

The Forecast Skill Horizon

Roberto Buizza, Martin Leutbecher and Martin Janousek
ECMWF, Shinfield Park, RG2 9AX, Reading, UK

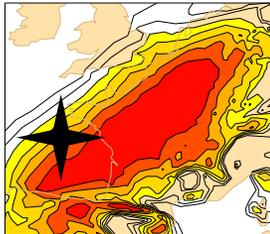
Outline

- 
1. The two key questions that we will discuss
 2. The data, the metric and the Forecast Skill Horizon diagram
 3. Scale dependency of the skill horizon
 4. Can we expect to further extend the forecast skill horizon in the future?
 5. Conclusions

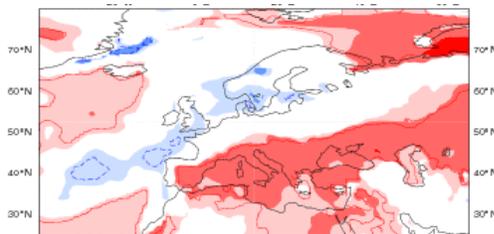
The two key questions we will discuss

1. Does the forecast skill horizon depend on the spatio-temporal scale of the event we are aiming to predict?

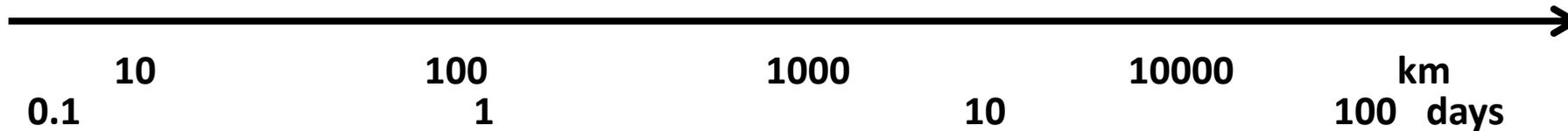
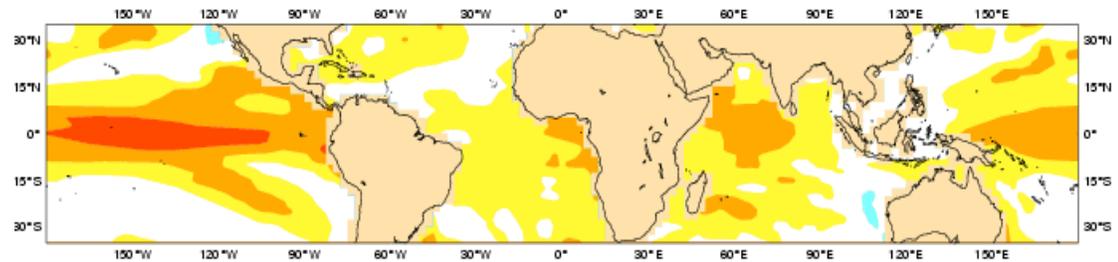
**Local,
instantaneous
wind-speed**



**Weekly-mean,
regional
temperature anomaly**

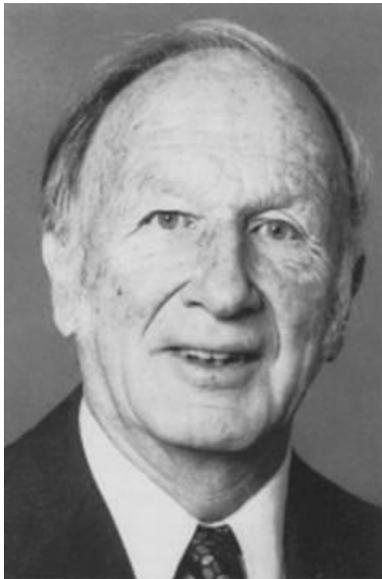


**Monthly-mean,
continental-scale
rain anomaly**

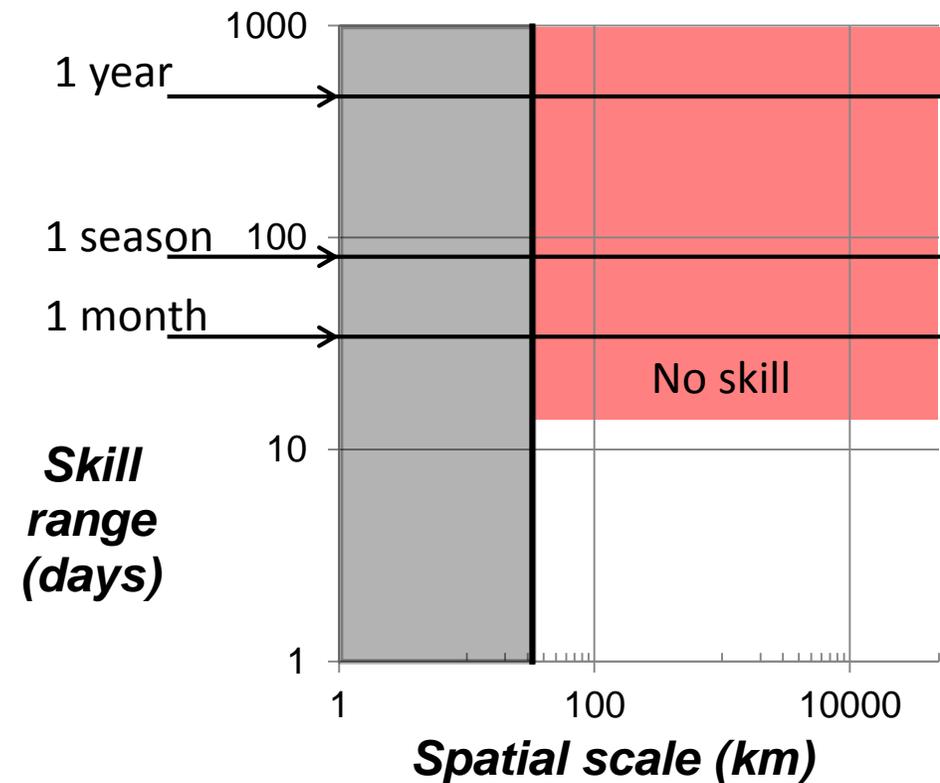


The two key questions we will discuss

2. Considering grid-point values, how far is the forecast skill horizon, and can we expect to further extend it?



*'.. the range of predictability is about **16.8 days** ..'*
'.. (there is) little hope for those who would extend the two-week goal to one month ...'

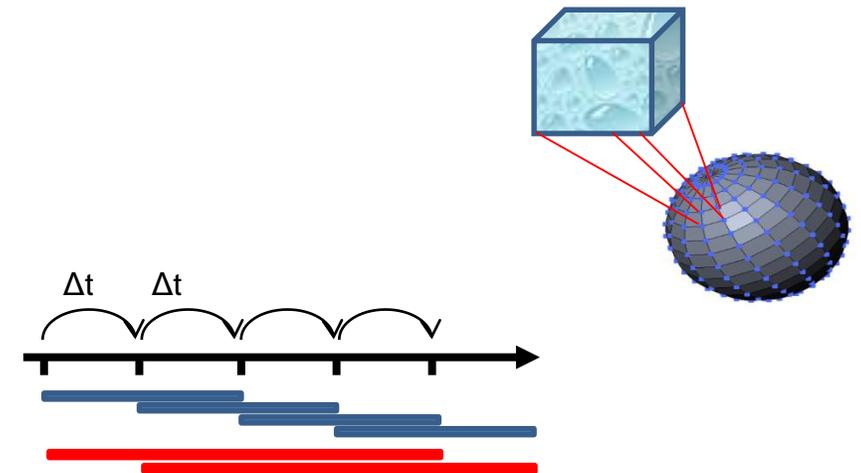
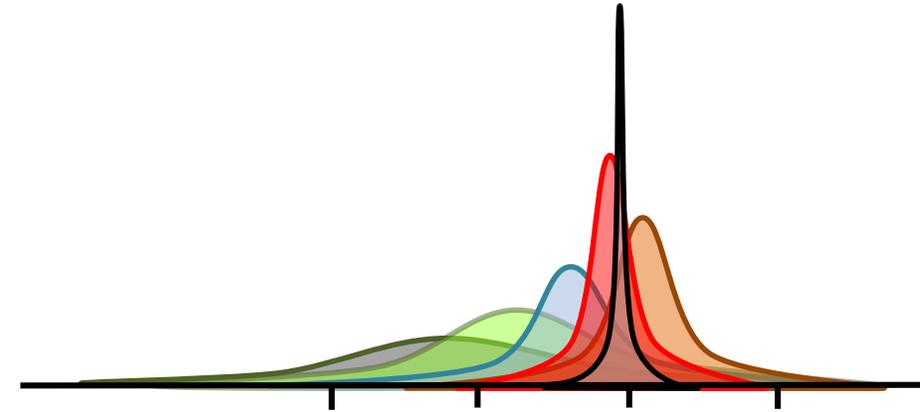


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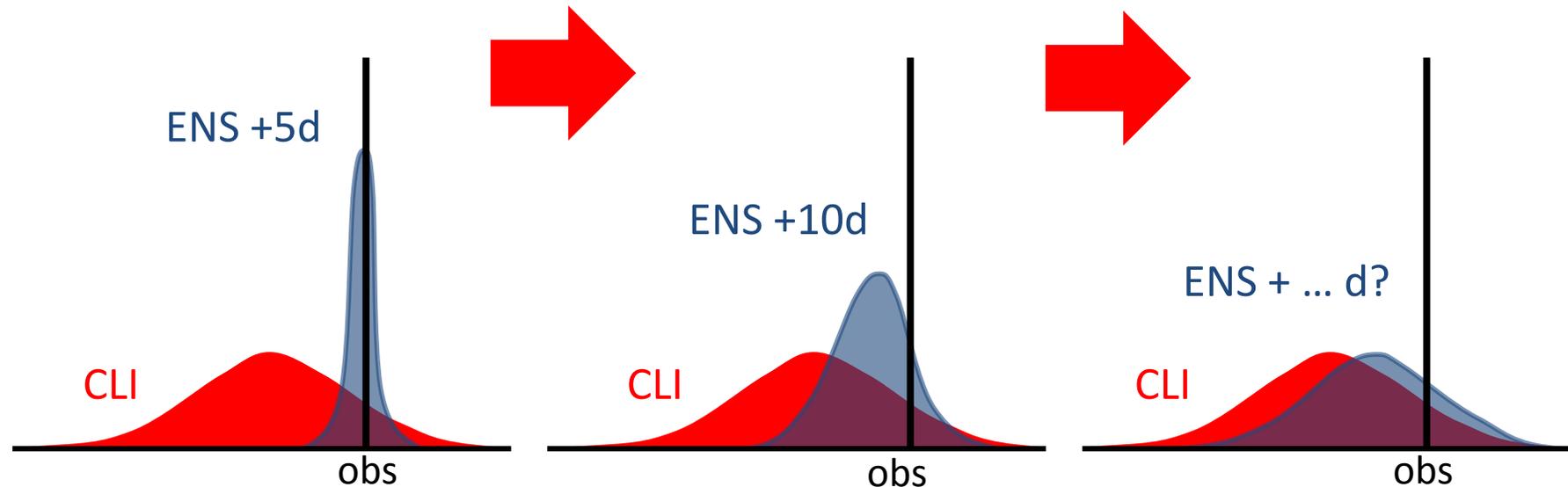
The forecasts: ensemble-based probabilistic

- ❖ Forecasts are ensemble-based, probabilistic to take into account observation (IC, DA, ..) and model uncertainties
- ❖ Ensemble-based probabilistic forecasts are more accurate and reliable than single-based forecasts, and are more consistent (i.e. consecutive forecasts jump less)
- ❖ All forecasts represent average values over a 4-dimensional space-time volume: even an instantaneous, local value represents an implicit spatial and temporal average



The data and the metric

- Forecasts are from the operational ECMWF medium-range ensemble (ENS)
- Accuracy is measured using the Continuous Ranked Probability Score against analyses
- Skill is measured by comparing the CRPS of ENS and of a climatological ensemble



The Forecast Skill Horizon for Z500 over NH (BL 2015)

z500hPa, Northern Extra-tropics

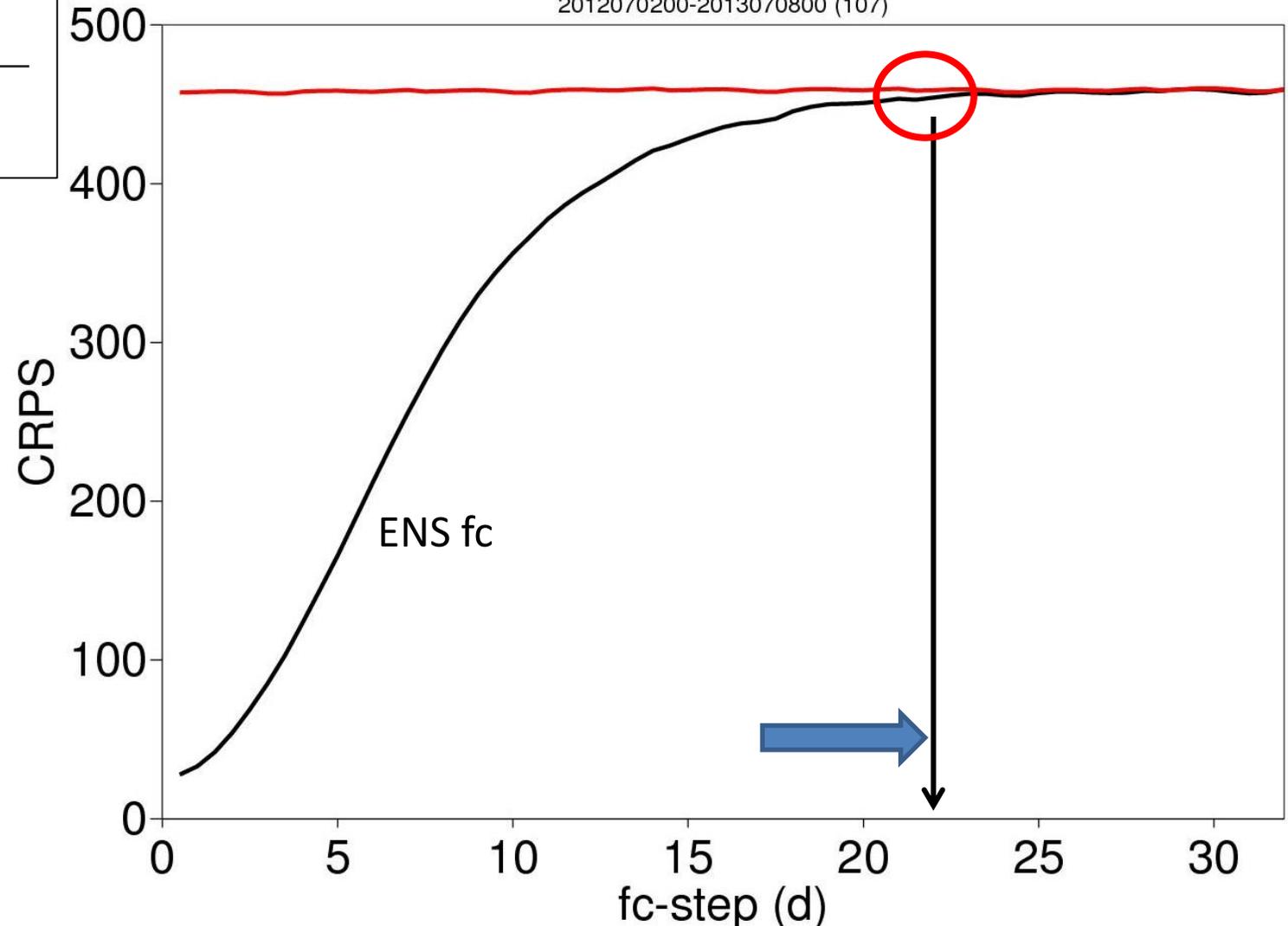
ContinuousRankedProbabilityScore
2012070200-2013070800 (107)



The forecast skill horizon

Roberto Buizza* and Martin Leutbecher
European Centre for Medium-Range Weather Forecasts, Reading, UK

Buizza & Leutbecher
(QJRMS, 2015; BL15)
showed that for the
instantaneous and local
(grid-point) probabilistic
prediction of Z500 over NH,
the FSH is about 22 days.



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‘Predictability in the midst of chaos’ (Shukla, 1998)

‘... It is now clear that certain aspects of the climate system have far more predictability than was previously recognized. It also should be recognized that some aspects of the climate system will always be difficult to predict.’

‘... it should be possible to predict the large-scale tropical circulation and rainfall for as long as the ocean temperature can be predicted. If changes in tropical Pacific sea-surface temperature are quite large, even the extratropical circulation over some regions, especially over the Pacific–North American sector, is predictable.’



Science
AAAS

Predictability in the Midst of Chaos: A Scientific Basis for Climate Forecasting
J. Shukla, *et al.*
Science **282**, 728 (1998);
DOI: 10.1126/science.282.5389.728

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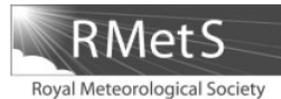


www.usbweb.com

'Noise and music' (Hoskins 2013)

'... despite the prevalence of chaos and turbulence in weather and climate, the optimistic notion has been developed that there could be predictive power on all time-scales.'

'... On all scales, there are phenomena and external conditions that may give predictability.'



Review Article
The potential for skill across the range of the seamless weather-climate prediction problem: a stimulus for our science*

Brian Hoskins^{a,b*}

^aGrantham Institute for Climate Change, Imperial College, London, UK

^bDepartment of Meteorology, University of Reading, UK

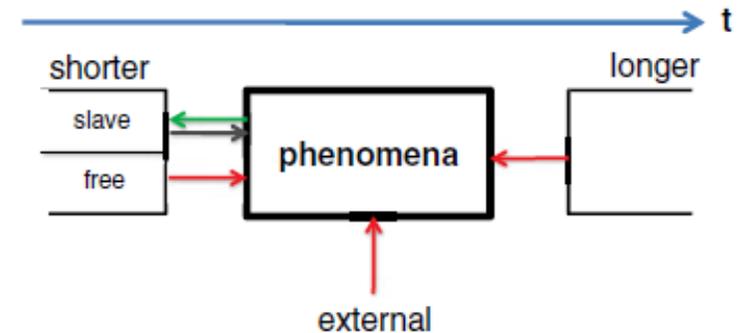
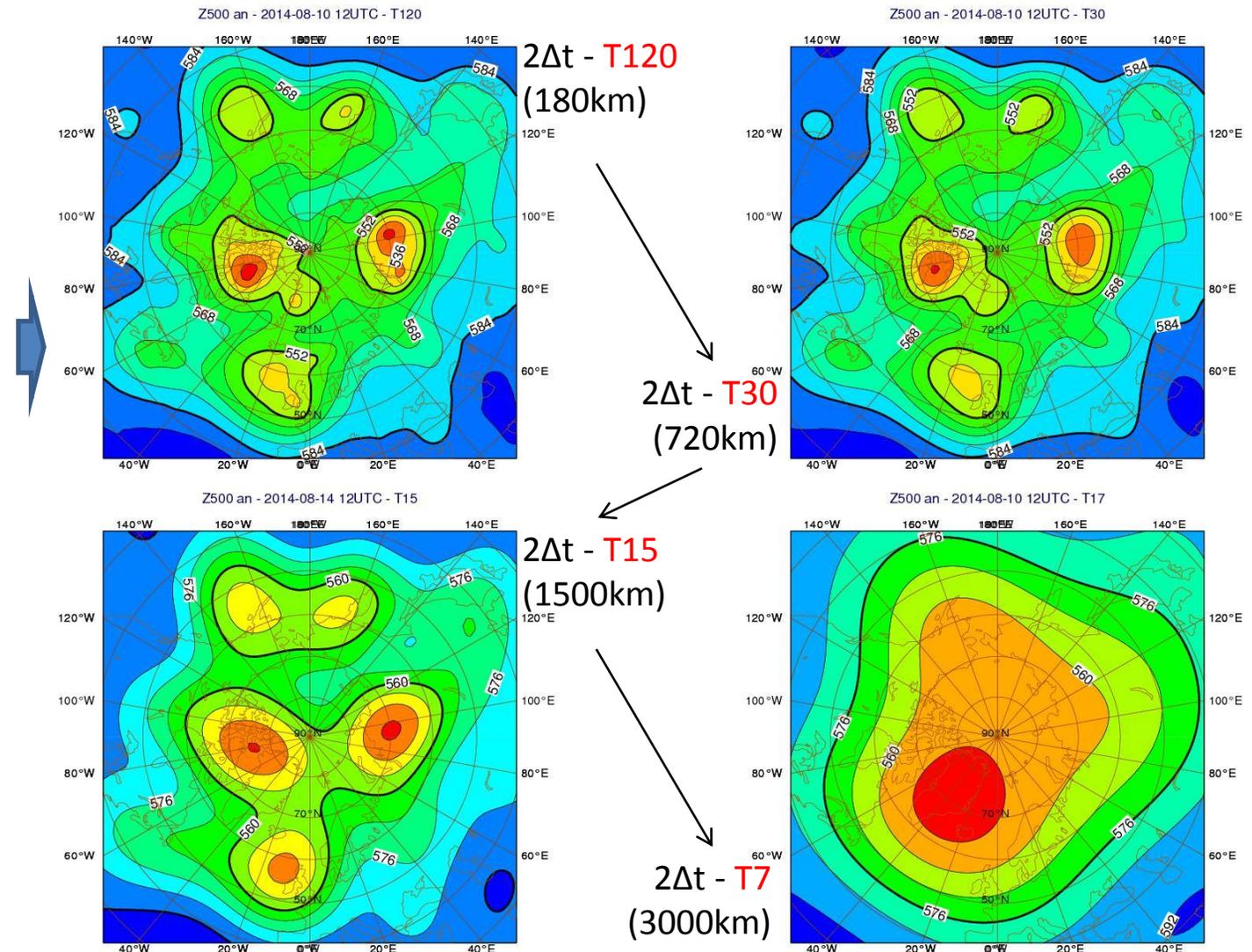


Figure 2. The prediction problem for a particular time-scale. External forcing and longer time-scales influence the behaviour. The evolution of phenomena on the time-scale of interest is central to the prediction. The smaller scales that are slave to these phenomena can be expected to feed back on them in a manner that can be represented in a deterministic fashion. Other variability on these scales (denoted 'free') will introduce a stochastic element to the parametrisation problem.

Scale-dependency of the FSH

We have considered increasingly coarser fields:

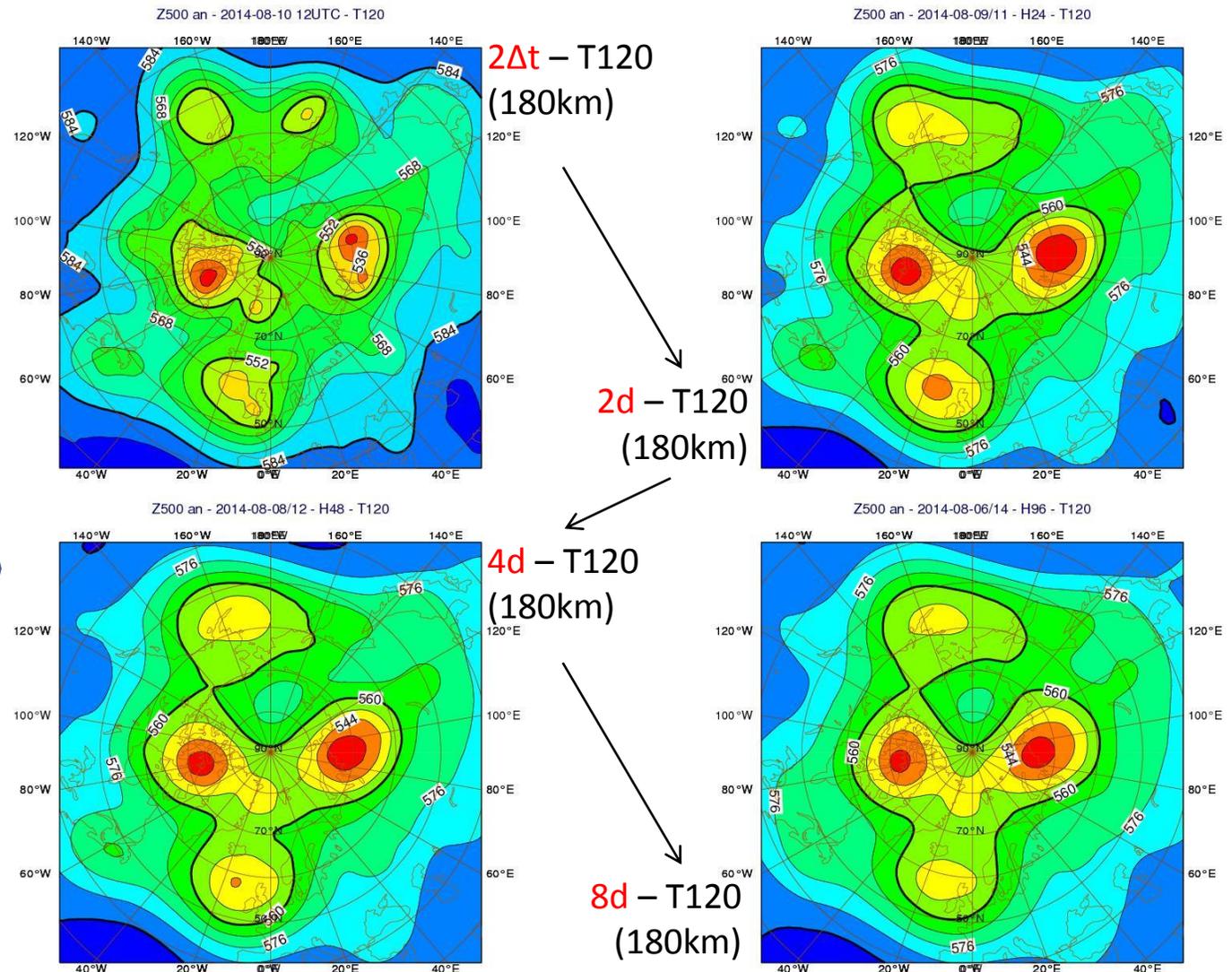
- Spatially: spectrally truncated from T120 (180km) to T60 (360km), T15, T7, T3
- Temporally: from $2\Delta t$ (40 minutes) to 1, 2, 4 and 8 day averages



Scale-dependency of the FSH

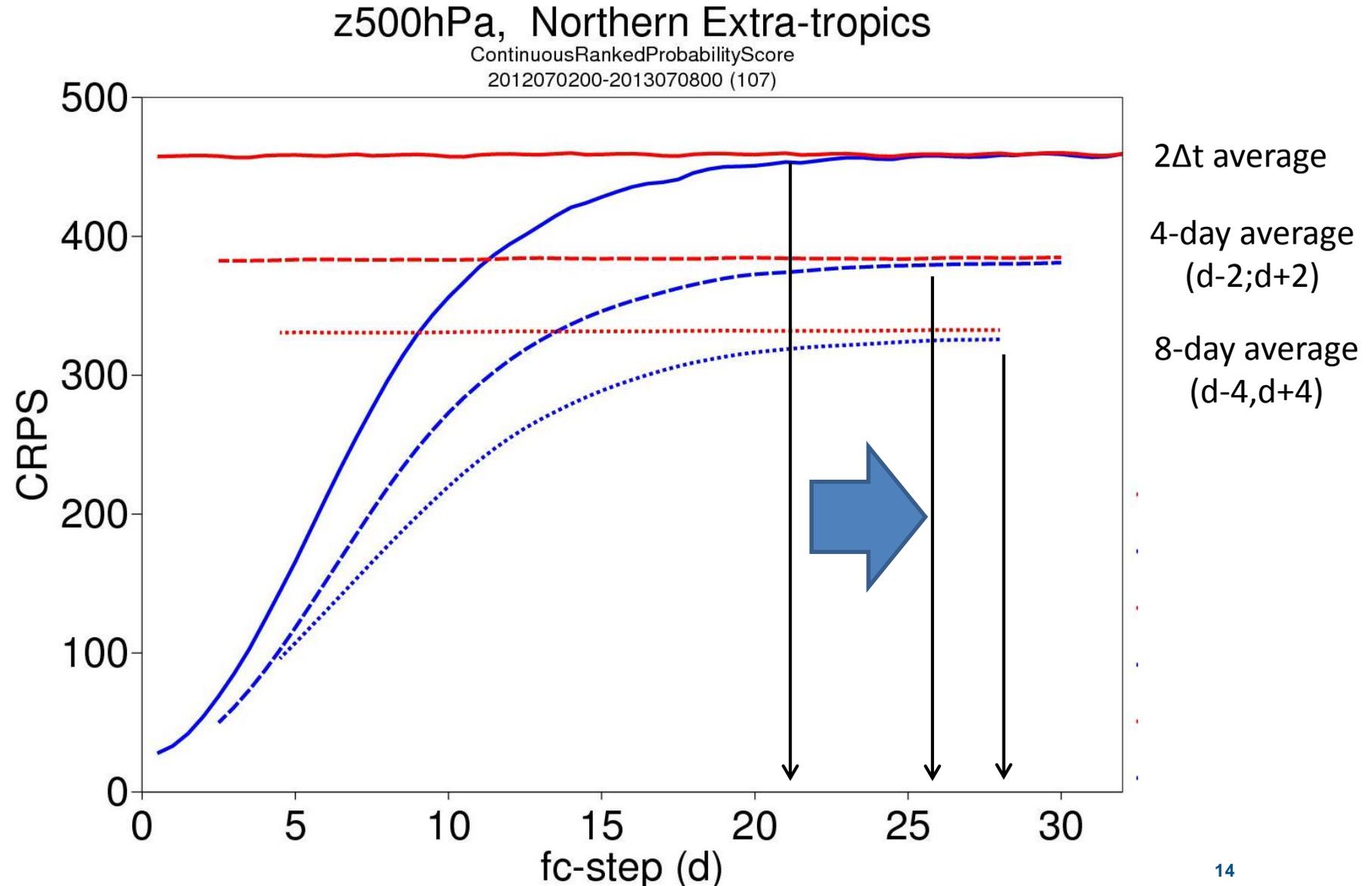
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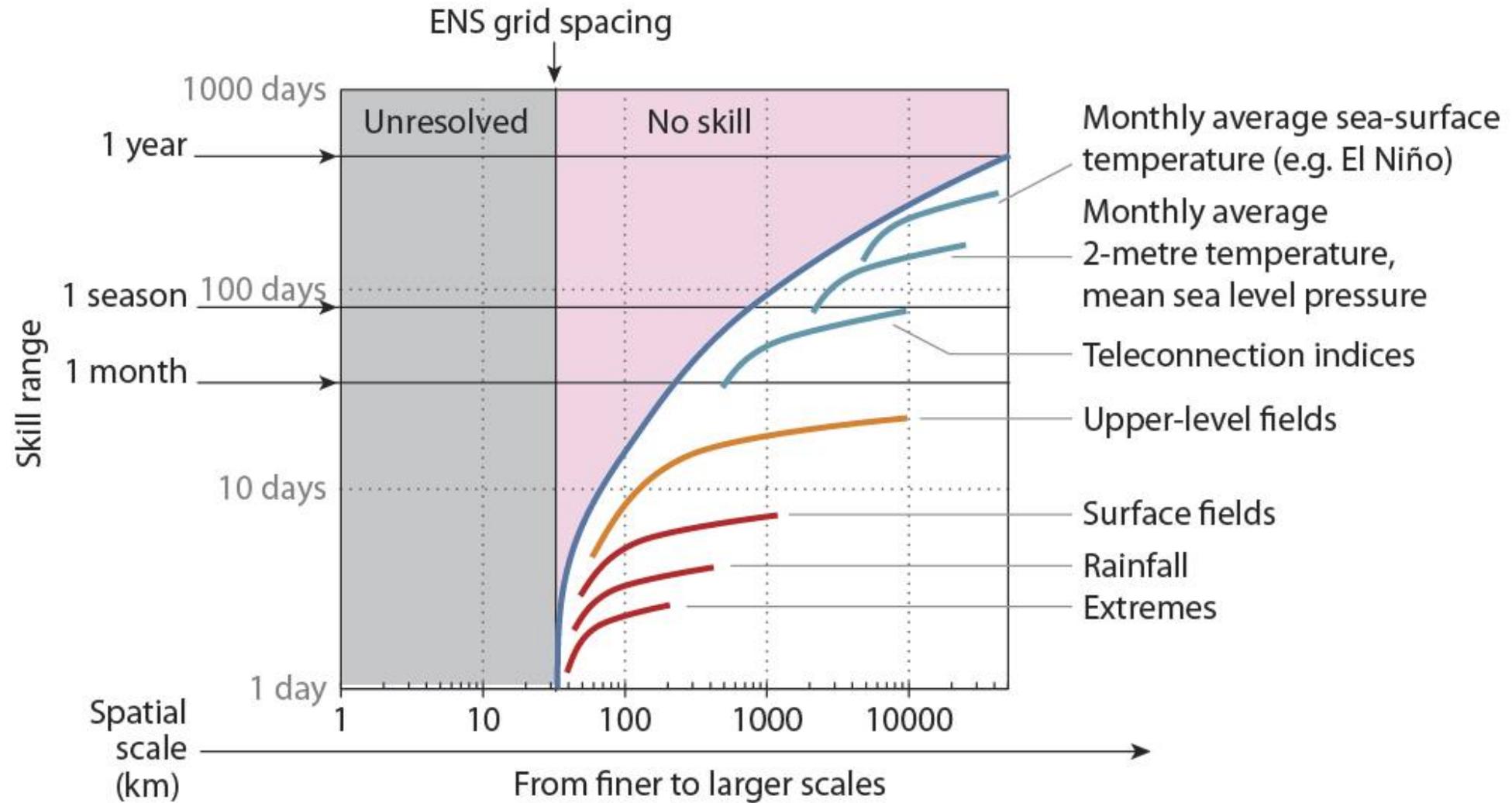


Scale-dependency of the FSH

BL15 evaluated the skill of ENS fcs for 1 year and showed that the FSH is longer for large-scale, low-frequency fields.



A schematic of the scale dependency of the FSH



Outline

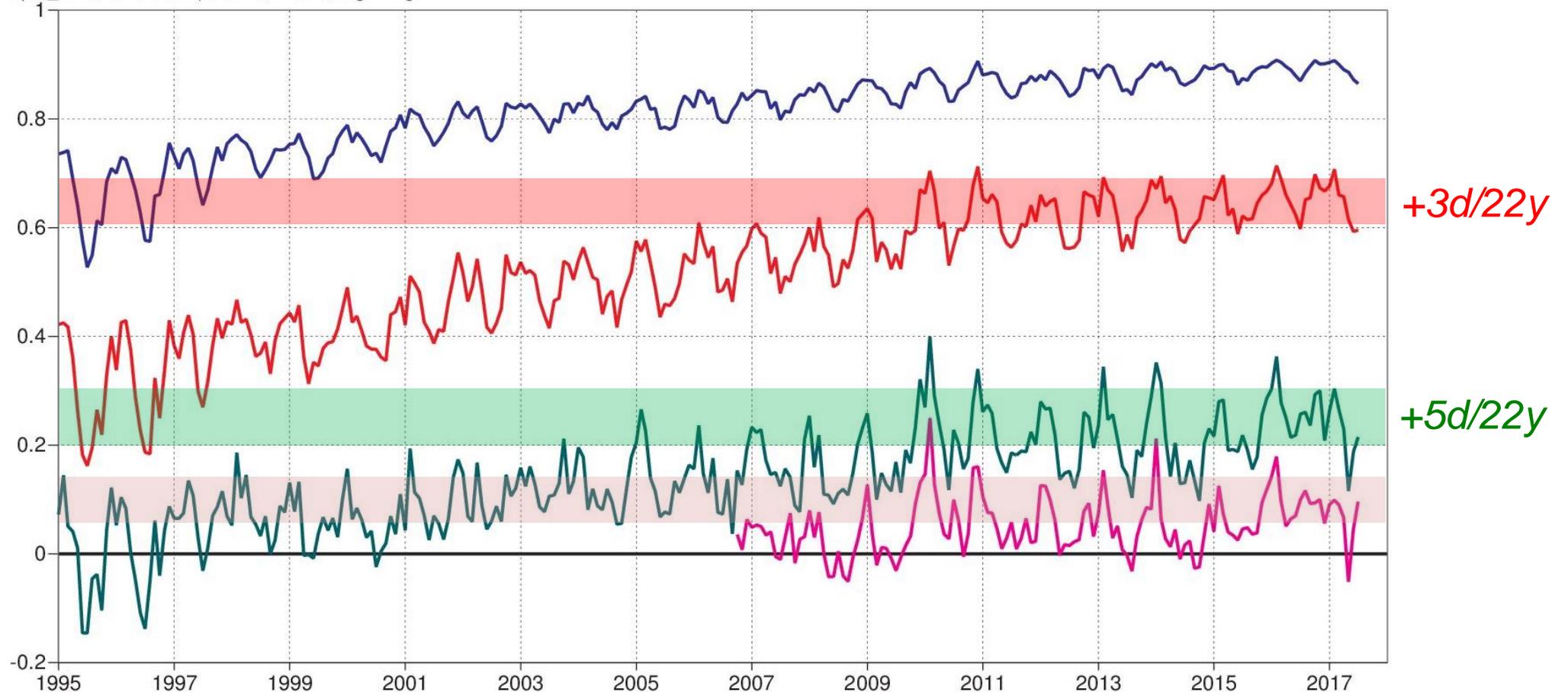
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The continuous improvement of ENS fcs of ~2 days/decade

500hPa geopotential
Continuous ranked probability skill score
NHem Extratropics (lat 20.0 to 90.0, lon -180.0 to 180.0)

T+360
T+240
T+120
T+48

oper_an od enfo 0001 | 00UTC,12UTC,beginning



The error growth equation

To investigate predictability and the evolution of the forecast skill we will use the error growth equation (Lorenz 1982, Dalcher and Kalnay 1987, Simmons et al 1995, Buizza 2010):

$$\frac{dE}{dt} = (a \cdot E + S) \left(1 - \frac{E}{E_{\infty}}\right)$$

- E: average error
- a: rate of growth of forecast error
- S: model deficiency
- E_{∞} : asymptotic level

Atmospheric predictability experiments with a large numerical model

By E. N. LORENZ,¹ *European Centre for Medium Range Weather Forecasts, Reading RG2 9AX, England*

Error growth and predictability in operational ECMWF forecasts

By AMNON DALCHER* and EUGENIA KALNAY, *Laboratory for Atmospheres, Code 611, NASA/Goddard Space Flight Center, Greenbelt, Maryland, USA*

Error growth and estimates of predictability from the ECMWF forecasting system

By A. J. SIMMONS^{1*}, R. MUREAU² and T. PETROLIAGIS¹
¹ *European Centre for Medium-Range Weather Forecasts, UK*
² *Royal Netherlands Meteorological Institute, The Netherlands*



Horizontal resolution impact on short- and long-range forecast error

Roberto Buizza

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Error growth equation: analytical solution

$$\frac{dE}{dt} = (a \cdot E + S) \left(1 - \frac{E}{E_\infty}\right) \quad \longrightarrow \quad \eta(t) \equiv \frac{E(t)}{E_\infty} = 1 - \frac{1 + \frac{S}{a \cdot E_\infty}}{1 + C_1 \cdot e^{C_2 \cdot t}}$$

- E: average error
- a: rate of growth of forecast error
- S: model deficiency
- E_0 : initial-time error
- E_∞ : asymptotic level

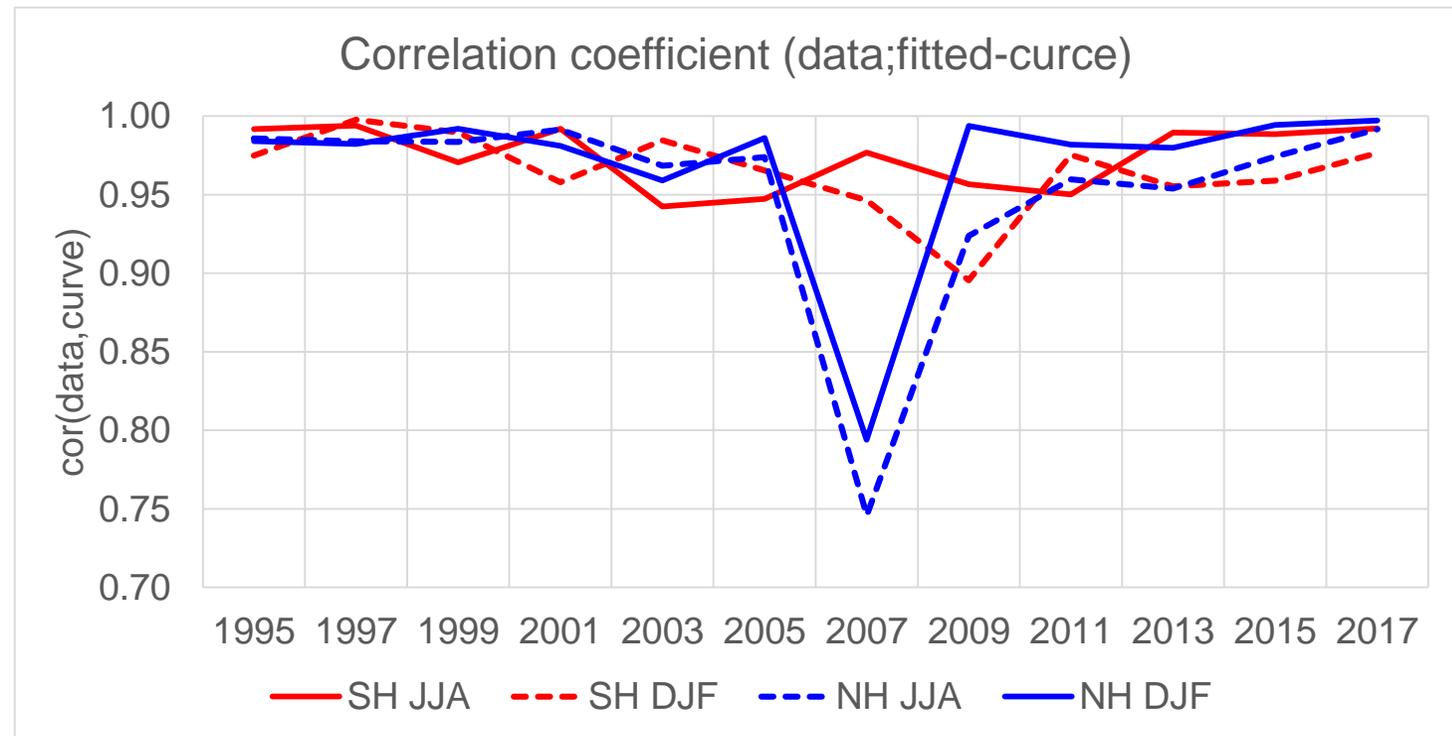
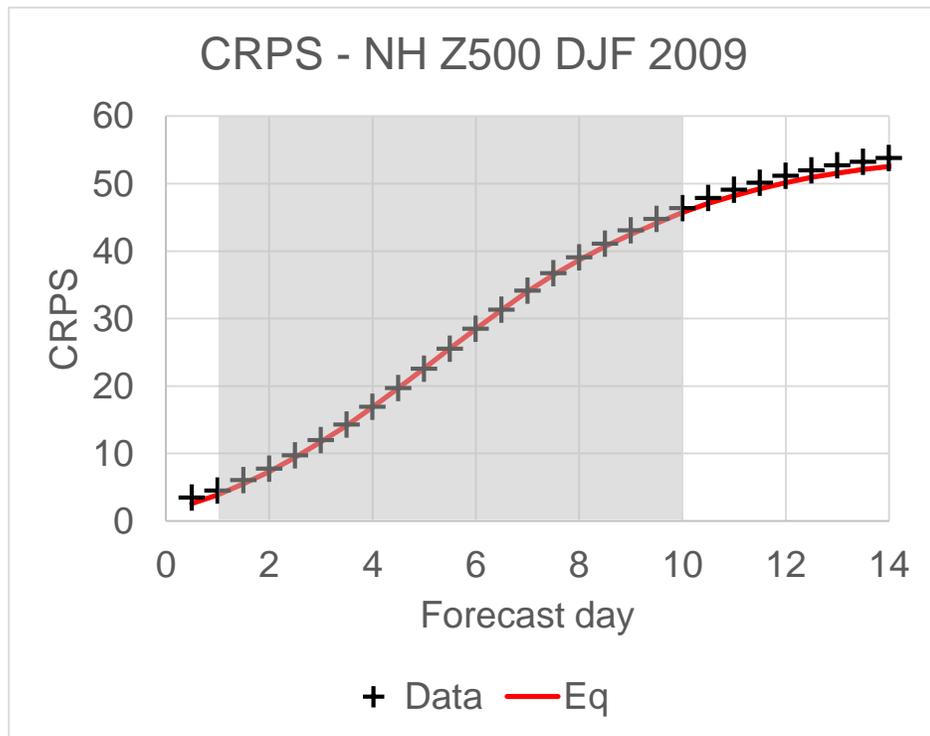
$$C_1 = \frac{E_0 + \frac{S}{a}}{E_\infty - E_0}$$

$$C_2 = a + \frac{S}{E_\infty}$$

The error growth eq. parametrizes well the CRPS evolution

The error-growth equation describes in general very well the time evolution of the CRPS of ENS probabilistic forecasts for Z500 over NH and SH winters and summers.

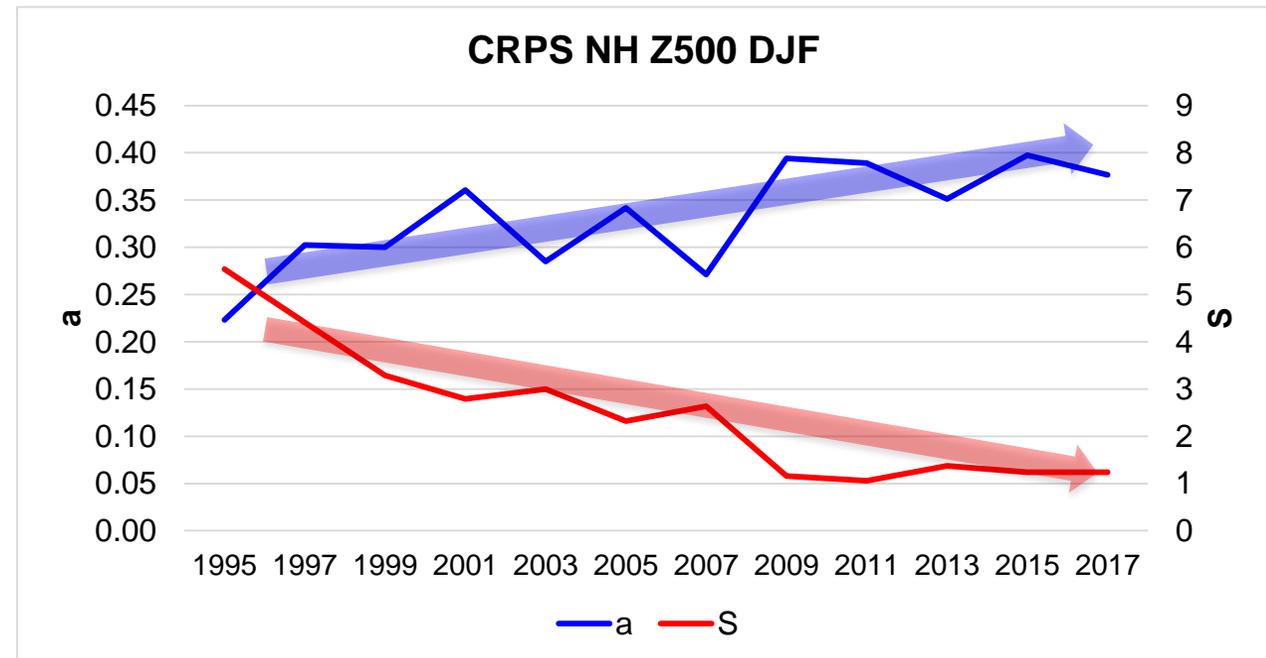
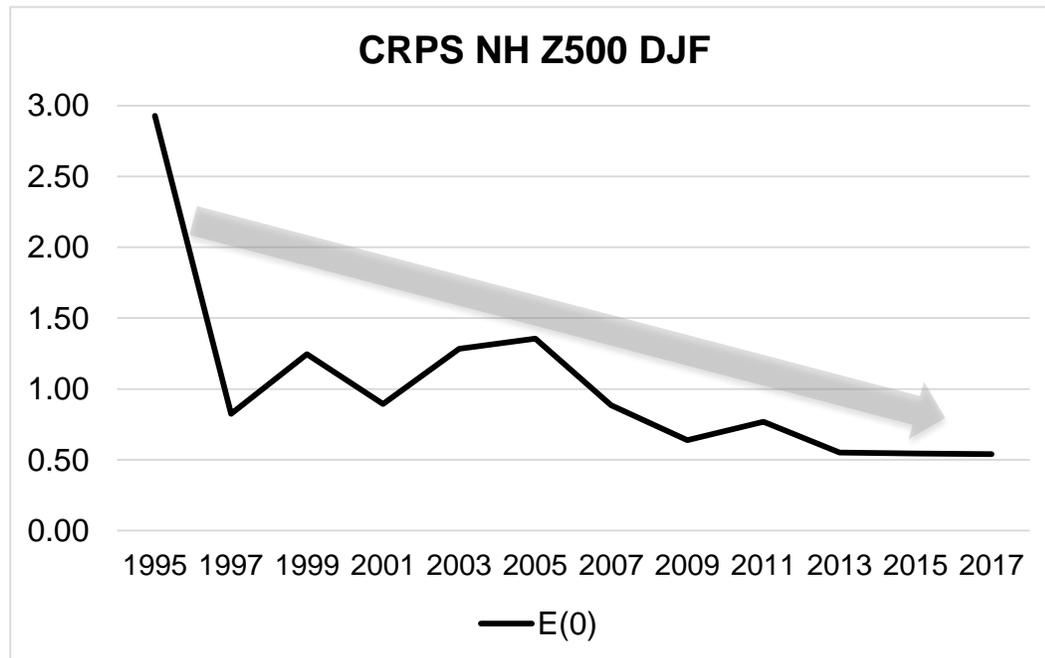
For all years from 1995 to 2017, every 2 years, coefficients have been estimated using best linear fit between d1 and d10.



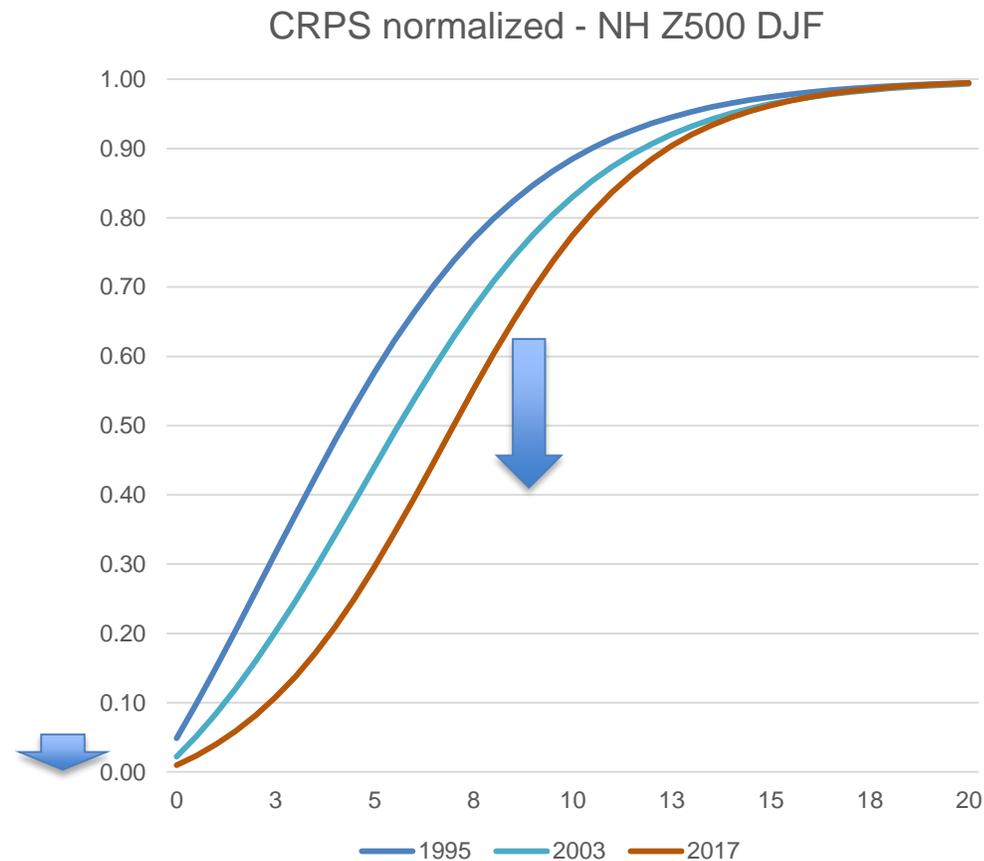
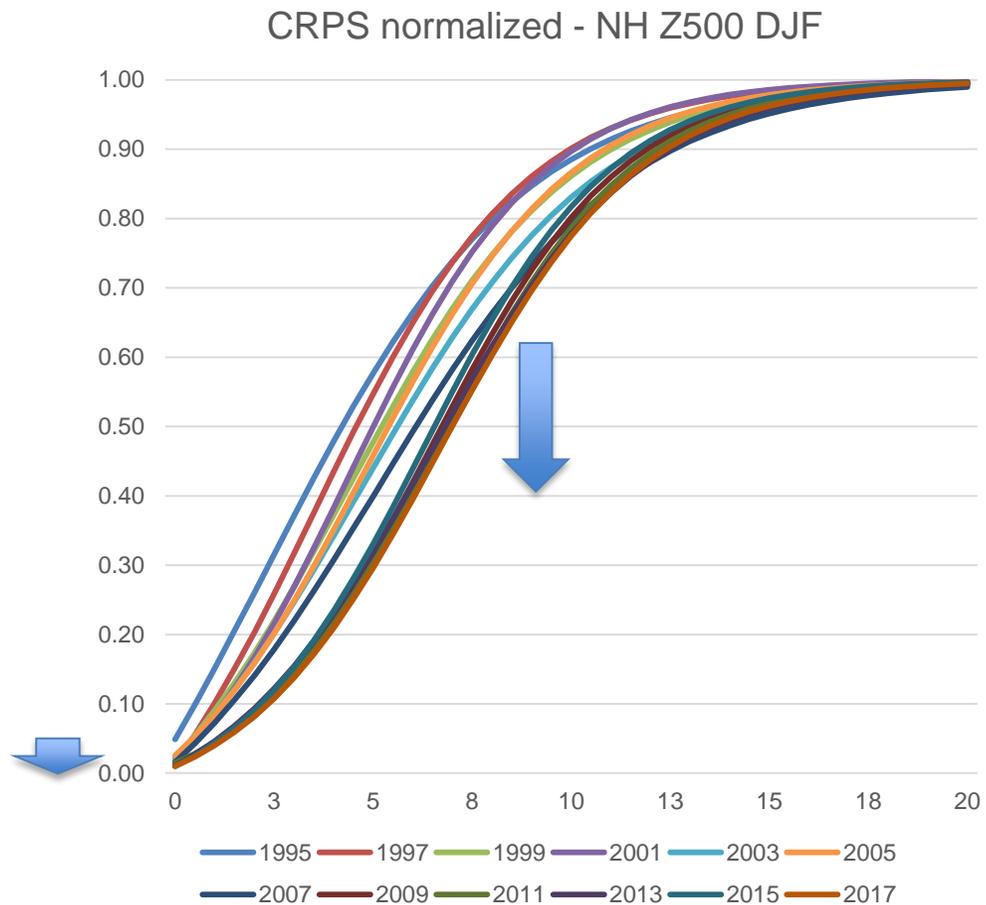
How do the error-growth coefficients evolve?

Results indicate that:

- $E(0)$ indicates that the initial-time error has been decreasing
- a indicates that in the short-term, the error has been growing faster
- S indicates that the model-error term has been decreasing



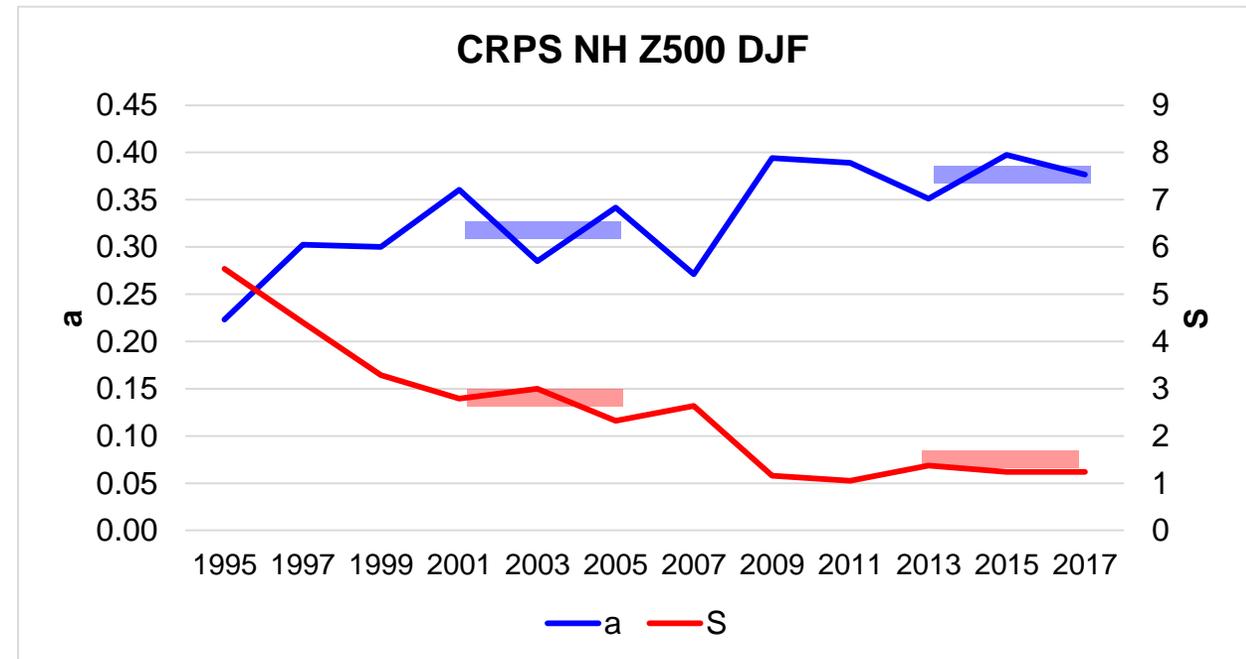
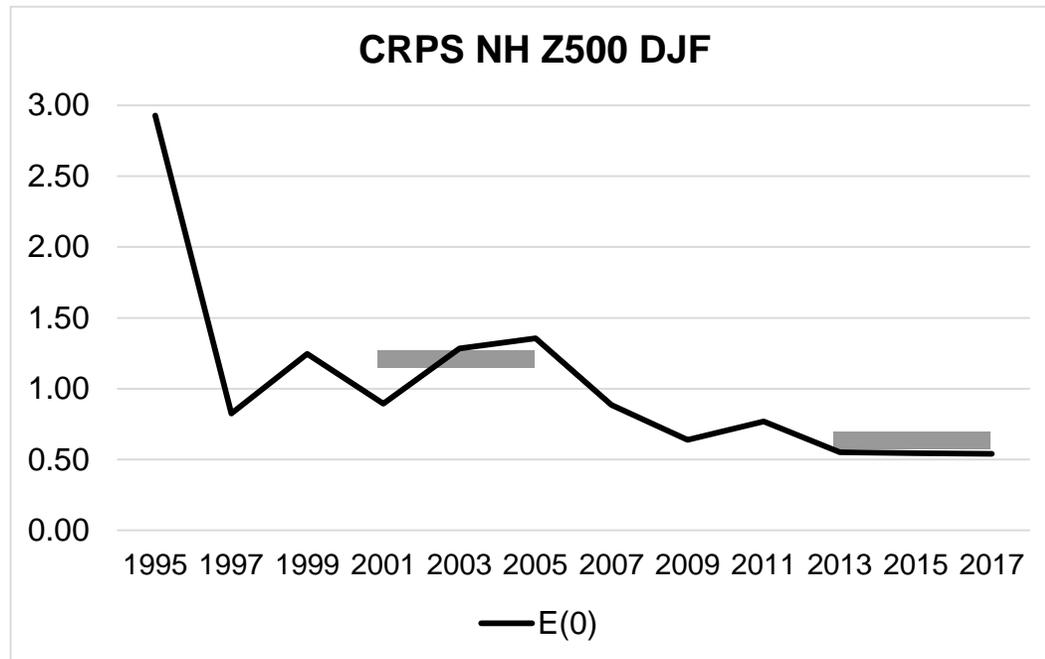
Can we gauge the potential gains linked to ICs?



Can we expect to extend further the forecast skill horizon?

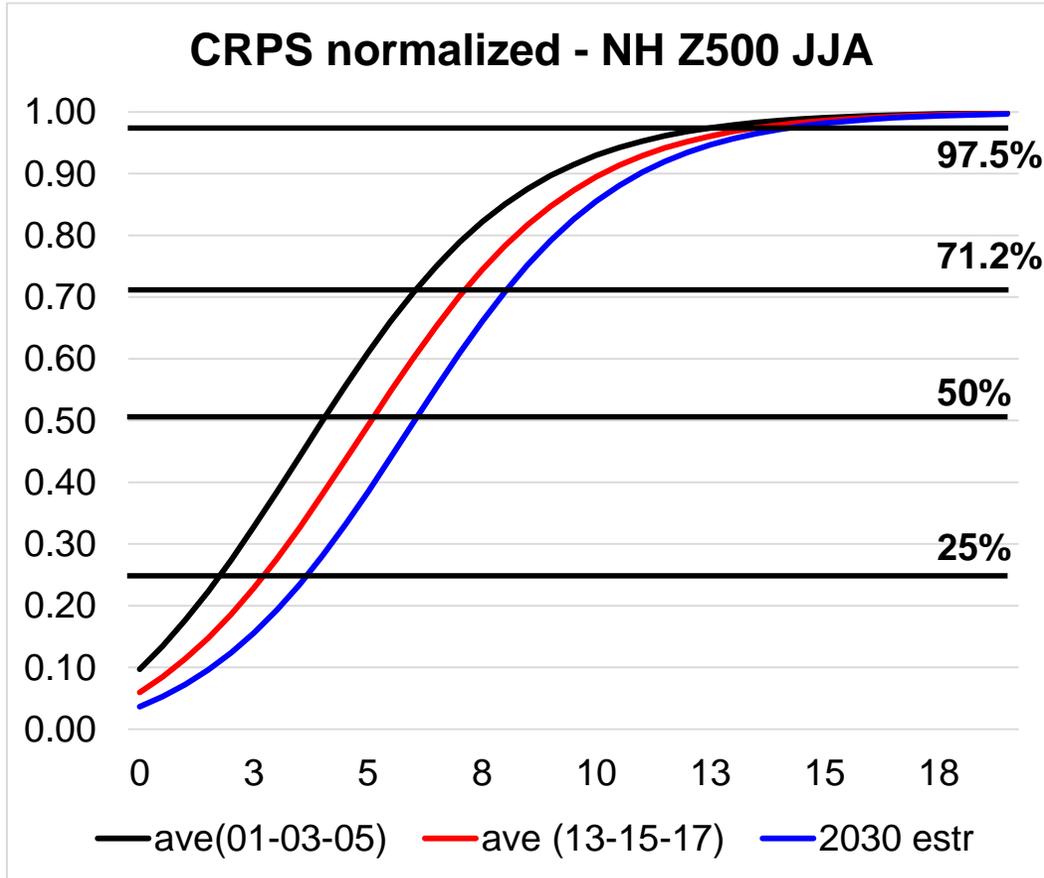
We can extrapolate to 2030 (e.g. for Z500 over NH):

- E(0): assume it will decrease as between <01-05> and <13-17> ($1.2 > 0.55 > \dots > 0.25$)
- a: assume it will increase as between <01-05> and <13-17> ($0.33 > 0.37 > \dots > 0.42$)
- S: assume it will decrease as between <01-05> and <13-17> ($2.7 > 1.3 > \dots > 0.6$)

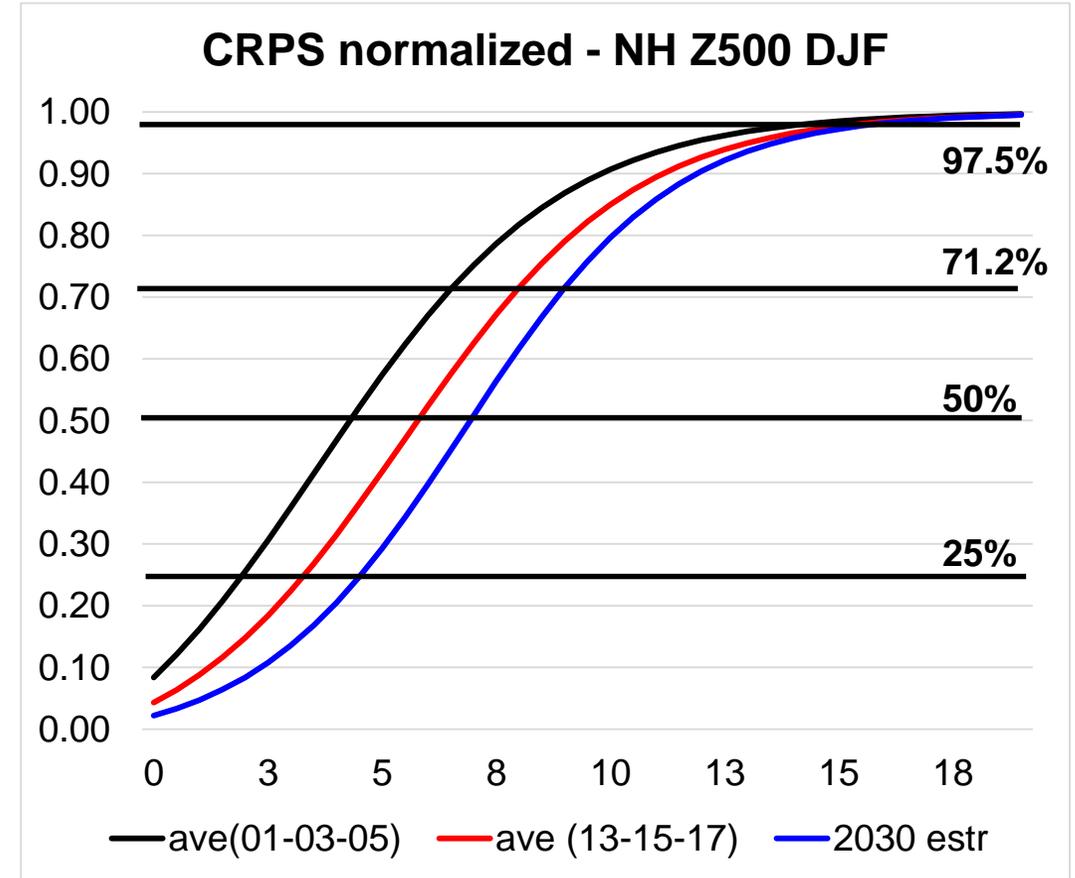


Can we expect to extend further the forecast skill horizon?

summer



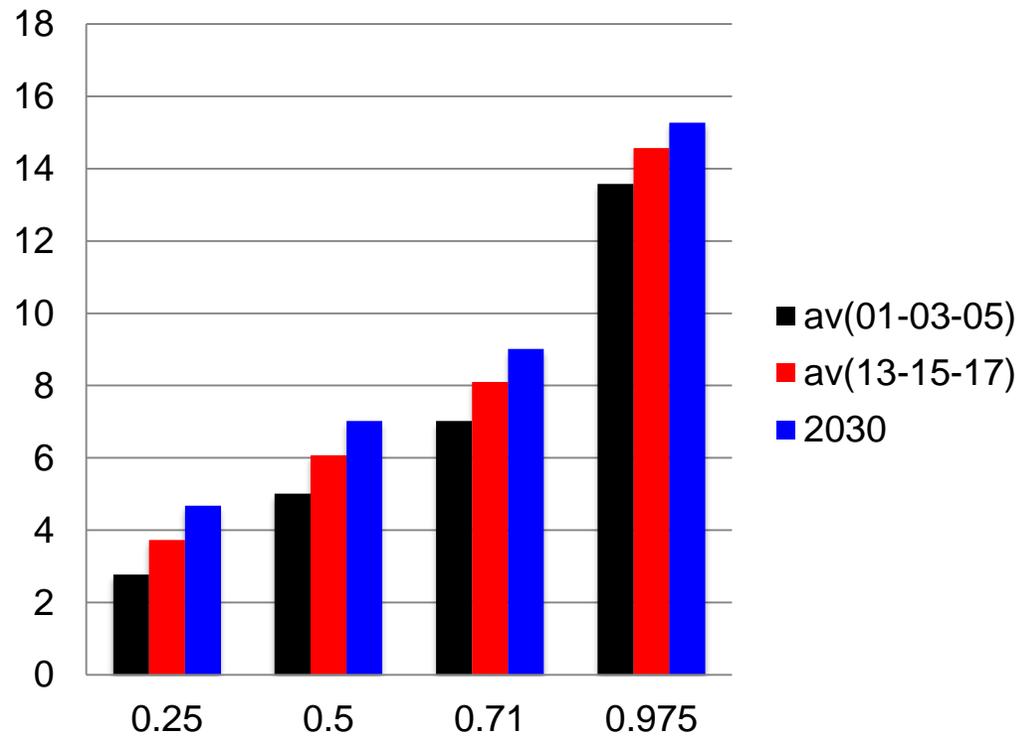
winter



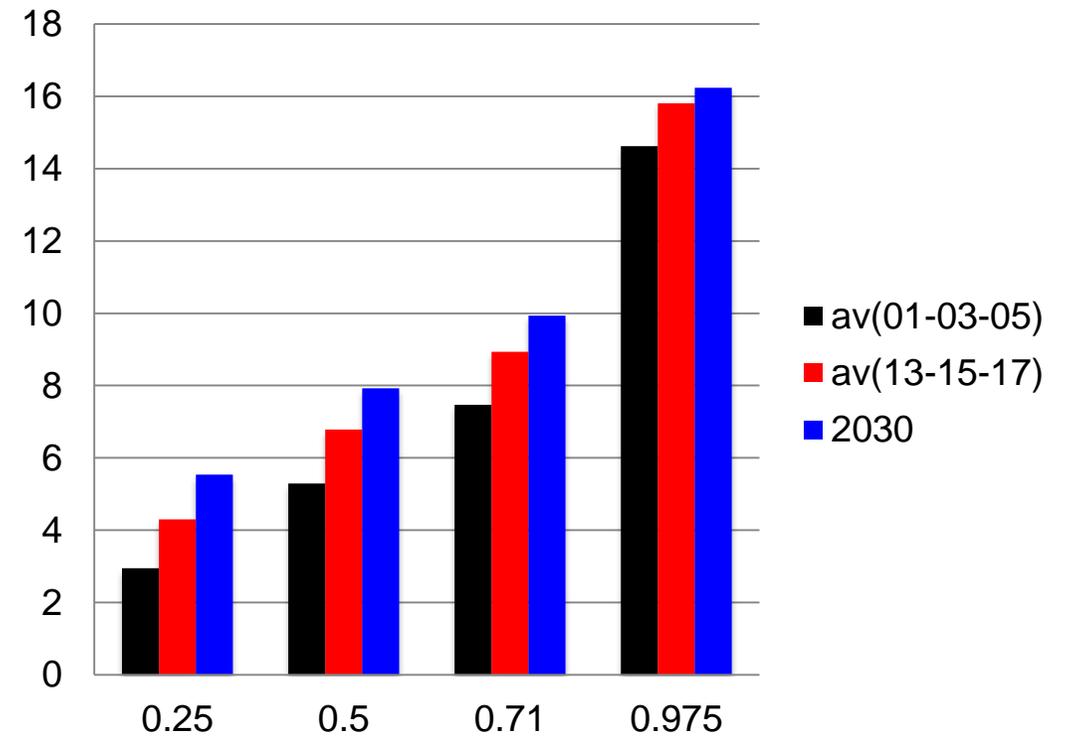
Can we expect to extend further the forecast skill horizon?

Results based on Z500 over NH indicate that if we are able to continue with the same rate of improvements, we can keep increasing the forecast skill in the short- and medium-range.

Forecast Skill Horizon - Z500 NH JJA



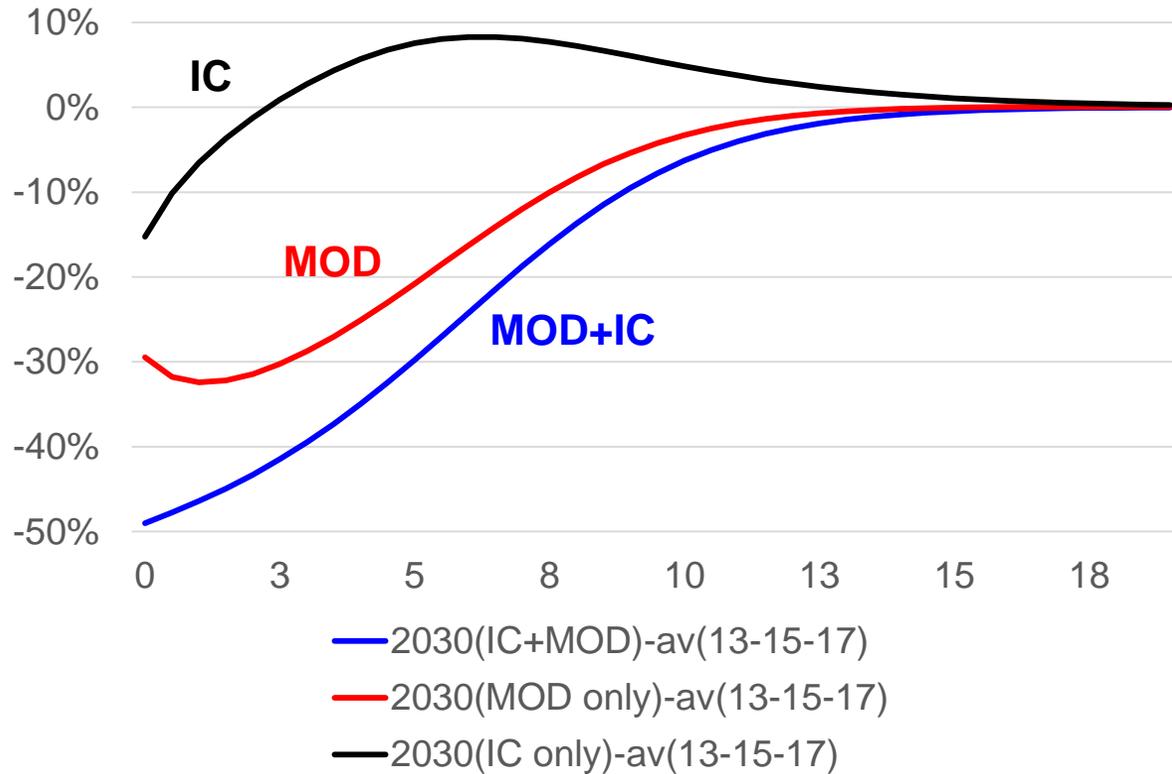
Forecast Skill Horizon - Z500 NH DJF



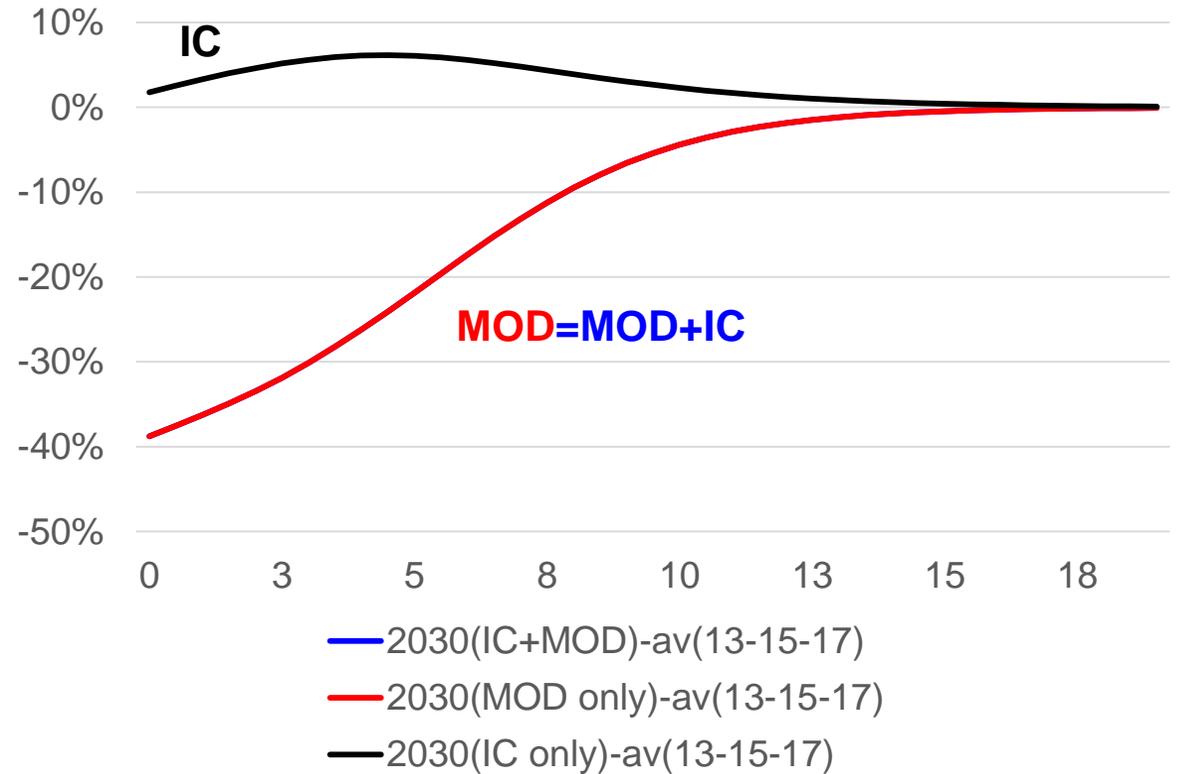
Looking ahead, how important is to improve the PDF model?

(model+ENS config)

Estimated gains in CRPS (NH Z500 DJF) due to IC and MOD improvements



Estimated gains in CRPS (NH Z500 JJA) due to IC and MOD improvements



Outline

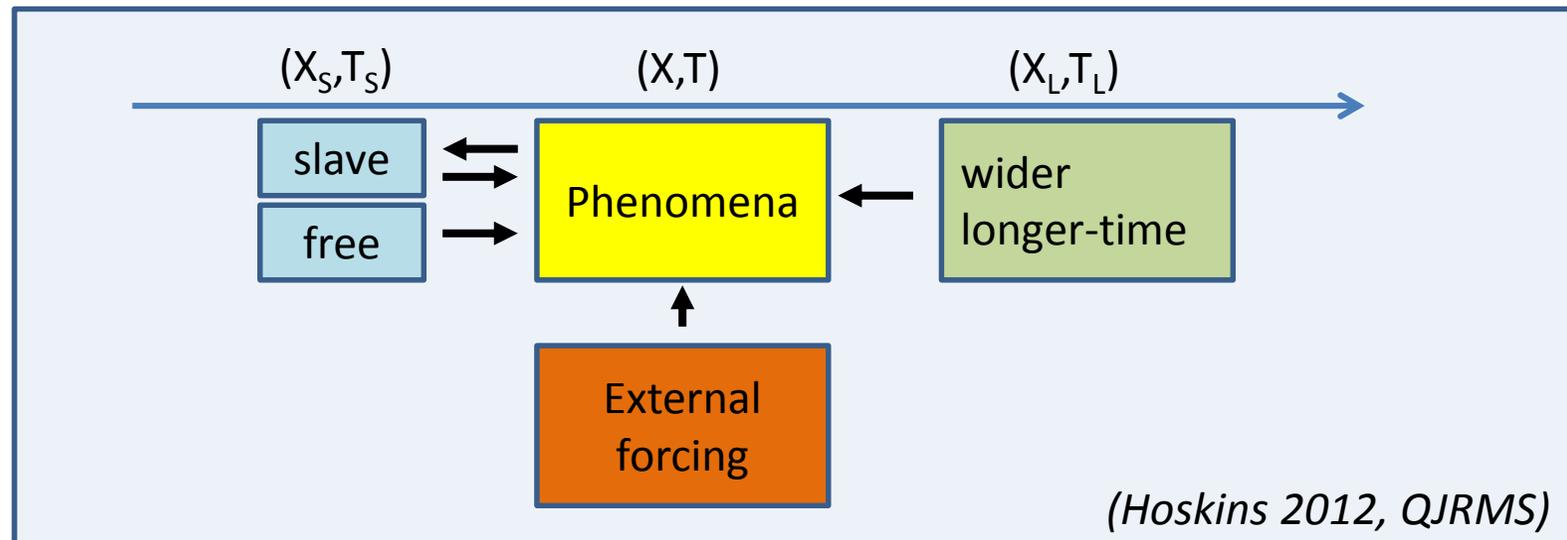
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How did we manage to extend the FSH beyond 2 weeks?

By improving our models and initialisation schemes so that all scales relevant to predict phenomena with a scale (X,T) are included, 'well' simulated and initialized.

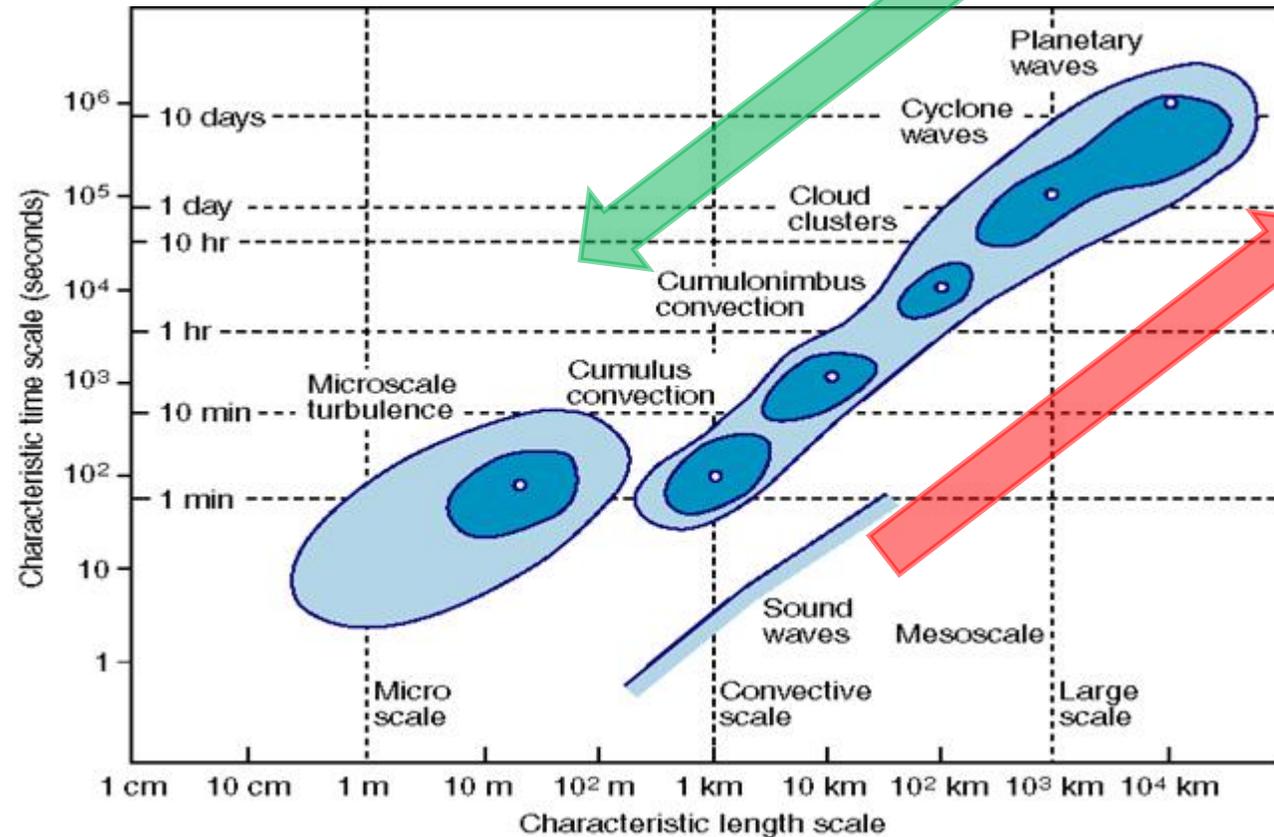
The forecast skill horizon is determined by the competition between:

- Errors propagating from the poorly initialized scales (mainly smaller/faster?), and
- Predictive signal propagating from the better initialized scales (mainly wider/slower?)



How did we manage to extend the FSH beyond 2 weeks?

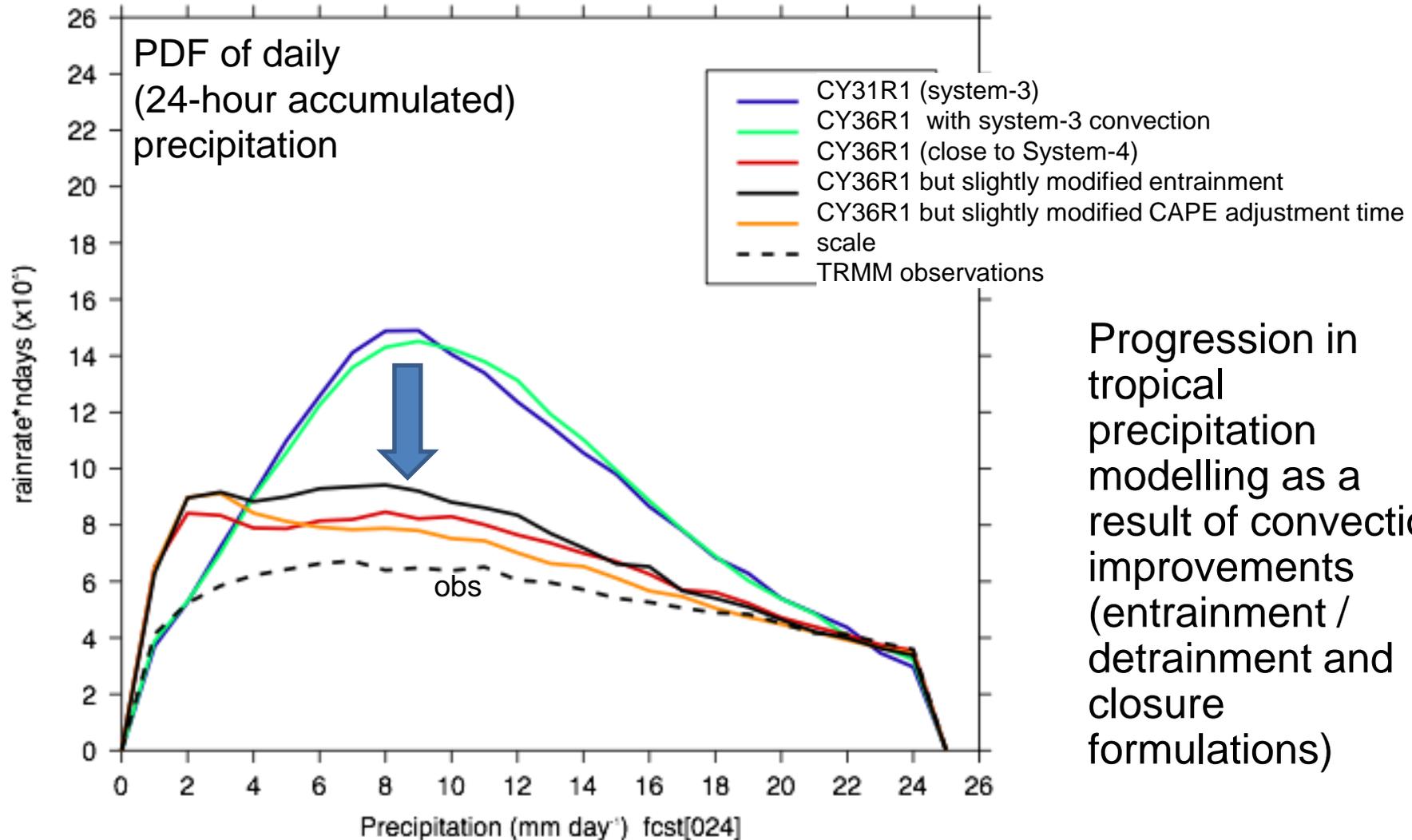
Predictable signals propagate from the better-initialized and more predictable scales ('mainly' the large scales, the slowly evolving components) to the less predictable (small/fast) scales



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

(Buizza and Leutbecher 2015, QJRMS)

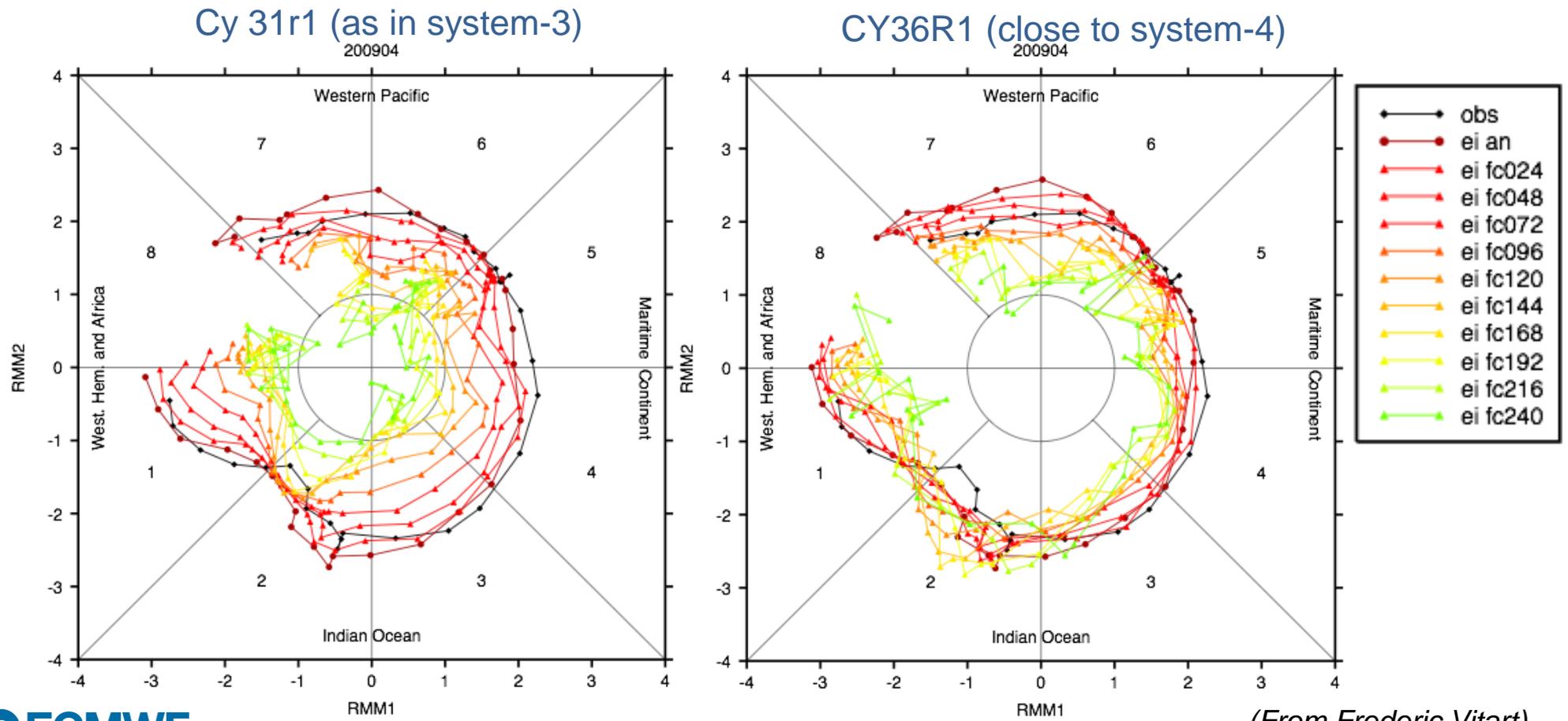
Changes in convection improves tropical precipitation ...



Progression in tropical precipitation modelling as a result of convection improvements (entrainment / detrainment and closure formulations)

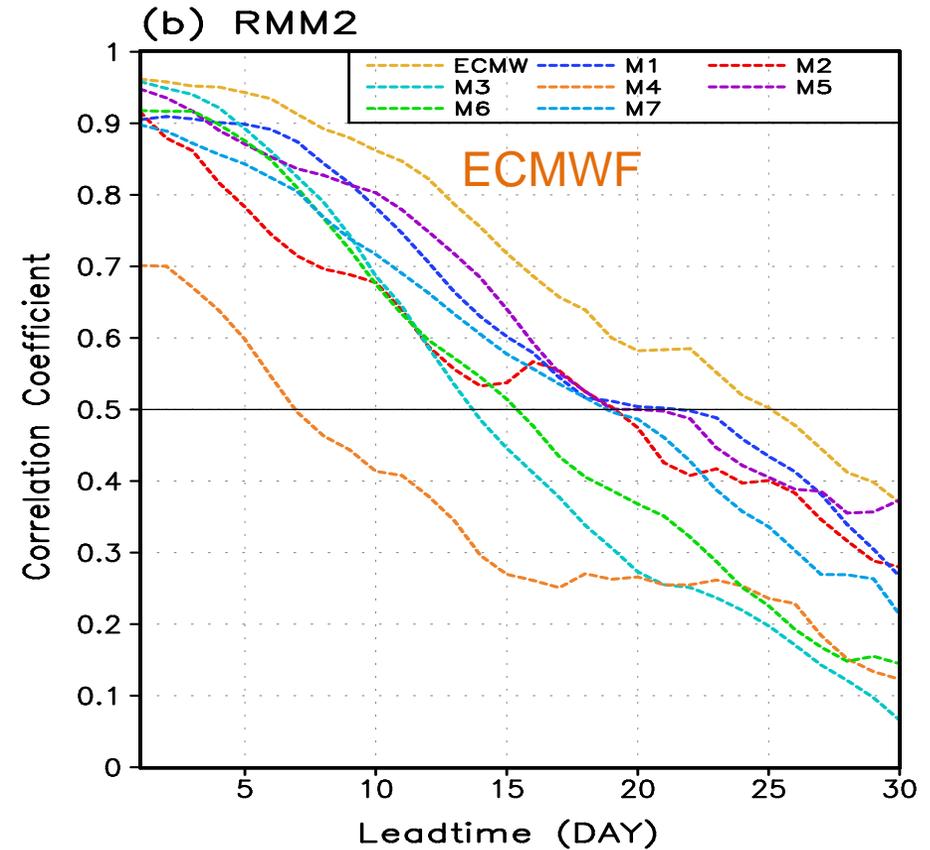
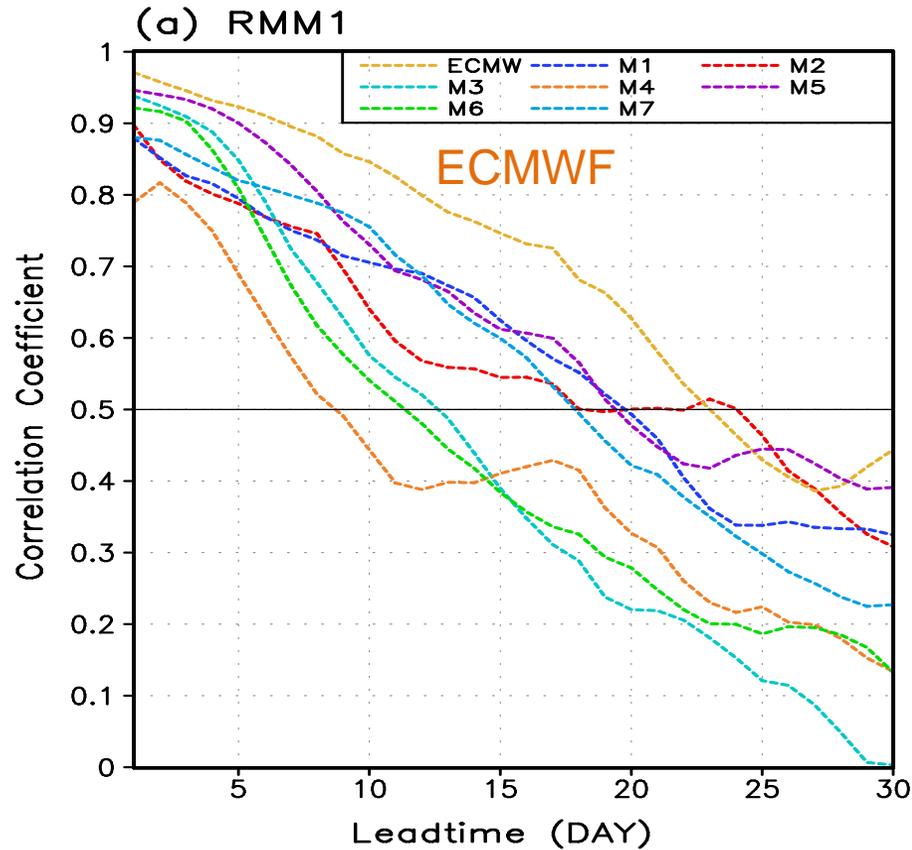
... and allows a more realistic MJO propagation ...

Progression in MJO modelling as a result of convection improvements (entrainment / detrainment and closure formulations).



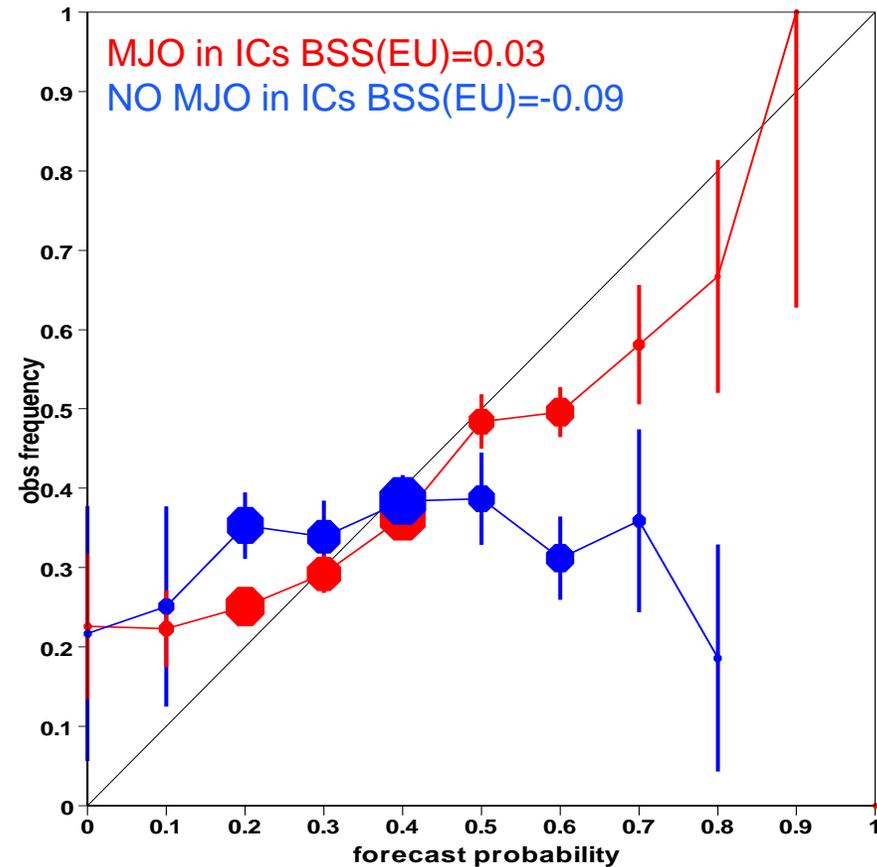
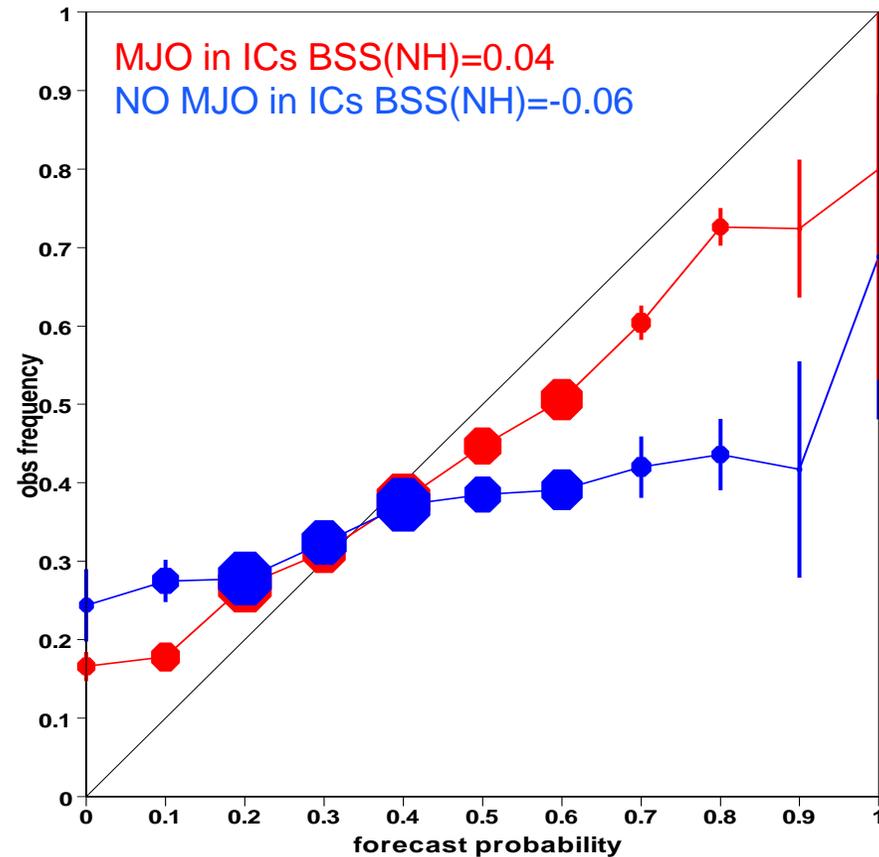
... leading to a more realistic and skilful MJO fcs up to w3

Considering the MJO, the ECMWF system is capable to predict it up to about 25 days.



Better MJO prediction > higher skill over Europe

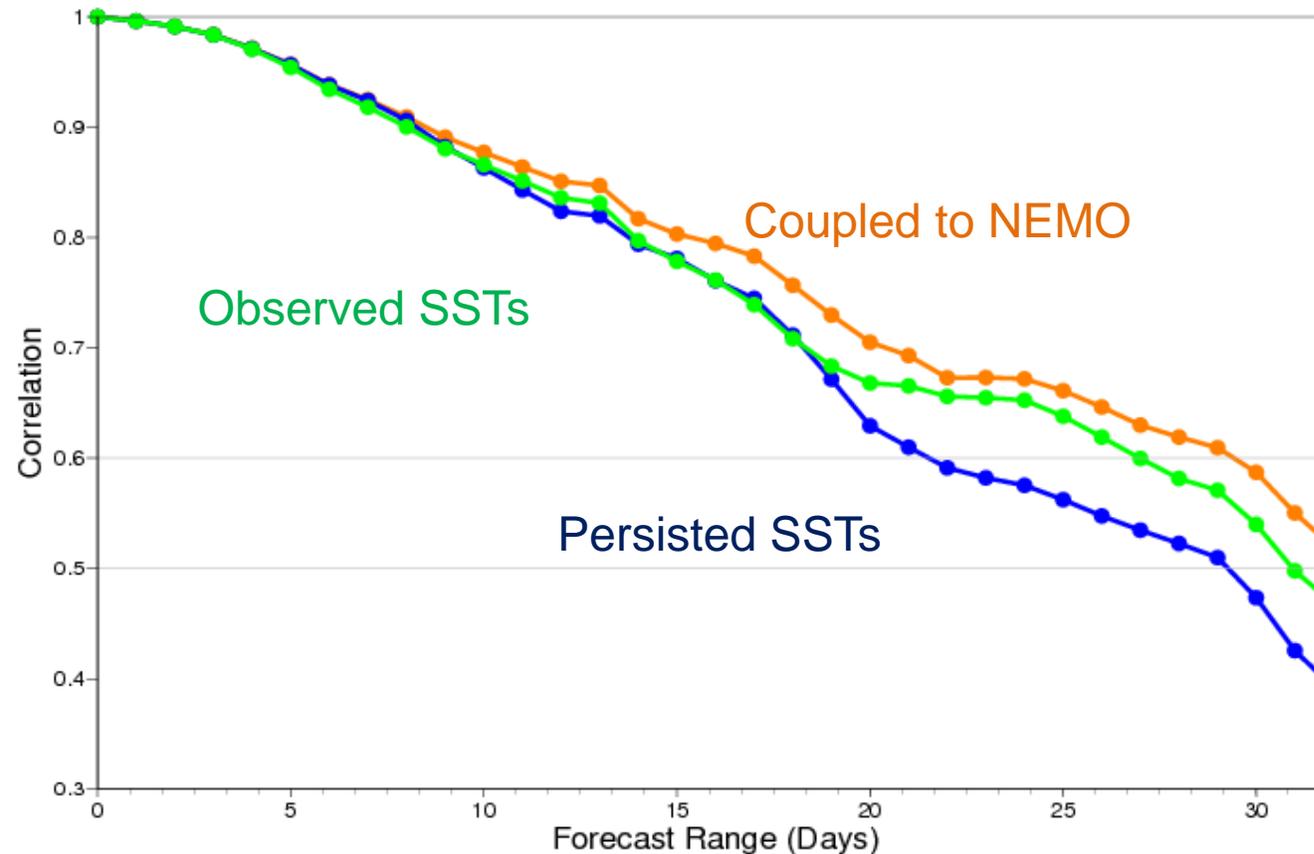
The skill of d19-25 PR(2mT>Upp3) forecasts is higher if there is an active MJO in the Ics. (results based on 45 cases, 1989-2008).



How did we extend the FSH beyond 2 weeks? 3D-ocean ...

For example, the coupling of the atmosphere to a 3-dimensional ocean model has led to ENS improvements (results are based on 80 ENS, starting on 1st Feb/May/Aug/Nov 1989-2008).

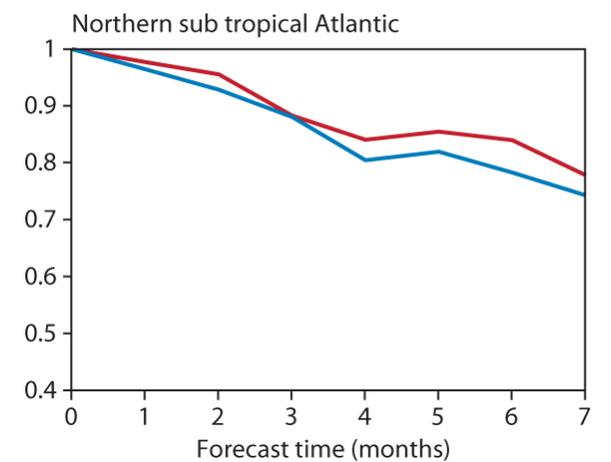
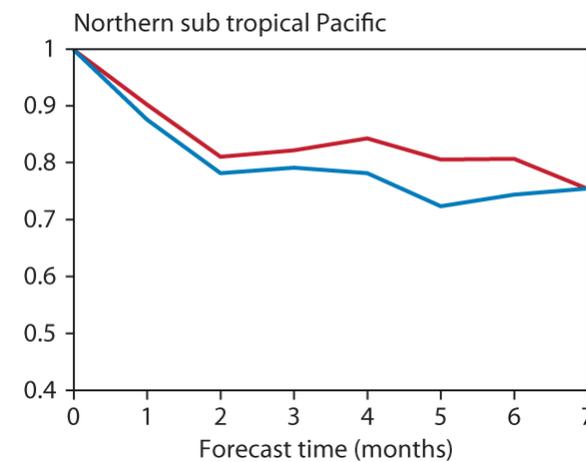
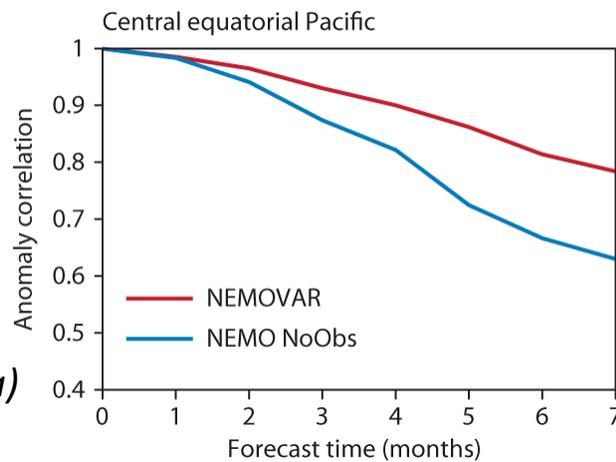
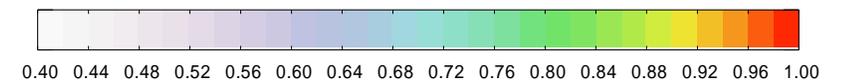
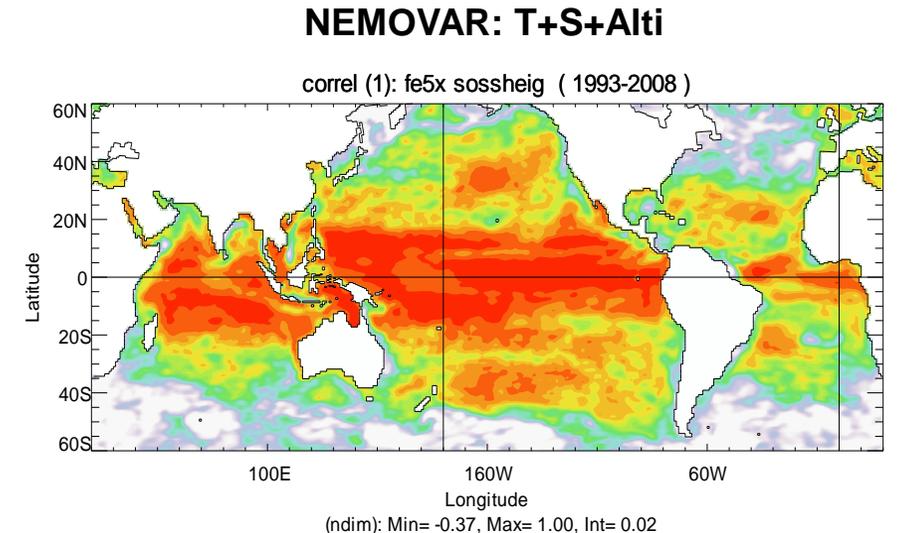
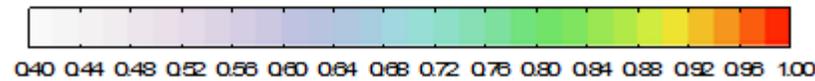
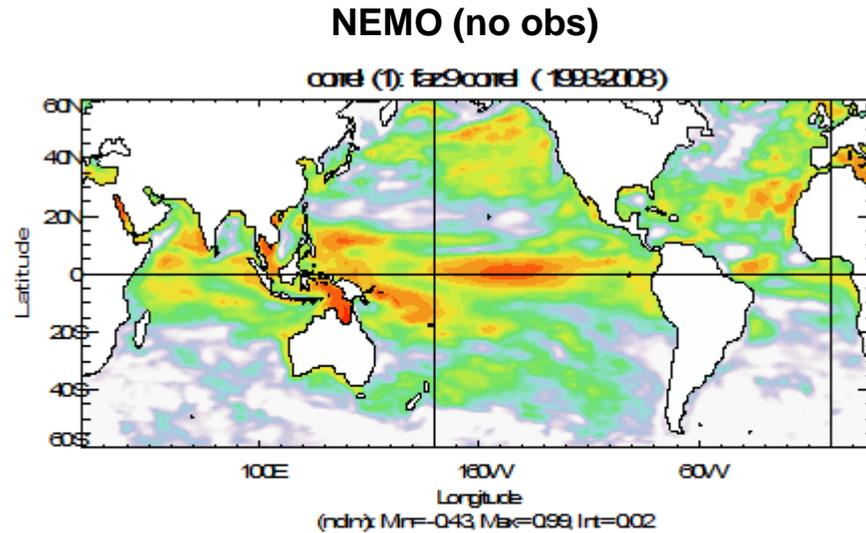
MJO Bivariate Correlation



(F Vitart)

How did we extend the FSH beyond 2 weeks? ICs ...

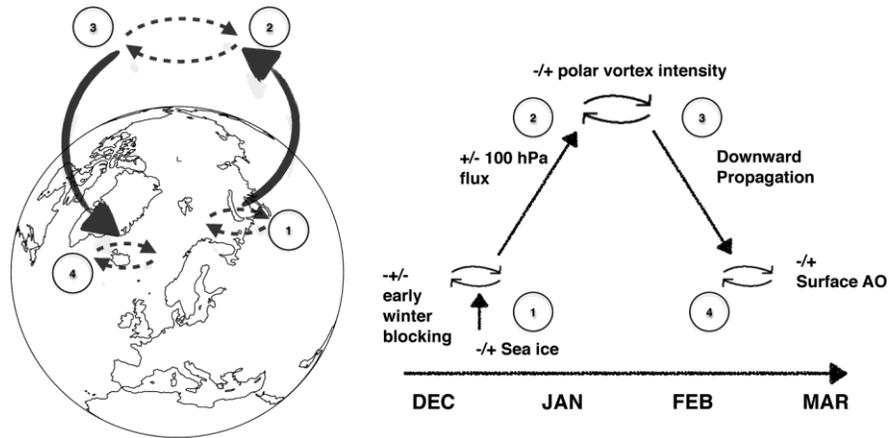
A proper initialisation played a key role.



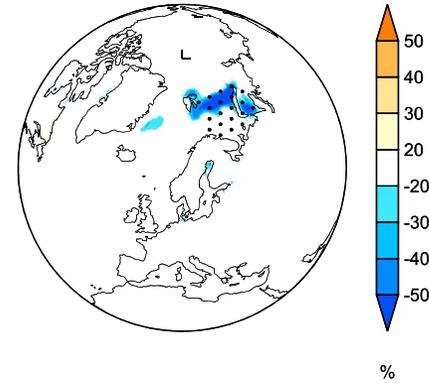
(F Vitart, M Alonso-Balmaseda)

Is there evidence that we can improve further? Sea-ice ..

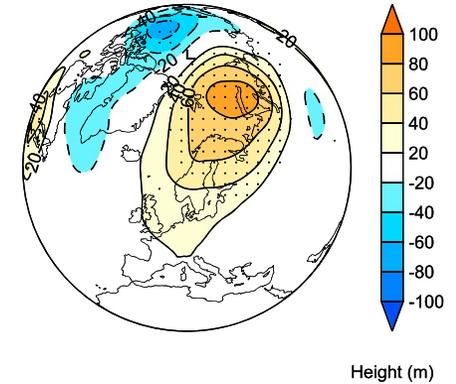
Ruggieri et al (2016, JGR) have shown that sea-ice concentration anomalies in the Barents-Kara seas in late autumn/early winter has an impact on weather variability over the Euro-Atlantic sector in late winter.



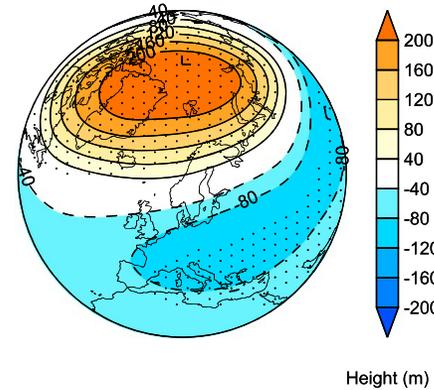
a) SIC LIYs minus HIYs DEC-JAN



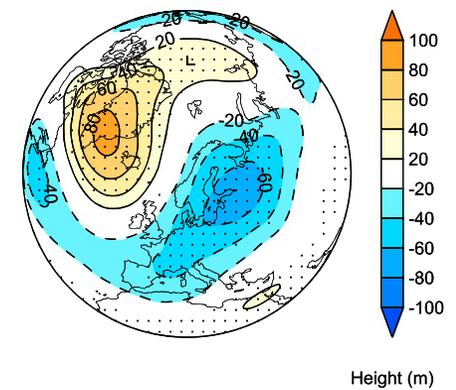
b) z500 LIYs minus HIYs DEC-JAN



c) z30 LIYs minus HIYs JAN-FEB



d) z500 LIYs minus HIYs FEB-MAR



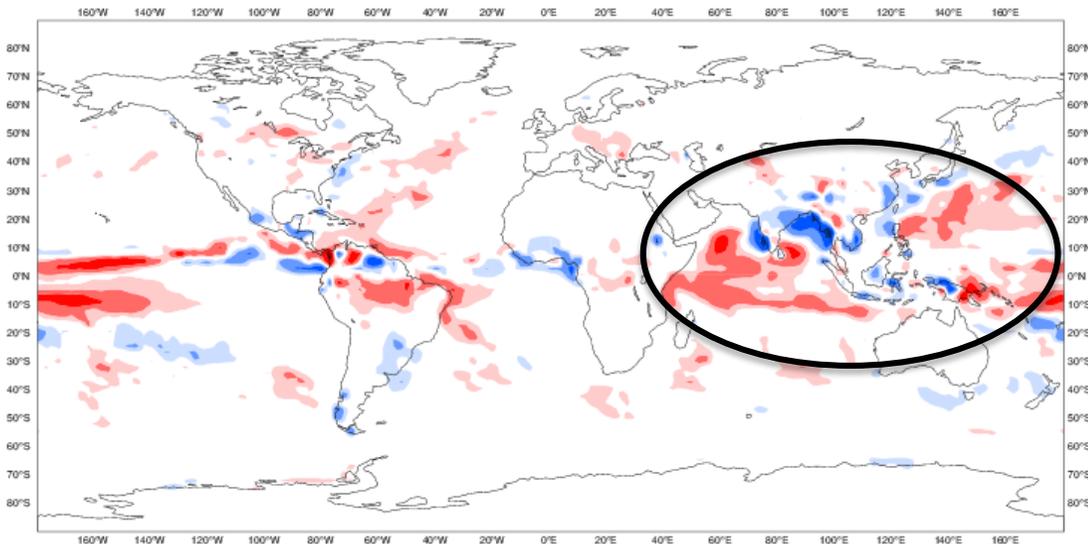
(P Ruggieri)

Is there evidence that we can improve further? Aerosols ..

Preliminary results show a bias reduction from using an interactive aerosols on meteorological fields (winds and precipitation). More prominent impact can be detected over the Indian Ocean.

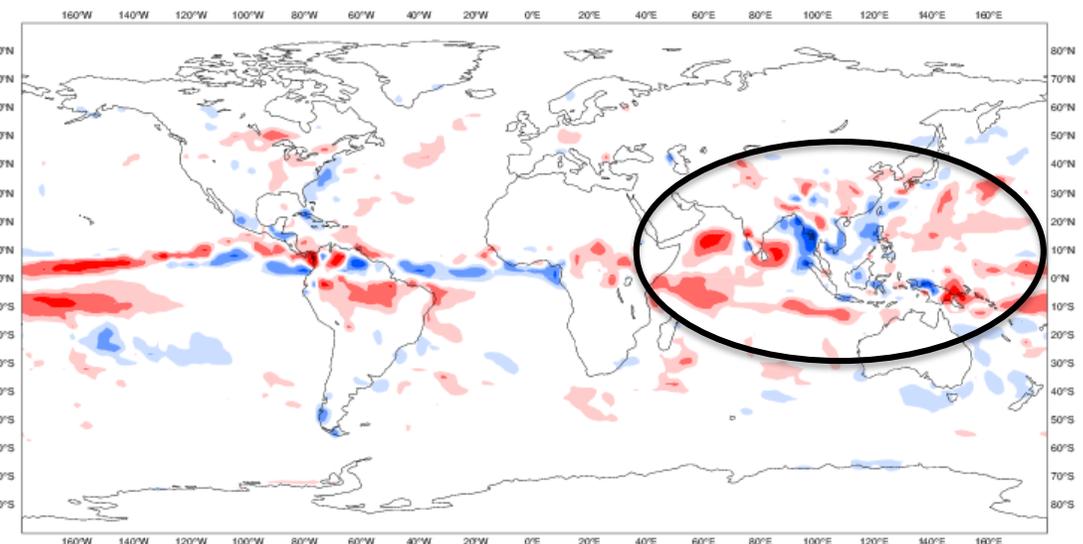
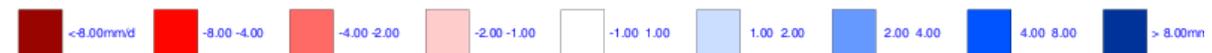
CONTROL RUN – PRECIPITATION BIAS WEEK 4

20030501-20140501



INTERACTIVE AEROSOL RUN – PRECIPITATION BIAS WEEK 4

20030501-20140501

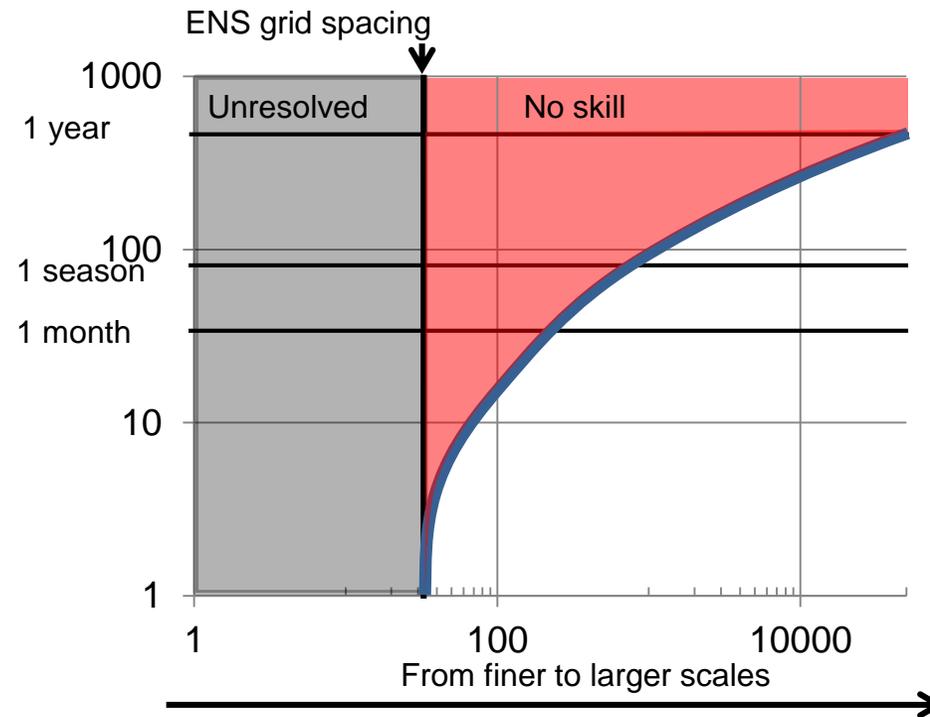


(A Benedetti, F Vitart)

Conclusions: Q1

1. Does the forecast skill horizon depend on the spatio-temporal scale of the event we are aiming to predict?

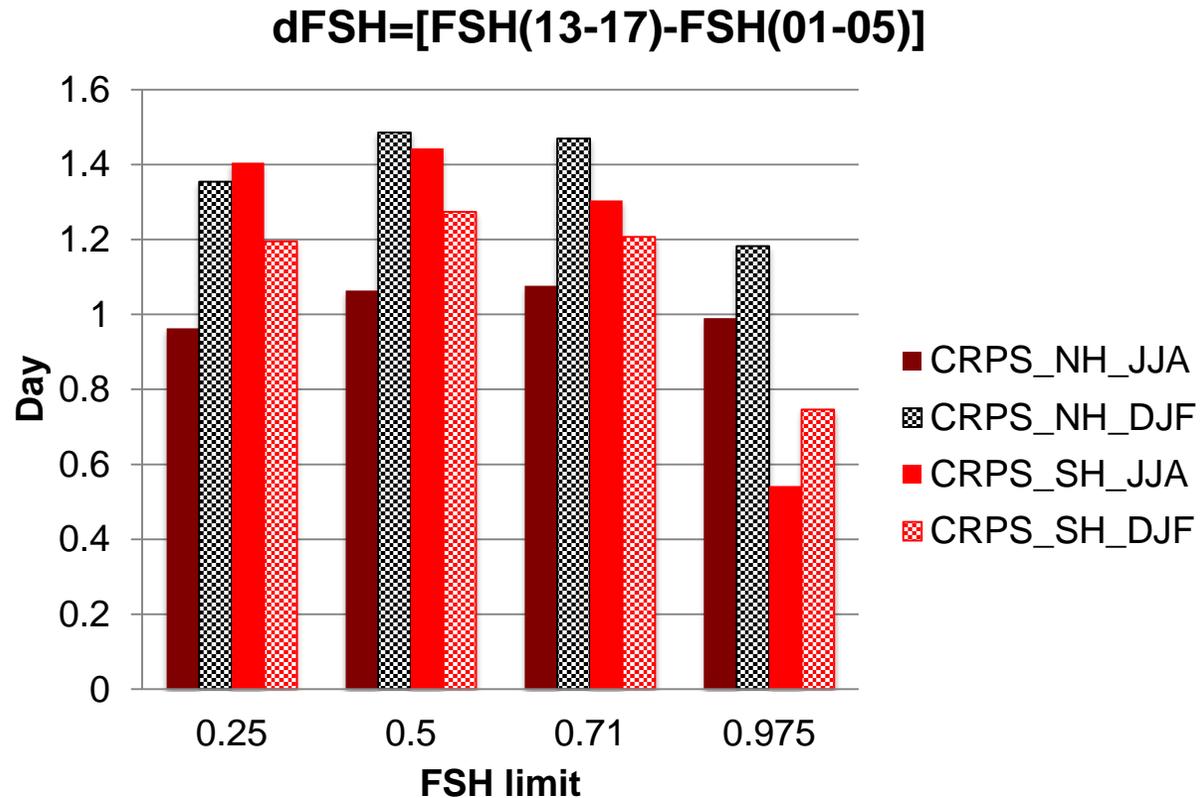
Yes, there is a clear evidence of this, e.g. from ECMWF ENS monthly forecasts and from results published in the literature.



Conclusions: Q2

2. Considering grid-point values, how far is the forecast skill horizon, and can we expect to further extend it?

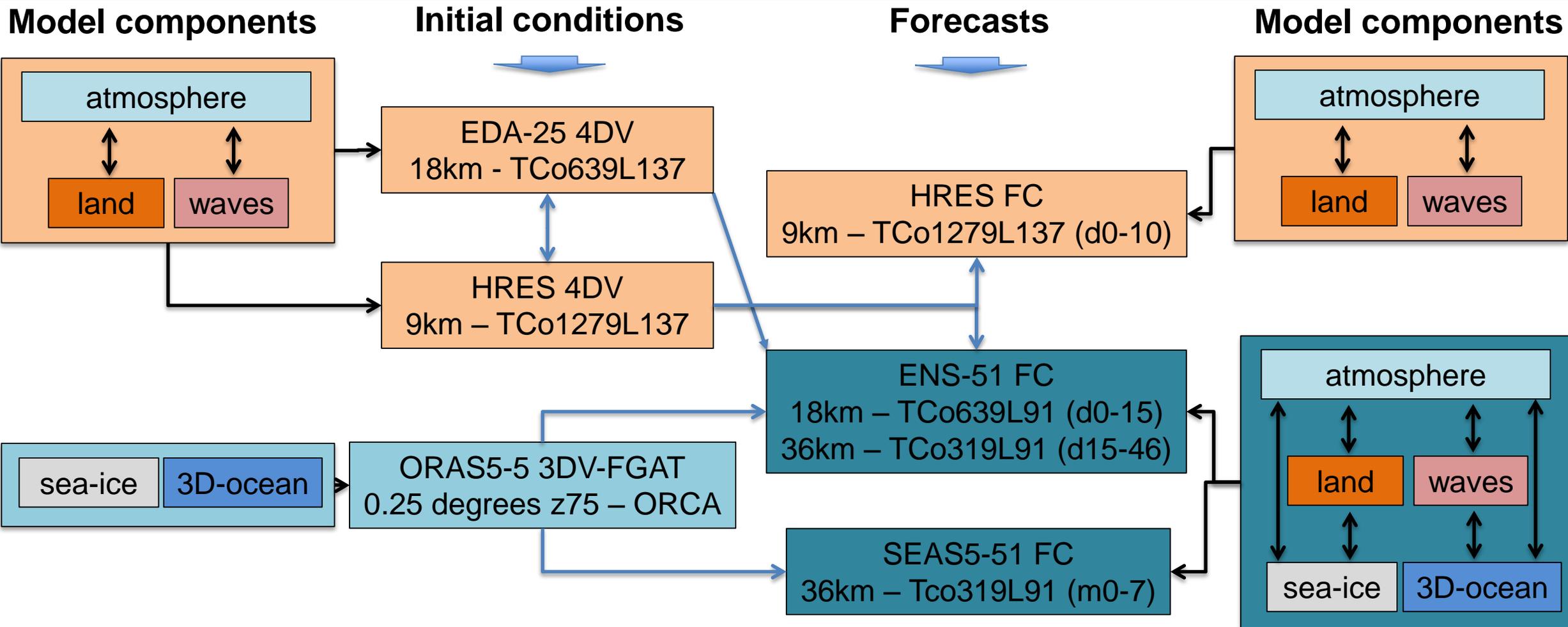
Yes, if we manage to keep improving the model and the estimation of the initial states, we should be able to extend the forecast skill horizon by **0.6-1.4 days in the next decade.**



Thank you for your attention ...

Extra slides ...

The ECMWF suites (Sept 2017)



Atmosphere grids: T_{Co} (cubic octahedral Gaussian reduced grid) or T_L (Gaussian linear grid)
 Ocean grid: ORCA (tri-polar grid)

The ECMWF suites (Sept 2017)

	Operational suite	Uncertainty sources		
		Obs	ICs	Model
HRES - 9km	T _{CO} 1279 L137 (0-10d)	--	--	--
4DVAR- 9km	T _{CO} 1279 (inner T _L 255/319/399) L137 (t0)	--	--	--
EDA – 18km	25 members: T _{CO} 639 L137 (t0)	δo	--	SPPT(1L)
ENS – 18km	51 members: T _{CO} 639 L91 (0-15d)	--	SVs ^{50*Nar} & EDA ²⁵	SPPT(3L) & SKEB
	T _{CO} 319 (~36km) L91 (15-46d) - 3D-ocean: NEMO ORCA25z75	--	ORAS5 ⁵	--
SEAS5 – 36km	51 members: T _{CO} 319L91 (1-7/13m)	--	SVs	SPPT(3L) & SKEB
	- 3D-ocean: NEMO ORCA25z75	--	ORAS5 ⁵	--

T_{CO} – Cubic octahedral Gaussian reduced grid

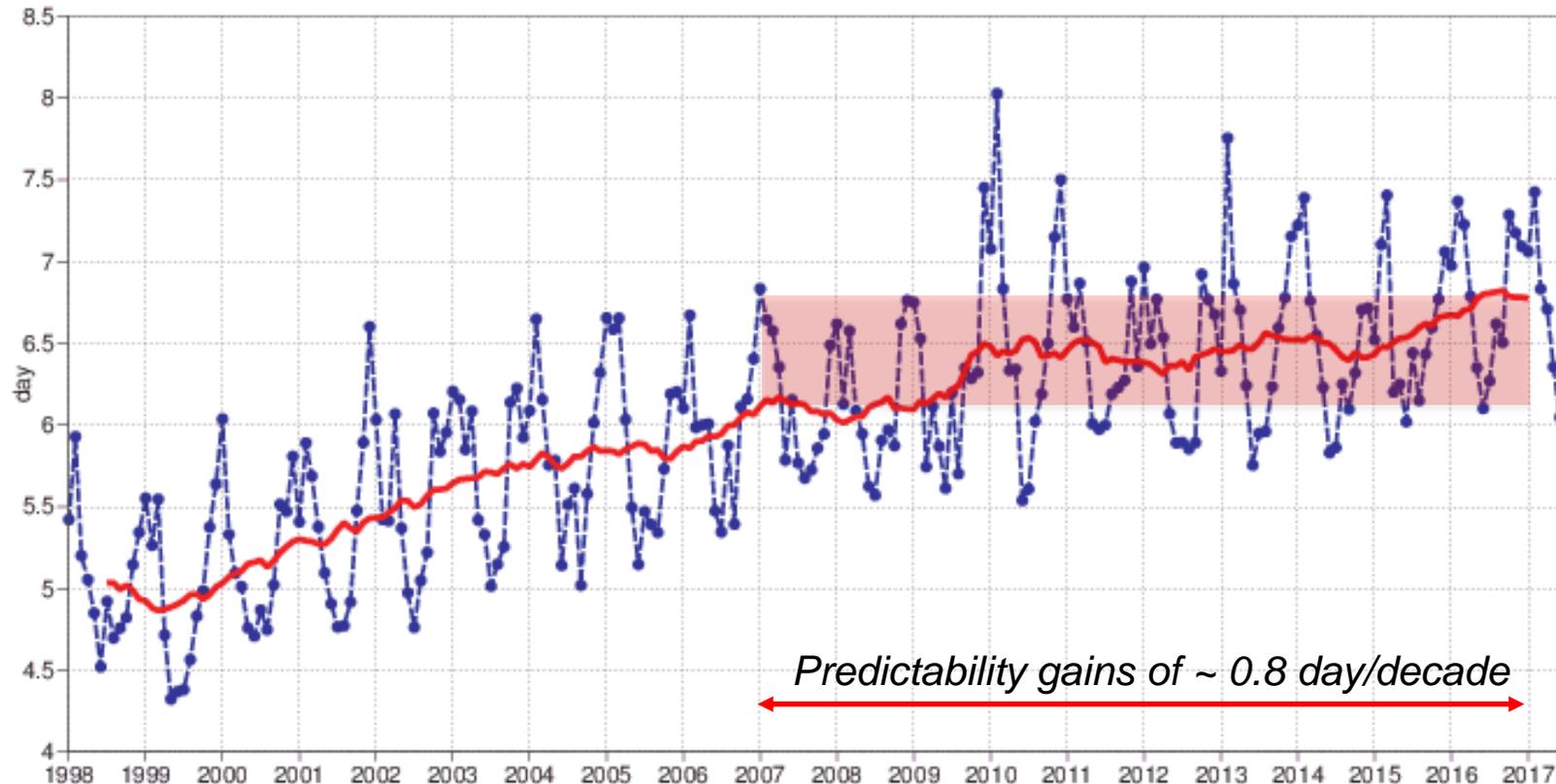
T_L – Gaussian linear grid

The quality of our forecasts: HRES 500 hPa geop height

HRES headline score: anomaly correlation for the 500 hPa height over the northern hemisphere.

500hPa geopotential
Lead time of Anomaly correlation reaching 80%
NHem Extratropics (lat 20.0 to 90.0, lon -180.0 to 180.0)

— score 12mMA reaches 80%
-●- score reaches 80%



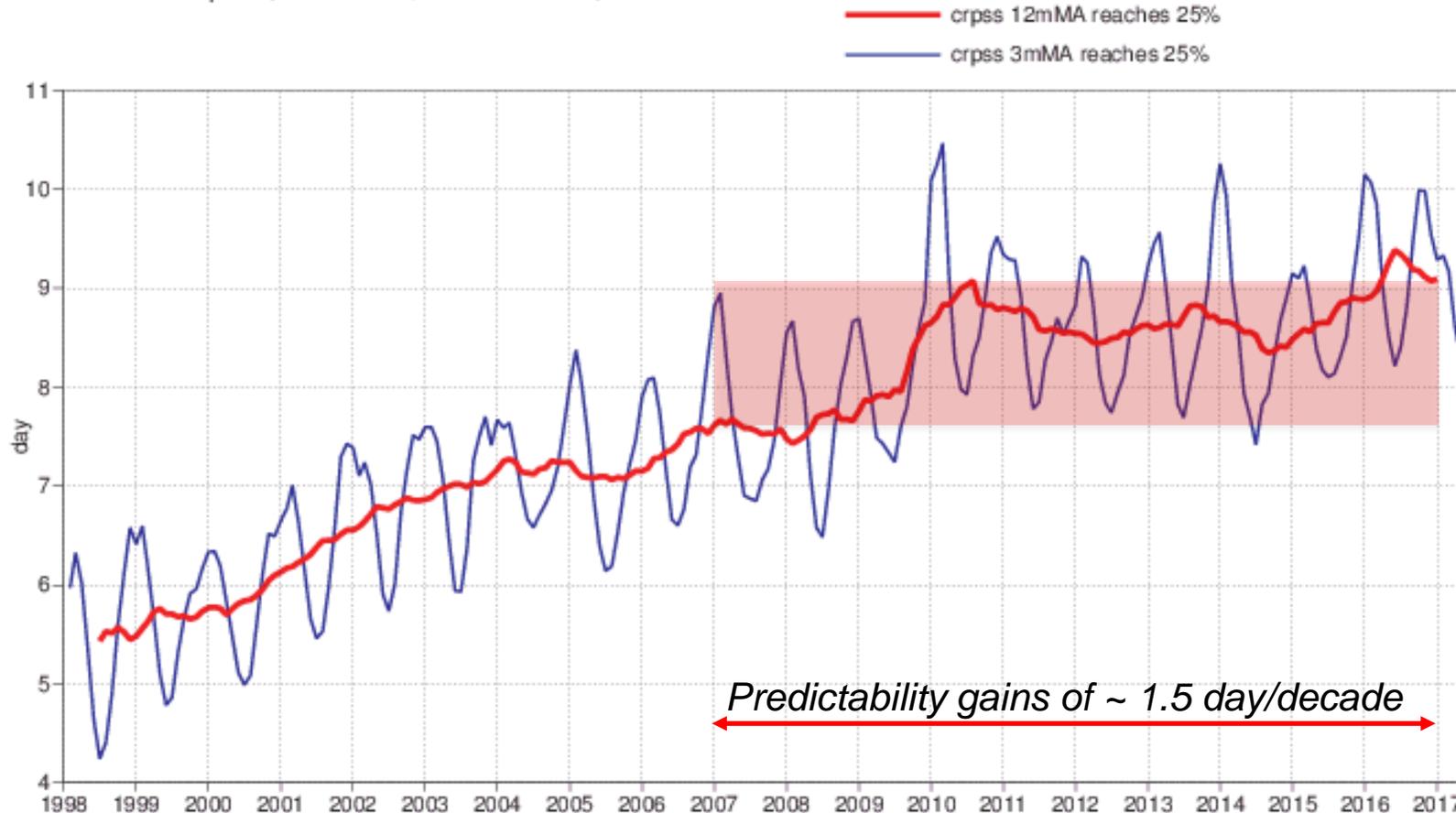
2007-2017:
+0.8d HRES Z500 NH

The quality of our forecasts: ENS Temp at 850 hPa

Results indicate that the reliability and accuracy of the ECMWF medium-range ensemble (ENS) has been increasing continuously, with gains of 1.5-2.0 days/decade.

850hPa temperature
Lead time of Continuous ranked probability skill score reaching 25%
NHem Extratropics (lat 20.0 to 90.0, lon -180.0 to 180.0)

2007-2017:
+0.8d HRES Z500 NH
+1.5d ENS T850 NH

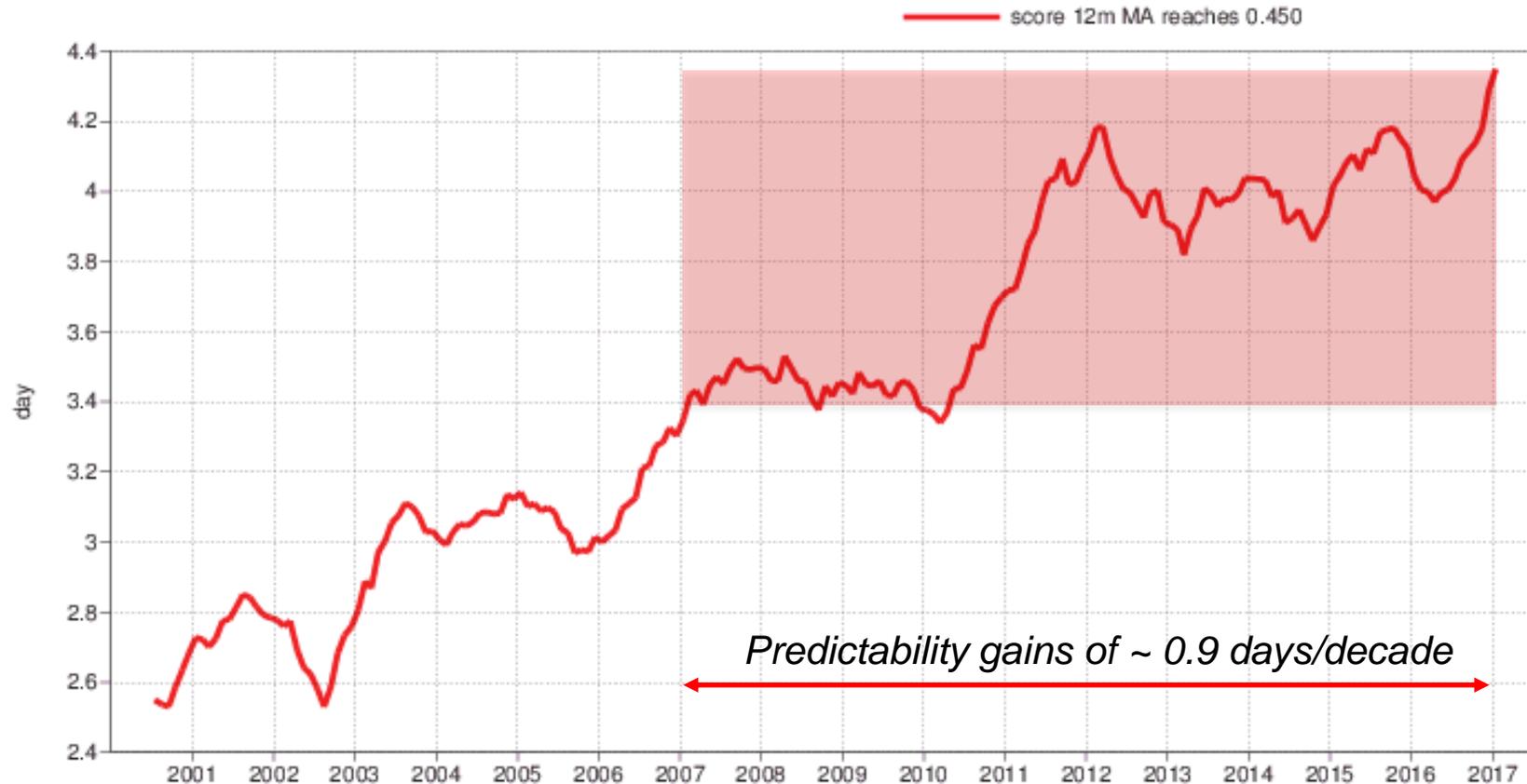


The quality of our forecasts: HRES precipitation forecast

Supplementary score for HRES forecasts: 1-SEEPS (Stable Equitable Error in Probability Space) score for 24-h precipitation totals in the northern extra-tropics (verified against synop observations).

total precipitation
1-SEEPS
Extratropics (lat -90 to -30.0 and 30.0 to 90, lon -180.0 to 180.0)

2007-2017:
+0.8d HRES Z500 NH
+1.5d ENS T850 NH
+0.9d HRES TP NH

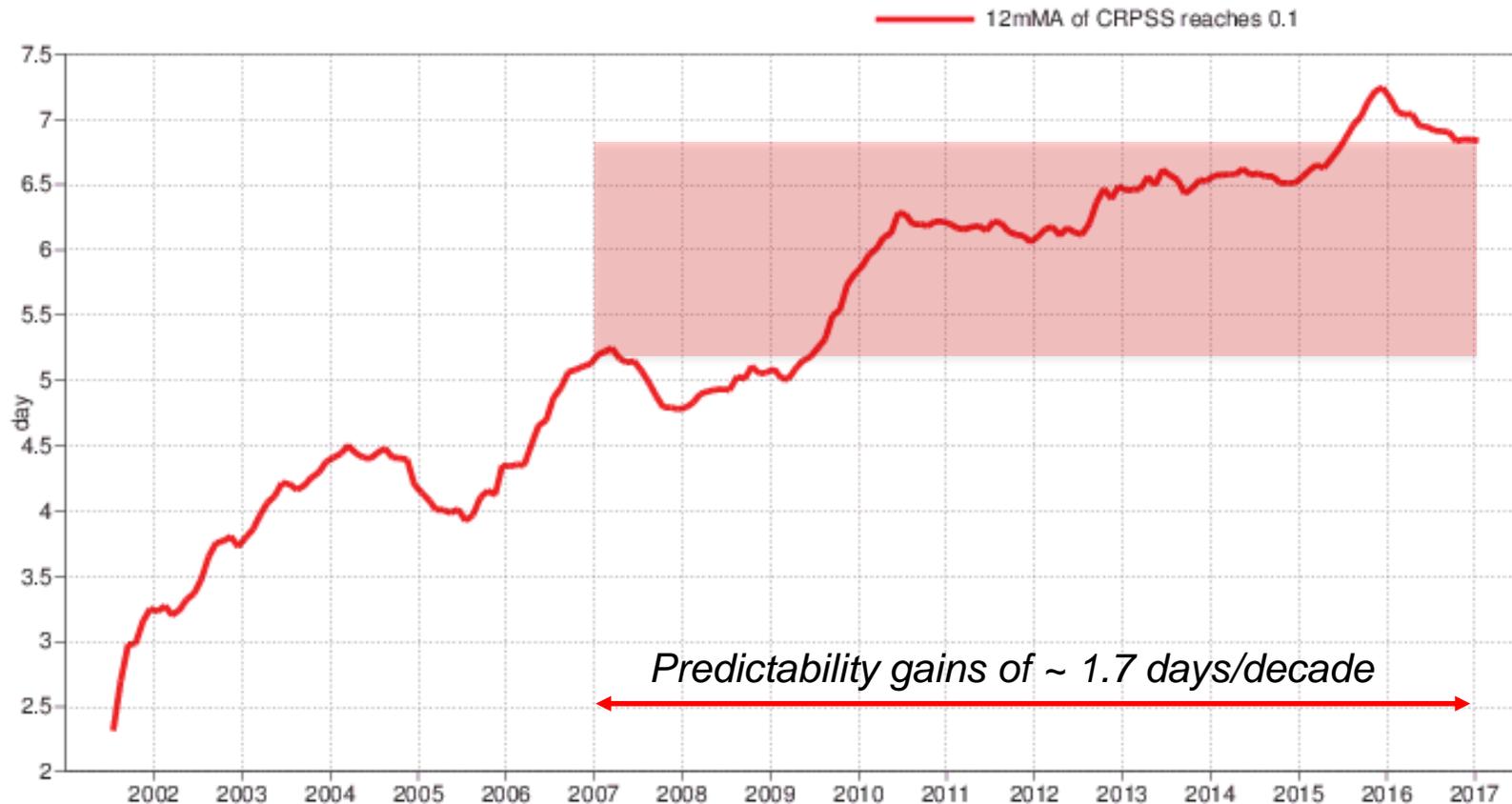


The quality of our forecasts: ENS precipitation forecasts

Supplementary score for ENS forecasts: Continuous Ranked probability Skill Score (CRPSS) for 24-h precipitation totals in the northern extra-tropics (verified against synop observations).

total precipitation
Continuous ranked probability skill score
Extratropics (lat -90 to -30.0 and 30.0 to 90, lon -180.0 to 180.0)

2007-2017:
+0.8d HRES Z500 NH
+1.5d ENS T850 NH
+0.9d HRES TP NH
+1.7d ENS TP NH

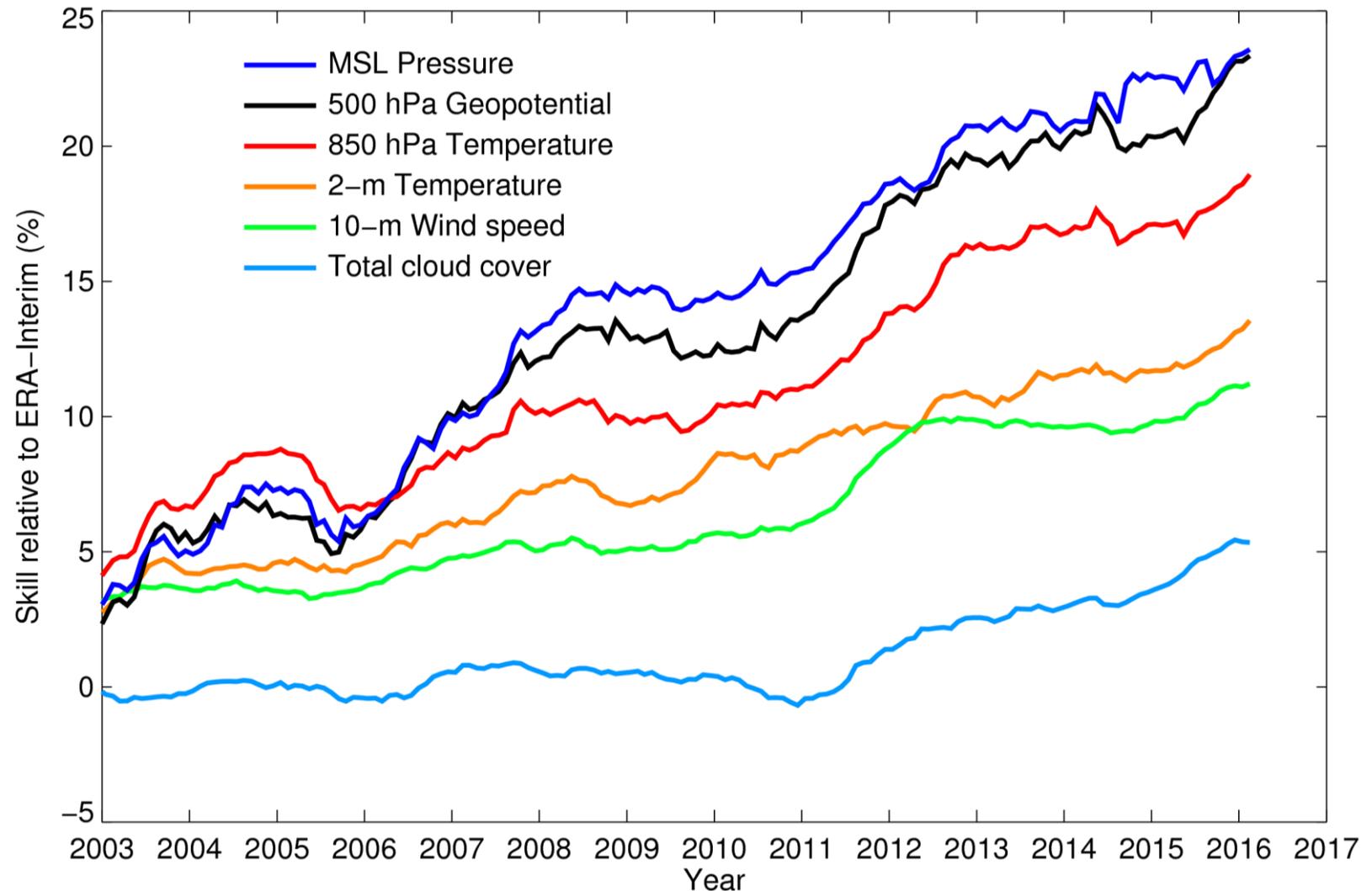


We have been improving also the prediction of surface weather

Improvements can be detected not only in the upper levels but also in surface weather variables such as cloud cover, wind and 2-m temperature.

Improvements are due to a mix of upgrades in model, data assimilation, use of observations and resolution.

Everything contributes!!

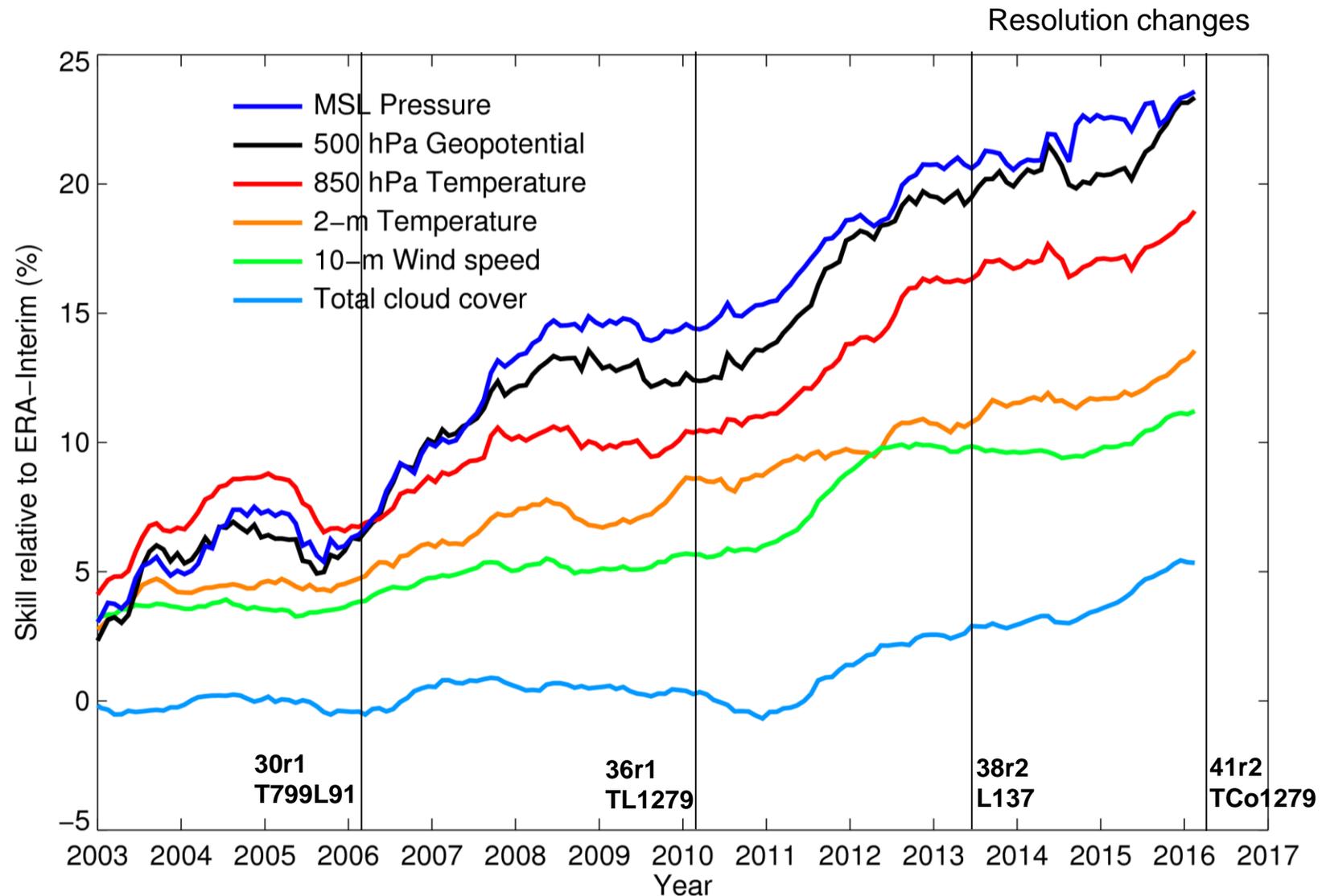


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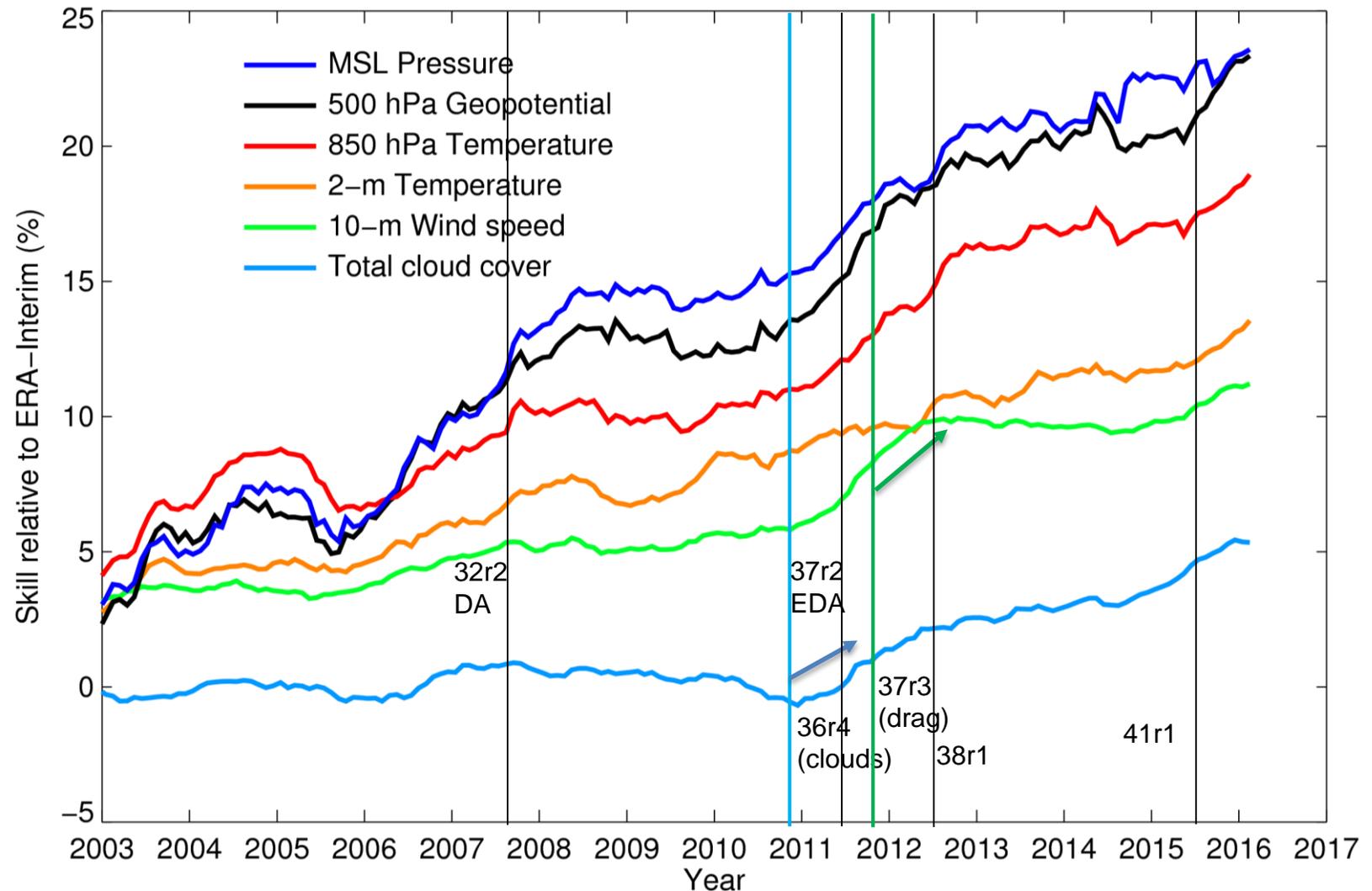
We have been improving also the prediction of surface weather

DA and model changes

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Everything contributes!!

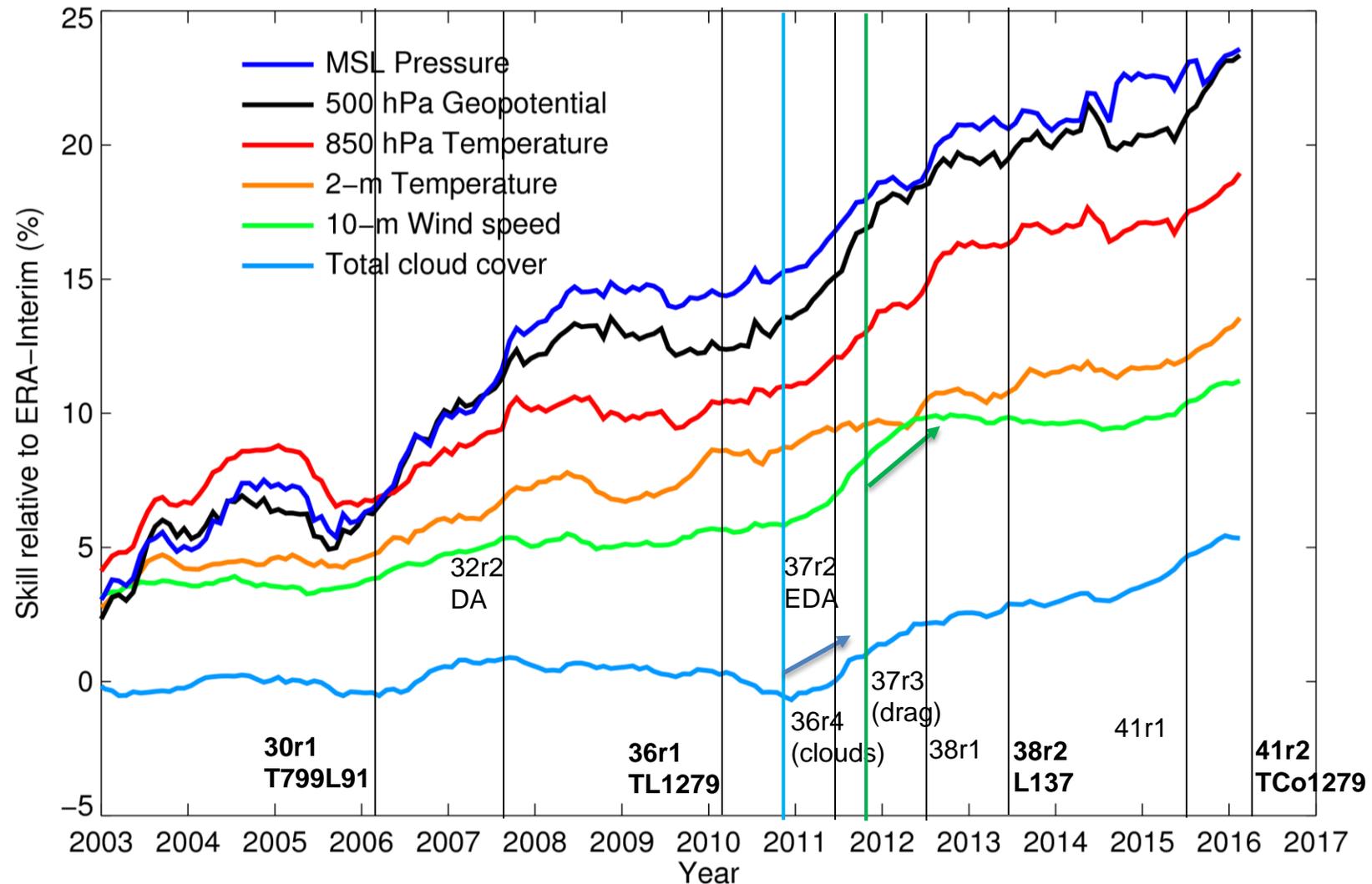


We have been improving also the prediction of surface weather

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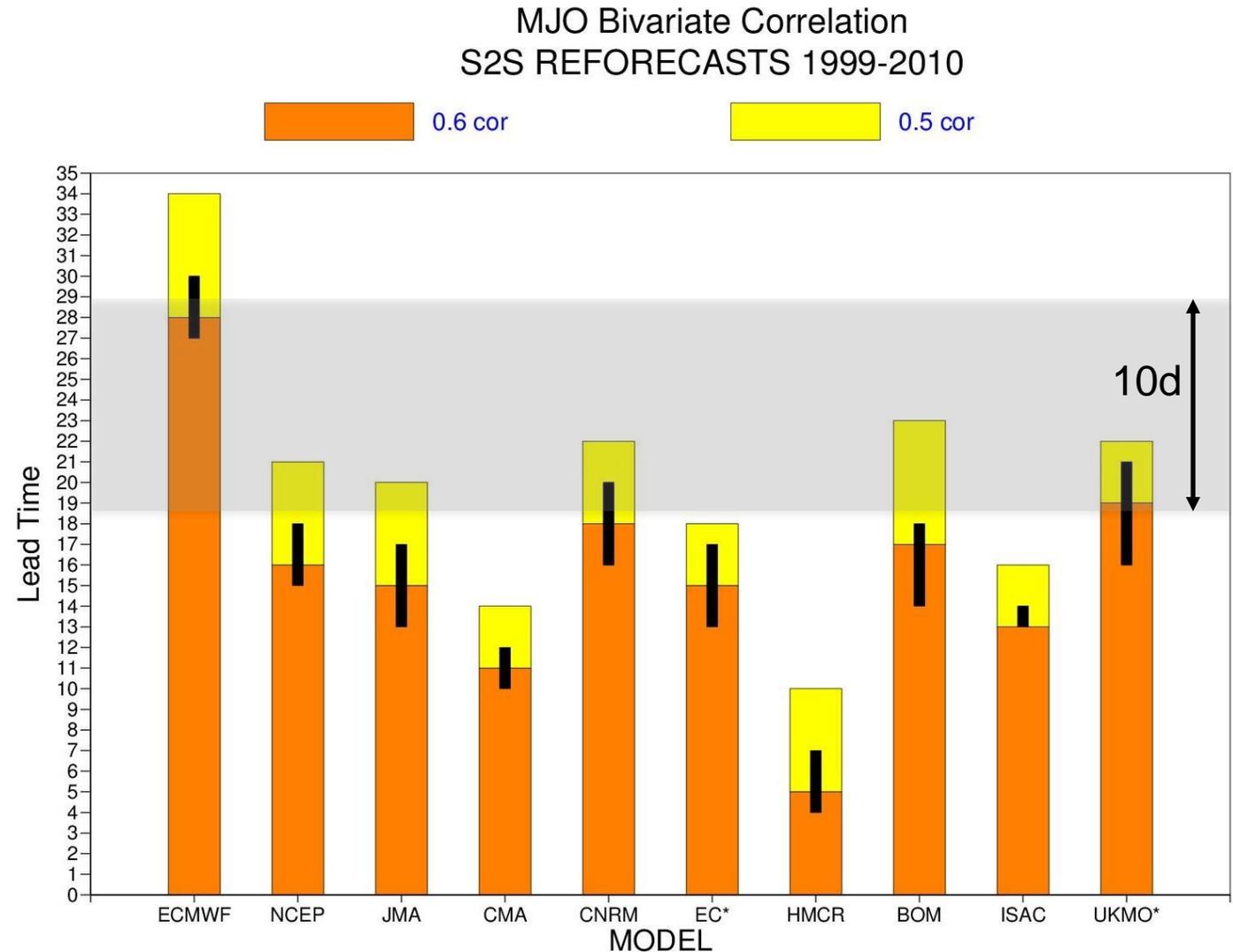
Everything contributes!!



Since 2002 we have also been producing monthly forecasts

Comparison of the forecast lead-time (in days) when the prediction of the MJO reaches 0.6 correlation (orange) and 0.5 correlation (yellow).

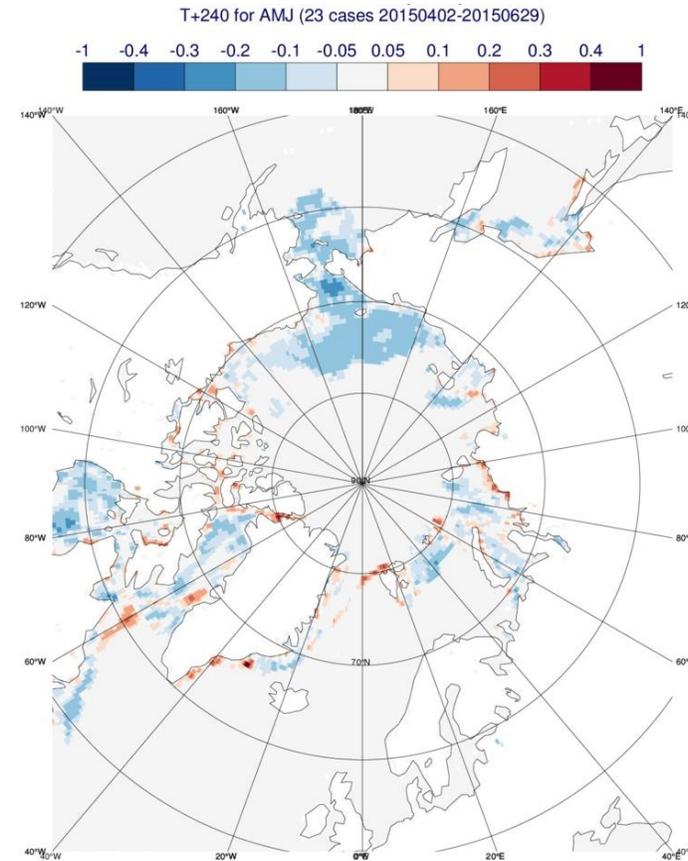
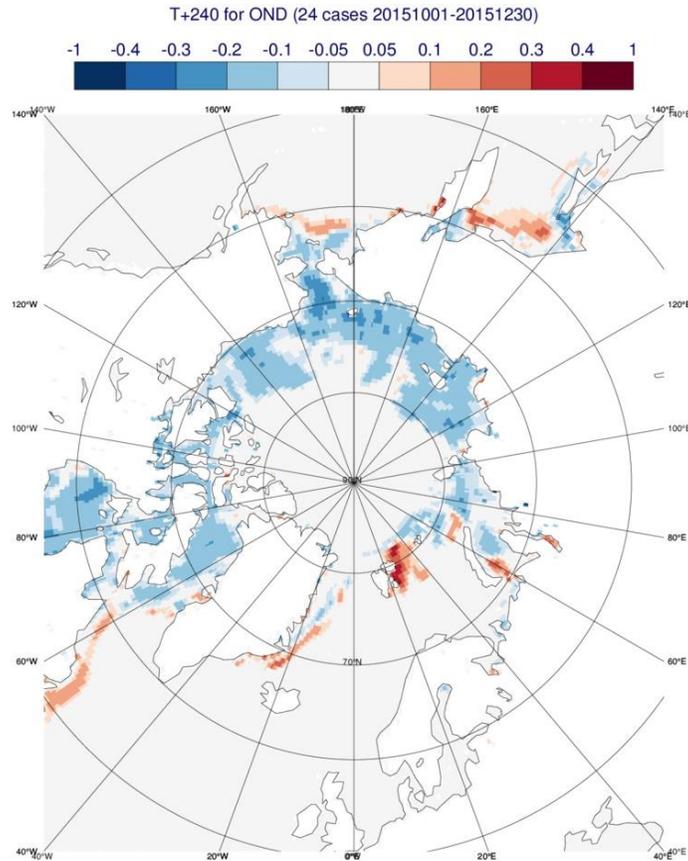
The data are from the Sub-seasonal to Seasonal (S2S) WWRP/WCRP WMO project.



Prognostic sea ice fraction

41R2: sea ice fraction fixed - 43R1: sea ice fraction predicted with NEMO/LIM2

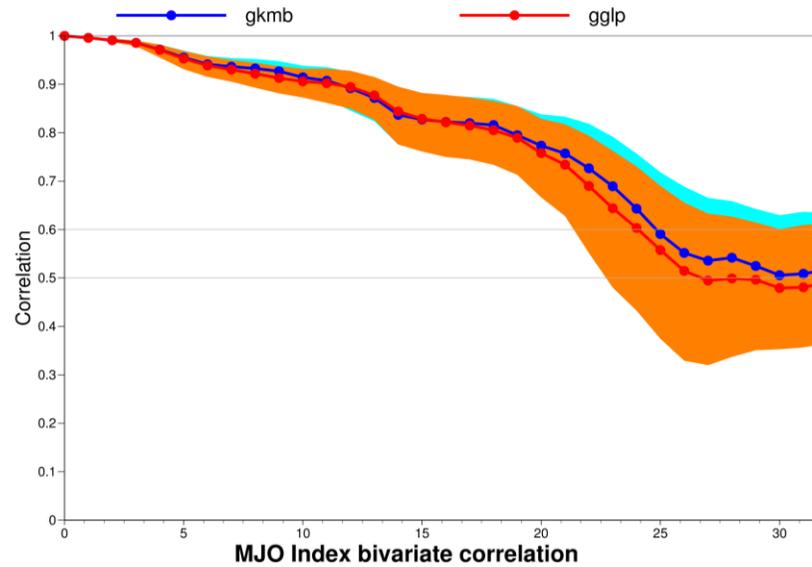
The figures show the Reduction in RMSE of ensemble-mean forecast of sea ice fraction for 10-day forecast



ENS MJO

- MJO: Nice improvement in MJO skill scores
- Correlations are higher (for both PC1 and PC2, but mostly PC1)
- RMS error is also reduced
- MJO spread is improved which makes it closer to RMS error

MJO Index - PC1 correlation



MJO Index - PC2 correlation

