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Predictive Optimisation Models for Climate Resilience: A Multi-Sector AI Approach

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Abstract

This study provides a robust, quantitative analysis of Artificial Intelligence's (AI) role in both climate change mitigation and adaptation. The core experimental work focuses on deploying deep learning models to optimise energy systems, leading to a projected 15-20% increase in renewable energy value by reducing curtailment and enhancing the accuracy of extreme weather prediction. While the paper successfully demonstrates compelling efficiency gains, the review critiques the handling of AI's own carbon footprint, arguing that the trade-off analysis needs greater resolution. The conclusion supports the central finding that strategically governed AI is crucial for the net-zero transition, aligning with broader international calls for technology integration.

Keywords: Artificial Intelligence, Climate Change Mitigation, Energy Grid Optimization, Predictive Modeling, Adaptation.

Introduction

The introductory section of Nguyen et al. (2025) provides an excellent rationale for leveraging **AI** in the face of the escalating climate crisis. The authors establish that the sheer volume, velocity, and complexity of global climate data necessitate advanced computational tools to move from descriptive modeling to prescriptive action (Garnett, 2023). The paper successfully frames its core objective: to quantify the advantages of AI across various domains, distinguishing between applications that **reduce emissions (mitigation)** and those that **enhance preparedness (adaptation)**.

The paper is commendable for grounding its work in existing successes, referencing breakthroughs like the 40% reduction in energy usage achieved by AI-optimized cooling systems in data centers (DeepMind, 2023). The primary research gap addressed is the lack of a unified, multi-sector performance metric for AI solutions. The study aims to bridge this by presenting a clear cost-benefit comparison, acknowledging the computational costs associated with modern deep learning models (Nguyen et al., 2025).

Experimental Work and Methodology

The paper employs a mixed-methods approach, combining sophisticated simulation with real-world sensor data analysis.

1. Renewable Energy Optimization

The core experiment utilizes a **Reinforcement Learning (RL) framework** coupled with a Graph Neural Network (GNN) to forecast variable renewable energy (VRE) output (solar and wind) 48 hours in advance. The RL agent, trained on a national grid simulation, then optimizes power dispatch and battery storage charging schedules. This methodology, building upon prior work in smart grid management (Li & Xu, 2022), is sound, using historical data validated against established grid models.

2. Adaptation and Monitoring

For adaptation, the researchers utilize a **Convolutional Neural Network (CNN)** for high-resolution analysis of satellite imagery to predict deforestation rates and monitor post-disaster damage. A separate model is deployed for early warning systems, predicting localized flash flood risks with a 72-hour lead time, using a methodology similar to that employed by organizations focused on disaster response (IBM, 2020).

3. Algorithmic Footprint Analysis (AFA)

Crucially, the methodology includes a detailed AFA, tracking the energy consumption of the AI models used. The authors calculate the carbon-intensity of the electricity consumed during model training and inference. While the inclusion of AFA is vital, the choice of using a single, aggregated metric for 'carbon cost' across diverse AI models (from the relatively small CNN for flood prediction to the massive GNN for grid optimization) risks oversimplification. This area of methodology could have been improved by adopting more granular, model-specific metrics (Chen et al., 2021).

Results and Discussion

The results section delivers strong evidence for AI's mitigation advantages:

- The RL model demonstrated an average **18% increase in the value of VRE** over baseline models by minimizing curtailment, a key financial and environmental metric.
- The CNN-based monitoring system identified **illegal deforestation with 94% accuracy**, significantly enhancing enforcement capabilities compared to manual analysis.
- The adaptation models successfully provided **actionable flood warnings** with a 60-hour lead time, exceeding current benchmark standards.

The discussion is strongest when addressing the quantified benefits, particularly in the energy sector. The 18% VRE value increase, for example, directly translates to reduced reliance on fossil fuel peaking plants, providing a clear path to decarbonization (Nguyen et al., 2025). However, the discussion's analysis of AI's trade-offs is less convincing. While the authors acknowledge that the energy consumption of AI is non-trivial, they conclude that the systemic efficiency gains *outweigh* the algorithmic footprint (Chen et al., 2021). This conclusion rests on the assumption of universal and optimized deployment, which may be vulnerable to the rebound effect—the phenomenon where efficiency gains lead to increased overall consumption (Mittal & Singh, 2024). For instance, optimized transport logistics could inadvertently encourage more shipping activity. The paper correctly highlights that the realization of these benefits is contingent on governance. The authors argue, supported by Sinha (2022), that without clear policy mandates to direct AI investment toward climate solutions, commercial interests could prioritize less beneficial applications, such as optimizing fossil fuel extraction. Furthermore, the discussion touches upon the global equity challenge, noting that regions most vulnerable to climate change often lack the necessary data infrastructure and technical capacity to deploy these sophisticated models (Nguyen et al., 2025).

Table 1: Experimental Works on Predictive Optimisation Models for Climate Resilience

Sr. No.	Sector	Objective	Data Used	AI / ML Model	Optimization Technique	Key Findings	Limitations	Study / Author (Year)
1	Agriculture	Crop yield prediction under climate variability	Satellite + weather data	Random Forest, ANN	Genetic Algorithm (GA)	Improved crop yield prediction accuracy by 18%	Limited regional dataset	Smith et al. (2020)
2	Water Resources	Flood prediction and management	Hydrological + rainfall data	LSTM	Particle Swarm Optimization (PSO)	Early flood prediction improved by 24 hrs	Data sparsity in rural areas	Kumar & Patel (2021)
3	Energy	Renewable energy demand forecasting	Smart grid data	Deep Neural Networks (DNN)	Gradient-based optimization	Enhanced grid stability	High computational cost	Chen et al. (2022)
4	Urban Planning	Smart city climate resilience	IoT sensor data	Reinforcement Learning (RL)	Q-learning optimization	Reduced urban heat impact	Requires real-time infrastructure	Garcia et al. (2021)
5	Disaster Management	Cyclone prediction and evacuation planning	Historical cyclone datasets	CNN + LSTM hybrid	Evolutionary Algorithms	Increased evacuation efficiency by 30%	Model complexity	Singh et al. (2023)
6	Agriculture	Soil moisture prediction	Remote sensing data	Support Vector Machine (SVM)	Bayesian Optimization	Improved irrigation efficiency	Limited scalability	Lee et al. (2022)
7	Water	Drought prediction	Climate time-series data	GRU networks	Multi-objective optimization	Early drought warnings	Data imbalance	Ahmed et al. (2023)
8	Energy	Solar power prediction	Weather + solar radiation data	ANN	PSO	Increased prediction accuracy	Weather uncertainty	Wang et al. (2020)
9	Transport	Climate-resilient transport systems	Traffic + climate data	XGBoost	Linear programming	Reduced congestion during extreme weather	Static model assumptions	Rao et al. (2022)
10	Multi-sector	Integrated climate resilience modeling	Multi-source datasets	Ensemble ML models	Hybrid optimization (GA + PSO)	Cross-sector resilience improved	Data integration challenges	Brown et al. (2023)

Conclusion

Nguyen et al. (2025) successfully demonstrate that Artificial Intelligence is a critical, high-potential tool for climate action, providing verifiable evidence of significant efficiency gains in energy management and measurable improvements in adaptation capabilities. The experimental results validate the use of RL and

GNNs for VRE integration and support the established benefits of precision modeling in areas like agricultural resource management (Schmidt, 2024). Ultimately, the paper's main conclusion—that AI offers a net positive benefit to the climate—is well-supported by the mitigation data. However, this review asserts that the net positive outcome is not guaranteed. Future work must rigorously address the governance deficit (Sinha, 2022) and proactively model the rebound effects (Mittal & Singh, 2024) to ensure the demonstrated technological potential translates into real-world, long-term environmental success, in line with global sustainability goals (UNFCCC, 2023). Experimental studies demonstrate that AI-driven predictive optimisation models significantly enhance climate resilience across sectors. However, future research should focus on: Developing scalable and interpretable models. Integrating multi-sector datasets. Implementing real-time adaptive systems

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