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TOPICAL REVIEW

Intelligent visibility forecasting at airports: a systematic review

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Abstract

Low visibility conditions caused by phenomena such as fog, heavy rain, or snowfall impose major operational and safety challenges at airports. Conventional numerical weather prediction models, although improved over time, still struggle to forecast low visibility accurately due to scale mismatches and uncertainties in physical parameterizations, among other factors. This review synthesizes findings on data-driven solutions, including machine learning and deep learning, that harness large datasets to reveal hidden patterns, offering better performance and adaptability. Ensemble methods and the integration of multiple data sources further enhance accuracy, particularly for short lead times. Several methods achieve correlation coefficients above 0.90 and root mean square error below 1 km, yet generalization and integration into real-time airport operations remain underexplored. Future work should focus on transferability across diverse climates, integration with advanced operational tools, and bridging gaps between model complexity and user interpretability. The next generation of hybrid forecasting frameworks has the potential to enhance safety, limit economic losses, and improve resilience in airport operations.

1. Introduction

Low Visibility Conditions (LVC), caused by fog, heavy rain, or snowfall, are associated with approximately 67%, 52%, and 46% weather-related accidents during take-off, approach, and landing, respectively [1]. According to current regulations, Low Visibility Procedures (LPV) are implemented when horizontal and/or vertical visibility is below airport-specific thresholds [2]. At many aerodromes, LPVs are applied when visibility along the runway decreases below 550m and/or the cloud base covering over half the sky drops below 60 m [3]. These procedures reduce airport capacity, leading to delays, cancellations, and operational disruptions [3], and demand additional fuel when alternate landing sites are required [4]. Regional studies further emphasize these challenges, as seen at Abu Dhabi International Airport, where fog occurrence varies from 8 to 51 days per year with diverse event durations [5], and in the Grand Casablanca region, where localized advection-radiation fog events adversely affect operations [6]. Therefore, accurate visibility forecasting is crucial for aviation safety and operational efficiency. However, an accurate prediction of LVC is a major challenge, especially when associated with fog, due to the multiscale complexity of fog physics, which involves a wide variety of processes, spanning from synoptic scales (1000 km) to the aerosol scale (10^{-7} m) [7].

Outputs from conventional Numerical Weather Prediction (NWP) models have long been used in visibility forecasting [8]. These models solve complex physical equations and use parameterizations to represent subgrid-scale processes [9]. Furthermore, their initial conditions require the assimilation of a large volume of observational data [10]. Thus, these models require high computational costs and, despite the improvement in computing power over the last few decades, operational NWP models still use insufficient horizontal and vertical resolutions to correctly represent the numerous interactions between the physical processes involved in small-scale weather [11]. Besides, other factors, such as uncertainties in the initial conditions [12, 13] or inaccuracies in the land surface representation [14] in NWP models may also lead to large errors in the visibility simulations associated with radiation fog.

Thus, forecasting LVC remains challenging for conventional NWP models, which reveal a low probability of detection of low visibility events [15, 16]. In addition, these models are often unable to correctly represent the life cycle of LVC [16–18].

To address these issues, alternative approaches have been developed. Data fusion techniques that combine Meteorological Aerodrome Reports (METAR), satellite observations, and interpolation methods have enhanced real-time assessments of visibility hazards [19]. Furthermore, parameterizations linking meteorological variables to runway visual range have demonstrated strong predictive performance [20], and statistical models based on multiple regression and k-nearest neighbors have proven effective in capturing the non-linear factors that affect visibility [21].

In general, Artificial Intelligence (AI), with a focus on conventional Machine Learning (ML), Deep Learning (DL), and more recently using Kolmogorov Arnold Networks [22], has emerged as suitable approaches to meteorological forecasting by processing large amounts of data, recognizing complex patterns and offering adaptive predictions [23]. Several studies have demonstrated the effectiveness of AI-based models in improving wind speed and direction forecasts [24], convective weather events [25], and fog-related visibility reductions [4]. The use of Artificial Neural Networks (ANNs) has proven advantageous for fog forecasting due to their ability to capture non-linear dependencies among atmospheric variables [26]. In addition, ensemble learning methods that combine multiple ML models have been successfully applied to reduce uncertainty and enhance predictive robustness for low visibility forecasting [23].

Despite these advances, important gaps remain. Although AI-driven forecasting methods have shown high accuracy in specific case studies, generalizing these models to diverse airport environments, especially in regions with high variability in weather conditions, is still challenging [27]. Transferability across different airport locations and adaptability to seasonal variations require further exploration. Moreover, many AI-based models currently lack real-time integration with operational air traffic management systems, which subsequently requires coordination with stakeholders. The latency associated with high temporal resolution forecasts, in ranges inferior to 1 hour, particularly for DL models, must be addressed to provide timely and actionable predictions. Furthermore, much of the existing research focuses on either fog formation [4] or convective weather [28] rather than adopting a holistic approach that integrates the multiple phenomena affecting visibility.

Given the increasing frequency of extreme weather events due to climate change [28] and the continued growth of global air traffic [29], there is an urgent need for intelligent visibility forecasting systems that offer accurate, real-time, and generalizable predictions.

This review provides a comprehensive synthesis of state-of-the-art AI methodologies for visibility forecasting in aviation, evaluating their strengths, limitations, and potential for operational integration. By critically assessing recent advancements, identifying key research gaps, and outlining future directions, this review aims to contribute to developing more effective AI-based visibility forecasting solutions tailored to modern airport operations.

The remainder of this paper is structured as follows. Section 2 describes the systematic approach used to identify and evaluate relevant studies, including search strategies, selection criteria, and the snowballing technique employed to expand the scope. Section 3 presents and discusses the key findings, comparing traditional statistical models, ML approaches, and hybrid techniques for visibility forecasting. Finally, section 4 summarizes the main insights and outlines future research directions for AI-driven visibility forecasting in airport operations.

2. Methodology

A systematic approach was implemented to identify and evaluate studies related to visibility forecasting with a focus on airport applications. The methodology comprised three different strings, a technique to broaden the scope of included studies.

2.1. Search strategy and study selection

The main search was conducted on the Google Scholar database on 10 January 2025 using the Boolean queries without temporal restrictions to capture all available literature. Citation results were excluded to prioritize original research articles. For the first string, the search yielded 11 articles, of which nine were retained after a screening process. Two articles were excluded because they focused on the verification of existing forecasting models rather than the development or testing of new methodologies. The second search was conducted,

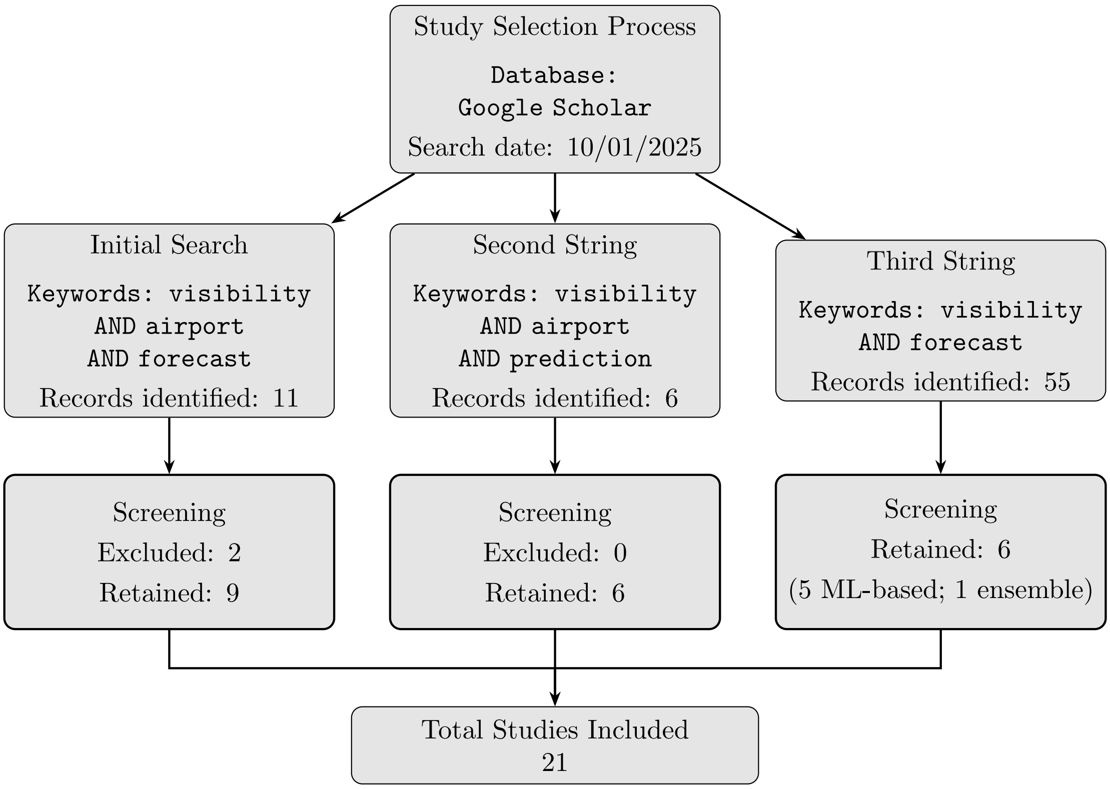

Figure 1. Flowchart illustrating the systematic methodology used for selecting studies on airport visibility forecasting.

switching the term 'forecast' to the term 'prediction', and 6 results were returned, all of which were included after the title and abstract screening process.

To address potential limitations in the specificity of these initial searches, a wider strategy was implemented. The search terms were broadened to 'visibility AND forecast' to identify additional studies not confined to airport contexts. This expanded search generated 55 articles, which were screened for relevance based on title and abstract, for relevance in the field of aeronautics. Six articles were subsequently retained based on title and abstract screening, which was conducted to verify their focus on aviation and artificial intelligence. Among these, five employed ML techniques, aligning with the review's focus on contemporary forecasting approaches. The sixth article, [15], was retained despite its reliance on traditional numerical models and rule-based fog detection methods because it examined ensemble approaches and resolution challenges, which are relevant for advancing ML-based visibility forecasting systems. Figure 1 illustrates the applied methodology, depicting the sequential steps undertaken in the systematic literature review. This visual representation outlines the search strategy, study selection process, and the incorporation of the snowballing technique, providing a clear overview of the methodology employed in identifying and evaluating relevant studies.

2.2. Inclusion and exclusion criteria

Studies were included if they addressed the development, testing, or enhancement of visibility forecasting models and if their methodological approach could contribute to the field of AI-based forecasts in the aeronautic field. Exclusion criteria comprised articles focused solely on forecast verification, those lacking empirical or technical contributions to model development, or those unrelated to visibility prediction. Articles that were not written in English were not considered or included. The final corpus comprised 21 articles.

3. Results and discussion

The reviewed literature on airport visibility forecasting reveals various performances across different approaches. Most studies report key performance metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) [30–32], Pearson correlation (R) [32] or the coefficient of determination (R^2) [33]. Some studies evaluate forecasting skills using scores based on contingency tables, such as the probability of detection (POD), critical success index (CSI), and False Alarm Rate (FAR) among others [34, 35]. Others combine RMSE and MAE metrics with scores derived from contingency tables [36].

Table 1. Summary of Visibility Forecast Studies, with targeted challenges, contexts, and practical considerations.

Study	Method/Model	Results	Res/Lead	Targeted Challenge & Operational Context	Advantages, Limitations & Applicability
[38]	FF-ANN (1 hidden layer) with moving time window, backprop	1 h: 86	1 h / 1 h	Short-range visibility forecasting at Rome airports (Ciampino, Fiumicino, Latina, Viterbo)	+ Outperforms persistence; - Degrades beyond 1 h; seasonal variability; suitable for hourly ops
[39]	LEPS ensemble calibrated by BMA	STL: ROCA 73	1 h / 12 h	Fog-type classification (radiation, advection, stratus) at CDG Airport	+ Reliable STL/RAD; - ADV challenging unless initialized; requires probability thresholds
[15]	Rule-based + ensembles (NAM-12, RUC-13, NMM-32, SREF 21-mem)	NAM-12 POD 0.29; RUC-13 POD 0.24; NMM-32 POD 0.185; ensemble doubled POD	1 h / 1 h	Low-visibility/fog detection over North America (5 000 stations)	+ Ensemble improves fog detection; - baseline models underperform; needs higher resolution
[40]	Deep DNN regression (MLP)	MAE = 706 m overall; 325 m when $\leqslant$ 1 000 m	1 h / 3 h	Hourly visibility at Urumqi Airport (2007-2016)	+ Good low-vis accuracy; - single-site; degrades at high vis; moderate compute
[37]	LSTM with weighted loss	RMSE = 4 708 m overall; 933 m (<1 600 m); 756 m (<800 m)	1 h / 1 h	Low-visibility focus at Beijing station "54511"	+ Outperforms regression/MLP for fog; - high RMSE overall; heavy training
[41]	DFA + MCM + MOE	DFA α = 1.37 (<10 h), 0.97 (>10 h); MOE accuracy >94%	1 h / 1 h	Persistence & short-term RVR at Valladolid Airport	+ Very high short-term accuracy; - limited to <1 h; needs meteorological inputs
[36]	TCN + Transfer Learning	24 h RMSE $\downarrow$ from 9.0 km to 6.2 km; MAE $\downarrow$ 5.2 km $\rightarrow$ 2.0 km; TS +0.11	1 h / 96 h	Offshore visibility in Qiongzhou Strait (ECMWF + obs)	+ Strong TL gains in data-sparse areas; - transfer overhead; best for short term
[42]	SVR-RBF after SPSS correlation	Accuracy 96	24 h / 48 h	Haze visibility at Changsha Huanghua Airport (Mar 2020)	+ Excellent fit; - high SV count (754); computationally heavy; needs factor selection
[32]	XGBoost, LightGBM, RAEMS fusion; SMOTE	24 h RMSE = 5.01 km; 48 h = 5.47 km; CC 0.80/0.77	24 h / 48 h	Urban visibility in Shanghai (2015-2019; pollutants, AOD, synoptics)	+ Outperforms standalone; - RAEMS errors propagate; station-specific variance
[33]	Quadratic regression + stepwise selection	R^2 = 0.912; RMSE = 300.6 m	24 h / 24 h	Airport visibility trends (Dec 2019-Mar 2020)	+ Simple, interpretable; - limited to fitted period; less robust for extremes
[43]	LSTM (PAVPM)	RMSE: 1 148 m (t+1 h) $\rightarrow$ 2 196 m (t+6 h)	1 h / 6 h	Plateau airport visibility in Urumqi (2015-2019 winters)	+ Strong 1-3 h forecast; - degrades >3 h; needs altitude-specific data
[44]	MLR, MPR, AlexNet CNN on video+met	MPR >MLR; CNN error <0.25	1 min / short	Fog visibility estimation via video at airport (15 s frames)	+ Very high precision; - single-day case; needs video infrastructure
[31]	PLS, CART, kNN, LAR, MLP, RF, RR, SGD, SVR	RF best: CC >0.9; lowest RMSE/MAE	1 h / 1 h	Multi-airport (47 China sites, 2010-2020)	+ Generalizable; - model choice site-dependent; data-intensive training
[34]	IMD-GFS + probabilistic weighting (9 params)	24 h POD = 0.92, CSI = 0.68; 48 h POD = 0.79, CSI = 0.49	1 h / 9 h	Fog/visibility at IGI New Delhi (Dec 2020-Jan 2021)	+ Good 24 h skill; - 48 h less reliable; equal weights oversimplify
[45]	PAR, IST, HBR, RANSAC, BRR, ENR, LASSO, ARD, TWD	HBR & RANSAC best; strong vis-pressure/humidity corr.	1 h / 1 h	Vertical met profiles & visibility at 47 intl. airports (2010-2020)	+ Captures vertical effects; - performance varies by site; omits human factors
[46]	Uni/multivariate LSTM & GRU	RMSE: multivariate GRU = 1.078 km (best)	1 h / 12 h	JFK Airport hourly visibility (2010-2018)	+ GRU stability; - rapid vis fluctuations remain challenging; tuning needed
[35]	IMD-GFS deterministic + probability method	24 h POD = 0.92$\rightarrow$0.73; CSI = 0.68$\rightarrow$0.54 across two winters	1 h / 48 h	Seasonal fog at IGI New Delhi (2020-22 winters)	+ Good 24 h consistency; - interannual drop; suggests weighted params
[47]		Accuracy = 93.22			

Table 1. (Continued.)

Study	Method/Model	Results	Res/Lead	Targeted Challenge & Operational Context	Advantages, Limitations & Applicability
	BPNN (24 hidden units) + Min-Max norm		30 min / 30 min	Low-vis event prediction at Juanda Intl., Indonesia	+ Very high short-term accuracy; - limited lead; needs more variables
[30]	26 regressors via GPR (Matern, SE) with CV k=5-15	SZB RMSE = 1.06 km; LGK RMSE = 0.85 km; MAE = 0.73-1.12 km	1 h / 6 h	Subang & Langkawi visibility (Apr-Jun 2023)	+ Identifies best regressor/k; - location-varying errors; CV cost
[48]	WRF-Chem (CBM-Z, MOSAIC) sensitivity tests	RH error ↓ 11.33	24 h / 24 h	Aerosol-meteorology feedback in Sichuan, YRD, NCP (2010)	+ Significant RH/vis gains; - seasonal bias; heavy comp.
[49]	GCN-GRU + mRMR feature selection	6 h: CORR +3.32	1 h / 96 h	Spatiotemporal vis in Jiangsu Province (70 met & 91 env stations)	+ Leverages spatial links; - extreme values; needs dense networks

Note: METAR: Meteorological Terminal Aviation Routine Weather Report, ICAO: International Civil Aviation Organization, NAM-12: North American Mesoscale model, RUC-13: Rapid Update Cycle model, NMM-32: Non-hydrostatic Mesoscale Model, SREF: Short Range Ensemble Forecast, Deep ANN: Deep Artificial Neural Network, LSTM: Long Short-Term Memory, TCN: Temporal Convolutional Network, TCN_TL: Temporal Convolutional Network with Transfer Learning, SVR: Support Vector Regression (with RBF kernel), RBF: Radial Basis Function, XGBoost: Extreme Gradient Boosting, LightGBM: Light Gradient Boosting Machine, RAEMS: Regional Atmospheric Environmental Modeling System, PLS: Partial Least Squares, CART: Classification and Regression Trees, kNN: k-Nearest Neighbors, LAR: Least Angle Regression, MLP: Multi-Layer Perceptron, RF: Random Forest, RR: Ridge Regression, SGD: Stochastic Gradient Descent, IMD-GFS: Indian Meteorological Department Global Forecast System, GRU: Gated Recurrent Unit, GPR: Gaussian Process Regression, SZB: (kernel variant in GPR, labeled SZB), LGK: (kernel variant in GPR, labeled LGK), WRF-Chem: Weather Research and Forecasting model coupled with Chemistry, CBM-Z: Carbon Bond Mechanism, MOSAIC: Model for Simulating Aerosol Interactions and Chemistry, GCN-GRU: Graph Convolutional Network - Gated Recurrent Unit, PhyDNetATT: Physical Dynamics Network with Attention.

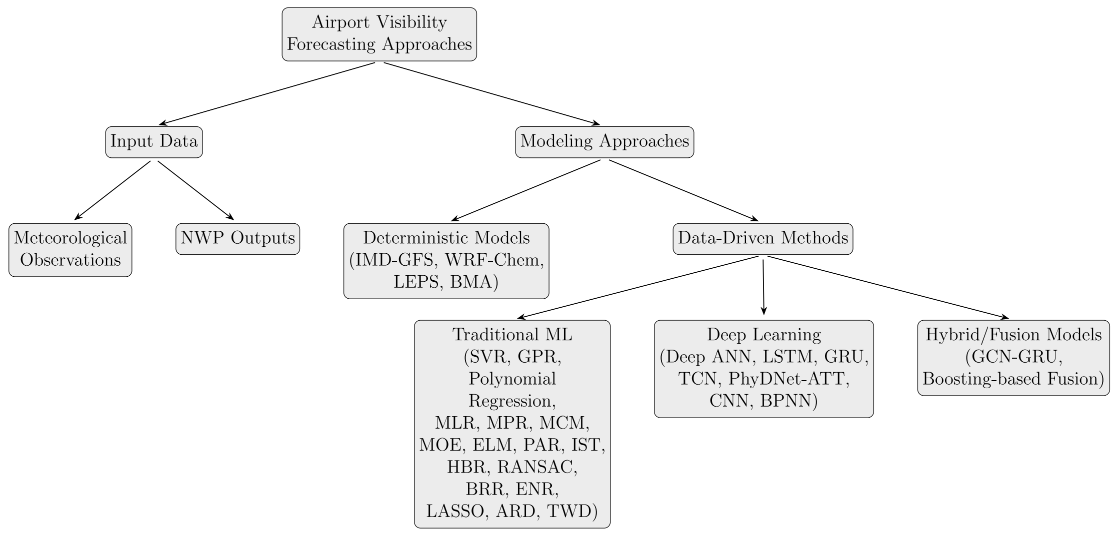

Figure 2. Classification of airport visibility forecasting approaches.

These metrics highlight that forecast performance strongly depends on the forecast lead time or spatial resolution. For example, conventional ML and DL methods have been optimized for short-term predictions (ranging from 1 to 3 hours) as well as for longer forecast windows (up to 48 hours), with some models reporting RMSE reductions down to 756 m under low-visibility conditions [37] and correlation coefficients exceeding 0.9 in 1-h lead time [31]. Classical statistical methods such as quadratic polynomial regression have achieved high R^2 values (up to 0.912) and low RMSE values [33], while Gaussian process regression has demonstrated enhanced performance through optimal kernel and cross-validation strategies [30]. Similarly, these performance trends are summarized in table 1, which outlines each study's methodology, forecast resolution, forecast range, and key results.

Additional observations from these studies highlight several practical considerations in visibility forecasting. For example, Pasini *et al* [38] reported that performance drops as the forecast lead time increases, while Zhou *et al* [15] emphasized that increasing data resolution is needed for accurate fog detection. Zhu *et al* [40] noted the limitations of relying on single-factor models for low visibility, and Deng *et al* [37] demonstrated that their Long Short-Term Memory (LSTM) approach outperforms traditional methods such as polynomial regression, regression trees, and standard ANNs.

Lu *et al* [36] showed that their Temporal Convolutional Network (TCN) model, enhanced with transfer learning, is particularly effective in data-sparse regions, whereas Liu *et al* [42] discussed the high computational cost associated with Support Vector Regression (SVR).

The boosting fusion strategy in Yu *et al* [32] proved especially suitable for low-visibility events, with variations observed between urban and island settings. Air pressure and wind speed were identified as key determinants of visibility by Feng *et al* [33], and Chen *et al* [49] denoted significant importance in incorporating aerosols and humidity variables as features for training and inference. Ding *et al* [31] observed regional impacts on model performance. Arun *et al* [34] attributed forecast inaccuracies to wind speed errors, and Saha *et al* [46] recommended an optimal sequence length of five time steps. Chahar *et al* [35] debated the merits of using equal versus weighted parameter schemes, while Jamaludin *et al* [30] highlighted differences in optimal cross-validation strategies for low visibility conditions. Zhang *et al* [48] and Chen *et al* [49] also underscored the importance of regional considerations and the challenges posed by extreme events.

Recent studies further enrich our understanding of low-visibility forecasting by incorporating persistence analyses, ensemble strategies, and DL approaches. Cornejo-Bueno *et al* [41] demonstrated that integrating persistence-based methods with ML techniques, such as Markov Chain Models and Mixture of Experts, significantly enhances short-term prediction accuracy. Similarly, Roquelaure *et al* [39] used a Local Ensemble Prediction System calibrated via Bayesian Model Averaging to effectively differentiate fog types, though challenges persist for advection fog. Complementing these approaches, Ding *et al* [45] applied advanced regression techniques to capture vertical meteorological trends across multiple airports, highlighting the spatial variability of model performance. Zixuan *et al* [43] and Qian *et al* [44] showcased that DL frameworks, using LSTM and CNN-based methods, respectively, can adeptly address the complex dynamics of short-term visibility changes, particularly under challenging conditions. Finally, moonlight *et al* [47] introduced a real-time BPNN system that offers high accuracy with frequent updates, reinforcing the potential for operational applications in aviation safety. Collectively, these investigations underscore the trend toward combining traditional persistence and ensemble methods with cutting-edge DL techniques to develop more robust, context-sensitive forecasting models.

While table 1 encapsulates the diverse performance metrics and temporal resolutions employed across the reviewed studies, the choice of modeling approach is equally varied. Figure 2 provides a taxonomy of the reviewed methods.

The diversity in modeling approaches shows that the optimal choice depends on operational requirements and data availability. While traditional ML methods and deterministic models offer reliable baseline performance with relatively modest computational costs, advanced DL and hybrid architectures capture the intricate temporal and spatial dependencies of meteorological data, even though they may have higher computational demands, like the SVR (with radial basis function) model's reliance on numerous support vectors [42]. Integrating multiple data sources, such as meteorological observations, pollutant measurements, and satellite-derived aerosol data, has effectively addressed challenges such as data sparsity and temporal variability. These insights show that the evolution of visibility forecasting is driven both by improvements in performance metrics and by innovations in the types of models deployed.

4. Conclusion

This review highlights the progression of intelligent visibility forecasting methods, spanning statistical, ML, and DL techniques for airport operations. Classic statistical tools, like polynomial regression (e.g., [33] achieving $R^2 = 0.912$ and RMSE = 300.6 m for 24 h airport visibility trends), and traditional ML algorithms, such as random forest (e.g., [31] identifying RF as best for multi-airport 1h forecasts with CC >0.9) and SVR, continue to offer robust baselines for short-term forecasting and demonstrate fast inference times. More advanced DL architectures, such as LSTM (e.g., [37] achieving an RMSE of 756m for visibility <800 m at a 1h lead, outperforming regression/MLP for fog) and TCN (e.g., [36] where TCN with Transfer Learning reduced 24h RMSE from 9.0 km to 6.2 km and MAE from 5.2 km to 2.0 km for offshore visibility), capture the temporal and spatial dependencies in visibility data, yielding marked improvements in predictive accuracy [36, 37, 45]. Hybrid and ensemble approaches that incorporate additional inputs, ranging from synoptic weather observations to pollutant and aerosol data, further refine predictions. For instance, the GCN-GRU model by [49] improved 6h forecast correlation by +3.32% and reduced RMSE by 17.5%, while [32] found their RAEMS fusion model (24h RMSE = 5.01 km) outperformed standalone models, particularly in data-sparse or highly variable environments.

In terms of quantitative benchmarks, recent results underscore the potential of ML-based and DL-based models to reach high correlation coefficients and reduced RMSE values. For example, [42] achieved 96% accuracy and 99.7% correlation for 24-48h haze visibility forecasts using SVR-RBF, and [31] reported Random Forest as the best performing model with CC >0.9 for hourly visibility across 47 Chinese airports. Model performance in fog and mist scenarios has improved substantially through specialized frameworks; for example, LEPS ensemble calibrated by BMA [39] achieved ROCA scores of 73% for stratus-type fog and hit rates of 79% for radiation fog at a 12h lead time. Additionally, the integration of atmospheric chemistry models (as in WRF-Chem by [48]) with data-driven corrections has minimized meteorological errors, reducing RH error from 11.33% to 3.88% and visibility deviation by 11.34% for 24h forecasts across several regions.

Variations in how studies define and compute key performance metrics, such as differing performance metrics and disparate validation periods (seasonal versus full-year splits, warm versus cool seasons), pose significant hurdles for meaningful cross-study comparisons. These inconsistencies can lead to inflated or misleading perceptions of model improvements when, in fact, evaluation protocols differ substantially. Developing and adopting standardized metric definitions and common validation frameworks, as proposed by Alves *et al* [50], would be crucial to ensure that the reported advances in precision are transparent and reproducible.

Despite the progress, challenges remain regarding generalization, model interpretability, and computational cost. Many algorithms still struggle with highly dynamic conditions (e.g., rapid onset of fog or mist) and may exhibit diminished skill over extended (24–48 hours) lead times, as seen with [35] where 24h POD dropped from 0.92 to 0.73 across two winters. Future research should (i) intensify efforts to unify evaluation protocols by adopting standardized definitions using RMSE, MAE, correlation, and based on contingency tables, so that a fair comparison across studies is achievable; (ii) clearly stratify results under various low-visibility conditions (as fog, mist, and haze) to better discern performance in each scenario; and (iii) explore additional data streams, such as satellite-based aerosol estimates and video data (e.g., [44] achieving <0.25% error with CNN on video), to address limitations in data coverage and resolution [47].

Moving forward, refinements in ANNs architectures and the strategic application of transfer learning, ensemble methods, and physics-aware models promise to deliver more robust, context-sensitive forecasts [36, 49]. Thus, the next generation of visibility prediction systems can lead to substantial enhancements in safety and operational efficiency for airport stakeholders.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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