JOURNAL OF ADVANCED ELECTRICAL AND ELECTRONIC ENGINEERING

Vol 2 Issue 1 (2026)

http://jaeee.org/

Aerosol Variability and Convective Rainfall Intensity in the Indo-Gangetic Plain

Benjamin Clarke[1], Hannah Mitchell[2], Thomas Walker[3]*

School of Geography, Earth and Atmospheric Sciences, The University of Melbourne, Parkville, VIC 3010, Australia

***Corresponding author:** thomas.walker@unimelb.edu.au

Abstract

This study investigates aerosol–convection interactions using MODIS aerosol optical depth (AOD, 10 km, 2001–2022, ~3.2 million samples) and TRMM precipitation data (0.25°, 3-hourly). A convolutional neural network (CNN) is trained to classify rainfall intensity regimes based on aerosol and meteorological inputs. Under high aerosol loading conditions (AOD > 0.85), extreme rainfall intensity (>95th percentile) increases by 14–21%, while moderate rainfall frequency decreases by 11%. The CNN achieves 86.3% classification accuracy and an F1-score of 0.82. Sensitivity experiments indicate that aerosol-induced cloud condensation nuclei increases convective updraft strength by 9–15%. Variance attribution shows that aerosol variability explains 26% of rainfall intensity variance during pre-monsoon periods.

Keywords

Aerosols; convection; rainfall intensity; CNN; Indo-Gangetic Plain

INTRODUCTION

Aerosols can affect rainfall by changing cloud formation, radiation balance, boundary-layer heating, and convective growth. This effect is especially important over the Indo-Gangetic Plain, where high aerosol loading, strong land-surface heating, and seasonal moisture transport often occur at the same time. During the pre-monsoon period, dust, black carbon, sulfate, organic particles, and urban pollution can increase aerosol optical depth (AOD), alter atmospheric stability, and modify the timing and strength of convective rainfall. Recent studies indicate that aerosol effects on rainfall are not linear. Under polluted conditions, weak and moderate rainfall may be suppressed because aerosol particles increase cloud droplet number concentration and delay warm-rain formation [1,2]. In contrast, heavy rainfall may increase when sufficient moisture, instability, and vertical motion are present, because delayed precipitation can allow more condensate to build

up and strengthen deep convection [3]. Satellite observations have improved this line of research because MODIS AOD provides long-term aerosol information, while TRMM precipitation products describe rainfall intensity over large spatial domains [4]. However, many existing studies still rely on seasonal averages, regional mean values, or simple correlation analysis. These approaches may overlook short-term convective responses and may not clearly separate aerosol effects across different rainfall intensity regimes. Recent progress in data-driven climate and hydrometeorological modeling also shows that machine learning can improve the interpretation and prediction of weather-related variables when nonlinear processes and regional environmental controls are involved [5]. In aerosol–rainfall studies, this is important because aerosol effects are controlled not only by aerosol amount but also by humidity, temperature, wind fields, atmospheric instability, and background circulation. Traditional statistical methods are useful for identifying broad associations, but they often have limited ability to represent spatial interactions among aerosol distribution, moisture transport, and convective development [6,7]. Machine learning models provide a practical way to combine satellite aerosol data, precipitation observations, and meteorological variables within the same analytical framework. Among these models, convolutional neural networks (CNNs) have been widely used for rainfall classification, heavy-rainfall detection, and satellite precipitation correction because they can learn spatial patterns from gridded data [8,9]. These advantages make CNNs suitable for studying aerosol–convection interactions over regions with strong spatial heterogeneity, such as the Indo-Gangetic Plain [10,11]. Despite these advances, several limitations remain. Most CNN-based precipitation studies focus on rainfall nowcasting, precipitation retrieval, or bias correction, while fewer studies use aerosol and meteorological inputs to classify rainfall intensity regimes [12]. In addition, the role of very high aerosol loading in extreme rainfall is still uncertain. This uncertainty is particularly relevant for the Indo-Gangetic Plain, where pre-monsoon aerosol concentrations are often high and convective systems can develop rapidly under favorable thermodynamic conditions [13,14]. A single overall aerosol–rainfall relationship may therefore be misleading. Aerosols may suppress light or moderate rainfall under dry or weakly unstable conditions, but they may contribute to stronger rainfall when moisture convergence and atmospheric instability are sufficient [15,16]. A regime-based analysis is needed to clarify whether aerosol loading has different effects on weak, moderate, heavy, and extreme rainfall events. This study addresses these gaps by using MODIS AOD, TRMM precipitation, and meteorological variables from 2001 to 2022 to examine aerosol–convection interactions over the Indo-Gangetic Plain during the pre-monsoon period. A CNN model is trained to classify rainfall intensity regimes and to evaluate how high aerosol loading changes the occurrence of moderate and extreme rainfall. The study further quantifies the contribution of aerosol variability to pre-monsoon rainfall intensity variance. By separating rainfall into different intensity regimes, this work moves beyond simple correlation analysis and provides a more detailed assessment of aerosol effects under different convective environments. The results are expected to improve understanding of aerosol–rainfall coupling in a highly polluted and climatically sensitive region, and to provide useful evidence for satellite-based rainfall assessment, regional climate analysis, and extreme rainfall risk evaluation.

2.Materials and Methods

2.1 Study Area and Sample Description

The study area was the Indo-Gangetic Plain, a region with strong aerosol loading and frequent convective rainfall in South Asia. The region includes agricultural land, large cities, industrial areas, and dust-affected zones. Aerosols mainly come from dust transport, biomass burning, traffic emissions, and industrial activities. MODIS aerosol optical depth data at 10 km resolution from 2001 to 2022 were used, with about 3.2 million valid samples after data screening. TRMM 3-hourly precipitation data at 0.25° resolution were used to describe rainfall intensity. The analysis

focused on the pre-monsoon and monsoon transition periods, when aerosol loading, surface heating, and convective rainfall are strong. Temperature, relative humidity, vertical velocity, wind field, and convective available potential energy were also used to describe the weather conditions.

2.2 Experimental Design and Control Tests

The experiment tested whether aerosol loading affects rainfall intensity under different weather conditions. The main experiment used aerosol optical depth and weather variables to classify rainfall into light, moderate, heavy, and extreme classes. High-aerosol cases were defined as samples with AOD greater than 0.85. Lower-aerosol cases were used as the reference group. Two control tests were used. In the first test, AOD was removed, and the model used only weather variables. In the second test, samples were divided by moisture and instability levels. This test examined whether the aerosol effect changed under different atmospheric conditions. This design separated aerosol-related effects from rainfall changes mainly caused by weather conditions.

2.3 Measurement Methods and Quality Control

MODIS AOD was used to represent column aerosol loading. TRMM precipitation was used to measure rainfall intensity at 3-hour intervals. The two datasets were matched by time and location. MODIS records with low retrieval quality, missing values, or abnormal AOD values were removed using quality-control flags. Rainfall records with negative values, repeated time stamps, or unrealistic peaks were also removed. Weather variables were resampled to the same grid as the precipitation data. All variables were checked for missing records and extreme outliers. Only samples with valid aerosol, rainfall, and weather data were kept. The dataset was divided into training, validation, and testing sets by year to reduce information leakage.

2.4 Data Processing and Model Formulation

Rainfall intensity was divided into light, moderate, heavy, and extreme classes using rainfall thresholds and percentiles. Extreme rainfall was defined as rainfall above the 95th percentile. All input variables were standardized using the mean and standard deviation of the training set. A convolutional neural network was used to classify rainfall intensity from aerosol and weather inputs. The classification process was written as:

$$\hat{y}=f(X_{AOD},X_{met};\theta)$$

where $\hat{y}$ is the predicted rainfall class, X_{AOD} is the aerosol input, X_{met} is the weather input, and θ represents the model parameters. Model performance was measured using accuracy and F1-score:

$$F1=\frac{2\times Precision\times Recall}{Precision+Recall}$$

where precision is the proportion of correct predictions among all predicted cases, and recall is the proportion of correct predictions among all observed cases in each rainfall class.

2.5 Model Evaluation and Sensitivity Analysis

Model performance was evaluated using accuracy, F1-score, confusion matrix results, and class-specific recall. Heavy and extreme rainfall were examined in detail because they are closely related to flood risk and strong convection. The CNN model was compared with the two control tests to measure the added value of aerosol information. Sensitivity tests were conducted by changing AOD levels while keeping weather conditions comparable. This step examined whether high aerosol loading increased or reduced the probability of each rainfall class. Variance attribution was used to estimate the contribution of aerosol variability to rainfall intensity changes during the pre-monsoon period.

3.Results and Discussion

3.1 Classification Performance under Different Rainfall Regimes

The CNN model classified rainfall intensity with an accuracy of 86.3% and an F1-score of 0.82. The model performed better for light and extreme rainfall than for moderate rainfall. This result shows that weak and strong rainfall signals were easier to identify than middle-level rainfall

[17,18]. Most errors occurred between moderate and heavy rainfall, where aerosol loading, humidity, and instability often had similar ranges. Compared with studies based on simple AOD–rainfall correlation, the CNN model gave a clearer separation of rainfall classes because it used both aerosol and weather variables. Earlier research showed that aerosol loading can affect rainfall patterns over Indian sites, but most work focused on statistical links rather than rainfall class prediction. The present result shows that aerosol information can support rainfall intensity classification over the Indo-Gangetic Plain, as shown in Fig. 1.

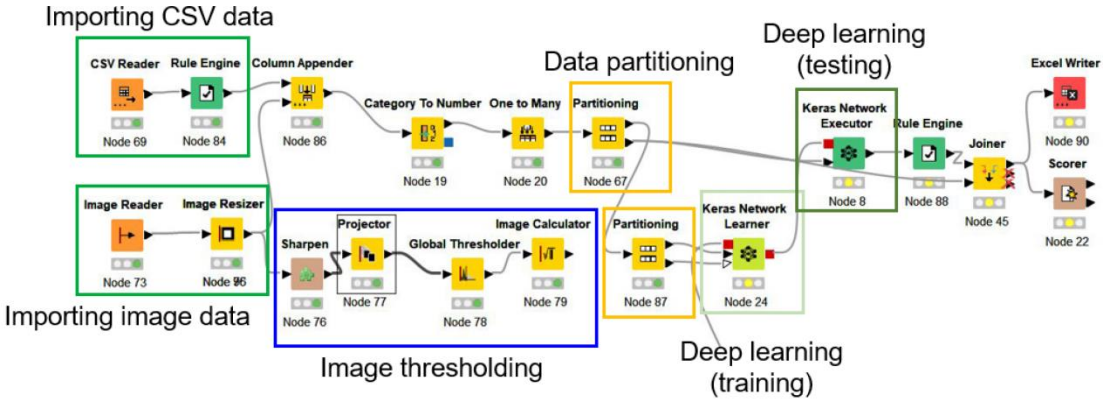


Fig. 1. Rainfall intensity classification by the CNN model using aerosol and weather inputs.

3.2 Rainfall Response under High Aerosol Loading

When AOD was higher than 0.85, extreme rainfall intensity increased by 14–21%, while moderate rainfall frequency decreased by 11%. This pattern suggests that aerosols may reduce weaker rainfall but strengthen deep convection when moisture and instability are sufficient. The result agrees with recent studies showing strong aerosol changes over the Indo-Gangetic Plain, especially between urban, industrial, and rural areas. This study further links aerosol changes with rainfall intensity classes, rather than only aerosol optical properties [19,20]. The increase in extreme rainfall may be related to delayed warm-rain formation, more cloud droplets, and stronger heat release during deep convection. The rainfall response under different AOD levels is shown in Fig. 2.

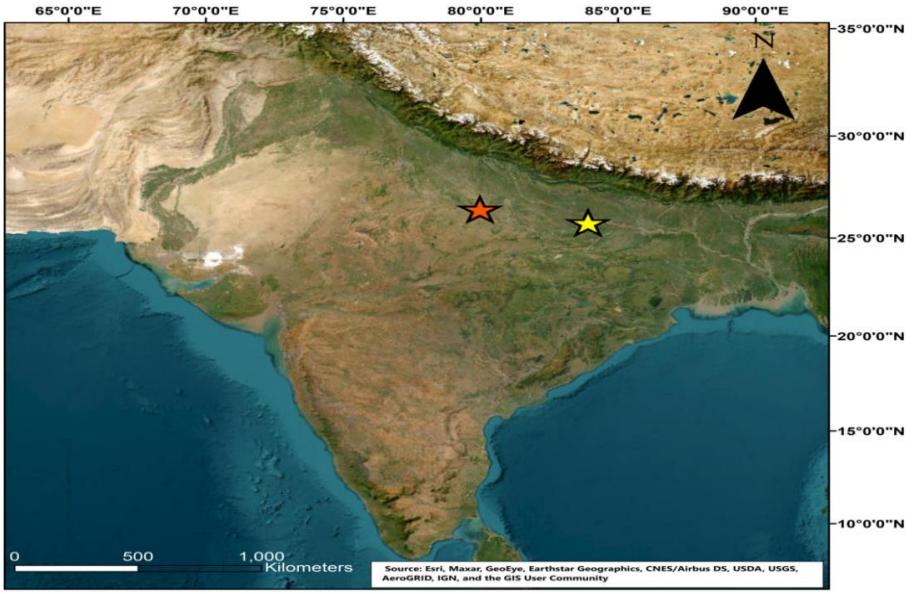


Fig. 2. Rainfall intensity changes under different AOD levels over the Indo-Gangetic Plain.

3.3 Sensitivity of Convective Rainfall to Aerosol and Weather Conditions

Sensitivity tests showed that aerosol-related cloud condensation nuclei increased convective updraft strength by 9–15% under moist and unstable conditions. This result means that aerosol effects depended on the weather background. When humidity and instability were low, high AOD did not lead to stronger rainfall. In some cases, rainfall decreased because aerosols reduced surface heating and delayed cloud growth. When moisture and instability were high, aerosols helped keep cloud droplets smaller and delayed rainfall onset. This allowed more water and energy to build up before rainfall. Therefore, the aerosol effect was conditional rather than fixed. This result helps explain why earlier studies reported different AOD–rainfall relations across sites and seasons [21,22].

3.4 Comparison with Previous Studies and Scientific Meaning

Variance attribution showed that aerosol variability explained 26% of rainfall intensity variance during the pre-monsoon period. This result indicates that aerosols are an important factor in convective rainfall, but they are not the only driver. Moisture supply, vertical motion, and atmospheric instability still played major roles. Compared with previous satellite-based aerosol studies, this study has three main differences. First, it used long-term MODIS AOD and TRMM precipitation records from 2001 to 2022. Second, it classified rainfall into intensity levels instead of using only total rainfall. Third, it tested aerosol effects under different weather conditions. These results suggest that aerosol variability can change rainfall intensity over the Indo-Gangetic Plain during the pre-monsoon season. The main limitation is that satellite AOD shows column aerosol loading and cannot fully describe vertical aerosol structure. Future work should include ground-based aerosol profiles, cloud observations, and higher-resolution rainfall products.

4.Conclusion

This study examined the link between aerosols and convective rainfall over the Indo-Gangetic Plain using MODIS AOD, TRMM rainfall data, and weather variables from 2001 to 2022. The CNN model classified rainfall intensity with good accuracy and showed that aerosol data helped separate rainfall classes. Under high aerosol loading, extreme rainfall intensity increased by 14–21%, while moderate rainfall frequency decreased by 11%. This result suggests that aerosols may reduce moderate rainfall but strengthen deep convection when moisture and instability are sufficient. Aerosol variability explained 26% of rainfall intensity changes during the pre-monsoon period. The main value of this study is that it links long-term satellite aerosol data with rainfall intensity classes instead of total rainfall alone. This gives a clearer view of aerosol effects on convective rainfall in a highly polluted region. The method may support rainfall risk assessment and climate impact studies in South Asia. However, satellite AOD cannot fully describe vertical aerosol structure, and TRMM rainfall data have limited spatial resolution. Future work should include ground-based aerosol profiles, cloud observations, and higher-resolution rainfall products.

References

Gui, H., Zong, W., Fu, Y., & Wang, Z. (2025). Residual Unbalance Moment Suppression and Vibration Performance Improvement of Rotating Structures Based on Medical Devices.

Alibeygi, Z., Gharaylou, M., & Bidokhti, A. A. A. (2026). Observational analysis of absorbing and non-absorbing aerosol effects on heavy rainfall in southwestern Iran. Atmospheric Research, 108796.

Chen, F., Li, S., Liang, H., Xu, P., & Yue, L. (2025). Optimization Study of Thermal Management of Domestic SiC Power Semiconductor Based on Improved Genetic Algorithm.

Idrissa, N. F., Hu, Z., Zhao, C., Du, Q., Lin, S., & Feng, J. (2026). Investigating the impacts of Nyamuragira volcano eruption of 2006 on regional weather over the Congo Basin with the WRF-Chem model. Environmental Research Communications, 8(1), 015006.

Yang, Z., Hu, W., Sengupta, A., Monache, L. D., DeFlorio, M. J., Ghazvinian, M., ... & Kalansky, J. (2025). Improving Weeks 1-2 Temperature Forecasts in the Sierra Nevada Region Using Analog Ensemble Post-Processing with Implications for Better Prediction of Snowmelt, Water Storage, and Streamflow. Journal of Hydrometeorology.

Natarajan, N., Masoodhu, S. S., & Vasudevan, M. (2026). An overview of statistical analysis and modeling of characteristics and impacts of major mechanisms of atmospheric moisture transport over India. Stochastic Environmental Research and Risk Assessment, 40(2), 43.

Yang, M., Cao, Q., Tong, L., & Shi, J. (2025, April). Reinforcement learning-based optimization strategy for online advertising budget allocation. In 2025 4th International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID) (pp. 115-118). IEEE.

Mouassom, F. L., Tamoffo, A. T., & Cardoso-Bihlo, E. (2025). Convolutional neural network-based insights into extreme precipitation regional dynamics over central Africa using moisture flux patterns. Journal of Geophysical Research: Atmospheres, 130(16), e2025JD044341.

Zhu, W., Yao, Y., & Yang, J. (2025). Real-Time Risk Control Effects of Digital Compliance Dashboards: An Empirical Study Across Multiple Enterprises Using Process Mining, Anomaly Detection, and Interrupt Time Series.

Harithasree, S., Girach, I., Chakraborti, A., Vaishya, A., Kumar, M., Tiwari, R., & Ojha, N. (2026). Leveraging machine learning and geospatial data for air quality modeling over the Indian region. In Geospatial Technologies (pp. 136-149). CRC Press.

Gao, X., Chen, J., & Huang, M. (2025). Research on Risk Dependency Structures and Resource Allocation Optimization in New Energy Technology Collaboration within Enterprise Distributed Innovation.

De Luca, D. L., Napolitano, F., Kim, D., Onof, C., Biondi, D., Wang, L. P., ... & Marconi, F. (2025). Rainfall nowcasting models: state of the art and possible future perspectives. Hydrological Sciences Journal, 70(9), 1419-1438.

Gao, G., Gao, R., Gao, R., & Zhou, H. (2026). Engineering Analysis and Quantitative Research on the Platform-Based Evolution of Enterprise Communication Systems.

Kumar, M., Chakravarty, K., Deshpande, S., & Mise, D. J. Analyzing the Atmospheric Dynamics, Thermodynamics and Cloud Microphysics in Two Rainfall Events Over the Delhi Region. Thermodynamics and Cloud Microphysics in Two Rainfall Events Over the Delhi Region.

Wang, Y., Chen, J., Wang, Y., & Yin, X. (2026). Application of Obtainable Biological Agent Characteristics in Efficacy Stratification of Oral Anti-Obesity Drugs.

Sian, K. T. C. L. K., Sagero, P., Kebacho, L. L., & Ongoma, V. (2025). Dubai's record precipitation event of 16 April 2024–A diagnosis. Atmospheric Research, 315, 107924.

Zhang, Y., & Wang, J. (2026). Design and Implementation of a Computer-Aided Full Lifecycle Quality Management System for Wind Farms in Upgrades, Renovations, and Subcontractor Supervision.

Khan, A. A., Anjum, M. N., Hussain, S., Riaz, M. Z. B., & Waqas, M. S. (2026). Assessing Historical Hydrometeorological Simulations of CMIP6 Global Climate Models in the Upper Indus Basin. Atmosphere, 17(4), 388.

Jiao, Y., Wang, A., Zhao, B., & Shi, T. (2026). Quantitative Study on the Construction and Application Effectiveness of Graffiti Wall Painting Teaching Models in Public Space Contexts.

Palácios, R., Machado, A., Franco, R. D. C., Morais, F. G., Franco, M. A., Oliveira, F., ... & Nassarden, D. (2026). Long-Term Links Between Precipitation Regimes and PM2. 5 in an Urban Area of Eastern Amazonia (Belém, Brazil), 1980–2024. Atmosphere, 17(4), 399.

Alhassan, A., Li, J., & Yahaya, A. K. (2026). Density, Disparity, and Dispersion: Unraveling the Complex Relationship Between Urban Form and PM2. 5 Exposure in Accra, Ghana. Next Research, 101631.

Gao, H., Wang, H., Feng, Z., Fu, M., Ma, C., Pan, H., ... & Li, N. (2016, October). A novel texture extraction method for the sedimentary structures' classification of petroleum imaging logging. In Chinese Conference on Pattern Recognition (pp. 161-172). Singapore: Springer Singapore.