Representation of Model Uncertainty in Ensemble Prediction Systems

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ECMWF

With acknowledgement to:

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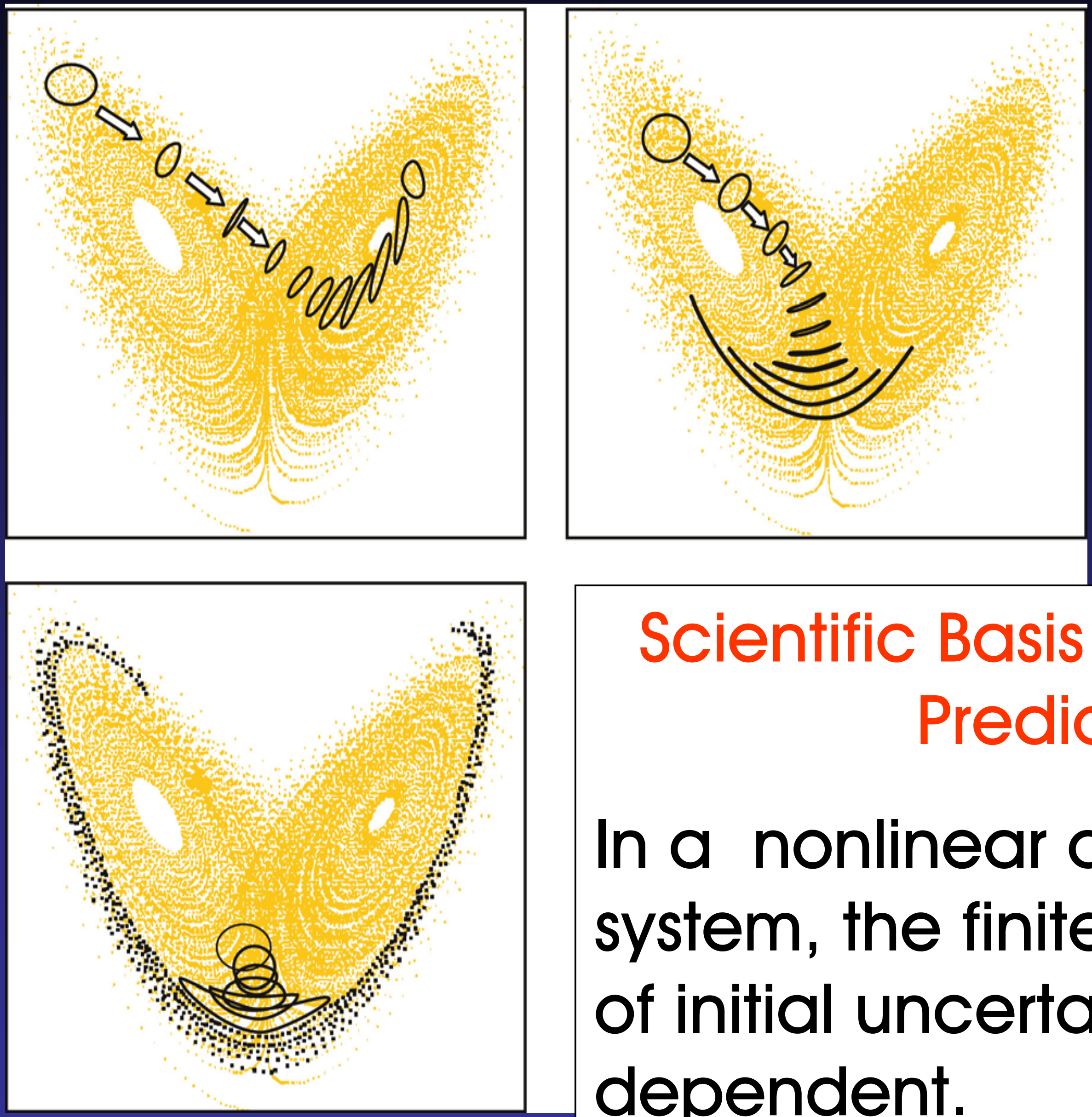
Paco Doblas-Reyes

Renate Hagedorn

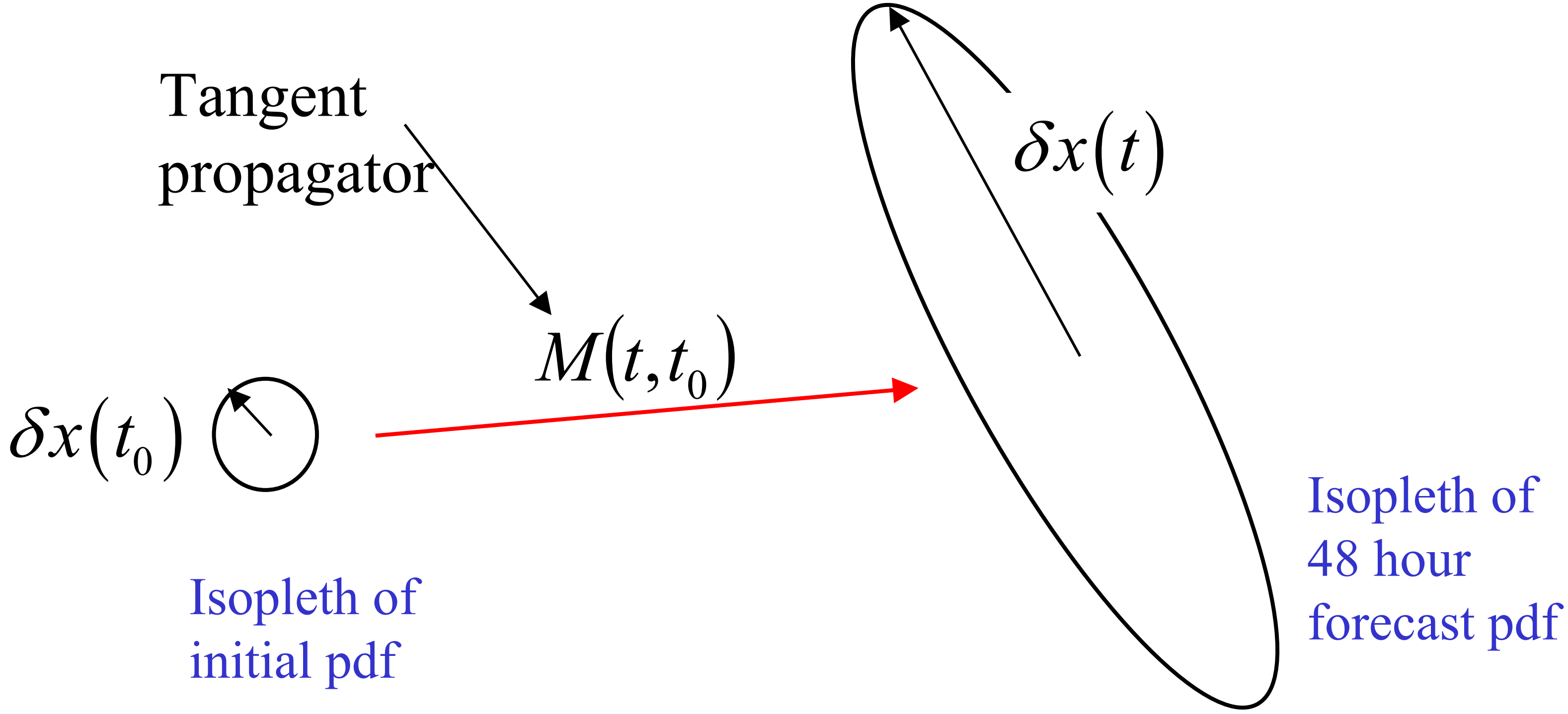
Magdalena Balmaseda

Glenn Shutts



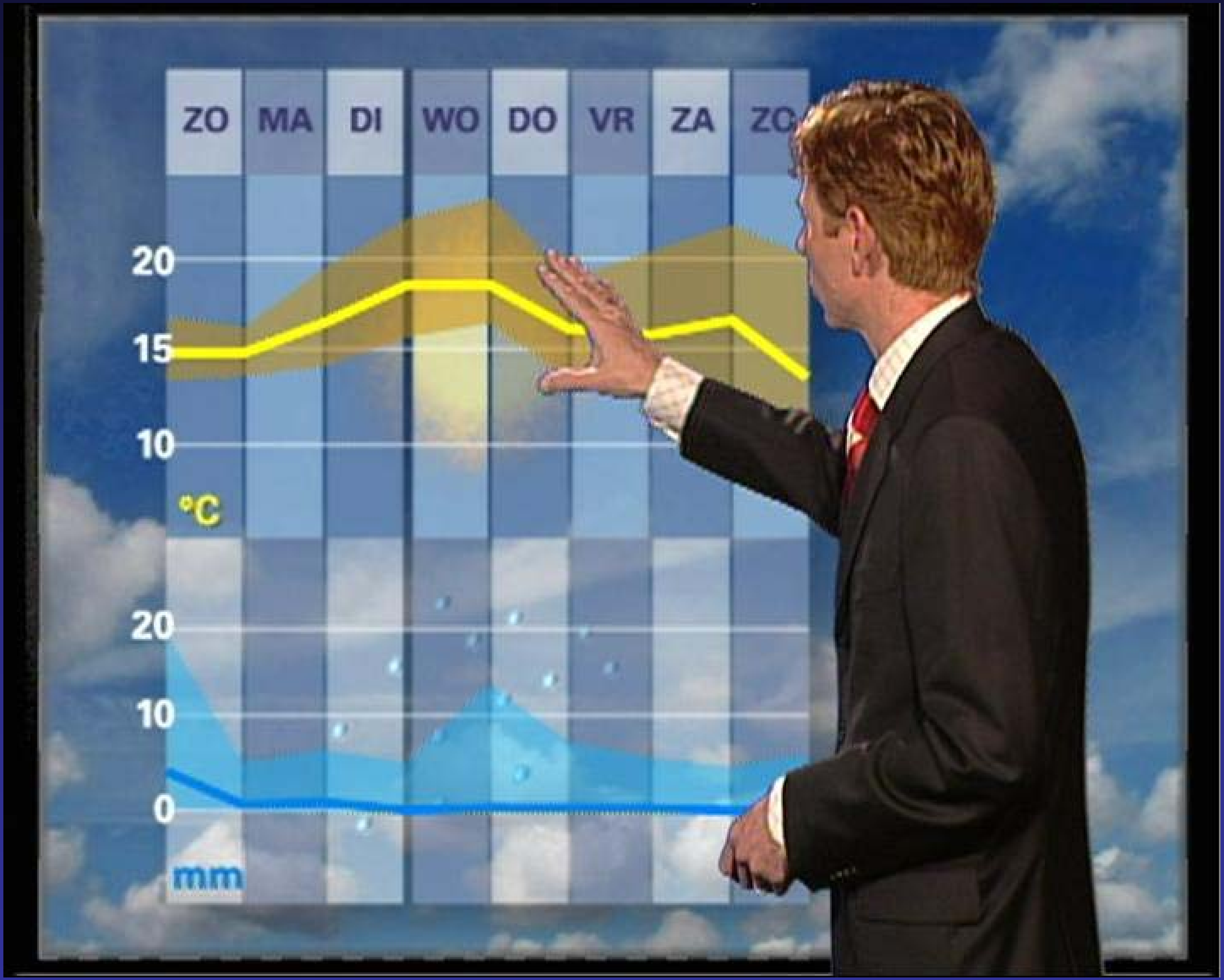
Scientific Basis for Ensemble Prediction

In a nonlinear dynamical system, the finite-time growth of initial uncertainties is flow dependent.

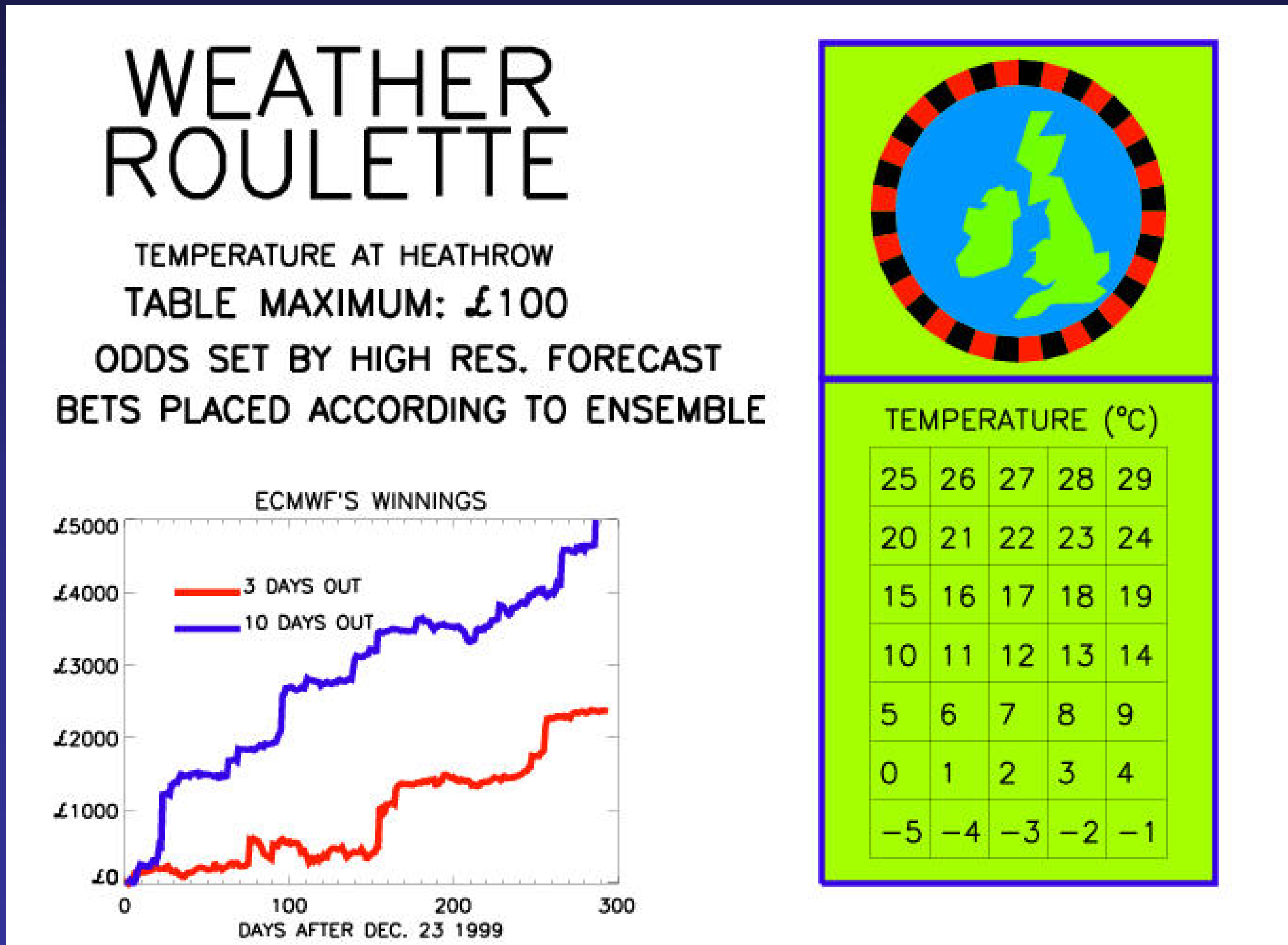


ECMWF EPS initial perturbations evolve to the leading major axes of the pdf of short-range forecast error (singular vectors of *M*).

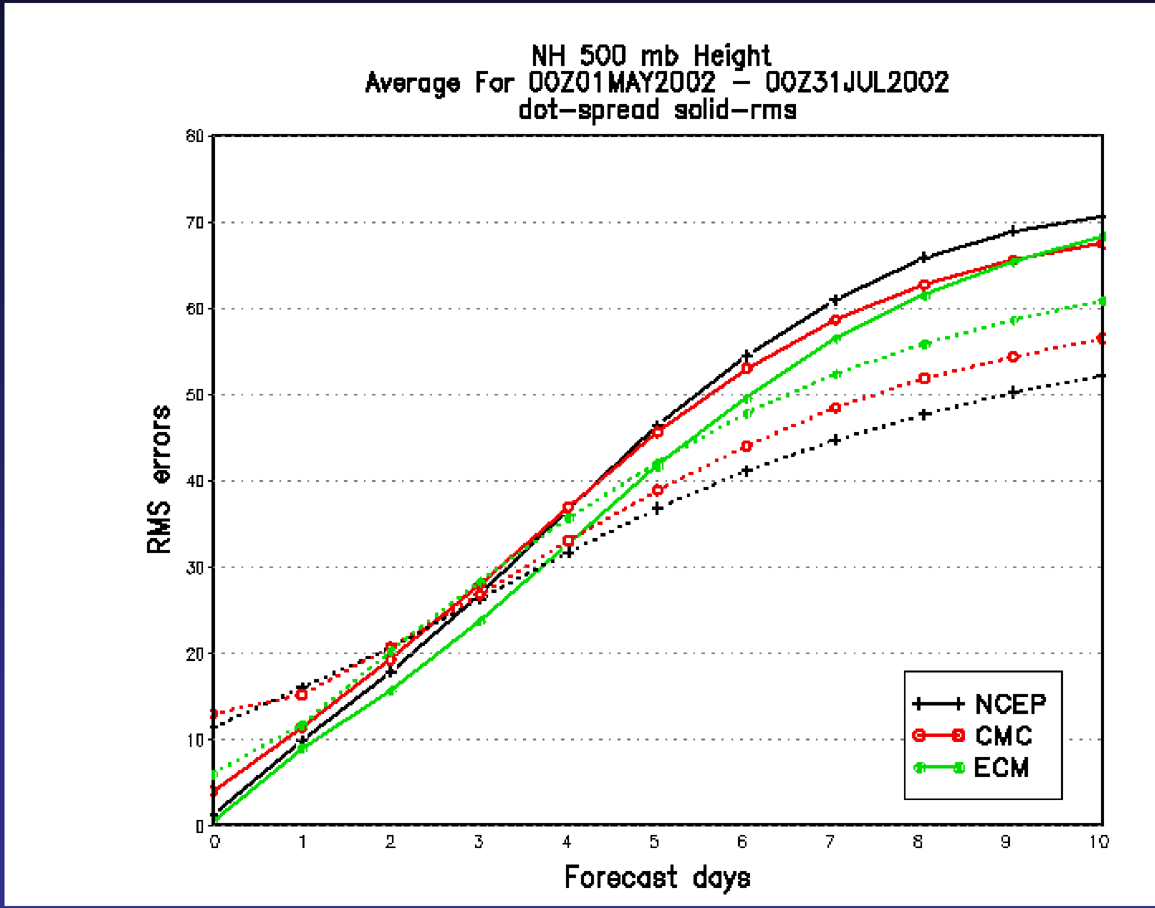
EPS appearing on Dutch TV



Value of EPS over high-res deterministic forecast for financial weather-derivative trading based on Heathrow temperature (Roulston and Smith, London School of Economics, 2003)



EPS Systems Start to Lack Spread After D+5

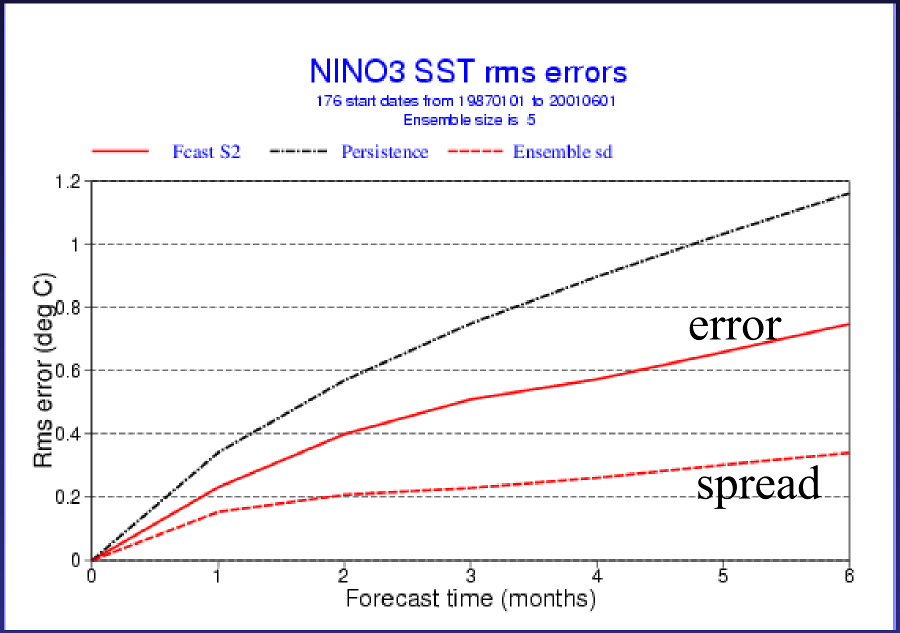


error

spread

Figure 6. May-June-July 2002 average RMS error of the ensemble-mean (solid lines) and ensemble standard deviation (dotted lines) of the EC-EPS (green lines), the MSC-EPS (red lines) and the NCEP-EPS (black lines). Values refer to the 500 hPa geopotential height over the northern hemisphere latitudinal band 20º-80ºN.

Lack of Spread Particularly Noticeable for Extended-range Prediction….



ECMWF Coupled Model

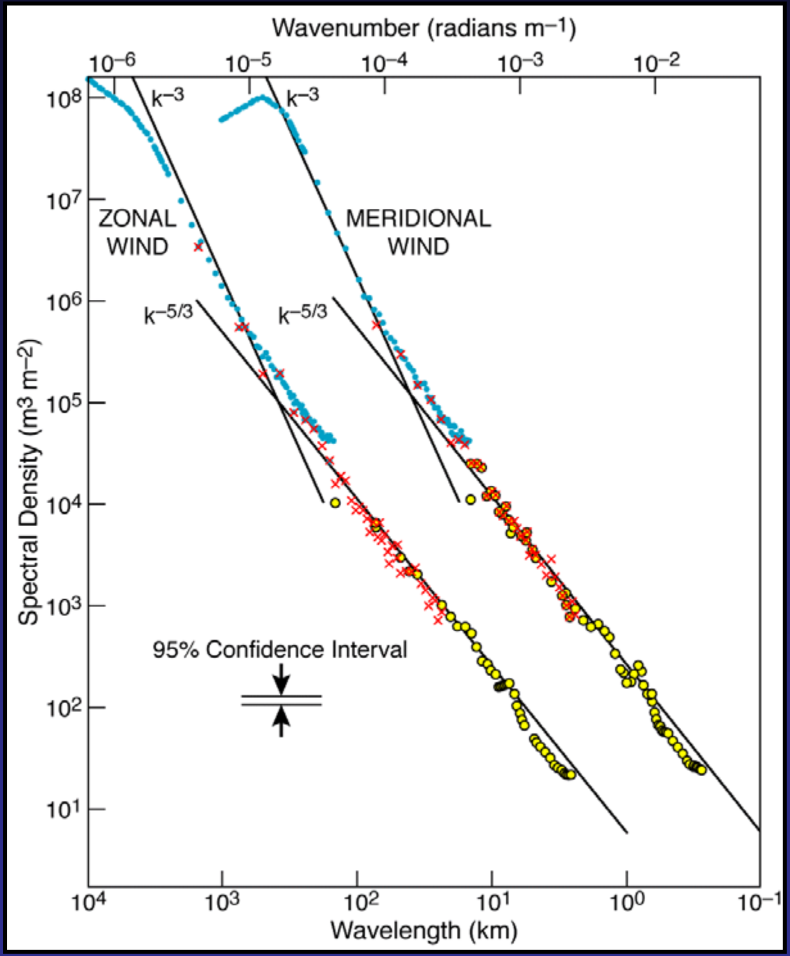
…due to inadequate representation of model uncertainty in the ensemble formulation

Why are models uncertain?

We know the equations of weather and climate well as PDEs – the uncertainties arise in converting these PDEs to ODEs

Parametrisations motivated by statistical mechanics (eg molecular diffusion), but…

Wavenumber spectra of zonal and meridional velocity composited from three groups of flight segments of different lengths. The three types of symbols show results from each group. The straight lines indicate slopes of –3 and –5/3. The meridional wind spectra are shifted one decade to the right. (after *Nastrom et al,* 1984).



…there is no scale separation between resolved and unresolved scales at NWP truncations

Representations of model uncertainty:

- Multi-model ensembles
- Perturbed parameters
- Stochastic physics
- Stochastic-Dynamic Sub-grid models
- Forced and parametric singular vectors

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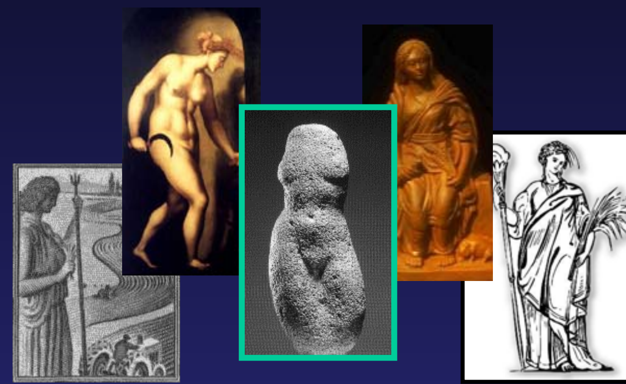


Development of a

European Multi-Model Ensemble System

for

Seasonal to Interannual Prediction

DEMETER Multi-model ensemble system

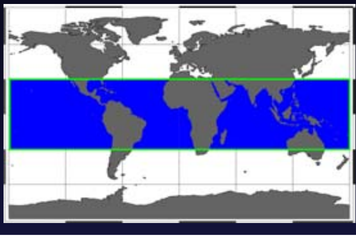
- 7 global coupled ocean-atmosphere climate models

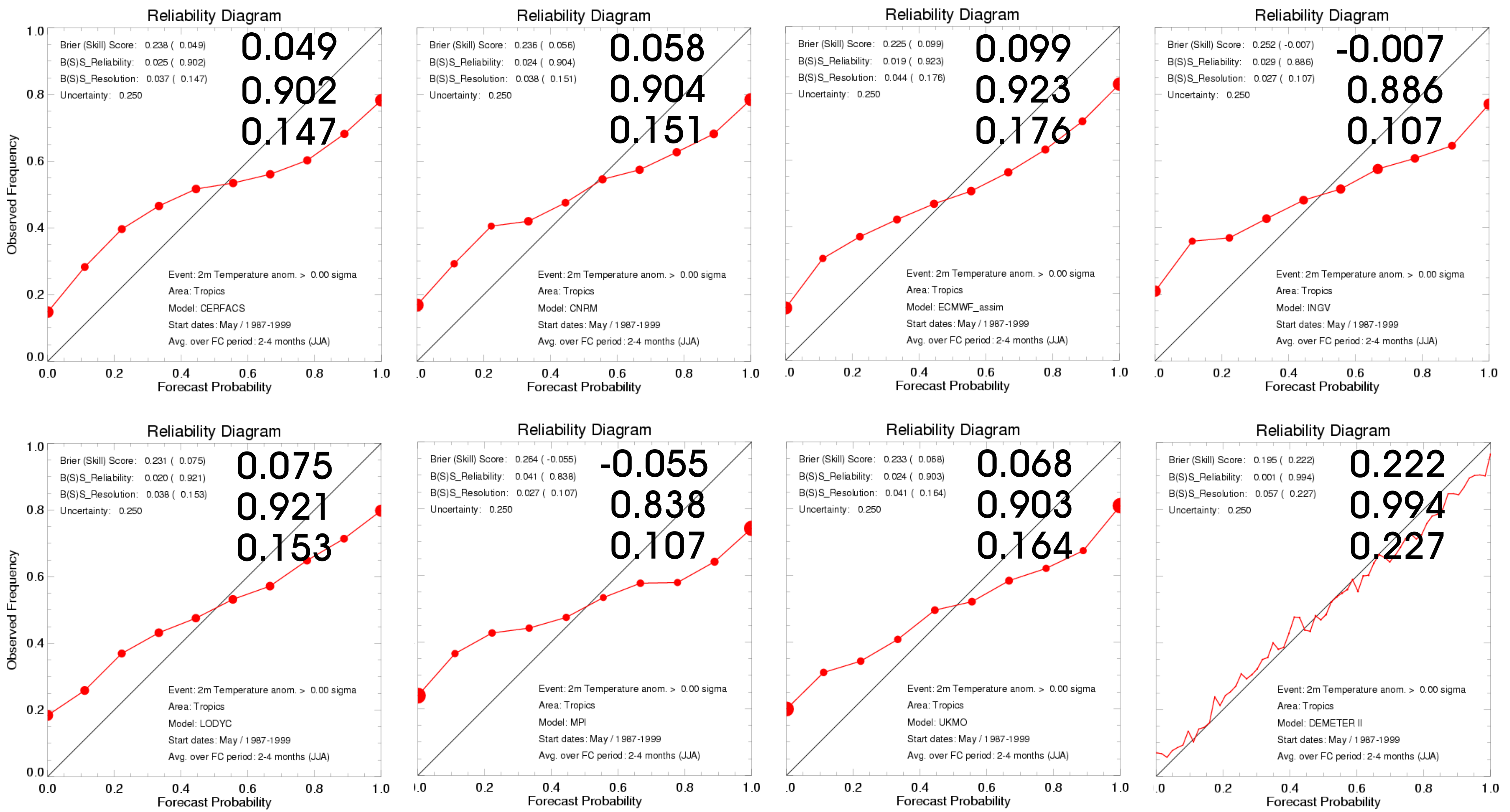
Partner	Atmosphere	Ocean
ECMWF	IFS	HOPE
LODYC	IFS	OPA 8.3
CNRM	ARPEGE	OPA 8.1
CERFACS	ARPEGE	OPA 8.3
INGV	ECHAM-4	OPA 8.2
MPI	ECHAM-5	MPI-OM1
UKMO	HadCM3	HadCM3

9 member ensembles
ERA-40 initial conditions
SST and wind perturbations
4 start dates per year
6 months hindcasts

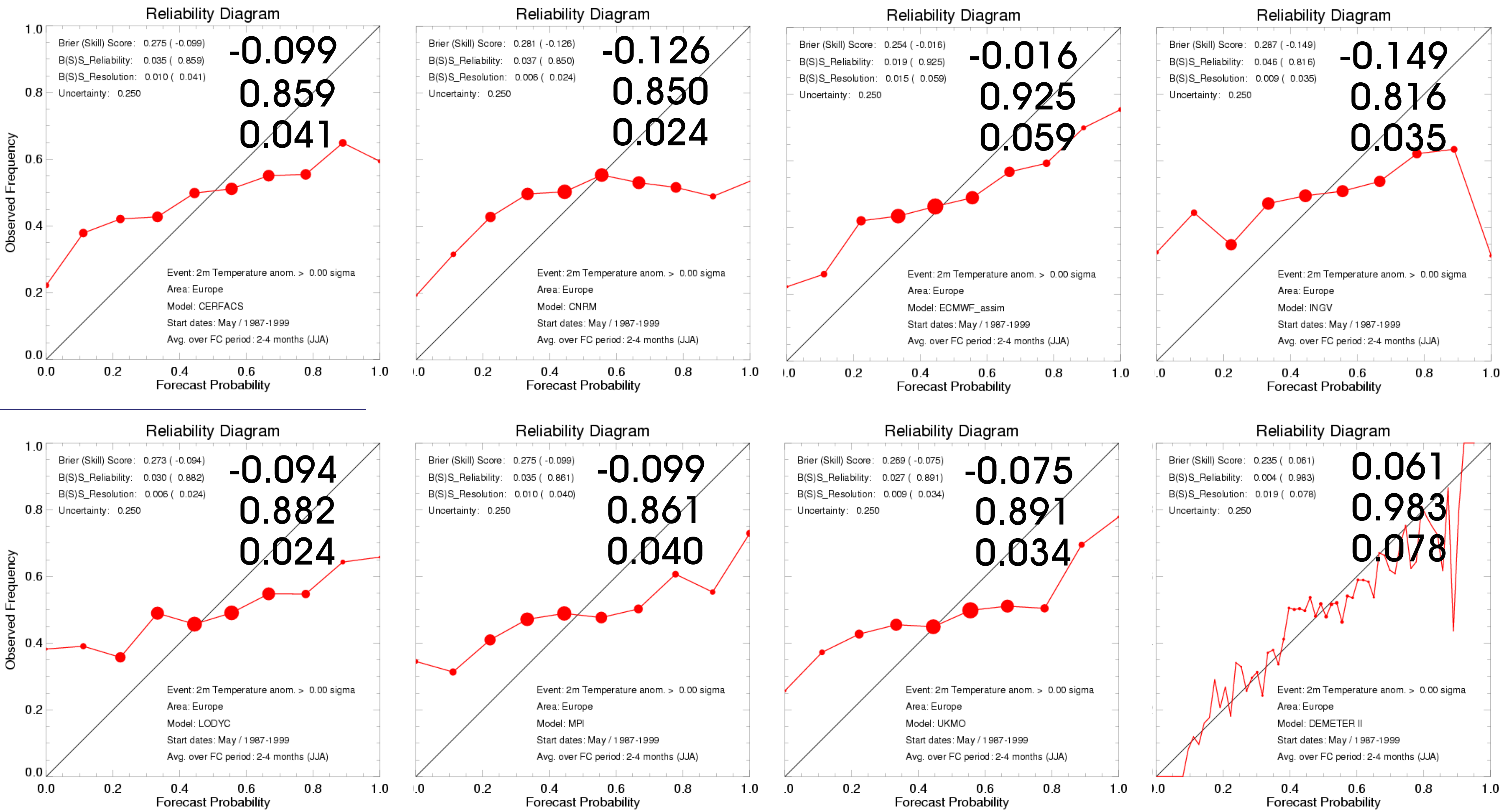
- Hindcast production for: 1987-1999 (1958-2001)

Reliability: 2m-Temp.>0

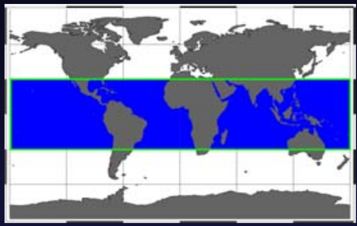


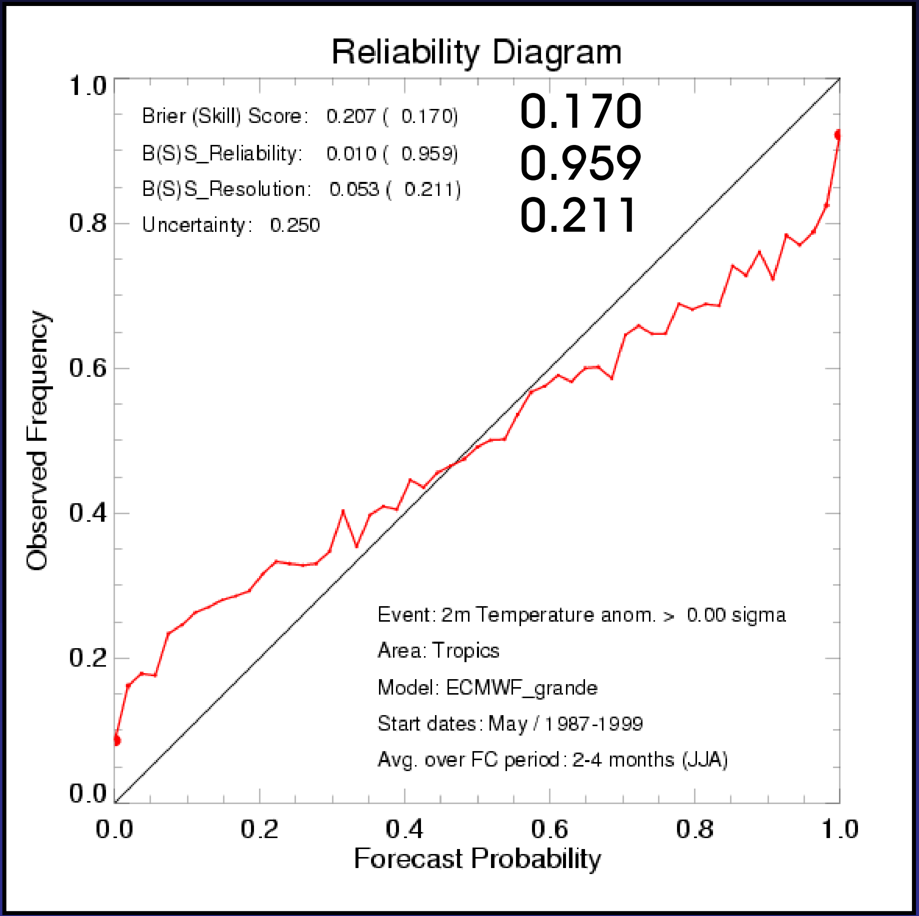


Reliability: 2m-Temp.>0

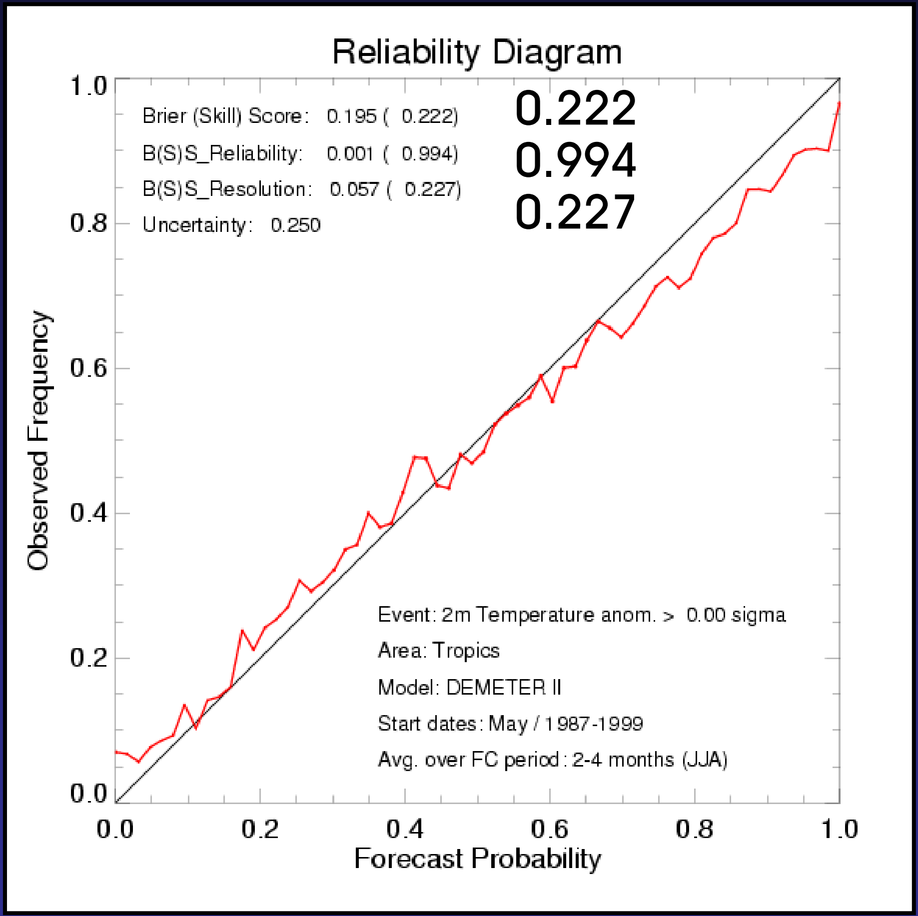


Reliability: 2m-Temp.>0



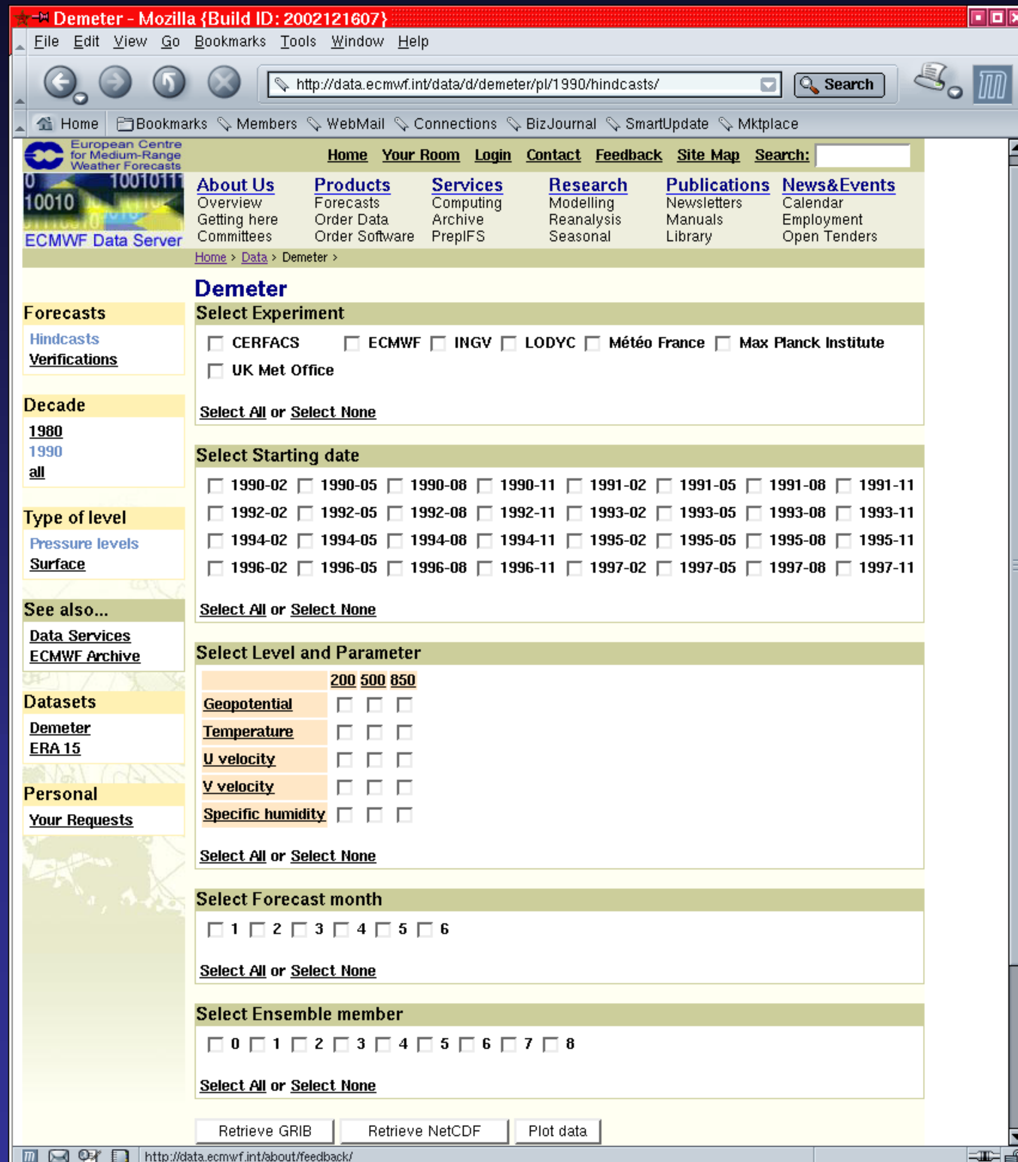


single-model (54 members)

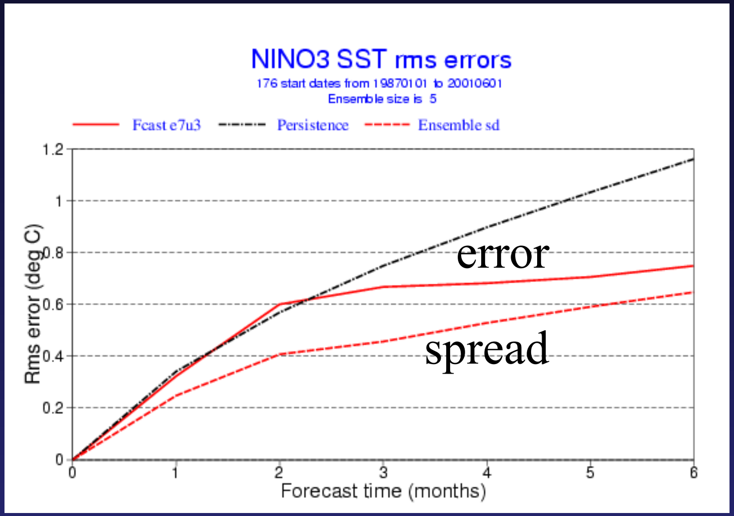


multi-model

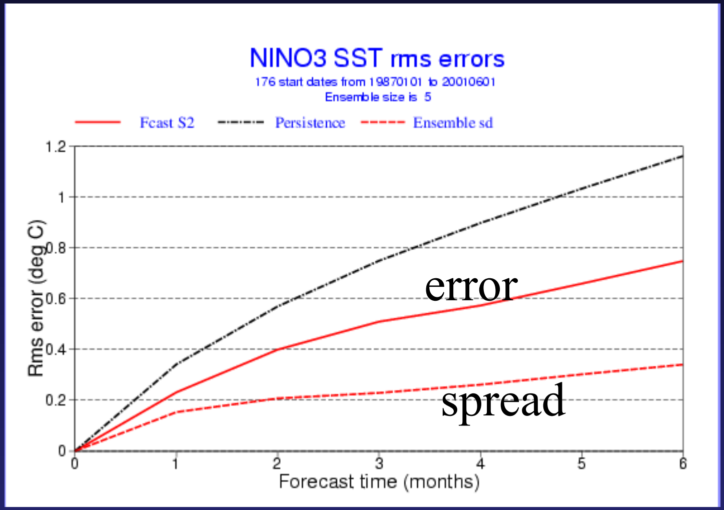
http://www.ecmwf.int



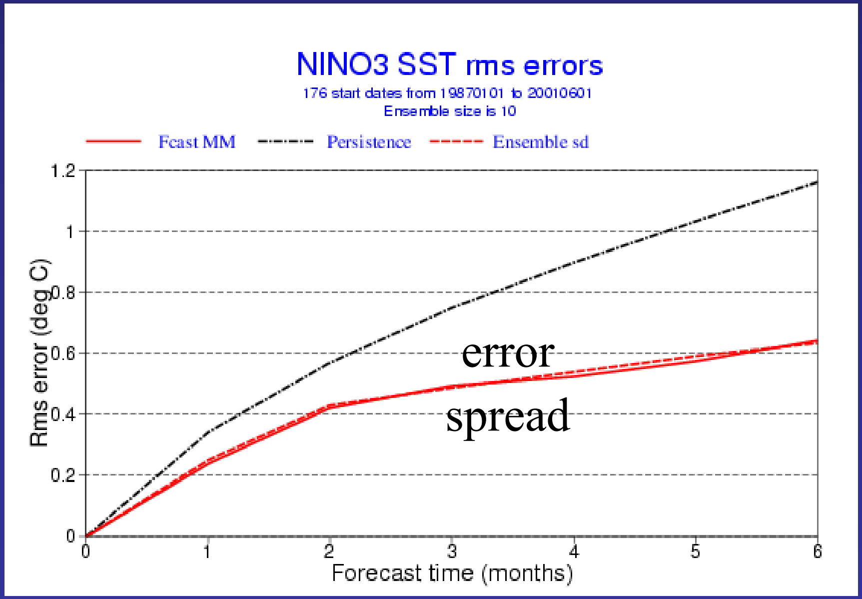
Met Office Coupled Model



ECMWF Coupled Model



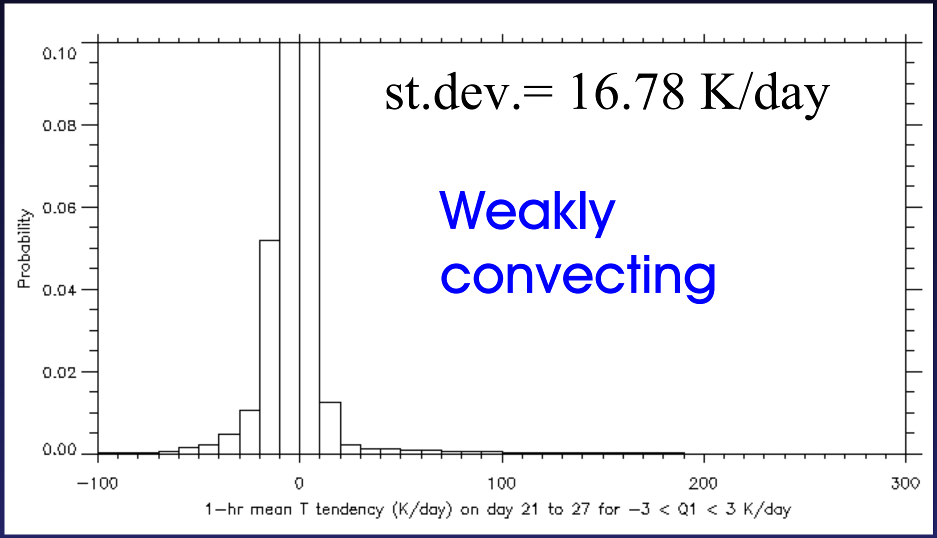
Multi-Model

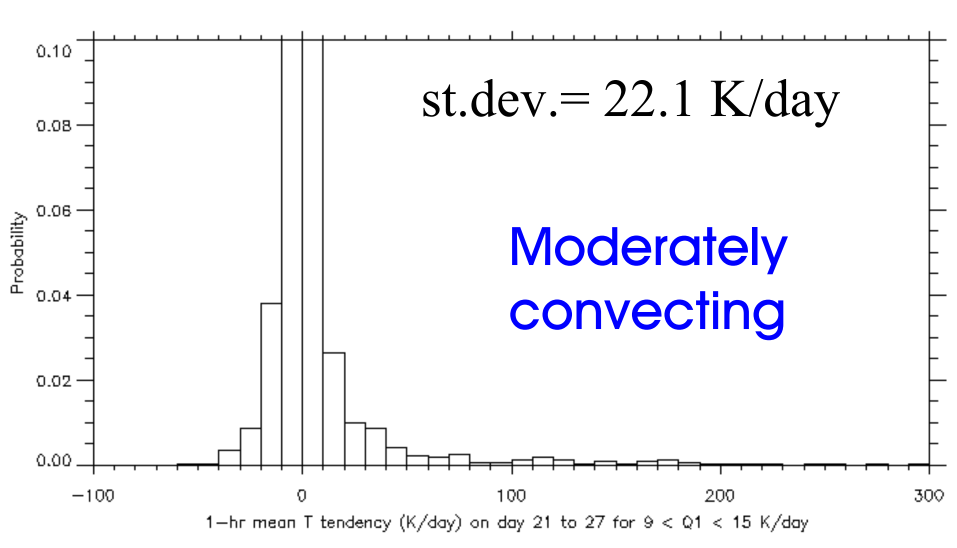


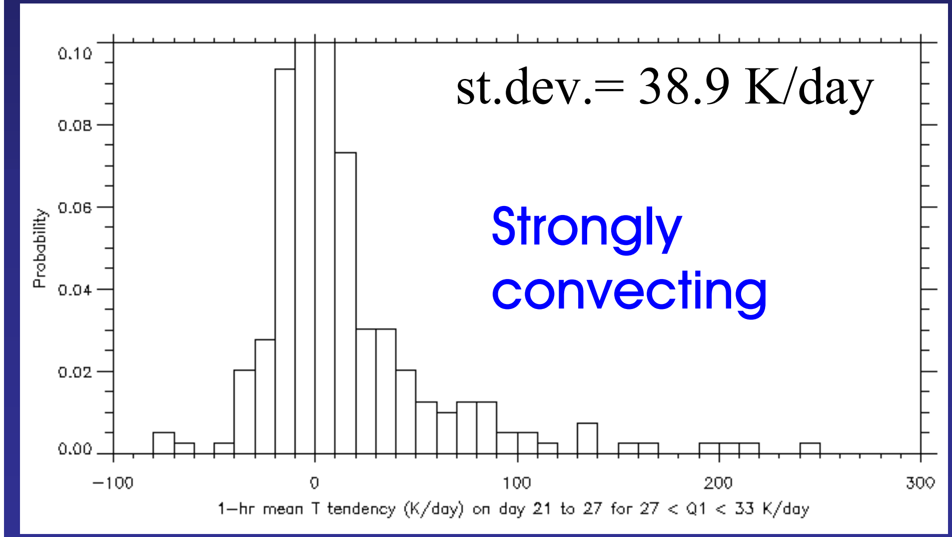
- Whilst multi-model ensembles provide a reasonable pragmatic approach to the problem of representing model error, this approach lacks clear scientific underpinning.
- Specifically, in multi-model (or perturbed parameter) ensembles, there is manifestly no representation of common model deficiencies (eg inadequate variability associated

- Calculate exact PDF of sub-grid temperature tendencies in a coarse-grained (~50km) grid box based on output from a cloud-resolving (~1km) model treated as "truth".
- PDFs are constrained such that parametrised tendencies based on coarse-grain input fields lie within boxes of width 6K/day.

Glenn Shutts (personal communication)







Width of pdf $\propto$ parametrised tendency

ECMWF stochastic physics scheme

$$\dot{X} = D + P + \varepsilon P$$

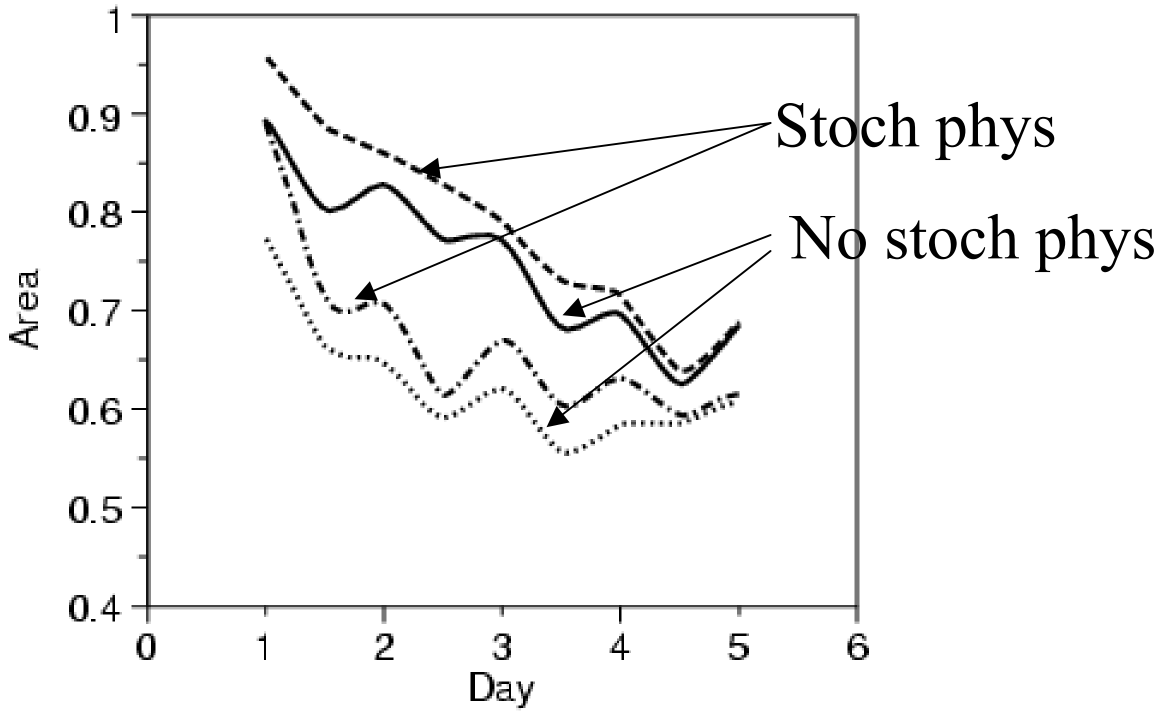
ε is a stochastic variable, drawn from a uniform distribution in [-0.5, 0.5], constant over time intervals of 6hrs and over 10x10 lat/long boxes

Buizza, Miller and Palmer, 1999

Stochastic forcing $\propto$ parametrised tendenc

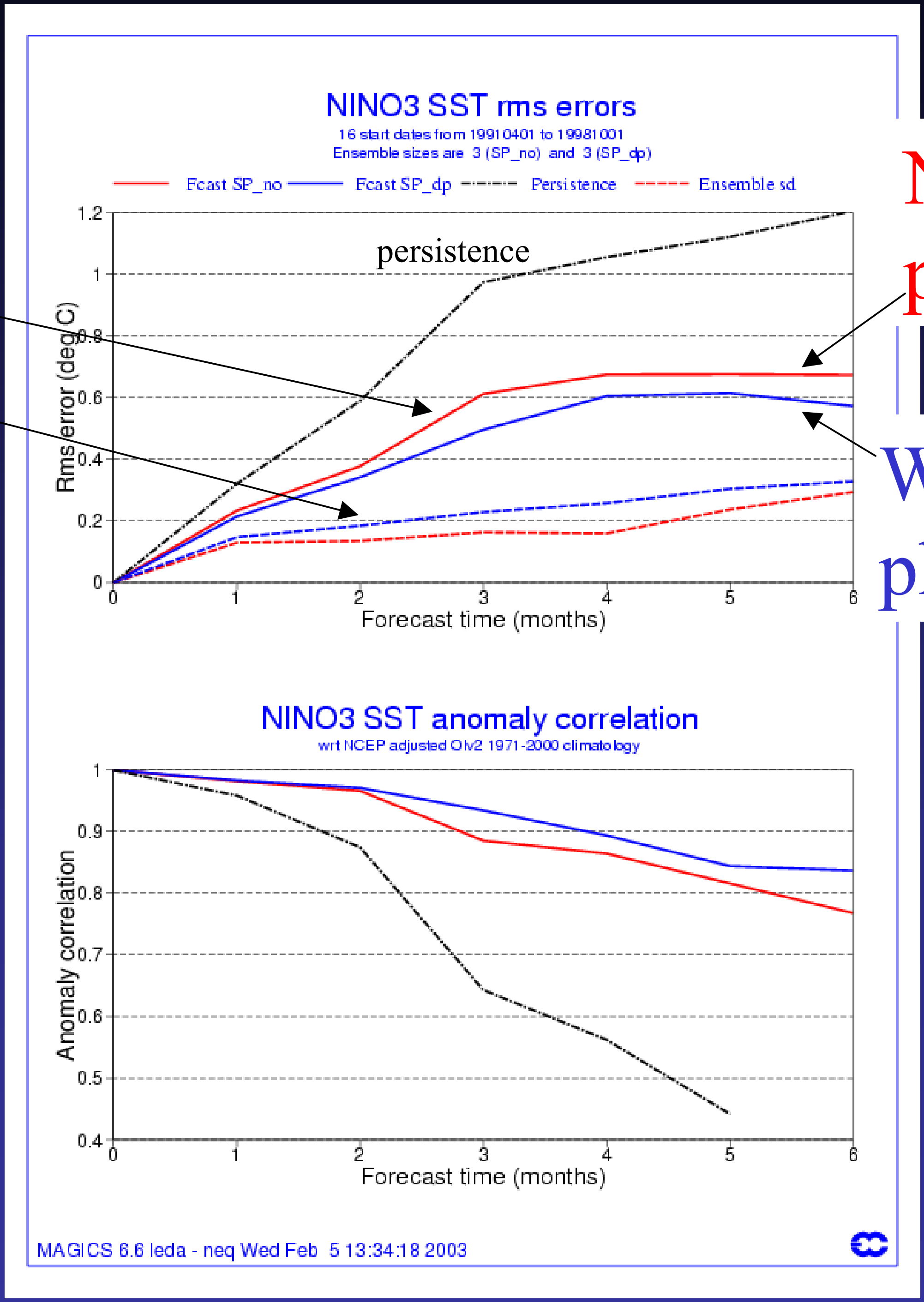
Stochastic Physics has a positive impact on medium-range EPS skill

Area under ROC curve. E: precip>40mm/day.
Winter- top curves. Summer – bottom curves



Buizza et al, 1999

ENSO prediction skill and spread

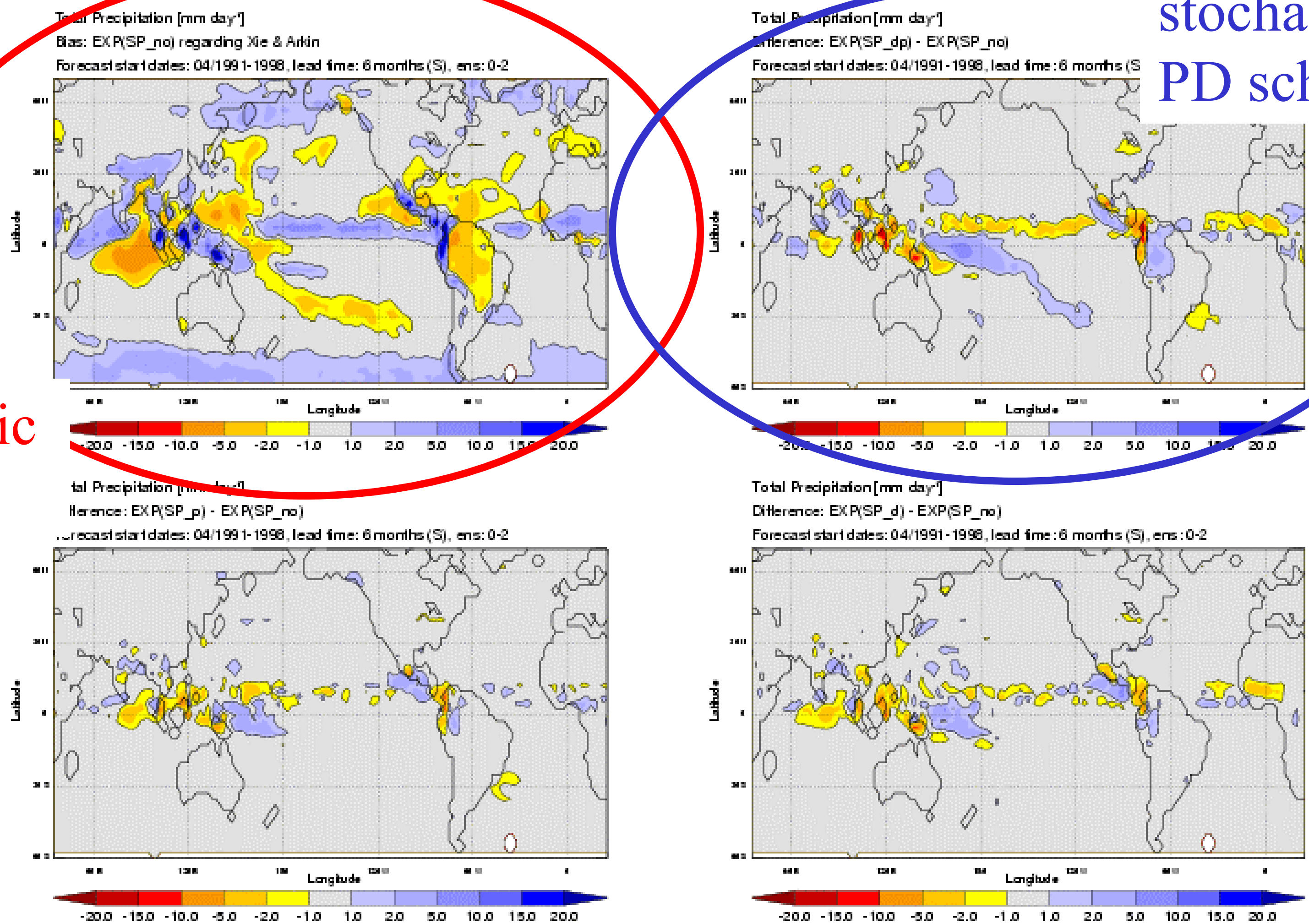


ECMWF coupled model

Stochastic physics has an impact on the mean state of the ECMWF model

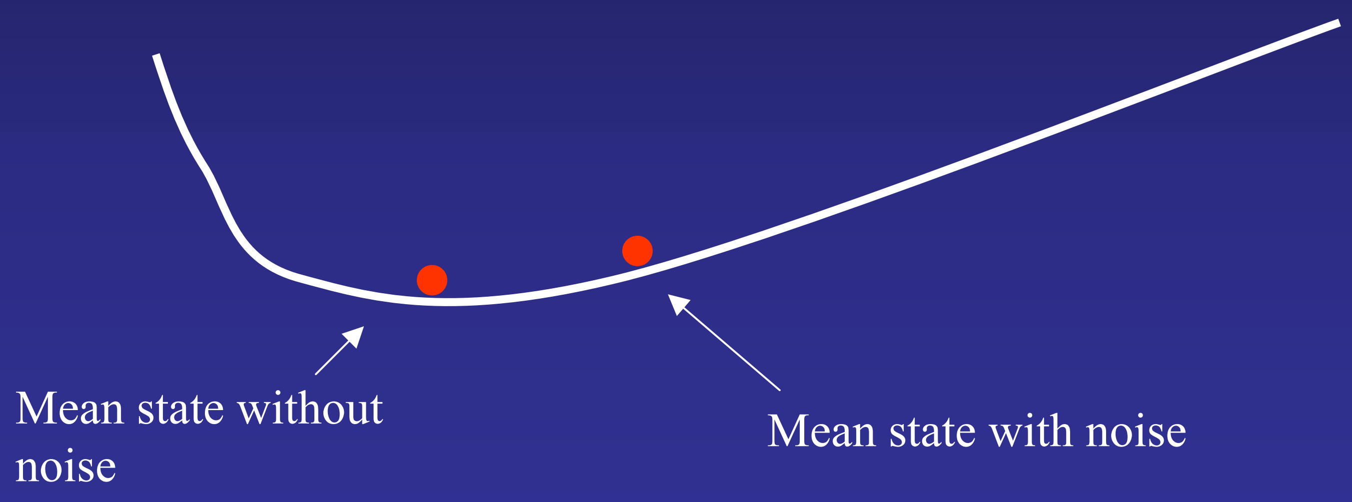
Impact of stochastic PD scheme

Systematic error



Could stochastically sampling the probability distribution of the sub-grid tendency, rather than always sampling the mode, make a difference? Yes if atmosphere is nonlinear!!

Eg 1) Ball-bearing in a skewed potential well



Eg 2) Lorenz(1963) in an EOF basis

$$\dot{a}_1 = 2.3a_1 - 6.2a_3 - 0.49a_1a_2 - 0.57a_2a_3$$
$$\dot{a}_2 = -62 - 2.7a_2 + 0.49a_1^2 - 0.49a_3^2 + 0.14a_1a_3$$
$$\dot{a}_3 = -0.63a_1 - 13a_3 + 0.43a_1a_2 + 0.49a_2a_3$$

3rd EOF only explains 4% of variance (Selten, 1995) .

Parametrise it?

Lorenz(1963) in a truncated EOF basis with parametrisation of a_3

$$\dot{a}_1 = 2.3a_1 - 6.2a_3 - 0.49a_1a_2 - 0.57a_2a_3$$

$$\dot{a}_2 = -62 - 2.7a_2 + 0.49a_1^2 - 0.49a_3^2 + 0.14a_1a_3$$

$$a_3 = f(a_1, a_2)$$

Good as a short-range forecast model (using L63 as truth), but exhibits major systematic errors compared with L63, as, by Poincaré-Bendixon theorem, the system cannot exhibit chaotic variability – system collapses onto a point attractor.

Stochastic-Lorenz(1963) in a truncated EOF basis

$$\dot{a}_1 = 2.3a_1 - 6.2a_3 - 0.49a_1a_2 - 0.57a_2a_3$$

$$\dot{a}_2 = -62 - 2.7a_2 + 0.49a_1^2 - 0.49a_3^2 + 0.14a_1a_3$$

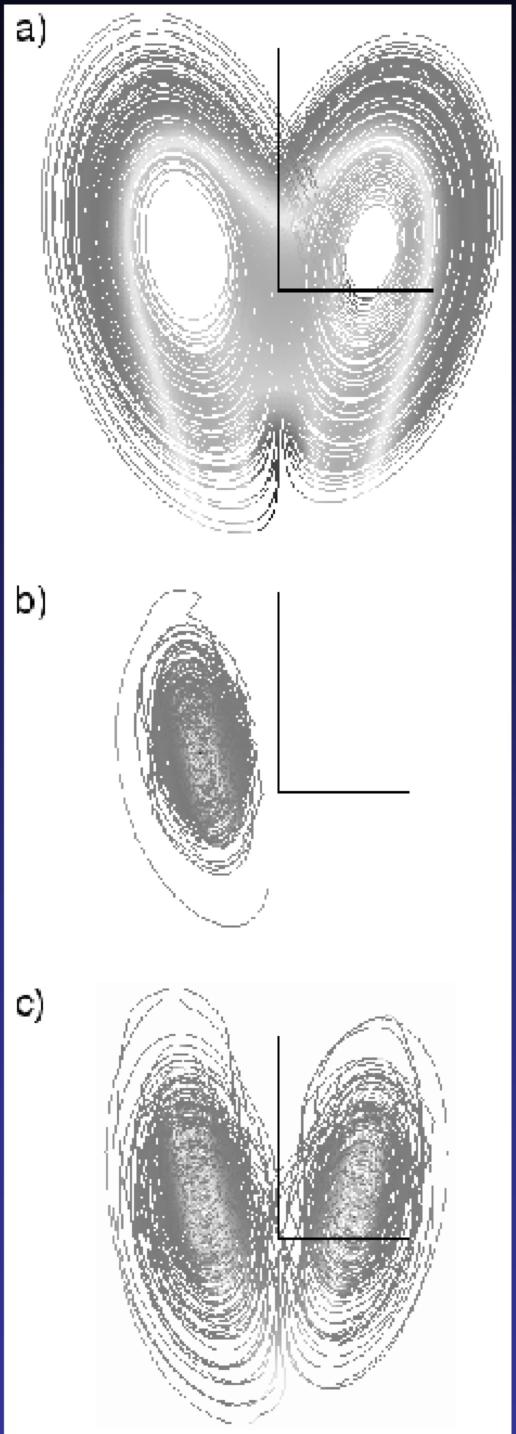
$$a_3 = \beta$$

Stochastic noise

Lorenz attractor

Truncated Stochastic-
Lorenz attractor –
weak noise

Truncated Stochastic-
Lorenz attractor



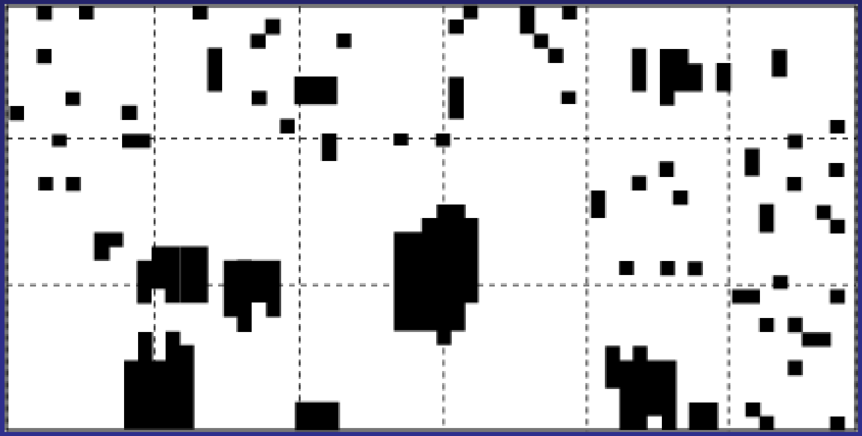
Error in mean
and variance

Palmer, 2001
(acknowledgment to
Frank Selten)

Stochastic-Dynamic Sub-Grid Models

1. Embed 2D Cloud Resolving Models in GCM (eg Grabowski, 2001; Randall, 2003). "superparametrisation". Very expensive!!

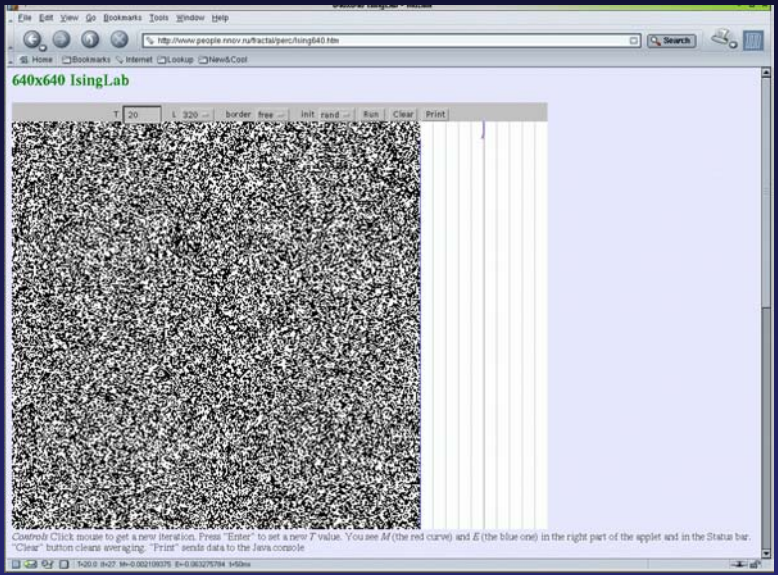
2. Stochastic-dynamic cellular automata



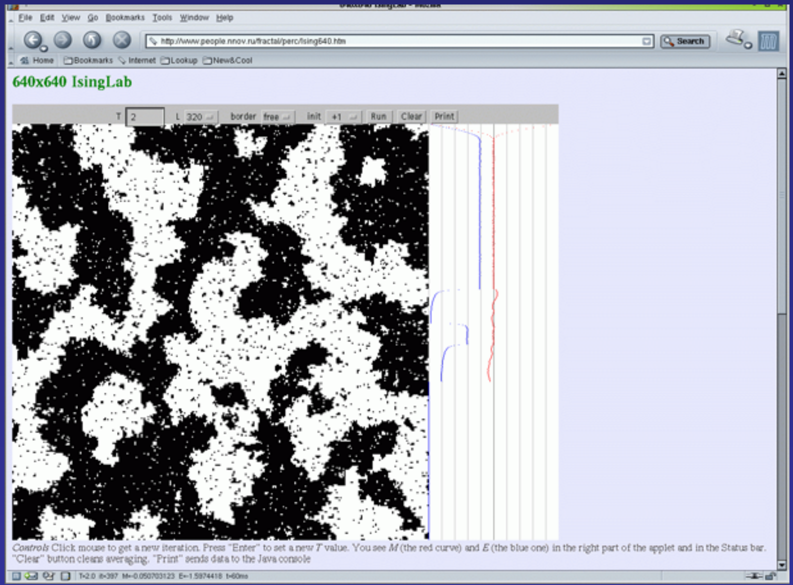
EG Probability of an "on"cell proportional to CAPE and number of adjacent "on" cells – "on" cells feedback to the resolved flow

(Palmer; 1997)

Ising Model (for Ferromagnetism) – Stochastic Cellular Automaton Model- only nearest neighbour interaction



Above Curie Point



Below Curie Point

http://bartok/ucsc.edu/peter/java/ising/keep/ising.html

Coarse-grained stochastic models for tropical convection and climate

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Contributed by Andrew J. Majda, August 4, 2003

Prototype coarse-grained stochastic parametrizations for the interaction with unresolved features of tropical convection are developed here. These coarse-grained stochastic parametrizations involve systematically derived birth/death processes with low computational overhead that allow for direct interaction of the coarse-grained dynamical variables with the smaller-scale unresolved fluctuations. It is established here for an idealized prototype climate scenario that, in suitable regimes, these coarse-grained stochastic parametrizations can significantly impact the climatology as well as strongly increase the wave fluctuations about an idealized climatology.

The current practical models for prediction of both weather and climate involve general circulation models (GCMs) where the physical equations for these extremely complex flows are discretized in space and time and the effects of unresolved processes are parametrized according to various recipes. With the current generation of supercomputers, the smallest possible mesh spacings are ≈50–100 km for short-term weather simulations and of order 200–300 km for short-term climate simulations. There are many important physical processes that are unresolved in such simulations such as the mesoscale sea-ice cover, the cloud cover in subtropical boundary layers, and deep convective clouds in the tropics. An

this article, one horizontal spatial dimension along the equator in the east–west direction is assumed for simplicity in notation and explanation. As mentioned above, the typical mesh spacing in a GCM is coarse with Δx ranging from 50 to 250 km depending on the time duration of the simulation. On the other hand, observationally, CIN is known to have significant fluctuations on a horizontal spatial scale on the order of 1 km, the microscopic scale here, with changes in CIN attributed to different mechanisms in the turbulent boundary layer such as gust fronts, gravity waves, and turbulent fluctuations in equivalent potential temperature (3). In ref. 1 it was proposed that all these different microscopic physical mechanisms and their interaction, which increase and decrease CIN, are too complex to model in detail in a coarse-mesh GCM parametrization and instead, as in statistical mechanics, should be modeled by a simple order parameter, σ_I, taking only two discrete values:

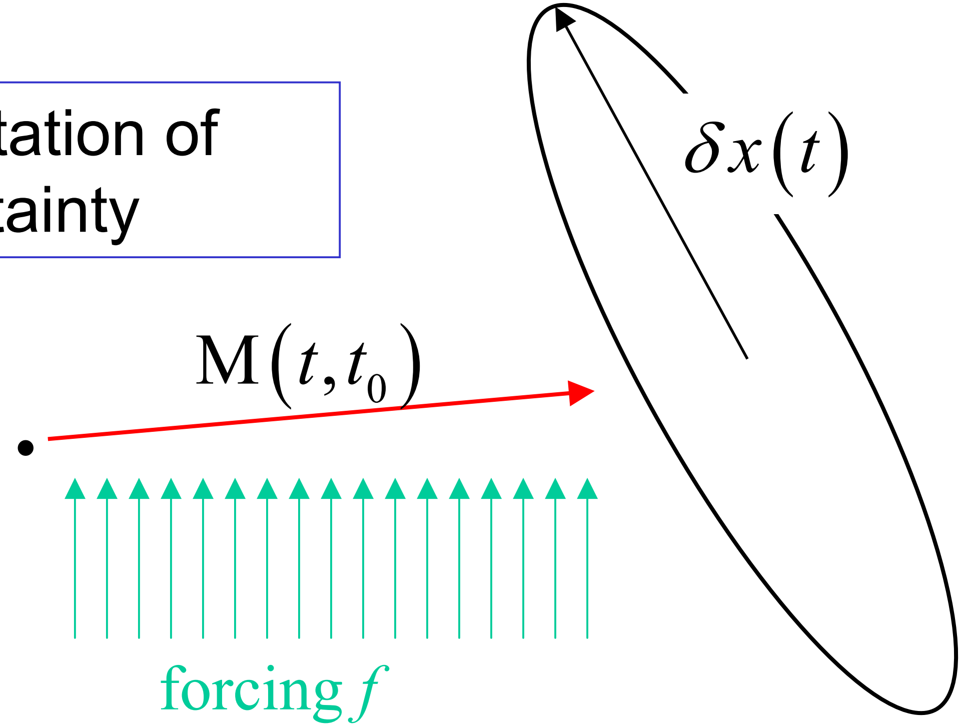
$$\begin{aligned} \sigma_I &= 1 \text{ at a site if convection is inhibited (a CIN site)} \\ \sigma_I &= 0 \text{ at a site if there is potential for deep convection} \\ &\quad \text{[a potential for deep convection (PAC) site].} \end{aligned} \qquad [1]$$

The value of CIN at a given coarse-mesh point is determined

APPLIED MATHEMATICS

It is envisaged that a stochastic-dynamic cellular-automaton-based sub-grid model will replace the current stochastic physics scheme in the EPS in 2004/2005.

SV representation of model uncertainty



$$\left(\iint_{t_0} \mathrm{M}^{\mathrm{T}}(s,t)\mathrm{M}(r,t)\,ds\,dr\right) f = \lambda f$$

Stochastic Optimals eg Farrell and Ioannou, 1996

$$\left(\int_{t_0} \mathrm{M}(s,t)\,ds\right)^{T}\left(\int_{t_0} \mathrm{M}(s,t)\,ds\right) f = \lambda f$$

Quasi-constant forcing. Barkmeijer, Iversen and Palmer, 2003

+ parametric singular vectors (collaboration with MIT)

Conclusions

- Based on seasonal prediction studies, forecast probability distributions from multi-model ensembles are intrinsically more reliable than those from single-model ensembles. Multi-model ensembles provide a useful pragmatic approach to the representation of model uncertainty.

- A more complete representation of unresolved and poorly-resolved scales in specific weather/climate models may be achievable using (computationally cheap) stochastic-dynamic sub-grid models.

- Unlike the multi-model approach, stochastic-dynamic parametrisations can impact (and hence potentially reduce) model systematic error (eg in long-standing systematic errors such as MJO and blocking frequency).

- SV techniques could be adapted to determine sensitive aspects of model uncertainty