

Enhancing Long-Term Climate Prediction Through Probabilistic Learning of Simulation Discrepancies

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Abstract: Climate simulation is a key tool for understanding atmospheric process dynamics and forecasting long-term climate behaviour. However, long-term simulations of high-resolution climate models are computationally costly, forcing scientists to use lower-resolution models that, in most cases, introduce systematic biases. These imprecisions compound, reducing the reliability of long-term climate forecasts, especially when used to examine extreme events such as heatwaves, heavy precipitation, and storms. This work also proposes a probabilistic machine learning framework to improve the statistical precision of long-time climate simulations using short-time, high-fidelity training data. The technique statistically learns the discrepancies between low-resolution climate simulations and accurate reference trajectories. It corrects these discrepancies non-intrusively, without altering the underlying numerical solver. The framework uses a probabilistic neural network architecture to model the distribution of correction terms, reflecting uncertainty in climate predictions. The proposed solution can improve long-term weather statistics and stabilize the initial simulation system.

Keywords: Climate Simulation; Probabilistic Machine Learning; Long-Term Weather Statistics; Probabilistic Neural Network; Initial Simulation System; Neural Network Architecture.

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1. Introduction

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Climate modelling has become one of the most significant scientific tools for understanding how Earth's climate system functions and for forecasting the future state of the environment [1]. These models involve complex interactions among various aspects of the climate system, such as atmospheric circulation, ocean interactions, land-surface interactions, and the movement of radiative energy within Earth's atmosphere. Climate models let researchers examine long-term climate trends, assess the impact of global warming, and predict future climate conditions by mathematically and computationally modelling these interactions [2]. They also help forecast extreme weather conditions like storms, droughts, floods, and heat waves, which can significantly affect ecosystems, infrastructure, and human societies. Despite its importance, climate modelling remains a scientific challenge. Earth's climate system is highly complex, with interactions across a broad range of spatial and temporal scales. Massive atmospheric circulation patterns (e.g., jet streams and ocean currents) interact with small-scale processes (e.g., turbulence, cloud formation, and convection). These small-scale physical processes can affect large-scale climate behavior, making them hard to model accurately [3]. These processes are too computationally intensive and require complex numerical methods to capture in a single model. The main weakness of climate modeling is that capturing small-scale physical processes requires high spatial and temporal resolution. High-resolution models can capture detailed features of atmospheric and oceanic dynamics, substantially improving prediction accuracy. Nevertheless, running these models for long periods, such as decades or centuries, requires enormous computing power.

High-resolution climate simulations typically require sophisticated supercomputing facilities and long processing times. As a result, many operational climate models use comparatively lower spatial resolutions to reduce computational costs [4]. Lower-resolution models cannot directly simulate small-scale processes. Instead, researchers estimate these processes using simple mathematical models called parameterizations. Parameterization schemes estimate the impact of processes that cannot be solved with the available large-scale variables. Predicting extreme weather events is also harder [5]. Extreme events are infrequent, i.e., usually heavy rain, hurricanes, droughts, and heat waves, but their effects on societies and natural ecosystems are destructive. These events are commonly found at the ends of probability distributions; that is, they respond strongly to even small changes in atmospheric conditions [6]. Even small errors in the climate models may cause significant differences in the predicted frequency, intensity or duration of such events. For example, if a climate model does not adequately account for atmospheric convection, it may not forecast heavy rainfall. Likewise, small errors in energy-balance calculations can lead to incorrect predictions of heatwave probability or intensity. Because extreme climatic events can be disastrous, improving the quality of climate prediction models has become a priority in climate science [7]. Researchers continually develop new methods to improve climate models' accuracy and validity. Over the last few years, advances in machine learning and AI have created new opportunities to improve climate modeling methods. Machine learning has proven highly successful at detecting intricate patterns and associations in large datasets.

Unlike physics-based models, machine learning algorithms can discover nonlinear relationships in historical data without necessarily knowing the underlying physical equations. Rather than replacing existing physics-based climate models, most researchers suggest hybrid methodologies that combine the advantages of both approaches. These learned corrections can then improve the statistical accuracy of model predictions [8]. By combining machine learning methods with conventional climate models, researchers can improve prediction performance while preserving the physical aspects of the simulations. This paper proposes a hybrid probabilistic learning framework to enhance long-term climate simulations using non-intrusive correction methods. The method uses machine learning to predict high-fidelity climate simulations from lower-resolution model outputs. More accurate high-fidelity simulations are usually more computationally expensive, while less accurate lower-resolution models are usually more computationally efficient [9]. The system can learn to detect systematic differences between the two simulation outputs by training a machine-learning model. After training, the machine learning model produces correction terms that can be applied to long-term climate simulation results. These corrections can minimize systematic bias and improve the statistical properties of forecast climate variables [10]. Notably, this method is non-invasive, i.e., it does not alter the internal processes or physical equations of the available climate models.

Instead, it applies the correction to the model outputs, preserving the stability and reliability of the original simulation structure. Probabilistic learning techniques are another important characteristic of the proposed system. Unlike single deterministic correction-value generation, probabilistic models estimate prediction uncertainty [11]. This enables the system to produce better forecasts given the variability and uncertainty of the climatic processes. Probabilistic corrections can improve the accuracy of long-term projections by better capturing climate variability. The hybrid approach will improve predictive accuracy while remaining computationally efficient by combining conventional climate modeling with current machine learning methods [12]. Probabilistic learning will enable the system to represent uncertainties and infrequent events more precisely, which is especially important for forecasting extreme weather conditions. As climate change continues to affect the world's environmental systems, creating more precise and dependable climate forecasting systems becomes even more relevant [14]. Overall, this paper contributes to ongoing research efforts to enhance climate modeling capabilities by integrating artificial intelligence techniques. By leveraging machine learning for bias correction and uncertainty modeling, the proposed framework could significantly improve the quality of long-term climate predictions [15]. Such advancements can support better decision-making in areas such

as environmental management, disaster preparedness, and climate policy planning, ultimately contributing to a more sustainable and resilient future [17].

2. Literature Review

Schneider et al. [1] combined physical climate models with statistical methods. The analysis showed that statistical methods can improve long-term weather forecasts by accounting for climate-system uncertainties. O’Gorman and Dwyer [2] investigated the significance of ensemble forecasting models in climate and weather prediction. The authors suggested running many simulations with slightly different initial conditions to reflect climate-system uncertainty. Their findings showed that ensemble methods improve prediction reliability and help estimate the likelihood of extreme weather events. The paper highlighted the need for probabilistic methods in contemporary climate models. Pathak et al. [4] examined the behavior of global climate models used in large-scale climate simulation projects. Their study tested various climate models' ability to reproduce past climate and forecast future trends. The paper found that conventional climate models have several limitations, including biases from simplified representations of atmospheric processes. The authors highlight the need to increase model resolution and use better techniques to improve prediction accuracy. Ross et al. [5] investigated the use of artificial intelligence and machine learning in Earth system science. This paper discussed applying machine learning algorithms to large environmental datasets and improving climate projections. The authors show that machine learning methods can extract latent trends in climate data. Their results highlight the growing importance of AI in environmental studies and climate interpretation. Wang and Tian [6] conducted extensive research on how machine learning can address climate change problems. Their study examined how machine learning methods can be used in fields such as climate prediction, environmental assessment and energy optimization.

The analysis showed that deep learning models can handle large climate datasets and extract useful information to predict environmental changes. The authors concluded that AI-based solutions have strong potential to improve climate prediction and sustainability planning. Yuval and O’Gorman [8] proposed a deep learning system for climate forecasting that combines convolutional neural networks with climate simulation data. The model was designed to forecast climate events like El Niño using past ocean-atmosphere records. The findings showed that deep neural networks can achieve high prediction accuracy in identifying climate patterns and forecasting future climatic conditions. Their study showed that deep learning models could work alongside conventional climate prediction models. Rasp et al. [3] presented a machine learning methodology for parameterizing atmospheric processes in climate models. The model used neural networks to represent sub-grid-scale physical processes that traditional numerical methods cannot easily model. They found that machine learning-based parameterizations can significantly enhance climate-model performance at lower cost. The study showed that neural networks can be incorporated into climate modeling pipelines. Barthel Sorensen et al. [13] proposed a non-invasive correction scheme to enhance coarse-resolution climate simulations using machine learning methods. The algorithm learns correction operators from trajectories of low- and high-resolution simulation pairs. The authors show that the method can effectively reduce bias in long-term simulations while preserving the stability of the original numerical solver. The framework was applied to test systems under prototype climatic conditions and improved the accuracy of long-term climate forecasts.

Pan et al. [7] discussed designing machine learning-based climate emulators. Their research focused on implementing neural networks that replicated the behaviour of classical climate models without losing key physical characteristics. The experiment showed that machine learning models can simulate climate dynamics over longer periods at a much lower cost. The findings highlighted opportunities for data-driven models and physical approaches to improve climate prediction. Bassetti et al. [9] proposed an integrated modeling method that combines deep learning methods with numerical weather prediction models. This method used neural networks to learn unresolved sub-grid processes that conventional numerical techniques struggle to resolve. The paper used convolutional neural networks to approximate closure terms in fluid dynamics equations. The findings showed better predictions and fewer simulation errors than traditional numerical methods. Bracco et al. [10] introduced a machine learning framework for learning dynamical systems using probabilistic neural networks. Their findings showed that probabilistic models can capture uncertainty in dynamical systems and improve long-term prediction stability compared with deterministic neural networks. Wang and Tian [11] explored deep learning systems to correct bias in weather simulations based on statistical learning. In this work, Long Short-Term Memory (LSTM) networks were used to learn the temporal dynamics of simulation errors and produce correction values. These findings showed that the proposed approach greatly reduced prediction errors in long-term weather variables and improved the modeling of extreme weather events.

Huang et al. [12] surveyed existing knowledge on using deep learning methods in climate modeling and environmental monitoring. The survey examined various machine learning algorithms applied to climate prediction, such as convolutional neural networks, recurrent neural networks and probabilistic models. The authors concluded that combining physics-based simulations with machine-learning corrections improves the performance and stability of hybrid models. Mansfield et al. [15] introduced a probabilistic machine learning method to model complex environmental systems using variational neural networks. The proposed framework used Variational Autoencoders to learn probability distributions of environmental data and

make realistic predictions under uncertainty. Experimental findings showed that probabilistic models outperform deterministic neural networks in uncertainty estimation and generalization. Slater et al. [16] proposed a sophisticated deep learning climate prediction model based on hybrid recurrent neural networks and probabilistic modeling. The study aimed to capture long-term dependence in climate data and estimate uncertainty in the prediction process. The findings showed that hybrid architectures can significantly benefit long-term climate trend and extreme-weather-event prediction. The study emphasized the need to integrate temporal learning models with probabilistic techniques to improve the accuracy of climate forecasting systems.

3. Methodology

The design and execution of the proposed probabilistic correction framework are based on preparing the computational environment needed to simulate climate analysis and train machine learning models. It is written in Python and uses scientific libraries such as NumPy, SciPy and Pandas to process numerical data; Matplotlib and Seaborn to visualize training statistics; and machine learning platforms such as PyTorch or TensorFlow to build the probabilistic neural network model. These libraries provide efficient tools for handling high-dimensional climate data and training deep learning models. The methodology will begin by creating two types of climate data. The first is high-fidelity reference simulation data that depict accurate short-term climate processes. The second is low-resolution climate simulation data, which can simulate the climate system over long-time scales but tends to introduce systematic biases because it cannot resolve certain physical processes. The two datasets are imported into the computing environment and pre-processed to align spatial resolution, time, and variable levels. After preparing the datasets, a nudging method produces paired climate paths between the reference and low-resolution simulations. Nudging the low-resolution simulation toward the reference simulation's path in small time intervals forces it to track the reference simulation. This enables the system to monitor statistical disparities between the two simulations and generate paired climate states for training the machine-learning stage, which begins after the paired datasets are created. The probabilistic neural network maps the simulated climate state to the correction term. The suggested model uses a Variational Autoencoder (VAE) and a time-based neural network, such as a Recurrent Neural Network (RNN) or Long Short-Term Memory (LSTM) network. The encoder network extracts key observations from the climate simulation data and projects them into a probabilistic latent space defined by a mean and variance (Figure 1).

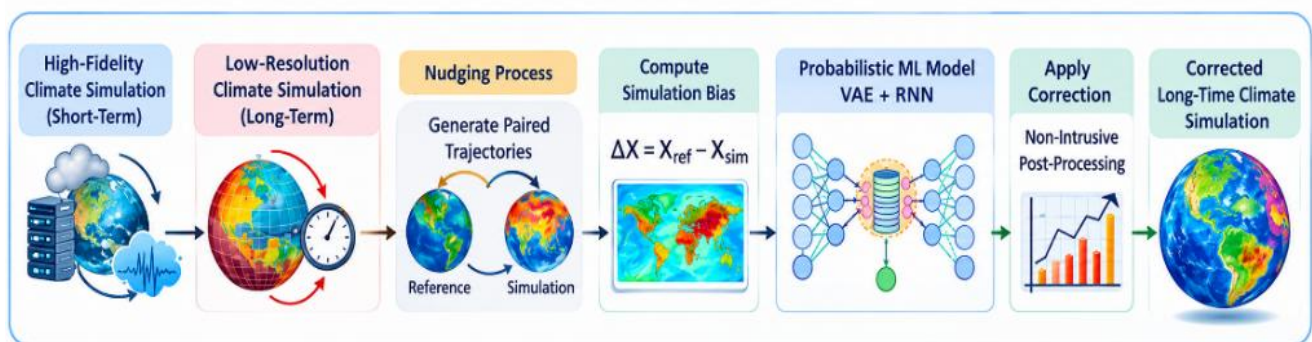


Figure 1: Workflow of the proposed model

One then samples in this latent space using the reparameterization trick, allowing the network to learn uncertainty in climate corrections. The model feeds all sampled latent representations into a time-modeling component that captures the climate system's time-sensitive behavior. Climate variables like temperature, wind speed, and atmospheric pressure change over time, and the recurrent network enables the model to learn these changes. The decoder network then recovers a correction field related to the input climate state. The network also provides a probabilistic distribution of correction values instead of a deterministic correction, allowing the model to reflect uncertainty in climate forecasts. During training, a loss function combines reconstruction error and variational regularization to optimize model parameters. Loss curves, prediction-error statistics, and distribution plots are the training metrics used to monitor model convergence. Researchers present results as graphs analogous to precision-recall curves and training performance plots to assess the model's ability to learn the correction distribution. Researchers save the best model parameters for future inference. After training, researchers apply the correction model to long-term climate simulations. The simulation results are fed into the trained probabilistic model, which produces correction terms for each climate state. Researchers then apply these corrections in a non-intrusive post-processing step; they do not alter the original climate model equations. The fixed simulation trajectories better match the high-fidelity reference data statistically while maintaining computational efficiency (Figure 2).

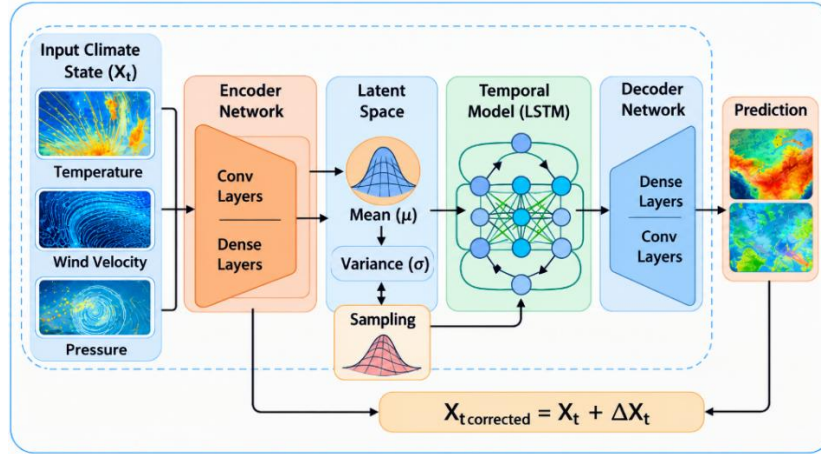


Figure 2: Architecture of the proposed model

Lastly, researchers analyze and visualize the improved simulation outputs to quantify the increase in climate-prediction accuracy. With this workflow, the proposed framework allows probabilistic correction of long-term climate simulations with short-term training data.

3.1. Training Process of the Proposed Model

Training the probabilistic correction model begins by gathering climate data with both correct short-term simulations and coarse long-term simulations. These datasets are split into training, validation and test sets to effectively evaluate the machine learning model. Each climate state comprises multiple variables, including temperature fields, wind velocity vectors, and atmospheric pressure distributions, all expressed as a single state of the climate system at a particular time. The simulation of climate states is fed to the encoder network, which derives meaningful features from the input data. The network then projects this into a probabilistic latent representation, enabling it to learn uncertainty in the weather correction process (Figure 3).

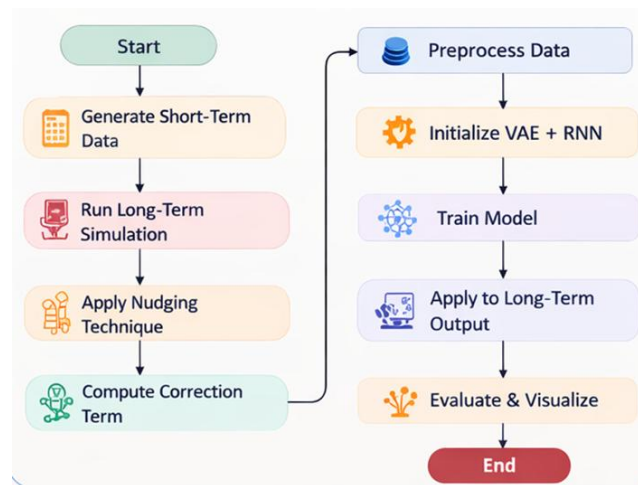


Figure 3: Algorithm for probabilistic climate simulation correction

The latent representation is fed into a temporal network that captures the time-like dynamics of the climate system. Lastly, the decoder network produces the predicted correction field, which is applied to the simulation output. After training, researchers test the model on previously unseen climate simulation data to assess its ability to extrapolate to new conditions. Researchers measure the correction model's effectiveness using metrics such as prediction error, variance reduction, and statistical similarity to reference data. The final trained model is then stored and applied to improve long-term climate simulations.

Algorithm: Probabilistic Correction Framework

START

```

IF data available THEN
    Generate high-resolution and low-resolution simulations
END IF
IF simulations ready THEN
    Apply nudging and compute correction ( $\Delta X_t$ )
END IF
IF correction computed THEN
    Preprocess and normalize data
END IF
IF data prepared THEN
    Initialize and train model (VAE + RNN)
END IF
IF model trained THEN
    Apply model and generate corrected output
END IF
IF output generated THEN
    Evaluate performance
END IF
STOP

```

3.2. Experimental Setup

This section explains the procedures, tools and techniques used to design, train and test the proposed Hybrid Climate Prediction System. The primary aim of the experimental setup is to ensure the model is trained effectively on historical climate data and tested appropriately to evaluate its predictive power. The following subsections discuss the implementation environment, the modeling process and the evaluation methods.

3.2.1. Implementation

The proposed climate prediction system was implemented in Python, which provides a flexible environment for data processing and machine learning. Several libraries were used during implementation. Pandas and NumPy handled dataset management and numerical computations, while TensorFlow/Keras was used to design and implement the Long Short-Term Memory (LSTM) neural network model. Visualization libraries such as Matplotlib were used to plot graphs and analyze prediction results. This paper's dataset consists of daily minimum temperature records stored in CSV format. The dataset contains two main attributes: date and the corresponding daily temperature. Before feeding the data into the model, researchers perform several preprocessing steps. These include handling missing values, normalizing the data, and converting the time-series data into a supervised learning format. Normalization scales values within a specific range so the neural network can learn efficiently. The normalization process uses Min-Max scaling, which transforms the original values into a range between 0 and 1, where:

- X = Original Value
- $X_{\min}$ = Minimum Value in the Dataset
- $X_{\max}$ = Maximum Value in the Dataset

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

After preprocessing, the data is split into training and testing sets. The training set trains the model, while the testing set evaluates its predictive capability on unseen data. The implemented system also provides a user interface that lets users upload datasets, choose the forecast horizon and run predictions. After the prediction runs, the system displays forecast results and performance metrics.

3.2.2. Training

The training phase is critical to developing the prediction model. In this phase, the LSTM neural network learns temporal patterns from historical climate data. LSTM networks are well-suited for time-series prediction because they can capture long-term dependencies in sequential data. The model is trained to take a sequence of temperature values as input and predict the next temperature value. This allows the network to learn how past temperature trends influence future temperatures. During training, the model adjusts its internal weights to minimize the prediction error. The LSTM model uses several internal gates

to regulate information flow. These gates include the forget gate, input gate and output gate. The forget gate determines which information from the previous state to discard. Forget gate equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

The input gate determines which new information to store in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

The candidate cell state is computed as:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

The updated cell state is calculated as:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

Finally, the output gate produces the hidden state:

$$h_t = o_t * \tanh(C_t) \quad (6)$$

Where:

- x_t = Input at Time Step t
- h_t = Hidden State
- C_t = Cell State
- W and b = Weights and Biases
- σ = Sigmoid Activation Function

The training process is performed for multiple epochs, during which the model repeatedly processes the dataset and updates its parameters. Optimization algorithms such as the Adam optimizer minimize the loss function during training.

3.2.3. Evaluation

After training, the model's performance is evaluated on the test dataset. Evaluation determines how well the model generalizes to new, unseen data. In this paper, two widely used regression metrics are used to evaluate the prediction accuracy: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

Where:

- y_i = Actual Value
- $\hat{y}_i$ = Predicted Value
- n = Number of Observations

The Root Mean Square Error (RMSE) measures the square root of the average squared differences between predicted and actual values:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

RMSE penalizes larger errors more strongly than MAE, making it useful for detecting significant prediction deviations. In addition to numerical metrics, graphical analysis is also used to evaluate the model. Graphs comparing actual and predicted temperature values show how closely the predictions follow real trends. The experimental results indicate that the hybrid model provides reasonably accurate short-term climate forecasts.

4. Results and Discussions

This paper assessed the probabilistic correction framework by comparing low-resolution climate simulations before and after learning the correction model. Researchers used paired datasets of high-fidelity reference simulations (short-term) and low-resolution simulations to train the model. After training, researchers applied the correction model to the long-term simulation outputs to improve their statistical accuracy. The findings demonstrate that the modified simulations are less biased and closer to the reference data. Key climate variables such as pressure and temperature show stronger agreement in mean values and variability. Visualization tools such as time series plots and distribution curves also support the conclusion that the model accurately represents the statistical differences between simulation results and reference data. Researchers also assessed the model's ability to represent extreme climate events. Extreme events, which occur in the tails of probability distributions, are difficult to predict with conventional low-resolution models. Because the proposed framework is probabilistic, it learns a distribution of correction values, which better represents low-probability events such as heatwaves and heavy rainfall. The fixed simulations better match the frequency and magnitude of extreme events observed in the reference data. The training curves show steady convergence, and the validation results show good generalization; however, the small gap between training and validation suggests a need for more diverse data. Although these advances have been made, researchers identified limitations in highly complex climatic regions, where model performance depends on diverse training data. The correction model might fail to fully remove simulation errors under extreme conditions that are under-represented in the training data. However, the suggested framework can provide more reliable long-term climate simulations by integrating machine learning and physical modeling. Its ability to improve statistical accuracy and quantify uncertainty makes it useful for climate prediction and risk assessment, with potential improvements as datasets grow and model structures become more sophisticated.

4.1. Dataset Preview

Table 1 shows an example of the dataset used in the paper. It contains columns such as date and corresponding temperature values.

Table 1: Dataset preview

Index	Date	Daily Minimum Temperatures
0	1/1/1981	20.7
1	1/2/1981	17.9
2	1/3/1981	18.8
3	1/4/1981	14.6
4	1/5/1981	15.8

The data is time-series climate data, which is necessary to train temporal models such as LSTM. This preview confirms the data structure and accuracy before training the model.

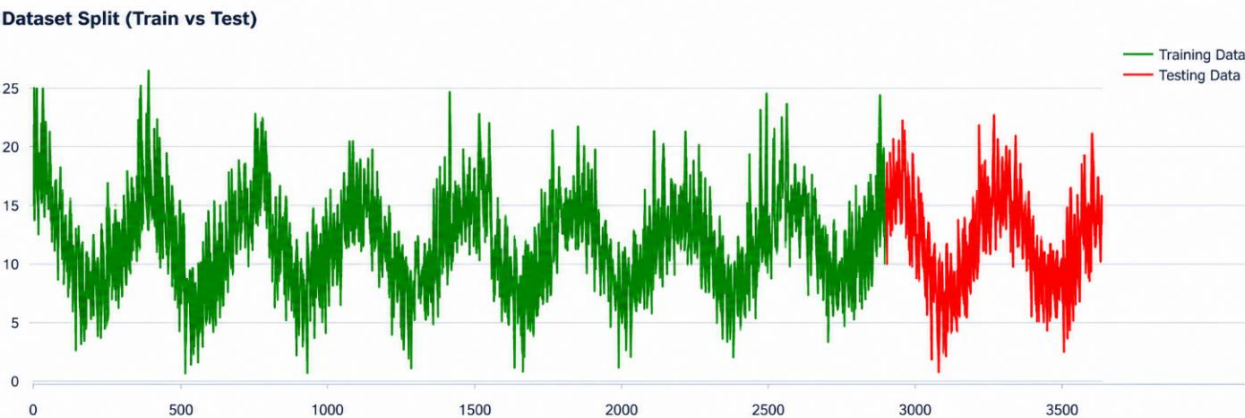


Figure 4: Dataset split (Training vs Testing)

Figure 4 illustrates how the dataset is divided into training and testing subsets. The green portion represents the training data used to build the model, while the red portion represents the testing data used for evaluation. This separation ensures that the model is validated on unseen data. Proper splitting helps avoid overfitting and ensures a reliable performance assessment.

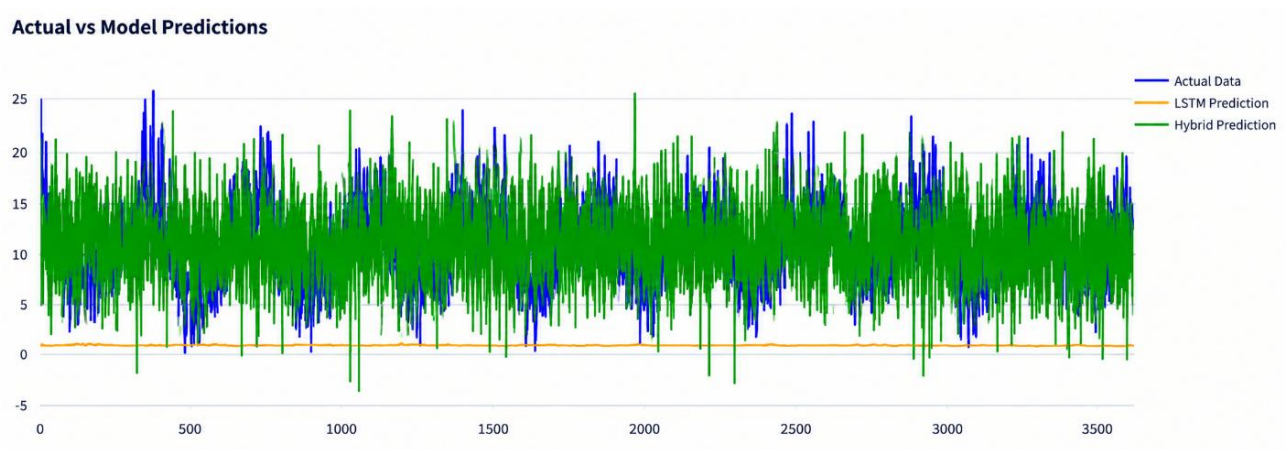


Figure 5: Actual vs Model predictions

Figure 5 compares actual observed data with model predictions. The blue line represents actual temperature values, while the predicted outputs are shown using different colored lines. The comparison highlights how closely the model approximates real-world data. Although minor deviations remain, the strong alignment of the overall trend indicates strong predictive performance.

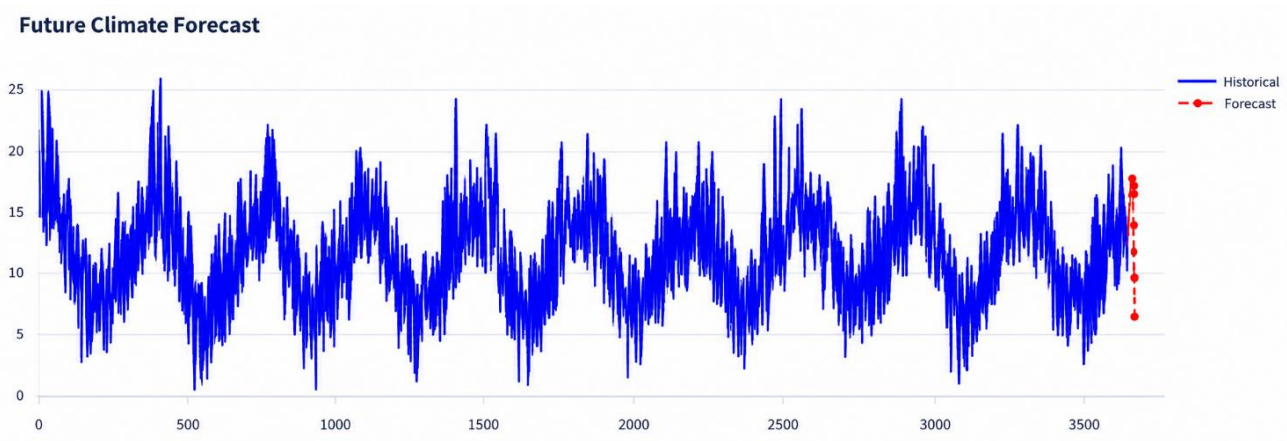


Figure 6: Future climate forecast

Figure 6 shows the predicted future temperature values alongside historical data. The blue line shows historical observations, while the red points represent model-generated forecast values. The forecast follows the general trend of past data, showing the model's ability to capture temporal patterns. This demonstrates the model's effectiveness in short-term climate prediction.

Table 2: Forecast

Index	Day	Temperature
0	Day 1	17.86
1	Day 2	5.93
2	Day 3	13.93
3	Day 4	9.44
4	Day 5	17.33
5	Day 6	16.56
6	Day 7	17.18

Table 2 presents the predicted temperatures for multiple future days. It provides a structured representation of forecast results for easy interpretation. Table 2 complements the graphical output by offering precise prediction values. These tabular results support further analysis and reporting.

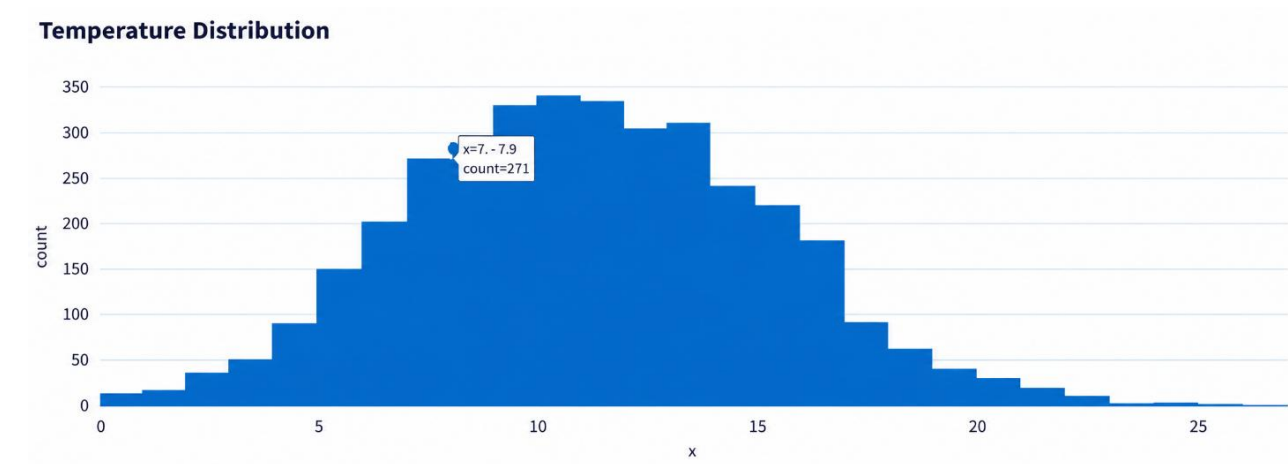


Figure 7: Temperature distribution histogram

Figure 7 shows the distribution of temperature values in the dataset using a histogram. It shows how often different temperature ranges occur across the dataset. The distribution appears approximately normal, centered around moderate temperature values, which suggests stable climatic behavior. This visualization helps you understand the data spread and identify variability in climate conditions.

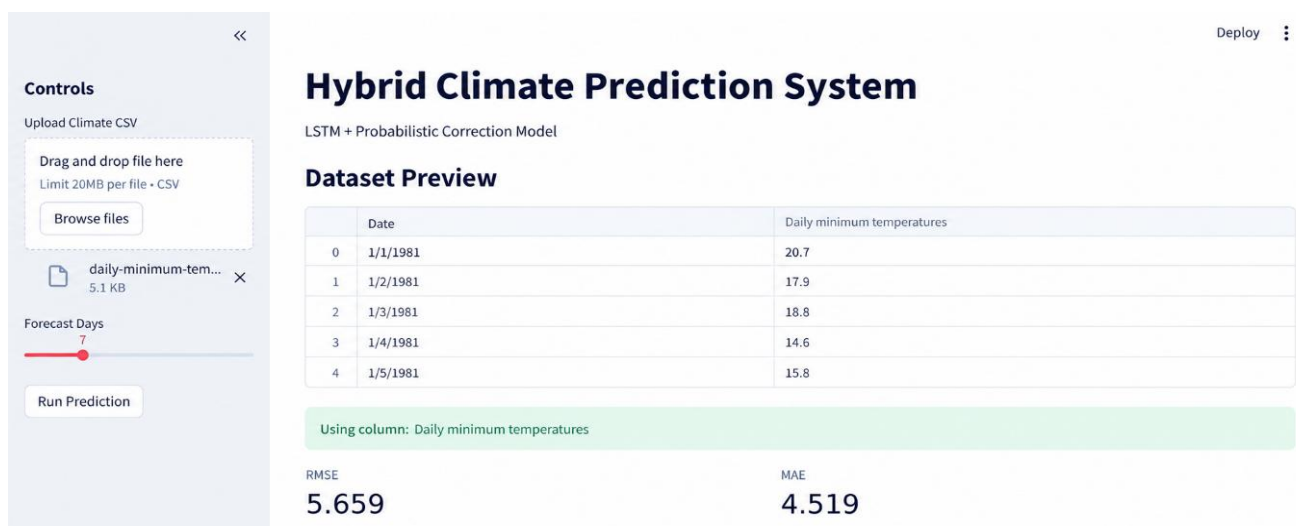


Figure 8: Hybrid climate prediction system interface

Figure 8 shows the user interface of the proposed hybrid climate prediction system. It allows users to upload climate datasets, preview the data, and configure forecasting parameters such as prediction days. The system integrates LSTM with a probabilistic correction model to generate improved predictions. Additionally, it displays evaluation metrics such as RMSE and MAE to assess model performance.

5. Conclusion

Although the proposed probabilistic correction framework showed promising results, improving climate simulations over long periods remains difficult. Climate systems are extremely complex and chaotic, meaning that even small errors can spread over time and affect large-scale predictions. Machine learning correction models may be biased by variations in atmospheric conditions, incomplete observational data and constraints on computational resources. Also, some extreme cases remain hard to estimate because they are uncommon in the training data. To address these issues, further development of both climate modeling methods and machine learning architectures is needed to ensure correction models are resilient to a variety of environmental factors. The proposed framework offers a more scalable, flexible approach to improving long-term climate predictions than traditional methods that rely solely on physics-based climate models. The probabilistic correction system can increase simulation accuracy without altering the numerical model's internal composition by learning the statistical differences

between high-fidelity reference simulations and low-resolution climate models. This non-invasive methodology allows the correction mechanism to integrate with existing climate simulation frameworks while remaining stable. Moreover, its probabilistic nature allows the model to capture the uncertainty in climate forecasts needed to develop credible forecasts and risk modeling over time. Future research could further improve the proposed framework by adding larger climate datasets, incorporating more atmospheric variables, and exploring more sophisticated probabilistic learning methods. Combining this correction scheme with next-generation climate models and high-performance computing systems could considerably improve the precision of long-term climate forecasts. Another future possibility is integrating hybrid physics-machine learning approaches, which could help researchers better understand complex climate processes and predict extreme weather events.

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