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Spatio-temporal Resolution and Aggregation Effects in Urban Air Quality Assessment: A Review of Recent Trends (2015–2025)

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***Abstract* - Urban air quality measurement and analysis have evolved significantly over past decade with extensive use of monitoring sensor networks and data analytic methods. An important yet under-utilized dimension in these methodologies is the influence of temporal and spatial resolution of air quality data aggregation strategies specifically its interpretation, accuracy and policy relevance. This systematic review synthesizes peer-reviewed literature published between 2015 and 2025 to examine how temporal granularity—from sub-hourly sensor observations to annual averages—and aggregation approaches affect urban air quality analysis outcomes.**

Relevant studies were identified across various major scientific databases and categorized according to monitoring modality, pollutant type, temporal scale, and analytical application. The review reveals that fine temporal resolution datasets enhance the detection of short-term pollution episodes, traffic-driven variability, and diurnal emission signatures, thereby improving predictive modelling and real-time decision support. Conversely, aggregated datasets provide stability for long-term trend analysis, epidemiological inference, and regulatory reporting but may obscure peak exposures and intra-day variability. Emerging hybrid approaches combining multi-scale temporal integration and sensor fusion demonstrate potential to reconcile these trade-offs, enabling more robust urban exposure characterization.

The synthesis further highlights methodological inconsistencies in temporal aggregation practices, limited reporting of uncertainty propagation, and gaps in standardized evaluation metrics across studies. These findings underscore the necessity for harmonized temporal data frameworks and context-aware aggregation strategies tailored to specific urban air quality objectives. By consolidating current evidence, this review contributes a structured understanding of temporal scale effects in air quality science and outlines research directions for multi-resolution analytics, integrated monitoring architectures, and policy-aligned assessment methodologies. The outcomes are expected to support researchers, practitioners, and urban planners in designing temporally informed air quality monitoring and analysis systems.

Keywords - Air Quality Index; Urban Air Quality; temporal aggregation; spatio-temporal aggregation; exposure characterization; air pollution monitoring; Ahmedabad

I. INTRODUCTION

Air pollution has emerged as one of the most pressing environmental and public health challenges in rapidly urbanizing regions worldwide. Increasing industrialization, vehicular emissions, construction activities, and energy consumption have significantly deteriorated urban air quality, particularly in developing countries [1]. To communicate air pollution levels to the public in a simplified manner, regulatory agencies across the world have adopted the Air Quality Index (AQI) as a standardized indicator that integrates multiple pollutant concentrations into a single interpretable metric [2]. AQI reporting enables governments, researchers, and citizens to monitor pollution trends, assess health risks, and formulate mitigation strategies [3]. For example, in Ahmedabad city in Gujarat India, similar AQI framework advisory is present as shown in Fig. 1 [4].

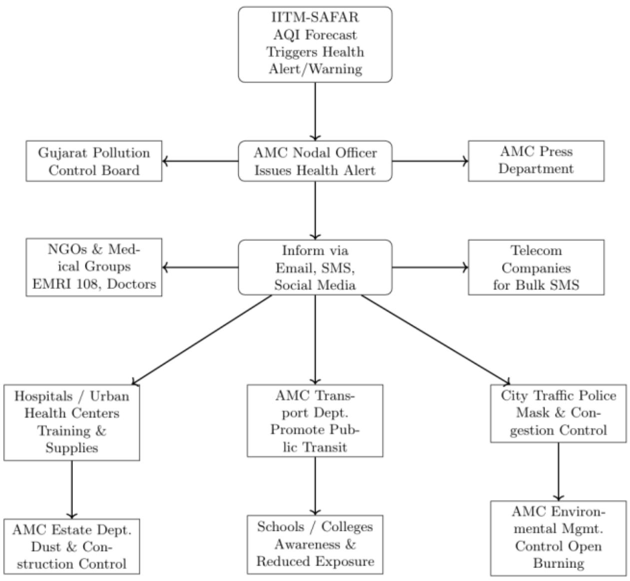

Fig. 1 - AQI Advisory Framework - Ahmedabad

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With advancements in sensing technologies and the proliferation of low-cost monitoring devices, urban environments are now witnessing the deployment of dense air quality sensor networks capable of capturing pollutant concentrations at high temporal resolutions [5], [6]. These developments have transformed traditional air quality monitoring frameworks that previously relied primarily on sparse regulatory stations providing hourly or daily averaged data [7]. High-frequency monitoring systems offer unprecedented opportunities to understand micro-temporal variations in pollutant concentrations, identify short-duration pollution events, and examine localized exposure dynamics within cities [8].

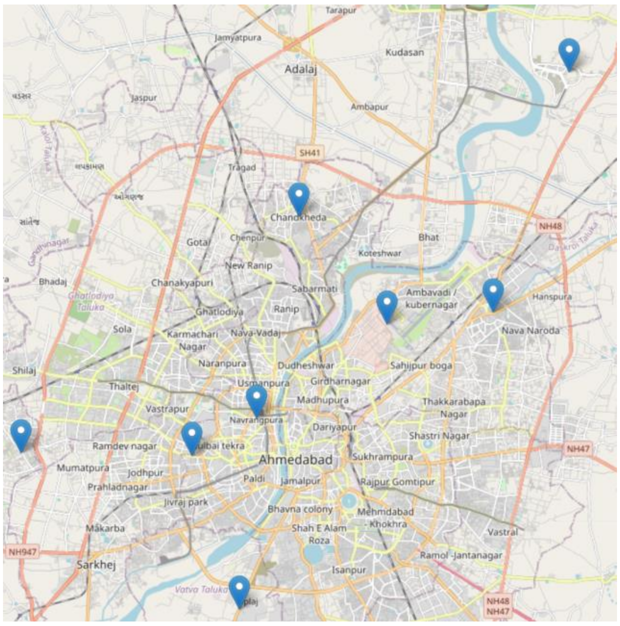

Fig. 2 - AQI Monitoring Stations – Ahmedabad

TABLE 1 - TEN AIR QUALITY MONITORING STATIONS BASED IN AHMEDABAD REGION

Sr. No.	AQMS Location	Institute/Organization	Latitude	Longitude
01.	Navrangpura	Sardar Patel Stadium-Navrangpura	23.06038	72.5737
02.	Pirana	AMC nursery, Gyaspur Forestry Plantation	22.9967	72.5535
03.	Rakhiyal	Shraminkranti Garden, Near Chakudia mahadev mandir	23.032778	72.6476
04.	Raikhad	Victoria Garden	23.021	72.5983
05.	Chandkheda	Kali cultural centre	23.12088	72.58188
06.	Bopal	SAC, ISRO	23.04105	72.4789
07.	Sattelite	SAC, ISRO	23.02761	72.5292
08.	Airport	IMD Ahmedabad	23.08238	72.629444
09.	Lekhwada	IIPHG, Gandhinagar	23.25005	72.7105
10.	GIFT City	GIFT City, Gandhinagar	23.17594	72.67816

Despite the availability of such granular data, most AQI reporting and research analyses continue to rely on aggregated temporal scales, typically hourly or daily averages. While aggregation facilitates data management and standardization, it may also mask transient pollution spikes, attenuate peak values, and potentially distort exposure assessments [9]. Consequently, the interpretation of urban air quality conditions based solely on aggregated metrics may not fully reflect the variability experienced by urban populations. This concern has prompted growing interest in investigating temporal resolution as a critical factor influencing air quality characterization [10].

Recent studies have explored temporal variability of pollutants, diurnal patterns, and seasonal dynamics across urban regions; however, systematic examination of the effects of temporal aggregation on AQI estimation remains limited [11], [12]. In particular, there is a lack of comprehensive synthesis addressing how different temporal resolutions influence information content, peak representation, and exposure-related interpretations in AQI-based studies. Furthermore, the increasing adoption of sensor-based monitoring systems underscores the need to reassess traditional reporting practices that were originally designed for lower-frequency datasets [13], [14].

In this context, the present systematic review aims to examine the role of temporal resolution and aggregation in urban air quality assessment over the past decade (2015–2025). The review seeks to synthesize existing literature on high-frequency air quality monitoring, aggregation methodologies, and exposure-related analyses to identify emerging trends, methodological approaches, and research gaps. By consolidating evidence across diverse studies, this review intends to provide a foundation for future investigations into aggregation-induced biases and to highlight the importance of high-resolution data in improving urban air quality interpretation and reporting frameworks.

II. REVIEW SCOPE AND METHODOLOGY

This study adopts a structured literature review approach to synthesize recent research examining the role of temporal resolution and aggregation in urban air quality assessment. The methodology was designed to ensure systematic identification, screening, and analysis of relevant studies published over the last decade.

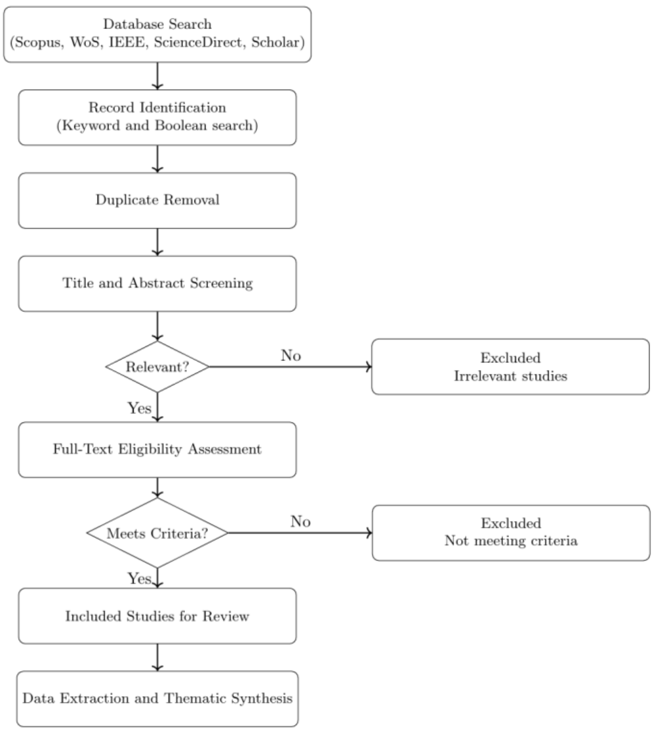

Fig. 3 - Literature Review Workflow

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A. Review Scope

The review focuses on peer-reviewed research articles investigating temporal characteristics of urban air quality data, aggregation practices, and the use of high-frequency monitoring systems. Particular emphasis is placed on studies that analyze Air Quality Index (AQI) reporting, sensor-based monitoring networks, temporal variability of pollutants, and exposure-related interpretations influenced by data resolution. The temporal window for the review spans 2015 to 2025, capturing recent developments associated with advancements in sensing technologies, growth of smart city monitoring infrastructures, and increasing interest in real-time environmental analytics. The review primarily considers urban and metropolitan contexts where population exposure and policy relevance are most significant.

B. Data Sources and Search Strategy

Relevant literature was retrieved from multiple scientific databases to ensure comprehensive coverage across environmental science, data science, and engineering domains. The primary databases consulted include:

- Scopus
- PubMed
- Web of Science
- IEEE Xplore
- ScienceDirect
- SpringerLink
- Google Scholar (for supplementary retrieval)

A combination of keyword-based and Boolean search strategies was employed to identify relevant publications. Core search terms included variations of Air Quality Index, temporal resolution, temporal aggregation, high-frequency air quality data, sensor-based monitoring, and urban air pollution variability. Searches were conducted using combinations of these terms, and database-specific filters were applied to restrict results to the defined time window.

C. Inclusion and Exclusion Criteria

To maintain relevance and consistency, explicit inclusion and exclusion criteria were established prior to screening.

1) Inclusion Criteria

- Peer-reviewed journal or conference publications between 2015 and 2025
- Studies focusing on urban or metropolitan air quality
- Research examining temporal variability, aggregation, or resolution of air quality data
- Studies involving AQI analysis, sensor networks, or exposure assessment

2) Exclusion Criteria

- Studies limited to indoor air quality or laboratory experiments
- Purely chemical or instrumentation-focused studies without temporal analysis
- Non-urban or rural-only investigations lacking broader applicability
- Non-English publications and non-peer-reviewed reports

D. Screening and Selection Process

The literature selection process followed a multi-stage screening procedure. Initially, titles and abstracts of retrieved records were reviewed to eliminate clearly irrelevant studies. Subsequently, full-text screening was conducted to assess alignment with the review objectives and inclusion criteria. Reference lists of selected articles were also examined to identify additional relevant studies through backward citation tracking. Duplicate records across databases were removed during the screening process. Studies meeting all eligibility criteria were retained for detailed synthesis and tabulation.

E. Data Extraction and Synthesis Approach

For each selected study, key information was extracted using a structured review template. Extracted attributes included publication year, study location, data resolution, pollutants analyzed, methodological approach, treatment of aggregation, major findings, and identified research gaps. This structured extraction enabled comparative analysis across studies and facilitated thematic categorization.

The synthesis process combined descriptive analysis with thematic grouping of literature into major domains, including AQI reporting practices, temporal variability studies, aggregation methodologies, sensor-based monitoring research, and exposure-related investigations. This approach supports identification of prevailing research trends as well as unresolved methodological gaps that motivate further investigation.

III. TEMPORAL RESOLUTION IN URBAN AIR QUALITY STUDIES

Temporal resolution plays a critical role in shaping the interpretation of urban air quality dynamics and pollutant exposure patterns. The frequency at which air quality measurements are recorded determines the ability to capture short-term variability, identify pollution episodes, and understand underlying emission processes. Over the past decade, studies have increasingly examined air pollution behavior across multiple temporal scales, ranging from daily averages to sub-hourly measurements enabled by emerging sensor technologies.

A. Conventional Hourly and Daily Monitoring Frameworks

Urban air quality assessment has historically relied on hourly and daily averaged observations from fixed regulatory monitoring stations. These datasets underpin regulatory compliance, long-term trend analysis, and seasonal variability

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assessment. Large-scale daily AQI analyses across China and other regions have demonstrated pronounced seasonal cycles and long-term improvements [3], [15], [16]. Daily AQI frameworks remain central to public reporting; however, their aggregation structure may smooth pollutant-specific dynamics [2]. Studies investigating COVID-19 lockdown effects further illustrate the dominance of daily composites in spatiotemporal evaluation, revealing significant reductions in NO_2 and AQI during restricted mobility periods [17], [18]. High-resolution daily modeling approaches using satellite fusion and land-use regression have significantly improved exposure estimation at 1 km or finer spatial scales [19], [20], [21], [22]. Nevertheless, these models predominantly operate at daily temporal resolution. Even when hourly data are used, such as in Guangzhou or Xiangyang case studies, analyses often aggregate to daily or seasonal summaries for interpretability [18], [19].

Thus, while daily and hourly frameworks provide regulatory robustness and comparability, they inherently compress short-term variability.

B. *Emergence of High-Frequency and Sub-Hourly Monitoring*

Recent advancements in sensing technologies have enabled high-frequency monitoring at minute, second, and even sub-second scales. Early mobile sensing systems demonstrated the feasibility of generating high spatiotemporal resolution pollution maps [54], [55]. Subsequent deployments of dense low-cost sensor networks confirmed substantial intra-urban heterogeneity [8], [51]. High-frequency modeling approaches have been extended using deep learning and graph-based architectures to capture fine-grained spatiotemporal dependencies [6], [25], [41]. Street-level machine learning frameworks have achieved 30–200 m spatial resolution with hourly dynamics [26], while high spatiotemporal kriging and sensor-fusion models have enhanced predictive reliability [33], [45]. Second-level exposure simulations suggest that total exposure may be dominated by brief, extreme peaks rather than sustained averages [39]. Functional data analysis approaches further demonstrate that dominant temporal components can capture seasonal cycles and episodic events distinctly [12]. Moreover, mobility-based exposure frameworks reveal discrepancies between residence-based averages and real-time exposure patterns [34], [56]. These findings collectively highlight that sub-hourly monitoring captures dynamic pollution spikes that aggregated daily AQI values may fail to represent.

IV. AGGREGATION EFFECTS ON VARIABILITY, PEAKS, AND EXPOSURE

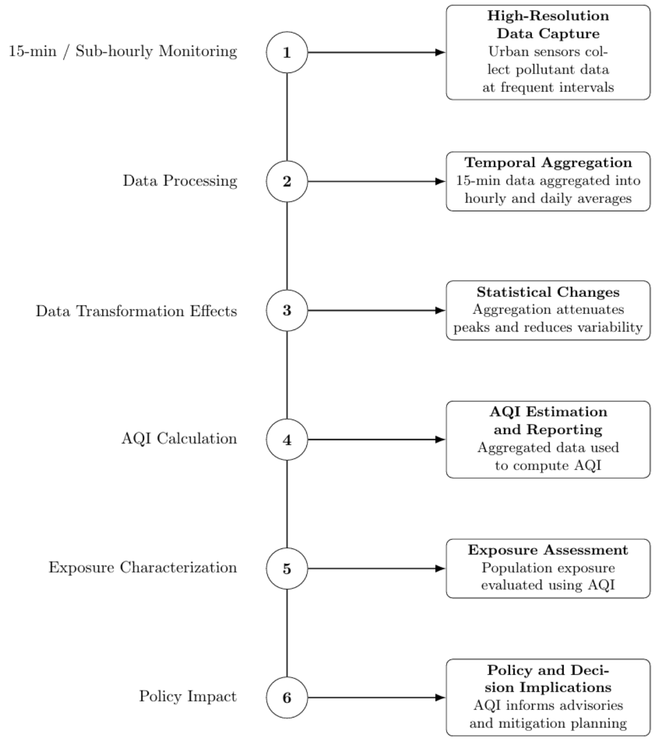

Fig. 4 - Conceptual framework illustrating the influence of temporal resolution and aggregation on urban air quality assessment

To conceptualize the role of temporal resolution in urban air quality assessment, Fig. 4 presents a simplified analytical pathway linking high-frequency data capture to policy-level outcomes. The framework illustrates how sub-hourly monitoring data undergo temporal aggregation, leading to statistical transformations that influence AQI estimation, exposure characterization, and ultimately policy decisions. By outlining this sequential process, the Fig. highlights how aggregation is not merely a technical preprocessing step, but a critical determinant shaping downstream analytical interpretations and public health communication.

Temporal aggregation—typically through arithmetic averaging—remains standard in AQI reporting systems [2]. However, empirical evidence suggests that such aggregation attenuates peak intensity and compresses variance.

Peak event analysis demonstrates that extreme short-duration particulate events may exceed mean values by orders of magnitude yet remain invisible in daily summaries [57]. Occupational and environmental exposure literature emphasizes the importance of peak intensity and frequency metrics rather than relying solely on time-integrated averages [9].Recent modeling frameworks explicitly examining resolution choices confirm that temporal lag incorporation improves PM predictions but produces pollutant-specific sensitivity differences [10]. Similarly, spatial–temporal aggregation in emission inventories and Google Earth Engin based AAQI modeling reveals how aggregation influences pollutant categorization [27].

TABLE 1 - SUMMARY OF REVIEWED STUDIES ON URBAN AIR QUALITY, EXPOSURE, MONITORING APPROACHES, AND HEALTH IMPACTS

Year	Author(s)	City/Country	Data Resolution	Pollutants	Method Used	Key Findings	Aggregation Discussed?	Research Gap
2025	Javan et al. (2025)	Global	10 km → sub-km; near-real-time; UAV high-res	NO_2, $PM_{2.5}$, PM_{10}, SO_2, CO, O_3	Systematic review and meta-analysis	RS advances; ~28% COVID pollutant drop (O_3 ↑)	Yes	Multi-sensor integration and harmonization
2025	[23])	Arabian Peninsula	Study-level (2013–2025)	Dust, NOx, $PM_{2.5}$, PM_{10}	Systematic review and meta-analysis	Industrial and dust major sources; calibration gaps	Yes	Lack of harmonized studies
2025	Munir et al. (2025)	Saudi Arabia	Spatiotemporal monitoring	$PM_{2.5}$	Trend and spatial analysis	Climatic-zone variability	Yes	Higher-resolution modeling needed
2025	Ahmad et al. [24]	Lahore, Pakistan	Hourly / Daily (1km)	AQI, PM2.5	Hybrid CNN-GCN network with Graph Smoothness Loss	Integrating AOD and population counts significantly improves AQI mapping accuracy.	No	Sparse distribution of Points of Interest (PoIs) limits model generalizability.
2025	S. Jayaraman et al. [25]	22 Indian Cities	6-hour window	AQI, PM, NO2, O3, NH3	TBS Hybrid (CNN + ARIMA) parallel model	CNNs effectively capture spatial patterns while ARIMA models temporal trends for 6-hour forecasts.	Yes	ARIMA performance declines significantly when applied to multi-city, diverse datasets.
2025	V. Shakhov et al. [14]	Simulation	Dynamic	Counts (Alerts)	Expectation-Maximization (EM) soft clustering	Soft clustering effectively distinguishes "normal" vs "polluted" zones for energy-efficient data transmission.	No	Model performance degrades when Poisson distributions significantly overlap.
2025	Zhalehdoost et al [10]	Tehran/Ahvaz, Iran	Daily	PM10, PM2.5, NOx	MLP, SVR, RF, and AR(4) models	MLP model accurately models mobile dispersion (R2=0.89); AR(4) lag is optimal for NOx.	No	Sensitivity of parameter estimation to small sample sizes.
2025	Long et al. [26]	China (Urban streets)	Street-level; hourly/mobile	PM2.5, NO2	Mobile monitoring + ML	High intra-urban variability captured; improved	Yes	Limited evaluation of temporal aggregation bias

						micro-scale prediction		
2025	Mustafa et al. [27]	Saudi Arabia	Satellite grid; monthly	AQI (multi-pollutant)	Google Earth Engine aggregation	Satellite aggregation introduces uncertainty	Yes	Ground validation insufficient
2025	Abdel-rahman et al. [27]	Middle East	Multi-scale index	PM2.5, O3	Aggregated AQI modeling	Index smoothing masks pollutant-specific extremes	Yes	Pollutant-specific exposure not separated
2024	Rautela and Goyal [28]	India	0.5° — 0.625° (Spatial); 1-hour (Temporal)	PM2.5, BC, Dust, OC, Sea Salt, Sulphates	Convolutional Autoencoder (Deep Learning)	Deep learning models achieved exceptional precision in forecasting PM2.5 across India; IGP highly vulnerable to anthropogenic aerosols.	No	Underdeveloped application of ensemble methodologies based on DL models.
2024	Tan et al. [2]	Beijing, China	1 km — 1 km grid sampling	AQI	Multi-scale Geographically Weighted Regression (MGWR)	MGWR superior to GWR; NDVI and GDP positive impacts, road density negative.	Yes	Heterogeneity analysis of driving factors on missing time scales.
2024	Haroon et al. [29]	Pakistan	Not specified	$PM_{2.5}$, COx, NOx, SOx, VOCs	Systematic review	$PM_{2.5}$ marginally linked to thermal comfort	No	Develop thermal comfort benchmarks
2024	Pouri et al. [30]	Global	Study-level	Dust, PM	Systematic review and meta-analysis	Dust linked to cardio-respiratory mortality	Yes	Regional exposure–response functions
2024	Sarah E. Chambliss et al. [31]	San Francisco Bay Area, USA	100m × 100m (0.01 km²)	NO2 and UFP count	Bayesian Additive Regression Trees (BART)	National models miss local peaks; UFP underestimated by >2x. Underprediction is higher in POC neighborhoods, masking exposure inequities.	Yes	LUR models lack localized peak representation (<100m). Scarcity of ground measurements in POC areas and for UFP.
2024	M. T. Abbasi et al. [11].	Tehran, Iran	Hourly	PM2.5, O3, CO, PM10, SO2, NO2	Wavelet-PCA, AHC clustering, and Bivariate Copula	AQMS dynamics are similar city-wide except for	Yes	Scarcity of ground truth clustering solutions and

					models	peripheral stations; pollutant associations strengthen in colder seasons.		reference measurements.
2024	C. Manchanda et al. [32].	West Oakland, CA, USA	15-minute / 30m	Black Carbon (BC)	Non-negative Matrix Factorization (NMF)	Merged mobile monitoring with fixed sensors to fill spatiotemporal measurement gaps.	Yes	Mobile monitoring coverage is predominantly limited to weekday daytime windows.
2024	Kar et al. [33]	US cities (OH, CO, PA)	High-frequency; neighborhood	PM2.5	Low-cost sensor calibration + ML	High-density sensors capture fine heterogeneity	Yes	Calibration drift over time
2024	Song et al. [34]	China	1-minute mobility-based	PM2.5	Mobility tracking + real-time sensors	Residence-based exposure underestimates variability	Yes	Longitudinal exposure needed
2023	Lindén et al. [35]	Not specified	Not specified	PM, NO_2	Systematic review	Vegetation removes PM and NO_2; leaf traits important	Not specified	Integrate vegetation traits into AQ models
2023	Faridi et al. [36]	Eastern Mediterranean	Not specified	PM, O_3, NO_2, SO_2	Review	Variation in AQ standards vs WHO	No	Harmonize health-based standards
2023	Zhou et al. [37]	Global (1312 cities)	2000–2020 dataset	$PM_{2.5}$	Spatiotemporal analysis	Persistent global $PM_{2.5}$ inequality	Yes	Stronger urban mitigation policies
2023	Abbasi-Kangevari et al. [38]	North Africa and Middle East	Regional burden estimates	PM, O_3, household air pollution	GBD systematic analysis	Air pollution reduces life expectancy	Yes	Country-specific exposure data needed
2023	Jianhua Cheng et al. [3]	368 major cities, Mainland China,	Daily AQI; 1km (socioeconomic); 9km (meteorological)	Air Quality Index (AQI)	Hot spot analysis, spatial autocorrelation, mean center, and geographic detector	Annual AQI average dropped from 94 to 67 (2014–2020). AQI follows a U-shaped seasonal trend (highest in winter, lowest in summer). Hot spots are clustered in North China and Xinjiang; 2-m temperature is the most significant	Yes	Prior studies focused on local areas or short time scales, failing to capture overall national trends or regional interactions. Future work needs model-based prediction.

						environmental driver		
2023	H. Woodward et al. [39]	London, UK	1-second	NOx	Fluidity (LES) + Agent-based simulation	total exposure is characterized by low levels punctuated by extreme peaks (< 1s duration).	No	Study is limited to few wind directions and lacks city-wide background concentrations.
2022	Kumari et al. [17]	Dublin, Ireland	1113.2 m (Satellite); 24h composite (Ground)	NO2, SO2, O3, CO, PM10, PM2.5	Sentinel-5P and MODIS Data Analysis	28% reduction in NO2 and 27.7% AQI improvement during 2020 COVID lockdown.	Yes	Need integratedweather modeling and lockdown phase differentiation.
2022	S. R. Iyer et al. [6]	Delhi, India	Fine-grained	PM2.5	Message-passing RNN (MPRNN) + Piecewise Cubic Splines	Capturing spatial interactions between sensors via distance embeddings minimizes residual errors.	No	Frequent network outages and communication issues plaguing low-cost sensor data.
2022	Z. Jin et al. [40]	Bogotá, Colombia	Hourly	PM2.5	Unsupervised clustering and Spatiotemporal variograms	Low-income strata face significantly higher exposure to poor air quality than wealthier groups.	Yes	Limitations in variogram flexibility and descriptive nature of study.
2022	Wang et al. [21]	China (Metro area)	1 km; daily	PM2.5, NO2, SO2	Spatiotemporal ML model	High-resolution reduces exposure misclassification	Yes	Sub-daily exposure modeling needed
2022	Dimakopoulou et al. [22].	London, UK	100 m–1 km; daily	NO2, PM2.5	Hybrid LUR + dispersion	Fine resolution improves intra-urban contrast	Yes	Impact on acute exposure unclear
2021	J.-J. Liaw et al. [13].	Kaohsiung, Taiwan	10-minute	AQI, PM2.5	Image high-frequency info extraction + SVR with RH	Visibility and building texture loss in images correlate strongly with rising AQI levels.	No	Need to integrate more image features (transmittance, entropy) to improve performance.
2021	Beloconi and Vounatsou [16]	Europe	1 km; annual	PM2.5	Bayesian hierarchical modeling	Long-term exposure improved via fine grids	Yes	Limited micro-scale urban analysis

2021	Mokhtari et al. [41]	France	Hourly; grid-based	PM2.5	Uncertainty-aware deep learning	Prediction intervals improve reliability	Partial	Limited health outcome linkage
2021	Baca-López et al. [42].	Mexico City	Station-based; daily	PM2.5, O3	Representativeness analysis	Monitoring network spatial bias exists	Yes	Mobile exposure missing
2020	Ulpiani [43]	16 countries	Not specified	UHI–UPI focus	3-decade systematic review	Strong UHI–UPI interaction framework	No	Integrated UHI–UPI modeling
2020	Vardoulakis et al. [44].	Global	Not specified	$PM_{2.5}$, PM_{10}, NO_2, VOCs, PAHs	Systematic review	Indoor exposure influenced by housing and behavior	No	Better indoor exposure assessment
2020	B. Mijling [45]	Amsterdam, Netherlands	Hourly / Street-level	NO2	Retina (AERMOD + Optimal Interpolation)	Integrating low-cost sensors (LCS) reduces RMSE and detects traffic shifts during road closures.	No	Global traffic flow data is often estimated rather than directly observed.
2020	van Zoest [46]	Eindhoven, NL	Sensor-grid; hourly	PM2.5	Bayesian spatiotemporal modeling	Low-cost sensor aggregation requires uncertainty propagation	Yes	Long-term health linkage not assessed
2020	Xue et al. [19]	China	10 km → 1 km; daily	O3	Data fusion modeling	Aggregation reduces CV accuracy	Yes	No pointwise uncertainty ranges
2019	Feinberg et al. [8]	Memphis, TN, USA	1-minute	PM2.5	Nonparametric Trajectory Analysis (NTA)	Identified local "environmental justice" sites where railyards drive 20% of PM mass.	No	High failure rates and mechanical instability of low-cost sensor pods mid-study.
2018	Newell et al. [47]	LMICs	Not specified	NO_2 (gaseous AAP)	Systematic review and meta-analysis	Gaseous AAP ↑ cardiorespiratory mortality	Yes	Limited LMIC gaseous studies
2018	Rybarczyk et al. [48]	Global	Not specified	PM, NOx, SO_2, O_3, CO	Narrative review	Major global health burden from air pollution	No	Stronger emission mitigation
2018	Daniela Dias et al. [49].	Review (Urban areas)	Review of 72 studies	Urban air pollutants	Conceptual classification of exposure methods (uniform vs. variable	Trajectory-based models with variable air quality are best for	Yes	Future quantitative comparison between different exposure

					quality)	capturing individual exposure variability.		quantification approaches is needed.
2018	Mukhopadhyay and Sahu [50]	England and Wales	Daily; admin units	NO2, PM10	Bayesian misalignment correction	Spatial misalignment biases admin-level exposure	Yes	Sub-city heterogeneity unresolved
2018	de Hoogh et al. [20]	Switzerland	1 km; daily	PM2.5	LUR + satellite	Sparse monitors need spatial smoothing	Yes	Peak exposure underestimation
2017	Xie et al. [51]	Global review	Multi-scale	Multiple	Monitoring and interpolation review	Sensor density strongly affects spatial uncertainty	Yes	Standardization across cities lacking
2017	Xue et al. [52]	China (National)	1 km; monthly/daily	PM2.5	Data fusion (Satellite + CTM + monitors)	Fusion reduces bias; resolution improves exposure gradient	Yes	Uncertainty intervals limited
2017	Lee et al. [53]	UK	Monthly; regional	PM2.5	Bayesian spatiotemporal model	Accounting for uncertainty changes health risk estimates	Yes	Real-time application lacking
2015	A. Marjovi et al. [54]	Lausanne, Switzerland	Hourly; Street-segment	LDSA (Ultrafine particles)	Network-based log-linear regression and PGMs	Street-segment discretization is more efficient than grids for modeling mobile sensors.	Yes; uses topology-based street segments instead of grid cells.	Scarcity of high-resolution traffic data and need for reactive pollutant modeling.

Exposure misclassification emerges as a critical concern. National-scale models may underestimate localized peaks, particularly in disadvantaged communities [31]. Representativeness analyses show that monitoring station placement influences spatial coverage and exposure inference [42], [50].

Data fusion methods reduce bias and improve completeness [19], [52], yet aggregation can still smooth high-frequency fluctuations relevant for acute health effects. Meteorological dynamics further complicate temporal interpretation, as shown in Delhi and Tehran case studies where temperature, rainfall, and seasonal stability significantly modulate AQI behavior [11], [58].

V. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite technological progress, systematic multi-resolution comparisons remain limited. Reviews of monitoring and modeling approaches emphasize the need for integrating mobile, stationary, and satellite data streams while accounting for uncertainty [1], [51], [59]. Emerging AI-based frameworks demonstrate resolution-sensitive performance variations across pollutants [10], [24]. However, standardized metrics quantifying aggregation-induced information loss are rarely implemented. Three major research gaps are evident:

- Lack of multi-temporal comparative evaluation within identical datasets.
- Insufficient quantification of peak attenuation and variance compression.
- Limited integration of high-frequency exposure metrics into AQI policy frameworks.

Future research should combine long-term high-frequency datasets, resolution-aware machine learning models, and peak-sensitive exposure metrics. Bridging analytics with regulatory reporting—such as adaptive or multi-scale AQI frameworks—could enhance representativeness and public health relevance.

VI. CONCLUSION

This review examined the influence of temporal resolution and aggregation on urban air quality assessment and AQI interpretation. Although advances in sensing technologies and modeling approaches now enable high-frequency, fine-scale monitoring, most reporting frameworks continue to rely on hourly or daily averages. Evidence synthesized in this study indicates that temporal aggregation reduces variability and suppresses short-duration pollution peaks, potentially affecting exposure characterization and acute health risk interpretation. While aggregated metrics remain essential for regulatory consistency and public communication, their limitations must be explicitly acknowledged. A clear research gap exists in the systematic quantification of aggregation-induced information loss across multiple temporal scales. Future work should focus on multi-resolution comparisons, development of peak-sensitive exposure metrics, and integration of high-frequency data into policy-relevant AQI frameworks. Recognizing temporal resolution as a critical analytical dimension will strengthen urban air quality evaluation and support more representative and health-relevant reporting systems.

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