Response to Commentsfrom Community #1 – Dr. Manmeet Singh

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Title: High-resolution mapping of on-road vehicle emissions with real-time traffic datasets based on big data

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General Comments: The article "High-resolution mapping of on-road vehicle emissions with real-time traffic datasets based on big data" represents a significant advancement in urban emission inventorying by leveraging real-time data from traffic monitoring networks. This study, conducted in Jinan, China, presents a methodologically robust framework for capturing the spatiotemporal complexity of on-road emissions with unprecedented resolution. By integrating traffic camera networks with advanced big data methods, the authors developed a 50 m by 50 m, high-resolution map of emissions across pollutants, including NO_x, CO, HC, and $PM_{2.5}$.

The study is particularly innovative in its bottom-up approach, employing spatial interpolation methods to address the challenges p=osed by gaps between monitoring points. The use of Gaussian smoothing and nearest-neighbor interpolation effectively compensates for the spatial discontinuities typical in urban traffic networks. The authors also apply clustering techniques to analyze and interpret diurnal emission patterns, uncovering "hotspot" areas with temporal overlap during peak traffic periods. This attention to dynamic, real-world traffic flows yields an emissions inventory that is not only spatially continuous but also highly reflective of the real-world variability in urban emissions.

One of the key strengths of this paper lies in its interdisciplinary approach, combining atmospheric science, AI, and traffic monitoring technologies to generate actionable insights for urban policymakers. The authors demonstrate how time series clustering and hotspot analysis can aid in targeted interventions, such as the prioritization of NEV deployment in high-emission zones and timing traffic management measures to mitigate peak pollution periods. The scenarios for NEV penetration are also forward-thinking, modeling emissions reductions with increased adoption of electric vehicles (EVs) and revealing reductions of up to 80% in certain pollutants in high-penetration scenarios. Such modeling highlights the potential benefits of decarbonizing transportation sectors within heavily trafficked urban centers.

This work is a valuable addition to the field of atmospheric chemistry and urban environmental management, providing a replicable model for other cities aiming to control air pollution at a fine scale. Future research could further enhance this study by incorporating low-cost sensor data or machine-learning-based gap-filling to expand coverage and reduce dependency on fixed monitoring networks. The paper underscores the transformative potential of AI and big data in developing comprehensive, dynamically updated emissions inventories that support air quality improvements and health outcomes.

Response to General Comments: We sincerely thank Dr. Singh for the thoughtful evaluation and constructive feedback on our study. We appreciate the recognition of the methodological innovations and practical implications of integrating real-time traffic data with big data approaches for high-resolution emission mapping. The suggestions on enhancing interdisciplinary applications and future research directions have been carefully addressed in the revised manuscript to strengthen the scientific rigor and policy relevance.

Detailed point-by-point responses to all comments are provided below. The comments are in black, while our responses and changes in the manuscript are in blue and in blue italic, respectively.

Specific Comments:

Comment #1: The current reliance on fixed traffic cameras could be complemented by integrating data from mobile low-cost sensors on public vehicles (e.g., buses or taxis) and citizen monitoring devices. This would improve coverage, especially in areas with fewer monitoring points, and provide higher temporal resolution. High-resolution satellite imagery or drone footage could supplement ground-level data, helping to capture emissions near intersections, construction zones, or other areas prone to congestion where cameras may have limited views. Authors of https://arxiv.org/abs/2410.19773 have shown some success in this direction.

Response to Comment #1: We sincerely appreciate Dr. Singh's constructive suggestion to integrate mobile low-cost sensors and citizen monitoring devices to further enhance spatial coverage and temporal resolution. Our current study focuses on utilizing existing fixed traffic camera networks and spatial interpolation techniques (e.g., Gaussian smoothing and nearest-neighbor methods). We fully agree the potential advantages of emerging techniques such as high-resolution satellite imagery and drone footage (Ghosal et al., 2024). The proposed methods are promising extensions for capturing hyperlocal emission variability in future research and will be of great benefit to future improvements of this study.

In this work, high spatial resolution of 50 m × 50 m and high temporal resolution of 1 hour were achieved based on the traffic monitoring points in Jinan (supported by more than 3,000 cameras) and interpolation methods, which can basically meet the resolution requirements for street-scale emission mapping. This design effectively addressed spatial gaps between monitoring points while balancing computational feasibility. Nevertheless, we agree that mobile sensors or drone-based data could provide granular insights into localized hotspots (e.g., intersections or construction zones) and will prioritize these approaches in subsequent studies, contingent on data accessibility and collaboration with municipal stakeholders.

References:

Ghosal, S., Singh, M., Ghude, S., Kamath, H., SB, V., Wasekar, S., Mahajan, A., Dashtian, H., Yang, Z.-L., Young, M., and Niyogi, D.: Developing Gridded Emission Inventory from High-Resolution Satellite Object Detection for Improved Air Quality Forecasts, arXiv [preprint], arXiv: 2410.19773, 14 October 2024.

Comment #2: Traditional emission factors could be replaced or augmented by machine learning models that dynamically predict emissions based on vehicle type, traffic density, and weather conditions. This could improve accuracy, especially for rapidly changing urban traffic conditions. Adding localized, real-time meteorological data (e.g., wind speed, temperature) from additional sources such as local weather stations or remote sensors would improve the emission model by accounting for variations in atmospheric dispersion conditions.

Response to Comment #2: We sincerely thank Dr. Singh for highlighting the potential of machine learning (ML) models to enhance dynamic emission predictions. We fully agree that integrating ML-based emission factors (e.g., incorporating real-time traffic density, vehicle types, and hyperlocal weather conditions) is a good idea, as it could improve model adaptability to rapidly changing urban scenarios. However, we acknowledge that transitioning to ML-driven emission factors requires extensive training data (e.g., vehicle-specific telemetry, high-frequency meteorological measurements) and robust validation frameworks, which are currently beyond the scope of this work.

In the current study, we adopted conventional emission factors to align with the widely recognized methodologies in Technical Guide for Compilation of Atmospheric Pollutants Emission Inventory from Road Motor Vehicles (Trial) (MEE, 2014). This approach ensures comparability with prior studies and facilitates policy applications. In addition, with consideration of emission variations caused by local conditions, localized corrections (e.g., environmental correction and traffic condition correction) were applied in this study for adjusting emission factors.

To address this limitation, we have revised the Discussion section to explicitly propose ML-based emission factor optimization as a critical future direction. Specifically, we emphasize the need for collaborations with transportation agencies to access granular vehicle activity data. We added the following to the revised manuscript.

Lines 555-557: "*Machine learning (ML) can further enhance the framework by dynamically optimizing emission factors based on traffic patterns, vehicle types, and meteorological conditions, thereby achieving real-time traffic data processing and dynamic updates of vehicle emission inventory.*"

References:

MEE (Ministry of Ecology and Environment of the People's Republic of China): Technical guidelines for compiling atmospheric pollutant emission inventory of road motor vehicles (Trial), available at: https://www.mee.gov.cn/gkml/hbb/bgg/201501/W020150107594587831090.pdf (last access: 17 May 2024), 2014 (in Chinese).

Comment #3: Expanding vehicle classifications (e.g., electric, plug-in hybrid, fuel cell, diesel) would allow for finer distinctions in emissions and support more precise electrification scenarios. Integrating land use data (e.g., residential, industrial, commercial) could reveal patterns in emissions by area type, helping tailor policies for specific zones, such as low-emission zones near schools or hospitals.

Response to Comment #3: We sincerely thank Dr. Singh for the valuable suggestions to refine vehicle classifications and integrate land use data. These points are indeed critical for advancing electrification scenarios precision, and making spatially targeted recommendations.

While expanding vehicle categories (e.g., electric, plug-in hybrid, fuel cell) would enhance electrification scenario analysis, the current study is constrained by the fineness of available traffic monitoring data. In Jinan's traffic camera network, specific types of NEVs cannot be distinguished, due to technical and regulatory limitations in real-time identification of specific powertrain technologies. We acknowledged this as a limitation and had provided clarification and specific explanations in Section 2.5. NEVs are mainly classified into battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs). Except for PHEVs, which emit pollutants in hybrid mode, all other NEVs produce no pollutants during driving. As to PHEVs, they only account for a relatively small proportion within NEVs and they primarily operate in electric mode in short-distance driving. Therefore, conducting scenario simulation without fine classification of different types of NEVs will not result in a large error.

We fully agree that land use patterns can reveal emission hot spots tied to urban functions. We would like to clarify that the available land use data in Jinan categorizes areas primarily into broad classes (e.g., water bodies, vegetation, and built-up areas) due to limitations in publicly accessible geographic datasets. Nevertheless, a rough analysis based on city maps shows that emissions are generally lower in residential areas than in commercial areas, and that emission hot spots are concentrated in central commercial areas, while emission cold spots usually occur in residential areas, as detailed in Fig.9 and Lines 445-449.