

Article

Air quality index forecasting under seasonal and long-term environmental dynamics

Shivani Jain*

Department of Computer Science and Applications, Madhya Pradesh – 458001, India

* Corresponding Author: shivani.jain@meu.edu.in

ABSTRACT

The Air Quality Index (AQI) indicates air pollution levels and their associated risks to human health and the environment. Factors influencing AQI include temperature, humidity, wind, precipitation, air pressure, seasonal variations, changes in industrial and urbanization patterns, and major pollutants such as PM_{2.5}, PM₁₀, NO₂, SO₂, CO, and O₃. This paper discusses AQI geography and timing, as well as the relationship between air pollution and climate systems. It gives special attention to seasonal fluctuations and regional differences in pollution, dispersion, radiative forcing, short-lived climate pollutants, deforestation, and urbanization. The study also addresses seasonal and long-term environmental variations that affect pollutant levels and AQI. The study recognizes the importance of AQI forecasting for pollution assessment, public information, health protection, resource allocation, enforcement, location ranking, trend analysis, and timely assessment. The assessment also highlights key challenges, including potential variation in pollutant locations, monitoring difficulties, data reliability, the lack of direct studies on air quality indexes, and limited validation for real-time applications. To develop efficient air-quality management plans and provide precise, trustworthy air-quality forecasts, it is crucial to understand these environmental and temporal factors.

Keywords: *Air pollution, Air Quality Index (AQI), Environmental dynamics, Seasonal variation, Spatial variation, Pollution dispersion*

Received: 02 August 2026

Received in revised form: 24 September 2026

Accepted: 16 October 2026

DOI: [10.55670/fpll.fer.1.1.5](https://doi.org/10.55670/fpll.fer.1.1.5)

1. INTRODUCTION

The environment plays a fundamental role in sustaining human life and maintaining public health. However, increasing urbanization, industrialization, and anthropogenic activities have contributed to growing environmental degradation [1]. The urgency of understanding, tracking, and addressing environmental factors that affect health is underscored by the serious risks these changes pose to human well-being. Air pollution is a global environmental crisis, and city dwellers are especially at risk for its harmful health impacts. Epidemiological research over the last several decades has shown that higher air pollution levels harm human health. Studies show that extended exposure to ambient air pollutants increases the risk of developing airborne illnesses, including cardiovascular disease, respiratory disease, and lung cancer [2]. Researchers in both industrialized and developing nations believe that air pollution is a major cause of illness. The AQI is a real-time, objective indicator of air pollution levels and their impact on human health. Although all EU

member states must abide by the same air quality laws, no standard AQI has been established, and each nation uses its own [3]. In Italy, a decentralized network of 21 regional environmental protection agencies (ARPAs) monitors and manages air quality, with the national-level agency (National System for the Environmental Protection, SNPA) coordinating these efforts. The AQI is developed using pollutant criteria that compare short-term average concentrations with the short-term limit values set by current legislation. The calculation may vary slightly between different Italian regions, but the basic principle remains the same [4]. The machine learning (ML) approach is quite precise and consistently predicts the AQI under all environmental circumstances. ML enables us to produce more precise AQI forecasts because of the growing amount of historical data available for research. The more they prove themselves to be a solid alternative to traditional statistical models in time-series forecasting, the more popular they become. Pollutant concentrations follow highly nonlinear processes, and our understanding of them is limited, making it challenging to build a statistical model

that can forecast such occurrences [5]. ML models are nonparametric and nonlinear, and they can produce more accurate predictions by learning associations among independent variables from historical data alone.

Seasonal and long-term environmental dynamics significantly influence air quality and the accuracy of AQI forecasting models [6]. Pollutant levels fluctuate with temperature, humidity, precipitation, wind velocity, solar irradiance, air pressure, and emission trends, resulting in varying pollution intensities across winter, summer, monsoon, and other seasonal periods [7]. Long-term trends in pollutant emissions, driven by climate variability, urbanization, industrialization, traffic growth, and shifts in emission sources, can further alter pollutant distributions and trends [8]. These changes produce highly non-stationary, dynamic air quality data, limiting confidence in models trained in a particular environmental context. Thus, models that capture seasonal cycles, temporal responses, and long-term environmental variations are needed to ensure high forecasting quality across periods and environments and meet the needs of effective ML-based AQI forecasting.

1.1 Structure of the paper

The paper is organized as follows: Section 2 discusses AQI and environmental dynamics. Section 3 explores seasonal and long-term environmental variations. Section 4 presents ML-based AQI forecasting, applications, and challenges. Section 5 examines recent research and identifies existing research gaps. Finally, Section 5 concludes the paper and highlights future research directions.

2. AIR QUALITY INDEX AND ENVIRONMENTAL

Air pollutant levels, including PM_{2.5}, PM₁₀, O₃, NO₂, SO₂, and CO, are the primary determinants of AQI. A wide range of climatic variables, including humidity, precipitation, temperature, wind speed and direction, and air pressure, affect the AQI. Air-quality conditions are variable in space and time because of seasonal variations, urbanization, industrial emissions, and climate variability.

2.1 Air quality index

The AQI is a standardized numerical indicator that translates concentrations of major air pollutants into an easy-to-understand number that reflects air pollution levels and health risks. The AQI is typically calculated by comparing the highest pollutant sub-index to the others, as shown in Figure 1. Air quality declines, and potential health impacts increase when the AQI is high [9].

Air pollution components and AQI formation: AQI is based on concentrations of major pollutants, including PM_{2.5}, PM₁₀, NO₂, SO₂, CO, and O₃. Sources include fuel burning, industrial processes, transportation, atmospheric reactions, and construction [10]. Emission sources, meteorological conditions, and seasonal variations affect overall AQI levels.

Influence of air pollution on meteorology: Atmospheric conditions and air pollution are closely linked, and air pollution can influence local weather and climate by changing the radiation balance [11]. Scattering and absorption of solar radiation can reduce surface temperature while warming upper atmospheric layers,

increasing atmospheric stability and affecting pollutant dispersion.

Seasonal variation in air pollutants: PM₁₀ and PM_{2.5} varied seasonally relative to O₃, SO₂, NO₂, and CO, respectively. Furthermore, a variance analysis compared seasonal changes in the AQI of numerous contaminants [12]. Most pollutants varied significantly across the tests. The findings indicate that several air pollutants show strong seasonal patterns, emphasizing the need for ongoing air quality monitoring and seasonally adaptive policy.

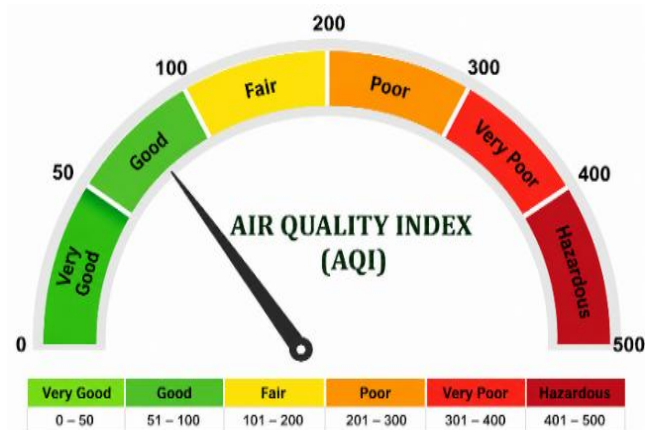


Figure 1. Air Quality Index (AQI)

2.2 Air pollution–climate system dynamics

Air pollution contributes to global warming through several channels, including SLCPs, GHG emissions, and human-caused land-use changes [13]. Several human activities increase particulate matter and ozone-precursor levels in the atmosphere, including burning fossil fuels, clearing land for agriculture and other industrial uses, and rising atmospheric greenhouse gas concentrations. Figure 2 shows how these air mass components create feedback loops between pollution and climate change by influencing regional weather patterns, clouds, radiative balance, and atmospheric chemistry.

Radiative forcing from particulate matter and greenhouse gases: These air pollutants affect Earth's climate system through radiative forcing. These pollutants trap long-wave infrared radiation in the atmosphere, impeding its escape to space and thereby increasing the greenhouse effect from GHGs such as CO₂, CH₄, and N₂O [14]. With a long atmospheric lifetime, CO₂, emitted mainly by burning fossil fuels, contributes most to positive radiative forcing. In contrast, gases such as nitrous oxide and methane may persist in the atmosphere in relatively low concentrations but possess higher GHG potentials than CO₂.

Short-lived climate pollutants: SLCPs, or short-lived climate pollutants, underpin the link between air pollution and climate change. Despite carbon dioxide's (CO₂) long atmospheric lifetime, short-lived climate pollutants (SLCPs) can exert substantial radiative forcing over the same time span, even though they remain in the atmosphere for only a few days to a few decades [15]. However, SLCPs do not last forever, and major pollutants like methane, black carbon, and tropospheric ozone contribute to climate change and air pollution.

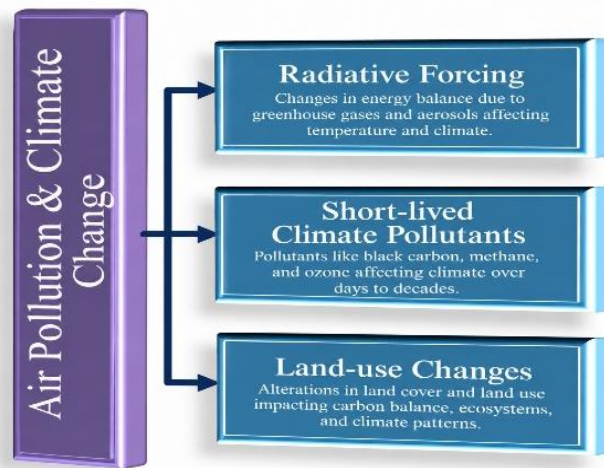


Figure 2. Air pollution and climate change

- **Black Carbon (BC):** It is a potent warming agent. Its atmospheric lifetime is only a few days to weeks. After deposition on surfaces, it absorbs solar radiation, heating the atmosphere and accelerating snow and ice melting [16]. The Arctic is more vulnerable because deposited BC on ice reduces the reflectivity and amplifies the warming through positive feedback loops.
- **Methane:** A precursor to ground-level ozone and a greenhouse gas. It has approximately 80 times the potential to trap heat over a 20-year horizon compared with CO₂. Sources of methane emissions include waste decomposition, agriculture (livestock), and fossil fuel extraction.
- **Ozone (O₃):** Ozone is a greenhouse gas formed through photochemical reactions involving methane, nitrogen oxides (NO_x), and VOCs [17]. Ground-level ozone is a harmful air pollutant and a short-lived climate forcer, while stratospheric ozone protects life on Earth from ultraviolet radiation.

Synergistic effects with deforestation and urbanization: Air pollution and land-use changes such as deforestation and increased urbanization could worsen climate change effects.

- **Deforestation:** The planet's carbon sequestration capacity is adversely affected, and atmospheric CO₂ concentration increases [18]. Similarly, emissions of biomass, particulates, and black carbon from deforestation affect the climate, accelerate global warming, and thereby reduce agricultural production and contribute to drought.
- **Urbanization:** Emissions from transport, industrial processes, and space heating are exacerbated by urban expansion, which creates concentrated pockets of air pollution [19]. Inappropriate urban form can increase energy consumption by 30–70% for residential buildings and by 10–20% for commercial buildings.

2.3 Spatial and temporal characteristics of AQI

AQI varies widely across areas and over time because emissions, meteorology, land use, and human activity differ. Spatial variations occur across urban, industrial, rural, and residential areas, while temporal variations reflect daily, seasonal, and longer-term changes [20]. These

characteristics are crucial for accurate, adaptive AQI forecasting.

Spatial distribution of pollutant concentrations:

The concentration distributions of 6 conventional pollutants (CODMn, NH₃-N, TP, TH, SO₄²⁻, and Cl⁻) in 26 groundwater. Fertilizer use may explain why the western sections of the industrial park had high CODMn concentrations, while the southern sections, along with agriculture, had significant NH₃-N concentrations [21].

Geographical variation of AQI: AQI varies geographically due to differences in pollutant concentrations across urban, industrial, residential, and rural areas. Traffic density, industrial activity, population distribution, and local climate influence these differences. Areas with intense emission sources tend to have higher AQI values, while areas with good atmospheric dispersion may have relatively lower pollution concentrations.

Pollution dispersion: Researchers study and predict air pollution dispersion using computer models, as with many other complex scientific and technical issues [22]. These support urban planners in finding solutions to improve air quality, safeguard human health, reduce environmental damage, and lower economic losses.

3. SEASONAL AND LONG-TERM ENVIRONMENTAL DYNAMICS IN AQI PREDICTION

Seasonal and long-term environmental dynamics significantly influence AQI prediction. Variations in temperature, humidity, wind speed, rainfall, and solar radiation affect pollutant concentrations across seasons. Long-term changes from urbanization, industrialization, climate variability, and shifting emission sources further modify air-quality patterns. Therefore, forecasting models must capture both seasonal fluctuations and environmental trends.

3.1 Seasonal variation of pollutant concentration

The seasonal averages of O₃, CO, NO₂, SO₂, PM₁₀, and PM_{2.5} during the daytime and night-time in Battaramulla and Kandy [23]. The daytime (06:00 hrs–18:00 hrs) is given without parentheses, whereas the night-time (18:00 hrs–06:00 hrs) is showcased inside the parentheses.

3.2 Air quality and meteorological data measurements

AQMS at Battaramulla and Kandy (hereinafter AQMSBat and AQMSKan) were installed in locations with unrestricted airflow and minimal influence from nearby buildings [24]. The quantities of sulphur dioxide (SO₂), nitrogen dioxide (NO₂), ozone (O₃), carbon monoxide (CO), and particulate matter (PM₁₀) and particulate matter (PM_{2.5}) were measured at both sites using samples. We collected these air samples 5 m above ground level to minimize turbulent effects near the ground. They were collected at hourly intervals from January 2019 to May 2021 (for 30 months).

3.3 Seasonal changes in concentration

Tampere has clear seasonal variation: winters are snowy and cold, and summers are mild or even warm [25]. Sunlight varies strongly by season: in winter, days are short with very little sunlight (only appr. 6 h at the shortest), and in summer, days are long (as long as 19 h).

3.4 Long-term environmental dynamics

AQI is influenced by long-term environmental dynamics, including changes in climate, urbanization, industrialization, population growth, and emission patterns. These variables change pollutant concentrations and their temporal and spatial distributions over time [26]. Therefore, to achieve accurate AQI predictions, ML models must incorporate environmental trends, especially when longer-term changes shift air-quality patterns.

4. MACHINE LEARNING-BASED AIR QUALITY INDEX FORECASTING

ML-based AQI forecasting refers to methods that forecast air-quality conditions based on historical pollutants and environmental data. The complex, nonlinear relationships between pollutants and environmental variables can be represented using models such as regression, decision trees, neural networks, and support vector machines. Neural networks, decision trees, random forests, and support vector machines can capture complex nonlinear interactions between meteorological factors and contaminants. These technologies can help with timely air-quality control and public health decisions while improving prediction accuracy.

4.1 Machine Learning-based prediction

ML-based prediction can learn patterns from past meteorological data and air quality to achieve accurate AQI forecasting [27]. These predictions are more accurate because they capture nonlinear connections between environmental factors and contaminants. Because they can capture complex patterns and correlations over time, neural networks are ideal for both short- and long-term AQI forecasting.

Supervised learning: It maps input parameters to an output based on knowledge from a supervisor, or teacher, who knows the environment [28]. The objective is to minimize the error between the output and the target values. Both classification and regression are part of supervised learning.

Unsupervised learning: It has no supervisor or teacher and uses only input parameters. It finds uniformities in the input parameters and aims to identify repeated patterns amongst the data. It creates various classes from unlabeled data. Clustering is part of unsupervised learning and finds groups or clusters in the input data.

Reinforcement learning: The system constantly interacts with its surroundings and learns through a series of actions. The system uses this interaction to learn from its actions [29]. These systems, with a critic, take actions and receive feedback as rewards or penalties.

4.2 Applications of air quality index forecasting

The AQI is applied for resource allocation, location ranking, standards enforcement, trend analysis, public information, pollution forecasting, health protection, and effective air quality management; the following six goals are served by an AQI.

- **Resource allocation:** Assisting administrators in funding allocation and prioritization. Enable assessment of trade-offs in alternative approaches for controlling air pollution.

- **Ranking of locations:** To help in comparing circumstances of air quality at distinct locations/towns. Identify potential hazards, including regions and frequencies.
- **Enforcement of standards:** To identify the extent of compliance with legislative standards and current criteria. It also helps identify defective standards and insufficient monitoring programs.
- **Trend analysis:** To find the air quality shift (degradation or enhancement) that has happened over a defined period of time. This enables air quality prediction (i.e., tracking pollutant transport in the atmosphere) and helps plan steps to control pollution.
- **Public information:** Informing the public about environmental circumstances (Environmental state). This helps individuals whose health is aggravated or affected by air pollution [30]. This allows them to change their daily actions when they are notified of elevated pollution concentrations.

4.3 Challenges and limitations

AQI forecasting faces challenges from spatial pollutant variation, large datasets, changing concentrations, limited direct AQI research data, reliability, monitoring complexities, and insufficient validation for real-time application [27]. The main obstacles and restrictions are outlined below:

- Pollutant concentrations vary across locations due to differences in natural conditions, traffic, industrial activities, and other emission sources.
- Pollutant levels change over time with weather conditions, seasonal patterns, and variations in human activities.
- AQI estimation involves multiple pollutants, each having different characteristics and potential adverse effects on human health.
- Monitoring stations commonly provide hourly or 24-hour average measurements, which may limit the availability of detailed data for real-time forecasting.
- Most previous research concentrates on forecasting individual pollutants, while comparatively limited research directly addresses comprehensive AQI forecasting.
- The information is supplied directly without scrutiny from the analysts for real-time AQI, so it may not be for a statutory purpose.

5. LITERATURE REVIEW

Recent studies have increasingly applied ML techniques to forecast AQI using meteorological and pollutant data. G. S. Manivannan et al. [31] improve the time-related representation; the proposed methodology combines STL for trend and seasonal extraction, residual threshold noise elimination, and rolling statistical feature extraction. The authors apply and compare several ensemble and boosting regression approaches, including AdaBoost, Random Forest, LightGBM, XGBoost, CatBoost, and NGBoost.

L. Troll et al. [32] improved ChronoShore, a virtual reality (VR) environment that lets users interact with ambient time at various temporal scales, giving users an even more immersive experience. The virtual environment

is based on a multi-resolution reconstruction of a real segment of Costa Rica's Caribbean coast, generated from heterogeneous geospatial datasets, including aerial point clouds, satellite-based elevation data, and global bathymetry. In ChronoShore, users can explore and alter time through diegetic environmental signals, or zeitgebers, that are integrated directly into the virtual world. This contrasts with typical timeline-based controls. You can now manage the simulation's passage of time over years or even decades by interacting with flora, including trees. This also adds the ability to manipulate time in the short term through celestial bodies like the sun and moon.

P. Gudimilla, et al. [33] introduced an enhanced model for AQI prediction by means of a hybrid approach which integrates time-series analysis and DL. The data utilized in this analysis were mostly sourced from the CPCB, India. The dataset comprised longitudinal measurements of multiple pollutants gathered from multiple cities. By combining a SARIMA model with a TLSTM network, it can uncover temporal patterns and establish long-term associations.

K. V. Reddy et al. [34] attempted to forecast Delhi AQI by analyzing data from numerous monitoring sites using a range of machine learning algorithms, including decision trees, random forests, linear regression, and support vector regression. Among the models, Decision Tree Regressor achieved the highest R-squared and the lowest RMSE. Modern preprocessing techniques reduced the air quality data's sensitivity to seasonal variations while increasing precision. V. Shah et al. [35] explore the potential role of AI in proactive control of air quality. This research examines three forecasting models in Alipur, Delhi, India, and compares their performance in predicting PM_{2.5} pollution levels and AQI. The models are SARIMAX, Bi-LSTM, and LSTM. The Bi-LSTM model outperformed the others in terms of AQI MAE (0.0754) and PM_{2.5} MAE (0.0411), two metrics used to evaluate model accuracy. S. Swamynathan et al. [36] constructed a number of models for making predictions.

Table 1. Summary of key studies on air quality index forecasting using machine learning

Reference	Objective	Study Area	Methodology	Key Findings	Limitations
[31]	Improve AQI forecasting through better temporal representation and data quality.	AQI data from Hassan district, Karnataka.	STL decomposition, residual threshold noise removal, rolling statistical features, RF, AdaBoost, XGBoost, LightGBM, Cat Boost, NG Boost.	Combining temporal decomposition, noise removal, and ensemble/boosting models improves AQI forecasting capability.	Limited to one geographical region; broader seasonal and long-term environmental dynamics require further investigation.
[32]	Enable exploration of environmental changes across short- and long-term temporal scales.	Caribbean coast of Costa Rica using aerial point clouds, satellite elevation data, and global bathymetry.	Chrono Shore VR, multi-resolution reconstruction, environmental temporal cues, vegetation-based long-term interaction.	Provides immersive exploration of environmental changes from short-term periods to years and decades.	Focuses on environmental visualization rather than ML-based AQI forecasting.
[33]	Develop an enhanced AQI forecasting model capable of capturing seasonal and long-term dependencies.	CPCB India data containing pollutants from multiple cities over an extended period.	TLSTM integrated with SARIMA.	Hybrid TLSTM-SARIMA effectively captures seasonal patterns and long-term temporal dependencies in AQI data.	Model complexity and dependence on historical data may affect generalization across different regions.
[34]	Predict AQI in Delhi using machine learning and improved preprocessing.	Air-quality monitoring-station data from Delhi.	Linear Regression, SVR, Decision Tree, Random Forest, advanced preprocessing.	Decision Tree achieved the lowest RMSE and highest R ² ; preprocessing improved prediction accuracy and seasonal handling.	Limited use of advanced DL methods and insufficient consideration of long-term environmental dynamics.
[35]	Forecast PM _{2.5} and AQI for proactive air-quality management.	PM _{2.5} and AQI data from Alipur, Delhi, India.	LSTM, Bi-LSTM, SARIMAX.	Bi-LSTM outperformed other models, obtaining MAE of 0.0411 for PM _{2.5} and 0.0754 for AQI.	Location-specific evaluation; long-term environmental changes are not comprehensively considered.
[36]	Evaluate ML-based AQI prediction across multiple locations.	Datasets from three different locations.	SVM, ANN, Naive Bayes, and stacking models.	ML and stacking approaches showed promising performance using MAE, RMSE, and R ² metrics.	Seasonal variability and long-term environmental trends are not deeply incorporated.
[37]	Forecast weekly and monthly air quality in Dhaka using multiple pollutants.	Hourly PM _{2.5} , PM ₁₀ , SO ₂ , CO, NO ₂ , and O ₃ data from Dhaka.	ARIMA, Auto-ARIMA, SARIMAX, VAR.	SARIMAX performed best by incorporating seasonal patterns, trends, and external factors.	Primarily statistical models; limited integration of advanced ML/DL and adaptive long-term forecasting.

When ML methods such as SVMs, ANNs, and NB are used to forecast AQI levels, they yield promising results. Nevertheless, NB, ANN, and SVM achieved the best prediction performance in many experiments, including datasets from three separate sites. The sum of the stacks' performances is unparalleled in terms of MAE, R-squared (R^2), and RMSE.

S. R. Sakib et al. [37] developed models to forecast Dhaka's air quality using ARIMA, Auto-ARIMA, SARIMAX, and VAR. Unlike earlier research, this study predicts air quality using hourly air pollution parameters, including PM_{2.5}, PM₁₀, SO₂, CO, NO₂, and O₃. We can forecast Dhaka city's air quality monthly and weekly using a novel approach. The SARIMAX model outperforms others in predicting Dhaka city's air quality because it accounts for trends, external effects, and seasonal patterns. RMSE and mean absolute percentage error are statistical metrics that are used to evaluate the precision of the model's predictions. Although much progress has been made in developing ML-based AQI prediction models, the literature remains fragmented across statistical modeling, ML, DL, seasonal analysis, and environmental data processing. Current methods mostly aim for more accurate predictions or focus on short-term seasonal variability, but do not simultaneously model interactions between short- and long-term environmental dynamics.

Current models show good forecasting skill, but they rely on location-specific data, limiting their transferability across regions, climates, and pollution types. Although hybrid models such as SARIMA-LSTM and ensemble learning can maintain temporal patterns, they struggle to adapt to new circumstances and manage concept drift over the long run. While data from pollution monitoring systems, meteorological measurements, satellite observations, and IoT sensors are valuable, incorporating them into existing forecasting systems remains challenging. Furthermore, advanced DL models may be unavailable for real-time deployment because of interpretability issues and high computational cost. These limitations are particularly evident in the comparative results in Table 1, underscoring the need to develop a unified, flexible, and interpretable AQI forecasting framework that integrates data from diverse environmental sources, seasonal evaluations, long-term trend analysis, real-time learning, and advanced ML techniques.

6. CONCLUSION

AQI is an effective tool for understanding air pollution status and its potential environmental and health effects. Pollutant concentrations, meteorological parameters, seasonal variations, urbanization, industrial activities, and climate variability all affect AQI patterns. The review underscores the importance of temporal and spatial differences in understanding air-quality conditions in various places and times. Other factors affecting the seasonal and long-term changes in pollutant concentrations and AQI patterns include environmental dynamics. AQI forecasting supports pollution monitoring, public awareness, health protection, resource allocation, regulatory enforcement, location comparison, and trend analysis. However, significant challenges to accurate forecasting include regional variability in concentrations

and pollutants, large data volumes, complicated monitoring, unreliable data, and lack of validation for real-time applications. To improve AQI evaluation and prediction, it is crucial to conduct a comprehensive examination of the environment, weather, season, and location. These enhancements can help achieve effective air-quality management, timely decision-making, and environmental protection. Future studies should focus on developing accurate, adaptive AQI forecasting techniques that combine pollutant levels with meteorological, seasonal, spatial, and long-term environmental conditions. Timely air quality management and public health decisions also require more precise data, real-time monitoring, continuous validation, and improved management of various pollutant trends.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The author declares no potential conflict of interest.

REFERENCES

- [1] A. Joon, "Smart Predictive Maintenance: AI-Driven Adaptation for Industrial Equipment," in 2025 IEEE North-East India International Energy Conversion Conference and Exhibition (NE-IECCCE), IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/NE-IECCCE64154.2025.11183108.
- [2] Kanchan, A. K. Gorai, and P. Goyal, "A review on air quality indexing system," Asian J. Atmos. Environ., vol. 9, no. 2, pp. 101–113, 2015, doi: 10.5572/ajae.2015.9.2.101.
- [3] K. Dimitriou, A. K. Paschalidou, and P. A. Kassomenos, "Assessing air quality with regards to its effect on human health in the European Union through air quality indices," Ecol. Indic., vol. 27, pp. 108–115, 2013, doi: 10.1016/j.ecolind.2012.11.023.
- [4] C. Andenna and R. V. Gagliardi, "Insights into Air Quality Index (AQI) Variability with Explainable Machine Learning Techniques," in The 7th International Electronic Conference on Atmospheric Sciences (ECAS-7), Basel Switzerland: MDPI, Aug. 2025, p. 1. doi: 10.3390/eesp2025034001.
- [5] A. Bekkar, B. Hssina, S. Douzi, and K. Douzi, "Air-pollution prediction in smart city, deep learning approach," J. Big Data, vol. 8, no. 1, p. 161, 2021, doi: 10.1186/s40537-021-00548-1.
- [6] A. Yenikar, V. P. Mishra, M. Bali, and T. Ara, "Explainable forecasting of air quality index using a hybrid random forest and ARIMA model," MethodsX, vol. 15, p. 103517, Dec. 2025, doi: 10.1016/j.mex.2025.103517.
- [7] K. Chatterjee et al., "HoST: integrating Heuristic knowledge with attention-based LSTM networks for

- Thunderstorm prediction," *Sci. Rep.*, Jul. 2026, doi: 10.1038/s41598-026-57889-1.
- [8] C. Ravaglioli, L. Benedetti-Cecchi, I. Bertocci, E. Maggi, M. Uyà, and F. Bulleri, "The role of environmental conditions in regulating long-term dynamics of an invasive seaweed," *Biol. Invasions*, vol. 24, no. 4, pp. 1175–1187, Apr. 2022, doi: 10.1007/s10530-021-02680-8.
- [9] A. Tiwari, A. Kumar, M. Pradesh, and M. Pradesh, "Air Quality Index Prediction : A Review of Machine Learning , Deep Learning , and Hybrid Approaches," vol. 060253, pp. 1–10, 2026, doi: 10.5281/zenodo.20626963.
- [10] IQAir. (n.d.), "India Air Quality Index (AQI) and Air Pollution information," 2023. <https://www.iqair.com/air-quality/india>
- [11] X. Wang, X. He, S. Miao, and Y. Dou, "Numerical simulation of the influence of aerosol radiation effect on urban boundary layer," *Sci. China Earth Sci.*, vol. 61, no. 12, pp. 1844–1858, 2018, doi: 10.1007/s11430-018-9260-0.
- [12] S. Alsowaidan, A. Al-Hurban, A. Alsaber, and A. Anbar, "Assessment of seasonal variations in the air quality index (2019–2022) in Al-Jahra city, Kuwait," *Kuwait J. Sci.*, vol. 51, no. 4, p. 100280, 2024, doi: 10.1016/j.kjs.2024.100280.
- [13] S. Mohapatra, J. G. Singh, and M. Mishra, "Inter-linkage between air pollution, climate change, and human health: A comprehensive review and AI-driven insights," *Clim. Phys. Atmos. Sci. Sci. Insights Soc. Challenges*, vol. 3–4, p. 100021, 2026, doi: 10.1016/j.cpas.2026.100021.
- [14] V. Ramanathan and Y. Feng, "Air pollution, greenhouse gases and climate change: Global and regional perspectives," *Atmos. Environ.*, vol. 43, no. 1, pp. 37–50, 2009, doi: 10.1016/j.atmosenv.2008.09.063.
- [15] D. Shindell et al., "Simultaneously Mitigating Near-Term Climate Change and Improving Human Health and Food Security," *Science (80-.)*, vol. 335, no. 6065, pp. 183–189, 2012, doi: 10.1126/science.1210026.
- [16] T. C. Bond et al., "Bounding the role of black carbon in the climate system: A scientific assessment," *J. Geophys. Res. Atmos.*, vol. 118, no. 11, pp. 5380–5552, 2013, doi: 10.1002/jgrd.50171.
- [17] P. S. Monks et al., "Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer," *Atmos. Chem. Phys.*, vol. 15, no. 15, pp. 8889–8973, 2015, doi: 10.5194/acp-15-8889-2015.
- [18] R. A. Houghton and A. A. Nassikas, "Global and regional fluxes of carbon from land use and land cover change 1850–2015," *Global Biogeochem. Cycles*, vol. 31, no. 3, pp. 456–472, 2017, doi: 10.1002/2016GB005546.
- [19] A. Karimi, P. Mohammad, A. García-Martínez, D. Moreno-Rangel, D. Gachkar, and S. Gachkar, "New developments and future challenges in reducing and controlling heat island effect in urban areas," *Environ. Dev. Sustain.*, vol. 25, no. 10, pp. 10485–10531, 2023, doi: 10.1007/s10668-022-02530-0.
- [20] X. Guo et al., "Air quality improvement and health benefit of PM_{2.5} reduction from the coal cap policy in the Beijing–Tianjin–Hebei (BTH) region, China," *Environ. Sci. Pollut. Res.*, vol. 25, no. 32, pp. 32709–32720, 2018, doi: 10.1007/s11356-018-3014-y.
- [21] M. Bose and K. Mali, "Designing fuzzy time series forecasting models: A survey," *Int. J. Approx. Reason.*, vol. 111, pp. 78–99, 2019, doi: 10.1016/j.ijar.2019.05.002.
- [22] S. Di Sabatino, R. Buccolieri, and P. Salizzoni, "Recent advancements in numerical modelling of flow and dispersion in urban areas: a short review," *Int. J. Environ. Pollut.*, vol. 52, no. 3/4, p. 172, 2013, doi: 10.1504/IJEP.2013.058454.
- [23] S. Shelton et al., "Seasonal Variability of Air Pollutants and Their Relationships to Meteorological Parameters in an Urban Environment," *Adv. Meteorol.*, vol. 2022, no. 1, p. 5628911, 2022, doi: 10.1155/2022/5628911.
- [24] S. Park et al., "Studying Air Pollutants Origin and Associated Meteorological Parameters over Seoul from 2000 to 2009," *Adv. Meteorol.*, vol. 2015, 2015, doi: 10.1155/2015/704178.
- [25] A.-A. M. Basil, C. C. Okwuosa, F. O. Uzuegbuanam, and L. E. Ugwu, "A seasonal investigation of indoor air quality in relation to architectural features in government office buildings in Enugu, Nigeria," *Sci. Rep.*, vol. 14, no. 1, p. 26885, Nov. 2024, doi: 10.1038/s41598-024-78160-5.
- [26] S. L. Allcock, "Long-term socio-environmental dynamics and adaptive cycles in Cappadocia, Turkey during the Holocene," *Quat. Int.*, vol. 446, pp. 66–82, Aug. 2017, doi: 10.1016/j.quaint.2017.06.065.
- [27] M. Karmoude et al., "Machine learning for air quality prediction and data analysis: Review on recent advancements, challenges, and outlooks," *Sci. Total Environ.*, vol. 1002, p. 180593, 2025, doi: 10.1016/j.scitotenv.2025.180593.
- [28] A. Pant, S. Sharma, and K. Pant, "Evaluation of Machine Learning Algorithms for Air Quality Index (AQI) Prediction," *J. Reliab. Stat. Stud.*, Dec. 2023, doi: 10.13052/jrss0974-8024.1621.
- [29] K. Rajesh and S. R. Kumar, "Deep Reinforcement Learning for Urban Air Quality Management: Multi-Objective Optimization of Pollution Mitigation Booth Placement in Metropolitan Environments," *IEEE Access*, vol. 13, pp. 146503–146526, 2025, doi: 10.1109/ACCESS.2025.3599541.
- [30] J. Bernacki and R. Scherer, "A Comprehensive Review of Data-Driven Techniques for Air Pollution Concentration Forecasting," *Sensors (Basel)*, vol. 25, no. 19, Oct. 2025, doi: 10.3390/s25196044.
- [31] G. S. Manivannan, R. Mariyam, and F. Zahara, "An Efficient Ensemble and Boosting Based Regression Framework for Air Quality Index Forecasting in Hassan District of Karnataka," in 2026 International Conference on Recent Advancement in Electrical, Computer and Communication Technologies (IECCT), 2026, pp. 1–5. doi: 10.1109/IECCT68664.2026.11541582.
- [32] L. Troll, Y. C. Law, and D. Zielasko, "ChronoShore: Diegetic Exploration of Short- and Long-Term Environmental Time in a Virtual Coastal Ecosystem," in 2026 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), 2026, pp. 1423–1424. doi: 10.1109/VRW70859.2026.00386.
- [33] P. Gudimilla, A. Banu, S. Hasanoddin, B. Maheshwari, and R. Vishal, "Enhanced Air Quality Index Prediction using SARIMA Model TLSTM Network and Hybrid Modeling," in 2025 2nd International Conference on Recent Trends in

Electrical, Electronics and Computing Technologies (ICRTEECT), 2025, pp. 1–6. doi: 10.1109/ICRTEECT67512.2025.11448937.

- [34] K. V. Reddy, C. M. Begum, A. Neeraja, and J. C., “Enhancing Air Quality Index Forecasting through Machine Learning Models,” in 2025 3rd International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC), 2025, pp. 1188–1194. doi: 10.1109/ISACC65211.2025.10969305.
- [35] V. Shah, K. Patel, R. K. Gupta, and H. Yagnik, “Advancements in Air Quality Forecasting using Artificial Intelligence: A Comprehensive Analysis,” in 2024 Asia Pacific Conference on Innovation in Technology (APCIT), 2024, pp. 1–6. doi: 10.1109/APCIT62007.2024.10673466.
- [36] S. Swamynathan, N. Sneha, S. P. Ramesh, R. Niranjana, D. D. N. Ponkumar, and R. Saravanakumar, “A Machine Learning Approach for Predicting Air Quality Index in Smart Cities,” in 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), 2024, pp. 1609–1615. doi: 10.1109/ICICNIS64247.2024.10823106.
- [37] S. R. Sakib et al., “Time Series Analysis and Forecasting of Air Quality Index of Dhaka City of Bangladesh,” in 2023 IEEE World AI IoT Congress (AIoT), IEEE, Jun. 2023, pp. 0063–0069. doi: 10.1109/AIoT58121.2023.10174539.



This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).