

Review

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A systematic review of urban road traffic CO₂ emission models

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Abstract

With rapid urbanization and increasing mobility demand, urban traffic systems face intensifying congestion, resulting in elevated CO₂ emissions. This paper provides a systematic review of the current status of models estimating CO₂ emissions from urban road traffic, considering their applicability across various traffic management scenarios. Urban road traffic CO₂ emission models can generally be categorized into two main types. Traditional models typically estimate emissions based on average speed, traffic conditions, or vehicle operation modes, whereas data-driven models leverage techniques such as machine learning and deep learning to capture complex emission patterns. The review proposes a set of model selection criteria, namely data availability, computational complexity, interpretability, and transferability. Based on a comparative evaluation of these criteria, the study finds that there is no one-size-fits-all model so far. Instead, model suitability depends heavily on local data infrastructure and specific application needs. Therefore, future work needs to enhance model localization and personalization to improve estimation accuracy, while the integration of spatiotemporal data-driven modeling approaches is likely to become a research hotspot in upcoming studies.

Keywords: Urban road traffic, CO₂ emission models, data-driven modeling, time-series analysis, spatiotemporal modeling, carbon emissions



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INTRODUCTION

Rapid economic growth and urbanization have significantly intensified mobility demands in cities, leading to increased energy consumption and mounting environmental concerns. Although modern vehicle technologies have improved mobility and accessibility, their widespread use has also become a major driver of greenhouse gas emissions. Urban road traffic is characterized by dense intersections and frequent stop-and-go conditions, which lead to elevated CO₂ emissions due to increased speed fluctuations and inefficient vehicle operation. In China, the transportation sector contributes approximately 10% of total carbon emissions, with road transport responsible for nearly 84% of this share^[1]. This high proportion is largely attributable to the extensive urban road networks and the prevalence of inefficient driving conditions, making accurate CO₂ quantification and effective mitigation strategies essential for traffic environmental management.

As an open, dynamic, and complex system shaped by the interactions among drivers, vehicles, infrastructure, and the environment, urban road traffic makes CO₂ emission estimation inherently a complex systems problem^[2]. Moreover, these emissions are highly context-sensitive and temporally variable. Unlike macro-level emission accounting methods^[3–6] that rely on aggregated indicators such as travel distance or fuel consumption and often fail to capture traffic dynamics, this study specifically focuses on urban road traffic CO₂ emission models that incorporate real-world traffic states and variations in vehicle operating behavior.

Several scholars have conducted reviews of emission modeling approaches. For instance, Zhong *et al.*^[7] examined traditional vehicle emission models and data-driven prediction models, comparing their data requirements, computational methods, and predictive accuracy across different application scenarios. Zhou *et al.*^[8] focused on fuel consumption models relevant to eco-driving and eco-routing, classifying models into white-box, gray-box, and black-box categories based on their interpretability. While these reviews provide valuable technical insight, most are confined to single-vehicle level emissions or specific use cases, such as eco-driving or laboratory-based assessments, limiting their applicability to complex urban traffic systems. This leaves a critical gap in understanding how models perform across different spatial scales and under diverse traffic management regimes, an area that remains underexplored but is vital for developing effective urban transport decarbonization strategies. Grote^[9], for example, reviewed CO₂ emissions at the network level, yet the review lacks timeliness and does not incorporate recent developments in trajectory-based modeling, data fusion, or AI-driven approaches.

In contrast, this study offers a comprehensive and up-to-date review of urban road traffic CO₂ emission models with a distinct focus on their applicability to traffic management. It explicitly addresses the gap between emission modeling and real-world urban traffic operation needs, an area that has received limited attention in prior reviews. By systematically categorizing both traditional and data-driven models according to operational granularity, data dependency, interpretability, and transferability, the study establishes a comparative framework designed for practical model selection and scenario matching. Furthermore, it incorporates recent advances in spatiotemporal modeling [e.g., Graph Convolutional Networks (GCN), Long Short-Term Memory (LSTM)] and discusses emerging challenges in data integration, personalization, and governance alignment.

Accordingly, the key research questions driving this review are as follows:

1. What are the key factors influencing CO₂ emissions in urban road traffic system?

2. What categories of emission models exist, and how do they account for traffic-related variables?
3. How do different models vary in terms of data requirements, complexity, interpretability, and transferability?
4. In which traffic management scenarios are these models most effectively applied?

RESEARCH METHODS

Systematic literature review process

A systematic literature review was conducted to comprehensively collect, screen, and critically evaluate existing research on urban road traffic CO₂ emission models. Unlike narrative reviews, a systematic literature review adheres to a rigorous, replicable, and verifiable protocol^[10]. In this study, the PRISMA checklist was adopted to guide the review process, ensuring comprehensive coverage of relevant literature and methodological transparency.

Keyword extraction

Given the extensive volume of retrieved publications, natural language processing (NLP) techniques, such as RAKE, TF-IDF, TextRank, and YAKE, were applied to automated keyword extraction and topic classification^[11]. In this study, YAKE was selected for its lightweight, unsupervised design, with proven strengths in computational efficiency and domain adaptability on small-to-medium-scale corpora. Benchmark comparisons by Campos *et al.*^[12] showed that YAKE achieved competitive or superior performance relative to baseline methods, with F1 scores ranging from 0.086 to 0.500 across eleven datasets, while requiring less computational overhead. In addition, YAKE also performs generally well for different domains and types of documents (e.g., agricultural papers, news articles, and scientific literature).

Text classification

To enhance classification accuracy and contextual understanding, advanced language models (e.g., ChatGPT and DeepSeek-R1) were employed for downstream text processing tasks^[13]. These models have consistently outperformed traditional methods across a range of NLP benchmarks. In particular, DeepSeek-R1 demonstrated strong generalization capabilities, achieving benchmark scores such as 90.8% on MMLU, 92.2% F1 on DROP, 87.6% on AlpacaEval 2.0, and 71.5% on GPQA Diamond^[14]. These results support its applicability to complex, high-stakes tasks such as scientific text classification within this review.

RESEARCH PROCESS

To enhance the efficiency and objectivity of the literature selection process, we adopted an AI-assisted systematic review approach, drawing on the methodology proposed by Noroozi *et al.*^[15]. The approaches comprise three main steps: (1) search query formulation, (2) document screening via large language models (LLMs), and (3) quality assessment. Limiting the results to studies published between 2020 and 2024, the review focuses on recent methodological advancements in CO₂ emission modeling. To provide historical context, [Supplementary Table 1](#) compares foundational (pre-2020) and contemporary (2020-2024) approaches in terms of modeling principles, data needs, and application scenarios.

Search query formulation

The core dataset was obtained from the Web of Science Core Collection, which includes over 21,100 peer-reviewed journals, conference papers, and books. An initial search query [[Figure 1](#)] was developed through expert consultation, internal discussions, and AI assistance. This query specifically targeted urban road traffic studies while excluding publications related to rail, air, and maritime transportation. To ensure

(TS=(emission model OR emission estimation OR emission quantification) AND TS=(carbon or CO₂ or greenhouse gas) AND TS=(traffic) NOT TS=(water OR aerial OR rail)) AND (PY=("2021" OR "2022" OR "2023" OR "2024") AND DT=("ARTICLE" OR "REVIEW"))

Figure 1. Initial search query.

relevance and temporal focus, the search was restricted to articles published between 2020 and 2024, yielding 1,389 records. The top 100 results ranked by relevance were manually reviewed, and relevant entries were annotated for further refinement. High-scoring terms generated by the YAKE algorithm were manually reviewed and selected. When a newly extracted keyword was semantically equivalent to an existing term in the original search query, it was incorporated using the “OR” operator. Table 1 presents an example of the high-ranking keywords identified in one iteration. These keywords were used to supplement the search query. The final version (see Figure 2) retrieved 1,969 articles, forming the basis for subsequent screening and analysis.

Paper relevancy identification

Given the scale of the retrieved literature, manual screening alone proved inefficient. DeepSeek R1, a large-scale language model fine-tuned for scientific literature understanding, was employed to assess article relevance based on abstracts. To evaluate its accuracy, the model’s screening decisions on the top 100 most relevant documents were compared with consensus labels provided by a three-member panel of domain experts. DeepSeek R1 achieved an agreement rate of 89%, demonstrating strong alignment with expert judgments and validating its applicability for supporting large-scale systematic literature reviews. By applying DeepSeek R1 to assess the relevance of 1,969 retrieved articles, the pool was narrowed down to 415 documents that aligned with the scope of this review.

Quality assessment

Following the initial automated screening, 415 records were identified as potentially relevant and advanced to the manual review stage. In the first stage of manual review, titles and abstracts were screened, resulting in the exclusion of 46 studies due to insufficient relevance to urban road traffic CO₂ emission modeling. For the remaining 369 records, full-text retrieval was attempted via academic databases and institutional access. Four articles were not accessible and thus excluded. The remaining 365 articles underwent full-text assessment based on the following inclusion criteria: (1) direct relevance to CO₂ or energy emissions from urban road transport; (2) methodological clarity in model design, data application, or emission quantification; (3) publication in peer-reviewed journals or reputable conferences; and (4) availability of the full text in English. Ultimately, 206 studies met all criteria and were included in the final systematic review. The complete selection process is illustrated in Figure 3.

FACTORS OF CO₂ EMISSIONS IN URBAN ROAD TRAFFIC

Traffic activity intensity

Traffic activity intensity, typically measured by vehicle miles traveled (VMT) or trip frequency, is a fundamental driver of carbon emissions. In urban road networks, total emissions are often estimated by multiplying VMT by emission factors (EF), with higher VMT generally resulting in greater emissions^[16].

Vehicle and energy types

Road vehicles are the dominant emission source of CO₂ emissions in urban traffic systems. Vehicle attributes, such as size, weight, emission standards, and age, directly influence emission intensity^[17,18]. The type of energy used (e.g., fossil fuels or electricity) also plays a crucial role^[19]. Electric vehicles (EVs) generally exhibit lower lifecycle environmental impacts^[20,21], making it essential for emission models to

Table 1. A sample of the top 10 terms with high scores from the NLP model

Keywords	Score
Estimate road traffic	0.0052
Accurately estimate road	0.0076
Global greenhouse gas	0.0101
Road traffic	0.0116
Formulate effective emission	0.0221
Estimate road	0.0332
Carbon dioxide	0.0397
Greenhouse gas	0.0436
Emission reduction policies	0.0451
Effective emission reduction	0.0453

NLP: Natural language processing.

```
(TS=(emission* model* OR emission* estimat* OR emission* quanti* OR emission* analysis OR emission* assess* )
AND TS=(carbon or CO2 or greenhouse gas OR GHG) AND TS=(traffic OR jam OR congestion) NOT TS=(water OR aerial
OR rail OR ship OR pavement OR aviation)) AND (PY=("2024" OR "2023" OR "2022" OR "2021") AND DT=("ARTICLE"
OR "REVIEW"))
```

Figure 2. Final refined search query.

account for both vehicle types and energy sources.

Actual operating conditions

Vehicle operating modes (e.g., acceleration, cruising, deceleration, idling) significantly affect emissions. Among these, acceleration typically produces the highest carbon emission rates, while idling results in extremely high emission factors due to zero speed but ongoing fuel consumption^[22]. Traffic conditions such as average speed, congestion level, and vehicle density also impact emissions. Intersections characterized by frequent stops and starts are often identified as localized high-emission zones^[23,24].

Other factors

Additional environmental and infrastructural variables also influence CO₂ emissions. Road gradient^[25] can alter engine load and fuel use, while meteorological factors such as ambient temperature and altitude affect fuel efficiency and combustion processes, thereby influencing emission levels^[26-28].

TRADITIONAL EMISSION MODELS

Traffic emission models are generally categorized into two broad types: traditional models grounded in mathematical or physical principles, which are widely adopted by governments and research institutions; and data-driven models, which have recently gained popularity due to their adaptability to specific data conditions and application needs.

In this review, traditional models are further classified into average speed, traffic situation, and modal models, following the framework proposed by Smit^[29]. Alternative classification schemes in the literature include categorizing models as macroscopic, mesoscopic, or microscopic based on their application scope, or as white-box, gray-box, and black-box models depending on their level of interpretability^[30]. However, there is currently no universally accepted taxonomy, and even the widely used macro-meso-micro classification remains controversial^[31].

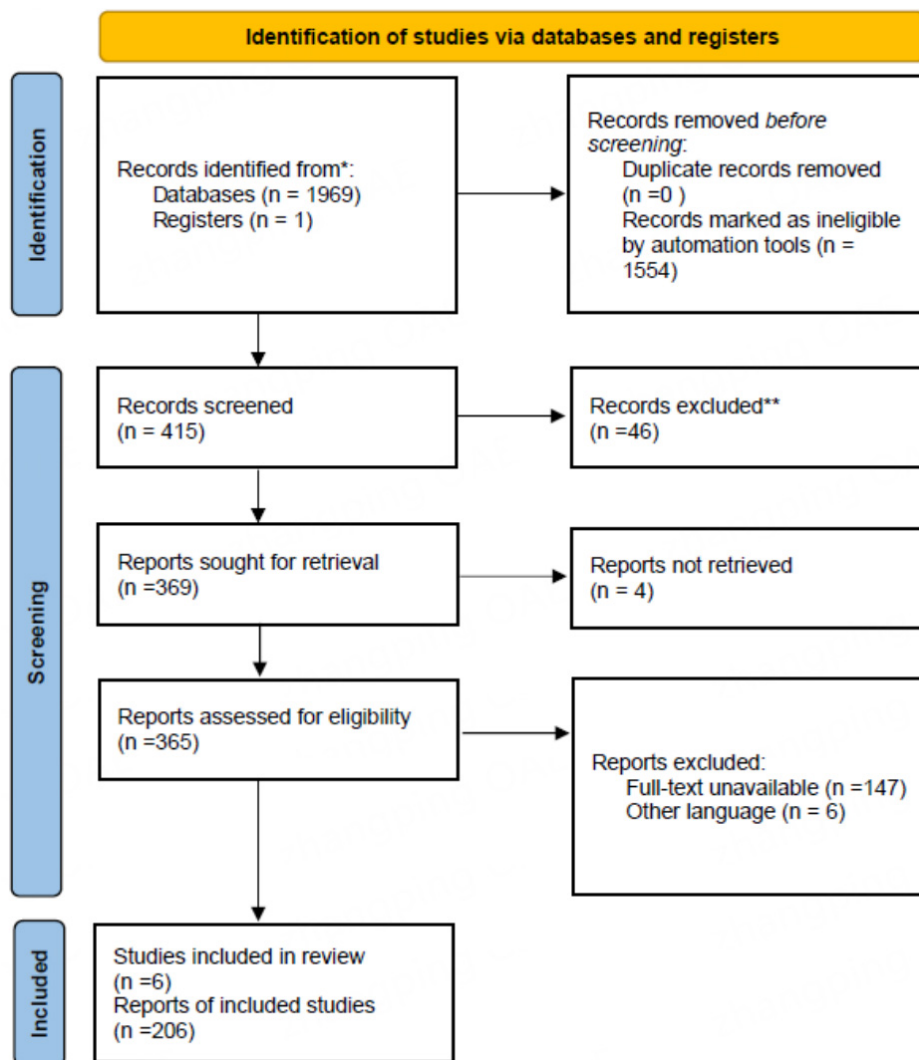


Figure 3. PRISMA 2020 flow diagram.

Average speed emission models

Average speed emission models estimate total emissions based on the average speed of vehicles (spatial average speed). These models are typically used to assess aggregate emissions and long-term trends at urban or national scales. Representative examples include Computer Program to calculate Emissions from Road Transportation (COPERT), Emission Factor (EMFAC), and Mobile Source Emissions Factor (MOBILE).

The COPERT model is the European Union (EU) standard vehicle emission calculator coordinated by the European Environment Agency (EEA)^[32]. It calculates emissions and energy consumption for specific countries or regions using input parameters such as vehicle fleet composition, mileage, average speed, and ambient temperature. COPERT distinguishes among three main emission sources: hot engine operation, cold starts, and fuel evaporation. The model estimates emission factors through speed-dependent regression functions^[33].

The EMFAC model, developed by the California Air Resources Board (CARB), is widely used to evaluate emissions from on-road vehicles in California. It defines emission factors across speed bins (typically in

5 m/s intervals) and incorporates calibration parameters that reflect operating conditions, vehicle specifications, and local environmental factors^[34].

The MOBILE model, developed by the U.S. Environmental Protection Agency (EPA), follows a similar logic to EMFAC but has not been updated since 2004 and does not include CO₂ emission estimates^[35].

Traffic situation models

Traffic situation models associate emission factors with specific driving conditions by analyzing real-world vehicle operation patterns^[36]. These models typically classify traffic situations based on factors such as region, road type, speed limit, and level of service, each corresponding to distinct emission factors^[37]. A representative model is Handbook Emission Factors for Road Transport (HBEFA).

HBEFA is the standard model for road pollutant analysis in Germany, Switzerland, and Austria, and is supported by the European Commission. It classifies emissions across multiple dimensions, including emission types, vehicle categories, years, pollutants, traffic conditions, and road gradients^[38]. HBEFA also provides part of the emission factor data used in the COPERT model^[33].

To further clarify the similarities and differences among commonly used traditional emission models, Table 2 presents a comparative summary of COPERT, EMFAC, MOBILE, and HBEFA in terms of their input requirements, spatial and temporal resolution, supported vehicle and energy types, road categories, and model versions.

Modal models

Modal models estimate vehicle emissions by segmenting vehicle operation into discrete modes defined by parameters such as speed, acceleration, and engine revolutions per minute (RPM). Each mode corresponds to an emission rate function that accounts for vehicle type, technology, and fuel characteristics. These models operate at a high temporal resolution (1 Hz), enabling per-second estimation of vehicle modes and their associated emission factors, which is why they are also referred to as instantaneous speed models^[29]. Widely used modal models include Motor Vehicle Emission Simulator (MOVES), Comprehensive Modal Emission Model (CMEM), and International Vehicle Emissions (IVE), along with various microscopic emission models such as Passenger Car and Heavy-Duty Emission Model (PHEM) and Virginia Tech microscopic energy and emission model (VT-Micro).

The MOVES model, developed by the U.S. EPA, is a comprehensive emission model that operates at macro, meso, and micro levels. It characterizes emission rates from vehicles under different operating modes based on Vehicle Specific Power (VSP) and vehicle speed bins. VSP represents the power demand imposed on the engine to overcome all driving resistances, including grade resistance, aerodynamic drag, tire resistance, and acceleration resistance^[39]. The MOVES model captures the emission performance of traffic flow on a given road segment through the distribution of vehicle operating modes.

The IVE model, developed by the University of California, Riverside, aims to simulate motor vehicle emissions in developing countries. It quantifies emissions based on VSP and engine load (ES) bins.

The CMEM model was sponsored by the National Cooperative Highway Research Program (NCHRP) and the EPA. This model takes inputs such as acceleration, air/fuel equivalence ratio, fuel rate, speed, road gradient, and auxiliary load. Data for modeling were collected by researchers using dynamometers, testing 300 real-world vehicles^[8]. The CMEM model consists of six main modules responsible for predicting engine

Table 2. The comparison of COPERT, EMFAC, MOBILE and HBEFA models

Model	COPERT	EMFAC	MOBILE	HBEFA
Input	Average speed, vehicle fleet composition, vehicle activity, weather conditions, etc.	Average speed, vehicle fleet composition, vehicle activity, weather conditions, etc.	Average speed, vehicle fleet composition, vehicle activity, weather conditions, etc.	Traffic situation, vehicle fleet composition, vehicle activity, gradient, weather conditions, etc.
Spatial scale	National, regional, local, link	Regional, project level	National, local	City, project level
Time scale	Year, month, week, day, hour	Year, season	Year, season, month, day	Year, month, week, day, hour
Vehicle type	Passenger cars, light-duty, heavy-duty, urban buses & coaches, motorcycles	Passenger cars, light-duty, heavy-duty, motorcycles, medium-duty, buses, motorcycle	Passenger cars, motorcycles, light- and heavy-duty trucks	Passenger cars, light commercial vehicles, heavy-duty trucks, urban buses & coaches, motorcycles
Energy type	Gasoline, diesel, liquefied petroleum gas	Gasoline, diesel, natural gas, electricity	Gasoline, diesel	Gasoline, diesel, electricity
Road type	Urban, rural and highway	/	Highway	Motorway, rural, urban, overall average
Driving cycle	European countries	FTP, California Unified Cycle	Different counties	European countries
Version	COPERT 5.8.1, 2024	EMFAC 2021	MOBILE 6.2, 2004	HBEFA 4.2, 2022
Reference	[33]	[34]	[35]	[36]

COPERT: Computer program to calculate emissions from road transportation; EMFAC: emission factor; MOBILE: mobile source emissions factor; HBEFA: handbook emission factors for road transport; FTP: federal test procedure.

power, engine speed, air/fuel ratio, fuel usage, engine emissions, and catalyst conversion efficiency.

A comparison of the MOVES, IVE, CMEM, PHEM, and VT-Micro models is summarized in Table 3.

Discussion

Data requirements

Microscopic emission models, which are suitable for estimating emissions at the individual vehicle level, compute emissions based on vehicle trajectories or operating conditions at a second-by-second resolution, resulting in substantial data requirements. These models incorporate dynamic parameters that continuously change during operation, such as acceleration and speed. In contrast, macroscopic and mesoscopic emission models rely on traffic aggregated variables.

Local governments typically have access to aggregated road traffic data, summarized at the traffic flow level rather than classified by individual vehicle^[9]. Urban traffic infrastructure, such as surveillance cameras and inductive loop detectors, is widely deployed, making it relatively easy to obtain parameters such as flow, speed, and density. Therefore, the data requirements of macroscopic and mesoscopic emission models are generally easier to satisfy.

For instantaneous vehicle emission models, trajectory data are a critical input for evaluating urban traffic emissions. Currently, there are three primary sources of such data: (1) GPS data or on-board diagnostics (OBD) data collected from commercial fleets, including ride-hailing services^[45], taxis^[46], buses^[47,48], trucks^[49], and increasingly, electric vehicles^[50]; (2) mobile phone signaling data and user location information obtained from navigation applications; (3) roadside sensors, surveillance cameras, and electronic toll collection (ETC) systems, particularly at signalized intersections and key roadway segments^[51].

Sparse trajectory data, which are often collected at intervals longer than one second, are common; however, most vehicle carbon emission estimation models require inputs at a one-second resolution. As a result,

Table 3. The comparison of MOVES, IVE, CMEM, PHEM and VT-Micro models

Model	MOVES	IVE	CMEM	PHEM	VT-Micro
Input	Vehicle operation mode, vehicle fleet composition, vehicle activity, weather conditions, etc.	Vehicle operation mode, vehicle fleet composition, vehicle activity, weather conditions, etc.	Physical parameters (engine capacity, vehicle mass, maximum power, torque, etc.), instantaneous driving pattern	Speed and gradient profiles of vehicles	Speed profiles of vehicles
Spatial scale	National, regional, project level	National, regional, local, link	Vehicle-level	Vehicle-level	Vehicle-level
Time scale	Hour, day, week, month, year	Hour, day, week, month, year	Real-time or instantaneous	Real-time or instantaneous	Real-time or instantaneous
Vehicle type	Passenger cars, trucks, buses, motorcycles, motorhomes	Bus, truck, small engine, motorcycle	Car, truck	Passenger cars, light-duty, heavy-duty, buses & coaches, motorcycles	Light duty vehicles and trucks
Energy type	Gasoline, diesel, CNG, LPG, electricity, ethanol (E85)	Gasoline, diesel, NG, ethanol, propane, CNG and LPG	Diesel, gasoline	Diesel, gasoline	Gasoline, diesel
Road type	Rural, urban	/	/	/	/
Driving cycle	Different counties	Developing countries	FTP, US06, MEC01	European countries	FTP
Version	MOVES 5.0.0, 2024	IVE 2007	CMEM 3.0, 2005	Continuously updated. Unavailable	VT-Micro 2.0, 2004
Reference	[40]	[41]	[42]	[43]	[44]

MOVES: Motor vehicle emission simulator; IVE: international vehicle emissions; CMEM: comprehensive modal emission model; PHEM: passenger car and heavy-duty emission model; VT-Micro: virginia tech microscopic energy and emission model; FTP: federal test procedure; CNG: compressed natural gas; LPG: liquefied petroleum gas; NG: natural gas.

researchers have increasingly focused on the problem of trajectory reconstruction for emission calculations^[52,53]. Ma *et al.*^[54] proposed a trajectory reconstruction method based on interpolation of acceleration distributions, demonstrating that the reconstructed trajectory closely approximates the real trajectory, achieving 2% to 17% higher accuracy compared to other methods. Shang *et al.*^[55] developed a traffic energy consumption model that integrates macroscopic and microscopic data, and reconstructed trajectories using a nonparametric kernel smoothing algorithm combined with variational theory. For data with varying sampling frequencies, this approach significantly improved the accuracy of emission estimates based on reconstructed trajectories.

Accuracy

Macroscopic and mesoscopic emission models rely on aggregated data (such as regional average speed and fleet age distribution), which obscure individual driving heterogeneity. This simplification can lead to the smoothing of emissions in localized hotspots, such as intersections, inherently limiting the accuracy of these models. Smit *et al.*^[56] found that based on data from portable emission measurement system (PEMS) for five SUVs, the emission factors under actual urban hot operating conditions were seven times higher for nitrogen oxides and four times higher for nitrogen dioxide than those estimated by the COPERT model in Australia.

Microscopic emission models, by contrast, capture individual driving behavior and thus offer the potential for higher accuracy than macroscopic and mesoscopic models, providing a more detailed representation of real-world vehicle emissions. However, the accuracy of these models is largely dependent on the precision of input parameters. The actual results may be constrained by sensor noise and the high costs of data cleaning, often resulting in effective accuracy that falls below laboratory calibration values^[57].

Moreover, emission models are frequently integrated with traffic simulation models. Existing research reveals inconsistencies in whether microscopic traffic simulation models can reliably reproduce real-world pollutant emission characteristics. One notable issue is the discrepancy between the VSP distributions generated by traffic simulators and those observed in reality^[58]. Lejri *et al.*^[59] found that COPERT may overestimate NO_x emissions during smooth traffic flow and underestimate them during congestion. Although PHEM performs well in terms of accuracy, its lack of detailed information on the actual fleet composition may introduce certain biases. The study noted that when using the PHEM model, the absolute global relative errors for fuel consumption and NO_x emissions could reach 5.0% and 9.2%, respectively. Gräbe *et al.*^[60] coupled MATSim with HBEFA to compare simulated emissions with PEM-based measurements. Their results showed that the greenhouse gas CO₂ emissions from light and heavy vehicles over a 61.7-kilometer route were 77% and 57% of the measured values, respectively, which may be related to errors in road classification and the HBEFA model's failure to account for road gradient effects.

Complexity

Microscopic emission models capture the state and behavior of individual vehicles, requiring highly detailed input data and substantial computational processing. As a result, these models can be computationally intensive and time-consuming when applied to large-scale traffic networks. For instance, coupling the microscopic traffic simulator VISSIM with the PHEM emission model involves extensive calibration and detailed speed profiles^[61]. In contrast, mission models based on average speed or aggregated traffic conditions enable much faster processing, making them more suitable for large-scale or real-time applications.

Transparency

Transparency refers to the extent to which a model's internal mechanisms, including its structure, parameters, and training process, and whether these elements can be accessible and comprehensible to humans. Zhou *et al.*^[8] categorize the emission models reviewed in this study as black-box models, which are data-driven and expressed through mathematical relationships. According to this framework, traditional emission models can be classified into physical models (e.g., CMEM, PHEM), hybrid models (e.g., MOVES, COPERT, HBEFA), and data-driven models (VT-Micro).

Transferability

Vehicle emission characteristics vary significantly across regions, heavily influenced by local traffic conditions, driving behaviors, vehicle emission levels, and fuel quality. Emission models are typically developed based on the local driving cycles, such as the U.S. Federal Test Procedure (FTP), and rely on extensive experimental or empirical datasets. However, many countries and regions have yet to establish comprehensive and standardized motor vehicle emission factor databases. This situation results in inconsistent methodologies and fragmented data sources. Although some researchers have attempted localized calibration of these emission factor models to enhance their applicability and accuracy^[62], challenges persist regarding their precision and practical usability in real-world applications.

Overall evaluation

Figure 4 presents a radar chart that offers a qualitative overview of five widely used traditional emission models (COPERT, HBEFA, MOVES, CMEM, and VT-Micro) evaluated across five key criteria: Data Requirements, Accuracy, Complexity, Transparency, and Transferability. The scoring values, ranging from 1 to 5, are primarily derived from accumulated domain knowledge and general experience reported in the literature, rather than from a standardized quantitative evaluation framework.

The radar chart clearly illustrates the inherent trade-offs among these models. Microscopic models such as CMEM and VT-Micro tend to achieve higher scores in Accuracy and Transparency, reflecting their detailed representation of vehicle behavior and model structure. However, these models require more granular and extensive input data, as evidenced by their higher Data Requirements scores. In contrast, macroscopic models like COPERT and HBEFA demonstrate strengths in lower data demands and reduced Complexity, making them more suitable for applications with limited data availability or computational resources. Nevertheless, this often comes at the expense of reduced accuracy and diminished capacity to capture localized emission variability. The model MOVES offers a balanced performance, with moderate scores across the evaluated criteria.

Given the diverse application scenarios and varying data complexities involved in deploying each model, there is currently no comprehensive scientific study that rigorously compares these models under uniform conditions. Differences in modeling assumptions, input data quality, geographic context, and computational methods pose significant challenges to direct benchmarking. To advance the field, future research efforts should prioritize the development of standardized evaluation frameworks and the establishment of shared benchmark datasets.

DATA-DRIVEN EMISSION MODELS

Data-driven emission models are computational frameworks that leverage large amounts of real-world data to predict, analyze, or optimize pollutant emissions. These models extract patterns from historical or real-time datasets using techniques such as machine learning, statistical analysis, and data mining, establishing complex, often nonlinear relationships between emissions and influencing factors.

Despite increasing interest, systematic reviews of data-driven emission models remain limited. For example, Zhang et al.^[63] categorizes data-driven models in their review of energy consumption models for new energy vehicles, dividing them into two categories based on methodology: machine learning and neural networks. Zhong et al.^[7], on the other hand, classified them based on data sources into bench test data and on-road measurement data. This paper adopts a classification framework based on the modeling object and the machine learning approach employed.

Microscopic models

Although this paper focuses on the quantification of emissions at the traffic segment or road network level, microscopic data-driven models are increasingly used for mesoscopic and even macroscopic applications^[64]. These models rely on high-resolution input data, such as bench test results, OBD data, or PEMS records, to learn the relationship between vehicle operating states and emission rates. Common input features include VSP, speed, acceleration, and sometimes engine parameters like RPM and torque. Machine learning models are trained to map these features to instantaneous emission rates^[39].

Statistical regression models

Various regression and classification algorithms have been employed in emission prediction, including

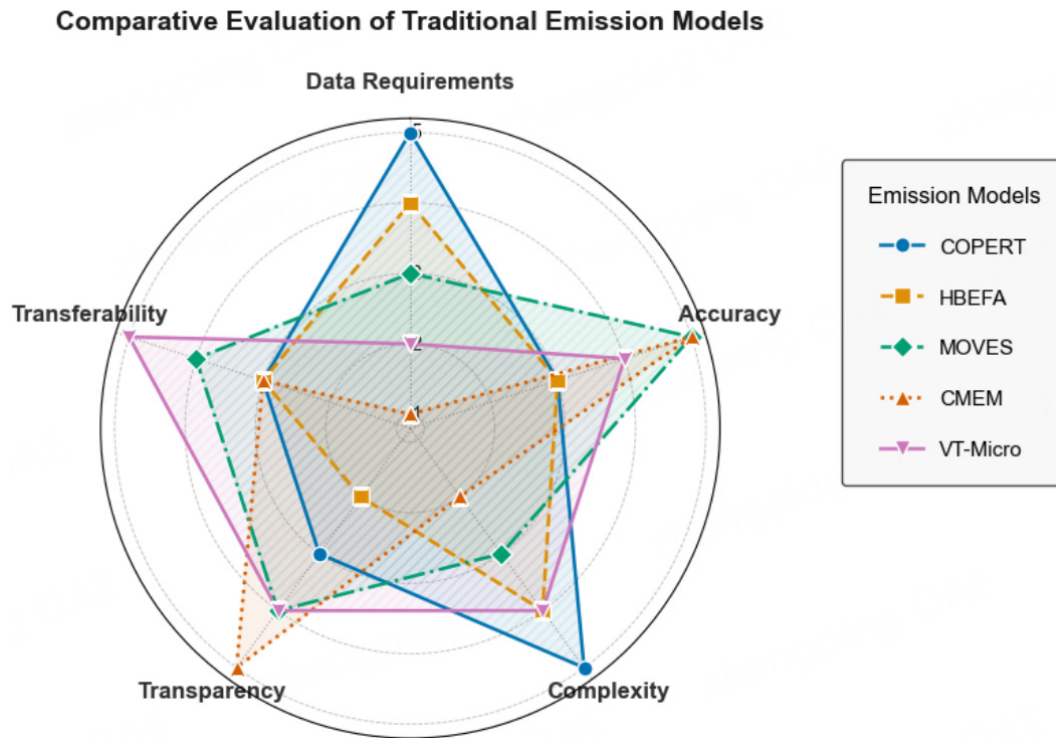


Figure 4. Radar chart evaluating traditional emission models across five criteria. Higher scores (1-5) indicate more favorable performance for each respective attribute.

Simple Linear Regression (SLR), Support Vector Regression (SVR), Decision Trees, and Random Forests. For instance, Chandrashekar et al.^[65] developed a speed-based emission model using SLR, SVR, and Piecewise Linear Regression (PLR), finding that PLR outperformed the others in predicting CO, CO₂, HC, and NO_x emissions. Similarly, Jia et al.^[66] used real-world vehicle emission data and applied a Random Forest model to estimate emissions of CO₂, CO, NO_x, and THC, achieving strong predictive accuracy ($R^2 > 0.85$ for all pollutants).

Artificial Neural Networks (ANNs) have also been widely used to model nonlinear relationships in vehicle emissions^[67,68]. For example, Madziel^[69] proposed a two-dimensional emission model for hybrid vehicles using artificial neural networks, achieving an R^2 coefficient of 0.73 and a Mean Squared Error (MSE) of 0.91.

Time-series models

Instantaneous vehicle emissions are inherently temporal, with key variables, such as speed, acceleration, and engine conditions, exhibiting strong time dependencies. As a result, time-series models have proven effective in modeling dynamic emission patterns based on high-frequency vehicle trajectory data. Popular methods include LSTM, Gated Recurrent Unit (GRU), and recurrent neural networks (RNNs)^[70].

Among them, LSTM is particularly effective in capturing both long-term and short-term dependencies in sequential data through its unique gating mechanisms, including the input gate, forget gate, and output gate, to regulate the flow and storage of information. This architecture enables the LSTM network to dynamically determine which information to retain, which to update, and which to output, thereby capturing complex dynamic patterns in time series data.

However, the effectiveness of these models is often constrained by the availability and quality of input data. In real-world applications, the collection of fine-grained vehicle operation data can be challenging due to limited sensor coverage, privacy concerns, or high data acquisition costs. To address this limitation, Sun *et al.*^[71] constructed a supervised system based on parallel theory to improve the estimation accuracy of vehicle CO₂ emissions. This system combines physical models with data-driven models, leveraging the robustness of the former when data are scarce and the high precision of the latter when data is abundant. Through two real-world case studies, it was verified that this system can effectively enhance the accuracy of emission estimates, and the physical model can maintain its robustness even when some parameters are unknown, serving as a complement to the data-driven model.

Table 4 summarizes representative studies that have employed time-series modeling approaches (e.g., LSTM, RNN, GRU) for vehicle-level emission estimation, highlighting their model structures, data sources, and input variables across three major dimensions: dynamic driving behavior, vehicle attributes, and environmental factors.

Macroscopic models

Macroscopic emission models estimate pollutant emissions using aggregate traffic parameters such as average speed, traffic density, and average delay rate^[29]. These models provide a generalized overview of the influence of traffic conditions on emissions, making them suitable for large-scale assessments and policy analysis.

Statistical regression models

At the road segment level, Grote *et al.*^[19] employed loop detector data to develop traffic emission prediction models. They analyzed the correlation between emissions derived from GPS data and traffic parameters captured by loop detectors. Their study compared the predictive performance of Multiple Linear Regression (MLR) and Multilayer Perceptron (MLP), achieving emission predictions for 24 types of vehicles.

At the intersection level, Song *et al.*^[77] proposed an emission model based on delay correction. This model associates emissions with traffic performance metrics such as average delay time and number of stops. By establishing baseline emission factors for different intersection types and adjusting them based on congestion severity, they developed a delay correction model capable of dynamically adjusting emissions. Comparative evaluations demonstrated the model's robustness and practical applicability.

Spatiotemporal models

Due to the spatial non-stationarity and temporal variability of vehicle emissions, spatiotemporal models have emerged to account for the topological structure of road networks and dynamic environmental factors. These models leverage techniques such as Geographically Weighted Regression (GWR), Graph Neural Networks (GNN), and GCN to model the complex spatial-temporal relationships in traffic emissions.

Liu *et al.*^[78] utilized large-scale vehicle trajectory datasets to estimate road-level CO₂ emissions and developed a Geographical Convolutional Neural Network Weighted Regression (GCNNWR) model. This hybrid model integrates convolutional neural networks to capture nonlinear spatial interactions and regression components to model emission intensity. Empirical evidence from Beijing demonstrated that the GCNNWR model significantly outperformed traditional spatial regression models in capturing spatial heterogeneity, providing valuable insights for urban emission mitigation strategies.

Table 4. Representative studies using time-series models for vehicle-level emission estimation

Reference	Model	Data source	Input variables		
			Dynamic driving behavior	Vehicle attribute	Environment
[72]	Wavelet transform, LSTM	Remote CO ₂ sensor, LPR data	Speed, acceleration	/	The wind speed and direction, the outdoor temperature, the relative humidity, the atmospheric pressure, hourly number of vehicles passing by the monitoring lanes, the average vehicle length
[73]	LSTM, RNN, GRU	Dynamometer test data	Speed	Engine family, engine manufacturer, engine model year, vehicle inertia, odometer reading, number of cylinders, fuel type	/
[74]	LSTM	GPS, PEMS, passenger data	Speed, acceleration	/	Grade and number of on-board passenger variables
[75]	LSTM	PEMS, GPS	Speed, acceleration, VSP	/	Road slope
[76]	RNN, LSTM	CO ₂ sensor, OBD	Speed, acceleration, engine RPM, fuel flow, throttle	/	Mileage

LPR: License plate recognition; PEMS: portable emissions measurement system; GPS: global positioning system; OBD: on-board diagnostics; LSTM: long short-term memory; RNN: recurrent neural networks; GRU: gated recurrent unit.

Table 5 summarizes several representative spatiotemporal emission models at the traffic level, highlighting their diverse data sources and input variables used to capture the complex spatiotemporal dynamics of traffic emissions.

Discussion

Data requirements

The data requirements for data-driven emission models are broadly comparable to those of classical emission models. However, unlike classical models that typically rely on predefined emission factor databases, data-driven approaches, particularly those employing machine learning and deep learning, require independent model training. This entails substantially higher demands in terms of both data volume and quality^[82]. Spatiotemporal models represent an emerging paradigm in traffic emission modeling, yet they have not been widely adopted in traffic management practice. One major barrier is their exceptionally high data requirements. For instance, models based on GNNs or GNNs require detailed Geographic Information System (GIS) data of the road network, high-resolution dynamic traffic flow information, and meteorological parameters for pollutant dispersion. These datasets are typically maintained by different government agencies or private entities, and they often vary significantly in format, coordinate systems, and temporal resolution. Beyond challenges in data acquisition, low data quality and the complexity of integrating heterogeneous data sources present substantial obstacles to the effective deployment of spatiotemporal emission models in real-world road networks.

Table 5. Representative spatiotemporal emission models at the traffic level

Reference	Model	Data source	Input variables
[79]	GCNNWR	GPS, OBD, road network	Driving behaviors (status, speed, speed variation), external factors (weather)
[80]	ST-GCN	Remote CO ₂ sensor, PEMS, speed sensor, road network, POI	Road network topology, traffic patterns, POIs, meteorological patterns
[81]	SAGE-GSAN	Street view image, road network, taxi GPS data	Street feature, graph structure, emission levels
[78]	GCNNWR	Trajectory data, POI data, road network	Number of POIs, road length

ST-GCN: Spatio-temporal graph convolutional network; SAGE-GSAN: graph sample and aggreGatE-graph spatial attention network; POI: point of interest; GCNNWR: geographical convolutional neural network weighted regression; GPS: global positioning system; OBD: on-board diagnostics; PEMS: portable emission measurement system.

Accuracy

The accuracy of data-driven emission models is influenced by multiple factors, including data quality, preprocessing methods, feature engineering, model architecture, algorithm adaptability, and training strategies such as hyperparameter optimization, making straightforward evaluation challenging^[83].

Complexity

In data-driven machine learning approaches, traditional models such as linear regression and decision trees offer high computational efficiency. Ensemble models (e.g., XGBoost and random forests), while requiring careful feature selection and overfitting control, still exhibit significantly lower computational demands than deep learning models. When applied to road network-level emission estimation, the strong spatiotemporal dependencies inherent in vehicular emissions substantially increase model complexity. External factors such as weather conditions, traffic patterns, and points of interest further compound this challenge. Due to the involvement of graph convolution operations and spatiotemporal attention mechanisms, these models have many parameters and require handling high-dimensional tensor operations during training, demanding significant GPU memory and computational resources. This is particularly challenging in large-scale road networks, where issues related to the storage and propagation efficiency of adjacency matrices may arise. For instance, spatiotemporal GNNs typically scale quadratically with sequence length and the number of links in the graph, hindering their application in large graphs and long time series^[84].

Transparency

When a linear relationship exists between model inputs and emission outputs, the model tends to exhibit higher transparency and interpretability^[77,85]. However, machine learning methods such as neural networks and deep learning are considered black-box models. Due to their complex internal structures and lack of explicit analytical formulations, these models offer limited insight into the decision-making process. When input data are noisy or uncertain, the opacity of such models may undermine confidence in the attribution of emissions, posing challenges for traffic managers and policymakers seeking transparent and explainable results.

Transferability

Regarding transferability, statistical regression-based emission models generally demonstrate strong transferability. When the feature distribution of the target dataset closely resembles that of the training dataset, these models can be directly transferred while maintaining high accuracy. Even in the presence of differences, quick adaptation can be achieved through local feature recalibration. However, for neural networks, the transferability of time series models is limited by vehicle type and driving behavior, while spatiotemporal models face restrictions related to road network topology, necessitating the re-encoding of

node attributes.

Overall evaluation

To facilitate a structured comparison, five representative data-driven emission models were evaluated across five dimensions: Data Requirements, Accuracy, Complexity, Transparency, and Transferability. The scores (1 = lowest, 5 = highest) are based on a synthesis of performance reports in the literature and prevailing expert understanding of model behavior in emission estimation contexts. While these values are not derived from uniform benchmarking experiments, they offer a qualitative overview of the trade-offs and design considerations associated with each modeling approach.

Figure 5 presents a radar chart summarizing the evaluation results of these data-driven models: Random Forest, LSTM, GCN, XGBoost, and a Hybrid Physics-Deep Learning approach. Among them, Random Forest and XGBoost demonstrate relatively strong performance in terms of Data Requirements, Complexity, and Transferability, highlighting their practical utility in diverse scenarios where data availability and model generalization are critical. LSTM and the Hybrid Physics-DL models achieve the highest scores in Accuracy, reflecting their ability to capture complex temporal dependencies and physical relationships in emission dynamics. However, these models tend to be more complex and less transparent, which may pose challenges in interpretability and computational demand. GCN, while offering moderate accuracy and transferability, scores lower on data requirements and complexity, possibly due to the need for structured graph data inputs and sophisticated model architectures. This qualitative assessment underscores inherent trade-offs in selecting data-driven emission models: simpler models with lower data demands and higher transparency may sacrifice some accuracy, while more complex models can better fit intricate emission patterns but at the cost of interpretability and data needs.

RELATED APPLICATIONS

High-resolution spatiotemporal emission inventories

Decision support for traffic management departments is derived from smart traffic systems that incorporate urban road traffic emission modules. The development of high-resolution emission inventories, featuring fine-grained spatial (e.g., 1×1 km) and temporal (e.g., hourly) resolutions, enables detailed accounting of both air pollutants and greenhouse gas emissions.

Current research typically achieves detailed emission calculations by integrating traditional emission models with trajectory data or traffic variable data. Studies have found that the spatiotemporal heterogeneity of emission inventories exhibits significant scale effects. At the spatial scale, emission hotspots show notable regional clustering characteristics; for instance, emissions from trucks are concentrated around railway stations. At the temporal scale, the emission intensity of freight vehicles on weekdays is higher than on weekends, and at the hourly scale, both passenger and freight vehicles demonstrate a bimodal characteristic. This confirms the necessity and feasibility of traffic operation management^[49].

To improve the accuracy of models based on average speed or traffic conditions, localizing emission factor databases is critical. Qiu et al.^[86] collected localized vehicle operating conditions in Shenzhen and matched them with typical conditions from the European HBEFA database, identifying 4,500 emission factors under various vehicle types, road conditions, and emission standards, thereby establishing a localized emission factor database for Shenzhen.

Beyond trajectory and traffic variable data, the incorporation of automatic license plate recognition (LPR) and vehicle registration data enables the construction of urban vehicle emission knowledge graphs. By

Comparative Evaluation of Traditional Emission Models

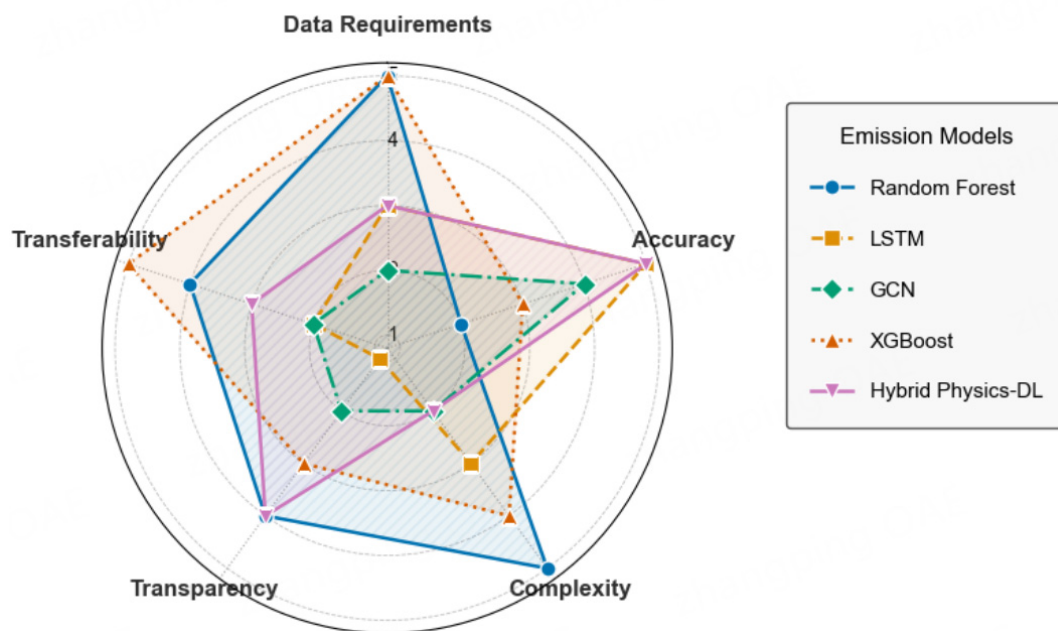


Figure 5. Radar chart evaluating data-driven emission models across five criteria. Higher scores (1-5) indicate more favorable performance for each respective attribute.

analyzing the characteristics of vehicle types, this approach can reveal regional traffic emission characteristics, indicating that a small subset of high-emission vehicles contributes disproportionately to total emissions^[87]. Furthermore, Wen *et al.*^[88] employed high-density traffic monitoring data and land use data to train a random forest model. Incorporating 272 traffic and land-use-related features, they developed a dynamic CO₂ emission inventory for the entire road network of Chengdu.

Analysis of factors associated with traffic emissions

Building upon the urban road traffic CO₂ emission inventory, further analysis can explore the correlation between emission hotspots and traffic-related factors. Although emission models themselves are products of correlation analysis, precise single-vehicle emission models can be used to investigate the relationships between traffic flow conditions and traffic infrastructure^[89,90]. For example, Sun *et al.*^[45] utilized Didi trajectory data combined with the COPERT model to calculate road traffic emissions in Shanghai, revealing the nonlinear relationship between carbon emission intensity and built environment features such as road classification and commercial land density. The study confirmed that optimizing urban spatial structure could indirectly reduce traffic emissions by 15%-20%. Peng *et al.*^[91] explored the spatial distribution patterns of CO₂ emissions from heavy-duty trucks (HDTs) in Xi'an during different time periods. They developed five XGBoost models using spatial data from various time windows and applied SHapley Additive exPlanations (SHAP) to interpret variable importance. The analysis identified spatiotemporal heterogeneity in key influencing factors, including road density, freight hub accessibility, point-of-interest (POI) density, and population characteristics.

Evaluation tools for emission reduction strategies

For traffic management, urban road traffic CO₂ emission models can evaluate the carbon reduction potential of emission reduction policies. By employing measures such as traffic demand management, traffic signal control, and travel mode guidance, these models can help alleviate traffic congestion and

subsequently reduce CO₂ emissions during urban road traffic operations^[24]. Traffic demand management can achieve coordinated control of network traffic flow through the dynamic coupling of traffic assignment models and emission models^[92]. In the field of signal control, due to the involvement of specific vehicle operating characteristics, micro-emission models are utilized, such as the HBEFA emission module built into Simulation of Urban MObility (SUMO)^[93] and the VSP bin classification^[64]. In addition, the integration of vehicle-road alignment technologies presents new opportunities for emission reduction. By enabling real-time communication between vehicles and infrastructure (e.g., traffic lights, roadside units), vehicle-road alignment can support eco-driving strategies, adaptive signal timing, and intelligent routing, thereby optimizing vehicle operation and minimizing idling and stop-and-go traffic, which are major contributors to excess emissions^[94,95]. In travel mode guidance, by calculating the CO₂ emissions of urban road traffic as a baseline scenario, the carbon reduction benefits of shared travel, slow traffic, and public transport policies can be assessed^[96,97].

Interdisciplinary extensions and policy

Beyond technical optimization within traffic systems, emission models are increasingly being applied in interdisciplinary domains such as smart city planning, carbon trading, and carbon neutrality policy evaluation. For instance, in the context of smart cities, real-time traffic emission models can be integrated into urban digital twin platforms to support dynamic traffic control and localized pollution mitigation strategies^[98]. Moreover, emission data can be aligned with carbon accounting frameworks to facilitate the design of urban carbon budgets and regional carbon quota allocation^[99]. In the realm of climate policy, model outputs serve as key inputs for assessing the effectiveness of low-carbon transport strategies and tracking progress toward carbon neutrality goals^[100,101]. Furthermore, emission models promote green consumption and advance carbon inclusiveness initiatives^[102] by providing transparent and accessible emission information that encourages sustainable travel behaviors and ensures equitable access to low-carbon benefits across diverse socioeconomic groups.

REQUIREMENT FOR FURTHER RESEARCH

Based on the development and application trends of different types of urban road traffic CO₂ emission models, future research can focus on the following aspects:

With advancements in real-time monitoring technologies such as on-board terminals, roadside IoT sensors, and satellite remote sensing, monitoring vehicle operating conditions has become feasible. Fine-tuned urban governance is expected to be a key development direction. Despite considerable research focused on real-time vehicle operation conditions to establish micro-emission models based on vehicle modalities, many models are limited to specific vehicle types and driving environments, making it challenging to accurately reflect the overall emissions from traffic flow. For instance, trajectory data often primarily include taxis, trucks, and buses, which may not fully capture the real emissions across the entire road network. Especially under complex urban conditions, how to leverage operational data from local vehicles, combined with fleet compositions and traffic flow characteristics, to assess the overall emissions level of traffic flow and construct a more accurate dynamic emission prediction system represents a key challenge to be addressed in future research. Advanced modeling approaches, such as Bayesian estimators or hierarchical LSTM-GNN architectures, could be explored to bridge the gap between individual-level inference and network-level aggregation.

Data-driven CO₂ spatiotemporal prediction models will be core tools for future urban traffic carbon emission research. By integrating multi-source data and mining spatiotemporal correlations, high-resolution and high-accuracy dynamic emission predictions can be achieved. Urban road traffic is a

dynamic, open, and complex system composed of various elements including people, vehicles, roads, and the environment, leading to multi-dimensional and multi-scale data characteristics. Therefore, advanced deep learning techniques, including spatiotemporal graph convolutional networks or adaptive graph recurrent units, hold promise for accurately modeling such nonlinear, time-varying relationships. Incorporating cross-attention mechanisms to dynamically fuse data sources of varying temporal granularity and quality could further enhance prediction robustness in real-world deployments.

Given the geographical differences in emission characteristics, localizing and personalizing models become crucial to meet the unique requirements of different regions and vehicle types. Hence, balancing personalized modeling (customized for specific cities or scenarios) with generalization (the ability to be applied across regions and scenarios) is key to enhancing the practical value of these models. Future research should aim to explore flexible architectures-such as modular backbones with city-specific adapters or domain adaptation techniques-that balance personalization with generalization. Defining quantifiable metrics to evaluate this trade-off, and developing continuous learning mechanisms for adaptive deployment, will be essential for enhancing the long-term utility and policy relevance of emission modeling systems.

CONCLUSION

In urban road traffic operations, key factors contributing to emission heterogeneity include traffic activity intensity, vehicle and fuel types, real-world operating conditions, and environmental influences. Both traditional emission factor models and emerging data-driven models explicitly or implicitly account for these factors in their formulations.

This review reveals the coexistence of classic emission models and modern data-driven approaches, each with distinct strengths and limitations. Traditional models typically estimate emissions via regression fitting or binning of vehicle operation parameters. While these models offer a transparent structure and strong interpretability, they often rely on manually defined parameters and lack adaptability to the variability of complex urban traffic conditions, which constrains their predictive performance.

Despite increasing research progress, urban traffic managers still face considerable challenges in leveraging emission models for actionable CO₂ mitigation. While commercial emission tools are available, trade-offs between model precision, generalizability, and computational cost remain unresolved. Moreover, the superiority of micro-scale emission models over macro-level approaches continues to be a topic of ongoing debate in both academia and practice.

DECLARATIONS

Authors' contributions

Responsible for overall research design, including structure and framework creation: Yu, C.

Provided research direction and specific guidance: Yang, X.

Conducted comprehensive literature collection and organization: Mu, J.

Performed proofreading and formal analysis: Liu, S.

Availability of data and materials

Not applicable.

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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