A Multi-Domain Urban Informatics Framework for Ambient Air Pollution Population Exposure Inequality Assessment

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Abstract

It is evident that urban ambient air pollution has disproportionately negative effect on socioeconomically disadvantaged communities living in downgraded urban environment. However, the factors that must be systematically considered when assessing population exposure inequalities have not been thoroughly addressed from an urban informatics perspective. In this paper a theoretical framework is proposed with respect to identifying the necessary factors for assessing inequalities in exposure to urban air pollution by means of urban informatics methods. A five -domain factor classification for assessing population's exposure to ambient urban air pollution is proposed, with use of urban informatics approaches and context. The five-domain classification is organized in: i) the source of pollution and its dispersion characteristics, (ii) the dynamics of population exposure, (iii) socioeconomic and demographic vulnerability, (iv) urban morphology and urban landscape, and (v) data infrastructure and methodological factors. Each domain is thoroughly examined by taking into consideration its significance, constituent factors, data requirements, analytical methodologies and evaluation. The proposed framework provides a systematic reference for urban informatics system design, with particular emphasis on equitable sensor deployment and integration of cadastral, planning, and socioeconomic data into environmental monitoring.

1. Introduction

In the aftermath of the 1952 Great Smog of London (5-9 December), which was identified as one of the deadliest episodes of urban air pollution, resulting in the loss of 4,000 lives within the five-day duration of the episode and an estimated additional 12,000 fatalities due to the subsequent consequences (London Museum, n.d.), ambient air pollution was put in the spotlight as a major environmental health hazard in the urban environment. Two years later the City of London Corporation enacted legislation on banning the production of smog in the Square Mile (City of London, 2024), leading to the 1956 Clean Air Act, the first official legislation, global scale, to establish measures with the aim of reducing ambient (outdoor) air pollution in urban areas ("Clean Air Act 1956," 1956). According to WHO ambient air pollution as caused 4.2 million premature deaths worldwide in 2019, with the 89% of those deaths are of people living in low- and middle-income countries (WHO, 2024).

Still urban areas and agglomerations are characterized for spatially dense concentration of air pollution sources and affected and exposed populations, whereas there is disproportionate exposure level and pattern on low income countries and cities rather in high income (Hajat et al., 2015; Jerrett and Finkelstein, 2005; Kenworthy and Laube, 2001). This disproportionate exposure is observed in city level where population living in deprived and downgraded communities is more exposed to ambient air pollution (Fairburn et al., 2019; Perperidou, 2010; Pratt et al., 2015). But still the systematic assessment of such inequalities examination is continuously subjected to changing conditions on that determine who is exposed, the extent of exposure, and the conditions under which exposure occurs.

Urban informatics are directly connected to the study of people, places, and technology in urban environments through data-driven approaches (Foth, 2018; Foth et al., 2011). As urban issues are both simple and complex and over the years expanded occurring in an extremely complex urban environment (Batty, 2016, 2013) the acquisition, integration and analysis of heterogenous urban data so as to produce new knowledge on the system "city" (Shi et al., 2022) can give new prospect on how exposure to air pollution and its relation to social and economic factors can be studied and assessed. Smart cities platforms also incorporate environmental monitoring enhancing the production of data for the support of environmental equity assessment (Batty, 2018). The recent advances in air pollution monitoring and modeling (Garcia et al., 2025; Kumari et al., 2025) provide more tools for the study and analysis of the air quality – air pollution evaluation and evolution even in street level, facilitating its correlation to social and economic conditions of urban communities, the urban landscape and the urban form.

However, a fundamental question remains: which factors should be taken into consideration, systematically and thoroughly, so as to produce valid assessments of pollution exposure inequality still remains, especially from a theoretical and methodological point of view. Studies tend to adopt ad hoc variable selection based on their availability or the problem under study (Burnett et al., 2018; Domínguez et al., 2024; Su et al., 2024; Yang et al., 2024). This methodological inconsistency, on what factors or parameters are taken into account when examining exposure to ambient air pollution is crucial and by omitting relevant factors may lead to biased estimates, while failing to point out interactions between physical, social, and data-related dimensions risks the formulation of misleading policy recommendations. At the same time, the spatial documentation of urban plans, land use regulations and property rights restrictions that shape the urban space and determine the proximity of population to air pollution sources is underrated and under-documented in cadastral and planning processes (Perperidou and Xydopoulos, 2021), revealing one more aspect of the complexity of the data-driven exposure assessment. And

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by taking under consideration weather and wind conditions in respect to the urban landscape the complexity of the exposure assessment is becoming more complicated.

This paper aims to address the gap deriving from the ad hoc approaches on population exposure assessment to ambient air pollution by introducing a comprehensive theoretical framework that identifies, classifies, and critically examines the factors necessary for assessing inequalities in exposure to ambient air pollution via an urban informatics lens. The decision to present in this paper a methodological framework is due to the complexity of the five-domain classification — spanning pollution science, mobility analysis, socioeconomic assessment, urban morphology, and data infrastructure — makes it essential to first establish a coherent conceptual architecture against which individual empirical studies can position their variable selections and methodological choices. Without such a framework, empirical studies risk perpetuating the ad hoc variable selection that this paper identifies as a fundamental limitation of current practice.

2. Theoretical Foundations

The environmental justice movement established the foundations for the analysis of the unequal distribution of environmental hazards across population groups (Bullard, 2000; Mohai et al., 2009). The distribution focuses on spatial correlations between environmental burdens and social disadvantage. Studies have documented socio-spatial aspects in air pollution exposure, with deprived urban areas and communities to indicate higher outdoor air pollutants levels and especially for the more hazardous like $PM_{2.5}$ (Fecht et al., 2015; Fischer et al., 2020). The estimation is based upon the accuracy and reliability of socio-economic-demographic data and compatible spatial level for analysis, forming a rigorous framework for urban informatics. Residential proximity to ambient air pollution sources is an imperfect factor for actual exposure due the spatiotemporal diversifications of residents' systematic activities-travel patterns (Perperidou, 2010), thus framework on exposure inequality assessment must take these patterns into consideration.

The relationship between ambient air pollution sources and population exposure is also affected by urban landscape and built-up urban environment morphology as in the complex urban environment the street canyon effects the efficiency of street corridor and the heat island effect determine the distribution and the concentrations of air pollutants thus population's exposure. In low-income neighborhoods – communities that usually are characterized by higher buildings and population densities, narrow streets and road network generally and small percentage of green space (in comparison to the area that cover), higher air pollutants concentrations are recorded further affecting more population's exposure to pollution. The intensive and dense vertical development can also lead to higher exposure rates, especially in densely populated urban areas that have narrow road network.

Within smart cities framework, urban informatics that is an interdisciplinary approach that integrates systematic theories and information technologies to understand, manage, and design cities (Foth et al., 2011; Shi et al., 2022, 2021), inequalities of population exposure to ambient air pollution can be thoroughly studied and analyzed, but there is a need to reprioritize the networks, e.g. of sensors, that collect many types of data so as to produce accurate and credible data on downgraded urban areas and marginalized communities. The human as a sensor, via social networks and applications, should also be enhanced, but within the rigorous legal framework that protection of personal data provides.

3. Five-Domain Factor Classification

Building upon the above theoretical foundations, we propose as five-domain factors classification for the estimation of population's exposure to ambient air pollution that are necessary for assessing exposure to ambient air pollution inequalities.

3.1 Domain I: Pollution Source and Dispersion Characteristics

Urban pollution is multi-source: road traffic, industrial facilities, domestic heating, and transboundary background pollution contribute differently across cities (Targa et al., 2025). Near street level concentrations are increased due to road traffic gasoline / diesel vehicles that are movable pollution sources and the street canyon effect, along with the overall urban morphology and landscape (Aarnio et al., 2005; Krzyzanowski et al., 2005). Spatiotemporal variability in hourly, daily, monthly, seasonal and episodic period is crucial especially for the estimation of the correlation of pollution peaks and population activity-travel patterns, thus exposure to ambient air pollution. For example in Mediterranean cities with high levels of sunshine, exposure to O_3, a secondary air pollutant that is formulated by primary air pollutants and sunlight, has significantly diversified distribution patterns within 24 hours period depending also on the season (Perperidou, 2010).

3.2 Domain II: Population Exposure Dynamics

Usually, population exposure models take into account air pollutants concentrations in residential areas, but as the urban space is complex and various human activities take place in different, than the residence, spatial location that are correlated to daily mobility patterns and are diversified air quality zones. The uncertainty in exposure patterns due to spatiotemporal diversifications of mobility patterns can often lead to misclassifications and misinterpretations of results (Kwan, 2009; Park and Kwan, 2017). Activity – based models that integrate activity spatial locations corelated to spatially-related travel patterns temporally evolved, and systematically repeated, provide more accurate estimation to exposure to ambient air pollution (Perperidou, 2010; Setton et al., 2011), while the use of GPS data for calculation of exposure to air pollutants but only during travels provide also more accurate exposure but concerns over the use of private data (GPS) are also raised (Dewulf et al., 2016). Considerations over the diversifications of microenvironments further complicate the assessment: indoor-outdoor pollutants concentrations vary according to buildings characteristics, while socioeconomic factors of housing qualities could lead to higher exposure patterns. Transport mode also affects exposure patterns as is demonstrated by WHO or EU initiatives (Aarnio et al., 2005; Fairburn et al., 2019).

3.3 Domain III: Socioeconomic and Demographic Vulnerability

Low-income and deprived communities are more exposed because their choices on quality housing and residential areas selection are limited (Hajat et al., 2015), and usually are obliged to live in downgraded areas usually close to industrial areas, or urban downgraded areas, usually central, that face heavy traffic conditions. This also stands for immigrants' communities that

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also seek housing in areas were rents are low, that also located near industrial areas, or urban downgraded areas, usually central, that face heavy traffic conditions or close to urban high ways. Distribution of population among age groups is also important as children and elder people are more vulnerable when it comes to exposure to air pollution (WHO, 2024, 2018). The role of spatial planning is crucial as spatial planning frameworks and their historical evolution over time determine current land uses, that are also results of social and economic pressures, leading disadvantage populations into specific urban zones.

3.4 Domain IV: Urban Morphology and Urban Landscape

Urban morphology and urban landscape play an important role between air pollutant sources, spatial distribution of air pollutants and population exposure. The street canyon increases air pollutants trapping, especially in roads with tall buildings (the taller the building the phenomenon gets more intense). Green and bleu infrastructures improve ambient air quality as plants are known for filtering air and removing dust and PM pollutants form the air, while improving the microclimate and stabilising the temperature, but its distribution throughout the urban space is unequal, with low-income urban residential areas to have lack in green areas, thus lack of greenery is directly connected to degradation. Building codes affect the three-dimensional development of urban structures, and the constructions of heating and ventilation systems (Perperidou and Xydopoulos, 2021), creating spatially complex ambient air pollutants distribution patterns, The restrictions imposed by building codes on height development determine the distribution patterns of air pollutants as they influence the street canyon geometry. Zoning legal framework also affects land use distribution, within the urban landscape, determining residential-commercial zones and industrial zones, thus air pollutants production.

3.5 Domain V: Data Infrastructure and Methodological Factors

A main aspect of this framework is the data infrastructure its self. For example, the disproportionate deployment of air pollution stations and, more recently, sensors in central or affluent areas enhances "data inequalities", mirroring environmental inequality (Gabrys, 2016). Low-cost sensors address the issue of infrastructure deployment thus addresses inequality on data acquisition, but certain challenges must be met with most important that for data accuracy, which varies according to conditions (Castell et al., 2017). The Modifiable Areal Unit Problem (MAUP) is predominant on how spatial scale choices lead to inequality conclusions (Openshaw, 1983). Inconsistencies between cadastral parcels, urban and spatial plans, urban morphology and landscape, poses difficulties into integrating and correlating population distribution and land use classification either with cadastral data or with the overall urban form and morphology, that derived from the framework on urban and spatial planning, while land use classification and population distribution modelling may contain systematic errors that propagate into exposure estimates. Concerns over protection of personal data, the link between individual – level health data with location – specific exposure to air pollution, and decoupling from political priorities and technological advancements, are considerations on how a system could be build having access to personalized data and at the same time preserving the protection of those personal data.

Table 1 summarises the constituent factors and key data requirements for each structural domain, providing a consolidated reference for the five-domain factor classification. This summary shows that the proposed framework is self-contained and systematically specifies the necessary variables – data across all five domains, rather than making ad hoc selections in respect to data availability in local level. As such, the Five Domain Classification for population exposure to ambient air pollution determination is transferable, ready to be adopted to geographically and socio-economically contexts and environments.

Domain	Constituent Factors	Key Data
I. Pollution Source & Dispersion Characteristics	Source typology (traffic, industry, domestic) Emission intensity & temporal profiles Atmospheric dispersion & chemistry Near-road spatial gradients	Emission inventories, met. records Dispersion model outputs / dense sensor data Weather conditions / sunshine
II. Population Exposure Dynamics	Residential vs. activity-based exposure Micro-environmental exposure (indoor/outdoor) Commuting mode & transport exposure/outdoor activity exposure Temporal profiles (daily, weekly, monthly, seasonal)	Census locations, mobile phone traces (transport- activity) Time-use surveys, O-D surveys, transit card records
III. Socioeconomic & Demographic Vulnerability	Income & material deprivation Racial/ethnic composition & migration status Age structure & biological susceptibility Health literacy & adaptive capacity	Census / administrative records Population registers, demographic statistics Educational attainment data Urban planning / cadastral data
IV. Urban Morphology and Urban Landscape	Building density & 3-D geometry Green & blue infrastructure (NDVI, parks) Land-use mix & zoning patterns Ventilation corridors & sky-view factor	3-D city models, LiDAR, building footprints Satellite NDVI, urban green audits LULC classification, cadastral / zoning maps
V. Data Infrastructure and Methodological Factors	Sensor network density & coverage equity Data quality, calibration & uncertainty Spatial scale & MAUP sensitivity Interoperability, open data, ethics / privacy	Sensor metadata & deployment maps Calibration protocols, co-location data Multi-scale analytical frameworks API standards, anonymization protocols Spatial unit analysis determination/ data calibration

Table 1. Five Domain Classification for population exposure to ambient air pollution estimation, Constituent Factors and Key Data.

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4. Cross-Domain Interactions

The interaction between the domains is complex and multy-level. Urban Morphology (Domain IV) plays and crucial role on how air pollutants are distributed across the urban landscape, thus identical emissions levels (Domain I) are producing different exposure patterns, whilst exposure to secondary pollutants affects areas far from the original emission source. Socioeconomical constraints (Domain III) put lower income populations in urban areas with higher ambient air pollutants levels and worse dispersion conditions, that combined to poor living conditions creates a triple disadvantage: poor socioeconomic level, poor living conditions, greater exposure to ambient air pollutants.

At the same time, daily mobility and activity patterns (Domain II) may lead to greater exposure to pollutants, thus reversing the exposure patterns and linking them directly not only to the location of the residence but also to the location of the work or other activities. In parallel, areas with sparse monitoring coverage (Domain V) have less precise estimations on the ambient air pollutants emission and concentration levels and dispersion patterns, and could render pollution burdens in downgraded communities statistically invisible.

Those interactions highlight the need for multivariate, spatially explicit and multiscale analytical approaches, Figure 1.

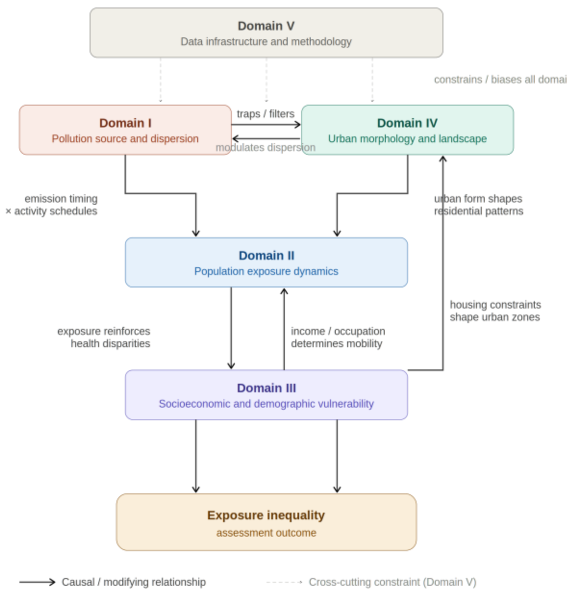

Figure 1. Five Domains interactions

In Table 2 the analytical methods for the implementation of each Domain are listed and valuated for their strengths and limitations.

Domain	Analytical Methods	Evaluation [+] / [-]
I. Pollution Source & Dispersion Characteristics	Land use, Dispersion modelling, Kriging / geostatistics	[+] Captures gradients, Mechanistic basis [-] Data-hungry, Model assumptions
II. Population Exposure Dynamics	Activity-space analysis, Questionnaires Agent-based modelling, GPS/mobile tracking	[+] Realistic profiles, Individual-level [-] Privacy concerns, Selection bias
III. Socioeconomic & Demographic Vulnerability	Composite indices (PCA), Spatial clustering (LISA), Intersectionality analysis	[+] Multi-dimensional, Policy-relevant [-] Ecological fallacy, Weighting subjectivity
IV. Urban Morphology and Urban Landscape	3D morphometrics (SVF, H/W), Simulation, NDVI / green space analysis	[+] Mechanistic power, Fine resolution [-] 3D data availability, Simulation cost
V. Data Infrastructure and Methodological Factors	Coverage equity audits, Uncertainty propagation, Multi-scale MAUP checks	[+] Meta-analytical rigour, Transparency [-] Added complexity, Ground truth needed

Table 2. Five-Domain Classification for population exposure to ambient air pollution estimation analytical methods and evaluation

5. Discussion

The Five Domain Classification for population exposure to ambient air pollution estimation is advancing beyond current approaches, which address this multi-functional problem with sectoral approaches. First, it highlights the importance of urban morphology as a structural component of the whole process and not just another variable, correlating urban's space physical form to both pollutants distribution mechanisms and socioeconomic stratification. The three-dimensional aspect, and properties, of urban environments, including building height restrictions, ventilation system emissions, and vertical development patterns, are essential components of this factor that traditional two-dimensional analysis tend to overlook.

Second, it treats data (and data acquisition) infrastructures as an active factor in inequality assessment. It engages cadastral and urban and spatial planning data as essential components to the exposure estimation process. It also introduces that inconsistences in fundamental spatial datasets, e.g. cadastral, urban- spatial can introduce systematic biases into pollution exposure estimates.

Third, the incorporation of systematic activities correlated to systematic travels and systematic outdoor activities into the exposure dynamics, the framework enhances recent literature, which shows that by taking into consideration only residential location for determining exposure patterns is insufficient and can lead to under or over estimations.

In the case of smart cities, the framework provides for equity as an explicit objective during the design of environmental monitoring systems and especially systems for ambient air pollution monitoring. Adjusting stations and sensors deployment so as to achieve equity in spatial coverage, incorporating vulnerability layers into smart cities dashboards and ensuring that population data are correlated to exposure conditions. Incorporating spatial data like cadastral, urban planning and regulations enhances the construction of a rigorous geospatial framework so as to build up an equity-oriented urban informatics system.

But there are also limitations that must be taken under consideration. The framework its self cannot be fully operational by a single study throughout the five Domains. The interaction between the Domains is in theoretical level and empirical tests and estimations are required. As the framework is primarily developed in the context of European cities and context, its applicability to under development countries and the Global South requires further work, especial in datasets acquisition and legislation sectors.

Ethical issues on personal data acquisition and use and overall privacy arise while decoupling structural inequality form political decisions and actions by intense use of technology cannot be solved theoretically. The use of socioeconomic and environmental data into politics give rise to questions on surveillance data ownership and the level on consent communities and individuals have. Furthermore, algorithms cannot solve real world problems on inequality, whilst in some cases might be the fundamental reason behind inequality aspects. Those concerns require continuous collaboration between researchers, communities and policy – makers.

6. Conclusion

In this paper a rigorous theoretical farmwork on identifying the necessary factors for using urban informatics to assess inequalities in exposure to urban ambient air pollution is presented. Unlike existing approaches that tend to select variables on an ad hoc basis depending on local data availability, the proposed framework provides a structured, transferable classification that integrates: (i) pollution source and dispersion characteristics, (ii) population exposure dynamics, (iii) socioeconomic and demographic vulnerability, (iv) urban morphology and urban landscape, and (v) data infrastructure and methodological factors.
The framework advances current practice in three specific aspects. First, it treats urban morphology as a structural mediator linking pollutant dispersion mechanisms to socioeconomic stratification, rather than as an isolated control variable. The three-dimensional properties of urban environments — including building height restrictions, ventilation system emissions, and vertical development patterns — are incorporated as essential components that traditional two-dimensional analyses tend to overlook. Second, it identifies data infrastructure equity as an independent domain, recognising that the disproportionate deployment of monitoring stations and sensors in central or affluent areas can itself reproduce environmental inequality by rendering pollution burdens in disadvantaged communities statistically invisible. Third, it incorporates systematic activity-travel patterns into exposure dynamics reinforcing the growing evidence that residential location alone is an insufficient element for actual exposure.
For each domain, the framework specifies the constituent factors, key data requirements, analytical methodologies, and evaluation criteria (Tables 1 and 2), and the inter-domain interactions are formalized in a directed influence diagram (Figure 1). The resulting classification is designed to be transferable across geographically and socioeconomically diverse urban contexts.
Three priorities for future research are identified. First, empirical validation through comparative case studies in European cities as first step. Second, the development of a modular urban informatics prototype implementing the five-domain architecture within a smart city dashboard. Third, quantitative modelling of cross-domain interactions — particularly the propagation of data-infrastructure biases (Domain V) into exposure inequality estimates — would strengthen the framework's analytical foundations and provide guidance on which domain investments yield the greatest improvements in assessment accuracy.

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