An Event-Adaptive Deep Learning Framework for Extreme Weather Prediction

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Abstract*:* Accurate prediction of extreme weather events remains a significant challenge due to nonlinear atmospheric interactions, temporal variability, and severe class imbalance in observational datasets. This study proposes an event-adaptive deep learning framework for prediction of extreme weather events such as heat wave, cold wave, heavy rainfall, and thunderstorm using multivariate surface observatory data. Sequential models including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) are compared with a tree-based boosting model (XGBoost). Class-weighted training is employed to address rare event imbalance. Performance is evaluated using operational meteorological metrics such as Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI). Results indicate that persistent temperature-driven extremes are better captured by memory-based architectures, while short-duration convective events favor boosting methods. The findings highlight the necessity of event-specific model selection in operational extreme weather forecasting systems.

Keywords: extreme weather prediction, multivariate data, deep learning, class imbalance.

I. INTRODUCTION

Extreme weather events have become increasingly frequent and intense in recent decades, driven by climate variability and global warming [1]. Weather phenomena such as heat wave, cold wave, heavy rainfall, and thunderstorm significantly disrupt socio-economic systems, impacting agriculture, water resources, energy demand, transportation networks, and public health infrastructure [2]. The growing vulnerability of densely populated regions to these events underscores the need for reliable and timely forecasting systems [3]. Accurate early prediction not only mitigates economic losses but also supports disaster preparedness and climate adaptation strategies [4].Conventional numerical weather prediction (NWP) models are based on solving complex physical equations governing atmospheric motion and thermodynamics. While physically interpretable and scientifically rigorous, these models demand substantial computational resources and high-resolution initial condition data [5]. Moreover, small uncertainties in initialization can propagate and amplify, particularly in short-duration convective systems [6]. In recent years, advances in machine learning and deep learning have provided alternative data-driven forecasting paradigms capable of learning nonlinear relationships directly from historical meteorological observations without explicitly modeling physical equations [7].

Despite promising results, extreme weather prediction remains challenging due to three fundamental characteristics of atmospheric systems. First, temporal dependency plays a crucial role, particularly for persistent thermal extremes such as heat wave and cold wave, which evolve gradually over multiple days [8]. Capturing such long-term dependencies requires models with memory mechanisms [9]. Second, nonlinearity dominates convective events such as heavy rainfall and thunderstorm, where rapid atmospheric instability leads to abrupt transitions that are difficult to model using linear assumptions [10]. Third, class imbalance presents a major statistical challenge, as extreme events constitute only a small fraction of total observations, often leading to biased models that favor normal weather conditions [11], [12].

Addressing these challenges requires an adaptive modeling strategy rather than a single universal predictive approach [13]. In this study, a unified multivariate deep learning framework is proposed for forecasting multiple extreme weather phenomena using surface and synoptic meteorological data [14]. Sequential architectures (RNN, LSTM, and GRU) are employed to capture temporal dependencies, while a gradient boosting model (XGBoost) is incorporated to model nonlinear threshold-driven behavior [15]. By systematically evaluating event-specific model suitability using operational meteorological performance metrics, this work establishes a principled link between atmospheric dynamics and computational learning architectures, contributing toward more reliable and operationally deployable extreme weather forecasting systems [16], [17]. Also, deep learning can improve disaster response and communication by analyzing extreme climate events, but requires collaboration across fields to create practical, understandable, and trustworthy solutions [18], [19]. The proposed model consists of the following key components:

- Introduces an event adaptive comparative framework linking atmospheric event dynamics with model suitability rather than relying on a single predictive architecture.
- Demonstrates that temporal persistence favors gated recurrent networks, while nonlinear convective extremes benefit from gradient-boosted ensembles, providing actionable guidance for operational forecasting systems.
- Establishes a unified, class-imbalance-aware deep learning pipeline for multi-event extreme weather classification with improved detection stability across heterogeneous extremes.

II. Related Work

Recent investigations highlight the growing effectiveness of deep learning techniques in modeling and predicting extreme weather phenomena. A data-driven forecasting framework that demonstrated measurable improvements over established numerical benchmarks, reporting substantial gains in heatwave intensity estimation and cyclone track prediction. Their findings reinforce the expanding role of learning-based systems in climate adaptation planning [20]. Comparative assessments of forecasting methodologies suggest that deep neural networks are particularly capable of learning complex spatiotemporal patterns present in extreme climate events, thereby strengthening early warning capabilities. In contrast, conventional machine learning models often provide competitive accuracy with lower computational overhead [21].

For thermal extremes, LSTM-based architectures enhanced with explainability mechanisms have shown reliable short-range prediction skill, delivering actionable lead times while maintaining interpretability for operational users [22]. Deep learning approaches have also improved the spatial resolution and accuracy of heavy rainfall and severe weather forecasts, complementing traditional physics-driven models [23]. Hybrid AI-climate frameworks integrating statistical and physical insights have demonstrated notable reductions in false alarm rates while improving overall forecasting performance, offering practical benefits for disaster mitigation strategies [24]. Architectures combining convolutional and recurrent networks further enhance predictive performance by capturing both spatial structure and temporal evolution, although challenges related to data consistency and computational requirements persist [25]. Broader analyses emphasize the need for improved uncertainty estimation, reproducibility, and generalization across diverse climatic regimes [26].

Advanced CNN and LSTM models have been successfully applied to detect and forecast convective extremes and heat-related events, contributing to improved preparedness planning [27], [28]. Deep classification systems have also achieved strong accuracy in multi-category weather identification tasks [29]. Reviews of AI in climate applications underscore its growing importance in accelerating forecast production workflows and reducing societal risk [30]. Scalable cloud-based infrastructures now enable large-scale deep learning training for meteorological applications, supporting adaptive forecasting systems [31]. Artificial neural networks continue to demonstrate steady gains in rainfall and temperature prediction, with performance influenced by architecture configuration and data preprocessing strategies [32], [35]. Hybrid stacked deep neural models have further enhanced forecast stability by leveraging complementary feature representations [33].

From a dynamical systems perspective, densely connected neural models have been shown to capture rare and highly skewed extreme events in complex systems [34]. Neural weather models trained with tailored loss formulations maintain overall forecast skill while improving sensitivity to extremes [36]. Recent efforts to fine-tune large pre-trained weather models, including GraphCast, incorporate uncertainty-aware mechanisms to improve risk identification [37]. Probabilistic stacked neural approaches provide forecast distributions comparable to advanced numerical systems while preserving computational efficiency [38]. Short-term forecasting frameworks based on forward-propagation networks have demonstrated high accuracy for near-term temperature prediction [39]. Furthermore, hybrid model-assisted deep learning strategies that integrate simulations with observational data have proven effective for rare event detection, with recurrent architectures exhibiting resilience to noisy inputs [40].

Overall, existing literature confirms the rapid advancement of deep learning in extreme weather forecasting while emphasizing the importance of architecture selection, interpretability, uncertainty quantification, and scalability for reliable operational deployment.

III. Methodology

A. Study Area and Data Sources

The study focuses on Nagpur (21.15°N, 79.08°E), a metropolitan city in central India characterized by a tropical savanna climate (Köppen Aw). The region exhibits distinct seasonal extremes: heatwave in pre-monsoon (March–May), thunderstorm and heavy rainfall during monsoon (June–September), and cold wave in winter (December–February). Nagpur's topography is predominantly flat at ~310 m elevation, influenced by nearby plateaus and rivers that enhance localized convection. This site was selected due to its susceptibility to diverse extreme events, as documented in Indian Meteorological Department (IMD) records, and the availability of comprehensive observational data.

Data were acquired from the IMD surface observatory at Sonegaon Airport, spanning January 1, 2015, to December 31, 2024. This 10-year period captures interannual variability, including El Niño–Southern Oscillation effects. The dataset includes Daily Surface Tab 2 records which are aggregated daily summaries of cumulative or extreme values over 24 h and Synoptic Tab 3 observations which recorded at UTC intervals (00, 03, 06, 09, 12, 15, 18, 21) for higher temporal resolution. Approximately 3,650 daily records and 29,200 synoptic entries were obtained. Data quality was ensured via IMD protocols, with outlier and consistency checks applied during acquisition.

Historical observations over a fixed look-back window are used as input to predict whether the current condition corresponds to normal weather, an extreme event, or a severe extreme event. This sequence-based formulation enables the models to learn temporal evolution patterns associated with persistent and rapidly developing atmospheric phenomena.

B. Data Preprocessing

In order to ensure statistical robustness and temporal coherence, a structured preprocessing pipeline is applied prior to model training. Missing values in numerical meteorological variables are handled using K-Nearest

Neighbors (KNN) imputation, which estimates incomplete entries based on similarity in the multidimensional feature space. This approach preserves local data structure and inter-variable relationships. For categorical or non-numeric attributes, missing entries are replaced using mode imputation to maintain distributional consistency without introducing artificial variability.

To enhance sensitivity to temperature-driven extremes, a extreme indicator is derived using climatological thresholds and departure-based criteria. This engineered feature encodes sustained extreme temperature anomalies relative to long-term normals, enabling the model to capture persistence patterns characteristic of extreme events. The transformation shifts the learning objective from normal weather event prediction to structured extreme-event identification.

All numerical predictors are scaled using Min–Max normalization, mapping features to a bounded interval (typically [0,1]). This preserves relative magnitudes while preventing scale dominance among variables. Normalization improves numerical stability, accelerates convergence in gradient-based optimization, and ensures consistent feature contribution during model training.

For recurrent architectures (RNN, LSTM, GRU), historical observations are organized into fixed-length sequential windows, enabling the models to learn temporal dependencies directly. For XGBoost, which lacks inherent temporal memory, historical values are explicitly encoded as lag features. This converts the sequential forecasting problem into a structured supervised learning task while retaining short-term atmospheric evolution information.

C. Handling Class Imbalance

Extreme weather events represent minority classes within the dataset. To prevent model bias toward the dominant normal class, class-weighting techniques are incorporated into the training objective. This strategy increases the penalty associated with misclassification of rare extreme events, thereby improving detection capability while maintaining overall model stability. Let: Ndenote total samples; $n_c$denote samples in class c, k denote number of classes.

Class weights (Wc) are computed as:

$$Wc = \frac{N}{k.nc}$$

The weighted cross − entropy loss is

$$L = -\sum_{c=1}^{k} WcYc.log\,(\mathrm{y^c})$$

This reweighting strategy amplifies gradient contributions from rare extreme classes, improving detection capability without synthetic resampling.

D. Model Development

a. Recurrent Neural Network (RNN)

The vanilla Recurrent Neural Network models temporal dependence through recursive hidden-state propagation:

$$h_t = \tan(W_t xt + W_h h_{t-1} + b)$$

$$\hat{y}_t = Softmax(Woht)$$

Where, $x_t$denotes the multivariate meteorological input at time$t$, $h_t$represents the hidden state, and $\hat{y}_t$is the predicted class probability vector. The RNN captures short-term temporal evolution by encoding past atmospheric information into a compact hidden representation. In the context of extreme weather, this enables learning of immediate precursor patterns such as rapid pressure drops or sudden humidity spikes preceding convective events. However, during backpropagation through time (BPTT), repeated multiplication of gradients across time steps can lead to vanishing gradients:

$$\frac{\partial L}{\partial h_{t-k}} \rightarrow 0 \; as \; k \rightarrow \infty$$

This limits the model's ability to capture long-duration dependencies, which are critical for persistent extremes such as multi-day heatwave and coldwave. Therefore, RNN primarily serves as a baseline sequential model.

b. Long Short-Term Memory (LSTM)

To overcome gradient degradation, LSTM introduces gated memory mechanisms that regulate information flow: *Forget gate:*

$$f_t = \sigma(W_f[h_{t-1}, x_t])$$

Cell state update:

Ct=ftCt−1+itC~t

Hidden state:

$$h_t = o_t tanh\,(C_t)$$

The cell state C_t acts as an explicit memory channel, allowing gradients to propagate over long temporal horizons with minimal attenuation. This architecture is particularly suitable for modeling sustained atmospheric anomalies where cumulative thermal or moisture build-up defines event onset.

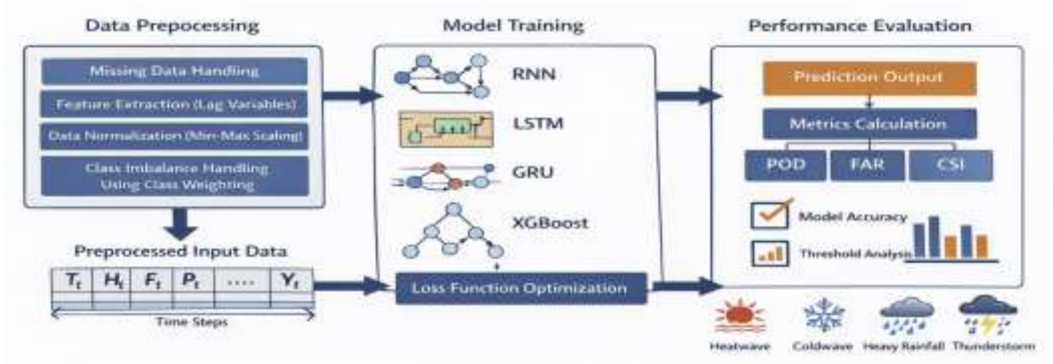

Figure 1. Proposed Methodology of Extreme Weather Prediction

In extreme heatwave prediction, for example, the gr adual accumulation of positive temperature anomalies across consecutive days can be effectively encoded within the LSTM memory cell. Similarly, coldwave persistence influenced by radiative cooling and synoptic-scale stability can be modeled through long-term state retention. Thus, LSTM is expected to perform optimally for slowly evolving and temporally persistent extremes.

c. Gated Recurrent Unit (GRU)

The GRU simplifies LSTM by merging gating operations while retaining temporal adaptivity:

Update gate:

$$z_t = \sigma(W_z x_t + U_z h_{t-1})$$

Hidden state update:

$$h_t = (1 - z_t)h_{t-1} + z_t \tilde{h}_t$$

The update gate dynamically balances retention of historical information and incorporation of new atmospheric inputs. Compared to LSTM, GRU reduces parameter complexity by eliminating separate memory cells and forget gates. From a computational standpoint, GRU requires fewer trainable parameters:

$$\text{Parameters}_{GRU} < \text{Parameters}_{LSTM}$$

This improves convergence speed and reduces overfitting risk, especially under moderate-sized meteorological datasets. GRU is particularly effective for events characterized by medium-range dependencies, such as transitional rainfall systems or short-lived but structured atmospheric disturbances.

d. XGBoost

XGBoost is a gradient-boosted decision tree ensemble designed for structured tabular data. The objective function is defined as:

$$L = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

where, $l(\cdot)$ denotes the differentiable loss (cross-entropy for classification), and $\Omega(f_k)$is a regularization term controlling model complexity:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$$

Here, T represents the number of leaves in the tree, w denotes leaf weights, γ penalizes tree complexity, and λ controls L2 regularization. Unlike recurrent architectures, XGBoost does not rely on hidden state propagation. Instead, temporal information is explicitly encoded using lag features. The model captures nonlinear interactions such as joint influence of humidity and temperature, Pressure-wind coupling effects, Threshold-based rainfall triggers. Tree-based splitting enables automatic learning of nonlinear decision boundaries and feature interactions without gradient instability issues. Furthermore, XGBoost is inherently robust to class imbalance when combined with scale-weight parameters and regularization.

IV. Results and Discussion

A. Experimental Setup

The proposed framework was evaluated on multivariate surface meteorological observations from Nagpur observatory stations. The dataset was divided into training and testing subsets using temporal splitting to preserve chronological integrity. Performance was assessed using Accuracy, Precision, Recall (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI), with particular emphasis on CSI due to the imbalanced nature of extreme weather events. Since extreme phenomena constitute a minority class, class weighting was incorporated during model training to reduce bias toward dominant non-event conditions.

B. Heatwave Prediction

For heatwave events, sequence-based architectures demonstrated superior performance compared to tree-based methods. LSTM achieved the highest overall classification accuracy and improved detection of prolonged temperature anomalies. This behavior is expected, as heatwave exhibit multi-day persistence and gradual thermal accumulation, which are effectively captured by gated memory mechanisms. GRU provided comparable performance with lower computational complexity, while standard RNN showed limitations due to vanishing gradient effects in long-duration sequences. XGBoost performed adequately but lacked the intrinsic temporal modelling required for persistent heat anomalies. These findings confirm that heatwave prediction is fundamentally a long-memory temporal problem, favoring gated recurrent architectures.

TABLE I. **PERFORMANCE METRICES FOR HEATWAVE**

Deep Learning	**Class**	**Precision**	**Recall**	**F-score**
RNN	No Heat Wave	0.99	0.82	0.90
	Heat Wave	0.14	0.71	0.24
	Severe Heat Wave	0.02	1.00	0.04
LSTM	No Heat Wave	0.99	0.89	0.94
	Heat Wave	0.23	0.84	0.36
	Severe Heat Wave	0.08	1.00	0.14
XGBOOST	No Heat Wave	0.99	0.99	0.99
	Heat Wave	0.60	0.67	0.63
	Severe Heat Wave	1.00	0.50	0.66
GRU	No Heat Wave	0.99	0.89	0.94
	Heat Wave	0.21	0.76	0.33
	Severe Heat Wave	0.05	1.00	0.09

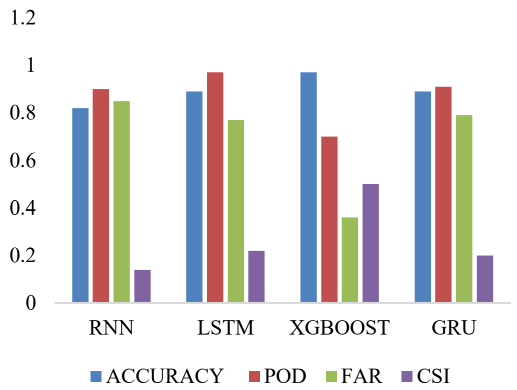

Figure 2. Comparison of Models for Heatwave

C. *Coldwave Prediction*

Coldwave events, characterized by sustained drops in minimum temperature, showed behavior similar to heatwave in terms of temporal persistence. LSTM again demonstrated strong detection capability due to its memory cell structure. GRU provided a balanced trade-off between detection rate and false alarms. XGBoost performance was moderate, suggesting that while nonlinear interactions are important, temporal continuity plays a more dominant role in coldwave evolution. This confirms that temperature-driven extremes are better captured using recurrent architectures with gating mechanisms.

TABLE II. PERFORMANCE METRICES FOR COLDWAVE

Deep Learning	Class	Precision	Recall	F-score
RNN	No Cold Wave	1.00	0.84	0.91
	Cold Wave	0.03	1.00	0.06
	Severe Cold Wave	0.02	0.75	0.03
LSTM	No Cold Wave	1.00	0.87	0.93
	Cold Wave	0.04	1.00	0.08
	Severe Cold Wave	0.02	0.75	0.05
XGBOOST	No Cold Wave	0.99	1.00	0.99
	Cold Wave	0.00	0.00	0.00
	Severe Cold Wave	1.00	0.25	0.40

GRU	No Cold Wave	1.00	0.87	0.93
	Cold Wave	0.04	1.00	0.08
	Severe Cold Wave	0.02	0.75	0.04

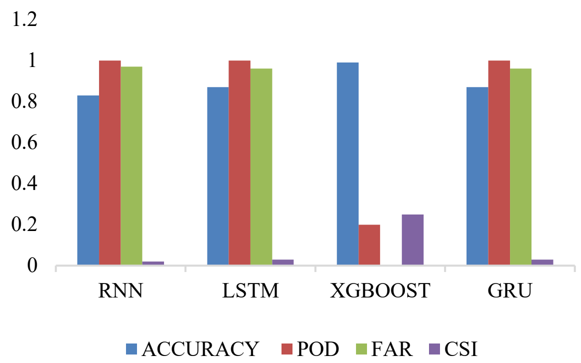

Figure 3. Comparison of Models for Coldwave

D. Heavy Rainfall Prediction

Heavy rainfall events are driven by nonlinear convective processes and moisture convergence. For this category, GRU and XGBoost demonstrated competitive performance. GRU effectively captured short-term atmospheric transitions, while XGBoost leveraged nonlinear feature interactions among humidity, pressure, and rainfall lags. LSTM showed stable performance but occasionally over-smoothed rapid precipitation bursts. RNN exhibited higher false alarm rates due to limited gating control. The results indicate that heavy rainfall prediction requires both nonlinear feature interaction modeling and short-term temporal sensitivity.

TABLE III. PERFORMANCE METRICES FOR HEAVY RAINFALL

Deep Learning	Class	Precision	Recall	F-score
RNN	Moderate	1.00	0.75	0.86
	Heavy rainfall	0.04	0.75	0.08
	Very Heavy Rainfall	0.00	0.00	0.00
LSTM	Moderate	1.00	0.82	0.90
	Heavy rainfall	0.06	0.50	0.10
	Very Heavy Rainfall	0.10	0.67	0.17
XGBOOST	Moderate	0.97	1.00	0.99
	Heavy rainfall	1.00	0.14	0.25
	Very Heavy Rainfall	0.00	0.00	0.00
GRU	Moderate	0.99	0.91	0.95
	Heavy rainfall	0.05	0.25	0.09
	Very Heavy Rainfall	0.14	0.33	0.20

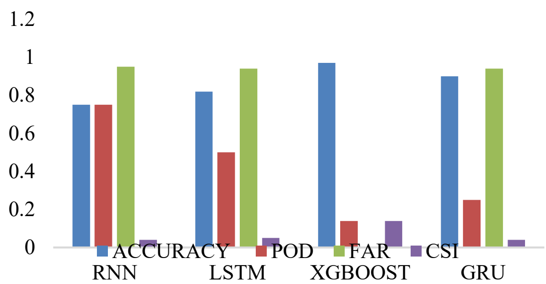

Figure 4. Comparison of Models for Heavy rainfall

E. Thunderstorm Prediction

Thunderstorm prediction presented a distinctly different behavior compared to temperature-driven extremes. Thunderstorms are short-duration, highly localized, and threshold-driven convective events. Although LSTM achieved high overall accuracy, it failed to detect a significant portion of thunderstorm events, resulting in low CSI. This indicates that accuracy alone is insufficient for evaluating rare-event prediction. RNN achieved high Probability of Detection (POD) but suffered from excessive false alarms, making it less suitable for operational forecasting. GRU demonstrated improved balance between POD and FAR, reflecting its ability to emphasize recent atmospheric evolution. Among all models, XGBoost achieved the highest CSI and lowest FAR while maintaining acceptable detection capability. This suggests that thunderstorm prediction is more sensitive to nonlinear threshold relationships among convective predictors rather than long-term memory modeling. Thus, tree-based ensemble methods appear particularly effective for short-memory, threshold-dominated extreme events.

TABLE IV. PERFORMANCE METRICES FOR THUDERSTORM

Deep Learning	Class	Precision	Recall	F-score
RNN	No Thunderstorm	0.94	0.42	0.58
	Thunderstorm	0.32	0.91	0.46
LSTM	No Thunderstorm	0.81	0.84	0.82
	Thunderstorm	0.34	0.30	0.32
XGBOOST	No Thunderstorm	0.84	0.91	0.88
	Thunderstorm	0.56	0.41	0.48
GRU	No Thunderstorm	0.82	0.67	0.74
	Thunderstorm	0.30	0.49	0.37

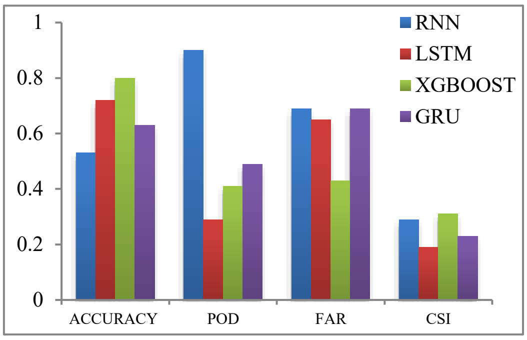

Figure 5. Comparison of Models for Thunderstorm

V. CONCLUSION

This work proposed a unified deep learning framework for multi-category extreme weather prediction using multivariate surface meteorological observations. RNN, LSTM, GRU, and XGBoost were rigorously evaluated within a standardized preprocessing and class-weighted optimization pipeline to investigate architecture–event compatibility. Rather than identifying a single dominant model, the work establishes a physics-consistent basis for architecture selection. Results demonstrate that predictive performance is intrinsically governed by atmospheric dynamics. Long-duration thermal extremes (heatwave and coldwave) are most effectively captured by LSTM due to its ability to model sustained temporal dependencies. In contrast, rapid convective thunderstorms are better represented by nonlinear ensemble learning, with XGBoost providing improved detection stability and reduced false alarms. Heavy rainfall exhibits hybrid dynamical behavior, where GRU and XGBoost achieve balanced performance. These findings indicate that event adaptive extreme weather forecasting is not a homogeneous classification problem; model suitability must align with event persistence and nonlinear structure. Future work will focus on hybrid recurrent–ensemble architectures, spatial data fusion from radar and satellite observations, and advanced imbalance-aware loss formulations to enhance rare-event detection robustness and operational reliability.

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