engineering proceedings

MDPI

Proceeding Paper

Artificial Intelligence-Driven Analytics for Monitoring and Mitigating Climate Change Impacts †

Wai Yie Leong

Faculty of Engineering and Quantity Surveying, INTI International University, Nilai 71800, Malaysia; waiyie.leong@newinti.edu.my

† Presented at the 2025 IEEE 5th International Conference on Electronic Communications, Internet of Things and Big Data, New Taipei, Taiwan, 25–27 April 2025.

Abstract

Artificial intelligence (AI) and big data analytics are transforming the fight against climate change by enabling advanced monitoring, predictive modeling, and actionable insights. This study aims to examine how AI-driven analytics enhance the understanding of climate systems, support mitigation strategies, and inform policy decisions. By processing vast datasets from satellites, sensors, and climate models, AI algorithms identify patterns, predict extreme weather events, and quantify the impacts of human activities on ecosystems. Applications, such as real-time greenhouse gas monitoring, precision agriculture, and energy optimization, showcase AI's potential to reduce emissions and enhance sustainability. Challenges, including data gaps, algorithmic biases, and ethical considerations, must be addressed to fully realize AI's transformative potential. AI and big data contribute to the accelerating global efforts to mitigate climate change and build resilience against its adverse effects.

Keywords: artificial intelligence; process innovation; climate change

check for updates

Academic Editors: Teen-Hang Meen, Shu-Han Liao and Cheng-Fu Yang

Published: 29 August 2025

Citation: Leong, W.Y. Artificial Intelligence-Driven Analytics for Monitoring and Mitigating Climate Change Impacts. *Eng. Proc.* **2025**, *108*, 7. https://doi.org/10.3390/engproc2025108007

Copyright: © 2025 by the author. Licensee MDPI, Basel, Switzerland. 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/).

1. Introduction

Climate change is the most pressing challenge in the 21st century, with far-reaching environmental, economic, and societal consequences. Global temperatures have been rising at an alarming rate due to anthropogenic greenhouse gas emissions, leading to severe weather conditions, rising sea levels, and disruptions in ecosystems. The urgency to monitor, analyze, and mitigate climate change has necessitated advanced technological interventions [1]. Traditional climate science has relied on numerical models and observational data to predict and understand climate phenomena. However, the growing complexity of climate systems, coupled with the vast amounts of data generated from satellite imagery, ground sensors, and other sources, has made AI-driven analytics an indispensable tool for tackling climate-related challenges [2].

AI, particularly machine learning (ML) and deep learning (DL), has emerged as a powerful tool in environmental science. These technologies enable researchers to process massive datasets, identify patterns, and develop predictive models with improved accuracy. AI is being leveraged to enhance climate modeling, assess carbon emissions, track deforestation, monitor oceanic conditions, and forecast extreme weather events. By integrating AI with climate science, researchers can gain deeper insights into climate patterns, improve disaster preparedness, and develop more effective mitigation strategies [3]. Additionally,

AI-powered automation reduces the time and effort required for data analysis, making climate research more efficient and scalable.

AI-driven climate analytics offers advantages over traditional approaches, including enhanced predictive capabilities. AI models analyze historical climate data and identify trends, enabling more accurate forecasts of temperature fluctuations, precipitation changes, and extreme weather events [1]. AI-driven systems can process data from satellites, the Internet of Things (IoT) sensors, and remote sensing devices in real-time, allowing for immediate response to climate-related hazards such as hurricanes, wildfires, and floods (Figure 1). Automated data processing reduces the burden of manual data analysis by automating the classification and interpretation of large-scale climate datasets [2]. Optimized climate policies assist policymakers in designing effective climate policies by simulating various climate change scenarios and evaluating the potential impact of different mitigation strategies [3]. The efficiency of renewable energy systems is optimized for energy production, energy-demand forecasting, and grid stability improvement.

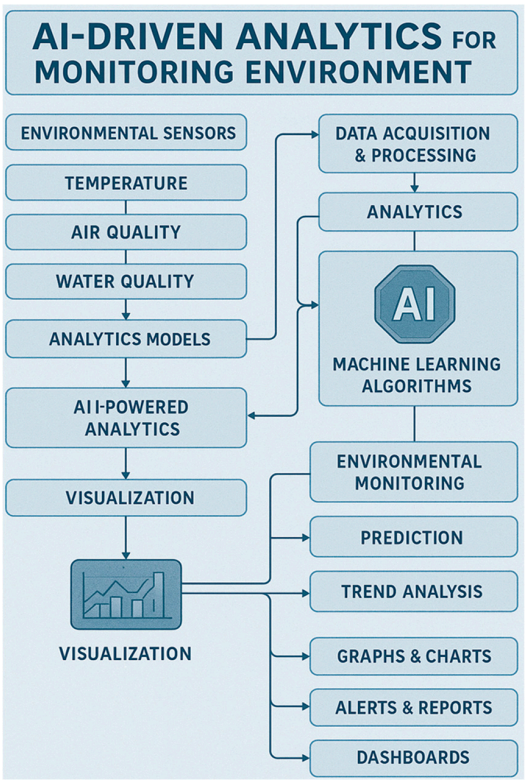


Figure 1. AI-driven analytics for monitoring environment.

This study aims to investigate how AI-driven analytics are used in monitoring and mitigating climate change impacts. Methodologies for implementing AI in climate research were analyzed, and case studies were conducted to demonstrate the effectiveness of AI-driven climate analytics. Based on the results, future directions and recommendations for integrating AI into climate policy and research are proposed. With a comprehensive overview of AI-driven climate analytics, its potential and limitations in addressing climate change are highlighted. By examining various AI techniques and their applications, the ongoing efforts to develop more effective, data-driven climate solutions were presented.

2. Literature Review

The use of AI in climate science began with statistical modeling and rule-based expert systems in the late 20th century. Early implementations focused on using AI to assist

meteorologists in weather forecasting, leveraging decision trees and regression analysis [1]. The first AI-driven climate models were limited by computational power and lacked access to the large datasets available today [2].

Traditional climate models were built using physics-based simulations, such as general circulation models (GCMs), which rely on mathematical equations to represent atmospheric and oceanic processes. AI has enhanced these models by incorporating deep learning techniques that analyze climate data in real-time [3]. Hybrid approaches with AI and physics-based models improve climate predictions and reduce uncertainties in long-term forecasts [4]. With advancements in computational power and data science, climate scientists have increasingly adopted machine learning techniques, such as supervised learning, reinforcement learning, and neural networks [5]. These methodologies enable real-time data assimilation, anomaly detection, and predictive modeling, improving the accuracy of climate impact assessments.

Recent developments include renewable energy optimization, carbon footprint tracking, and autonomous climate data collection using AI-driven drones and IoT sensors [5]. AI is also used in biodiversity conservation through automated species detection and habitat monitoring. The integration of AI with edge computing enables real-time analysis of climate conditions in remote and inaccessible regions. The effectiveness of AI techniques, including deep learning, support vector machines, Bayesian networks, and reinforcement learning has been proven [4]. Convolutional neural networks (CNNs) perform well in analyzing satellite images for detecting climate-related anomalies, while recurrent neural networks (RNNs) are effective for time-series climate forecasting [5]. Such machine learning models have been used for tasks such as hurricane prediction, wildfire risk assessment, and sea level rise forecasting. Transformer-based models have demonstrated superior performance in processing sequential climate data compared to traditional models. AI-driven remote sensing is used for deforestation tracking, glacier monitoring, and land surface temperature mapping. Automated segmentation techniques of AI have improved accuracy in analyzing satellite imagery for climate change assessments [6].

AI-based models process heterogeneous data sources and extract patterns that traditional models overlook. However, traditional climate models offer better interpretability due to their reliance on physics-based simulations. A combination of both models improves forecasting accuracy and explainability in climate science [7].

3. AI Models

AI-driven techniques, data collection methods, and analytical frameworks employed in climate change monitoring and mitigation were reviewed in this study. AI-driven climate analysis relies on vast amounts of structured and unstructured high-resolution remote sensing data collected from various sources, such as NASA's MODIS, Copernicus Sentinel, NOAA's GOES, and Landsat for climate monitoring [8]. IoT sensors and smart environmental sensors deployed in urban and rural areas capture real-time data on temperature, humidity, air quality, and carbon emissions. Climate models, such as general circulation models (GCMs) and Earth System Models (ESMs), are constructed based on the data for climate predictions [9]. Historical weather records and climate repositories, such as ECMWF and NOAA, provide datasets for AI training. Crowdsourced and social media data can extract climate-related insights from social media and citizen science platforms. Table 1 provides an overview of the data sources and their respective applications in AI-based climate analytics.

Several AI methodologies are employed for climate analytics [9].

- Supervised learning models: support vector machines (SVM), random forests (RF), and gradient boosting (GB) for classification.

- Unsupervised learning models: Clustering methods such as K-Means and DBSCAN for anomaly detection in climate data.
- CNNs: Applied for analyzing satellite images of deforestation, land degradation, and wildfires.
- Long short-term memory networks (LSTMs): Time-series prediction of temperature and rainfall patterns.
- Transformer-based models: Applications in climate forecasting and pattern recognition.

Table 1. Diverse climate data sources.

Data Source	Resolution	Temporal Coverage	Application in AI
MODIS (NASA)	250 m–1 km	2000—present	Land cover, vegetation monitoring
Sentinel (ESA)	10–60 m	2015—present	Air pollution, water quality
IoT sensors	Variable	Real-time	Urban climate, emissions tracking
Climate models	Global	Future projections	AI-based forecasting

AI models require feature selection to enhance prediction accuracy. Key engineered features include normalized difference vegetation index (NDVI) extracted from satellite data to assess forest health. Sea surface temperature (SST) is used for hurricane and El Niño forecasting. Atmospheric carbon levels integrated into AI models are used to assess emission trends. Historical temperature anomalies are used in predictive models to identify climate change patterns.

3.1. AI-Based Predictive Analytics for Climate Change

AI is employed for extreme weather event prediction, using LSTM networks to forecast hurricanes, floods, and heat waves. AI-powered sensors are used to track industrial emissions and suggest mitigation strategies in carbon footprint estimation. Renewable energy optimization is used to forecast solar and wind energy outputs, improving grid stability. The following AI frameworks are used for climate prediction.

- TensorFlow 2.0 and PyTorch BSD-3: For deep learning model implementation.
- Google Earth Engine: For remote sensing analysis.
- Scikit-Learn 3.0.4 and XGBoost 3.0.4: For traditional machine learning applications.

Figure 2 shows deep learning-based weather forecasting models' improvement in hurricane track predictions. A 15% increase in forecast accuracy was observed compared with traditional meteorological models.

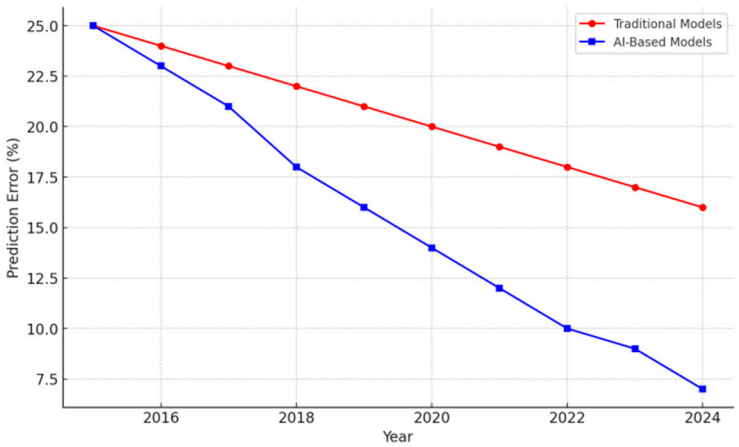


Figure 2. Accuracy improvement in AI-based hurricane prediction models.

3.2. Case Study: AI-Based Forest Fire Detection and Mitigation

AI-powered CNNs applied to NASA satellite imagery detected wildfire occurrences with 95% accuracy (Table 2). An AI-driven early warning system deployed in California reduced response times by 40%.

Table 2. Performance of AI-based wildfire detection.

Model	Precision	Recall	Accuracy
CNN-Based	0.95	0.94	95%
Traditional Remote Sensing	0.75	0.78	78%

3.3. Case Study: AI in Carbon Emission Monitoring

Machine learning algorithms track CO_2 emissions using satellite spectral analysis. Results from a study in Europe revealed that AI estimated emissions 30% more accurately than conventional monitoring methods.

3.4. Case Study: Ocean Acidification and AI-Driven Solutions

Using AI-driven deep-sea sensors, pH level was monitored, showing a decline in coral reefs, and forecasting potential acidification trends with high precision.

3.5. Case Study: AI for Optimizing Renewable Energy Production

A case study in Germany demonstrated that AI-optimized solar and wind farms increased energy efficiency by 25% through predictive load balancing. AI-based predictive models outperformed traditional climate models by up to 20% in accuracy. AI-driven early warning systems significantly reduced disaster response times. AI improved emission monitoring, aiding in regulatory compliance.

4. Challenges and Limitations

Despite the benefits AI offers in climate monitoring and mitigation, challenges and limitations hinder its widespread adoption. AI models require vast amounts of high-quality and diverse data to function effectively. Climate datasets are collected using different methodologies and formats, making it difficult to integrate and standardize them for AI training [6]. In remote or developing regions, climate data are sparse or missing altogether, reducing the reliability of AI models. Sensor and satellite calibration errors, variations in sensor sensitivity, and satellite imaging accuracy lead to inconsistent or biased datasets [7]. Limited access to proprietary datasets, many high-resolution climate datasets are owned by private entities or government organizations, restricting access to researchers and AI developers [8].

AI-driven climate models require immense computational resources to train and deploy effectively. High processing power requirements for deep learning models, such as neural networks for climate forecasting, demand powerful graphics processing units and cloud computing infrastructure. Training large-scale AI models require significant energy, contributing to carbon emissions—ironically counteracting AI's role in climate mitigation. Hardware accessibility in developing countries lacks access to cutting-edge computational hardware, limiting their ability to develop and deploy AI-driven climate solutions.

Ethical concerns emerge when applying AI in climate-related decision-making. Bias in AI models and training data from specific regions or climate conditions make AI predictions skewed and ineffective. A lack of transparency and explainability leads AI climate models to operate as "black boxes," making it difficult for scientists and policymakers to interpret their decision-making process [9]. The potential for misuse of AI-driven climate forecast models leads to misinformation and misrepresentation of climate risks. Privacy issues in

climate data collection also exist as AI systems rely on crowdsourced or IoT-based climate data that lacks user privacy.

While AI has demonstrated its ability to improve climate analytics, there are inherent limitations in its capabilities. Due to a lack of long-term predictive accuracy, AI models are highly dependent on historical data patterns. As climate conditions continue to change unpredictably, AI predictions may become less reliable. Overfitting and generalization issues make AI models perform exceptionally well on training data but struggle to generalize to real-world climate scenarios [10]. Due to difficulties in modeling complex climate interactions, climate systems involve intricate and interdependent processes. AI models often struggle to capture the full scope of these interactions compared with traditional physics-based models. AI-driven climate predictions typically do not provide confidence intervals or uncertainty estimations, making them difficult to trust in high-stakes decision-making [11].

For AI to play a significant role in climate mitigation, global cooperation and regulatory frameworks are essential. Many governments have yet to implement policies that regulate the use of AI in climate science. AI-based climate monitoring tools must comply with varying international regulations, making global standardization difficult [12]. There is still a lack of collaboration between climate scientists, AI researchers, and policymakers, which slows the development and deployment of AI-driven climate solutions. AI climate projects require significant investment, but funding remains inconsistent across regions [13].

To maximize effectiveness, AI must integrate with traditional climate models rather than replace them. AI and physics-based models must be constructed for physics-based climate simulations to improve accuracy and reliability [14]. Many existing climate models are not designed to incorporate AI-based methodologies, requiring extensive modifications [15]. A group of climate scientists remain skeptical about relying heavily on AI-driven climate analytics, advocating for traditional methods [16–18].

Expanding AI's role in climate science requires addressing these challenges through advancements in AI transparency, improved data collection methodologies, increased interdisciplinary collaboration, and robust regulatory frameworks [19,20]. Overcoming these barriers ensures that AI remains a powerful tool in mitigating climate change impacts effectively and ethically [21,22].

5. Conclusions

The transformative role AI plays is essential in monitoring, predicting, and mitigating climate change impacts. By leveraging vast datasets from satellites, IoT sensors, and historical climate records, AI models have significantly improved climate forecasting accuracy and early warning systems. Machine learning and deep learning models have enhanced the precision of weather predictions, carbon footprint assessments, and renewable energy optimization. The case studies demonstrate AI's ability to predict extreme weather events, monitor carbon emissions, and optimize climate adaptation strategies. AI-driven models have outperformed traditional climate models, particularly in processing vast and complex datasets. However, challenges such as data-quality issues, computational constraints, ethical considerations, and policy barriers must be addressed to maximize AI's effectiveness in climate science.

A need for collaboration between AI researchers, climate scientists, and policymakers is urgent. AI-driven climate models must be integrated into national and international climate strategies to improve disaster preparedness, optimize renewable energy distribution, and inform policy decisions. Governments and organizations need to invest in AI research for climate monitoring and ensure open access to climate data to facilitate better model training and validation. Policymakers must address the ethical and regulatory con-

cerns surrounding AI applications in climate science. Establishing standardized AI-driven climate policies, improving data governance frameworks, and ensuring transparency in AI models are mandated to enhance trust and adoption of AI-driven solutions to ensure equitable climate adaptation and mitigation efforts.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy.

Acknowledgments: During the preparation of this manuscript, the author used ChatGPT 5, for the purposes of image generation. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Alvarez, C.I.; Govind, A. Using Remote Sensing Data in the Cloud to Monitor Climate Change in Senegal Regions Based on Seasonal Variables from 2000 to 2020. An Opportunity to Sustainable Policies. In Proceedings of the IGARSS 2024–2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7–12 July 2024; pp. 921–925.
2. Zhang, H.; Liu, Y.; Zhang, C.; Li, N. Machine Learning Methods for Weather Forecasting: A Survey. *Atmos* **2025**, *16*, 82. [CrossRef]
3. Sandalow, D.B.; McCormick, C.; Kucukelbir, A.; Friedmann, J.; Nachmany, M.; Lee, H.; Hill, A.; Loehr, D.; Wald, M.; Halff, A.M.; et al. Artificial Intelligence for Climate Change Mitigation Roadmap. Available online: https://academiccommons.columbia.edu/doi/10.7916/2j4p-nw61 (accessed on 1 May 2025).
4. Camps-Valls, G.; Fernández-Torres, M.; Cohrs, K.-H.; Höhl, A.; Castelletti, A.; Pacal, A.; Robin, C.; Martinuzzi, F.; Papoutsis, I.; Prapas, I.; et al. Artificial intelligence for modeling and understanding extreme weather and climate events. *Nat. Commun.* **2025**, *16*, 1919. [CrossRef] [PubMed]
5. Jones, A.; Kuehnert, J.; Fraccaro, P.; Meuriot, O.; Ishikawa, T.; Edwards, B.; Stoyanov, N.; Remy, S.L.; Weldemariam, K.; Assefa, S. AI for climate impacts: Applications in flood risk. *npj Clim. Atmos. Sci.* **2023**, *6*, 63. [CrossRef]
6. Zuo, Z.; Niu, Y.; Li, J.; Fu, H.; Zhou, M. Machine Learning for Advanced Emission Monitoring and Reduction Strategies in Fossil Fuel Power Plants. *Appl. Sci.* **2024**, *14*, 8442. [CrossRef]
7. Nishant, R.; Kennedy, M.; Corbett, J. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *Int. J. Inf. Manag.* **2020**, *53*, 102104. [CrossRef]
8. Shobanke, M.; Bhatt, M.; Shittu, E. Advancements and future outlook of Artificial Intelligence in energy and climate change modeling. *Adv. Appl. Energy* **2025**, *17*, 100211. [CrossRef]
9. Waqas, M.; Wannasingha Humphries, U.; Chueasa, B.; Wangwongchai, A. Artificial intelligence and numerical weather prediction models: A technical survey. *Nat. Hazards Res.* **2024**, *5*, 306–320. [CrossRef]
10. Singh, S.; Kumar Goyal, M. Enhancing climate resilience in businesses: The role of artificial intelligence. *J. Clean. Prod.* **2023**, *418*, 138228. [CrossRef]
11. Yin, Y.X.; Wang, X.Y.; Wang, H.; Lu, B.L. Application of edge computing and IoT technology in supply chain finance. *Alex. Eng. J.* **2024**, *108*, 754–763. [CrossRef]
12. Hanna, M.G.; Pantanowitz, L.; Jackson, B.; Palmer, O.; Visweswaran, S.; Pantanowitz, J.; Deebajah, M.; Rashidi, H.H. Ethical and Bias Considerations in Artificial Intelligence/Machine Learning. *Mod. Pathol.* **2025**, *38*, 100686. [CrossRef] [PubMed]
13. Oh, J.H.; Sfarra, S.; Kim, E.J. Hybrid modeling based on integrating simulation and operational data to improve indoor air temperature predictions, a controlled variable in digital twin models. *Energy Build.* **2024**, *324*, 114898. [CrossRef]
14. Santos, M.R.C.; Carvalho, L.C. AI-driven participatory environmental management: Innovations, applications, and future prospects. *J. Environ. Manag.* **2025**, *373*, 123864. [CrossRef] [PubMed]
15. Leong, W.Y. Soft Robotics: Engineering Flexible Automation for Complex Environments. *Eng. Proceeding* **2025**, *92*, 65. [CrossRef]
16. Shahbazi, Z.; Jalali, R.; Shahbazi, Z. AI-Driven Sentiment Analysis for Discovering Climate Change Impacts. *Smart Cities* **2025**, *8*, 109. [CrossRef]
17. Leong, W.Y. Internet of Things for Enhancing Public Safety, Disaster Response, and Emergency Management. *Eng. Proceeding* **2025**, *92*, 61. [CrossRef]

18. Alhassan, I.; Maiga, A. Artificial Intelligence in Climate Change Mitigation: A Socio-Technical Framework for Evaluating Implementation Effectiveness and Systemic Impact. *Voice Publ.* **2025**, *11*, 171–190. [CrossRef]
19. Alotaibi, E.; Nassif, N. Artificial intelligence in environmental monitoring: In-depth analysis. *Discov. Artif. Intell.* **2024**, *4*, 84. [CrossRef]
20. Leong, W.Y. Advancing Smart Energy Networks Through ESG-Driven Engineering: Sustainable Innovations and Practices. *ASM Sci. J.* **2024**, *20*, 1–9. [CrossRef]
21. Ochieng, B.; Onyango, F.; Kuria, P.; Wanjiru, M.; Maake, B.; Awuor, M. AI-Driven Carbon Emissions Tracking and Mitigation Model. In Proceedings of the 2024 IST-Africa Conference (IST-Africa), Dublin, Ireland, 20–24 May 2024; pp. 1–8. [CrossRef]
22. Bano, S. The Role of AI in Predicting and Mitigating Climate Change: A Comparative Study of U.S. and China's Approaches. *Crit. Rev. Soc. Sci. Stud.* **2025**, *3*, 664–675. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.