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ADVANCING AVIATION METEOROLOGY: AIRPORT VISIBILITY PREDICTION USING RANDOM FOREST REGRESSOR ON INTEGRATED METAR PARAMETERS

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Abstract. To provide accurate and reliable visibility information in support of aviation safety at Soekarno-Hatta International Airport, a visibility prediction system was developed using the Random Forest Regressor algorithm based on 2024 METAR data. Visibility is a critical parameter for flight safety, particularly under adverse weather conditions. The dataset includes wind direction and speed, temperature, dew point, air pressure, weather phenomena, and cloud parameters that were numerically encoded. After preprocessing and quality control, the data was input into a Random Forest model optimized using Grid Search. Evaluation results show strong predictive performance with an R^2 value of 0.8736, MAE of 607.45 m, and RMSE of 772.29 m. Feature importance analysis identified haze, temperature, and mist as the most influential factors affecting visibility. These findings demonstrate that integrating meteorological observational data with machine learning approaches can provide accurate visibility predictions to support aviation operational decision-making.

Keywords: airport visibility, METAR, random forest, machine learning.

Abstrak. *Untuk menyediakan informasi visibilitas yang akurat dan dapat diandalkan dalam mendukung keselamatan operasional penerbangan di Bandara Soekarno-Hatta, maka dilakukan pembuatan sistem prediksi visibilitas berbasis algoritma Random Forest Regressor menggunakan data METAR tahun 2024. Visibilitas merupakan parameter krusial dalam keselamatan penerbangan, terutama dalam kondisi cuaca buruk. Data yang digunakan meliputi arah dan kecepatan angin, suhu, titik embun, tekanan udara, fenomena cuaca, dan parameter awan yang telah dikodekan secara numerik. Setelah melalui proses prapemrosesan dan quality control, data dimasukkan ke dalam model Random Forest yang telah dioptimasi melalui teknik Grid Search. Hasil evaluasi menunjukkan bahwa model memiliki kinerja prediktif yang sangat baik dengan nilai* R^2 *sebesar 0.8736, MAE 607.45 m, dan RMSE 772.29 m. Analisis feature importance mengidentifikasi haze, suhu, dan mist sebagai faktor dominan yang mempengaruhi visibilitas. Hasil ini menunjukkan bahwa integrasi data observasi meteorologi dengan pendekatan machine learning mampu memberikan prediksi visibilitas yang akurat untuk mendukung keputusan operasional penerbangan.*

Kata kunci: *visibilitas bandara, METAR, random forest, machine learning.*

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1. Introduction

The safety and efficiency of modern aviation operations depend heavily on atmospheric conditions. Airport visibility plays an important role for aviation meteorology as it is useful in the process of aircraft take-off and landing, especially in bad weather [1]. Atmospheric phenomena such as fog, heavy rain, dust, or smoke can cause a decrease in visibility, which is often the main reason for flight cancellations and delays as a result, accurate and timely visibility prediction is essential for effective air traffic management and flight safety.

So far, visibility prediction is usually done using deterministic methods based on numerical models or with simple statistical approaches [2]. Numerical methods such as NWP (Numerical Weather Prediction) often require high computation and have spatial and temporal resolutions that are not detailed enough for airport prediction needs [3]. On the other hand, classical statistical approaches are often unable to understand the complex relationships between meteorological components that affect visibility. Therefore, an alternative approach is needed that can understand the nonlinear and complex relationships between weather variables.

Machine learning approaches have shown great potential in modelling atmospheric phenomena in recent years [4]. These approaches include the prediction of weather parameters that depend on surface observations, such as METAR data. Algorithms such as Random Forest Regressor have the ability to handle very large datasets and discover nonlinear patterns, and they can provide excellent predictions without strict statistical distribution assumptions [5]. In addition to providing accurate and important estimates for each input parameter, Random Forest also has the advantage of overcoming multicollinearity between features [6]. As a result, this method is considered suitable for visibility prediction involving many meteorological variables with complex and non-linear dynamics.

METAR data routinely generated by meteorological stations at airports provides a comprehensive picture of the current weather conditions, including atmospheric pressure, temperature, dew point, wind direction and speed, significant weather events, and details on cloud formations [7]. If this data is analysed in a structured way through machine learning techniques, it can be used as a predictor of visibility determination. Previous research has shown that the incorporation of METAR parameters has a strong relationship with actual visibility values, especially during extreme weather conditions [8]. By using this data as input, the Random Forest-based visibility prediction model is expected to provide more precise and relevant prediction results in the context of flight operations.

This research aims to develop an airport visibility prediction model using Random Forest Regressor by utilising a comprehensive integration of METAR parameters from Soekarno Hatta Class I Meteorological Station. By analysing the complex relationships between various meteorological parameters such as air pressure, temperature, dew point, wind direction, wind speed, and weather phenomena, total cover, and cloud base height, this research is expected to produce an accurate and reliable prediction system to support operational decision making in the aviation world. The implementation of an effective visibility prediction model will contribute significantly to improving flight safety, airport operational efficiency, and reducing the economic impact of weather disruptions on the aviation industry.

2. Research Methods

2.1 Data Preparation

To determine visibility prediction, this study utilizes METAR data obtained from the Soekarno -Hatta Meteorological Station. The METAR reports are routinely collected at 30 minute intervals to represent atmospheric conditions within each respective time segment. This research employs METAR data from the year 2024 to assess visibility conditions at Soekarno-Hatta International Airport during that period. Each METAR entry contains various meteorological parameters, including observation time, wind direction (°), wind speed (knots), visibility (m), weather phenomena, cloud cover (oktas), lowest cloud base height (feet), air temperature (°C), dew point temperature (°C), sea-level pressure (mb), and trend forecast.

The METAR data were systematically retrieved from the official website web-aviation.bmkg.go.id and compiled in a Microsoft Excel workbook in .xlsx format. The dataset comprises 30-minute interval METAR reports from Soekarno-Hatta Meteorological Station (WIII) throughout 2024. The raw data were organized by parameter into separate columns, which include visibility (vis), wind direction (wind_d), wind speed (wind_s), temperature (temp), dew point (dew_point), sea-level pressure (press), cumulonimbus cloud presence (cb), rain (rain), thunderstorm (ts), haze (haze), mist (mist), cloud cover category (cloud), and cloud base height (height).

Quality control was conducted to ensure format consistency and completeness, including cross-verification and removal of empty or NIL METAR entries. Weather conditions were further categorized to assess their potential influence on visibility values. These include Haze (HZ), Mist (BR), Rain (RA), and Thunderstorm (TS), with each condition represented in binary value. The value 1 denotes the presence of the condition and 0 indicates its absence. The presence of cumulonimbus clouds was encoded in the same binary manner, with 1 indicating observation and 0 indicating non-observation. Cloud cover classifications were also numerically encoded; the code FEW corresponds to the value 1, SCT to 2, BKN to 3, and OVC to 4. In contrast, cloud codes such as NSC representing no significant cloud, NCD indicating no cloud detected, and SKC referring to sky clear were uniformly represented with the value 0. The dataset, once finalized and structured through this encoding process, was then utilized as the input for the Random Forest Regressor model.

2.2 Random Forest Regressor Algorithm

Random Forest Regressor, as a robust ensemble learning algorithm, has been proven effective in handling datasets with diverse features and complex non-linear relationships among variables [9]. Figure 1 illustrates the decision tree structure used for decision-making processes, wherein data sharing similar classification characteristics are iteratively partitioned through a series of tree splits based on attribute-specific features. This recursive partitioning allows data to be categorized effectively. Although a single suboptimal decision tree may yield inconsistent and random predictions, the aggregation of multiple trees in a forest leads to more stable and accurate outcomes. As demonstrated by [10], random forests do not overfit as the number of trees increases, and their generalization error converges to a limit, making them a reliable method for both classification and regression tasks.

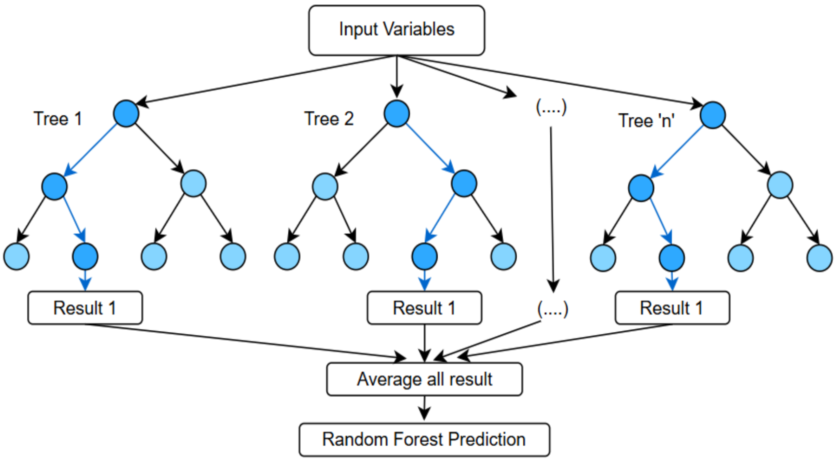

Figure 1. Random Forest Algorithm

In the decision-making process, the Random Forest model performs multiple iterations, denoted by k, resulting in a sequence of classifications represented $\{h_1(x), h_2(x), ... h_k(x)\}$ which are then aggregated to classify the input data according to Equation (1).

$$H(x) = \arg max \sum_{i=1}^{k} I(h_i(x) = X_i) \quad (1)$$

In this equation, $H(x)$ denotes the final aggregated classification result produced by the ensemble model, h_i represents an individual decision tree classifier within the forest, and X_i is the actual output class. The function I is an indicator function that returns 1 if the prediction $h_i(x)$ is equal to the true class Y, and 0 otherwise.

This study developed a Random Forest Regressor model using Python 3.10 on the Google Colab platform. The hyperparameter settings presented in Table 1 were determined through an iterative process based on Grid Search process to identify the parameter combination yielding optimal performance. This method is widely adopted for model optimization due to its systematic exploration of the parameter space. The configuration employed 100 decision trees (n_estimators), a value shown to be sufficient for error stabilization without imposing excessive computational burden [10]. The splitting criterion (criterion) is set to 'squared_error', appropriate for regression tasks. The tree depth is limited to 40 (max_depth), with a minimum of 10 samples required for each split (min_samples_split=10), and no minimum constraint on the number of samples per leaf (min_samples_leaf=1). The number of features considered at each split is restricted to the square root of the total number of features (max_features='sqrt') to enhance ensemble diversity. Bootstrap sampling is enabled (bootstrap=True), and reproducibility is ensured through a fixed random state (random_state=42). Additional settings include warm_start=True for iterative efficiency, no complexity pruning (ccp_alpha=0.0), and no sampling restriction (max_samples=None). This configuration balances the bias-variance trade-off and computational efficiency, in accordance with empirical recommendations [11].

Table 1. Hyperparameters setting

Hyperparameters	Value
n_estimators	100
criterion	squared_error
max_depth	40
min_samples_split	10
min_samples_leaf	1
min_weight_fraction_leaf	0.0
max_features	sqrt
max_leaf_nodes	None
min_impurity_decrease	0.0
bootstrap	True
random state	42
verbose	0
warm_start	True
ccp_alpha	0.0
max_samples	None

2.3 Model Evaluation

The evaluation of model performance involves the calculation of several accuracy and error metrics. Performance assessment in machine learning requires a multidimensional approach by employing various metrics that offer a comprehensive perspective on the model's predictive capability. Mean Squared Error (MSE), as shown in Equation (2), quantifies the average squared deviation between predicted and actual values. It is sensitive to outliers and can reveal systematic biases in the model [12].

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2 \tag{2}$$

Root Mean Squared Error (RMSE) is the square root transformation of MSE producing an error value in the same unit as the original data which facilitates practical interpretation of prediction accuracy, particularly for visibility expressed in meters [13].

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \tag{3}$$

In addition, Mean Absolute Error (MAE), as presented in Equation (4), calculates the average of absolute differences between predicted and actual values. MAE offers an intuitive measure of error and is less affected by outliers, making it a relevant metric in visibility prediction, where accurate estimation across both low and high visibility values is equally critical [12].

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i| \tag{4}$$

Meanwhile, the coefficient of determination (R^2) shown in Equation (5), represents the proportion of variance in the observed data that can be explained by the model. An R^2 value close to 1 indicates a strong predictive capability in capturing actual data patterns [14]. In the context of airport visibility prediction, this combination of metrics validates the operational reliability of the model in supporting flight safety, particularly in critical low-visibility scenarios [15].

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\bar{Y} - Y_i)^2} \tag{5}$$

In these equations, X_i denotes the predicted value generated by the model, while Y_i represents the actual observed value. The term $\bar{Y}$ is the mean of all observed values, and m refers to the total number of samples in the dataset. These metrics are collectively employed to evaluate the model's performance in predicting visibility based on meteorological observation data.

3. Results and Discussion

The distribution of visibility value at Soekarno-Hatta Airport is represented using the Q-Q plot shown in Figure 2. The results show a tendency towards normal distribution in the middle quantile, as most of the visibility values are around the diagonal line. However, the upper quantile shows significant deviation, indicating that there is positive skewness in the data. The censoring process at the maximum visibility value in the METAR data of 10,000 metres is responsible for [16], [17] this condition. This kind of censoring in airport meteorological observations is caused by limitations of visibility observation instruments or reporting standards, which restrict the maximum recorded value, even though actual visibility may exceed that threshold [16], [17]. Data pengukuran yang dimaskud ditampilkan pada Tabel 1.

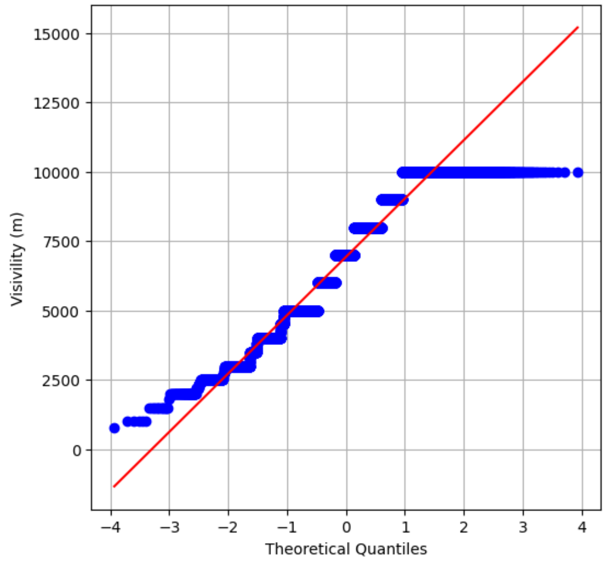

Figure 1. Distribution of visibility in Soekarno Hatta Airport

As shown in this Q-Q plot, distributional conditions that deviate from normality have a significant impact on the applicability and selection of predictive models. Random Forest Regressor is non-parametric and does not require a normal target distribution. However, the accumulation of values at the maximum limit can cause bias in model estimation, especially when using plateau or outlier data [18]. Therefore, to improve the reliability of the estimates, pre-processing approaches such as logarithmic transformation or the use of censored regression models should be considered [19].

Figure 3. shows the results of the feature importance analysis of the Random Forest Regressor model used to predict visibility. The results show that haze is the variable that contributes the most to visibility estimation, with haze contributing the most to temp, mist, and wind speed. Previous studies have shown that particles such as mist and fine dust (haze) suspended in the atmosphere play an important role in reducing horizontal visibility, especially at airports in tropical environments with high humidity levels [20]. In addition, wind speed and temperature are also highly influential as they are directly related to the capacity of air to hold water vapour and the efficiency of particle dispersion in the atmosphere [21]. In ensemble learning-based predictive models, the systematic integration of METAR variables is supported by the strong correlation between visibility values and thermodynamic features.

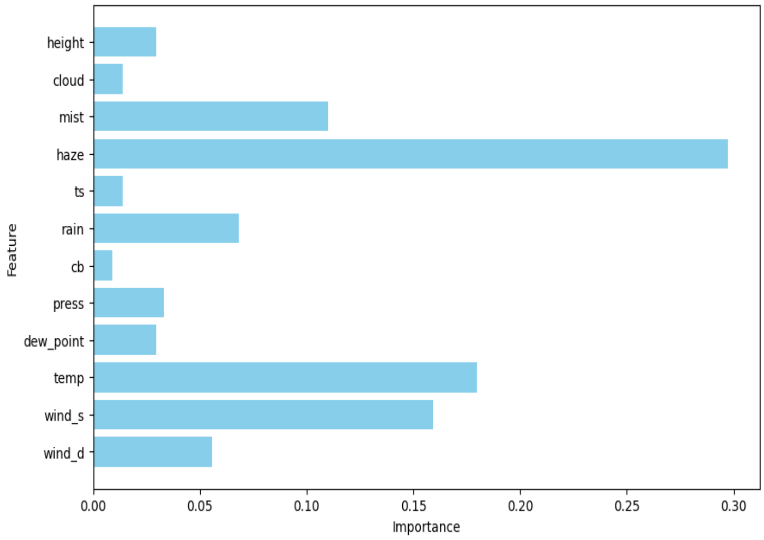

Figure 3. Feature importance of random forest regressor model

The comparison of actual visibility values with predicted values is shown in the visualisation of Figure 4. This value illustrates the ability of the model to replicate the variability pattern of the visibility parameter based on the selected METAR data; most data points are close to the y = x line. However, the higher the visibility value (more than 8,000 m), the spread of observations shows a systematic bias so that the predictions tend to be below the actual value, and the vertical spread widens. This shows the limitation of the model in capturing extreme visibility [22]. This pattern corresponds to the distribution of censored targets, which is shown in the Q-Q plot (Figure 2). This is due to the fact that the maximum reporting limit of METAR is 10,000 m.

As dominant features such as haze, mist, and temperature work better to explain low to moderate visibility conditions, the model faces difficulties in the high visibility range (Figure 3). The new study shows that, in addition to the Random Forest approach, using group methods or combining post-processing techniques with specific probabilistic models can help overcome the censoring effect [23]. For example, considering the upper limit of visibility, a mixture of distribution models (gamma and truncated normal) can reduce prediction bias and improve the reliability of estimates in extreme domains [24]. In addition, it has been shown that data fusion of atmospheric variables such as visibility trend and relative humidity can improve the prediction accuracy in low visibility situations [25].

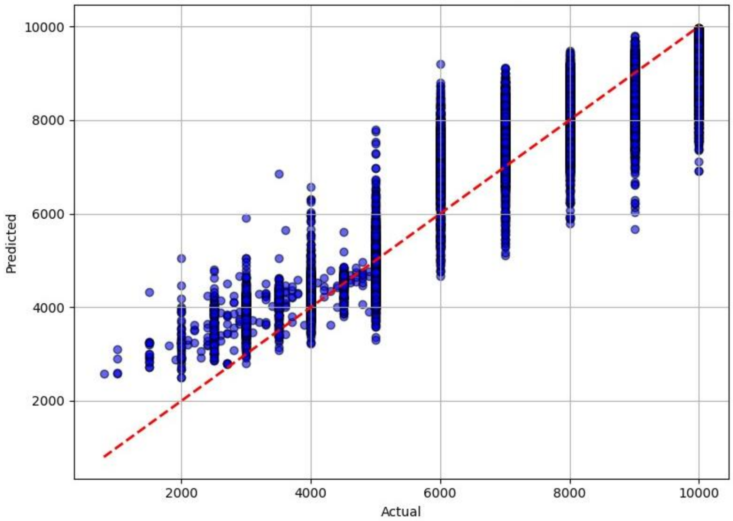

Figure 4. Comparison of actual and predicted data

The dominant distribution of visibility targets at high values (more than 6,000 m) in both training and test data, with a peak distribution in the 10,000 m category is represented in Figure 5. This favourable skewness suggests that most visibility observations at Soekarno-Hatta Airport occur in sunny conditions. Figure 2 shows the tendency of the Random Forest model for overfitting in the high visibility domain, while Figure 4 shows the distribution mismatch between the low (<4,000 m) and high visibility classes. In addition, Figure 4 shows that there is difficulty in accurately describing the dynamics of low visibility, also known as low-high bias [26].

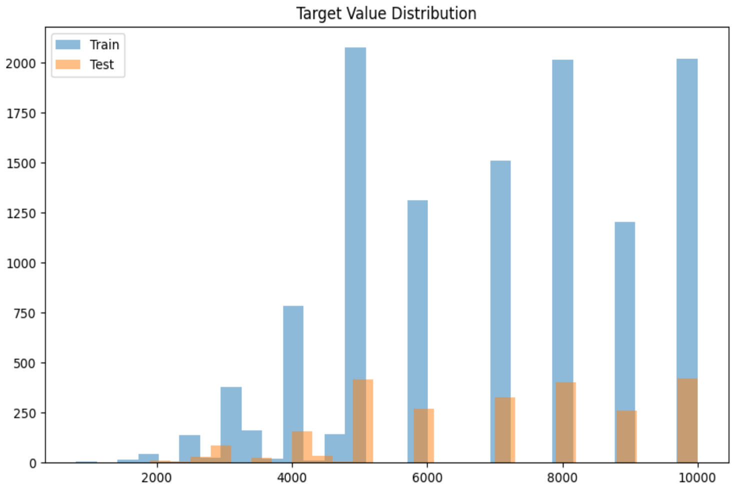

Figure 5. Target value distribution

These distribution characteristics implicitly indicate that atmospheric regression modelling of censored variables faces many problems. According to recent studies, such as [27] and [28], the imbalance of the target distribution may decrease the sensitivity of the model to minority classes and may also obscure important features in tree selection-based models. To address this, label transformation techniques such as monotonic binning and quantile regression have been shown to be effective in aligning the train-test distribution and improving accuracy across the visibility range [29], [30].

The performance evaluation results of the Random Forest Regressor model for visibility prediction at Soekarno-Hatta Airport are presented in Table 1. With a high coefficient of determination (R2 = 0.8736), the model can explain about 87% of the total variability of visibility data. This indicates that the model has an excellent level of fit in terms of operational meteorological predictions. This performance is in line with the results of [31], who stated that the Random Forest model shows significant capability in non-linear multivariate regression, especially in terms of complex interactions between atmospheric parameters such as temperature, humidity, and haze concentration.

Table 1. Random Forest Regressor Evaluation

Model Evaluate	Score
MSE	596427.62
RMSE	772.29
MAE	607.45
R^2	0.8736

In addition, the mean prediction deviation (RMSE) value of 772.29 and the mean accurate value (MAE) of 607.45 indicate that the mean prediction deviation is within the range of ±600-770 metres from the observed values. The smaller MAE value indicates that the model error is generally stable, although the RMSE value indicates the presence of extreme predictions (outliers) that are quite far from the actual values. According to [32], the difference between RMSE and MAE in environmental regression models is an important metric to evaluate the stability of predictions to extreme variability. Then, the mean square error (MSE) value of 596,427.62 indicates that the accumulated square error is still within a reasonable threshold according to [33], given a visibility scale of 10,000 metres.

4. Conclusions

The developed Random Forest Regressor model demonstrates high predictive capability in estimating airport visibility using integrated METAR parameters. With a coefficient of determination reaching 0.8736, the model reliably captures visibility patterns across various meteorological conditions, particularly under low-to-moderate visibility scenarios. However, limitations remain in predicting high visibility values due to target distribution censoring. Feature importance analysis confirms the dominant influence of haze, mist, temperature, and wind speed. These results emphasise the practical applicability of machine learning for aviation meteorology, offering a robust tool to enhance flight safety and operational efficiency in environments with dynamic atmospheric variability.

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References

1. Kwasiborska, M. Grabowski, A. N. Sedláčková, and A. Novák, “The influence of visibility on the opportunity to perform flight operations with various categories of the instrument landing system,” Sensors, vol. 23, no. 18, p. 7953, 2023.

2. K. Ait Ouadil, S. Idbraim, T. Bouhsine, N. Carla Bouaynaya, H. Alfergani, and C. Cliff Johnson, “Atmospheric visibility estimation: a review of deep learning approach,” Multimed Tools Appl, vol. 83, no. 12, pp. 36261–36286, 2024.
3. S. G. Benjamin et al., “A North American hourly assimilation and model forecast cycle: The Rapid Refresh,” Mon Weather Rev, vol. 144, no. 4, pp. 1669–1694, 2016.
4. T. Arcomano, I. Szunyogh, J. Pathak, A. Wikner, B. R. Hunt, and E. Ott, “A machine learning‐based global atmospheric forecast model,” Geophys Res Lett, vol. 47, no. 9, p. e2020GL087776, 2020.
5. Y. Zhang, Y. Wang, Y. Zhu, L. Yang, L. Ge, and C. Luo, “Visibility prediction based on machine learning algorithms,” Atmosphere (Basel), vol. 13, no. 7, p. 1125, 2022.
6. J. Y.-L. Chan et al., “Mitigating the multicollinearity problem and its machine learning approach: a review,” Mathematics, vol. 10, no. 8, p. 1283, 2022.
7. D. Nyberg, “Development of weather services for aviation personnel,” 2021.
8. S. H. Alhathloul, A. K. Mishra, and A. A. Khan, “Low visibility event prediction using random forest and K-nearest neighbor methods,” Theor Appl Climatol, vol. 155, no. 2, pp. 1289–1300, 2024.
9. N. Penov and G. Guerova, “Sofia airport visibility estimation with two machine-learning techniques,” Remote Sens (Basel), vol. 15, no. 19, p. 4799, 2023.
10. L. Breiman, “Random Forests,” Mach Learn, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.
11. P. Probst, M. N. Wright, and A. Boulesteix, “Hyperparameters and tuning strategies for random forest,” Wiley Interdiscip Rev Data Min Knowl Discov, vol. 9, no. 3, p. e1301, 2019.
12. C. J. Willmott and K. Matsuura, “Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance,” Clim Res, vol. 30, no. 1, pp. 79–82, 2005.
13. T. Chai and R. R. Draxler, “Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature,” Geosci Model Dev, vol. 7, no. 3, pp. 1247–1250, Jun. 2014, doi: 10.5194/gmd-7-1247-2014.
14. D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” PeerJ Comput Sci, vol. 7, p. e623, 2021.
15. I. Gultepe et al., “A Review of High Impact Weather for Aviation Meteorology,” Pure Appl Geophys, vol. 176, no. 5, pp. 1869–1921, 2019, doi: 10.1007/s00024-019-02168-6.
16. I. Gultepe et al., “Fog research: A review of past achievements and future perspectives,” Pure Appl Geophys, vol. 164, no. 6, pp. 1121–1159, 2007.
17. D. Bari, T. Bergot, and R. Tardif, “Fog decision support systems: A review of the current perspectives,” Atmosphere (Basel), vol. 14, no. 8, p. 1314, 2023.
18. Z. Yu, Y. Qu, Y. Wang, J. Ma, and Y. Cao, “Application of machine-learning-based fusion model in visibility forecast: A case study of Shanghai, China,” Remote Sens (Basel), vol. 13, no. 11, p. 2096, 2021.
19. M. Zhen et al., “Application of a fusion model based on machine learning in visibility prediction,” Remote Sens (Basel), vol. 15, no. 5, p. 1450, 2023.

20. K. Chandu, A. Dharmaraju, S. V. J. Kumar, Gc. Satyanarayana, and M. Dasari, “Determinants and impact of fog, mist and haze phenomena: the case of Rajiv Gandhi International Airport, Hyderabad,” Mausam, vol. 74, no. 1, pp. 19–28, 2023.
21. N. Ravshanov, T. R. Shafiev, and S. Daliev, “Study of the main factors affecting the spread of aerosol particles in the atmosphere,” in Journal of Physics: Conference Series, IOP Publishing, 2021, p. 12083.
22. J. He, W. Wang, M. Fu, and Y. Wang, “Insights into global visibility patterns: Spatiotemporal distributions revealed by satellite remote sensing,” J Clean Prod, vol. 468, p. 143069, 2024.
23. A. Gul, M. Mohsin, M. Adil, and M. Ali, “A modified truncated distribution for modeling the heavy tail, engineering and environmental sciences data,” PLoS One, vol. 16, no. 4, pp. e0249001, 2021.
24. S. Jewson, T. Sweeting, and L. Jewson, “Reducing reliability bias in assessments of extreme weather risk using calibrating priors,” Adv Stat Climatol Meteorol Oceanogr, vol. 11, no. 1, pp. 1–22, 2025.
25. C. Zhang et al., “Weather visibility prediction based on multimodal fusion,” IEEE Access, vol. 7, pp. 74776–74786, 2019.
26. M. Zarei, M. Najarchi, and R. Mastouri, “Bias correction of global ensemble precipitation forecasts by Random Forest method,” Earth Sci Inform, vol. 14, no. 2, pp. 677–689, 2021.
27. M. Wasikowski and X. Chen, “Combating the small sample class imbalance problem using feature selection,” IEEE Trans Knowl Data Eng, vol. 22, no. 10, pp. 1388–1400, 2009.
28. L. Wang, M. Han, X. Li, N. Zhang, and H. Cheng, “Review of classification methods on unbalanced data sets,” IEEE Access, vol. 9, pp. 64606–64628, 2021.
29. J. Cherian, I. Gibbs, and E. Candes, “Large language model validity via enhanced conformal prediction methods,” Adv Neural Inf Process Syst, vol. 37, pp. 114812–114842, 2024.
30. H. Khandor, R. Y. Dhurandhar, D. Shah, and N. Batra, “Distribution-Free Uncertainty Quantification and Calibration for Energy Disaggregation,” ACM Journal on Computing and Sustainable Societies, 2025.
31. A. Shankar and B. C. Sahana, “Early warning of low visibility using the ensembling of machine learning approaches for aviation services at Jay Prakash Narayan International (JPNI) Airport Patna,” SN Appl Sci, vol. 5, no. 5, p. 132, 2023.
32. A. Murad, F. A. Kraemer, K. Bach, and G. Taylor, “Probabilistic deep learning to quantify uncertainty in air quality forecasting,” Sensors, vol. 21, no. 23, p. 8009, 2021.
33. M. A. Rehman, N. Abd Rahman, A. N. H. Ibrahim, N. A. Kamal, and A. Ahmad, “Estimation of soil erodibility in Peninsular Malaysia: A case study using multiple linear regression and artificial neural networks,” Heliyon, vol. 10, no. 7, 2024.