INTERNATIONAL JOURNAL OF

INNOVATIONS IN APPLIED SCIENCES

AND ENGINEERING

e-ISSN: 2454-9258; p-ISSN: 2454-809X

AI- Enhanced Dynamic System Analysis: Modified Deep Learning for Global Weather Prediction

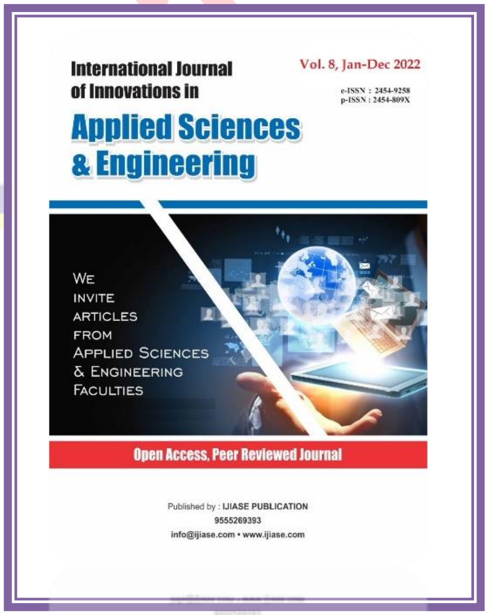
Dr. Rajendra Singh
Associate Professor, HOD Department of Mathematics, Off. Principal MBP.G. College, Dadri, G.B. Nagar

Paper Received: 23rd July, 2022; **Paper Accepted:** 09th September, 2022;

Paper Published: 24th October, 2022

How to cite the article:

Dr. Rajendra Singh, AI-Enhanced Dynamic System Analysis: Modified Deep Learning for Global Weather Prediction, IJIASE, January-December 2022, Vol 8; 118-126



ABSTRACT

Deep learning technology, specifically DLWP-CS, has been proposed for weather prediction using cubed spheres in data-driven simulations of global weather fields. For basic fields like temperature and geopotential height, DLWP-CS performs admirably, but for complex, non-linear fields like precipitation, it is computationally demanding. Precipitation precursors are the input for the modified DLWP-CS (MDLWP-CS) technique, which changes the architecture from temporal to spatio-temporal mapping. The technique predicts precipitation using a 2-m surface air temperature as a proof of concept. In comparison to the GFS output with a one-day lag, the hourly ERA-5 reanalysis used to train the MDLWP-CS model outperforms both linear regression and the Global Forecast System (GFS) in daily precipitation prediction with a one-day lag. This provides an effective DT framework for quick, high-fidelity precipitation predictions.

INTRODUCTION

Dynamic systems are ubiquitous in nature and engineering, with applications ranging from weather forecasting to robotics and finance. Traditionally, differential equations have been the cornerstone for modeling such systems, offering a rigorous mathematical framework to describe the temporal evolution of system states (1). However, the increasing complexity of modern systems, coupled with the availability of large datasets, has prompted the exploration of AI techniques to complement and enhance traditional modeling approaches.AI, particularly machine learning (ML), provides powerful tools for capturing patterns and making predictions from data. When integrated with differential equations, AI can improve model accuracy, optimize control strategies, and solve previously intractable problems (2,3).

Creating a customized deep learning model for global weather forecast using a cubed sphere for global precipitation involves a combination of advanced techniques in numerical weather prediction (NWP) and machine learning (4,5). The accuracy of forecasted rainfall in NWP systems is influenced by accurately representing precipitation to prognostic variables. However, challenges in physical processes and uncertainties in the current system necessitate simpler, computationally efficient, and cost-effective approaches (6,7). Deep learning (DL) has emerged as a powerful technology for developing Digital Twins (DT), solving composite, nonlinear problems by unwrapping non-linearity in neural networks. This, particularly in computer vision, has led to efficient solutions for recognizing handwritten decodings (4,8). Advances in deep learning (DL) have been facilitated by the availability of memory-intensive hardware and open-source Python libraries, this reduced entrance barriers because they were unavailable at the time convolution neural networks were initially presented (9). Lately, several initiatives have concentrated on the weather forecasting of worldwide data fields, including temperature, wind, and geopotential height (prognostic variables), employing DL as a substrate for NWP the most difficult variable to predict, worldwide precipitation (diagnostic variables), has, nonetheless, seen very few attempts at forecasting (10,11). Furthermore, there is a lack of comparison with operational products and a depiction of the global datasets' spherical shape in the literature previously mentioned. Weyn et al. (2019) employed Deep Learning Weather Prediction (DLWP) data (12) and U-NET to estimate 500-hPa geopotential height. In a reexamination, they employed cubed spheres to convert worldwide data and forecast temperature at 850 hPa and geopotential height at 500 hPa using DLWPCS. Both methods use a temporal learning framework similar to traditional models, demonstrating U-NET's potential for NWP prediction (13). The same variables are required for model implementation. The researchers aim to create a self-sustaining model that is independent of existing NWPs, allowing recursive input and simulations similar to NWPs. They used the six faced cubed sphere projection to minimize spherical distortion, benefiting from DL and computer vision developments. The cubic sphere projection is created by transforming the global spherical dataset. A temporal mapping approach called DLWP-CS has demonstrated encouraging results for temperature and geopotential height, but it would be more computationally demanding for complicated, non-linear fields like precipitation (14). Because it depends on prognostic environmental co-variables, multivariate setups find it challenging.Precipitation precursors are accepted as input in the modified DLWP-CS (MDLWP-CS) technique, which converts the U-NET architecture from a univariate to a multi-variate spatio-temporal mapping. This modification aims to capture linkages from simple precursors for precipitation prediction while maintaining dynamical scale tele connections.

METHODOLOGY

The Deep Learning Weather Prediction (DLWP) model uses a U-NET-based deep convolutional neural network (CNN) to predict the future state of the atmosphere by learning from historical weather data. This approach, which is similar to temporal learning methods like RNN or ARIMA, focuses on forecasting geopotential height.

The model was enhanced with DLWP-CS, which applies a cubed sphere (CS) mapping to minimize distortions in global data and improve forecast stability. By transforming spherical data into a cube with six faces, DLWP-CS allows for more accurate convolution operations, leading to better weather predictions.

DLWP-CS maintains the same variables in both input and output, enabling recursive simulations similar to Numerical Weather Prediction (NWP). It has been shown to outperform the European Centre for Medium-Range Weather Forecasting's IFS42 system.

However, DLWP and DLWP-CS are computationally intensive due to their multivariate nature, especially when predicting variables like precipitation. The proposed MDLWP-CS model reduces these costs by allowing variable inputs and outputs, making it faster and more efficient for real-time weather prediction.

The Global Forecast System (GFS) operational numerical weather prediction model and linear regression are the two benchmark models used to assess the performance of the MDLWP-CS model. It compares day-1 lead projections alone. For every grid point on Earth, a linear regression model is built that uses the surface air temperature to forecast precipitation. Using hourly ERA-5 reanalysis data, MDLWP-CS and the linear regression model are trained. To evaluate the MDLWP-CS model, a preliminary test is conducted by using 2-meter surface air temperature to predict precipitation. This approach is chosen due to the physical relationship between temperature and precipitation, as well as computational and storage limitations. Early stopping, a unique CubedSphereConv2D class for variable mapping, and a unique data generator for training, validation, and testing are some of the features of the MDLWP-CS implementation. The MDLWP-CS implementation strategy is described in this section.

DATA PREPROCESSING AND COMPUTATIONAL PLATFORM:

The MDLWP-CS model uses 2-meter surface air temperature (input) and precipitation (target) data, normalized and transformed into a cubed sphere (CS) mapping. Due to hardware limitations, the CS resolution was set to 512x512, and data were split into daily files. Final preprocessing yielded a 96x96 resolution per CS face.

MODEL IMPLEMENTATION AND HYPERPARAMETERS:

Built with Keras and Dask for parallel processing, the model uses a learning rate of 1e-4, the RELU activation function, and early stopping to avoid overfitting. Training employs a mean squared error loss function over 10,000 epochs. The datasets and code are publicly available.

TRAINING, TESTING, AND COMPUTATIONAL TIME:

Training on ERA5 data (1979-2009) took 17-20 hours per epoch. Validation of data showed that global forecasts could be generated in about 2 hours for 4 years. The trained model outputs predictions much faster than traditional NWP systems, demonstrating its efficiency.

RESULTS WITH DISCUSSION

In order to compare the performance of MDLWP-CS with GFS (the operational NWP system) and linear regression at day-1 lead time, the evaluation is conducted throughout the boreal summer season (May–August, or MJJA) for the years 2014–2018. The relevant output from the GFS model was compared with the test data projections for MJJA 2014–2018. Present study compares the MDLWP-CS with the GFS projections at the day-1 lead, as explained in the methodology. When compared to ERA5, it can be noted that GFS and MDLWP-CS show comparable patterns in mean precipitation, however linear regression is unable to capture the spatial pattern. Furthermore, mean precipitation is overestimated by linear regression, particularly for land areas. The ERA5, GFS, and MDLWP-CS all clearly display the intertropical convergence zone (ITCZ), one of the key dynamic meteorological aspects. In particular, as compared to the ERA5 reanalysis, MDLWP-CS somewhat underestimates the precipitation across the tropical regions.Globally, the linear regression models exhibit high wet bias. While the general pattern of bias between MDLWPCS and GFS is similar, in tropical regions MDLWP-CS has a dry bias over the ocean. There are some noteworthy discrepancies over land; for example, MDLWP-CS shows a little dry bias over the Eastern Pacific, whereas GFS shows a wet bias over the Sahel area. Not only that, but MDLWP-CSoutperforms GFS in both North and South America.In northern India, MDLWPCS has a dry bias, but in southern India, it shows a wet bias.

For the years 2014–2018, the grid-wise temporal correlations (Pearson correlation coefficients) between the GFS, MDLWP–CS, and linear regression models and the ERA5 reanalysis daily precipitation have been calculated. GFS outperforms linear regression in terms of skill. However, generally, and particularly over land, the MDWLP-CS Pearson correlation coefficient values are significantly higher than those of the benchmark models.

It is evident that, in every location, MDWLP-CS correlation coefficient values are significantly greater than those of GFS and linear regression.The Critical Success Index (CSI) (15) and Index of Agreement (IOA) (16) are computed for different areas in order to further quantify the performance of MDWLPCS in comparison to GFS. The range of both skill ratings is 0 to 1, with 1 denoting an ideal forecast and 0 denoting no skill at all. The ratio of the total number of accurate event forecasts (hits) to the entire number of forecasts, including the number of misses (hits + false alarms + misses), is used to determine the classification skill index (CSI) for a given threshold. The number of nonevent forecasts (right rejections) has no bearing on the CSI. With regard to both criteria, MDWLP-CS has a higher CSI than GFS. Moreover, MDLWPCS outperforms GFS in terms of skill. Because of the cubic sphere transformations, MDLWP-CS may maintain the world scale teleconnections, and these connections improve the model's performance. Furthermore, when more precipitation precursors (such as lowerlevel humidity, wind, and outgoing longwave radiation) are employed, the MDLWP-CS's proficiency will increase.

Table 1: Showing Pearson correlation coefficients averaged over different land regions

Region	GFS	MDLWP-CS	LR
North Asia	.26	.66	.20
Europe	.30	.65	.06
United states	.23	.63	.1
Central Asia	.25	.54	.15
South Asia	.34	.63	.16

Table 2: Showing critical success index (for a threshold 0.5mm/day averaged over the land regions)

Region	GFS	MDLWP-CS
North Asia	.54	.53
Europe	.49	.48
United states	.51	.50
Central Asia	.46	.48
South Asia	.50	.50

Table 3: Showing critical success index (for a threshold 3mm/day averaged over the land regions)

Region	GFS	MDLWP-CS
North Asia	.26	.24
Europe	.38	.39
United states	.29	.36
Central Asia	.43	.46
South Asia	.48	.49

Table 4: Showing index of agreement

Region	GFS	MDLWP-CS
North Asia	.76	.83
Europe	.82	.72
United states	.81	.85
Central Asia	.80	.66
South Asia	.92	.95

CONCLUSION

Recent efforts have aimed at using deep learning (DL) for weather prediction, specifically for simulating global weather fields as an alternative to traditional numerical weather prediction (NWP). However, predicting global precipitation with DL has been challenging. Building on previous work by Weyn et al. (2019, 2020), this study advances a DL framework by modifying it to incorporate spatio-temporal mapping, allowing it to use precipitation precursors as inputs. The study demonstrates that using 2-meter surface air temperature to predict precipitation with the new model, MDLWP-CS, yields better results compared to linear regression and the operational GFS model. This research provides a foundation for using DL in multi-scale precipitation forecasting and suggests future studies will focus on improving predictions for high-impact rainfall events.

The MDLWP-CS model outperforms linear regression and operational NWP systems in predicting daily precipitation, particularly over land regions relative to oceans. Its performance is attributed to its use of a single input, 2 m surface air temperature, with precipitation as the target, highlighting the importance of surface air temperature in precipitation prediction.

REFERENCES

1. Baker, N., Alexander, F., Bremer, T., Hagberg, A., Kevrekidis, Y., Najm, H., ... & Lee, S. (2019). *Workshop report on basic research needs for scientific machine learning: Core technologies for artificial intelligence*. USDOE Office of Science (SC), Washington, DC (United States).
2. Singh, M., Kumar, B., Rao, S., Gill, S. S., Chattopadhyay, R., Nanjundiah, R. S., & Niyogi, D. (2021). Deep learning for improved global precipitation in numerical weather prediction systems. *arXiv preprint arXiv:2106.12045*.
3. Maher, P., Vallis, G. K., Sherwood, S. C., Webb, M. J., & Sansom, P. G. (2018). The impact of parameterized convection on climatological precipitation in atmospheric global climate models. *Geophysical Research Letters*, *45*(8), 3728-3736.
4. Yano JI, Ziemiański MZ, Cullen M, Termonia P, Onvlee J, Bengtsson L, Carrassi A, Davy R, Deluca A, Gray SL, Homar V. Scientific challenges of convective-scale numerical weather prediction. Bulletin of the American Meteorological Society. 2018 Apr 1;99(4):699-710.
5. Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I 13* (pp. 818-833). Springer International Publishing.
6. Scher, S., & Messori, G. (2019). Weather and climate forecasting with neural networks: using general circulation models (GCMs) with different complexity as a study ground. *Geoscientific Model Development*, *12*(7), 2797-2809.
7. Weyn, J. A., Durran, D. R., & Caruana, R. (2019). Can machines learn to predict

weather? Using deep learning to predict gridded 500-hPa geopotential height from historical weather data. *Journal of Advances in Modeling Earth Systems*, *11*(8), 2680-2693.

8. Weyn JA, Durran DR, Caruana R. Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. Journal of Advances in Modeling Earth Systems. 2020 Sep;12(9):e2020MS002109.
9. Mesinger, F. (2008). Bias adjusted precipitation threat scores. *Advances in Geosciences*, *16*, 137-142.
10. Willmott, C. J. (1982). Some comments on the evaluation of model performance. *Bulletin of the American Meteorological Society*, *63*(11), 1309-1313.
11. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195-204.
12. Xu, L., Chen, N., Chen, Z., Zhang, C., & Yu, H. (2021). Spatiotemporal forecasting in earth system science: Methods, uncertainties, predictability and future directions. *Earth-Science Reviews*, *222*, 103828.
13. Fu, M., Fan, T., Ding, Z. A., Salih, S. Q., Al-Ansari, N., & Yaseen, Z. M. (2020). Deep learning data-intelligence model based on adjusted forecasting window scale: application in daily streamflow simulation. *Ieee Access*, *8*, 32632-32651.
14. Wang, B., Lu, J., Yan, Z., Luo, H., Li, T., Zheng, Y., & Zhang, G. (2019, July). Deep uncertainty quantification: A machine learning approach for weather forecasting. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 2087-2095).
15. Chen, R., Zhang, W., & Wang, X. (2020). Machine learning in tropical cyclone forecast modeling: A review. *Atmosphere*, *11*(7), 676.
16. Alkhayat, G., & Mehmood, R. (2021). A review and taxonomy of wind and solar energy forecasting methods based on deep learning. *Energy and AI*, *4*, 100060.