Supplement of Geosci. Model Dev., 19, 4817–4833, 2026
https://doi.org/10.5194/gmd-19-4817-2026-supplement
© Author(s) 2026. CC BY 4.0 License.

Geoscientific
Model Development
Open Access

Supplement of

Why does the signal-to-noise paradox exist in seasonal climate predictability?

Shivamurthy Yashas et al.

Correspondence to: Subodh Kumar Saha (subodh@tropmet.res.in)

The copyright of individual parts of the supplement might differ from the article licence.

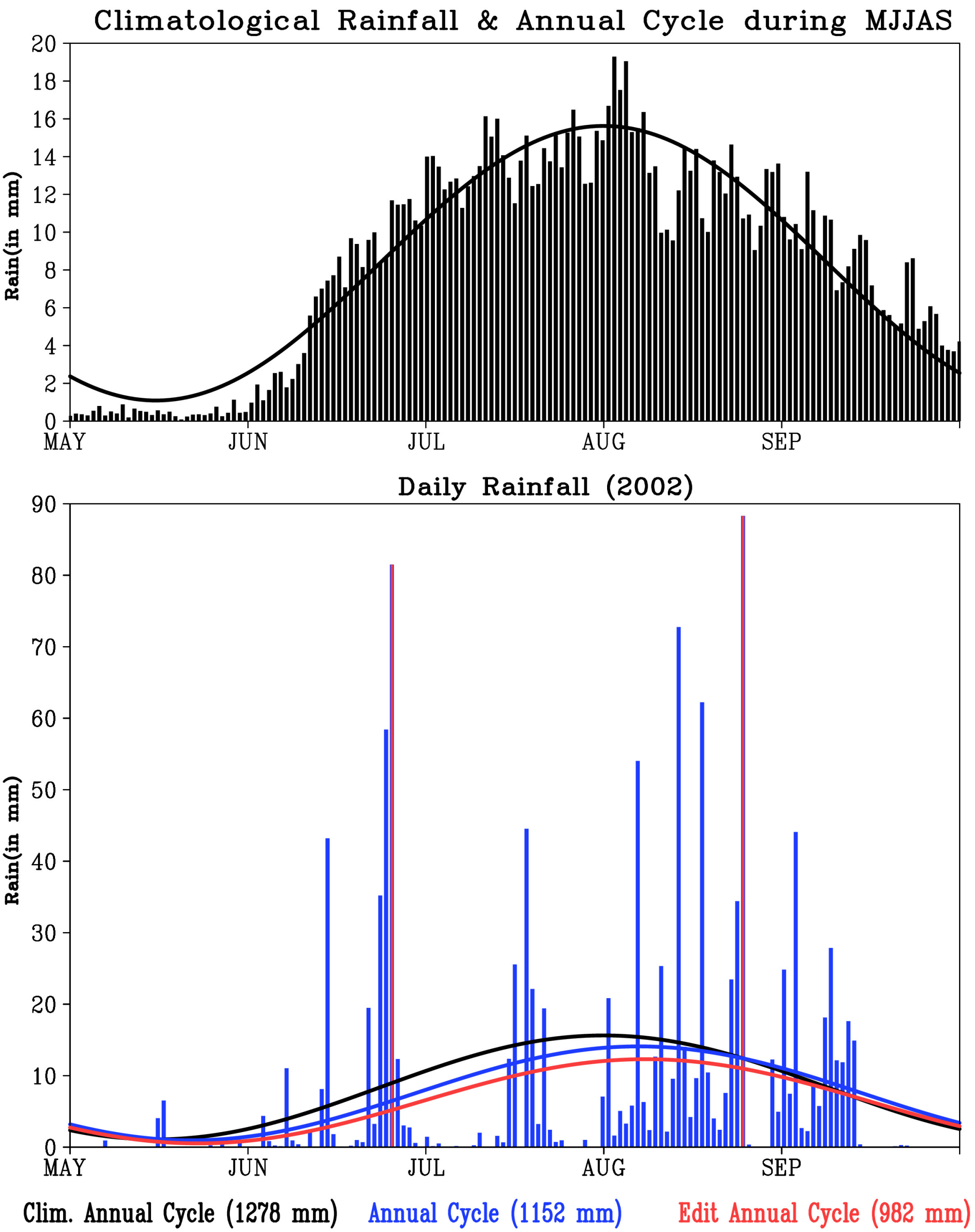
Supplement

Unlike variables such as temperature or surface pressure, which vary smoothly in time, rainfall is inherently discrete and typically occurs in pulses (rain or no-rain) concentrated within preferred time bands (i.e., sub-seasonal bands). Furthermore, the amplitude of these events is often much larger than that of the annual cycle. As a result, variations in sub-seasonal rainfall can significantly modify the annual cycle or seasonal anomaly.

To illustrate this, here we use daily $1^\circ \times 1^\circ$ IMD rainfall over a grid point in central India (20°N, 80° E), a homogeneous monsoon region. The amplitude of the climatological mean annual cycle (1901–2018) is about 20 mm/day (Figure S1, upper panel). The daily rainfall and corresponding annual cycle for a particular year (here, 2002; Figure S1, lower panel) show strong temporal fluctuations with large amplitudes (blue). The smooth annual cycle is reconstructed using the mean and the first three harmonics. The difference between the climatological mean annual cycle (black curve) and the annual cycle for 2002 represents the seasonal summer monsoon rainfall anomaly (a deficit monsoon year).

To demonstrate how rainfall event of just one or two days could influence the annual cycle and seasonal anomaly, two-day rainfall event (>80 mm/day; red bar in Figure S1, lower panel) are removed, assuming it arises from sub-seasonal variability. The reconstructed annual cycle, without these two days rainfall becomes visibly weaker (red curve). The resulting change in seasonal mean rainfall amounts to about 59% of the interannual standard deviation. We also note that only two 1-day rainfall events are removed here; if a complete event is removed, as happens, the impact on the seasonal anomaly would be substantially larger. This highlights why sub-seasonal components are often termed the “building blocks” of the monsoon.

Because rainfall is a discrete phenomenon, it does not possess true, physically persistent modes. Thus, global predictors influence monsoon rainfall primarily by modulating the sub-seasonal components either through their strength, their duration, or both. The “persistent modes” that emerge from various data-analysis techniques are projections or statistical composites of these sub-seasonal rainfall components. The variance of sub-seasonal components in a season represents its energy or vigour, which also, in principle, should be linked with seasonal rainfall anomaly (i.e. last term in equation 12). A strong correlation of all India seasonal rainfall (i.e. ISMR) anomaly with variance of individual sub-seasonal components (Figure S2) support our arguments that sub-seasonal components are key to generating seasonal anomaly.


Climatological Rainfall & Annual Cycle during MJJAS

Daily Rainfall (2002)

Figure S1. Climatological mean daily rainfall (black solid bar) and smooth annual cycle (black line) over an area in the homogeneous central India region are shown in the upper panel. The lower panel shows rainfall of a particular year (here 2002) with smooth annual cycle (blue line), smooth annual cycle after removing two days of rainfall events (red line) and climatological mean smooth annual cycle (black line).

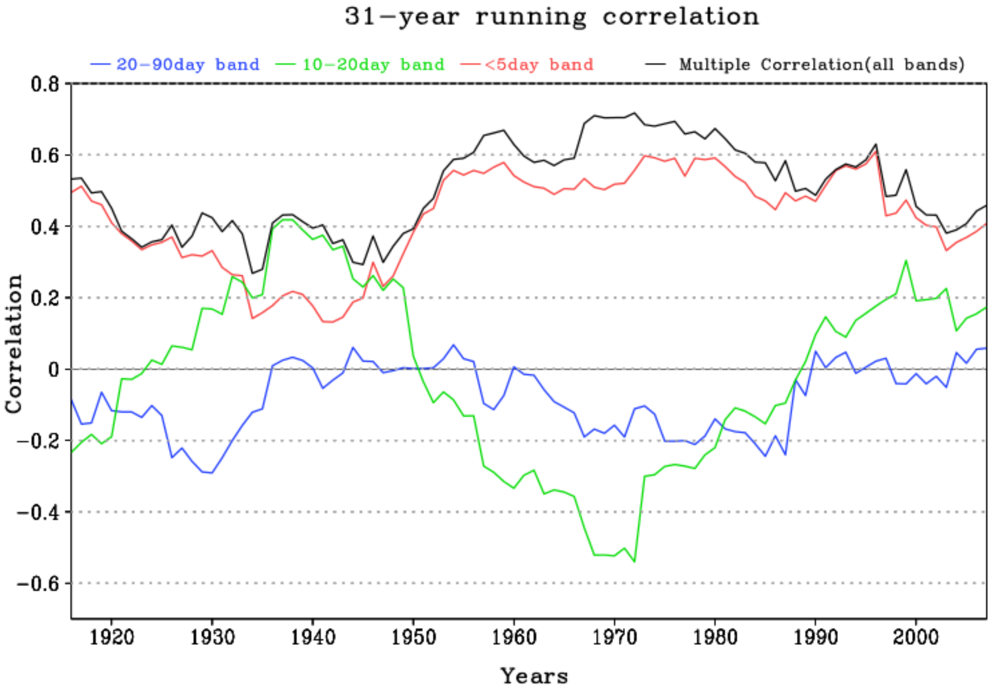


Figure S2. Linking sub-seasonal components of ISMR with its seasonal anomaly. Moving window correlation (31-years) between I and V_f (20-90 days, 10-20 days, <5 days band) and multiple correlation. Correlations > 0.35 (< -0.35) are significant at 95% level.

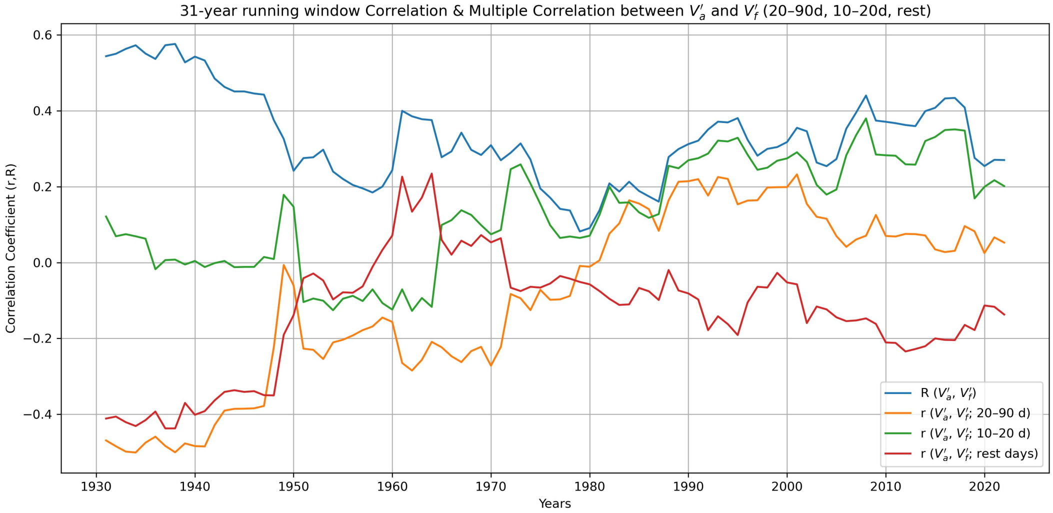


Figure S3. Linking sub-seasonal components of ISMR with anomalous annual cycle (i.e. seasonal anomaly) in terms of their variances. Moving window correlation (31-years) between V_a and V_f (20-90 days, 10-20 days, <10 days band) and multiple correlation.

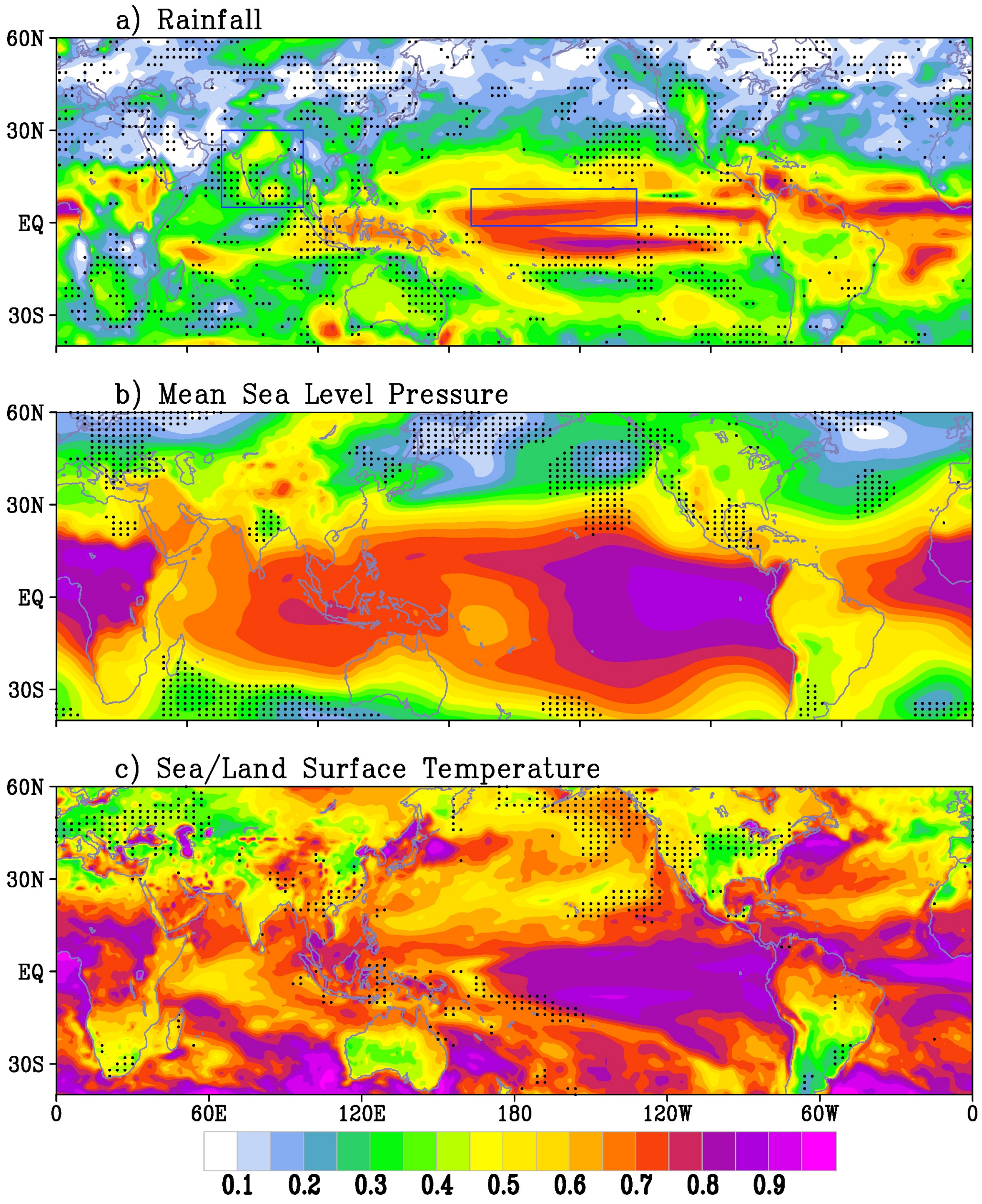


Figure S4. Same as Figure 01, but for the time period 1997-2021. Potential predictability based on ANOVA method for JJAS averaged a) rainfall, b) mean Sea level pressure, and c) Sea/land surface temperature using CFSv2 re-forecast of 25 years (1997-2021) and 52 ensemble members. Paradox regions (where model correlation skill with observations is higher than the potential predictability) are stippled. White semi-transparent regions, mostly coinciding with stippled regions, represent $RPC > 1.0$.

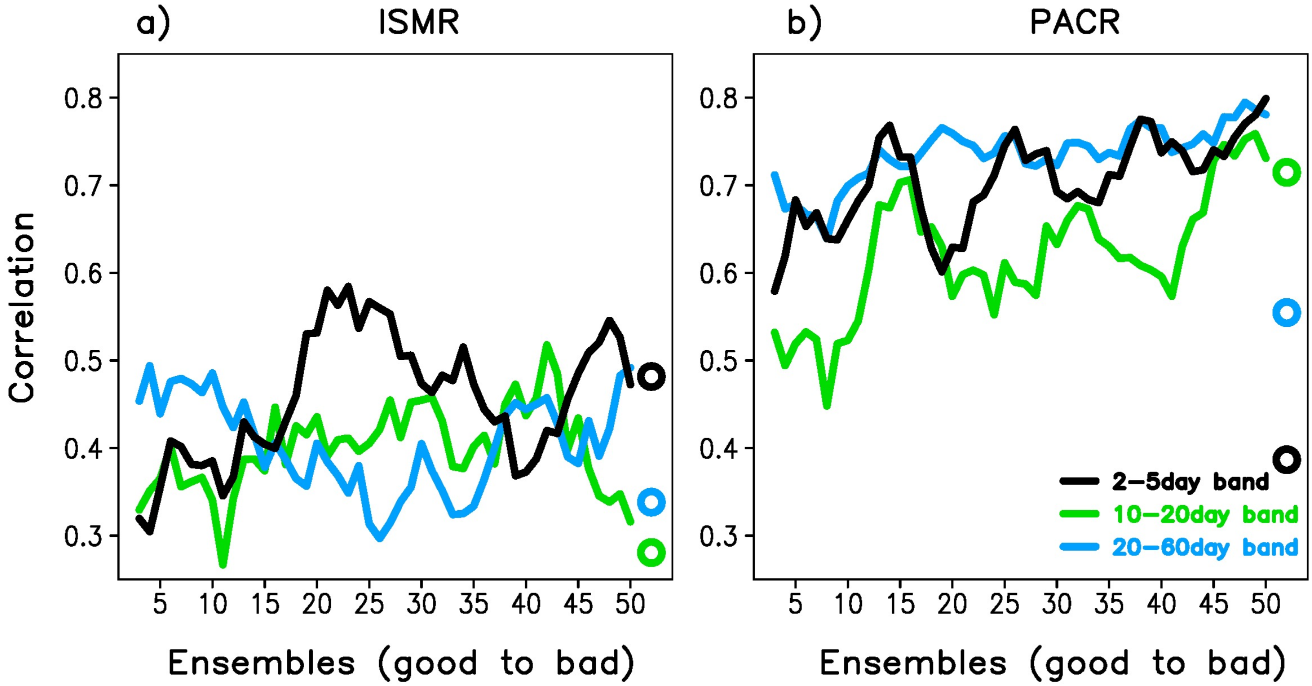


Figure S5. Same as Figure 09, but arranged from good to poor ensemble members, showing variation of co-variability between predictant and four predictors. Open circles represent Observed multiple correlation value.

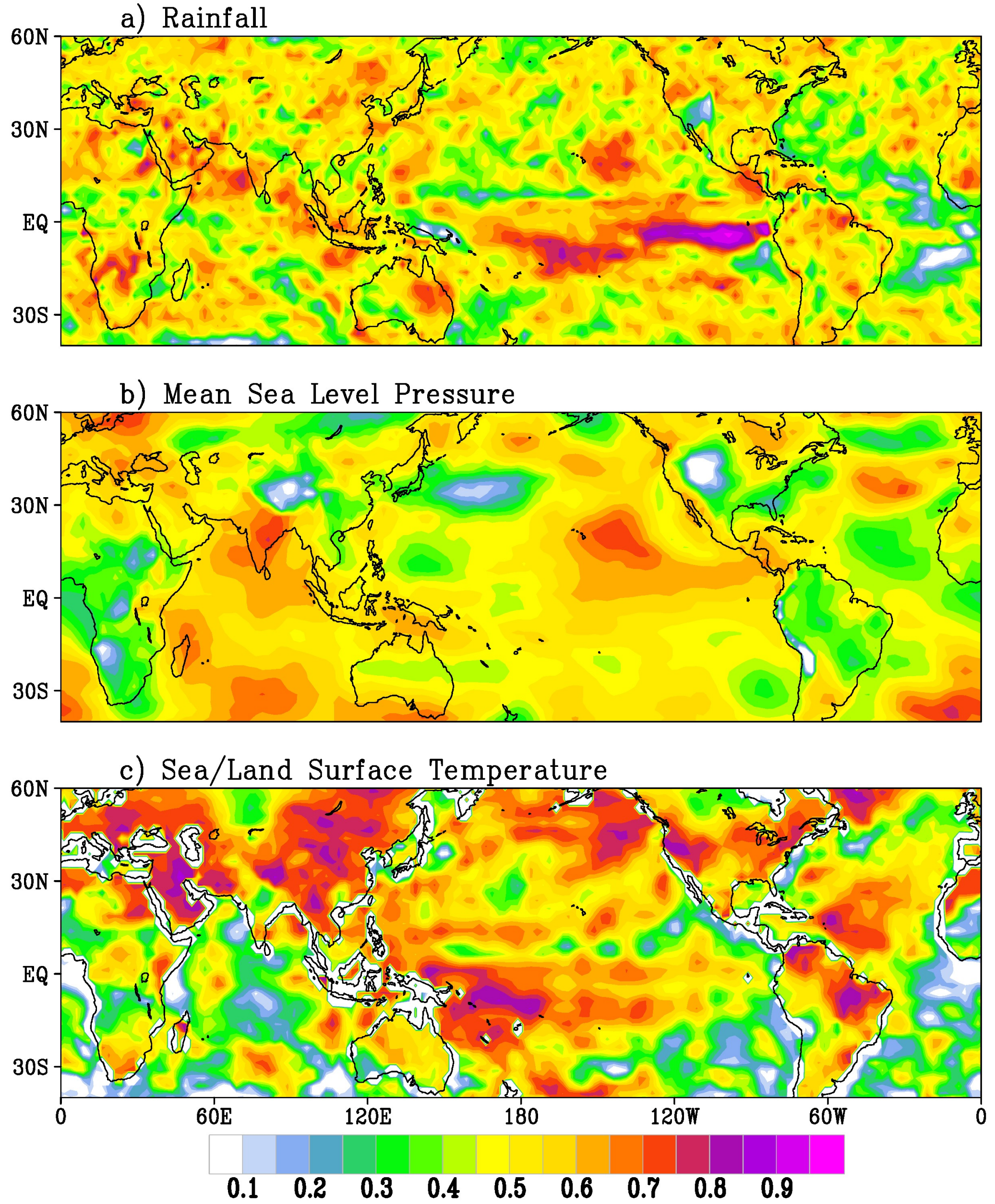


Figure S6. Maximum Correlation at each grid point using 100 thousand Bootstrapped re-sampling of 10 ensemble average from 52 ensembles and 41 years (1981-2021) simulation by IITM-CFS. Maximum correlation in JJAS-averaged a) Rainfall, b) Mean Sea Level Pressure, and c) surface temperature (SST over Ocean and 2m temperature over land).