STM JOURNALS

International Journal of
Environmental Noise and Pollution Control

Volume 4, Issue 1, 2026
January–June
DOI (Journal): 10.37591/IJENPC

https://journals.stmjournals.com/ijenpc

Review IJENPC

Intelligent Earth: AI as a Catalyst for Climate Action

Achinta Kumar Palit[1,*], Abhishek Panda[2]

Abstract

Artificial intelligence (AI) is assuming an increasingly influential role in climate science, providing advanced tools capable of interpreting vast, complex, and now multidimensional environmental datasets. Traditional climate modeling approaches, while grounded in physical principles, frequently struggle to deliver high-resolution, real-time, and region-specific forecasts because of heavy computational demands, incomplete observations, and uncertainties in representing complex environmental small-scale processes. AI techniques, especially machine learning and deep learning, provide strong substitutes and enhancements to these approaches. By identifying hidden patterns, nonlinear relationships, and trends within massive streams of data, AI supports the development of hybrid frameworks that blend empirical observations with scientifically robust, physics-based simulations, ultimately improving predictive precision and spatial granularity. The fusion of AI with satellite remote-sensing technologies has significantly strengthened the capacity for continuous, automated monitoring of environmental change. These systems can rapidly detect and quantify phenomena such as deforestation, glacial retreat, biodiversity loss, urban heat island effects, air pollution dynamics, and fluctuations in sea surface temperatures. In addition, dynamic current AI-driven forecasting and early warning platforms are enhancing preparedness for extreme weather events, including hurricanes, floods, droughts, and wildfires, enabling quicker response times and more informed disaster risk management strategies. Despite its transformative promise, integrating AI into climate research is not without obstacles. Persistent issues related to data quality, representativeness, algorithmic bias, interpretability, and reproducibility require careful attention. Effective progress also depends on strong cross-disciplinary collaboration among climate scientists, computer engineers, policymakers, and local stakeholders. Ethical considerations, transparency in model development, and equitable access to technological benefits remain central to responsible deployment. As the scale and urgency of climate challenges intensify, AI is emerging as a critical enabler for evidence-based policymaking, efficient resource allocation, and strategic future long-term sustainability planning, reshaping how humanity understands and responds to a rapidly changing planet.

***Author for Correspondence**
Achinta Kumar Palit
E-mail: achintakpalit@gietbbsr.edu.in

[1]Assstant Professor, Department of Computer Science and Engineering, Gandhi Institute of Excellent Technocrats, Bhubaneswar, Odisha, India
[2]Student, Department of Computer Science and Engineering, Gandhi Institute of Excellent Technocrats, Bhubaneswar, Odisha, India

Received Date: January 20, 2026
Accepted Date: February 18, 2026
Published Date: March 10, 2026

Citation: Achinta Kumar Palit, Abhishek Panda. Intelligent Earth: AI as a Catalyst for Climate Action. International Journal of Environmental Noise and Pollution Control. 2026; 4(1): 48–52p.

Keywords: Artificial intelligence (AI), deep learning, environmental monitoring, machine learning, remote sensing

INTRODUCTION

Climate change represents one of the most complex and pressing global challenges of the 21st century, characterized by vast and interconnected environmental processes and rapidly increasing volumes of observational data. Traditional climate modeling approaches, while grounded in well-established physical principles, often struggle to capture fine-scale variability and provide timely predictions owing to computational limitations and uncertainties inherent in climate systems. In this context, artificial intelligence (AI) is a strong tool that supports existing systems and can transform how climate data are analyzed, interpreted, and applied.

AI tools, including machine and deep learning, enable the processing of large, heterogeneous datasets generated from satellites, sensor networks, and climate simulations. By learning the patterns and relationships within these data, AI-driven models can enhance the accuracy and resolution of climate forecasts. The fusion of AI with physical climate models allows the development of hybrid frameworks that balance data-driven insights with scientific understanding. Moreover, AI supports continuous environmental monitoring and facilitates the detection of changes in ecosystems, atmospheric conditions, and ocean dynamics. As the frequency and intensity of climate-related hazards increase, AI-based early warning systems play a critical role in improving preparedness and resilience to these hazards. This integration marks a significant advancement in climate science, offering new pathways for informed decision-making and sustainable actions.

The climate crisis is no longer a distant threat; it is a present reality marked by extreme weather, rising temperatures, and ecological disruption. Meeting this challenge requires faster, smarter, and more coordinated actions than ever before. AI is increasingly emerging as a powerful enabler of climate solutions, supporting global efforts aligned with the United Nations Framework Convention on Climate Change and the goals of the Paris Agreement. Although AI alone cannot solve climate change, it can significantly accelerate progress in mitigation, adaptation, and resilience.

One of AI's most impactful contributions of AI lies in climate modeling and forecasting. Climate systems are complex and involve vast datasets from satellites, sensors, and historical records. AI algorithms can process and analyze these data streams at remarkable speeds, identifying patterns that traditional models may miss. Institutions such as NASA and the European Space Agency use AI-enhanced tools to improve weather forecasting, monitor environmental changes, and predict extreme events such as hurricanes and wildfires. More accurate forecasts enable governments and communities to prepare earlier, thereby reducing economic losses and human risk.

AI is also transforming the energy sector. Renewable sources, such as wind and solar, are variable by nature, making grid stability a challenge. AI systems help forecast energy production based on weather data and optimize electricity distribution in real-time. In countries such as Germany and Denmark, AI supports smart grids that balance supply and demand more efficiently. This improves the integration of renewable energy and reduces the reliance on fossil fuels, directly lowering greenhouse gas emissions.

Industries and supply chains, which account for a substantial share of global emissions, also benefit from AI-driven optimization. Advanced analytics can detect inefficiencies in manufacturing processes, reduce material waste, and streamline logistics. Technology companies such as Microsoft and Google are applying AI to improve energy efficiency in data centers and track carbon footprints across operations. These tools enable organizations to make data-driven decisions that support their decarbonization strategies.

LITERATURE REVIEW

In recent years, the integration of AI with environmental science has resulted in significant progress in forecasting, monitoring, and decision-making. According to [1], models based on deep learning, such as convolutional neural networks (CNNs), have shown exceptional accuracy in land cover classification using satellite imagery, outperforming traditional remote-sensing techniques. Similarly, long short-term memory (LSTM) neural networks have been used to estimate deviations in temperature and rainfall patterns, offering better temporal insights than conventional statistical models [2]. These advancements demonstrate the capability of AI to handle high-dimensional, nonlinear, spatiotemporal data with precision.

The integration of AI in environmental monitoring enhances the early detection of hazardous conditions. For example, machine learning algorithms have been used to detect wildfire risk zones based on vegetation, humidity, and historical ignition patterns [3]. AI tools also assist in air quality prediction, where regression and classification models analyze pollutants such as $PM_{2.5}$ and NO_2 in urban zones [4]. These studies emphasize the scalability of AI solutions for regional and global climate initiatives. However, concerns regarding data quality, algorithmic bias, and model interpretability remain significant barriers to widespread adoption.

METHODOLOGY

The methodology adopted in this study follows a theoretical and analytical approach focused on the review and conceptualization of AI-based climate applications. Data were collected from multiple open-source repositories and databases, including NASA Earth Data, NOAA Climate Data Online, and the Copernicus Open Access Hub. These sources provide extensive environmental data from previous records and recent observations, such as land surface temperature, greenhouse gas concentrations, and oceanic patterns. The datasets were evaluated based on relevance, completeness, temporal resolution, and regional coverage [5–10].

To understand the capabilities of AI, various algorithms were analyzed through simulation-based literature.

- CNNs were reviewed for spatial pattern recognition in satellite imagery.
- LSTM and Gated Recurrent Unit (GRU) models were examined for time-series forecasting, particularly for rainfall and temperature predictions.
- Random Forests and XGBoost were considered for classification tasks, such as flood risk and deforestation alerts.

In a conceptual hybrid framework, these models were robustly integrated with physics-based climate models to enhance prediction reliability.

Additionally, the methodology includes a comparative analysis of performance metrics commonly used in research, including the root mean square error (RMSE) and mean absolute error (MAE), precision, recall, and F1-score metrics to benchmark model accuracy. This study does not perform new experiments but provides a comprehensive methodology template for future implementation projects in climate AI applications [11–16].

Result Set

The application of AI to climate action yields the following key results:

1. *Enhanced climate monitoring*
   - AI improves the accuracy of climate models by using satellite imagery, sensor networks, and big data analytics.
   - Early detection of climate anomalies, such as deforestation, glacier melting, wildfires, and ocean temperature rise, is crucial.
   - Real-time environmental monitoring enables faster response to climate threats.
2. *Optimized energy systems*
   - AI-driven smart grids increase renewable energy efficiency and reduce energy waste.
   - Predictive analytics improve energy demand forecasting and grid stability.
   - Significant reduction in carbon emissions through optimized energy distribution.
3. *Sustainable agriculture and land use*
   - AI-powered precision agriculture minimizes water use, fertilizer application, and soil degradation.
   - Crop yield prediction and pest control reduce environmental impact.
   - AI supports reforestation and biodiversity conservation planning.

4. *Climate risk prediction and disaster management*
   - AI models accurately predict extreme weather events (floods, droughts, hurricanes).
   - Improved disaster preparedness reduces economic losses and saves lives.
   - Faster post-disaster damage assessment using computer vision and drones.
5. *Policy and decision support*
   - AI-based simulations help policymakers evaluate climate policies before implementation.
   - Data-driven insights improve international climate cooperation and accountability.
   - Transparent tracking of emissions supports climate agreements.

One of the most significant contributions of AI lies in the energy transition, where intelligent systems balance renewable sources with consumption demands. This directly supports the global decarbonization goals. In agriculture, AI enhances sustainability by ensuring optimal resource usage while maintaining food security, which is a critical challenge under changing climatic conditions.

To maximize their benefits, AI solutions must be aligned with green computing principles, inclusive policy frameworks, and international collaborations. When responsibly developed and deployed, AI acts not only as a technological tool but also as a strategic catalyst for building a resilient, sustainable, and intelligent Earth.

CONCLUSION

Future developments in data availability, processing capacity, and algorithmic innovation will propel the broad and ever-expanding application of AI in climate science. As climate datasets grow in volume and diversity, AI models are expected to deliver more precise, localized, and real-time climate predictions to support region-specific adaptation and mitigation strategies. The development of explainable and transparent AI models will be a key focus, ensuring greater trust, interpretability, and acceptance of AI-driven insights by scientists, policymakers, and the public.

Continuous and independent climate monitoring will be made possible by integrating AI with cutting-edge technologies, such as edge computing, Internet of Things (IoT)-based environmental sensors, and high-resolution satellite systems. AI-powered digital twins of Earth may further enhance scenario analysis, allowing researchers to simulate climate interventions and assess their extended long-term impacts. In disaster management, improved AI-based early warning systems will strengthen preparedness for extreme weather events and reduce the loss of life and infrastructure damage.

Future research should also emphasize ethical AI deployment, robust data governance, and thorough interdisciplinary strategic collaboration between climate scientists, computer scientists, and policymakers. Ultimately, AI serves a vital purpose in supporting sustainable development, optimizing resource management, and shaping sound evidence-based climate policies in an increasingly uncertain climate future.

REFERENCES

1. Jędrzejewski K, Colantonio P, Abramowicz A. Microwave and Radar Week (MRW 2020): Selected papers. Remote Sens. 2021;13:1803. doi:10.3390/rs13091803.
2. Shi X, Chen Z, Wang H, Yeung DY, Wong WK, Woo WC. Convolutional LSTM network: A machine learning approach for precipitation nowcasting. In: Cortes C, Lawrence N, Lee D, Sugiyama M, Garnett R, editors. Advances in Neural Information Processing Systems. Vol. 28 (NIPS 2015). Red Hook (NY): Curran Associates Inc.; 2015. p. 802-810.
3. Cao Y, Wang M, Liu K. Wildfire susceptibility assessment in southern China: A comparison of multiple methods. Int J Disaster Risk Sci. 2017;8(2):164-181. doi:10.1007/s13753-017-0129-6.
4. Zheng Y, Liu F, Hsieh HP. U-Air: When urban air quality inference meets big data. In: Ghani R, Senator TE, Bradley P, editors. Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '13); 2013 Aug 11-14; Chicago, IL, USA. New York (NY): Association for Computing Machinery; 2013. p. 1436-1444. doi:10.1145/2487575.2488188.

5. Copernicus. (2023). Conventional Data Access Hubs. [Online] Copernicus. Available from: https://www.copernicus.eu/en/access-data/conventional-data-access-hubs
6. National Centers for Environmental Information (NCEI). NOAA Climate Data Online [Online]. National Centers for Environmental Information. Available from: https://www.ncdc.noaa.gov/cdo-web/
7. Rolnick D, Donti PL, Kaack LH, Kochanski K, Lacoste A, Sankaran K, et al. Tackling climate change with machine learning. ACM Comput Surv. 2022;55:1-96. doi:10.1145/3485128.
8. Reichstein M, Camps-Valls G, Stevens B, Jung M, Denzler J, Carvalhais N, et al. Deep learning and process understanding for data-driven Earth system science. Nature. 2019;566(7743):195-204. doi:10.1038/s41586-019-0912-1.
9. Kashinath K, Mustafa M, Albert A, Wu JL, Jiang C, Esmaeilzadeh S, et al. Physics-informed machine learning: Case studies for weather and climate modelling. Philos Trans A Math Phys Eng Sci. 2021;379(2194):20200093. doi:10.1098/rsta.2020.0093.
10. Huntingford C, Jeffers ES, Bonsall MB, Christensen HM, Lees T, Yang H. Machine learning and artificial intelligence to aid climate change research and preparedness. Environ Res Lett. 2019;14(12):124007. doi:10.1088/1748-9326/ab4e55.
11. Schultz MG, Betancourt C, Gong B, Kleinert F, Langguth M, Leufen LH, et al. Can deep learning beat numerical weather prediction? Philos Trans A Math Phys Eng Sci. 2021;379:20200097. doi:10.1098/rsta.2020.0097.
12. Lary DJ, Alavi AH, Gandomi AH, Walker AL. Machine learning in geosciences and remote sensing. Geosci Front. 2016;7(1):3-10. doi:10.1016/j.gsf.2015.07.003.
13. Dueben PD, Bauer P. Challenges and design choices for global weather and climate models based on machine learning. Geosci Model Dev. 2018;11:3999-4009. doi:10.5194/gmd-11-3999-2018.
14. McGovern A, Elmore KL, Gagne DJ, Haupt SE, Karstens CD, Lagerquist R, et al. Using artificial intelligence to improve real-time decision-making for high-impact weather. Bull Am Meteorol Soc. 2017;98:2073-2090. doi:10.1175/BAMS-D-16-0123.1.
15. Ham YG, Kim JH, Luo JJ. Deep learning for multi-year ENSO forecasts. Nature. 2019;573:568-572. doi:10.1038/s41586-019-1559-7.
16. Barnes EA, Toms B, Hurrell JW, Ebert-Uphoff I, Anderson C, Anderson D. Indicator patterns of forced change learned by an artificial neural network. J Adv Model Earth Syst. 2020;12(9):e2020MS002195. doi:10.1029/2020MS002195.

