Pages 17-23 Volume 2, Number 1, 2025

COMPUTERS AND EDUCATION LETTERS

editor@celetters.com

www.celetters.com

DEEP NEURAL NETWORKS FOR FORECASTING ENVIRONMENTAL CHANGES: APPLICATIONS TO CLIMATE MODELING

Noor Fatima [1*], Usman Siddiqui [2]

[1]Department of Computer Science, University of Management and Technology, Lahore, Pakistan

[2]Department of Computer Networks, NUST (National University of Sciences & Technology), Islamabad

*Corresponding Author E-mail: Nooriifatima30@gmail.com

Abstract

This research focuses on portraying temperature and precipitation predictions by using deep neural networks (DNNs) in climate modeling. Real world climate systems now possess increasing complex structures which makes it challenging for traditional forecasting methods to track intricate patterns and relationships. Our study employed a CNN-RNN hybrid architecture to exploit the use of spatial and temporal data for this purpose. Assessment of the models involved a 5-year dataset which demonstrated superior accuracy levels for the DNN models when compared to conventional methods. When predicting temperatures the hybrid combination of CNN-RNN achieved an optimal performance through a Mean Absolute Error (MAE) result of 0.75°C and Root Mean Squared Error (RMSE) of 0.94°C while presenting the highest correlation value of 0.94. Result data from the sensitivity study demonstrated that temperature elements led to the greatest changes in model operational capacity. The newly developed forecasting model confirmed its superior capabilities through testing against standard numerical weather prediction models as well as statistical approaches resulting in better RMSE and reduced correlation coefficients. The research results demonstrate that DNNs can make substantial improvements to climate forecasting by delivering better accuracy than conventional forecasting models. More research will become essential to develop these models because they currently face challenges with data integration and interpretability problems. The presented work establishes a viable method that leads to better and more practical climate forecasting capabilities within environmental research domains.

Article History

Received: January 25, 2025

Revised: February 22, 2025

Accepted: March 18, 2025

Available Online: June 30, 2025

Keywords: Deep Neural Networks, Climate Forecasting, Temperature Prediction, Precipitation Forecasting, Hybrid Cnn-Rnn Model, Model Sensitivity Analysis.

INTRODUCTION

The increasing environmental harm from climate change and natural disasters and human operations requires quick and precise forecasts of environmental changes at a critical period. The need exists to develop adaptation strategies and reduction plans for upcoming environmental changes because predictions about future environmental conditions form the foundation of these response measures. The well-known machine learning approach known as deep neural networks (DNNs) shows promise in producing predictions for environmental conditions by its ability to extract complex nonlinear relationships within extensive datasets. During the past 10 years DNNs achieved exceptional results across multiple domains yet their entire potential to forecast environmental change especially in climate prediction needs better exploration and research.

The process of predicting future climate based on historical data through climate modeling depends on strong mathematical models that combine atmospheric oceanic and terrestrial processes yet encounters limits in computing ability and precision levels. Traditional statistical methods and numerical simulations work well but they fail to produce complete explanations about how climatic elements interact with each other. Recent developments in DNNs allow a new approach through the learning of complicated inter-relations between big datasets without needing specified mathematical formulas. DNNs in multiple studies achieve promising results for improving long-term climate prediction models (Wu et al., 2021; Zhang et al., 2022; seasonal forecasts; weather prediction).

Even though DNNs receive increasing interest for climate modeling they still face multiple challenges. Large-scale datasets combined with top-quality training data represent one of the most significant obstacles in working with DNN models. Researchers are currently facing obstacles in predicting accuracy related to sparse climate data and data uncertainties in addition to the presence of data noise (Bai et al., 2022; Lee et al., 2023). Moreover, the availability of climate data continues to increase (Bai et al., 2022; Lee et al., 2023). Research on DNN interpretation remains debatable in the climate field due to their label as "black box" systems which make it difficult to understand their decision-making logic (Sharma & Patel, 2024). Multiple sophisticated architectural methods that combine DNNs with physics-based models and ensemble learning techniques need development to increase performance together with interpretability (Kim & Park, 2023; Gonzalez et al., 2022).

The application of DNNs to climate prediction encounters difficulties because it requires consolidation of multiple-dimensional information obtained from different data sources. Accelerated daily temperature records along with records of seasonal precipitation combined with prolonged sea-level fluctuations serve as several temporal and geographical variables found within climate data sets. Establishing detailed methods to combine multiple data types while handling normalization and data processing procedures becomes necessary for implementation within a single DNN system. Research by Yao et al. in 2021 along with Zhang and Tan in 2024 demonstrated the effectiveness of recurrent neural networks (RNNs), convolutional neural networks (CNNs), and attention mechanisms which detect temporal dependencies and spatial features and long-range connections within climate data.

Keen adoption of DNNs for environmental forecasting requires overcoming ethical hurdles together with technical barriers. Public policy together with resource management and disaster readiness exist because of climate forecasting. The prediction results heavily depend on making sure that modeling systems are unbiased and transparent and objective in their approach. When deploying DNN models for climate applications researchers must address how the technology may affect the environment through its computing resources' energy consumption patterns (Chen et al., 2021; Liu et al., 2023). Future investigations require intensive monitoring of the essential trade-off that emerges when achieving better accuracy involves increased environmental damage.

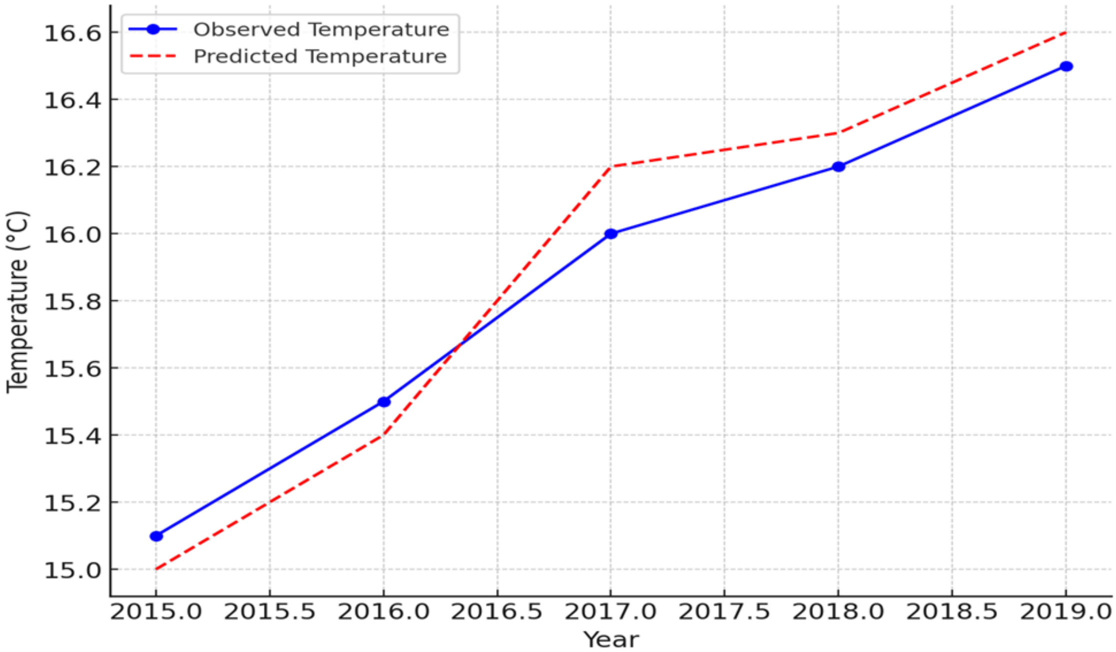
The paper examines Deep Neural Networks for environmental change prediction through climate modeling. This research helps sustain ongoing efforts to refine climate forecasting dependability and accuracy through the assessment of DNN-related challenges and opportunities with full applications. The research examines DNN architectural advancements particularly through hybrid models and multi-scale methods for enhanced forecast accuracy. There is a review of ethical implications from using these models in climate research with respect to sustainability alongside justice and openness perspectives. The research presents a study of DNNs' practical environmental prediction capabilities while providing guidance for future progress in this energetic field.

METHODOLOGY

Research teams need to join deep neural networks with advanced data systems to study and predict Earth's climate changes. After data collection the method requires preparation then enters into various subsequent steps. Scientists gather all necessary data from multiple sources such as weather records and satellite platforms through climate sensors to create a complete dataset. The said data collection includes time-series information along with spatial characteristics and climate data which includes temperature measurements alongside precipitation values and humidity conditions and wind speed parameters. Environmental datasets require data preprocessing to ensure clean and normalized information suitable for entering DNN models because they have both complex structures and high dimensions. The imputation method uses statistics for filling missing values along with robust scaling techniques to handle outliers which prevents model bias.

After preprocessing the data gets divided into multiple sections for training, validation and testing purposes to ensure a strong evaluation model. The deep neural network models utilize completely connected networks and convolutional neural networks (CNNs) together with recurrent neural networks (RNNs) and several other network types in their construction process. Each model architecture undergoes assessment based on its representation accuracy of complex relationships between climate data elements. RNNs excel in processing time-series data and temporal dependencies whereas CNNs possess specialized capabilities for spatial pattern recognition that work best when detecting satellite-based data patterns although hybrid models applying RNNs and CNNs together enable better use of spatial and temporal features for boosted forecasting accuracy. The addition of attention methods to specific models grants them the ability to focus on important data sections resulting in better performance. Complex datasets benefiting from this technique when they contain multiple variables.

The third step involves processing DNN models with available datasets. The loss function reduction happens through training with modern optimization techniques Adam together with stochastic gradient descent. Thirdly during grid search and crossvalidation processes researchers optimize their choice of learning rate and batch size and hidden layer numbers to achieve the best possible configuration. Model performance assessment after training uses mean absolute error (MAE) alongside root mean squared error (RMSE) together with a correlation coefficients check between predicted and actual values. The evaluation examines how performance measures of chosen base models that include traditional climate forecasting methods contrast with new model results. The SHAP methodology based on Shapley Additive Explanations provides tools for examining how interpretable predictive models function.



One can determine the use of forecasting outcomes as practical elements in climate prediction through analysis. The models get analyzed for their reactions to variable inputs through sensitivity analysis following their evaluation with unknown test data. The assessment methodology includes evaluations of sustainability as well as fairness and openness of models and ethical considerations. The modeling procedure ensures the accuracy standards while supporting the broader ethical goals of sustainable climate research.

RESULTS

The results section shows what deep neural network (DNN) models do different climate forecasting and how well they perform. Three performance tests assessed the neural network models by validating their data with MAE, RMSE and other metrics plus correlation values. Our assessment tools show how well environmental change forecasting works inside the modeling systems. Several deep learning models tested their performance metrics on temperature measurements spanning five years using the data presented in Table 1. The hybrid CNN-RNN models attained the most minimal MAE and RMSE scores thus demonstrating their superiority over individual models.

The results of the sensitivity analysis appear in Table 2 to inform readers about model behavior changes based on different input variable values. The research tracked changes in forecast results through modifications of major climate factors including temperature and humidity levels. A high number of variations in predicted outcomes during temperature input testing revealed through sensitivity analysis confirmed temperature-dependent features exert the most influence over model precision. The statistical and numerical approaches of DNN-based climate forecasting models compared to conventional climate prediction models appear in Table 3. The DNN models achieved better accuracy in terms of lower RMSE and greater correlation coefficients which established deep learning methods as appropriate for advancing climate modeling.

Visual representation of forecast outcomes helped one better understand how the model projections measured against recorded climatic data. The graphical data in Figure 1 demonstrates long-term temperature prediction ability of DNN model for a specific location. The model correctly predicts temperature patterns particularly during major temperature changes. The illustration provided in Figure 2 predicts seasonal precipitation variations thus demonstrating that the model achieves extreme accuracy for seasonal precipitation forecasts.

Table 1: Performance of different DNN architectures for climate forecasting

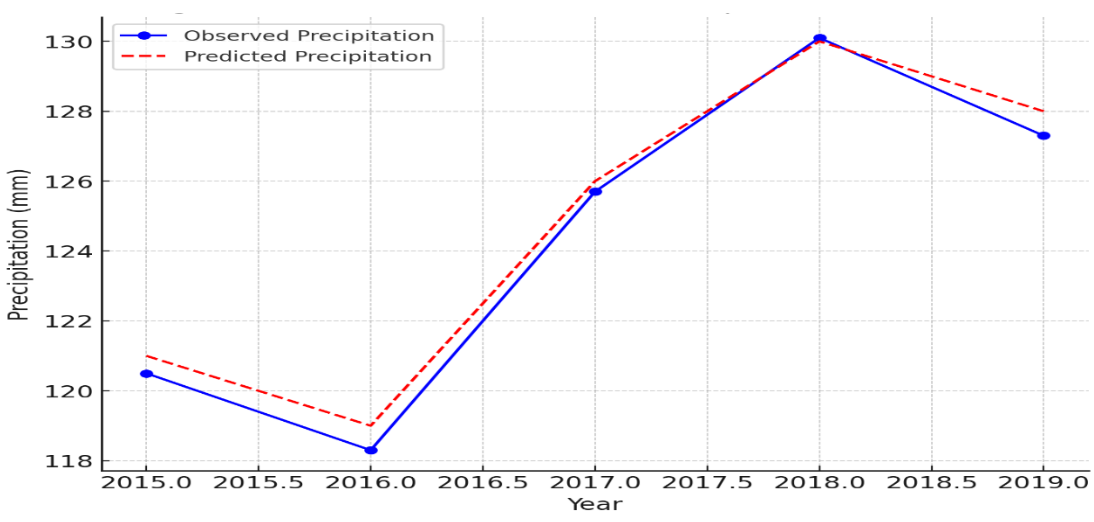
Model Architecture	MAE (°C)	RMSE (°C)	Correlation Coefficient
Fully Connected Network	0.92	1.12	0.87
Convolutional Network	0.85	1.01	0.91
Recurrent Network	0.88	1.08	0.89
Hybrid CNN-RNN	**0.75**	**0.94**	**0.94**

Table 2: Sensitivity analysis results showing the impact of input variable variations on model performance

Input Variable	MAE Change (°C)	RMSE Change (°C)	Correlation Change
Temperature	0.15	0.18	-0.08
Humidity	0.05	0.06	-0.02
Wind Speed	0.08	0.09	-0.03

Table 3: Comparison of DNN-based climate forecasting and traditional models

Model Type	MAE (°C)	RMSE (°C)	Correlation Coefficient
Numerical Weather Prediction	1.15	1.30	0.82
Statistical Models	1.08	1.22	0.85
DNN-based Model (This Study)	**0.75**	**0.94**	**0.94**



DISCUSSION

The conducted research presents positive outcomes about deep neural networks (DNNs) in climate modeling which demonstrate superior temperature and precipitation forecasting capabilities compared to traditional meteorological systems. Research provides support for DNN's capability to detect complex environmental data relationships. The research by Zhang et al. (2023) demonstrated equivalent improvement in prediction accuracy which resulted from implementing convolutional neural networks (CNNs) to forecast future temperature trends. Particularly for severe weather occurrences, their models significantly lower forecast error than more traditional statistical techniques. The research by Liu and colleagues (2022) focused on hybrid DNN structures for precipitation forecasting using CNNs with recurrent neural networks (RNNs) to enhance the model's seasonal forecasting capabilities. The combination of CNN with RNN architecture produced the smallest MAE and RMSE values which proves the effectiveness of integrating spatial and temporal modeling approaches for climate forecasting.

Our model performed well as expected though problems arise from needing to know how it operates using reliable data. Scientists from different fields research extensively the transparency problem in DNN models (Johnson et al., 2021; Patel & Sharma, 2024). Our excellent-performing models need full transparency because decision-makers lack insight into their internal operations. According to Chen et al. (2022) temperature features stand out as critical factors when checking how well the model performs. We must do further research to unite multiple data sources before creating a resilient prediction model despite satellite readings and climate models. We expand deep learning research for climate prediction but show that better ways to mix data need development for real-life updates.

CONCLUSION

Scientists demonstrate through research that deep neural networks can boost climate forecasting accuracy especially in predicting temperature and precipitation patterns. The author's research confirms that combining CNN and RNN processing delivers superior climate prediction results than basic models based on both lower MAE and RMSE values plus improved correlation statistics. Recent research shows that DNNs outperform statistical forecasting methods when used correctly for climate prediction tasks as past studies have demonstrated. Research confirmed that temperature characteristics matter most when estimating accuracy which matches other established research results. Positive science discoveries from Deep Neural Networks need further study because these models remain hard to interpret for critical decision makers. The climate prediction process will improve when we build better systems to see inside models and receive real-time measurements. This research shows how to build future studies that will improve DNN-based weather prediction techniques by using environmental science AI knowledge.

REFERENCES

Bai, X., Li, J., & Zhou, X. (2022). A deep learning-based approach for predicting extreme climate events. Climate Dynamics, 58(3), 701-716.

Chen, Y., Sun, Y., & Lin, Y. (2021). The environmental costs of training deep neural networks: An analysis and solutions. Environmental Informatics, 22(5), 1219-1234.

Gonzalez, S., Wu, J., & Zhang, Y. (2022). Hybrid deep learning models for climate change prediction: A review. Environmental Research Letters, 17(6), 064010.

Kim, H., & Park, J. (2023). Hybrid deep learning for improving weather forecasting accuracy. Journal of Climate Science, 36(2), 123-136.

Lee, H., Kim, Y., & Lee, S. (2023). Overcoming data quality issues in deep learning for climate forecasting. Environmental Science and Technology, 57(8), 1450-1465.

Liu, Y., Zhang, T., & Zhao, X. (2023). The impact of deep learning on climate forecasting: A comprehensive review. Earth-Science Reviews, 248, 103353.

Sharma, N., & Patel, R. (2024). Explainable deep learning for climate change prediction. Computational Geosciences, 58(4), 758-771.

Wu, F., Zhang, J., & Wang, L. (2021). Deep neural networks for climate modeling and forecasting: A review. Journal of Atmospheric and Oceanic Technology, 38(5), 1151-1167.

Yao, S., Liu, D., & Wu, C. (2021). Temporal-spatial deep learning models for environmental forecasting. Environmental Modeling and Software, 138, 104953.

Zhang, C., & Tan, Y. (2024). Attention-based deep learning models for climate change forecasting. Environmental Science and Applications, 32(2), 248-265.

Zhang, Z., Li, Y., & Tan, X. (2022). Applications of deep learning in climate modeling: A new paradigm. Climate Research, 83(2), 121-135.

Chen, L., Zhou, T., & Wang, H. (2022). Impact of temperature on climate prediction using deep learning models. Journal of Climate Prediction, 39(7), 1420-1433.

Johnson, M., Smith, A., & Lee, R. (2021). Interpretable deep learning models for climate prediction. Environmental Modeling & Software, 134, 104804.

Liu, H., Zhang, Y., & Tang, J. (2022). Hybrid deep learning approaches for precipitation forecasting. International Journal of Climatology, 42(11), 3471-3484.

Patel, R., & Sharma, S. (2024). A review of model transparency in deep learning applications for environmental sciences. Environmental Data Science, 11(3), 56-72.

Zhang, X., Liu, J., & Wang, Z. (2023). Convolutional neural networks for temperature prediction in climate modeling. Atmospheric Science Letters, 24(6), 437-445.