Subseasonal Extended Range Prediction and Long-Range Prediction

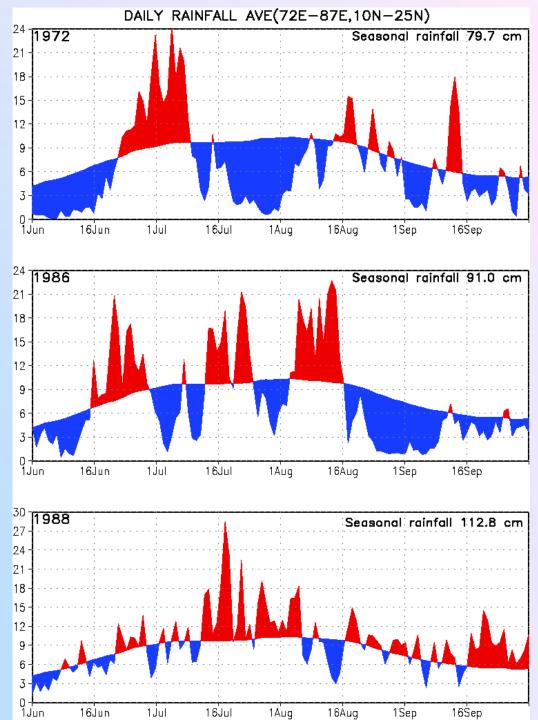


Rajib Chattopadhyay E-mail: <u>rajib@tropmet.res.in</u> rajib.Chattopadhyay@imd.gov.in Active-break spells (cycles)

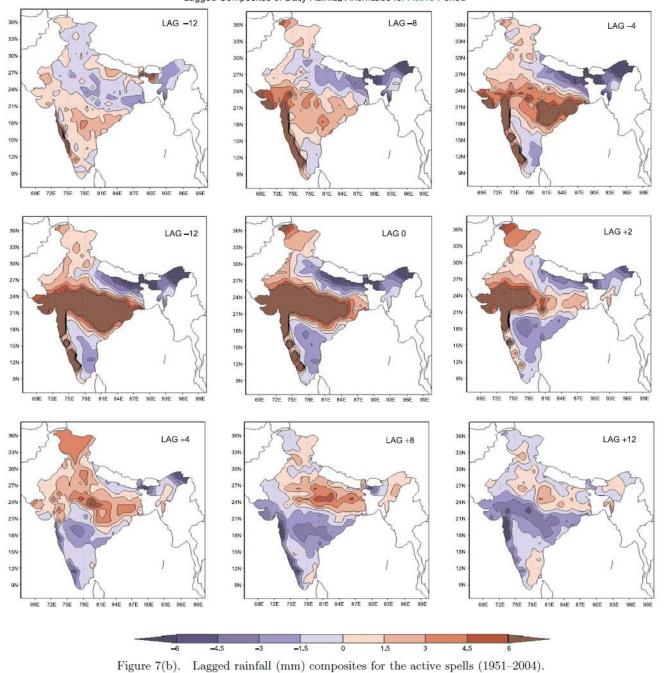
Daily rainfall (mm/day) over central India for three years, 1972, 1986 and 1988

The smooth curve shows long term mean.

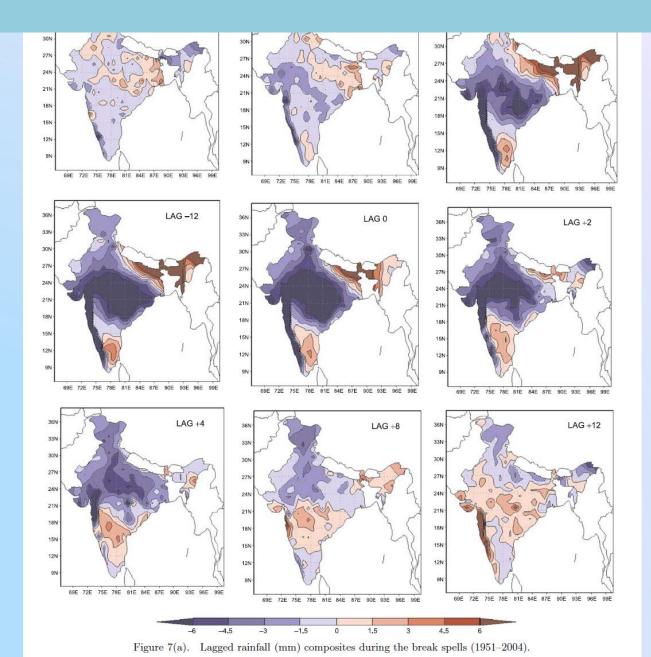
Red shows above normal or wet spells while blue shows below normal or dry spells







Active Composite



Break Composite

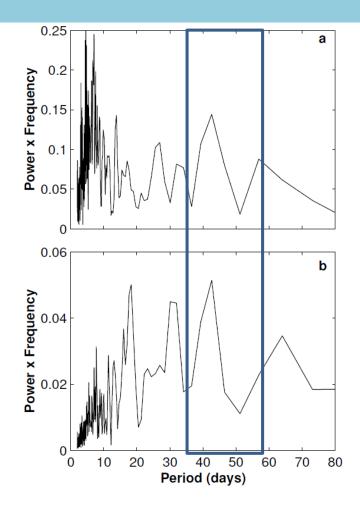
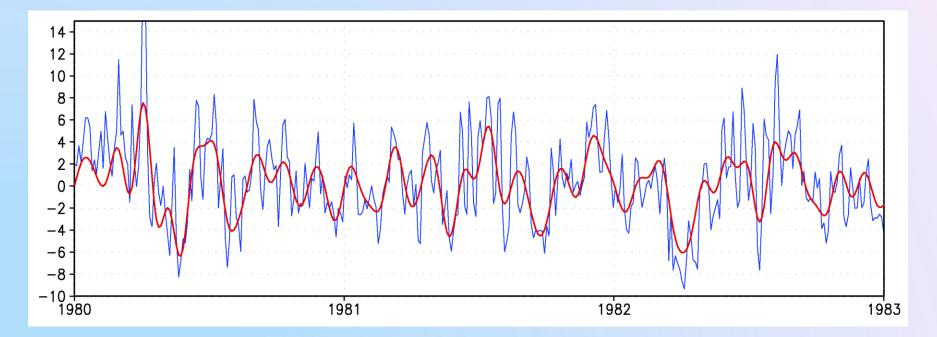


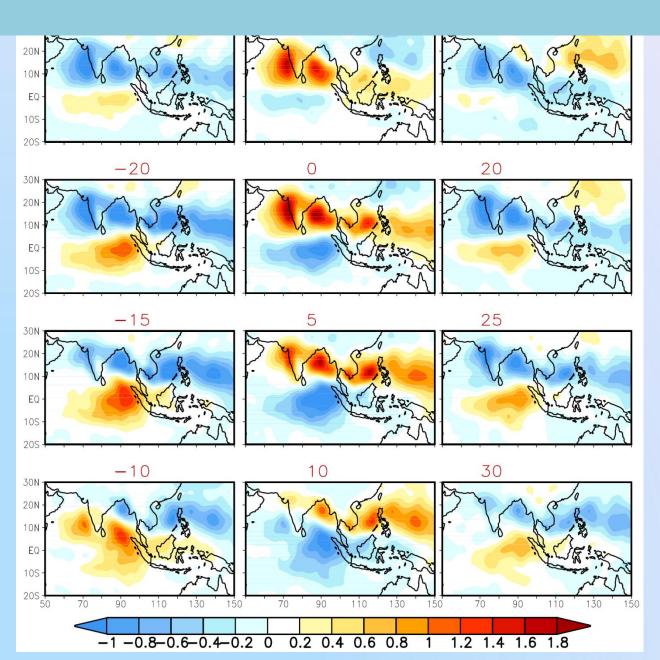
Figure 1: Spectrum of (a) rainfall anomalies for 20 (1971-1989) summer seasons (1 June -30 September) from station data averaged over 75E-85E and 15N-25N and (b) zonal wind anomalies at 850 hPa for 20 (1979-1998) summer seasons from NCEP reanalysis averaged over 55E-65E and 5N-15N.

Monsoon Intraseasonal Oscillation

Active Break Spells With Northward Propagation of ITCZ

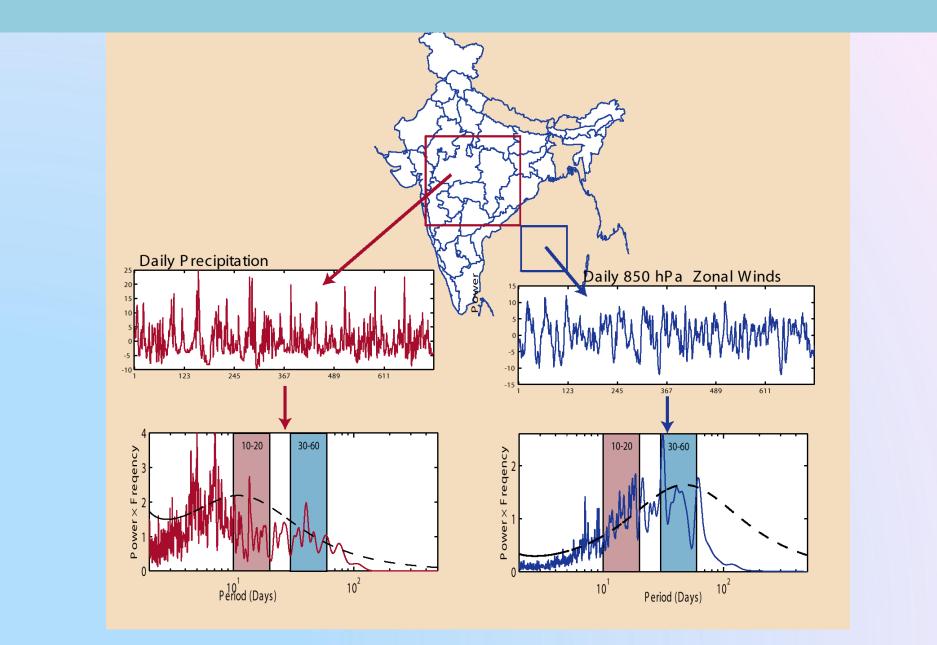


Time series of daily rainfall anomaly (mm/day) over central India (blue) during 1 June – 30 Sept. for three years and 10-90 day filtered (red) rainfall.



Observed evolution of the precipitation anomaly patterns over a full cycle of the 30-70 day mode.

Lag regressions of the 30-70 day filtered CMAP anomalies with respect to a reference time series over the monsoon region.



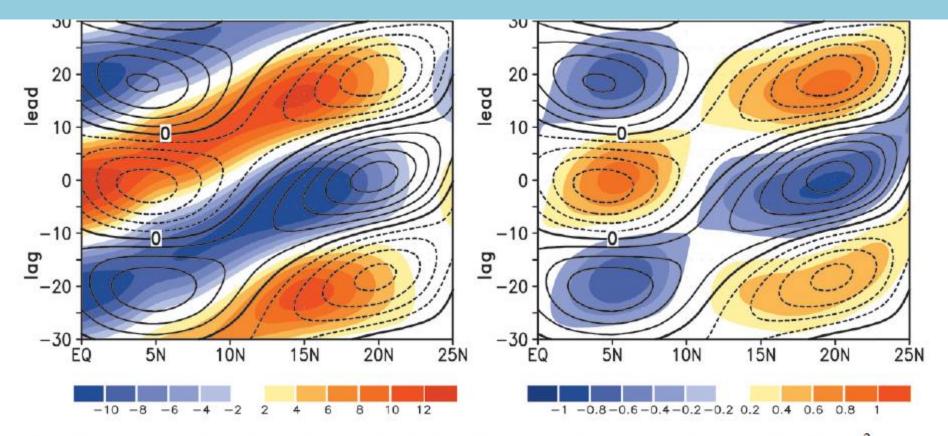
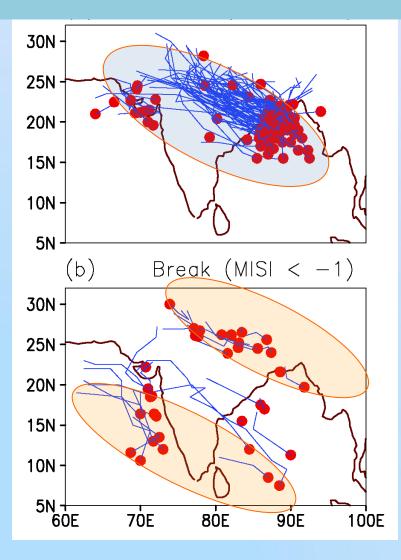


Figure 2.16. (a) Regressed 30 to 60-day filtered anomalies of OLR (shaded; W m⁻²) and 850 hPa relative vorticity (contour, positive solid and negative dashed, contour interval $1 \times 10^{-6} \text{ s}^{-1}$) with respect to the reference time series described in Figure 2.10 averaged over $80^{\circ}\text{E}-90^{\circ}\text{E}$. (b) Regressed 30 to 60-day filtered anomalies of 850 hPa relative vorticity (contour, positive solid and negative dashed, contour interval $1 \times 10^{-6} \text{ s}^{-1}$) and divergence at 925 hPa (shaded; 10^{-6} s^{-1}) with respect to the same reference time series.

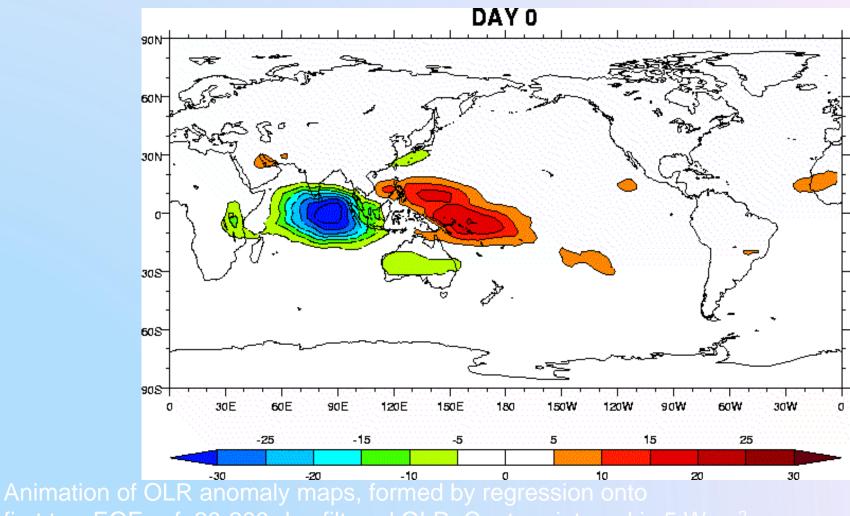
mean absolute value of the difference between JJAS mean and DJF mean for the 1997–2007 period from GPCP.



Tracks of LPS for the period 1954-1983 during extreme phases of monsoon ISO. (a) 'Active' ISO phase (MISI > +1) and (b) 'Break' ISO phase (MISI < -1). Red dots represent the genesis point and their lines show the tracks.

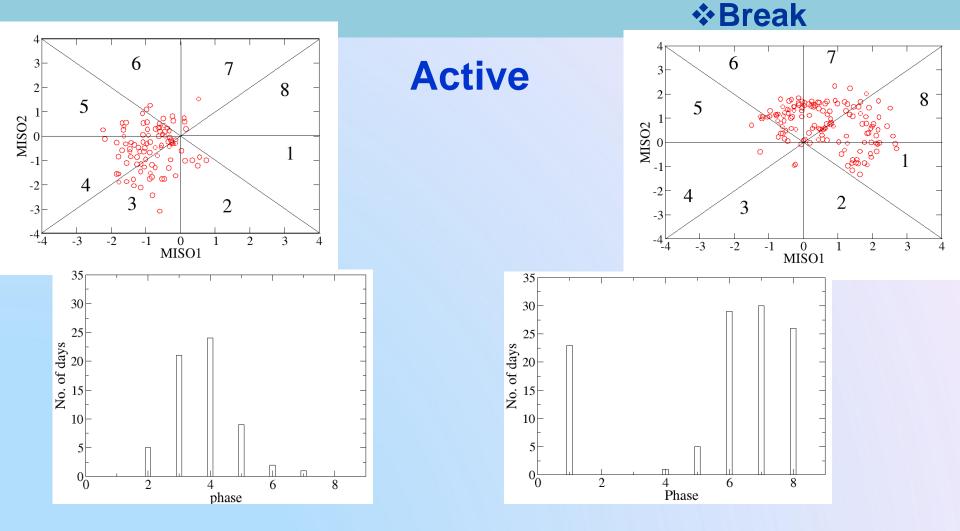
Goswami et al. 2003, *GRL*, 30, doi:10.1029/2002GL016734

MJO life cycle: Convection



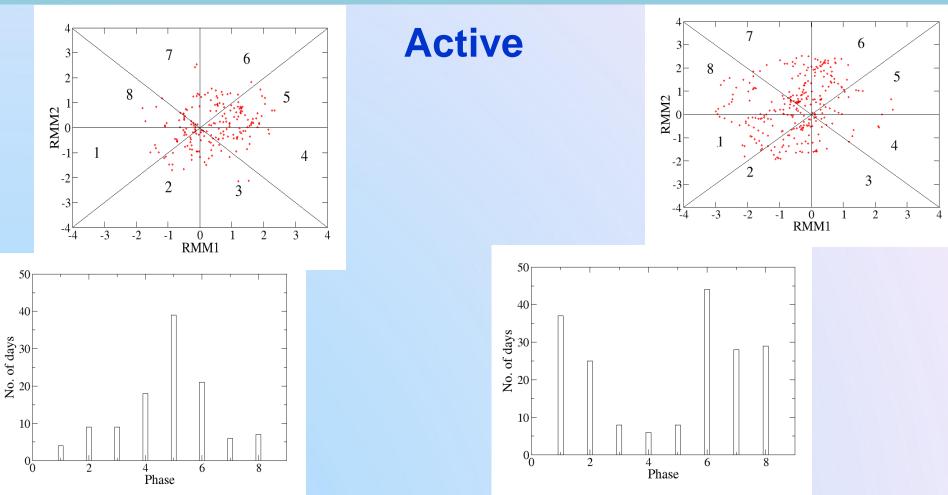
first two EOFs of 20-200-day filtered OLR. Contour interval is 5 W m⁻².

Relationship between Active/Break spell with phases of MISO.



Phase1: Peninsular India, phase2:CI, phase3: CI, Phase4: NI, phase5:Foothills, phase6: South IO, Phase7: IO, phase8: Southern Tip

Relationship between Active/Break spell with phases of MJO.



Phase 2 & 3: Indian Ocean, phase 4 & 5: Maritime Continent, phase 6& 7: Western Pacific, Phase 8 &1: West Hem. & Africa,

*Break

Prediction of MISO/MJO

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]

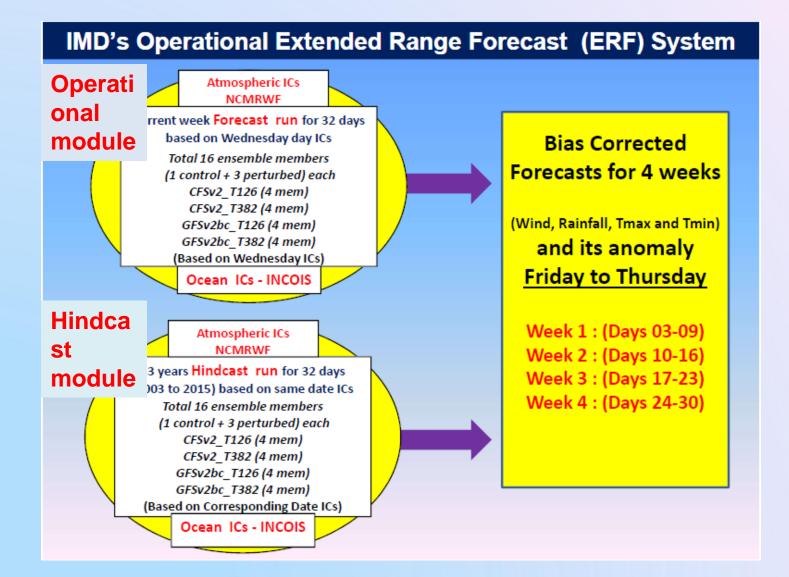
2014: CFS based Grand EPS Implemented

[Abhilash etal., 2015, JAMC; Sahai etal., 2015, Cur. Sci]

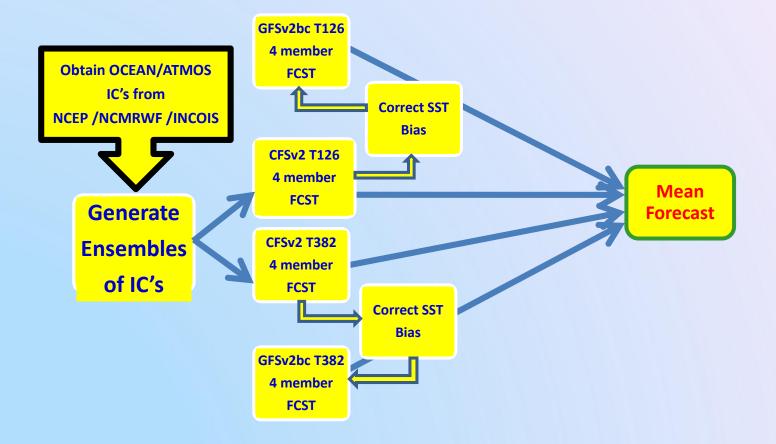
2015: Forecast for winter and other seasons started

2016: Forecast for Heat Waves started

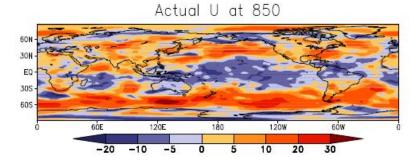
[Applications: Onset Prediction: Joseph etal, 2014, JC; Uttrakhand Heavy Rainfall: Joseph etal, 2014, CD; Skill of CFST126: Abhilash etal., 2014, CD; Comparison 2013 and 2014 June extremes: Joseph etal., QJRMS, 2015; Prediction skill of MJO: Sahai et al.,



IMD/IITM Ensemble Prediction System



Development, Testing, tuning and reliability of Ensemble Prediction System (EPS)



Perturbed U at 850

60N

30N

EQ

305

60S

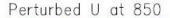
60E

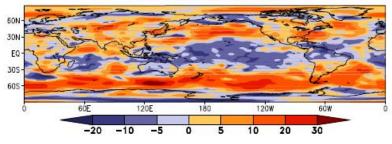
-20

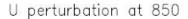
120E

-5

-10







180

5

0

120W

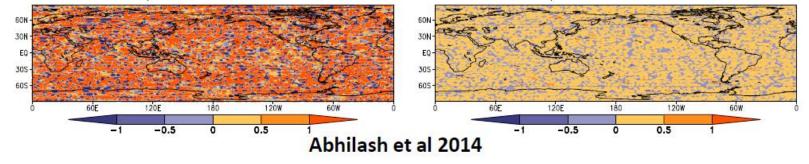
20

10

60W

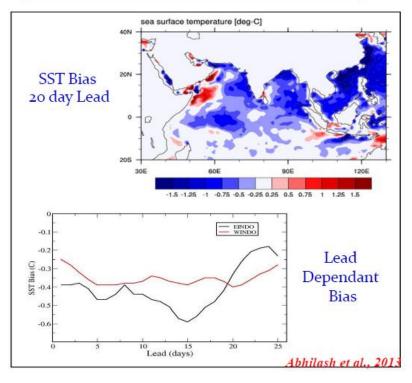
30

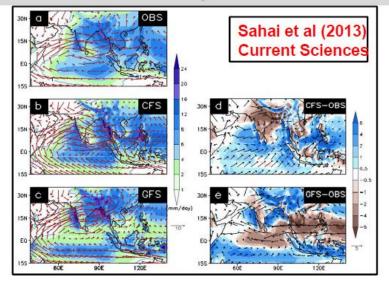
U perturbation at 850

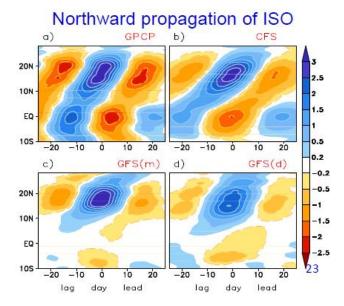


Development of Bias-correction Technique

SST Bias from Long Simulation

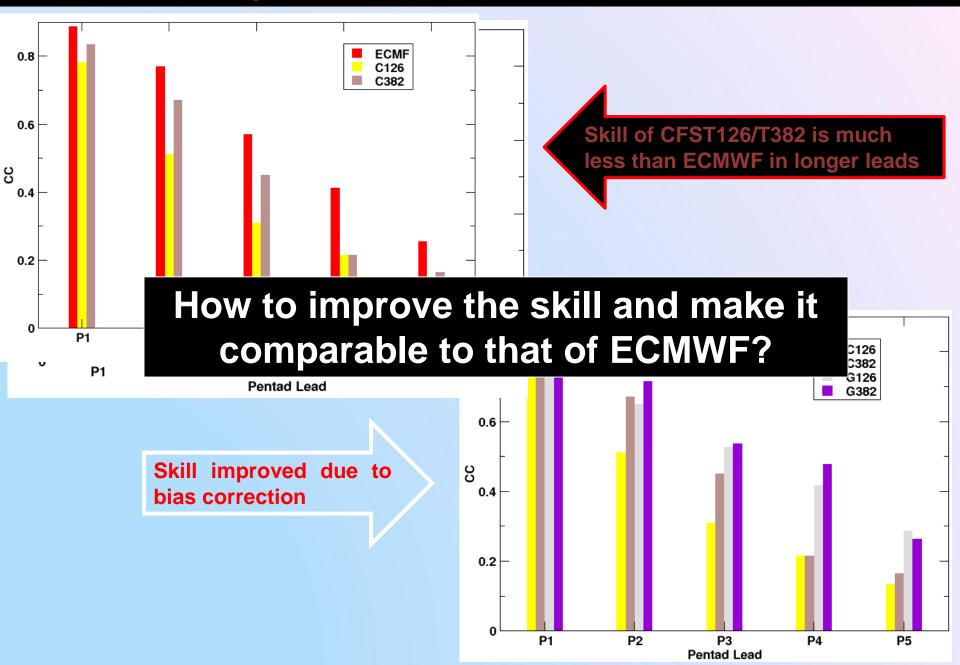




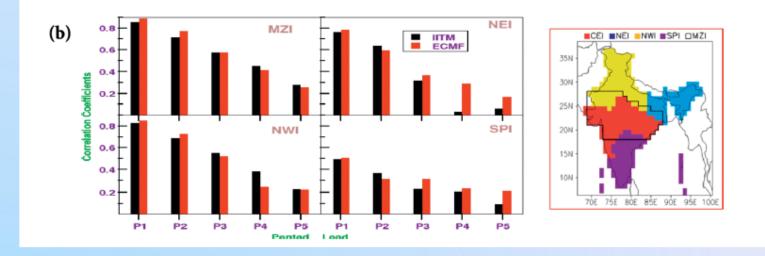


Relook: Why MME? Comparison of IITM-ERPS with ECMWF

Comparison of IITM-ERPS with ECMWF



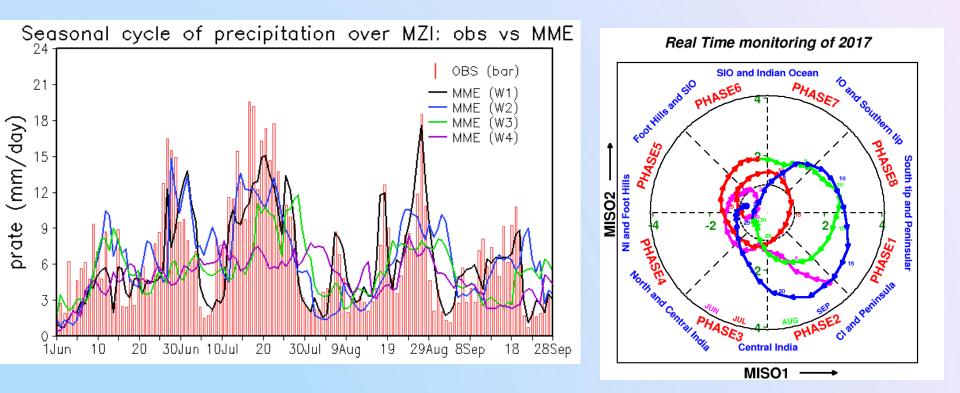
Extended Range Forecast Skill



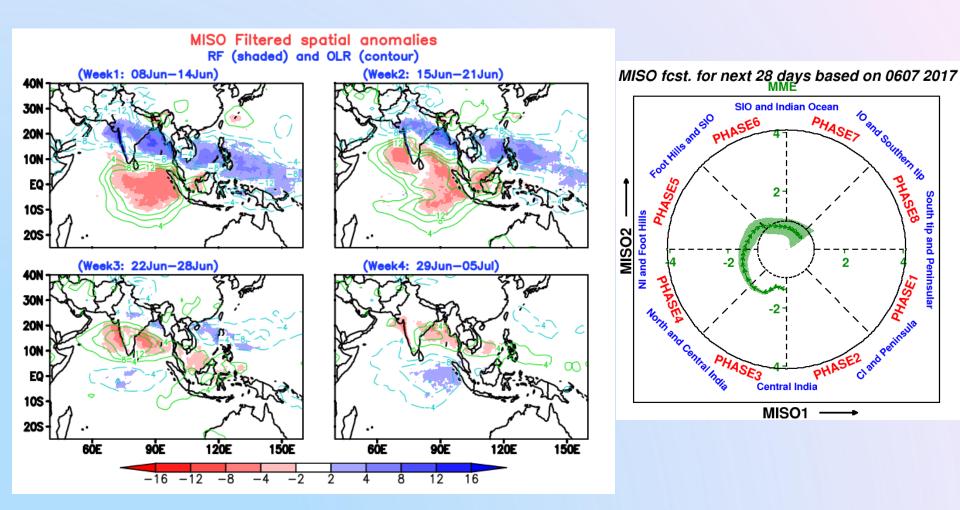
Applications of IITM ERPS: Some Examples

Observed and Predicted seasonal cycle of rainfall over MZI Region

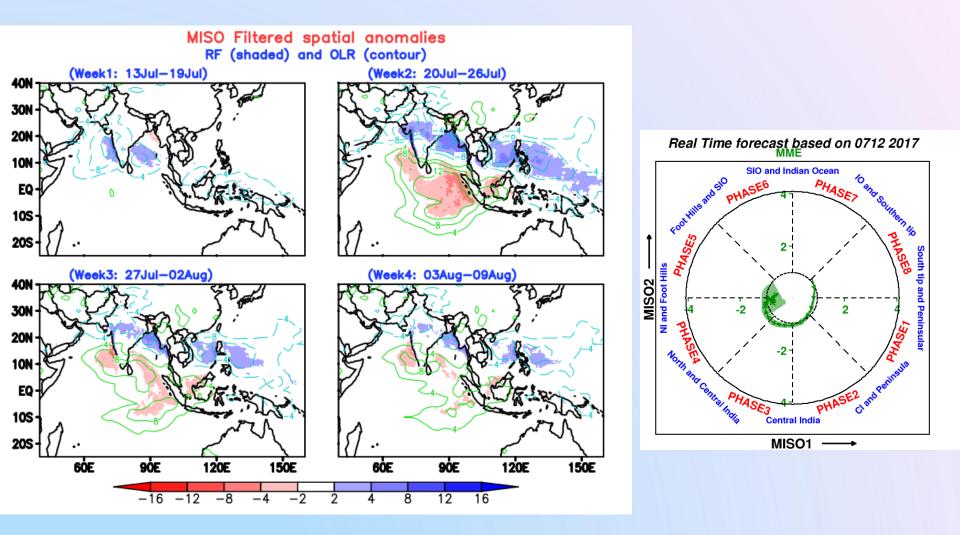
MISO



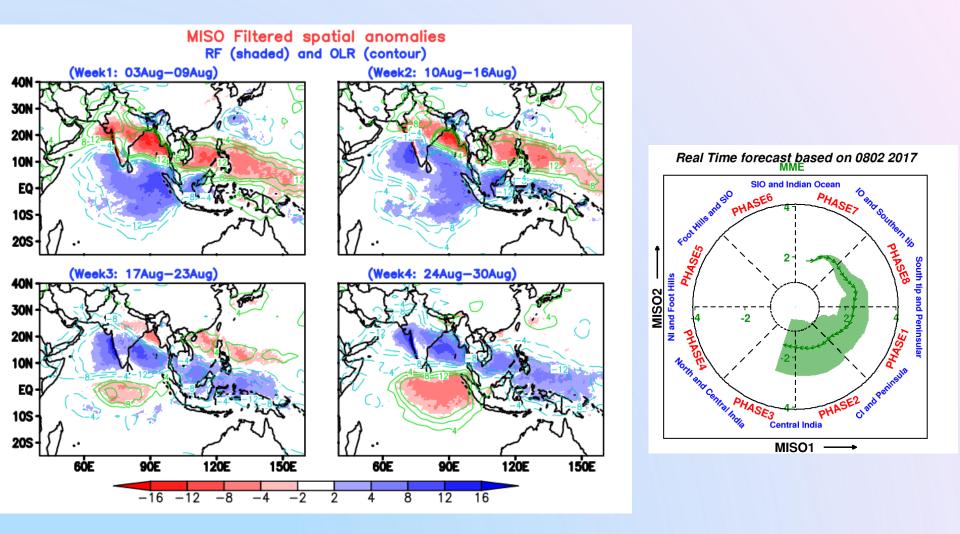
MISO forecast for 28 days during June 2017



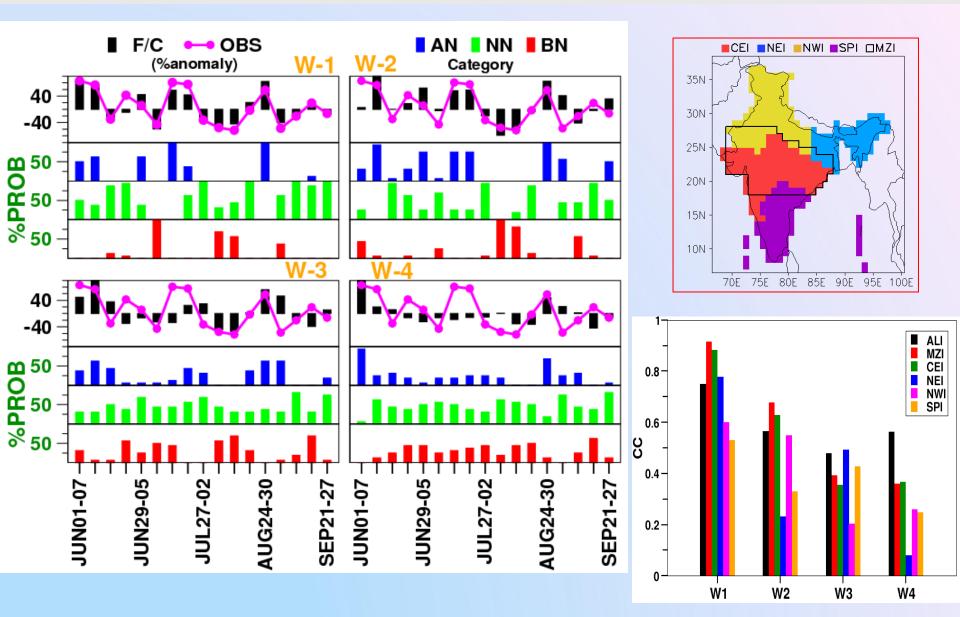
MISO forecast for next 28 days



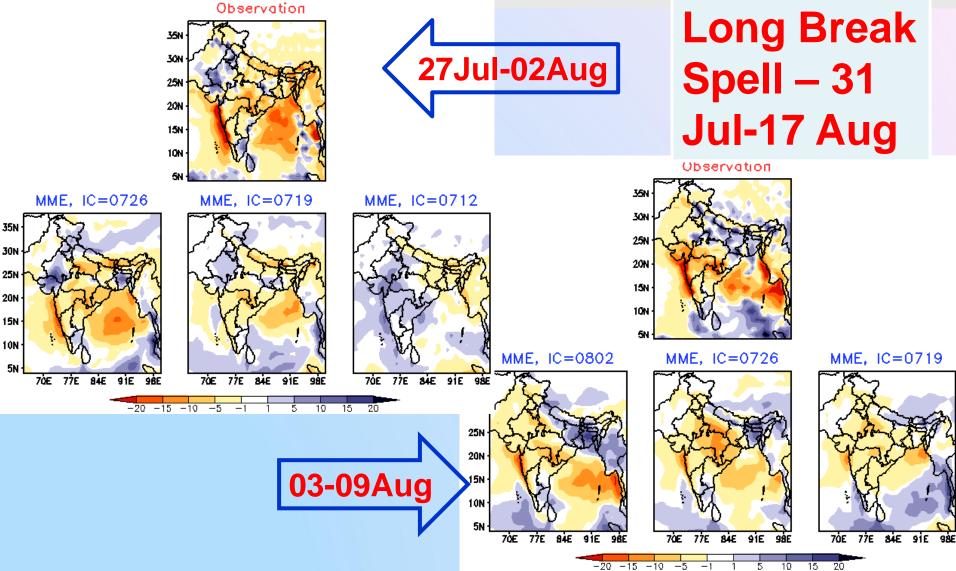
MISO forecast for next 28 days



Week-wise verification of rainfall over MZI Region

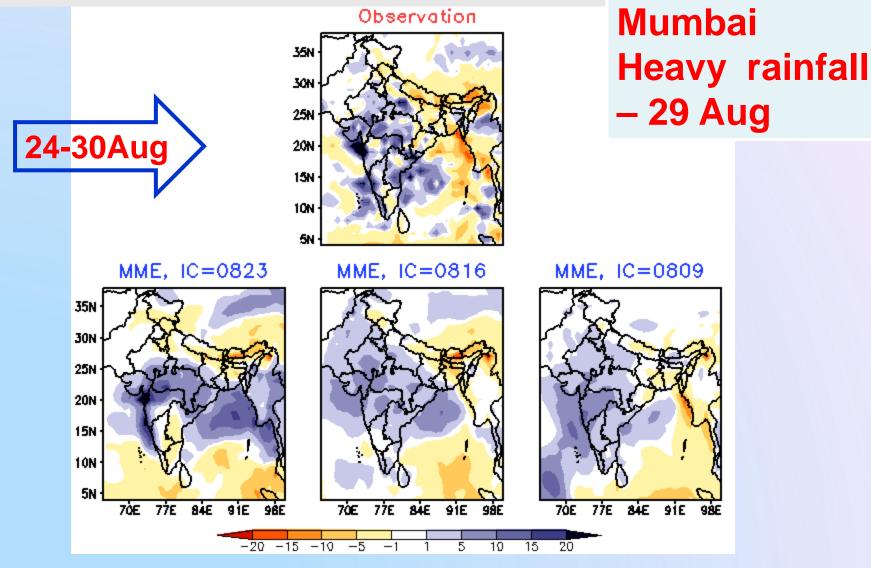


Observed as well as predicted weekly averaged rainfall

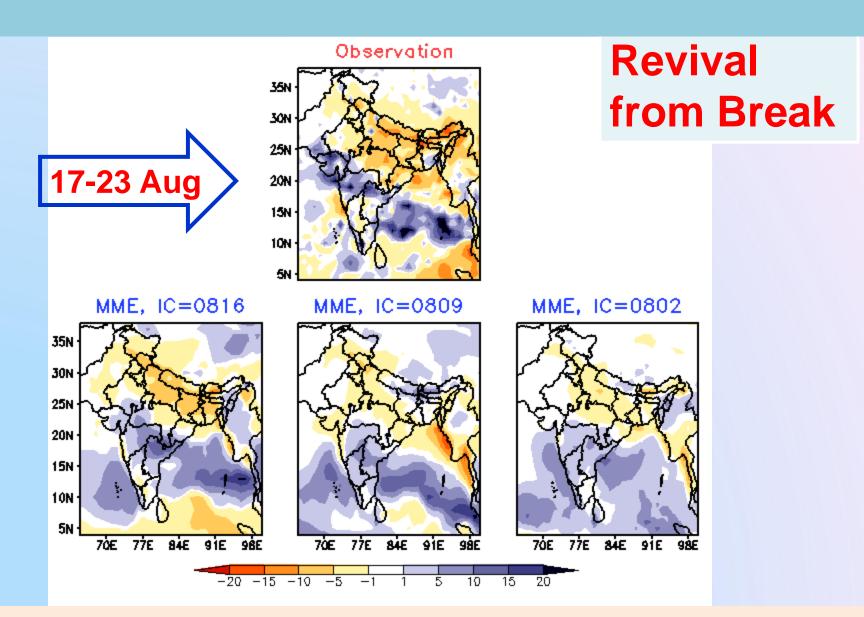


Verification of Selected Active/Break Spells

Observed as well as predicted weekly averaged rainfall

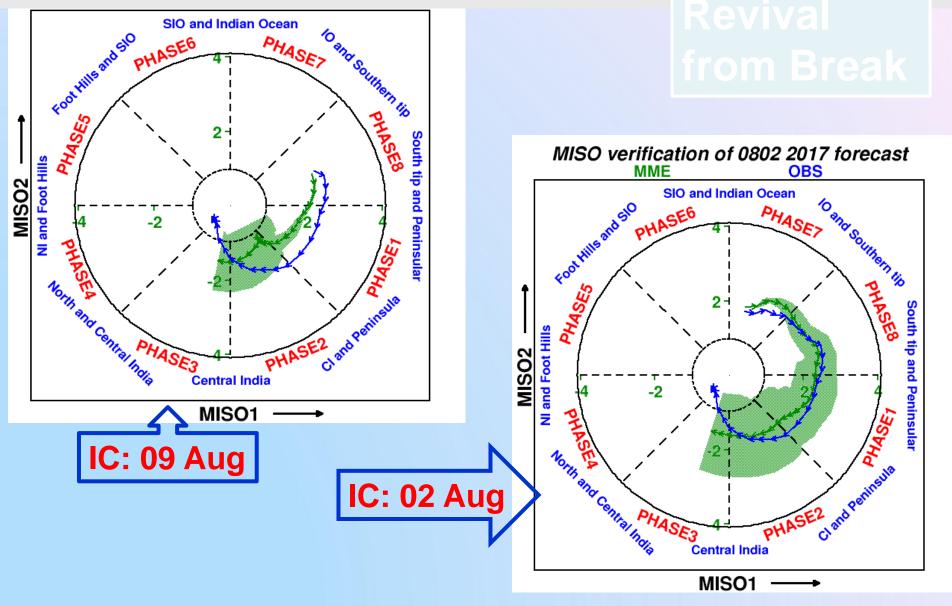


Verification of Selected Active/Break Spells

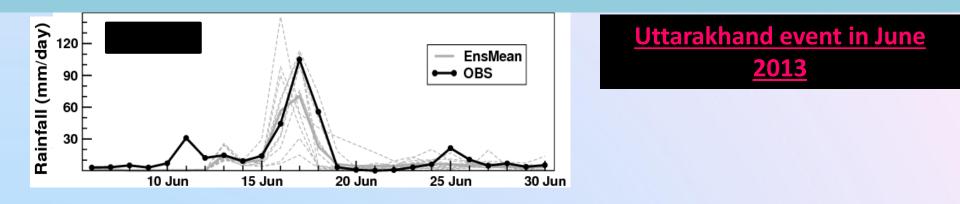


Verification of Selected Active/Break Spells

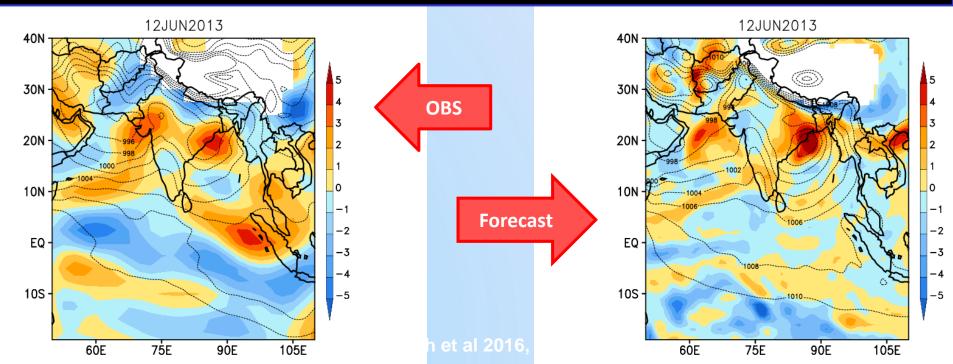
Observed as well as predicted MISO during 2017

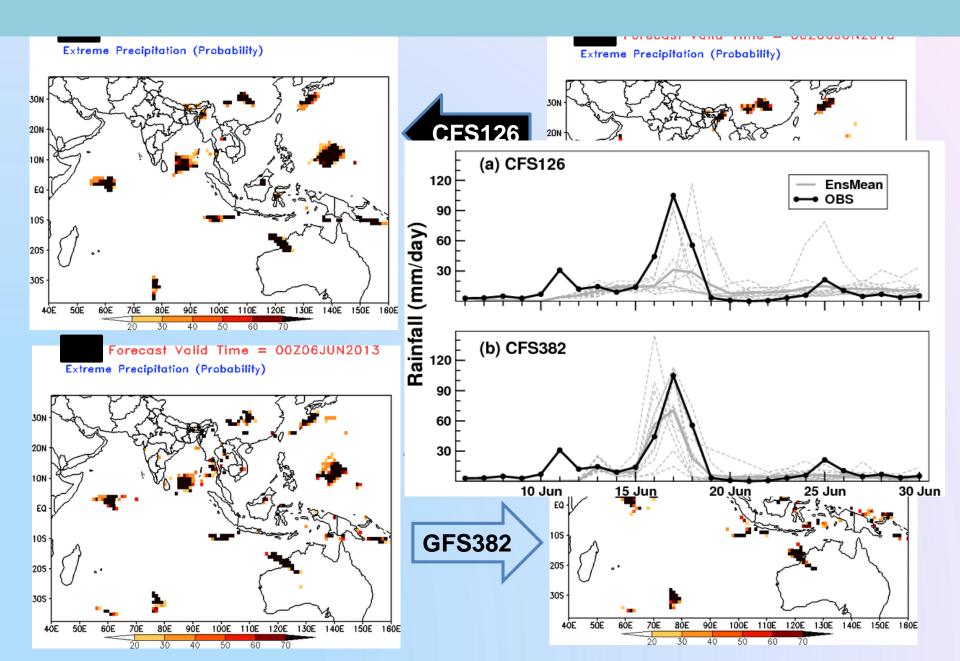


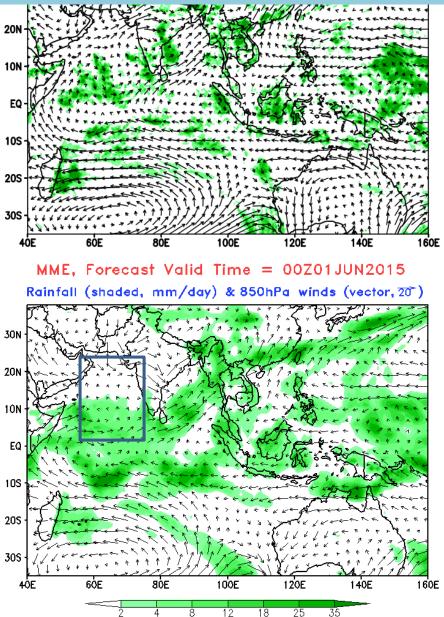
EXTREME EVENTS



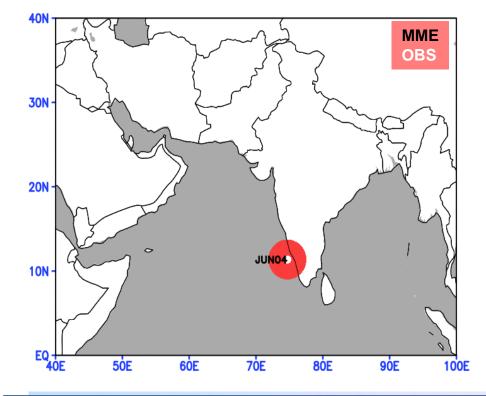
Evolution of Potential Vorticity (PV; x10⁻⁷ s⁻¹) anomalies at 700 hPa and mean sea level pressure





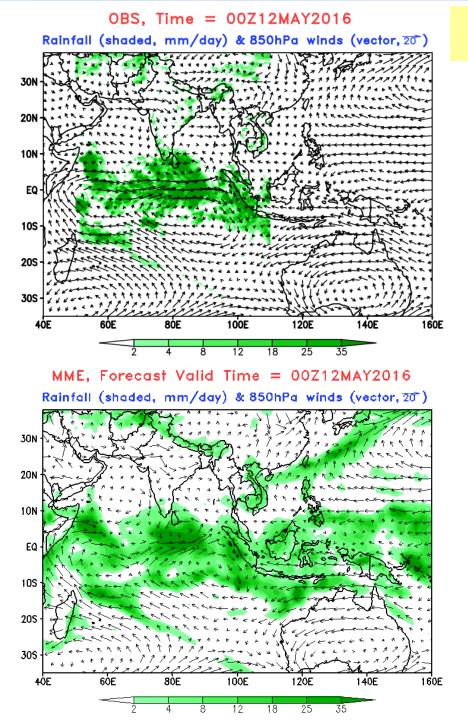






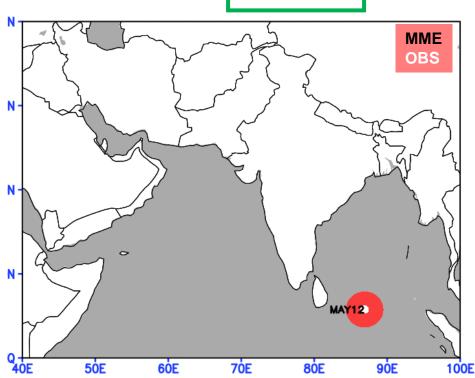
IC: 0531

Low Pressure System (LPS) over southern tip of peninsula is likely to intensify and move towards Oman coast. This system may dissipate around 11th June and till then the monsoon activity will be weaker than normal over India.



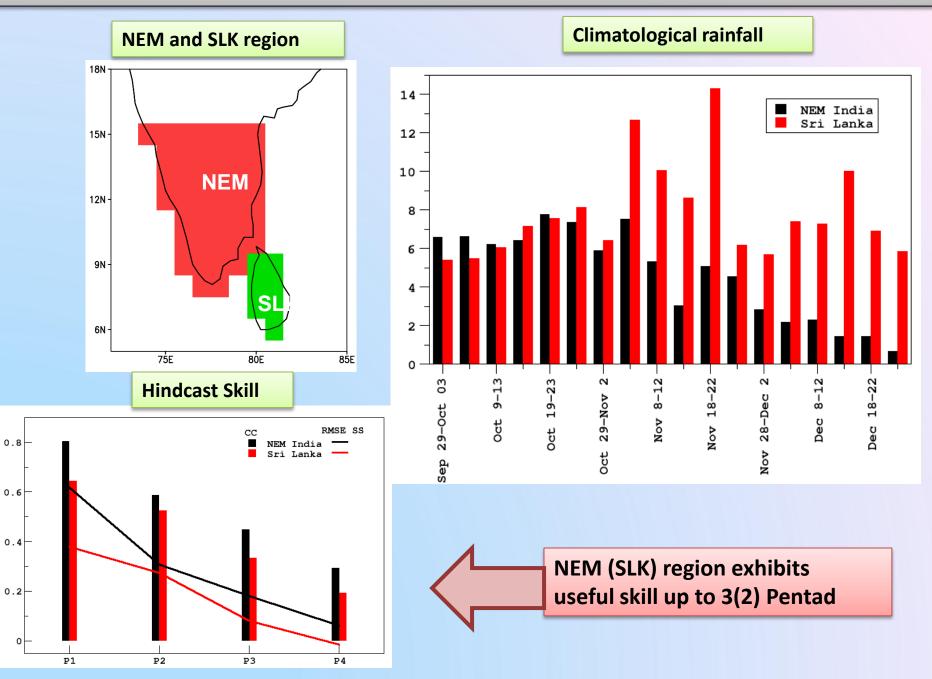
Prediction of Cyclogenesis

Cyclone Roanu in May 2016

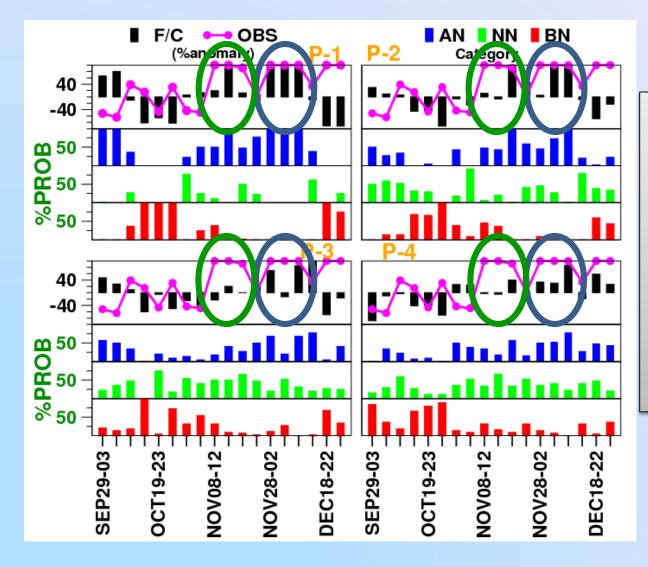


Prediction of North-East Monsoon (NEM)

Hindcast Skill for Post Monsoon/NEM



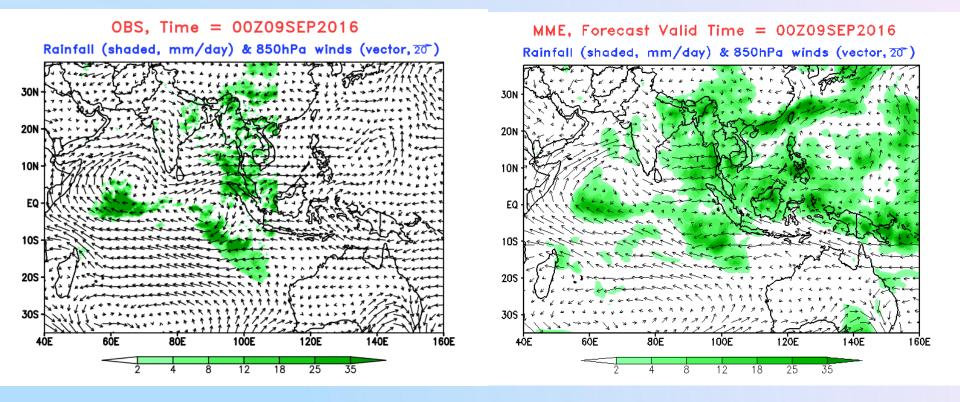
Area averaged rainfall over NEM region during 2015 predicted by MME



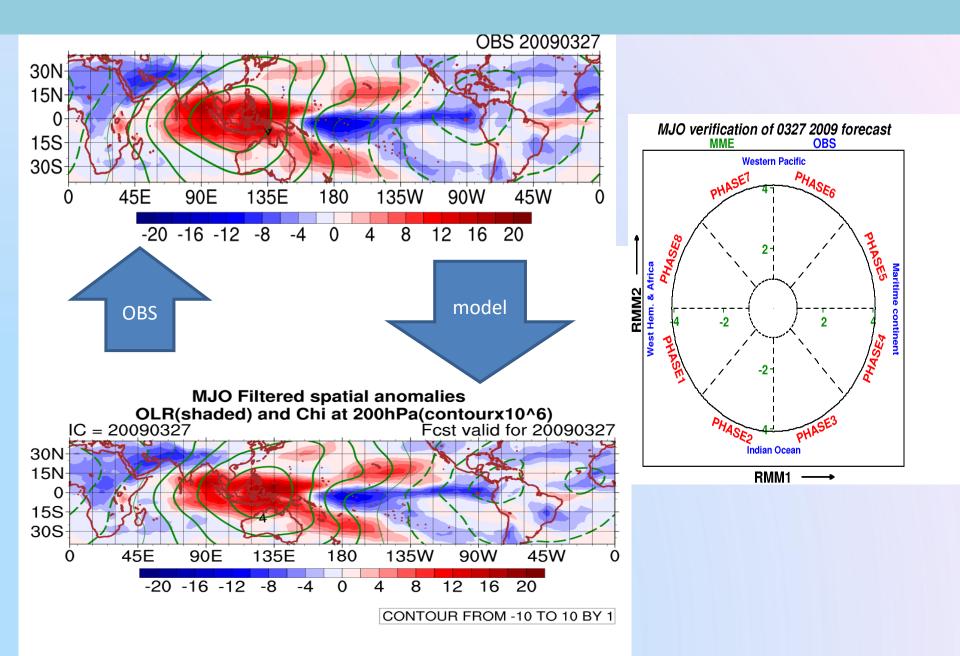
The CGMME system predicted above normal rainfall the activity over Chennai and NEM region well in advance. The CGMME system able to capture this high impact continuous rainfall activity during the last week of November and first week of December around Chennai region from 4th pentad lead

Case Example :Withdrawal of ISM 2016 (IC: 0908)

The revival of monsoon due to the formation of a LPS around 13-14 September and subsequent westward movement was forecasted well from 08 September IC.



MADDEN-JULIAN OSCILLATION



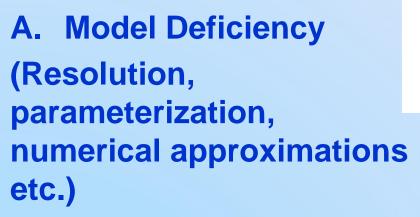
Conclusions

- The CGEPS MME from operational runs could realistically provide an outlook on the intraseasonal fluctuations within the 2017 monsoon season.
- The EPS proved to be useful but imperfect prediction technology, in the face of the mostly-unpredictable.

✓ It can supplement the weather information.

Forecast Verification

Why is a forecast Errorneous?



- **B. Error in Initial**
- conditions
- (Error in instrument, data assimilation, spatially or temporal sparse)

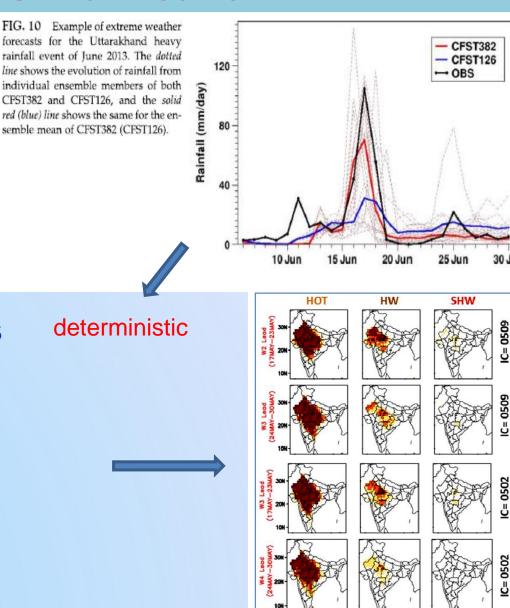


Fig. 11. Weekly averaged probabilistic forecasts of HOT, HW and SHW conditions for different lead time for HW spell

Forecast Verification

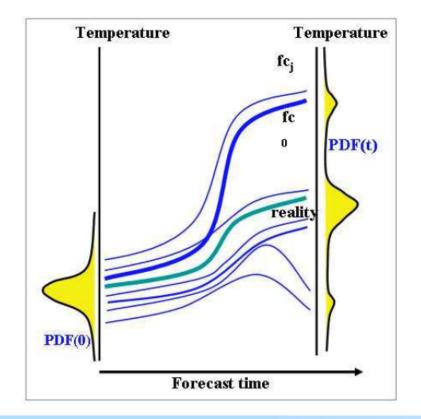
https://www.hereon.de/imperia/md/assets/ clm/neu3_tl4.pdf

https://www.cawcr.gov.au/projects/verification/

Why verification?

- The forecast is x % better/worse than a reference forecast (e.g. climatology, persistence,other model)
- The forecast is valuable up to a lead-time of x days?
- Forecast quality depends on time of the day, region, season, meteorological conditions...
- Will I have economical benefit from using the forecasts for decision making?
- The forecast is/is not calibrated
- The forecast is capable of representing the location, timing, shape, magnitude of objects (e.g. rain cells)

Types of forecasts



Deterministic model

 Decide for in initial state and start a single integration

Ensemble prediction

 Make many integrations (e.g. from different initial states, or multi model or analogue ensemble...)

However,

The Observation may or may not represent g ground truth

Verification against observations is (almost) always flawed

 Model value is a grid box average and observations within a grid box might vary strongly. Many ways exist to match observation to grid point

Is the observed value really what you want you model to predict?

• Gridded observations or analysis might be a work around but then, those rely on models (statistical or physical) again and might not be independent from the forecast.

Deterministic prediction system

- **Bias mean error, absolute error**
- Association e.g. correlation, root-mean square, index of agreement
- **Ensemble prediction system**
- **Reliability conditional bias over several categories** (usually forecast probabilities)
- **Resolution ability to resolve events in different subsets**
- **Sharpness spread of the forecast distribution**
- **Uncertainty observation variability**

Both deterministic and ensemble forecast : Skill - Value w.r.t. a reference forecast (e.g. persistence or climatology) Value - Is the forecast helpful for decision making

Types of verification

Continuous

For deterministic predictions as time-series, spatial data or both combined Example: temperature, pressure, upper-air variables

Dichotomous (binary, 2 categories, yes/no, special case multiple categories)

For deterministic predictions as time-series, spatial data or both combined Example: rain yes or no? cloud amount category, wind speed, warnings

Ensemble

For ensemble models considering the forecast distribution Example: Does the ensemble spread capture the forecast uncertainty

Probabilistic

For probabilities derived from ensemble models Example: probability to exceed wind speed of 10 m/s?

Spatial

Mostly deterministic model Example: Are objects predicted at the correct location?

Deterministic Forecast

BIAS (mean error)

Mean Error
$$= \frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)$$

Shows the average direction of the error (positive or negative)

In NWP defined positive (negative) if model forecast quantities are larger (smaller) than observed

Does not indicate the magnitude of the error as positive an negative values might cancel each other out

Same unit as variable

BIAS (mean error)

$$Mean \; Error = \frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)$$

Shows the average direction of the error (positive or negative)

In NWP defined positive (negative) if model forecast quantities are larger (smaller) than observed

Does not indicate the magnitude of the error as positive an negative values might cancel each other out

Same unit as variable

MAE (mean absolute error)

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |F_i - O_i|$$

RMSE (root mean squared error)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2}$$

Correlation coefficient & anomaly correlation

$$r = \frac{\sum (F - \overline{F})(O - \overline{O})}{\sqrt{\sum (F - \overline{F})^2} \sqrt{\sum (O - \overline{O})^2}} \qquad \qquad AC = \frac{\sum (F - C)(O - C)}{\sqrt{\sum (F - C)^2} \sqrt{\sum (O - C)^2}}$$

Correspondence between forecast and observations

Measures linear association and phase errors.

Independent from biases.

Can give misleading results if verification sample is inhomogeneous (e.g. temperature correlation with day and night values in one sample)

(Anomaly correlation should be used to reduce effects of inhomogeneity)

Combined CC and RMSE Indices

Wilmott's index of agreement

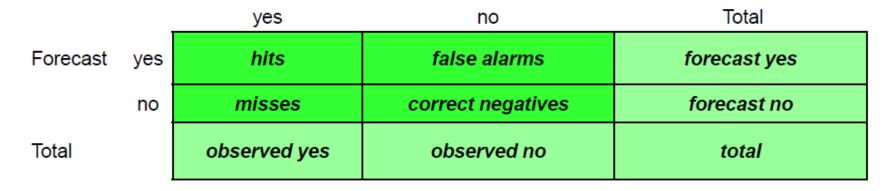
Willmott (1981) proposed an index of agreement (d) as a standardized measure of the degree of model prediction error which varies between 0 and 1. The index of agreement represents the ratio of the mean square error and the potential error. The agreement value of 1 indicates a perfect match, and 0 indicates no agreement at all. The index of agreement can detect additive and proportional differences in the observed and simulated means and variances; however, d is overly sensitive to extreme values due to the squared differences.

$$d = 1 - \frac{\sum_{i=1}^{n} (o_i - P_i)^2}{\sum_{i=1}^{n} (|P_i - \bar{o}| + |o_i - \bar{o}|)^2} \quad , \qquad 0 \le d \le 1$$

where Oi is the observation value and Pi is the forecast value and Obar is the average observation values and Pbar is the average forecast values.

Categorical Forecasts

- Used for binary data
- If data is not binary, decide for a threshold (e.g. precipitation > 10mm/h) and make your data binary
- Sum up all entries in the contingency table



Observed

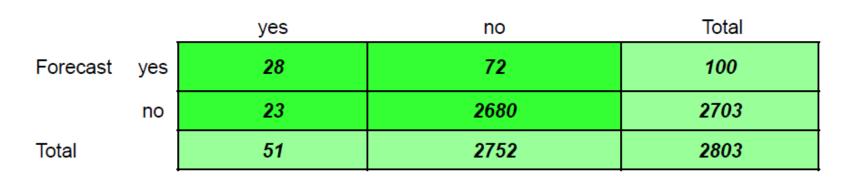
Categorical Forecasts

!!CAUTION!!

Famous example: Tornado forecast verification Collection of tornado forecasts (yes/no) and outcomes



Lieutenant John Park Finley Signal Service, United States Army



Observed

Accuracy = (28+2680)/2803 = 96.6% (published in Americ. Meteorol. Journal 1884)

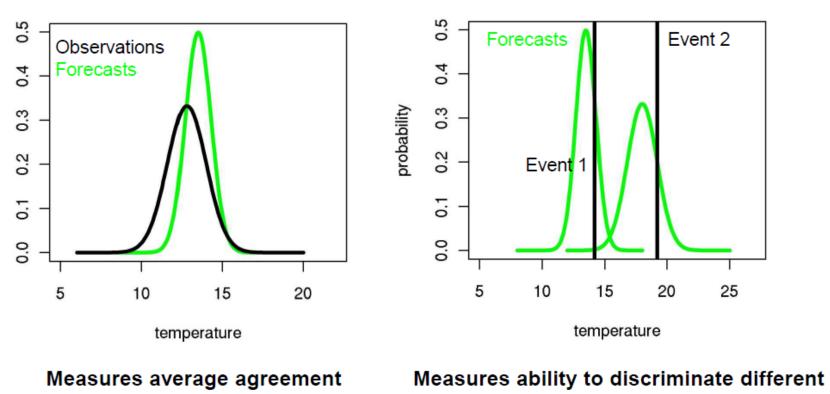
If no tornados were forecast at all: Accuracy = (0+2752)/2803 = 98.2%

It is advisable to use more measures than just accuracy...

Ensemble Forecasts

probability

Reliability



events

Resolution

197

Categorical Forecasts

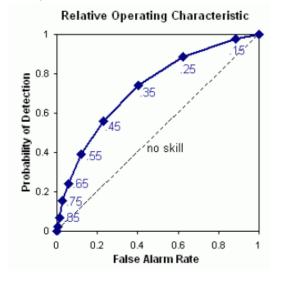
Accuracy = hits + correct negatives	fraction of correct forecasts (best=1)
BIAS = <u>hits + false alarms</u> hits + misses	under or over forecasting (best=1)
POD = <u>hits</u> hits + misses	correctly forecast events (best=1)
$FAR = \frac{false \ alarms}{hits + false \ alarms}$	wrongly forecast events (best=0)

HK =	hits	_	false alams	
	hits + misses		false alarms + correct negatives	

Can forecast separate yes from no events (best=1)

Probabilistic Forecasts

ROC (relative operating characteristic)



• Decide for an event threshold

- · Calculate contingency table entries for a set of probability thresholds
- Plot POD against FAR
- Perfect when area under ROC curve = 1
- Measures forecast resolution (forecasts can discriminate events)
- If line falls under diagonal, forecast is worse than a random guess
- Can be used to compare with deterministic forecast



question: What is the relative improvement of the forecast over some reference forecast?

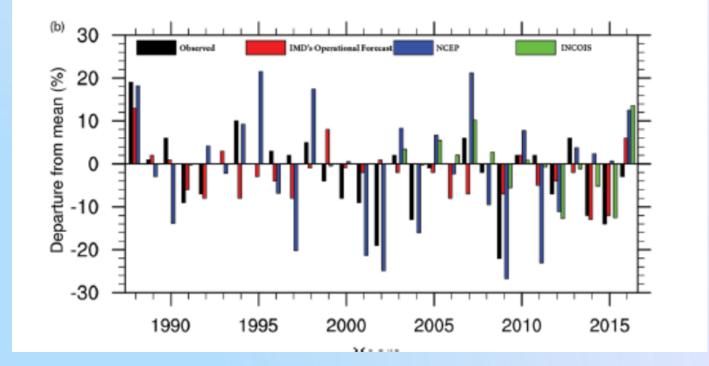
SCOTE perfect to recast = SCOTE reference

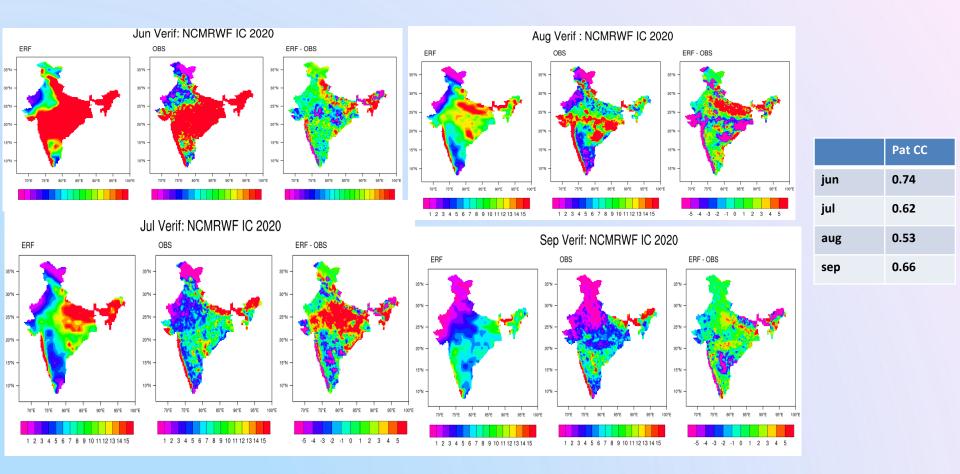
Brier Score: The Brier score was originally proposed to quantify the accuracy of weather forecasts, but can be used to describe the accuracy of any probabilistic forecast. Roughly, the Brier score indicates how far away from the truth your forecast was.

The Brier score is the squared error of a probabilistic forecast. To calculate it, we divide your forecast by 100 so that your probabilities range between 0 (0%) and 1 (100%). Then, we code reality as either 0 (if the event did not happen) or 1 (if the event did happen). For each answer option, we take the difference between your forecast and the correct answer, square the differences, and add them all together. For a yes/no question where you forecasted 70% and the event happened, your score would be (1 - 0.7)2 + (0 - 0.3)2 = 0.18. For a question with three possible outcomes (A, B, C) where you forecasted A = 60%, B = 10%, C = 30% and A occurred, your score would be (1 - 0.6)2 + (0 - 0.1)2 + (0 - 0.3)2 = 0.26. The best (lowest) possible Brier score is 0, and the worst (highest) possible Brier score is 2.

$$BS = \frac{1}{N} \sum_{i=1}^{N} (p_i - o_i)^2 = Brier skill score - BSS = \frac{BS - BS_{reference}}{0 - BS_{reference}} = 1 - \frac{BS}{BS_{reference}}$$

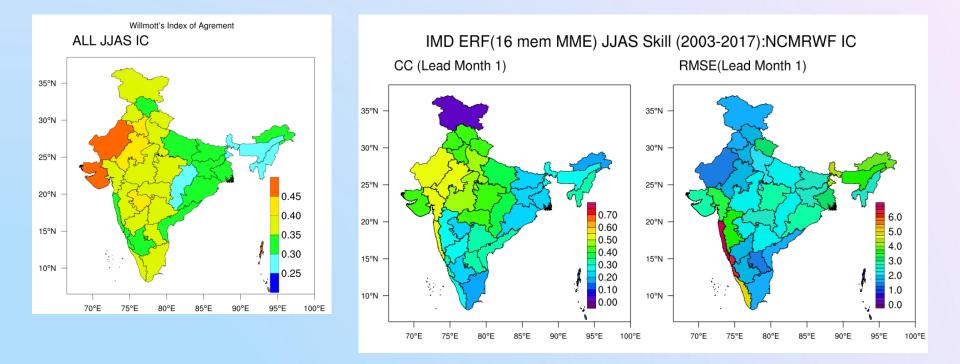
Examples of IMD Forecast Verification





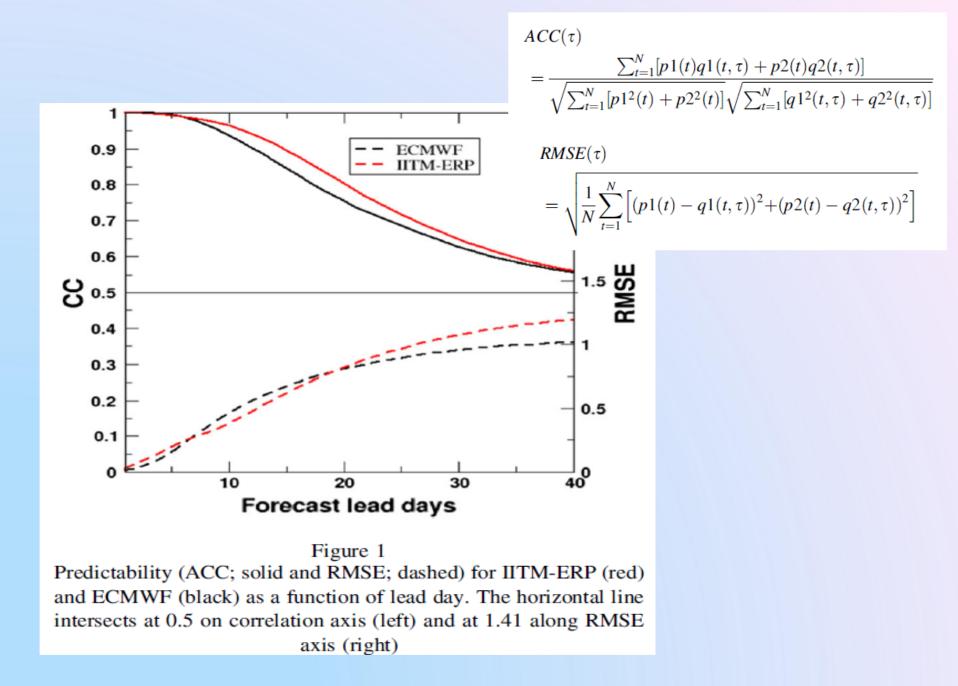
2020 Verification ICs : 03/06 01/07 29/07 09/02

AII IC JJAS: IMD ERF



Wilmott's index of agreement CC rmse

Low RMSE, higher CC better Index of agreement



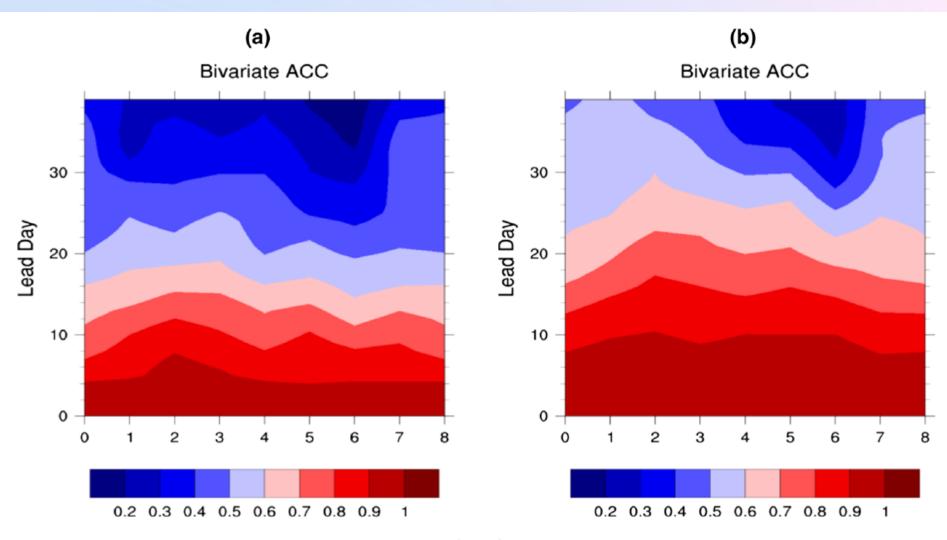


Figure 3 Bivariate ACC a IITM-ERP and b ECMWF as a function of lead time and initial phase

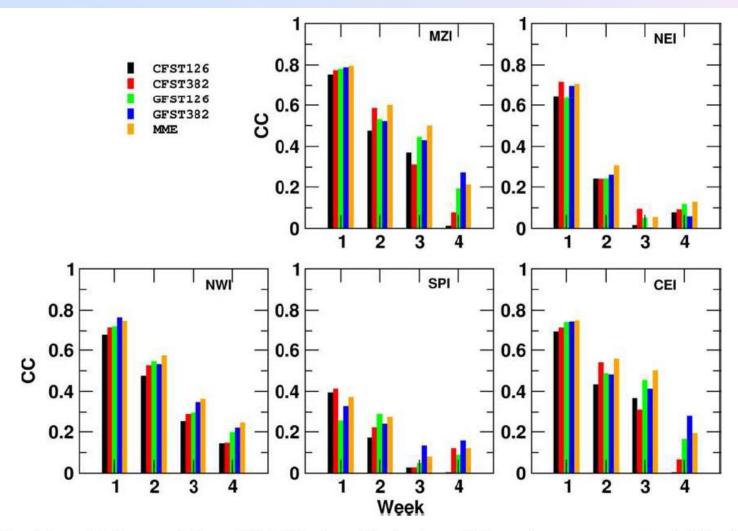


FIG. 7 The deterministic correlation skill (CC) of weekly lead prediction of area-averaged rainfall with observations for the hindcast period (2003–14) over the homogeneous zones of India.

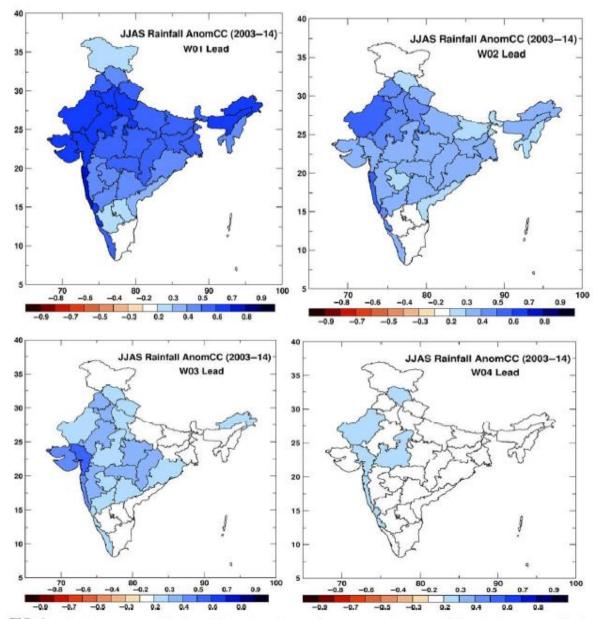


FIG. 8 The deterministic skill of weekly lead prediction of area-averaged JJAS rainfall with observations for the hindcast period over the meteorological subdivisions of India.

Brier Skill Score From IITM extended Range models

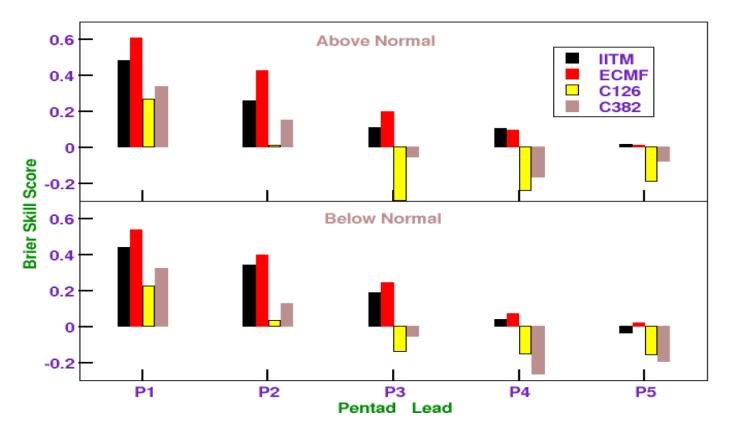


Figure 3: Brier Skill score for the monsoon zone for the above normal and below normal categories for the IITM MME and the ECMF ENS. Also shown the same for individual component models. Skill score is based on 11 members taken from each of the models.

R OC Curve Example

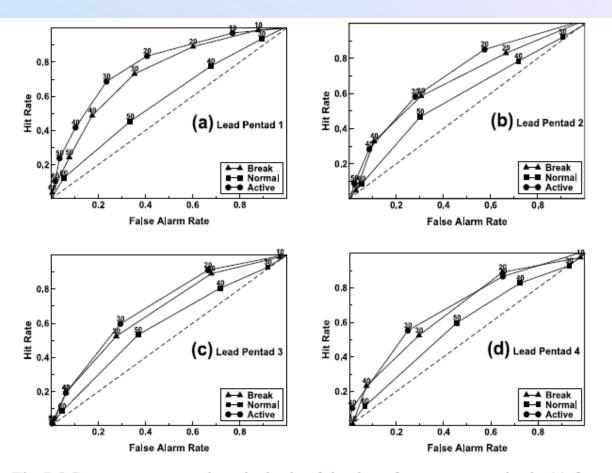
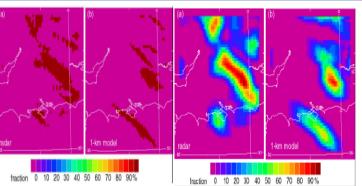


Figure 7. The ROC curve constructed on the basis of the three forecast categories in (a) first pentad, (b) second pentad, (c) third pentad, and (d) fourth pentad lead for the hindcast period. The area under the curve (AUC) for each category is listed in Table 3.

Spatial Verification

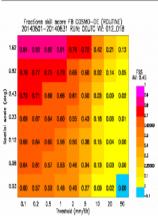
FUZZY (neighborhood)



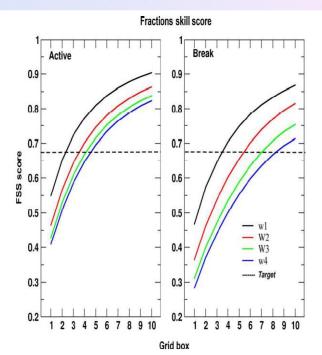
- Decide for a set of thresholds
- Gradually smooth forecast and/or observed fields
 (set of smoothing functions are possible)
- Decide for a verification measure, e.g. Fraction Skill Score

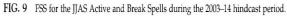
 $FSS = 1 - \frac{\frac{1}{N} \sum_{i=1}^{N} (P_{fcst} - P_{obs})^{2}}{\frac{1}{N} \sum_{i=1}^{N} P_{fcst}^{2} + \frac{1}{N} \sum_{i=1}^{N} P_{obs}^{2}}$

- Useful if forecast and observation are available as grid (e.g. observation from rain radar)
- · Shows useful scales of predictability
- · Popular for comparing models with different horizontal resolution
- Reduced double penalty effect with larger scales
- Many dichotomous or probabilistic scores can be used for analysis



IMD ERPS FSS





Monthly Forecast Verification

Homogeneous region mask skill Single IC: IMD ERF and Glosea5 (inside braces)

June(29/05)	сс	RMSE
WNW	0.71(<mark>0.75</mark>) 0.88	0.69 <mark>(0.89</mark>) <u>0.82</u>
CE	0.66 <mark>(0.48)</mark> <u>0.70</u>	1.32(1.88) <u>1.53</u>
ENE	0.52 (<mark>0.42)</mark> 0.67	1.51 <mark>(2.21)</mark> <u>1.40</u>
SP	0.54 (0.64) 0.53	1.01(1.04) <u>1.03</u>
MZI	0.64 <mark>(0.48)</mark>	1.12(<mark>1.53</mark>)
AI	0.47(<mark>0.71)</mark>	0.99 <mark>(0.83)</mark>

July(01/07)	сс	RMSE
WNW	0.47 <mark>(0.63)</mark> 0.42	1.15(1.38) 1.04
CE	0.35 <mark>(0.64)</mark> 0.14	1.71(<mark>2.23)</mark> 2.03
ENE	0.42(<mark>0.01)</mark> 0.18	1.98(<mark>2.38)</mark> <u>1.69</u>
SP	0.42 <mark>(0.82)</mark> 0.52	1.19 <mark>(0.92</mark>) <u>1.20</u>
MZI	0.34(0.62)	1.34(1.88)
AI	0.62(<mark>0.64)</mark>	0.77 <mark>(1.03)</mark>
		Skill w

Aug(31/07)	сс	RMSE
WNW	0.43(<mark>0.72)</mark> <u>0.43</u>	1.31(<mark>0.97</mark>) <u>1.24</u>
CE	0.46(<mark>0.66)</mark> 0.70	2.15(1.68) 1.83
ENE	0.18 <mark>(0.56)</mark> <u>0.04</u>	2.26(1.61) 2.06
SP	0.32 <mark>(0.76)</mark> <u>0.25</u>	1.40(<mark>0.96)</mark> <u>1.21</u>
MZI	0.56(<mark>0.77)</mark>	1.62 <mark>(1.13)</mark>
AI	0.53(<mark>0.67)</mark>	0.80 <mark>(0.64)</mark>

		Sep(02/09)	сс	RMSE
8)		WNW	0.79 (<mark>0.69)</mark> <u>0.68</u>	0.87 (1.07) 1.03
3)		CE	0.58 <mark>(0.81)</mark> 0.55	1.63(<mark>1.19)</mark> <u>1.22</u>
8)		ENE	0.33 <mark>(0.26)</mark> <u>0.47</u>	1.72(1.71) 1.26
2)		SP	0.37 <mark>(0.68)</mark> 0.10	1.33(0.98) 1.30
8)		MZI	0.64 <mark>(0.85)</mark>	1.28 (0.90)
03)		AI	0.67 <mark>(0.77)</mark>	0.82 <mark>(0.67</mark>)
Skill wrt to IMD 0.25 deg data				

