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Perspective

Considering human mobility is essential for accurate environmental exposure assessment

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Environmental exposure directly affects human health—air pollution contributes to respiratory diseases, water pollution causes digestive tract illnesses, and limited green space exposure impacts mental health. Assessing population-level environmental exposure is essential for promoting health and well-being (SDG 3), creating sustainable cities and communities (SDG 11), and reducing inequalities (SDG 10), ultimately providing data support for creating inclusive urban environments. Recent studies have revealed environmental exposure disparities, such as Wu et al.'s [1,2] findings on global green space exposure inequality across different cities and Jbaily et al.'s [3] discovery of air pollution exposure differences across racial and income groups. These studies, which predominantly rely on static residence-based data like census information, lack consideration of human mobility, potentially affecting the reliability of research conclusions [4,5]. This paper aims to: (1) critically examine the limitations of static residence-based exposure assessments; (2) synthesize emerging methods for mobility-based exposure assessment; (3) systematically classify the methodological evolution and its application scenarios in environmental exposure research; and (4) explore the potential applications of AI in advancing environmental exposure research.

Considering mobility in environmental exposure assessment. People's daily activities are inherently dynamic, often divided into approximately 8 h at home, 8 h at work, and the remaining time in various locations like parks, shopping centers, and commuting. Accurate assessment of personal environmental exposure requires a comprehensive consideration of exposure throughout the day (Fig. 1). Kwan [6] was among the first to identify the impact of human mobility on environmental exposure, summarizing it as the Neighborhood Effect Averaging Problem (NEAP), where daily activities may amplify or diminish residence-based exposure. She suggested that "for health outcomes that are also affected by exposures to environmental factors in people's nonresidential neighborhoods as they move around in their daily life (mobility-dependent exposures), using residence-based neighborhoods to estimate individual exposures to and the health impact of environmental factors will tend to misestimate the statistical significance and effect size of the neighborhood effect because it ignores the confounding effect of neighborhood effect averaging that arises from human daily mobility". Emerging methods, such as GPS tracking and real-time mobile sensing, were initially employed to examine this hypothesis, involving hundreds of participants to collect diverse environmental exposure data, including green/blue exposure, light exposure, air pollution exposure, and noise exposure (GLAN). The findings revealed that individual-level mobility-based environmental exposure tends toward average levels compared to residence-based exposure (including upward averaging and downward averaging). Although surveys offer detailed exposure records and precise participant attributes, they remain costly and limited in coverage [7,8].

Concurrently, spatiotemporal big data methods emerged, enabling the reconstruction of individual spatiotemporal trajectories using behavioral data from mobile phone signals, taxi trajectories, social media check-in records, and app positioning data [9]. The scalability of these methods facilitates their application across multiple cities or even nationwide, readily incorporating thousands of individuals and reconstructing their spatial mobility trajectories. However, these methods are not without limitations. For instance, Zhang et al.'s [10] street view image-based Green View Index (GVI) measurements and Wang et al.'s [9] Normalized Difference Vegetation Index (NDVI) measurements, while somewhat indicative of people's green exposure, exhibit lower temporal resolution compared to survey-based methods and face challenges in ensuring exposure consistency issues [11]. To address this issue, Testi et al. [4] proposed high-resolution spatiotemporal models for fine-grained air pollution mapping. However, their models primarily rely on static land use, with a dependence on unchanging landscape features that limits the model's ability to capture daily variations, presenting ongoing challenges for large-scale and long-time series coverage.

Development stages of environmental exposure research. Environmental exposure research has transitioned from static to dynamic approaches and from simplistic to complex methodologies (Fig. 2). Early research primarily relied on static assessment methods or comprehensive evaluations, which calculated exposure levels based on residential and workplace locations or entire areas. This approach directly utilizes census data, with simple calculation methods, low data acquisition costs, and stable data sources. However, it overlooks the spatial heterogeneity of population

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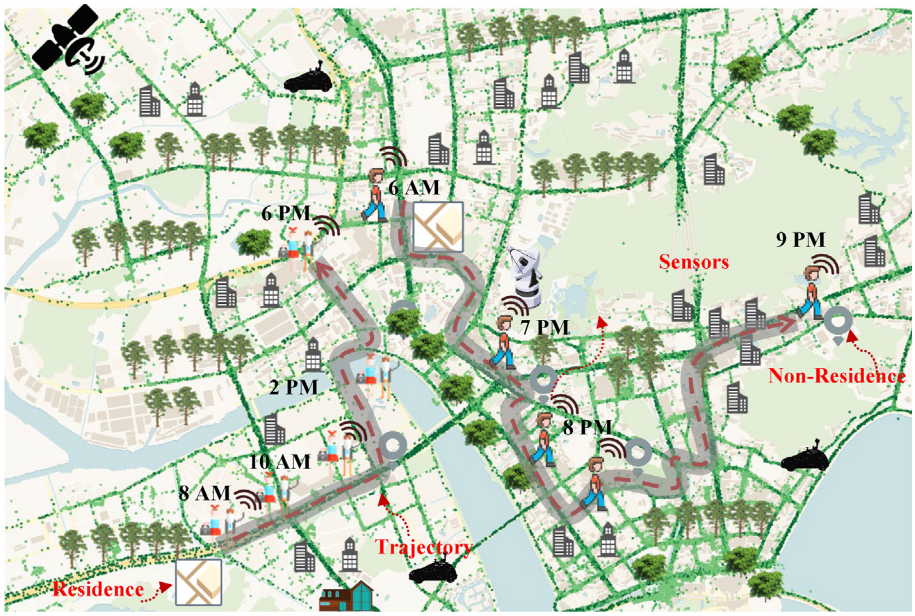

Fig. 1. The illustration of human mobility-based exposure assessment.

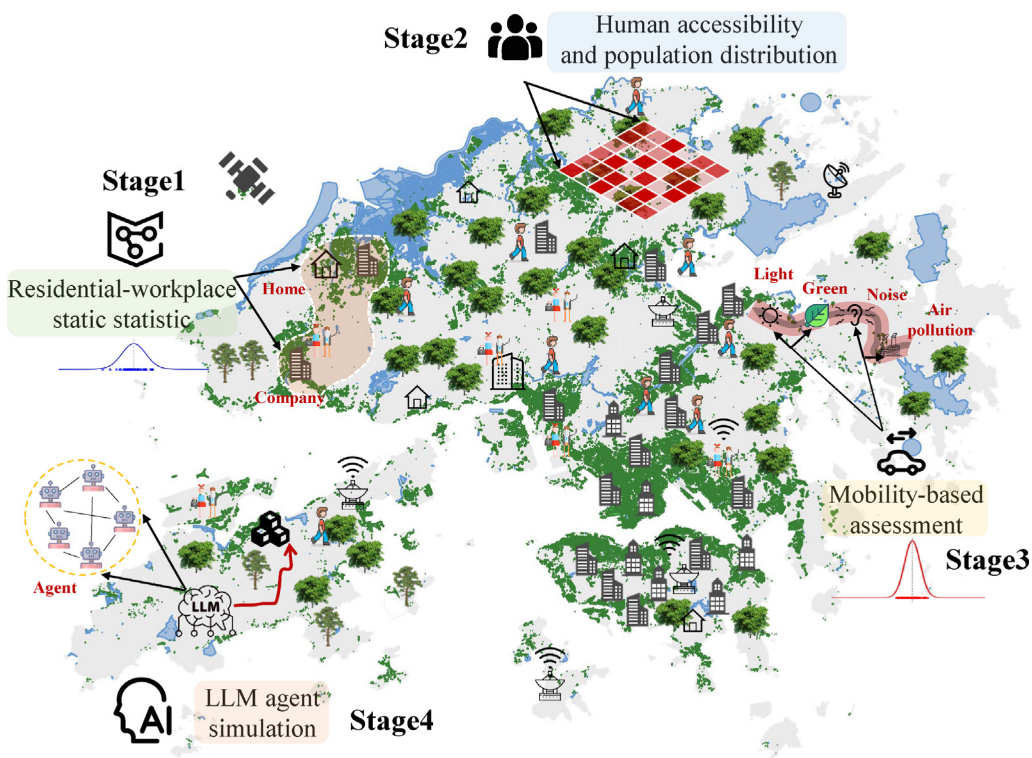

Fig. 2. The different stages of human environmental exposure research.

distribution and disregards differences in individual activity trajectories. It also has extremely low temporal resolution, making it unable to capture intra-day variations. This can lead to serious estimation biases for specific population groups (e.g., workers in high-exposure scenarios cannot be adequately assessed using only residential exposure data). The methods at this stage are more suitable for long-term trend analysis and large-scale planning, and policy evaluation research.

The second stage introduced human accessibility and spatial population-weighted distribution, better addressing varying exposure levels in built-up areas and high-density populations [12]. The methods in this stage can utilize population density data and integrate transportation data such as road networks, offering a closer approximation to residents' actual exposure conditions compared to static assessments. It has some relatively mature methodologies, such as the distance-based measures, gravitybased models, and the floating catchment area (FCA) methods. The drawback is that they remain essentially static assessment methods, unable to overcome the fundamental limitation of ignoring individual spatiotemporal mobility. This approach is suitable for studies requiring refined spatial differentiation but lacking mobility data, such as public resource allocation.

In the third stage, human mobility was integrated, and real-time mobile sensing along with spatiotemporal big data methods became mainstream. At this stage, the former technical approach (using GPS tracking, wearable sensors, etc.) provides extremely high spatial–temporal resolution (down to minute and meter levels). It enables the simultaneous collection of multiple environmental exposure data and accurately records individual environmental exposure variations (such as differences in exposure between indoor and outdoor environments and at different heights). However, sample sizes are typically constrained to hundreds of participants, potentially leading to population sample bias. Additionally, the high implementation costs make large-scale deployment challenging, while privacy concerns remain a significant barrier.

The latter approach, which leverages social sensing data such as mobile phone signals and taxi trajectories, has the most significant advantage in its large sample size, potentially covering tens of thousands of people, with relatively lower costs, and the capability to effectively reconstruct individual spatial mobility trajectories. However, environmental exposure measurements remain relatively indirect, as they often rely on satellite-based environmental data, which exhibits lower temporal resolution (typically hourly or daily). Furthermore, different environmental exposure factors involve trade-offs between spatiotemporal resolution, coverage area, and quality. Both approaches face ongoing challenges related to privacy protection and data anonymity [13].

Therefore, the first approach is more suitable for detailed case studies in health geography, observing the long-term health impacts on residents through precise exposure assessments. The second approach is more appropriate for large-scale population exposure assessments and comparative urban studies.

Artificial intelligence, particularly large language models, offers unprecedented opportunities and is highly likely to initiate the fourth stage of this field. The LLM-driven agent method could help us overcome the limitations of sample representativeness in complex urban systems, generating diverse individual trajectory data for different population groups while ensuring privacy protection. Simultaneously, large amounts of high-quality multi-modal exposure data can also enable comprehensive modeling of various exposure types. For instance, exposure intensity to factors such as light and noise can be inferred from social media images, building morphology, and spatiotemporal trajectories.

These AI-driven methods, often referred to as "AI for Science", have the potential to transform traditional research paradigms by generating large amounts of simulation data. Those data could address sample representation limitations and privacy issues, providing scenario analysis and decision support that balances scale and precision. For example, interactions between individuals can be simulated using various LLM agents, then to generate diverse, representative, yet anonymous human mobility trajectories. In detail, the generalization capabilities of LLMs and in-context learning can be utilized to simulate diverse virtual populations, with each agent exhibiting different behavioral patterns based on predefined socioeconomic characteristics [14]. Chain-of-thought reasoning can be employed to construct decision-making processes for these virtual populations, facilitating interactions between different roles, while generating daily activity trajectories aligned with their response to environmental feedback. Environmental exposure calculations can integrate multimodal technologies for environmental perception with large models' internet data retrieval capabilities to connect with external environmental databases (e.g., simulate the heat exposure). This ultimately simulates exposure patterns for different population groups, thereby assessing environmental risk disparities across diverse demographics.

However, these approaches remain in development, and face concerns including algorithmic bias (where AI systems produce unfair outcomes, such as facial recognition systems misidentifying light-skinned faces or healthcare algorithms allocating fewer resources to female patients); sampling bias (failure to adequately represent diverse population segments in training data); substantial computational resource requirements; and the critical need for validation against real-world data to ensure accuracy and reliability.

At present, second-stage technical methods can satisfy most research needs for policy and social inequality studies. Third-stage technical methods, benefiting from rich and detailed data records, are more suitable for research requiring individual information, such as environmental health impact studies. For research on future scenario predictions, fourth-stage technical methods can be prioritized and combined with historical data and model results from other stages, achieving a better balance between resolution and accuracy.

Future Prospects. In the context of climate change and urbanization, frequent extreme weather events make accurate urban environmental exposure assessment increasingly important. For example, analyzing different groups' activity patterns and exposure risks during heat waves can optimize urban cooling facility distribution [15] and provide more equitable blue-green space exposure [16]. Traditional research methods, which often overlook human mobility patterns, result in incomplete and potentially inaccurate exposure assessments. The differences between residence-based and mobility-based exposure raise critical concerns about the reliability of prior environmental exposure studies and their conclusions. We emphasize the significance of incorporating mobility-based environmental exposure and introduce the multi-method framework that integrates GPS tracking, mobile sensing, and spatiotemporal big data. The evolution from static to mobility-based assessment methods represents a significant methodological advancement. Further, emerging AI technologies, particularly generative models, can address current methodological limitations by simulating representative yet privacy-preserving mobility patterns for different population groups.

We recommend advancing mobility-based environmental exposure research by: (1) establishing standards that address the underrepresentation of elderly, rural, and low-income populations; (2) developing open platforms for sharing anonymized mobility-environment datasets; and (3) exploring AI applications while maintaining rigorous privacy standards. These efforts will ensure research findings can translate into actionable and equitable urban policies.

Conflict of interest

The authors declare that they have no conflict of interest.

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