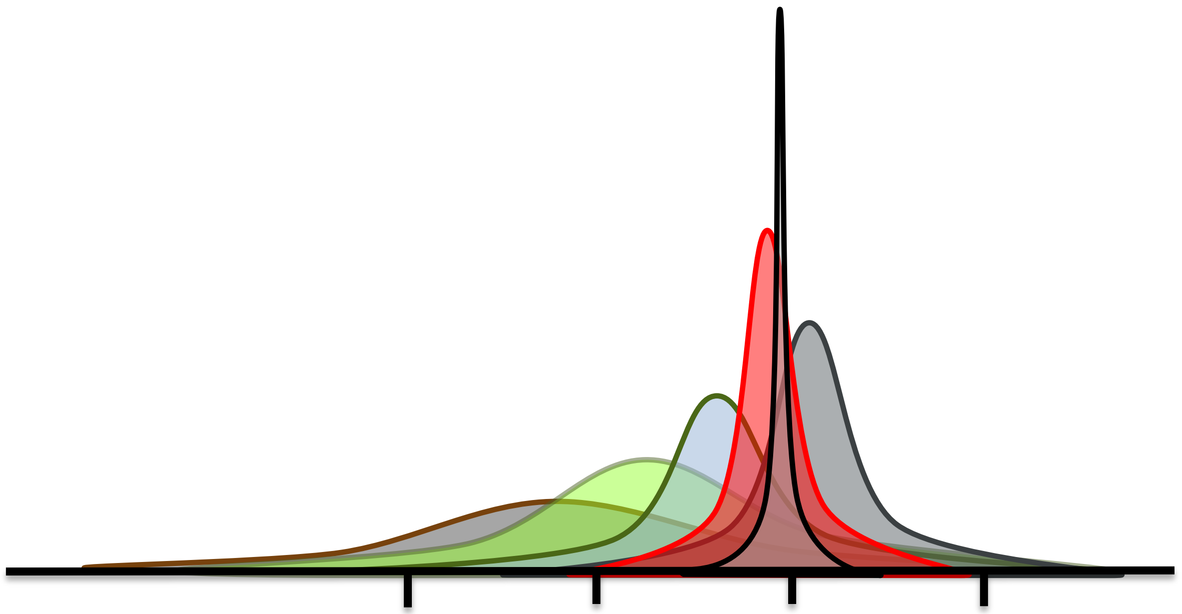
Ensembles: invaluable tools to predict extremes

Roberto Buizza
Scuola Universitaria Superiore Sant'Anna Pisa



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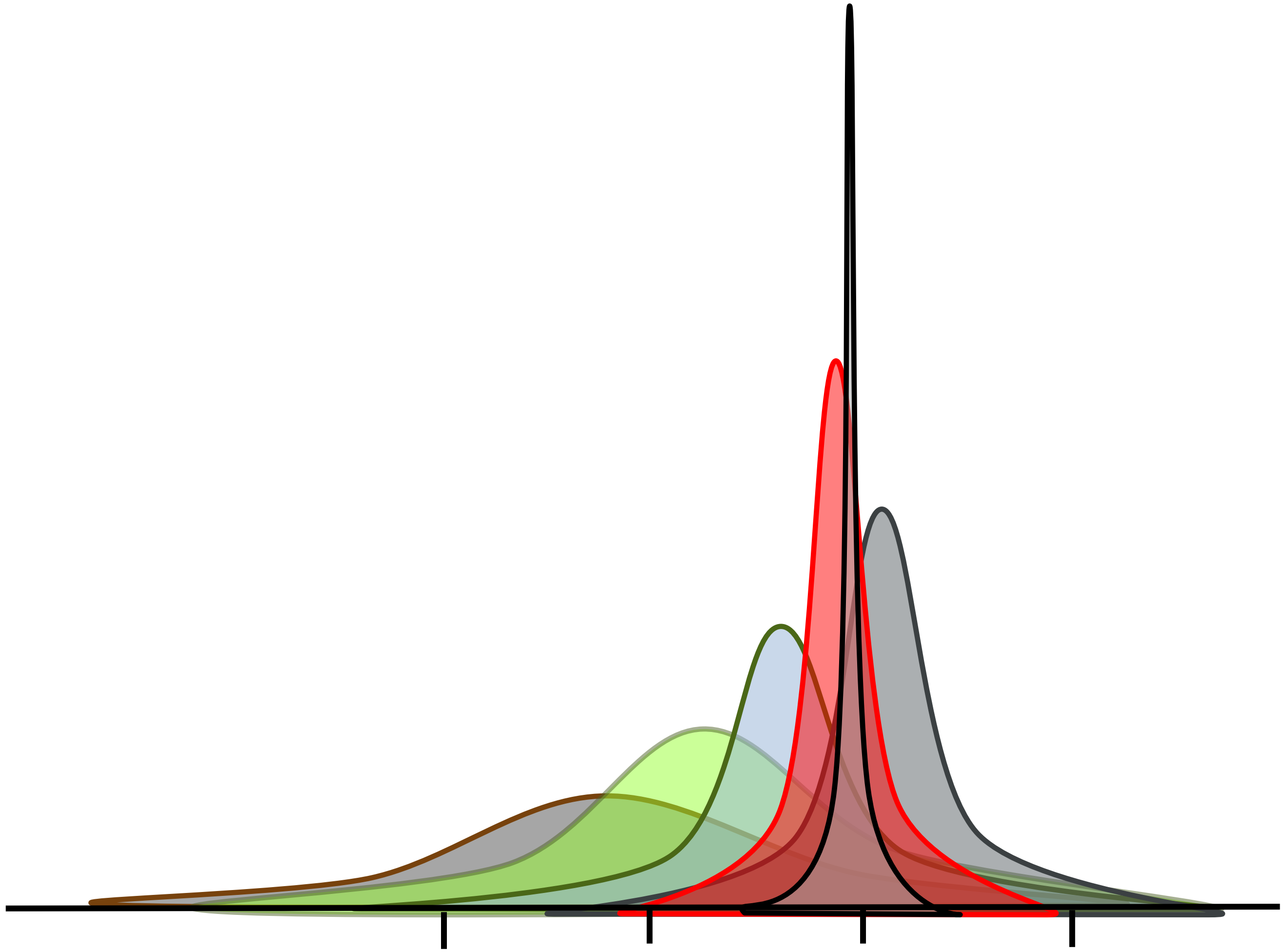
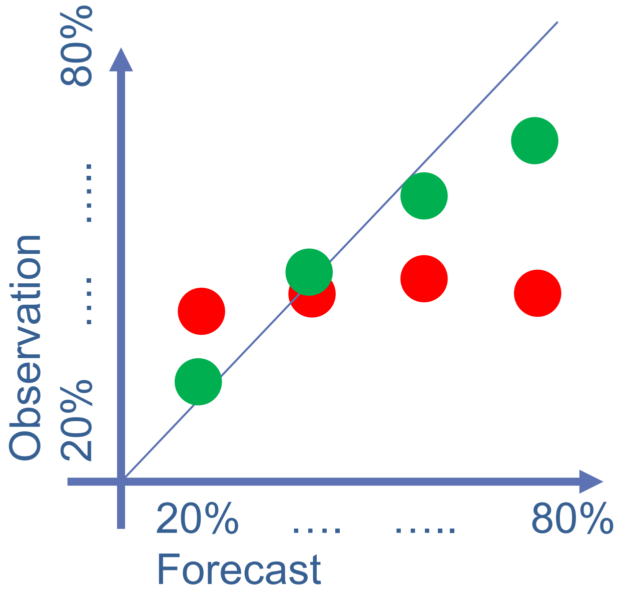
Outline

1. Ensembles must be reliable to be valuable
2. The ECMWF ensembles
3. How far ahead can we provide skilful probabilistic forecasts?
4. Predicting precipitation extremes with the ECMWF ensembles
5. Conclusions

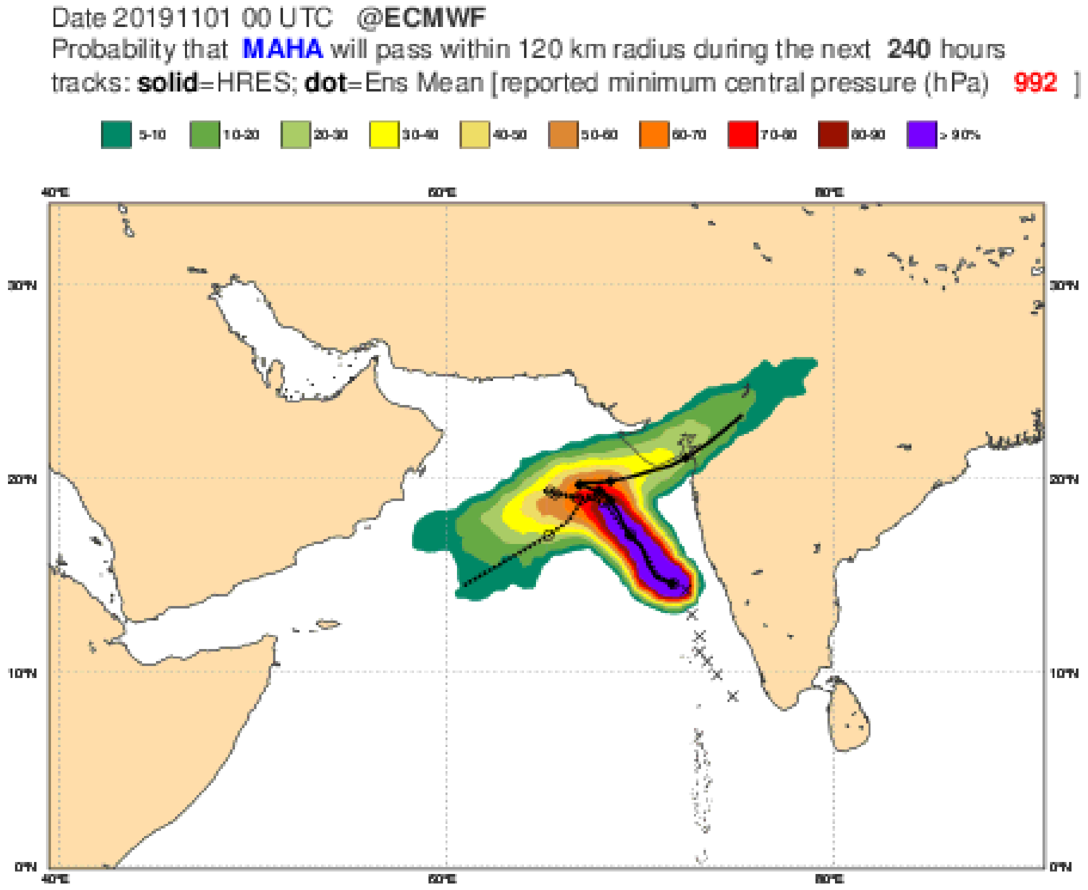
Reliable probabilistic forecasts

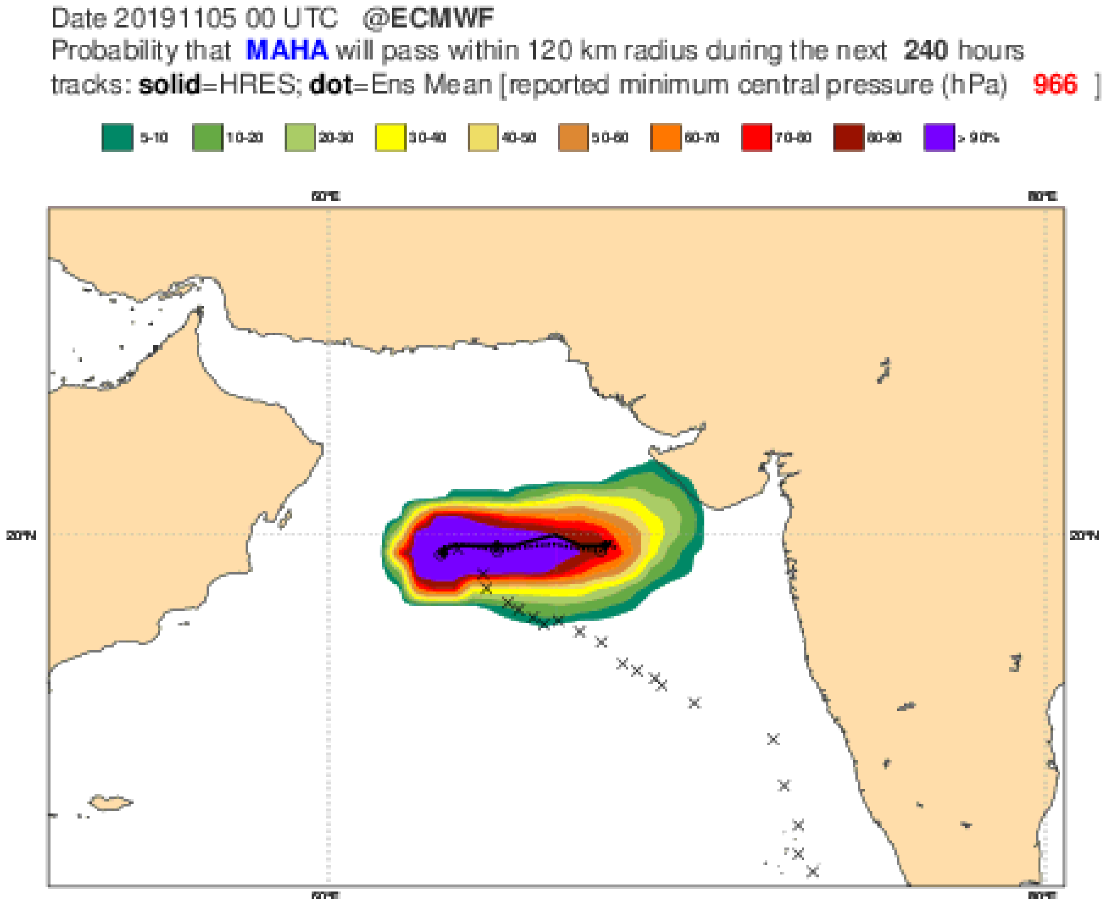


Reliable probabilistic forecast allow to identify predictable events.



In a reliable ensemble, small spread>small error





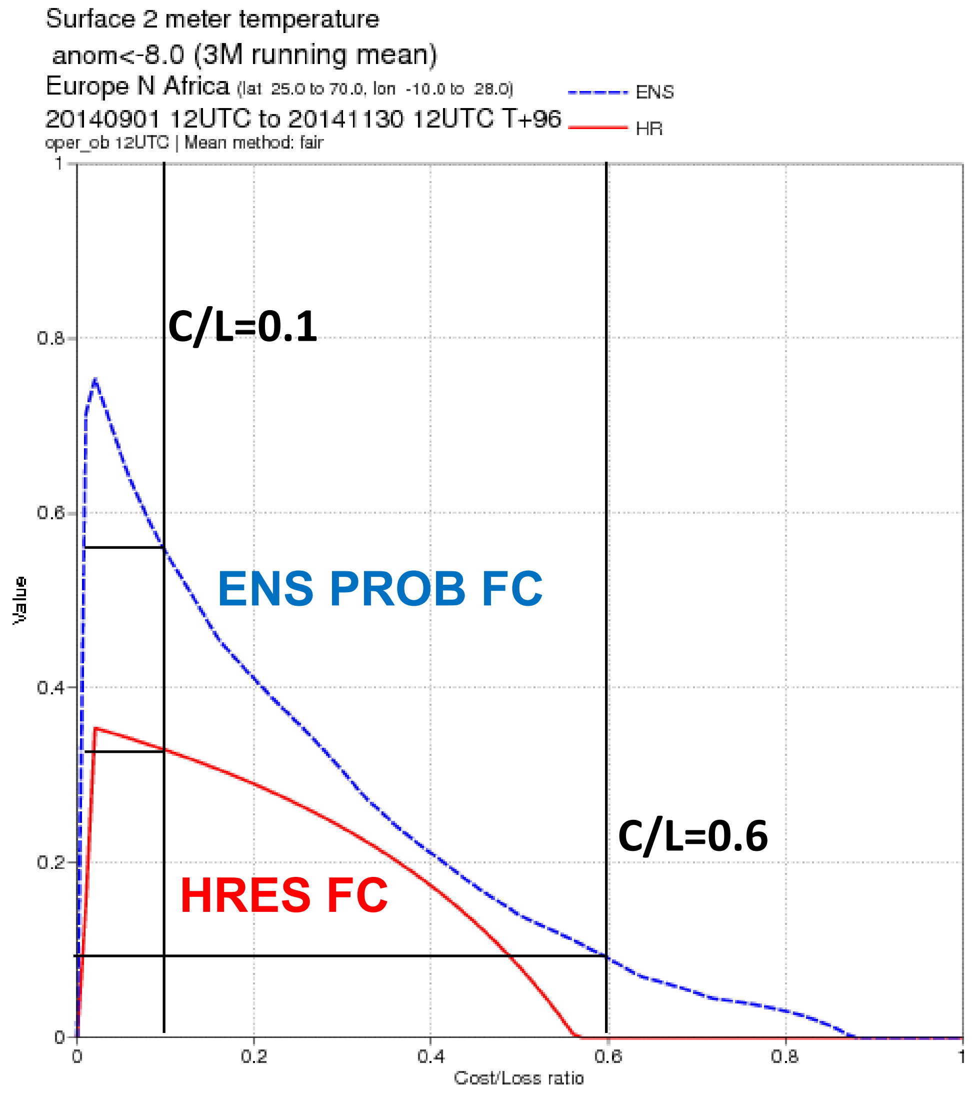
(Roberto Buizza, IITM Pune (26 Nov 2019)

Reliable ensembles are more valuable than single fcs

For example, consider users that need to decide to take an action to protect against a loss.

For them, it is important to have a prediction system capable to **discriminate between the occurrence and non-occurrence** of events.

Ensemble-based probabilistic forecasts discriminate better than single, deterministic ones.



(Roberto Buizza, IITM Pune (26 Nov 2019)

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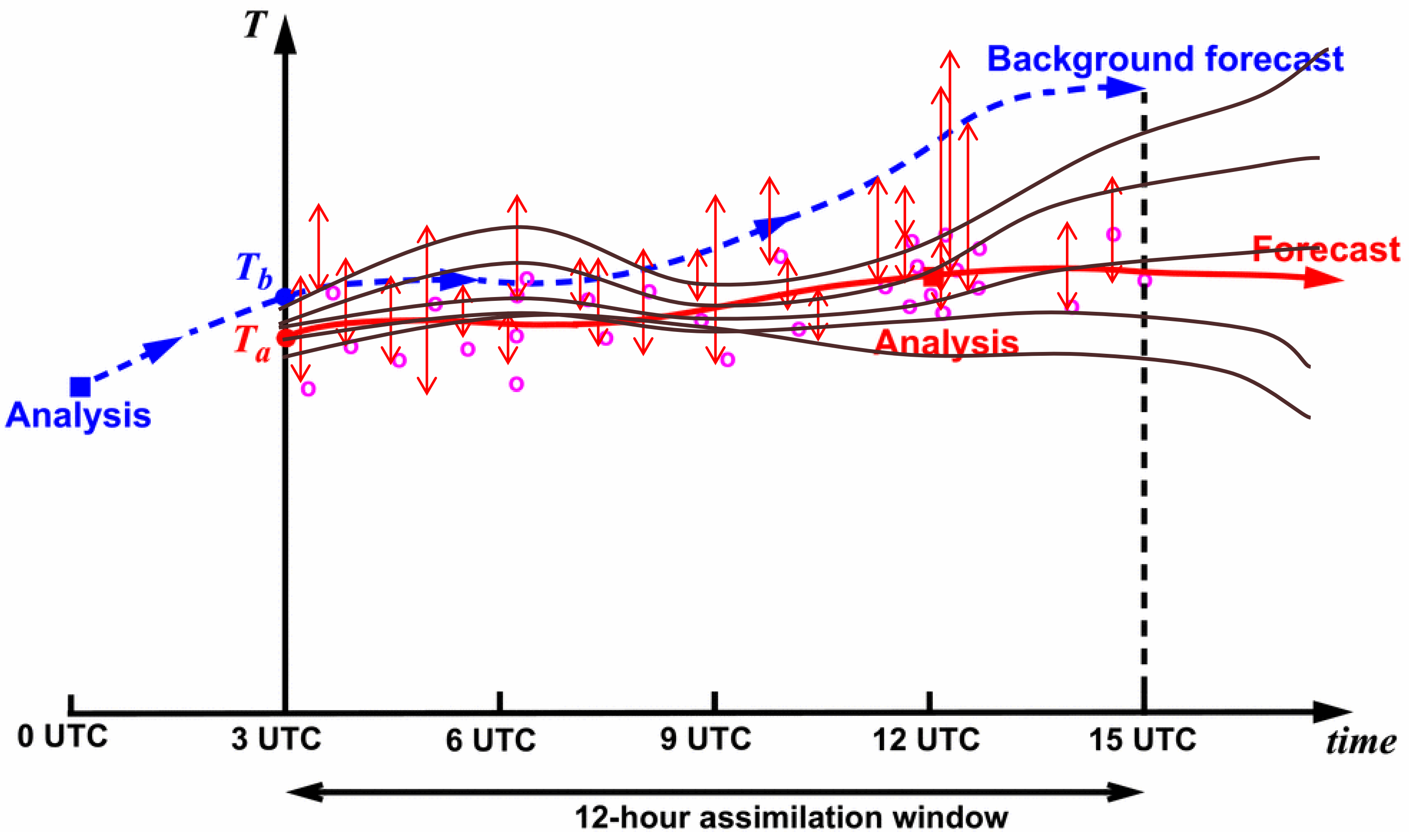
The 4 ECMWF ensembles

Since 2008, ECMWF has been running 4 ensembles:

- **The 51-member Ensemble of Data Assimilation (EDA)**



(Roberto Buizza, IITM Pune (26 Nov 2019))

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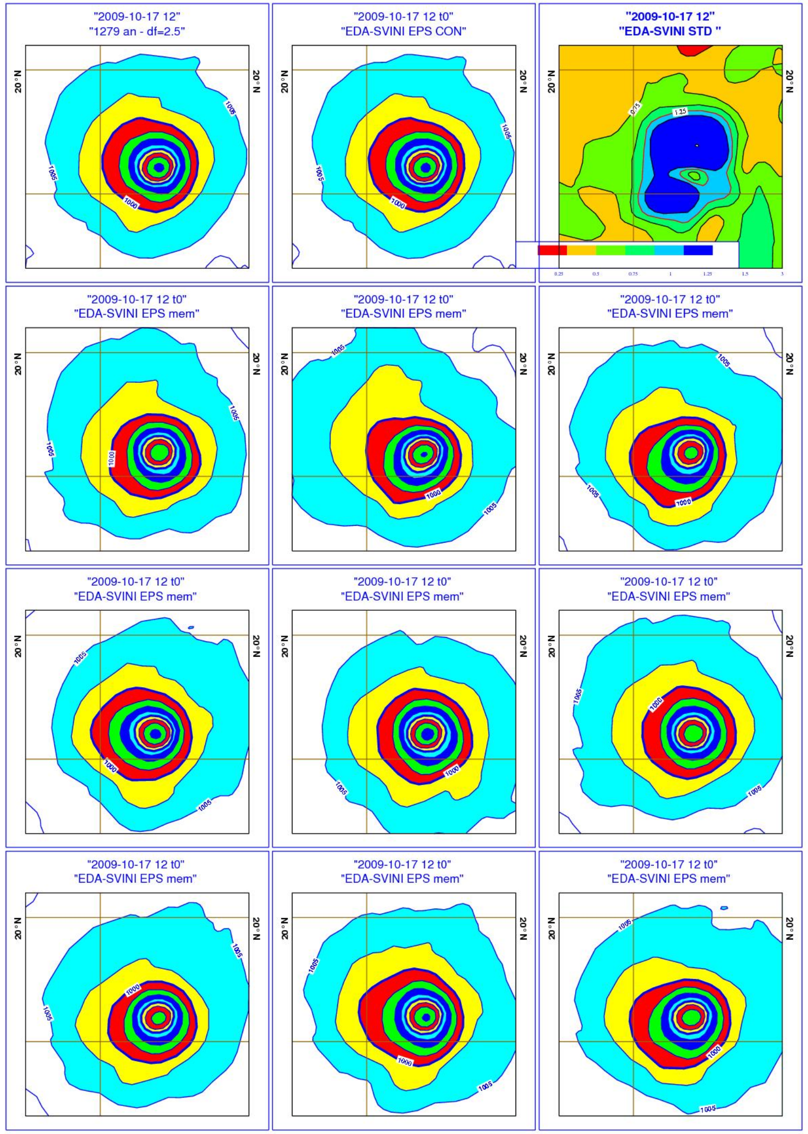


The 4 ECMWF ensembles

The EDA 51 members provide the next cycle's analyses (the HRES 4d-Var and the EDA) with flow dependent background error statistics.

- Un-pert obs
- EDA(-12h) var/covar

$4DV_{00}$

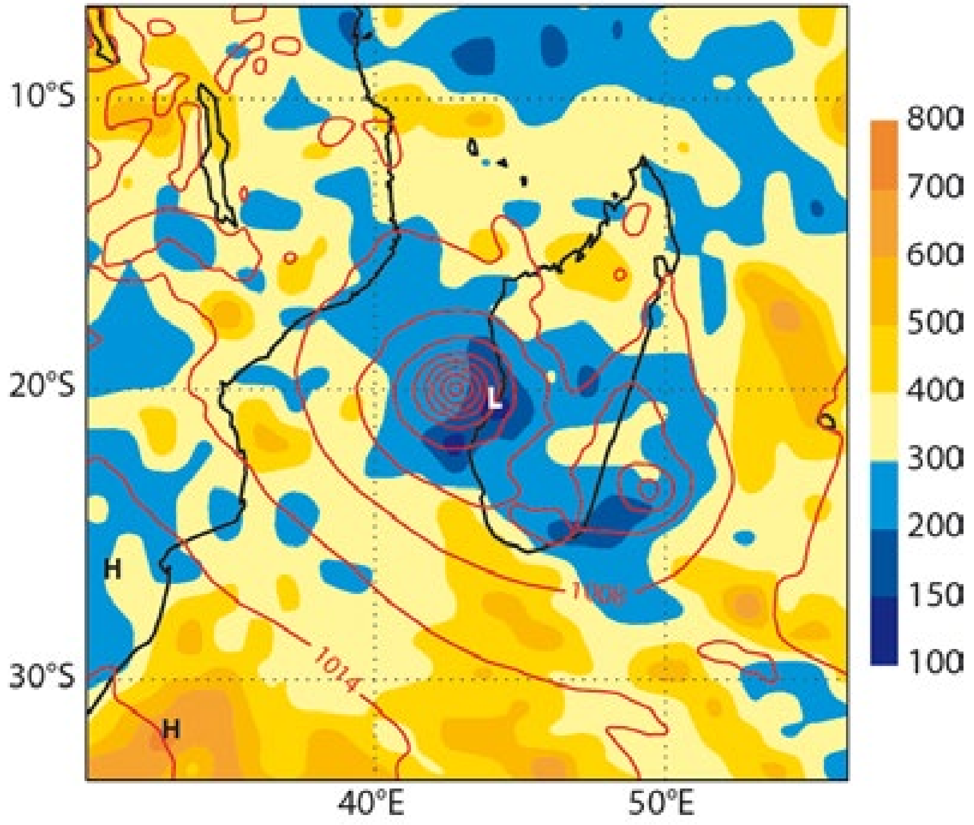
EDA_{00}

- Perturbed obs
- Model err
- EDA(-12h) var/covar

- Un-pert obs
- EDA(-12h) var/co-var

$4DV_{12}$

Background error correlation length scale for long(p_{msl}) and p_{msl}

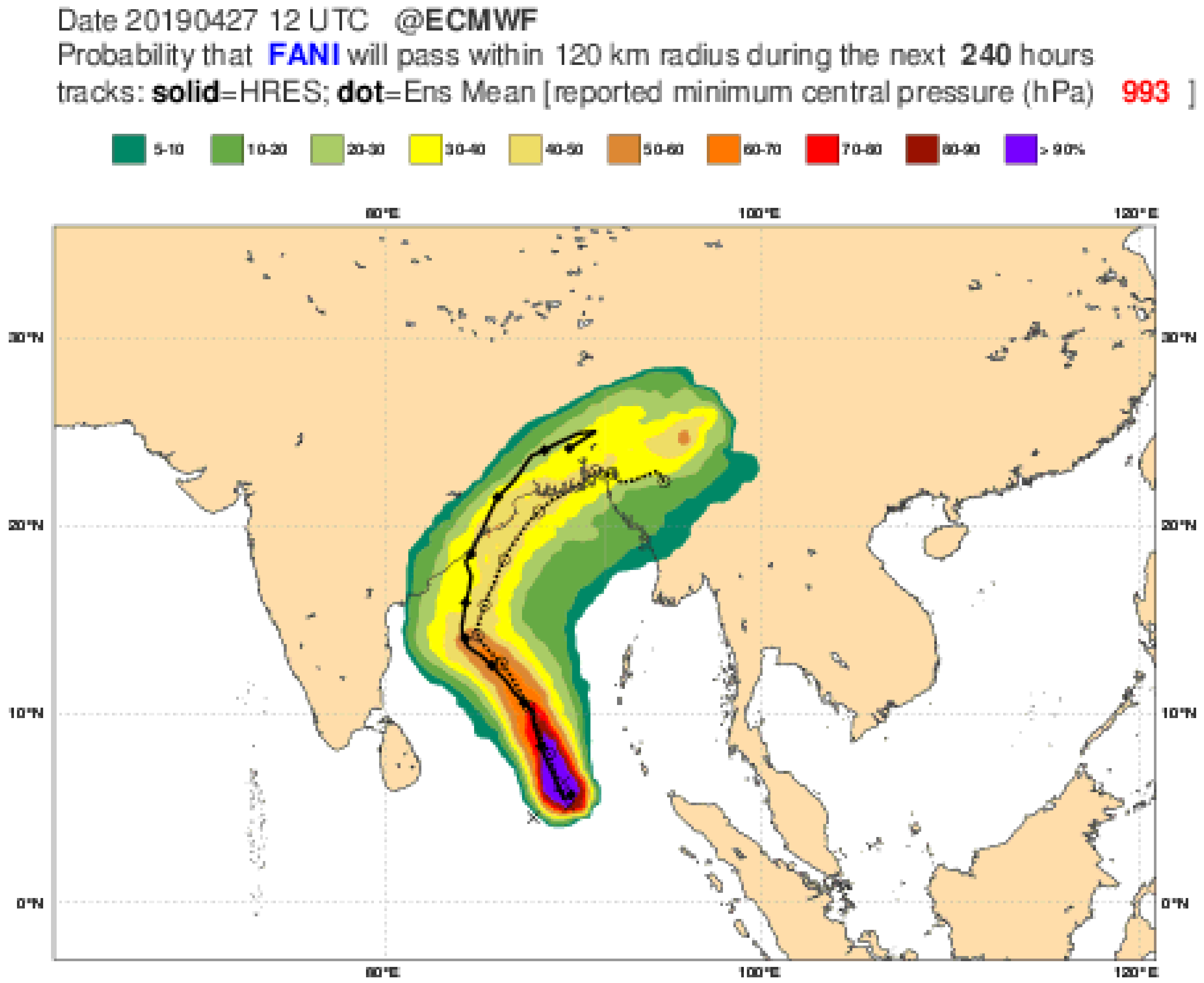


(M Bonavita)

The 4 ECMWF ensembles

Since 2008, ECMWF has been running 4 ensembles:

- The 51-member Ensemble of Data Assimilation (EDA)
- **The 51-member medium-range/monthly ensemble (ENS)**



(Roberto Buizza, IITM Pune (26 Nov 2019)

The 4 ECMWF ensembles

Since 2008, ECMWF has been running 4 ensembles:

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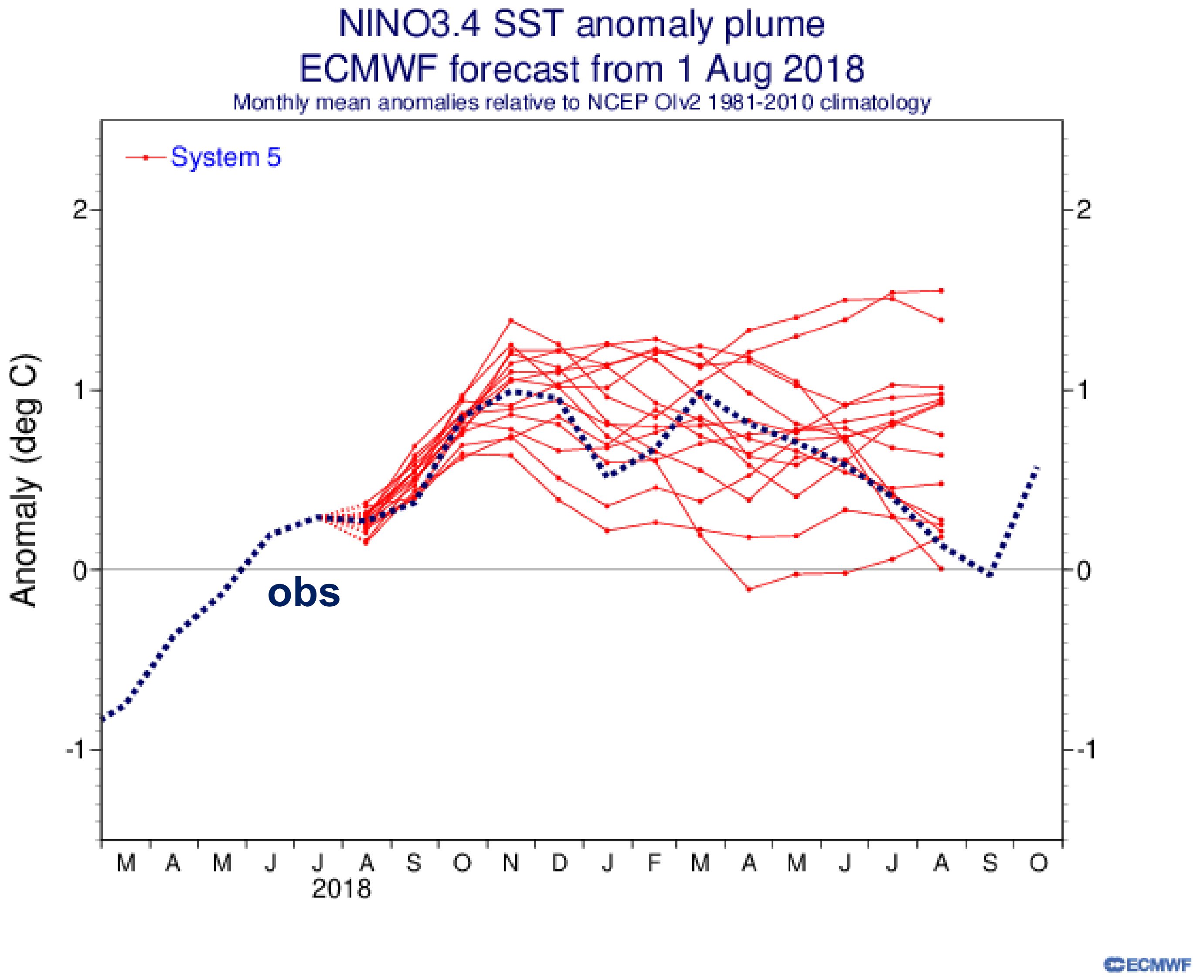
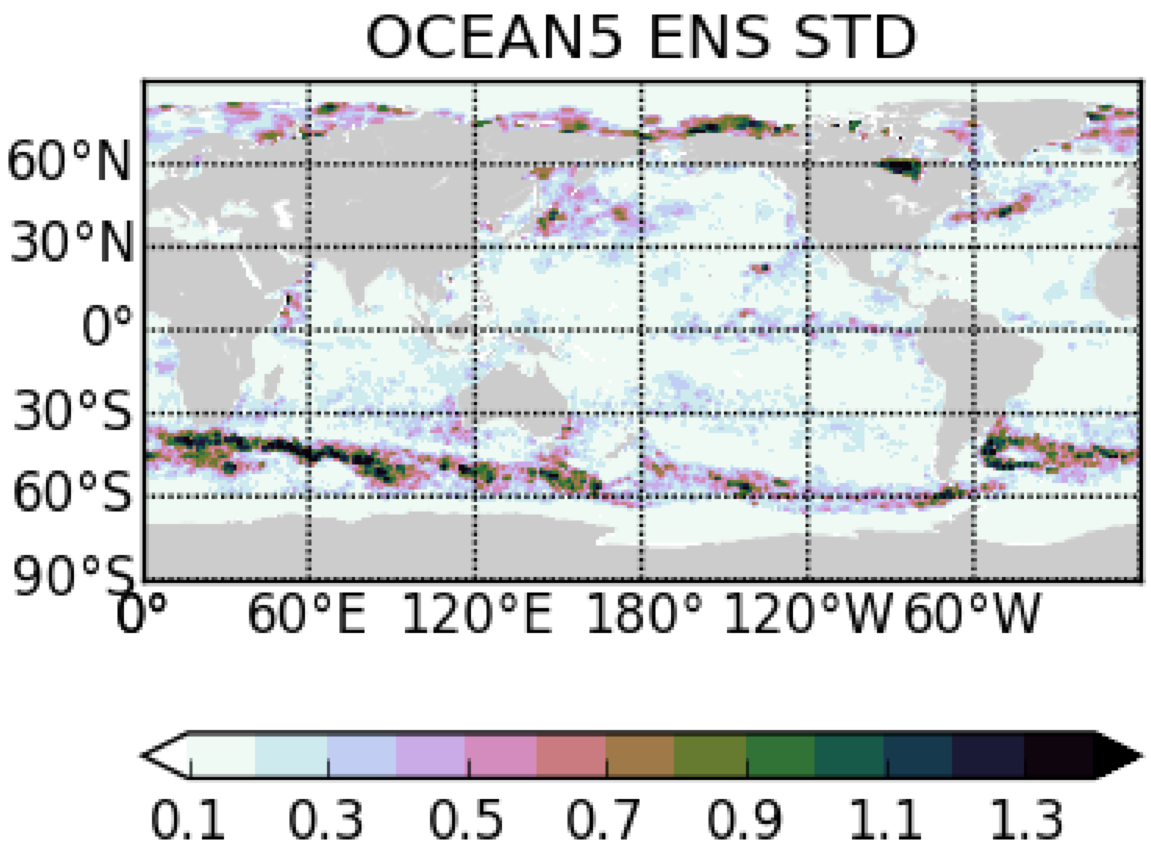
- **The 51-member seasonal ensemble (SEAS5)**



The 4 ECMWF ensembles

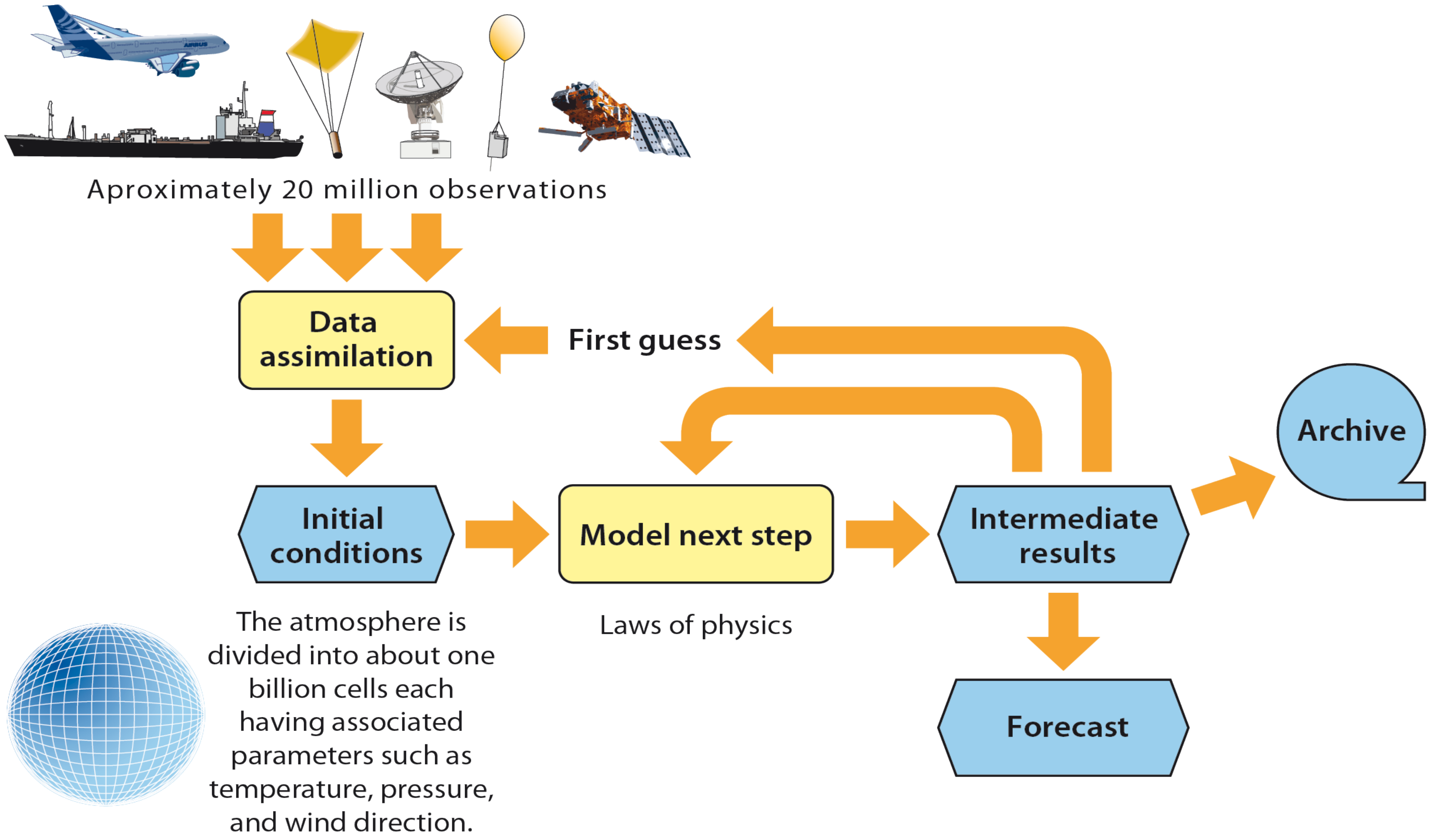
Since 2008, ECMWF has been running 4 ensembles:

- The 51-member Ensemble of Data Assimilation (EDA)
- The 51-member medium-range/monthly ensemble (ENS)
- The 51-member seasonal ensemble (SEAS5)
- **The 5-member ocean ensemble (OCEAN5)**



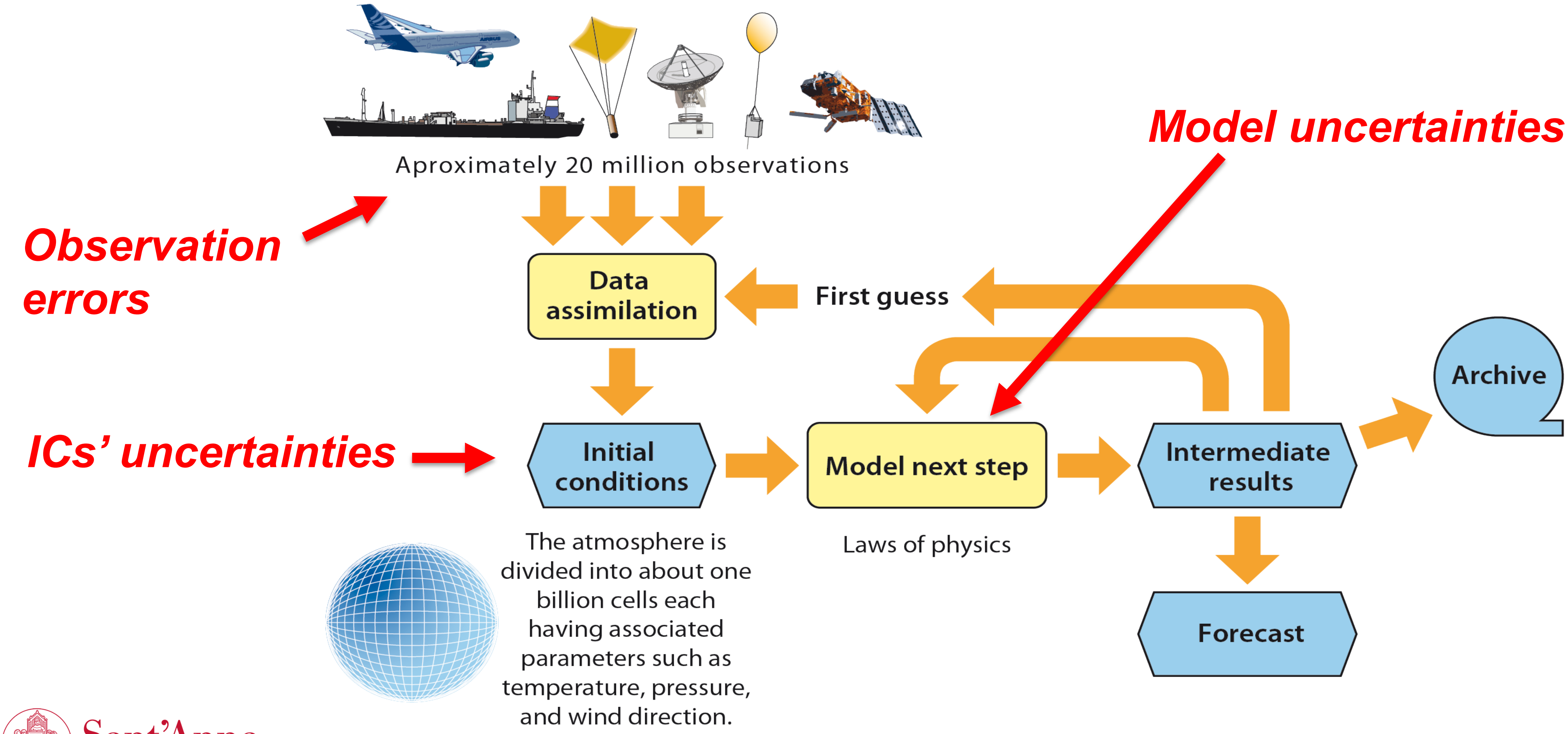
(H Zuo, K Mogensen)

The NWP process: from obs to forecasts



The NWP process: from obs to forecasts

The ECMWF ensembles aim to simulate all sources of errors.



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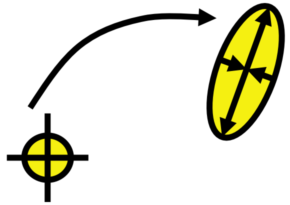
Key characteristics of the ECMWF ensembles

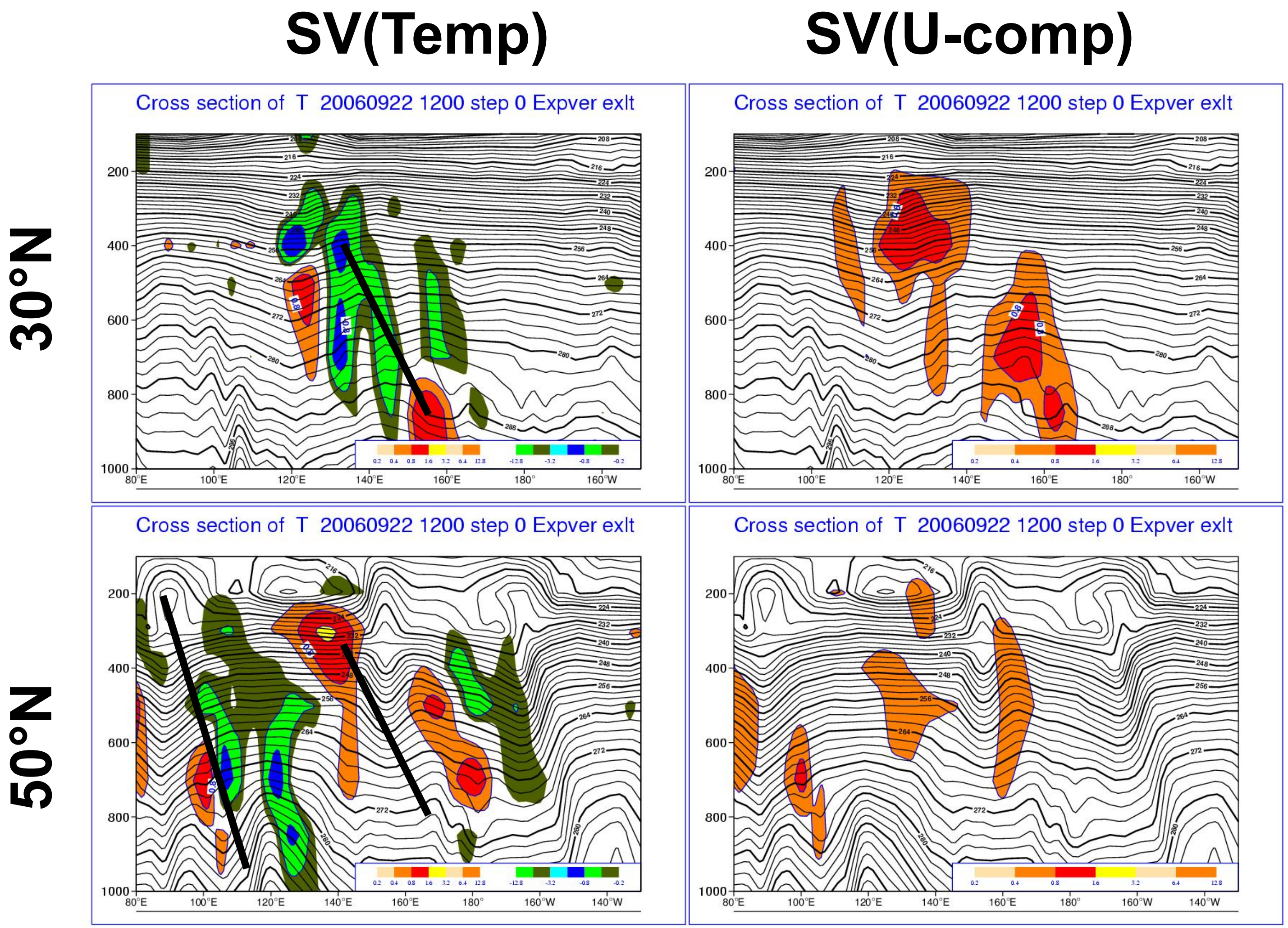
	Ensemble	#	IFS Resolution	Ocean Resolution	Sea-ice	OBS/IC unc	Model unc	Frequency
Analysis	4DVAR	1	Tco1279L137 (9km)	--	--	--	--	4 x day
	EDA	51	Tco639L137 (18km)	--	--	pOBS	SPPT	2 x day
	OCEAN5	5	--	0.25deg-z75 (25km)	LIM2	pOBS	--	1 x day
Forecasts	HRES (d0-10)	1	Tco1279L137 (9km)	0.25deg-z75 (25km)	LIM2	--	--	4 x day
	ENS (d0-15)	51	Tco639L91 (18km)	0.25deg-z75 (25km)	LIM2	SV + EDA	SPPT	2 x day (4 x day to d6.5)
	ENS (d15-46)	51	Tco319L91 (36km)	0.25deg-z75 (25km)	LIM2	SV + EDA	SPPT	2 x week
	SEAS5 (m0-7/13)	51	Tco319L91 (36km)	0.25deg-z75 (25km)	LIM2	SV	SPPT + SKEB	1 x month (4 x year to 13m)

ENS ICs: the SV-based perturbations

- Spatially localized;
- At initial time, have a larger component in potential than kinetic energy
- Show a westward tilt with high, typical of baroclinically unstable structures;
- are computed solving an eigenvalue problem:

$$E_0^{-1/2} L^* E L E_0^{-1/2} \nu = \sigma^2 \upsilon$$

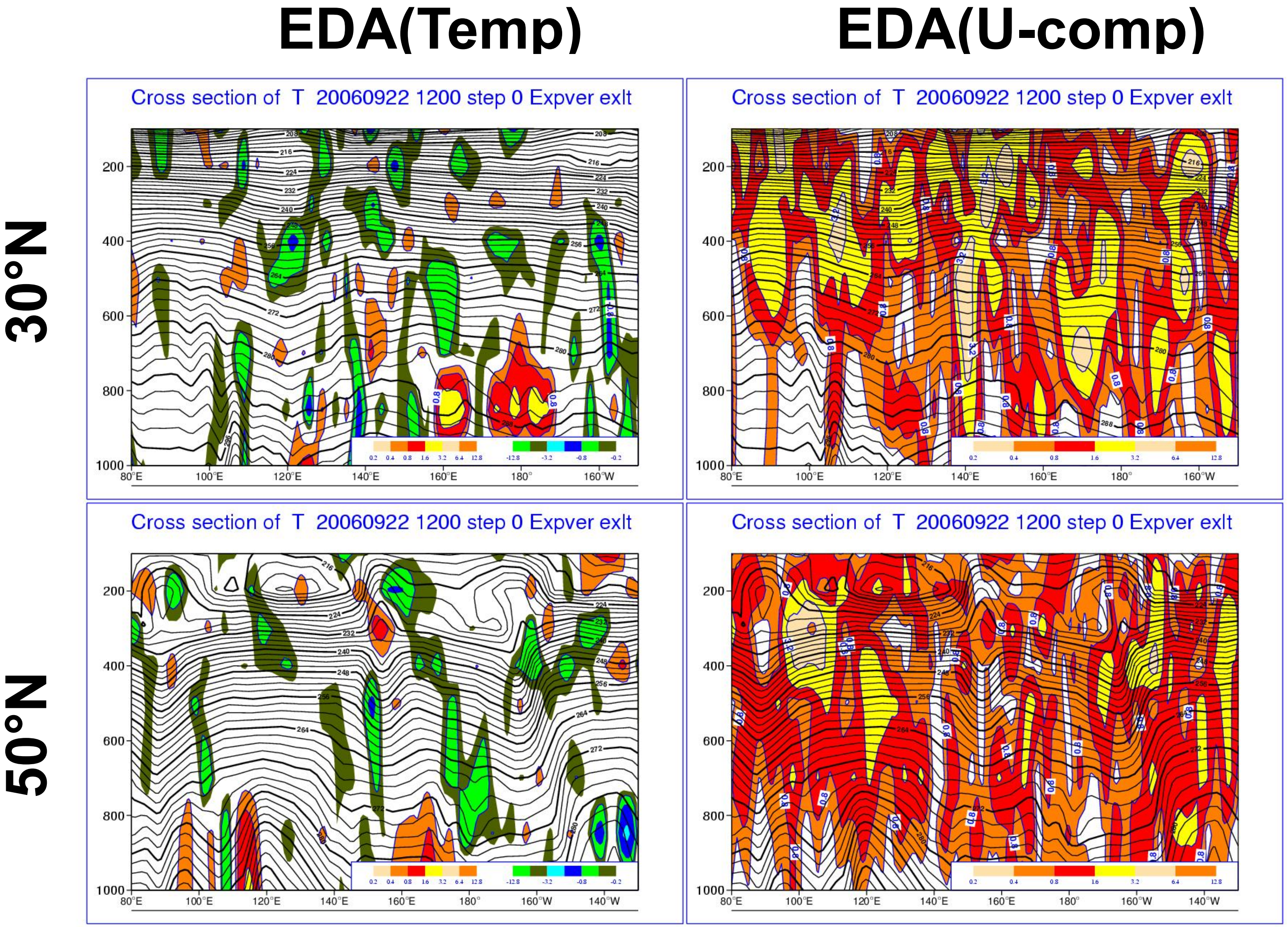




(Roberto Buizza, IITM Pune (26 Nov 2019)

ENS ICs: the EDA-based perturbations

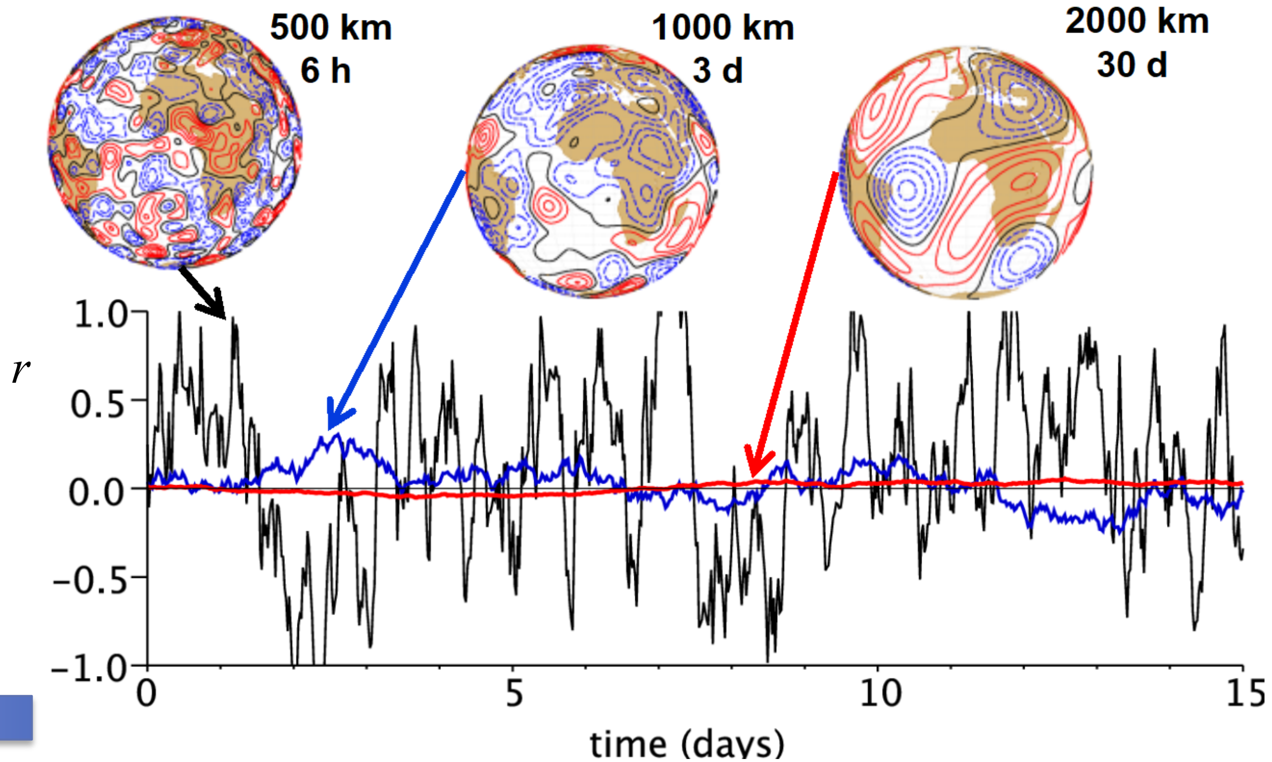
- Are less spatially localized than SVs;
- At initial time, have a similar amplitude in potential and kinetic energy;
- They are sensitive to observations’ density and accuracy



Stochastic model uncertainties [SPPT(3L)]

Model uncertainties are linked to the approximate description of the physical processes, and to the unresolved scales due to the coarse resolution of our models.

They are simulated by perturbing the tendencies by stochastic perturbations with 3 spatial and temporal characteristic scales.



(M Leutbecher)

$$e_j(T) = e_j(0) + \int_{t=0}^{T} [P_j(e_j,t) + dP_j(e_j,t) + A_j(e_j,t)]dt$$

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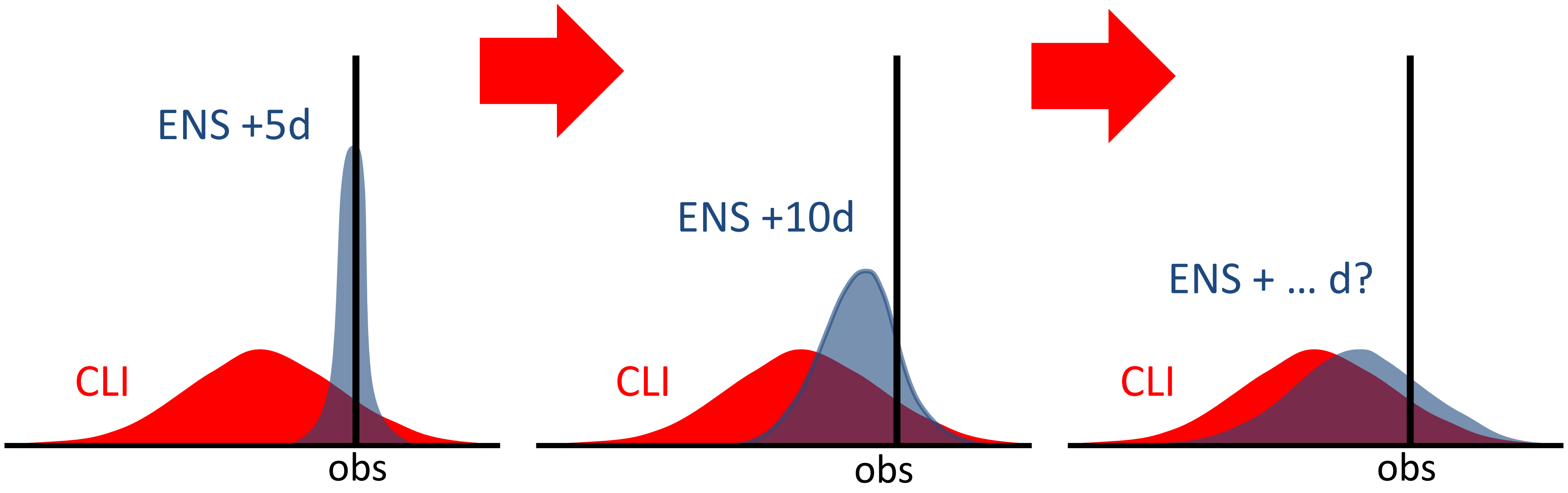
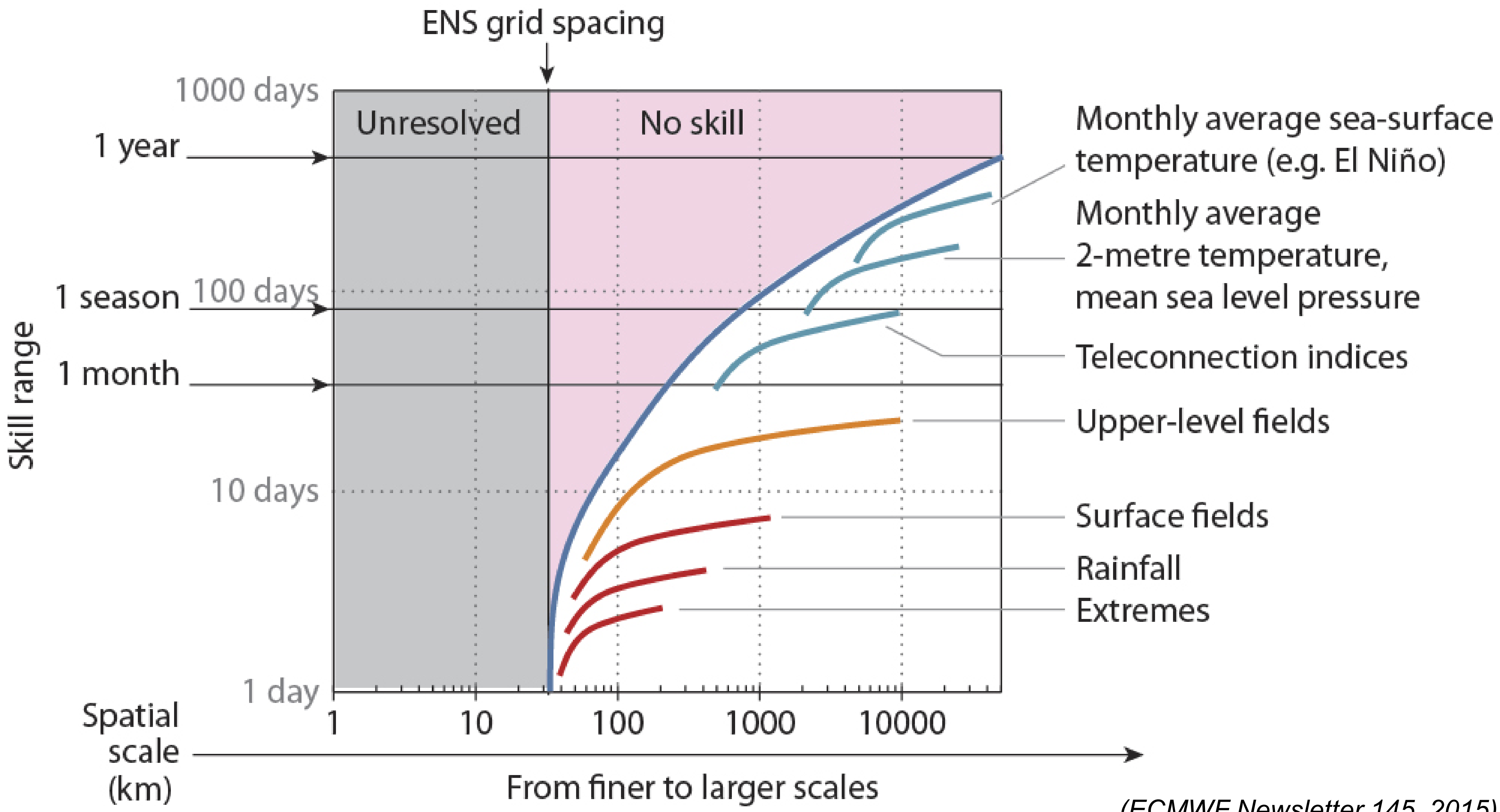
The skill of ENS fcs is measured with CRPS

ENS forecast probabilities are compared with observations (a very narrow Gaussian). A climatological distribution is used as a reference fc.

- Accuracy is measured using the Continuous Ranked Probability Score
- A forecast is skilful if CRPS(ENS fc) < CRPS(climatological ensemble)



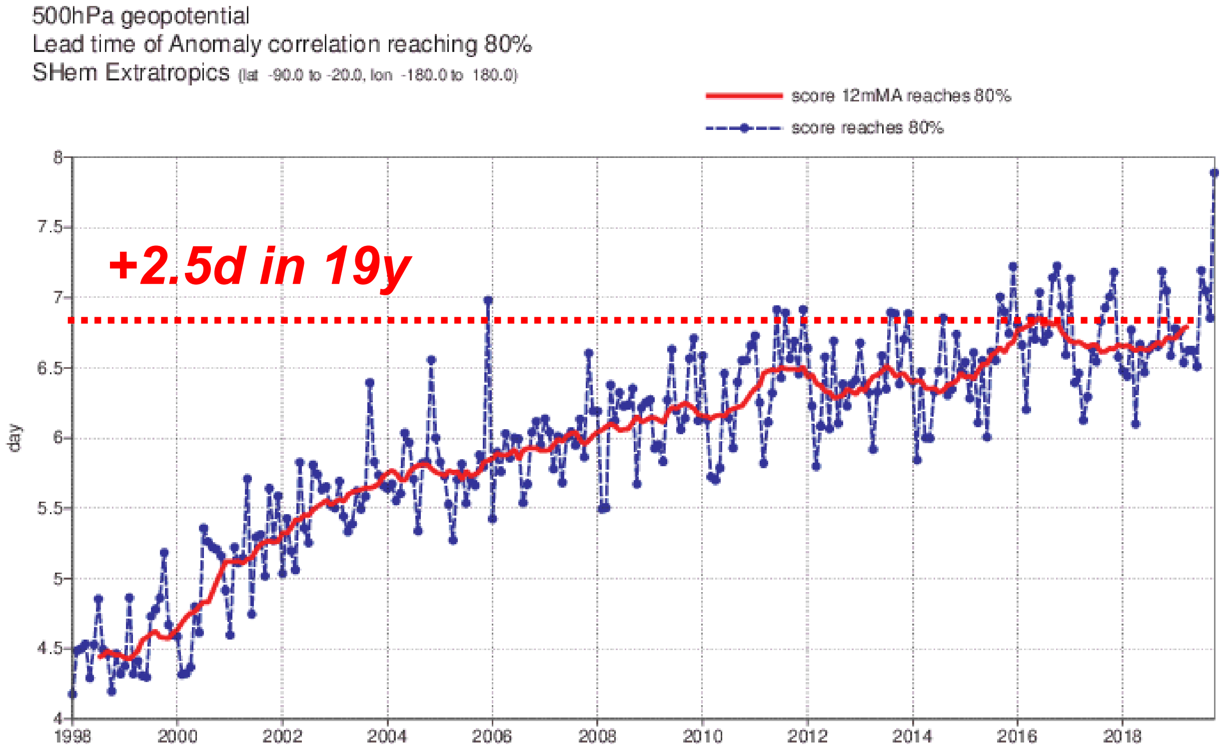
Scale-dependency of the skill horizon

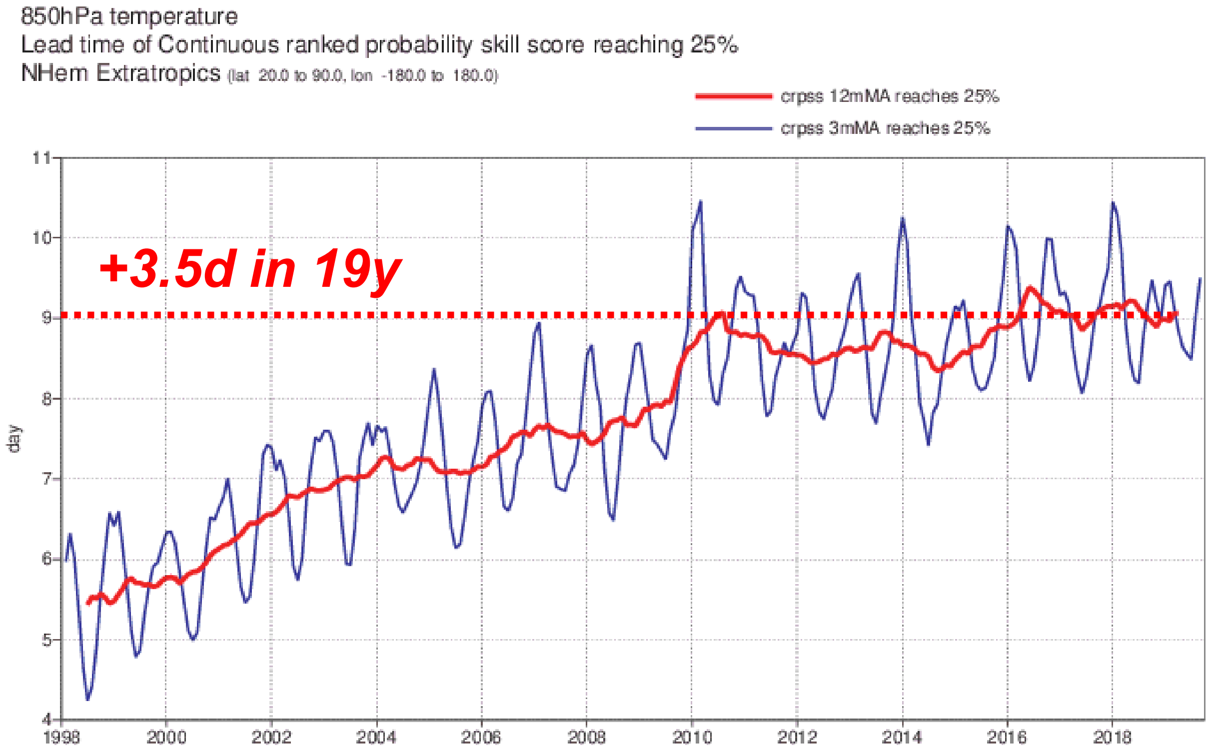


(ECMWF Newsletter 145, 2015)

How did we get there? Thanks to advances in …

1. **Modelling** (including the simulation of model uncertainties)
2. **Initialisation** (including the simulation of the obs uncertainties)
3. **Understanding predictability** (how can we extract predictable signals?)





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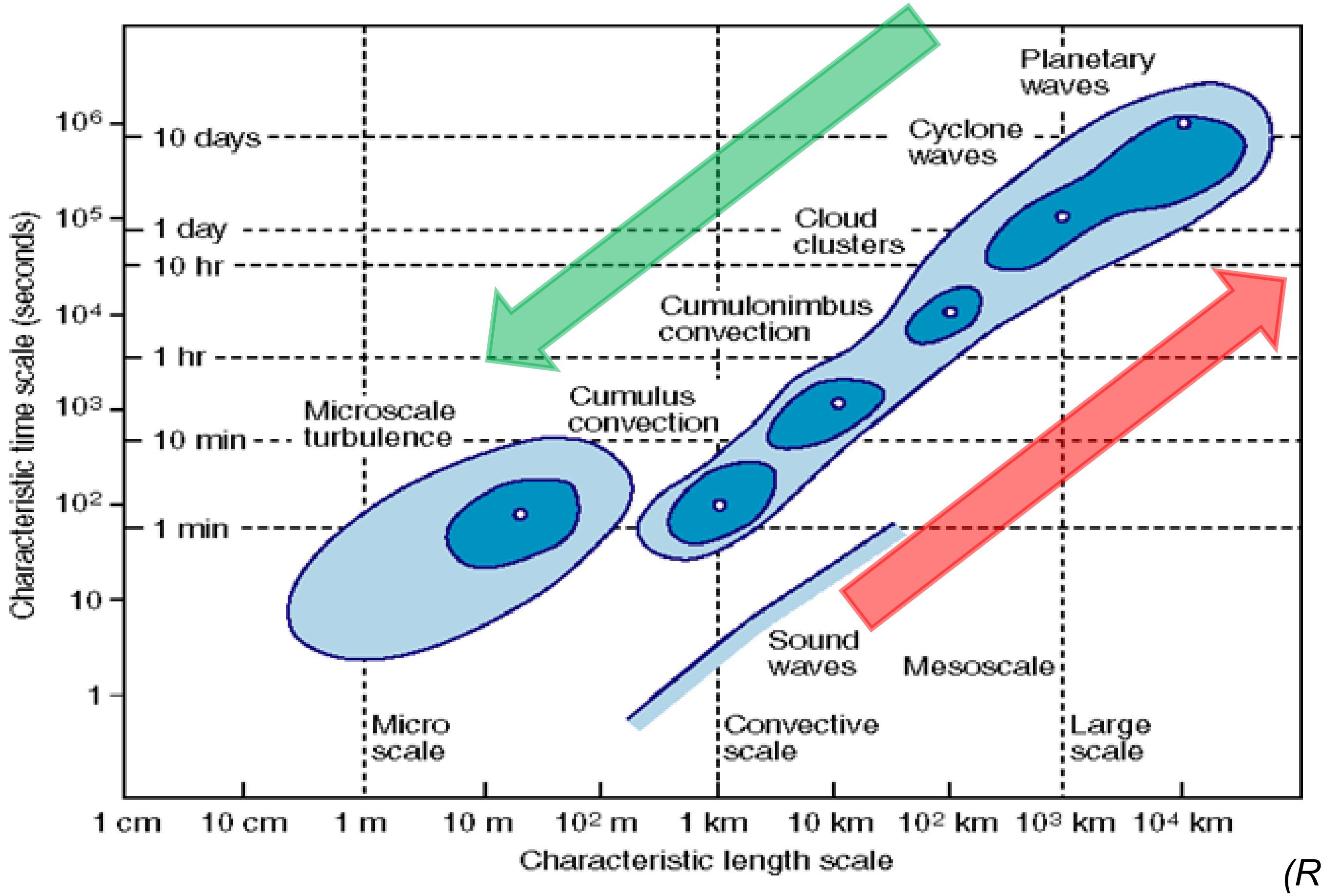
Predictable signals versus errors

Predictable signals propagate from the better-initialized and more predictable scales ('mainly' the large scales, the slowly evolving components) to the less predictable (small/fast) scales



Errors propagate from poorly initialized scales ('mainly' the smaller scales) thus reducing the predictive skill

(R Buizza and M Leutbecher, QJRMS 2015)

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Extremes populate the tails of the distributions

- Ensemble-based probabilistic systems have low resolution in probability space (e.g. in weather, 50 members can resolve dp=2%)
- Diagnosing the performance of numerical models in predicting extremes is difficult because they are rare, and each is different: thus building a solid statistics is difficult

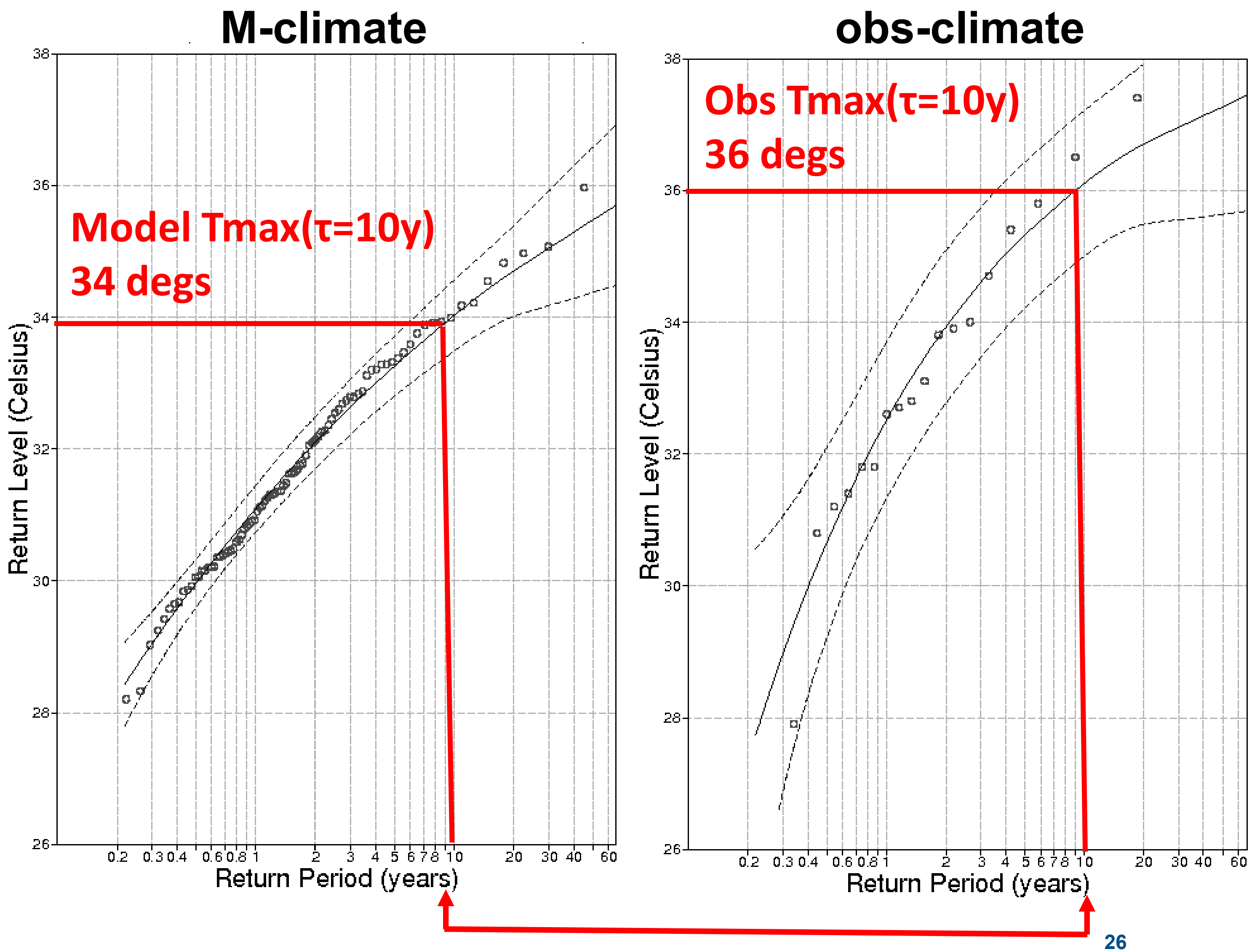
‘Extreme-value theory’ can be applied to extract signals

‘Extreme-Value theory’ can be used to calibrated probabilistic forecasts (by mapping from the model to the observation spaces).

An example is the ‘Extreme Forecast Index’ (EFI) used to predict surface weather variables.

(from Prates and Buizza, QJRMS 2011)

TMAX for Hannover

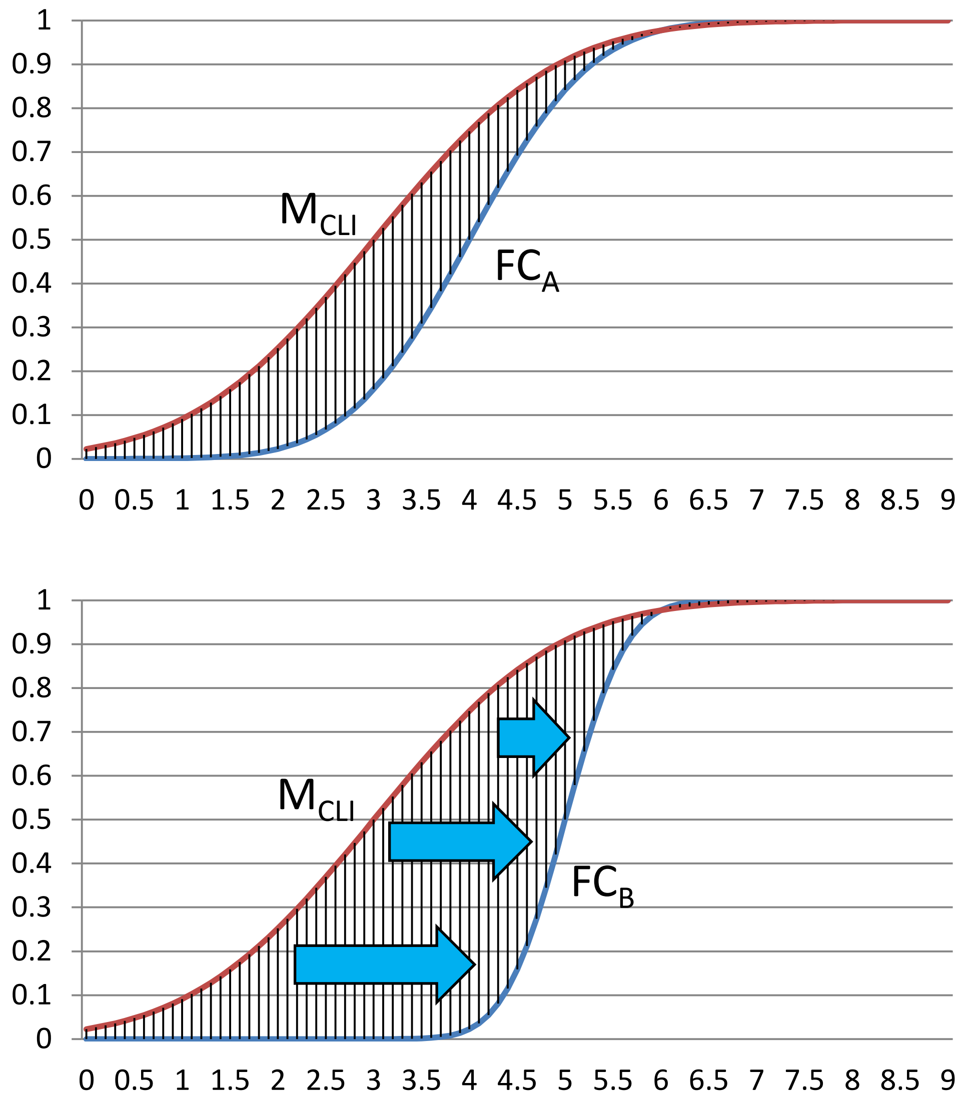


EFI: compares the CDF of the fc and the model climate

Extreme Forecast Index (EFI):

- Compute the model climate M_{CLI} CDF and the latest available forecast CDF
- Compute the area between the two curves
- If the normalized area is close to 1, there is a high probability of an extreme event

$$EFI = \frac{2}{\pi}\int_0^1 \frac{p - CDF(p)}{\sqrt{p(1-p)}}\,dp$$



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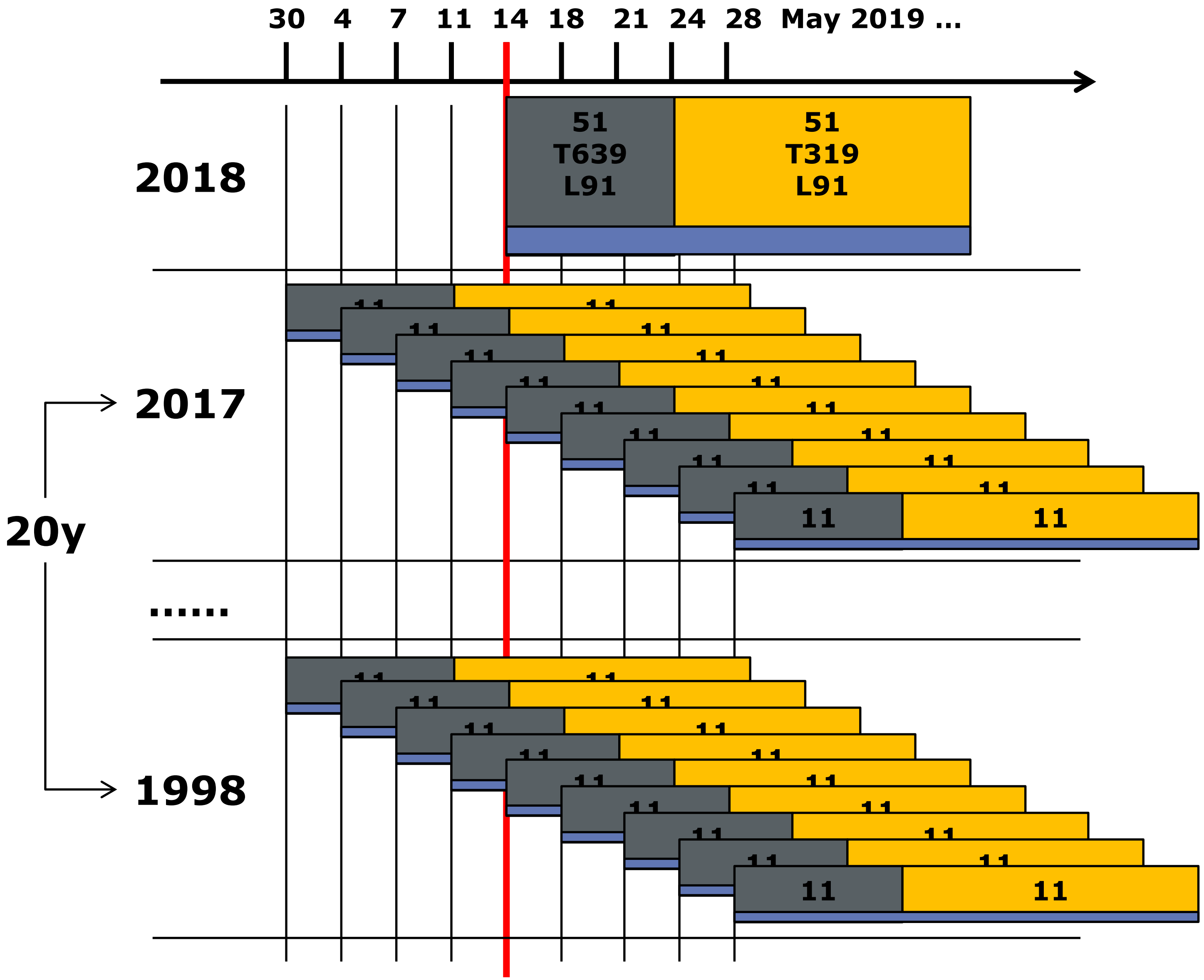
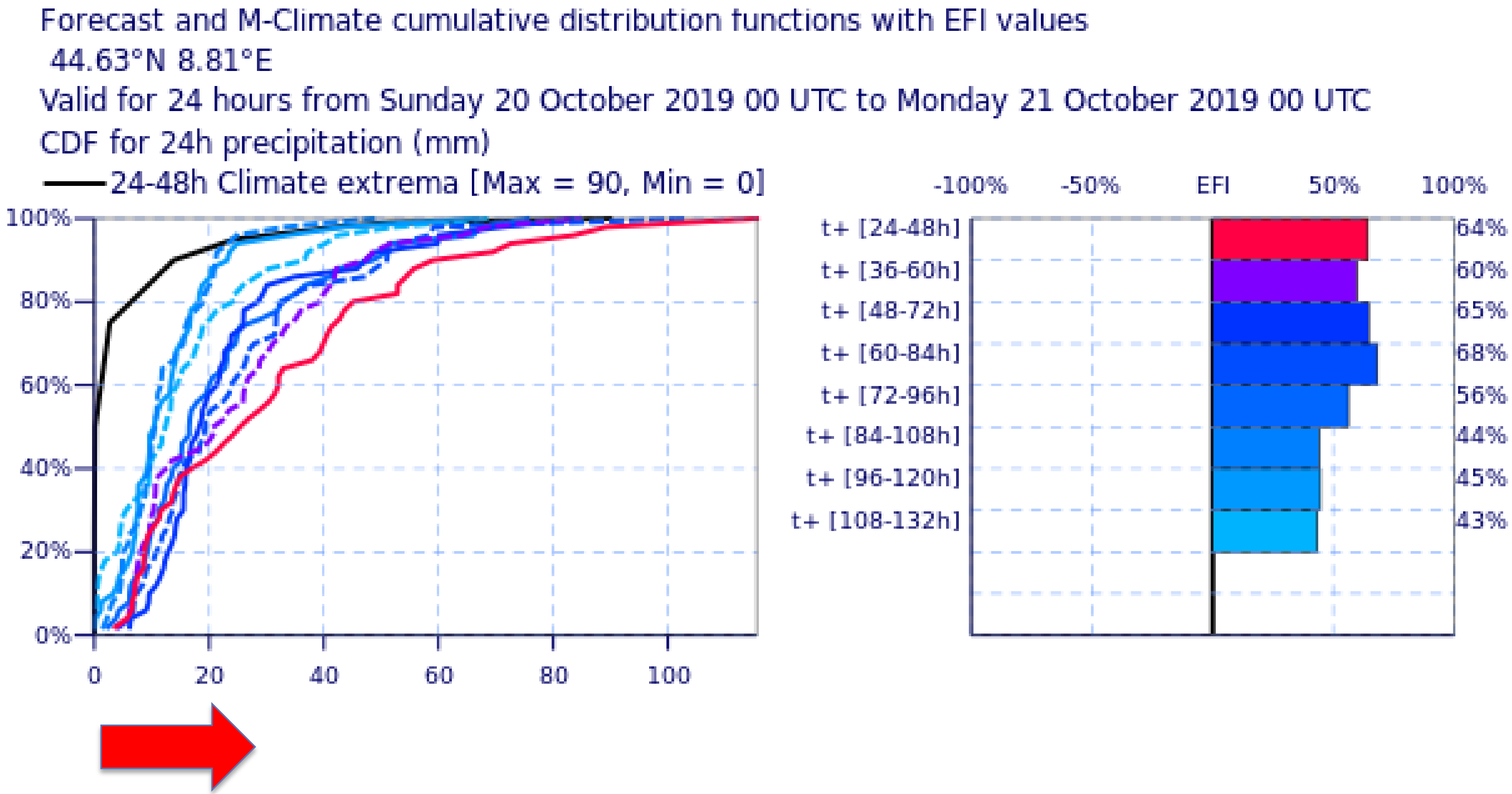
The model climate is computed using reforecasts

Reforecasts are smaller-size ensembles, run twice-a-week, for the past 20 years.

To compute M_{CLI}, the 5 closest 11-member ensembles for the past 20 years are used (1100 members).



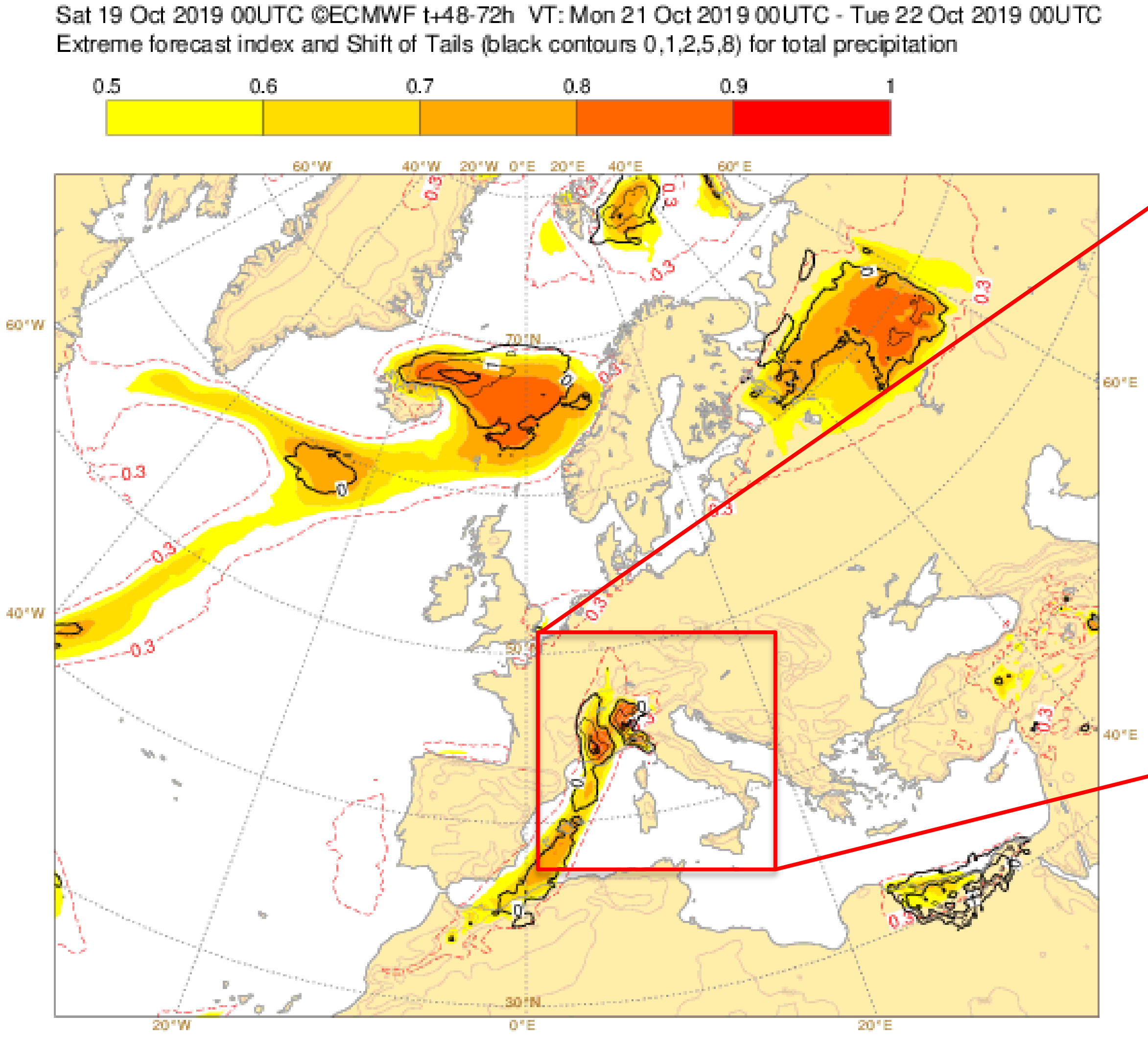
2019: EFI precipitation for Gavi Italy (21 Oct)

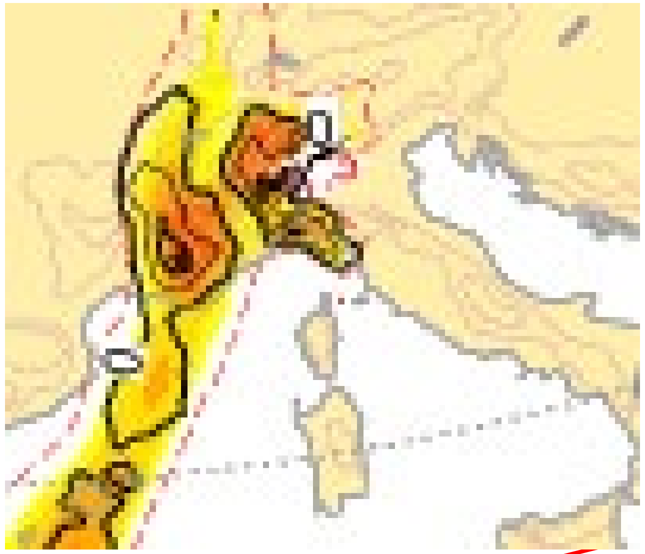


(Roberto Buizza, IITM Pune (26 Nov 2019)

2019: EFI map for total precipitation valid for 21 Oct

ECMWF ENS Extreme Forecast Index – 19/10@00+48-72h





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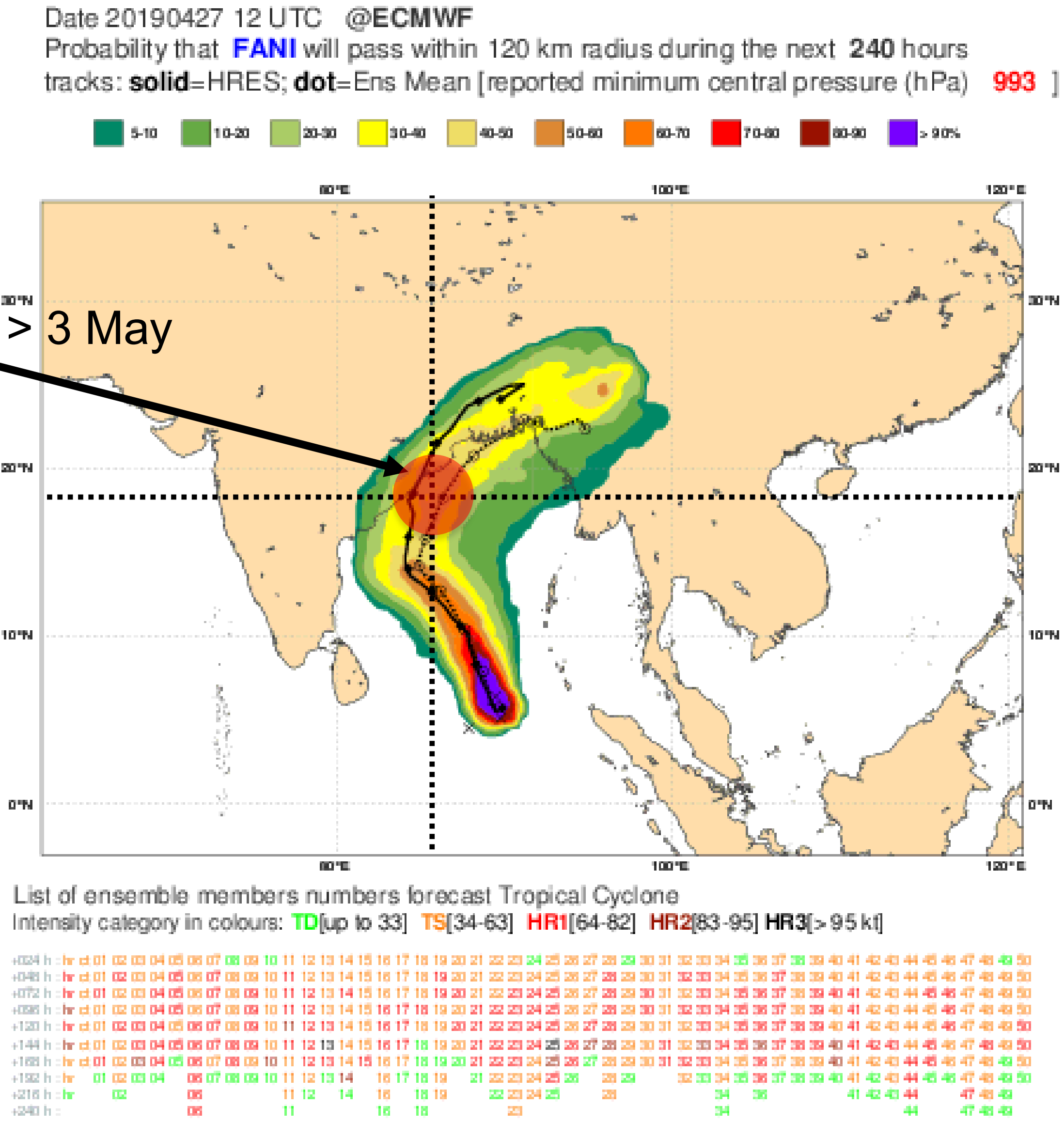
Three examples focussing on India

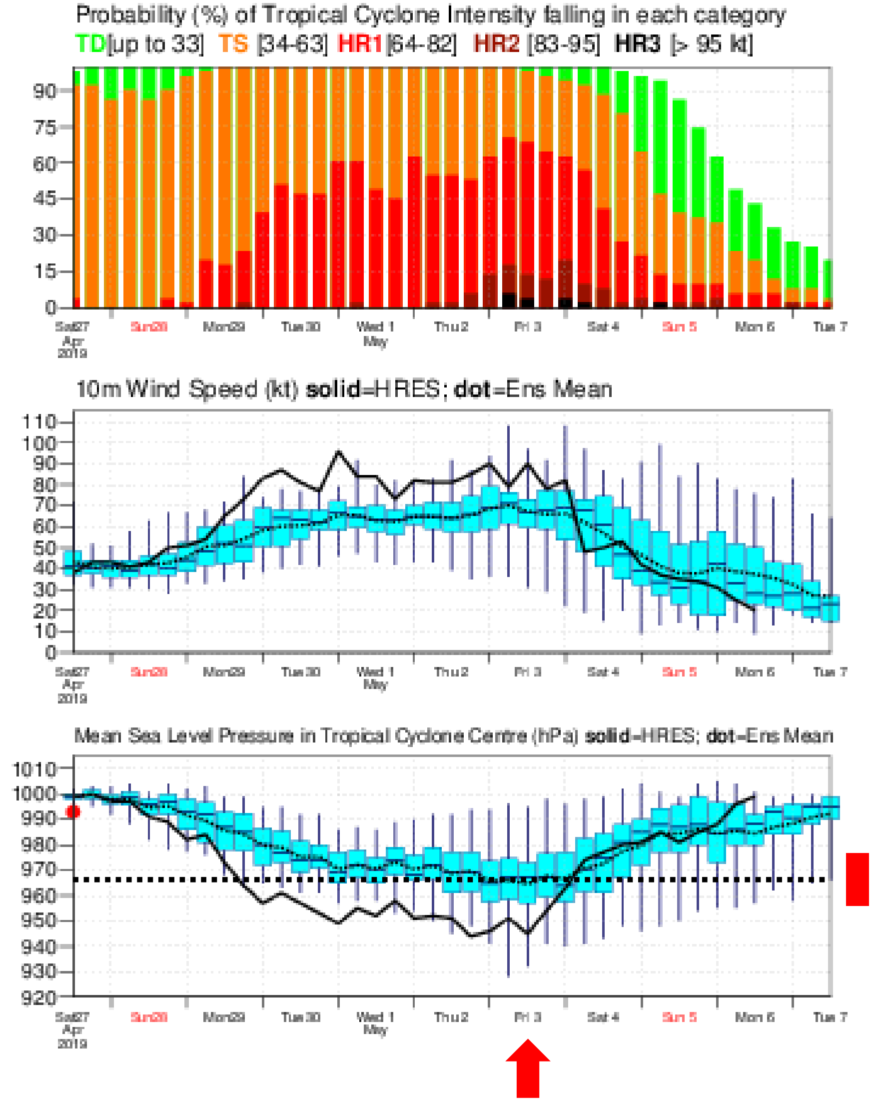
- Tropical cyclone FANI (Apr 2019)
- Ensemble based prediction of weekly-average precipitation anomalies
- Seasonal precipitation prediction

Ex 1: medium-range ensemble strike probability

27 Apr +6d > 3 May



ENS: 20190427@12+10d



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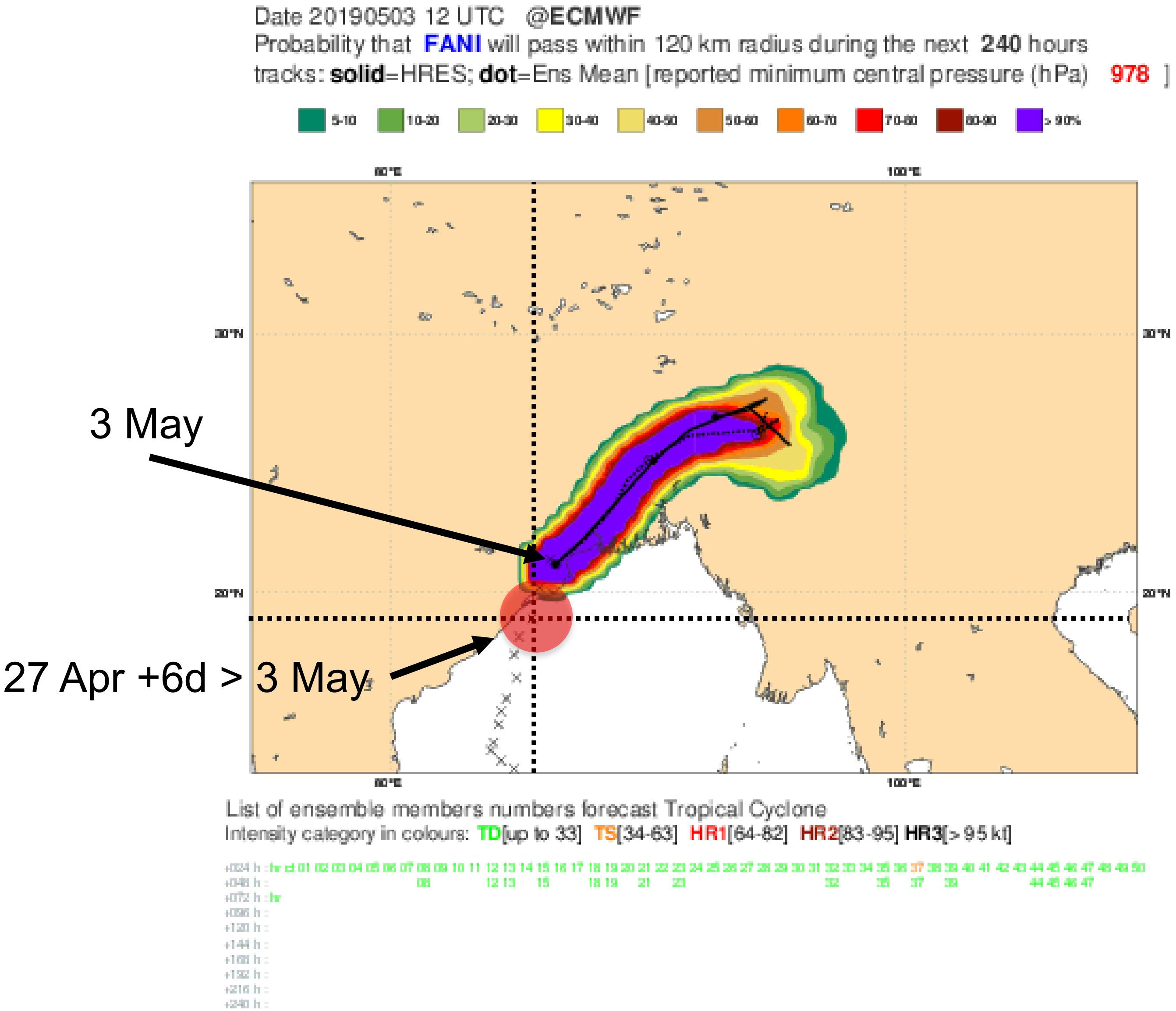
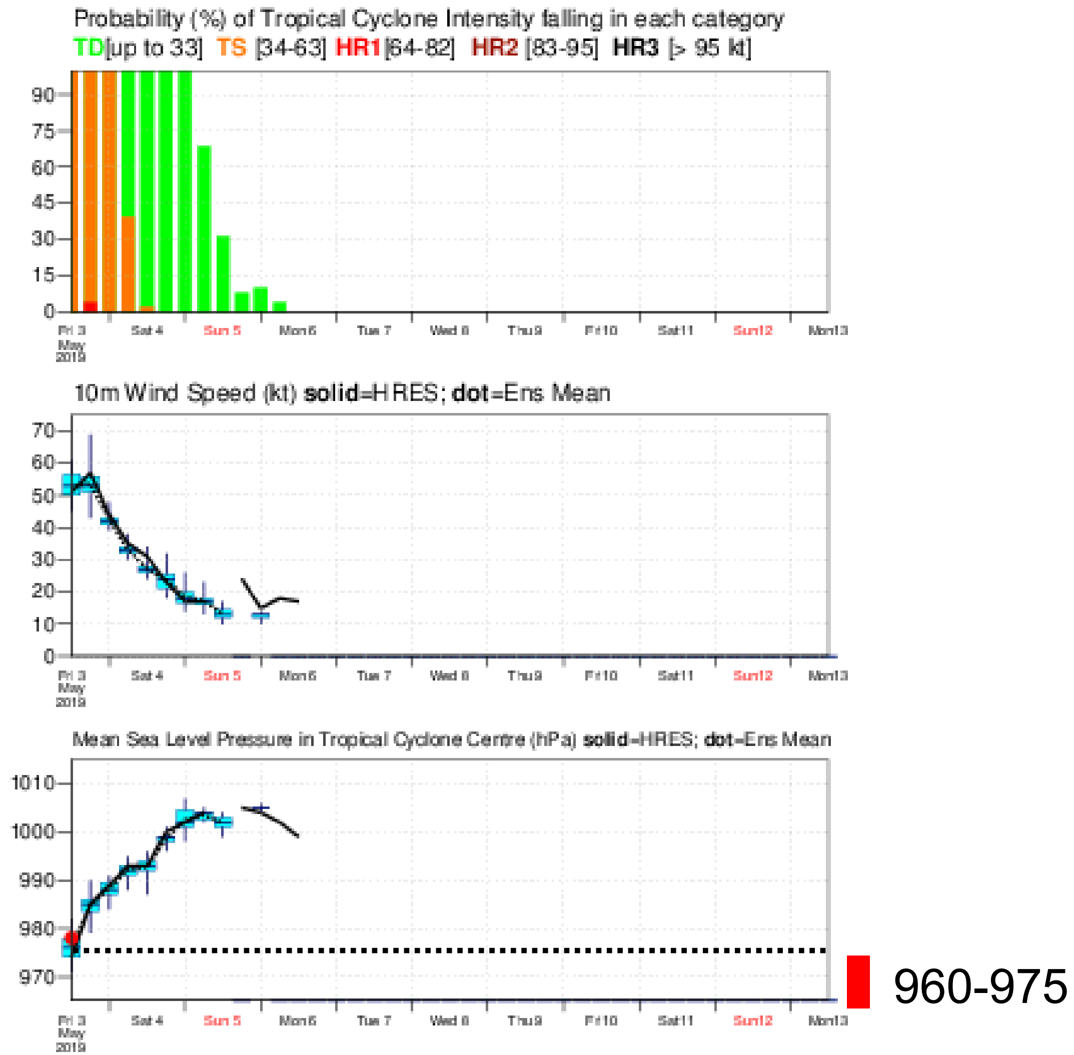
Ex 1: medium-range ensemble strike probability

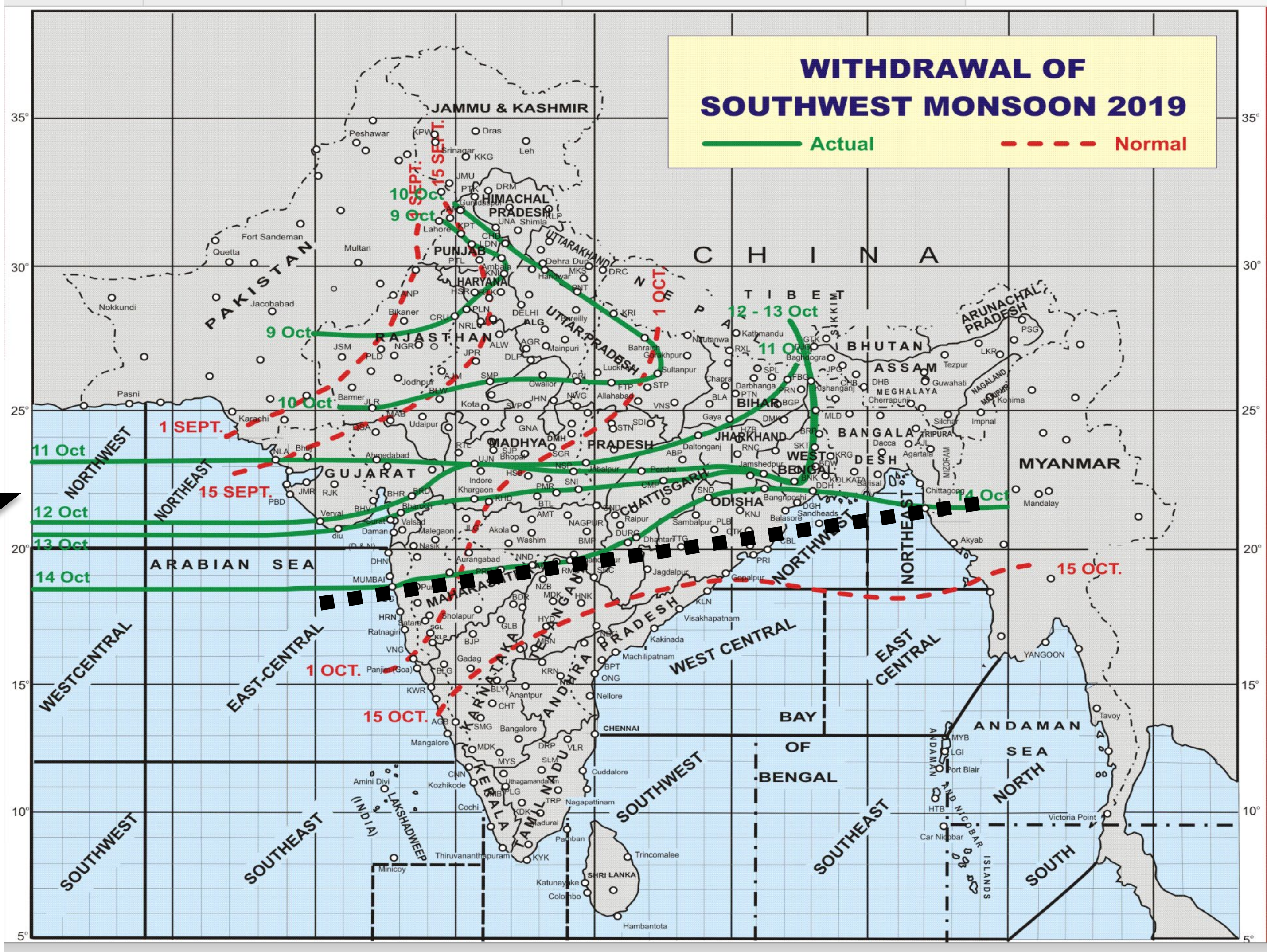


ENS: 20190503@12+10d



Ex 2: weekly-average precipitation

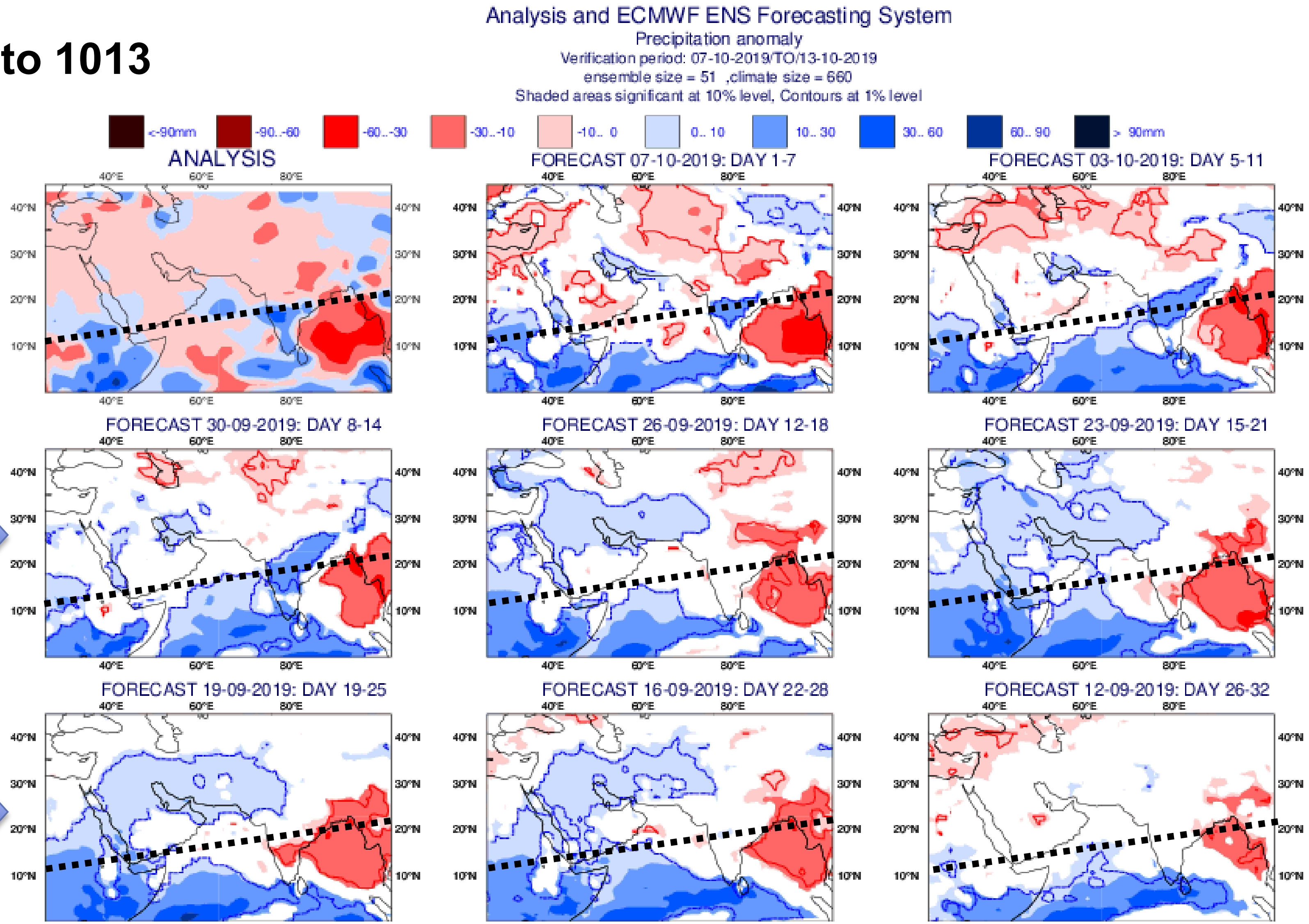
7-13 Oct



http://www.imd.gov.in/pages/monsoon_main.php

Ex 2: weekly-average precipitation (up to +4.5w)

ENS: vt 20191007 to 1013

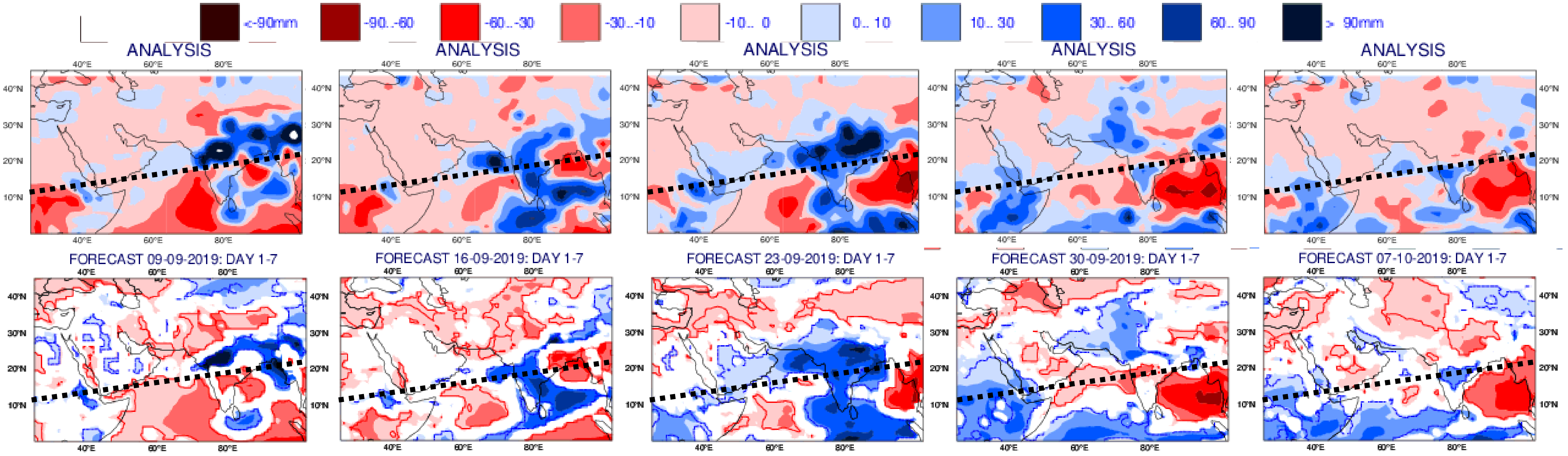


+d8-14

+d19-25

Ex 2: weekly-average precipitation +d1-7

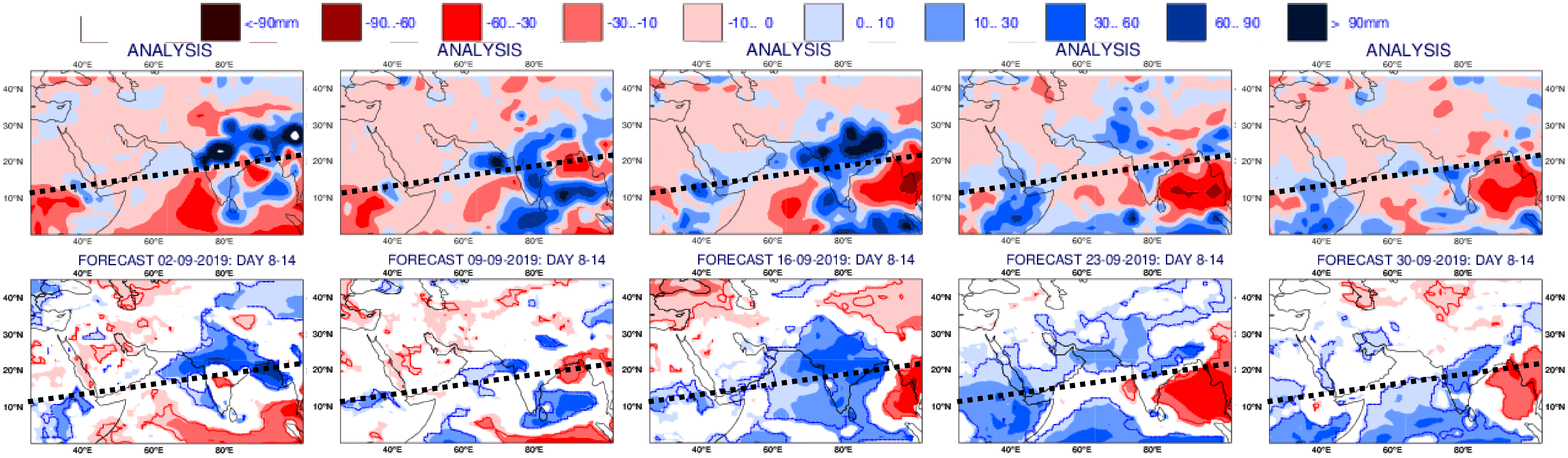
20190909 to 0915 - 0916 to 0922 0923 to 0929 0930 to 1006 1007 to 1013



Good 1-week forecasts of precipitation anomalies

Ex 2: weekly-average precipitation +d8-14

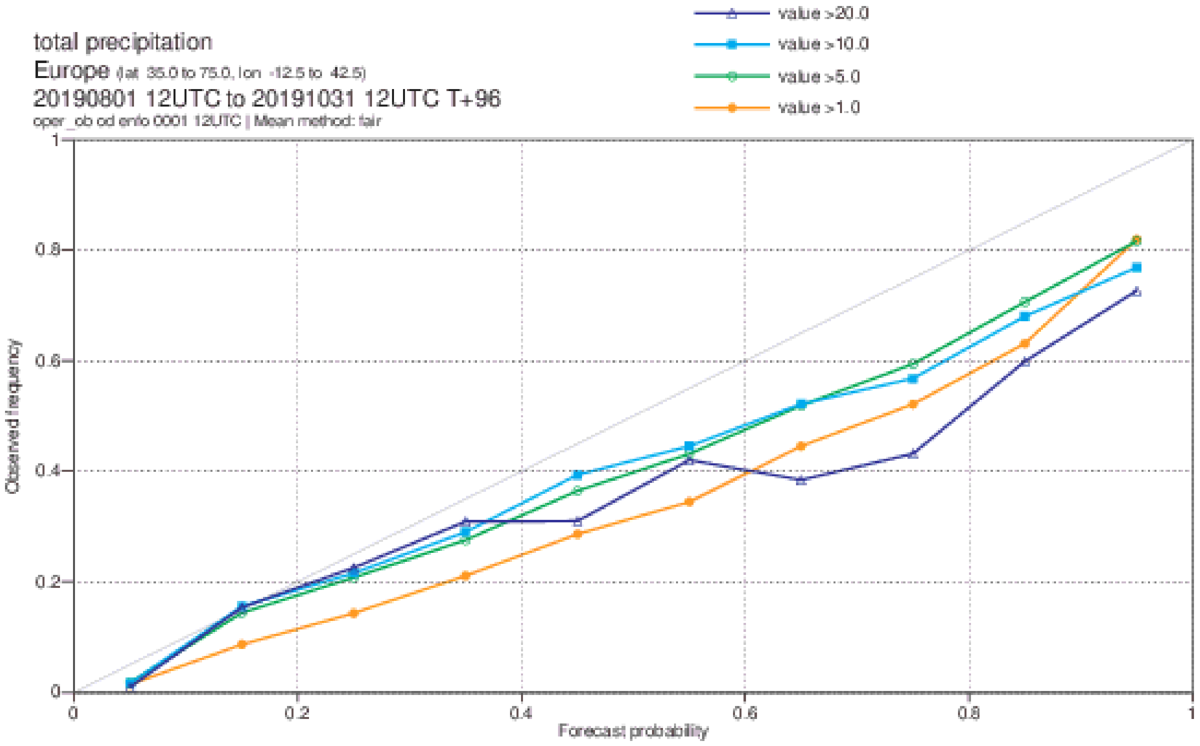
20190909 to 0915 - 0916 to 0922 0923 to 0929 0930 to 1006 1007 to 1013



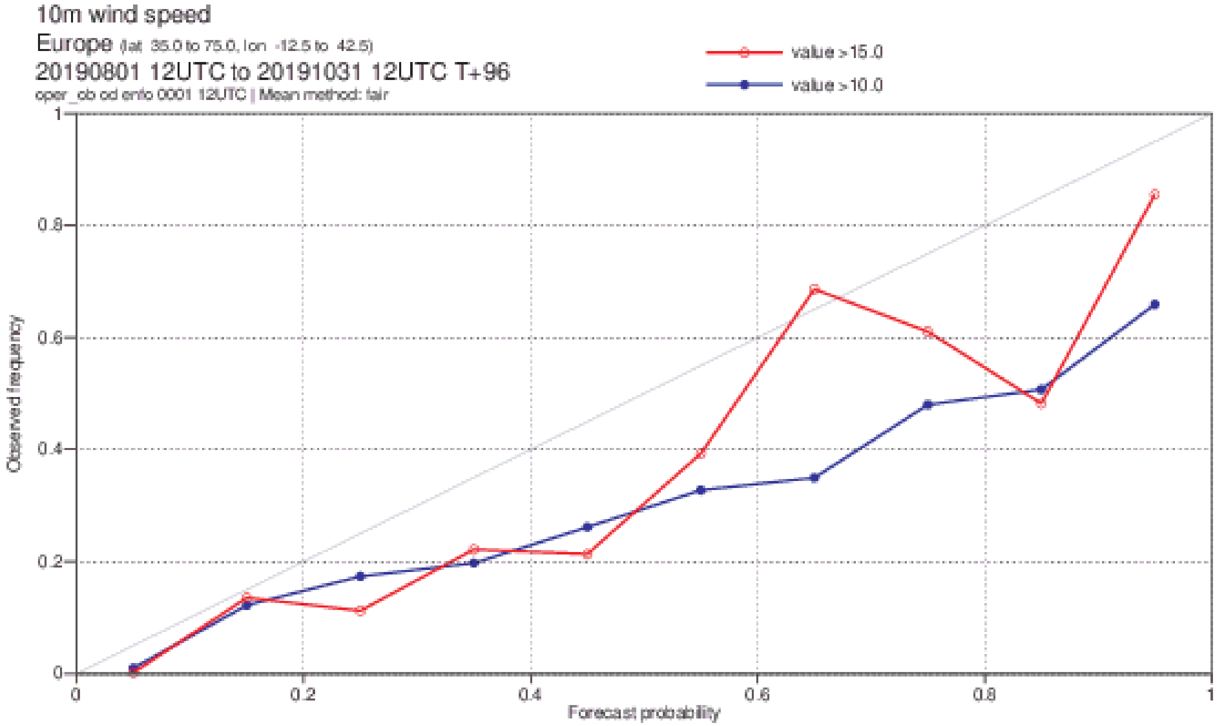
Good 1-week forecasts of precipitation anomalies, but rather poor 2-week forecasts!
What are we missing to get this large-scale pattern right?

Ex 2: rainfall and 10m wind-speed reliability T+4d

T+4 d - Prob (24TP > 1, 5, 10, 20 mm/d)



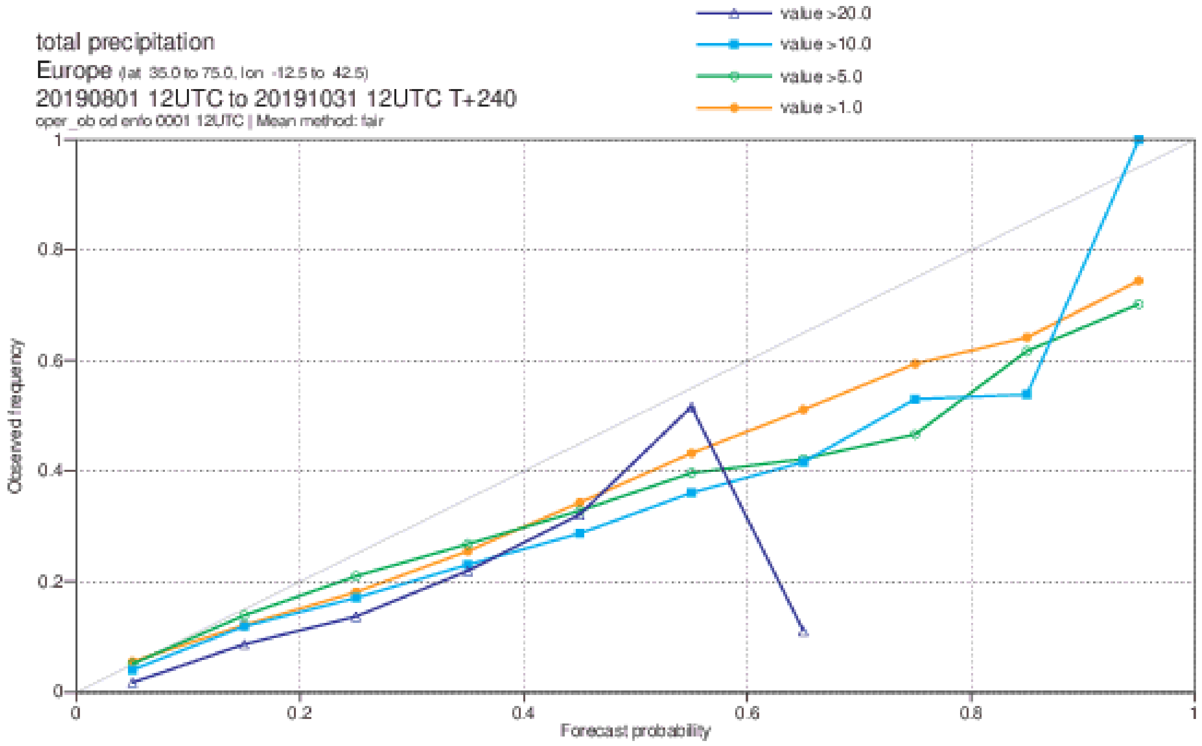
T+4 d - Prob (10WS > 10, 15 m/s)



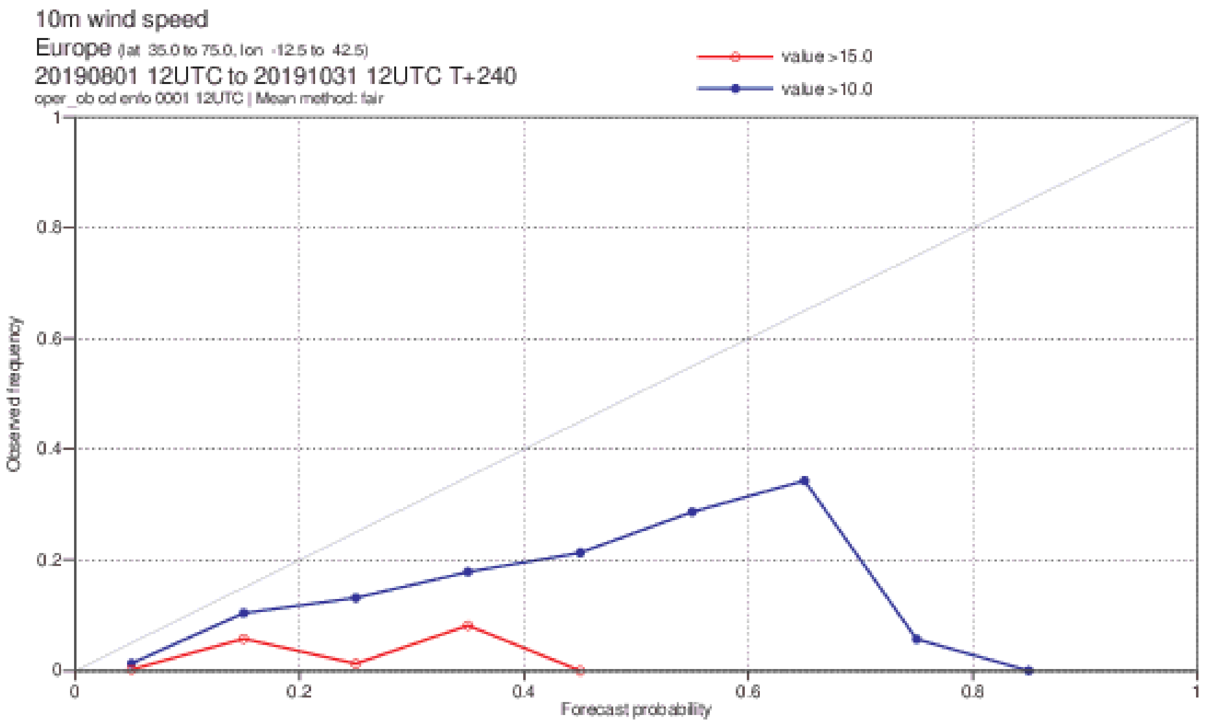
(Roberto Buizza, IITM Pune (26 Nov 2019)

Ex 2: rainfall and 10m wind-speed reliability T+10d

T+10d - Prob (24TP > 1, 5, 10, 20 mm/d)



T+10d - Prob (10WS > 10, 15 m/s)



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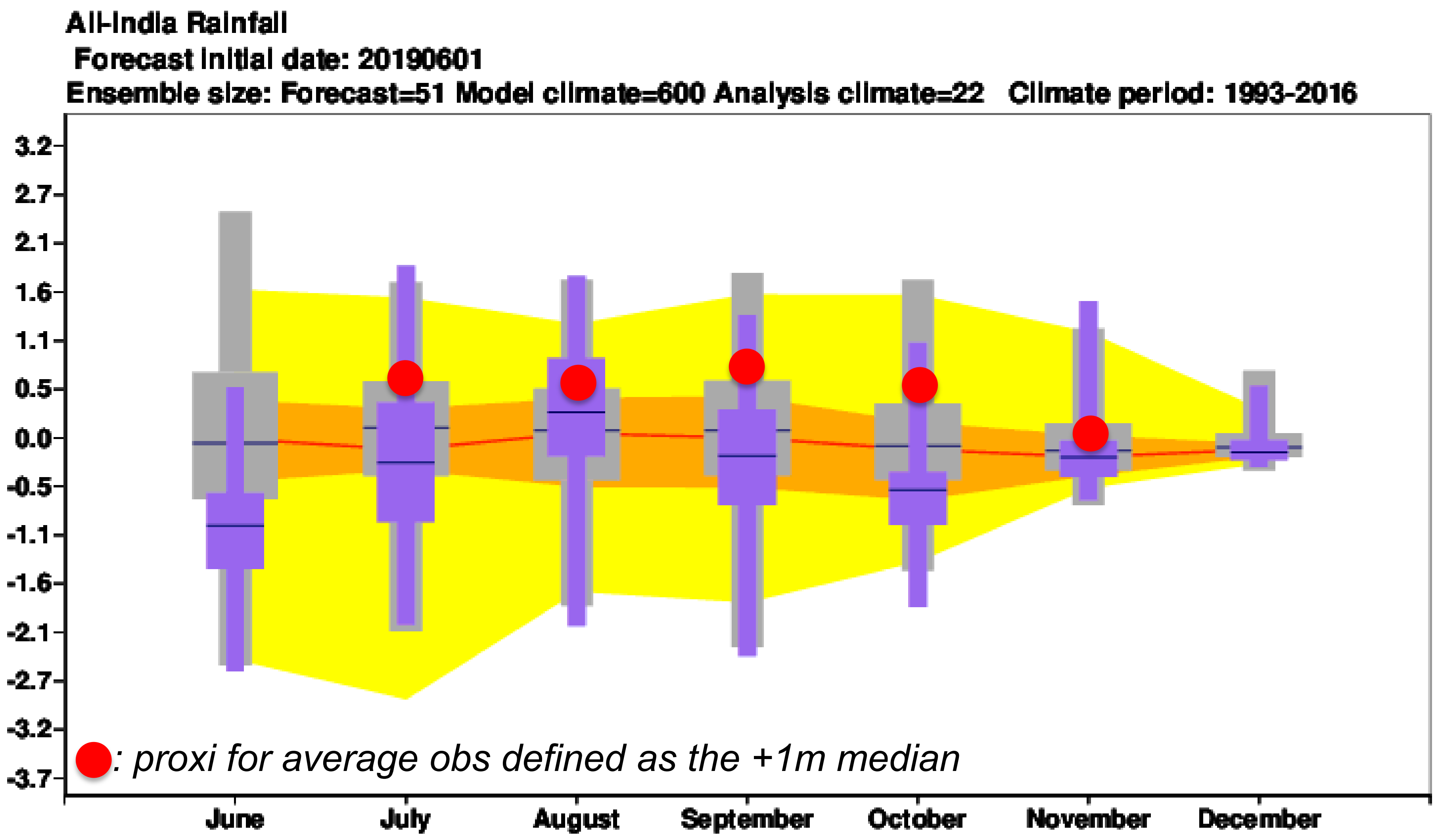
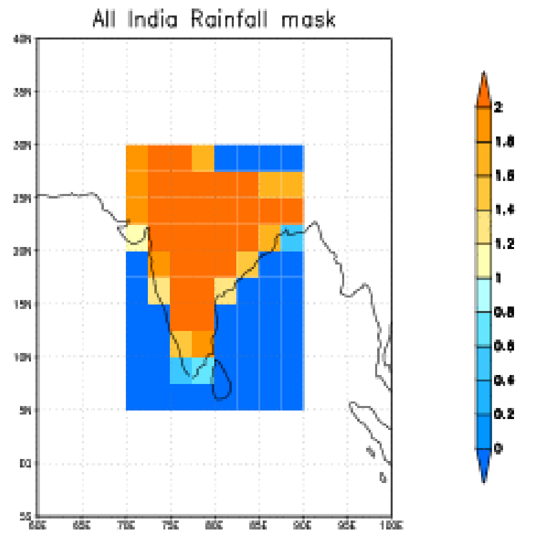
Ex 3: Seasonal all-India rainfall

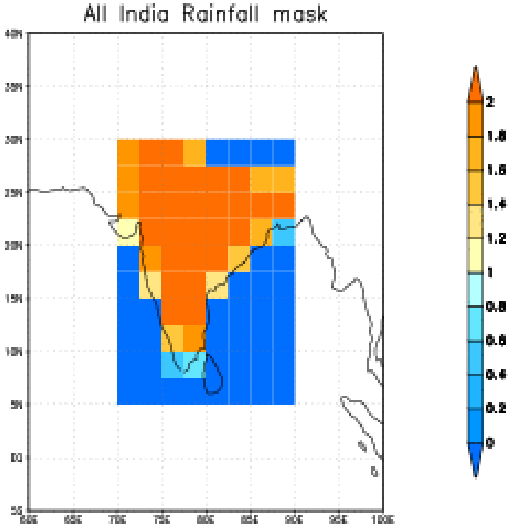


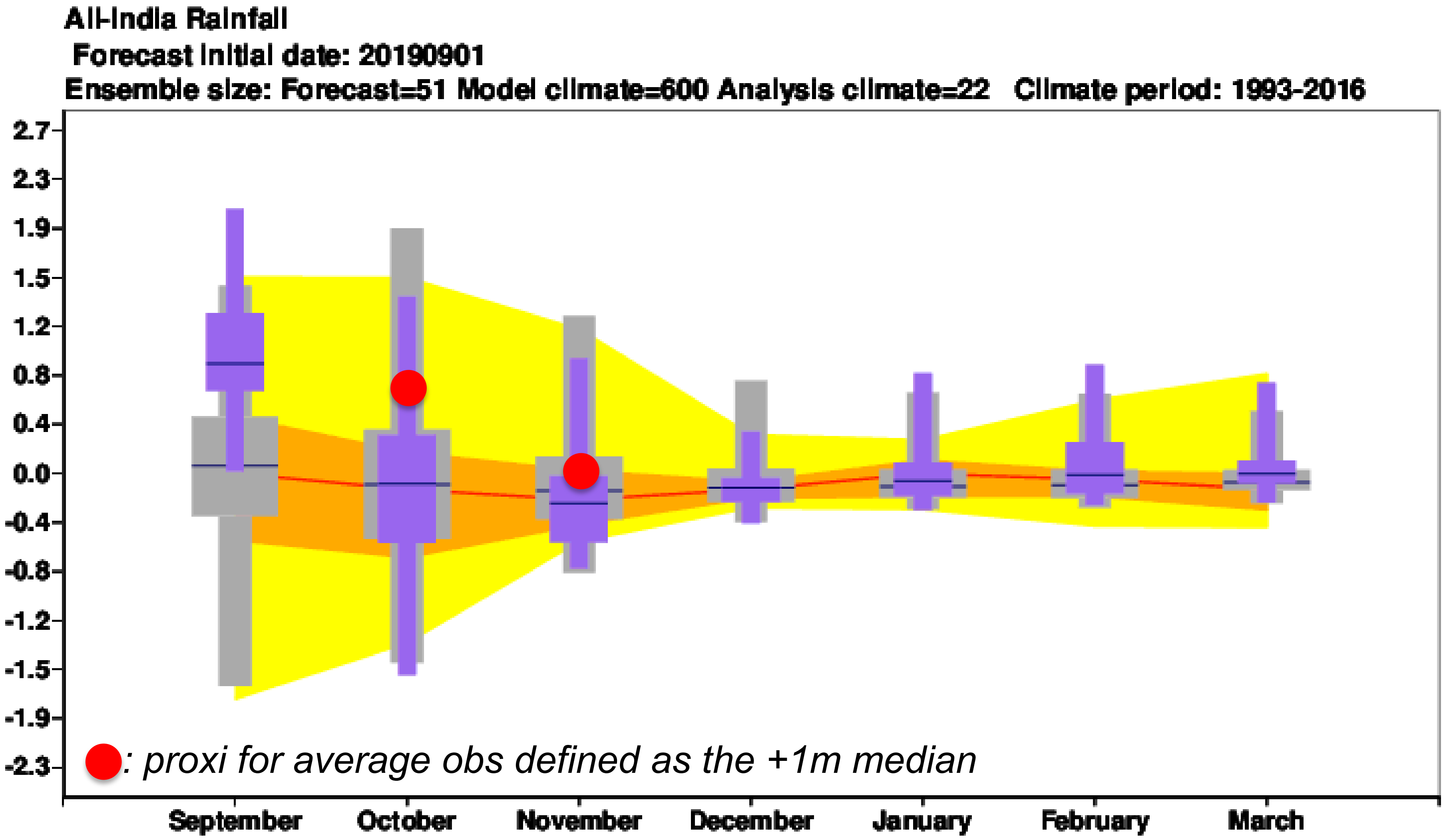
'From Jun to Sep 2019, India received the highest amount of monsoonal rain in the past 25 years' (NASA observatory).



Ex 3: Seasonal all-India rainfall

'According to the [India Meteorological Department](), those rains are not expected to retreat until at least October 10' (NASA observatory).





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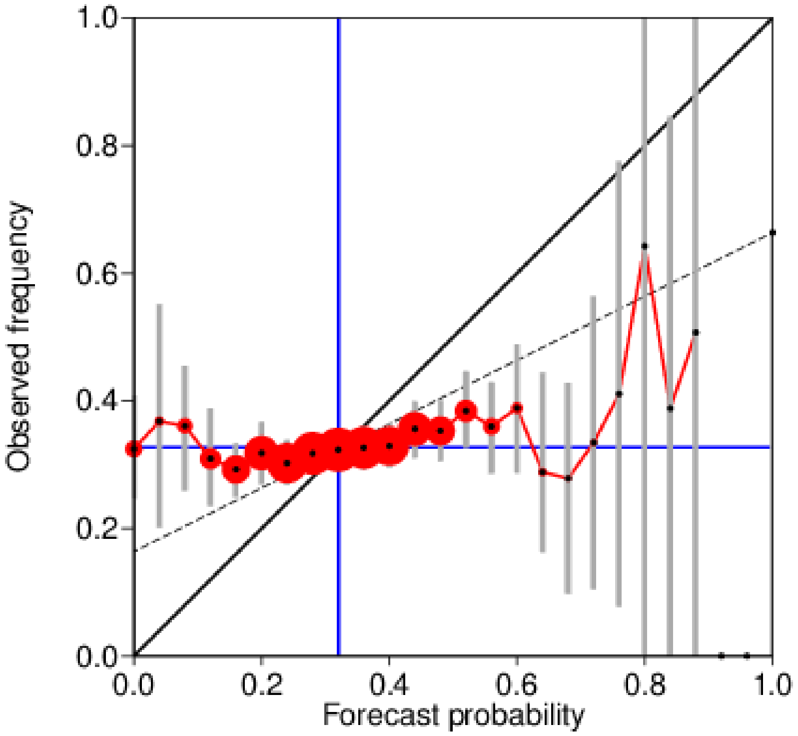
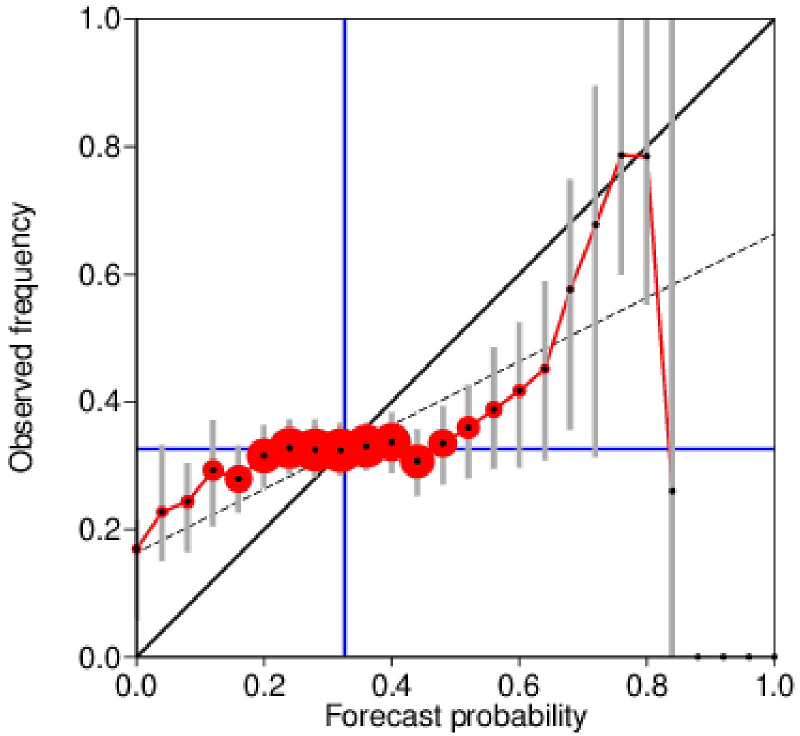
Ex 3: Seasonal all-India rainfall reliability

Reliability diagram for 0001 with 25 ensemble members
Precipitation anomalies below the lower tercile
Accumulated over Asia (land points only)
Hindcast period 1981-2014 with start in June average over months 2 to 4
Skill scores and 95% conf. intervals (1000 samples)
Brier skill score: -0.058 (-0.085,-0.034)
Reliability skill score: 0.939 (0.910, 0.958)
Resolution skill score: 0.003 (0.002, 0.010)



Reliability diagram for 0001 with 25 ensemble members
Precipitation anomalies below the lower tercile
Accumulated over Asia (land points only)
Hindcast period 1981-2014 with start in September average over months 2 to 4
Skill scores and 95% conf. intervals (1000 samples)
Brier skill score: -0.037 (-0.070,-0.008)
Reliability skill score: 0.953 (0.920, 0.972)
Resolution skill score: 0.009 (0.004, 0.024)

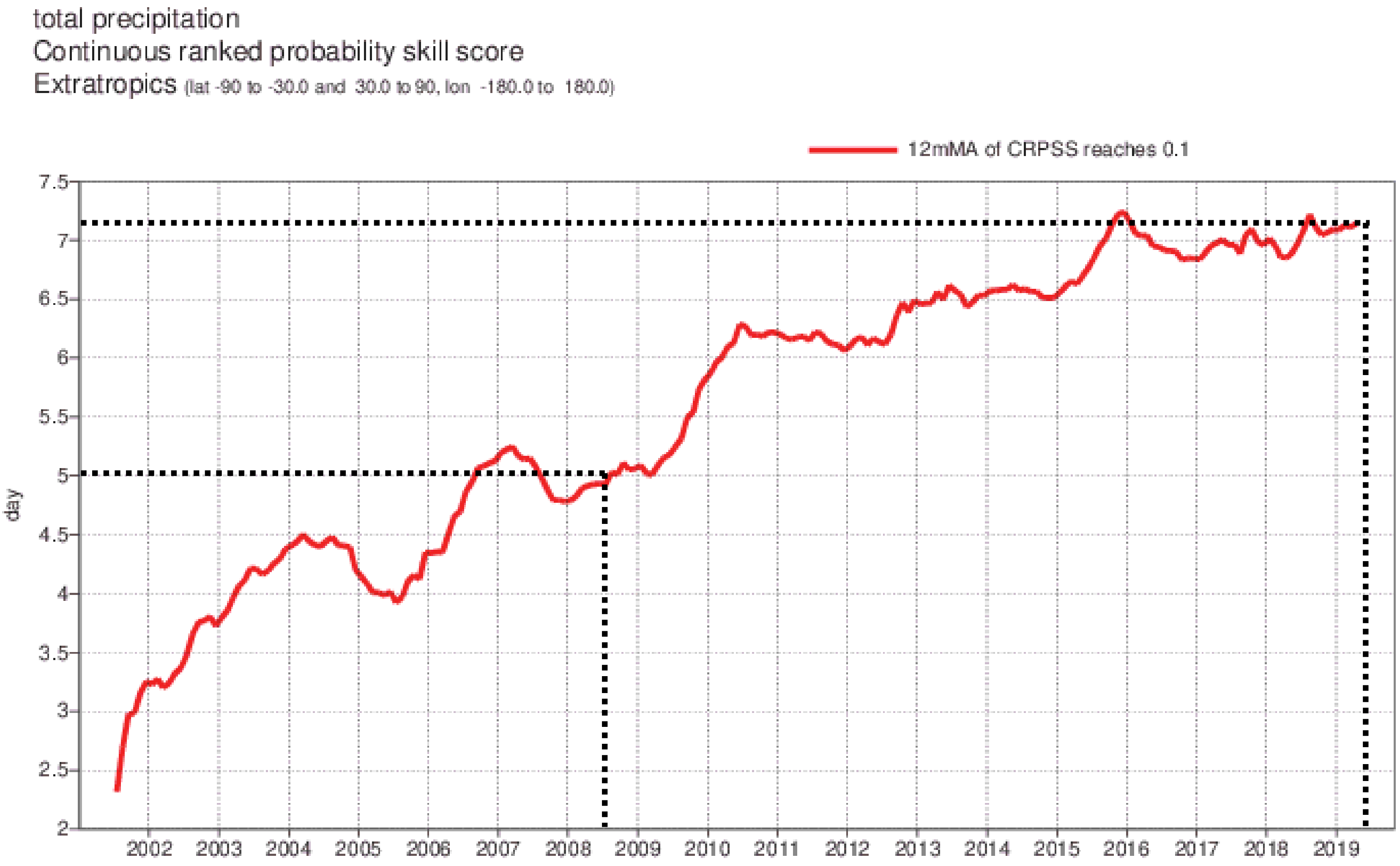


Outline

1. Ensembles must be reliable to be valuable
2. The ECMWF ensembles
3. How far ahead can we provide skilful probabilistic forecasts?
4. Predicting precipitation extremes with the ECMWF ensembles
5. Conclusions

Conclusions: PPP skill has been improving ..

Although during the past 10 years, **probabilistic precipitation prediction skill** has improved by ~ 2 days, the 2019 examples indicate that there is still a lot of work to do to extend skilful PPP beyond 1 week!



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(Roberto Buizza, IITM Pune (26 Nov 2019)

How can we make further progress?

Areas of active developments should include:

1. Improving the '**ensemble model':** processes (improve existing, add missing ones) and the simulation of the model uncertainties
2. Improving the estimation of the **initial PDF:** coupled DA, use of more obs, and better simulation of observations' and DA's uncertainties
3. Building **more consistent ensembles of analyses and forecasts**
4. Increasing **resolution** (to resolve better the small/fast processes)
5. **Understanding predictability** (from where, and how, can we extract predictable signals?)

Always remember: an ensemble is better than one, even if it is special!!