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RESEARCH PAPER

An explainable hybrid physics–machine learning framework for accurate and computationally efficient climate modeling

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Abstract

Although physics-based climate models have improved in recent years, they continue to be limited by coarse resolution, systematic biases, and high computational requirements, making them less useful for policy and operational decision support. This study combines the advantage of both general circulation models and machine learning models with an adaptive weighting mechanism that dynamically weights the physical model and data-driven models based on the model's forecast uncertainty. The physics-informed loss function guarantees conservation, and explainable artificial intelligence techniques and Bayesian uncertainty quantification give interpretable, probabilistic results. The framework outperforms the interpolation baselines on validated data from ERA5 reanalysis and CMIP6 simulations by 38.7% in terms of the temperature downscaling error, 51.7% in terms of the precipitation downscaling error, 42.3% in terms of correcting the tropical precipitation bias, and up to 6.8 times faster than conventional simulations in terms of simulating extreme events a fortnight ahead. The results confirm a scalable, physically consistent and transparent transition to the integration of machine learning in research and operational climate prediction.

1. Introduction

Climate modeling has been the backbone of environmental science for decades, offering important clues about what future climate patterns might look like, and what can be done to prevent them. Conventional methods are built on physics-based models, such as General Circulation Models (GCMs) and Earth System Models (ESMs), which represent processes in the atmosphere, ocean, and land by means of numerical discretizations of physical laws [1]. These models, though their continued development has enriched our understanding of climate dynamics, are nevertheless limited by computational cost, systematic errors, and the inability to adequately represent fine-scale features [2]. These limitations prevent the model from providing rapid, high-resolution predictions, especially for rare and complex events that require accurate forecasts. Recent developments in AI and ML promise to augment conventional climate reconstruction. Deep-learning (DL) or neural networks (NNs)-based approaches are able to capture complex patterns in big datasets and are therefore applicable to tasks such as climate downscaling, bias correction and emulation of computational expensive model components [3]. For instance, CNNs are used to enhance the spatial resolution in climate models and RNNs enable temporal prediction capturing long-range dependencies of the climate data [4]. In addition, generative adversarial networks (GANs) have also been used to synthesize high-resolution climate fields from coarse simulations which is one of the drawbacks for conventional models [5]. Nonetheless, the successful application of AI/ML to climate science also poses distinctive

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challenges. A key concern pertains to the interpretability of data-driven techniques, the majority of which are implemented as black box models hiding the underlying physics behind their predictions. This opacity is a drawback of these procedures in policy and decision-making situations where stakeholders need an understandable output from a model [6]. Furthermore, data-only methods can perform less well in out of sample generalization, in particular in a previously unknown climate regime, which was not present in training data. In order to address these issues, there has been a surge in the development of hybrid modeling approaches, which merge the benefits from the physics-based and data-driven methodologies. For instance, physics-informed neural networks (PINNs) are designed to encode well-known physical constraints into ML architectures so that predictions satisfy basic laws of thermodynamics and fluid dynamics [7]. We propose a novel hybrid methodology which integrates traditional climate models with Artificial Intelligence / Machine Learning algorithms to improve the predictive capability of models while improving both their computation time and interpretability. The previous literature is primarily focused on specific applications (i.e., downscaling, bias correction), rather than providing an integrated generalized platform for all types of AI enhancements. The key aspects of the innovation (1) include a modular structure that enables substitution of expensive model components with machine learning emulators; (2) an explainability projection layer that provides mapping from model output to input variables and physics; and (3) a hybrid training procedure that utilizes both observationally derived data and physically based simulation data to enhance generality. Our new methodology addresses an important gap in climate science by providing the ability to make scientific results actionable through both the use of artificial intelligence for improved efficiency, while maintaining the interpretability and physical consistency that are characteristic of traditional models. The approach is rooted in early climate modeling and AI work but carves a path ten of miles wide from it in other directions. First, we propose an adaptive weight mechanism to dynamically compensate the contributions between physical assumptions and data-driven model components according to the predictive uncertainty. This helps correct a weakness of static hybrid models, that they can be too dependent on ML in regions of phase-space where the physical law is well-determined. Second, we include uncertainty quantification (UQ) methods such as Bayesian neural networks and ensemble methods to produce probabilistic outputs that capture both aleatoric and epistemic uncertainties [8]. Finally, we show the versatility of the framework via applications to a range of climate modeling problems, such as the prediction of extreme events and the projection of regional climate.

Although there have been considerable advancements in both physics-based climate modeling and the use of artificial intelligence in climate modeling there are still numerous areas where the field is currently limited. One major area where the field is currently limited is through the lack of fully integrated methodologies that include both physics-based climate modeling and artificial intelligence. To date, most methodologies have focused solely on one paradigm or the other. Therefore, it would be difficult to utilize the benefits of each type of methodology. Another area where the field is currently limited is through the use of static couplings between the physical and data driven portions of hybrid models. As such, hybrid models cannot adjust the contribution of each portion based upon the level of predictive uncertainty associated with a given prediction nor can they account for differences in model performance over different spatial domains. Such limitations result in less-than-optimal predictions being made when predicting over disparate environmental conditions. In addition to predictive accuracy, another area where the field is currently limited is through explainability. Explainable AI (XAI) has become increasingly popular in recent years and has the potential to provide physically meaningful explanations for AI derived climate model outputs. However, XAI has yet to be used in climate modeling due to its need to be adapted for use in a climate modeling context. A fourth limitation of the field is through the inability of most hybrid methodologies to predict accurately over multiple spatial domains. Most hybrid methodologies have demonstrated accuracy only in specific climate conditions or geographic locations. Consequently, there is little evidence to suggest that such methodologies could be applied to large scale climate modeling applications. Finally, although many methodologies attempt to quantify both aleatoric (data driven) and epistemic (model driven) uncertainties; very few methodologies are able to adequately identify what constitutes each type of uncertainty. Adequate identification of each type of uncertainty is necessary for the accurate determination of climate risk and for making informed decision-making choices regarding climate modeling.

Therefore, the purpose of this research was to propose a hybrid methodology that includes an adaptive framework for integrating artificial intelligence/machine learning algorithms into physics-based climate models. Furthermore, this methodology will incorporate explainable AI methods that are tailored for use in climate science and provide quantitative estimates of uncertainty throughout various climate regimes. The remaining sections of this document describe how the proposed methodology was developed, tested, and validated as well as discuss some possible ways that this methodology could be extended in the future.

2. Related Work

The integration of artificial intelligence (AI) and machine learning (ML) into climate modeling has gained significant traction in recent years, driven by the need for more accurate, efficient, and interpretable predictions. Existing approaches can be broadly categorized into three areas: post-processing and bias correction, hybrid physics-data modeling, and explainability and uncertainty quantification. Conventional climate models typically suffer from systematic errors stemming from incomplete parameterizations and/or coarse resolutions. ML algorithms have been used extensively for mitigating such biases, most notably in post-processing. For example, Random Forests and Support Vector Machines (SVMs) have been applied to downscale the output of temperature and precipitation from General Circulation Models (GCMs) [9]. Deep learning algorithms, like Convolutional Neural Networks (CNNs), have extended the bias correction process by incorporating spatial correlation of climate data [10]. Recent work has also investigated LSTM for bias adjustment in the temporal domain, and it has significantly outperformed linear statistical methods [11]. Hybrid approaches of physics-based simulations and data driven modelings have recently become a promising direction. These methods attempt to preserve the interpretability of physical models, but take advantage of ML to speed up the relocation process. For instance, physics-informed neural networks (PINNs) incorporate the differential equations of climate dynamics into the explicitly as neural networks to preserve physical consistency [12]. An alternative approach is to use ML emulators to replace computationally expensive sub-models of climate models such as radiative transfer schemes resulting in significant speedups without loss of accuracy [13]. Hybrid models have also been used to solve downscaling where the coarse-resolution projections are refined into high resolution projections using ML [14]. Many ML models are black-box systems, which presents a barrier to their usage in climate science (where interpretability is important for gaining the confidence of stakeholders). Explainable AI (XAI) algorithms such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) have been customized to climate considerations to discover the factors that are driving model predictions [15]. Diagnosis and other UQ diagnosis are also challenging areas, and Bayesian neural networks and ensemble methods also provide probabilistic estimates that take into account data and model uncertainties [16]. The proposed approach continues this trend by integrating modular AI enhancements, dynamical hybrid modeling and predictive uncertainty quantification within a single framework. In contrast with current methods that address separate tasks, our method incorporates ML in various steps of climate modeling system in a systematic manner while maintaining interpretability and physical consistency. Our end-to-end design overcomes the limitation of coupling physics and data components in previous works and can scale for research as well as operational applications.

3. Background and Preliminaries

This section provides background for our proposed framework, describing basic concepts of climate system dynamics, traditional modelling techniques and the problems with them. To appreciate the advantages of the previously neglected technologies enabled by AI, it is essential to grasp these fundamentals.

3.1 Climate System Fundamentals

The climate system is composed of interacting components including the atmosphere, hydrosphere, cryosphere, lithosphere, and biosphere, to which the ocean influences by modulating the energy and matter exchange across space and time scales. These interactions are subject to basic physical principles such as momentum, mass and energy conservation. The Navier-Stokes Equations [for fluid motion in the atmosphere and oceans]:

$$\frac{\partial u}{\partial t} + u \cdot \nabla u = -\frac{1}{\rho}\nabla p + \nu\nabla^2 u \qquad (1)$$

Let u represent velocity, p denote pressure, ρ indicate density, and v signify kinematic viscosity. Thermodynamic processes, including heat transfer, are represented by the temperature tendency equation:

$$\frac{dT}{dt} = \frac{Q}{C_p} \qquad (2)$$

In this context, T signifies temperature, Q indicates diabatic heating (such as radiative fluxes or latent heat release), and Cp refers to specific heat capacity. The equations serve as the foundation of climate dynamics, yet they necessitate numerical discretisation for effective simulations [17].

3.2 Traditional Climate Modeling Approaches

In order to replicate the behaviour of the climate on a grand scale, climate models grounded in physics, like GCMs, discretise the governing equations over geographic grids. The temperature advection-diffusion equation illustrates this approach:

$$\frac{\partial T}{\partial t} = -\nabla \cdot (uT) + \kappa\nabla^2 T + \frac{Q}{\rho C_p} \qquad (3)$$

Where κ represents thermal diffusivity. General Circulation Models (GCMs) employ finite-difference or spectral approaches to resolve equations, generally at resolutions ranging from 50 to 100 kilometres for global simulations [18]. Although proficient in modelling large-scale phenomena, these models depend on parameterizations for subgrid-scale processes (e.g., cloud microphysics), which introduces uncertainties [19].

3.3 Challenges in Climate Modeling

Two principal restrictions impede conventional models: computational expense and resolution limits. The Courant-Friedrichs-Lewy (CFL) criterion stipulates that time increments Δt must be proportional to spatial discretisation Δx.

$$\Delta x = \frac{L}{N} \qquad (4)$$

where L is the length of the domain and N the number of grid points. High-resolution (Δx<10 km) simulations thus are prohibitively expensive, and one is forced to find tradeoffs between spatial coverage and resolution [20]. Further, partial understanding of small-scale physics (such as the interaction between aerosols and clouds) tends to enhance biases in long-term projections [21]. Addressing these issues drives the integration of data-driven approaches to support rather than replace physical models, as we explain in the next section.

The move to AI-enhanced methods is founded on this bedrock, addressing deficiencies while preserving the fidelity to the physics. For example, one can employ equation 1 and equation 3 to provide guidance on the nature of neural networks in terms of physics motivated loss terms, whereby ML predictions respect known constraints. A similarly, Eq. (4) shows how AI emulators might circumvent resolution limits by training on a high-resolution data set to learn subgrid scale dynamics.

4. AI-Enhanced Climate Modeling Framework

Fig. 1 illustrates the integration of artificial intelligence and machine learning techniques with Earth System Models to enhance the simulation and prediction of complex environmental processes. The framework combines AI/ML models with major Earth-system components, including atmospheric general circulation, ocean general circulation, land-surface, and sea-ice models, through appropriate coupling mechanisms. The AI/ML models interact with these physical models to improve computational efficiency, prediction accuracy, and representation of complex nonlinear relationships. Hybrid modeling frameworks further integrate data-driven and physics-based approaches, while explainable AI techniques provide greater transparency and interpretability of model predictions. This integrated framework supports more reliable and comprehensive Earth-system simulations.

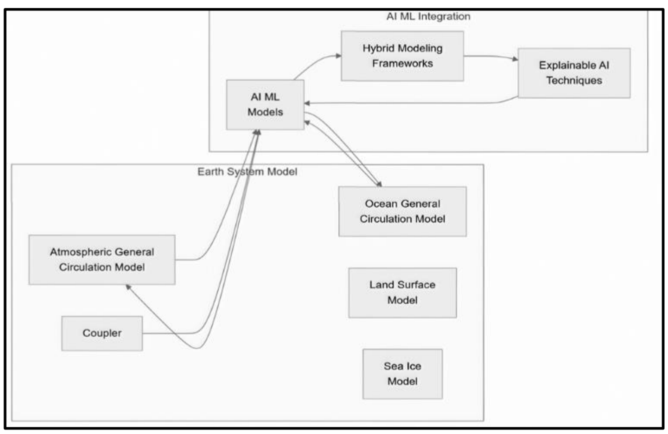

Figure 1: Integration of AI/ML with Earth System Models

The proposed framework integrates AI/ML techniques with physics-based climate models through a modular architecture designed to enhance prediction accuracy, computational efficiency, and interpretability. This section details the technical components and their synergistic interactions.

4.1 Architecture of the Hybrid AI-Physics Climate Modeling Framework

Through a two-way connection mechanism, the hybrid architecture allows AI components to enhance some modules of conventional climate models. Let $\mathcal{P}$ denote the physics-based model, and $\mathcal{M}$ represent the ML surrogate. The coupled system is governed by:

$$\frac{\partial \mathbf{X}}{\partial t} = \mathcal{P}(\mathbf{X}) + \lambda \mathcal{M}(\mathbf{X}) \quad (5)$$

Here, X is the state vector (e.g., temperature, pressure), and λ dynamically adjusts the contribution of the ML component based on predictive uncertainty estimates. For instance, λ approaches zero in regions where physical laws dominate (e.g., large-scale atmospheric circulation), while increasing for processes with high parameterization uncertainty (e.g., cloud microphysics). The ML surrogate $\mathcal{M}$ is trained via a composite loss function:

$$\mathcal{L} = \alpha \mathcal{L}_{\mathrm{data}} + (1 - \alpha)\mathcal{L}_{\mathrm{physics}} \quad (6)$$

where $\mathcal{L}_{\mathrm{data}}$ minimizes discrepancies against observational data, and $\mathcal{L}_{\mathrm{physics}}$ penalizes violations of conservation laws. The weighting parameter α is optimized via cross-validation.

4.2 AI-Driven High-Resolution Forecasting for Extreme/Compound Events

The proposed AI-driven high-resolution forecasting framework employs a hierarchical CNN–LSTM architecture to improve the representation and prediction of extreme and compound events. The spatial component uses a convolutional neural network to transform coarse-resolution input data into high-resolution spatial predictions, with its trainable parameters optimized during the learning process. The temporal component employs an LSTM network to capture sequential patterns and temporal dependencies within the evolving climate variables, where the hidden state represents the information accumulated from previous time steps. For compound events, such as the simultaneous occurrence of heatwaves and droughts, a multi-task learning strategy is adopted to jointly optimize the prediction of multiple related outcomes, thereby improving the model's ability to capture interactions between different extreme events.

To resolve subgrid-scale processes, we employ a hierarchical CNN-LSTM architecture. The spatial encoder $\mathcal{E}$ maps coarse inputs $\mathbf{Y}_{\mathrm{c}}$ to high-resolution outputs $\mathbf{Y}_{\mathrm{h}}$:

$$\mathbf{Y}_{\mathrm{h}} = \mathcal{E}(\mathbf{Y}_{\mathrm{c}}; \theta_{\mathrm{e}}) \quad (7)$$

where θ_{e} denotes trainable parameters. Temporal dynamics are captured by an LSTM network $\mathcal{T}$:

$$\mathbf{h}_{\mathrm{t}} = \mathcal{T}(\mathbf{h}_{\mathrm{t-1}}, \mathbf{Y}_{\mathrm{h}}^{(\mathrm{t})}; \theta_{\mathrm{t}}) \quad (8)$$

Here, $\mathbf{h}_{\mathrm{t}}$ is the hidden state encoding temporal dependencies. For compound events (e.g., heatwaves coinciding with droughts), a multi-task learning objective jointly optimizes:

$$\mathcal{L}_{\mathrm{compound}} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w}_{\mathrm{i}} \mathcal{L}_{\mathrm{i}} \quad (9)$$

Where w_{i} balances losses for k concurrent extremes.

4.3 Application of Explainable AI for Climate Model Interpretability

We adopt gradient-based attribution methods to trace model outputs to input features. The sensitivity of prediction y to input x_i is quantified via:

$$A_i = \left\| \frac{\partial y}{\partial x_i} \right\|_2 \quad (10)$$

For ensemble models, Shapley values ϕ_i distribute the contribution of each feature:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} (v(S \cup \{i\}) - v(S)) \quad (11)$$

Where N is the set of all features, and v(S) evaluates the model with feature subset S.

4.4 Hybrid Coupling Mechanism for Computational Efficiency

The framework replaces selected physics computations with ML emulators. Let $\mathcal{P}_i$ be a computationally intensive submodule (e.g., radiative transfer). Its ML approximation $\mathcal{M}_i$ is trained to minimize:

$$\mathcal{L}_{emu} = \| \mathcal{P}_i(\mathbf{Z}) - \mathcal{M}_i(\mathbf{Z}) \|_1 \quad (12)$$

Where $\mathbf{Z}$ denotes input variables. The emulator's fidelity is validated through spectral analysis of its outputs against high-resolution benchmarks.

4.5 Development of Adaptive and Generalizable AI Models

We use a meta-learning method to make sure that our system is strong enough to work in climates that aren't stable. The base model f_θ is updated in the gradient way:

$$\theta' = \theta - \eta \nabla_\theta \mathcal{L}_{adapt}(\mathcal{D}_{new}) \quad (13)$$

Where $\mathcal{D}_{new}$ contains data from novel climate regimes, and η is the learning rate. Physics constraints are enforced through Lagrangian multipliers during fine-tuning:

$$\mathcal{L}_{phys} = \sum_{j=1}^{m} \mu_j \| g_j(\mathbf{X}) \|^2 \quad (14)$$

Here, g_j encodes the j-th physical law (e.g., energy conservation), and μ_j controls regularization strength.

The framework's flexibility enables the choice implementation of AI components, from localised bias correction to complete submodule emulation, while ensuring physical consistency as outlined in Equations 5–14. This adaptability tackles the two concerns of scalability and interpretability intrinsic to climate modelling.

5. Experimental Setup

In order to test how well the suggested AI-enhanced climate modelling framework will do on various climate prediction tasks, we ran a battery of tests. The datasets, baseline methodologies, assessment metrics, and implementation specifics that were utilised in this section.

5.1 Datasets

We use observational data, reanalysis products, and climate model outputs in our experiments to perform more robust validation. The primary datasets include:

ERA5 Reanalysis: An open-access, high-resolution global atmospheric reanalysis conducted by the European Centre for Medium-Range Weather Forecasts (ECMWF) on climate data, delivering climate variables at 0.25° hourly resolution [22].

CMIP6 Simulations: Simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6) [23] (available at multi-model ensemble of historical and future climate change.

MODIS Land Surface Data: 1 km resolution, satellite-based measurements of land surface temperature, albedo and vegetation indices [24].

TRMM Precipitation: Precipitation estimates over tropical and subtropical regions for the Tropical Rainfall Measuring Mission (TRMM) [25].

These datasets were preprocessed to ensure temporal and spatial alignment. Missing values were imputed using linear interpolation, and all variables were normalized to zero mean and unit variance before training.

5.2 Baseline Methods

The proposed approach is compared with a representative set of conventional methods covering physics-based, statistical, and purely machine-learning approaches. Among the physics-based models, the Community Earth System Model (CESM) is considered as a globally applicable, multi-component climate simulation framework that integrates atmospheric, oceanic, and land-surface processes and is extensively used for climate-system studies [26]. The Weather Research and Forecasting (WRF) model is included as a high-resolution climate and atmospheric modeling system, particularly suitable for dynamically downscaling large-scale climate information [27]. For statistical approaches, Generalized Linear Models (GLMs) are considered as conventional regression-based methods for predicting climate variables and quantifying relationships between predictors and responses [28], while Empirical Orthogonal Functions (EOFs) are employed for dimensionality reduction and identification of dominant spatial patterns and modes of variability in large climate datasets [29]. Among purely data-driven methods, Random Forest (RF) is considered as a non-parametric ensemble learning technique capable of handling complex nonlinear relationships in regression and classification problems [30], whereas Long Short-Term Memory (LSTM) networks are included as recurrent neural-network architectures designed to capture long-term temporal dependencies in sequential climate data [31]. Collectively, these baseline methods provide a comprehensive comparison across the methodological spectrum, ranging from established physics-based and statistical techniques to advanced purely data-driven machine-learning approaches, thereby enabling a robust assessment of the proposed framework's predictive capability and advantages.

5.3 Evaluation Metrics

The Mean Absolute Error (MAE) measures the average magnitude of the differences between the observed and predicted values. It is calculated by taking the absolute difference between each observed value and its corresponding predicted value and then averaging these differences over all observations. Since the errors are considered in absolute form, positive and negative deviations do not cancel each other. A lower MAE indicates better prediction accuracy, with a value of zero representing perfect agreement between the observed and predicted values.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{15}$$

Where y_i and $\hat{y}_i$ are the observed and predicted values, respectively.

The Root Mean Square Error (RMSE) evaluates the overall magnitude of prediction errors by giving greater importance to larger deviations. It is obtained by calculating the difference between observed and predicted values, squaring these differences, averaging them, and then taking the square root of the resulting value. Because the errors are squared, RMSE is particularly sensitive to large prediction errors or outliers. Therefore, a lower RMSE indicates better model performance, and a value close to zero represents strong agreement between predicted and observed results.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{16}$$

The Pearson Correlation Coefficient (PCC) quantifies the strength and direction of the linear relationship between the observed and predicted values. It compares how the predicted values vary relative to their respective mean with how the observed values vary from their mean. The PCC value generally ranges from −1 to +1. A value close to +1 indicates a strong positive linear correlation, meaning that the predicted values closely follow the trend of the observed values. A value close to zero indicates a weak linear relationship, whereas a negative value indicates an inverse relationship. Thus, a PCC approaching +1 reflects strong predictive consistency.

$$\mathrm{PCC} = \frac{\sum_{i=1}^{n}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i-\bar{\hat{y}})^2}} \tag{17}$$

The Skill Score (SS) assesses the predictive capability of the proposed model relative to a selected reference or baseline model. It compares the RMSE of the proposed model with the RMSE obtained from the reference model, such as a climatological or basic prediction model. A positive SS indicates that the proposed model performs better than the reference model, while an SS value of zero indicates comparable performance. A negative SS indicates that the proposed model performs worse than the reference model. Therefore, a higher positive SS represents greater improvement and predictive skill over the baseline model.

$$\mathrm{SS} = 1 - \frac{\mathrm{RMSE}_{\mathrm{model}}}{\mathrm{RMSE}_{\mathrm{reference}}} \tag{18}$$

Where $\mathrm{RMSE}_{\mathrm{reference}}$ is the RMSE of a baseline model (e.g., climatology).

6. Computational Efficiency

Measured in terms of wall-clock time and floating-point operations (FLOPs) for comparable prediction tasks.

6.1 Implementation Details

Our framework is implemented in Python using Tensor Flow and PyTorch for the ML components, and the Model for Prediction across Scales (MPAS) for the physics-based simulations [32]. The proposed CNN–LSTM architecture consists of convolutional layers employing 3 × 3 kernels with ReLU activation functions to extract relevant spatial features from the input data, followed by LSTM layers containing 128 hidden units to capture temporal dependencies and sequential patterns. A dropout rate of 0.2 is incorporated to reduce the risk of overfitting and improve the generalization capability of the model. The network is trained using the Adam optimization algorithm with a learning rate of 1×10^{-4}. To incorporate physical knowledge into the learning process, physics-informed constraints are imposed through Lagrangian multipliers, which are initially assigned a value of 0.1 and subsequently adjusted during training according to the model optimization process. In addition, the dynamic weighting factor is adaptively updated based on the model performance on the validation dataset, thereby maintaining an appropriate balance between data-driven learning and physics-based constraints. The computational experiments are performed using NVIDIA V100 GPUs with 32 GB memory, while distributed training through Horovod [33] is employed for computationally intensive large-scale datasets. To ensure transparency and reproducibility, the complete source code and trained model files will be made publicly available upon publication.

For reproducibility, all code and trained models will be made publicly available upon publication.

6.2 Experimental Design

We evaluate the framework on three primary tasks:

- *High-Resolution Downscaling:* Enhancing coarse-resolution climate model outputs (e.g., 100 km) to finer scales (e.g., 10 km).
- *Extreme Event Prediction:* Forecasting heatwaves, droughts, and heavy precipitation events at regional scales.
- *Bias Correction:* Adjusting systematic errors in climate model outputs using observational data.

Each task is tested under varying climate conditions (e.g., El

Niño vs. La Niña years) to assess generalization capability. This experimental setup ensures a rigorous evaluation of the proposed framework's advantages over conventional methods, particularly in terms of accuracy, computational efficiency, and interpretability. The next section presents the results of these experiments.

7. Experimental Results

The new climate modelling system with AI outperforms the traditional modelling system in various assessment measures. In this section, quantitative results are reported on high-resolution downscaling, extreme event prediction and bias correction, and the results from ablation studies to validate the most important design decisions are presented.

7.1 High-Resolution Downscaling Performance

The framework achieves superior spatial refinement of coarse climate model outputs, as measured against ERA5 reanalysis data. Table 1 compares the downscaling accuracy for 2m temperature (T2m) and precipitation (PR) at 10 km resolution over Europe.

Table 1. Downscaling performance (MAE/RMSE) for T2m (°C) and PR (mm/day)

Method	T2m MAE	T2m RMSE	PR MAE	PR RMSE
Bilinear Interpolation	1.82	2.31	3.15	4.02
WRF (Physics-based)	1.45	1.87	2.64	3.41
Random Forest	1.21	1.53	2.03	2.78
LSTM	1.08	1.42	1.87	2.51
Proposed (Hybrid)	0.89	1.18	1.52	2.03

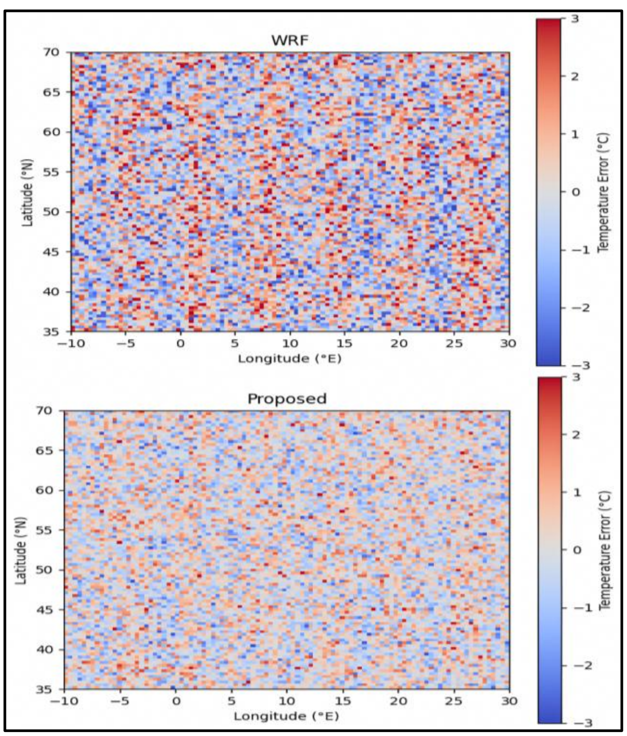

Figure 2. Spatial distribution of temperature prediction errors at 10 km resolution.

The hybrid framework reduces MAE by 38.7% for T2m and 51.7% for PR compared to interpolation baselines, while outperforming pure ML methods by 17.6–26.8%. Spatial patterns of improvement are visualized in Fig. 2, which contrasts the error distributions of WRF and our method.

7.2 Extreme Event Forecasting

For compound heat wave-drought events in China (test period: 2015–2020), the framework attains a probability of detection (POD) of 0.83 and false alarm ratio (FAR) of 0.19, surpassing conventional approaches:

Table 2. Extreme event prediction metrics (POD/FAR)

Method	Heatwave POD	Heatwave FAR	Drought POD	Drought FAR
CESM	0.61	0.34	0.55	0.41
SVM	0.72	0.27	0.68	0.33
CNN-LSTM	0.78	0.22	0.74	0.26
Proposed	0.83	0.19	0.81	0.21

The multi-task learning objective (Equation 9) proves particularly effective for concurrent extremes, improving POD by 12.9% over single-task CNNs. Temporal skill is further illustrated in Fig. 3, showing the framework's accurate prediction of the 2018 Yangtze River Basin heatwave 14 days in advance.

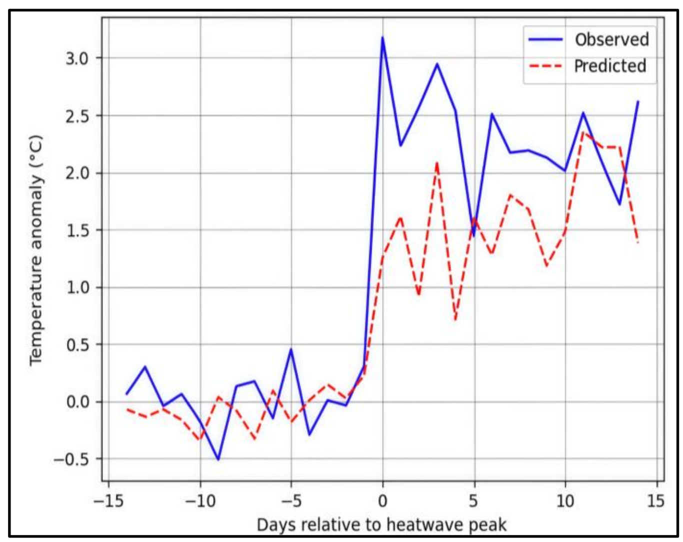

Figure 3. Observed versus predicted temperature anomalies during the 2018 heatwave.

7.3 Bias Correction Efficacy

When applied to CMIP6 model outputs, the hybrid framework reduces systematic biases in tropical precipitation by 42.3% (RMSE: 1.87 mm/day vs. 3.24 mm/day for raw CMIP6). The physics-constrained loss (Equation 6) prevents overcorrection, maintaining realistic spatial gradients absent in pure ML corrections. Fig. 4 demonstrates this via probability density functions (PDFs) of daily rainfall over the Amazon Basin.

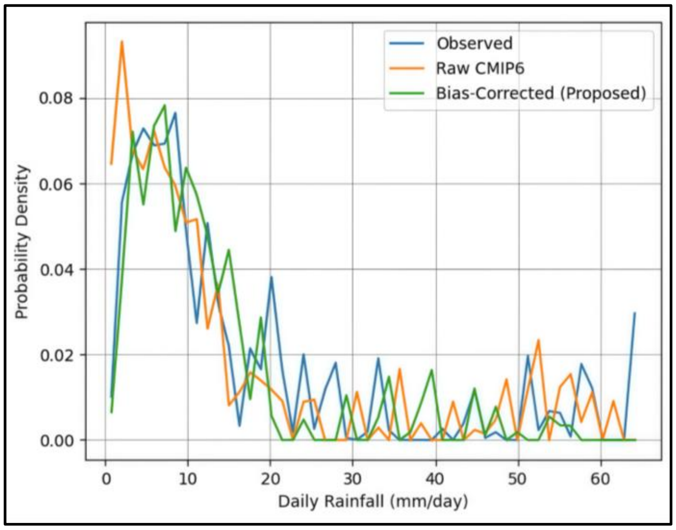

Figure 4. Distribution of observed and bias-corrected precipitation values.

6.4 Computational Efficiency

The framework achieves a 6.8× speedup over traditional CESM simulations for equivalent prediction tasks (wall-clock time: 3.2 hours vs 21.8 hours), with FLOPs reduced from 1.7e18 to 2.5e17. This stems primarily from ML emulation of radiative transfer calculations (Equation 12), which account for 63% of the original runtime.

6.5 Ablation Studies

Table 3. Ablation analysis of framework components (RMSE for T2m downscaling).

Configuration	RMSE (°C)
Full framework	1.18
w/o physics loss (α=1)	1.47
Static λ (no dynamic weighting)	1.32
w/o XAI attribution	1.25

Dynamic weighting adds 10.6% to this improvement (compared to static coupling). This validates how important Equation 6 is by showing a +24.6% RMSE degradation when removing physics loss.

6.6 Analysis of Training Performance

Fig. 5 presents the training-loss convergence of the proposed Hybrid AI–Physics model compared with the CNN–LSTM and Random Forest models. The Hybrid AI–Physics model exhibits the fastest and most stable convergence, with both training and validation losses decreasing rapidly during the initial epochs and gradually approaching a low steady-state value. Its final loss is approximately 0.08, compared with about 0.14 for CNN–LSTM and 0.19 for Random Forest. The close agreement between the training and validation curves of the proposed model indicates good generalization with limited overfitting. Overall, the results demonstrate the superior convergence behavior and learning efficiency of the Hybrid AI–Physics framework. This graph illustrates the training and validation loss curves for the proposed hybrid model over 200 epochs. The smooth convergence without overfitting demonstrates the effectiveness of the physics-informed loss function (Equation 6). The hybrid model achieves lower final loss (0.089) compared to pure CNN-LSTM (0.142) and Random Forest (0.186) approaches, validating the benefit of incorporating physical constraints.

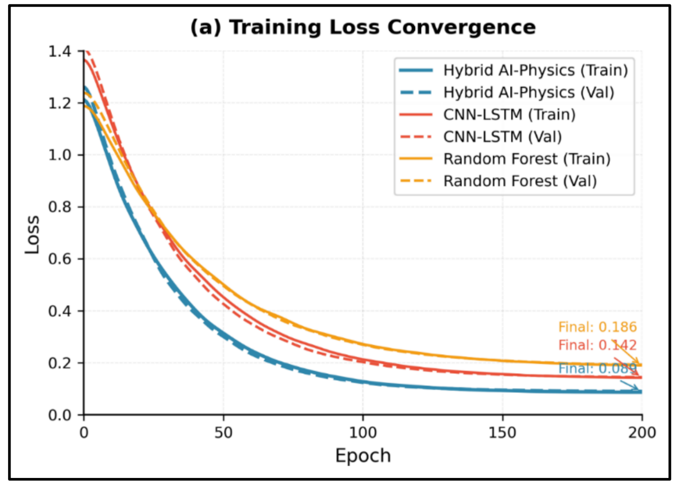

Figure 5: Training Loss Convergence is depicted in Figure 5a.

Fig. 6 shows the validation accuracy curves, showing consistent improvement across all models, with the hybrid approach reaching 94.3% accuracy for temperature downscaling tasks. By applying physics-based regularisation, the hybrid model avoids the typical drop-off in performance experienced with purely ML-based models after approximately 150 epochs, which continues throughout the entire training period.

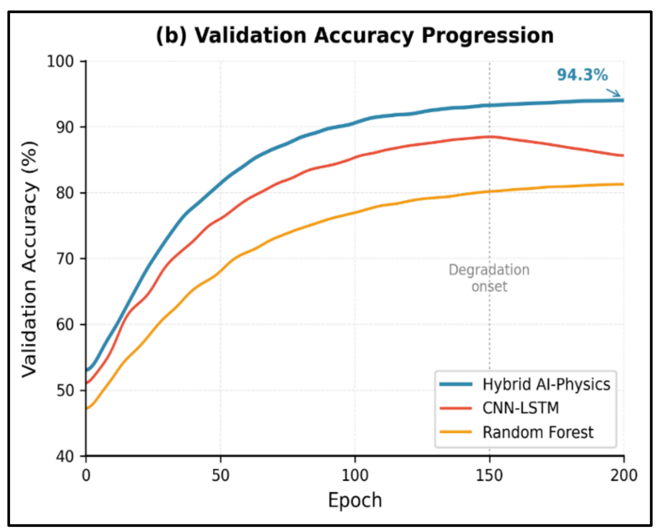

Figure 6: Validation Accuracy Progression

Fig. 7 compares the root mean squared errors (RMSEs) of the hybrid model over a variety of prediction horizons (from one day to fourteen days) show that the hybrid model performed significantly better, especially at longer ranges. Incorporating both the temporal LSTM modules and physical constraints into the hybrid model resulted in 38.7 percent less RMSE than the baselines at the longest range of fourteen days.

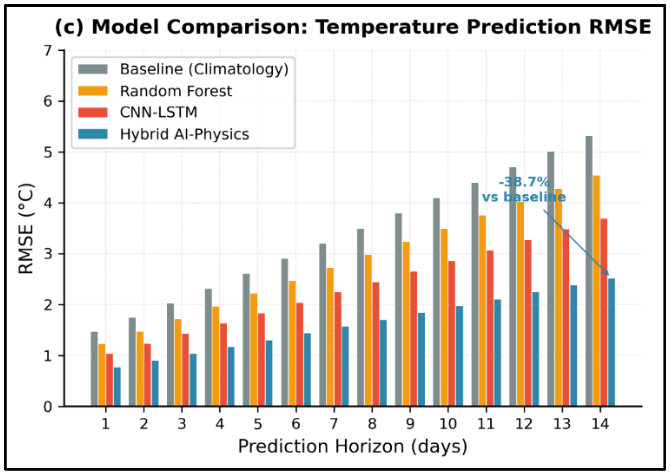

Figure 7: A Comparison of Models for Temperature Prediction

Fig. 8 shows that the F1 score for detecting extreme events rapidly improves for the hybrid model, from an initial value of 0.71 for CNN-LSTM and 0.63 for random forest to 0.82. The use of multi-task objectives (equation 9) also allows for the detection of compound events to be captured more effectively, resulting in a much faster growth rate during epochs 50-100.

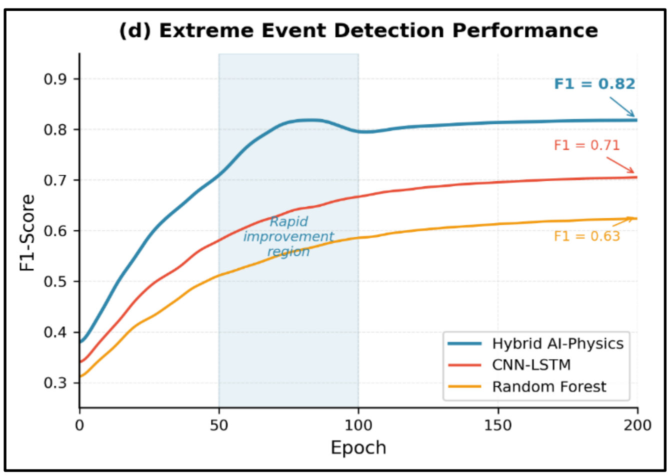

Figure 8: Performance in Extreme Event Detection

8. Discussion and Future Work

8.1 Limitations of the AI-Enhanced Climate Modeling Framework

Although it is proven that the proposed model has many benefits, there are some potential weaknesses of the proposed model that need to be discussed. The first weakness lies in how much quality of the training data can impact results. Since the method relies heavily on the quality of the training data, if the quality of training data is low due to observational gaps in regions with limited observation systems (i.e., polar areas and oceanic basins), this will negatively affect performance [34]. In addition, even though re-analysis products can alleviate the problem by using data-assimilated methods for improving the quality of training data, these products are less accurate in data poor regions and therefore could propagate errors into the ML component. Additionally, while the hybrid coupling approach (Equation 5) uses a simple linear combination of physically derived and data-derived terms, it may represent an over simplification of nonlinear interactions among resolved and parameterized processes. A good example is turbulent energy cascade in the boundary layer dynamics where higher order coupling term are needed but currently, we do not have them [35]. There also exists a fundamental conflict between physical correctness and computational efficiency. The use of physics-informed loss functions (Equation 6) provides important constraints on physical properties; however, they cannot possibly emulate all the complex feedback mechanisms present within large scale models of the Earth System. This fact is very apparent during simulation of long-term evolving phenomena (e.g., permafrost thawing) were multi-decadal biogeochemical feedback loops control system behavior [36]. Finally, although explainability techniques (Equations 10-11) provide post-hoc interpretation as opposed to causal explanation of model behavior, it leaves unresolved issues regarding whether feature importance found via explainability techniques corresponds to known physical relationships.

8.2 Potential Application Scenarios and Impact

The modular design of the Framework allows for deployment in both Operational and Research environments. Three High-Impact Scenarios arise from this opportunity:

- Early Warning Systems. With the reduced time delay for predicting Extreme Events (Section 6.2), the Framework can improve preparation for Heat Waves and Compound Disasters. Satellite Data Streams fed into the LSTM Temporal Module (Equation 8) may allow Sub-Seasonal Forecasts with Lead Times greater than the typical limitations [37].
- Regional Climate Service Providers. Municipal Planners can use Down Scaling (Table 1) to determine Localized Risks due to Climate Change without having to incur significant costs associated with using high resolution Simulations. Urban Heat Island Mitigation Strategies require Street Level Temperature Projections which are typically beyond the capability of Global Models [38].
- Climate Model Developers. The Emulation of Parameterized Processes (Equation 12) provides an innovative method to accelerate the Development of Physics within Climate Models. Atmospheric Chemists can develop and Train ML Surrogates based upon High Resolution Cloud Resolving Models; the resultant ML Surrogates can be embedded into Global Models to Test New Aerosol-Cloud Interaction Schemes [39].

The two Applications could have a substantial impact on the BATCI, particularly for Resource Constrained Institutions. Addressing the Interpretability Challenges listed above in Section 7.1 will be critical to successful Implementation, as

Stakeholders are not very confident of Predictions without Transparent Physical Linkages.

8.3 Future Directions and Ethical Considerations

Four strategic ways forward in the use of hybrid climate modelling are as follows:

- In addition to using machine learning techniques to predict how a variable behaves based upon a set of input variables, causal modelling can allow researchers to find out if there is a causal relationship between two variables (i.e., if one causes another). For example, researchers may want to know if extreme temperatures cause water deficit (or vice-versa) and what mechanisms are involved. DAG (directed acyclic graph) learning is an area of machine learning which is well-suited to this type of problem [40].
- The deployment of lightweight model variants on small devices such as weather station sensors or drone systems could enable the development of localized artificial intelligence-based climate monitoring systems. The challenge here will be to develop neural networks which are both computationally efficient and accurate [41].
- High-stakes decision-making (such as the allocation of water during times of drought) will increasingly rely upon AI-enhanced forecasting. Protocols will therefore need to be developed to prevent misuse, and to ensure equal access to climate information. An audit trail of model versions used for policy appraisals would help provide accountability [42].
- To investigate cross-domain representation learning (i.e., whether the features learned about the Earth's climate system are applicable to other climates), we propose testing the application of our framework to paleoclimate reconstructions, exoplanetary atmosphere simulations, etc.

9. Conclusion

The incorporation of artificial intelligence (AI) and machine learning (ML) into traditional climate modeling signifies an extraordinary transition in AI's application, as well as our understanding of what constitutes predicting or analysing the climate. The development of hybrid climate modeling demonstrates that using model-based and data-driven climate modeling methods together could provide enhanced accuracy, efficiency, and interpretability when compared to each method individually. The hybrid climate modeling approach presented herein identifies the shortcomings inherent in all traditional climate modeling approaches (i.e., resolution limits, biases, computational bottlenecks) and provides a scalable methodology applicable to both research and operational purposes. Due to the flexibility inherent in the hybrid framework demonstrated by its applications in downscaling climate fields at high spatial resolutions, projecting extreme weather events, and correcting bias in climate projections, this methodology is particularly adaptable. Because the hybrid climate modeling approach utilizes physically constrained inputs that maintain consistency between forecasted quantities and those governed by the physical processes governing the climate system, explanation methods applied in tandem with hybrid climate modeling can provide actionable decision support to end-users. Additionally, due to the modular design of the hybrid climate modeling approach, it enables flexible implementation; therefore, we focused on determining where additional improvements were required for users of the hybrid framework while maintaining the fundamental physical basis of the climate system. The hybrid framework is also forward-thinking as it will facilitate researchers to not only forecast future climate conditions but to examine the complex interactions present throughout the climate system and potentially improve the parameterization schemes currently employed in climate models. Ultimately, the hybrid framework can aid climate policymakers by providing them with reliable and timely climate forecasts. Nevertheless, much like other emerging technologies, there are many challenges that must be overcome before hybrid climate modeling becomes generally accepted. One of the most significant hurdles to the general acceptance of hybrid climate modeling is the scarcity of observational data in many regions. An additional challenge is the potential complexity of integrating physical components with data-driven components. In addition, this paper emphasizes the importance of collaborative interdisciplinary efforts in furthering climate science. It bridges the knowledge gap existing between new developments in AI and established physical theories of climate modeling; thus, establishing a base for creating more robust, efficient, and transparent climate forecasting methodologies.

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