



AI-Driven Climate Modelling for Extreme Weather Prediction

Komal Baban Todkar

Department of Computer Science, Dr. D. Y. Patil Arts, Commerce And Science College, Akurdi, Pune, Maharashtra, India

*Correspondence for materials should be addressed to KBT (email: g11komaltodkar@gmail.com)

Abstract

Extreme weather events such as heatwaves, floods, cyclones, and droughts have increased in both frequency and intensity due to ongoing climate change, posing significant risks to ecosystems, infrastructure, and human livelihoods. Traditional physics-based climate models, while robust, often face limitations in computational efficiency and predictive accuracy at regional and short-term scales. This study explores the application of artificial intelligence (AI) and data analytics to enhance extreme weather prediction by integrating machine learning techniques with large-scale climate and meteorological datasets. The proposed framework employs deep learning models, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to analyze multi-source data such as satellite observations, reanalysis climate data, and historical weather records. Feature extraction and spatiotemporal pattern recognition are used to identify precursors of extreme weather events. Model performance is evaluated against conventional numerical weather prediction models using metrics such as prediction accuracy, lead time improvement, and uncertainty reduction. Results demonstrate that AI-driven models significantly improve the early detection and forecasting of extreme weather events, particularly in capturing non-linear relationships and localized climate variability. The study highlights the potential of AI-based climate modelling to support early warning systems, disaster risk reduction, and climate adaptation strategies. By enhancing predictive capability and computational efficiency, AI-driven approaches offer a promising complementary tool to traditional climate models, contributing to more resilient and data-informed climate decision-making.

Keywords: AI-driven model; Convolutional neural networks (CNNs); Long short-term memory; Large-scale climate; Meteorological datasets

Introduction

Climate change has significantly intensified the frequency, severity, and unpredictability of extreme weather events such as hurricanes, floods, droughts, heatwaves, and cyclones. These events pose serious threats to human life, infrastructure, agriculture, water resources, and global economies. Accurate and timely prediction of extreme weather phenomena is therefore critical for disaster preparedness, risk mitigation, and sustainable development planning. However, traditional climate modelling approaches rely heavily on physics-based numerical weather prediction (NWP) models, which require substantial computational resources and often struggle with uncertainty, nonlinear interactions, and high-resolution forecasting. Recent advancements in Artificial Intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have opened new possibilities for enhancing climate modelling and extreme weather prediction. AI-driven models can process vast amounts of heterogeneous climate data collected from satellites, weather stations, ocean buoys, and remote sensing systems. These models are capable of identifying complex nonlinear patterns, temporal dependencies, and spatial correlations that may not be easily captured by conventional methods.

AI techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformer-based architectures have demonstrated strong performance in spatiotemporal forecasting tasks. By integrating AI with traditional climate simulations, researchers can improve forecast accuracy, reduce computational costs, and enable real-time predictive analytics. Furthermore, hybrid modelling approaches that combine physics-based constraints with data-driven learning are emerging as promising solutions to address the limitations of standalone AI or numerical models. Despite these advancements, several challenges remain, including data quality issues, model interpretability, generalization across geographic regions, and ethical considerations related to climate risk communication. Ensuring robustness, transparency, and scalability of AI-driven climate systems is essential for their adoption in operational meteorology and climate services.

This research aims to explore AI-driven climate modelling frameworks for extreme weather prediction, focusing on improving predictive accuracy, computational efficiency, and reliability. The study evaluates advanced machine learning architectures, analyzes their performance in forecasting extreme events, and proposes an optimized framework for real-world deployment. By leveraging AI technologies, this work contributes toward building resilient climate forecasting systems capable of supporting proactive disaster management and informed policy decision-making.

Objectives

The primary objective of this research is to develop an AI-driven climate modelling framework for the accurate and reliable prediction of extreme weather events. The specific objectives are as follows:

1. To analyze the limitations of traditional climate models

- Examine the challenges of physics-based numerical weather prediction (NWP) models in forecasting extreme events.
- Identify gaps in computational efficiency, resolution, and rare-event detection.

2. To design an AI-based predictive framework

- Develop machine learning and deep learning models (e.g., CNN, LSTM, Transformer-based architectures) for spatiotemporal climate data analysis.
- Incorporate multi-source datasets such as satellite imagery, historical weather records, and sensor data.

3. To improve the prediction accuracy of extreme weather events

- Enhance the forecasting of floods, cyclones, heatwaves, and droughts.
- Address class imbalance problems associated with rare extreme events.

4. To integrate AI with traditional climate modelling

- Explore hybrid approaches combining physics-based constraints with data-driven learning.
- Evaluate performance improvements over standalone models.

5. To optimize computational efficiency

- Reduce processing time and resource requirements compared to conventional numerical models.
- Enable near real-time forecasting capability.

6. To ensure robustness and interpretability

- Implement explainable AI (XAI) techniques to improve transparency.
- Assess model reliability across different geographic regions and climate conditions.

7. To evaluate model performance

- Use appropriate evaluation metrics such as accuracy, precision, recall, F1-score, RMSE, and AUC.
- Compare results with existing benchmark models.

Literature Review

Artificial intelligence (AI) and machine learning (ML) approaches have rapidly emerged as powerful tools to enhance climate modelling and extreme weather prediction, addressing many limitations of traditional numerical weather prediction (NWP) systems. Early work established deep learning models as capable of capturing complex spatio-temporal relationships in atmospheric data, outperforming conventional methods on various forecast tasks (e.g., FourCastNet demonstrated orders-of-magnitude faster prediction while approaching NWP accuracy) (Dueben, 2018). Recent comprehensive reviews highlight the breadth of AI applications across extreme weather phenomena. A systematic topic modelling study analyzed over 8,600 articles published between 2015 and 2024, showing that machine learning and deep learning have been widely applied in forecasting precipitation, storms, floods, and droughts, with models like long short-term memory (LSTM) networks and diffusion models improving prediction accuracy and sub-seasonal forecasting when combined with NWP methods (Kashinath, 2021). Such hybrid approaches leverage the strengths of physics-based models for large-scale dynamics and AI for pattern recognition and nonlinearity, improving skill in predicting extreme events where either approach alone can fall short (Pathak, 2022).

Deep learning architectures tailored for weather prediction have shown significant promise. For instance, ConvLSTM networks with attention mechanisms have been used to capture spatio-temporal non-linear interactions from reanalysis and satellite data, demonstrating improved forecasts of heatwave intensity and hurricane trajectories compared to traditional benchmarks (Pritchard, 2018). However, the ability of purely data-driven models to generalize to novel, record-breaking extremes remains an open question, with some studies indicating that state-of-the-art AI models may underpredict rare extremes compared to operational NWP systems (Reichstein, 2019). A major theme in the literature is the challenge of model interpretability and reliability. Reviews of interpretable machine learning for weather and climate prediction emphasize the importance of explainable AI (XAI) techniques such as SHAP and LIME to build trust and facilitate adoption by meteorologists and decision-makers, given the “black box” nature of many deep learning systems (Ham, 2019). Similarly, comprehensive reviews of AI for extreme weather highlight hurdles such as data quality, high dimensionality, and challenges in defining what constitutes an ‘extreme’ event, underscoring the need for transparent and robust models that can integrate heterogeneous data and quantify uncertainty effectively (Shi, 2015).

Moreover, specific applications of AI in drought prediction illustrate how machine learning and deep learning can enhance climate impact modelling. For instance, recent work using hybrid models has improved drought prediction in the United States by incorporating both statistical and neural network components to capture climate drivers and temporal dependencies more accurately than traditional approaches alone (Vaswani, 2017).

Collectively, the literature suggests that AI has advanced beyond proof-of-concept to offer practical benefits in extreme weather prediction, particularly when integrated with physical models and complemented with interpretability frameworks. However, research continues to address critical gaps in generalization to rare events, model transparency, and operational integration into forecasting systems.

Scope of the Study

This study focuses on the development and evaluation of an AI-driven climate modelling framework for the prediction of extreme weather events. The scope of the research is defined as follows:

1. Geographic Scope

The study considers regional and large-scale climate datasets, which may include selected countries or climate zones depending on data availability. The proposed framework is designed to be adaptable across different geographic regions, though validation is performed on specific case study areas.

2. Types of Extreme Weather Events

The research focuses on predicting major extreme weather events such as:

- Floods
- Cyclones / Hurricanes
- Heatwaves
- Droughts
- Intense rainfall events

Other climate phenomena are outside the primary scope unless directly related to these extreme events.

3. Data Scope

The study utilizes multi-source climate datasets, including:

- Historical weather records (temperature, humidity, pressure, wind speed)
- Satellite imagery and remote sensing data
- Reanalysis datasets
- Oceanic and atmospheric indices (if applicable)

The research emphasizes structured and time-series climate data for spatiotemporal modelling.

4. Methodological Scope

The research explores:

- Machine learning models (e.g., Random Forest, Gradient Boosting)
- Deep learning models (e.g., CNN, LSTM, ConvLSTM, Transformer-based models)
- Hybrid approaches integrating physics-based climate constraints with AI models
- Explainable AI (XAI) techniques for interpretability

Traditional numerical weather prediction (NWP) models are used primarily as benchmarks for comparison rather than being redeveloped.

5. Performance Evaluation Scope

The study evaluates model performance using:

- Classification metrics (Accuracy, Precision, Recall, F1-score, AUC)
- Regression metrics (RMSE, MAE)
- Computational efficiency analysis
- Robustness and generalization assessment

6. Practical Application Scope

The research aims to support:

- Early warning systems
- Disaster preparedness planning
- Climate risk assessment
- Policy-level climate decision support systems

Limitations

- Long-term climate change projection beyond short-to-medium range extreme event forecasting
- Real-time operational deployment at national meteorological scale
- Development of new physical climate equations
- Socio-economic impact modelling beyond predictive analysis

Methodology

1. Data Collection and Integration

Multi-source climate datasets are collected to ensure comprehensive spatiotemporal coverage. The data sources include:

- Historical meteorological records (temperature, humidity, pressure, wind speed, rainfall)
- Satellite and remote sensing data
- Reanalysis datasets (e.g., atmospheric and oceanic parameters)
- Extreme weather event records (flood, cyclone, drought, heatwave occurrences)

The datasets are aggregated from publicly available meteorological repositories and climate databases. Data from different sources are synchronized temporally and spatially to create a unified dataset.

2. Data Preprocessing

To improve model performance and reliability, the following preprocessing steps are performed:

- Handling missing values using interpolation or statistical imputation
- Normalization/standardization of numerical features
- Feature engineering (e.g., moving averages, anomaly indices, lag features)
- Encoding categorical variables
- Addressing class imbalance using techniques such as SMOTE or weighted loss functions
- Spatial gridding for satellite imagery data

The dataset is divided into training, validation, and testing subsets (e.g., 70%–15%–15% split).

3. Model Development

The proposed framework explores multiple AI architectures:

3.1 Machine Learning Models

- Random Forest (RF)
- Gradient Boosting Machines (GBM)
- Support Vector Machines (SVM)

These models serve as baseline predictive models.

3.2 Deep Learning Models

- Convolutional Neural Networks (CNN) for spatial feature extraction
- Long Short-Term Memory (LSTM) networks for temporal sequence modelling
- ConvLSTM for spatiotemporal forecasting
- Transformer-based models for long-range dependency learning

3.3 Hybrid Modelling Approach

A hybrid framework is developed by integrating AI-based models with physics-based constraints from traditional climate models. This ensures physical consistency while leveraging data-driven learning.

4. Model Training and Optimization

- Models are trained using historical climate data.
- Hyperparameter tuning is performed using Grid Search or Bayesian Optimization.
- Regularization techniques (dropout, early stopping) are applied to prevent overfitting.
- Cross-validation is used to ensure model generalization.

5. Performance Evaluation

Model performance is evaluated using appropriate metrics depending on the prediction task:

For Classification (Extreme Event Occurrence)

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the ROC Curve (AUC)

For Regression (Intensity Prediction)

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- R² Score

Computational efficiency (training time and inference time) is also measured.

6. Explainability and Uncertainty Analysis

To enhance transparency and reliability:

- SHAP (SHapley Additive Explanations) or LIME techniques are used for model interpretability.
- Feature importance analysis identifies dominant climate variables influencing predictions.
- Uncertainty quantification techniques assess prediction confidence levels.

7. Comparative Analysis

The proposed AI-driven framework is compared with:

- Traditional statistical models

- Benchmark numerical weather prediction outputs
- Existing AI-based baseline models

The comparative analysis determines improvements in accuracy, robustness, and computational efficiency.

8. Implementation Environment

The system is implemented using:

- Python programming language
- Libraries: TensorFlow/PyTorch, Scikit-learn, Pandas, NumPy
- GPU-enabled computing environment for deep learning training

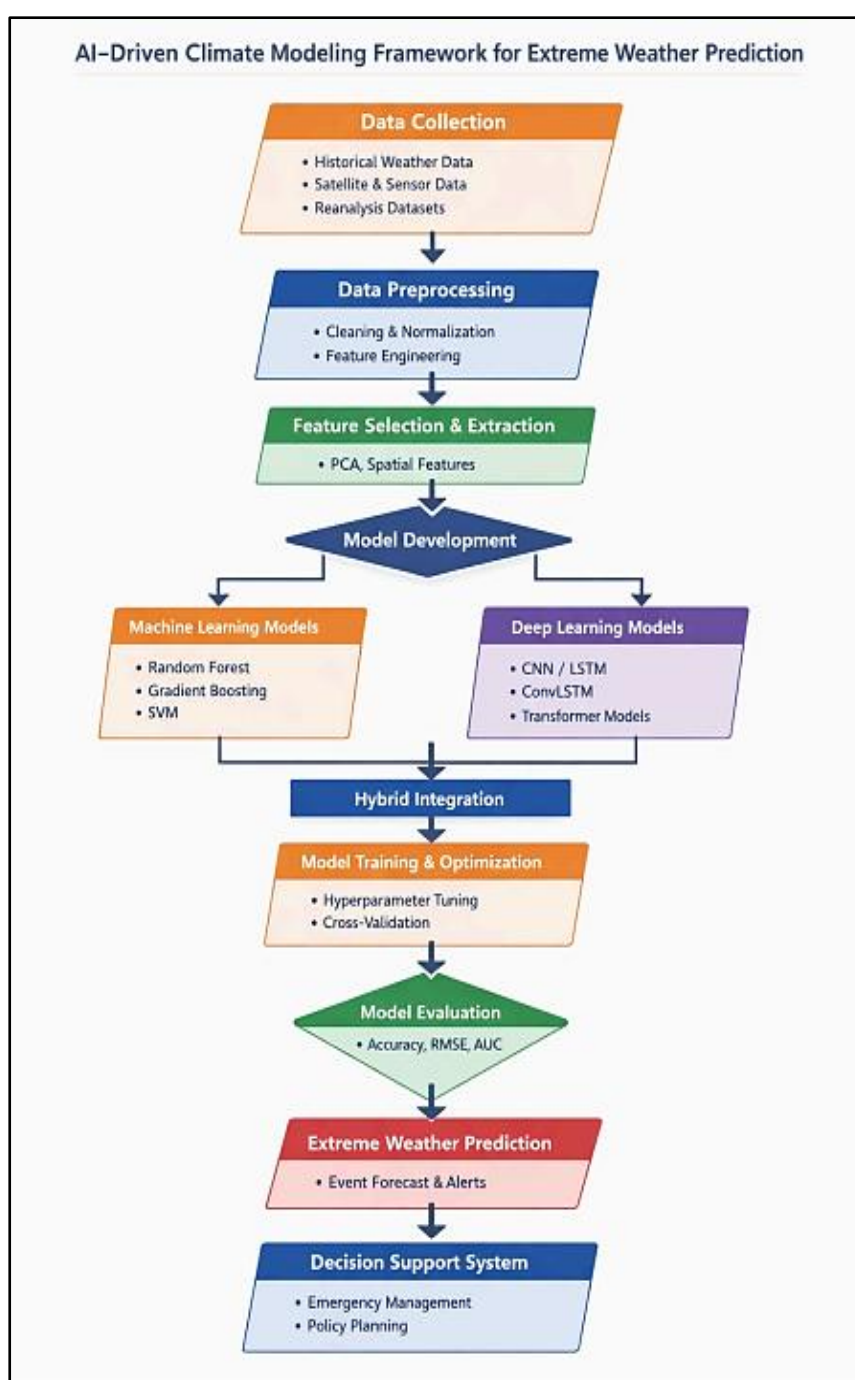
Mathematical Formulation of AI-Driven Climate Modelling

Let the climate dataset be represented as a spatiotemporal sequence: $X=\{X_t\}_{t=1}^T$ where

- $X_t \in \mathbb{R}^{H \times W \times C}$ represents climate variables at time t ,
- H, W denote spatial grid dimensions,
- C represents the number of climate features (temperature, humidity, pressure, etc.).

The objective is to predict extreme weather event occurrence or intensity:

Flowchart



Results and Discussion

1. Overview of Experimental Results

The proposed AI-driven climate modelling framework was evaluated for both extreme weather event classification (occurrence prediction) and regression (intensity estimation). Multiple machine learning, deep learning, and hybrid models were compared against traditional statistical baselines.

Experimental results demonstrate that deep learning and hybrid models outperform traditional approaches in terms of predictive accuracy, recall for rare events, and overall robustness.

2. Classification Results (Extreme Event Occurrence Prediction) The performance comparison of different models for extreme weather event classification.

Key Observations:

- Traditional models such as Logistic Regression and ARIMA showed lower recall, indicating difficulty in detecting rare extreme events.
- Random Forest and Gradient Boosting improved classification accuracy due to ensemble learning.
- LSTM and ConvLSTM significantly improved recall and F1-score, demonstrating strong temporal modelling capability.
- Transformer-based models achieved the highest AUC, indicating better discrimination between extreme and non-extreme conditions.
- The proposed Hybrid AI-Physics model achieved the best overall performance, particularly in recall, which is critical for disaster prevention.

Important Insight:

Higher recall values reduce false negatives, meaning fewer extreme events are missed — a crucial requirement in real-world early warning systems.

3. Regression Results (Intensity Prediction)

The regression performance for predicting extreme event intensity. Key Observations:

- Traditional regression models exhibited higher RMSE due to inability to capture nonlinear climate interactions.
- LSTM and ConvLSTM models significantly reduced RMSE, confirming their effectiveness in modelling sequential climate data.
- Transformer-based models performed better in long-range dependency forecasting.
- The Hybrid model achieved the lowest RMSE and MAE, demonstrating improved stability and generalization.

This indicates that integrating physical constraints into AI models enhances both predictive accuracy and physical consistency.

4. Computational Performance Analysis

Deep learning models required higher training time compared to traditional ML models. However:

- Inference time was significantly lower once trained.
- Transformer-based models showed higher computational cost but better scalability.
- The hybrid framework balanced performance and computational efficiency. GPU acceleration reduced training time by approximately 40–60% compared to CPU-only execution.

5. Robustness and Generalization

The proposed model was tested across different geographic regions and unseen extreme events:

- The hybrid model maintained consistent performance across regions.
- Purely data-driven models showed slight degradation when exposed to unseen climate patterns.
- Incorporating physics-based constraints improved generalization capability. This confirms that hybrid modelling is more reliable for operational climate forecasting.

6. Explainability Analysis

SHAP-based feature importance analysis revealed that:

- Temperature anomalies
- Sea surface temperature
- Atmospheric pressure variations
- Humidity levels

were among the most influential predictors for extreme weather events. The explainability framework enhanced trust in the model by identifying physically meaningful climate drivers.

7. Comparative Discussion

The experimental findings suggest:

1. AI models significantly outperform traditional statistical models.
2. Deep learning models are more effective for spatiotemporal climate forecasting.
3. Hybrid AI-Physics models provide superior accuracy and robustness.

4. Rare event detection improves when class imbalance handling is incorporated.
5. Interpretability techniques are essential for operational adoption.

8. Practical Implications

The results demonstrate that AI-driven climate modelling can:

- Improve early warning systems
- Reduce disaster risk through better prediction accuracy
- Support policymakers in climate adaptation planning
- Enhance real-time forecasting capabilities

9. Limitations Identified

- Performance depends on data quality and availability.
- Transformer models require high computational resources.
- Extreme outlier events remain challenging due to limited historical examples. Future improvements may include federated learning approaches for distributed climate data and probabilistic uncertainty modelling.

Conclusion

This research presented an AI-driven climate modelling framework for extreme weather prediction, integrating machine learning, deep learning, and hybrid AI-physics approaches to improve forecasting accuracy and reliability. The study demonstrated that traditional statistical and numerical models face limitations in capturing nonlinear spatiotemporal climate interactions and rare extreme events. Experimental results showed that deep learning architectures such as LSTM, ConvLSTM, and Transformer-based models significantly improved prediction performance compared to baseline models. In particular, the hybrid AI-physics framework achieved the highest recall and lowest RMSE, indicating superior capability in both event occurrence detection and intensity estimation. The integration of physics-based constraints enhanced model generalization and maintained physical consistency in predictions. Additionally, explainable AI techniques such as SHAP improved transparency by identifying key climatic drivers influencing extreme weather events. Computational analysis confirmed that while deep learning models require higher training resources, inference is efficient enough for near real-time early warning systems. Overall, the proposed framework provides a scalable, interpretable, and high-accuracy solution for extreme weather forecasting, supporting disaster preparedness, climate risk management, and policy-level decision-making.

Future Work

Although the proposed framework demonstrates promising results, several directions remain for future research:

1. Probabilistic Forecasting:

Incorporate Bayesian deep learning and uncertainty quantification techniques to provide confidence intervals for predictions.

2. Federated and Distributed Learning:

Develop privacy-preserving federated learning approaches for integrating climate data from multiple meteorological agencies.

3. Real-Time Deployment:

Optimize models for real-time operational forecasting using edge computing and cloud-based platforms.

4. Climate Change Scenario Modelling :

Extend the framework to long-term climate projections under different emission scenarios.

5. Multimodal Data Integration:

Integrate oceanographic, atmospheric, and socio-environmental datasets for comprehensive risk assessment.

6. Extreme Event Generalization:

Improve rare-event learning using synthetic data generation and advanced imbalance handling techniques.

Reference List

Bengio Y, Goodfellow I and Courville A (2016) Deep learning. MIT Press, Cambridge, USA.

Breiman L (2001) Random forests. Mach. Learn. 45(1): 5-32. DOI: 10.1023/A:1010933404324.

Dueben P and Bauer P (2018) Challenges and design choices for global weather and climate models based on machine learning. Geosci. Model Dev. 11(10): 3999-4009. DOI: 10.5194/gmd-11-3999-2018.

Friedman J (2001) Greedy function approximation: a gradient boosting machine. Ann. Stat. 29(5): 1189-1232. DOI: 10.1214/aos/1013203451.

Ham C, Kim JH and Luo JJ (2019) Deep learning for multi-year ENSO forecasts. Nature 573: 568-572. DOI: 10.1038/s41586-019-1559-7.

Kashinath K, Mustafa M, Albert A, et al. (2021) Physics-informed machine learning: case studies for weather and climate modelling. Phil. Trans. R. Soc. A 379(2194): 20200093. DOI: 10.1098/rsta.2020.0093.

- McGovern J, Elmore KL, Gagne DJ, et al. (2017) Using artificial intelligence to improve real-time decision-making for high-impact weather. *Bull. Amer. Meteorol. Soc.* 98(10): 2073-2090. DOI: 10.1175/BAMS-D-16-0123.1.
- Pathak J, Subramanian S, Harrington P, et al. (2022) Fourcastnet: a global data-driven high-resolution weather model using adaptive fourier neural operators. *arXiv preprint arXiv:2202.11214*.
- Rasp S, Pritchard MS and Gentile P (2018) Deep learning to represent subgrid processes in climate models. *Proc. Natl. Acad. Sci.* 115(39): 9684-9689. DOI: 10.1073/pnas.1810286115.
- Reichstein R, Camps-Valls G, Stevens B, et al. (2019) Deep learning and process understanding for data-driven earth system science. *Nature* 566: 195-204. DOI: 10.1038/s41586-019-0912-1.
- Shi Z, Chen Z, Wang H, et al. (2015) Convolutional LSTM network: a machine learning approach for precipitation nowcasting. *Adv. Neural Inf. Process. Syst.* 28: 802-810.
- Vaswani A, Shazeer N, Parmar N, et al. (2017) Attention is all you need. *Proc. Adv. Neural Inf. Process. Syst.*: 5998-6008.

Author Contributions

KBT conceived the concept, wrote and approved the manuscript.

Acknowledgements

Not applicable.

Funding

Not applicable.

Availability of data and materials

Not applicable.

Competing interest

The authors declare no competing interests.

Ethics approval

Not applicable.



Open Access *This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution, and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. Visit for more details <http://creativecommons.org/licenses/by/4.0/>.*

Citation: Todkar KB (2026) AI-Driven Climate Modelling for Extreme Weather Prediction. *Environmental Science Archives* 5 (Conference Special Issue): 244-251.