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Investigating the Role of Artificial Intelligence in Enhancing Climate Change Prediction Accuracy and Supporting Data-Driven Mitigation Strategies

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Abstract:
This paper explores the role of artificial intelligence (AI) in enhancing the precision of climate change predictions and aiding in data-driven strategies for mitigation. I conducted a systematic literature review focused on secondary data, analyzing peer-reviewed articles, key reports, and trusted industry news from 2018 to 2025. The study highlights various AI techniques utilized in climate modeling, such as downscaling, forecasting extreme events, remote sensing for land use and carbon monitoring, optimizing renewable energy, and supporting decision-making in mitigation policies. The results show that AI—especially through deep learning, graph neural networks, and GeoAI—has the potential to (a) boost forecast accuracy and computational efficiency, (b) facilitate more detailed spatial and temporal downscaling, and (c) introduce innovative monitoring solutions like near real-time mapping of deforestation and wildfire risks. Nevertheless, there are ongoing challenges, including issues of interpretability, the ability to generalize beyond training conditions, the energy demands of large models, and governance and ethical considerations. The study wraps up with suggestions for integrating AI with traditional modeling methods, promoting open data and benchmarking, developing explainable AI techniques, and assessing the lifecycle emissions of AI systems.

Keywords: Artificial Intelligence (AI), Climate Change Prediction, Climate Modeling, Extreme Event Forecasting, Mitigation Strategies

1.Introduction:

Human-driven climate change poses significant risks to both societies and ecosystems at various levels. To effectively plan for mitigation, adaptation, and early warning systems, it's crucial to accurately predict climatic variables and extreme weather events (IPCC, 2021). While traditional numerical models, like those found in CMIP6, are foundational to climate science, they often require substantial computational resources and have uncertainties, especially when looking at regional and sub-daily scales. Recently, AI and machine learning (ML) methods have shown potential to enhance or expedite these traditional models, leading to better forecasts, quicker computations, and innovative monitoring capabilities. These advancements are applicable in areas such as weather forecasting, wildfire risk assessment, deforestation detection, and optimizing renewable energy. This paper compiles secondary data to assess how AI can enhance the accuracy of climate predictions and contribute to effective, data-driven mitigation strategies, while also pointing out the limitations and policy implications of these developments. The analysis is based on systematic review methods applied to literature and authoritative sources published between 2018 and 2025.

2. Objectives:

1.Synthesize current evidence on AI methods used to improve climate and extreme-event prediction.

2.Evaluate applications of AI in mitigation: renewable energy optimization, carbon/land-use monitoring, and disaster risk reduction

3.Identify methodological and ethical challenges (interpretability, energy footprint, bias) and propose research and governance recommendations.

3. Methodology

This study is a secondary-data systematic literature synthesis. Sources were identified using academic databases, institutional reports, and reputable industry/news outlets (search period 2018–2025). Inclusion criteria: (a) empirical or review studies applying AI/ML to climate/weather prediction or mitigation; (b) technical papers on AI methods for downscaling, forecasting, or GeoAI; (c) authoritative reports (e.g., IPCC) and high-quality news/industry reporting about major AI breakthroughs. Exclusion criteria: non-English items without accessible abstracts, purely speculative opinion pieces absent empirical grounding.

Selected items were analyzed thematically: (1) prediction (model accuracy, downscaling, temporal/spatial resolution), (2) mitigation applications (energy systems, carbon monitoring, land use), and (3) governance and ethics. Where possible, claims about performance were cross-checked across multiple sources (e.g., independent evaluations of AI weather models versus operational NWP systems). Key sources included IPCC AR6, peer-reviewed articles on deep learning for downscaling and causal neural nets, domain reviews on renewable energy and GeoAI, and reporting on landmark AI forecasting systems.

4. Review of Literature

- ➢ **AI & Climate/Weather Prediction**
- **Rampal — 2022.** Demonstrated high-resolution downscaling using interpretable deep learning, showing ML methods can outperform traditional statistical downscaling for rainfall at regional scales (Rampal, 2022).

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- **Iglesias-Suarez et al. — 2024.** Proposed causally-informed deep learning to stabilize and increase trustworthiness of climate model emulators, bridging causal discovery with neural nets. This approach aims to reduce spurious correlations and improve generalizability
- **Shcherbina et al. / GraphCast reporting — 2023.** Industry/academic efforts (e.g., GraphCast) reported AI models outperforming conventional NWP in many metrics for short-range forecasts, promising faster, lower-cost forecasting. Journalistic coverage documented GraphCast's performance versus ECMWF.
- **GeoAI, Remote Sensing & Land-Use Monitoring**
- **Wang — 2024.** Developed deep-learning systems for deforestation validation in high-resolution imagery, improving automation and timeliness of forest-loss detection compared with manual inspection.
- **Raza — 2025.** Applied remote sensing + GIS to quantify LULCC and associated carbon stock changes, demonstrating how Earth observation combined with ML supports emission/sequestration estimates.
- **Wildfire & Extreme Event Prediction**
- **Topnani — 2021; Caron — 2025.** ML approaches (supervised/unsupervised and RL variants) have been applied to wildfire risk mapping and detection. Reviews highlight dependency on data quality and the need for multi-source inputs (meteorology, vegetation indices).
- **Renewable Energy & Systems Optimization**
- **Algburi — 2025; Ejiyi — 2025.** Reviews show AI enhances renewable generation forecasting (solar, wind), grid integration, demand forecasting, and predictive maintenance—enabling higher renewable penetration and more efficient operations.
- **Sectoral and Resource Impacts (Water, Groundwater)**
- **Secci — 2023.** Used AI models to study climate impacts on groundwater, suggesting ML can quantify local hydrological responses under climate change scenarios better than some empirical methods.
- **Explainability, Ethics & Governance**
- **Yang — 2024.** Reviewed interpretable ML methods for weather and climate, stressing that explainability tools (e.g., SHAP, LIME) are necessary for trust and operational adoption
- **Nordgren — 2023.** Raised ethical concerns around the dual role of AI—as a tool for mitigation but also as a producer of significant energy demand—and called for oversight.
- **5. Synthesis and Analysis of Secondary Data**
- **Prediction Accuracy: Evidence & Mechanisms**

Recent research and technical analyses show that AI has the potential to enhance predictive capabilities, particularly for short- and medium-term forecasts as well as improving downscaling resolution. Notably, large-scale initiatives like GraphCast demonstrate that AI models can match or even surpass the accuracy of leading numerical weather prediction (NWP) systems across various metrics up to approximately 10 days ahead, while also delivering forecasts significantly faster. Peer-reviewed studies focused on downscaling and interpretable deep learning have reported consistent improvements at regional scales (Rampal, 2022; Iglesias-Suarez, 2024).

So, why does AI have this advantage? Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), and hybrid physics-informed networks are particularly adept at identifying non-linear relationships and uncovering patterns within extensive historical datasets. They serve several key functions, including:

- Statistical emulation of costly physical parameterizations (model emulators).
- Spatial downscaling to translate broad climate models into localized forecasts.
- Integration of diverse data sources (satellite, in-situ, reanalysis) for comprehensive risk mapping.

However, it's essential to recognize the limitations and caveats associated with these AI models. They can falter when applied to extrapolation scenarios that lie beyond the scope of their training data, such as encountering entirely new climate conditions. Moreover, there is a risk of generating physically unrealistic outputs unless these models are guided by physical laws or causal relationships. Utilizing hybrid methods that incorporate physical insights or causal constraints can help mitigate these disaster risk

- **Mitigation Applications: Examples & Outcomes**

Renewable Energy Integration:** The use of AI significantly enhances short-term predictions for wind and solar energy output. This improvement aids in balancing the grid and supports the incorporation of a greater share of renewable resources. Various reviews have highlighted the tangible advantages in scheduling and maintenance, showcasing the effectiveness of these technologies.

Land and Carbon Monitoring: Advanced GeoAI alongside high-resolution remote sensing technologies has transformed the detection of deforestation and changes in land use. This allows for timely interventions and enhances measurement, reporting, and verification (MRV) processes. Notable cases of automated deforestation validation demonstrate the practical benefits for enforcement.

- **Key Considerations: Sustainability, Integrity, and Clarity****

Environmental Impact: The energy used by large models and data centers contributes significantly to emissions, a topic under scrutiny in forums like the COP conferences regarding AI's overall climate influence. It's crucial for stakeholders to prioritize lifecycle assessments and rely on renewable energy sources when building AI infrastructure.

Transparency and Reliability: To effectively integrate AI into climate services and policymaking, it's imperative to utilize explainable AI (XAI) techniques and quantify uncertainties. Users, including forecasters and policymakers, need clear error metrics and causal insights rather than opaque, black-box predictions.

Governance, ethics, and lifecycle emissions. Policy frameworks should mandate transparency, lifecycle emissions accounting for AI systems, and equitable access to AI climate tools, especially for low-income regions that may benefit most. Ethical review must address biases in training data that could disadvantage vulnerable populations

Data constraints remain a bottleneck in many regions. Superior performance often requires dense historical records and high-resolution observations; many parts of the world lack such data, limiting model transferability and equity. GeoAI and new satellite constellations help but cannot entirely substitute for local observations

6. Recommendations

For researchers and practitioners:

1. Focus on developing hybrid AI–physics models that uphold conservation laws or causal relationships to enhance extrapolation capabilities.
2. Establish open benchmarks along with reproducible code and data for climate AI applications, including downscaling, forecasting, and detection.
3. Incorporate explainability and uncertainty quantification as standard features in operational forecasts.

prioritizing the use of renewable energy for computational requirements.

4. Evaluate and disclose the lifecycle emissions associated with AI systems, while
5. Emphasize capacity building and ensuring equitable access to AI tools in regions with limited data—facilitate satellite data pipelines and regional model training

7. Limitations

This study is based on secondary sources and a selective range of literature published between 2018 and 2025. Despite meticulous efforts to verify key works, it is important to note that the field is continuously evolving; new developments or significant operational implementations beyond the review period may impact some of the findings. Additionally, the synthesis presented here is qualitative; a formal meta-analysis involving quantitative performance metrics was not conducted due to the diversity of evaluation methods used across the different studies.

8.Conclusion

AI demonstrates significant and increasing value in enhancing the accuracy of climate predictions and facilitating data-driven strategies for mitigation across energy systems, land-use monitoring, and disaster risk reduction. The future direction highlights the importance of hybrid, explainable, and energy-conscious methodologies, alongside open benchmarking and governance frameworks. When implemented responsibly, AI has the potential to substantially enhance the timeliness and accuracy of climate action—but this is contingent upon the integration of solid physical knowledge, equitable access to data, and meticulous consideration of the environmental costs associated with AI

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