

The Impact of Extreme Weather on Air Quality: A Satellite-Based Deep Learning Analysis for Air Quality Prediction A Case in Democratic Republic of the Congo

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ABSTRACT

Air quality is a major concern in tropical regions such as equatorial Africa, where extreme weather and limited ground-based monitoring complicate pollution assessment. This study analyzed the effects of heat waves, extreme rainfall, and stagnant winds on fine particulate matter (PM_{2.5}) concentrations in the Democratic Republic of the Congo during 2014–2024. Satellite observations from TROPOMI, MODIS, and GPM were integrated with ERA5 meteorological reanalysis data to examine meteorological–air quality interactions. Stagnant winds increased PM_{2.5} accumulation by limiting atmospheric dispersion, whereas extreme rainfall reduced concentrations through wet deposition. High temperatures also promoted surface ozone formation through photochemical processes. LSTM and hybrid CNN–LSTM models were applied to forecast PM_{2.5} concentrations up to 48 hours ahead. The CNN–LSTM model achieved $R^2 = 0.892$, RMSE = 5.21 $\mu\text{g}/\text{m}^3$, and MAE = 3.84 $\mu\text{g}/\text{m}^3$, outperforming the standalone LSTM model ($R^2 = 0.762$, RMSE = 8.47 $\mu\text{g}/\text{m}^3$, MAE = 6.12 $\mu\text{g}/\text{m}^3$). These findings demonstrate the potential of satellite-based deep learning for short-term PM_{2.5} forecasting and early warning applications in tropical regions with limited ground-based observations.

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1. INTRODUCTION

Air quality is essential for human health and environmental sustainability. Exposure to pollutants such as fine particulate matter (PM_{2.5}), nitrogen dioxide (NO₂), and carbon monoxide (CO) increases the risk of respiratory and cardiovascular diseases. These risks are particularly high in urban areas with intensive industrial and transportation activities (Maharani & Aryanta, 2023; Setiawan & Lestari, 2022). Air pollution also reduces visibility, disrupts crop productivity, and alters the Earth's energy balance and hydrological cycles (Prananta Perangin, 2022). Therefore, understanding the factors influencing air quality is essential for supporting public health and climate change mitigation policies.

Meteorological conditions play an important role in air quality dynamics by influencing the dispersion, accumulation, and removal of atmospheric pollutants (J. Wang et al., 2023). Interactions among weather, water, and atmospheric conditions influence the transport, deposition, and transformation of air pollutants (Nugraha & Firmansyah, 2021). Meteorological factors such as precipitation, relative humidity, temperature, and wind speed can significantly influence atmospheric pollutant concentrations and their temporal variability (Ni et al., 2023). For instance, precipitation



can reduce atmospheric particulate matter through wet scavenging processes (R. Wang et al., 2023). Dry conditions combined with sufficiently strong winds can promote the resuspension of surface dust, thereby increasing airborne particulate matter concentrations (Linda et al., 2025).

Extreme weather conditions can substantially alter atmospheric pollutant concentrations through changes in meteorological factors that influence pollutant dispersion, transport, removal, and formation (Ni et al., 2023). Heat waves can also limit vertical pollutant dispersion, leading to accumulation near the surface. Conversely, storms and strong winds may transport dust and biomass-burning smoke over long distances, increasing PM_{2.5} and NO₂ concentrations far from emission sources (Liu & Zhou, 2020). Thus, extreme weather can either improve or deteriorate air quality depending on the meteorological conditions.

Equatorial Africa has distinctive hydrometeorological characteristics that influence interactions between extreme weather and air quality (Adeyemi & Kamau, 2023). The seasonal migration of the Intertropical Convergence Zone (ITCZ) and associated atmospheric circulation are closely linked to rainfall seasonality across Central Africa, although regional rainfall is also strongly influenced by thermodynamic and moisture-related processes (Longandjo & Rouault, 2024). Large-scale climate variability, particularly the Indian Ocean Dipole (IOD), can significantly influence precipitation patterns across Central Equatorial Africa (Jiang et al., 2021). Hydrometeorological variations can affect air pollution through processes such as wet deposition and meteorologically driven changes in pollutant concentrations (Ni et al., 2023). The diversity of anthropogenic and natural emission sources also contributes to complex air pollution patterns across Africa (Bililign et al., 2024). Furthermore, strong convective activity and complex atmospheric variability make Central Africa an important region for investigating interactions between atmospheric conditions and environmental processes (Tikeng et al., 2024).

The main obstacle in air quality research in equatorial Africa is the limited in-situ observation network. Many countries in this region do not yet have adequate air monitoring systems to cover large areas (Nwosu & Ahmed, 2025). Therefore, satellite data is an important source of information to fill in the gaps in surface observation data. Satellite and reanalysis datasets provide complementary information for air quality and hydrometeorological analysis. TROPOMI provides observations of atmospheric trace gases such as NO₂, while MODIS-derived aerosol optical depth (AOD) can support the estimation of surface PM_{2.5} concentrations (Rudke et al., 2023). GPM/IMERG provides precipitation information, whereas ERA5 provides meteorological variables such as temperature, humidity, and wind, enabling the integration of atmospheric and hydrometeorological information in air quality analysis (J. Wang et al., 2022; Hersbach et al., 2020). Satellite observations also provide broad spatial coverage that supports air quality monitoring, particularly in regions where ground-based observations are limited (Rudke et al., 2023).

Advances in artificial intelligence, particularly deep learning, offer new opportunities for improving air quality prediction by capturing complex nonlinear and spatiotemporal patterns in air quality data (Z. Zhang et al., 2024). CNN and LSTM models can capture complex patterns in PM_{2.5} and meteorological data, while the CNN-LSTM architecture can further improve prediction performance (Bai et al., 2024). Integrating these models with satellite observations enables adaptive air quality forecasting and early warning of pollution episodes associated with extreme weather (Kurniawan & Prasetyo, 2025). This approach is particularly relevant to equatorial Africa, where ground-based observations remain limited, and can support improved air quality prediction and climate mitigation and adaptation strategies.

Similar studies have also been conducted in tropical regions of Southeast Asia, where rapid urbanization, biomass burning, and monsoon circulation strongly influence air quality. In Indonesia, Malaysia, and Thailand, satellite observations combined with meteorological data have been widely used to analyze PM_{2.5} dynamics and transboundary haze events. Several studies have demonstrated that deep learning models, including CNN and LSTM, can effectively predict PM_{2.5} concentrations by integrating satellite-derived aerosol information with meteorological variables. These findings indicate that remote sensing and artificial intelligence provide reliable approaches for air quality monitoring in tropical environments. However, compared with Southeast Asia, equatorial Africa remains underexplored because of limited ground monitoring networks and fewer integrated studies using

satellite observations and deep learning techniques. This study aims to analyze the effects of extreme weather conditions on PM_{2.5} concentrations in the Democratic Republic of the Congo using satellite and hydrometeorological data and to develop and evaluate LSTM and CNN–LSTM models for short-term PM_{2.5} prediction.

2. DATA AND METHOD

2.1 Extreme Weather and Air Quality

Extreme weather is a meteorological phenomenon that deviates from normal climatic conditions and often has a significant impact on the environment and human health. Types of extreme weather include heat waves, extreme rainfall, storms, and wildfires (Zhu et al., 2023). The relationship between extreme weather and air quality is mainly mediated by atmospheric dynamics: changes in temperature, humidity, wind speed, as well as vertical circulation patterns that affect the process of dispersion and accumulation of pollutants.

Extreme weather events are commonly identified using percentile-based thresholds to characterize conditions that deviate substantially from the local climatological distribution (IPCC, 2021; Perkins & Alexander, 2013). In this study, extreme heat and extreme rainfall were identified using the 95th percentile of temperature and precipitation, respectively. Stagnant wind conditions were identified using a wind-speed threshold below 1.5 m/s, which represents limited atmospheric dispersion conditions (Xiong et al., 2023). A minimum duration of 12 consecutive hours was additionally applied as an operational criterion in this study.

Physically, during heat waves, the atmosphere tends to be stable due to temperature *inversion* in the atmospheric boundary layer. This condition limits vertical convection and causes pollutants to be trapped near the surface, increasing the concentration of PM_{2.5} and O₃ (Muthukumar et al., 2022). On the other hand, extreme rainfall events have the potential to reduce pollutants through the process of atmospheric washing (wet deposition), although under certain conditions they can increase secondary emissions due to post-rain photochemical reactions.

Forest fires are an extreme example that shows a direct link between meteorological events and deteriorating air quality. Shrestha pointed out that fire smoke can be dispersed up to thousands of kilometers and increase particulate concentrations up to three times the quality threshold (Shrestha et al., 2022). The 2023 Canadian wildfires caused a significant increase in cross-continental PM_{2.5} concentrations, with substantial health implications across North America and Europe (M. Zhang et al., 2025).

In addition to direct impacts, extreme weather also changes the chemical composition of the atmosphere. Forest fire emissions contain black carbon, volatile organic compounds, and nitrates that accelerate the formation of tropospheric ozone. These changes contribute to radiation imbalances and regional warming (Holloway et al., 2021). Therefore, understanding this mechanism is important for developing early warning systems and air quality mitigation strategies based on atmospheric science.

2.2 Satellite Data for Environmental Monitoring

Satellite-based air quality monitoring has become a key approach in Earth observation science due to its wide scope and long-term data availability. Sensors such as MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) are used to measure Aerosol Optical Depth (AOD) which is closely related to the concentration of particulate matter in the atmosphere. The Sentinel-5P/TROPOMI is capable of detecting tropospheric columns of pollutant gases (NO₂, SO₂, CH₄, CO) with high spatial resolution (Y. Zhang & Li, 2021). Geostationary satellites such as GEMS (Geostationary Environment Monitoring Spectrometer) provide hourly real-time observations for the East and Southeast Asia regions (Zhu et al., 2023). This high temporal coverage makes GEMS important in monitoring dynamic extreme events such as wildfires and heat waves.

Satellite products provide a wide range of atmospheric parameters, including AOD, aerosol index, surface temperature, relative humidity, and wind speed. The relationship between satellite-derived AOD and surface PM_{2.5} is influenced by meteorological and geographical conditions. Therefore,

integrating AOD with meteorological and geographical variables through deep learning can improve high-resolution PM_{2.5} estimation and capture complex spatiotemporal variations in air pollution (Li et al., 2023).

The main advantage of satellite data is its ability to provide broad spatial coverage, including remote areas with limited ground-based monitoring. Long-term satellite observations also support the analysis of air pollution trends (Holloway et al., 2021). However, satellite-derived aerosol products are affected by cloud cover, retrieval uncertainty, and differences between column-integrated aerosol measurements and surface PM_{2.5} concentrations. Integrating satellite AOD with meteorological and geographical information through deep learning can help improve surface PM_{2.5} estimation (Li et al., 2023).

Although satellite observations provide broad spatial coverage, they have several limitations. Cloud contamination, retrieval uncertainty, and differences in spatial resolution may introduce errors into PM_{2.5} estimation. Furthermore, satellite-derived aerosol products represent column-integrated atmospheric conditions rather than direct surface concentrations, requiring additional modeling and meteorological corrections. The scarcity of ground-based monitoring stations in equatorial Africa also limits comprehensive validation of satellite observations. Consequently, the prediction results should be interpreted with consideration of these inherent uncertainties.

2.3 Deep Learning for Spatiotemporal Prediction

The development of *deep learning* is revolutionizing the way atmospheric data analysis has been carried out. Models such as CNN (Convolutional Neural Network) extract spatial features from satellite data grids, while LSTM (Long Short-Term Memory) study temporal dependencies between days (Hu, 2022). A hybrid deep learning approach incorporating neighborhood selection and spatiotemporal attention has demonstrated improved performance in PM_{2.5} prediction compared with benchmark models (Chen et al., 2025). Another rapidly growing approach involves the integration of Graph Neural Networks (GNNs) to capture inter-regional relationships in pollutant distribution patterns. GNNs enable the representation of spatial networks based on the geographical distribution of observation stations (Agbehadji & Obagbuwa, 2024).

Deep learning has been widely applied to a wide range of time and space scales from short-term (hours) predictions to long-term spatial estimation. Most deep learning models are able to reduce prediction errors by up to 20–35% compared with classical multivariate regression models (Agbehadji & Obagbuwa, 2024). Satellite-derived aerosol optical depth (AOD) can be integrated with meteorological and geographical variables through deep learning to improve high-resolution PM_{2.5} estimation and capture complex spatiotemporal variations in air pollution (Li et al., 2023).

The proposed CNN–LSTM architecture consists of two one-dimensional convolutional layers with 64 and 128 filters, respectively, using a kernel size of 3 and ReLU activation. Each convolutional layer is followed by a MaxPooling1D layer to reduce feature dimensionality. The extracted spatial features are then passed into two stacked LSTM layers containing 64 and 32 memory units to capture temporal dependencies. A dropout layer with a rate of 0.2 is applied after each LSTM layer to reduce overfitting. Finally, a fully connected dense layer with one output neuron produces the predicted PM_{2.5} concentration. The model was trained using the Adam optimizer with a learning rate of 0.001 and Mean Squared Error (MSE) as the loss function.

Spatiotemporal deep learning models can jointly capture spatial and temporal dependencies in air pollution data, while attention mechanisms can further enhance the representation of relevant features for PM_{2.5} prediction (S. Zhou et al., 2024). However, the main challenge is non-stationarity during extreme events. Therefore, modern models are beginning to adopt transfer learning and physics-informed neural networks (PINNs) to ensure that prediction results do not deviate from atmospheric physical principles (Agbehadji & Obagbuwa, 2024). This approach paves the way for the development of AI-based early warning systems that are accurate, adaptive and can be executed in real-time.

The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. The training set was used to optimize model parameters, the validation set was used to monitor model performance and prevent overfitting, and the testing set was used for final model evaluation. Model

performance was evaluated using the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) as regression performance metrics.

2.4 Methodology

This research method applies a quantitative approach based on secondary data obtained from remote sensing and meteorological reanalysis to examine the relationship between extreme weather phenomena and PM_{2.5} concentrations in the Democratic Republic of the Congo over the period 2014–2024. The quantitative approach was chosen because it was able to explain the cause-and-effect relationship in a measurable and objective manner through the integration of high spatial-temporal resolution atmospheric data (Fang et al., 2021; Petrić et al., 2024). The study area was selected based on the distinctive hydrometeorological characteristics of Central Africa, including strong convective activity, seasonal rainfall variability, and complex atmospheric circulation, which make the region relevant for analyzing extreme weather dynamics (Longandjo & Rouault, 2024; Tikeng et al., 2024). The main data consisted of several types: meteorological variables from ERA5 (air temperature, relative humidity, wind speed, and surface pressure), precipitation data from GPM/IMERG, AOD aerosol data from MODIS, and atmospheric gas concentrations (NO₂ and CO) from Sentinel-5P/TROPOMI. In addition, PM_{2.5} concentrations were obtained from OpenMeteo satellite datasets with daily resolution. The data is then harmonized into a uniform spatial grid to reduce resolution bias between sources (Y. Zhang & Li, 2021; Y. Zhou, 2024).

Extreme weather phenomena are identified based on a statistical approach using percentile thresholds: extreme heat is set at the 95th percentile of temperature, extreme rain is set at the 95th percentile of precipitation, and stagnant winds are defined when wind speeds are below 1.5 m/s for at least 12 hours. This method is commonly used in the study of extreme climatology in the tropics (Langue et al., 2023; Suhadi et al., 2023). The pre-processing process includes spatial interpolation, data cleansing through temporal interpolation to handle missing values, normalization using MinMaxScaler for model training stability, and the establishment of a time series structure with a 24-hour input window to predict the next 24–48 hour conditions. The dataset is then divided into training (70%), validation (15%), and testing (15%) data.

The development of deep learning models is carried out using two main architectures. The LSTM model was used to capture temporal dependencies in air quality time-series data, while the CNN–LSTM hybrid model was used to capture spatiotemporal patterns through convolutional feature extraction and temporal modeling (Hu, 2022; Bai et al., 2024). The LSTM architecture consists of two hidden layers with 64–128 units and a ReLU activation function, while the CNN-LSTM is equipped with batch normalization and dropout (0.2) to reduce overfitting. The entire modeling process was carried out using Python 3.10 with TensorFlow/Keras, and supported by NumPy, Pandas, Matplotlib, and xarray. Model performance was evaluated using the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) as regression performance metrics.. This comprehensive evaluation approach follows recommendations in the current literature on spatiotemporal modeling of air quality (Tao et al., 2025; Liao et al., 2020). The overall research workflow, including data acquisition, preprocessing, extreme weather identification, deep learning model development, and performance evaluation, is summarized in Figure 1.



Figure 1 Overall Research Methodology for PM_{2.5} Prediction Using Satellite Data and Deep Learning

3. RESULT AND DISCUSSION

3.1 Temporal and Spatial Patterns

Analysis of temporal weather patterns in Central Africa indicates that seasonal variability is closely associated with regional atmospheric circulation, convective activity, and rainfall seasonality (Longandjo & Rouault, 2024; Tikeng et al., 2024). Multi-year meteorological data indicate variations in temperature, precipitation, and humidity, together with episodic extreme events. Large-scale climate variability, particularly the Indian Ocean Dipole (IOD), can significantly influence precipitation patterns over Central Equatorial Africa (Jiang et al., 2021). This phenomenon affects atmospheric stability, pollutant transport, and surface conditions that determine the potential for accumulation or cleanup pollutants.

Spatially, the distribution of extreme events shows concentrations in equatorial lowlands and large river basins that are susceptible to convective storm formation. These areas tend to experience extreme rainfall and wind disturbances that affect the dispersion pattern of pollutants. This is in line with tropical hydrometeorological studies which state that topography and surface structure play a role in determining the intensity and location of extreme events (Nugraha & Firmansyah, 2021). In addition, atmospheric dynamics such as regional winds and the formation of strong convection systems also influence the movement of pollutants, including the transport of biomass fire smoke and the long-distance transport of particulate matter driven by convection systems and strong winds (Liu & Zhou, 2020).

The use of reanalysis and satellite datasets, such as ERA5, MODIS, and TROPOMI, provides a detailed picture of extreme spatial-temporal patterns, especially in areas with minimal aerial monitoring

stations. This data allows mapping of hotspots of extreme events and areas susceptible to increased pollutants during extreme weather episodes (M. Zhang et al., 2025; Siregar & Hartono, 2024). Remote sensing products such as AOD and NO₂ columns are also effective indicators in understanding the interaction between the atmosphere and air quality dynamics, especially in tropical regions with high meteorological variability (Kai-Sikhakhane et al., 2024; Nur et al., 2023). Meteorological time series show seasonal variations in temperature, precipitation, and wind speed, which influence pollutant dispersion and accumulation. Extreme meteorological conditions, including high temperatures, heavy precipitation, and stagnant winds, can substantially modify PM_{2.5} concentrations (Ni et al., 2023).

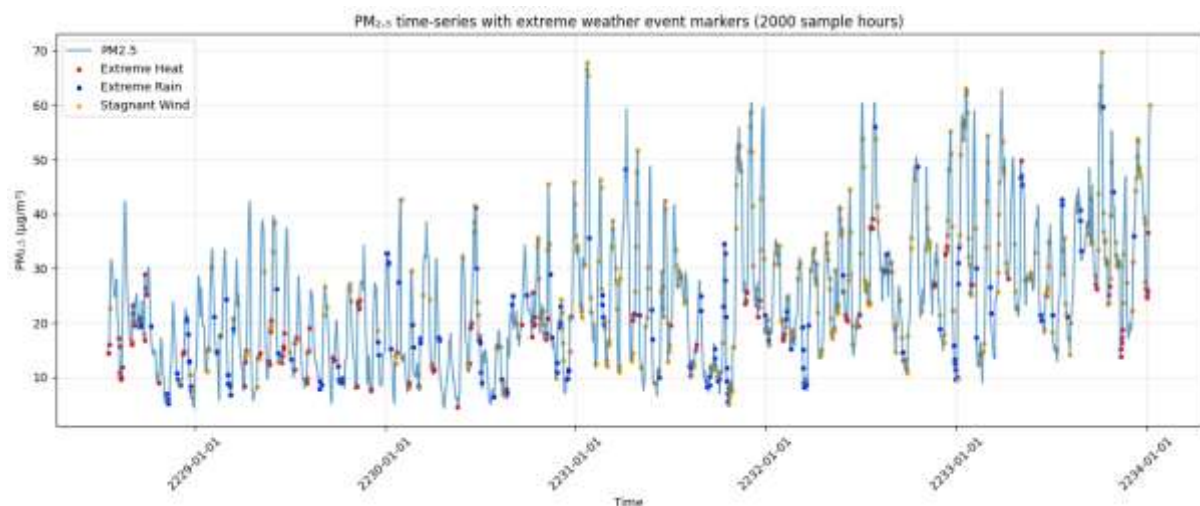


Figure 2 PM_{2.5} time-series with extreme weather event markers (2,000 sample hours)

Figure 2 illustrates the fluctuations of PM_{2.5} along with markers of extreme events. The increase in PM_{2.5} is especially seen in periods of stagnant winds, which is consistent with the finding that the weakness of atmospheric ventilation increases the accumulation of pollutants. In contrast, extreme rainfall can reduce PM_{2.5} concentrations by enhancing the removal of atmospheric particles through wet deposition (Ni et al., 2023). From the visualization, it can be seen that stagnant winds are the most frequent condition associated with PM_{2.5} spikes, while extreme rains cause a decrease in pollutant concentrations through wet deposition mechanisms.

3.2 Air Quality Variation Patterns

Variations in air quality in the equatorial region of Africa reveal temporal and spatial patterns influenced by regional hydrometeorological dynamics as well as natural and anthropogenic emission activities. On a seasonal scale, PM_{2.5} and NO₂ concentrations increase significantly during dry periods, biomass burning seasons, and unstable atmospheric conditions. Peak concentrations of these pollutants have been associated with the removal of dust and smoke by strong winds and long-distance transport from savanna and semiarid regions, driven by regional wind patterns and atmospheric convection activity (Liu & Zhou, 2020). The spatial trends seen on the AOD MODIS satellite and the NO₂ TROPOMI column show a strong correlation between pollution and meteorological dynamics, although the accuracy of the estimate still relies on calibration by surface observations (Handsuh et al., 2023).

Daily to weekly variations show sharp changes in PM_{2.5} concentrations due to the rapid transition between intense rains and dry periods. Extreme precipitation acts as a mechanism for air purification through the rainout and washout processes, which significantly lowers PM_{2.5} concentrations. This is in line with previous findings regarding the negative relationship between precipitation intensity and satellite AOD in the tropics (Harisdianto et al., 2023). On the contrary, dry periods with high atmospheric stability and weak winds allow the accumulation of particles on the surface thus triggering a surge in PM_{2.5}. The interaction between meteorological factors and sources of these emissions is

increasingly evident in regions with biomass burning activities, land cover changes, and rapid urbanization (Shikwambana et al., 2024).

Figure 3 shows a non-normal distribution pattern with a long tail, indicating the frequency of high pollution events under certain atmospheric conditions.

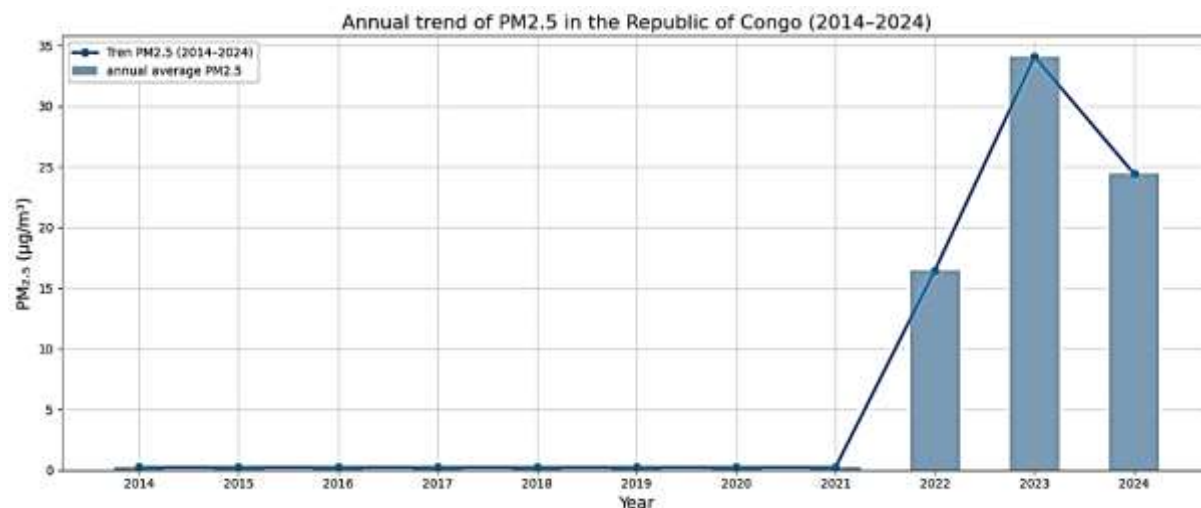


Figure 3 Spatial Distribution of PM_{2.5} Concentration during Extreme Heat Events (2014–2024)

The annual PM_{2.5} trend for the period 2014–2024 shows a stable pattern in the early years stemming from the reconstruction of the LSTM model due to limited satellite data before 2022, while fluctuations are more pronounced in the period 2022–2024 when observational data is fully available. This variability reflects the sensitivity of air quality to annual meteorological dynamics, especially in dry season conditions and stagnant winds that exacerbate pollutant accumulation. Overall, the integration of satellite meteorological data and deep learning models has proven to provide consistent historical estimates of PM_{2.5} while being a relevant scientific basis for long-term monitoring and development of air quality early warning systems.

3.3 The Relationship of Extreme Weather and Air Quality

The relationship between extreme weather and air quality is influenced by variations in temperature, humidity, precipitation, and wind conditions. High temperatures can accelerate photochemical reactions involving VOCs and NO_x, thereby enhancing surface ozone formation (Meng et al., 2023), while high relative humidity can promote secondary aerosol formation by increasing aerosol liquid water and facilitating heterogeneous and aqueous-phase reactions (Meng et al., 2024).

Rainfall contributes to atmospheric cleansing through wet deposition, and variations in precipitation can influence PM_{2.5} concentrations by enhancing the removal of airborne particles (Ni et al., 2023). During the dry season, biomass burning and regional transport can contribute to substantial increases in PM_{2.5} concentrations (Dezfuli et al., 2024). The complexity of this meteorological interaction confirms the need for a prediction model capable of representing non-linear relationships (Tao et al., 2025).

Strong convective activity and complex atmospheric variability over Central Africa highlight the importance of integrating satellite observations with high-resolution meteorological data to characterize regional atmospheric processes (Tikeng et al., 2024). In addition, the diversity of anthropogenic and natural emission sources across Africa contributes to complex regional air pollution patterns and atmospheric composition (Bililign et al., 2024). ERA5 reanalysis helps link meteorological conditions to pollutants, but needs local validation to reduce bias (Liao et al., 2020). The empirical results of the study showed that an increase in temperature was positively correlated with PM_{2.5}, intense rainfall lowered PM_{2.5} through wet deposition, while stagnant winds produced the highest PM_{2.5} concentration. This suggests that the dynamics of the tropical atmosphere are the main regulators of surface pollutant concentrations. To further illustrate the influence of extreme weather on air quality,

the average PM_{2.5} concentrations under normal and extreme meteorological conditions are compared in Figure 4.

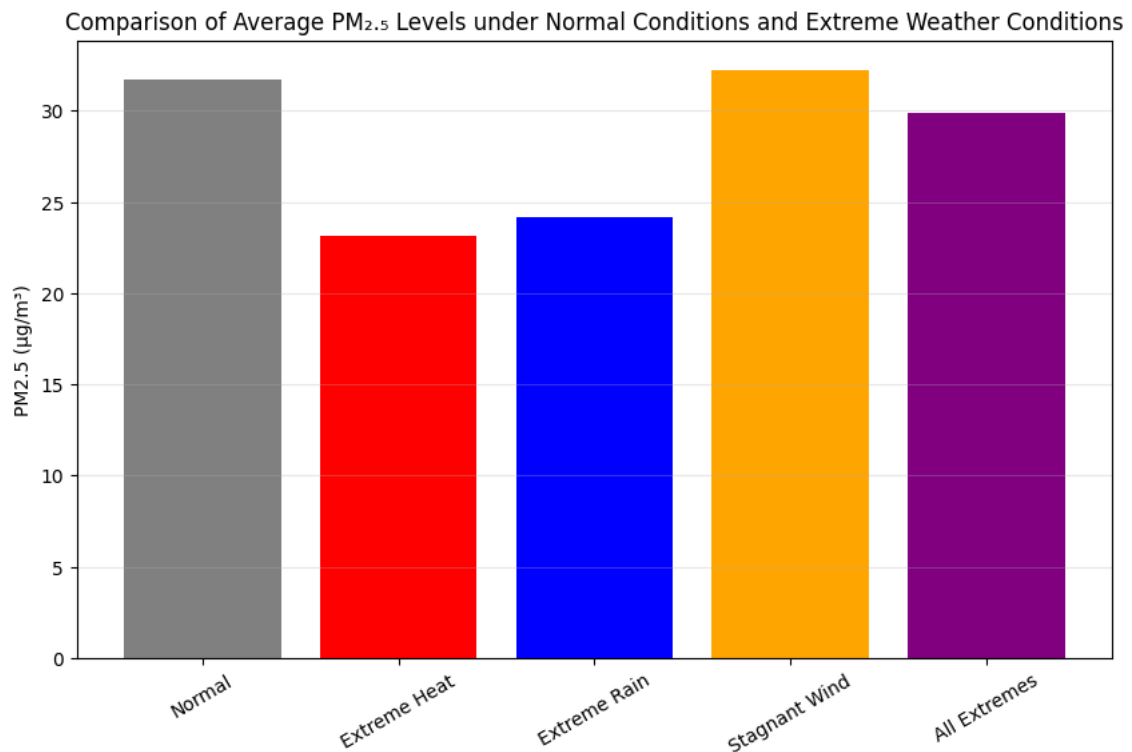


Figure 4 Average Comparison of PM_{2.5} Under Normal and Extreme Conditions

Figure 4 demonstrates that stagnant wind conditions produce the highest PM_{2.5} concentrations because limited atmospheric mixing suppresses pollutant dispersion. In contrast, extreme rainfall substantially decreases PM_{2.5} concentrations through wet deposition, highlighting the important role of precipitation in removing atmospheric particles. The CNN–LSTM model consistently outperformed the standalone LSTM model. It achieved an R^2 value of 0.892, an RMSE of 5.21 $\mu\text{g}/\text{m}^3$, and an MAE of 3.84 $\mu\text{g}/\text{m}^3$, whereas the conventional LSTM obtained an R^2 of 0.762, RMSE of 8.47 $\mu\text{g}/\text{m}^3$, and MAE of 6.12 $\mu\text{g}/\text{m}^3$. These results demonstrate that incorporating convolutional layers significantly improves the extraction of spatial features from satellite observations, leading to more accurate PM_{2.5} prediction.

3.4 Performance Evaluation of LSTM and CNN-LSTM Models

To evaluate the predictive performance of the developed models, the LSTM and CNN–LSTM architectures were compared using three regression metrics: the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics were used to assess the models' ability to reproduce PM_{2.5} concentration variability and quantify prediction errors. A higher R^2 value indicates better agreement between observed and predicted values, while lower RMSE and MAE values indicate smaller prediction errors. The overall performance comparison of the two models is presented in Table 1.

Table 1 Performance Comparison of LSTM and CNN-LSTM Models for PM_{2.5} Prediction

Model	R^2	RMSE ($\mu\text{g}/\text{m}^3$)	MAE ($\mu\text{g}/\text{m}^3$)
LSTM	0.762	8.47	6.12
CNN-LSTM	0.892	5.21	3.84

As shown in Table 1, the CNN–LSTM model consistently outperformed the conventional LSTM model across all evaluation metrics. The CNN–LSTM achieved a higher R^2 (0.892) and lower RMSE ($5.21 \mu\text{g}/\text{m}^3$) and MAE ($3.84 \mu\text{g}/\text{m}^3$) than the LSTM model, which obtained an R^2 of 0.762, an RMSE of $8.47 \mu\text{g}/\text{m}^3$, and an MAE of $6.12 \mu\text{g}/\text{m}^3$. These results indicate that incorporating convolutional layers improves the extraction of relevant features from satellite and meteorological data, while the LSTM component captures temporal dependencies, resulting in more accurate $\text{PM}_{2.5}$ predictions.

3.5 Implications

3.5.1 Potential Use of Models for Early Warning of Air Quality

Satellite data-based air quality prediction models and deep learning techniques have great potential as a core component of early warning systems due to their ability to capture broad spatial patterns and project a decline in air quality before public health impacts are widespread. The integration of satellite products such as AOD and gas columns with reanalysis meteorological variables enables the utilization of real-time or near-real-time inputs that are critical to the operation of early warning systems (Bhowmik et al., 2023; Amiri & Zare Shahne, 2025). This model-based system can be applied at the regional level to support public policy, health decisions, and the drafting of outdoor activity advisories during high-pollution episodes.

The model's ability to generate spatial risk maps as well as detect pre-episodic patterns is a significant advantage in early warning implementation (Oucheikh et al., 2025). Deep learning models can be trained to recognize *early-warning signatures* that appear consistently before a spike in pollutants during extreme events such as heat waves or biomass fires. Although satellites have temporal limitations due to the frequency of *overpasses* and cloud disturbances, the integration of reanalysis data and surface observations is able to overcome these temporal gaps so that predictions remain stable and sustainable (Bhowmik et al., 2023). In addition, the model can be optimized to run on intermediate computing infrastructures, allowing for wider adoption without the need for large supercomputers (Ocaña et al., 2020).

The application of the LSTM model in predicting $\text{PM}_{2.5}$ concentrations for the next 24 to 48 hours provides a picture of risks classified into four categories: normal ($< 35 \mu\text{g}/\text{m}^3$), unhealthy ($> 35 \mu\text{g}/\text{m}^3$), very high ($> 55 \mu\text{g}/\text{m}^3$), and hazardous ($> 150 \mu\text{g}/\text{m}^3$). The results of the initial prediction show that the model is able to provide an early indication of potential pollution spikes, especially in atmospheric conditions with stagnant wind characteristics that have historically been associated with the accumulation of pollutants in the surface layer. Thus, an LSTM-based prediction system has the potential to be a key component in a proactive air quality early warning system that is responsive to meteorological dynamics.

Feature importance analysis indicates that air temperature, Aerosol Optical Depth (AOD), wind speed, and precipitation are the most influential variables in predicting $\text{PM}_{2.5}$ concentrations. Temperature strongly contributes to secondary aerosol formation through photochemical reactions, whereas AOD reflects atmospheric aerosol loading that is closely related to particulate concentrations. Wind speed controls pollutant dispersion, while precipitation reduces $\text{PM}_{2.5}$ through wet deposition processes. The combination of these meteorological and satellite-derived variables enables the CNN–LSTM model to capture complex atmospheric interactions more effectively than models relying on meteorological variables alone. The observed and predicted $\text{PM}_{2.5}$ concentrations obtained using the CNN–LSTM model are compared in Figure 5.

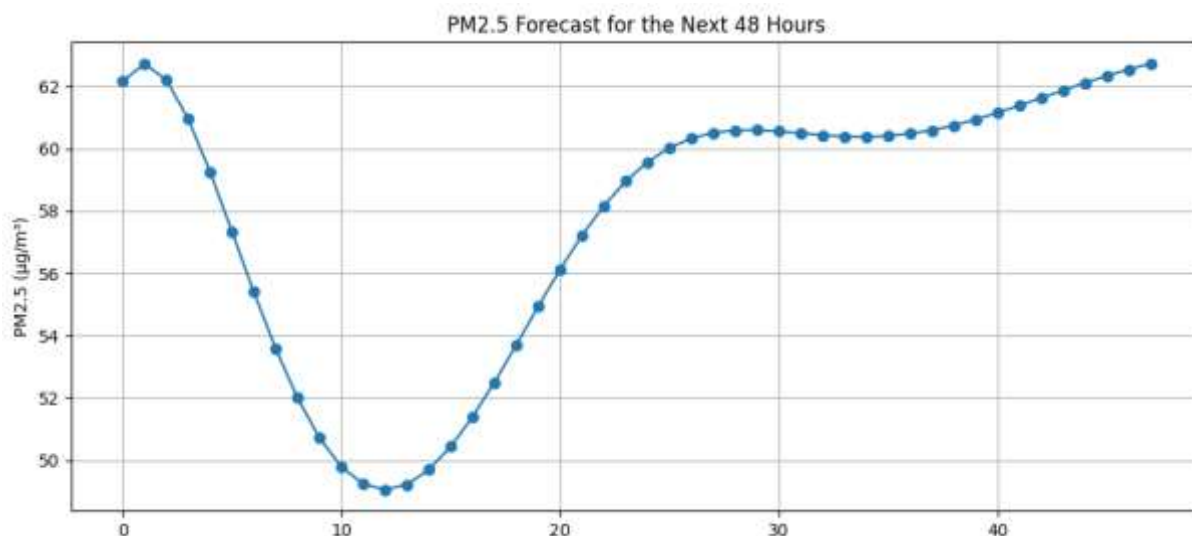


Figure 5 Comparison of Observed and Predicted PM_{2.5} Concentrations Using CNN–LSTM Model

3.5.2 Relevance to Health Impact

Reliable air quality predictions allow for early public health interventions such as health advice, restrictions on outdoor activities, or distribution of masks to vulnerable groups to reduce morbidity and mortality from air pollutants (Handschuh et al., 2023). Consistent data and predictions also provide evidence for policymakers to design long-term policies on emissions control and spatial planning in developing countries with limited institutional capacity. For equatorial regions of Africa that are vulnerable to a combination of extreme weather and air pollution, the integration of model results with climate change adaptation strategies can strengthen public health resilience (Omokpariola, 2025). As such, this study has strong practical implications for health impact reduction and for evidence-based environmental policy formulation at the national and regional levels.

Simulations that reduce vehicle emissions or combustion can show a peak decline in pollutant concentrations during heat waves or fire episodes, thus supporting the *cost-benefit* argument in public policy (Ming et al., 2014). These quantitative results are useful for policymakers in countries with limited resources in assessing mitigation investments. Investment in focused in-situ observations and long-term satellite validation programs will strengthen predictive reliability and policy basis (Zhao et al., 2024). Responsive policies must also consider socio-economic aspects so that mitigation measures do not disproportionately burden vulnerable groups. International collaboration and financing for technology transfer can support equatorial African countries in adopting such predictive technologies and early warning systems. Overall, the integration of satellite data-based deep learning models into mitigation policies can increase the public's capacity to adapt to the impact of extreme weather on air quality.

4. CONCLUSION

Extreme weather such as heat waves, heavy rains, and stagnant winds have a significant impact on air quality in the equatorial region of Africa, particularly the Democratic Republic of the Congo. The analysis shows that stagnant wind conditions cause the accumulation of fine particulate matter (PM_{2.5}) due to the lack of atmospheric dispersion, while extreme rains are effective in reducing pollutant concentrations through the wet deposition process. On the other hand, high temperatures accelerate photochemical reactions that form secondary pollutants such as surface ozone. Given the limited network of ground-based aerial monitoring, satellite data (such as TROPOMI, MODIS, GPM, and ERA5) are crucial sources for monitoring meteorological variables and pollutant concentrations spatially and temporally. The integration of this data with deep learning techniques, especially LSTM

and CNN-LSTM models, has been proven to be able to predict air quality with high accuracy, even under extreme conditions.

The predictive model developed not only describes a non-linear relationship between extreme weather and air pollution, but also has the potential to become an early warning system for mitigating health and environmental risks. In the long term, this approach supports evidence-based policies for emissions control, spatial planning, and adaptation to climate change in vulnerable tropics. Thus, the combination of hydrometeorological approaches, remote sensing, and artificial intelligence provides a strong scientific foundation for understanding, predicting, and responding to air quality dynamics in regions with limited observational data such as equatorial Africa.

Future research should include validation using ground-based air quality monitoring stations to further improve model reliability. In addition, integrating socio-economic variables, land-use characteristics, emission inventories, and population exposure data may enhance the applicability of the model for environmental policy, public health risk assessment, and climate adaptation planning across tropical regions.

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