Eighth WMO International Workshop on Monsoons (IWM-8)

Poster Session-3: Simulation and Prediction of Monsoons, including Extremes

Hybrid Post-Processing of NCEP GEFSv12 Reforecasts for Extreme Rainfall Events over India

Murali Nageswara Rao Malasala[1], and Vijay Tallapragada[2]

[1]CPAESS, University Corporation for Atmospheric Research at NOAA/NWS/NCEP/EMC, College Park, MD

[2]NOAA/NWS/NCEP/EMC, College Park, MD

Corresponding Author: Murali Nageswara Rao Malasala (murali.n.malasala@noaa.gov & murali@ucar.edu)

1. Background and Motivation

- Human-induced warming (~0.85°C) has increased atmospheric water vapor by 7% per 1°C, intensifying extreme rainfall events (ER) without altering total rainfall amounts, particularly in South Asia, causing floods, infrastructure damage, and loss of life.
- In India, ER events during the Indian Summer Monsoon, often driven by Bay of Bengal depressions, are increasing, causing ~$3 billion annually (10% of global losses), highlighting the need for better prediction and disaster preparedness for sustainable development.
- Advances in numerical modeling have improved extra-tropical forecasts; however, prediction skill remains limited in tropical and monsoon regions, making extended-range forecasts a major challenge. NOAA NCEP's GEFSv12 (2020) provides sub-seasonal reforecast data (2000–2019) with 5 ensemble members (16 days) and 11 members (35 days weekly).
- Despite these advancements, raw GEFSv12 outputs often lack precision in predicting extreme rainfall (ER) events, particularly on sub-seasonal time scales. To improve forecast accuracy and usability, advanced statistical post-processing techniques are essential.
- This study introduces a Hybrid method combining Artificial Neural Networks (ANN) deep learning with Quantile-Quantile (QQ) techniques to enhance sub-seasonal predictions of rainfall extremes using GEFSv12 raw data.
- The proposed Hybrid method is evaluated against standalone QQ and ANN techniques over India. It aims to improve the accuracy of sub-seasonal (Week-1, 2, 3 to 4 and monthly scale) forecasts, particularly for ER events in India, enabling better risk management, disaster preparedness, and decision-making in the face of increasing climate variability.

2. Data and Methodology Used

2.1 Data Used:

Model	: GEFSv12 (Zhou et al. 2022; Nageswararao et al.2022)
Period used	: 2000-2019
Horizontal Resolution	: 0.25° X 0.25° for Day-1 to 10 and 0.5° X 0.5° for Day-11 to 35
Members used	: 11 members (c00, p01, p02, p03, p04, p05, p06, p07, p08, p09 and p10) based on every Wednesday 00 UTC initial conditions for the forecast lead time Day-1 to Day-35.
Reference data sets	: India Meteorological Department (IMD) high Resolution (0.25° X 0.25°) grided observational Rainfall dataset (Pai et al. 2014).
Various Rainfall categories Detection Criteria	: As defined by IMD (Nageswararao et al. 2019).

2.2 Rainfall event's categories Classified:

Table 1 Rainfall categories defined by India Meteorological Department.

Rainfall category (short form)	Range of rainfall per day
Wet days (Wet)	Wet > 2.5 mm
Very light rain (VLR)	0.1 < VLR ≤ 2.4 mm
Light rain (LR)	2.5 mm ≤ LR < 7.5 mm
Moderate rain (MR)	7.6 mm ≤ MR < 35.5 mm
Rather heavy rain (RHR)	35.6 mm ≤ RHR < 64.4 mm
Heavy rain (HR)	64.5 mm ≤ HR < 124.4 mm
Very heavy rain (VHR)	124.5 mm ≤ VHR < 244.4 mm
Extremely heavy rain (EHR)	EHR > 244.5 mm

2.3 Artificial Neural Network (ANN):

Artificial Neural Networks (ANNs) are powerful tools for modeling complex, nonlinear relationships in high-dimensional datasets. This study employs a Feedforward Neural Network (FNN) architecture with 3 hidden layers, each consisting of 19 neurons. The first and second hidden layer utilizes the ReLU activation function, while the third layer employs sigmoid. GEFSv12 outputs, comprising 11 ensemble members, are used as model inputs. The dataset is randomly split into 70% for training and 30% for validation, following a leave-one-out cross-validation approach. Each prediction is performed independently to ensure robustness and accuracy. The method is developed independently for each lead time and grid point. A brief details of the ANN architecture is provided below:

Table 2: The following factors are considered to develop a simple ANN model to improve the GEFSv12 prediction skill in predicting JJAS rainfall and Associated ER Events over India.

No. Hidden layers:	3
No. of neurons in the hidden layers	[19,19,19]
Neural Network used	Feedforward network
Activation Functions in Neural Networks	Hidden layer 1: ReLU Hidden layer 2: ReLU Hidden layer 3: Sigmoid
Data divided function	70% data for training and 30% data for validation in random way after withheld prediction time step (Leave-one-out cross validation way)
Learning rate	0.001
Max number of epochs used	1000
Error tolerance for stopping	1e-14
Training function used	Supervised weight/bias training function with Sequential order weight/bias training (trains)
Neural Network Performance Functions used	Mean squared error performance function

The Hybrid Post-processing Method (ANN-QQ) applies the Quantile-Quantile (QQ) method to ANN outputs for improved rainfall extreme predictions. Its performance is evaluated against IMD-OBS by comparing Hybrid, Raw, QQ, and ANN methods using statistical metrics (Mean Bias, RMSE, Correlation Coefficient, Index of Agreement), categorical skill scores (ACC, Frequency Bias, POD, FAR, SR, TS, ETS), and ensemble probabilistic skill scores (BS, BSS, Reliability, RPS, RPSS, CRPS, CRPSS) for both deterministic and ensemble probabilistic forecasts.

3. Performance of Hybrid method for JJAS Mean Rainfall and its variability on Week-1, 2, 3 to 4 and Monthly Scales over India

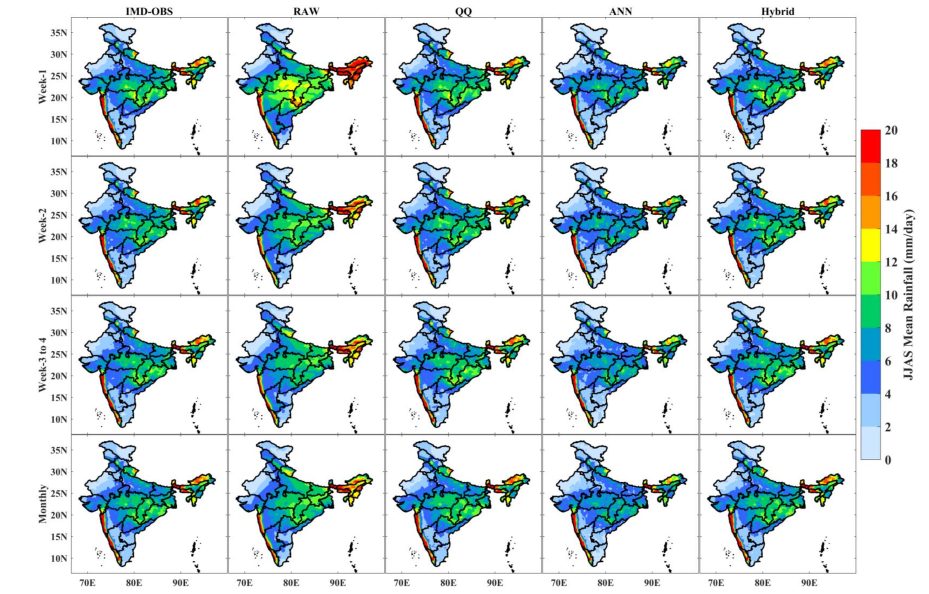

Fig. 1: Spatial distribution of JJAS mean rainfall (mm/day) over India from IMD-OBS, Raw, QQ, ANN, and Hybrid methods (Columns 1 to 5, respectively) across Week-1, 2, 3 to 4, and Monthly scales (Rows 1 to 4, respectively) for the reforecast period (2000–2019).

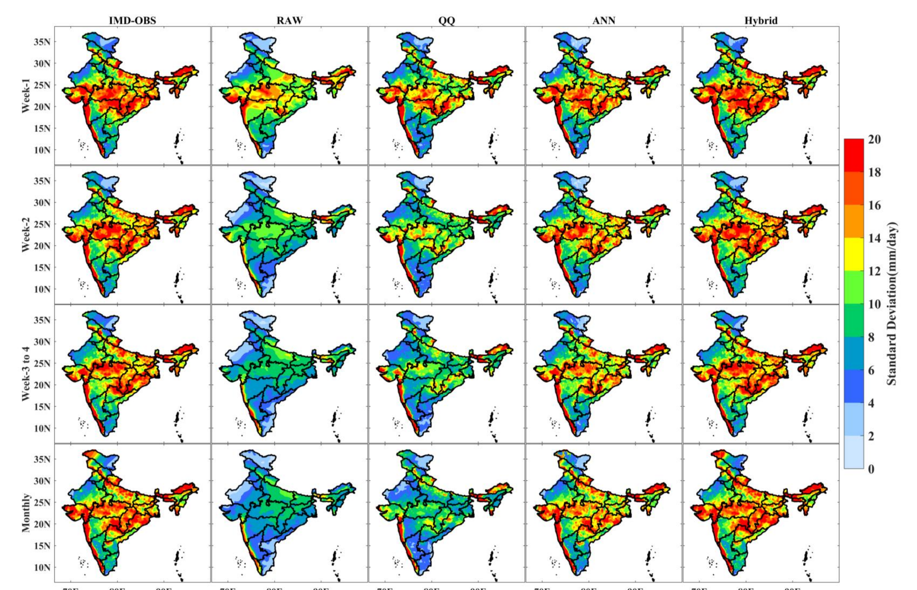

Fig. 2: Spatial distribution of Interannual variability of JJAS rainfall (mm/day) over India from IMD-OBS, Raw, QQ, ANN, and Hybrid methods (Columns 1 to 5, respectively) across Week-1, 2, 3 to 4, and Monthly scales (Rows 1 to 4, respectively) for the reforecast period (2000–2019).

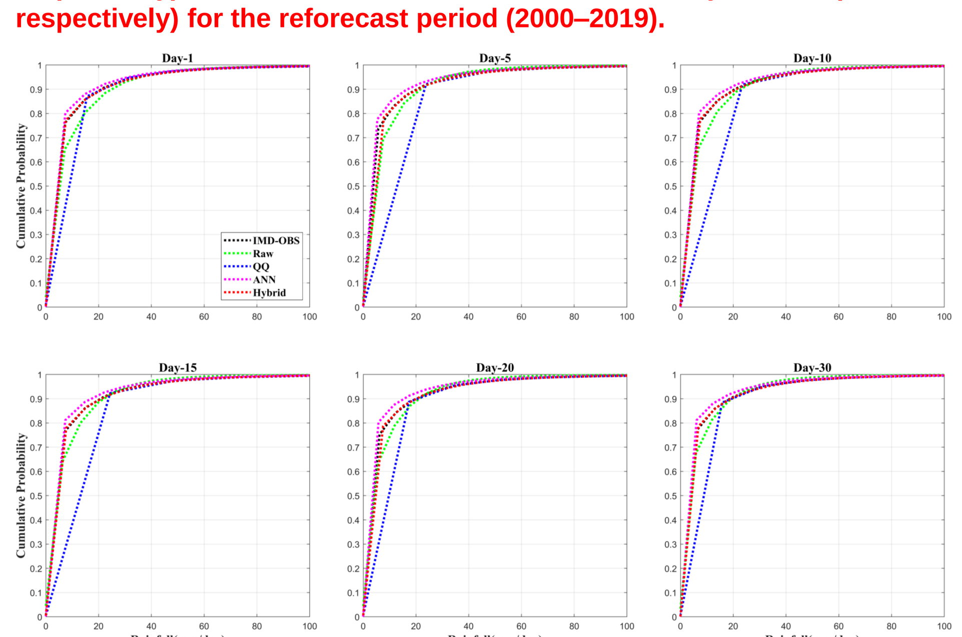

Fig. 3: CDF of JJAS 24-hour accumulated precipitation for day-1, day-5, day-10, day-15, day-20, and day-30 from IMD-OBS (black dotted lines), Raw (green dotted lines), QQ (blue dotted lines), ANN (magenta dotted lines), and Hybrid (red dotted lines) forecasts over India for the period 2000–2019.

4. Statistical skill scores of the Hybrid method for JJAS rainfall prediction

4.1. Statistical skill scores of the Hybrid method with lead times Day-1 to 35

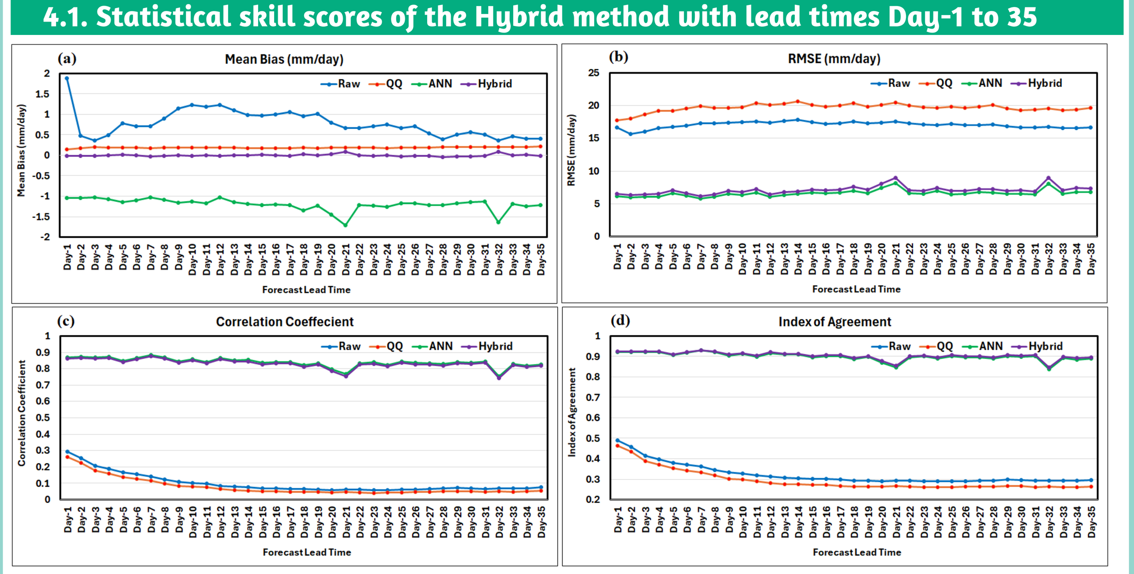

Fig. 4: Statistical skill scores of Raw, QQ, ANN, and Hybrid methods against IMD-OBS for predicting JJAS daily rainfall over India (a) Mean Bias (mm/day), (b) RMSE (mm/day), (c) Correlation Coefficient, and (d) Index of Agreement for the reforecast period 2000-2019.

4. 2. Statistical skill scores of the Hybrid method with lead times Week-1, 2, 3 to 4 and Monthly scales.

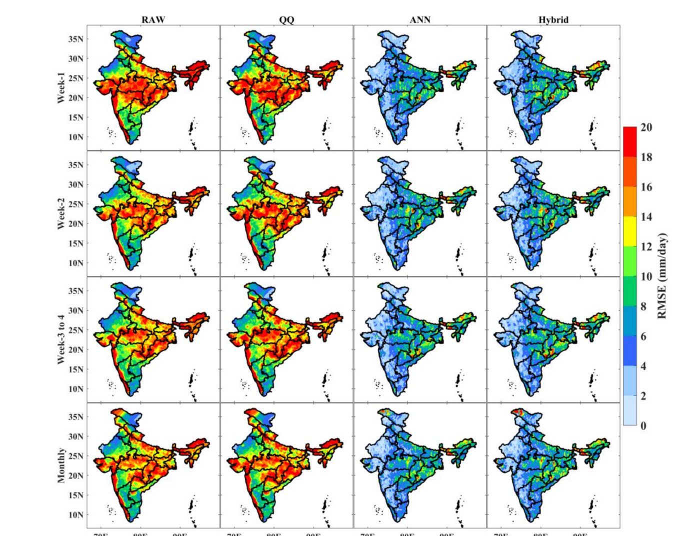

Fig. 5: RMSE of Raw, QQ, ANN, and Hybrid methods (Columns 1 to 4) against IMD-OBS for predicting JJAS rainfall (mm/day) across Week-1, 2, 3 to 4, and Monthly scales (Rows 1 to 4) over India for the period 2000–2019.

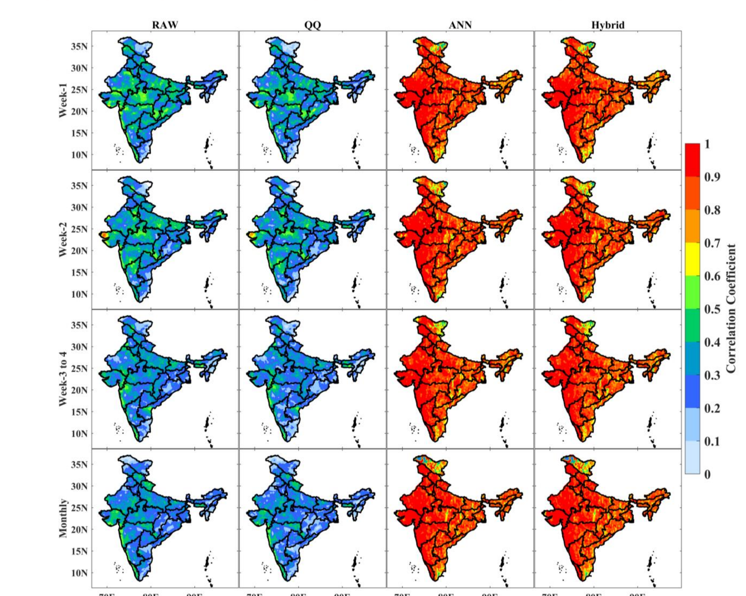

Fig. 6: Correlation Coefficient of Raw, QQ, ANN, and Hybrid methods (Columns 1 to 4) against IMD-OBS for predicting JJAS rainfall (mm/day) across Week-1, 2, 3 to 4, and Monthly scales (Rows 1 to 4) over India for the period 2000–2019.

5. Statistical Categorical skill scores of the Hybrid method for detecting light (VLR-LR), moderate (MR-RHR), and extreme (HR-HER) rainfall events across lead times of Week-1, 2, 3 to 4, and Monthly scales

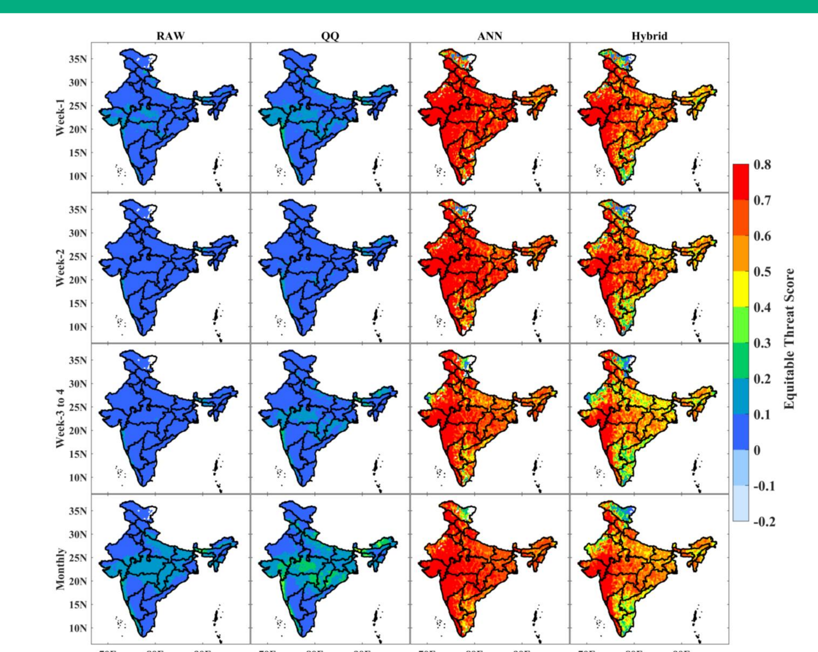

Fig. 7: Equitable Threat Score (ETS) of Raw, QQ, ANN, and Hybrid methods (Columns 1 to 4) against IMD-OBS in detecting Extreme Rainfall Events (HR to EHR) across Week-1, 2, 3 to 4, and Monthly scales (Rows 1 to 4) over India for the period 2000–2019.

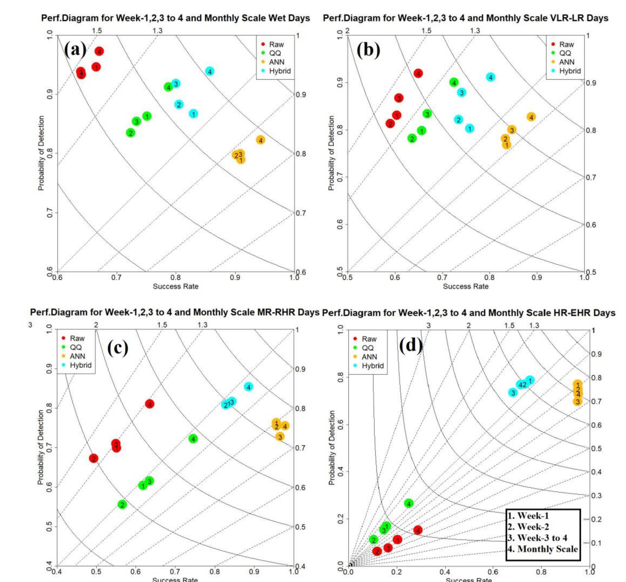

Fig.8: Performance Diagram of Hybrid method in depicting JJAS Wet, light, Moderate and Extreme rainfall days on Week-1, 2, 3 to 4, and Monthly Scale in comparison with Raw, QQ, and ANN for the Reforecast period 2000-2019.

6. Ensemble Probabilistic Skill scores of Hybrid Method in detecting various categorical JJAS rainfall Events over India

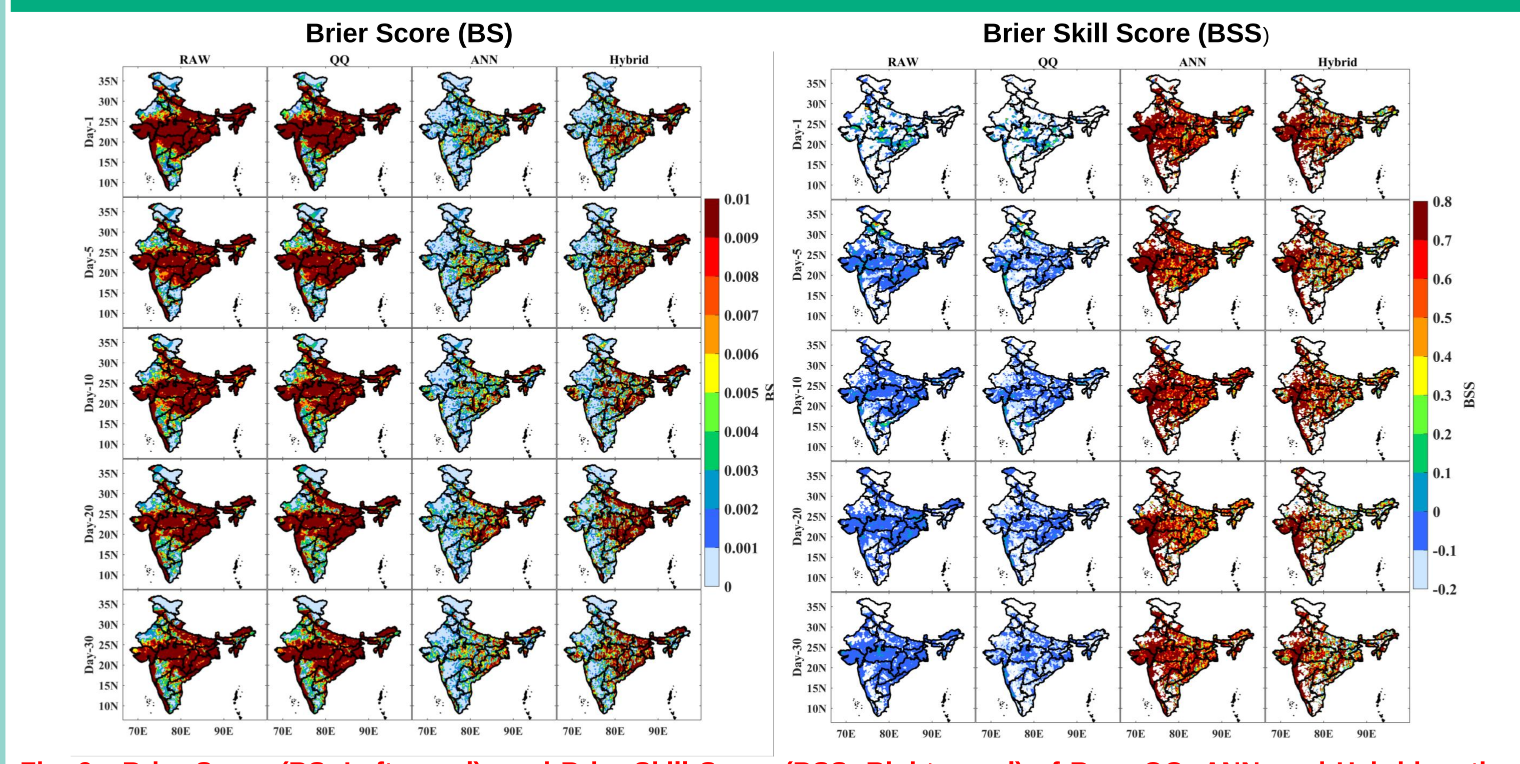

Fig. 9: Brier Score (BS, Left panel) and Brier Skill Score (BSS, Right panel) of Raw, QQ, ANN, and Hybrid methods (Columns 1 to 4) against IMD-OBS in detecting Extreme Rainfall Events (HR to EHR) with different lead time forecasts Day-1, 5, 10, 15, 20 and 30 (Rows 1 to 5) over India for the reforecast period 2000-2019..

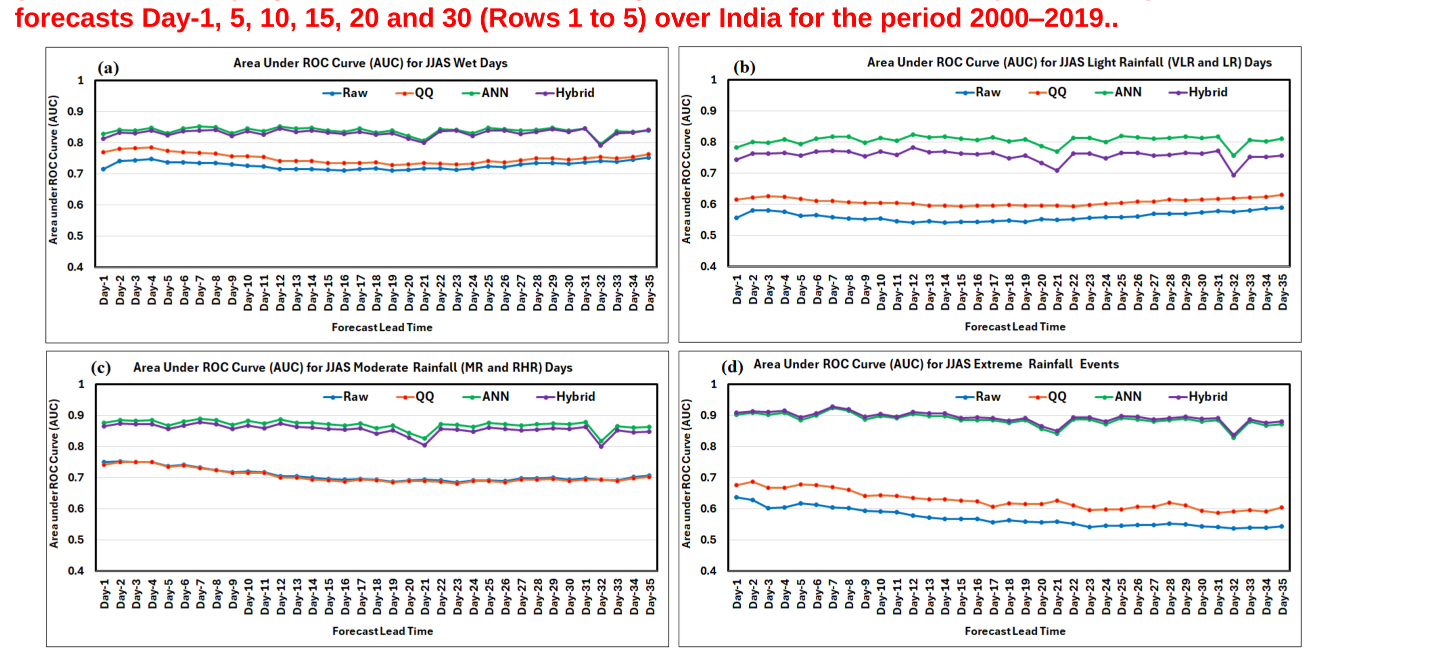

Fig. 10: Area Under ROC Curve (AUC) of Raw, QQ, ANN, and Hybrid methods against IMD-OBS for JJAS Wet, Light (VLR to LR) Moderate (MR to RHR) and Extreme (HR to EHR) Rainfall days over India with forecast lead time Day-1 to 35 for the reforecast period 2000-2019.

7. Summary & Conclusions

- The Hybrid method improves spatial representation of JJAS mean rainfall over India across all forecast lead times, closely aligning with IMD-OBS observations. It reduces wet biases and enhances rainfall intensity forecasts, particularly over the Western Ghats, northeast India, and central regions, demonstrating its effectiveness in improve the sub-seasonal prediction skill.
- The Hybrid method provides a more accurate representation of JJAS rainfall interannual variability over India than Raw, QQ, and ANN methods, particularly in high-variability regions like the Western Ghats, northeast, and central India. It reduces underestimation of variability, which is notably present in the Raw model and worsens with lead time, offering improved performance across all forecast lead times.
- The Hybrid method closely matches IMD-OBS CDFs of JJAS 24-hour rainfall across all lead times (day-1 to day-35), improving consistency in capturing light and extreme events. It reduces biases in the distribution tails, especially for high rainfall, demonstrating robustness in probabilistic rainfall forecasting over India (2000–2019).
- The Hybrid and ANN methods outperform Raw and QQ for JJAS daily rainfall prediction over India (2000–2019), with the Hybrid method showing the lowest bias and RMSE, highest correlation, and strongest spatial agreement with IMD-OBS across all lead times. While ANN also improves predictions, it exhibits a slight dry bias, whereas the Hybrid method effectively reduces prediction errors, especially in high rainfall regions, demonstrating superior capability in capturing spatial and temporal rainfall variability for sub-seasonal forecasts.
- The ANN method shows slightly better Equitable Threat Score (ETS) than the Hybrid method in detecting extreme rainfall events across all lead times (Week-1 to Monthly) over central, western, and northeastern India, with both methods outperforming Raw and QQ. However, performance diagrams reveal that the Hybrid method consistently outperforms ANN in detecting wet, light, moderate, and extreme rainfall days by maintaining a better balance between probability of detection and success rate, while ANN tends to underestimate rainfall events, highlighting the Hybrid method's superior accuracy across various rainfall intensities.
- Both ANN and Hybrid methods outperform Raw and QQ in probabilistic forecasting of JJAS rainfall intensities (wet, light, moderate, extreme) across all lead times (Day-1 to 35) with better performance than the reference climatological forecast (AUC > 0.5). ANN shows slightly better Brier Scores and Brier Skill Scores, particularly for moderate rainfall, while the Hybrid method is more robust at longer lead times and for extreme events. Both methods significantly improve extreme rainfall forecasting, essential for flood management and disaster preparedness.
- Therefore, the Hybrid method demonstrates strong potential for improving sub-seasonal JJAS precipitation forecasts and associated rainfall extremes over the Indian region. This method will be applied to NOAA NCEP UFS-GEFSv13 outputs over India and expanded to other seasons to further investigate its significance and enhance its applicability

Acknowledgments

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