Predictability of the Indian Summer Monsoon Rainfall

by

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Outline

- Sources and Limit of Seasonal Predictability
- Predictive Modes of the Global Monsoon
- Predictability of the Indian Summer Monsoon
- Conclusions

Sources and Limit of Seasonal Predictability

Slowly varying boundary conditions (SST, soil moisture, snow, sea ice etc.) and their interactions with atmosphere forms the basis of seasonal/decadal prediction (*Charney and Shukla, 1977; Shukla 1998*).

"............ so, ironically, the seasonal mean in the tropic are more predictable than the extratropics, in contrast to the situation for weather predictability" (*Shukla & Kinter 2006*)

ENSO alone explains about 20-25% interannual variance of ISMR.

Previous studies indicates that about 50% of IAV of ISMR is predictable.

So, what are the other sources of predictable part of the ISMR variability ?

Predictive Modes of the Global Monsoon

Clim Dyn
DOI 10.1007/s00382-015-2928-z

Predictability of global monsoon rainfall in NCEP CFSv2

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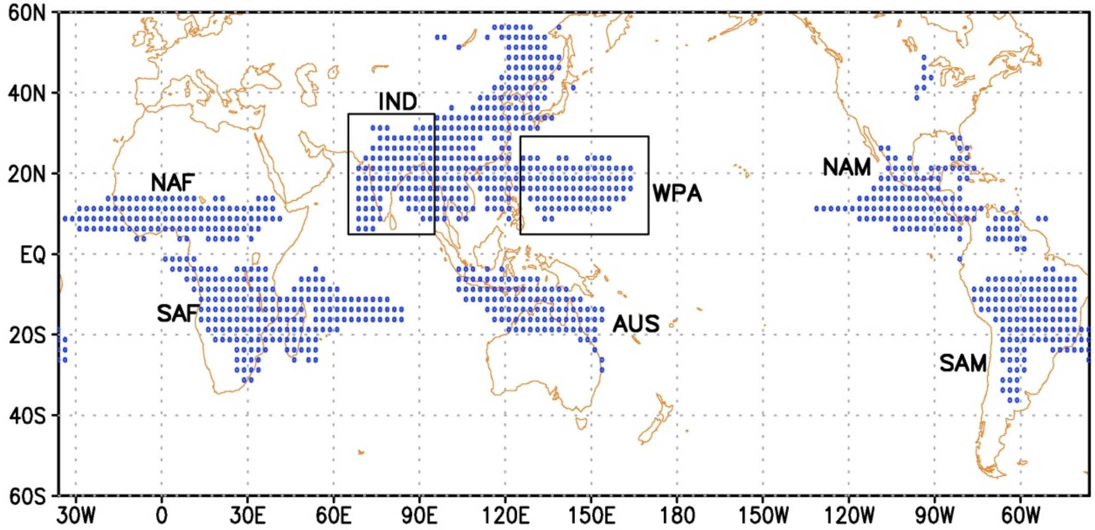


Teleconnections in PLS Regression (OBS)

LV 1

LV 2

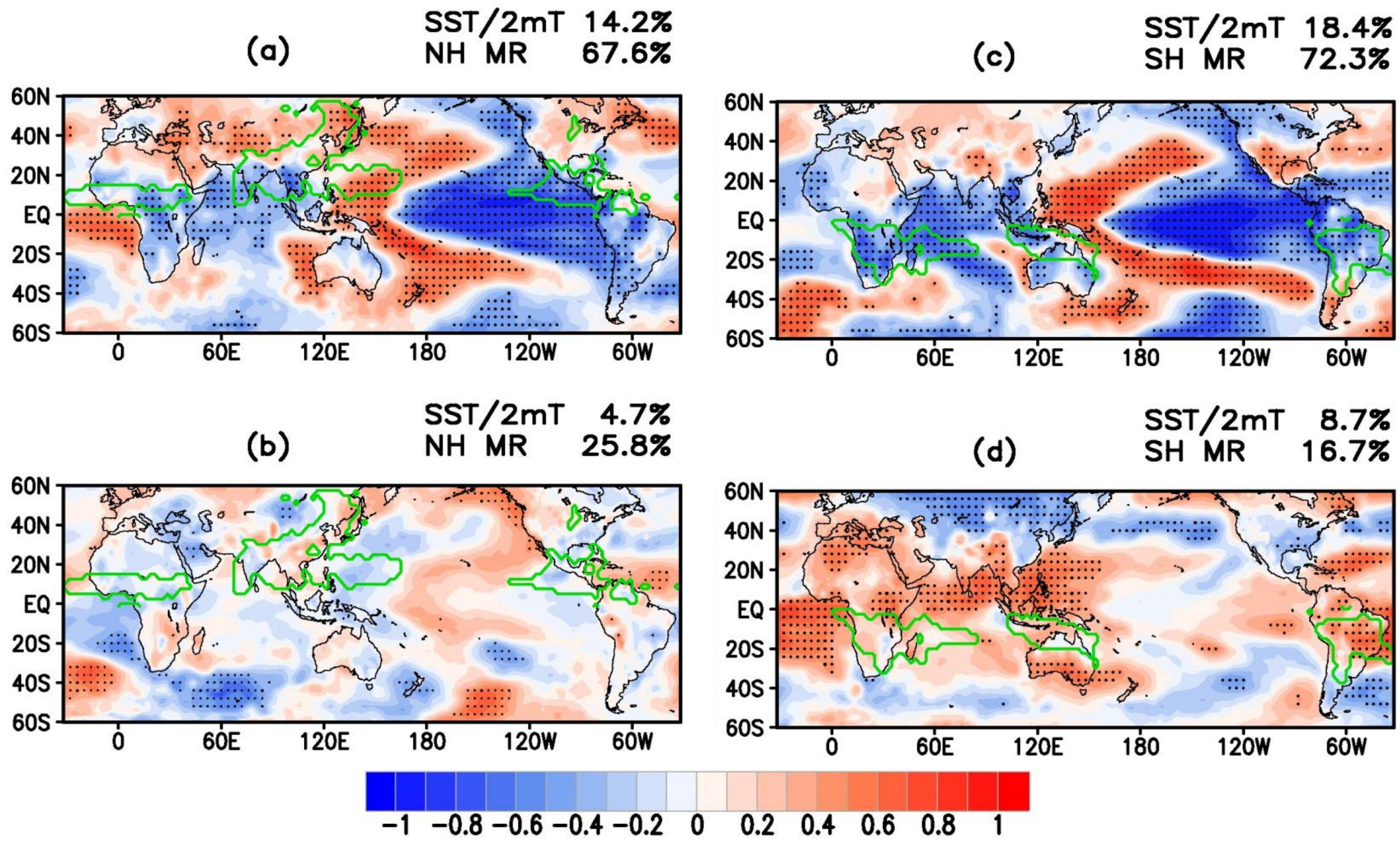


Fig. 13 PLS regression using observed NHSM/SHSM rainfall and SST, 2 m air temperature (land). a Correlation between first latent vector and MJJAS averaged SST, 2 m air temperature (land), b same as (a) but using second latent vector. c, d are same as (a), b) respectively but for the SHSM. Correlations significance at 95 % level are stippled

- **While the first latent vector indicates ENSO influence, the second latent vector shows strong and significant mid-latitude influences.**

Teleconnections in PLS Regression (CFSv2)

LV 1

LV 2

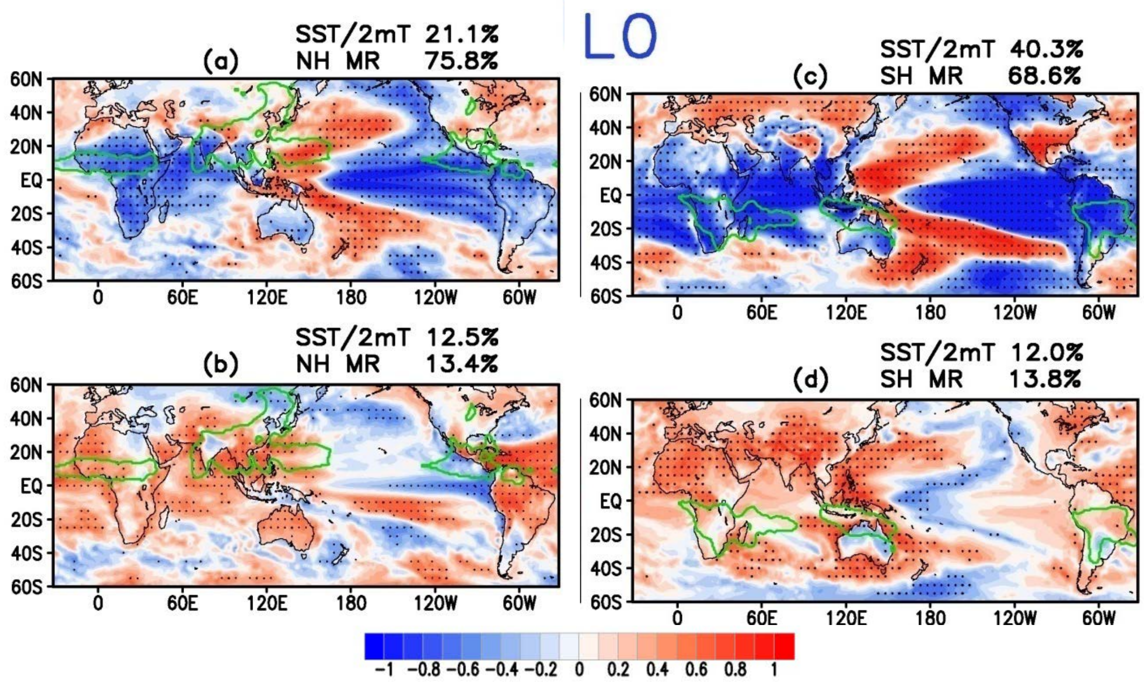
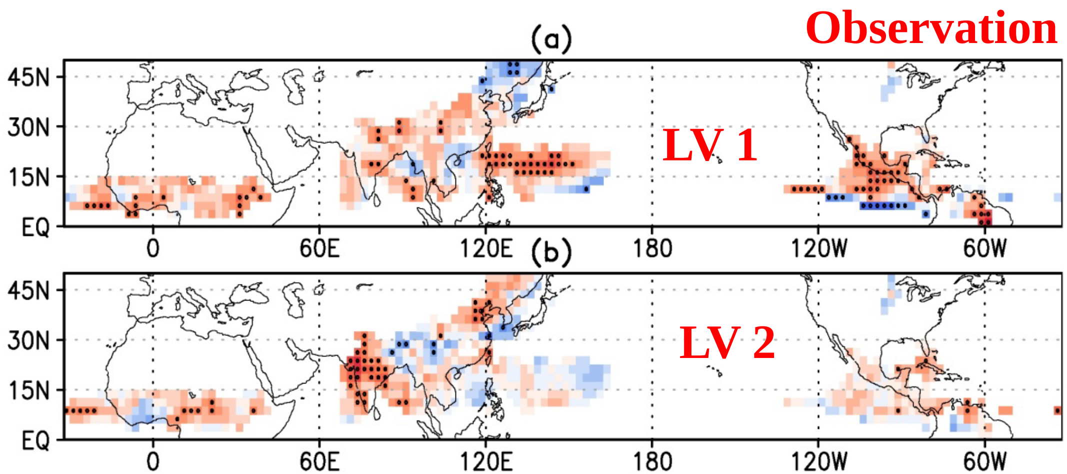


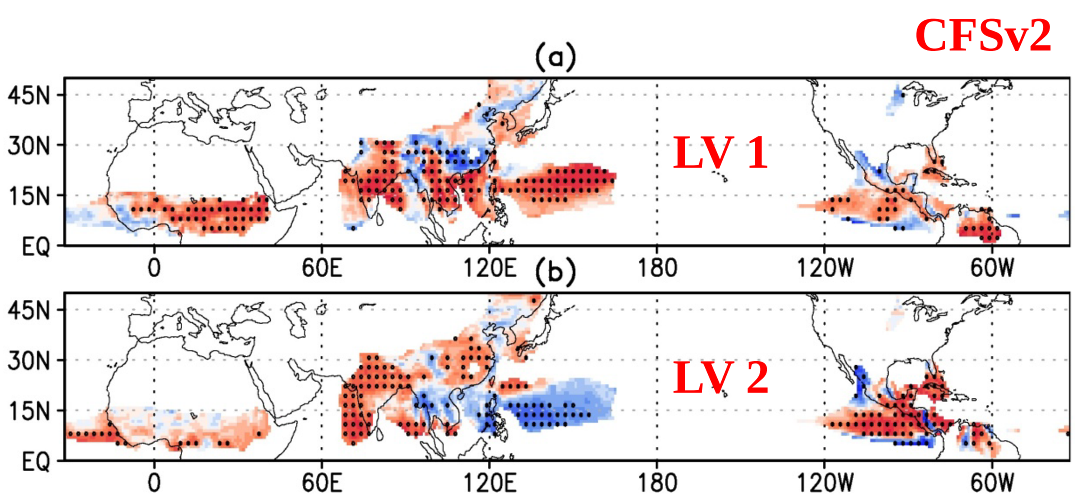
Fig. 14 PLS regression using CFSv2 NHSM/SHSM rainfall and SST, 2 m air temperature (land). a Correlation between first latent vector and MJJAS averaged SST, 2 m air temperature (land), b same as (a) but using second latent vector. c, d are same as (a), b) respectively but for the SHSM. Correlations significance at 95 % level are stippled

The major predictor of the boreal and austral summer monsoon rainfall variability is much stronger in the model.

The second mode is associated with the non-ENSO variability and the model has very poor skill.

Teleconnections in PLS Regression (NHSM)

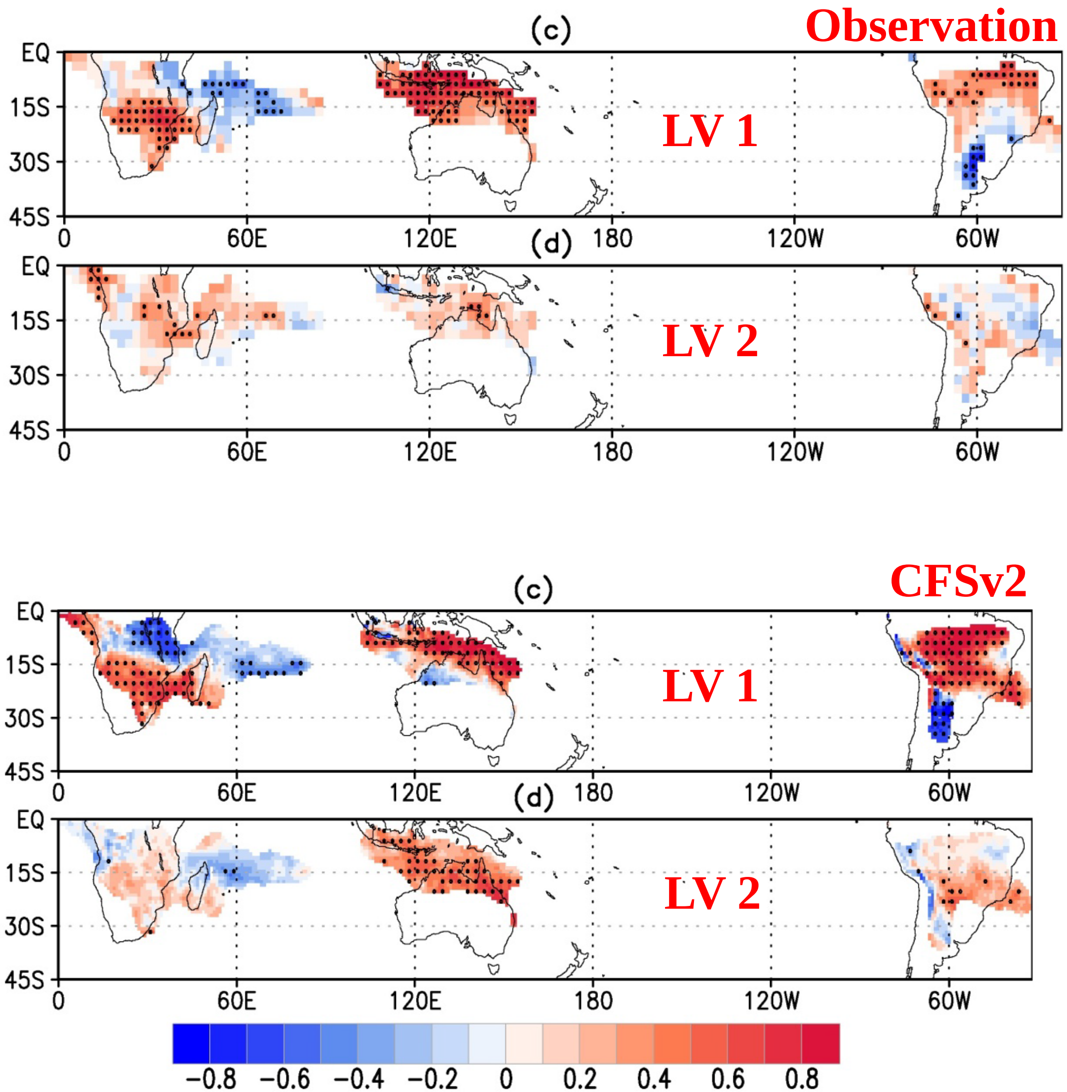




In the boreal summer monsoon regions, a large variability of the Indian summer monsoon is due to non-ENSO sources

Correlation between latent vectors and seasonal monsoon rainfall at each grid point

Teleconnections in PLS Regression (SHSM)



In the austral summer monsoon regions, a large variability is associated with ENSO.

Correlation between latent vectors and seasonal monsoon rainfall at each grid point

Predictability of the Indian Summer Monsoon

AGU PUBLICATIONS

Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1002/2015MS000542

Key Points:
- Potential predictability of ISMR simulated by CFSv2 is estimated
- In general, potential predictability increases with decrease in lead forecast time
- Actual ISMR prediction skill is highest (second highest) with February (April) initial conditions

Potential predictability of Indian summer monsoon rainfall in NCEP CFSv2

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Key Points:

- What is the predictability limit of the ISMR in CFSv2 ?
- ENSO skill is highest in L0 (May Ics), but ISMR skill is highest in L3 (Feb Ics). Therefore, non-ENSO source of predictability exists in CFSv2.
- Very likely, the sources of predictive signal or the slowly varying boundary conditions are the initial conditions (snow, soil moisture, SST).

Measures of Predictability

ANOVA based SNR, Rlimit

Information Theory based RE, MI

Classical Perfect Model Correlation

Mahalanobis distance measures the distance of a point from a data distribution (*Mahalanobis 1936*).

Relative Entropy is quantitative measure of the distance between climatological mean and forecast distribution.

RE is a prognostic measure of predictability, which retains the initial state information.

Potential & Actual Skill

	SNR		Rlimit		MI based PS		Perfect Corr.		Actual Corr.
	SM	Rain	SM	Rain	SM	Rain	SM	Rain	Rain
Lead-4	0.59	0.35	0.61	0.51	0.42	0.31	0.61	0.48	0.35
Lead-3	0.55	0.46	0.59	0.56	0.41	0.36	0.59	0.54	0.58
Lead-2	0.85	**0.65**	0.67	**0.63**	0.50	**0.45**	0.67	**0.62**	0.34
Lead-1	0.74	0.52	0.65	0.58	0.51	0.44	0.66	0.60	0.57
Lead-0	0.87	0.58	0.68	0.61	0.50	0.41	0.68	0.61	0.43

Table 1. Lead-wise measures of potential predictability of all India averaged rainfall, soil moisture (SM; top 1m depth) and actual prediction skill of all India averaged rainfall in CFSv2. The measures of potential predictability are SNR, Rlimit, MI based potential skill (PS) and classical perfect correlation. Correlation values of 0.330, 0.388, 0.453 and 0.496 are significant at 90%, 95%, 98% and 99% the respectively.

- **Potential skill is maximum at L2, but actual skill is maximum at L3/L1, which indicates that statistical characteristic of model predicted time series is very sensitive to the initial conditions.**

ISMR & ENSO, IOD Teleconnections

ISMR-ENSO

ISMR-IOD

	R_{12}	$R_{12.3}$	R_{13}	$R_{13.2}$
OBS	-0.41	-0.49	0.21	0.36
Lead-4	-0.67	-0.49	-0.55	-0.22
Lead-3	-0.77	-0.54	-0.68	-0.27
Lead-2	-0.76	-0.70	-0.42	0.03
Lead-1	-0.77	-0.68	-0.50	-0.14
Lead-0	-0.82	-0.73	-0.56	-0.23

Table 2. Partial and total correlation using indices of Indian summer monsoon rainfall (ISMR=1), ENSO (Niño3.4=2) and Indian Ocean Dipole (IOD=3). R_{12}, R_{13} are correlation between ISMR, Niño3.4 and ISMR, IOD indices respectively. $R_{12.3}$ ($R_{13.2}$) is partial correlation between ISMR and Niño3.4 without IOD (ISMR and IOD without Niño3.4) indices.

- **While the ISMR-ENSO teleconnections is much stronger than the observation, the ISMR-IOD relation is completely out of phase in CFSv2.**

Relative Entropy (RE)

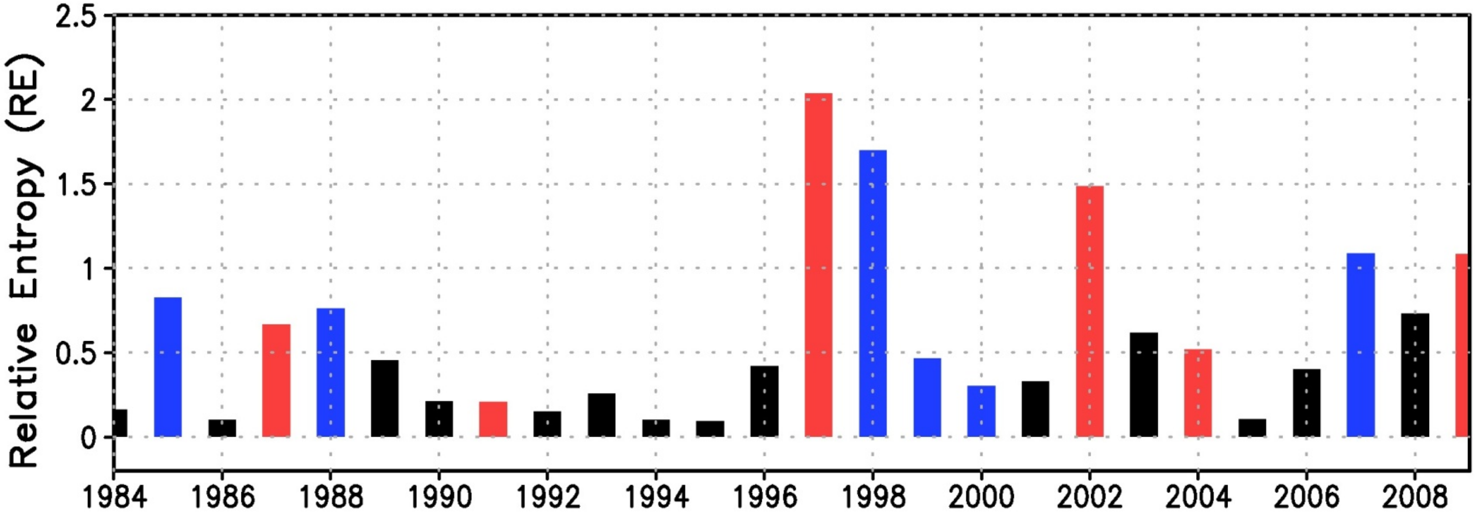
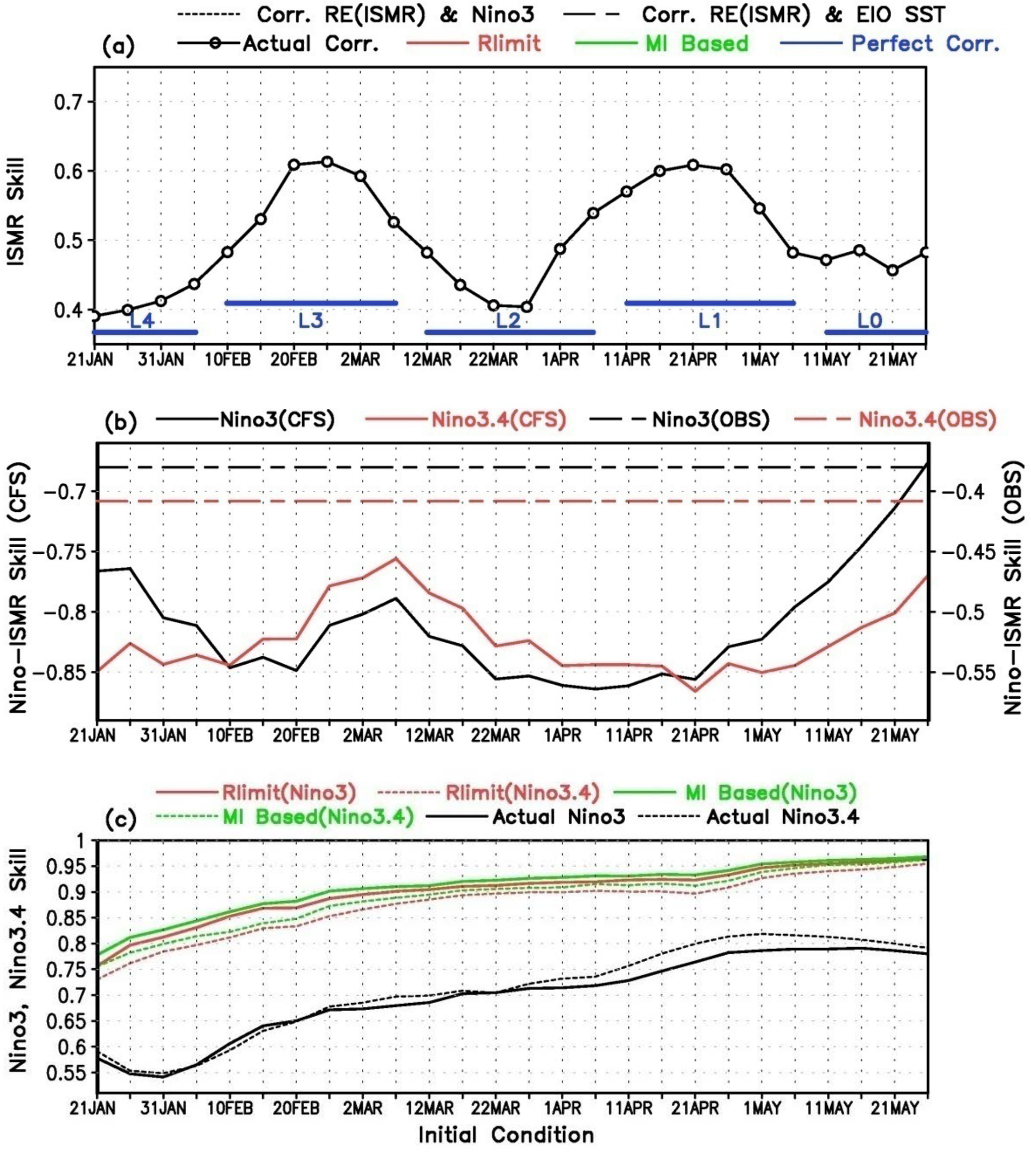


Figure 5. Relative entropy (RE) based on ISMR of lead-0 forecast. Red and blue color indicate El Nino and La Nina year respectively in the observation. If Nino3.4 SST (JJAS averaged) is >=0.5(<= -0.5) then it is considered as an El Nino (La Nina) year.

A large (small) RE is indicative of large (small) predictability of a year. Most of the larger REs are associated with ENSO year.

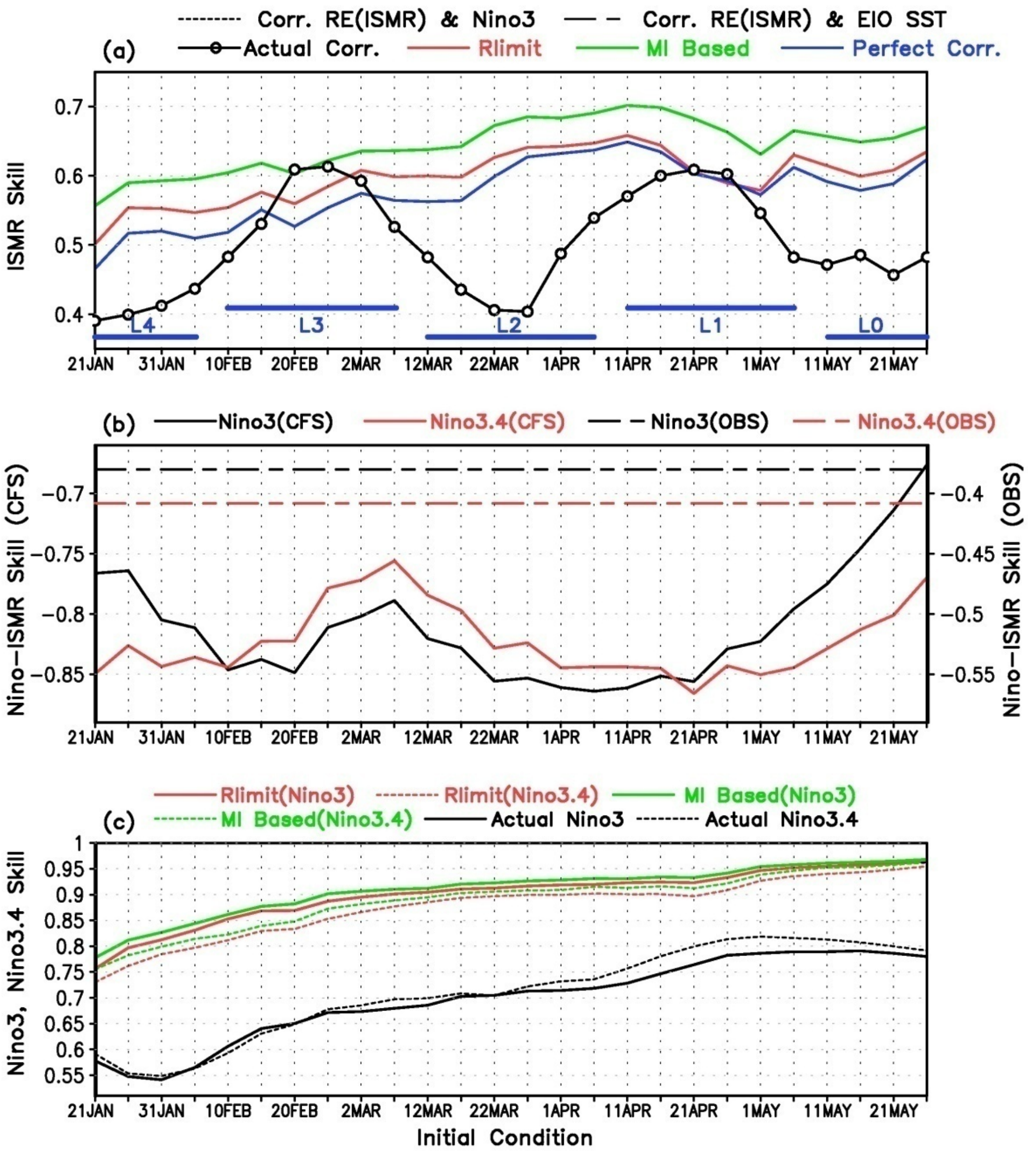
RE may be used as a level of confidence in the forecast

Sliding Skill (Actual & Potential)



Sliding actual ISMR skill (five pentad window/20 ensemble member) of CFSv2.

Sliding Skill (Actual & Potential)



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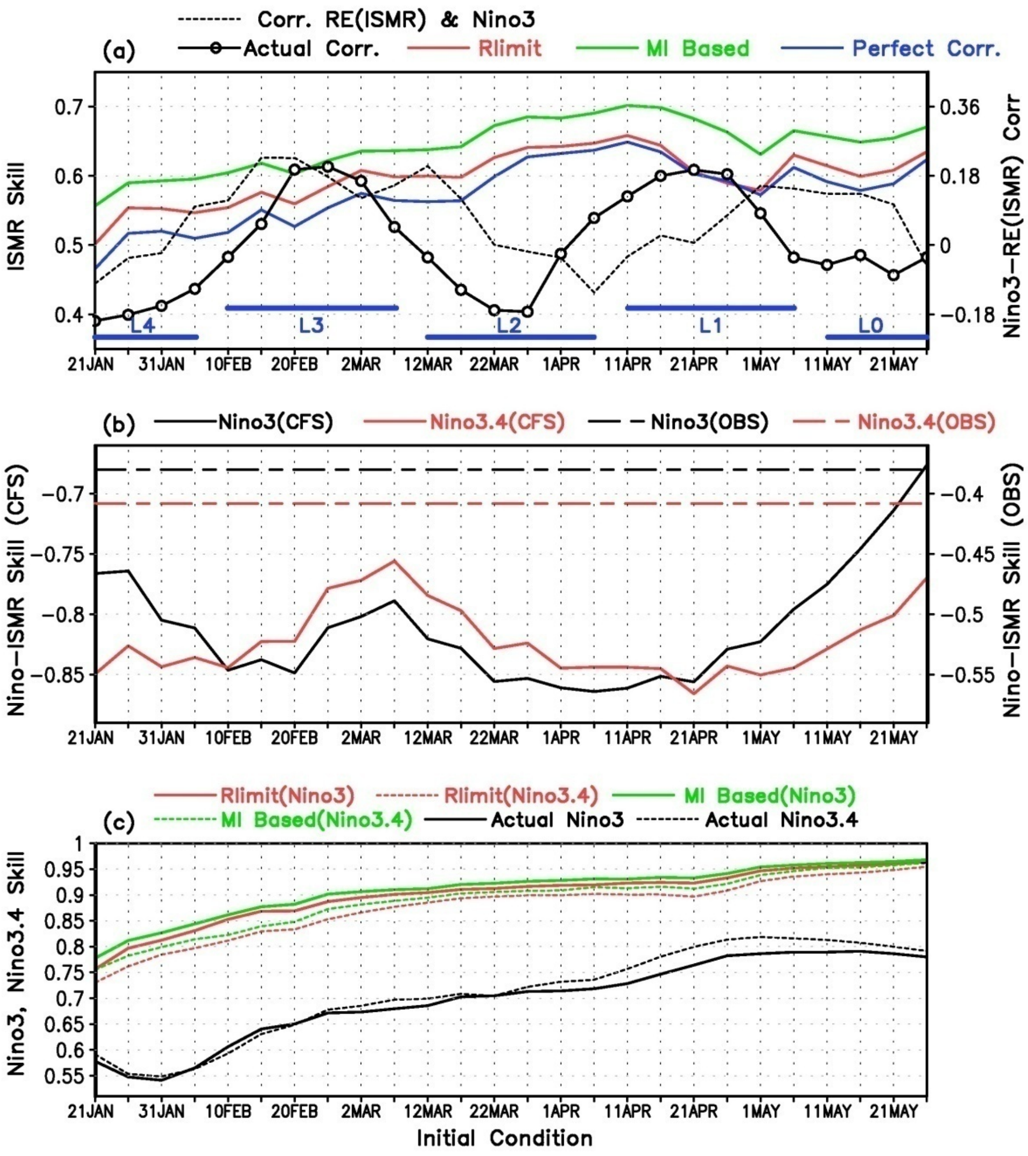
Sliding Skill (Actual & Potential)



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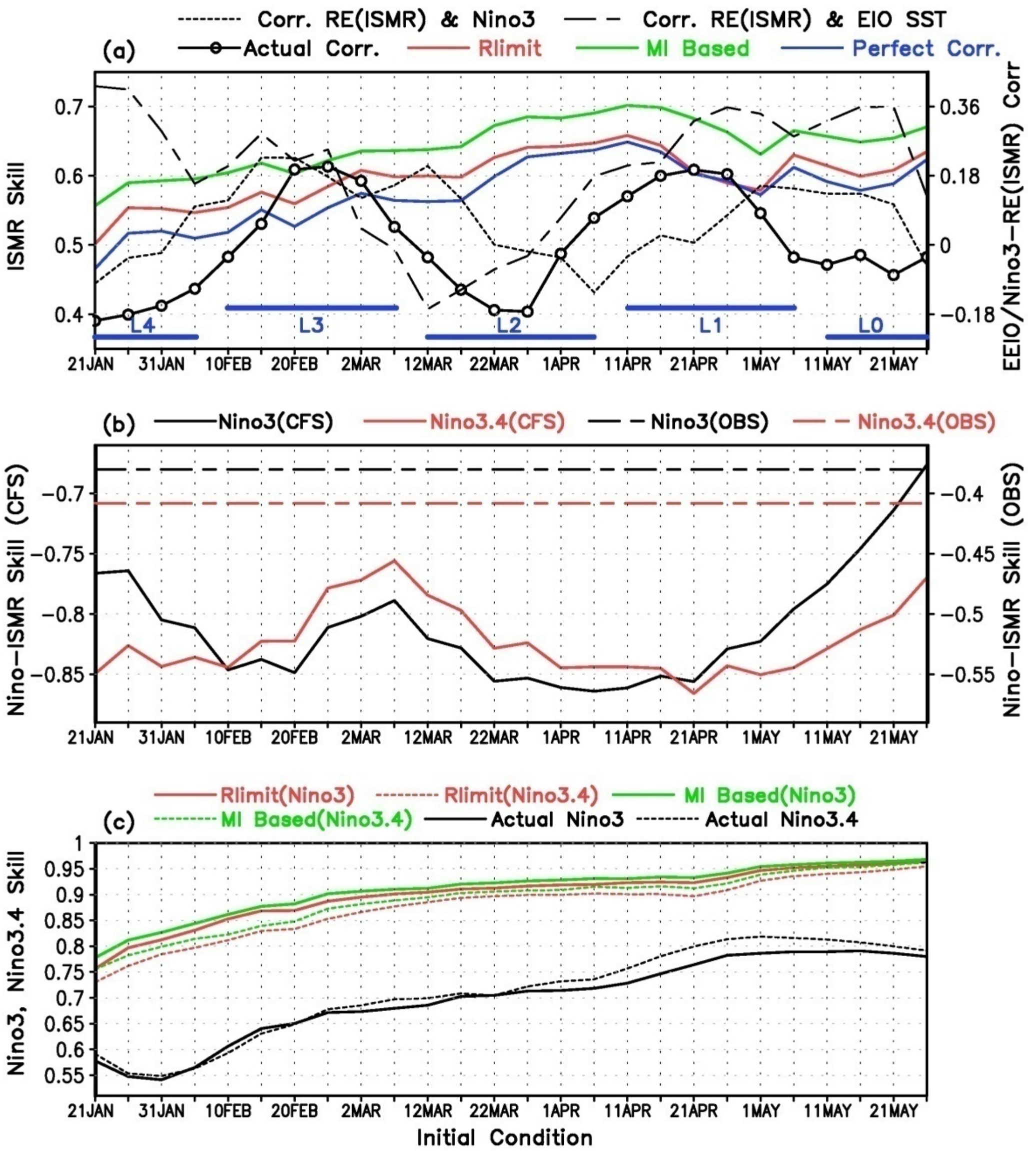
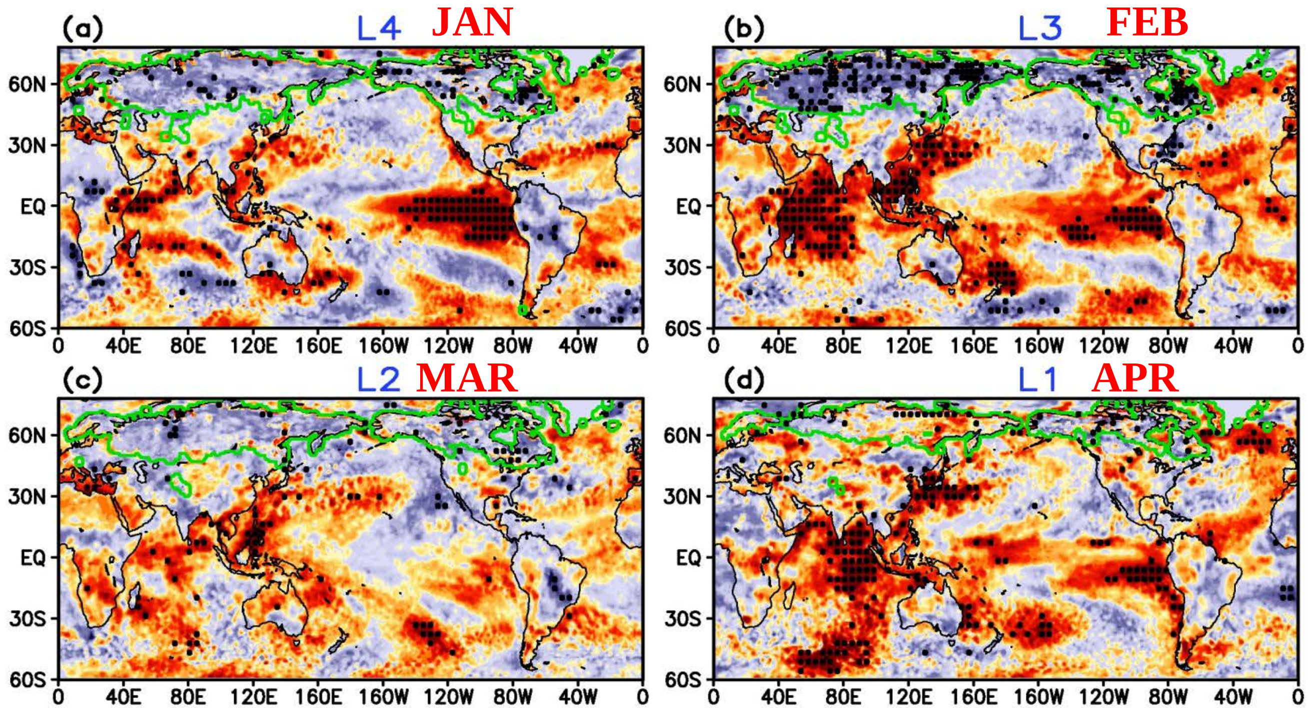
Sliding Skill (Actual & Potential)



Sliding actual ISMR skill (five pentad window/20 ensemble member) of CFSv2.

Highest actual prediction skill of the ISMR in CFSv2 is due to the combined effects of initial snow and SST



February ICs

April ICs

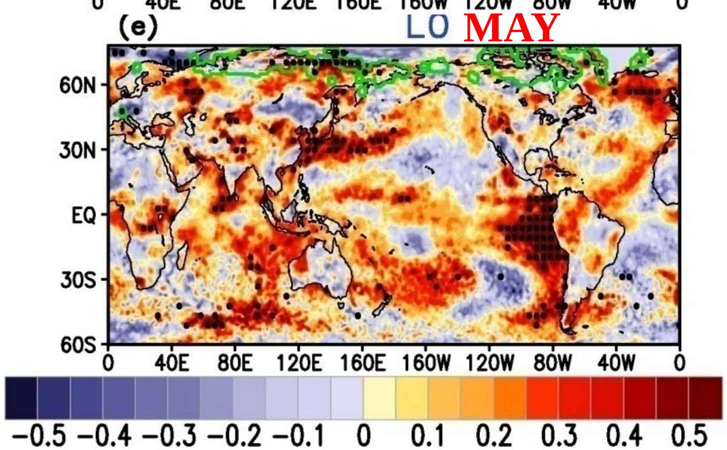
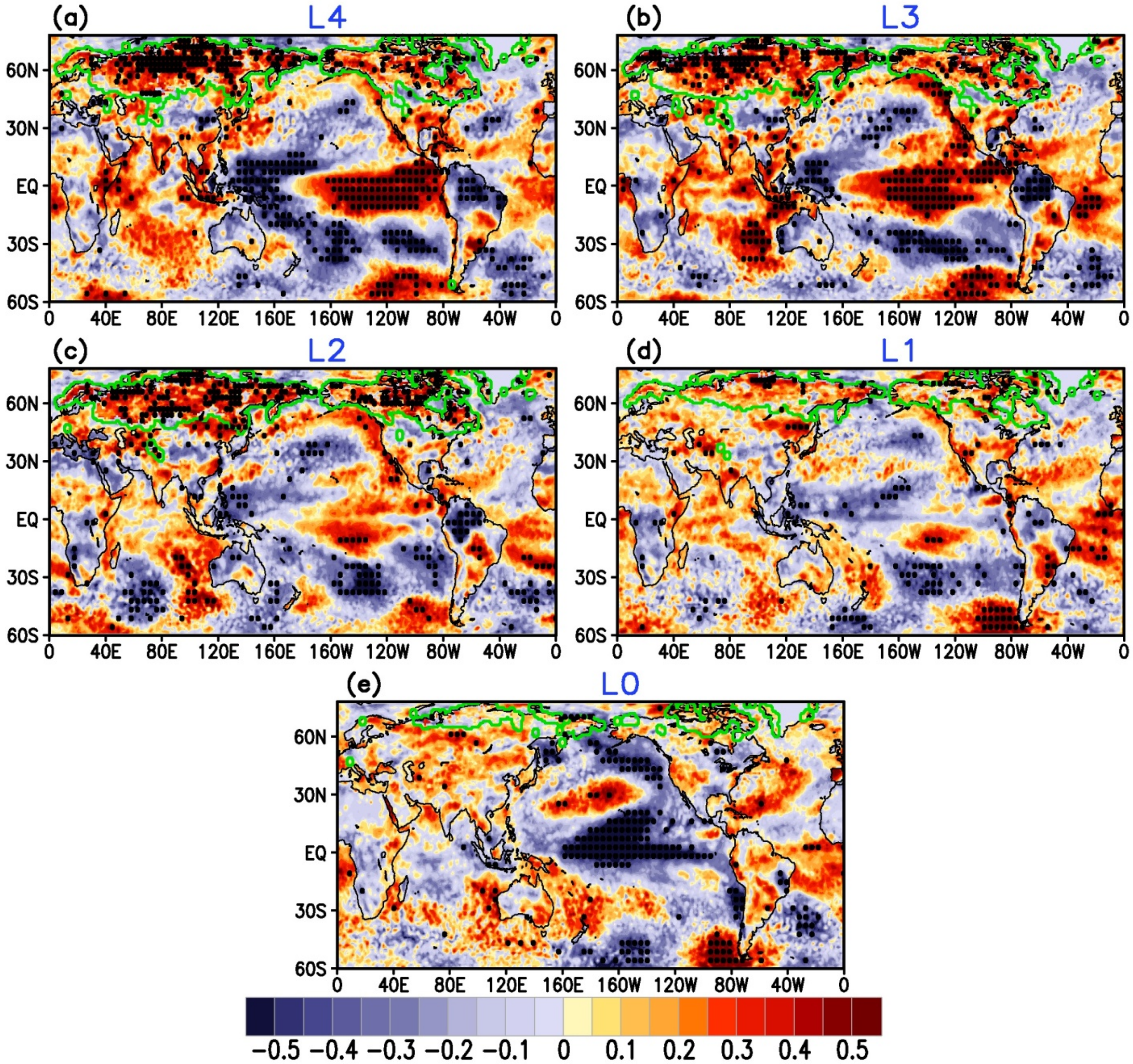
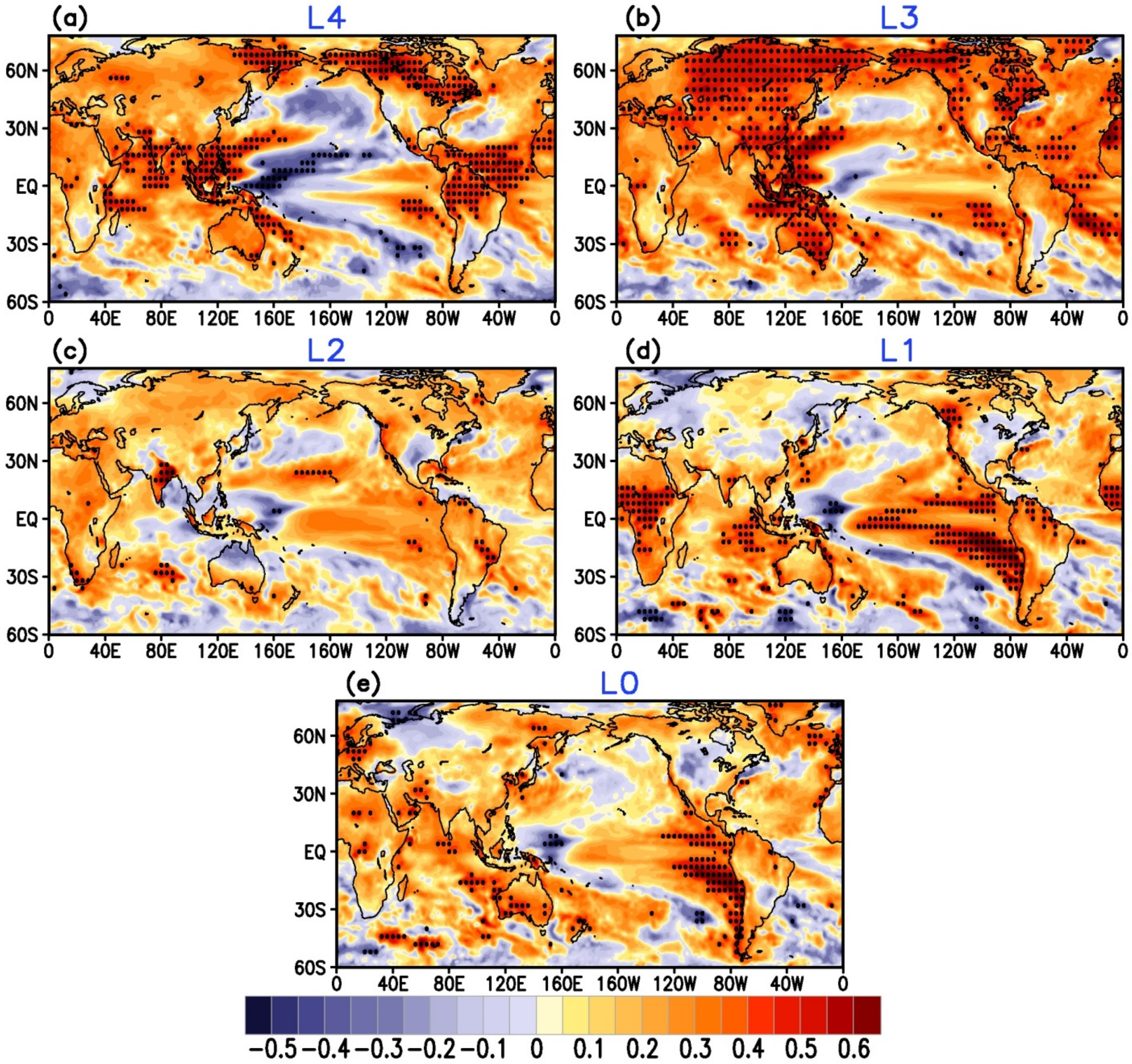


Figure 10. Correlation between RE (based on ISMR) and initial SST (over Oceans), soil moisture (top 1m) and snow water equivalent (over land only) at (a) Lead-4, (b) Lead-3, (c) Lead-2, (d) Lead-1 and (e) Lead-0. Here, ensemble averaged values (i.e. initial conditions and ISMR) are used to calculate correlation. In the presence of initial SWE > 20mm (green contour), correlation between ISMR and SWE instead of ISMR and soil moisture is shown. Correlation signicant above 95% level are stippled.

Correlation between ISMR & Ics (SST, SM, Snow)



Correlation between RE (ISMR) & JJAS SST, 2mT



Some Studies on non-ENSO Sources of ISMR variability

Climate Dynamics (1999) 15:475–489

R. H. Kripalani · A. Kulkarni

Climatology and variability of historical Soviet snow depth data: some new perspectives in snow – Indian monsoon teleconnections

“Results reveal that the winter-time snow depth over western Eurasia surrounding Moscow (eastern Eurasia in central Siberia) shows signi"cant negative (positive) relationship with subsequent IMR.”

Other studies by ***Hahn and Shukla 1976; Vernekar et al. 1995; Sankar Rao et al. 1996; Bamzai and Shukla 1999; Fasullo 2004; Singh and Oh 2 etc.***

Some Studies on non-ENSO Sources of ISMR variability

AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Atmospheres

RESEARCH ARTICLE

10.1002/2015JD023159

Key Points:
- Link between preonset land atmospheric conditions and ISMR is explored
- This link will enhance our ability to predict monsoon in non-ENSO years

Influence of preonset land atmospheric conditions on the Indian summer monsoon rainfall variability

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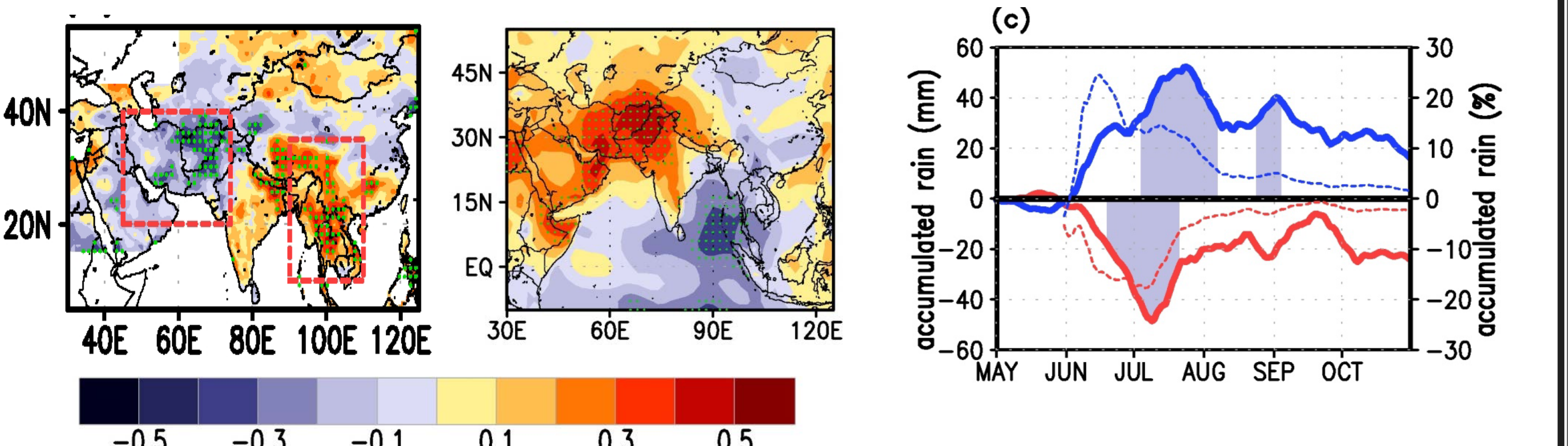
[1]Indian Institute of Tropical Meteorology, Pune, India, [2]Center for Ocean-Land-Atmosphere Studies, George Mason University, Fairfax, Virginia, USA



Some Studies on non-ENSO Sources of ISMR variability

INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. (2016)
Published online in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.4648

Royal Meteorological Society

On the relationship between Iran surface temperature and northwest India summer monsoon rainfall

Ramesh Kumar Yadav*
Indian Institute of Tropical Meteorology, Pashan, Pune, India

- **Role of Southern Annular Mode (SAM) on ISMR by *Prabhu et al., 2015; Viswambharan and Mohandakumar (2013)***

- **Role of NAO/North Atlantic on ISMR by *Dugam et al. 1996; Kakade and Dugam 2006; Yadav (2009) etc.***

- **Midlatitude Interactions during Droughts by *Krishnan et al. 2009 etc.***

- **Role of extratropical SST (*Chattopadhyay et al. 2015*)**

Conclusions

- A combined effect of the initial states of the Eurasian snow along with SSTs during February makes the model (CFSv2) most skilful for the ISMR prediction.

- Realization of Non-ENSO sources of predictability will be critical for further improving the ISMR predictability in the model.

- Need further understanding of the non-ENSO sources of ISMR variability.

Thank You!