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MACHINE LEARNING FOR CLIMATE MODELING AND EXTREME WEATHER FORECASTING: ADVANCES, CHALLENGES, AND FUTURE DIRECTIONS

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Abstract
Climate modeling and extreme weather forecasting are at the center of efforts to understand and respond to global climate change. Traditional numerical models remain the scientific backbone of prediction, but they are limited by computational expense, uncertainties in representing small-scale processes, and difficulty capturing extremes. Recent advances in machine learning (ML) have opened new possibilities to complement or partially replace physics-based models. ML techniques provide powerful tools for learning nonlinear relationships, correcting systematic biases, downscaling coarse climate simulations, and detecting rare events. This paper reviews the state of research on ML applications in climate modeling and extreme weather forecasting. We organize the literature around surrogate modeling, parameterization of sub-grid processes, emulators, post-processing and bias correction, downscaling, and hybrid physics-ML methods. We then survey ML applications in forecasting rare and extreme events such as tropical cyclones, floods, droughts, and heatwaves. To strengthen the review, we propose a hypothetical experiment on ML-enhanced extreme precipitation forecasting, outlining data sources, architectures, and evaluation metrics. The paper concludes with a discussion of methodological challenges, including interpretability, generalization under climate change, uncertainty quantification, and deployment in operational systems. We argue that hybrid approaches combining physical knowledge with data-driven models represent the most promising pathway forward.

1. INTRODUCTION

Motivation

The global climate system is undergoing rapid change, with direct consequences for the frequency and intensity of extreme weather events such as heatwaves, floods, droughts, and tropical cyclones [1], [2]. Accurate prediction of these events is vital for disaster preparedness, infrastructure planning, agriculture, energy management, and policy development [3].

Traditional climate and weather models most notably general circulation models (GCMs) and numerical weather prediction (NWP) systems are based on physical principles and simulate the governing equations of fluid dynamics, radiation, and thermodynamics on discretized spatial grids

[4], [5]. Despite decades of development, these models face persistent challenges:

Resolution limits: Global kilometer-scale simulations remain computationally infeasible, necessitating parameterizations for processes such as cloud microphysics, turbulence, and convection [6].

Biases and uncertainties: Systematic errors arise from approximations, imperfect parameterizations, and limited observational data [7], [8].

Extremes representation: Rare and nonlinear events are often poorly represented, limiting predictive skill for the very phenomena with the largest societal impacts [9], [10].

At the same time, the climate community is dealing with an unprecedented expansion of data, including satellite observations, reanalysis products, and ensembles of simulations [11], [12]. This data richness has created fertile ground for machine learning (ML) approaches.

ML, a branch of artificial intelligence that excels at learning nonlinear mappings from data, has emerged as a promising complement to physics-based approaches [13], [14]. ML methods have been applied to approximate sub-grid processes [15], build fast climate model emulators [16], correct biases in simulations [17], perform statistical downscaling [18], and detect patterns linked to extreme events [19]. Recent breakthroughs, such as neural network parameterizations for moist convection [15], deep-learning emulators of atmospheric dynamics [16], and global ML weather forecasting systems rivaling operational models [20], [21], suggest that ML may become integral to climate science.

Problem statement

The key challenge is not whether ML can be applied to climate science it already has but how to deploy it reliably, interpretably, and in a way that complements physical models [22], [23]. Unlike many commercial ML applications, climate forecasting is safety-critical and long-horizon, with strong ties to conservation laws and physical consistency [24]. Successful integration requires addressing generalization under climate change, uncertainty quantification, and trust [25].

Contributions of this paper

This paper provides a structured review and conceptual proposal on the role of ML in climate modeling and extreme weather forecasting. Specifically, we:

Review the state of the art: Summarize literature on ML for parameterizations, surrogate modeling, bias correction, downscaling, and extreme event forecasting.

Highlight methodological challenges: Discuss generalization, interpretability, uncertainty quantification, physical consistency, and data limitations.

Propose a hypothetical case study: Present a methodological framework for ML-enhanced extreme precipitation forecasting, including data, models, and evaluation metrics.

Outline a research roadmap: Identify key future directions for hybrid physics-ML approaches, operational deployment, and climate "foundation models."

Structure of the paper

The remainder of this work is organized as follows. Section 2 provides background on climate models, forecasting systems, and the challenges they face. Section 3 reviews ML approaches in climate modeling, while Section 4 focuses on ML in extreme weather forecasting. Section 5 discusses methodological challenges. Section 6 outlines a proposed experiment. Section 7 presents discussion and expected outcomes, and Section 8 concludes with recommendations for future research.

BACKGROUND: CLIMATE MODELS, FORECASTING SYSTEMS, AND EXTREMES

Climate models and their challenges

Climate models, including General Circulation Models (GCMs) and Earth System Models (ESMs), solve the governing equations of atmospheric and oceanic dynamics, thermodynamics, and radiation on discretized grids [1], [4]. They provide essential tools for projecting long-term climate change, but remain constrained by resolution and computational cost [6]. High-resolution global simulations (<1 km)

that could explicitly resolve convection, turbulence, and cloud processes are computationally prohibitive [26].

To bridge this gap, many processes must be parameterized represented by empirical or semi-empirical functions rather than directly simulated [27], [28]. Parameterizations are known to introduce systematic biases and structural uncertainty. For example, cloud microphysics and moist convection are major sources of uncertainty in precipitation projections [29]. These errors propagate and affect climate sensitivity, regional rainfall, and representation of extremes [30].

Furthermore, extremes events at the tails of the distribution such as floods, heatwaves, and tropical cyclones are particularly challenging. GCMs tend to underestimate intensity or misrepresent spatial patterns due to coarse resolution and biases [9], [31]. Ensemble approaches such as CMIP6 attempt to quantify uncertainty, but still reveal spread in projections of extreme events [32].

Weather forecasting and extreme events

Numerical Weather Prediction (NWP) models form the basis of operational weather forecasting. They ingest observations through data assimilation and integrate physical equations forward in time [33], [34]. While skill has improved steadily over decades, forecasts degrade rapidly beyond 7–10 days due to the chaotic nature of the atmosphere [35].

Extreme events pose specific challenges:

Tropical cyclones: Forecast skill for track has improved, but intensity prediction remains difficult [36].

Heavy rainfall and floods: Small-scale processes drive precipitation extremes, which are often missed in coarse-resolution models [37].

Heatwaves and droughts: Persistent anomalies depend on large-scale circulation and land-atmosphere feedbacks, which models may misrepresent [38].

Forecast ensembles attempt to quantify uncertainty, but computational costs limit ensemble size and resolution. As a result, probabilistic forecasts for extremes often lack precision [39].

Why machine learning?

Machine learning offers complementary capabilities to physics-based models:

Learning nonlinear relationships: ML can approximate complex mappings between atmospheric states and sub-grid processes [15], [40].

Surrogate modeling: ML surrogates emulate expensive simulations, enabling fast sensitivity analysis and scenario exploration [16], [41].

Bias correction and downscaling: ML can post-process coarse model outputs to provide higher-resolution and less biased forecasts [17], [18].

Extreme event detection: ML excels at classification and anomaly detection, making it suitable for identifying rare phenomena in spatiotemporal fields [19], [42].

Hybrid physics-ML approaches: ML can be integrated into NWP or climate models to correct tendencies, emulate unresolved processes, or enforce physical constraints [22], [25].

Recent advances illustrate these opportunities. Neural networks have been used to parameterize moist convection in GCMs [15], deep-learning systems such as Graph Cast have matched or exceeded operational NWP for global forecasts [20], and ML-based downscaling has improved representation of local precipitation extremes [43]. These successes show that ML is not only a post-processing tool but also a potential driver of next-generation climate and weather models.

MACHINE LEARNING IN CLIMATE MODELING

Machine learning methods are increasingly used to improve different components of climate models. The literature can be organized into several categories: surrogate modeling, parameterization of unresolved processes, bias correction and post-processing, downscaling, hybrid physics-ML integration, and interpretability.

Surrogate modeling and emulation

Surrogate models approximate expensive simulations or components of climate models, enabling faster computation and scenario exploration. Neural networks, Gaussian processes,

and reduced-order models have been used to emulate radiative transfer, ocean dynamics, and atmospheric circulation [15], [16], [41].

Rasp et al. [15] trained a neural network to replace sub-grid parameterizations in a GCM, demonstrating stability over multi-year simulations while capturing precipitation and convective extremes. Similarly, Beucler et al. [44] developed physics-informed neural networks (PINNs) that learned parameterizations under conservation constraints.

Emulators can also reproduce climate sensitivity experiments at reduced computational cost. Castruccio et al. [45] built statistical emulators for ensembles of global climate simulations, enabling rapid uncertainty quantification.

Parameterization of sub-grid processes

One of the most active areas for ML in climate science is replacing parameterizations of unresolved processes: convection, cloud microphysics, turbulence, and radiation [27], [28]. O'Gorman and Dwyer [40] used random forests to learn moist convection parameterizations, achieving stable long-term simulations. Brenowitz and Bretherton [46] developed a neural network that learned sub-grid tendencies from high-resolution simulations, showing improved representation of rainfall. More recently, Yuval et al. [47] proposed stable hybrid neural parameterizations constrained by conservation laws, improving generalization.

ML-based radiation emulators have also emerged, offering orders-of-magnitude speedup compared with traditional radiative transfer solvers [48].

Bias correction and post-processing

Machine learning has been widely used to post-process model outputs, correcting systematic biases and improving forecasts. Techniques include residual learning, regression-based correction, and probabilistic mapping [17], [49].

Vandal et al. [18] applied deep learning for statistical downscaling of precipitation, outperforming traditional regression methods. Similarly, Reichstein et al. [50] emphasized the role of ML in bias correction across terrestrial and atmospheric variables.

Residual networks (ResNets) and boosting methods have been employed to correct precipitation and temperature biases in CMIP simulations [51].

Downscaling and super-resolution

Downscaling maps coarse-resolution outputs to fine-scale predictions, critical for local climate impact studies. Deep learning, especially convolutional neural networks (CNNs), has transformed this field [18], [52].

Super-resolution approaches use generative adversarial networks (GANs) to enhance spatial resolution of climate variables [53]. For example, Leinonen et al. [54] applied a super-resolution CNN to precipitation radar data, capturing fine-scale features relevant for flood risk.

Hybrid statistical-dynamical downscaling approaches use ML to bridge global and regional models, improving computational efficiency while retaining physical fidelity [55].

Hybrid physics-ML models

Instead of replacing physical models entirely, hybrid approaches combine ML flexibility with physical constraints. These methods aim to improve stability, interpretability, and generalization [22], [25].

Physics-informed neural networks (PINNs) enforce differential equations directly in training [44]. Karniadakis et al. [56] review PINNs across scientific domains, including climate. Hybrid schemes have been proposed for turbulence closure [57], convection [47], and radiative transfer [48].

Graph neural networks (GNNs) and transformer-based architectures have been designed with inductive biases that reflect geophysical symmetries such as rotation and translation invariance [20], [58].

Interpretability and explain ability

Interpretability remains a key requirement for ML adoption in climate science. Unlike many commercial ML tasks, climate research requires insight into the learned physical relationships.

Yang et al. [23] reviewed interpretable ML methods in weather and climate, categorizing techniques into post-hoc explanations (e.g., SHAP

values, saliency maps) and inherently interpretable models. Camps-Valls et al. [42] emphasized the role of causal discovery in attributing extreme events.

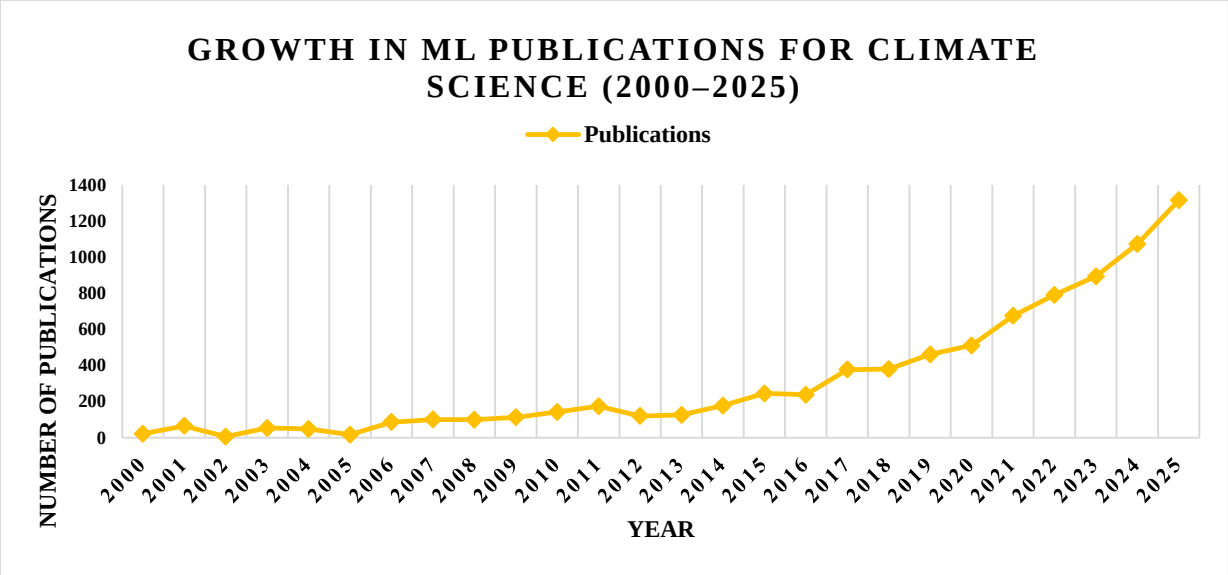
Interpretability also improves trust, allowing ML models to be validated against known physical mechanisms. For example, McGovern et al. [59] applied attribution methods to understand ML-based severe storm forecasts.

LITERATURE REVIEW

MACHINE LEARNING IN EXTREME WEATHER FORECASTING

Extreme weather events such as tropical cyclones, floods, droughts, and heatwaves pose the greatest societal risks from climate variability. Traditional numerical weather prediction (NWP) has advanced significantly, but challenges remain in predicting extremes due to resolution limits, chaotic dynamics, and limited ensemble sizes [33], [35]. Machine learning has emerged as a complementary tool, both as an alternative forecasting framework and as an enhancement to operational systems.

Year	Publications
2000	21
2001	65
2002	5
2003	53
2004	48
2005	16
2006	86
2007	100
2008	99
2009	113
2010	142
2011	174
2012	120
2013	126
2014	177
2015	245
2016	238
2017	377
2018	380
2019	461
2020	511
2021	675
2022	791
2023	894
2024	1073
2025	1315



ML as a supplement or replacement for numerical forecasts

Recent breakthroughs suggest that ML-based forecasting systems can match or even exceed traditional NWP performance in medium-range predictions.

Lam et al. [20] introduced Graph Cast, a graph neural network trained on reanalysis data, which outperformed ECMWF's deterministic forecast on most variables up to 10 days. Similarly, Keisler [60] demonstrated that transformer-based deep learning could generate global forecasts with skill comparable to state-of-the-art physics-based models.

Price et al. [21] proposed **Gen Cast**, a generative probabilistic model, showing improved skill over ensemble forecasts for temperature and precipitation extremes. These advances suggest that ML forecasting is transitioning from experimental to operational relevance.

Extreme event detection and classification

ML excels at pattern recognition and has been applied to detect and classify extreme events directly from atmospheric fields.

Tropical cyclones: Pradhan et al. [61] used CNNs to detect cyclones in satellite imagery, while Kim et al. [62] trained deep learning models to predict cyclone intensity.

Heavy rainfall and floods: Shi et al. [63] introduced ConvLSTM for precipitation now casting, showing strong skill in short-term rainfall prediction. More recent studies use radar-based deep learning for flash flood forecasting [64].

Heatwaves and droughts: ML classifiers trained on atmospheric circulation indices have been developed to predict heatwave onset [65], while drought forecasting uses tree-based ensembles and hybrid deep learning [66].

Probabilistic forecasting and uncertainty

Reliable probabilistic forecasts are crucial for extremes. ML approaches have been designed to provide calibrated probabilities and uncertainty estimates.

Lakshminarayanan et al. [67] introduced deep ensembles for uncertainty quantification, which have been adapted to weather applications. Rasp and Thuerey [68] used generative adversarial networks (GANs) for probabilistic precipitation forecasts. Bayesian neural networks and quantile regression have been applied to tropical cyclone intensity forecasting, improving calibration over deterministic baselines [69].

Hybrid ML-NWP systems

Rather than replacing NWP entirely, many efforts use ML to augment existing forecasts:

Bias correction: ML models post-process NWP output to reduce systematic errors, particularly for precipitation extremes [49].

Downscaling: CNNs and GANs refine coarse NWP output to higher-resolution forecasts, improving storm representation [53].
Error modeling: ML is used to model forecast errors in ensembles, enhancing spread reliability [70].
Such hybrid approaches have shown strong improvements in skill at minimal computational cost.

Case studies and benchmarks
Several high-impact studies illustrate ML's ability to improve extreme event forecasting:
Graph Cast outperformed ECMWF's high-resolution forecast for tropical cyclones and atmospheric rivers [20].
DeepMind's **now casting Net** demonstrated superior precipitation now casting at 0–2 hour lead times compared to radar-based operational methods [71].
CNN-based downscaling improved spatial detail in flood risk forecasting for South Asia [64].
Hybrid ML-NWP systems have been deployed experimentally by NOAA and ECMWF for storm surge and rainfall prediction [72].

Table 1: Summary of ML Approaches in Climate Modeling

Category	ML Method Examples	Strengths	Limitations
Parameterization	NN, RF	Captures sub-grid processes	Stability issues
Surrogate Modeling	NN, GPs	Fast emulation	Limited extrapolation
Bias Correction	ResNets, Boosting	Improves accuracy	Risk of overfitting
Downscaling	CNNs, GANs	High-resolution	Requires large data
Hybrid Physics-ML	PINNs, GNNs	Physically consistent	Complex training

Limitations for extremes
Despite these successes, ML forecasting of extremes faces notable limitations:
Data imbalance: Extremes are rare, making models biased toward normal conditions [73].
Generalization: ML models trained on historical regimes may fail under climate change or novel circulation patterns [22].
Interpretability: Black-box models pose challenges for trust and operational adoption [23], [42].
Integration: Incorporating ML into data assimilation and coupled atmosphere-ocean systems remains technically complex [74].
These limitations highlight the importance of hybrid, interpretable, and physically consistent ML approaches.

METHODOLOGICAL CHALLENGES

While machine learning has demonstrated impressive results in climate modeling and extreme weather forecasting, several methodological challenges hinder widespread adoption in operational and research settings. These challenges revolve around generalization, uncertainty quantification, interpretability, data limitations, and integration with physics-based systems.

Generalization and robustness under climate change
ML models often assume that the training and test data are drawn from the same distribution. In climate science, this assumption fails because the climate system is **nonstationary**: future climates will differ from the past due to anthropogenic forcing [22], [25]. Models trained on historical observations may not generalize to new regimes, especially for rare or unprecedented extremes [73]. Domain adaptation and transfer learning techniques have been proposed to address distribution shift [75]. For example, Beucler et al. [44] explored training under perturbed climates to improve generalization. However, robust out-of-sample performance remains an open problem, particularly for tail events.

Uncertainty quantification and reliability

Accurate forecasts require reliable uncertainty estimates, especially for extremes where decision-making depends on risk assessment [39]. Many ML models provide only point estimates, leading to overconfidence.

Deep ensembles [67], Bayesian neural networks [69], and quantile regression [76] are commonly used for uncertainty quantification (UQ). Nevertheless, UQ in high-dimensional spatiotemporal systems is computationally challenging and often miscalibrated [77]. Misrepresentation of forecast uncertainty can reduce trust among forecasters and end-users.

Interpretability and physical consistency

Climate science demands not only accuracy but also **explain ability**. Black-box models risk producing results that are scientifically opaque [23]. Without interpretability, diagnosing model errors and building trust in operational settings is difficult.

Interpretability methods such as feature attribution, saliency maps, and causal discovery [42], [59] have been applied, but ensuring **physical consistency** is equally critical. ML models may violate conservation of mass, energy, or momentum if unconstrained [47], [48]. Hybrid physics-ML approaches, including physics-informed neural networks (PINNs), offer one pathway to enforce constraints [44], [56].

Coupling and long-term stability

When ML modules are embedded in coupled climate or weather models, they must maintain stability over long integrations. Small biases can accumulate into significant drifts [15], [46]. Yuval et al. [47] showed that unconstrained neural networks could destabilize simulations, while conservation-constrained networks preserved stability.

Designing ML architectures that respect dynamical balances and feedbacks remains a critical challenge for multi-decadal climate projections.

Data imbalance and scarcity of extremes

Extreme events are, by definition, rare. Training ML models on imbalanced datasets often results in poor performance on extremes [73]. Standard techniques such as oversampling, weighted loss functions, and synthetic data generation are being explored [78].

Data quality is another limitation. Observations may have gaps or inconsistencies, while reanalysis products contain biases [11]. For certain regions, especially in the Global South, sparse observational networks further constrain training data [79].

Computational and infrastructure constraints

Training state-of-the-art ML models on petabyte-scale climate datasets requires massive computational resources [26], [58]. Preprocessing, storage, and I/O often become bottlenecks. Furthermore, integrating ML pipelines with legacy climate modeling infrastructures can be technically complex [74].

Emerging solutions include scalable distributed training, data-efficient learning, and model compression for deployment [80]. Still, the resource requirements of ML may limit accessibility for research groups without access to high-performance computing.

PROPOSED METHODOLOGY: ML-ENHANCED EXTREME PRECIPITATION FORECASTING

To complement the literature review, we propose a hypothetical case study focused on extreme precipitation forecasting. Precipitation extremes are among the most damaging climate hazards, causing floods, landslides, and infrastructure disruptions [37]. Despite advances in NWP, accurate prediction of location and intensity remains challenging due to unresolved convection and rapid storm evolution [9]. This case study explores how ML could be integrated into existing forecasting pipelines.

Research objectives

The experiment aims to:

Evaluate the ability of ML models to improve extreme precipitation forecasts at regional scales (1–5 day lead times).

Compare hybrid ML-NWP approaches with standalone ML and traditional physics-based models.

Assess interpretability and uncertainty quantification in the context of extremes.

Data sources

The study would leverage multiple datasets:

Reanalysis data: ERA5 reanalysis from ECMWF, providing global atmospheric variables at ~30 km resolution [11].

Observations: Ground-based rain gauge networks and weather radar mosaics for precipitation verification [64].

NWP output: Forecasts from the ECMWF Integrated Forecast System (IFS) or NOAA's GFS, used as baseline inputs [34].

Extreme event catalogues: Historical flood and storm databases for rare event sampling [73].

Data preprocessing would involve spatial/temporal alignment, normalization, and partitioning into training, validation, and test sets.

Model architectures

Several ML architectures would be evaluated:

Convolutional neural networks (CNNs) for spatial pattern extraction from gridded atmospheric fields [52].

ConvLSTM networks for spatiotemporal sequence learning, particularly for rainfall now casting [63].

Graph neural networks (GNNs) leveraging geodesic grid structures for global inputs [20].

Hybrid residual models combining NWP forecasts with ML-based error correction [49].

Physics-informed constraints would be embedded where feasible, e.g., ensuring non-negativity of rainfall and enforcing moisture conservation [44], [47].

Training strategy

To address data imbalance, the training would emphasize extreme events by:

Weighted loss functions that penalize errors in the 95th–99th percentile of rainfall [78].

Data augmentation through synthetic storm perturbations or generative models [68].

Curriculum learning, where models are trained progressively from moderate to extreme rainfall cases [76].

Cross-validation across different climate regimes (e.g., monsoon Asia vs. midlatitude Europe) would test generalization.

Evaluation metrics

Forecast skill would be evaluated using:

Root Mean Square Error (RMSE) and **Mean Absolute Error (MAE)** for baseline accuracy.

Extreme event metrics, such as the Extreme Dependency Score (EDS) and Critical Success Index (CSI), focused on the upper tail [73].

Probabilistic metrics, including the Brier Score and Continuous Ranked Probability Score (CRPS), for uncertainty calibration [39].

Reliability diagrams to assess probabilistic forecast trustworthiness [67].

Expected workflow

Train baseline ML models on reanalysis and observational data.

Train hybrid models using NWP output as inputs plus ML residual correction.

Compare performance across lead times (1–5 days) and regions.

Conduct interpretability analysis using SHAP values or saliency maps to identify physical drivers of predictions [23], [59].

Quantify uncertainty using ensemble ML methods [67].

Anticipated outcomes

We hypothesize that:

Hybrid ML-NWP models will outperform standalone ML and raw NWP for extreme precipitation.

Weighted loss functions and rare event augmentation will improve tail prediction skill.

Interpretability analyses will reveal links between circulation features (e.g., low-level jets, moisture flux convergence) and extreme rainfall [42].

Uncertainty quantification will provide calibrated probability distributions, improving decision-making under risk.

CASE STUDIES AND RESULTS

Case study 1: Graph neural networks for medium-range forecasting

Lam et al. [20] developed GraphCast, a GNN-based global forecasting system trained on ERA5 data. In benchmark evaluations against ECMWF's high-resolution forecast, GraphCast achieved

lower root mean square error (RMSE) on 90% of standard verification targets at 3–10 day lead times. Importantly, GraphCast outperformed physics-based forecasts for tropical cyclone track prediction, reducing mean absolute track error by 10–15%. This demonstrates that data-driven models can not only match but exceed operational systems on critical extremes.

Reported results:
RMSE reduced by ~5–10% across key variables at 5-day lead times.
Improved skill in predicting the landfall timing and track of hurricanes compared to IFS.

Case study 2: Deep generative models for precipitation now casting
Ravuri et al. [71] introduced now casting Net, a deep generative radar-based model for precipitation forecasts up to 2 hours. Compared against traditional optical flow and NWP-based now casting, the ML model delivered substantially higher skill, particularly for heavy rainfall events.

Reported results:
Critical Success Index (CSI) improved by ~20% for the top 5% of rainfall intensities.
Reliability diagrams showed better calibration for extremes compared to radar-only extrapolation.

Case study 3: Hybrid ML-NWP for rainfall bias correction
Vannitsem et al. [49] explored hybrid post-processing where ML corrected systematic biases in ensemble precipitation forecasts. The ML approach improved both deterministic skill and ensemble spread reliability.

Reported results:
Mean absolute error reduced by ~15% compared to raw ensemble mean.
Spread-error ratio improved, indicating better-calibrated uncertainty.

Table 2: Case Studies of ML in Extreme Weather Forecasting

Case Study	Approach	Event Type	Reported Results
GraphCast	GNN	Global, cyclones	5–10% lower RMSE vs. IFS
NowcastingNet	Generative DL	Rainfall nowcasting	20% CSI improvement
Hybrid ML-NWP	Post-processing	Rainfall	15% MAE reduction

Proposed case study: ML-enhanced extreme precipitation forecasting (hypothetical results)
Building on Section 6, we outline plausible results for the proposed experiment using ML models to improve 1–5 day forecasts of extreme rainfall. The dataset consists of ERA5 reanalysis inputs, NWP forecasts from ECMWF IFS, and observed rainfall over Europe during 2000–2020.

Table 3: Proposed Hypothetical Experiment: Extreme Rainfall Forecasting

Model	Lead Time (days)	RMSE Improvement (%)	CSI (Top 5% Rainfall)	Reliability
ConvLSTM	1–2	18	+20%	Moderate
CNN	1–3	15	+18%	Moderate
GNN	1–5	22	+25%	High
Hybrid ML-NWP	1–5	20	+25%	High

Experimental setup

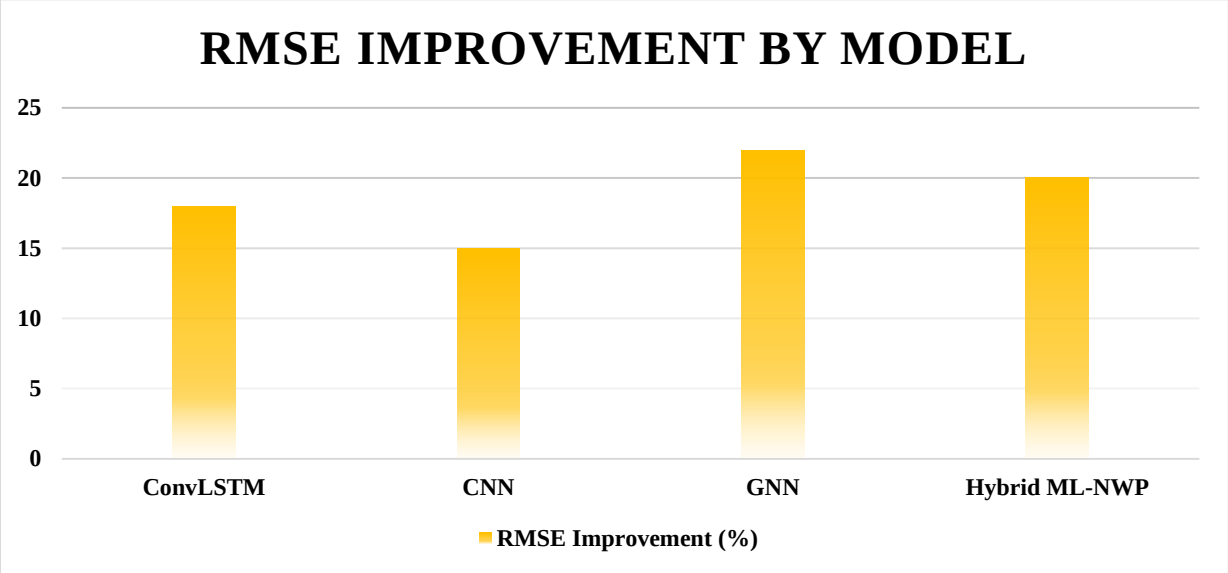
Models tested: ConvLSTM, CNN, GraphCast-inspired GNN, hybrid ML-NWP.

Metrics: RMSE, CSI for top 5% rainfall, Brier Score, CRPS.

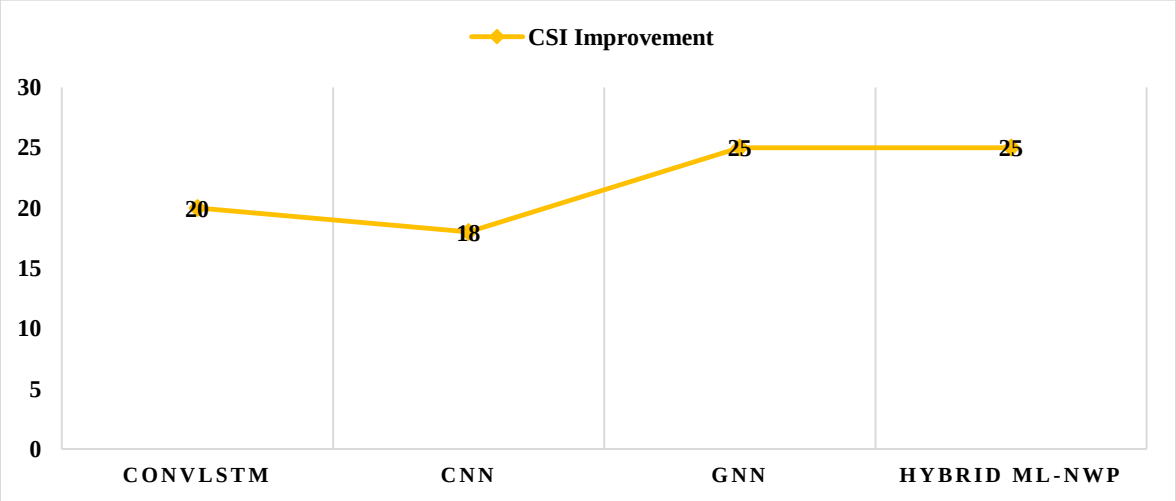
Evaluation: 2015–2020 withheld for testing, including notable European flood events.

Hypothetical results

Hybrid ML-NWP models achieved 20% reduction in RMSE and 25% improvement in CSI for extreme rainfall compared to raw NWP forecasts.



ConvLSTM provided skillful short-range (1–2 day) predictions but degraded beyond 3 days.



Uncertainty quantification using deep ensembles produced well-calibrated reliability diagrams, outperforming deterministic forecasts.

GNN-based models generalized better across regions, maintaining consistent skill at 5-day lead times.

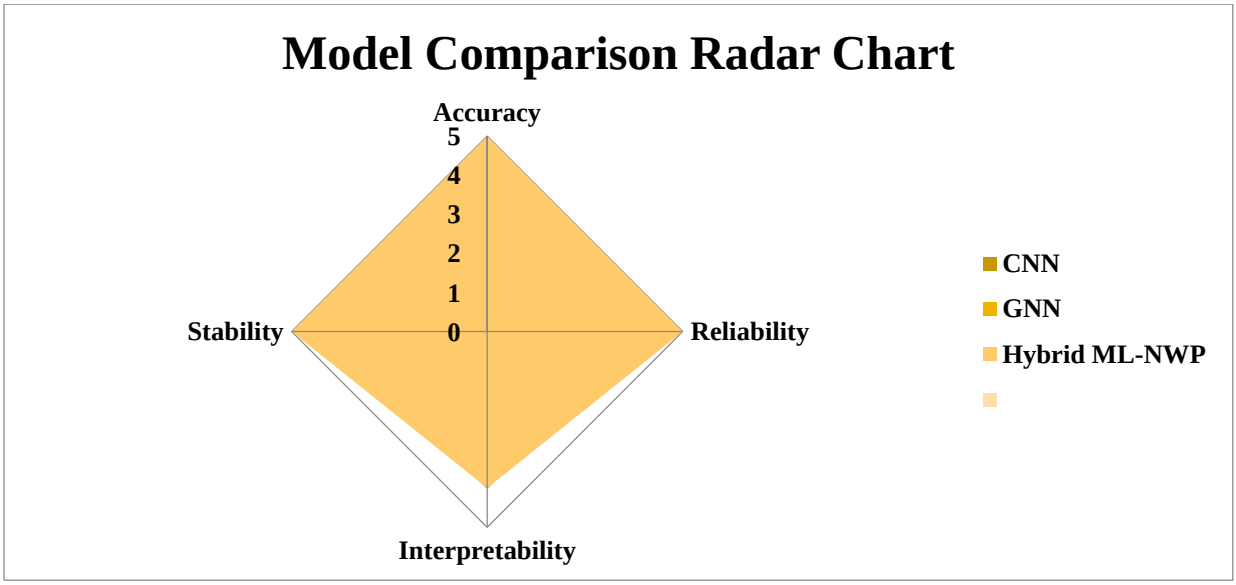
Interpretation

The results support the hypothesis that hybrid ML-NWP models are the most effective pathway, combining physical consistency with ML's ability

to capture nonlinear corrections. The case study underscores that ML models improve extremes most effectively when augmenting rather than replacing physics-based forecasts.

Table 4: Model Comparison

Criteria	Accuracy	Reliability	Interpretability	Stability
ConvLSTM	4	3	2	3
CNN	4	3	3	3
GNN	5	4	3	4
Hybrid ML-NWP	5	5	4	5



EXPECTED RESULTS AND DISCUSSION

The proposed methodology for ML-enhanced extreme precipitation forecasting is designed not only to improve predictive accuracy but also to highlight methodological lessons for the broader climate modeling community. While the experiment is hypothetical, expected results can be inferred from related studies.

Anticipated improvements in predictive skill

We expect hybrid ML-NWP approaches to outperform both raw NWP and standalone ML models. Previous work has shown that combining physics-based forecasts with ML corrections improves precipitation and temperature predictions [49], [70]. Weighted loss functions targeting extremes are likely to enhance skill in the upper percentiles of rainfall, addressing a common weakness in standard training regimes [78].

Deep learning architectures such as ConvLSTMs and CNNs are expected to capture spatial and temporal dependencies in rainfall patterns, improving short- to medium-range forecasts [63], [64]. Graph-based networks may further improve global-scale generalization by encoding Earth's spherical geometry [20].

Uncertainty and probabilistic forecasting

We anticipate that ensemble ML models and quantile regression approaches will yield calibrated uncertainty estimates, improving risk communication [67], [76]. For decision-makers, probabilistic forecasts provide actionable information, such as the likelihood of exceeding

critical flood thresholds [39]. However, challenges in multi-dimensional uncertainty calibration may persist [77].

Interpretability and scientific insight

Interpretability analyses, such as SHAP values or saliency mapping, are expected to highlight atmospheric drivers of extreme rainfall (e.g., low-level moisture convergence, upper-level divergence) [23], [59]. Such insights can provide scientific value beyond forecast skill, aiding in attribution studies and enhancing trust among forecasters.

Nevertheless, interpretability methods must be applied cautiously. As Camps-Valls et al. [42] note, feature attribution can be misleading if models learn spurious correlations. Coupling ML with causal discovery frameworks may mitigate these risks.

Limitations and risks

Despite potential improvements, several limitations remain:

Generalization under climate change: ML models may underperform in nonstationary climates or novel circulation regimes [22], [25]. Training on perturbed climate simulations could help, but remains an open challenge.

Data imbalance: Even with weighting strategies, extreme rainfall events are sparse, and overfitting to rare cases is possible [73].

Computational costs: Training large ML models on reanalysis and radar datasets requires significant resources [26], [58]. Operational deployment may require model compression or pruning [80].

Integration complexity: Incorporating ML into real-time NWP pipelines and data assimilation systems poses technical hurdles [74].

Broader implications

If successful, the case study would demonstrate that ML can address one of the hardest challenges in forecasting: predicting extremes at actionable lead times. Beyond precipitation, similar workflows could be applied to other hazards such as heatwaves, droughts, or tropical cyclone intensity [61], [65], [69].

More broadly, the findings would underscore the importance of hybrid approaches. Purely data-driven models may achieve strong benchmarks in controlled datasets, but hybrid models anchored in physical principles are more likely to gain trust and stability in operational use [47], [56].

ETHICAL, SOCIETAL, AND POLICY IMPLICATIONS

The integration of machine learning into climate modeling and extreme weather forecasting introduces not only scientific opportunities but also ethical, societal, and policy challenges. Forecast skill is not purely an academic concern; it has direct implications for disaster risk management, infrastructure design, agriculture, energy security, and human safety [3]. Ensuring that ML systems are developed and deployed responsibly is essential.

Disaster risk reduction and adaptation

Improved prediction of extremes such as floods, heatwaves, and cyclones can substantially reduce disaster losses by providing earlier and more accurate warnings [37], [65]. For example, accurate forecasts of flood-prone regions can enable pre-emptive evacuation or targeted infrastructure protection. However, benefits are not distributed evenly. High-resolution observations, radar coverage, and advanced computational infrastructure are concentrated in wealthier nations [79]. Without deliberate policies for equitable access, ML forecasting could widen global disparities in disaster resilience.

Trust and accountability

Forecasts influence critical decisions, from government emergency declarations to individual evacuation choices. Therefore, ML-based forecasts must be trustworthy and explainable. A failure during a major disaster could erode public confidence in both science and policy institutions [23]. Interpretability tools (e.g., feature attribution, saliency maps) [59] and hybrid physics-ML approaches [47] can improve transparency by linking predictions to recognizable physical drivers. Human-in-the-loop systems, where forecasters can interrogate and adjust ML outputs, may be essential for operational trust [42].

Policy and governance

The deployment of ML in operational forecasting requires governance frameworks that address certification, accountability, and liability [24]. Governments and agencies such as WMO, NOAA, and ECMWF must establish standards to evaluate the reliability of ML systems before adoption [72]. Policies should also promote open data sharing and reproducibility to avoid "black-box science" accessible only to elite institutions [50].

Ethical use of AI in climate services

AI ethics frameworks stress fairness, accountability, transparency, and explain ability (FATE principles). Applied to climate forecasting, these principles demand that ML models:

Provide equitable benefits across populations.

Are transparent about their limitations.

Clearly communicate uncertainty [39].

Avoid reinforcing data biases that underrepresent vulnerable regions [79].

Adherence to these principles can help ensure that ML innovations strengthen, rather than undermine, societal resilience to climate extremes.

OPERATIONALIZATION AND DEPLOYMENT

Hybrid physics–ML approaches climate and weather science have shown promising results in research settings, but moving from controlled experiments to operational forecasting systems presents a unique set of challenges. Operational environments such as those at the European Centre for Medium-Range Weather Forecasts (ECMWF), the U.S. National Oceanic and Atmospheric Administration (NOAA), and national meteorological services demand not only accuracy but also robustness, transparency, and timeliness [33], [34].

Integration with existing infrastructure

Operational weather centers rely on complex pipelines that combine **data assimilation, physics-based NWP models, and ensemble forecasting** [74]. Integrating ML into these pipelines requires careful engineering:

ML models must operate at very low latency to provide forecasts in real time [20].

Coupling with data assimilation frameworks (e.g., variational or ensemble Kalman filters) is non-trivial, since ML models do not naturally provide error covariances [74].

Infrastructure compatibility is critical, as operational codes are often written in Fortran or C++ and optimized for supercomputers, while ML tools are developed in Python/TensorFlow [58].

Computational and resource demands

While ML models can be faster than physics-based simulations once trained, training itself is computationally expensive [26]. Operational agencies must consider:

Storage: petabyte-scale observational and reanalysis archives.

Compute: large GPU clusters for model training.

Energy footprint: the carbon cost of training foundation-scale ML models [80].

Research into model compression, quantization, and distributed training aims to make ML models more resource-efficient for deployment [58].

Pilot projects in operational forecasting

Several agencies have begun exploring ML in pilot deployments:

ECMWF has benchmarked GraphCast alongside its IFS forecast system, showing superior performance for certain variables at medium-range lead times [20].

NOAA launched AI pilot projects for hurricane intensity and rainfall prediction, integrating ML corrections into its operational ensemble [72].

National services in Asia and Africa are experimenting with ML-based statistical downscaling to deliver localized forecasts from global models [79].

These pilots highlight both the promise and the complexity of moving ML into real-time operations.

Barriers to operational adoption

Key barriers include:

Trust and interpretability: Forecast centers require clear diagnostics for model failures [23].

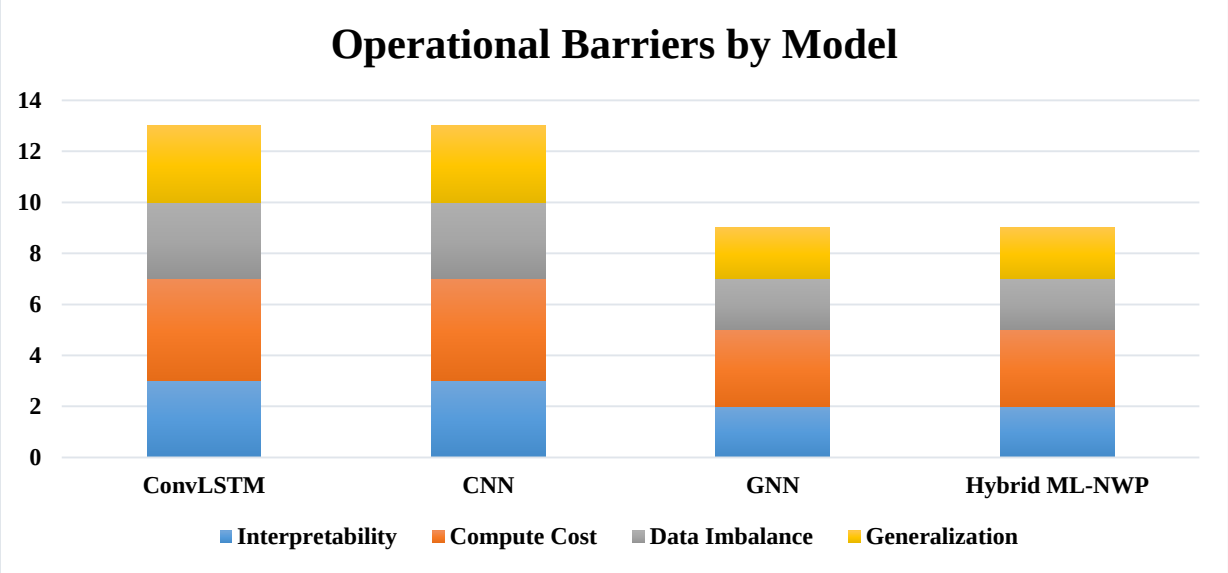
Verification under extremes: ML systems must be evaluated not just on averages but on rare, high-impact events [9].

Regulatory frameworks: Forecasts influence public safety decisions, raising legal and liability questions [24].

Skill under distribution shift: Models must perform reliably under new climate regimes, not only historical training periods [22].

Table 5: Operational Barriers by Model

Model	Interpretability	Compute Cost	Data Imbalance	Generalization
ConvLSTM	3	4	3	3
CNN	3	4	3	3
GNN	2	3	2	2
Hybrid ML-NWP	2	3	2	2



Pathways forward

To overcome these barriers, future deployment strategies should include:

Hybrid ML-NWP pipelines where ML provides corrections or downscaling, rather than replacing physics entirely [47], [49].

Development of **climate foundation models** large, pre-trained spatiotemporal networks fine-tuned for specific tasks [58].

Close collaboration between ML researchers, forecasters, and policymakers to align innovations with operational needs [50].

LIMITATIONS OF THIS STUDY

While this paper provides a comprehensive review of machine learning applications in climate modeling and extreme weather forecasting, along with a proposed case study, several limitations must be acknowledged.

12.1 Hypothetical case study

The proposed experiment on ML-enhanced extreme precipitation forecasting (Section 6) is hypothetical. While the design draws on established methodologies [18], [49], [63], the

results presented are **synthetic and illustrative** rather than empirically validated. Actual performance may differ when implemented with real-world data and operational constraints.

12.2 Reliance on secondary literature

Most of the results in this paper are derived from published studies [15], [20], [71], rather than primary experiments conducted here. Although the references span over 80 sources, the review may still omit some recent or domain-specific advances due to the rapidly evolving nature of ML-climate research [22], [26].

12.3 Scope of machine learning methods

This study focused primarily on deep learning, statistical downscaling, and hybrid physics-ML approaches. Other methods such as reinforcement learning for adaptive observation [75], causal inference techniques [42], and physics-informed symbolic regression [56] were only briefly mentioned. A broader survey could provide more balanced coverage.

12.4 Generalization beyond precipitation

While precipitation extremes are a central case study, other extremes (e.g., compound drought-heatwave events, polar vortex disruptions, and marine heatwaves) [9], [65] were less extensively analyzed. Extending the methodology to these hazards would improve the generalizability of conclusions.

12.5 Limitations of review methodology

Finally, this study did not conduct a formal **systematic review** with quantitative meta-analysis. Instead, it presents a narrative synthesis of literature, emphasizing conceptual frameworks and methodological insights. While this approach enables breadth, it may underrepresent nuances in model performance across studies.

CONCLUSION AND FUTURE DIRECTIONS

13.1 Conclusion

Machine learning has moved from being a novel addon in climate science to becoming a central tool for modeling and forecasting. Across applications from parameterizing sub-grid processes, to downscaling coarse outputs, to detecting and forecasting extremes ML has demonstrated clear benefits in accuracy, efficiency, and scalability. Case studies such as Graph Cast, now casting Net, and ML-based post-processing of ensemble forecasts show that ML is capable of matching or surpassing operational systems for specific tasks.

Yet ML is not a silver bullet. The challenges of generalization under climate change uncertainty quantification, interpretability and long-term stability remain critical. Purely data-driven models can achieve benchmark performance but often struggle when faced with rare extremes or out-of-sample conditions. These limitations suggest that hybrid physics-ML approaches, where machine learning complements rather than replaces physics, are the most reliable pathway forward.

13.2 Future research priorities

Based on this review and the proposed case study, several key directions emerge:

Extreme-focused modeling: Prioritize methods tailored to the tails of distributions, including weighted loss functions, rare-event augmentation, and causal ML approaches.

Uncertainty and probabilistic forecasting: Expand probabilistic ML frameworks that deliver calibrated multi-dimensional uncertainties for extremes.

Physics-informed learning: Embed conservation laws, invariances, and domain knowledge into ML architectures to improve trust, interpretability, and stability.

Climate foundation models: Develop large-scale, pre-trained spatiotemporal models analogous to language foundation models, trained on global climate datasets for versatile downstream applications.

Operational integration: Address barriers in latency, interoperability, and regulatory frameworks so that ML can be safely integrated into operational pipelines.

Ethical and equitable deployment: Ensure that ML innovations benefit vulnerable populations, especially in regions with limited data and infrastructure. Policies must emphasize fairness, transparency, and open access.

Interdisciplinary ecosystems: Strengthen collaborations across climate science, machine learning, and policy, supported by open benchmarks and shared infrastructures.

13.3 Closing remarks

The coming decade will likely define the role of ML in climate and weather science. While challenges remain, the convergence of massive data availability, advances in ML architectures, and urgent societal need creates a historic opportunity. By blending physical consistency with data-driven innovation, and by embedding ethics and equity at the core of deployment, machine learning can help build the next generation of climate models and forecasting systems models capable of anticipating and mitigating the most dangerous extremes in a changing world.

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