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Advancing air pollution exposure assessment model: challenges and future perspectives

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Abstract

In recent years, air pollution exposure assessment models have experienced significant advancements, particularly in integrating advanced technologies. However, the intrinsic deficiency of the geostatistical model in existing studies restricted further development of the air pollution exposure model. In this perspective, we summarized several emerging technologies that can overcome the limitations and estimate air pollution exposures with high spatial and temporal resolutions. As these technologies evolve, they are expected to play an increasingly significant role in improving public health and managing environmental challenges.

Keywords: Air pollution, exposure model, advanced technologies

INTRODUCTION OF AIR POLLUTION EXPOSURE MODEL

Air pollution is a complex environmental issue influenced by various factors such as natural and anthropogenic sources, meteorology, and topography. Traditional air quality monitoring typically relies on fixed monitoring stations, as seen in studies like the Harvard Six Cities Study[1]. However, this approach has limitations[2,3]. First, the number of monitoring stations is limited, and populations residing far from these stations are excluded from the study. Second, populations near adjacent stations are assigned the same pollution concentration despite the highly uneven spatial distribution of air pollutants, with significant concentration differences even between points in close proximity[4]. Third, in specific contexts, the spatial differences within a city can be as substantial as those between different cities. Epidemiological research has shown that the disparities in particulate matter air pollution within cities often exceed those observed between cities[5].

As a result, exposure modeling has become a primary method for prediction in large-scale studies[6,7]. High spatiotemporal exposure models, through dynamic data collection and analysis, offer more detailed and accurate information on air pollution exposure[8]. These models can capture the temporal and spatial variations in pollutant concentrations, revealing their distribution characteristics under specific environmental conditions. This is crucial for understanding the health impacts of air pollution, as health outcomes are closely linked to the surrounding air quality. In epidemiological studies, estimating individual-level exposure to air pollution is essential for assessing the relationship between pollution and participants' health outcomes. This provides new perspectives for scientific research and supports the development of public policy and public health protection. Over the past two decades, significant progress has been made in air pollution exposure modeling, evolving from simple spatial interpolation methods (e.g., kriging, inverse distance weighing) and exposure indicator variables (e.g., traffic intensity at the residential address or distance to a major road) to statistical techniques like land use regression[9-11] and advancing to machine learning approaches that integrate multiple data sources[12]. These advancements have created high-resolution spatiotemporal models at different scales, laying a solid data foundation for air pollution epidemiology research.

LIMITATIONS OF CURRENT SPATIAL MODELS OF AIR POLLUTION EXPOSURE

In air pollution exposure assessment, spatial analysis is a critical tool that leverages geographic information systems (GIS) and spatial statistical techniques to study pollutant distributions and population exposure. However, this approach faces several limitations.

First, the accuracy of spatial data represents a fundamental challenge. Spatial analysis relies on high-quality geographic data to pinpoint pollution sources and affected populations[5], but in practice, data resolution - such as satellite image granularity and the uneven distribution of monitoring stations - often affects the practical application of the model[11].

Second, temporal scale limitations are evident. Air pollution is a dynamic phenomenon influenced by seasonal variations, climatic conditions, and human activities[13,14]. However, spatial analysis typically provides static "snapshots", making capturing temporal pollutant-level fluctuations difficult. This temporal mismatch can result in exposure assessments failing to reflect actual conditions, as they overlook variations in pollutant concentrations across different periods[11].

Third, the choice of spatial scale significantly impacts the analysis results. Different spatial scales can produce vastly different outcomes. At larger scales, local pollution hotspots may be overlooked, whereas, at finer scales, regional pollution trends may not be effectively captured. Thus, selecting an appropriate spatial scale is crucial for enhancing assessment accuracy[5].

Fourth, uncertainty is a critical issue. Incomplete data, measurement errors, and model assumptions contribute to uncertainty in assessment results[15]. Although advanced statistical models can address such uncertainties to some degree, they also increase model complexity and place higher demands on data quality.

Finally, individual activity patterns play an essential role in exposure assessment. Personal exposure levels are closely linked to the time spent at different locations, individual behaviors, and pollutant concentrations at those locations[16]. However, spatial analysis often fails to account for variations in individual activity patterns, such as differences between weekdays and weekends or exposure variations due to different modes of transportation[17]. This limitation primarily stems from the difficulty of collecting data on individual activities across time and space, as well as pollutant concentrations in microenvironments.

Based on these limitations, this study highlights current technological advancements in exposure monitoring techniques that offer potential directions for the development of air pollution exposure models.

DEVELOPMENT OF AIR POLLUTION EXPOSURE MONITORING TECHNIQUES

Personal monitoring based on wearable devices

In the context of rapid technological advancement, wearable devices have increasingly become an integral part of daily life, particularly in the fields of personal health and environmental monitoring. These devices enable users to access real-time health data, track physical activity, and monitor environmental air quality, thereby improving quality of life and driving innovation in health management. The application of wearable devices in health monitoring is extensive. Smartwatches and fitness trackers, such as the Huawei Watch, Apple Watch, and Fitbit, offer features like heart rate monitoring, sleep analysis, and step counting to help users manage their health[18-20]. Additionally, these devices can track running distance, duration, and calorie expenditure, assisting athletes in planning their training scientifically and reducing the risk of injury[21].

As public awareness of air quality grows, some wearable devices have started to integrate environmental monitoring functions, allowing users to track the levels of air pollution, such as $PM_{2.5}$ and carbon dioxide concentrations, in real time. This feature is precious for individuals living in highly polluted areas, as it provides timely alerts for preventive actions[22]. In addition, most people spend their time indoors, so their exposure is driven by the exposure in the home, office, school, *etc.* However, few models ever try to account for these drivers of exposure. The wearable devices would provide a good opportunity for model development.

However, wearable devices face data privacy and security challenges, as well as issues concerning their accuracy and reliability. Manufacturers need to enhance data protection measures, and users should exercise caution by consulting professional medical advice when using these devices.

Wearable devices have opened new avenues for personal health and environmental monitoring, contributing to smart and personalized health management. In the future, they are expected to play an even more significant role in addressing health and environmental challenges.

Human mobility

Applying population mobility big data in air pollution exposure assessment is increasingly becoming an important research direction in environmental science and public health[23]. This technology leverages data sources such as mobile devices[24-26] and location-based services[27,28] to track population activity patterns and locations in real time, providing precise information for assessing exposure to air pollution. By analyzing the movement trajectories of populations, researchers can gain insights into the amount of time individuals spend in different environments and the frequency of their activities, enabling the evaluation of how air quality in specific areas affects the population[29]. This approach is more flexible and efficient than traditional monitoring methods, offering timelier risk assessments.

Furthermore, by integrating meteorological data and air quality monitoring networks, mobility data can facilitate the development of more complex models to predict exposure levels under different temporal and spatial conditions. By optimizing urban planning, traffic management, and health education measures, it is possible to reduce population exposure in high-pollution areas.

In summary, population mobility data provide new perspectives and methodologies for air pollution exposure assessment, fostering more profound research into environmental and health issues. As data collection and analysis technologies continue to advance, the potential applications in this field will expand, offering significant support for improving public health and enhancing quality of life.

Low-cost sensors

Emerging low-cost sensors have the potential to significantly alter how, where, and when air pollution monitoring is done[30]. Low-cost sensing technologies offer benefits in enhancing the spatial resolution of air pollution measurements and supplementing regulatory data at a significantly lower cost[31,32]. The advantages of low-cost sensor technologies have opened up new avenues for air pollutant exposure modeling. When deployed in dense arrays, these low-cost sensors can deliver near real-time data on air pollutants with a spatial resolution that reflects neighborhood dynamics. They can reveal the impact of local pollution sources over various temporal and spatial dimensions often overlooked by the typically sparse regulatory monitoring systems[33-35]. Consequently, the increasing availability of data from these sensor networks has spurred research on integrating continuous measurements from low-cost sensors with land use information to produce comprehensive air quality data across space and time[36].

Mobile monitoring technologies

Vehicle-based mobile observation technology has made innovative progress in air pollution research in recent years[37,38]. Compared to fixed monitoring stations, this technology offers higher spatial coverage and flexibility, allowing for a more detailed capture of pollution variations across urban streets. By equipping vehicles with air quality monitoring devices, air pollution data can be collected in real time at different times and locations, including concentrations of harmful gases such as particulate matter, nitrogen oxides, and ozone, as well as some unregulated pollutants (ultrafine particles, black carbon, volatile organic compounds)[39,40]. Onboard monitoring provides real-time data and covers areas difficult for traditional monitoring stations to reach, such as street canyons, busy intersections, and commercial and residential districts. These high-resolution data offer new perspectives for understanding the complexity and dynamic changes in urban air quality[40,41].

When constructing air pollution exposure models, the data obtained from mobile observation technologies reveal the spatiotemporal distribution characteristics of pollutants, which is critical for accurately assessing population exposure levels. The high temporal resolution data collected by vehicle-based monitoring can highlight the sharp fluctuations in pollutant concentrations during peak traffic hours, helping researchers identify hotspots at specific times and locations. This information is crucial for developing targeted intervention measures and policies, effectively guiding resource allocation, and implementing pollution control strategies.

Artificial intelligenc and machine learning

Applying machine learning and artificial intelligence (AI) technologies has significantly enhanced the understanding and performance of air pollution exposure models[42]. These technologies help researchers and policymakers accurately assess the impact of air pollution on human health and ecosystems by processing and analyzing large volumes of environmental data. Machine learning algorithms can learn patterns from historical air quality data, identifying the sources and trends of pollutants. Machine learning models can construct complex air pollution prediction models using diverse data sources, such as meteorological data, traffic flow, industrial emissions, and satellite remote sensing.

More advanced AI techniques also show significant potential in exposure models[43,44]. These technologies can automatically extract features from unlabeled, complex data, helping to identify and classify pollution sources, thereby improving the accuracy of air pollution source apportionment. AI technologies can offer more precise pollution predictions and spatial distribution analyses by integrating various data sources, such as real-time sensor data, social media information, and traffic data.

CONCLUSION

The rapid advancement of cutting-edge monitoring technologies, coupled with the exponential growth of high-resolution environmental data, has revolutionized the field of air pollution exposure assessment. These developments have enabled unprecedented precision in characterizing ambient air pollutant exposure, offering transformative opportunities for public health research and policy interventions. However, the integration of traditional exposure models with emerging technologies remains a critical challenge, requiring innovative approaches to bridge the gap between conventional methodologies and modern data-driven paradigms. Future research must prioritize the development of sophisticated model fusion frameworks that effectively combine the strengths of mechanistic models with machine learning algorithms and AI capabilities. This integration should be complemented by advancements in big data processing, including edge computing for real-time analysis and federated learning for secure data sharing. Furthermore, the construction of next-generation exposure models should incorporate multi-omics data, personal exposure monitoring, and socio-economic factors to create a comprehensive exposure assessment ecosystem. Such advanced models will not only enhance our understanding of the complex interactions between air pollution and human health but also enable predictive capabilities for early warning systems and personalized exposure mitigation strategies. Ultimately, these technological advancements promise to support more informed decision making and evidence-based policy formulation, potentially leading to transformative changes in urban planning, transportation systems, and public health interventions to mitigate the global burden of air pollution.

DECLARATIONS

Authors' contributions

Conceptualization, methodology, investigation, writing - original draft, writing - review and editing, project administration, funding acquisition: Han, B.
Methodology, investigation, writing - original draft, writing - review and editing: Xu, J.
Conceptualization, methodology, investigation, writing - review and editing: Zhang, K.

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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