Problems and prospects in Extended Range Prediction of Monthly Extremes, monsoon active/break spells and Tropical Cyclones,

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Outline

- MISO, Need for ERP and problems
- IITM Ensemble Prediction System
- Prediction of Monthly Extremes
- Extended Range Prediction of Active/break spells
- Extended Range Prediction of Cyclogenesis
- Conclusions
- Way Forward

Need for extended range prediction

Seasonal rainfall anomalies are nearly homogeneous over Indian region during extreme monsoon years (droughts/floods).

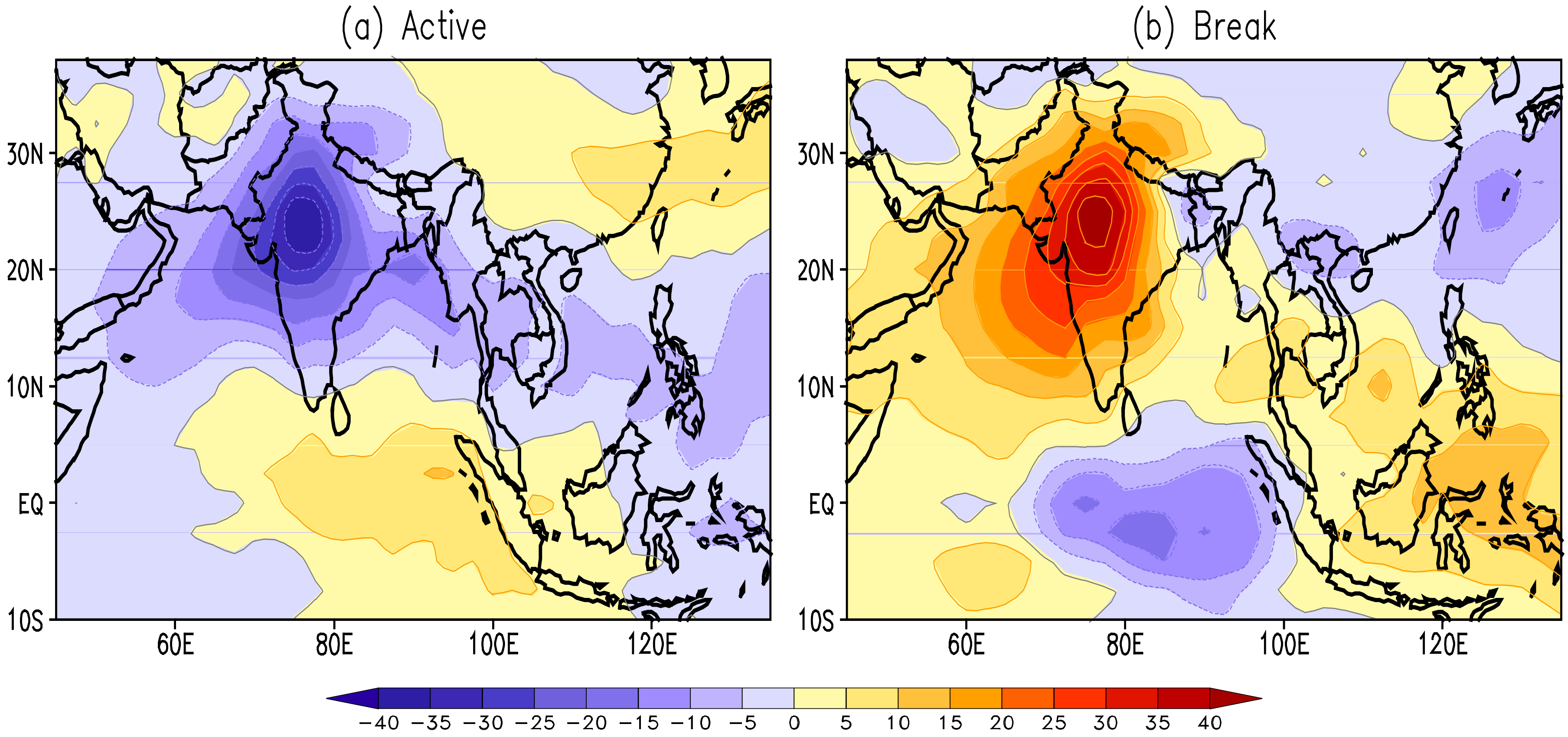
But, mostly (~70%) monsoon years are normal and during normal years the rainfall anomalies are inhomogeneous over the country, contributing to large degree of spatial variability !!!

Adding to this is the variability of rainfall on temporal scales within the season

Although the prediction of a 'normal' all India rainfall may have a comfort factor, it may not be useful for agricultural planning.

Therefore, in addition to the seasonal mean All India rainfall, we need to predict some aspects of monsoon 3-4 weeks in advance on a relatively smaller spatial scale that will be useful for farmers.

OLR anomaly during Active/Break Spells



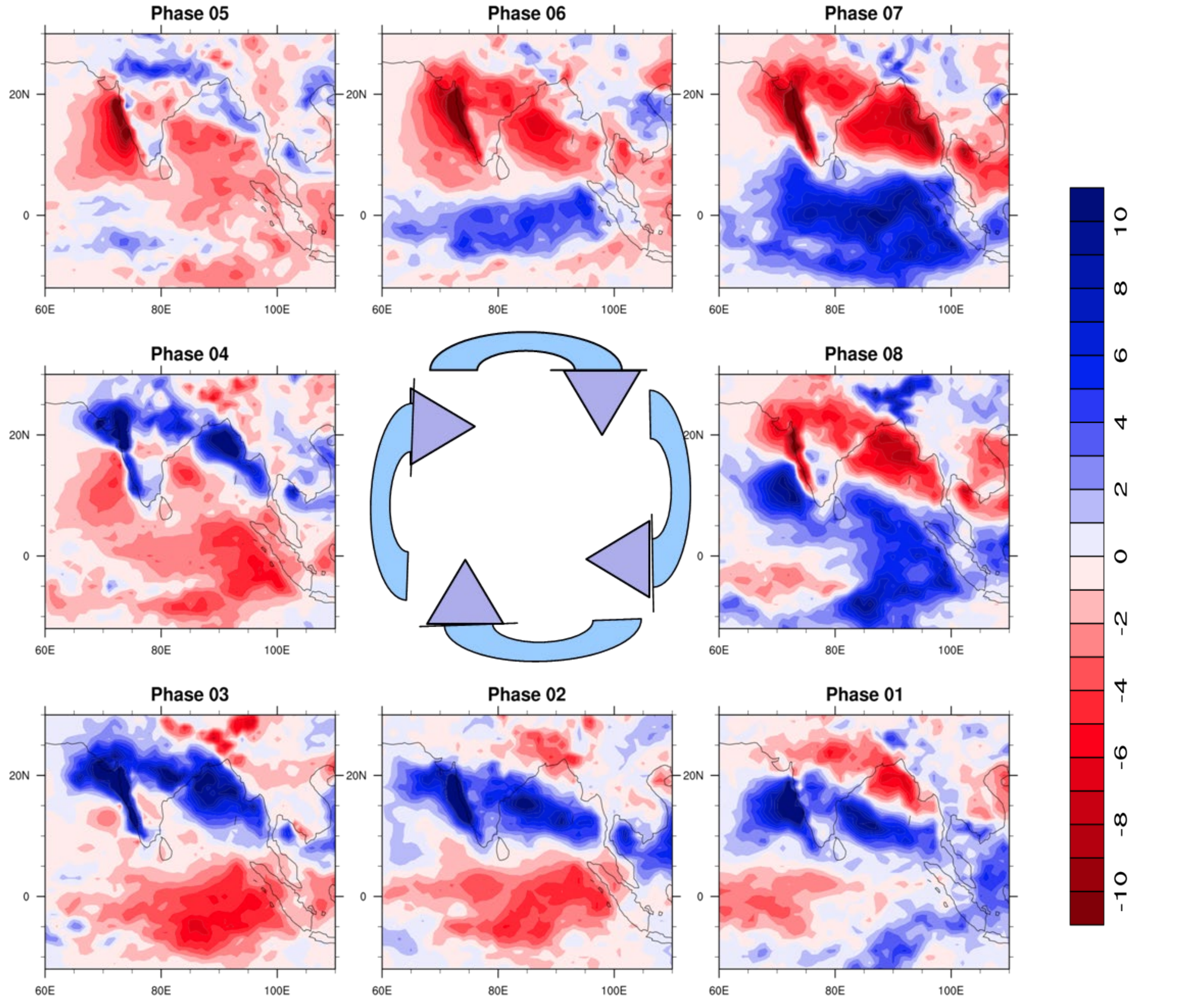
How MISO indices are computed

RMM------------------------→ BSISO---------------→ MISO
Whiller and Hendon,2004 ---→Kikuchi, 2012; Lee etal, 2013 ---->*Suhas et al., 2013*

- EOF analysis is carried out similar to Wheeler and Hendon 2004, but used standardized rainfall anomalies up to lag 14 days.
- The 60-95E averaged rainfall anomalies for latitudes 12-30N and for day 0 to lag 14 days are appended side by side to create the extended data matrix for EEOF.
- The EEOF analysis is carried out using IMD-TRMM merged data from 1998-2011. (Borah et. al. 2013, IITMRR)
- The amplitude of EOF1 and EOF2 (PC1 and PC2) are plotted in a PC1/PC2 phase space similar to Wheeler Hendon 2004 to get an idea of the evolution of ISO and its strength.

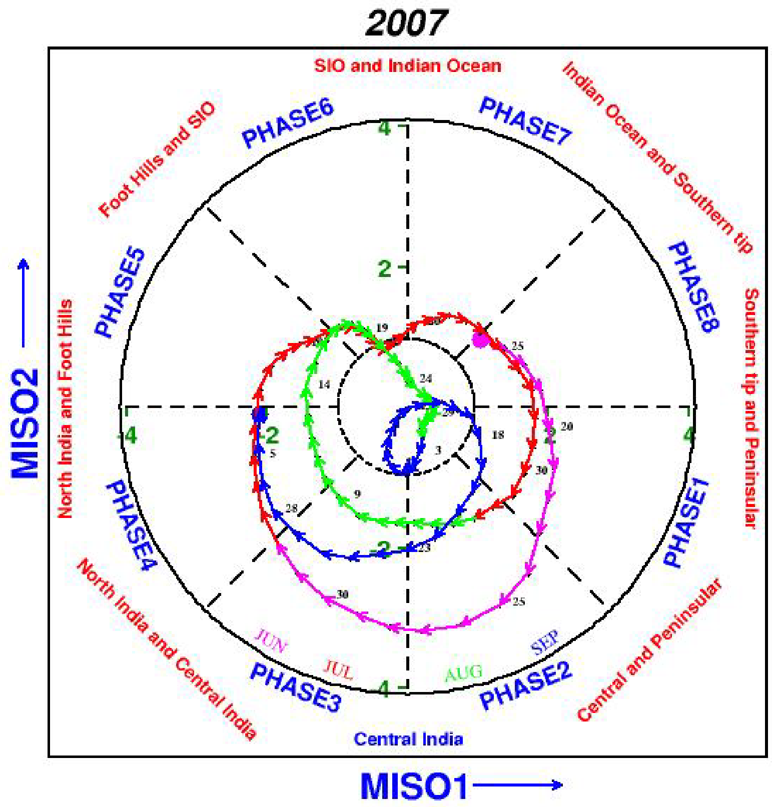
Composite Rainfall anomalies in different phases

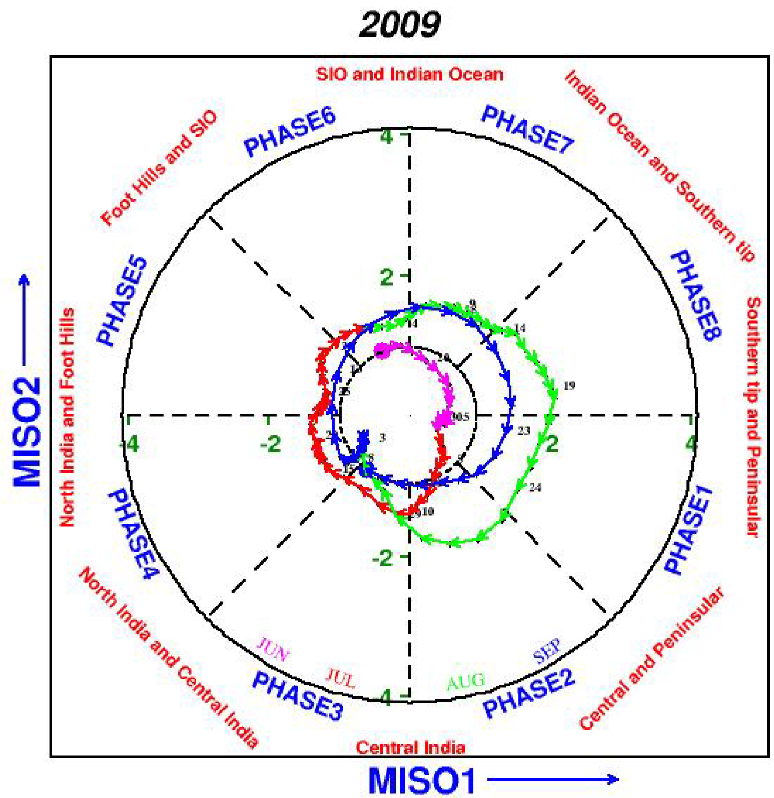
Phase1: Peninsular India
Phase2: Central India
Phase3: Central India
Phase4: North India
Phase5: Foothills
Phase6: South IO
Phase7: Indian Ocean
Phase8: Southern tip



Borah, Sahai et. al. 2013, IITMRR

Examples of evolution of MISO indices





Association between droughts and very long breaks (VLB)

Drought Years	Long breaks identified from IMD rainfall data	Drought Years that co-occurred with ElNino (E) / No ElNino (NE)
1951	-	-
1965	2-15 Aug	E
1966	2-12 Jul	NE
1968	22 Aug-5 Sep	E
1972	12 Jul-4 Aug	E
1974	26 Aug-8 Sep	NE
1979	13-29 Aug	NE
1982	27 Jun-8 Jul	E
1985	-	-
1986	23 Aug-8 Sep	NE
1987	16-26 Jul	E
2002	2-31 Jul	E
2004	26 Aug-5 Sep	E

List of drought years (below 10% of its long period average) during the period 1951-2004

- VLBs are identified when the standardized rainfall anomalies, averaged over the Indian core region is below -1.0 for a duration of more than 10 days.
- It may be noted that 85% of ISM droughts during this period are associated with at least one VLB.
- Hence VLBs in the monsoon are responsible for ISM droughts.

Joseph, Sahai et al., 2009, ClimDyn

Modulation of monsoon ISOs by ENSO

		No. of days per events at each SOM node (El-Nino; *La Nina*)	Correlation of the cumulative rainfall anomalies associated with the days clustered at each SOM node with ENSO Index
Method-1*	Break	12.95; *6.27*	-0.53
	Active	6.67; *12.07*	-0.35
Method-2#	Break	11.87; *7.84*	-0.38
	Active	9.55; *8.65*	-0.07

*With ENSO effect on seasonal mean

#Without ENSO effect on seasonal mean

Particular MISO phases are preferred during ENSO years, that is, the canonical break phase is preferred more in the El Niño years and the typical active phase is preferred during La Niña years.

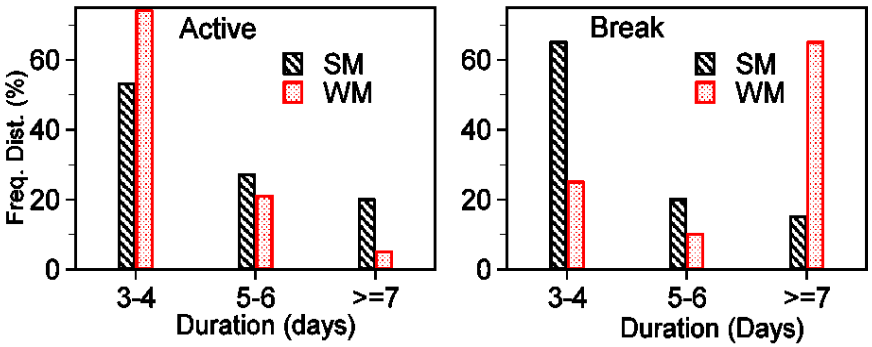
Interestingly, if the ENSO effect on seasonal mean is removed, the preference for the break node remains relatively unchanged; whereas, the preference reduces/vanishes for the active node.

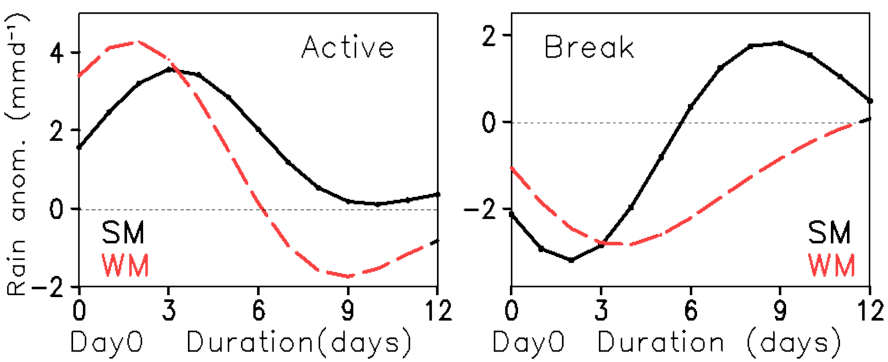
The results indicate that the El Niño–break relationship is almost independent of the ENSO-monsoon relationship on seasonal scale whereas the La Niña–active association seems to be interwoven with the seasonal relationship.

Joseph, Sahai et al., 2011, JGR

Asymmetry in MISO during Extreme Monsoon

Frequency and duration of active/break spells

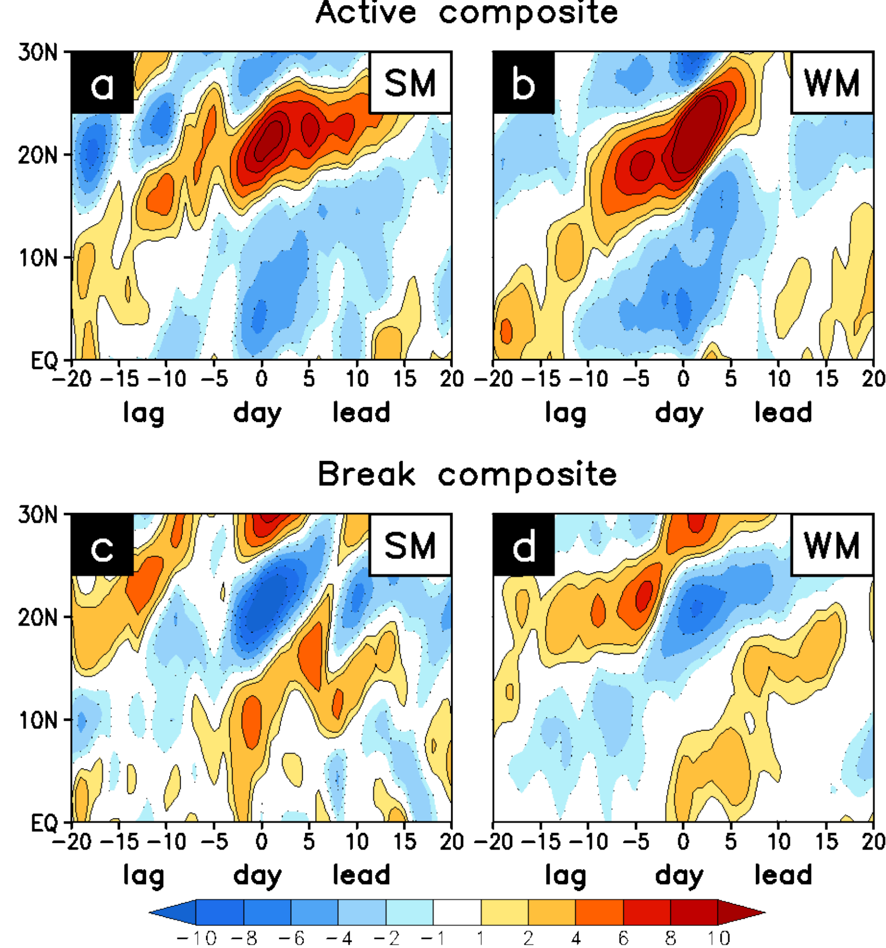




Long active spells (>5 days) → SM (~47%)
Short active spells → WM (~73%)
Prolonged break spells → WM (65%)
Short break spells → WM (~65%)

Sharmila, Sahai et al., 2014, I.J.Clim

Time-latitude diagram

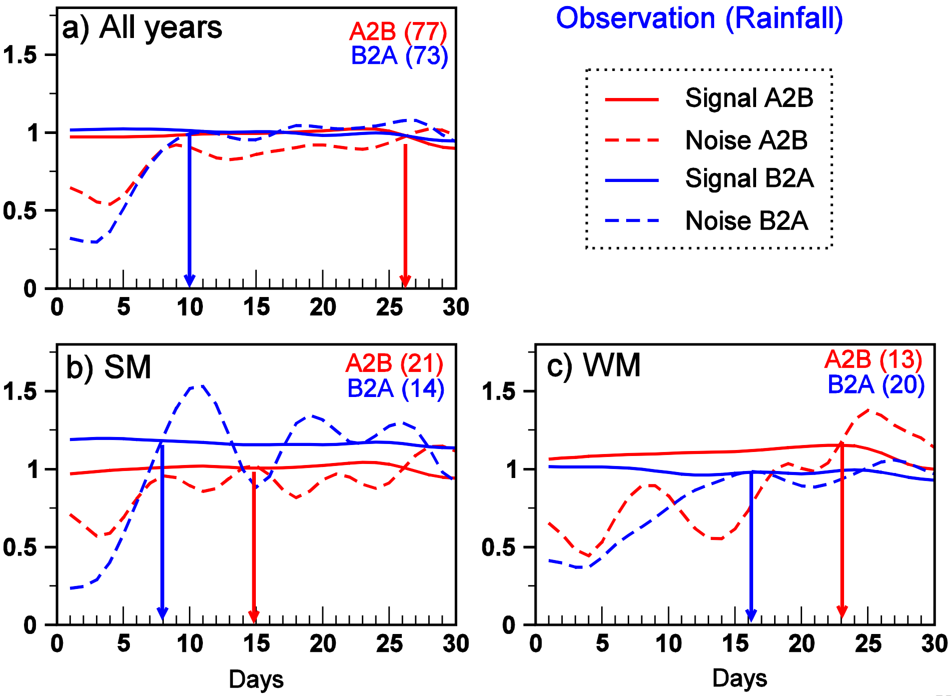


SM→ Slow (fast) propagation during active (break) phase
WM→ Fast (slow) propagation during active (break) phase

Potential Predictability of MISO during Extreme Monsoon

Estimated Observed Potential Predictability of Active/Break Spell Transitions

Potential Predictability of Active/Break Cycle over Central India



Observation

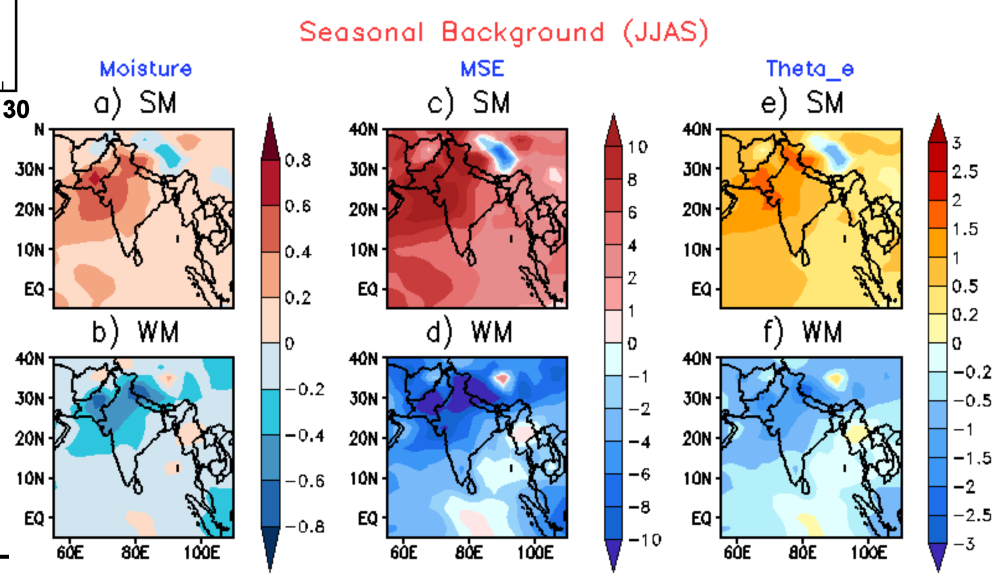
SM: A2B → 15 days
B2A → 8 days

WM: A2B → 23 days
B2A → 16 days

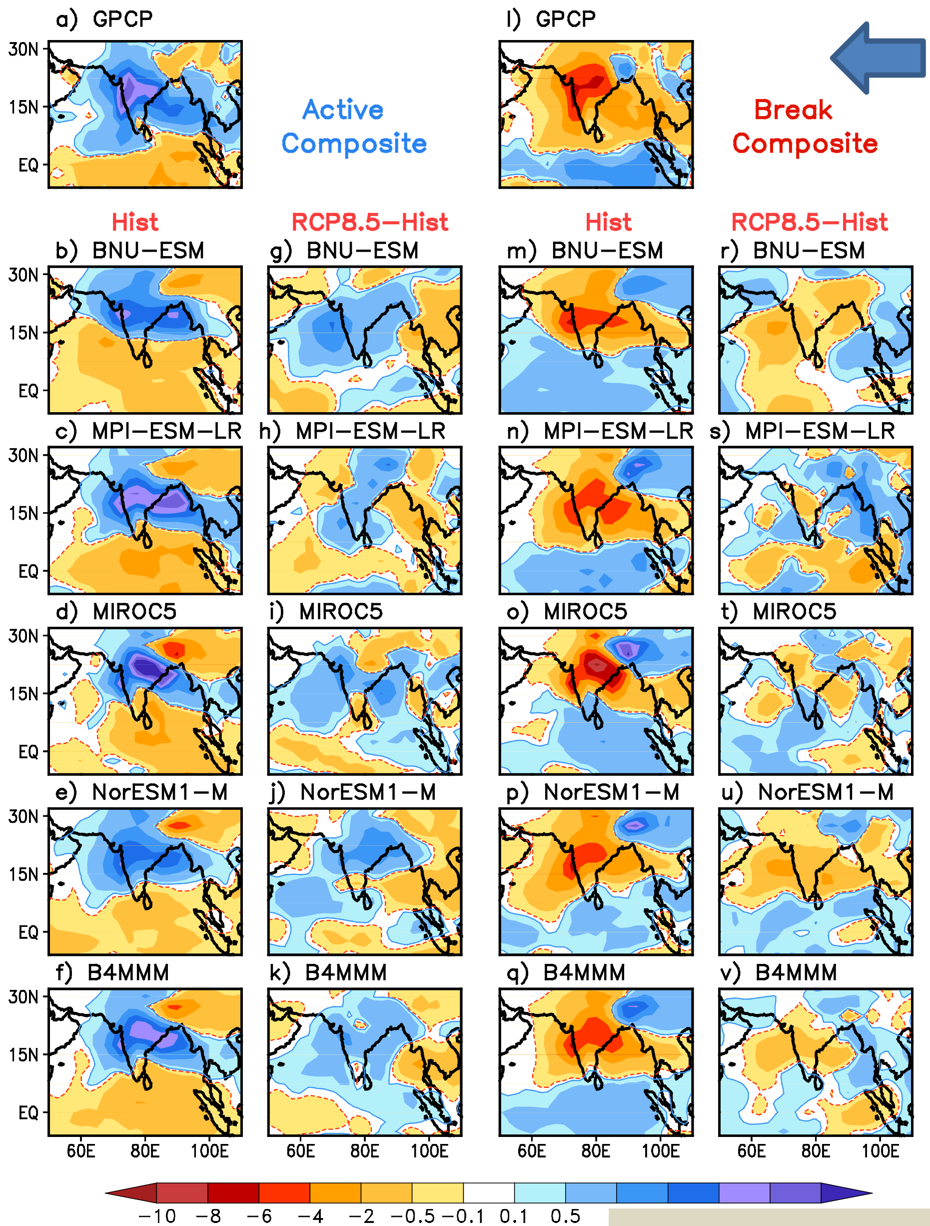
Phase dependent potential predictability of A2B and/or B2A phase transitions is considerably asymmetric during SM and WM years.

The anomalously high (low) background instability could reduce (enhance) the predictability limit through modulating the growth of error considerably during phase transitions of SM (WM) years.

Sahai et al., 2017, Nat. Haz



Future Projection: Spatial Changes during wet/dry cycle



Active/Break composite of 10-90 day filtered daily precipitation anomalies and Projected changes under RCP8.5

The precipitation anomalies would become more intense and regionally extended over Indian land during active/break cycles in future climate.

Such intensification of the active-break cycles may be caused by the overall intensification in the hydrological cycles due to significant change in the moisture content along with the substantial changes in the large scale circulation.

Sharmila, Sahai et al., 2015, GaPCh

Future Projection: Wet/Dry spells during Extreme Monsoon

Longer active spells will be more frequent, while breaks will be fewer and shorter, leading to wetter SM in future.

In contrast, WM will be drier due to the high

In such a scenario prediction of Extreme events becomes challenging which affects management of water resources, agricultural yields, infrastructure and in turn lives of millions over Indian subcontinent

Sharmila, Sahai et al., 2015, GaPCh

Since 2011, IITM has started Extended Range Prediction using Climate Forecast System (CFS) coupled model from NCEP, under the "National Monsoon Mission" Project of Govt. of India.

Time Line of development of IITM ERPS using CFSv2

2011: Ensemble Prediction System developed, [Abhilash etal., 2014, IJOC]

2012: Bias Correction of CFS forecasted SST implemented
[Abhilash etal., 2014, ASL; Sahai etal., 2013, Cur. Sci.]

2013: High Resolution CFST382 implemented
[Sahai etal., 2014, CD;Borah etal, 2014, IJOC]

2014: CFS based Grand EPS Implemented
[Abhilash etal., 2015, JAMC; Sahai etal., 2015, Cur. Sci]

2015: Forecast for winter and other seasons started

2016: Forecast for Heat Waves started, ERP System transferred to IMD

[Applications: Onset Prediction: Joseph etal, 2015, JC; Uttarakhand Heavy Rainfall: Joseph etal, 2015, CD; Skill of CFST126: Abhilash etal., 2014, CD; June extremes: Joseph etal., 2016, QJRMS; Prediction skill of MJO: Sahai et al., 2016, IITM-RR; Dey et al., 2018, PaGeoph; Cyclogenesis Prediction: Saranya et al., 2018, NatHaz; GRL; Heatwave Prediction: Joseph et al., 2018, IITM-RR; Mandal et al., 2019, Sci Rep]

Development of Ensemble Prediction

Each ensemble member is generated by slightly perturbing the initial atmospheric conditions with a random matrix (random number at each grid point) generated from a random seed. Fraction of the 24 hour tendency of different model variables are added to or subtracted from the unperturbed analysis with random perturbation between -1 and +1 times the 24 hour tendency so that the perturbation follow Gaussian distribution.

The perturbed IC,

$$X'_{x,y,z,t} = X_{x,y,z,t} - n\,[r\,\Delta X_{x,y,z,t}]$$

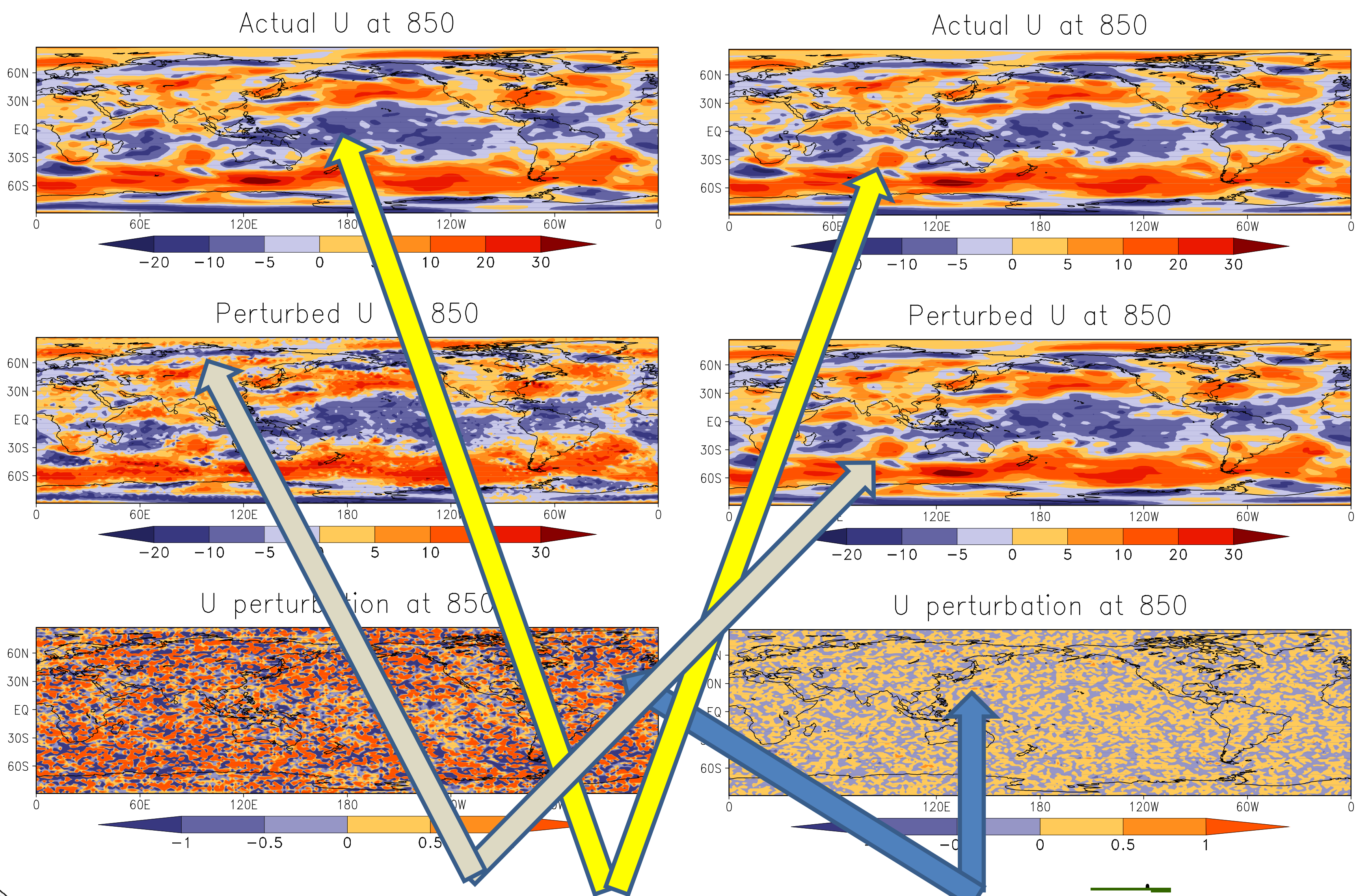
where, $\Delta X = X_{x,y,z,t} - X_{x,y,z,t-1}$; r -> taken from a random matrix and lies between -1 and +1; n -> tuning factor such that $0 \leq n \leq 1$

We perturb the wind, temperature and moisture fields and the amplitude of perturbation for all variables are scaled according to the magnitude of each variable at a given vertical level.

- ❖ *It has the potential to generate infinite number of perturbed ICs.*
- ❖ *Amplitude of perturbation can be adjusted by changing the tuning factor.*
- ❖ *Sensitivity of perturbing each Individual variables can be evaluated.*

Abhilash ,Sahai et al. (2012, IITM Res Rep); Abhilash,Sahai et al. (2014, Int . J. Climatol.)

U-850 (p100) **U-850 (p5)**



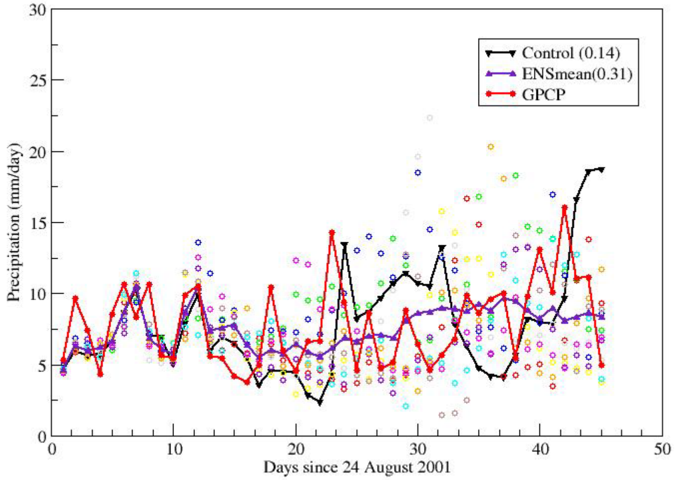
$$X'_{x,y,z,t} = X_{x,y,z,t} - n[r(X_{x,y,z,t} - X_{x,y,z,t-1})]$$

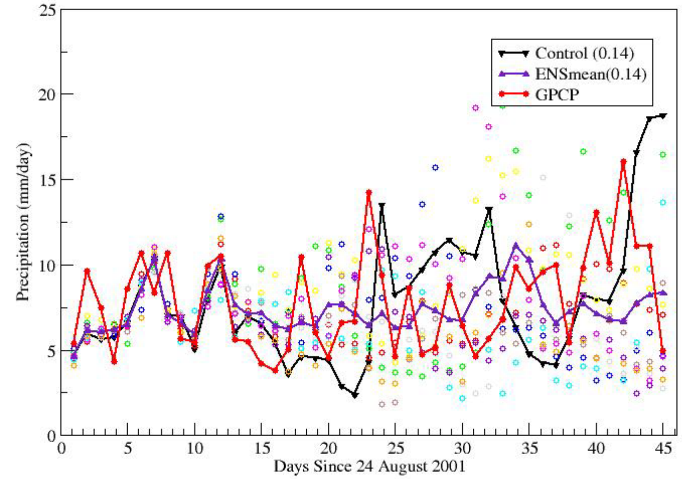
Initial condition of 24 August 2001

Without Q perturbed

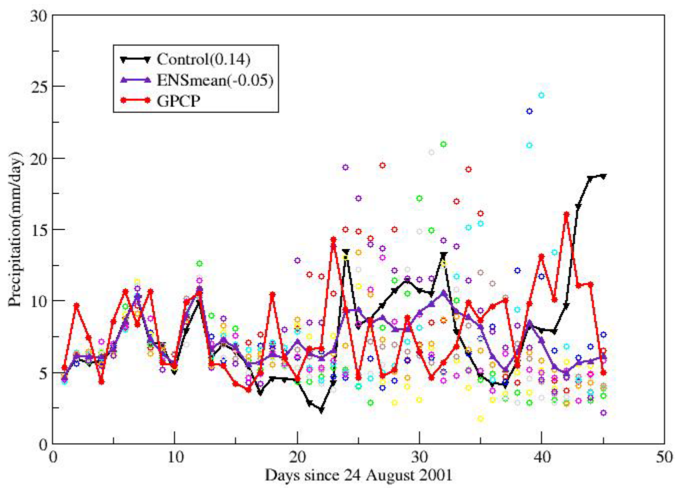
With Q perturbed

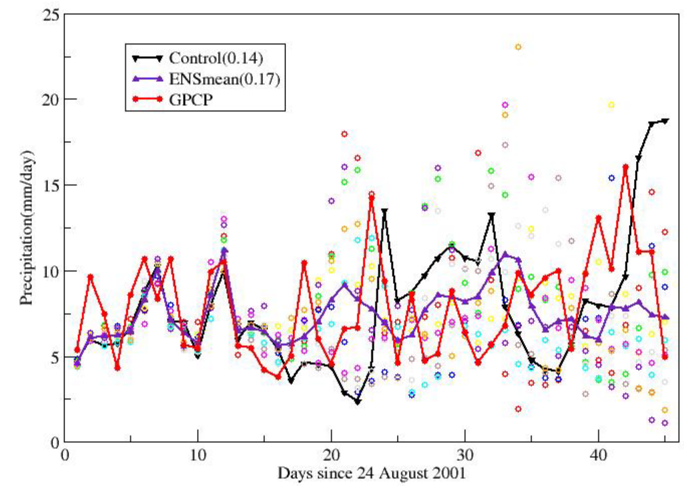
P100





P5

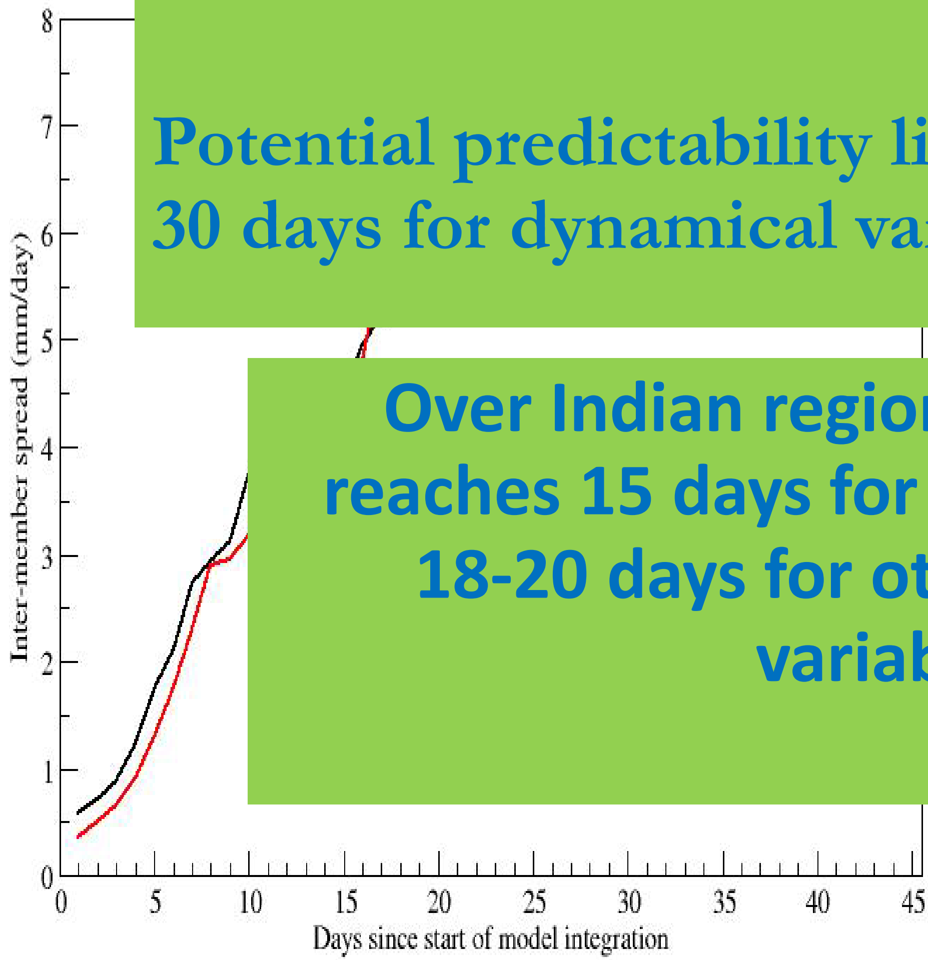




Growth of

EPS system is underdispersive during early forecast leads

Potential predictability limit is extended to 30 days for dynamical variables



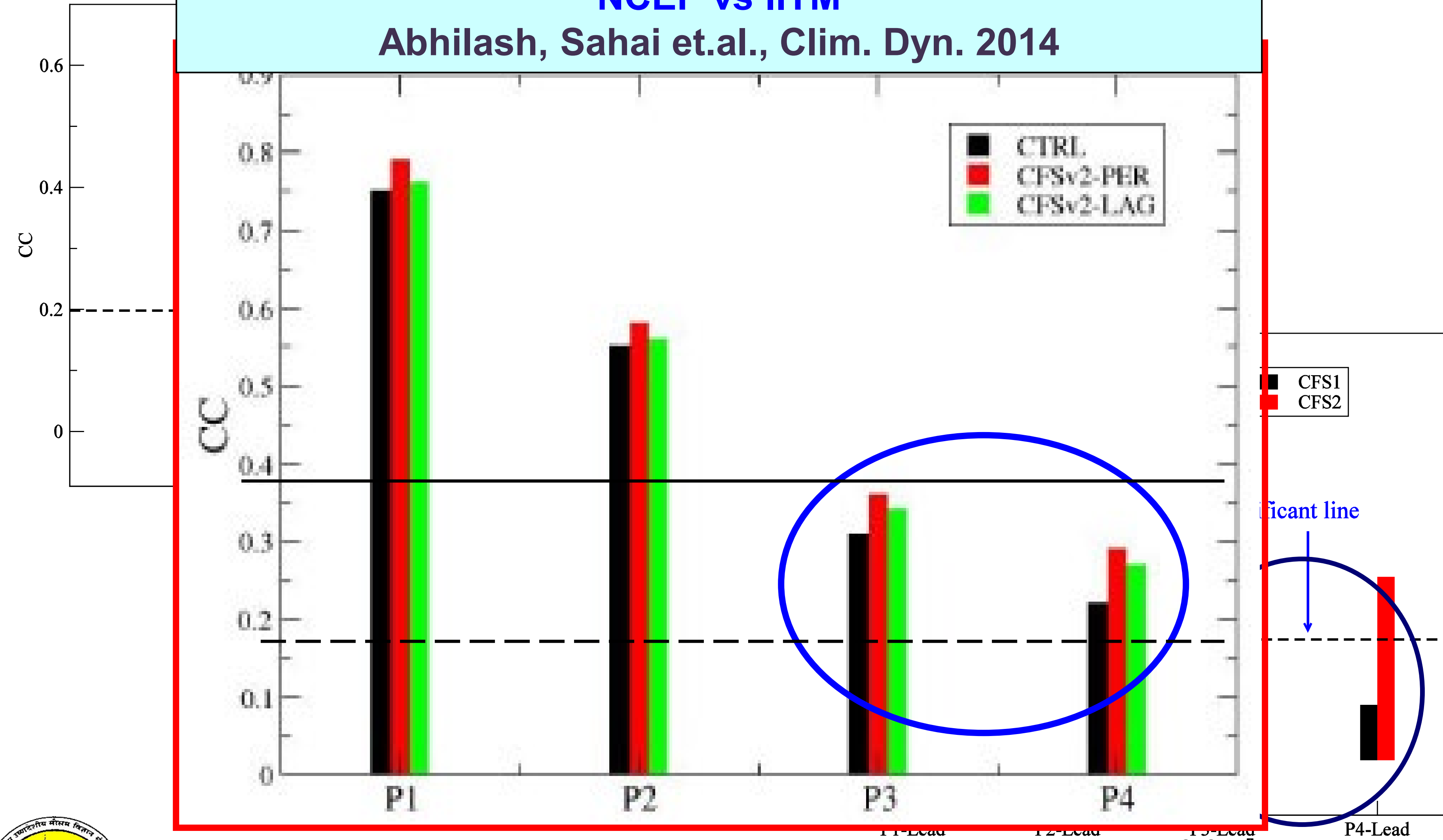
Over Indian region, predictability reaches 15 days for precipitation and 18-20 days for other dynamical variables

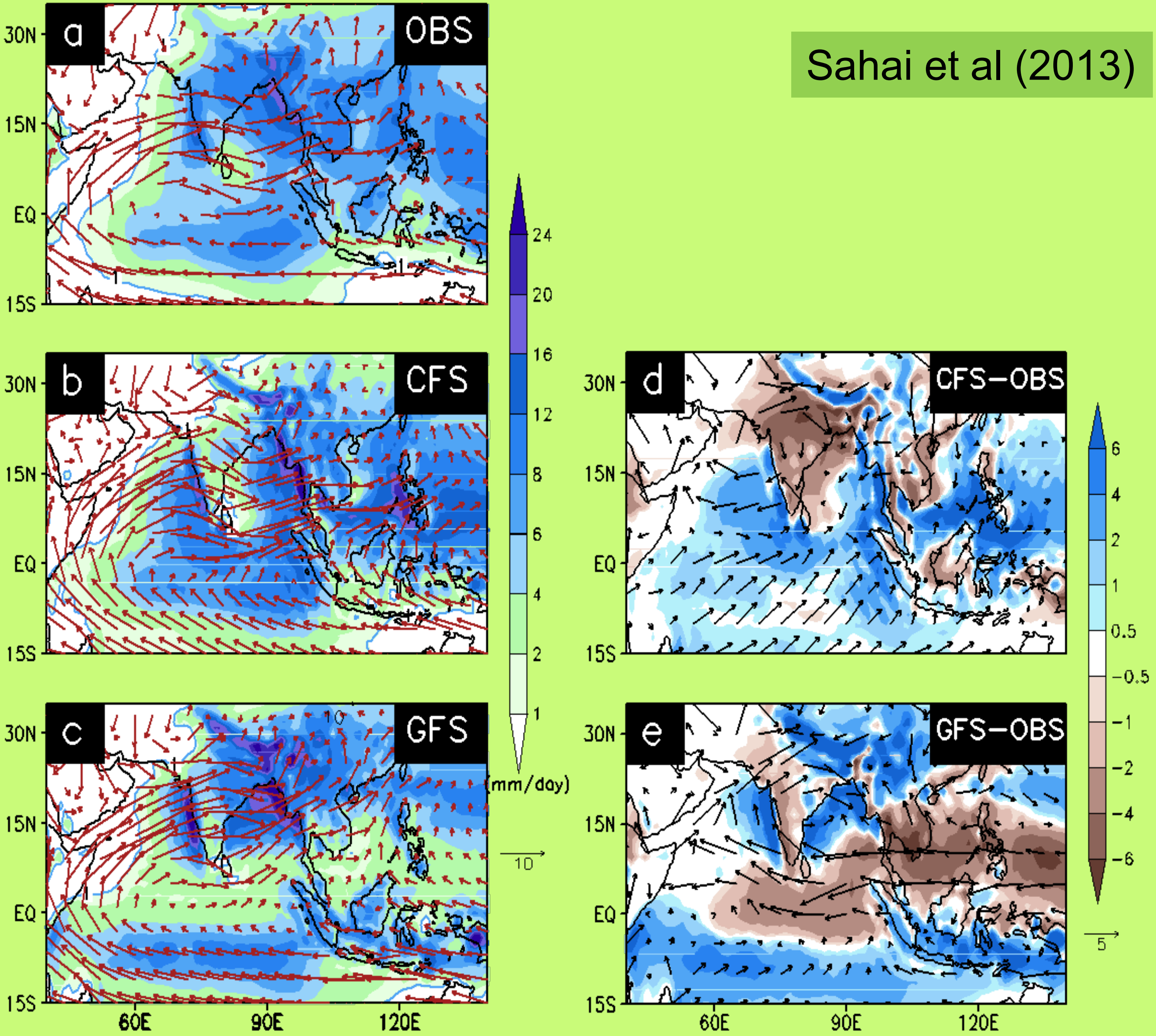
Abhilash et al (2013) IJOC

CC for 24 pentads per year for 7 years (168 points)

NCEP vs IITM

Abhilash, Sahai et.al., Clim. Dyn. 2014

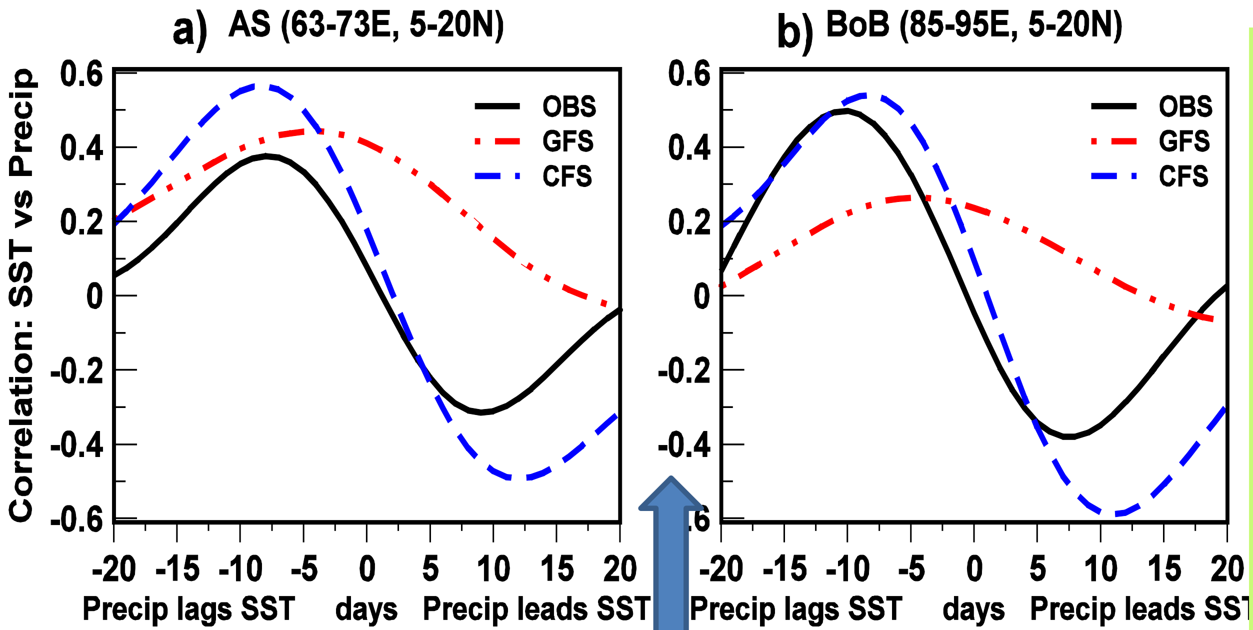




Sahai et al (2013)

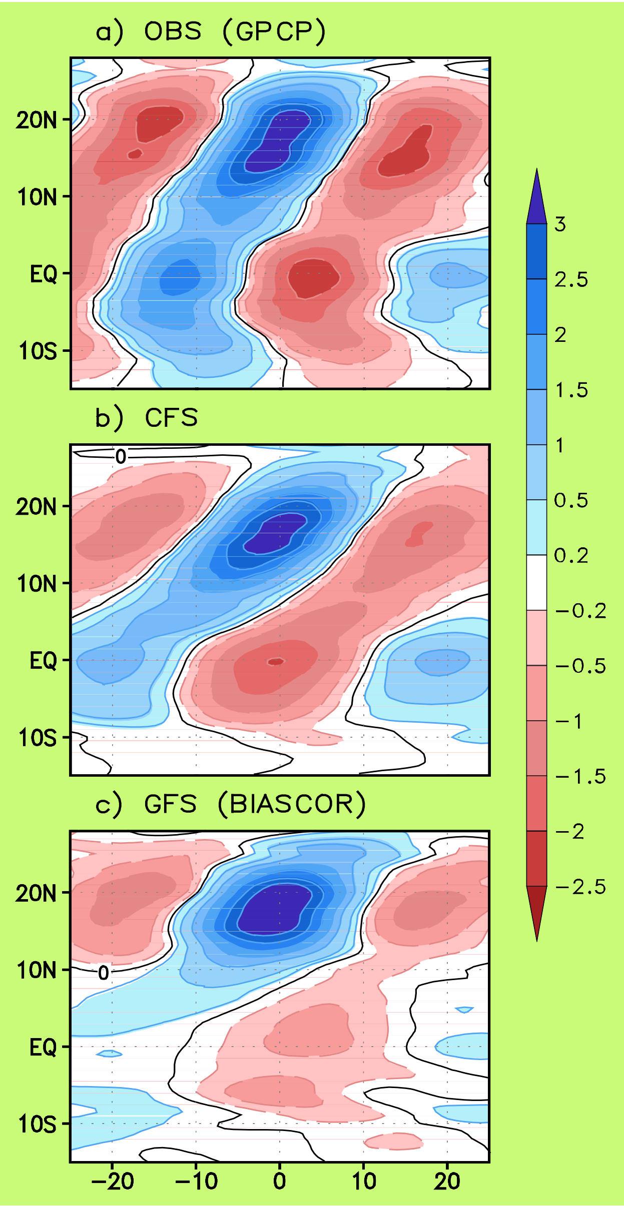
Seasonal (JJAS) mean precipitation ($mmday^{-1}$, shaded) and low level (850hPa) wind (ms^{-1}, vector).

JJAS precipitation bias in CFS and GFS (bias corrected SST) are shown in 2nd column



Lag-lead correlation of daily precipitation anomalies with respect to daily SST anomalies (20-100 day filtered) averaged over a) AS (63°E-73°E; 5°N-20°N) and b) BoB (85°E-95°E; 5°N-20°N)

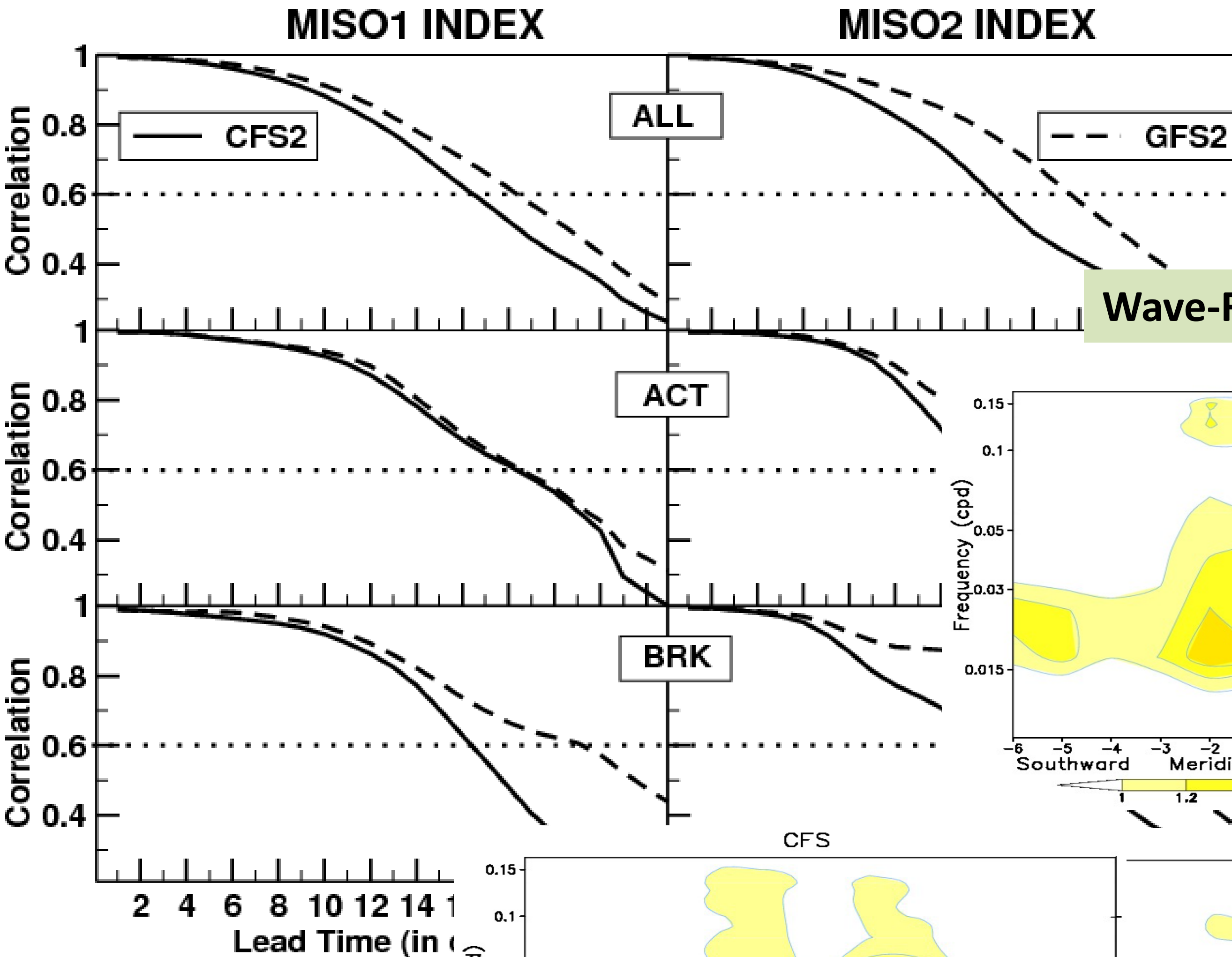
Time-latitude plots of regressed precipitation anomalies (20-100 day filtered; mmday^{-1}) averaged over 65°-90°E



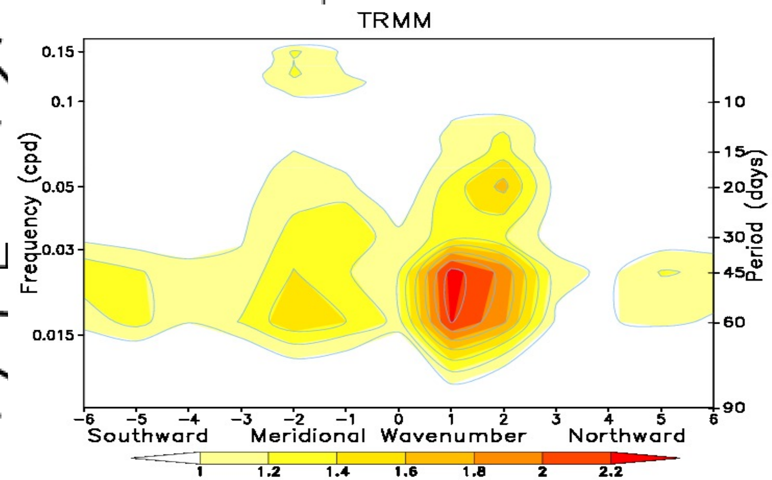
Sharmila, Sahai et.al., Clim. Dyn., 2013

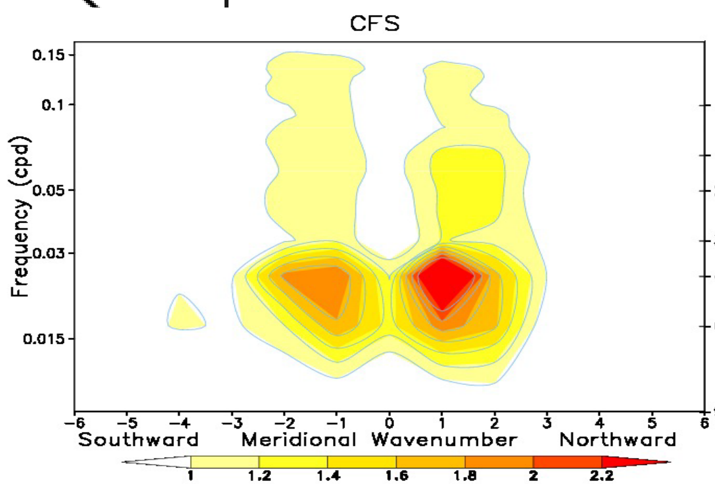
Therefore, coupled models are essential for the simulation of MISO.

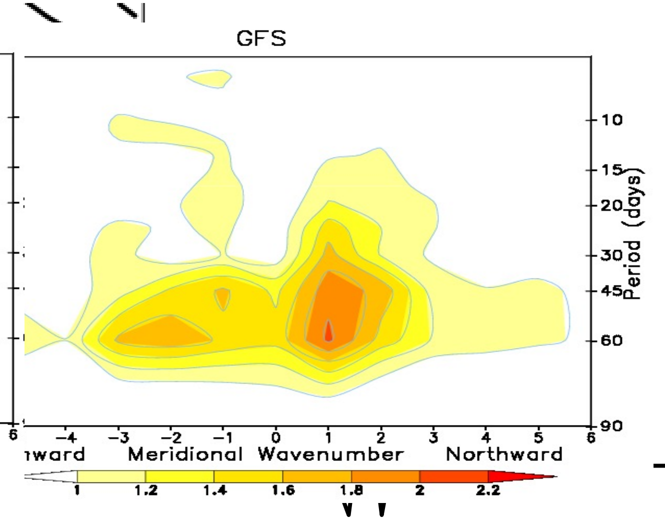
….But, What about prediction?



Wave-Frequency Spectra



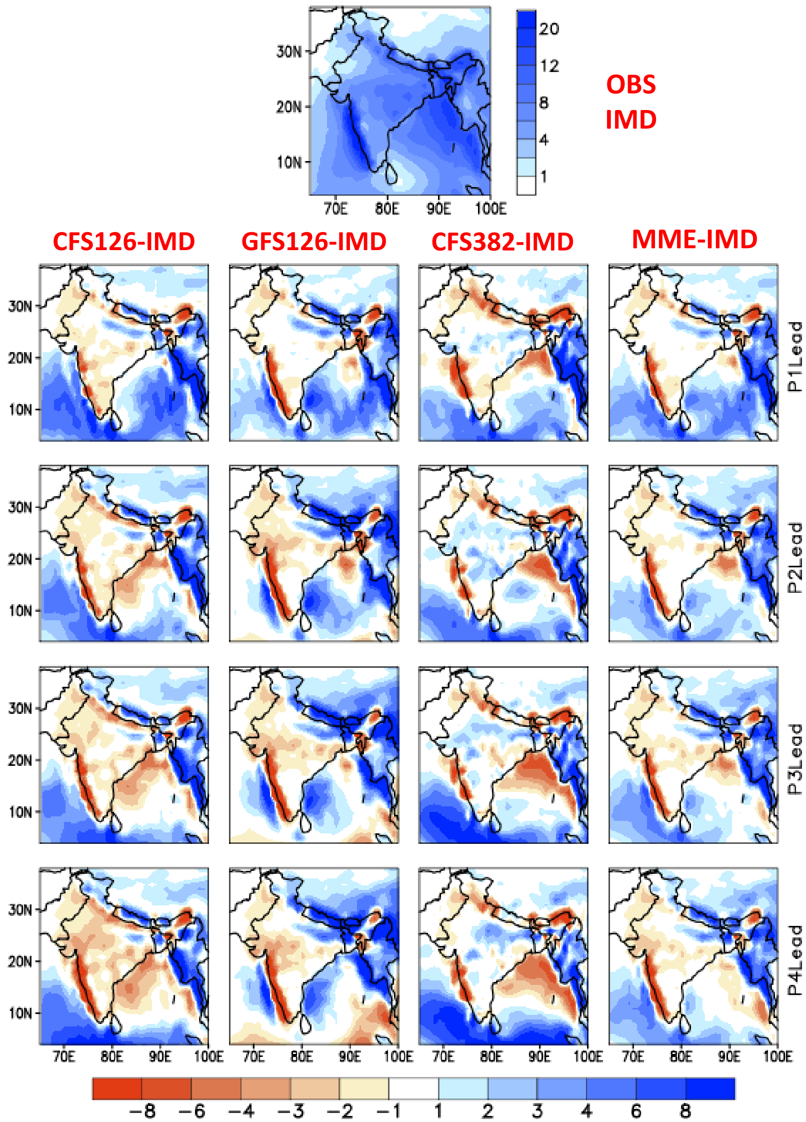




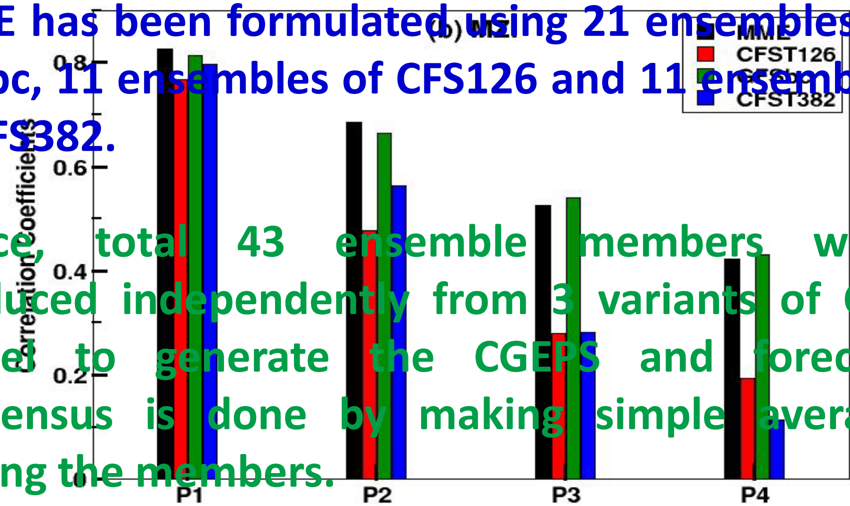
Skill in pre

Development of MME

Seasonal mean and difference from OBS



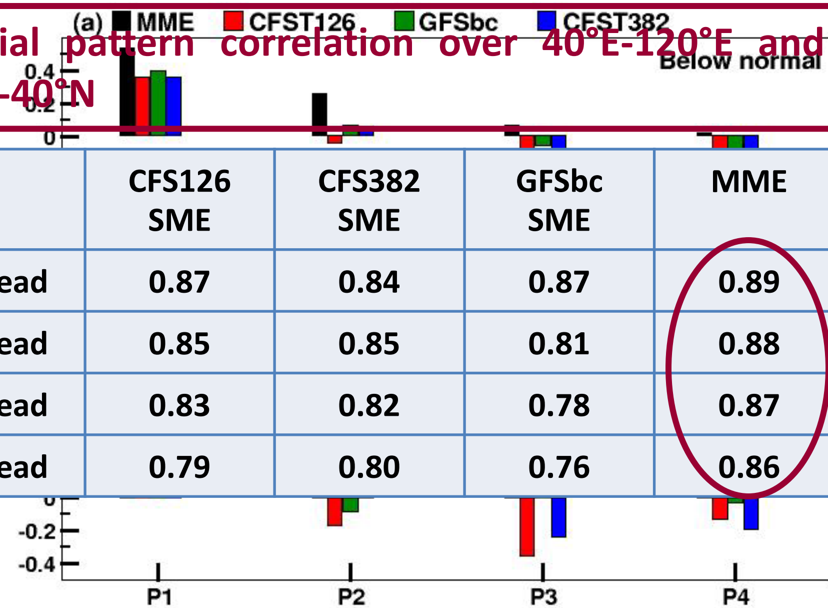
Deterministic prediction Skill



MME has been formulated using 21 ensembles of GFSbc, 11 ensembles of CFS126 and 11 ensembles of CFS382.

Hence, total 43 ensemble members were produced independently from 3 variants of CFS model to generate the CGEPS and forecast consensus is done by making simple average among the members.

Probabilistic Prediction Skill

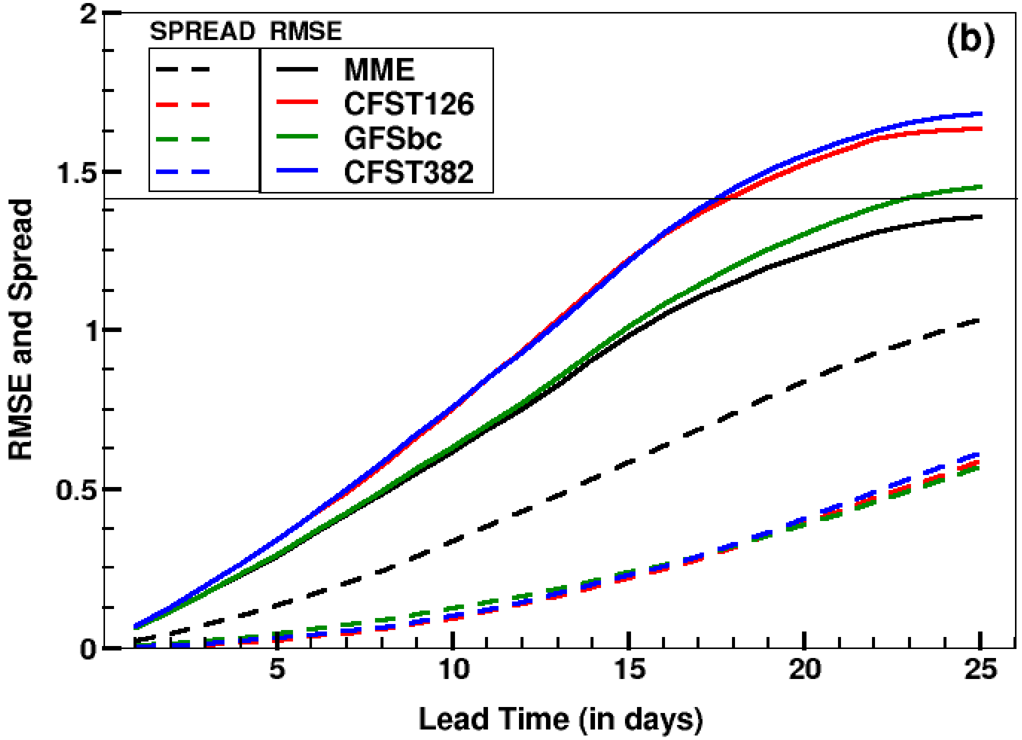


Spatial pattern correlation over 40°E-120°E and 40°S-40°N

	CFS126 SME	CFS382 SME	GFSbc SME	MME
P1 Lead	0.87	0.84	0.87	0.89
P2 Lead	0.85	0.85	0.81	0.88
P3 Lead	0.83	0.82	0.78	0.87
P4 Lead	0.79	0.80	0.76	0.86

Abhilash et al. 2015, JAMC

RMSE and spread of MISO indices



Bivariate RMSE: RMSE w.r.t. observation

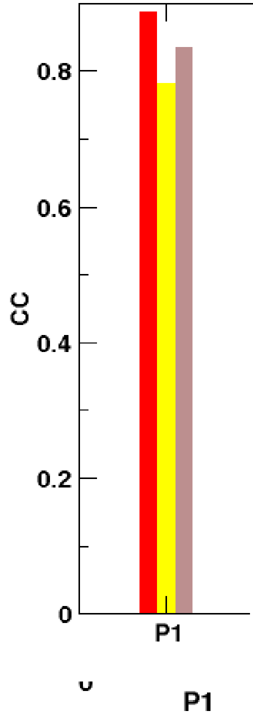
Bivariate Spread: Std. Dev of iindividual models w.r.t. Ensemble mean

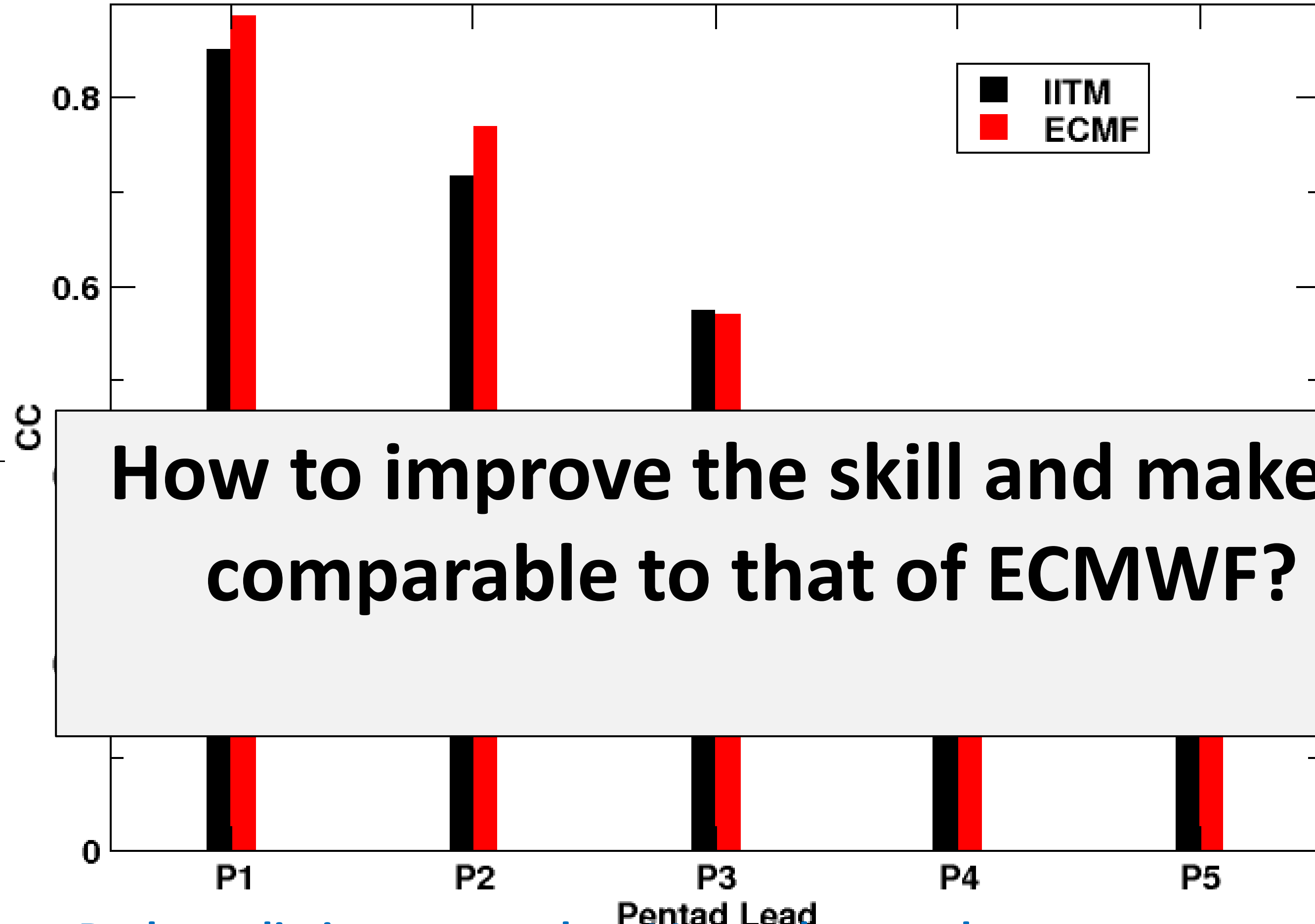
Considerable improvement in MME is contributed from the increased spread, which overcomes the under-dispersive nature of the individual models in EPS.

Abhilash, Sahai et al. 2015, JAMC

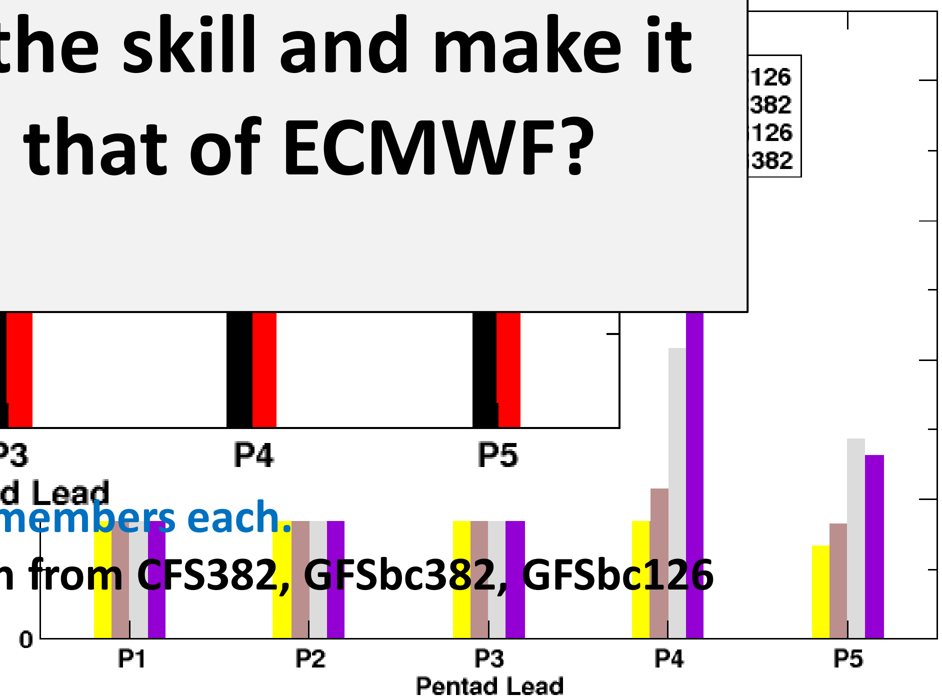
Comparison of IITM-ERPS with ECMWF

Chattopadhyay, Sahai et. al. IITM RR-139





much less
ads



How to improve the skill and make it comparable to that of ECMWF?

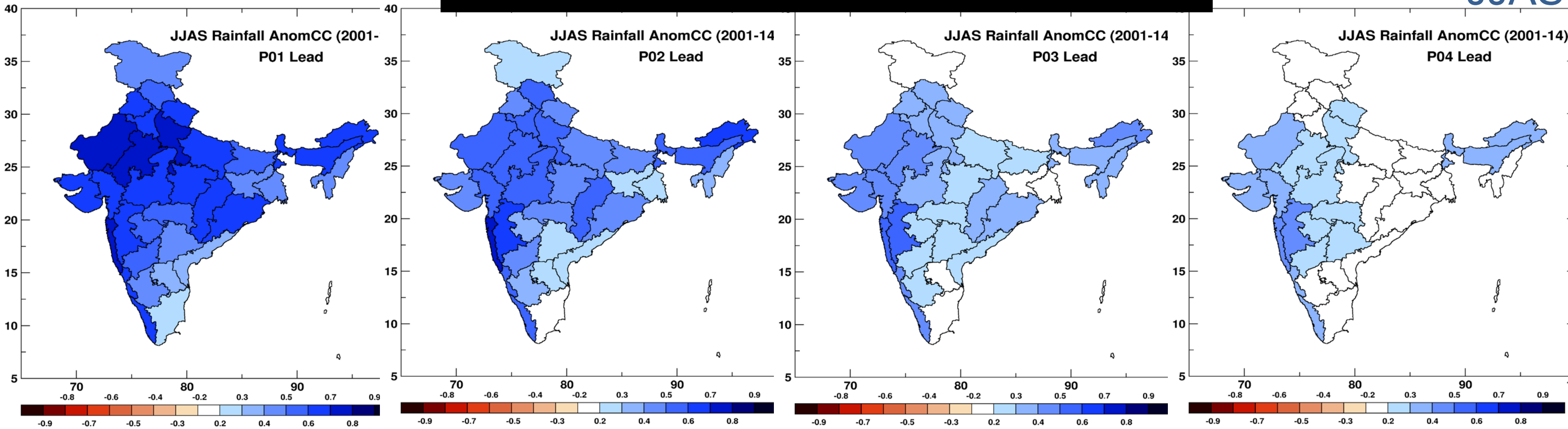
Both prediction systems has 11 members each.

IITM-MME uses 3 members each from CFS382, GFSbc382, GFSbc126 and 2 from CFS126

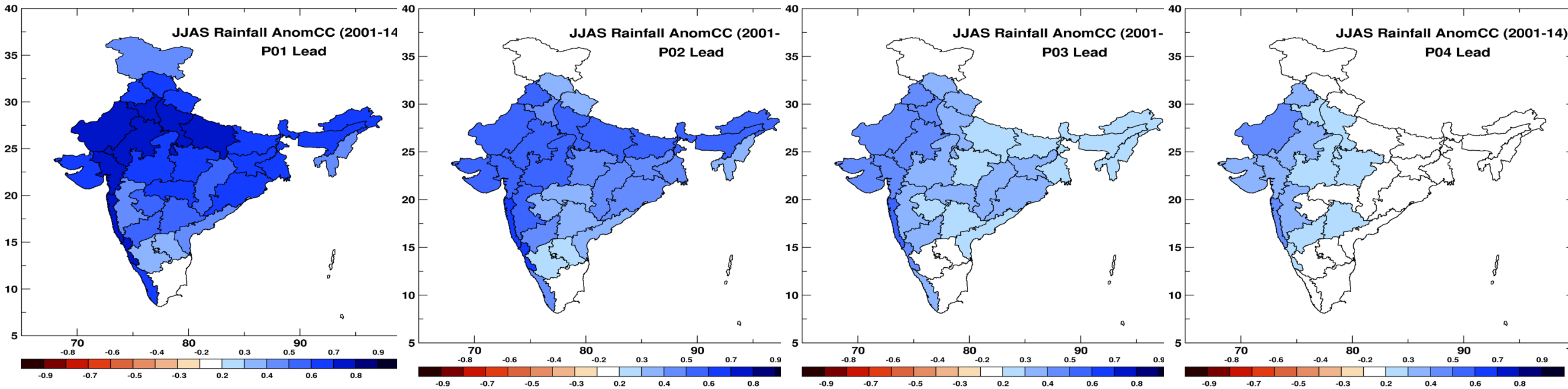
Subdivision Wise Statistics

ECMF MME

JJAS



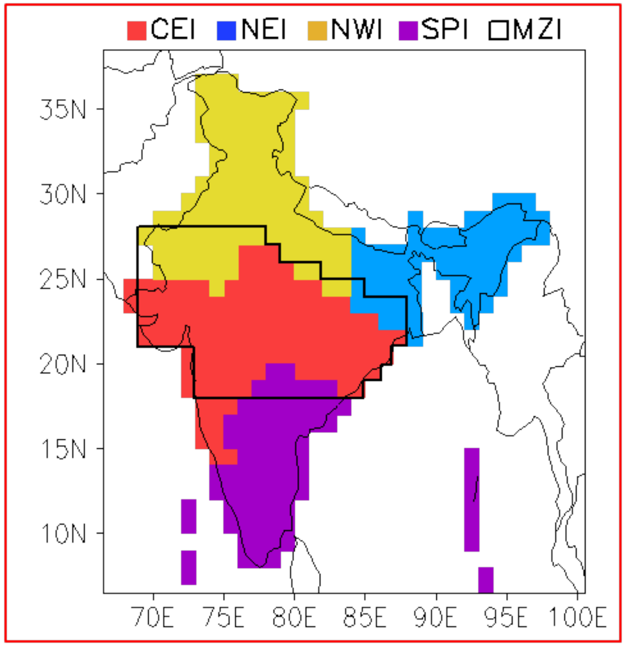
IITM MME

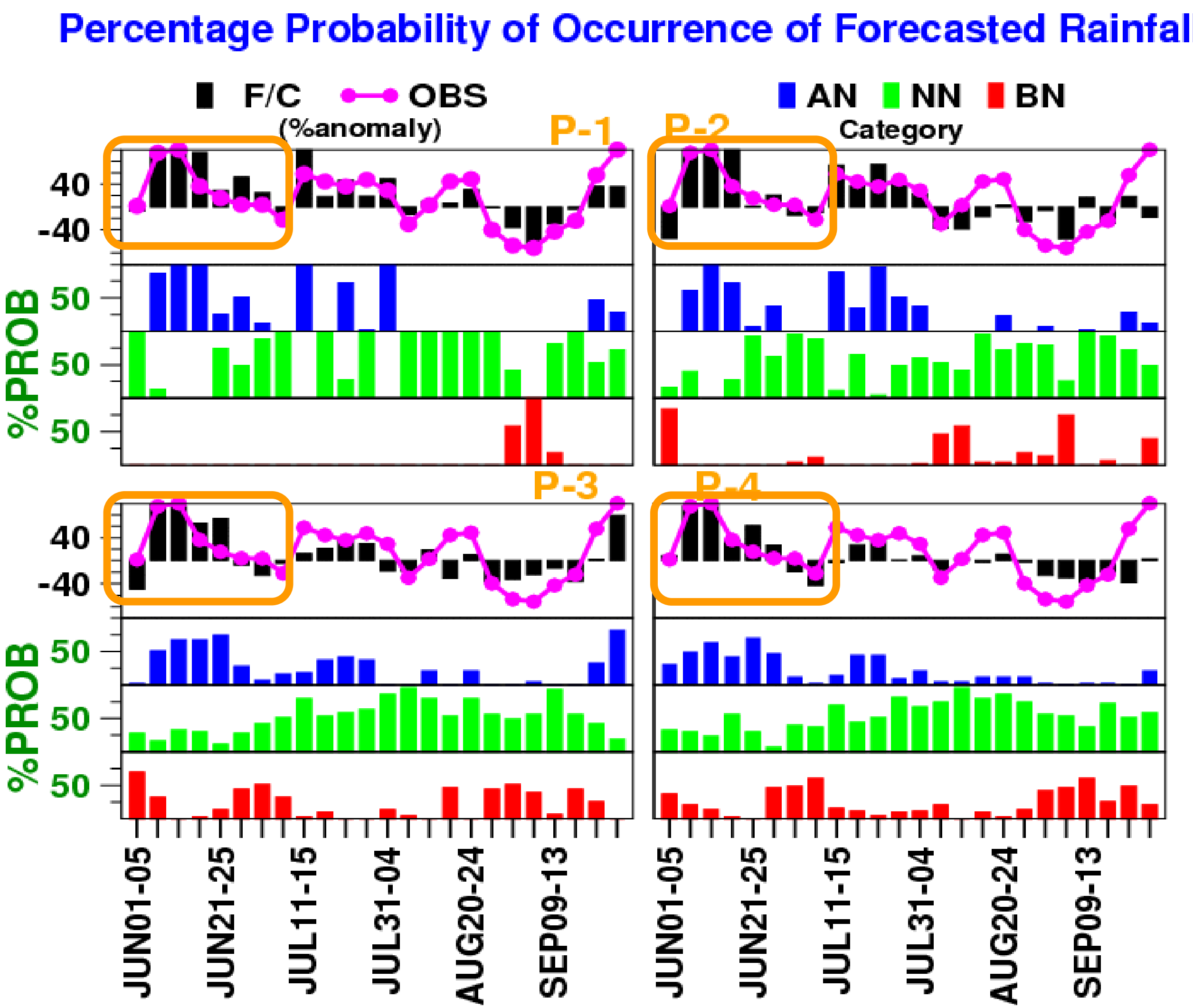


Chattopadhyay, Sahai et. al. IITM RR-139

MONTHLY EXTREMES

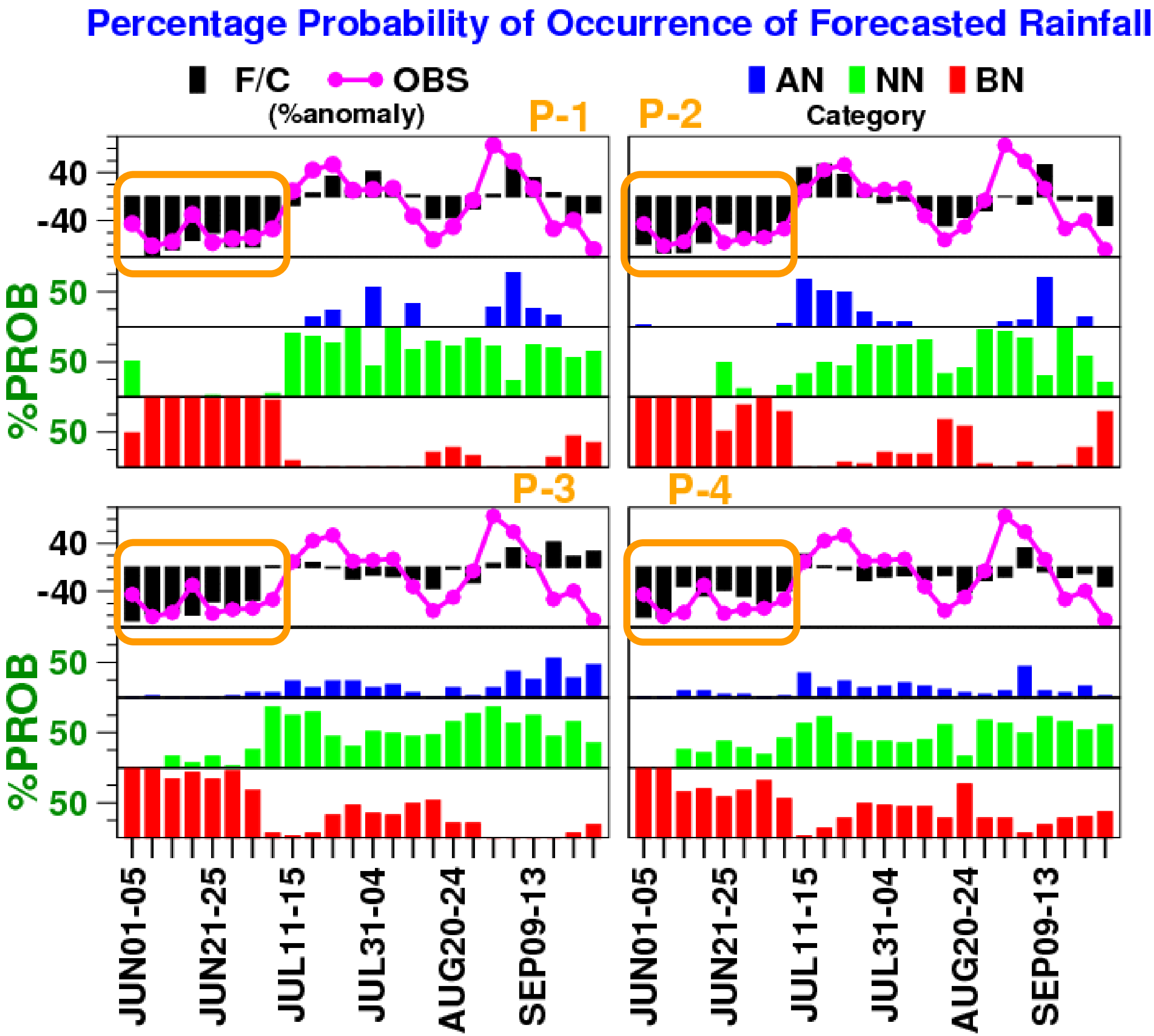
Forecast of 2013 ISM over monsoon zone (MZI)





	CC	RMSE (%)
P1	0.83	29
P2	0.66	41
P3	0.75	34
P4	0.64	39

Forecast of 2014 monsoon over MZI



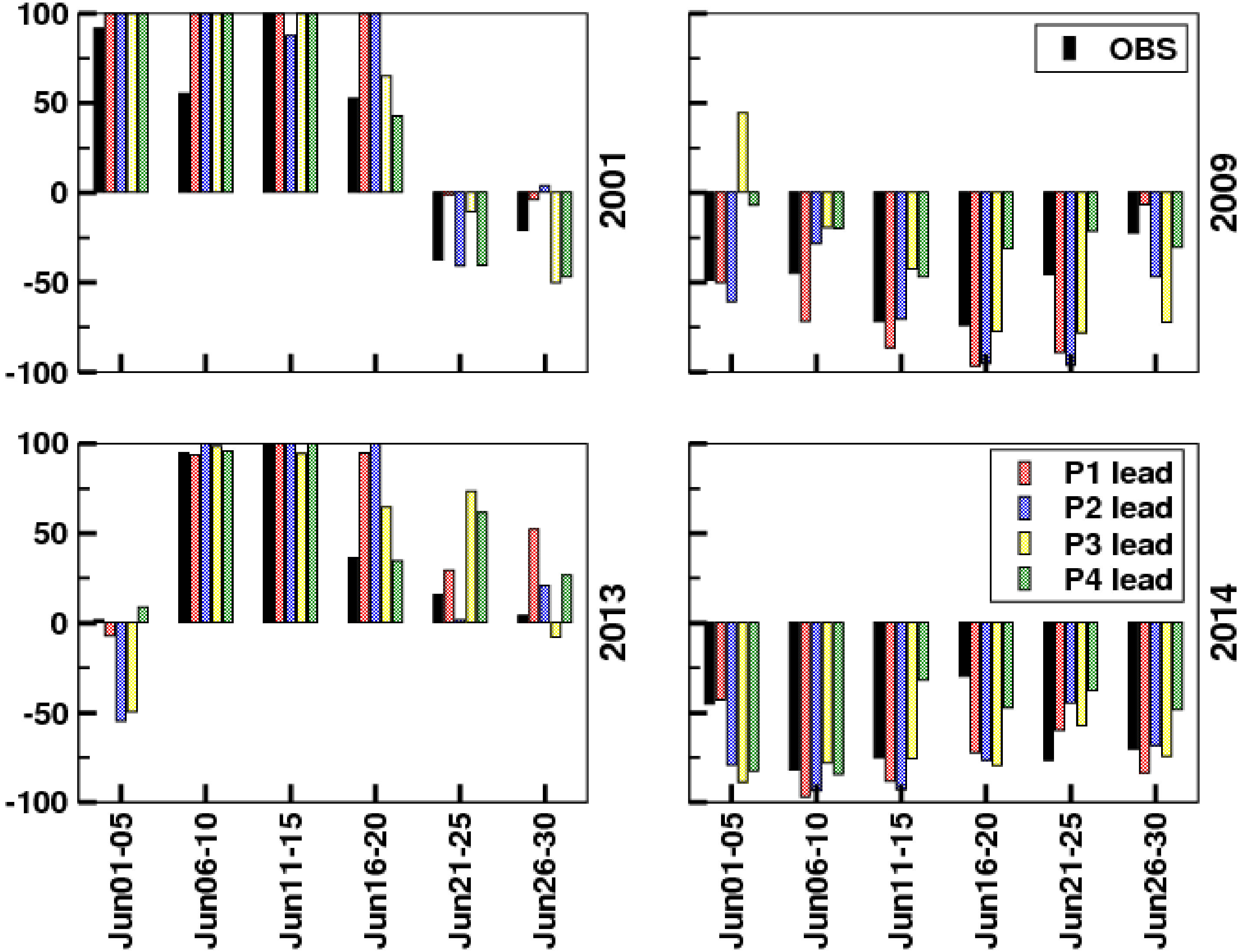
	CC	RMSE (%)
P1	0.82	31
P2	0.79	34
P3	0.57	46
P4	0.72	38

Observed June Rainfall during 2001-14

Year	June Rainfall	Departure from Mean
2001	219.0	35.6
2002	180.1	9.4
2003	179.9	9.8
2004	158.7	-0.8
2005	143.2	-9.5
2006	141.8	-12.7
2007	192.5	18.5
2008	202.0	24.3
2009	85.7	-47.2
2010	138.1	-15.6
2011	183.5	12.2
2012	117.8	-28.0
2013	219.8	34.4
2014	92.4	-43.5

Joseph, Sahai et al. 2016, QJRMS

ERP of June extremes by CGEPS MME



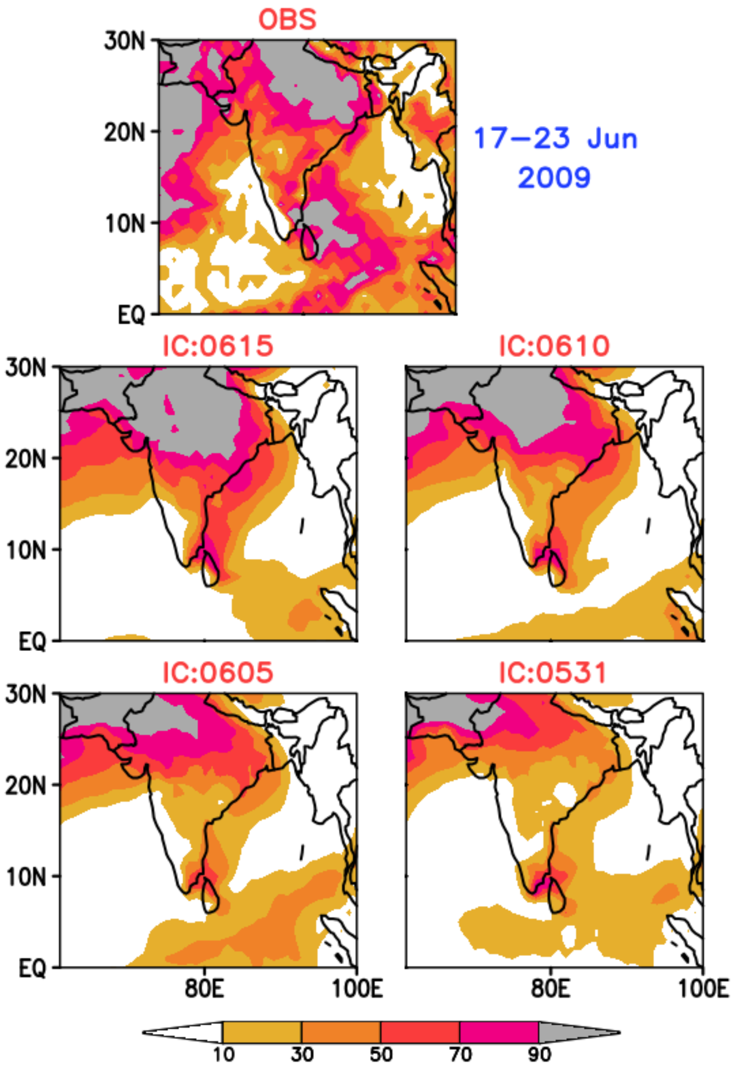
The model has remarkable skill in predicting the June extremes !!!

Joseph, Sahai et al. 2016, QJRMS

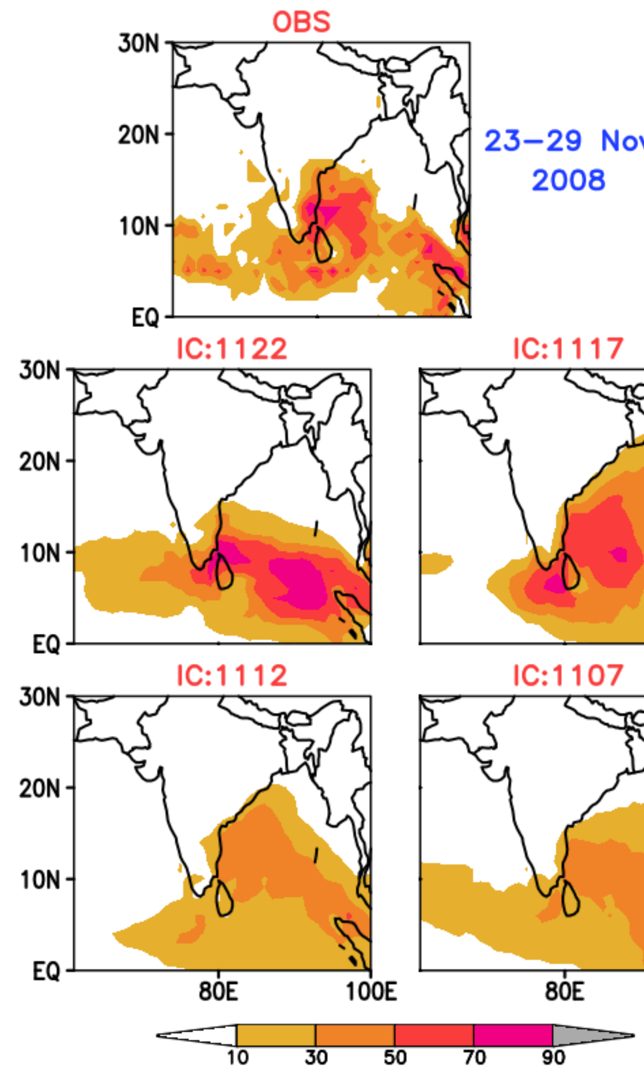
PREDICTION OF ACTIVE/BREAK

Probability forecast of extremes in rainfall – Few Examples

Break Spell (no rain) during SW monsoon

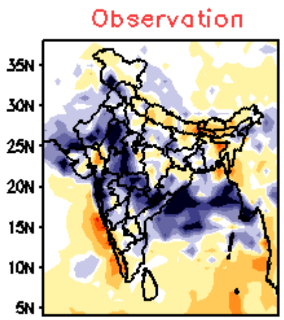


Active Spell (> 15 mm/day) during NE monsoon

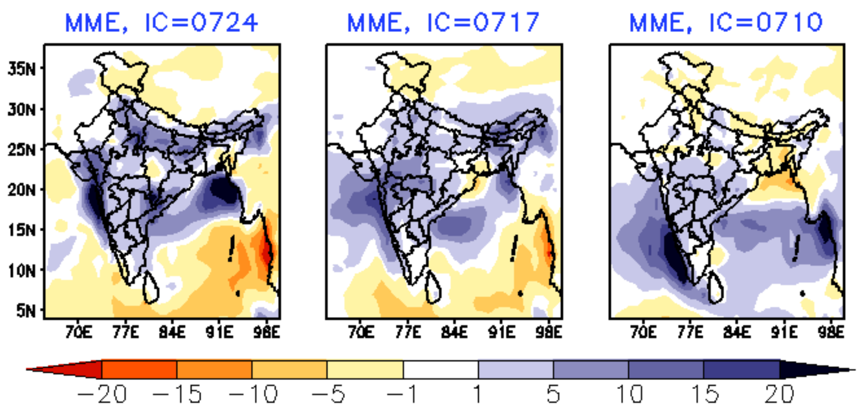


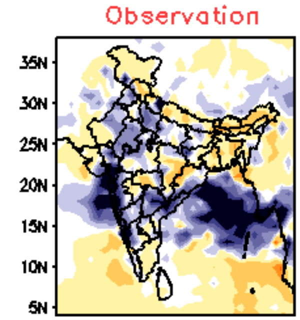
Joseph, Sahai et al. 2019, WAF

Prediction of Selected Active Events in 2019

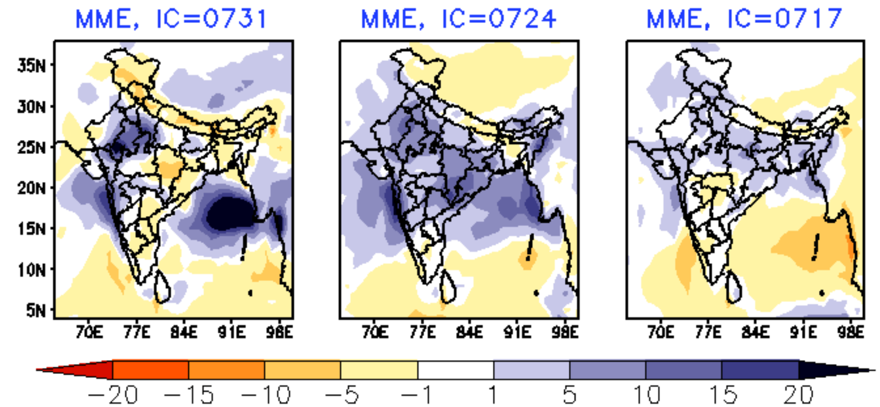


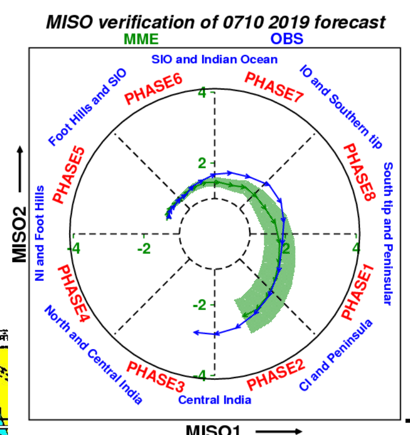
25–31 July

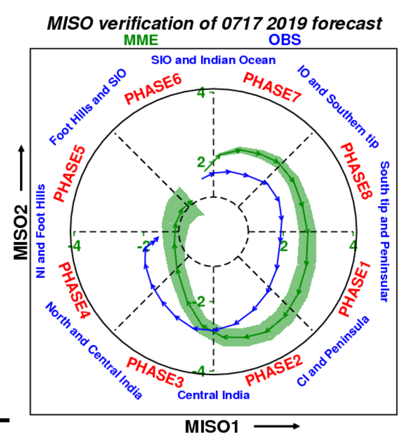


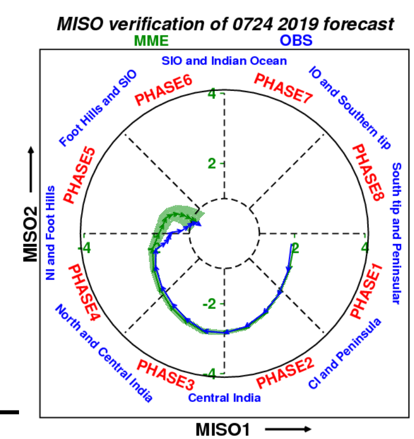


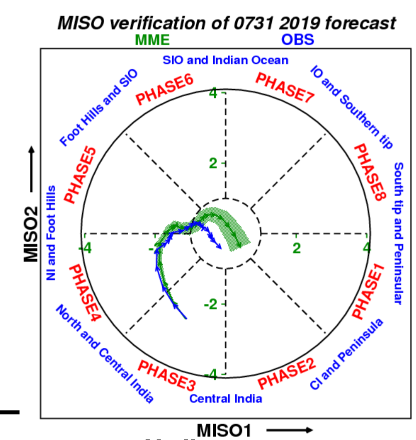
01 – 07 Aug



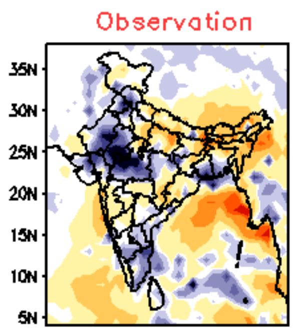




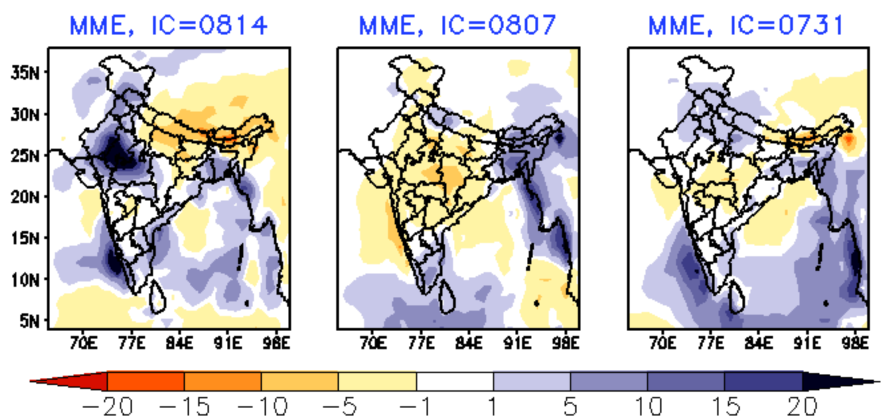


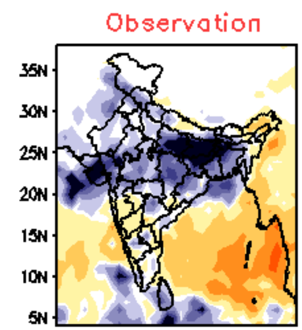


Prediction of Selected Active Events in 2019

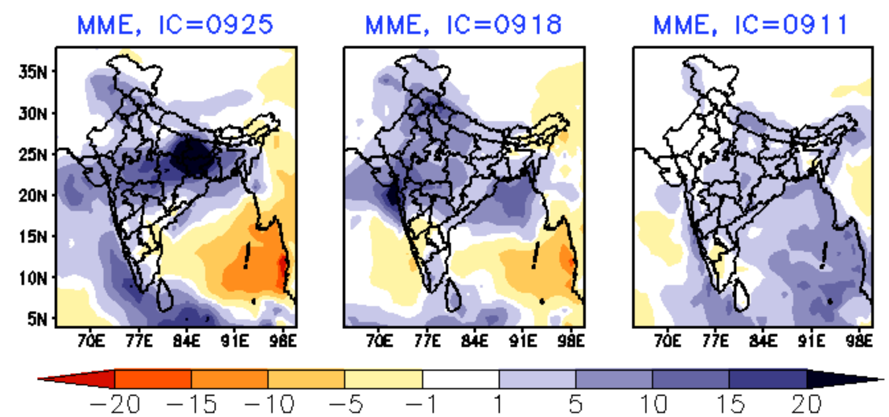


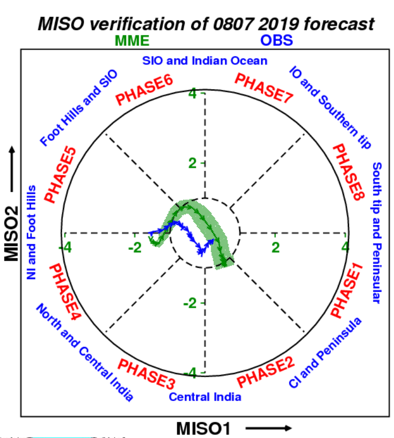
15 – 21 August

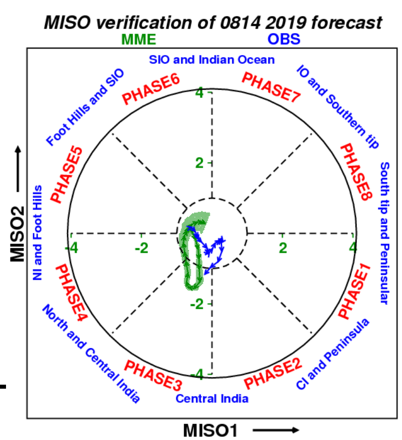


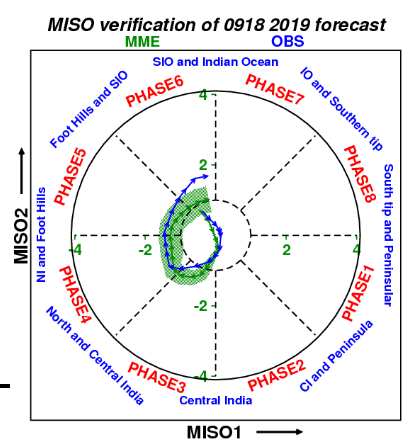


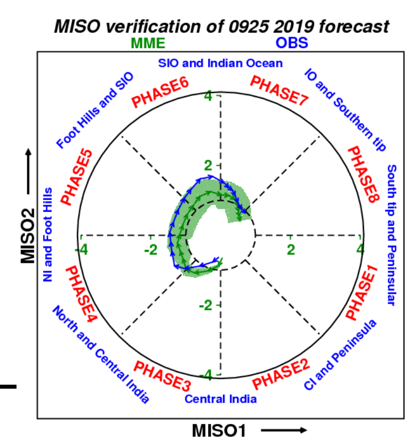
26Sep – 02Oct







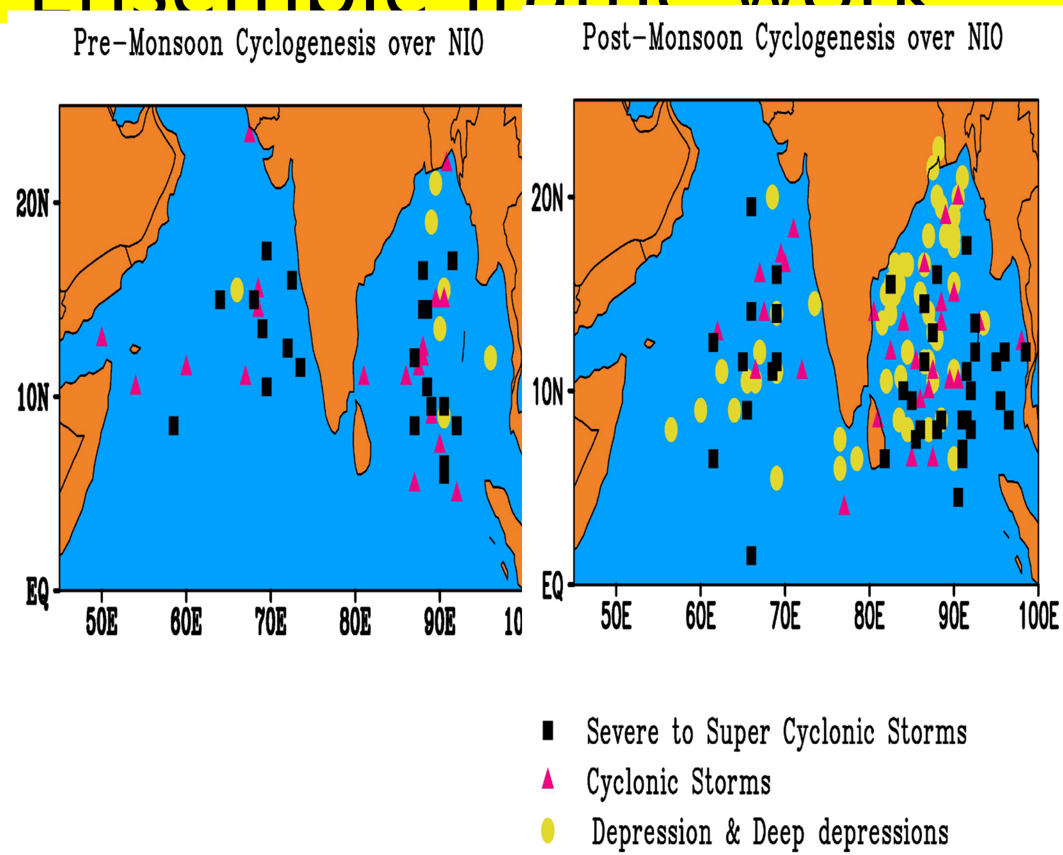




PREDICTION OF CYCLOGENESIS

Development of a prediction system for North Indian Ocean Tropical cyclones in a Multi-model Ensemble frame work

- **An Index for capturing the genesis and evolution of cyclonic storms**
- **An Objective tracking scheme for predicting cyclone tracks**
- **A post-processing technique for improving the track and intensity forecasts**
- **An attempt to downscale**



Existing GPI used by IMD – Kotal et. al (2009)

Low-level relative vorticity (ξ_{850}),

Vertical wind shear between 200 and 850hpa (S),

Middle tropospheric relative humidity between 700 and 500 hPa,

$$M = \frac{[\mathrm{RH} - 40]}{30}$$

& Middle tropospheric instability

$$\mathrm{I} = (T_{850} - T_{500})\ ^{\circ}\mathrm{C}$$

$$\mathrm{GPP} = \frac{\xi_{850} \times M \times I}{S}$$

$$\text{if } \xi_{850} > 0, M > 0 \text{ and } I > 0$$

$$= 0 \quad \text{if } \xi_{850} \leq 0, M \leq 0 \text{ or } I \leq 0$$

New Genesis Potential Index

Low level (850 hPa) relative vorticity (ξ_{850})

Atmospheric instability with averaged equivalent potential temperature between 1000 hPa and 500 hPa

$$I=(\theta e_{1000}+\theta e_{500})/2$$

Magnitude of vertical wind shear between 200 and 850 hPa averged over an annular region between 200 km and 100 km radius from the storm center , V_{shear}

Mid tropospheric relative humidity between 700 hPa and 500 hPa

$$MRH= (RH_{700}+RH_{500})/2$$

$$GPI=A \times B \times C \times M$$

where,

$$A=(10^5\, \xi_{850})$$

$$B=\frac{(I-273.15)}{6}$$

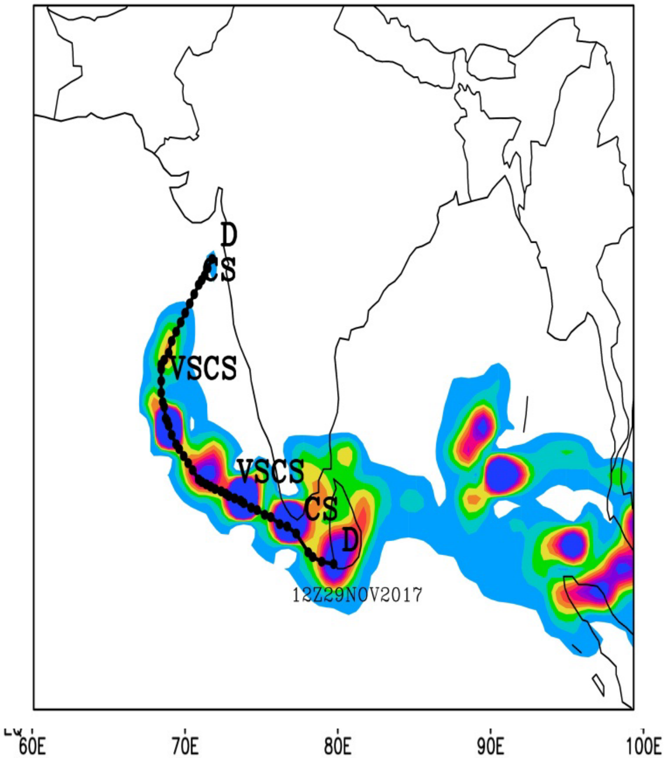
$$C=(1+0.1V_{shear})^{-2}$$

$$M=\frac{(MRH-40)}{30}$$

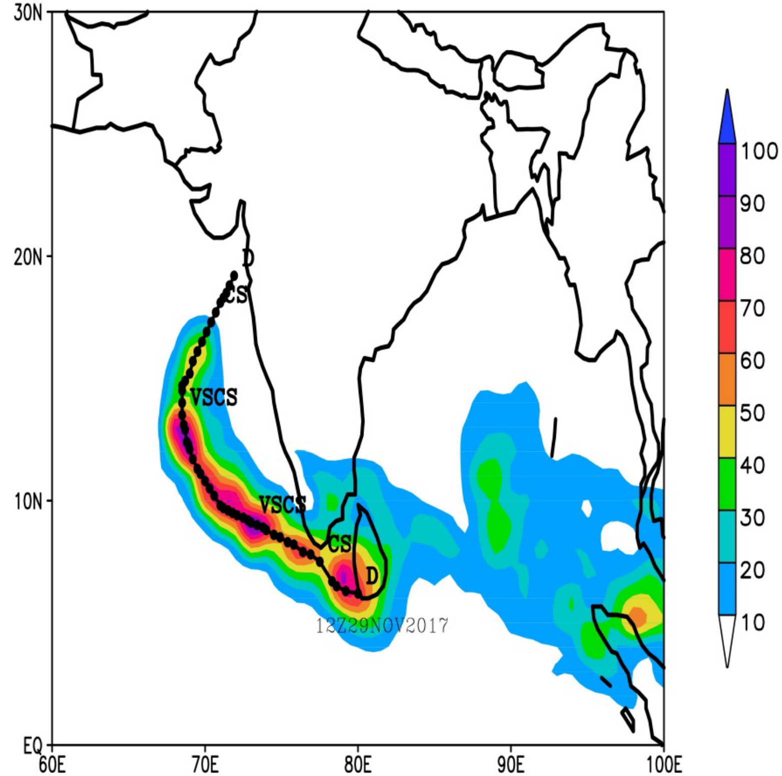
$A>0$, $B>0$, $C>0$, $M>0$

Cyclone Ockhi 29 Nov- 5 Dec 2017

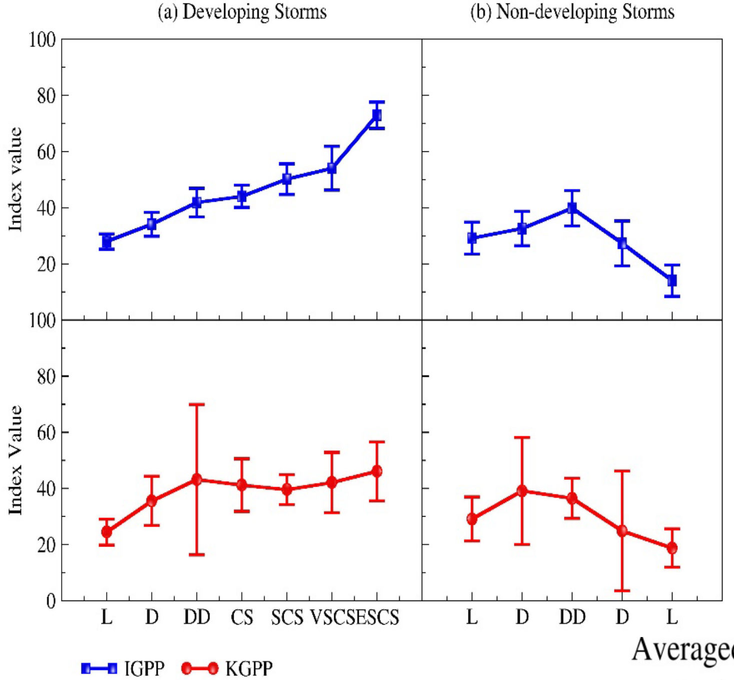
KGPP



IGPP



- **ERA-5 daily averaged datasets**
- **Maximum value of indices during storm evolution**

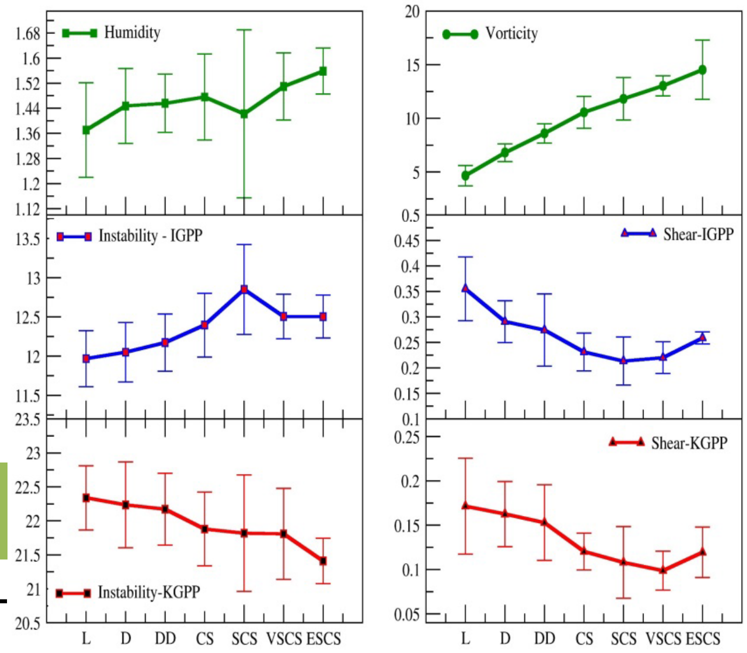


Linear Correlation Coefficients

CONSTITUENT PARAMETERS	Developing storms		Non-developing storms	
	KGPP	IGPP	KGPP	IGPP
Vorticity parameter	0.86	0.95	0.49	0.74
Humidity parameter	0.93	0.73	0.95	0.94
Thermodynamic Term	-0.84	0.82	-0.72	0.88
Shear Term	-0.54	-0.67	0.65	0.70

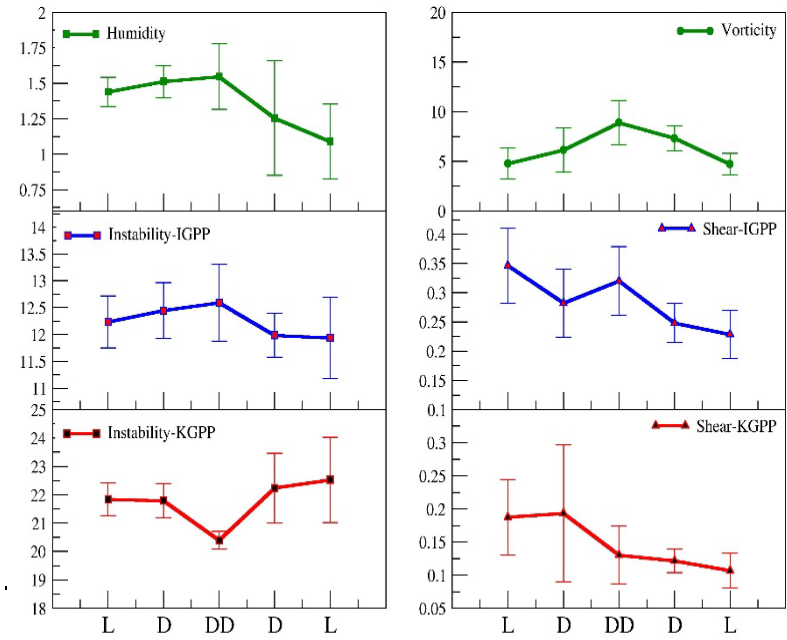
Averaged genesis parameters

Developing Storms



Averaged Genesis Parameters

Non-developing storms



Cases selected : 15 developing and 11 non-developing storms (2008-2017 period over NIO)

Saranya Ganesh et al., 2019 under review

Tracking of cyclonic storms

1. Check for VORTICITY MAX (850 hPa) $>1.6 \times 10^{-4}$ /s and fix vort_max position

2. Check for WIND MAX (850 hPa) >10 m/s

3. Locate local MINIMUM SEA LEVEL PRESSURE <1002 hPa; fix MSLP position if it is within 4 degree from vort_max

4. Check for PRESENCE OF A WARM CORE T (500-200 hpa)

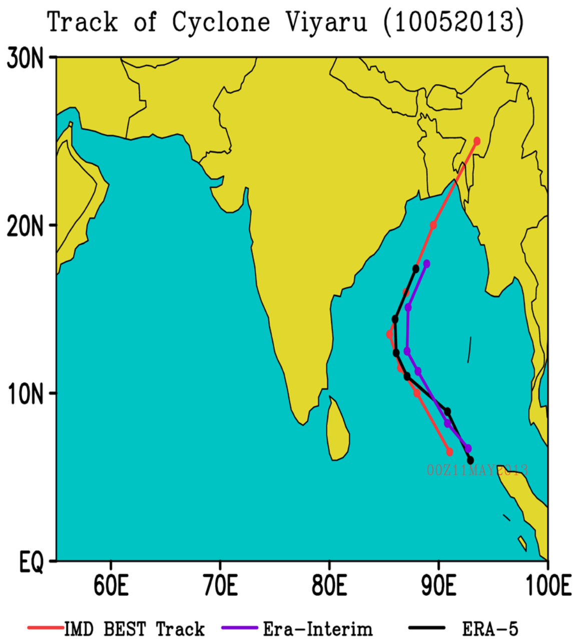
5. CHECK FOR maximum value of Geopotential height Gph (1000-200 hPa)

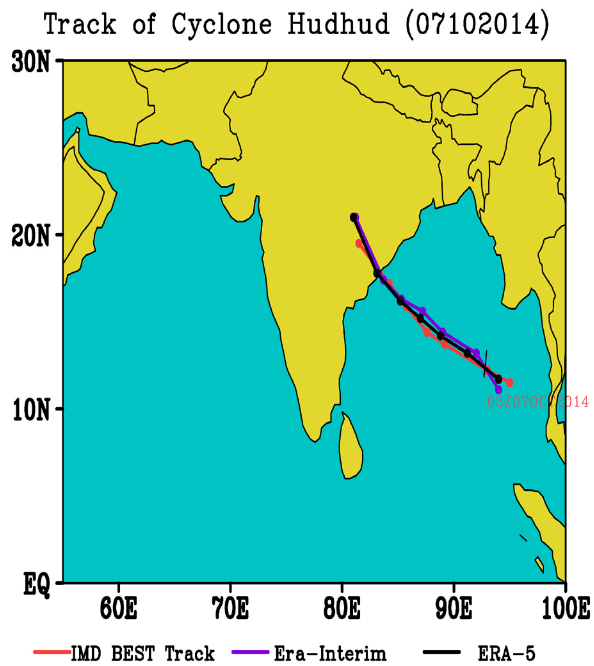
YES

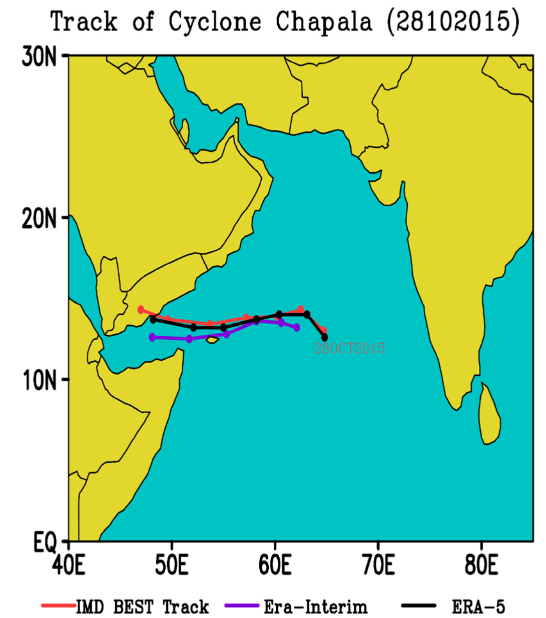
WE HAVE A TROPICAL STORM

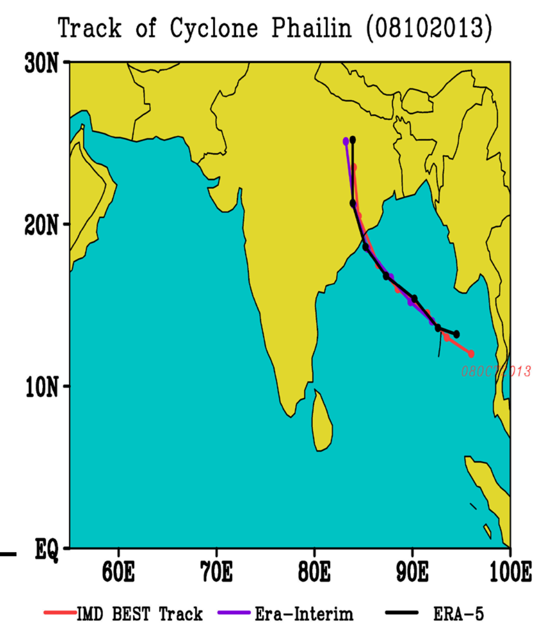
Outputs: Lat, Lon, Wind_Max, Vort_Max, Mslp_Min, Twc_Max, Thick_Max

ERA-Interim & ERA-5 Tracks From Vortex Tracker compared with IMD Best Tracks









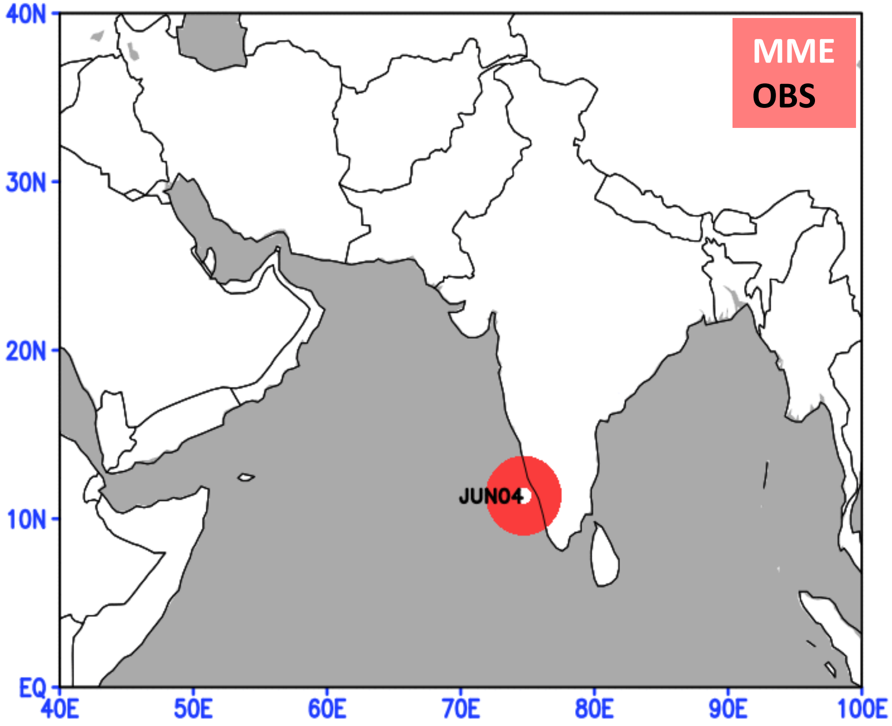
Tracks detected by algorithm are at par with IMD best tracks

Saranya Ganesh et al., NatHaz, 2018

Prediction of Cyclogenesis

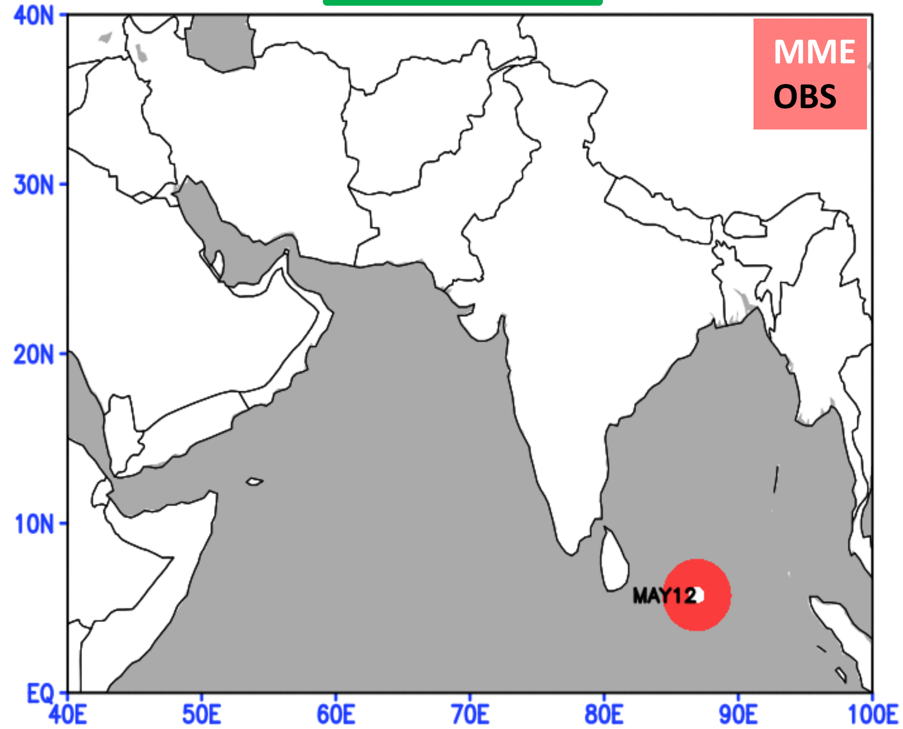
Cyclone "Ashobaa" during Onset phase of 2015 monsoon

IC: 0531



Cyclone Roanu in May 2016

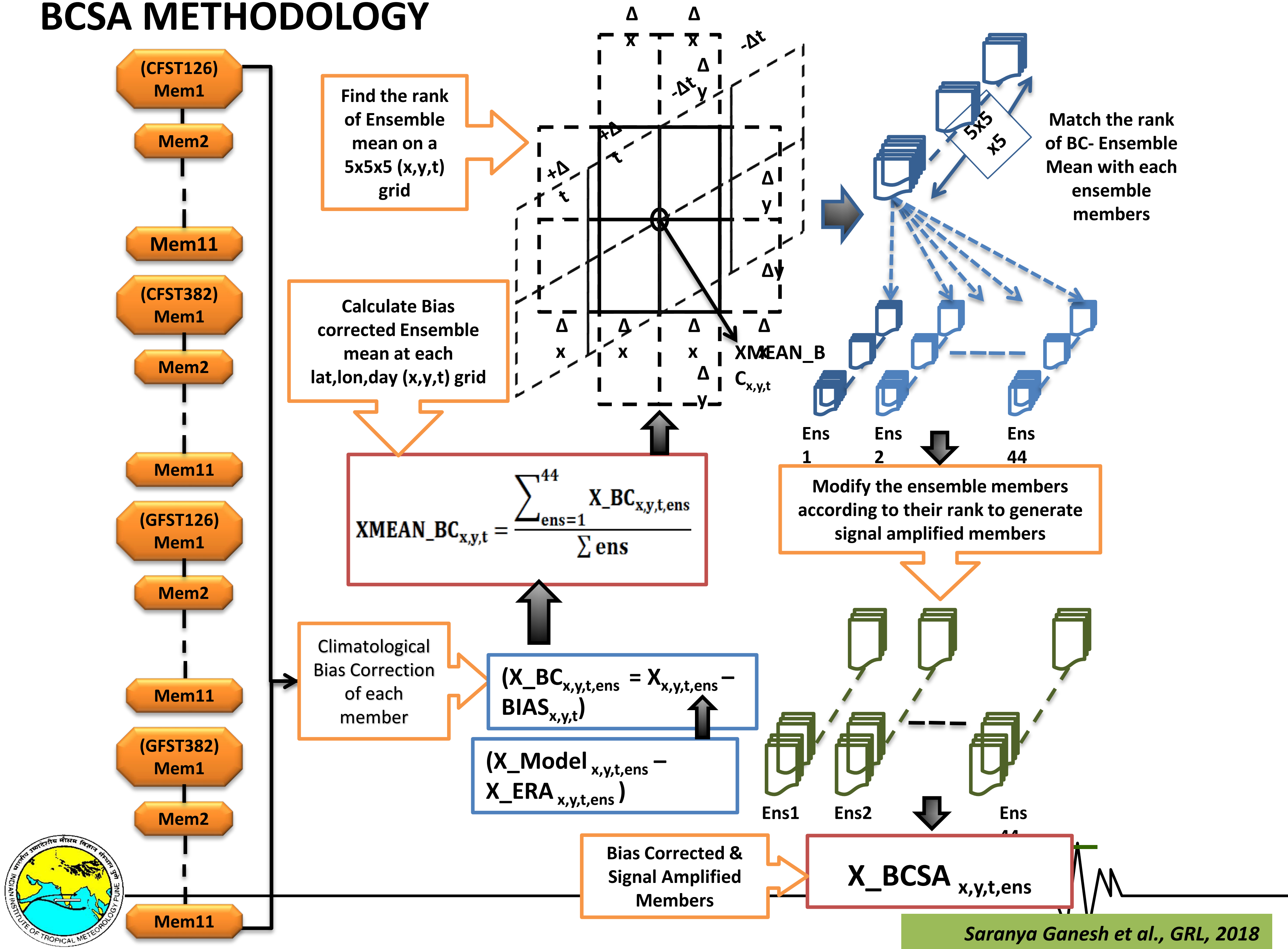
IC: 11 May

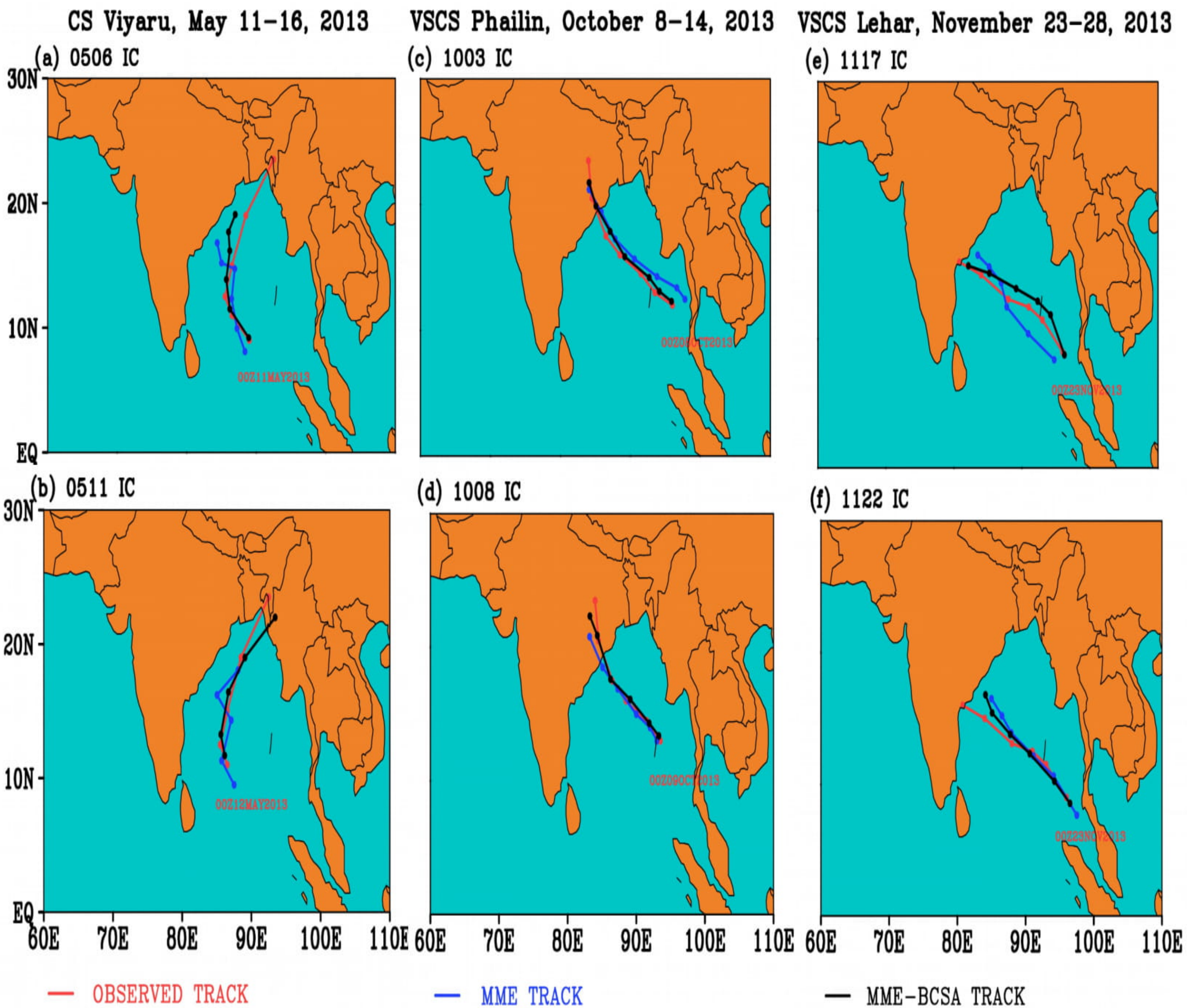


Development of a Bias-Correction and Signal Amplification Technique for further improvements in track and intensity prediction

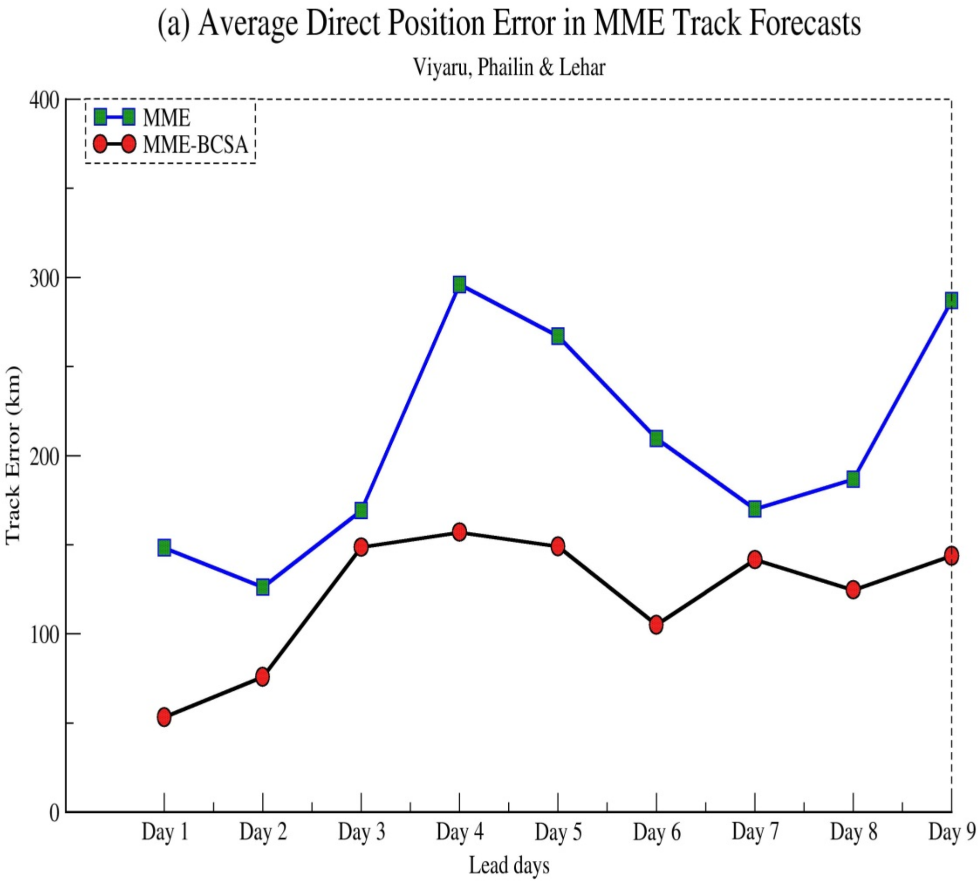
- A major challenge in MMEPS is that storm intensity gets underestimated and forecast track lags behind observations as lead time increases as numerous ensemble members from different models give diverse path for the same system thereby increasing timing and directional errors.
- In this frame work, an objective tracking algorithm will always produce large spread in the track, which in turn increase the cone of uncertainty at higher leads, and the ensemble mean tracks obtained from raw MME may not be as smooth as observed.
- Bias Correction and Signal Amplification method is proposed to overcome this drawback by correcting the lead-dependent bias in the raw model predictions and applying a 2-point space and time correction of ensembles based on the leading signal (Ensemble mean). (u850, v850, MSLP, T200, T500, Z200, and Z1000)

BCSA METHODOLOGY





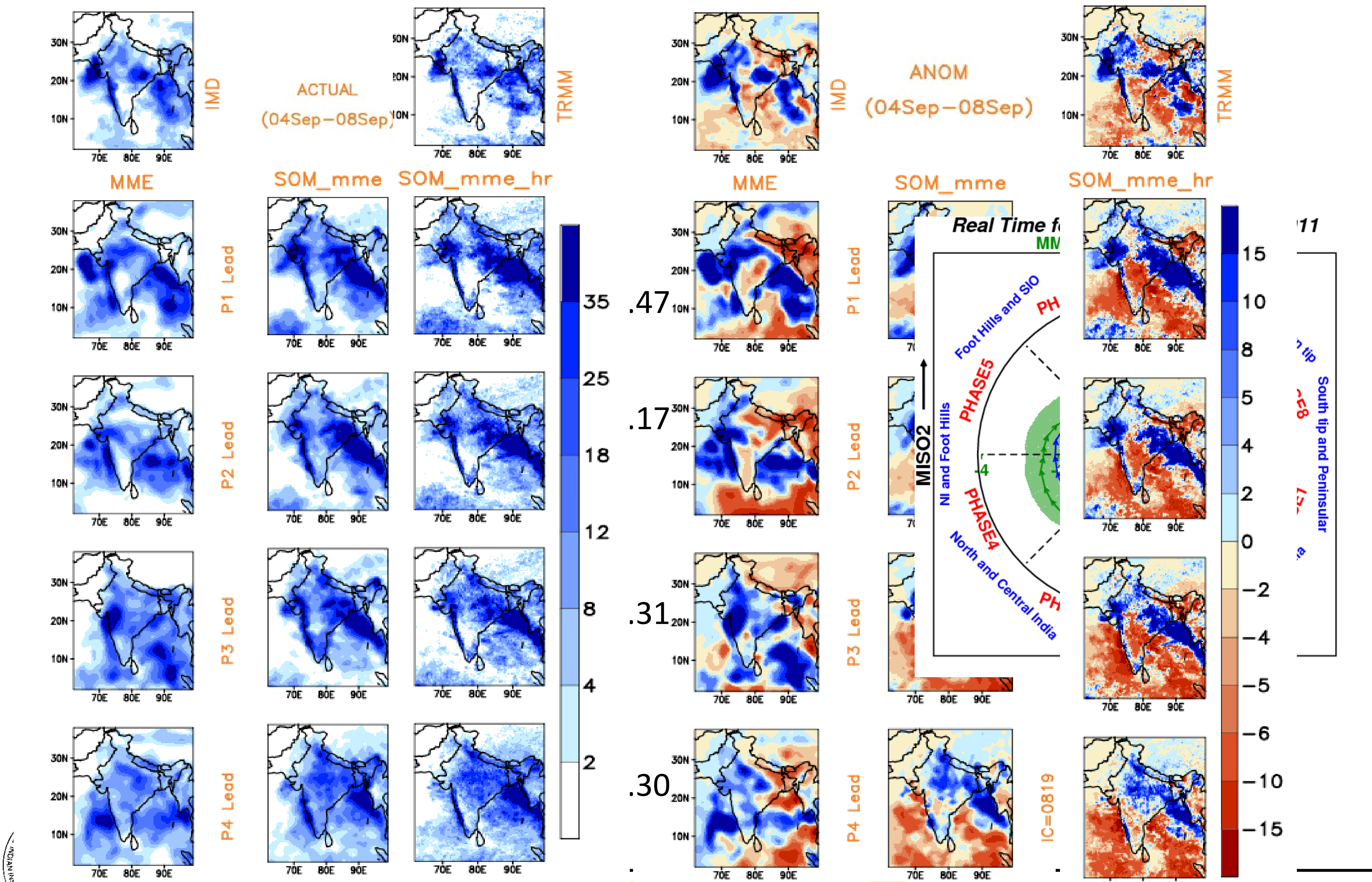
CS Viyaru, May 11-16, 2013
VSCS Phailin, October 8-14, 2013
VSCS Lehar, November 23-28, 2013
(a) 0506 IC
(c) 1003 IC
(e) 1117 IC
(b) 0511 IC
(d) 1008 IC
(f) 1122 IC
30N
20N
10N
EQ
60E
70E
80E
90E
100E
110E
00Z11MAY2013
00Z12MAY2013
00Z08OCT2013
00Z09OCT2013
00Z23NOV2013
OBSERVED TRACK
MME TRACK
MME-BCSA TRACK



9-days average DPE - MME=206.7530834
9-days average DPE - BCSA= 97.5024516
Percentage of Improvement ~ 50%

- **Results show that bias-correction and signal amplification technique is, indeed, improving the track forecasts of selected cyclonic storm cases with significant reduction in track errors even at longer lead times.**
- **Track verification also shows that forecasts from MME-BCSA outperform MME for all lead days. A weakness of this method is that ATE has higher frequencies than CTE at longer leads for most cases.**
- **Even then, BCSA is a unique postprocessing tool and computationally less expensive as it can be used on any number of already available MME outputs.**

SOM based Bias correction and Downscaling: Application to ERP of Mahanadi flood in September 2011



Sahai et al 2016, Clim. Dyn.

Conclusions

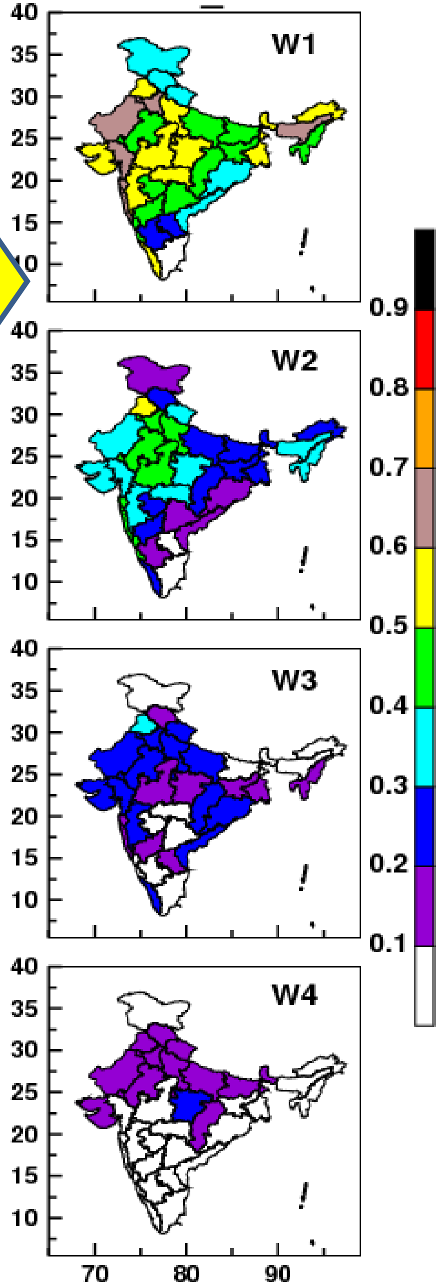
- ✓ The extended range ensemble prediction system has reasonable skill in predicting the extreme rainfall events and genesis and track of tropical cyclones.
- ✓ However, spatio-temporal errors are noticed in most cases.
- ✓ Efforts are underway to reduce these errors using post-processing techniques, dynamical downscaling and artificial intelligence.

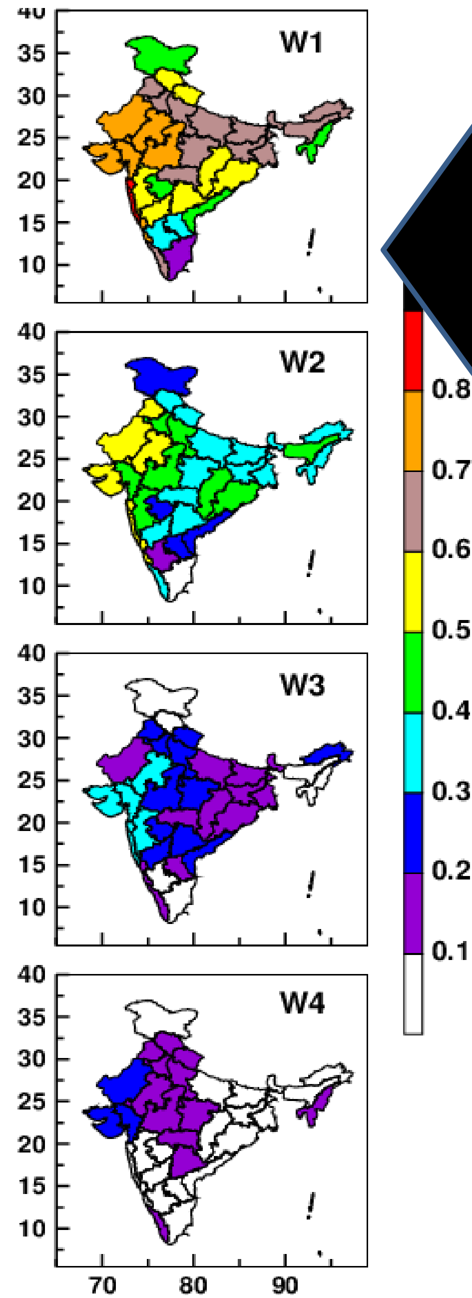
Way Forward

- How multiphysics parameterization improves prediction skill?
- How downscaling improves prediction skill?

Multi-physics parameterization

Current system
CFST126 + CFST382 (8mem)





Multi-Physiscs
CFS
4 phys (only ctrl)

Skill has improved in MPP

Application of downscaling

Severe Cyclonic Storm Mora

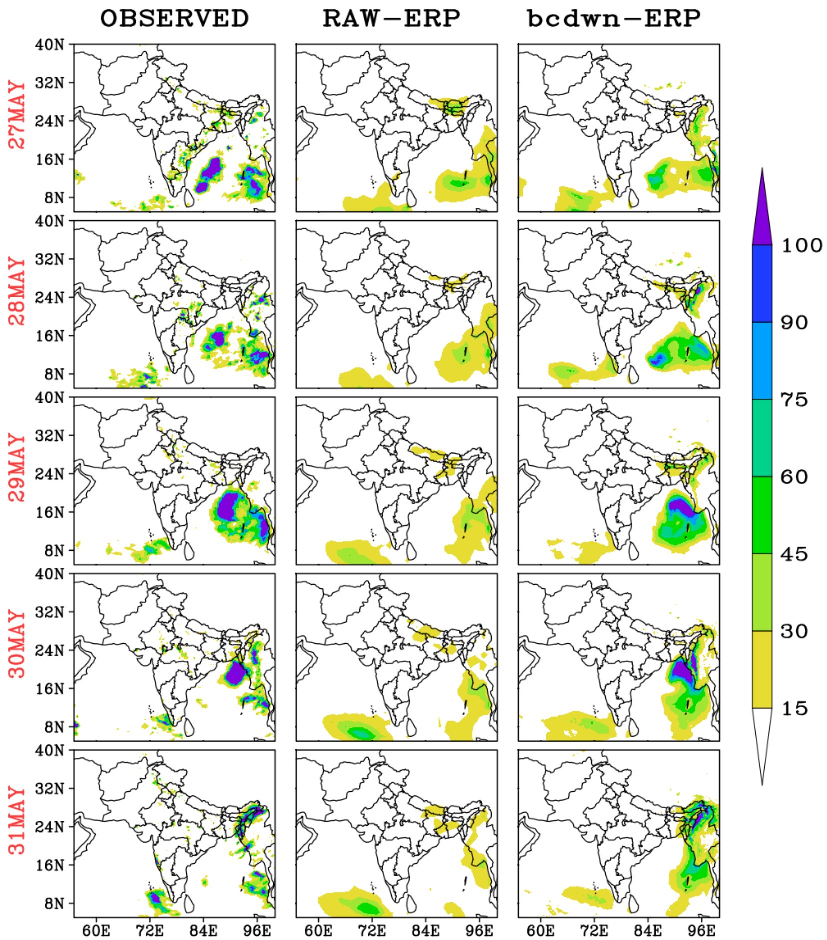
28 – 31 May 2017 (ERP IC : 0524)

Severe Cyclonic Storm Okhi

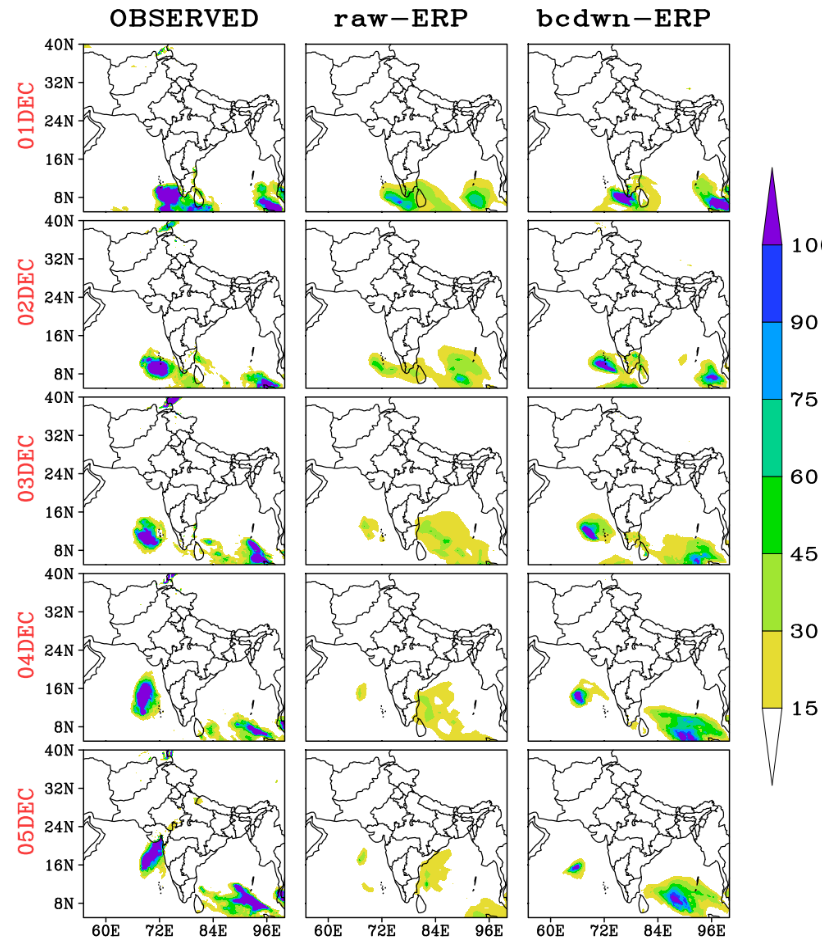
29Nov – 05Dec 2017 (ERP IC : 1129)

Spatial Rainfall Pattern

IC:0524 (Cyclone Mora)

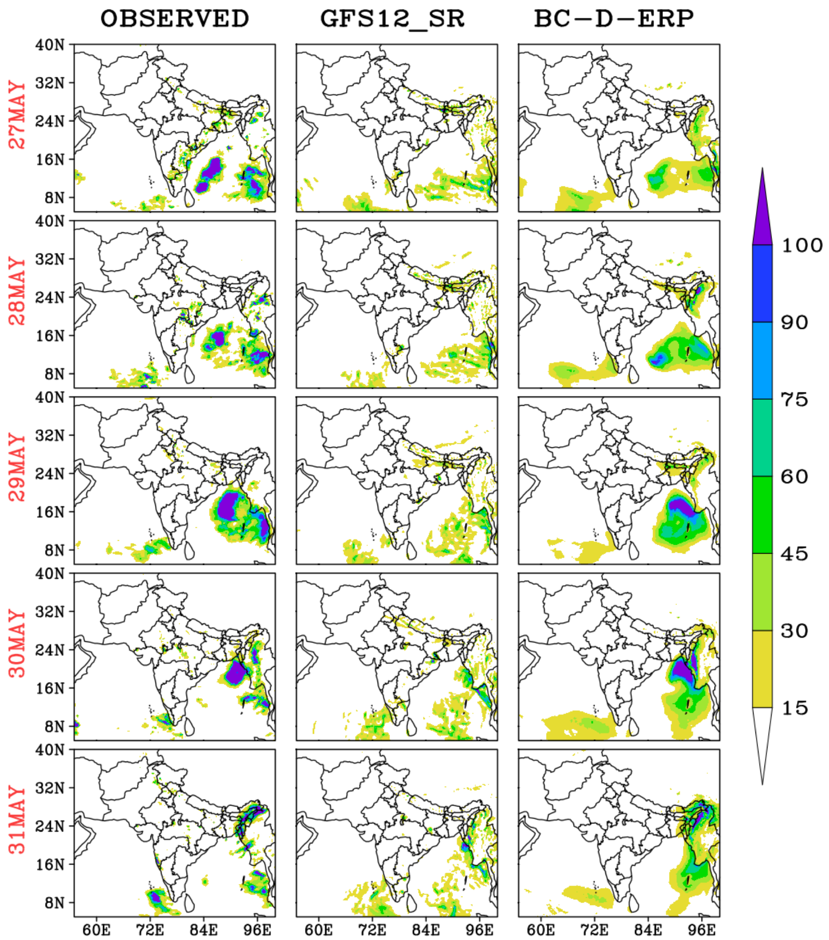


IC:1129 (Cyclone Ockhi)

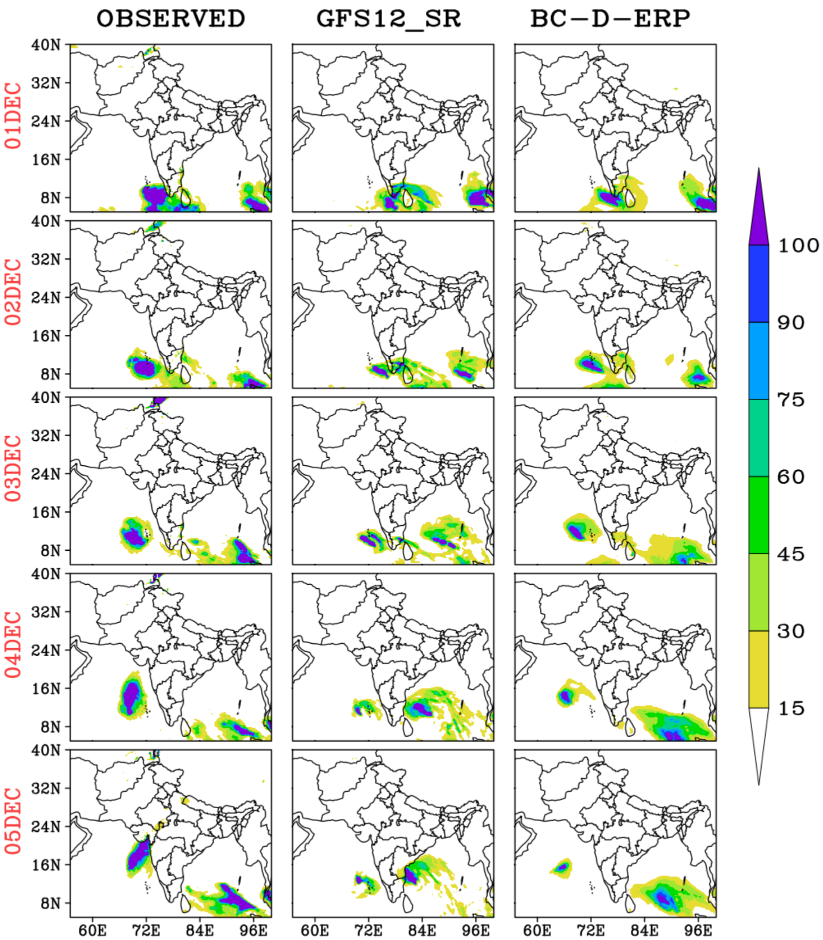


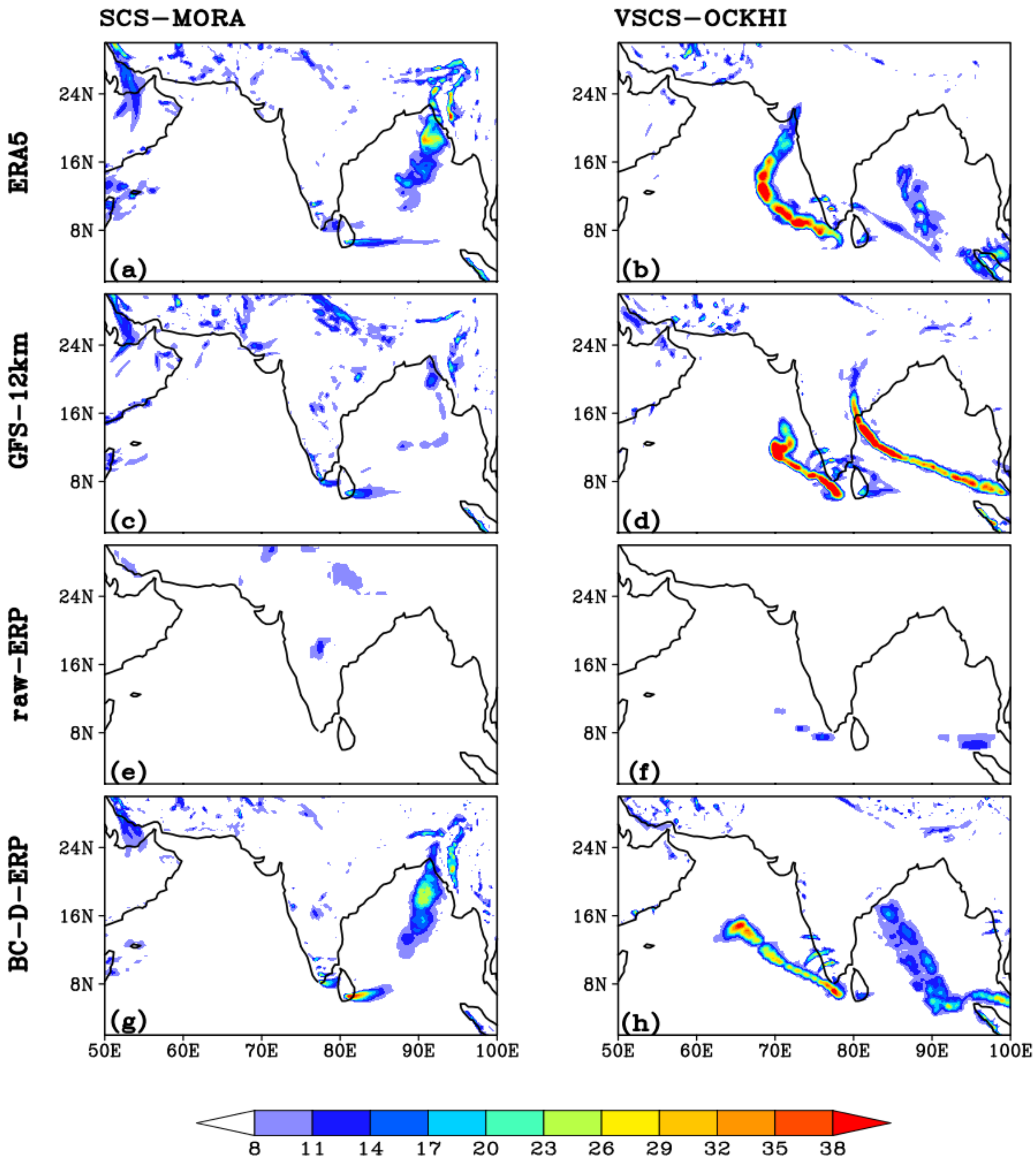
Spatial Rainfall Pattern

IC:0524 (Cyclone Mora)



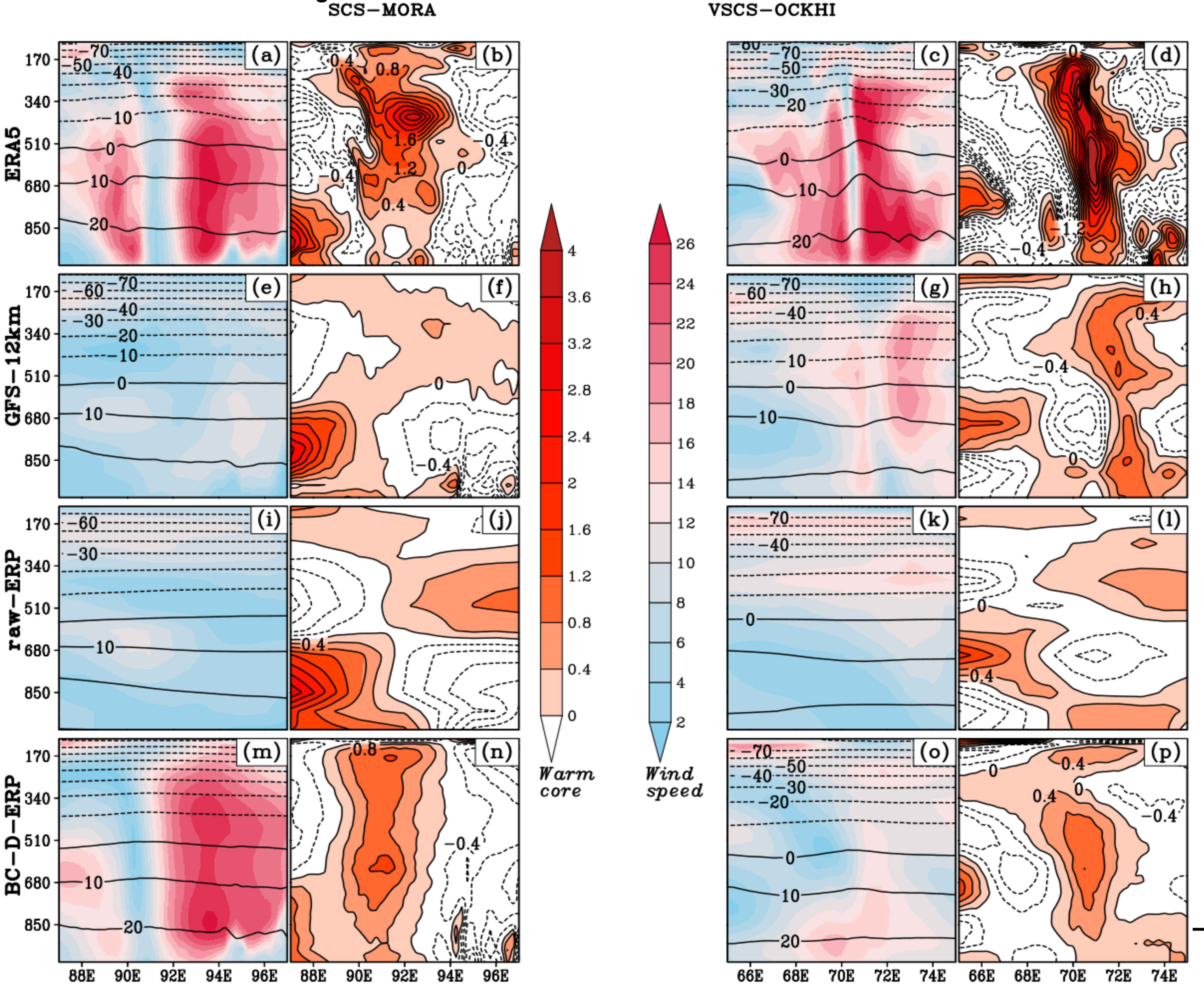
IC:1129 (Cyclone Ockhi)



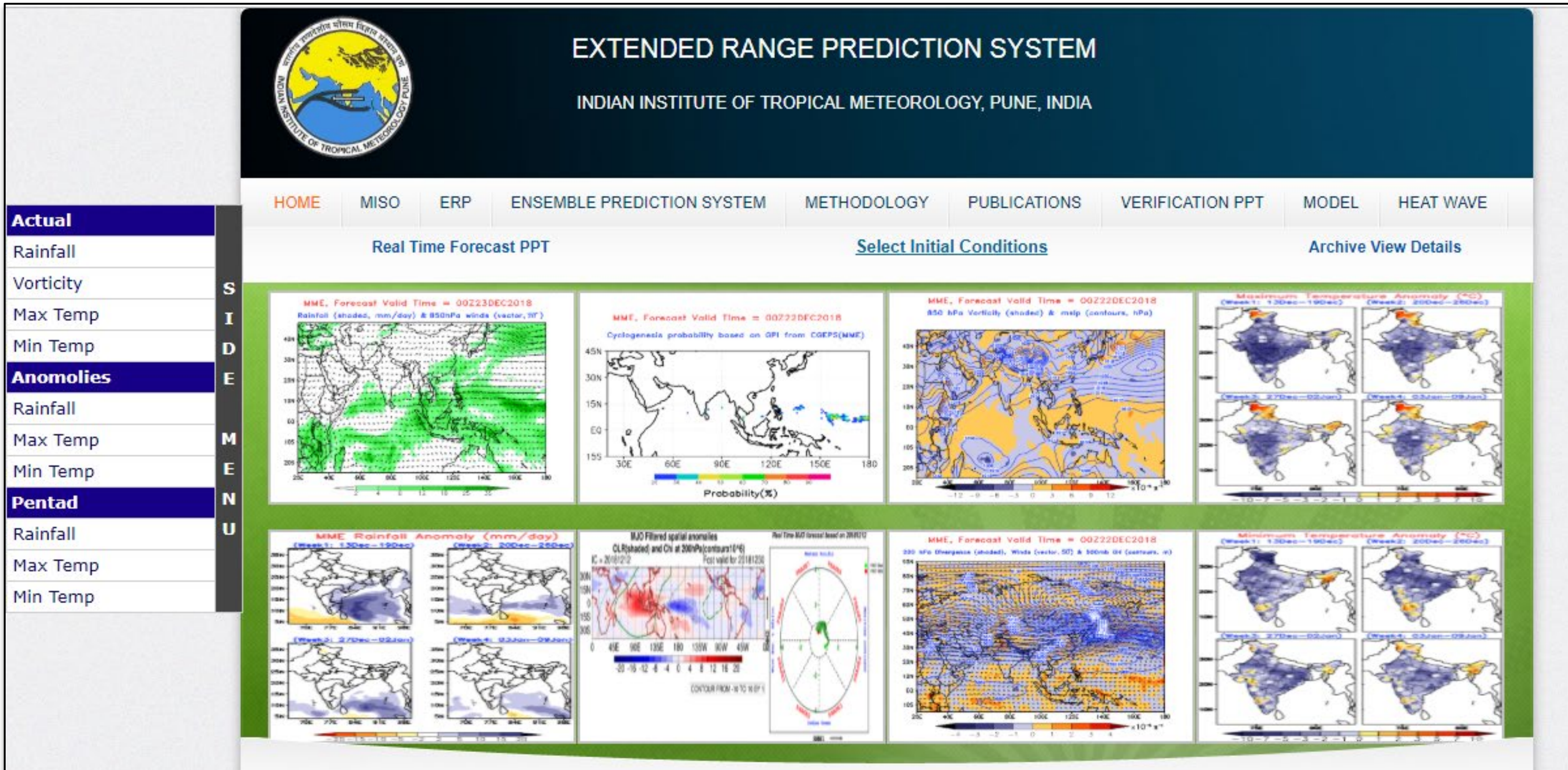


Kaur et. al., 2019, submitted

Vertical Profiles of Mature Stage



http://www.tropmet.res.in/erpas/index.php



Thank You!!!