Enhancing the prediction skill of monsoon intraseasonal oscillations: a deep learning approach

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Introduction

The Indian Summer Monsoon (ISM) is a critical climate phenomenon that sustains agriculture and water resources in South Asia. A key feature of the ISM is the Monsoon Intraseasonal Oscillation (MISO), a 30–60 day oscillation that drives active and break phases of rainfall, significantly influencing sub-seasonal rainfall variability. Predicting MISO is essential for improving sub-seasonal to seasonal (S2S) forecasts, which are vital for agriculture, water management, and disaster preparedness. However, traditional numerical weather prediction (NWP) models struggle to accurately forecast MISO due to its complex, nonlinear dynamics. Recent advances in deep learning, particularly Transformer models, offer a promising alternative. Transformers, known for their ability to capture long-range dependencies and complex spatiotemporal patterns, have shown success in time series forecasting and atmospheric science applications. This study explores the use of a Transformer-based model to predict MISO indices, amplitude, and phase, aiming to enhance S2S forecasting accuracy with reduced computational costs compared to traditional NWP models.

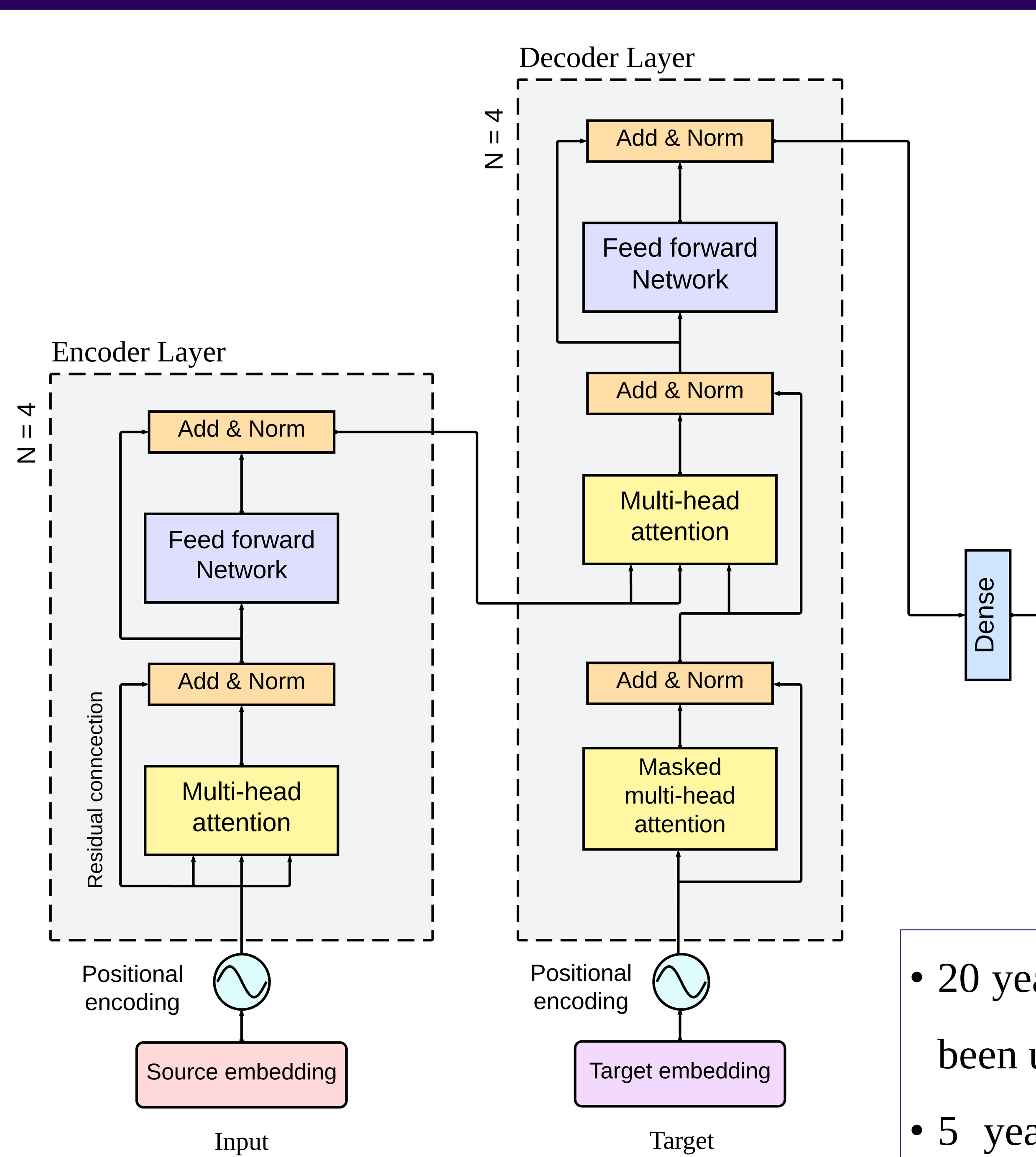
Data and Methodology

Precipitation Data: Daily precipitation data from the Tropical Rainfall Measuring Mission (TRMM) 3B42 V7 (1998–2019) and the Global Precipitation Measurement (GPM) mission 3B-DAY-Early run V6 (2020–2022) were used. GPM data, with a higher resolution (0.10° × 0.10°), was upscaled to match TRMM's resolution (0.25° × 0.25°) using linear interpolation.

Seasonal Forecasts: Seasonal forecasts from the Copernicus Climate Change Service (C3S) were used for comparison. These include forecasts from the UK Met Office (UKMO) Unified Model (UM) (2018–2022) and the NCEP Climate Forecast System (CFS) (2020–2022). Ensemble mean forecasts from NCEP CFSv2 (1° × 1° resolution) were also used to compare spatial rainfall patterns.

MISO indices: Extended Empirical Orthogonal Function (EEOF) analysis was applied to longitudinally averaged (60.5°E–95.5°E) unfiltered rainfall anomalies for the June-July-August-September (JJAS) season (1998–2022). Anomalies were calculated by removing daily climatological values. MISO1 and MISO2 indices were derived by projecting the past 15 days of data onto the first two EEOF modes (Suhas et al., 2012). These indices capture the dominant modes of intraseasonal variability, forming a time series of over 9,000 data points.

Model Architecture

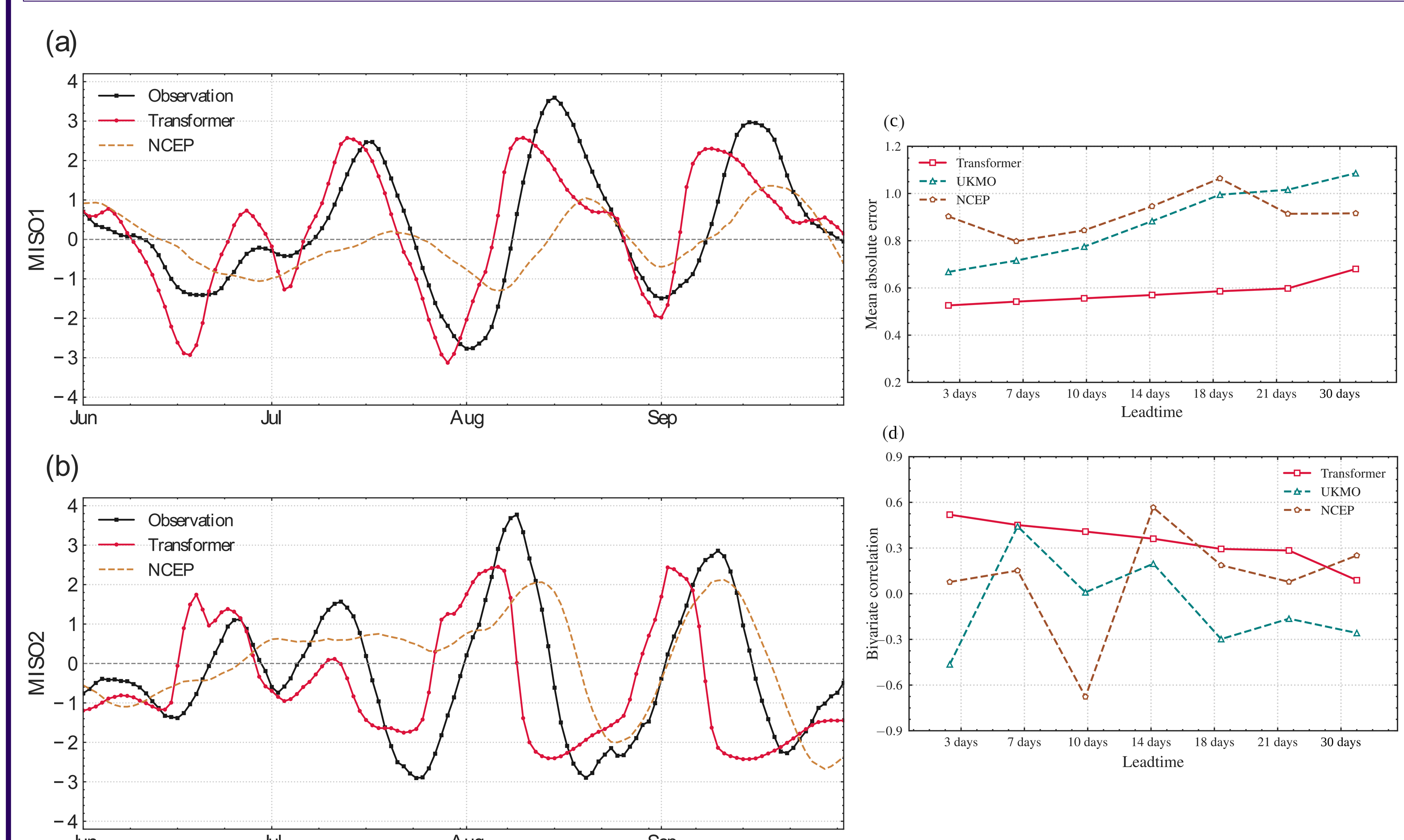


- Optimizer : AdamW
- Learning rate : 0.0001
- Loss function : MSE loss
- No. Of epochs : 75
- D model: 120
- No. of head : 8
- No. layers: 4

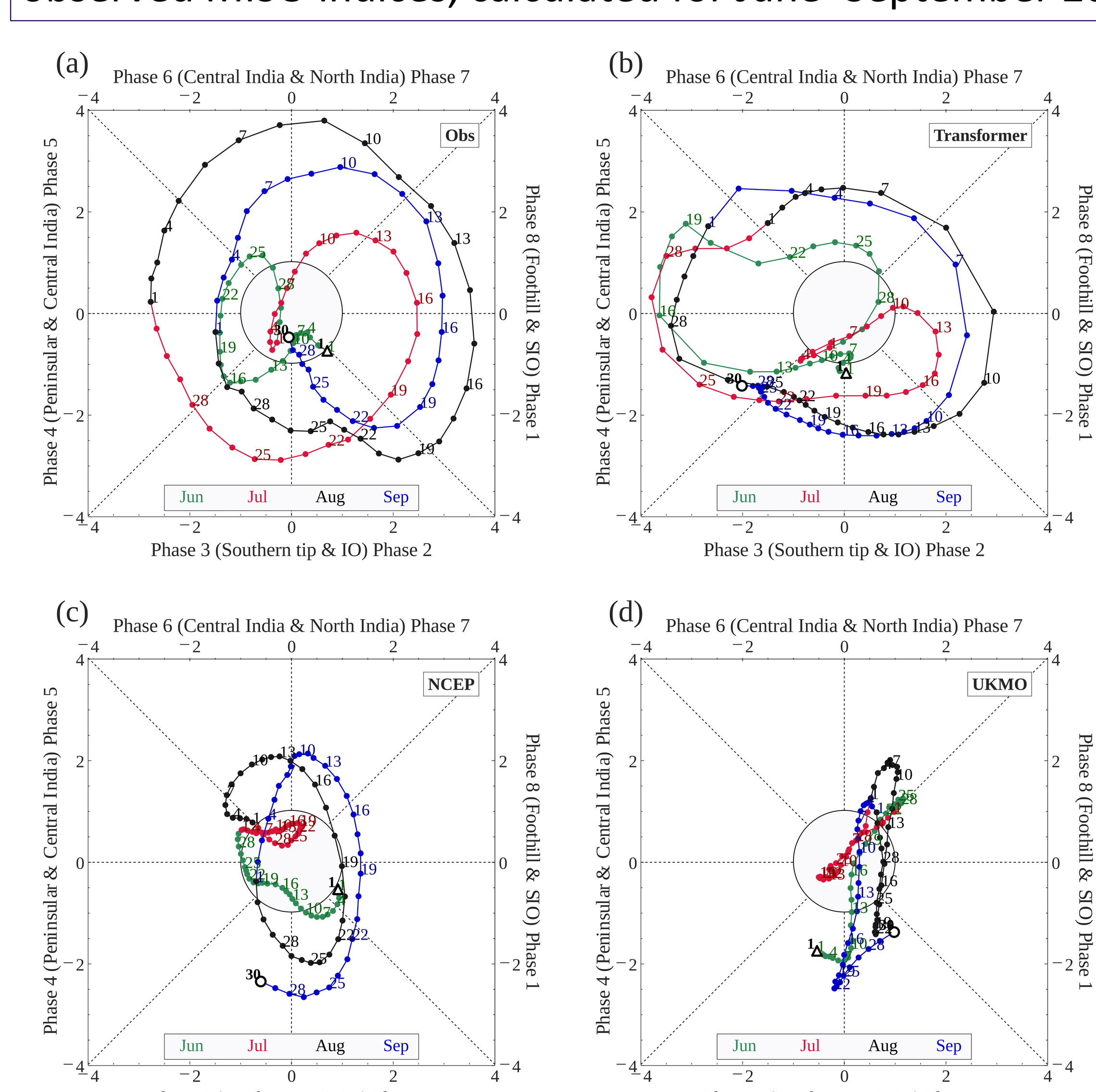
- 20 years(1998-2017) of data have been used for training.
- 5 years(2018-2022) of data for testing

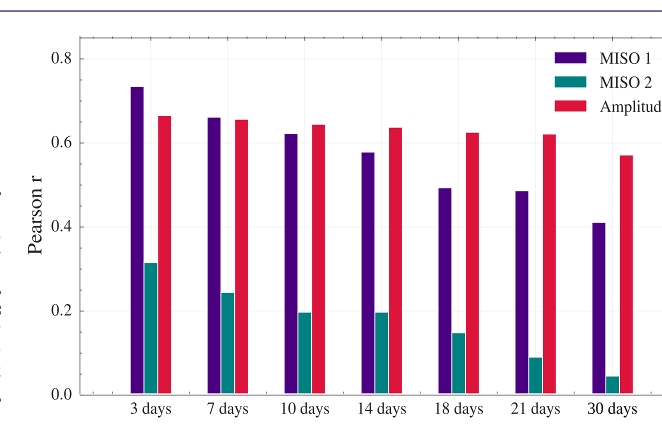
Predicting daily MISO indices

The model demonstrated skillful predictions of MISO indices for 2018–2022, with forecast lead times extending to 18 days, consistently outperforming traditional NWP models like UKMO and NCEP. It exhibited minimal error growth in MISO amplitude predictions, with mean absolute error (MAE) increasing slowly as lead time extended, unlike NWP models, which showed rapid error growth beyond 7 days. The Transformer maintained significantly lower MAE values at all lead times and achieved higher correlation with observed MISO indices, even at 21 days, while NWP models often struggled with inconsistent or negative correlations.



Time series of (a) MISO1 and (b) MISO2 indices predicted by the Transformer (14-day lead) and NCEP CFS V2, compared to observed GPM precipitation for the 2022 monsoon season. (c) MAE in MISO amplitude and (d) bivariate correlation coefficient for predicted vs. observed MISO indices, calculated for June–September 2018–2022 (2020–2022 for NCEP).





Observed and 14-day ahead predicted MISO phase space diagrams for 2022: (a) Observation, (b) Transformer, (c) NCEP, and (d) UKMO. (e) Pearson correlation coefficient for MISO indices and amplitude as a function of lead time for the Transformer model, calculated for June–September 2018–2022 using TRMM+GPM rainfall data.

Conclusions

This study develops a deep learning-based Transformer model to predict MISO indices derived from EEOF analysis of high-resolution precipitation data, capturing MISO amplitude and phase. The model achieves skillful phase prediction up to 21 days and amplitude prediction up to 14 days, enabling accurate monsoon active/break cycle forecasts three weeks ahead. This capability is crucial for sub-seasonal to seasonal (S2S) planning in agriculture and disaster preparedness. Compared to NWP models, the Transformer demonstrates superior skill in MISO prediction, offering reliable S2S forecasts with significantly lower computational resources. The study also used a modified Vision Transformer to predict the spatiotemporal evolution of MISO, generating spatial patterns of daily precipitation anomalies. While the model excelled in predicting MISO indices, accurately capturing the spatiotemporal evolution of rainfall remains a challenge and requires further refinement.