Artificial Intelligence for Climate Action: A Survey of Data-Driven Techniques and a Framework for Sustainable Climate Analytic

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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.

Literature review

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/m³	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 highlight the expanding role of AI in climate monitoring, prediction, and sustainability. Techniques such as CNNs, deep learning, hybrid CNN-LSTM models, and large-scale machine learning frameworks address complex climate challenges.

- Environmental monitoring: Vaughan et al. (2024) and Groshenry et al. (2022) used deep learning to detect methane plumes from satellite imagery, while Ehret et al. (2021) tracked global methane emissions with recurrent satellite data.
- Climate prediction: Ham et al. (2019) applied deep learning to ENSO forecasting, and Guo et al. (2024) proposed CNN-LSTM models for monthly climate variables.
- Extreme events: Nearing et al. (2024) developed ML models predicting floods in ungauged watersheds worldwide.
- Broader applications: Reviews by Chen et al. (2023), Uriarte-Gallastegi et al. (2024), Kazanskiy et al. (2025), and Rolnick et al. (2019) emphasize AI's interdisciplinary potential in renewable energy, carbon monitoring, and climate adaptation.

Common limitations include reliance on large datasets, high computational demands, limited interpretability, and challenges in generalization. Overall, AI enhances climate analysis and forecasting, but future work must prioritize scalable, interpretable, and energy-efficient frameworks for responsible climate action.

Methodology

The proposed Climate AI System Architecture integrates multi-source climate data, artificial intelligence models, and decision-support mechanisms to enable data-driven climate monitoring and prediction.

In the first layer, climate data sources are collected from heterogeneous inputs such as satellite imagery, environmental sensors, and historical climate records. These datasets provide spatial and temporal information necessary for climate analysis.

The second layer performs data preprocessing and feature engineering, where raw climate data is cleaned, normalized, and transformed into meaningful features. This stage includes handling missing values, noise removal, and extraction of relevant climate indicators required for AI modeling.

The AI modeling layer applies machine learning and deep learning techniques to analyze climate patterns and predict environmental outcomes. Different models such as machine learning algorithms, deep neural networks, time-series forecasting models, and reinforcement learning approaches can be used depending on the prediction or optimization task.

The prediction and optimization layer generates outputs such as climate forecasts, emission patterns, risk assessments, and impact analyses. These outputs help identify potential environmental risks and support strategic climate interventions.

The decision support layer converts AI-generated insights into actionable strategies, including early warning systems and resource optimization for climate adaptation and mitigation.

Finally, the responsible AI layer ensures that the system operates in a sustainable and ethical manner by focusing on energy-efficient models, fairness in predictions, and interpretability of AI decisions. Continuous monitoring and feedback mechanisms enable model auditing and performance improvement over time.

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