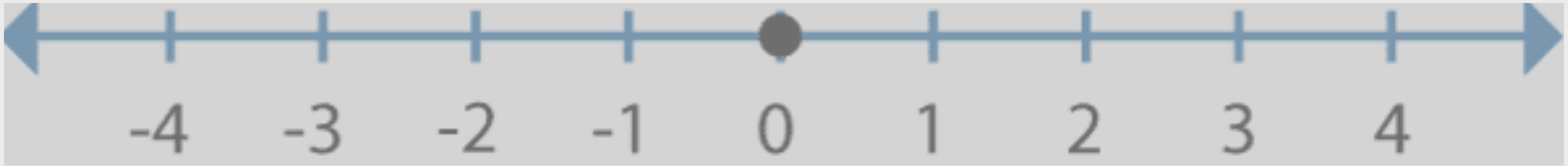
Stochastic parametrisations – toward a new view of weather and climate

DCMIP summerschool workshop, June 5-10, 2016

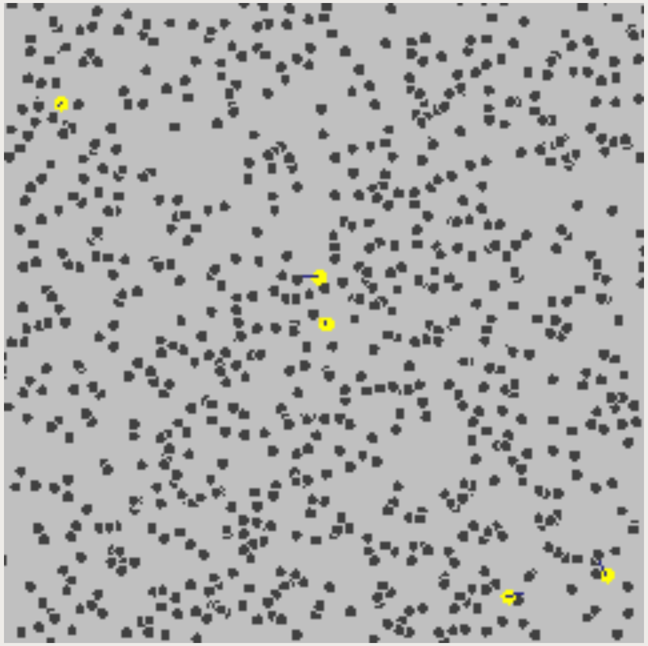
Judith Berner

- Brownian motion and random walks
- Cecile – drinken bla bla, infinite variance
- Stochastic differential equations
  - Ito an Stratonovitch calculus
- How can random numbers improve weather and climate predictions
- Mathematical approaches

Random walk



Brownian motion

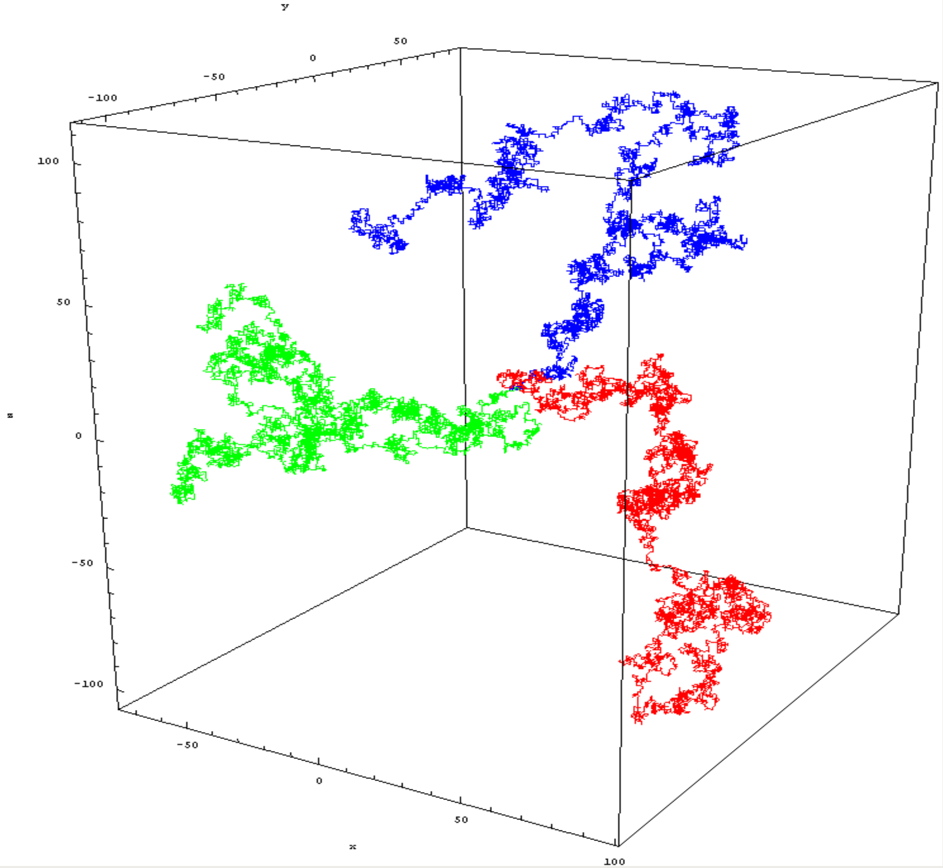


Brownian motion or pedesis (from Greek: πήδησις"leaping") is the random motion of particles suspended in a fluid resulting from their collision with the quick atoms or molecules in the gas or liquid.

A Wiener process is a random walk in the limit of infinitely small steps.

Wiener Process refers to the mathematical model used to describe such Brownian Motion.

Random walk in 3D



- A Wiener process is a random walk in the limit of infinitely small steps.

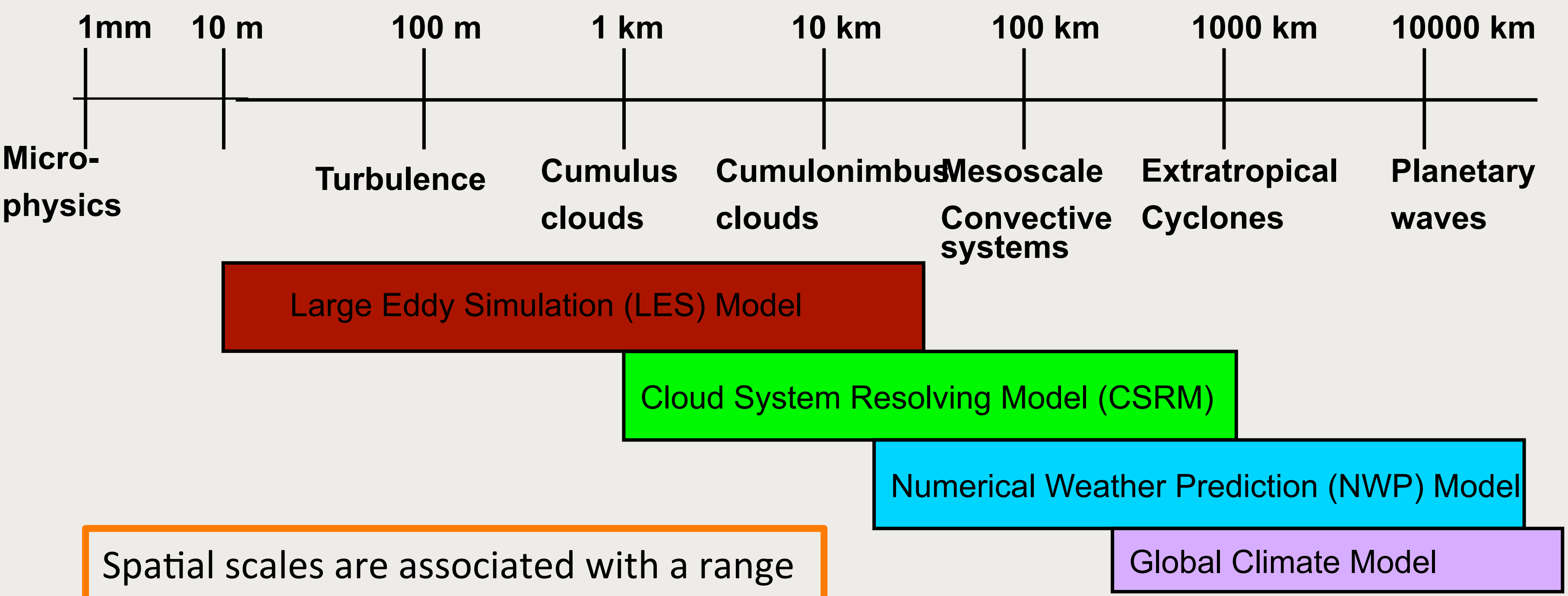
Random walk

- Imagine a drunkard walking randomly in an idealized city. The city is effectively infinite and arranged in a square grid, and at every intersection, the drunkard chooses one of the four possible routes (including the one he came from) with equal probability.
- Will the drunkard ever get back to his home from the bar? Is is the same in 2D and 3D?

Random walk

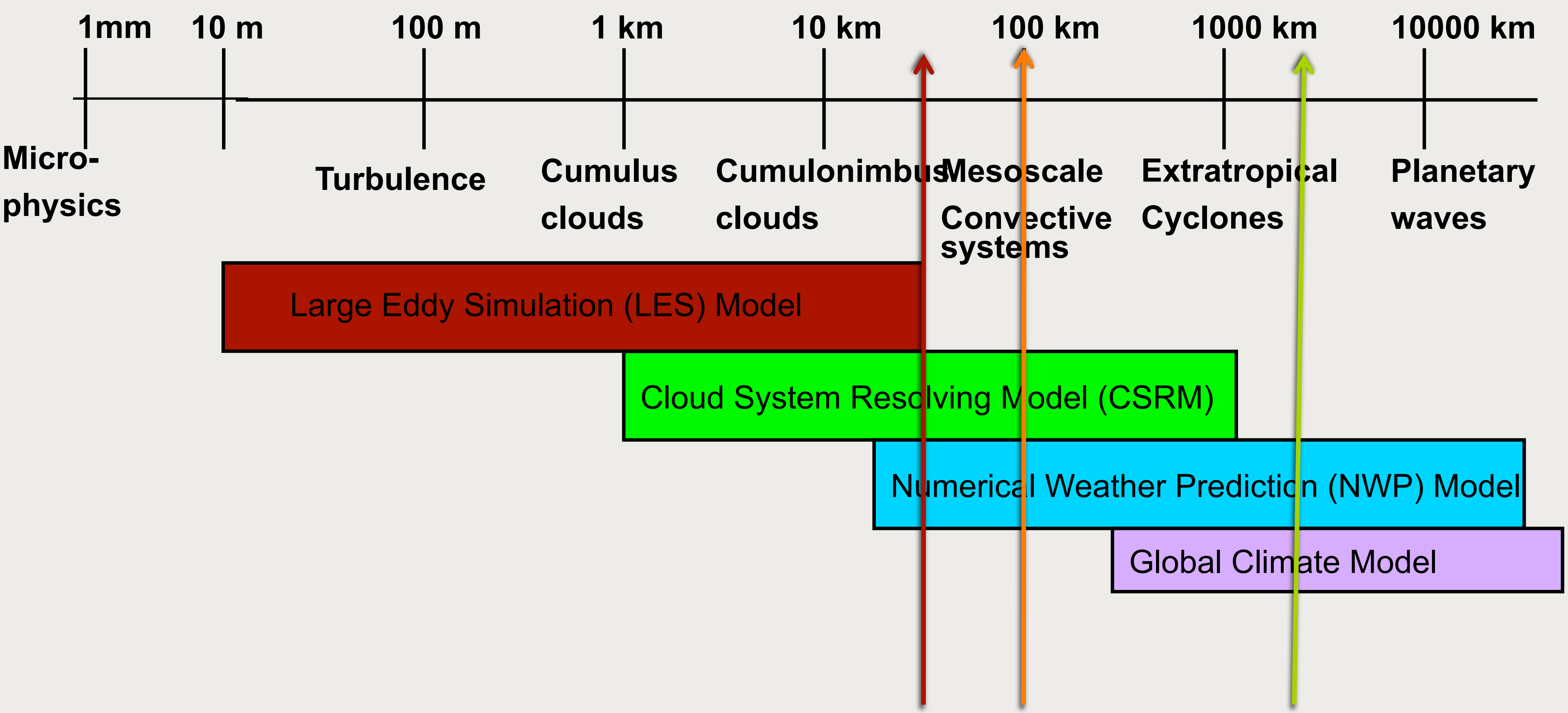
- Imagine a drunkard walking randomly in an idealized city. The city is effectively infinite and arranged in a square grid, and at every intersection, the drunkard chooses one of the four possible routes (including the one he came from) with equal probability.
- Will the drunkard ever get back to his home from the bar?
- If the city is 2D - Almost surely (i.e. the event happens with probability one)
- If the city is 3D – only with a probability of 34%.

Multiple scales of motion



Spatial scales are associated with a range of temporal scales here omitted. Multi-scale nature.

Multiple scales of motion

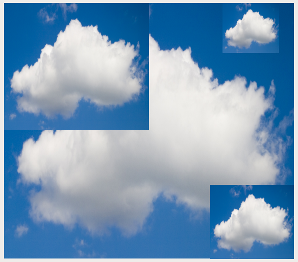


What is a stochastic parameterization?

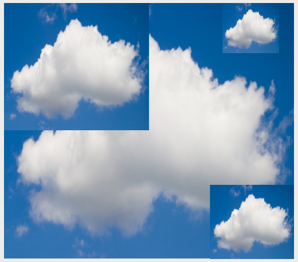
- A deterministic parameterizations aims at representing the mean effect of a subgrid-scale process on the resolved scale (bulk paremeterization)
- A stochastic parameterization aims at representing the mean effect plus its fluctuations.

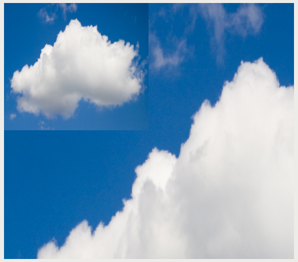
Closure problem

Closure problem



Closure problem





Potential of stochastic parameterizations

- Estimating uncertainty in weather and climate predictions
- Reducing systematic model errors arising from unrepresented subgrid-scale fluctuations
- Triggering noise-induced regime transitions
- Capturing the response to changes in the external forcing

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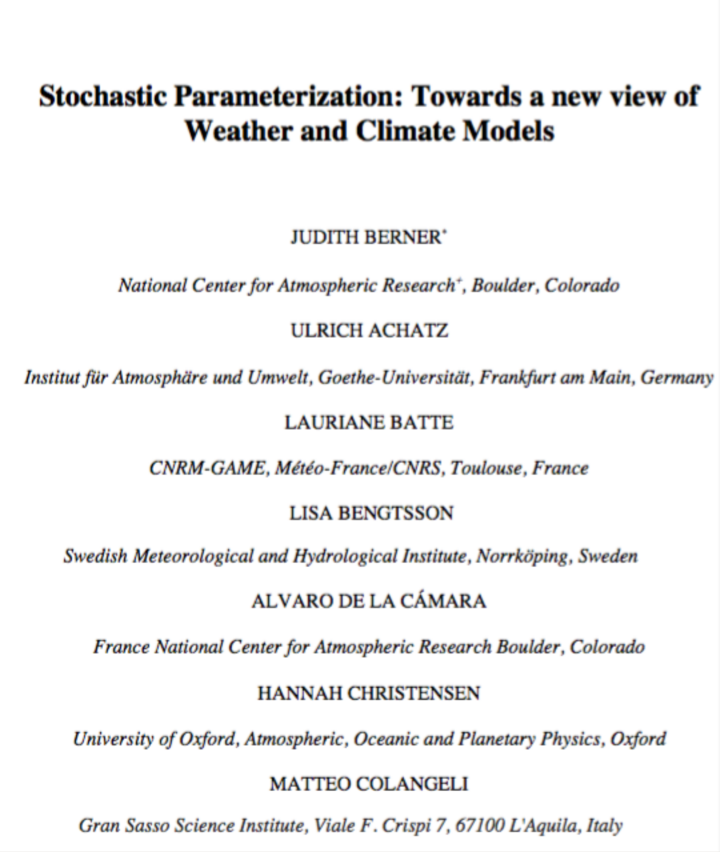
BAMS article



Stochastic Parameterization: Towards a new view of Weather and Climate Models

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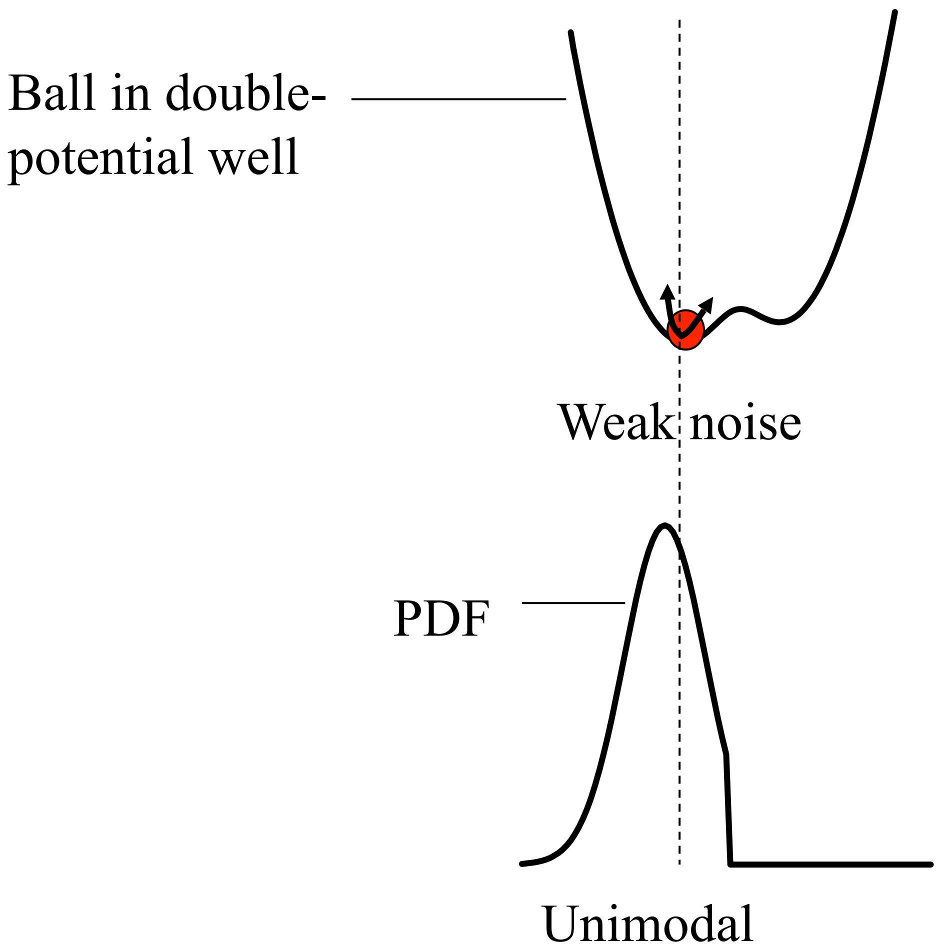
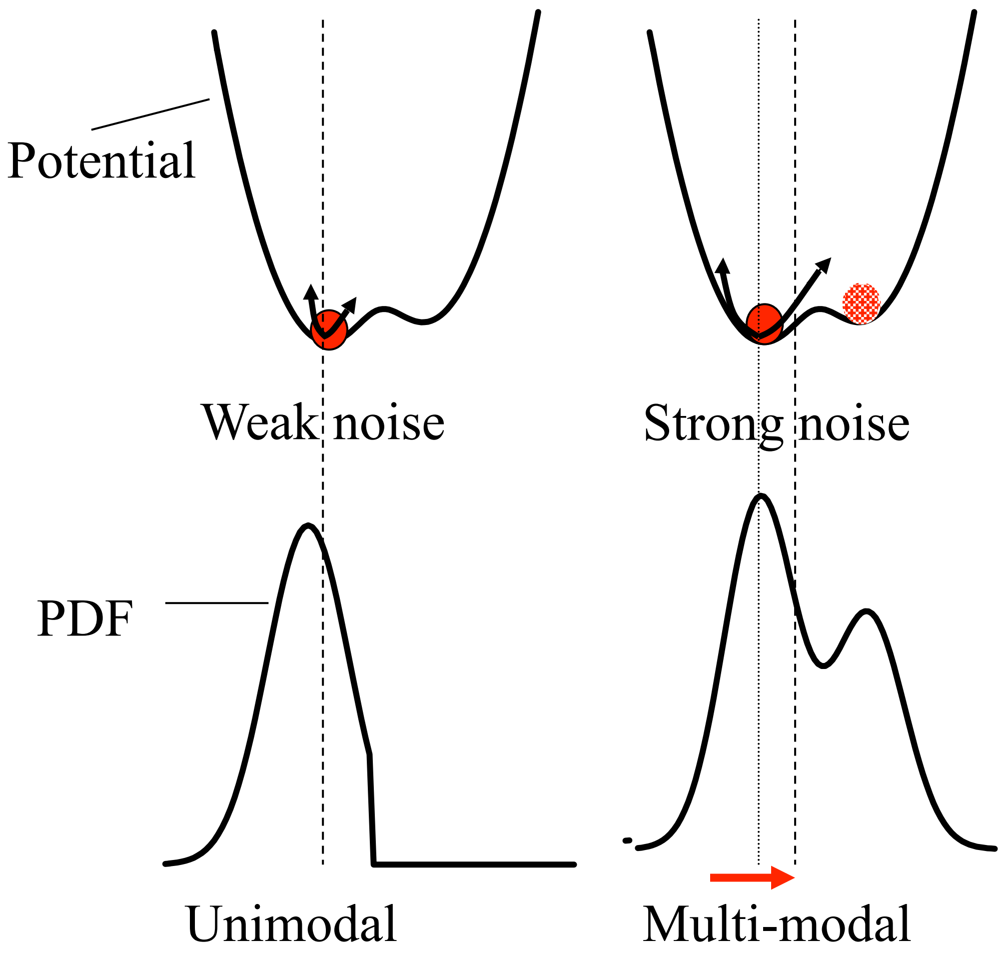
Potential of stochastic parameterizations to reduce model error

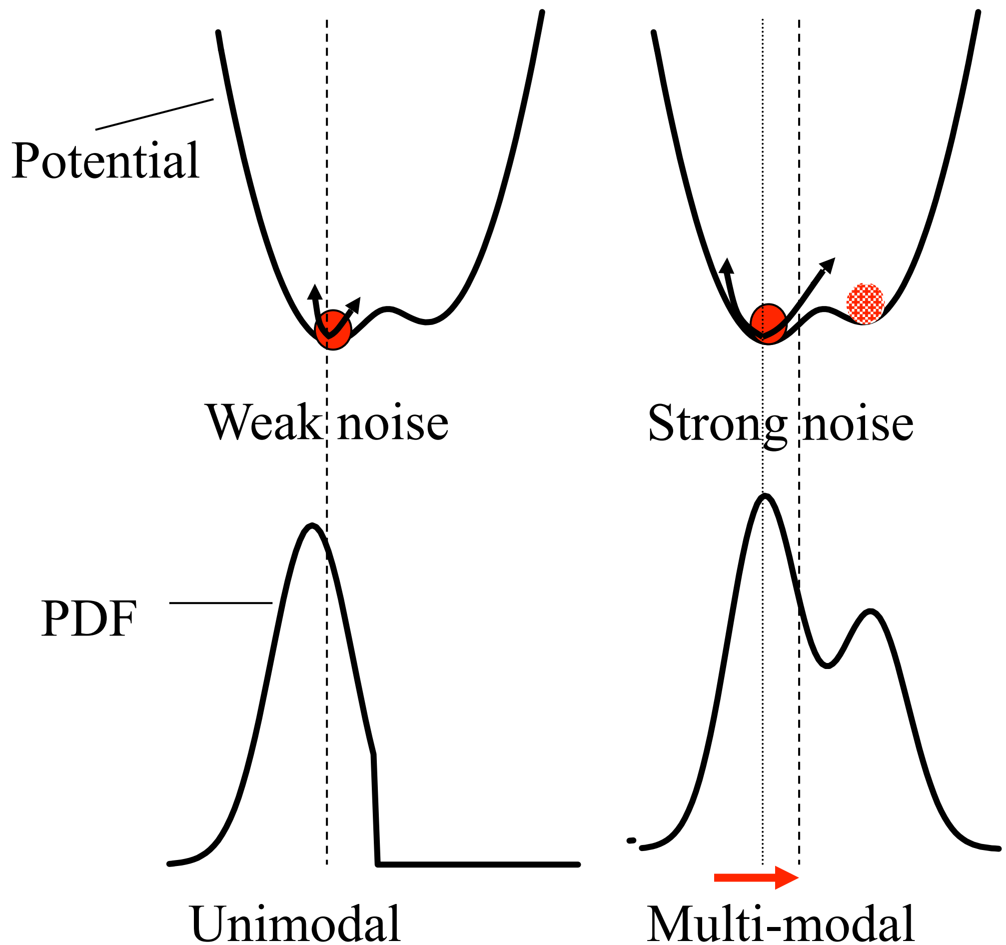


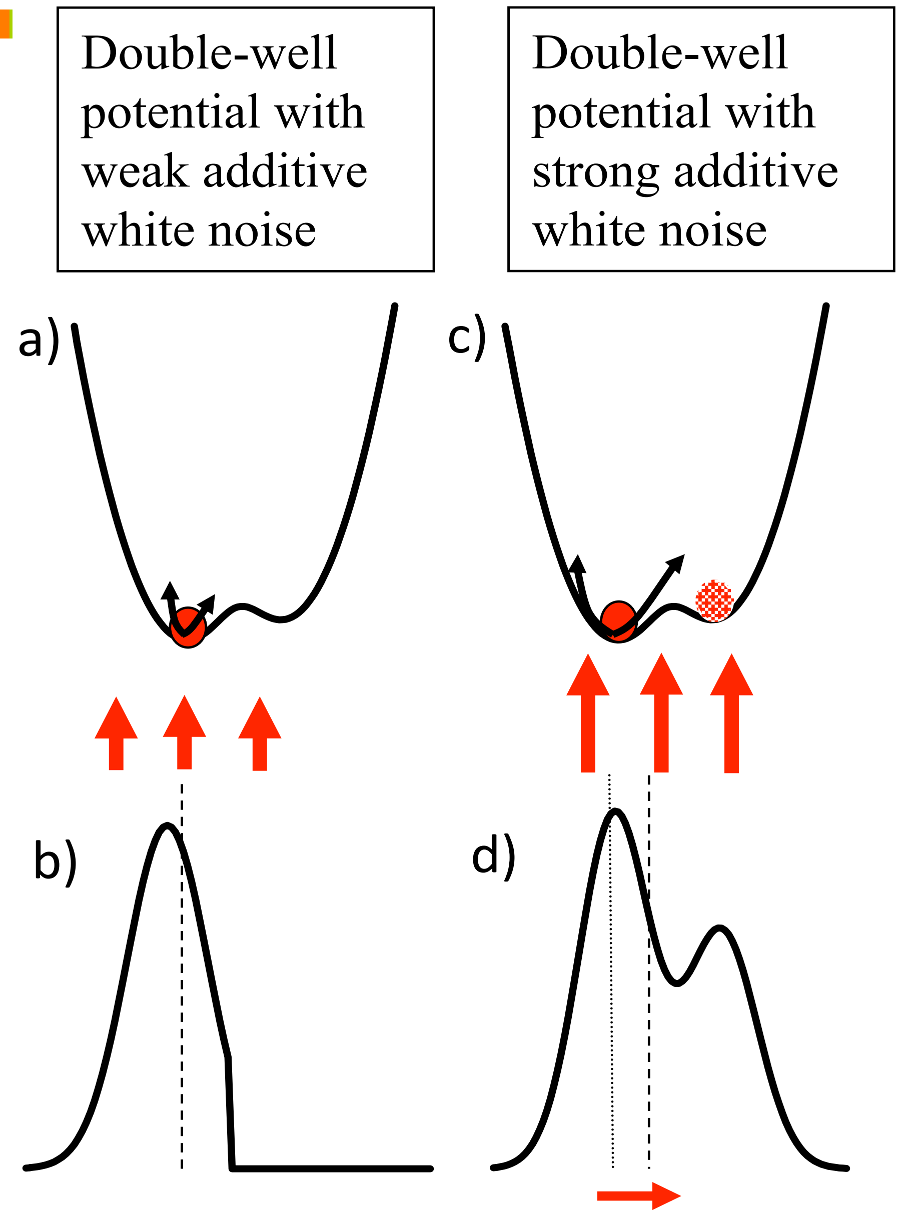
Potential of stochastic parameterizations to reduce model error



Potential of stochastic parameterizations to reduce model error

- Stochastic parameterizations can change the mean and variance of a PDF
  - Impacts variability
  - Impacts mean bias





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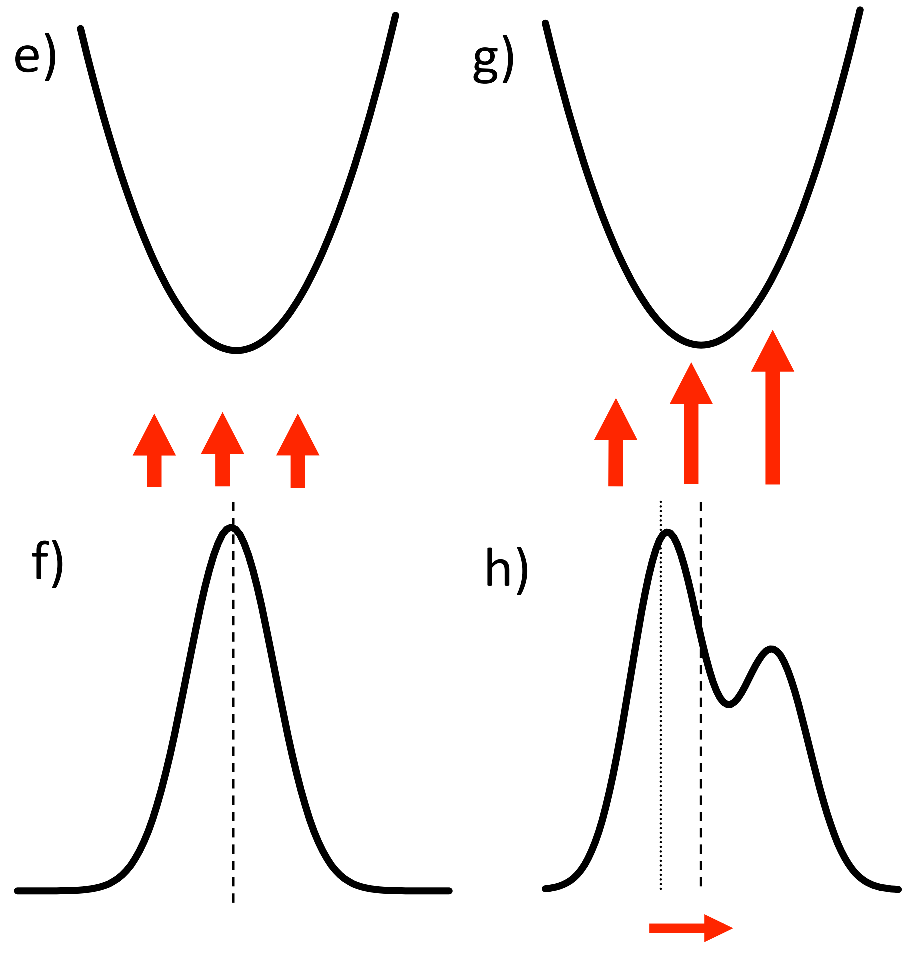
  - Impacts variability
  - Impacts mean bias

Potential well with additive white noise

Potential well with multiplicative white noise

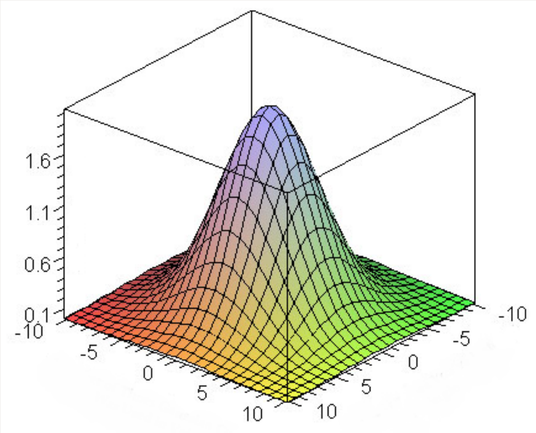


Outline

- The stochastic parameterization problem
- Climate application: Impact in coupled and uncoupled simulations with the Earth System Model CESM
- Weather application: Improving reliability and reducing analysis error in cycled and uncycled forecasts with the weather model WRF

Stochastically perturbed tendency scheme (SPPT)

Rationale: Especially as resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale state should be sampled (Buizza et al. 1999, Palmer et al. 2009, Berner et al. 2014)

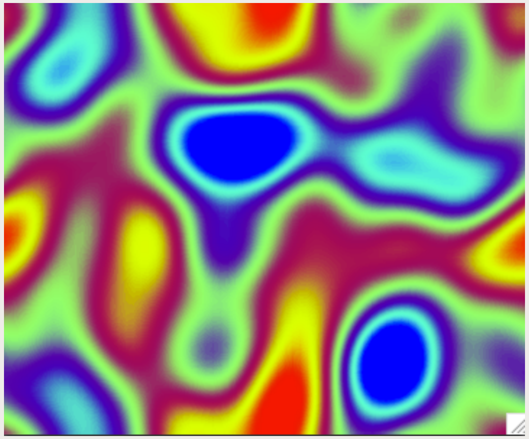


$$\frac{\partial X}{\partial t} = D_X + (r+1)P_X$$

Local tendency for variable X

Dynamical tendencies => Resolved scales

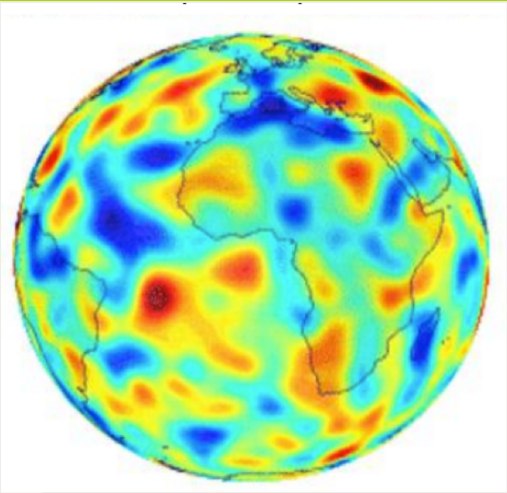
Physical tendencies => Unresolved scales



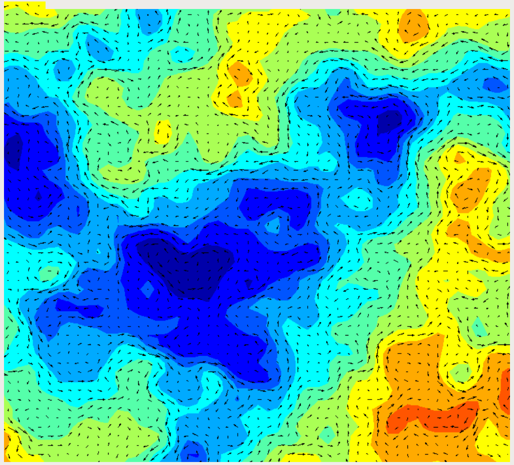
- Perturbs accumulated U,V,T,Q tendencies from physical parameterizations packages
- Same pattern for all tendencies to minimize introduction of imbalances

Stochastic-kinetic energy backscatter scheme (SKEBS)

Rationale: A fraction of the subgrid-scale energy is scattered upscale and acts as random streamfunction and temperature forcing for the resolved-scale flow (Shutts 2005, Berner et. al 08,09). Here simplified version with constant dissipation rate: can be considered as additive noise with spatial and temporal correlations.



Stochastic Forcing Pattern



$$\frac{\partial X}{\partial t} = D_X + P_X + dD_{X,STOCH}$$

Local tendency for variable X =U,V,T

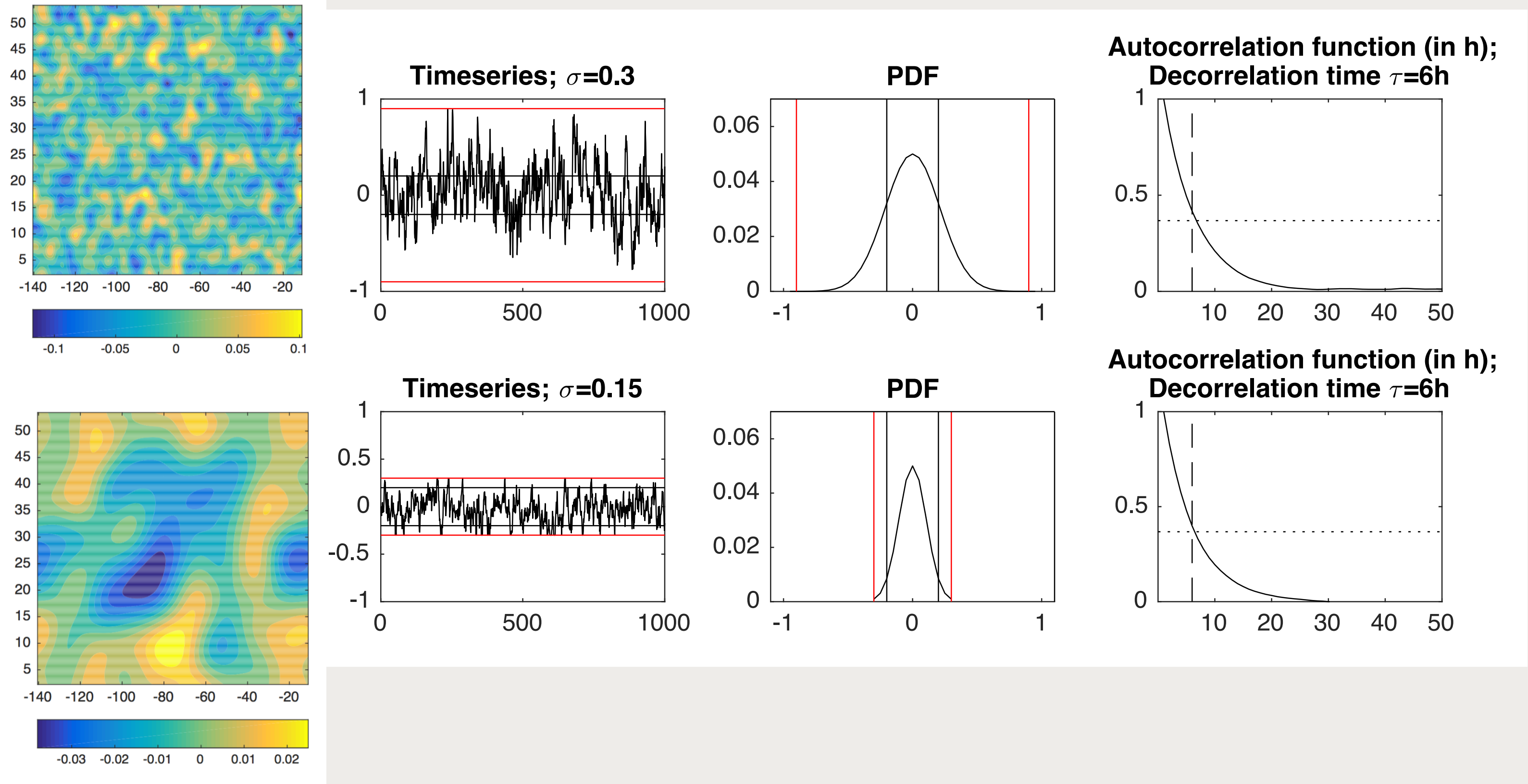
Dynamical tendencies => Resolved scales

Physical tendencies => Unresolved scales

Additive stochastic perturbation tendencies => Unresolved scales

Stochastic parameter perturbations (SPP)

Stochastic pattern perturbs parameter in Grell convection scheme (closure tendencies)



Turbulent mixing length, subgrid cloud fraction, thermal and moisture roughness lengths in MYNN PBL

Outline

- The stochastic parameterization schemes
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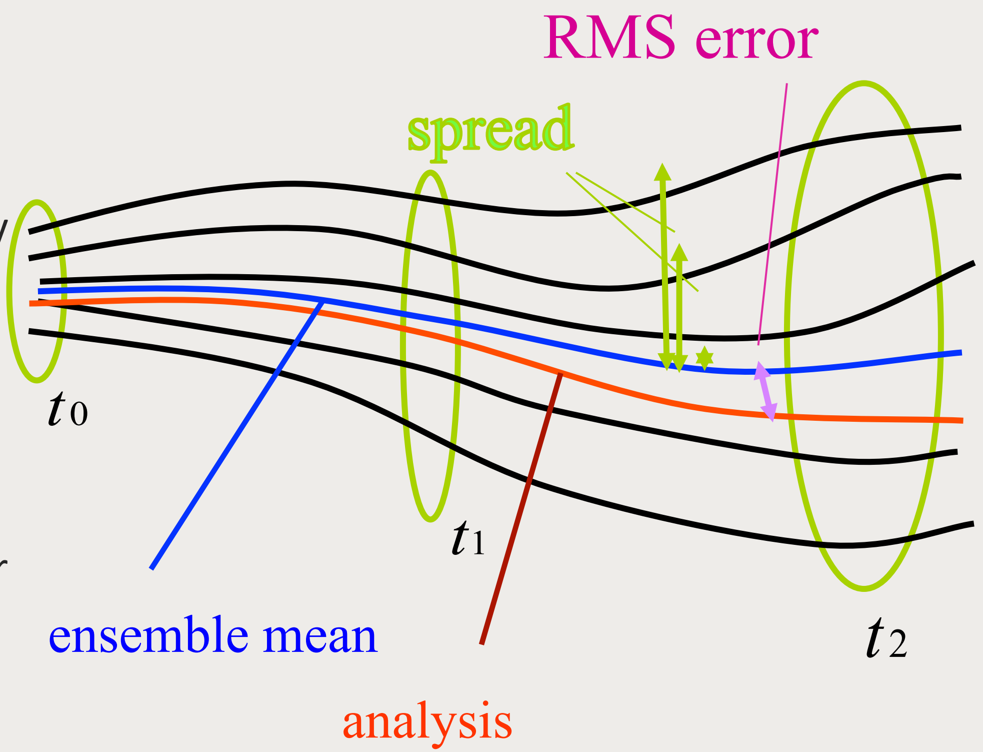
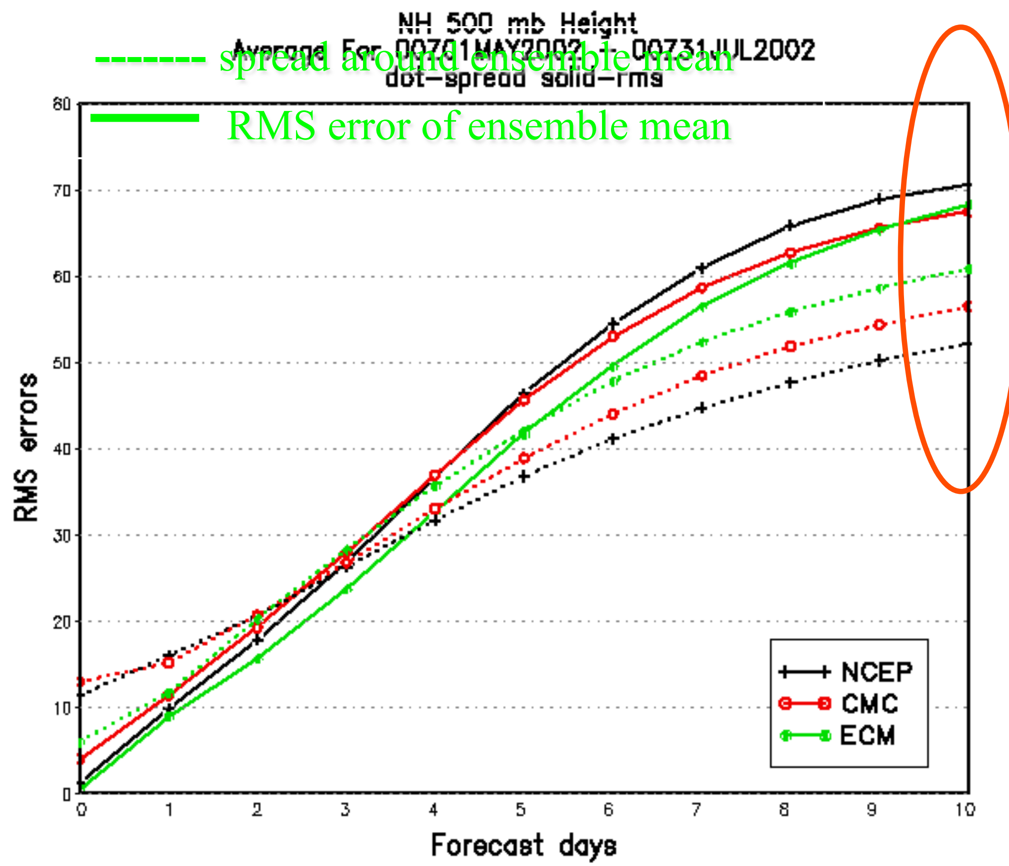
Representing initial uncertainty by an ensemble of states

- Forecast uncertainty in weather models: \
  - Initial condition uncertainty
  - Model uncertainty
  - Boundary condition uncertainty
- Represent initial forecast uncertainty by ensemble of states
- Reliable forecast system: Spread should grow like ensemble mean error
  - Predictable states with small error should have small spread
  - Unpredictable states with large error should have large spread



Underdispersivness of ensemble systems



Buizza et al., 2004

The RMS error grows faster than the spread

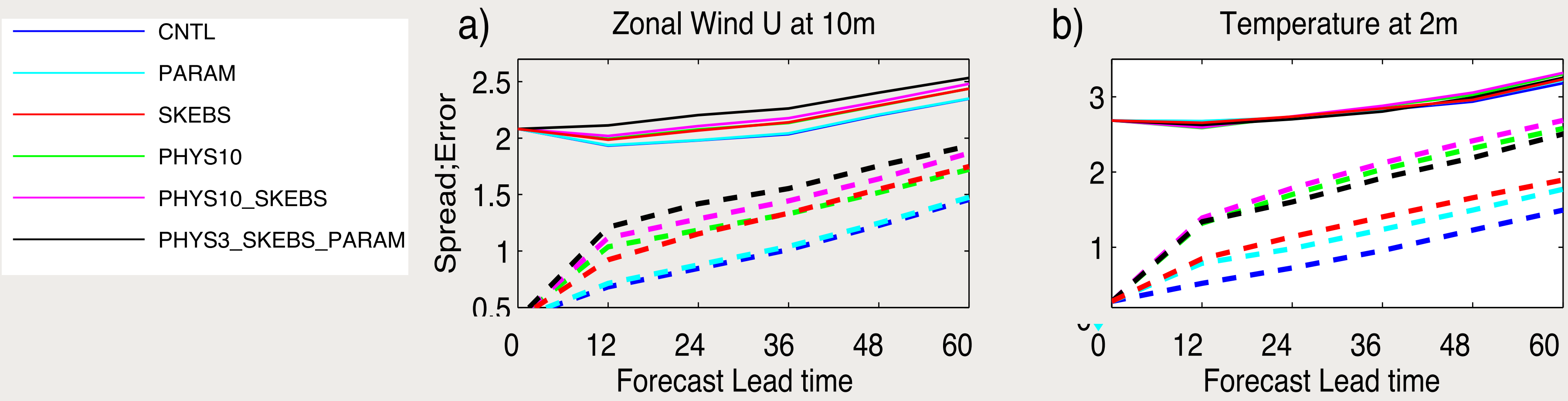
➢Ensemble is

➢Ensemble forecast is **overconfident**

➢Underdispersion is a form of **model error**

➢***Forecast error = initial error + model error + boundary error***

Spread and error near the surface

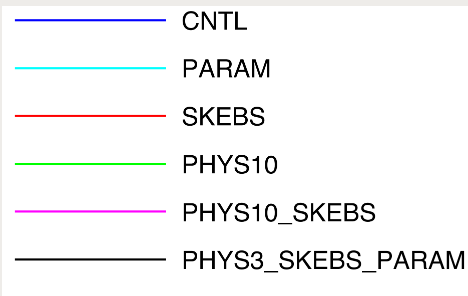


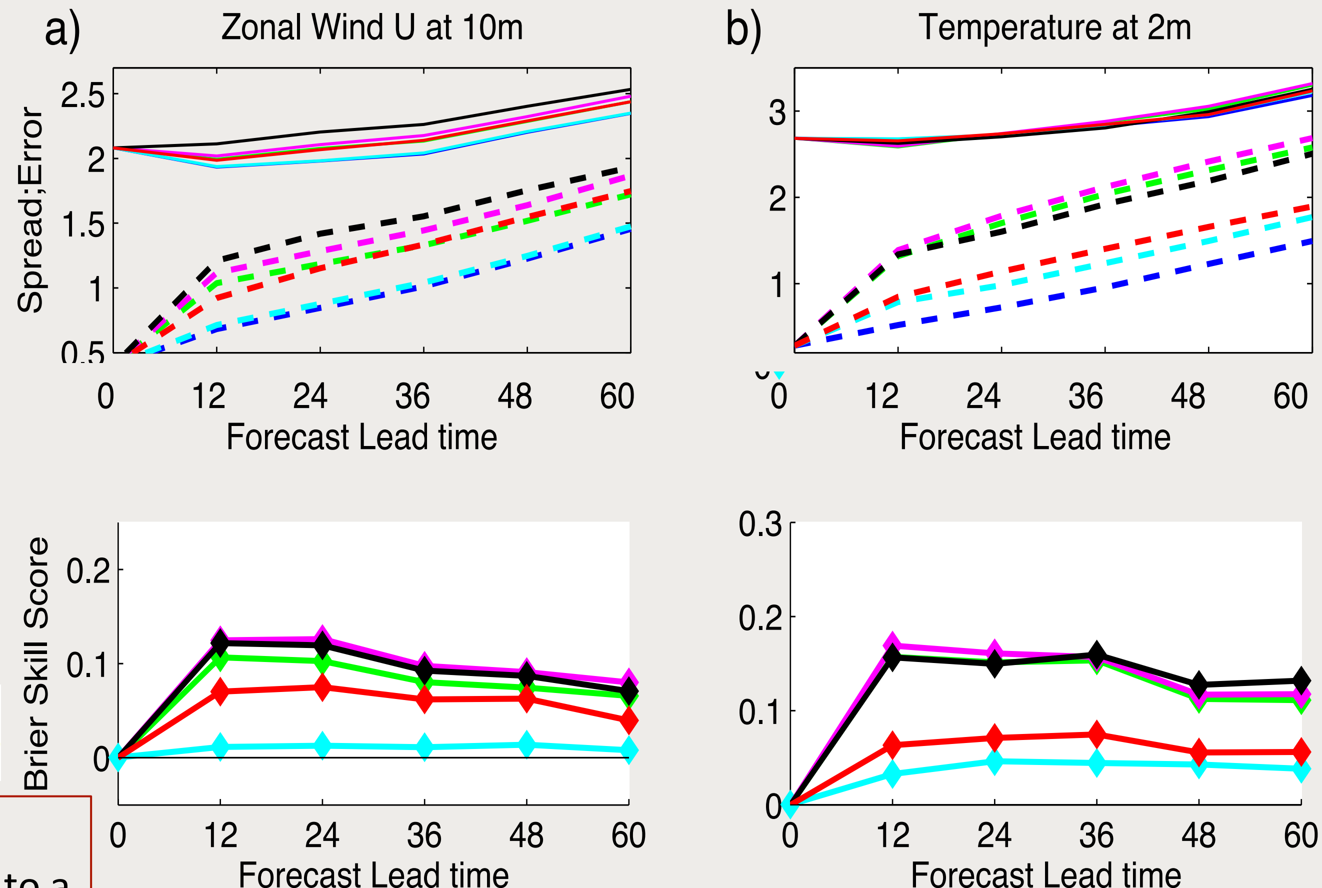
Solid lines: rms error of ensemble mean

Dashed: spread

- Ensemble is underdispersive (= not enough spread)
  - Unreliable and over-confident
  - Depending on cost-loss ration potentially large socio-economic impact (e.g. should roads be salted)

Brierscore skill score near the surface





$$\mathrm{BSS}_{\mathrm{exp}} = \frac{\mathrm{BS}_{\mathrm{ref}} - \mathrm{BS}_{\mathrm{exp}}}{\mathrm{BS}_{\mathrm{ref}}}$$

Brier skill measures probabilistic skill in regard to a reference (here CNTL).
Verified event: μ<x<μ+σ

Berner et al., et al 2015

(Epstein and Pitcher 1972; Lorenz 1975; Pitcher 1977; Palmer 2001), if only to provide reliable estimates of model uncertainty, then a fundamental conclusion of this study is that such a posteriori addition of stochasticity to an already tuned model is simply not viable. This in turn suggests that stochasticity must be incorporated at a very basic level within the design of physical process parameterizations and improvements to the dynamical core.

Acknowledgments. We thank Paco Doblas-Reyes, Antje Weisheimer, and Roberto Buizza for many motivating discussions throughout the years. The Newton Institute in Cambridge hosted the first and third author during their program on "Stochastic modeling in the climate sciences" in 2010, which gave them the opportunity to work on this manuscript. We are indebted to Annabel Bowen and Bob Hine for improving the graphics. Thanks to Joe Tribbia and three anonymous reviewers whose insightful suggestions and comments improved earlier versions of this manuscript.

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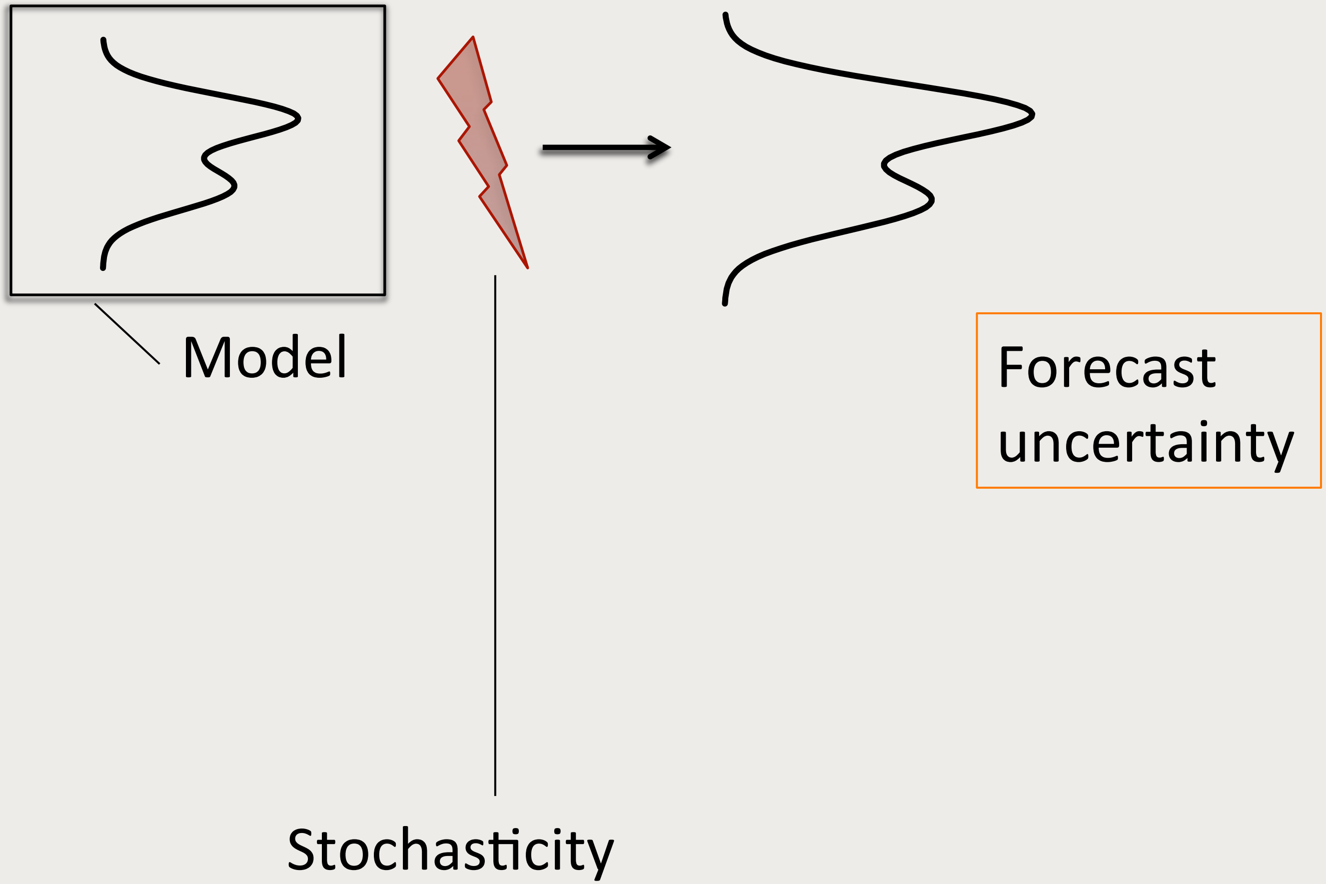
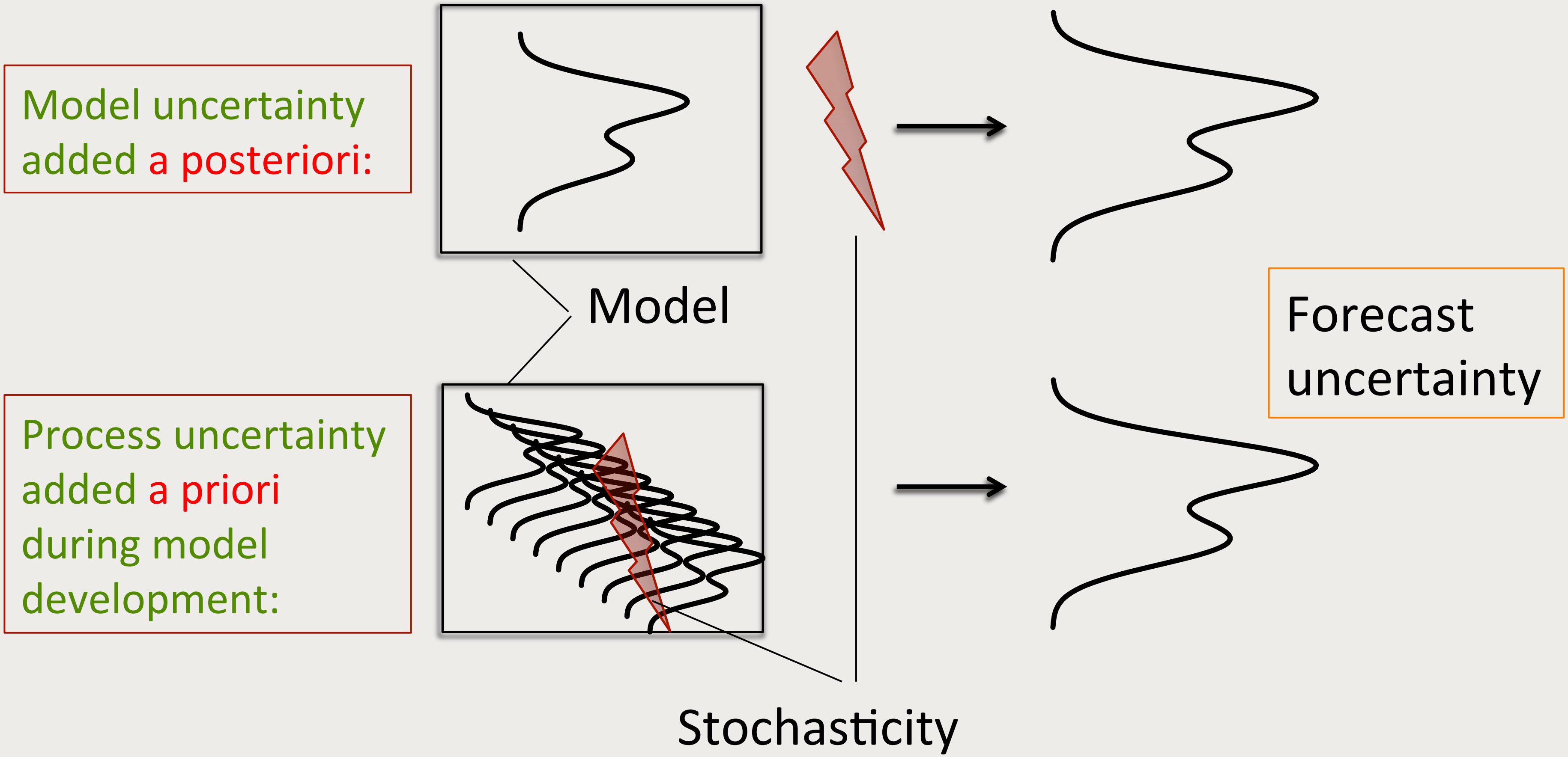
A priori vs a posteriori

Model uncertainty added a posteriori:



A priori vs a posteriori



Stochastically Perturbed Parameters

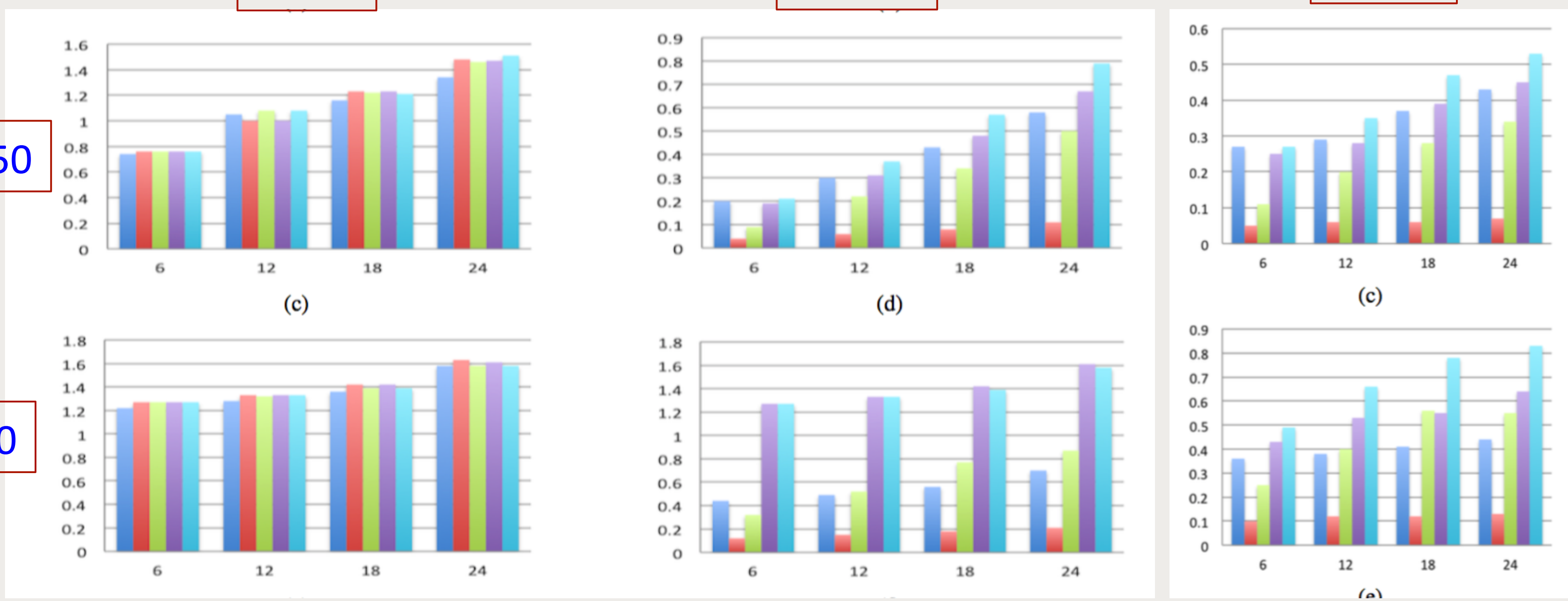
RMSE

Spread

CRPSS

T850

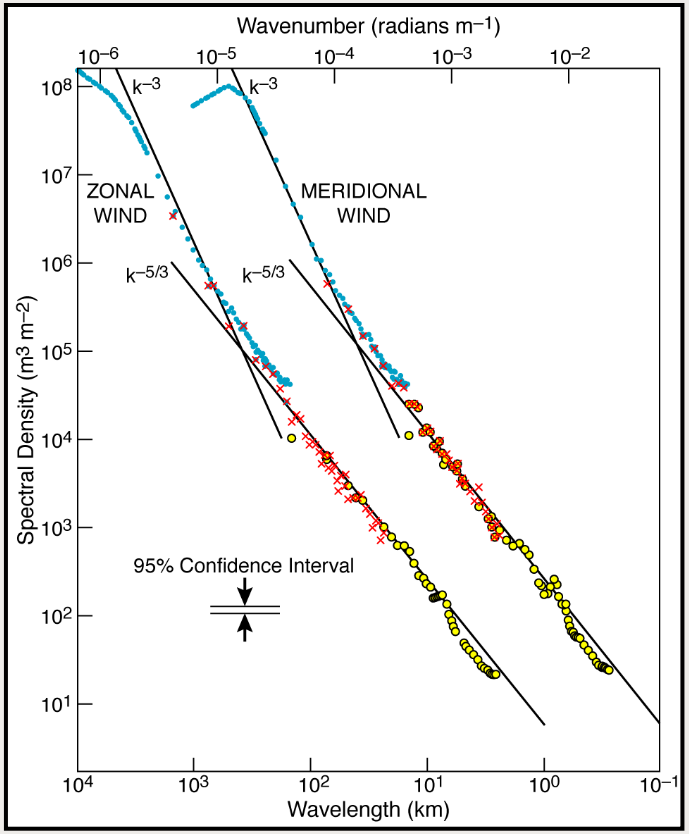
U10



Jankov et al., submitted

CNTL
SPP
SPPT
SKEBS
SPPT+SKEBS+SPP

Kinetic energy spectra



Nastrom and Gage, 1985

Limited vs unlimited predictability in Lorenz 1969

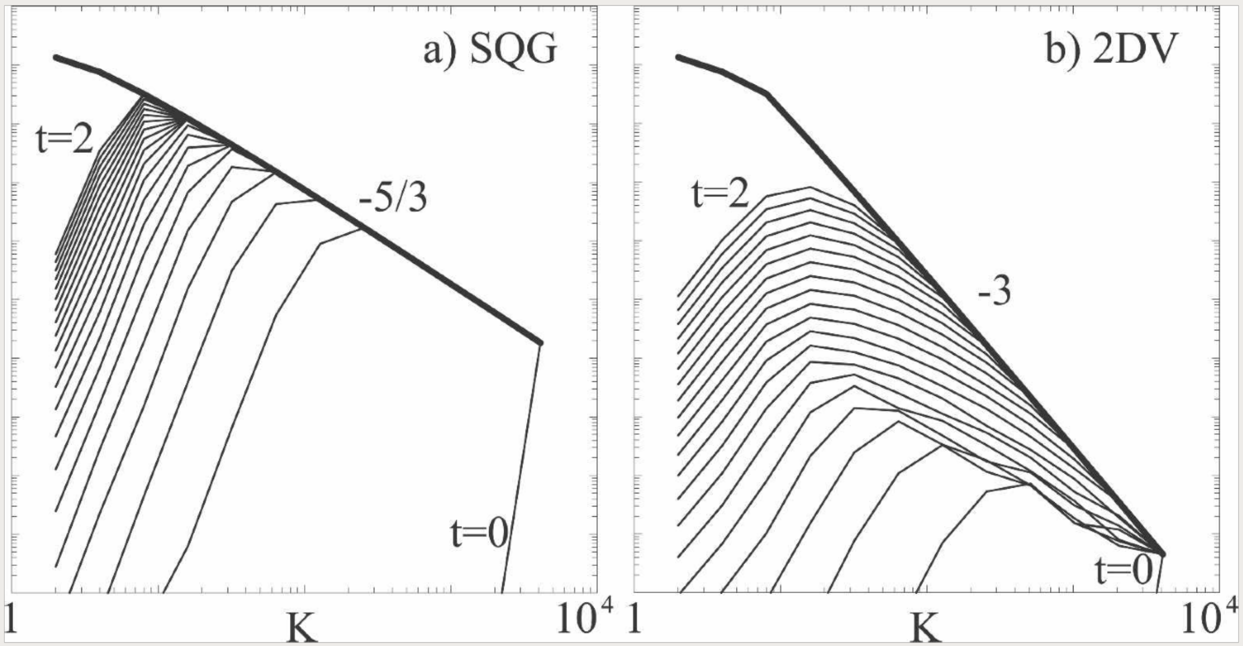


FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K, t)$ for $t = 0, 2$ in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a $-5/3$ slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

see also: Tribbia and Baumhefner 2004

Forecast error spectra

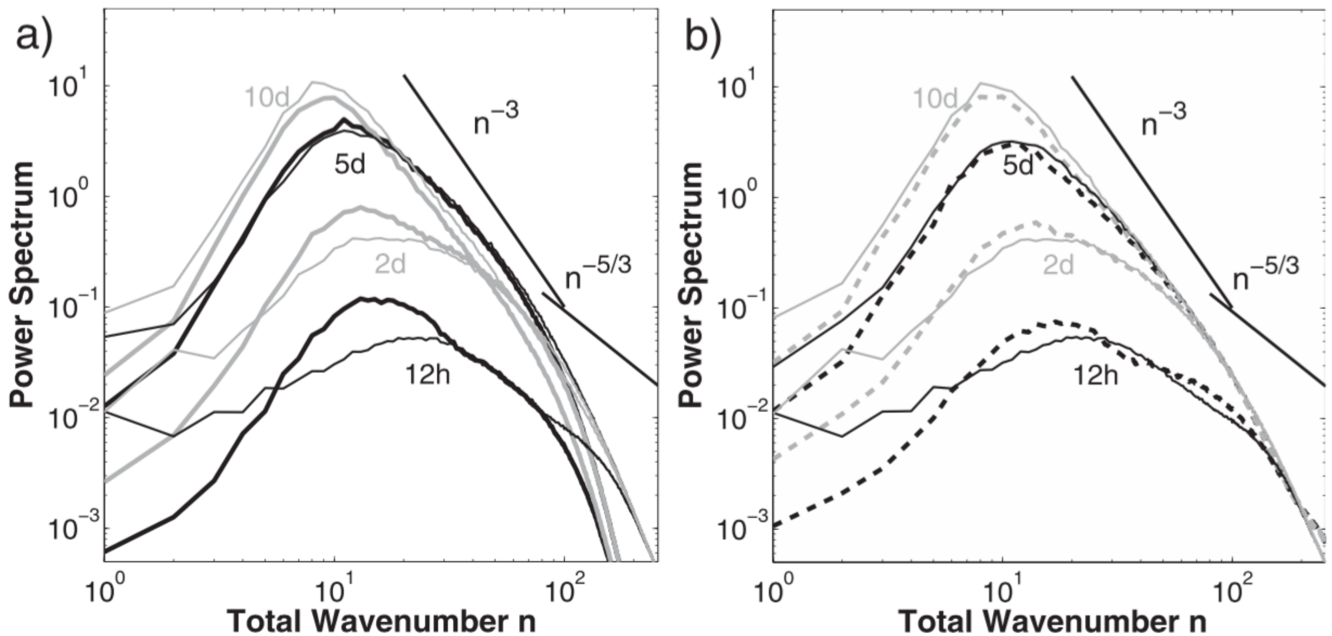


FIG. 8. Power spectrum of the error of the ensemble-mean forecast (thin solid lines) and spread (thick lines) in 500 hPa for fixed forecast lead times of 12 h, 2 days, 5 days, and 10 days for (a) the operational ensemble configuration (spread in OPER: thick solid line) and (b) the ensemble system with a stochastic backscatter scheme and reduced initial perturbations (spread in SSBS: thick dashed line). SSBS is short for SSBS-FULLDISS. Lines for forecast lead times of 12 h and 5 days are shown in black and for 2 days and 10 days in gray. See text for details.

Berner et al. 2009

The closure problem

The "spectral gap" argument (Stull 1960)

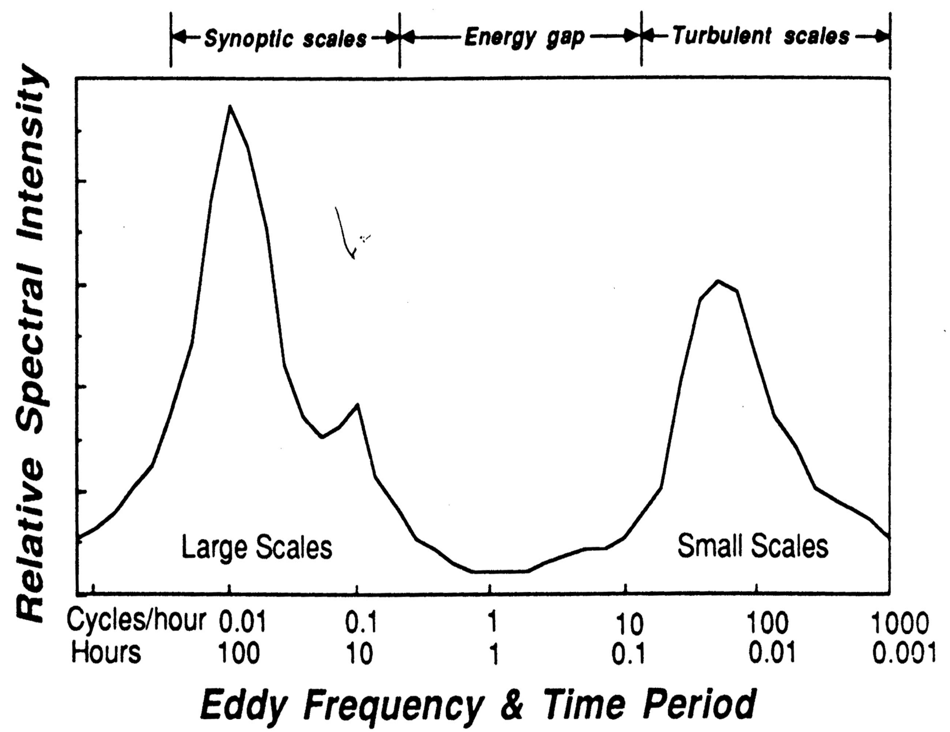
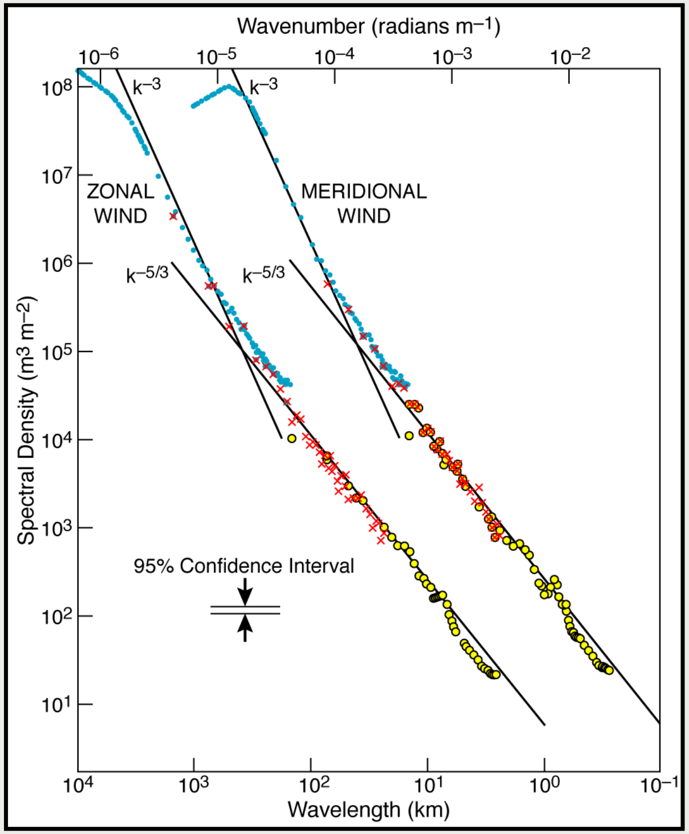


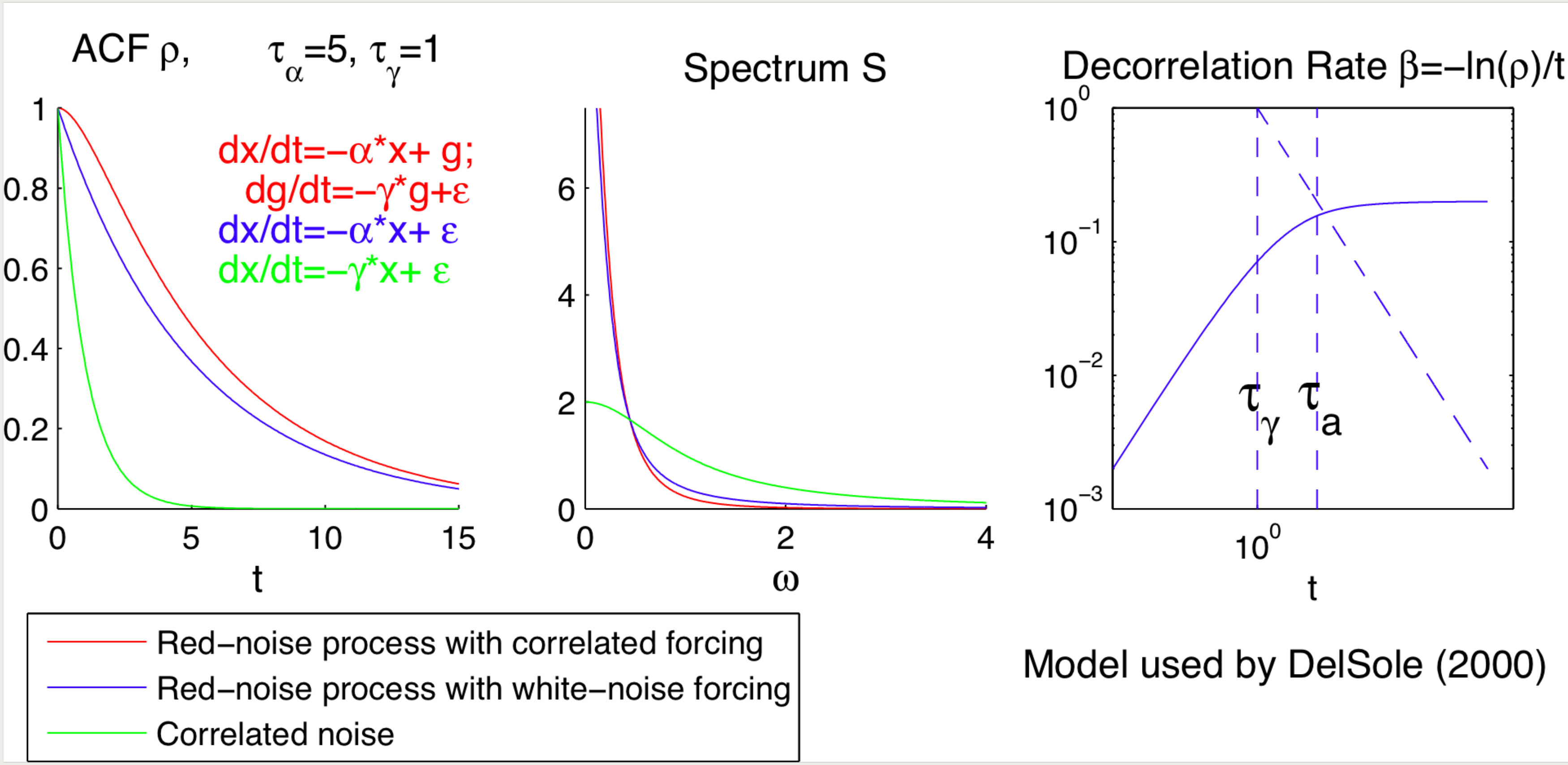
Fig. 2.2 Schematic spectrum of wind speed near the ground estimated from a study of Van der Hoven (1957).

Kinetic energy spectra



Nastrom and Gage, 1985

Spectral gap not necessary for stochastic parameterizations



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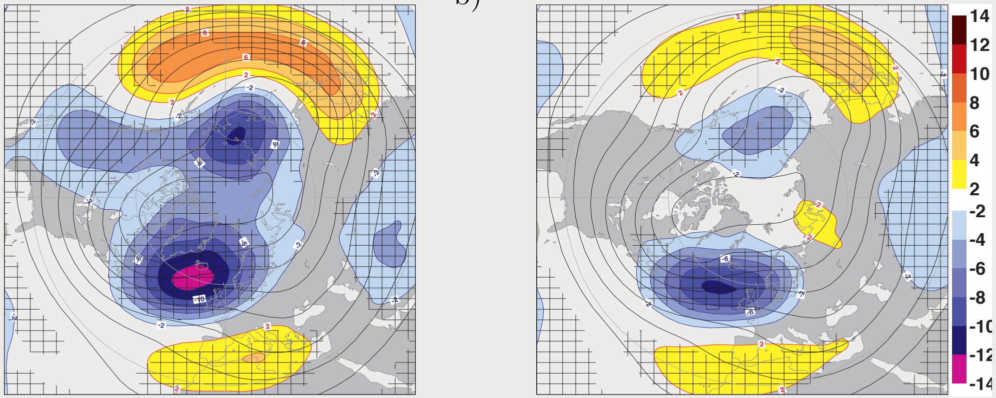
  - missing degrees of freedom are represented stochastically
  - low-resolution model with stochastic parameterization should look like high-resolution model

Mean systematic error of 500 hPa geopotential height fields

LOWRES

HIGHRES

b)



Mean systematic error of 500 hPa geopotential height fields

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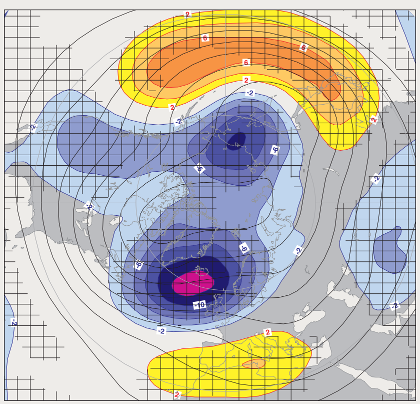

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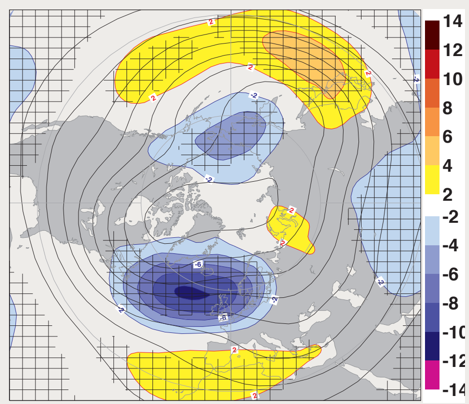
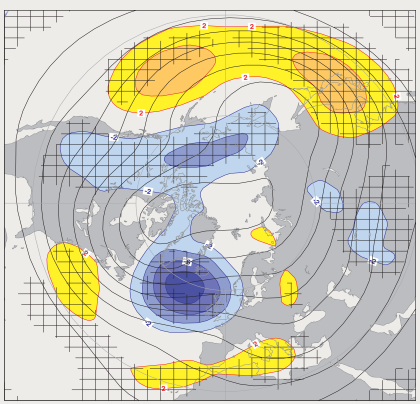


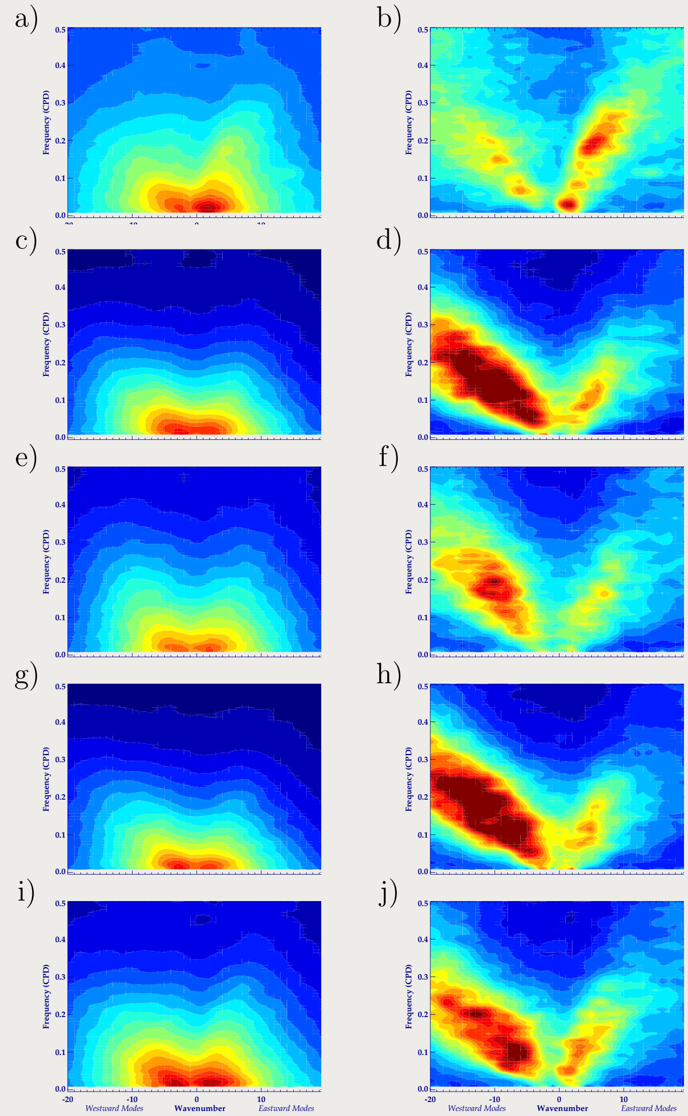
SKEBS



- Reduction of z500 bias in all simulations with model-refinement

Berner et al., 2012

Frequency-Wavenumber spectra of OLR in IFS



NOAA

CNTL

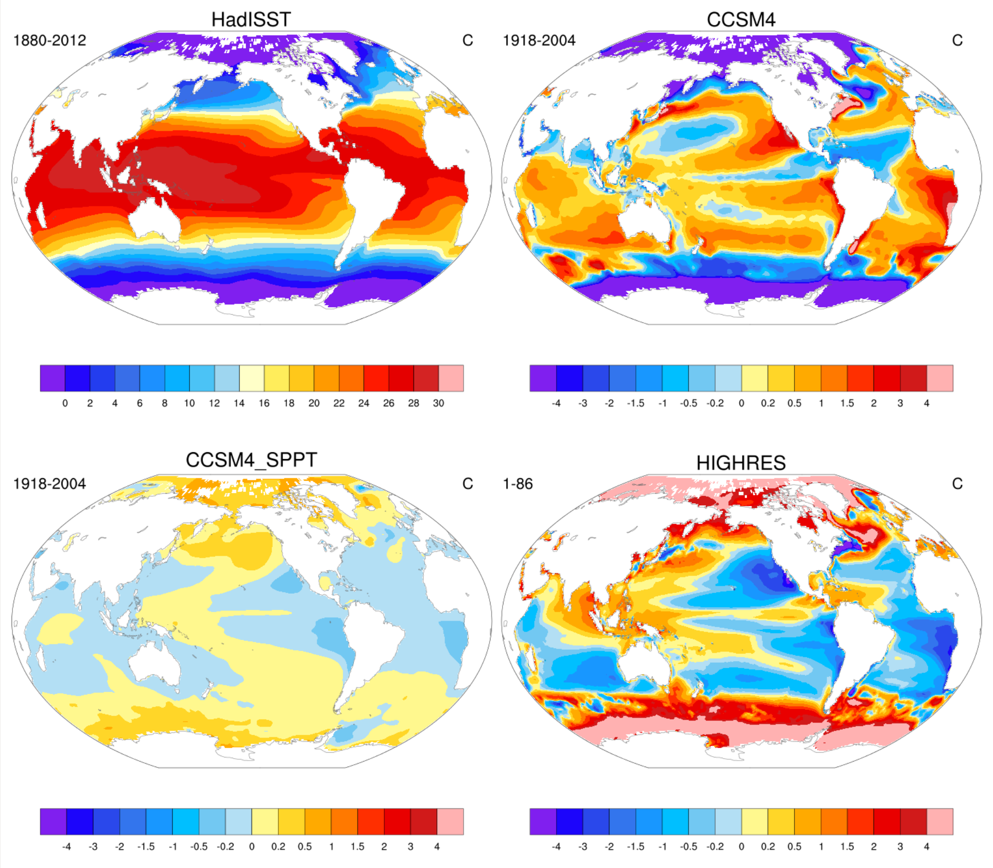
SKEBS

HIGHRES

PHYS

Berner et al. 2012

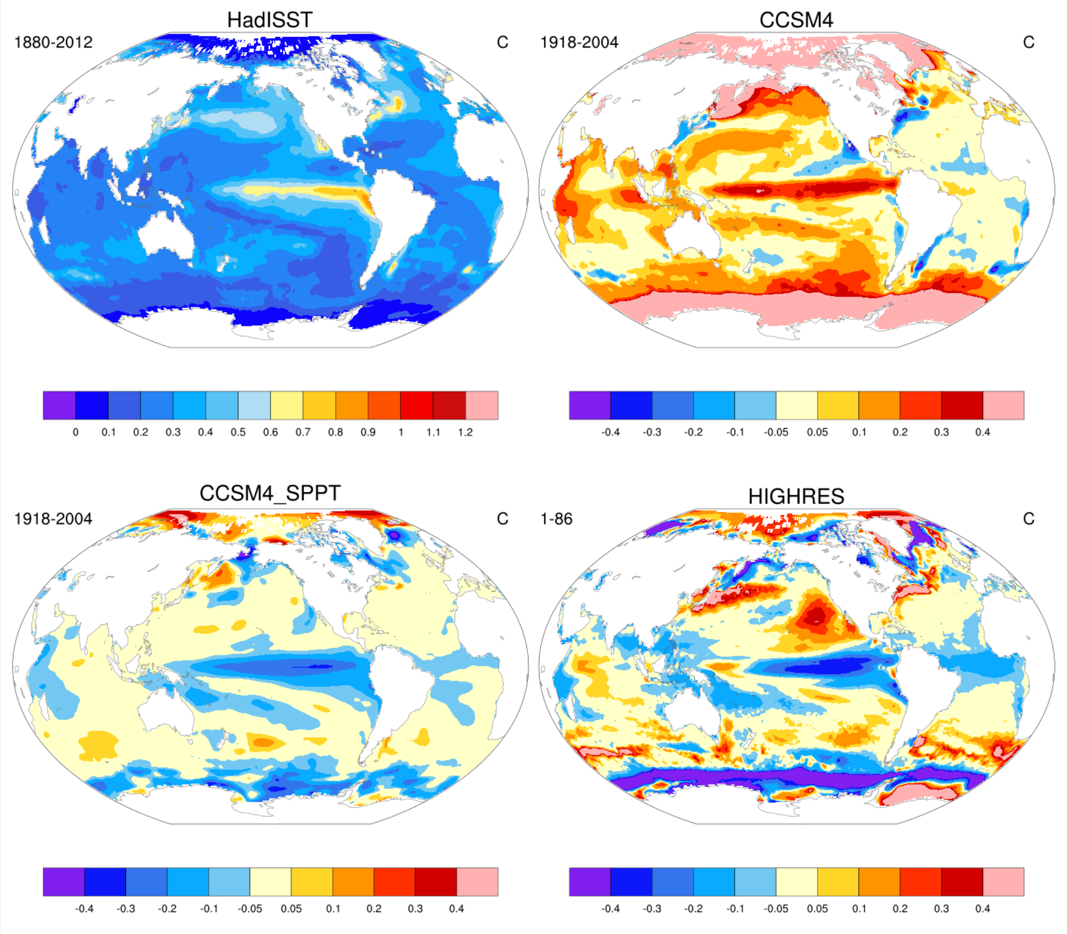
Difference in SST Mean



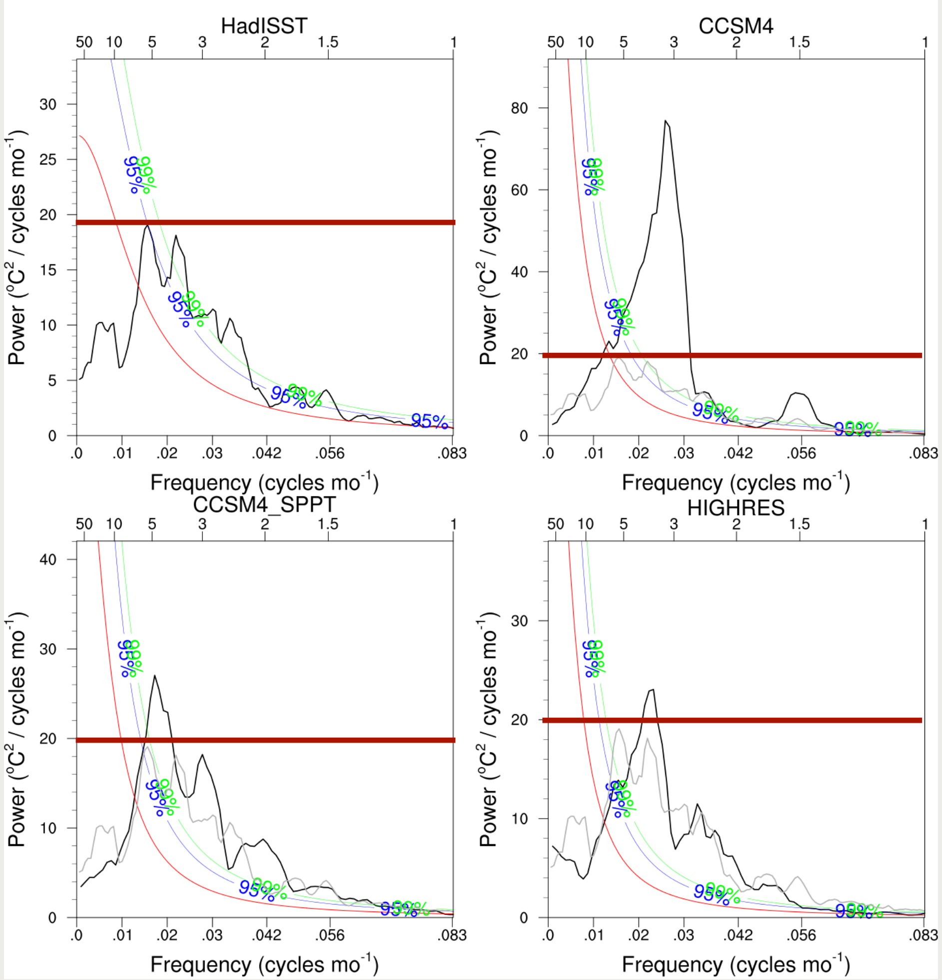
With Hannah Christensen and Justin Small

See Christensen et al. 2016, submitted

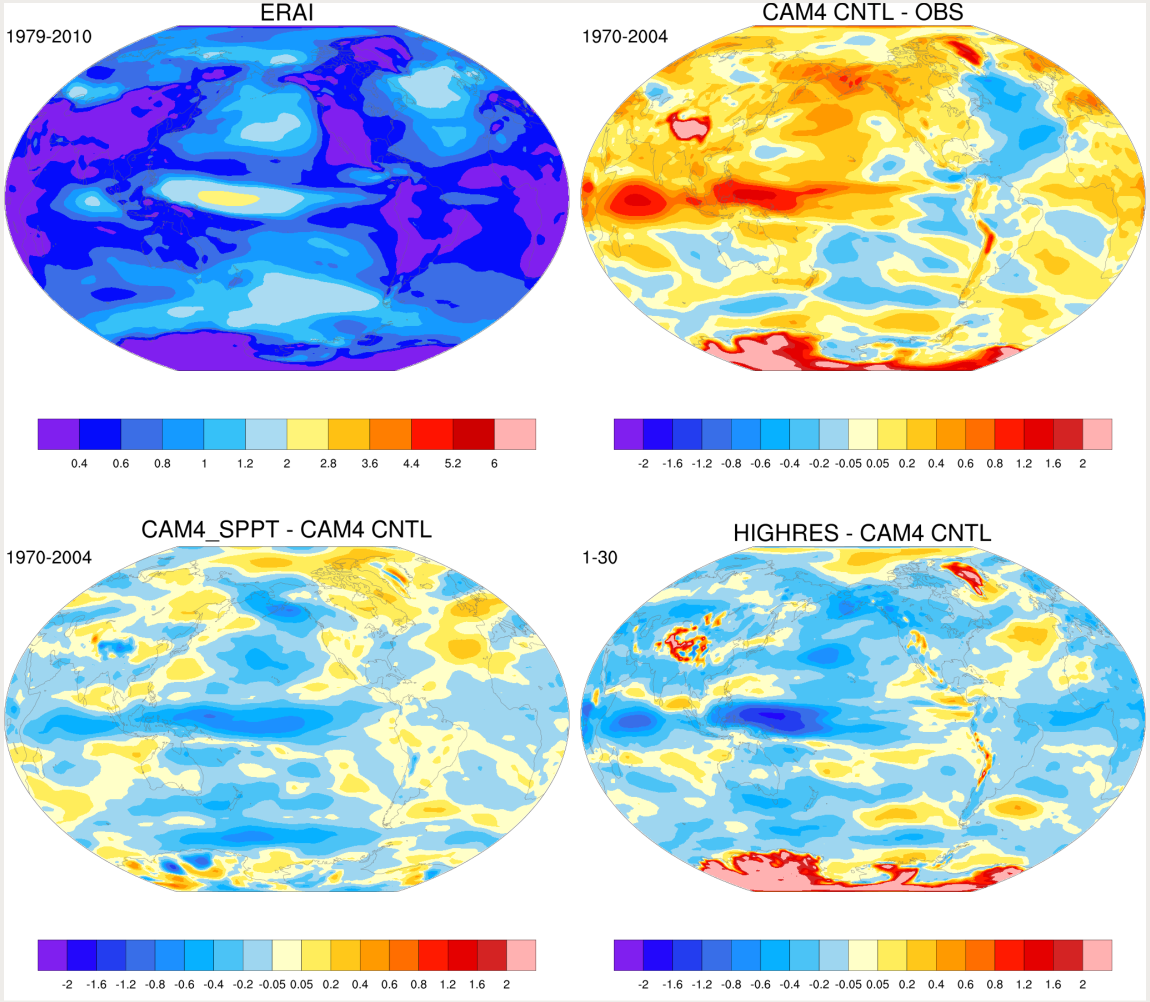
Difference in SST standard deviation



Nino3.4 Power spectra



Difference in U850 standard deviation



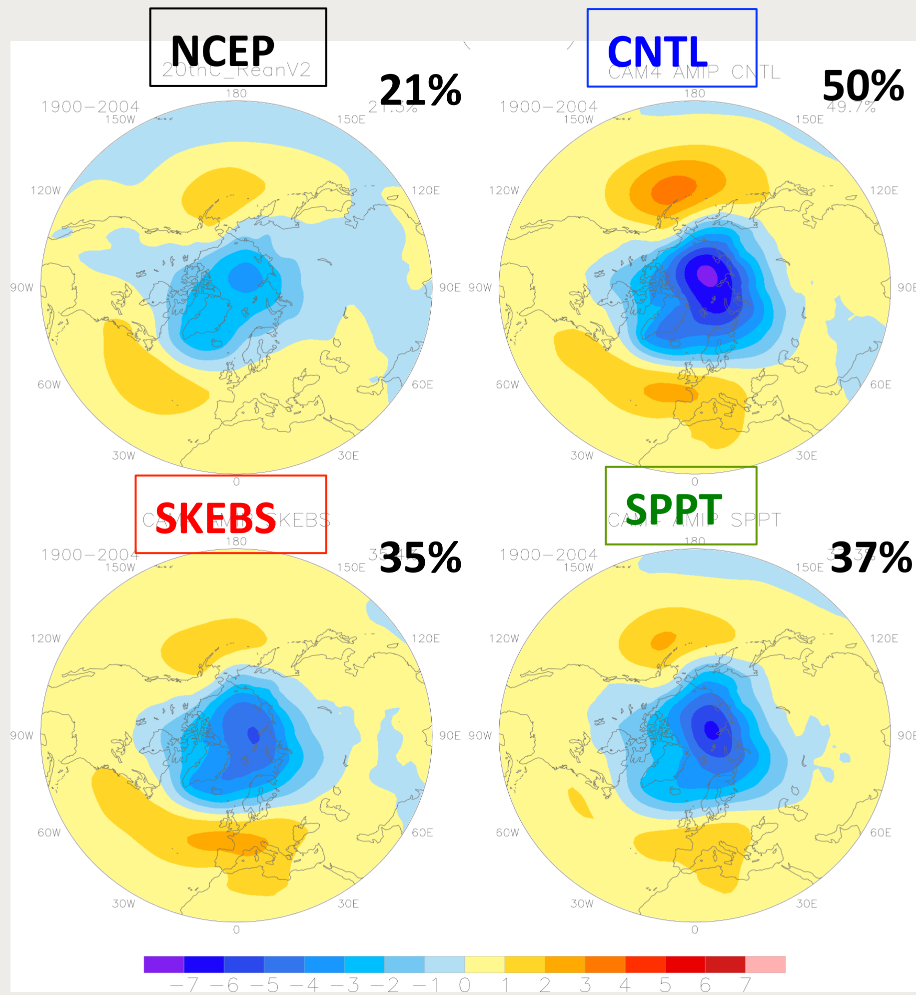
Northern Annular Mode (MAM)

1st EOF of sea level pressure over Northern Hemispheric Extratropics

- CAM4 AMIP simulations (prescribed SSTs), 1900-2004

- Stochastic parameterization improves pattern and reduces explained variance

- Degenerate response: SKEBS and SPPT have same effect



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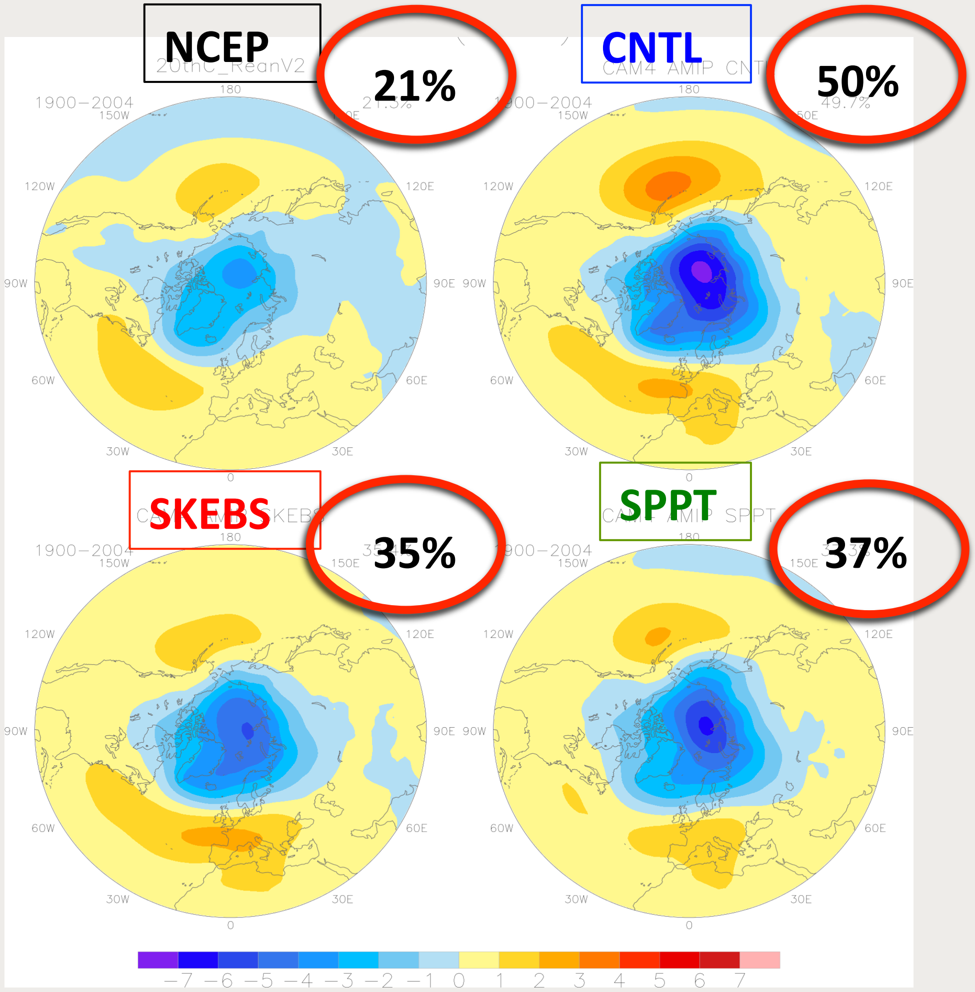
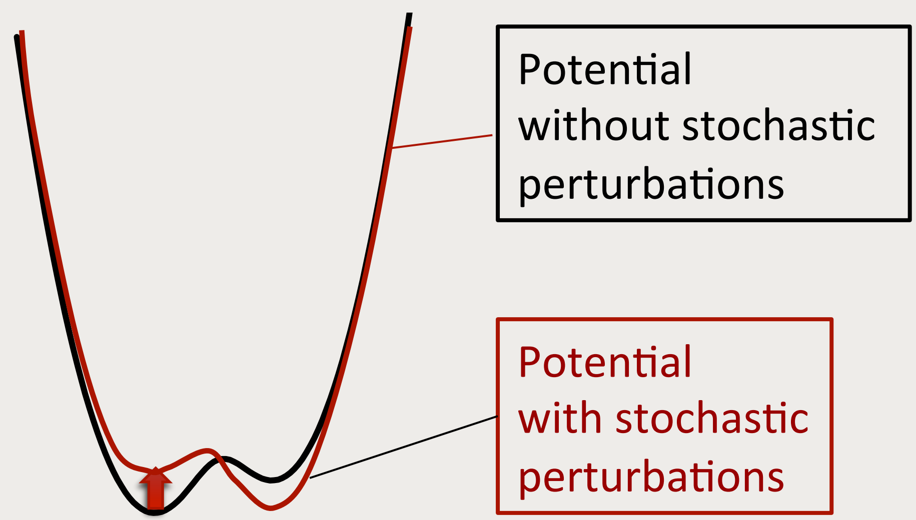


Sketch: CAM4 behavior

- Including a stochastic parameterization does not lead to large changes in the pattern of modes of variability, but to decreased explained variances
- This is consistent with a shallowing of a potential well

Stochastic parameterizations can also lead to a depending of a potential well.



ECMWF Workshop on Model Uncertainty, 20 – 24 June 2011

4. Include uncertainty resulting from the dynamical core and physics-dynamics interactions in the assessment of model uncertainty.

In addition to uncertainty arising from the need to represent and parameterize physical processes, uncertainty arises from the truncation error of the different dynamical cores and, more importantly, interactions between the physics and the dynamics. While the difference in precision and accuracy between different dynamical cores might be small compared to typical physical parameterization errors, there is increasing evidence that the same physics parameterization might behave differently when coupled to different dynamical cores (e.g. Reed and Jablonowski, 2011). The study of uncertainty related to using different dynamical cores coupled to physics-packages is an emerging field in the "dynamical core community" and their findings should be in the awareness of the

"uncertainty community", e.g. as part of the systematic intercomparison proposed in recommendation (1). A separate source of dynamical model error is associated with truncation error per se and can lead to different kinetic energy spectra in the model and potentially different predictability behavior (limited vs unlimited).

ECMWF Workshop on Model Uncertainty, 20 – 24 June 2011

Recommendation of Working Group 2:
Merits and drawbacks of different methods of representing model uncertainty

1. **Design concepts for the systematic comparison of different schemes representing model uncertainty across a range of space and time-scales, both in full and hierarchically less complex models (including small planet).**

2. **The principles the different model uncertainty schemes are based upon should be stated (bottom-up)**

3. **The effects of different schemes generating spread should be compared and validated (top-down).**

4. **Include uncertainty resulting from the dynamical core and physics- dynamics interactions in the assessment of model uncertainty.**

Key points

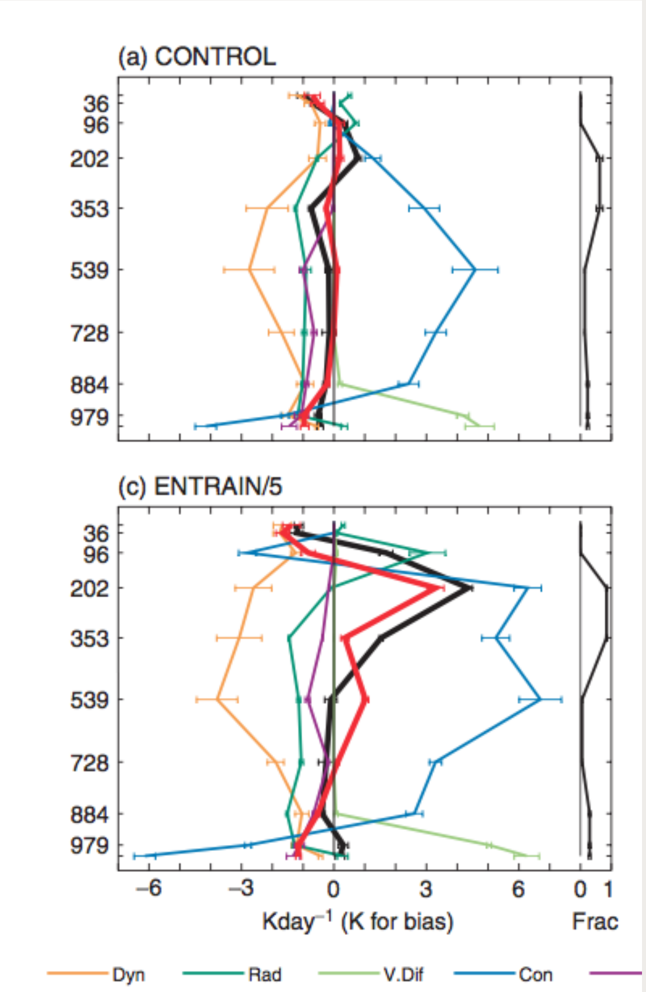
- There is model uncertainty in weather and climate prediction.
- It is essential to represent model uncertainty.
- In weather (NWP) the problem is well defined, because we can use observations to determine model uncertainty.
- In the climate sciences the estimation of model uncertainty is more challenging.

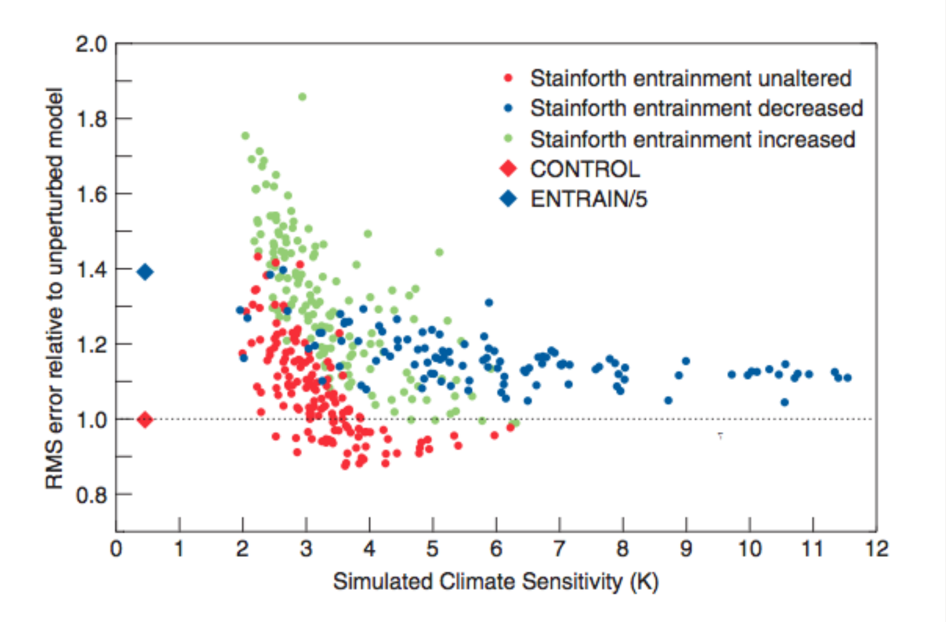
Key points

- Stochastic parameterization are essential for
  - Estimating uncertainty in weather and climate predictions
  - Reducing systematic model errors arising from unrepresented subgrid-scale fluctuations
  - Triggering noise-induced regime transitions

Thank you!

Using NWP to constrain climate parameters



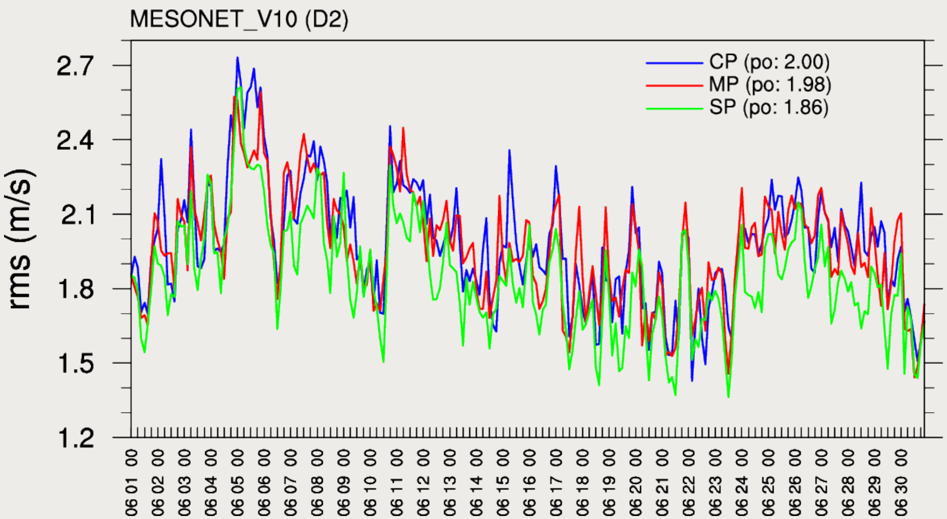


Rodwell and Palmer, 2007

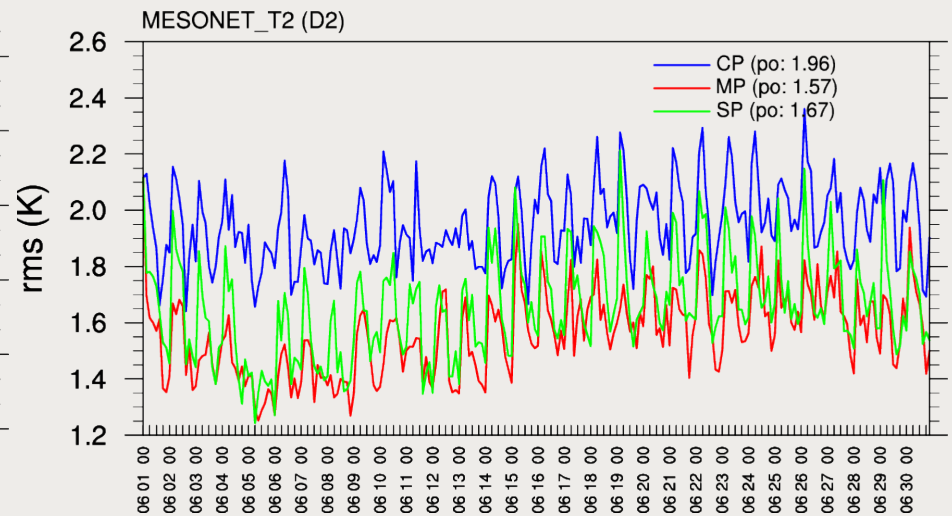
See also: Stainforth et al. 2005, Phillips et al. 2004 (CAPT)

WRF-DART:Verification of surface analysis against independent observations

V-10m



T-2m



CNTL
SKEBS
PHYS

- Including a model-error representation reduces the RMS error of the surface analysis (also prior) in 10m wind and Temperature at 2m

Ha et al. 2015