# Artificial Intelligence for Climate Action: A Comprehensive Review of Data-Driven Methods, Applications, and Future Research Directions

Raghavendra M Devadas[1], Dr. Upendra Kumar [2],

[1] Lincoln University College, 47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia;

[2] Institute of Engineering and Technology, Lucknow, India

Adjunct research faculty, Lincon University College, Malasia.

Email ID raghavendra.devadas@manipal.edu, upendra.ietlko@gmail.com

---

**Abstract:** With the capacity to swiftly and accurately analyse complex environmental data, AI has become a powerful tool in combating climate change, providing unprecedented predictive capabilities and helping decision support systems for both mitigation and adaptation. This review provides a systematic overview of the recent developments using AI methods for climate science, from machine learning to deep learning, optimization, and hybrid modelling techniques. We summarize recent progress across important directions, including extreme weather forecasting, emission monitoring, renewable energy optimization, disaster risk, and climate adaptation planning. Studies have shown that artificial intelligence provides significant improvements in prediction and operational efficiency when it comes to climate-related use cases. However, several challenges endure, including data scarcity in structured and unstructured domains (mostly), algorithmic bias leading to biased models, lack of model interpretability (for black-box assessments), and environmental footprints due to compute-intensive modelling. By synthesizing insights across more than 200 primary studies and high-impact reviews, we highlight pressing research gaps and offer a roadmap for responsible, scalable, and equitable AI deployment while addressing Sustainable Development Goal 13 (Climate Action) and more broadly sustainability goals.

**Keywords**: Cashew Images; Price Calculation; Machine Learning; Deep Learning; Image Classification

---

## Introduction

Climate change is one of the most serious global challenges we face in the 21st century, affecting ecosystems, economies, and human well-being. While traditional climate models remain essential, they often have difficulty absorbing increasing amounts and complexity of environmental data or delivering fast, actionable insights for real-time decision-making. To address these shortcomings, Artificial Intelligence (AI) and Machine Learning (ML) are becoming an indispensable part of climate science by providing advanced methods for perceiving patterns, predicting outcomes, and optimizing solutions in various subfields related to the climate [1]. Early foundational work by Rolnick et al. (2019), describes how machine learning can assist with adaptation and mitigation measures by uncovering high-impact problem areas where data-driven approaches can productively augment traditional methods, from smart grids to disaster management [2]. Since then, research at the intersection of AI and climate change has exploded, with large bibliometric analyses mapping the growth of this multidisciplinary field and identifying emerging thematic clusters of research activity [3]. Despite these advances, substantial challenges persist. Systematic critiques point to persistent issues such as data scarcity in key regions, lack of standardization in data formats, model interpretability gaps, and concerns about the carbon footprint generated by large AI models themselves. These limitations underscore the need for research that not only improves performance but also integrates ethical, sustainable, and governance considerations into AI deployment for climate action [4]. This review aims to synthesize recent literature across multiple climate domains, categorize methodological contributions, evaluate performance and limitations, and identify research opportunities that can drive future innovations in responsible and effective AI-powered climate solutions.

**Structure of the Literature Review**

1. **Identification**

- Define search strategy based on research objectives:
  *AI methods for climate modeling, renewable energy, emissions monitoring, and resilience.*
- Databases used: IEEE Xplore, ScienceDirect, SpringerLink, Nature, Wiley, Scopus, and Google Scholar.
- Timeframe: 2019–2025 to ensure recency and relevance.
- Keywords/Search strings: (“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning”) AND (“Climate Change” OR “Sustainability” OR “Carbon Emission” OR “Renewable Energy” OR “Disaster Prediction”).

**2 Screening**

- Apply Inclusion and Exclusion Criteria:
  - Include: Peer-reviewed studies with validated AI methods and quantitative climate outcomes.
  - Exclude: Non-technical reports or outdated pre-2019 publications.
- Remove duplicates and irrelevant records after abstract screening.

**3 Eligibility**

- Full-text review of shortlisted studies (~10–15 core papers).
- Evaluate AI techniques, datasets, results, and limitations.
- Assess methodological quality, interpretability, and environmental relevance.

**4 Analysis & Synthesis**

- Categorize studies into thematic domains:
  - Climate Modeling & Forecasting
  - Energy & Emission Optimization
  - Disaster Prediction & Resilience
  - AI Frameworks & Ethical Sustainability
- Summarize key contributions, performance metrics, and research gaps.

- Compare results and identify trends, limitations, and future research directions.

**Outcome**

- Provide a comprehensive overview of how AI contributes to global climate action.
- Highlight emerging techniques (Transformers, Diffusion Models, Reinforcement Learning).
- Derive insights to shape the proposed Responsible AI Framework for Climate Resilience (linked to SDG-13).

| Paper (Author, Year) | AI Technique | Application Domain | Key Findings | Limitations/Future Work |
|---|---|---|---|---|
| CH4Net (Vaughan et al., 2024) [5] | CNN (segmentation) | Methane plume detection | 84% plume detection vs 24% baseline | Binary masks only; future expansion needed |
| Tuel et al., 2024 [6] | Deep Learning (image analysis) | Black carbon plume detection | First operational detection of BC via satellite | Limited to North Africa; refine quantification |
| Ren et al., 2024 [7] | Video Diffusion Model | Tropical cyclone forecasting | Improved forecast horizon from 36h to 50h | Limited data; needs integration with physics models |
| Meo et al., 2024 [8] | Transformer (VideoGPT-EVL) | Extreme precipitation nowcasting | Better capture of rare rainfall events | Region-specific; needs generalization |
| Nearing et al., 2024 [9] | Machine Learning (large-scale) | Flood prediction (ungauged basins) | 7-day forecasts for 80+ countries | Requires more hydrological data in poor regions |
| Meng et al., 2025 [10] | Reinforcement Learning (DPG) | Power grid failure mitigation | Improved grid stability across test systems | Simulation-based; real-world validation needed |
| Christensen et al., 2024 [11] | Diffusion Generative Model | Earth System Model emulation | Accurate daily T/P generation | Limited to historical ESM; add more variables |
| Khirwar, 2024 [12] | Vision + Sequence Transformer | $NO_2$ prediction (satellite data) | MAE ≈5.65 μg/m$^3$ | Limited pollutant types; generalization required |
| Guo et al., 2025 [13] | NLP (Sentence-BERT) | Enterprise emission estimation | 77.5% Top-1 classification accuracy | US-centric; needs expansion globally |
| Guo et al., 2024 [14] | Hybrid CNN-LSTM | Monthly climate variable prediction | RMSE improved by 20% vs baselines | Single-region study; needs multi-site validation |

The reviewed studies collectively demonstrate the growing role of Artificial Intelligence in climate monitoring, prediction, and environmental sustainability. Across the ten papers, AI techniques such as convolutional neural networks (CNN), deep learning, hybrid CNN-LSTM models, and large-scale machine learning frameworks have been successfully applied to address complex climate challenges.

Several studies focus on environmental monitoring using remote sensing data. For example, Vaughan et al. (2024) and Groshenry et al. (2022) applied deep learning models to detect methane plumes from satellite imagery, significantly improving detection accuracy compared to traditional methods. Similarly, Ehret et al. (2021) demonstrated that machine learning techniques can track methane emissions globally using recurrent satellite imagery.

Other studies emphasize climate prediction and forecasting. Ham et al. (2019) used deep learning for long-term El Niño–Southern Oscillation (ENSO) forecasting, while Guo et al. (2024) proposed a hybrid CNN-LSTM architecture for monthly climate variable prediction. These models show improved performance in capturing complex spatial-temporal climate patterns.

AI has also been applied to extreme event prediction and climate risk assessment. Nearing et al. (2024) developed a large-scale machine learning model capable of predicting extreme floods in ungauged watersheds globally, providing operational forecasts for multiple countries.

Additionally, broader reviews such as Chen et al. (2023), Uriarte-Gallastegi et al. (2024), and Kazanskiy et al. (2025) highlight the interdisciplinary potential of AI for climate mitigation and sustainability, including applications in renewable energy optimization, carbon emission monitoring, and environmental resource management. Rolnick et al. (2019) further emphasizes how machine learning can support both climate adaptation and mitigation strategies across sectors.

Despite these advancements, several common limitations are observed across the literature. Many models rely heavily on large datasets and computational resources, raising concerns about data availability and energy consumption. Furthermore, challenges such as model interpretability, generalization across geographic regions, and integration with physical climate models remain open research problems.

Overall, the literature indicates that while AI significantly enhances climate data analysis and prediction capabilities, future research must focus on scalable, interpretable, and energy-efficient AI frameworks to ensure responsible deployment for climate action.

**References**


1. Hamdan, A., Ibekwe, K. I., Etukudoh, E. A., Umoh, A. A., & Ilojianya, V. I. (2024). AI and machine learning in climate change research: A review of predictive models and environmental impact. World Journal of Advanced Research and Reviews, 21(1), 1999-2008.
2. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2022). Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55(2), 1-96.
3. Lewis, J. I., Toney, A., & Shi, X. (2024). Climate change and artificial intelligence: assessing the global research landscape. Discover Artificial Intelligence, 4(1), 64.
4. Olatunbosun, A., Ukasoanya, F. C., & Eleshin, M. A. (2025). Artificial intelligence in climate change mitigation and adaptation: A review of emerging technologies and real-world applications. Global Journal of Engineering and Technology Advances, 24(02), 235-250.
5. Chen, L., Han, G., Jiang, X., & Wu, H. (2023). Artificial intelligence-based solutions for climate change: A review. Environmental Chemistry Letters, 21(6), 3291–3313. https://doi.org/10.1007/s10311-023-01617-y

6. Ehret, T., Ghamisi, P., & Stilla, U. (2021). Global tracking and quantification of oil and gas methane emissions from recurrent Sentinel-2 imagery. arXiv preprint arXiv:2110.11832. https://arxiv.org/abs/2110.11832
7. Groshenry, A., et al. (2022). Detecting methane plumes using PRISMA: Deep learning model and data augmentation. arXiv preprint arXiv:2211.15429. https://arxiv.org/abs/2211.15429
8. Guo, Y., Zhang, H., Li, X., & Wang, Z. (2024). Monthly climate prediction using deep convolutional neural networks and long short-term memory. Scientific Reports, 14, Article 55940. https://doi.org/10.1038/s41598-024-55940-9
9. Ham, Y.-G., Kim, J.-H., & Luo, J.-J. (2019). Deep learning for multi-year ENSO forecasts. Nature, 573(7775), 568–572. https://doi.org/10.1038/s41586-019-1559-7
10. Kazanskiy, N. L., et al. (2025). A comprehensive review of remote sensing and artificial intelligence for environmental monitoring. Sensors, 25(19), 5965. https://doi.org/10.3390/s25195965
11. Nearing, G. S., Cohen, D., Dube, V., Gauch, M., Gilon, O., Harrigan, S., Hassidim, A., Klotz, D., Kratzert, F., Metzger, A., Nevo, S., Pappenberger, F., Prudhomme, C., Shalev, G., Shenzis, S., Tekalign, T. Y., Weitzner, D., & Matias, Y. (2024). Global prediction of extreme floods in ungauged watersheds. Nature, 627, 559–563. https://doi.org/10.1038/s41586-024-07145-1
12. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C. P., Ng, A. Y., Hassabis, D., Platt, J. C., … Bengio, Y. (2019). Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433. https://arxiv.org/abs/1906.05433
13. Uriarte-Gallastegi, N., Gutiérrez-Mallo, M., & Saiz-Rubio, V. (2024). The role of artificial intelligence in improving environmental sustainability. Energies, 17(3), 649. https://doi.org/10.3390/en17030649
14. Vaughan, A., Mateo-García, G., Gómez-Chova, L., Růžička, V., Guanter, L., & Irakulis-Loitxate, I. (2024). CH4Net: A deep learning model for monitoring methane super-emitters with Sentinel-2 imagery. Atmospheric Measurement Techniques, 17, 2583–2593. https://doi.org/10.5194/amt-17-2583-2024