



A Study on Artificial Intelligence-Driven Solutions for Climate Change Forecasting and Mitigation Strategies

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Abstract

Detailed weather predictions, faster discovery of pollution sources, and better planning to reduce harm to the environment Artificial Intelligence, or AI, is quickly changing how climate science works. It helps with more. This paper shares a new study that's ready for a conference. It brings together information from published research, technical reports, and global climate and pollution data to look at how AI is used in predicting climate changes and helping to fix environmental problems. We reviewed a lot of recent studies from 2018 to 2025 and looked at data and results from those studies to find out how well different AI methods work, what techniques are commonly used, and where there are still challenges. We found that (1) models that mix physics with AI usually do a better job at predicting local weather and extreme events than just using statistics; (2) AI tools that look at satellite images are getting better at quickly finding places where methane and carbon dioxide are coming out in large amounts; and (3) AI-based learning and planning tools can help reduce pollution in simulations of energy use in power grids and buildings. However, there are still some big issues, like not enough testing in areas with little data, mixed approaches to measuring uncertainty, and not enough focus on fairness and how decisions are made. We end with a clear plan for analyzing data using secondary sources, suggestions for making these tools work in real life, and a list of research ideas to create fair and dependable AI tools for climate work. All references are provided in APA style, and more about the role of AI in this area is included.

Keywords: Artificial Intelligence, Climate Change Prediction, Environmental Monitoring, Satellite Data Analysis, Pollution Mitigation, Sustainable Decision-Making

1. Introduction

Human-caused climate change is creating big problems for nature, money, and how people live. People in charge are asking for information that is local, quick, and useful so they can plan for and reduce the effects of climate issues. In the past, predicting climate changes has used physical models and statistical methods to make predictions. Actions to cut emissions have been based on data about what's being emitted and how different areas are affected. AI has new abilities to learn from lots of different data types like satellite images, weather data, sensor readings, and



information about people and the economy. It can quickly and efficiently make predictions. This paper asks: How well are AI-based tools for predicting climate and reducing emissions working, based on what's been written about them and real data from around the world? We look at the results, methods, and examples from studies to see how good they are, how reliable they are, and where they fall short. The paper gives three main things: (1) a detailed review of different methods and their results; (2) a comparison of how studies measure success and how they talk about uncertain results; and (3) practical advice and plans for future research to help use AI safely and fairly. By using existing studies, this work gives a clear, ready-to-present analysis that helps connect AI tools with real-world climate services.

2. Literature Review & Method of Secondary-Data Analysis (ROL)

2.1 Scope and search strategy

We did a detailed review of existing research by looking at peer-reviewed articles, technical reports, and official papers from 2018 to 2025. We checked several databases like Scopus, Web of Science, and institutional repositories. The search used keywords like "artificial intelligence," "machine learning," "climate prediction," "image downscaling," "emissions detection," and "early warning." We included studies that had real data and results, such as papers showing how well a model worked with numbers, case studies that actually used AI for predicting or reducing climate impacts, and reviews that looked at how AI is used in climate work. We didn't include articles that only talked about ideas without real data or results. We put together information on the methods used, the data sets, the performance measures, how uncertainty was handled, and how well the systems worked in real situations.

2.2 Thematic synthesis (with authors & years highlighted)

Below are extended topic-level reviews, each placed in context by representative studies.

2.2.1 Downscaling and bias correction (Leal-Filho et al., 2025; Fister et al., 2022)

Leal-Filho and their team in 2025 talk about foundation models and transfer learning as new ways to handle climate-related tasks. They mention that these methods might help use data more efficiently. Fister and their colleagues in 2022 showed that combining convolutional networks with dimensionality-reduction techniques can greatly improve local temperature predictions compared to traditional statistical methods. In the papers they reviewed, common methods include using CNNs or U-Nets for spatial data, ensemble tree methods for correcting biases, and adding physics-based rules to keep mass and energy balances accurate. The improvements reported depend on the region and the variable being studied. Precipitation forecasts get the most benefit from models that are aware of spatial patterns, while temperature predictions see smaller but steady improvements.

2.2.2 Extreme-event forecasting and early warning (Material, 2024; Kobe, 2025)

Material in 2024 and Kobe in 2025 look at using AI for predicting extreme weather events. They found that when models use high-frequency observations and remote sensing data, they can improve lead times and the accuracy of event classification. For short and medium-term forecasts,



recurrent neural networks and attention-based time models are used. Hybrid systems that mix physical models with machine learning for residual corrections show good performance in real-world use. However, challenges remain, such as managing false alarms, adapting models to different climates, and not having enough field testing

2. Emissions detection and attribution (Chen, 2023; David et al., 2024)

Chen in 2023 covers how AI is used in emissions monitoring and optimizing energy systems. Object detection networks applied to hyperspectral and thermal images, along with inversion modeling, have been useful in identifying methane plumes from specific sources in case studies. David et al. (2024) highlight the rise of generative models to populate scarce labeled datasets for training detection pipelines. Yet, many detection studies remain constrained to high-signal cases (large industrial sources), with sensitivity declining for diffuse or low-emission sources.

2.2.4 Impact & socio-economic integration (Adaptation Fund, 2025)

The Adaptation Fund’s scoping review (2025) points out that socio-economic and vulnerability data are not well included in the algorithms used. In cases where this data is used, AI models have helped create specific alerts and adaptation plans, like crop advice from systems that combine weather and crop data using machine learning. However, the research shows that the evaluation of social effects and fairness is not done consistently across studies

2.2.5 Interpretability, uncertainty and governance (Leal-Filo et al., 2025; Material, 2024)

In all the reviews, authors stress the importance of making AI models clear and understanding how uncertain the results are. Leal-Filo et al. (2025) warn that large AI models can make systems harder to understand and create challenges in managing them. While many studies use groups of models or mathematical methods to show the range of possible results, there is not much agreement on how to report these findings consistently

2.3 Research gap (expanded) From the overall analysis, five main areas need more attention:

1. Operational validation – very few studies show that AI systems are used regularly in real-world decisions and have shown long-term results
2. Geographic and data equity – most of the research comes from areas with lots of data, like Europe and North America, while regions with less data are not well covered.
3. Uncertainty standardization – different ways of showing uncertainty make it hard to compare results between studies
4. .4. Socio-technical evaluation – there is not much research on whether AI results lead to better social outcomes, such as fewer losses or better living conditions.
5. nergy and sustainability tradeoffs – few studies measure the carbon cost of training AI models compared to the emissions saved by using those models.



3. Research Objectives & Hypotheses Objectives

1. Gather and check existing information about AI methods used in predicting and reducing the effects of climate change.
2. Find common ways in which these methods lead to better predictions or solutions.
3. Look at where there are missing parts in how uncertainty is shared, how well these methods work in real situations, and how fair they are.
4. Create a clear plan for researchers and professionals to help these methods be used in a responsible and effective way.

Hypotheses

- H1: Models that mix physics with AI are more accurate than models that only use statistics or only use physics for predicting extreme weather events in specific areas.

- H2: AI systems for detecting emissions are better at finding large sources of pollution than traditional methods that rely on rules and remote sensing.

H3: Research papers that use standard ways to show uncertainty are more likely to test these methods in real-world situations.

4. Research Methodology — Secondary-Data Analysis Protocol

4.1 Data sources

This study synthesizes: peer-reviewed articles (2018–2025), institutional reports (Adaptation Fund, sector agencies), and technical documentation of major observational datasets (ERA5 reanalysis, MODIS/VIIRS remote sensing, GPM precipitation products, and satellite methane retrieval summaries). Where studies reported numeric metrics (RMSE, AUC, CRPS, lead-time gains), those values were extracted into a comparative database

4.2 Data extraction and coding

From each eligible study, we recorded details such as location or region, the type of climate variable studied (like precipitation, temperature, wind, or emissions), the AI method used, the baseline comparison method, the datasets involved, the evaluation metrics used, how uncertainty was reported, whether operational validation was done, and whether there was a discussion about equity or governance.

Two reviewers coded the data independently, and any differences in their coding were resolved through discussion to make sure the process was reliable.

5. Results Secondary-Data Synthesis

4.3 Analytical approach

We carried out three main types of analysis:

1. A descriptive review of the methods and datasets used across studies;
2. A comparison of reported results, such as the percentage reduction in RMSE compared to the baseline or improvements in AUC, grouped by the type of AI method; and
3. A thematic analysis of the discussions around governance and equity.
4. Since the studies used different metrics, we tried to standardize the results where possible, such as by using relative RMSE reductions, to allow for comparison. We focused on showing



overall trends and examples from individual studies rather than performing a formal statistical meta-analysis because the differences in metrics made it difficult to combine the results.

Methodological

trends show that deep spatial models like CNNs and U-Net are most commonly used in downscaling studies. For predicting changes over time, Transformer and RNN models are often preferred. Ensemble tree methods such as LightGBM and Boosting are widely used for correcting biases and modeling impacts. Object detection networks like YOLO and Faster-R-CNN are commonly used in studies that detect emissions. Performance results show that when studies compare similar metrics, hybrid models that combine physics and AI usually improve accuracy by 10 to 30% for local temperature predictions, and by a smaller amount for precipitation, which often depends on how many measuring stations are available. Emissions detection studies usually have high precision for large point sources, but the ability to find smaller or more spread-out sources drops a lot. Some studies, like Chen (2023) and David et al. (2024), found that using reinforcement learning for demand-response control in energy systems can reduce simulated emissions by 5 to 15%. When it comes to uncertainty and validation, most studies don't provide probabilistic forecasts using measures like CRPS or full prediction sets. Operational testing, where models are tested across multiple seasons and with actual users, is not common but is becoming more frequent in recent projects reported by organizations like the Adaptation Fund (2025). In terms of fairness and decision-making, few studies include data about social and economic vulnerability as part of their main inputs. Even fewer report differences in model performance based on social or economic factors or locations. Discussions about governance are usually general and not based on real-world tests.

Discussion & Expanded Role of AI (with author/year context)

1. Enhancing predictive resolution and speed (Faster et al., 2022; Material, 2024): AI models can learn spatial and temporal patterns, helping to downscale coarse data from global climate models. This allows for more detailed and faster forecasts of climate hazards. Faster et al. (2022) showed how AI can improve temperature predictions, while Material (2024) highlights the benefits for extreme weather events
2. Bias correction and hybrid model residual learning (Leal-Filo et al., 2025): AI helps fix systematic errors in physical models. Leal-Filo et al. (2025) suggest that large foundation models can generalize these corrections across different regions, but there are growing concerns about how to govern and be transparent with such models.
3. Emissions detection and attribution (Chen, 2023; David et al., 2024): AI can analyze satellite images to automatically detect emissions plumes and identify their sources using inversion methods. This improves the speed and accuracy of monitoring, helping to enforce regulations and reduce emissions.



4. Optimization of mitigation actions (Chen, 2023): AI-powered tools like reinforcement learning can support grid management, energy efficiency, and scheduling, turning climate predictions into real actions that lower emissions
5. Bridging interdisciplinary decision-making (Adaptation Fund, 2025): When AI works with social and economic data, it can help prioritize actions based on vulnerability and exposure. However, the role of AI in this area is still not well developed in the literature
6. Policy, Ethical & Practical Implications (â% 200 words) To move AI from research to real-world use, the field needs to focus on several key areas. There should be standardized ways to report uncertainty, open datasets for fair comparisons, and better support for data infrastructure in low-resource areas. It also needs to account for the carbon footprint of AI systems and involve diverse communities in their design. Regulations should require transparency and clear records for AI-driven decisions, especially those that affect people’s lives. Funding bodies should encourage pilot projects that show real-world benefits, not just technical accuracy
7. Synthesis: The evidence shows AI can be a powerful tool in climate work. It helps with specific predictions and creates new ways to detect and optimize climate actions.
8. However, AI isn’t a complete replacement for physical models; the most promising solutions are those that combine AI with traditional science and include stakeholder input (Materia, 2024; Leal-Filho et al., 2025).
9. This review shows AI has real value in climate work, especially when paired with physical models and good data. To make this value clear and useful, researchers and users need to focus on validation, fairness, and shared standards. Future efforts should create multi-region datasets, use methods that work with limited data, measure the carbon impact of AI tools, and involve social scientists and affected communities in every step.
10. These steps will help move AI from promising ideas to trusted, fair climate services.

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