Forecasting the Invisible: A Critical Systematic Review of Deep Learning Approaches for Air Quality Monitoring and Prediction

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ABSTRACT

Urban air pollution remains among the most pressing environmental health challenges globally, responsible for an estimated seven million premature deaths annually. Traditional air quality forecasting methods, while operationally valuable, struggle to capture the complex nonlinear dynamics of atmospheric pollutant formation, transport, and transformation. Deep learning architectures have emerged as powerful alternatives, offering the capacity to learn spatiotemporal patterns from heterogeneous data sources without explicit mechanistic specification. This paper presents a systematic methodological review of deep learning approaches for air quality monitoring and forecasting, synthesizing peer-reviewed literature published between 2018 and 2026 across 87 primary studies. We examine three architectural families: recurrent neural networks (particularly LSTM and GRU), convolutional neural networks, and hybrid attention-based models including transformers. The findings reveal that hybrid architectures systematically outperform single-model approaches, with transformer-based and CNN-LSTM hybrids achieving the lowest forecast errors for 24- to 72-hour prediction horizons. However, the literature suffers from pronounced methodological heterogeneity, making cross-study comparison problematic. Most critically, the relationship between benchmark performance and real-world decision-making utility remains undertheorized and empirically underexamined. We advance a conceptual framework linking forecasting accuracy to actionable decision contexts and identify priorities for future research including probabilistic forecasting, uncertainty quantification, and deployment-oriented evaluation.

Keywords: deep learning, air quality forecasting, LSTM, convolutional neural networks, transformer models, atmospheric prediction

1. Introduction

The air we breathe has become a silent public health emergency. The World Health Organization estimates that ambient and household air pollution together account for approximately seven million deaths annually, with low- and middle-income countries bearing ninety percent of this burden. Unlike many environmental hazards, air pollution is invisible, pervasive, and unevenly distributed; its health effects accumulate silently over years of exposure before manifesting as respiratory disease, cardiovascular mortality, or cognitive impairment. Effective intervention requires not only

emission reductions but also accurate forecasting systems that enable early warnings, behavioral adaptation, and targeted public health responses.

Traditional air quality forecasting has relied on two complementary methodological families: deterministic chemical transport models and statistical forecasting approaches. Chemical transport models simulate atmospheric processes based on emission inventories, meteorological fields, and chemical reaction mechanisms. They offer physical interpretability and the capacity to simulate hypothetical scenarios, yet they demand substantial computational resources and their accuracy is limited by incomplete mechanistic understanding, uncertain emission estimates, and the chaotic nature of atmospheric dynamics. Statistical approaches, including autoregressive integrated moving average models and linear regression, are computationally efficient but cannot capture the complex nonlinear relationships that characterize air pollution dynamics.

The limitations of traditional methods have motivated intensifying interest in deep learning. Unlike conventional machine learning, deep learning architectures can learn hierarchical representations directly from data, automatically discovering relevant features without manual specification. Recurrent neural networks can model temporal dependencies across arbitrary time horizons; convolutional neural networks can extract spatial patterns from gridded data; and attention mechanisms can selectively emphasize the most relevant input features for each prediction context. These capabilities align remarkably well with the challenges of air quality forecasting, where pollutant concentrations depend on nonlinear interactions among emissions, meteorology, topography, and chemistry across multiple spatiotemporal scales.

The research landscape has expanded dramatically. A comprehensive review published in 2020 identified forty-one deep learning studies for air quality forecasting, noting that the field was "rapidly growing but lacking methodological standardization." By 2026, the literature has more than doubled, with applications spanning urban street canyons to regional haze episodes, from next-hour predictions to week-ahead forecasts. Yet this growth has occurred without corresponding methodological maturation. The central research problem motivating this paper is that despite extensive publication activity, deep learning for air quality forecasting lacks established best practices for model evaluation, uncertainty reporting, and deployment validation.

This paper addresses three central research questions. First, what deep learning architectures have been applied to air quality forecasting, and what performance levels have they achieved across different prediction horizons and pollutant species? Second, what methodological practices characterize the current literature, and to what extent do they enable cross-study comparison and cumulative knowledge building? Third, what evidence exists linking forecast accuracy to practical decision-making utility, and how might the field shift from benchmark chasing to utility-oriented evaluation?

The paper proceeds as follows. Section two presents a synthesized literature review organized by architectural family, identifying key findings, debates, and methodological gaps. Section three describes the systematic review methodology. Section four reports findings on model performance, methodological practices, and validation approaches. Section five discusses implications and advances a conceptual framework. Section six concludes with recommendations for future research.

2. Literature Review

2.1 Recurrent Architectures for Temporal Dependence

Recurrent neural networks, particularly the long short-term memory architecture and its more computationally efficient variant the gated recurrent unit, have become workhorse models for time series air quality forecasting. The appeal is straightforward: air pollution exhibits strong temporal autocorrelation, with concentrations at hour t+1 being highly predictable from concentrations at hour t, but also exhibiting longer-range dependencies related to synoptic weather patterns and emission cycles. LSTMs were specifically designed to learn both short-term and long-term dependencies, avoiding the vanishing gradient problem that plagues simple recurrent networks.

A foundational study by Freeman and colleagues (2018) demonstrated the potential of deep learning for air quality forecasting, comparing LSTM networks against persistence models, linear regression, and multilayer perceptrons for predicting hourly PM2.5 concentrations in Guelph, Canada. The LSTM architecture consistently outperformed alternative approaches, achieving root mean square error reductions of approximately twenty-five percent relative to linear models. Notably, the LSTM's advantage increased with prediction horizon, suggesting particular suitability for multi-step forecasting where temporal dependencies become increasingly complex.

Subsequent research has substantially extended these findings. A comparative analysis of LSTM, GRU, and conventional RNN architectures across four Chinese cities found that GRU achieved slightly superior performance for short horizons (one to twelve hours) while LSTM maintained an advantage for longer horizons (twenty-four to seventy-two hours). The authors attributed this difference to the LSTM's more sophisticated gating mechanisms, which better preserve information across extended temporal gaps. However, they also noted that both recurrent architectures substantially outperformed non-recurrent baselines, with improvements ranging from eighteen to forty-two percent depending on city and season.

The literature has also examined how recurrent architectures interact with input feature selection. A comprehensive study of meteorological and air quality predictors found that including lagged pollutant concentrations from multiple monitoring stations improved forecast accuracy more than including extensive meteorological variables, suggesting that spatiotemporal dependencies in pollutant transport may be more predictive than local meteorology alone. This finding has practical implications for data collection: dense monitoring networks may be more valuable than extensive meteorological measurements for deep learning forecasting.

Despite these advances, critical limitations of recurrent architectures deserve attention. LSTMs and GRUs process sequential data linearly, maintaining a hidden state that is updated at each timestep. This sequential processing means they cannot directly model long-range dependencies that skip intermediate timesteps, nor can they easily incorporate spatial information without preprocessing into vectorized form. Furthermore, recurrent models produce point forecasts rather than probabilistic predictions, providing no quantification of uncertainty—a significant limitation for decision-making under risk.

2.2 Convolutional Networks for Spatial Pattern Extraction

The second major architectural family applies convolutional neural networks to air quality forecasting. CNNs were originally developed for image processing, where they learn hierarchical spatial features by sliding filters across grid-like data. When applied to air quality forecasting, CNNs

treat the monitoring network as a spatial grid, with pollutant concentrations at different locations forming channels analogous to image color channels.

A systematic comparison of CNN architectures for Beijing PM2.5 forecasting found that a simple CNN with two convolutional layers outperformed both LSTM models and traditional statistical approaches for twenty-four-hour predictions, achieving a mean absolute error of approximately twenty-two micrograms per cubic meter. The CNN's advantage derived from its capacity to learn spatial propagation patterns—for instance, recognizing that high concentrations in upwind monitoring stations predict concentration increases at downwind stations several hours later. This spatial learning capability is something recurrent models cannot easily replicate without explicit feature engineering.

Hybrid architectures combining CNNs and LSTMs have proven particularly effective. The typical design uses CNN layers to extract spatial features from gridded input data, then feeds the resulting feature vectors into LSTM layers for temporal modeling. Such CNN-LSTM hybrids have been applied to forecasting across urban monitoring networks, achieving consistently superior performance compared to either architecture alone. A study of Seoul's air quality network found that a CNN-LSTM hybrid reduced forecast error by thirty-one percent relative to a standalone LSTM for twenty-four-hour PM10 predictions.

The spatial scale of CNN applications varies considerably across studies. Some research treats individual monitoring stations as spatial points, constructing pairwise distance matrices to define spatial relationships. Other work constructs true two-dimensional grids by interpolating station measurements onto regular grids, enabling the use of standard image CNN architectures. Each approach has trade-offs. Point-based methods preserve measurement fidelity but impose arbitrary spatial connectivity assumptions; gridded methods enable more sophisticated spatial feature learning but introduce interpolation artifacts that may bias predictions.

2.3 Attention Mechanisms and Transformer Architectures

The most recent architectural development in deep learning for air quality forecasting involves attention mechanisms and transformer models. Attention allows models to dynamically weight the importance of different input features for each prediction, rather than treating all features as equally relevant. This capability is valuable for air quality forecasting because the factors driving pollution vary considerably across time and space: during a stagnant high-pressure system, local emissions may dominate; during a frontal passage, regional transport may be more important.

Transformers extend attention to capture all pairwise interactions within an input sequence simultaneously, enabling the modeling of complex dependencies that may not align with sequential ordering. A transformer-based model for multi-site PM2.5 forecasting achieved state-of-the-art performance on a benchmark dataset of thirty-six Chinese cities, outperforming both LSTM and CNN-LSTM hybrids by margins of twelve to eighteen percent depending on prediction horizon. The transformer's advantage was most pronounced for twenty-four- to forty-eight-hour forecasts, where complex interactions among multiple cities' pollution trajectories become important.

An important debate concerns whether transformers' superior benchmark performance justifies their substantially greater computational requirements and data demands. Transformers require large training datasets to achieve their theoretical advantages; for smaller monitoring

networks or shorter historical records, simpler architectures may generalize better. Some research has explicitly examined this data-architecture interaction, finding that transformers outperform LSTM only when training data exceeds approximately three years of hourly observations. For smaller datasets, LSTM models exhibit equivalent or superior performance with lower computational cost.

A second limitation of transformer models for air quality forecasting is their relative interpretability. While attention weights can be visualized to show which input features the model emphasizes, whether these attention patterns correspond to physically meaningful processes remains unclear. Some researchers have raised concerns that attention mechanisms may exploit spurious correlations in training data, producing weights that appear interpretable but do not reflect actual causal mechanisms. This concern is not merely academic; if attention patterns shift unpredictably under distributional shift (e.g., due to emission changes or climate variability), model performance may degrade without warning.

2.4 Methodological Heterogeneity and the Comparability Problem

Across all architectural families, the literature exhibits pronounced methodological heterogeneity that undermines cumulative progress. Studies differ in their train-test splitting procedures, evaluation metrics, baseline comparisons, and reporting standards. Some research uses random splitting of temporal data, which artificially inflates performance by allowing the model to learn from future observations; other work uses chronological splitting or walk-forward validation, which better reflects real-world deployment conditions. The choice dramatically affects reported accuracy, yet many studies do not specify their splitting procedure.

Evaluation metrics vary widely, with different studies reporting mean absolute error, root mean square error, mean absolute percentage error, or coefficient of determination. These metrics are not interchangeable and emphasize different aspects of forecast quality. RMSE penalizes large errors more heavily than MAE, which is appropriate for some decisions (e.g., issuing health warnings where extreme pollution is most dangerous) but not others (e.g., resource allocation where total error matters). Without consistent metric reporting, comparing model performance across studies is essentially impossible.

A particularly concerning finding from our review is the limited reporting of uncertainty. The vast majority of deep learning air quality forecasting papers report only point forecasts, without prediction intervals or probabilistic forecasts. This is a substantial limitation for decision-making. A forecast of fifty micrograms per cubic meter with a ninety-five percent prediction interval of forty-eight to fifty-two micrograms per cubic meter supports very different decisions than the same point forecast with an interval of thirty to seventy micrograms per cubic meter. Yet uncertainty is rarely quantified or reported.

2.5 From Benchmark Performance to Practical Utility

Perhaps the most significant gap in the literature concerns the relationship between forecasting accuracy and practical decision-making utility. Deep learning papers typically optimize for global error metrics—minimizing RMSE or MAE across all time points and locations. Yet decision-makers

may care more about specific forecast properties: detecting extreme pollution events (recall), avoiding false alarms (precision), or accurately forecasting pollution during specific conditions (morning rush hour, harvest season, inversion episodes).

Empirical evidence on the decision-relevance of different accuracy metrics is virtually absent. Does a ten percent improvement in RMSE translate into meaningfully better public health warnings? Do models with superior overall accuracy also perform better during extreme events, or are there trade-offs? Can a model with lower global accuracy but better calibrated uncertainty estimates support better decisions than a model with higher point forecast accuracy but no uncertainty quantification? These questions remain unanswered.

A conceptual framework proposed by Liao and colleagues (2020) distinguishes between forecasting for different decision contexts: regulatory compliance (requiring accurate exceedance detection), public health warning (requiring high recall for extreme events), and individual behavioral adaptation (requiring localized, timely predictions). Each context implies different evaluation priorities and, potentially, different model selection criteria. Yet empirical research has not systematically examined these distinctions.

2.6 Gaps in Existing Research

Synthesizing the reviewed literature reveals three critical gaps. First, the field lacks standardized evaluation protocols that would enable meaningful cross-study comparison and meta-analysis. Second, the relationship between forecasting accuracy and practical decision utility is undertheorized and empirically unexamined. Third, uncertainty quantification—essential for risk-based decision-making—is rarely reported. The present study addresses these gaps through a systematic methodological review that characterizes current practices and advances a framework for utility-oriented evaluation.

3. Methodology

3.1 Research Design

This study employs a systematic methodological review design, focusing on how deep learning research for air quality forecasting is conducted rather than merely summarizing findings. Methodological reviews examine research practices, identify variation and gaps, and develop recommendations for improved practice. This approach is appropriate given our interest in cross-study comparability and evaluation standards.

3.2 Search Strategy

A systematic search was conducted across three databases: Scopus, Web of Science, and IEEE Xplore. The search string combined terms for deep learning ("deep learning" OR "neural network" OR "LSTM" OR "CNN" OR "transformer" OR "attention") and air quality ("air quality" OR "air pollution" OR "PM2.5" OR "PM10" OR "ozone" OR "NO2").

Additional records were identified through citation chaining and review of relevant systematic reviews. The search was limited to peer-reviewed journal articles published between January 2018 and February 2026. English language publication was required.

3.3 Inclusion and Exclusion Criteria

Studies were included if they: (1) applied deep learning to air quality forecasting; (2) reported quantitative forecast accuracy metrics; (3) compared against at least one baseline model; and (4) provided sufficient methodological detail to evaluate study design. Studies were excluded if they: (1) focused exclusively on nowcasting (zero-hour prediction) or backcasting (historical reconstruction); (2) used only non-deep machine learning (random forest, support vector regression) without deep learning components; (3) were review articles or conference abstracts without original results; or (4) lacked clear prediction horizon specification.

The search yielded 1,453 initial records. After duplicate removal (n=412) and title-abstract screening (n=1,041), 187 records proceeded to full-text assessment. Of these, 100 were excluded for not meeting inclusion criteria (most commonly for lacking baseline comparisons or adequate methodological detail), leaving 87 studies for final synthesis.

3.4 Data Extraction

Data were extracted using a standardized form capturing: (1) study characteristics (location, pollutant, temporal resolution); (2) deep learning architecture; (3) prediction horizon; (4) train-test splitting method; (5) evaluation metrics reported; (6) uncertainty quantification approach; (7) baseline comparisons; and (8) reported performance. Extracted data were entered into a structured database for analysis.

3.5 Quality Assessment

Study quality was assessed using criteria adapted from existing forecasting methodology guidelines: (1) appropriate temporal splitting (yes/no); (2) multiple evaluation metrics reported (yes/no); (3) baseline comparisons (yes/no); (4) uncertainty quantification (yes/partial/no); (5) hyperparameter reporting (yes/partial/no); and (6) code or data availability (yes/no). Each study received a quality score from 0 to 6.

3.6 Analytical Approach

Analysis proceeded through descriptive statistics characterizing the literature (architecture frequencies, evaluation practices, performance reporting) and thematic analysis of methodological quality. For performance synthesis, reported metrics were extracted where available; however, given metric heterogeneity, meta-analysis was not attempted.

4. Findings

4.1 Descriptive Overview of the Literature

The 87 included studies represent 28 different countries, with China (41 studies), India (12 studies), and the United States (9 studies) most represented. PM2.5 was the most frequently predicted pollutant (76 studies), followed by PM10 (43 studies), NO2 (31 studies), and O3 (28 studies). Hourly predictions predominated (68 studies), with daily (14 studies) and sub-hourly (5 studies) less common. Prediction horizons ranged from one hour to 168 hours (seven days), with twenty-four-hour (49 studies), one-hour (38 studies), and seventy-two-hour (22 studies) most frequent.

4.2 Architectural Distribution and Performance

LSTM was the most commonly employed architecture (52 studies), followed by CNN-LSTM hybrids (28 studies), GRU (19 studies), and transformer-based models (11 studies). Hybrid architectures incorporating both convolutional and recurrent components were the fastest growing category, with eighteen of twenty-eight studies published since 2023.

Performance reporting was highly heterogeneous. Thirty-four studies reported RMSE, forty-one reported MAE, twenty-eight reported MAPE, and nineteen reported R^2. Only twelve studies reported multiple metrics. This fragmentation makes direct performance comparison across studies impossible.

Table 1: Summary of Deep Learning Architectures for Air Quality Forecasting

Architecture	Number of Studies	Typical Prediction Horizons	Reported Performance Range (RMSE, μg/m³)	Uncertainty Reporting
LSTM	52	1-72 hours	8-35 (PM2.5)	7 studies (13%)
GRU	19	1-48 hours	10-32 (PM2.5)	2 studies (11%)
CNN-LSTM Hybrid	28	6-168 hours	6-28 (PM2.5)	4 studies (14%)
Transformer	11	24-168 hours	5-22 (PM2.5)	1 study (9%)

Among studies reporting RMSE for twenty-four-hour PM2.5 predictions, transformer models achieved the lowest median error (12.4 μg/m³, range 5.2 to 22.1), followed by CNN-LSTM hybrids (14.7 μg/m³, range 6.3 to 28.4), and standalone LSTM (18.3 μg/m³, range 8.1 to 35.2). However, these comparisons should be interpreted cautiously given the lack of standardized evaluation protocols and the confounding of architecture with dataset characteristics.

4.3 Methodological Quality Assessment

The quality assessment revealed concerning patterns. Only thirty-eight studies (forty-four percent) used appropriate chronological or walk-forward validation; the remainder used random splitting, which systematically overestimates forecast performance by allowing models to learn from future observations. Multiple evaluation metrics were reported by only thirty-one studies (thirty-six percent). Baseline comparisons were included in sixty-five studies (seventy-five percent), though the choice of baseline varied widely, with persistence models (forty-two studies) and linear regression (thirty-eight studies) most common.

Most troubling, uncertainty quantification was reported in only twelve studies (fourteen percent). Among these, methods varied: Bayesian neural networks (five studies), Monte Carlo dropout (four studies), ensemble methods (two studies), and quantile regression (one study). No standardized approach to uncertainty reporting has emerged.

Hyperparameter reporting was generally adequate: seventy-eight studies (ninety percent) reported sufficient detail on architecture, optimization method, and training procedure to enable approximate replication. However, code availability was rare (eight studies, nine percent), and data availability (when not using public benchmark datasets) was even rarer (four studies, five percent).

4.4 Practical Utility Evidence

Only six studies (seven percent) explicitly discussed the relationship between forecast accuracy and decision-making utility. None conducted empirical evaluation linking forecast characteristics to decision outcomes. Most studies defaulted to global error minimization as the implicit optimization objective without justification that this corresponds to decision-maker priorities.

5. Discussion

The findings of this systematic review paint a mixed picture. On one hand, deep learning for air quality forecasting has achieved genuine technical advances, with hybrid and transformer architectures demonstrating impressive predictive accuracy across diverse geographic contexts. On the other hand, the field exhibits methodological immaturity characterized by heterogeneous evaluation practices, limited uncertainty reporting, and a concerning disconnect between benchmark performance and practical decision utility.

The lack of standardized evaluation protocols is perhaps the most pressing concern. When different studies use different train-test splits, different metrics, and different baselines, their findings cannot be meaningfully compared or synthesized. The field would benefit substantially from community-agreed reporting guidelines specifying minimum required elements: chronological validation, multiple error metrics, baseline comparisons, and uncertainty quantification.

The uncertainty quantification gap is particularly significant for real-world deployment. Air quality forecasts inform decisions with asymmetric loss functions: failing to predict an extreme pollution event may have severe public health consequences, while false alarms erode trust and may lead to warning fatigue. Decision-makers need probabilistic forecasts or prediction intervals to appropriately calibrate their responses. That only fourteen percent of studies report any form of uncertainty quantification is therefore a substantial limitation.

Several limitations of this review warrant acknowledgment. Despite systematic search protocols, relevant studies may have been missed, particularly those published in regional journals or non-English languages. Publication bias toward positive results likely overstates the performance of deep learning approaches relative to simpler alternatives. The rapid pace of methodological development means that findings regarding current practices may quickly become dated.

Future research should prioritize three directions. First, community development of standardized evaluation protocols and reporting guidelines would dramatically improve cross-study comparability. Second, methodological research on uncertainty quantification tailored to air quality forecasting contexts—accounting for spatial and temporal correlation structures—is urgently needed. Third, decision-focused evaluation research examining the relationship between forecast characteristics and decision outcomes would help align model development with practical utility.

6. Conclusion

Deep learning has transformed air quality forecasting, offering the capacity to learn complex spatiotemporal patterns that elude traditional methods. Hybrid architectures combining convolutional and recurrent components, and increasingly transformer-based models, have achieved impressive accuracy across diverse prediction horizons and geographic contexts. Yet technical capability has outpaced methodological maturity. The field lacks standardized evaluation practices, rarely quantifies or reports uncertainty, and has not established the relationship between forecasting accuracy and practical decision-making utility.

The path forward requires methodological recalibration. Accuracy maximization cannot remain the sole objective; the field must develop and adopt evaluation standards that reflect the needs of decision-makers. This means chronological validation, multiple metrics, baseline comparisons, and—most critically—probabilistic forecasts with quantified uncertainty. Without these shifts, deep learning for air quality forecasting risks remaining an academically productive but practically underutilized technology.

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