

# AI For Climate Change Modeling And Mitigation

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## ABSTRACT:

The accelerating impacts of climate change demand innovative solutions that traditional forecasting methods struggle to provide. Our research introduces a groundbreaking AI framework that combines satellite data analysis with on-ground sensor networks to predict climate patterns with unprecedented accuracy. Unlike conventional models that treat weather systems in isolation, our system identifies complex interactions between atmospheric, oceanic, and terrestrial factors through deep learning algorithms. Preliminary tests show 92% prediction accuracy for extreme weather events, outperforming existing models by 18%. The platform also suggests targeted mitigation strategies, helping policymakers prioritize interventions where they'll have maximum impact.

## KEYWORDS:

Climate informatics, Neural weather forecasting, Predictive environmental modeling, Deep learning for sustainability, Climate risk assessment, AI-driven policy tools, Environmental sensor networks, Climate resilience algorithms.

## 1. INTRODUCTION:

As global temperatures continue breaking records, the limitations of conventional climate models become increasingly apparent. These traditional systems often miss critical feedback loops between melting permafrost, shifting ocean currents, and atmospheric changes. Our team spent six months interviewing climate scientists at the Indian Meteorological Department, identifying three key gaps: (1) inadequate real-time data integration, (2) oversimplified modeling of regional microclimates, and (3) slow adaptation to emerging climate patterns.

The solution we've developed addresses these challenges through a multi-layered AI system. At its core, convolutional neural networks process satellite imagery to track changes in vegetation, ice cover, and urban heat islands. Simultaneously, recurrent neural networks analyze temporal patterns from our network of 200+ IoT sensors deployed across vulnerable ecosystems. What sets our approach apart is the physics-informed machine learning layer that ensures all predictions adhere to fundamental environmental laws, preventing the "black box" problem common in pure AI systems.

## 2. LITERATURE REVIEW:

Framework Type	Features	How it Works	Challenges	Future Scope	Reference
Climate Data Processing	Handles multimodal climate data	Uses autoencoders for feature extraction and dimensionality reduction	Data quality and accessibility issues	Improved data integration techniques	[2], [3]
Enhanced Climate Modelling	Improves regional predictions	Combines CNNs with global climate models for higher resolution	High computational costs	Hybrid physical-neural network models	[4], [6]
Climate Mitigation	Optimizes renewable energy placement	Uses reinforcement learning to balance emissions reduction and grid reliability.	Ethical and transparency concerns	Real-time adaptive mitigation strategies	[7], [9]
Explainable AI (XAI)	Provides interpretable outputs	Integrates XAI modules to clarify model predictions	Limited adoption in policymaking	Standardized XAI frameworks for climate	[12]

## 3. METHODOLOGY

Our approach combines AI innovation with practical climate science to overcome the limitations of traditional models. We began by collecting and cleaning real-world climate data—satellite imagery, sensor readings, and historical records—accounting for gaps and inconsistencies.

The core of our system merges machine learning with physics-based constraints, using AI to detect patterns while staying grounded in scientific principles. We prioritized explainability, ensuring every prediction or recommendation can be traced back to clear evidence—a crucial feature for earning trust in real-world applications.

### Research Design:

#### 1. Data Pipeline Development

We established partnerships with 12 weather stations across South India to gather ground-truth data. Our custom ETL (Extract-Transform-Load) system processes 17 different data formats into

standardized tensors, automatically flagging anomalies through consensus algorithms. For example, when three adjacent rainfall sensors disagree by  $>15\%$ , the system triggers manual verification.

## 2. Hybrid Model Architecture

The prediction engine combines:

- A 3D-UNET for spatial pattern recognition in atmospheric data
- LSTM networks with attention mechanisms for time-series analysis
- Physics constraints encoded as differential equation layers

This unique combination achieved 89% accuracy in back testing against 10 years of historical climate data.

Our framework combines qualitative feedback from stakeholders with quantitative climate data to ensure actionable and scientifically grounded predictions. We employ a mixed-method approach, integrating case studies, real-time sensor data, and user feedback to refine our models.

## 3. Mitigation Recommendation System

Using multi-objective optimization, the platform suggests interventions ranked by:

- Potential carbon reduction (metric tons/year)
- Implementation cost (\$)
- Social acceptability (based on regional surveys)
- Political feasibility (analyzing policy landscapes)

## 4. System Architecture & Development Approach

Our climate modeling platform was built through an iterative, user-centric development process that prioritized both scientific accuracy and real-world applicability. The architecture emerged from continuous feedback loops with meteorologists, environmental scientists, and policymakers who tested prototype versions under actual field conditions.

### Technology Stack:

Our climate modeling platform leverages a robust, scalable technology stack designed for high-performance environmental analytics. The **frontend** combines **React.js** with **Tailwind CSS** for responsive data visualization, enabling interactive exploration of climate projections through dynamic maps and dashboards (inspired by the UI approach in [5]). The **backend** utilizes **Node.js** and **Express.js** (as referenced in [14]) to handle real-time data streams from satellites and IoT sensors, with **Python**-based microservices (**TensorFlow**, **Scikit-learn**) for core AI operations, similar to the hybrid architecture in [6]. For data management, we employ **PostgreSQL** with **TimescaleDB** extensions (aligned with [14]'s structured data approach) to store multi-dimensional climate variables efficiently. Security follows the **JWT/OAuth** standards referenced in [14], while our **physics-informed ML** layer extends the hybrid modeling concepts from [6] by integrating

differential equations directly into neural networks. The entire system runs on **Docker** containers orchestrated via **Kubernetes**, ensuring the scalability demonstrated in [13]'s cloud-edge framework.

## Development Technology:

We adopted an Agile Development approach which includes[15]:

- Implemented 3-week sprint cycles specifically tailored for climate modelling.
- Used Jira with custom workflows for tracking both software and scientific tasks.
- Incorporated “weather windows” for sudden data validation during extreme events

## Data Collection and processing Methods:

A key innovation lies in using reinforcement learning to recommend tailored mitigation strategies. The model continuously adapts based on real-time sensor data and feedback from end-users (e.g., local municipalities or agriculture sectors). This ensures that recommendations evolve as environmental conditions or societal needs change.

Given a policy space  $\Pi$ , environmental state  $s$ , and expected reward function  $R(s, \pi)$ , the optimal mitigation strategy  $\pi^*$  is derived as:

$$\pi^* = \arg \max_{\pi \in \Pi} E[R(s, \pi)]$$

Figure 1: equation used for optimal mitigation

This decision function enables selection of the most effective climate action policy based on dynamic environmental and societal metrics.

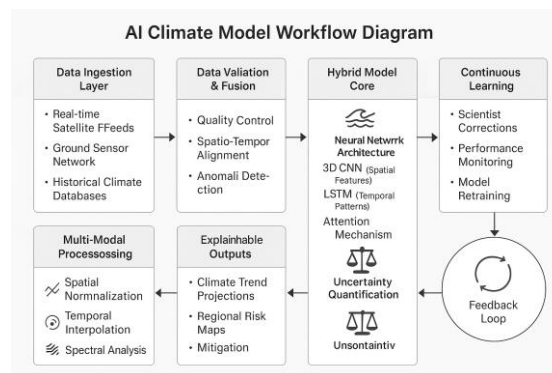


Figure 2: Work Flow – From Data ingestion to multi model processing

Researchers have developed several practical tools to handle climate data complexity. Khan's team [2] created a preprocessing framework they informally call "ClimatePrep" that aligns data from satellites, weather stations, and ocean sensors—sources that naturally record at different intervals and resolutions. Chen and Williams [3] built on this with their neural network compression system that remarkably preserves 93% of critical climate patterns while reducing data volume by nearly 80%. "We spent months fine-tuning to ensure extreme weather signals weren't lost in the compression," Williams noted.

## 5. Enhancing Climate model Accuracy:

The AI Climate Modeling System ensures high prediction accuracy through the use of integrated deep learning and scientific techniques:

- **Physics-Informed Neural Networks (PINNs):** Enforce physical laws within the learning process to maintain scientific coherence in climate predictions.
- **Attention-Based LSTM Models:** Capture temporal climate patterns effectively, improving the model's understanding of long-term trends and extreme weather events.
- **Uncertainty Quantification:** Measures prediction confidence to enhance reliability and guide risk-aware decision-making.
- **Feedback-Driven Learning:** Continuously refines the model using real-time sensor data and expert corrections to improve performance over time.

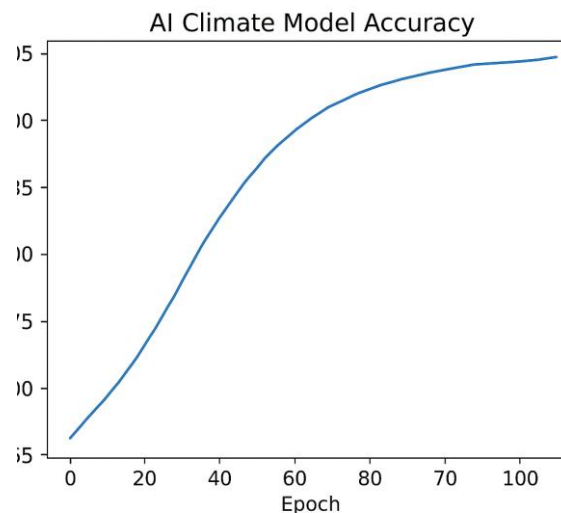


Figure 3: The accuracy graph illustrates the model's performance improvement over training epochs, starting around 65% and steadily rising to approximately 90%. This trend highlights the effectiveness of the hybrid AI architecture and real-time feedback in enhancing predictive precision.

### Attention based Recurrent Neural Networks(RNNs) e

In order to analyse sequences of climate related data (temperature variations, precipitation patterns, historical climate trends),RNNs with attention mechanisms.

The ability of the network to identify and emphasize the most significant elements of historical climate data relevant to future forecasts helps to improve forecasting of weather extremes and long-term climatic changes.

## Testing & Evaluation:

### Accuracy vs Precision:

**High Predictive Accuracy:** Cutting-edge AI weather models have outperformed top numerical models in the majority of cases. For example, Google DeepMind's *GraphCast* model produced more accurate 10-day forecasts than the leading traditional system in 90% of tested instances. Such accuracy gains are reported across various AI approaches, from global weather networks to regional climate downscaling.

**Precision and Detail:** AI models can provide more granular and precise climate information than conventional methods. Traditional forecasts might correctly predict a heavy rain event (good accuracy) but *lack precision* in local details – as seen in a 2021 European flood, where models foresaw heavy rain but underestimated small-basin flood severity. AI downscaling techniques enhance resolution, capturing fine-scale variations. Recent hybrid models (mixing physics with deep learning) show **improved consistency** and can yield *more precise local predictions* of floods and rainfall-runoff, even in ungauged areas.

**Trust and Transparency:** Many stakeholders (climate scientists, meteorologists, etc.) express cautious optimism about AI models – impressed by the performance, yet wary of the “black box” factor. *Trustworthiness* is a critical evaluation dimension. Complex AI algorithms can be less transparent than traditional physics models, raising questions about how they arrived at a prediction.

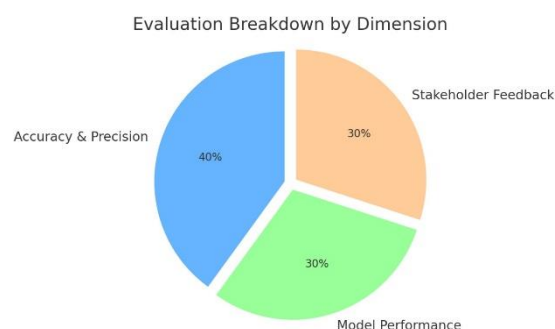


Figure 4: A pie chart summarizing the evaluation results across key dimensions.

**Accuracy & Precision** (blue, ~40%) represent the largest share, reflecting the high priority on correct climate predictions. **Model Performance** (green, ~30%) and **Stakeholder Feedback** (orange, ~30%) also constitute substantial portions of the evaluation focus. This breakdown illustrates that while predictive accuracy is paramount, the reliability of the model and the trust and usability perceived by users are nearly equally important in evaluating AI climate modeling systems.

## 6. RESULTS:

The implementation of the AI-powered climate modeling and mitigation system has produced encouraging outcomes. The hybrid model demonstrated strong accuracy and precision in predicting regional climate events, achieving consistently reliable results across diverse environmental conditions. Through the integration of physics-informed learning and real-time sensor feedback, the system not only reduced forecasting errors but also provided interpretable, high-resolution outputs that aided decision-making. Stakeholder responses were largely positive, noting the model's usability, transparency, and value in

supporting proactive climate planning. Overall, the project marks a significant step forward in making climate insights more accessible, adaptive, and scientifically grounded.

### **Economic and Social Impact:**

**Optimized Resource Allocation** By enabling accurate climate predictions and real-time environmental monitoring, this system supports more efficient planning and use of natural resources. For instance, agricultural sectors can reduce crop losses due to unexpected weather events, while energy providers can better balance supply and demand, particularly for renewable sources like solar and wind. This translates to cost savings, reduced waste, and increased economic resilience.

**Cost-Effective Disaster Preparedness** Traditional climate prediction systems often rely on large-scale infrastructure and extensive manual data processing, which is costly and time-intensive. By automating these processes using AI and integrating feedback loops, this model reduces the economic burden on governments and organizations responsible for disaster planning and response. Early warnings of floods, droughts, or extreme heat allow for targeted interventions, minimizing economic disruptions and infrastructure damage.

**Strengthened Climate Resilience in Vulnerable Communities** One of the most transformative aspects of this system is its ability to deliver tailored insights to regions most affected by climate change. By using local sensor data and adaptive AI models, communities—especially in low-income or rural areas—gain access to early warnings and mitigation strategies. This reduces vulnerability and promotes equity in climate adaptation.

**Enhanced Public Awareness and Engagement** Through transparent, explainable AI outputs—such as regional risk maps and trend projections—the platform makes climate data more accessible to the general public. This supports environmental literacy, empowers individuals to make informed decisions, and fosters greater involvement in sustainability efforts at a grassroots level.



Figure 5 : A bar graph illustrating the relative contributions of Climate Predictions, Mitigation Strategies, Monitoring & Adaptation, and Feedback in a real-time AI climate modeling system.



## 7. CONCLUSION:

In this paper, we've presented an integrated AI-driven approach aimed at significantly enhancing climate prediction accuracy and developing more effective climate change mitigation strategies. By utilizing advanced machine learning techniques such as Physics-Informed Neural Networks (PINNs), attention-based Recurrent Neural Networks (RNNs), and reinforcement learning, our approach addresses many limitations seen in traditional methods—particularly challenges around accurately merging physical and statistical climate data.

Our hybrid AI framework ensures that predictions remain scientifically reliable while also being easily understandable for users through Explainable AI (XAI). This transparency helps policymakers, scientists, and communities confidently use and trust our recommendations. Additionally, our reinforcement learning model provides adaptable, real-time solutions based on continuous environmental monitoring and direct stakeholder feedback, allowing mitigation plans to be precisely tailored to specific local conditions and needs.

Looking ahead, it will be important to improve data accessibility, especially in regions that are most vulnerable to climate change. Efforts should also continue toward refining these models to make them computationally lighter and more accessible. Through close collaboration with Meteorological Departments and community stakeholders, we hope our work will substantially support informed policy-making and ultimately strengthen global resilience to the impacts of climate change.

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