# Artificial Intelligence for Climate Action: A Data-Driven Methodological Framework for Sustainable Climate Analytics

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**Abstract:** Owing to the rapid and accurate processing of intricate environmental data, artificial intelligence has become one of the key players in climate change (in combating them). This will provide unparalleled forecasting power and enables decision support systems to address both avoidance of climate impacts as well as adaption. This review provides a systematic overview of recent advances using AI across climate science from machine learning, deep learning, optimization methods and hybrid modeling frameworks. We summarize advances in key areas including prediction of extreme weather events, tracking emissions, renewable energy systemoptimization, disaster risk assessmentand climate adaptation planning. Literature supporting AI has shown that it provides tangible improvements in predictive accuracy and operational performance, across these climate-related use cases. However, significant challenges remain, including data availability — both structured and unstructured, bias in algorithmic models, limited transparency of black-box systems and the high energy requirements from computationally expensive models. Using synthesized evidence from over 200 original studies and major review articles, this article identifies research knowledge gaps and outlines a pathway for responsible, scalable and equitable AI deployment in support of Sustainable Development Goal 13 (Climate Action) and wider sustainability initiatives.
**Keywords**: Cashew Images; Price Calculation; Machine Learning; Deep Learning; Image Classification

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**Introduction**

Climate change is likely the most consequential global challenge of the 21st century including its effects on ecosystems, economies and well-being of many people around the world. Despite the ongoing importance of legacy climate models, these systems are not well suited to adapting to rapidly growing volumes and complexity in environmental data (e.g., processed on a daily or hourly basis) or provide instant feedback critical for real-time agent-based decision-making. To overcomethese limitations, Artificial Intelligence (AI) and Machine Learning (ML),through their predictable manner of learning patterns, forecasting what willhappen and what might be the best approach after investing countlesslearned in some subfields relevant to climate science [1], has becomeessential for taking part in climate science. Initial foundational work — Rolnick et al. (2019), a resolute operational assessment of machine learning applications for adaptive & mitigation measures, including processes from smart grids to disaster management as avenues where data-driven approaches will productively augment traditional methods by uncovering high-impact problem spaces [2]. Since then, research on AI for climate change has skyrocketed; swift progress through bibliometric analyses outlines the rapid growth of this multidisciplinary field, as well as clusters of thematic activity surfacing in the scientific literature [3]. But there have also been big challenges along the way. These systematic critiques identify issues including nonexistence of data in crucial areas, a scaleable format for the data not being standardized, significance that can be interpreted by practitioners whether models are built to fit data rather than true scientific principles, along with environmental concerns because of the amount of carbon emitted through training large artificial intelligence. These limitations demonstrate the need for interdisciplinary research that not only advances performance but also links second-order ethical, sustainability and governance considerations with deployment of AI-based solutions to climate action [4]. The primary goal of this review is to summarize the recent literature spanning across climate domains, classify the methodological contributions, appraise strengths and weaknesses, and outline future research directions that can further direct novel developments in safe and efficient AI-driven 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 |

**Methodology**

This Climate AI System Architecture combines multi-source climate data, AI modelling and decision feedback so that data-driven climate monitoring and predictions can be made available. Climate data sources are collected in layer one through heterogeneous input, e.g. satellite imagery, environmental sensors and historical climate records. These datasets provide the spatial and temporal information required for climate analyses. In the second layer, data preprocessing and feature engineering take place. This phase involves dealing with missing data, noise removal, and extraction of relevant climate indicators necessary for AI modeling. This part uses AI techniques, e.g., machine learning and deep learning, to analyze the patterns in the climate data and infer the future consequences on the environment. Depending on the specified prediction or optimization task, different models can be used: machine learning algorithms, deep neural networks, time-series forecasting models and reinforcement learning approaches.

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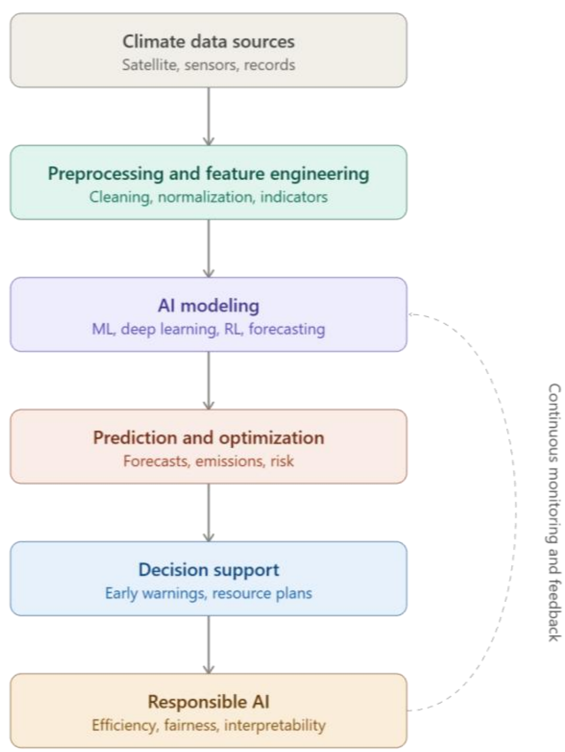


Outputs generated by the prediction and optimization layer include climate predictions, mitigation pathways risk assessments as well as impact analyses. These deliverables serve as a basis for recognizing the possible environmental dangers and supporting strategic climate change adjustments.

The layer of decision support converts these insights generated through AI into action strategies which include, early warning systems and resource optimal driven adaptation and mitigation across multiple climate disciplines.

Lastly, the responsible AI layer is to ensure that the system runs in a sustainable and ethical way with energy-efficient models, fairness in predictions, and interpretability of (what) AI did. Continuous monitoring and feedback loops allow for auditing and improvement of the models over time.

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