

Towards the Probabilistic Weather and Climate Prediction Simulator:

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Experimental monthly long-range forecasts for the United Kingdom

Part II. A real-time long-range forecast by an ensemble of numerical integrations

By J.M. Murphy and T.N. Palmer*

(Meteorological Office, Bracknell)

Summary

The use of an ensemble of integrations for long-range prediction has been studied with a hemispheric version of the Meteorological Office 5-level general circulation model. Some results, showing the potential of the technique, are described. The method is now being used with the global 11-level model to produce real-time long-range forecasts for the long-range forecasting conference in the Synoptic Climatology Branch of the Meteorological Office. Results from the first of these real-time ensemble forecasts are discussed.

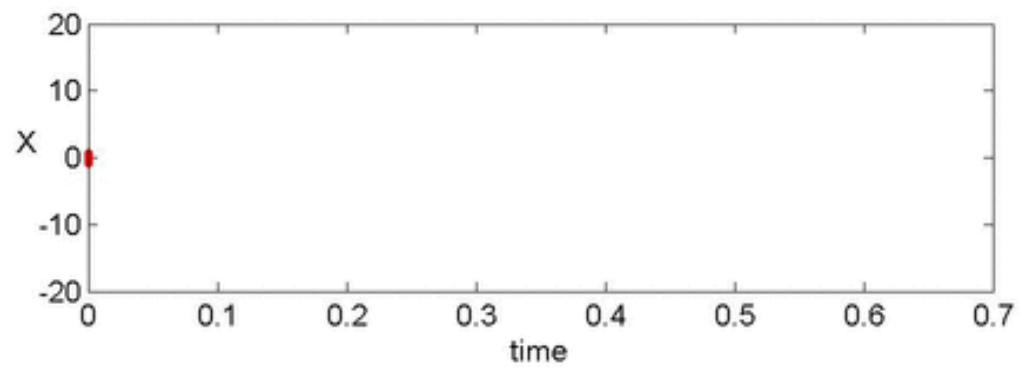
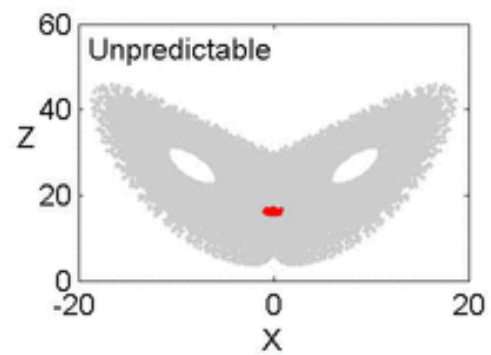
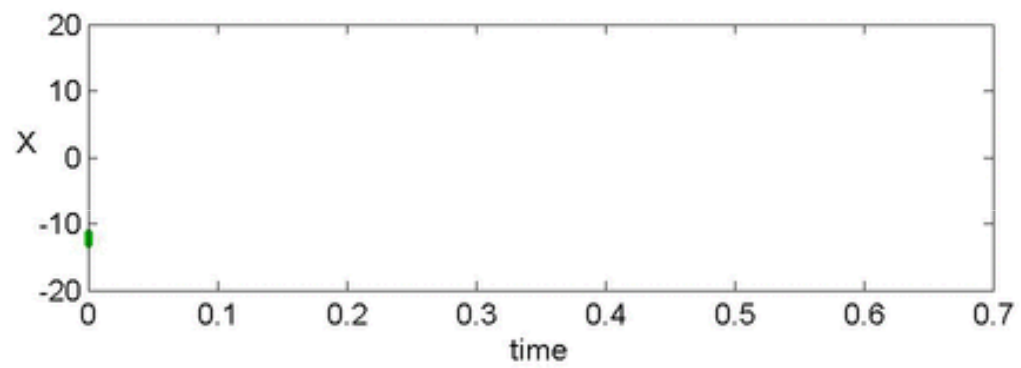
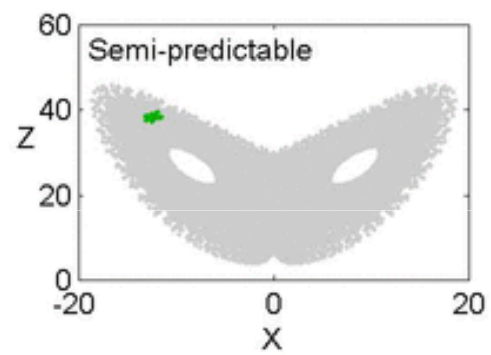
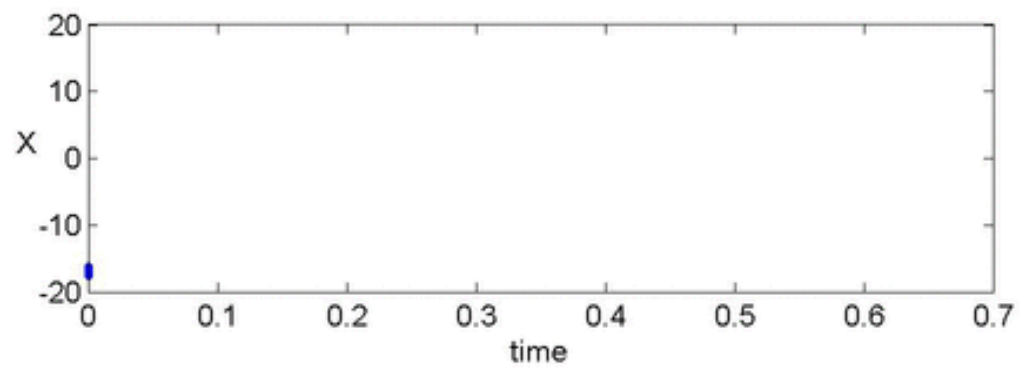
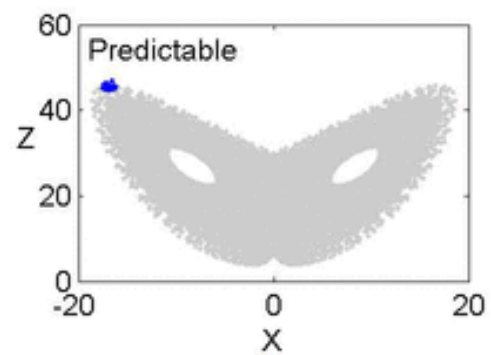
1. Introduction

The short-range predictive skill of numerical weather prediction (NWP) models has steadily improved over the years. Despite this, attempts to use such models to forecast the instantaneous state of the atmosphere a month into the future have not enjoyed much success. The fundamental reasons for this lie not only with deficiencies in the numerical models, but also with the very equations of motion which the models integrate.

Specifically, the difference between two or more integrations of an NWP model whose initial states differ by a small amount (representing, say, analysis error) will increase with time until at some stage the integrations are completely independent of one another, in the sense that they can be thought of as random states in some climatological distribution. This suggests that the atmosphere has some 'limit of deterministic predictability' and attempts to estimate this (e.g. Lorenz 1982, Mansfield 1986) suggest that, on average, it is considerably less than 1 month. This limit can be extended by considering the model's forecast of only the planetary-scale modes and/or time-averaged fields (Shukla 1981), though this approach ignores a fundamental problem that forecasting on the monthly time-scale has a marked probabilistic element, and is not strictly deterministic. The multivariate statistical model (Maryon and Storey 1985, Folland and Woodcock 1986), the backbone of the operational long-range forecasting system in the Meteorological Office, has this notion built into its basic formulation; it does not predict one pattern of surface pressure, but assigns probabilities to a number of pre-defined patterns.

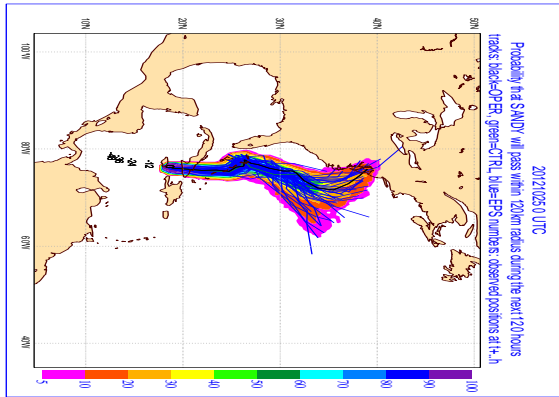
* Now on secondment to the European Centre for Medium Range Weather Forecasts, Shinfield Park, Reading.

The first real-time ensemble forecast, for commercial customers

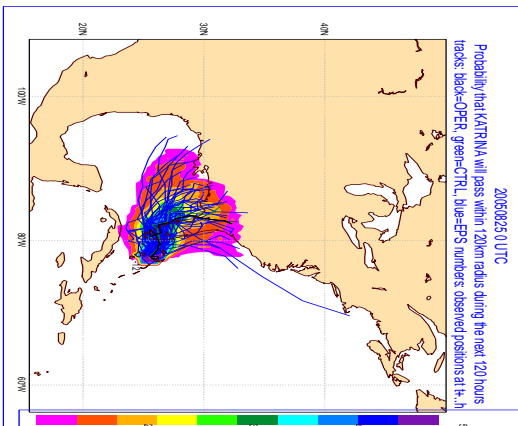


Hannah Arnold

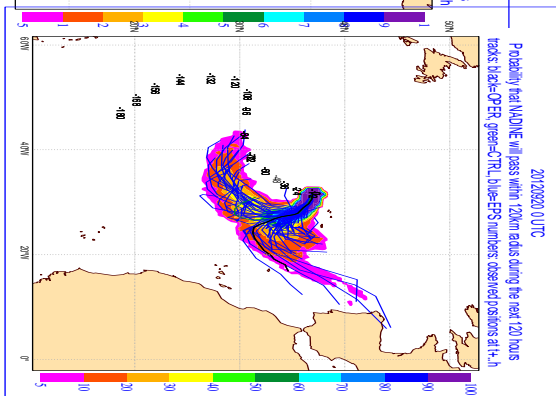
Hurricane-Superstorm Sandy : Predictable



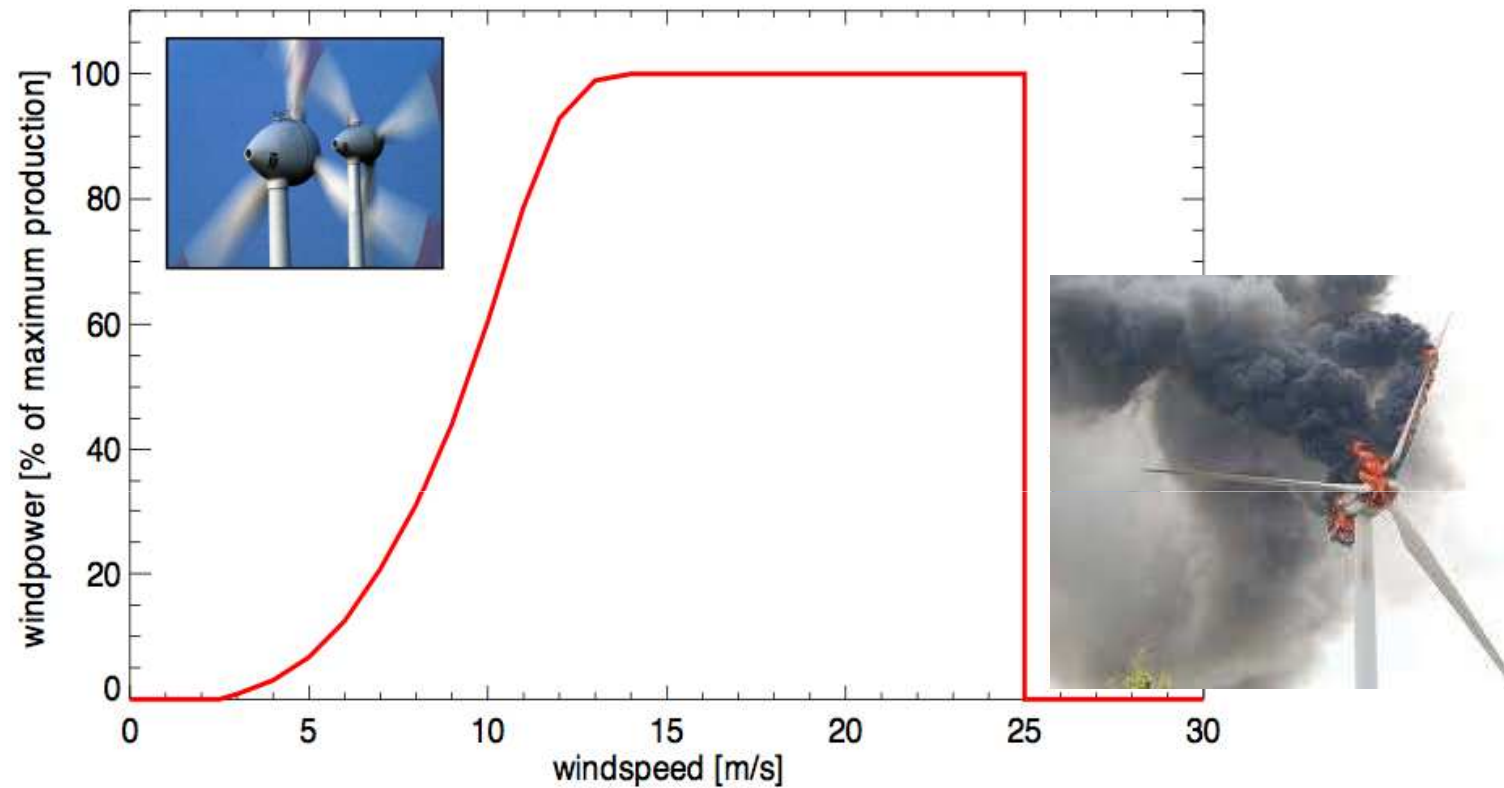
Hurricane Katrina: Semi-Predictable

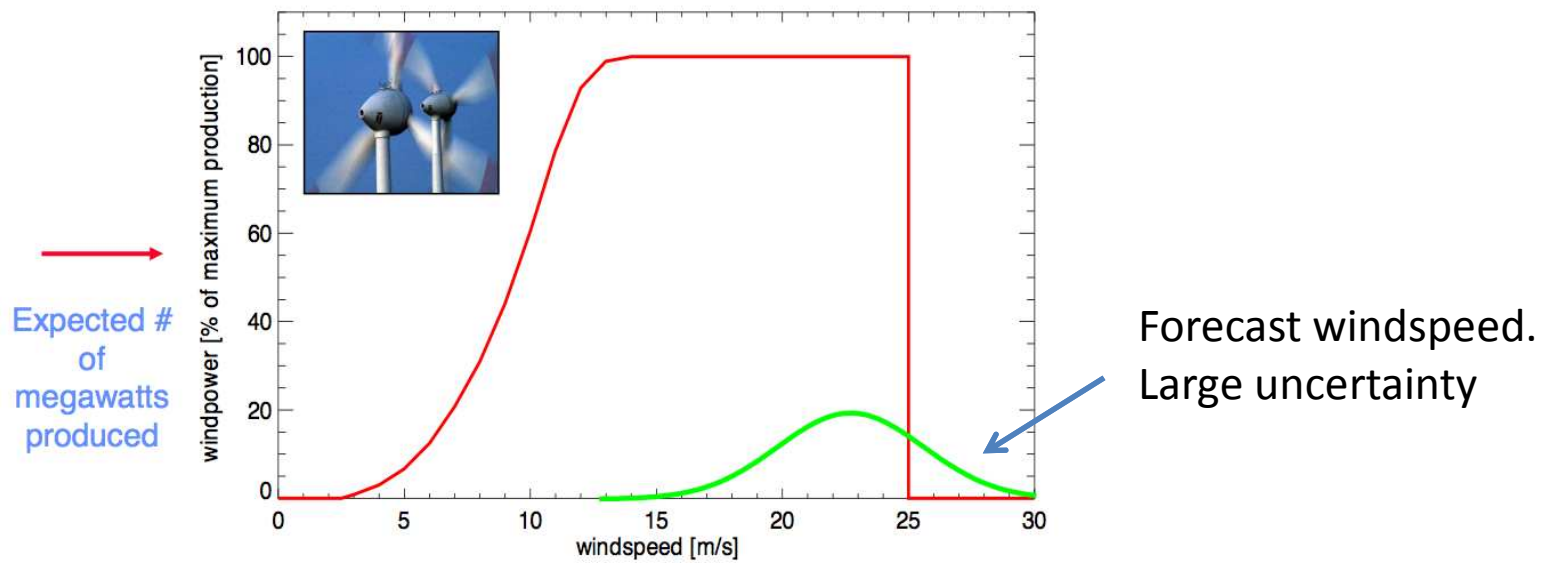
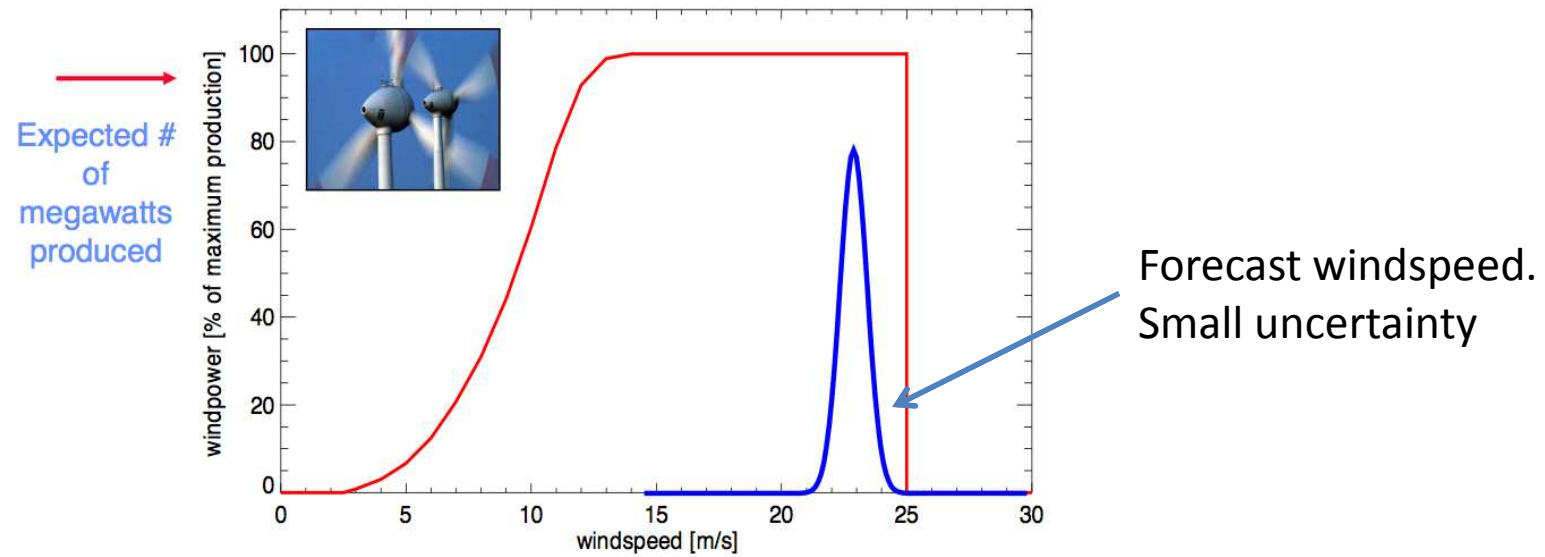


Hurricane Nadine: Unpredictable



Electricity Production vs Windspeed





Ensemble Prediction for Decision Making

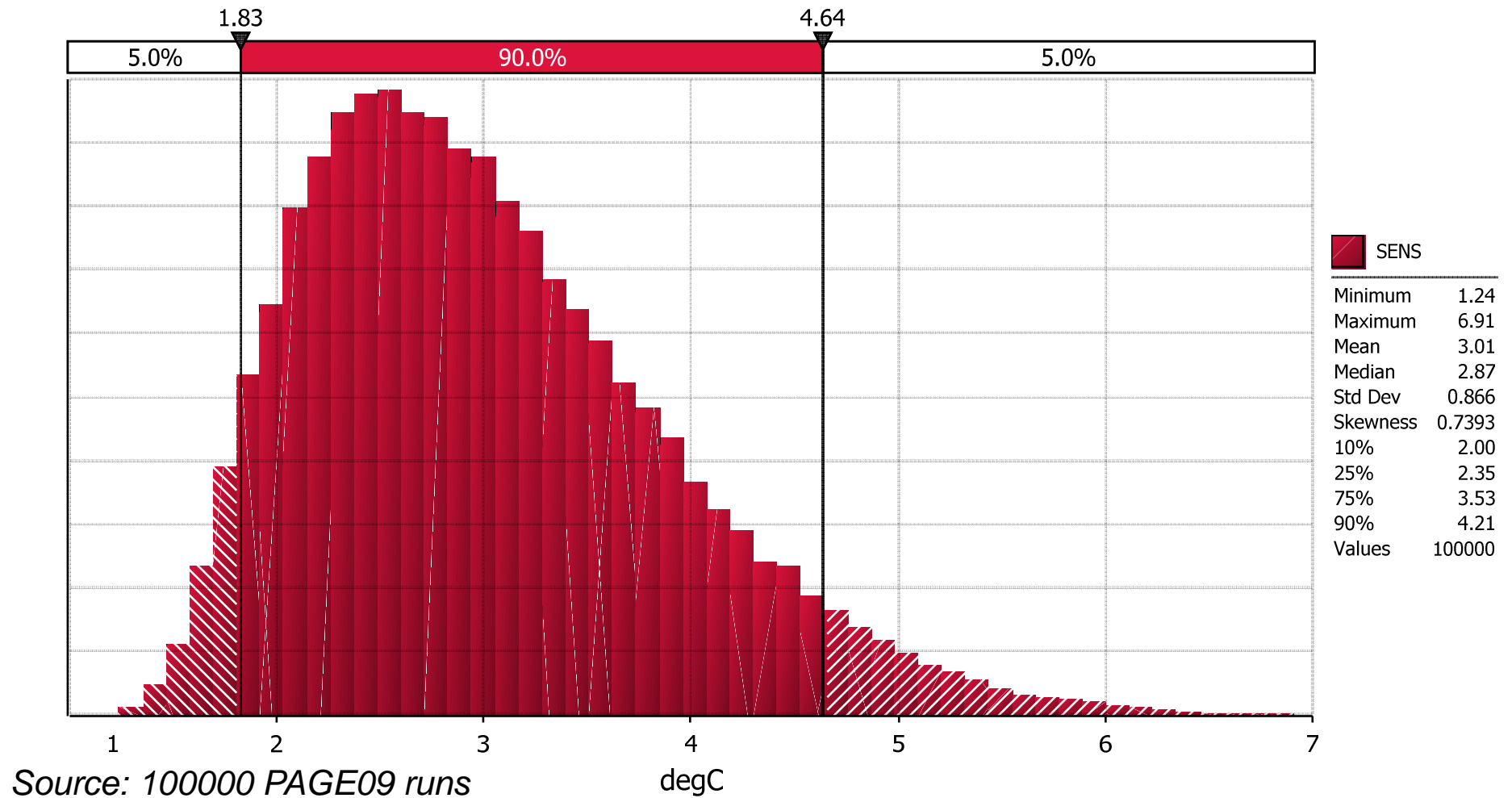
$$\langle U(x) \rangle \equiv \int_x U(x) p(x) dx \neq U(\langle x \rangle)$$

Utility Function

Meteorological Variables

Expected utility – this is
what decision makers
should use to make
decisions!

Pdf of climate sensitivity



Cost of mitigation \approx \$ 150 trillion

Based on the most likely climate change only:

Expected damage/ impacts = \$ 150 trillion

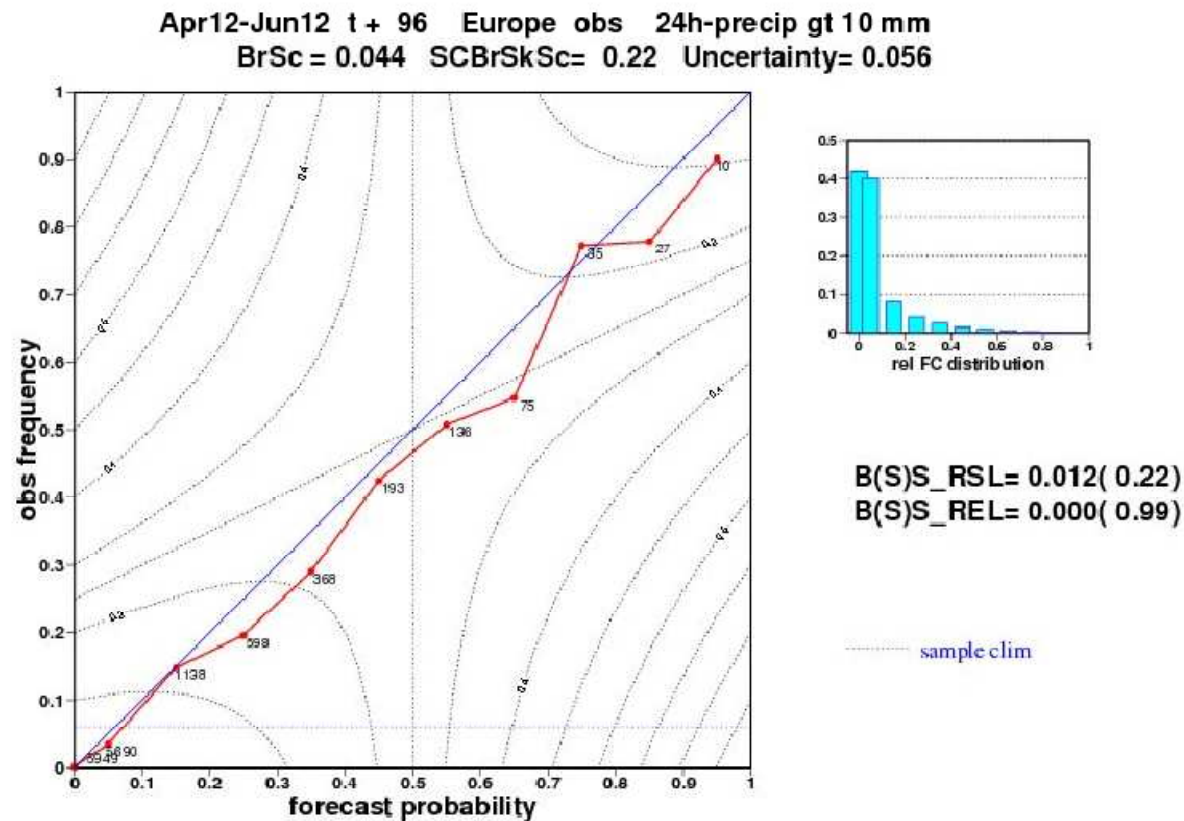
Based on the probability distribution of possible climate change:

Expected damage/ impacts = \$ 314 trillion

Chris Hope, U. Cambridge

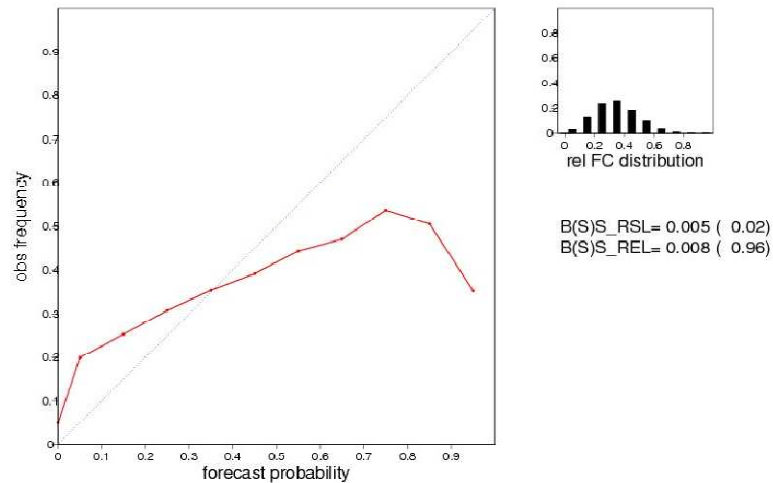
Reliability of ECMWF Ensemble Prediction System

50 members, T639 (c. 30km) resolution



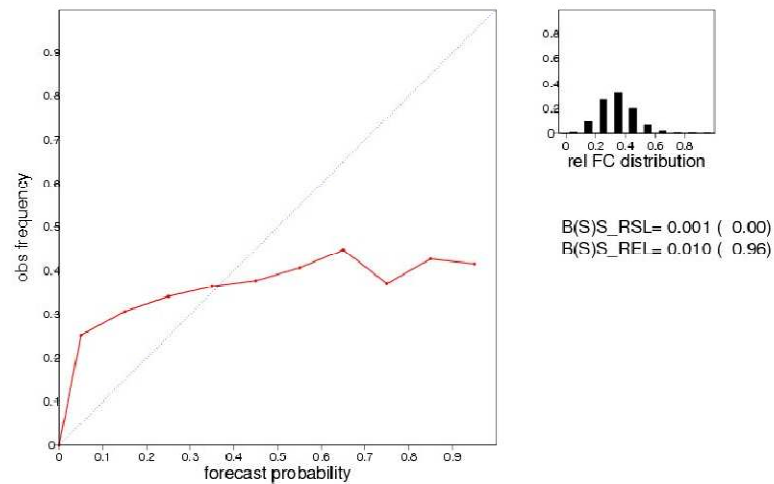
Beyond the medium range, precipitation forecasts start to lose reliability.

ECMWF Monthly Forecast, Precip in upper tercile , Area:Europe
Day 12-18 20041007-20120705
BrSc = 0.229 LCBrsSc= -0.01 Uncertainty= 0.227



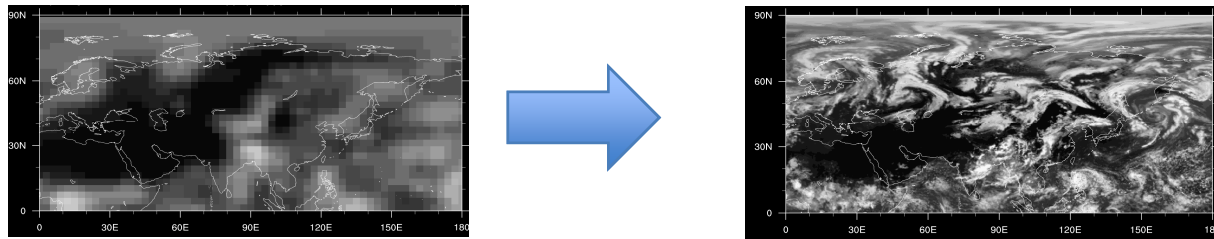
This is also a problem for short-range prediction of extreme precipitation events

ECMWF Monthly Forecast, Precip in upper tercile , Area:Europe
Day 19-32 20041007-20120705
BrSc = 0.238 LCBrsSc= -0.03 Uncertainty= 0.230



How Can We Improve our Forecasts?

- More and Better Observations. Better ways to Assimilate Observations into models
- Higher resolution models, improved parametrisations

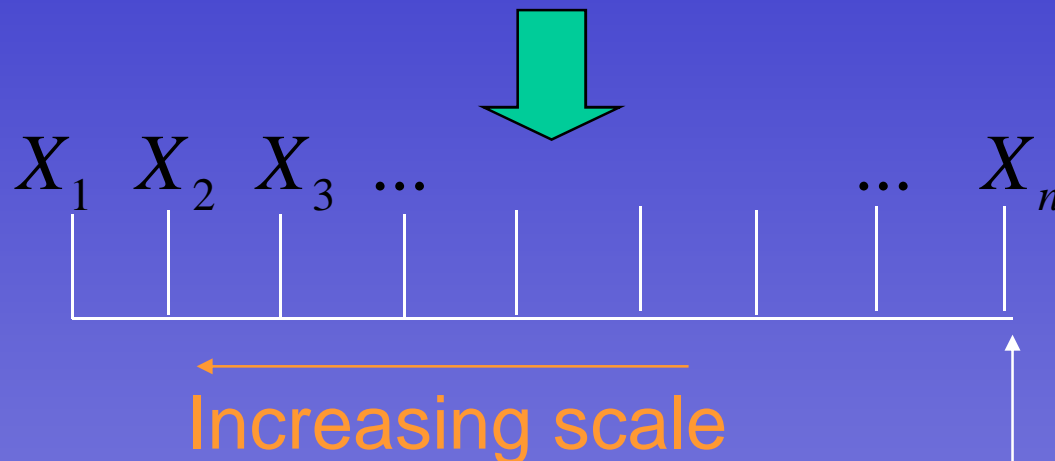


- Better representations of the inherent uncertainty in the observations and the models.

Traditional computational ansatz for weather/climate simulators

Eg

$$\rho \left(\frac{\partial}{\partial t} + \mathbf{u} \cdot \nabla \right) \mathbf{u} = \rho \mathbf{g} - \nabla p + \nu \nabla^2 \mathbf{u}$$



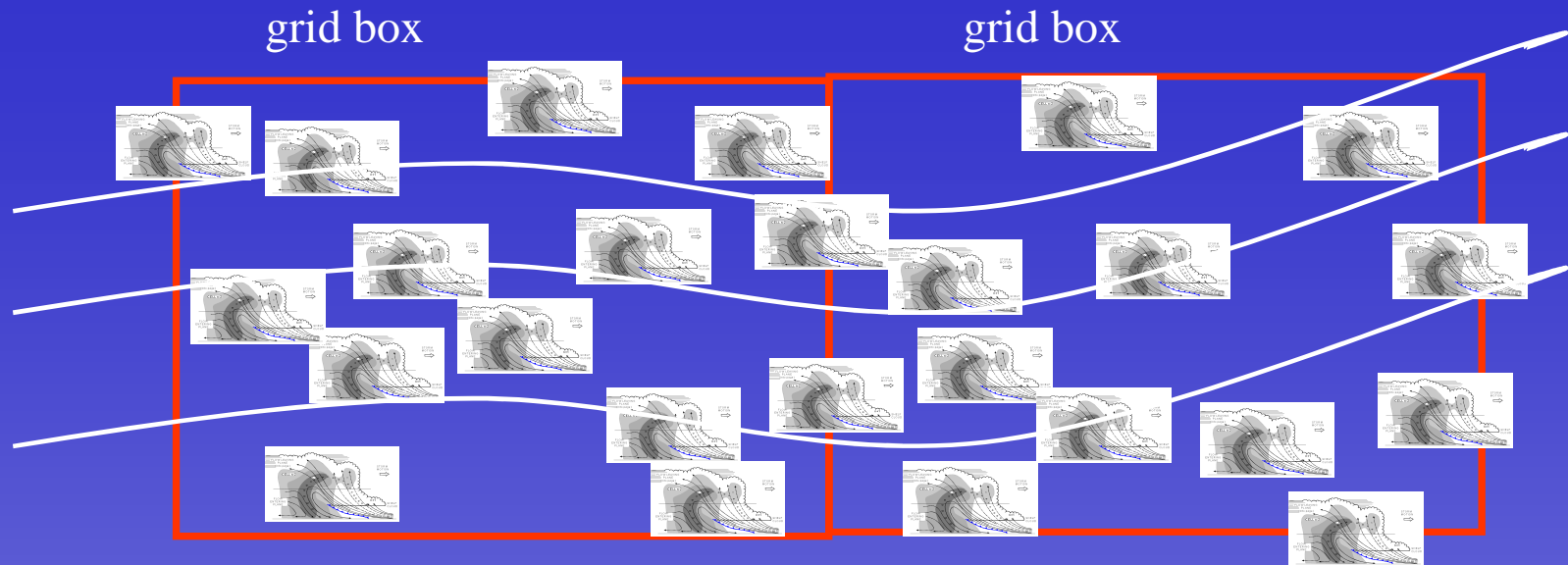
Eg momentum “transport” by:

- Turbulent eddies in boundary layer
- Orographic gravity wave drag.
- Convective clouds



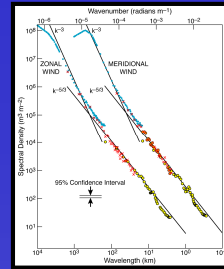
Deterministic local
bulk-formula
parametrisation

$$P(X_n; \alpha)$$

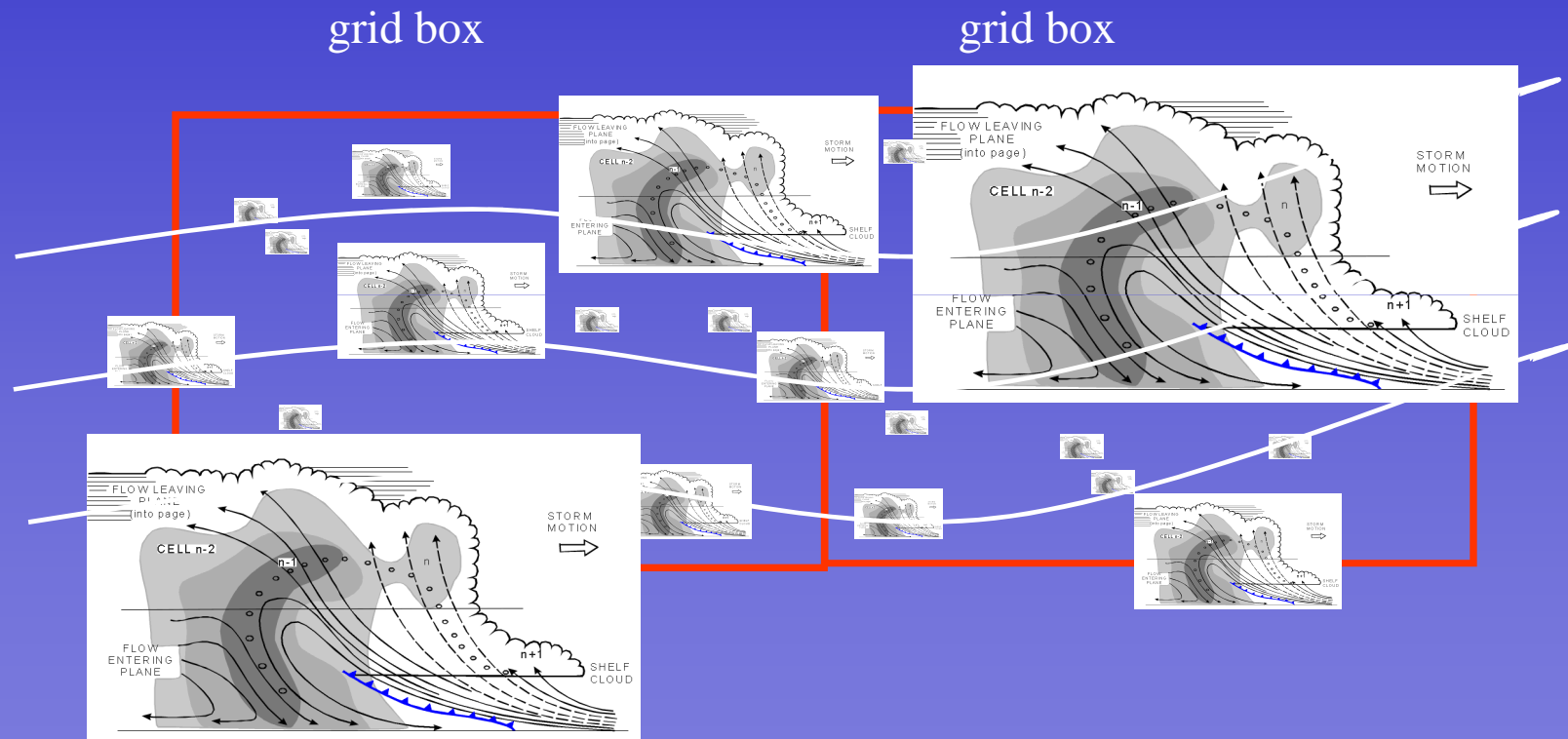


Deterministic bulk-formula parametrisation is based on the notion of averaging over some putative ensemble of sub-grid processes in quasi-equilibrium with the resolved flow (eg Arakawa and Schubert, 1974)

However,



reality is more consistent with



Stochastic Parametrisation

- More consistent with power-law behaviour
- Describes the sub-grid tendency in terms of a pdf constrained by the resolved-scale flow.
- Provides stochastic realisations of the sub-grid flow, not some putative bulk average effect.
- Can incorporate physical processes (eg energy backscatter) not easily described in conventional parametrisations.
- Parametrisation development can be informed by coarse-graining budget analyses of very high resolution (eg cloud resolving) models.

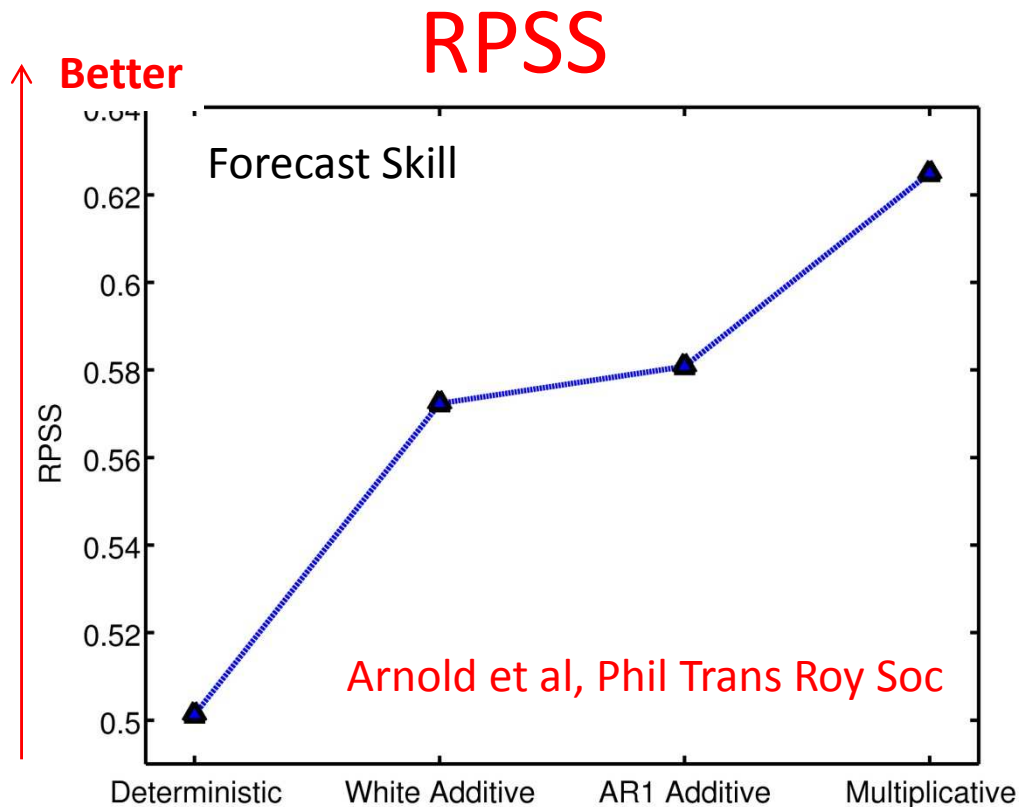
Experiments with the Lorenz '96 System

$$\frac{dX_k}{dt} = -X_{k-1} (X_{k-2} - X_{k+1}) - X_k + F - \frac{hc}{b} \sum_{j=J(k-1)+k}^{kJ} Y_j$$

$$\frac{dY_j}{dt} = -cbY_{j+1} (Y_{j+2} - Y_{j-1}) - cY_j + \frac{hc}{b} X_{\text{int}[(j-1)/J+1]}$$

Assume Y unresolved

Approximate sub-grid tendency by U



Deterministic: $U = U_{\text{det}}$

Additive: $U = U_{\text{det}} + e_{w,r}$

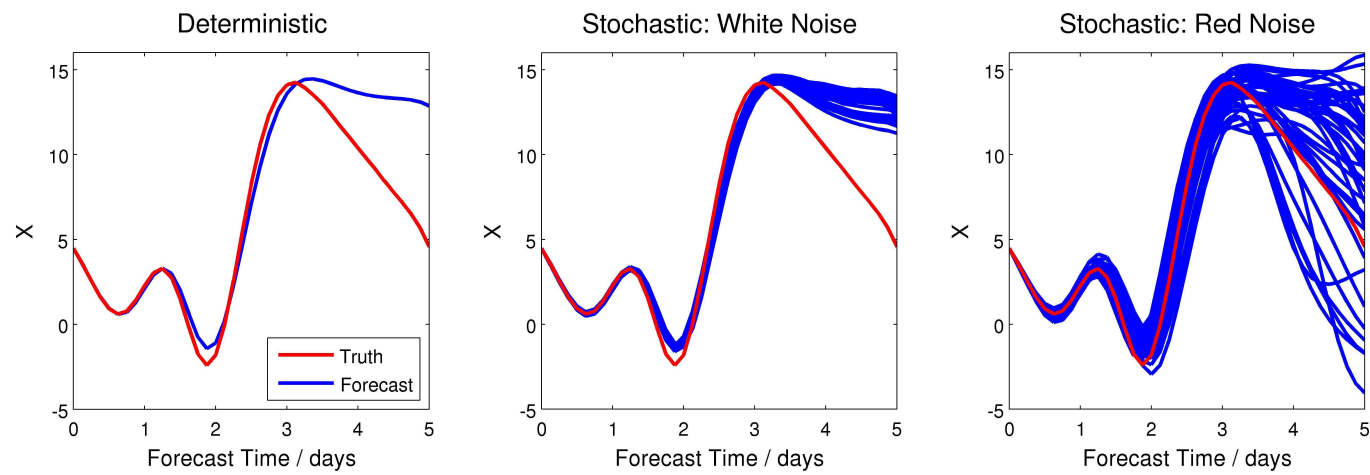
Multiplicative: $U = (1+e_r) U_{\text{det}}$

Where:

U_{det} = cubic polynomial in X

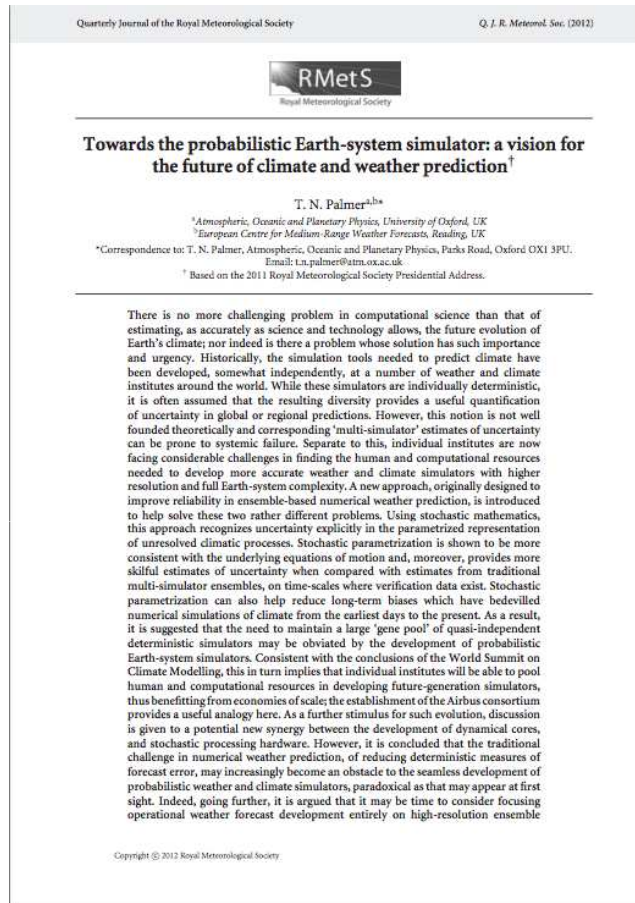
$e_{w,r}$ = white / red noise

Fit parameters from full model



From Hannah Arnold

Palmer, 1997, 2001: Buizza et al, 1999....



Brier Skill Score: ENSEMBLES MME vs ECMWF stochastic physics ensemble (SPE)

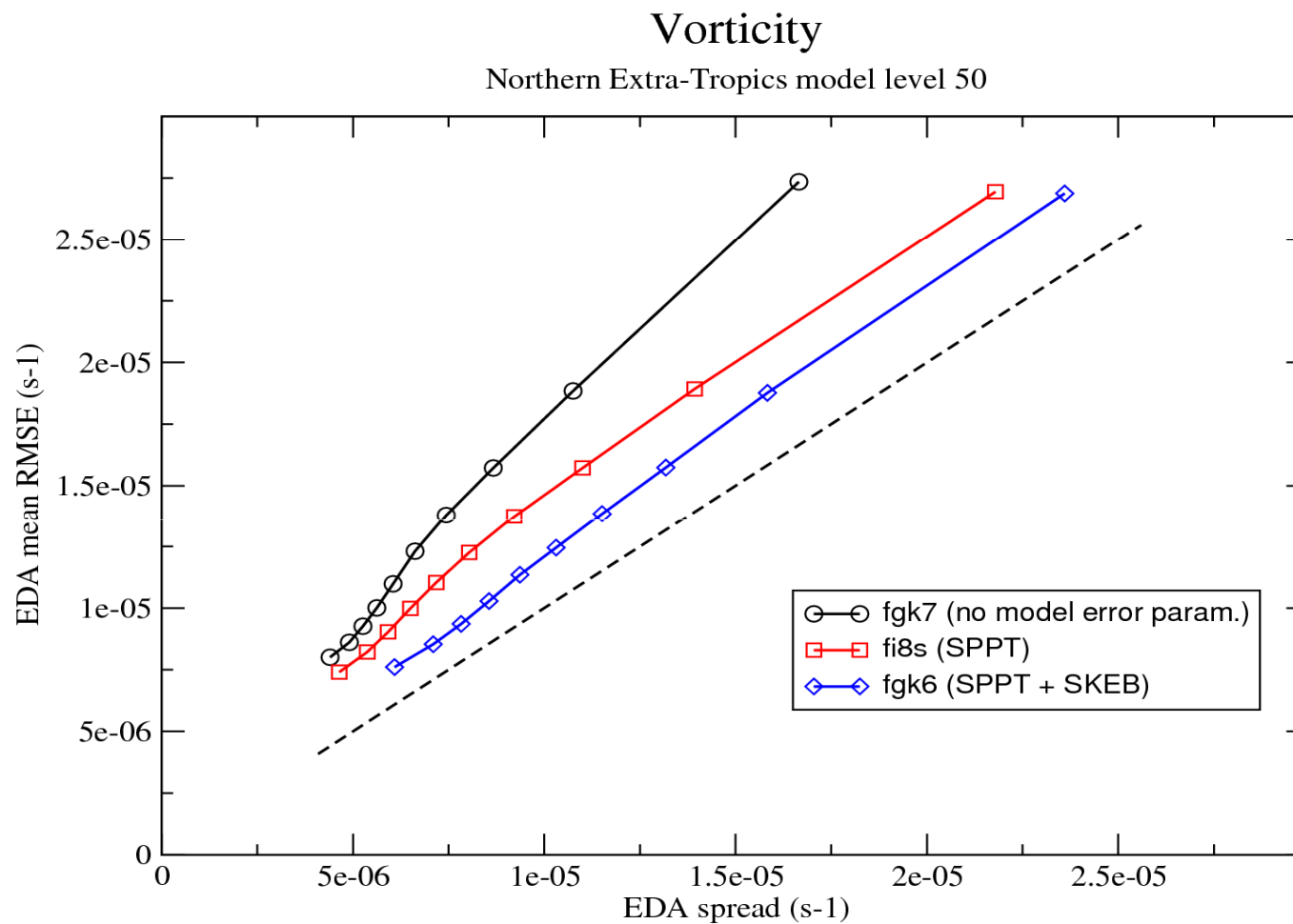
lead time: 1 month

T2m					precip			
	May		Nov		May		Nov	
	cold	warm	cold	warm	dry	wet	dry	wet
MME	0.178	0.195	0.141	0.159	0.085	0.079	0.080	0.099
SPE	0.194	0.192	0.149	0.172	0.104	0.118	0.095	0.114
CTRL	0.147	0.148	0.126	0.148	0.044	0.061	0.058	0.075

Hindcast period: 1991-2005

SP version 1055m007

Weisheimer et al GRL (2011)



Performance of stochastic parametrisation in data assimilation mode. M. Bonavita, personal communication.

Impact of uncertainties in the horizontal density gradient upon low resolution global ocean modelling

Jean-Michel Brankart*
LEGI/CNRS, Grenoble, France

September 12, 2012

Abstract

In this study, it is shown (i) that, as a result of the nonlinearity of the seawater equation of state, unresolved scales represent a major source of uncertainties in the computation of the large-scale horizontal density gradient from the large-scale temperature and salinity fields, and (ii) that the effect of these uncertainties can be simulated using random processes to represent unresolved temperature and salinity fluctuations. The results of experiments performed with a low resolution global ocean model show that this parameterization has a considerable effect on the average large-scale circulation of the ocean, especially in the regions of intense mesoscale activity. The large-scale flow is less geostrophic, with more intense associated vertical velocities, and the average geographical position of the main temperature and salinity fronts is more consistent with observations. In particular, the simulations suggest that the stochastic effect of the unresolved temperature and salinity fluctuations on the large-scale density field may be sufficient to explain why the Gulf Stream pathway systematically overshoots in non-stochastic low resolution ocean models.

1 Introduction

One of the most salient feature of today's state-of-the-art ocean models is that they are essentially *deterministic* models, in the sense that they do not involve *random numbers* to represent uncertainties in the model equations, parameters and forcing, or to simulate the effect of unresolved processes. Yet, this deterministic model dynamics is known to become chaotic as soon as mesoscale eddies are resolved by the model, so that the simulated mesoscale flow can only be viewed as one random realization sampled from a large set of possibilities. It is thus only in a statistical sense that the mesoscale can be compared to the real world, and it is only as a stochastic process that the effect of the mesoscale in the model can be analysed. Mesoscale fluctuations indeed produce a considerable effect on the general circulation of the ocean (Zhai et al., 2004; Penduff et al., 2010), with prominent contributions to momentum, heat and salt fluxes, which cannot be easily parameterized in low resolution models.

As a general rule, the effect of uncertainties or unresolved processes (even if unbiased) does not average to zero in a nonlinear model. For instance, if the wind is fluctuating or if it is uncertain, then neglecting the fluctuations or the uncertainties systematically underestimates the air-sea momentum flux (proportional to the square of the wind speed). In the same way, the average effect of the mesoscale fluctuations does not vanish in the two nonlinear terms of the primitive equations: the advection term and the equation of state. Concerning advection

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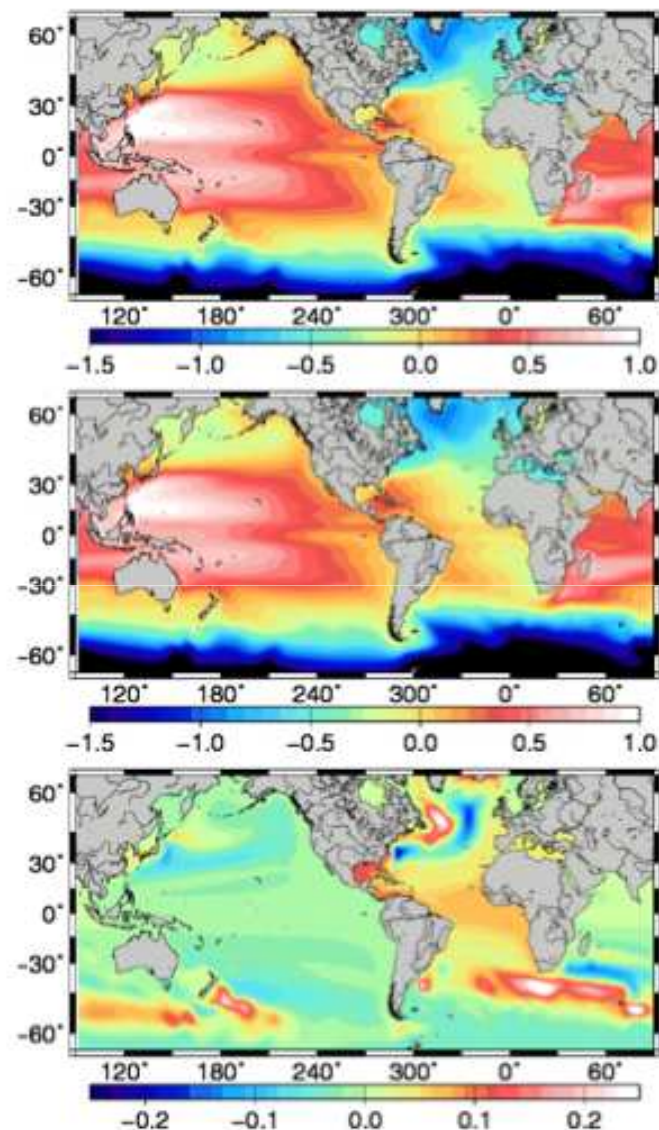


Figure 5: Mean sea surface height (in m), as obtained (i) with the standard ORCA2 configuration (top panel), and (ii) with the stochastic parameterization of the equation of state (middle panel). The bottom panel shows the difference produced by the stochastic parameterization.

Effects of stochastic ice strength perturbation on

Arctic finite element sea ice modelling

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Thomas Rackow

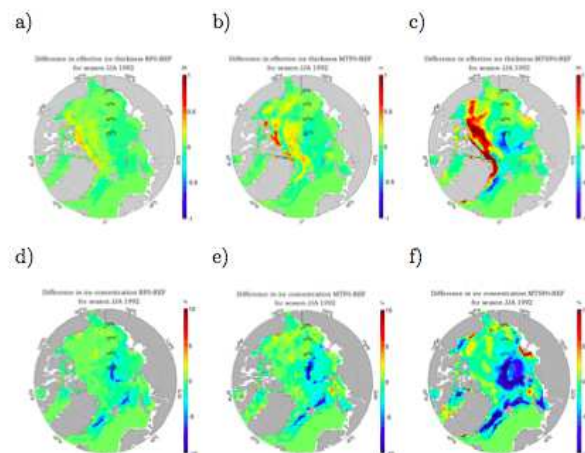
Alfred Wegener Institute for Polar and Marine Research, Bremerhaven, Germany

18.06.2012

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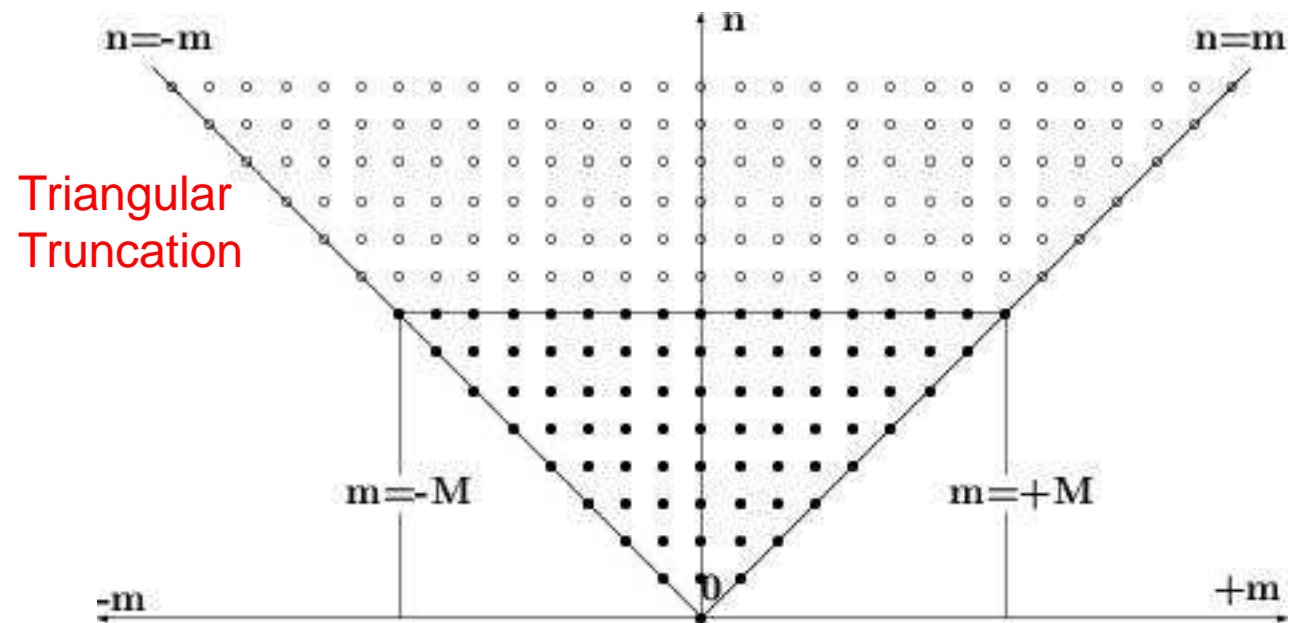
Impact of different versions of stochastic P^* with respect to a reference run. Top: Sea ice thickness. Bottom: sea ice concentration.

- The ice strength parameter P^* is a key parameter in dynamic-thermodynamic sea ice models. Controls the threshold for plastic deformation. Value affected by the liquid content in the sea ice. Cannot be measured directly.
- A stochastic representation of P^* is developed in a finite element sea-ice-ocean model, based on AR1 multiplicative noise and spatial autocorrelation between nodes of the finite element grid
- Despite symmetric perturbations, the stochastic scheme leads to a substantial increase in sea ice volume and mean thickness
- An ensemble of eight perturbed simulations generates a spread in the multiyear ice comparable with interannual variability in the model.
- Results cannot be reproduced by a simple constant global modification to P^*

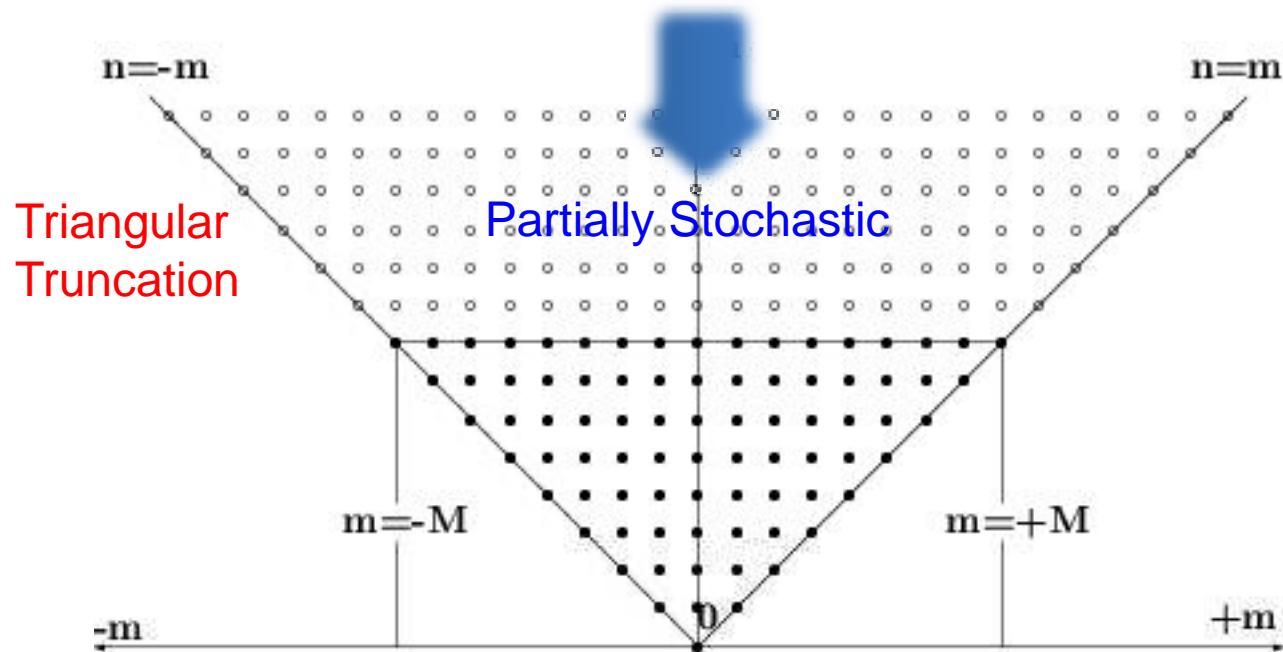
Spectral Dynamical Core

$$\zeta = \sum_{m,n}^{\infty} \zeta_{m,n} e^{im\lambda} P_n^m(\phi)$$

Parametrisation



Stochastic Parametrisation



If parametrisation is partially stochastic, are we “over-engineering” our dynamical cores by using double precision bit-reproducible computations for wavenumbers near the truncation scale?

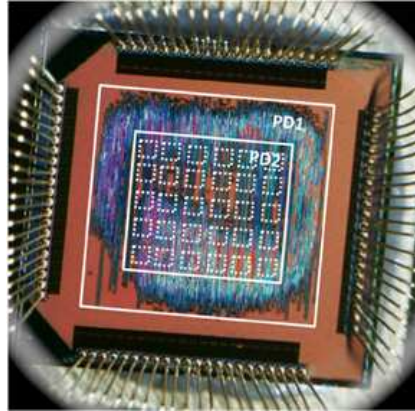
If we could relax the precision of the calculations near the truncation scale, would this allow EPS system to progress to high (10km, 1km...) resolution, reaping the benefits of high resolution, without the punitive computational costs?

Superefficient inexact chips

<http://news.rice.edu/2012/05/17/computing-experts-unveil-superefficient-inexact-chip/>



Krishna Palem.
Rice, NTU
Singapore



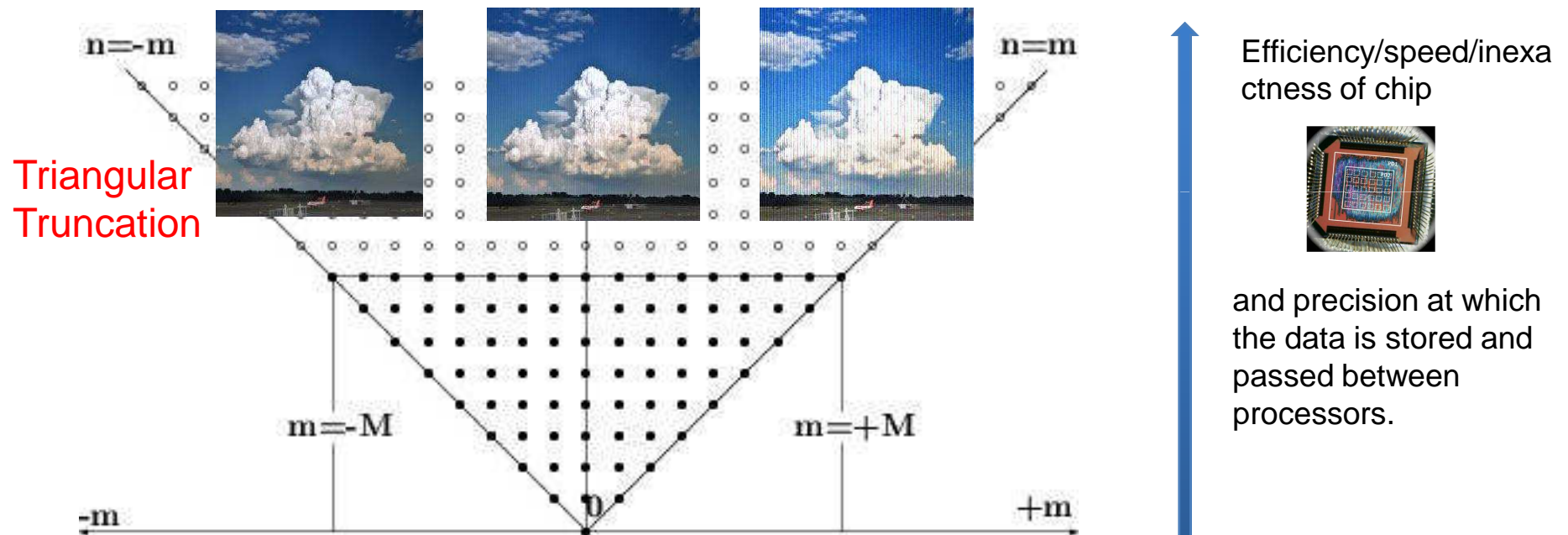
In terms of speed, energy consumption and size, inexact computer chips like this prototype, are about 15 times more efficient than today's microchips.



This comparison shows frames produced with video-processing software on traditional processing elements (left), inexact processing hardware with a relative error of 0.54 percent (middle) and with a relative error of 7.58 percent (right). The inexact chips are smaller, faster and consume less energy. The chip that produced the frame with the most errors (right) is about 15 times more efficient in terms of speed, space and energy than the chip that produced the pristine image (left).

Towards the Stochastic Dynamical Core?

Stochastic Parametrisation



At Oxford we are beginning to work with IBM Zurich, Technical Uni Singapore and U Illinois to develop these ideas...

Will bit-reproducible computation continue to be a *sine qua non* in HPC?

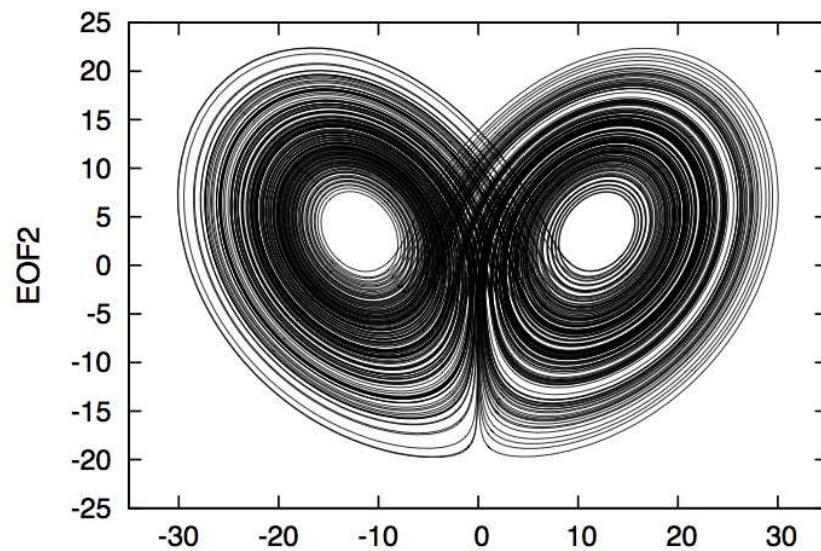
In a recent presentation on **Challenges in Application Scaling in an Exascale Environment**, IBM's Chief Engineer for HPC, Don Grice, noted that:

“Increasingly there will be a tension between energy efficiency and error detection”,

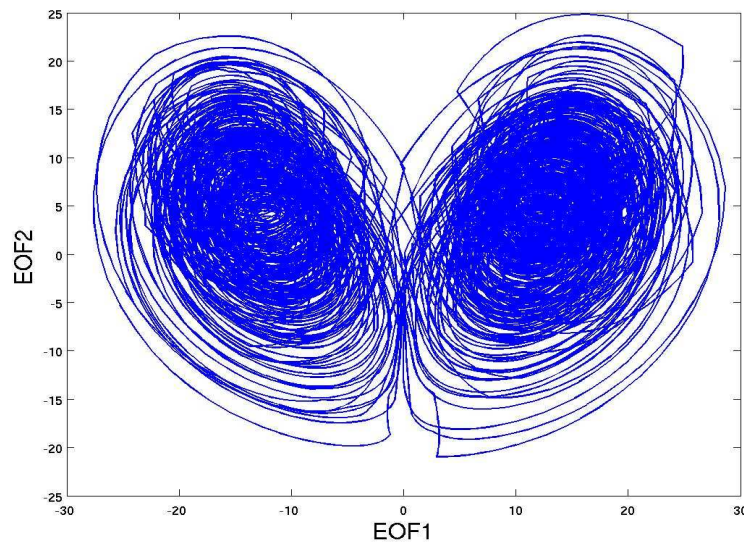
and asked whether :

“...there needs to be a new software construct which identifies critical sections of code where the right answer must be produced” – implying that outside these critical sections errors can (in some probabilistic sense) be tolerated.

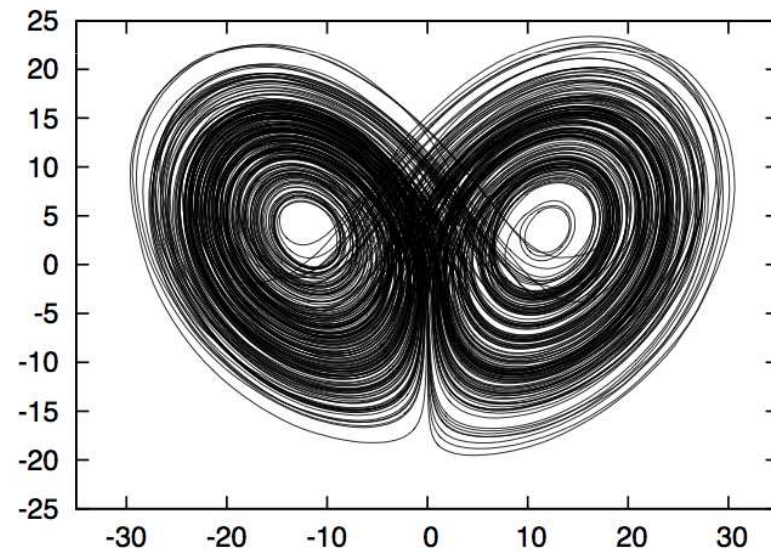
([http://www.ecmwf.int/newsevents/meetings/workshops/2010/high performance computing 14th/index.html](http://www.ecmwf.int/newsevents/meetings/workshops/2010/high%20performance%20computing%2014th/index.html))



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



Represent a_3 by stochastic noise



Integrate 3rd equation on emulator
of stochastic chip.

Peter Düben

20 Years Ago

Dynamics

Parametrisation

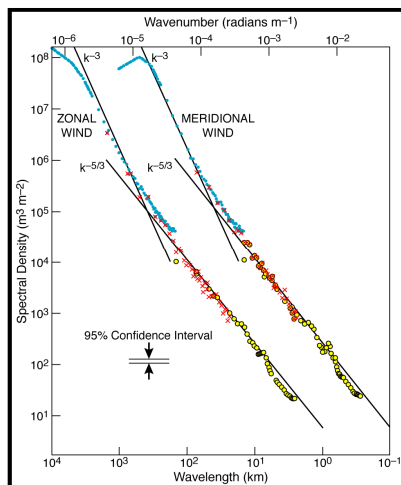
$O(100\text{km})$
)

Now

Dynamics

Parametrisation

$O(10\text{km})$



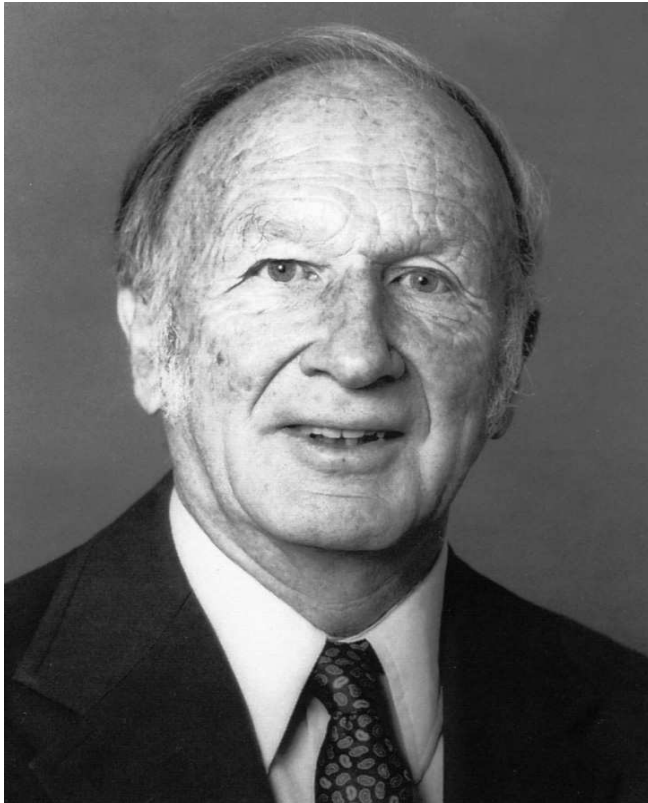
In 20 years

Dynamics

Parametrisation

$O(1\text{km})$

Edward Norton Lorenz (1917-2008)



I believe that the
ultimate climate
models..will be
stochastic, ie random
numbers will
appear somewhere in
the time derivatives
Lorenz (1975).