emission inventory accuracy for Indian megacities. This work provides a robust basis for urban air quality management and policy interventions, emphasizing the urgent need for stringent vehicle emission standards, fleet renewal, and reduction of older, high-polluting vehicles.

Saberiyansani *et al.*[17] present a comparative review of the COPERT and Indian Vehicle Emission (IVE) models, evaluating their performance based on accuracy, sensitivity to input data, usability, and applicability in policy contexts across diverse geographic regions. The review identifies COPERT as excelling in standardization, facilitating national-scale emission reporting, and aligning well with CORINAIR guidelines, making it particularly suited for regulatory compliance within European Union countries. In contrast, the IVE model employs a vehicle specific power (VSP) approach that integrates variables such as speed, acceleration, road slope, and vehicle mass, producing more realistic emission estimates in complex urban environments with heterogeneous driving patterns and terrain variability.

The authors recommend COPERT for broad-scale emission inventories and regulatory frameworks, while highlighting IVE's superiority in capturing localized emissions, especially for urban hotspots or areas with varied topography and driving behaviours. They further propose that integrating COPERT's structured standardization with IVE's detailed and sensitive modelling could enhance emission inventories, thereby supporting more effective policy-making and health impact assessments.

Mishra *et al.*[35] conducted a comparative evaluation of the U.S. EPA MOVES and European COPERT emission models within the framework of Indian urban environments. The study developed vehicle activity datasets, encompassing fleet composition, vehicle kilometres travelled (VKT), and representative speed profiles derived from Indian city transport statistics and localized traffic surveys. Both models were calibrated with Indian-specific input parameters where applicable. Results indicated that COPERT, which relies on average speed emission factors, generally underestimated emissions of carbon monoxide (CO), nitrogen oxides (NOx), and particulate matter (PM) compared to MOVES, particularly under conditions of high traffic congestion. The MOVES model, utilizing a vehicle specific power (VSP) approach, demonstrated superior responsiveness to urban driving dynamics and vehicle load variations, yielding more realistic emission estimates. Nonetheless, MOVES required substantial regional adaptation, as default U.S.-based emission factors underestimated CO and NOx emissions by up to an order of magnitude for Indian vehicle fleets. Calibration with Indian data significantly improved MOVES' alignment with observed emissions, particularly for heavy-duty vehicles and two-wheelers. The authors advocate for a hybrid modelling strategy that employs COPERT for broad national emission inventories and MOVES for detailed, project-level urban assessments. This approach seeks to combine COPERT's strengths in standardized reporting with MOVES' finer resolution of urban traffic conditions, supporting informed air quality management and regulatory planning.

2.8 Comparison of studies for Delhi, India

The summary of mobile EI studies for Delhi using different models is presented in Table 8, highlighting variation in estimated emission loads for pollutants:

This comparison illustrates pronounced discrepancies in emissions estimates for the same urban area. For example, CO emissions range from 464 tons/day (COPERT) to 783.2 tons/day (MOVES), NOx estimates vary from 194 tons/day (IVE) to 495.1 tons/day (MOVES), and PM emissions are reported between 26.1 tons/day (COPERT) and 46.7 tons/day (MOVES). These differences stem from structural and methodological variances across models, compounded by inconsistencies in the input data such as vehicle population, vehicle kilometres travelled (VKT), fuel consumption patterns, fleet age distribution, engine technologies, and the emission factor databases employed. Such discrepancies undermine confidence in emission inventory outcomes, posing significant challenges for formulating evidence-based air quality policies. When model outputs diverge substantially for the same locale, it complicates the selection of reliable data to inform regulatory frameworks, infrastructure planning, and pollution mitigation efforts. This risk of misguided policy interventions may result in inefficient resource allocation and delayed progress towards compliance with air quality standards. Moreover, non-standardized methods impede effective collaboration among agencies, slowing implementation and reducing stakeholder trust in inventory studies. Therefore, to ensure emission estimates are robust, comparable, and policy-relevant especially in rapidly urbanizing megacities like Delhi it is critical to standardize methodologies, adopt uniform data collection protocols, and harmonize model input requirements. This approach will foster greater consistency in emissions data, enhancing the reliability of air quality management strategies and regulatory decision-making.

2.9 Other additional studies

A review of 25 studies highlights diverse approaches and models used for mobile source emission inventories, with top-down methods predominating (Table 9). Common tools include

Table 8 — Comparative summary of mobile emission inventory studies for Delhi

References	City	Model	Pollutants	Results
Singh *et al.* (2013)[14]	Delhi	IVE	PM, CO, & NOx	CO: 509 TPD; NOx: 194 TPD; PM: TPD
Biswal *et al.* (2023)[10]	Delhi	COPERT	PM2.5, CO & NOx	PM2.5: 27 TPD; NOx: 314 TPD; CO: 464 TPD.
Mishra *et al.* (2022)[35]	Delhi	MOVES vs COPERT	PM, CO, & NOx	MOVES: CO: 783.2 TPD, NOx: 495.1 TPD, PM: 46.7 TPD; COPERT: CO: 489.4 TPD, NOx: 301.7 TPD, PM: 26.1 TPD

Table 9 — Detailed description of other additional studies.

References	Year	Approach	Tool / Model	Limitations/ Failures
Patino-Aroca *et al.*[36]	2022	Top-down	IVE	Outdated emission factors; Higher emission load; Constant VKT for each vehicle category
Velamuri *et al.*[37]	2024	Top-down	Excel	Need for ongoing monitoring and refinement of emission estimation techniques to improve accuracy and reliability
Ekstrom *et al.*[32]	2004	Top-down	COPERT	Improvements in the Vehicle count as well as in the data processing can be made, to further refine the use of model
Smit *et al.*[38]	2010	Review article	Review article	future emission models must incorporate the capability to quantify prediction errors, and clear guidelines should be developed internationally with respect to expected accuracy.
Nagpure[39]	2012	Top-down	Excel based VAPI model	Model needs cumulative registered vehicle population for calculation. Less number of vehicle categories is available in the model, which restricts its use at the international level.
Lei *et al.*[27]	2024	Top-down	MOVES	Real world data is required; emission factors only for China and US; Need to develop and validate single emission factors for all countries
Yao *et al.*[40]	2014	Top-down	MOVES	The vehicle specific power (VSP) and scaled tractive power (STP) including the grade and acceleration should be further studied
Boadh *et al.*[41]	2022	Bottom-up	Excel	Non-uniform monitoring data; Assumptions in vehicle emissions, challenges in high resolution
Venkitasamy[42]	2016	Bottom-up	Excel	Use of Real-time VKT; Vehicle count; fuel usage was based on assumptions
Jansakoo[43]	2022	Top-down	Excel	Only NOx emission inventory was developed, other pollutants were not considered
Effiong[44]	2016	Bottom-up	Excel	Nodal traffic points; Avg traffic volume is considered
Yang *et al.*[45]	2019	Top-down	Excel	The actual data was not reflected;
Kazimierz[46]	2015	Bottom-up	Excel	VKT adjustment factor is proposed along with using a multi-factorial compound models to estimate.
Zheng[47]	2012	Bottom-up	MOBILE	Relies on city-level aggregated data, limiting fine-scale accuracy; Not easily applicable in regions lacking detailed traffic statistics; Assumed uniform traffic flow via standard road length conversions; Outdated model use, limiting emission factors accuracy; evaluation done over a short period of 4 days; assumptions were applied in converting actual road length into standard road length for all roads.
Zhai *et al.*[48]	2017	Bottom-up	MOVES	Did not validate the results using the MOVES model; Used emission rate from a single vehicle; did not considered variation in vehicle technology, fuel type or emission factors; Neglected other key pollutants like NOx, PM, HC and CO; No validation for modelled emissions with real-world emission inventories.
Weerasekara *et al.*[49]	2017	Top-down	Excel	Failed to integrate real-world traffic congestion data; unable to convert VKT into daily emission loads; Estimated VKT using aggregate traffic volume data and average trip length rather than individual vehicle activity.
Jiang *et al.*[50]	2022	Top-down	IVE; MOVES; COPERT and MOBILE	Insufficient real-world data integration; inconsistent and outdated emission factors; lack of spatial and temporal resolutions; assumption of homogeneous fleet behaviour; etc.
Quoc *et al.*[51]	2024	Bottom-up	Excel	EF imported from European context; lack of real-time traffic volume data; roads are classified to urban and national, not considered lane-wise or congestion roads; Annual average VKT is considered.
Hu *et al.*[52]	2021	Bottom-up	Excel and IVE	Emission factors and vehicle activity data have considerable uncertainty; use of average VKT and annual fleet data
Mangaraj *et al.*[53]	2022	Bottom-up	Excel	No primary data for vehicle fleet; VKT; BS-IV and BS-VI not considered; Road congestion impact not quantified; uncertainty is very high (± 34%)
Marinello *et al.*[54]	2024	Top-down	Excel	Focuses on disaggregating large scale emission inventories into finer spatial and temporal scales using proxy variables (vehicle count; EF, VKT)
Cuellar Alvarez *et al.*[55]	2023	Bottom-up	COPERT	Outdated vehicle fleet data; Average annual VKT; no temporal and spatial variations; Assumption of uniform road type distribution
Zhivkov *et al.*[56]	2025	Bottom-up	Excel	Does not estimate emissions in kg/day or ton/day; Lacks vehicle categorization, fuel type, age, engine technology and norms; Road length is not taken into consideration
Ma *et al.*[57]	2024	Bottom-up	MOVES	Failed to estimate PM2.5 load in western cities particularly in peak hours

MOVES, COPERT, IVE, and Excel-based estimations, each possessing distinct advantages and limitations. Key challenges across studies are outdated emission factors, inconsistent vehicle count and road network data, and a lack of localized driving cycle information for model calibration, which collectively affect emission accuracy. While MOVES and COPERT offer robust frameworks, their applicability in developing regions is limited by data gaps and default parameters unrepresentative of local fleets, whereas Excel methods, though flexible, often lack sufficient temporal and spatial resolution.

3 Results and Discussion

This comprehensive review synthesized critical insights from a wide range of mobile source emission inventory models, including COPERT, MOVES, MOBILE, IVE, and Excel-based frameworks applied across varied geographic regions and urban scales, with a particular focus on Indian metropolitan contexts. These models differ not only in their structural frameworks and computational approaches but also in data requirements, vehicle classification schemes, and sensitivity to local driving and fleet conditions. Despite their widespread use, a prevailing limitation is the insufficient incorporation of road-type-specific Vehicle Kilometre Travelled (VKT) and vehicle activity patterns, which significantly compromises the spatial and temporal resolution of emission inventories. The failure to segment VKT by road classification and operational behaviour results in homogenized emission estimates that inadequately capture real-world heterogeneity in traffic dynamics, fleet composition, and congestion effects factors especially pertinent in rapidly urbanizing and traffic-dense cities such as Delhi, Mumbai, and Bengaluru.

Models like MOVES and COPERT represent advanced methodologies that include modal emissions factors and drive cycle variability; however, their transferability to developing country contexts is constrained by data inadequacies and emission factors calibrated primarily for Western fleets. The IVE model's vehicle specific power (VSP) based approach addresses some of these gaps, offering greater sensitivity to local driving behaviours and terrain variations, demonstrating enhanced performance in complex urban environments with diverse vehicle types. Hybrid modelling strategies that integrate the standardized reporting and regulatory strengths of COPERT with the dynamic, vehicle-level precision of MOVES or IVE offer promising avenues for improving emission characterization fidelity.

Robust emission inventories underpin effective air quality management and policy interventions, yet inconsistencies in input data such as fleet age distributions, fuel use, and traffic activity across studies undermine confidence in model outputs and complicate regulatory decision-making. Empirical validations using real-world measurement campaigns highlight that conventional model often underestimate emissions during congestion and stop-and-go traffic conditions prevalent in many developing cities. Consequently, there is an urgent need for localized calibration, integration of real-time traffic data, and comprehensive characterization of fleet deterioration and emission control technology penetration.

4 Conclusion

Going forward, the adoption of granular, activity-based VKT frameworks that explicitly factor in vehicle type, road classification, and spatial heterogeneity will greatly enhance the accuracy, comparability, and policy relevance of emission inventories. Such approaches enable targeted identification of emission hotspots, support effective deployment of mitigation measures including congestion pricing and low-emission zones, and facilitate compliance with stringent national and international air quality standards. This evolution in modelling practice is essential for rapidly growing urban centres that face escalating air pollution challenges and demand data-driven, context-specific solutions for sustainable transportation and environmental health outcomes.

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