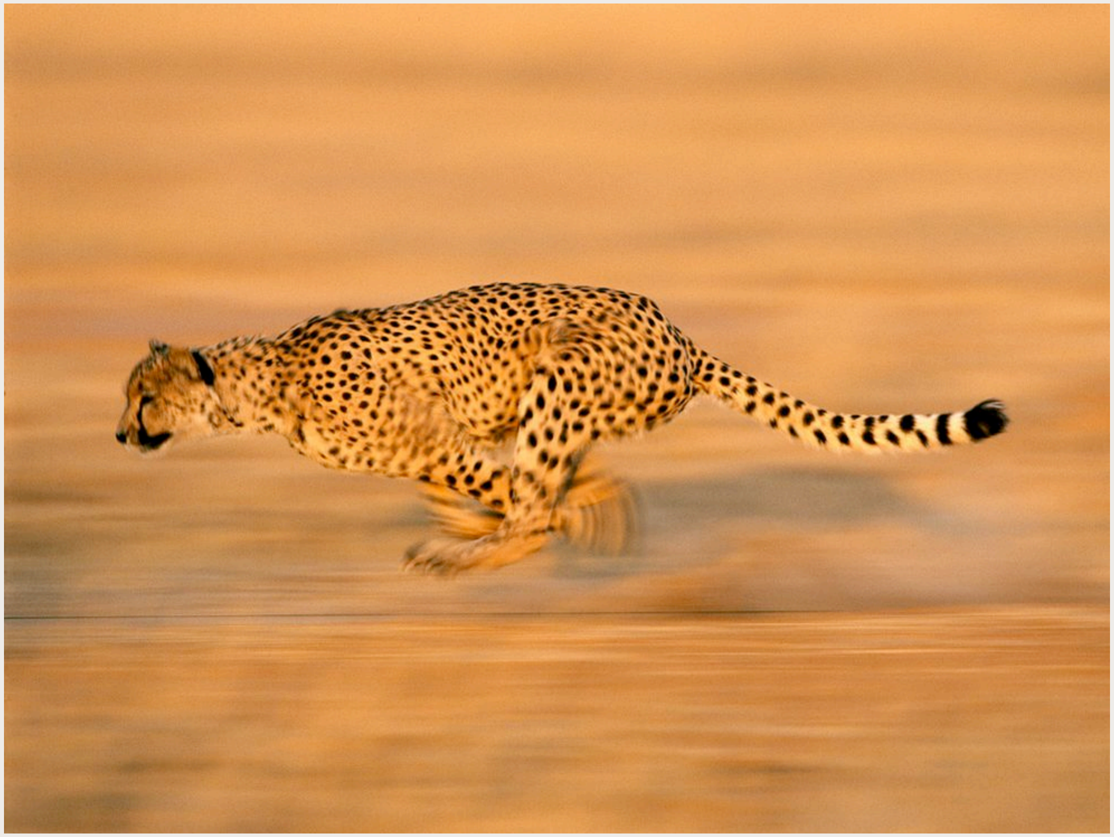
Principal of stochastic physical parameterizations: what is their promise?

Judith Berner (NCAR)

Run!!!



Uncertainty Prediction Across the Scales

- with emphasis on stochastic parameterizations

But also:

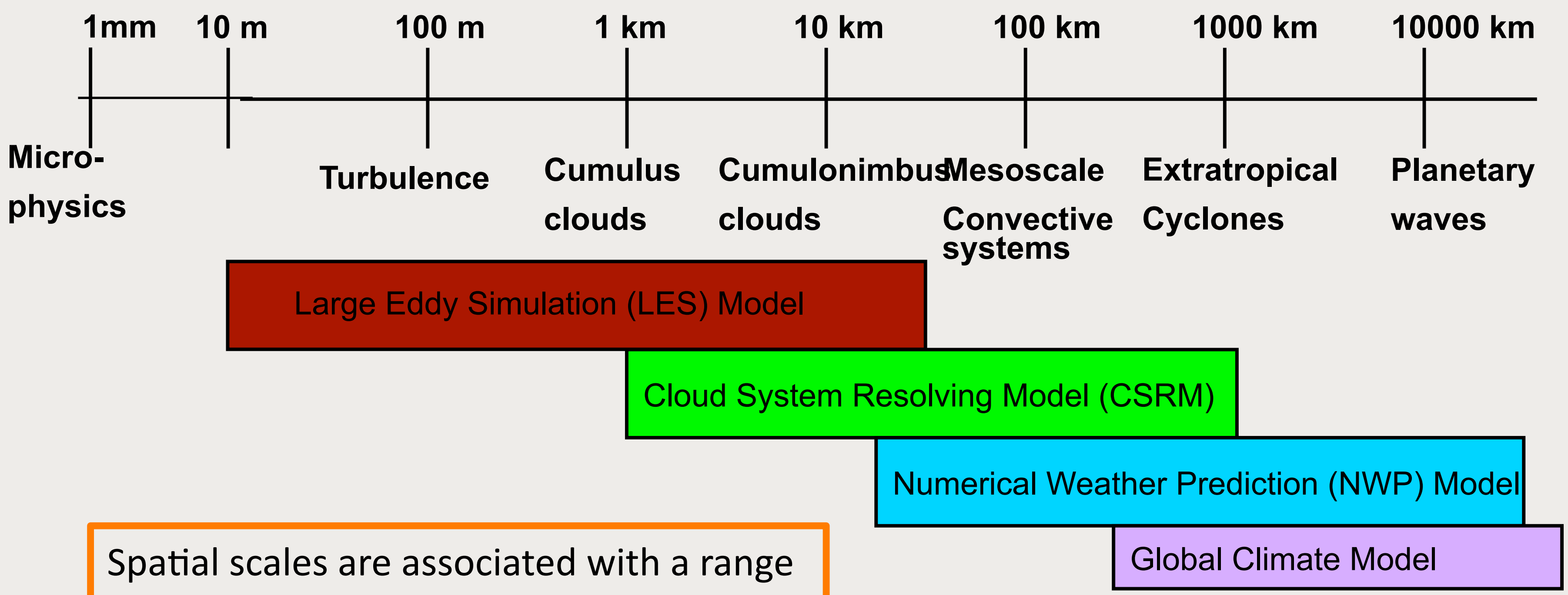
- how to design and evaluate (multi-model) ensembles

- uncertainty in weather vs climate

Key points

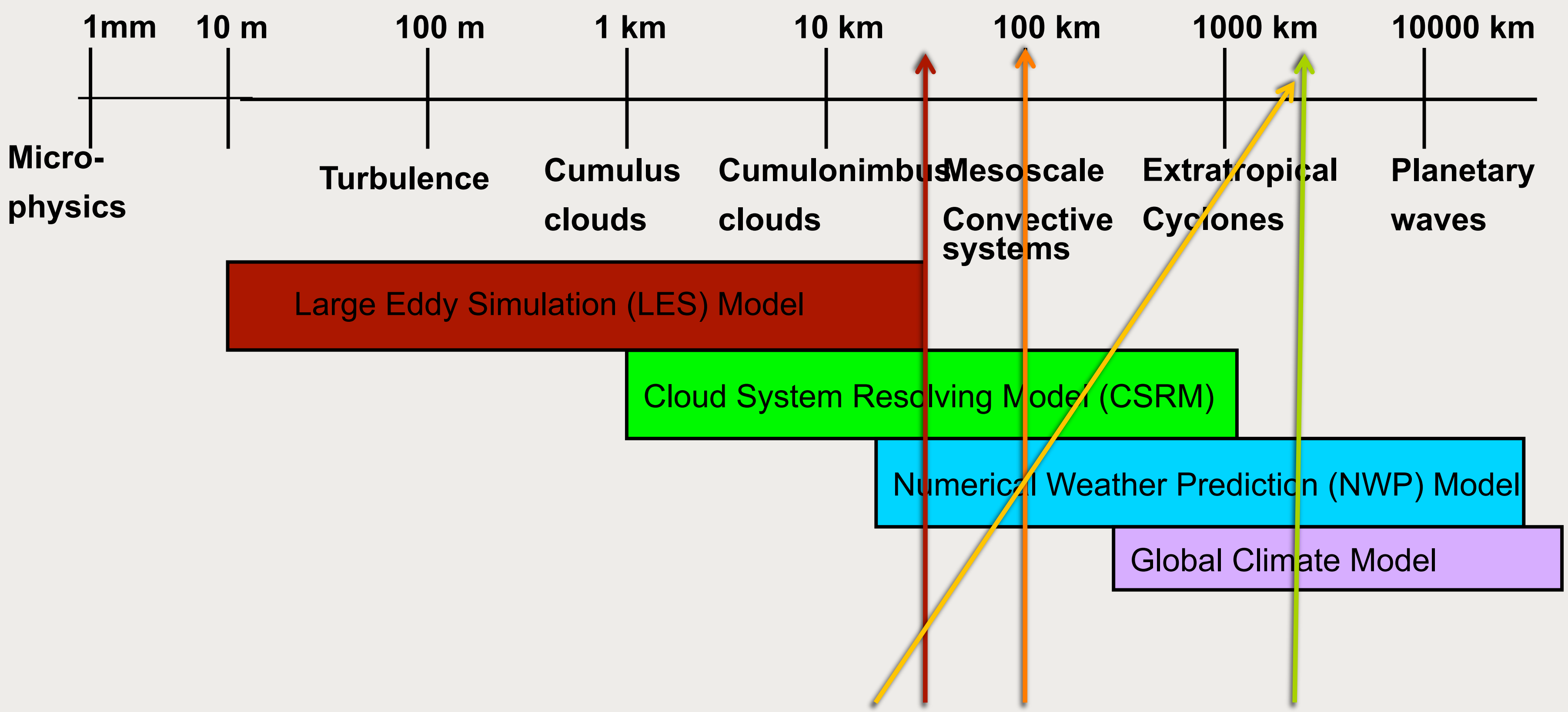
- There is model uncertainty in weather and climate prediction.
- It is essential to represent model uncertainty.
- In weather (NWP) the problem is well defined, because we can use observations to determine model uncertainty.
- On the climate scales the estimation of model uncertainty is more challenging, since verifying data is limited
- Stochastic parameterizations are starting to become a alternative to other model-error representations

Multiple scales of motion



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

Multiple scales of motion



The closure problem

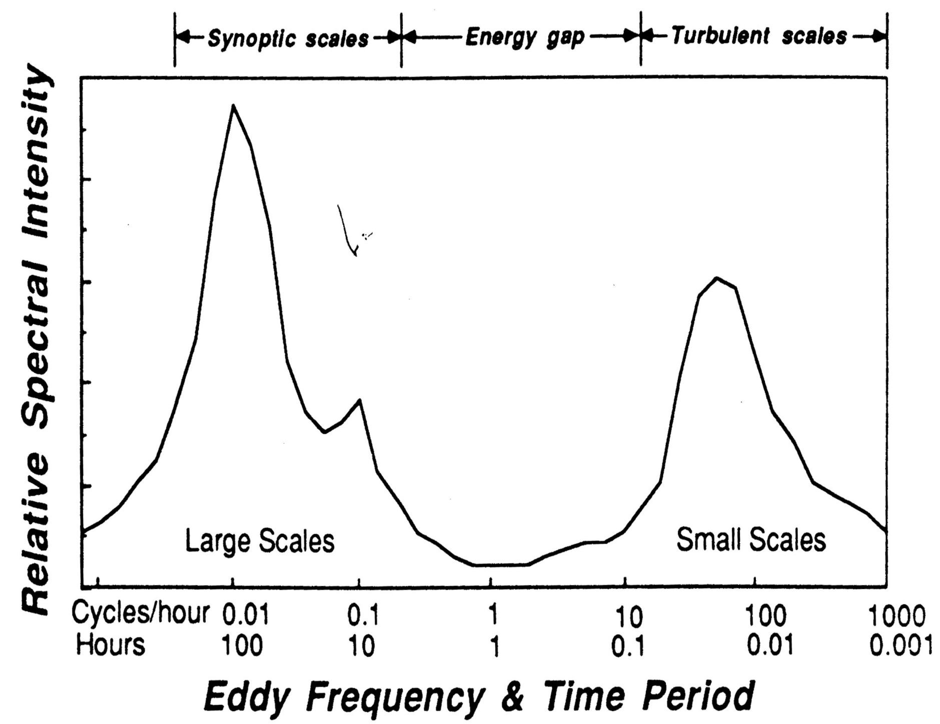


Fig. 2.2 Schematic spectrum of wind speed near the ground estimated from a study of Van der Hoven (1957).

The "spectral gap" argument (Stull 1960)

The closure problem

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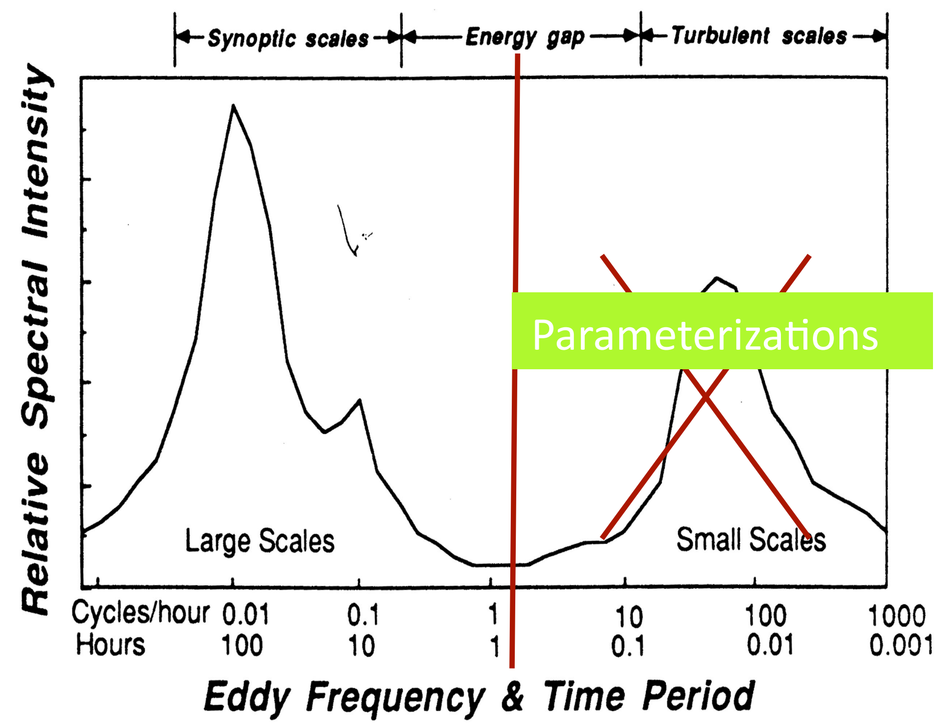

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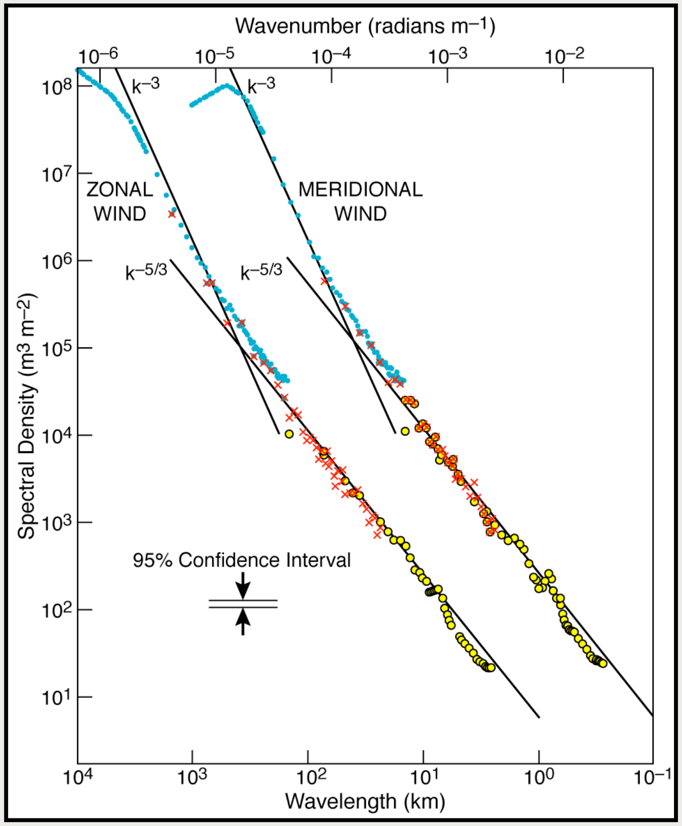
Kinetic energy spectra



Nastrom and Gage, 1985

Limited vs unlimited predictability in Lorenz 1969

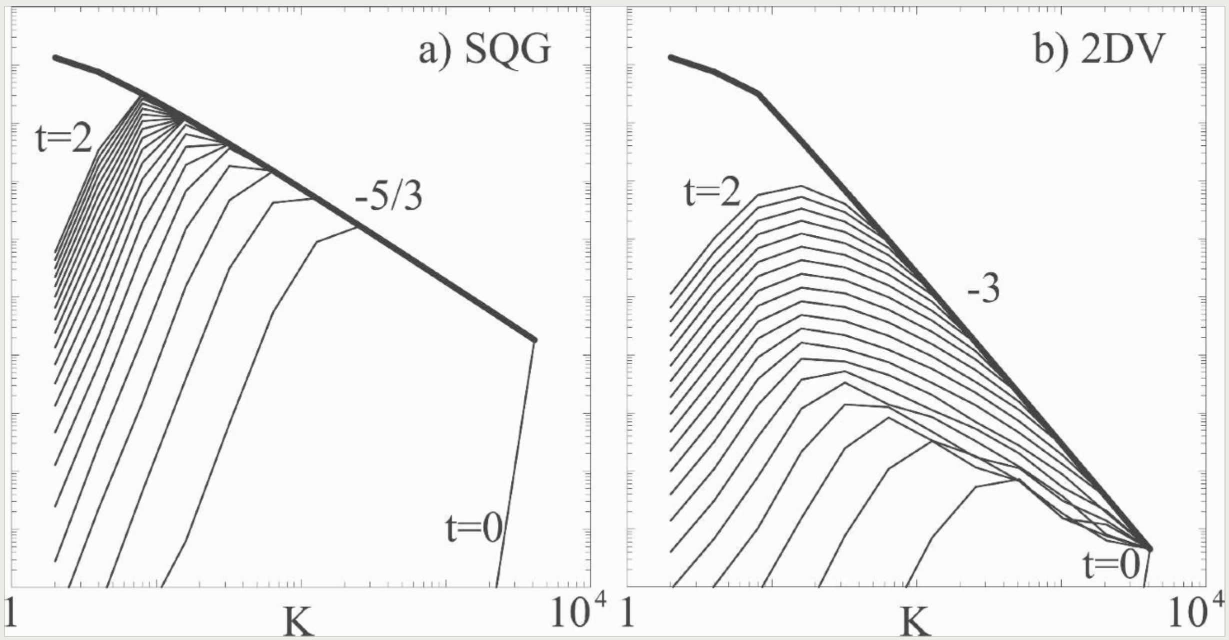
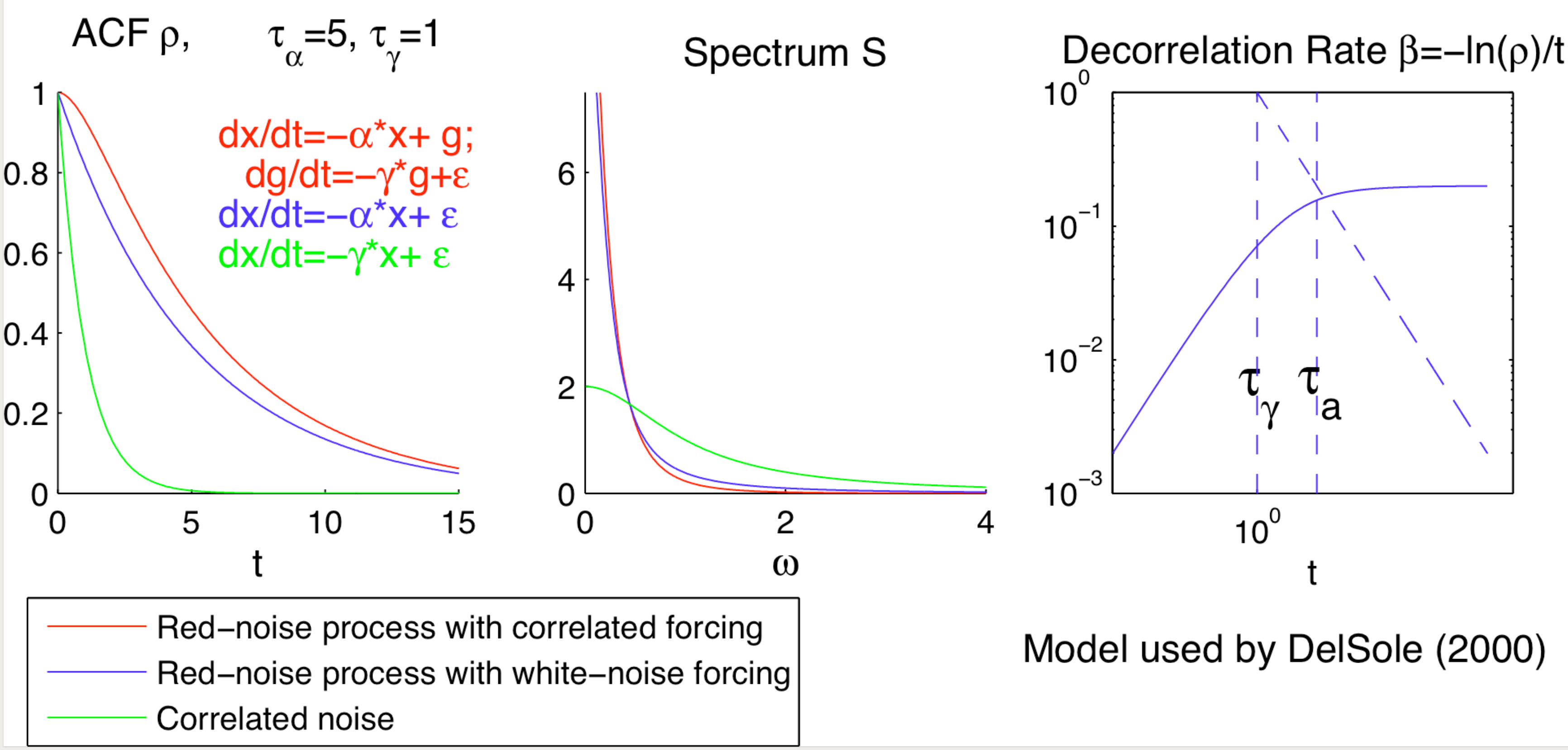


FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K, t)$ for $t = 0, 2$ in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a $-5/3$ slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

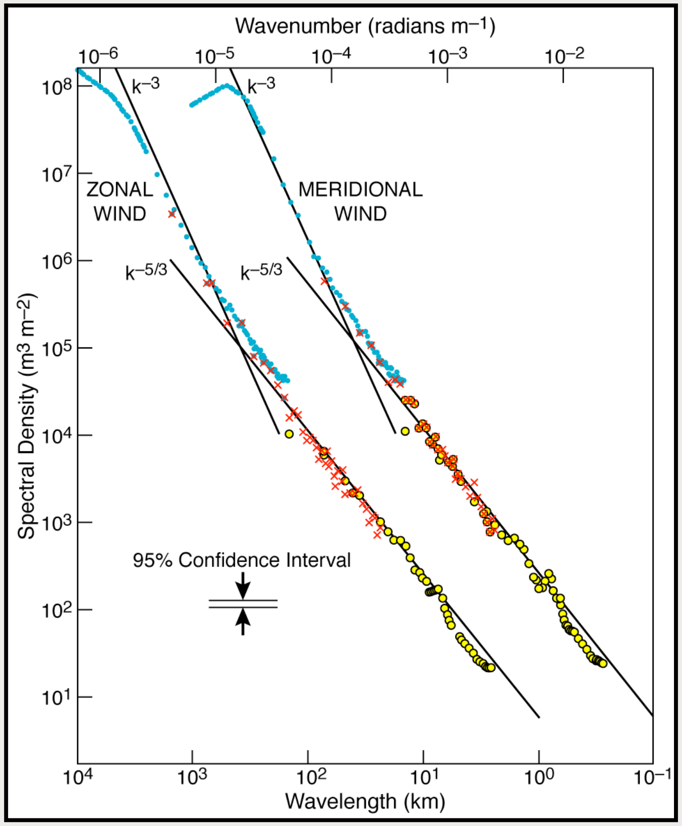
see also: Tribbia and Baumhefner 2004

Spectral gap not necessary for stochastic parameterizations



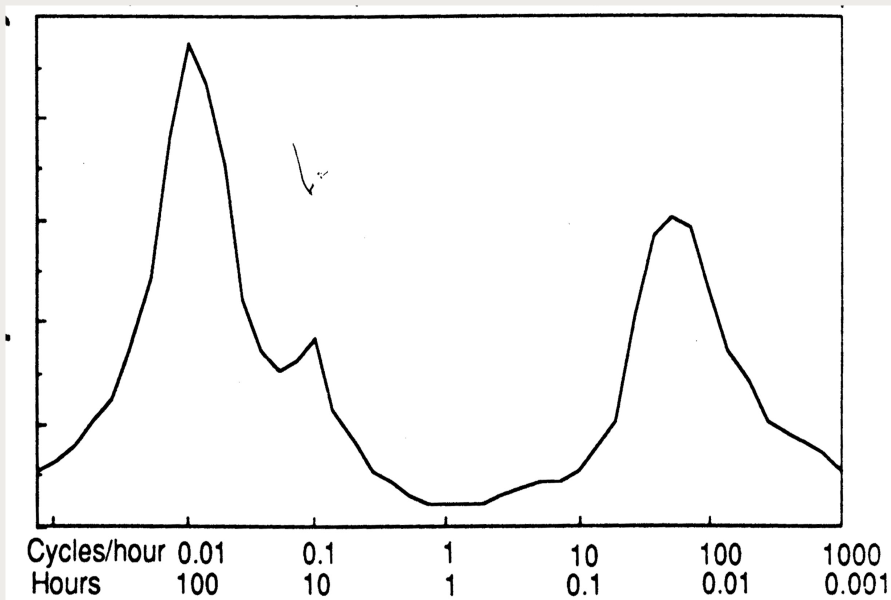
Model used by DelSole (2000)

Kinetic energy spectra

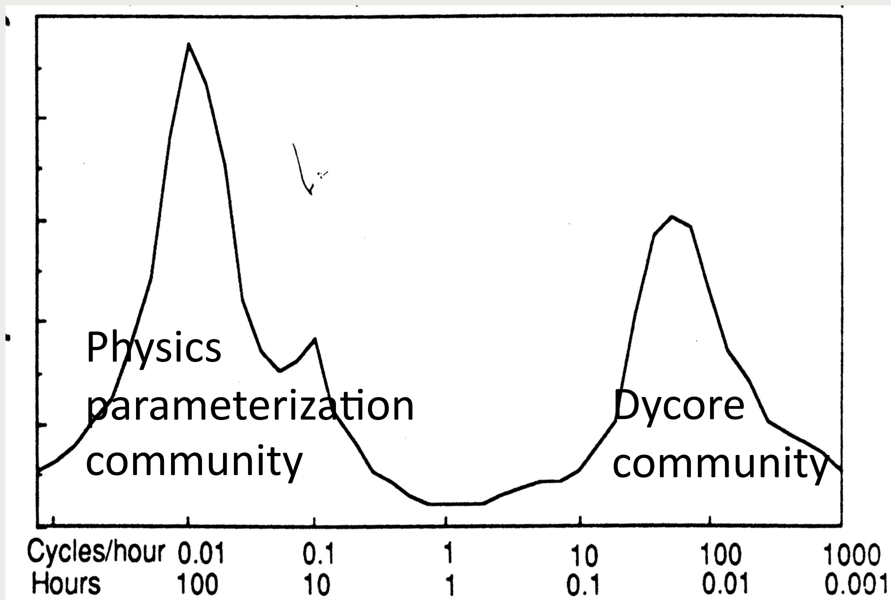


Nastrom and Gage, 1985

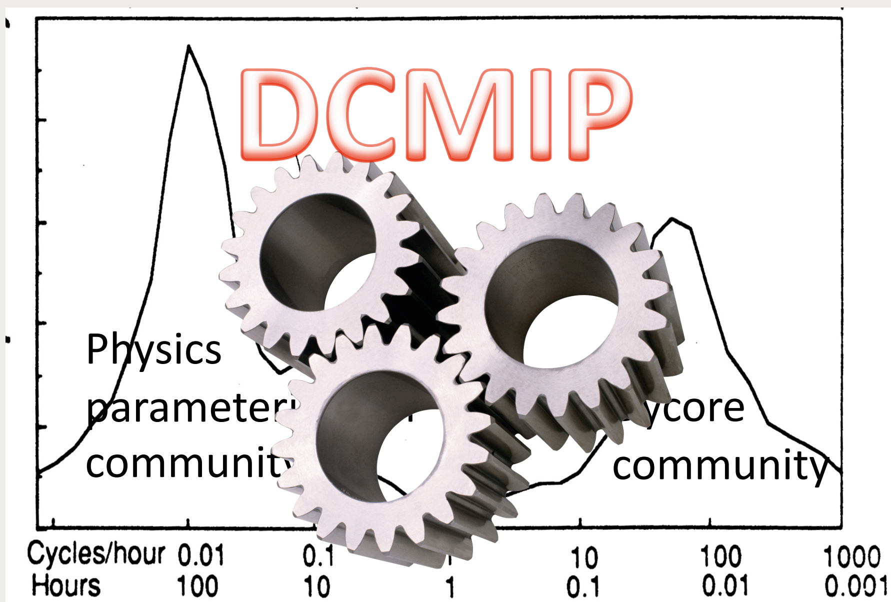
The " Gap"



The uncertainty“ Gap”



Closing he uncertainty“ Gap”



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.**

ECMWF Workshop on Model Uncertainty, 20 – 24 June 2011

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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).

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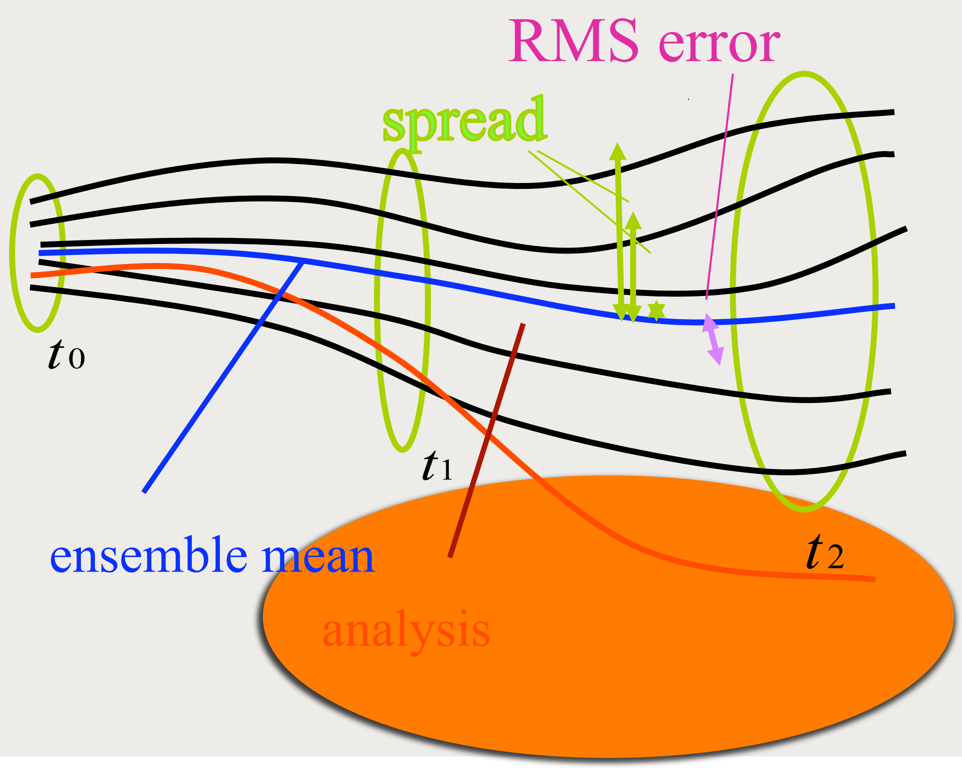
Model error in NWP

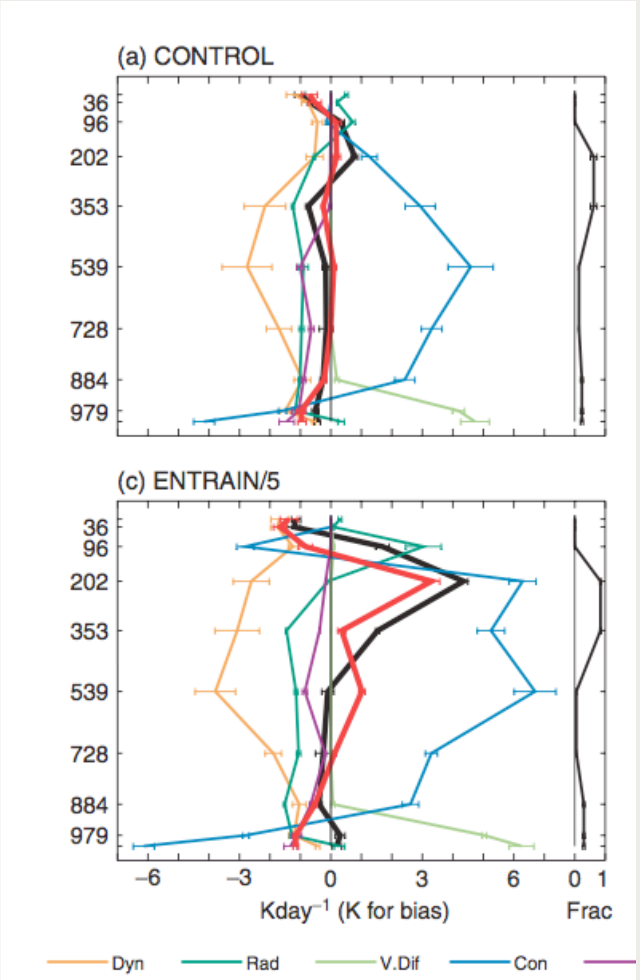
- Represent/sample subgrid-scale fluctuations (SPPT)
- Represent structural model error (SKEBS)

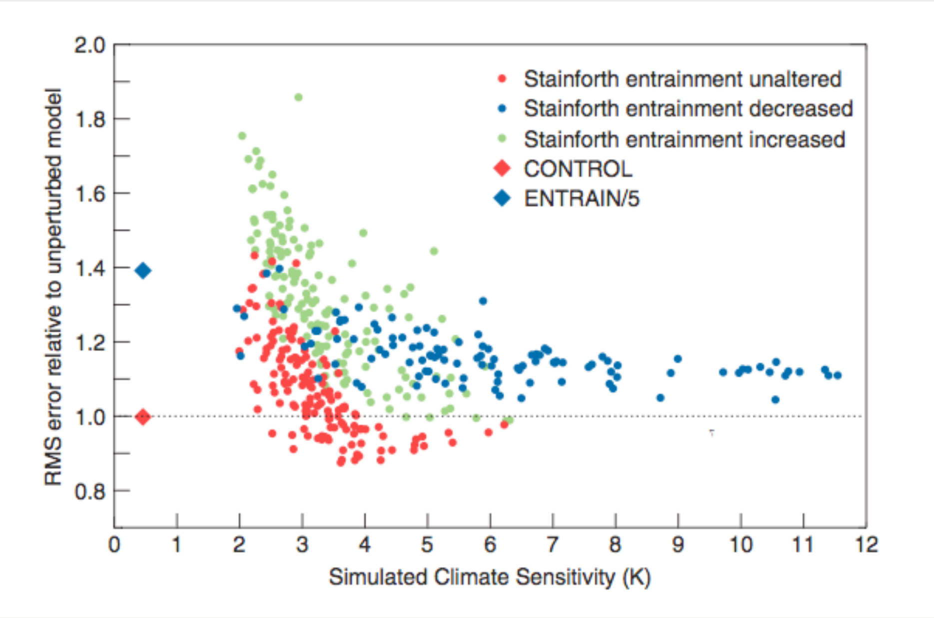


Representing model error in ensemble systems

- The multi-parameter approach: each ensemble member uses the control physics, but the parameters are varied from one ensemble member to the next
- The multi-parameterization approach: each ensemble member uses a different set of parameterizations (e.g. for cumulus convection, planetary boundary layer, microphysics, short-wave/long-wave radiation, land use, land surface)
- Stochastic parameterizations: each ensemble member is perturbed by a stochastic forcing term that represents the statistical fluctuations in the subgrid-scale fluxes (stochastically perturbed physics tendencies) as well as altogether unrepresented interactions between the resolved an unresolved scale (stochastic kinetic energy backscatter)

Using NWP to constrain climate parameters





Rodwell and Palmer, 2007

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

Sources for uncertainty in weather and climate

Weather

- Large sensitivity to initial conditions
- Parameter perturbations insufficient
- Stochastic parameterizations well established
- Multi-models very skillful, but impractical
- Boundary conditions secondary(maybe for regional models)
- Biases large, but not as limiting as in climate

Climate

- Smaller sensitivity to initial conditions
- Parameter perturbations effective
- Stochastic parameterizations not (yet) well established
- Multi-model = model of opportunity, (generated by different centers)
- Boundary and forcing essential (scenarios)
- Large biases

Dependency of Multi-Models

If many models agree, how do you know if they are correct or just related?
- Also relevant DMIP

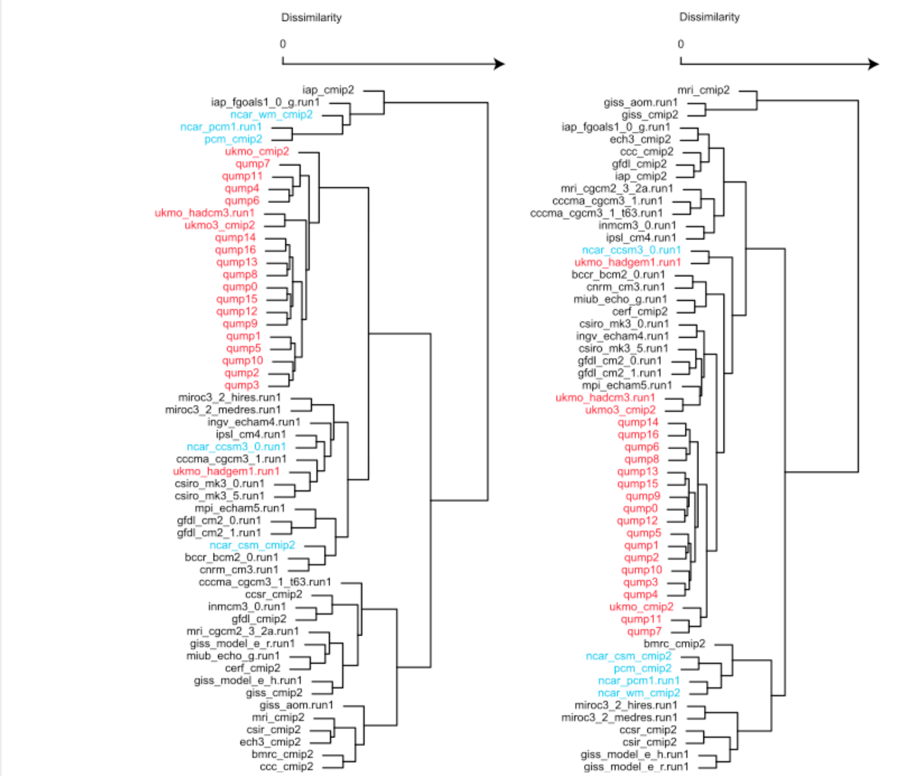
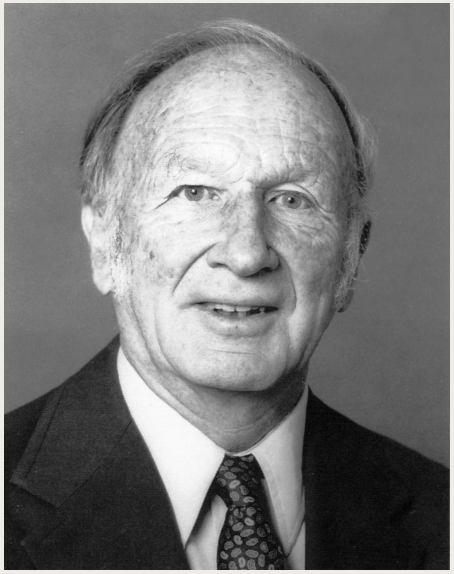


Figure 2. Hierarchical clustering of the CMIP3, CMIP2 and QUMP perturbed physics ensemble for (left) surface temperature and (right) precipitation in the model control state. Models developed by the UK Metoffice Hadley Centre are shown in red, models developed by NCAR are marked in blue.

Masson and Knutti, 2008

Stochastic parameterizations in weather and climate models



"I believe the ultimate climate models…will be stochastic, i.e. random numbers will appear somewhere in the time derivatives." (Lorenz, 1975)

Stochastic parameterization schemes

Stochastic kinetic-energy backscatter scheme (SKEBBS)

- Rationale: A fraction of the dissipated kinetic-energy is scattered upscale and available as forcing for the resolved flow.

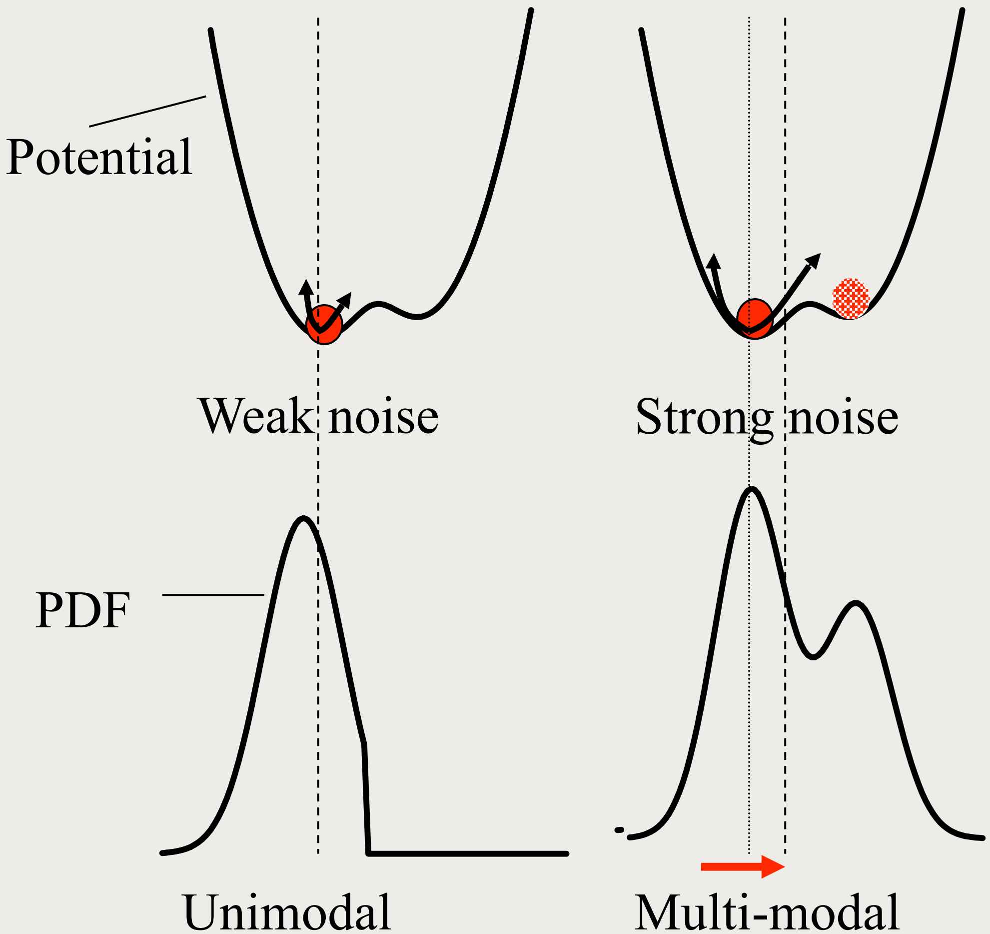
Stochastically perturbed parameterization scheme (SPPT)

- Rationale: Especially as resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale state should be sampled.

$$\underbrace{\frac{\partial X}{\partial t}}_{\text{Local tendency}} = \underbrace{D_X}_{\substack{\text{Resolved scales} \\ = \text{“dynamics”}}} + \underbrace{P_X}_{\substack{\text{Unresolved scales} \\ = \text{“physics”} \\ \text{(cloud microphysics, ...)}}} + \underbrace{K_X}_{\substack{\text{Horizontal} \\ \text{diffusion}}} + \underbrace{\delta P_X}_{\substack{\text{Stochastic} \\ \text{perturbations}}}$$

Potential of stochastic parameterization to reduce model error

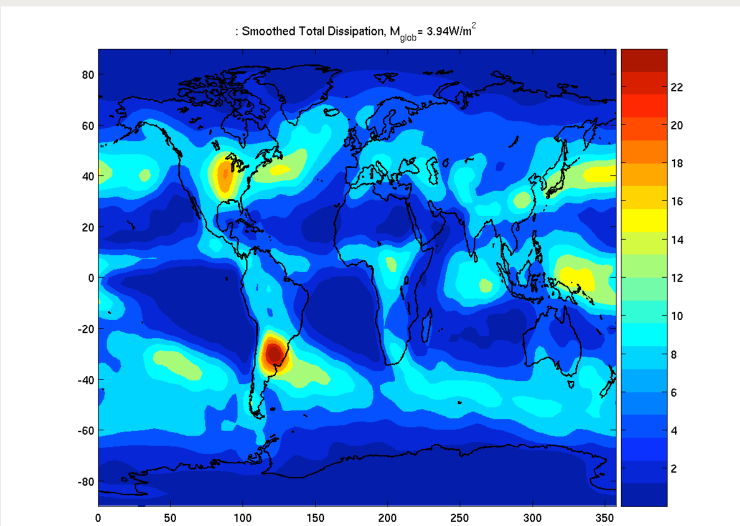
- Stochastic parameterizations can change the mean and variance of a PDF
- Impacts variability of model (e.g. internal variability of the atmosphere)
- Impacts systematic error (e.g. blocking precipitation error)



Stochastic kinetic-energy backscatter scheme

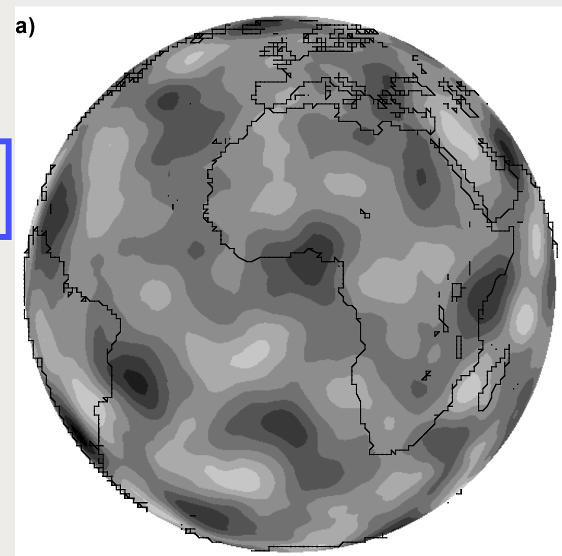
Rationale: A fraction of the dissipated energy is scattered upscale and acts as forcing for the resolved-scale flow

$$\boxed{du/dt = du_{phys}/dt + du_{stoch}/dt}$$



Total Dissipation rate.

ψ'



Spectral Markov chain: temporal and spatial correlations prescribed

Stochastic kinetic-energy backscatter scheme

Assume a streamfunction perturbation in ***spherical harmonics*** representation

$$\psi'(\phi,\lambda)=\sum_{n=0}^{N}\sum_{m=-n}^{n}\psi_n'^m(t)P_{n,m}(\mu)e^{im\lambda}$$

Assume furthermore that each coefficient evolves according to the ***spectral Markov process***

$$\psi_n'^m(t+1)=(1-\alpha)\psi_n'^m(t)+g_n\sqrt{\alpha}\epsilon(t)$$

Find the wavenumber dependent noise amplitudes $g_n = b\ \ n^p$

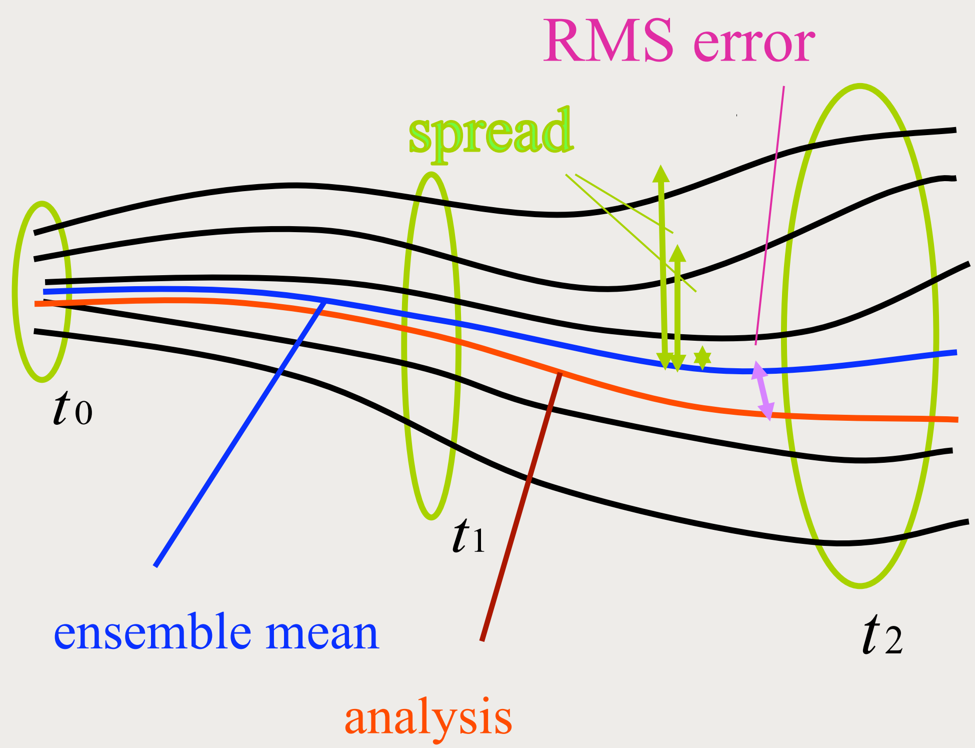
so that prescribed kinetic energy dE is injected into the flow

$$b = \left(\frac{4\pi a^2\alpha}{\sigma_z\Gamma}\,dE'\right)^{\frac{1}{2}}$$

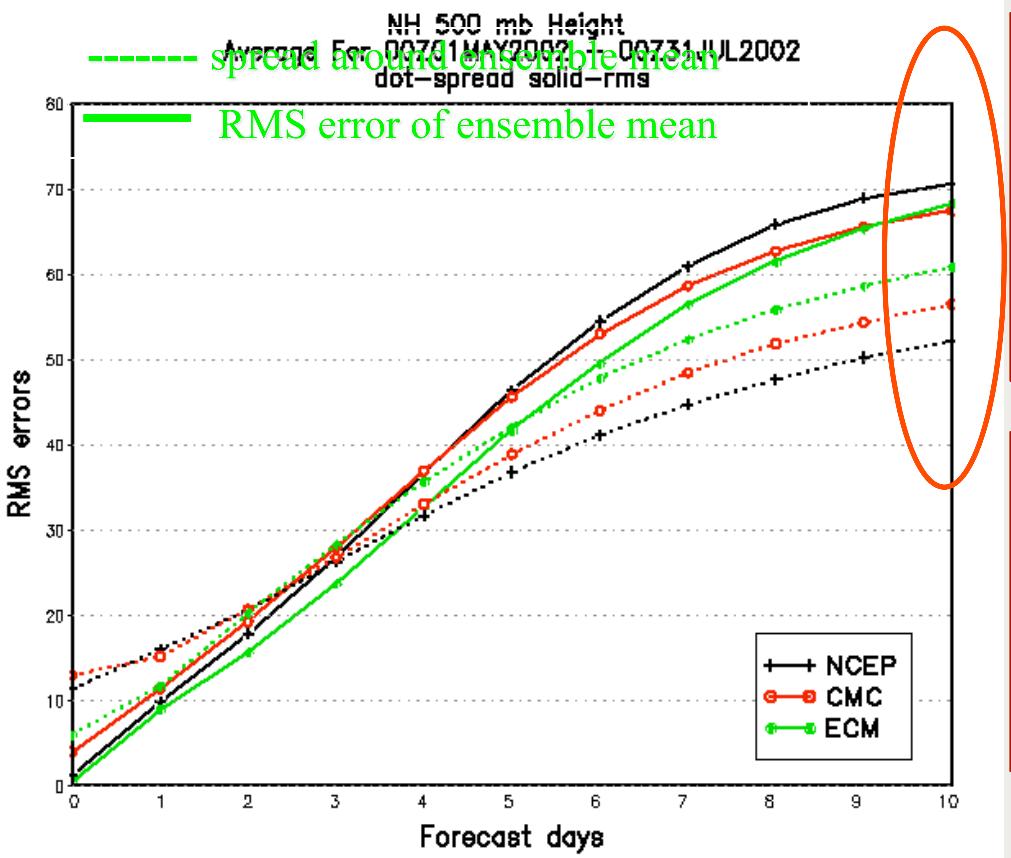
with $\Gamma=\sum_{n=n_1}^{n_2} n(n+1)(2n+1)n^{2p}$

Representing initial uncertainty by an ensemble of states

- Represent initial uncertainty by ensemble of states
- Flow-dependence:
  - Predictable states should have small ensemble spread
  - Unpredictable states should have large ensemble spread
- ***Ensemble spread should grow like RMS error***
- True atmospheric state should be indistinguishable from ensemble system



Underdispersivness of ensemble systems



Buizza et al., 2004

The RMS error grows faster than the spread

- Ensemble is **underdispersive**
- Ensemble forecast is **overconfident**

- Underdispersion is a form of **model error**
- ***Forecast error = initial error + model error + boundary error***

Verification against Observations

Spread-Error Consistency in WRF (without obs error estimate)

CNTL
STOCH
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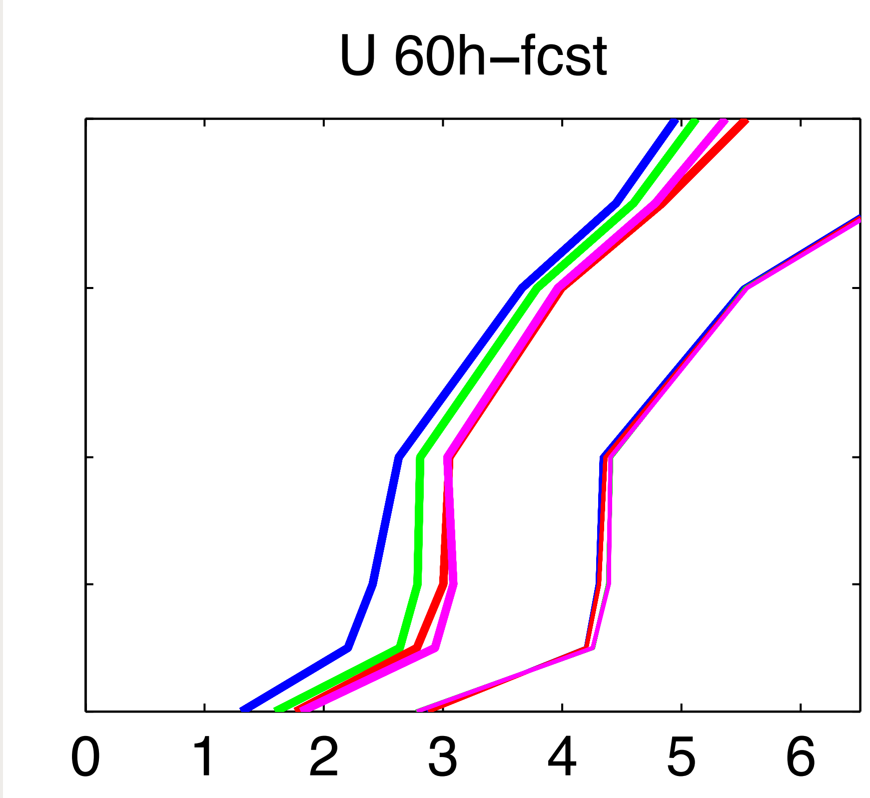
PHYS_STOCH



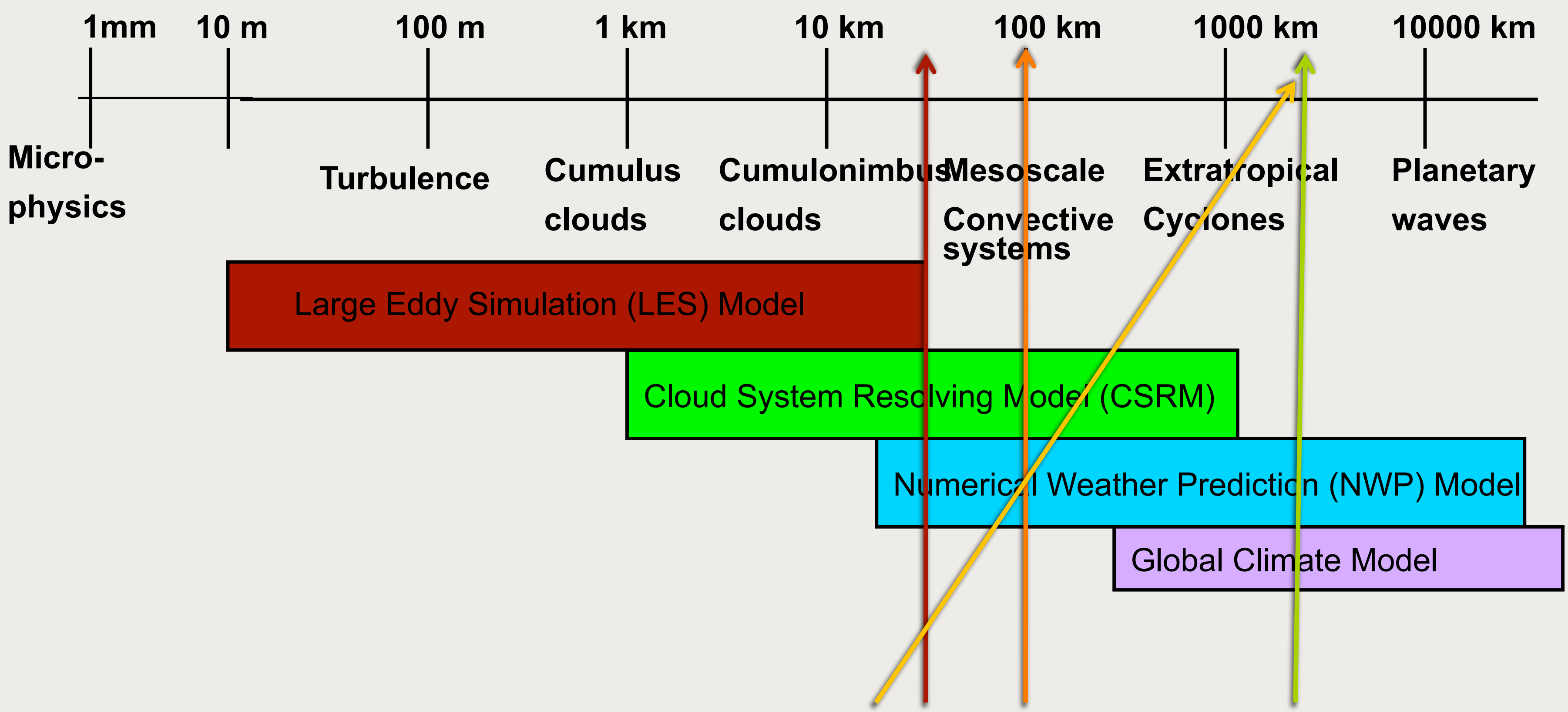
Berner et al. 2011

Will uncertainty decrease as model resolution increases?

Will uncertainty decrease as model resolution increases?

One can speculate if there will be a need for stochastic parameterizations as computational resources allow us to increase horizontal resolutions of weather and climate models to cloud-resolving levels. To the extent that stochastic parameterizations represent subgrid-scale fluctuations around the equilibrium state, they can be expected to play an even more important role as resolution increases. Insofar as they represent the upscale effect of unresolved dynamical processes, one would hope that their magnitude will become smaller as more and more interactions are explicitly resolved. Presumably this will depend partly on the capability of next-generation climate models to capture the shallower "$-5/3$" slope of the atmospheric energy spectrum in addition to the "-3" geostrophic regime.

Multiple scales of motion



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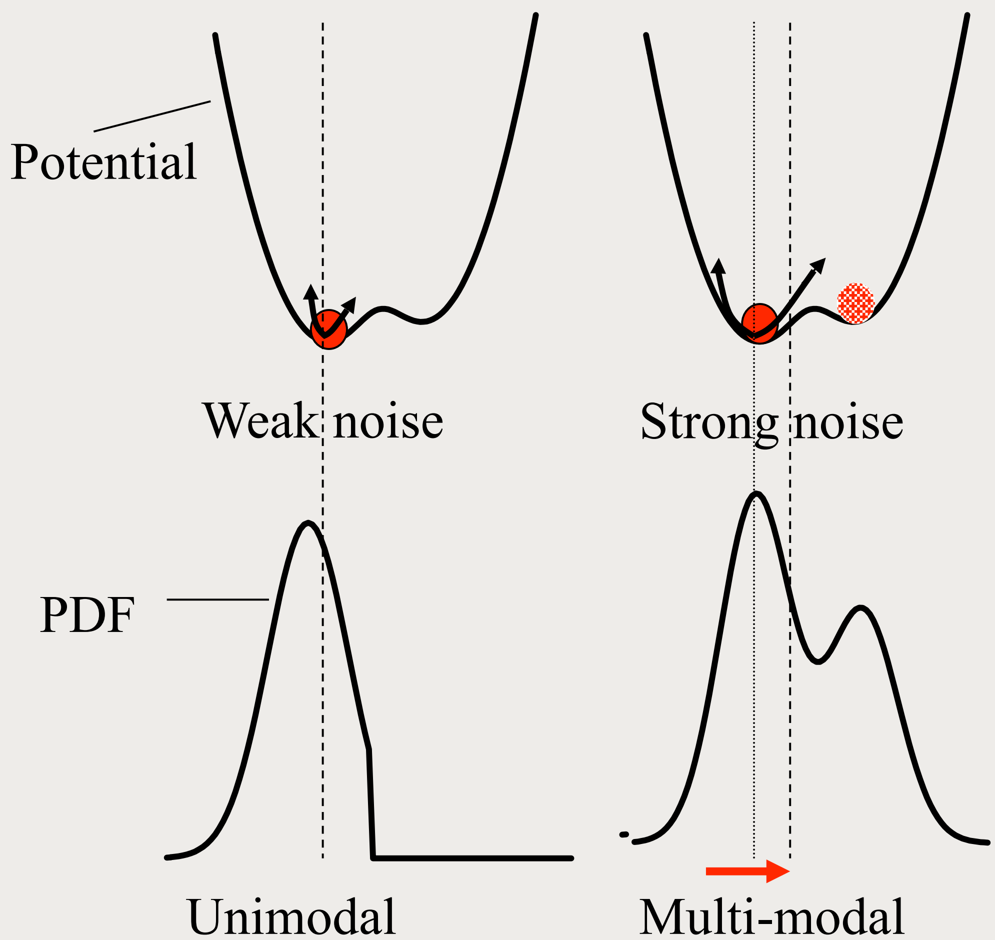

Bias of z500 in IFS

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SKEBS

HIGHRES

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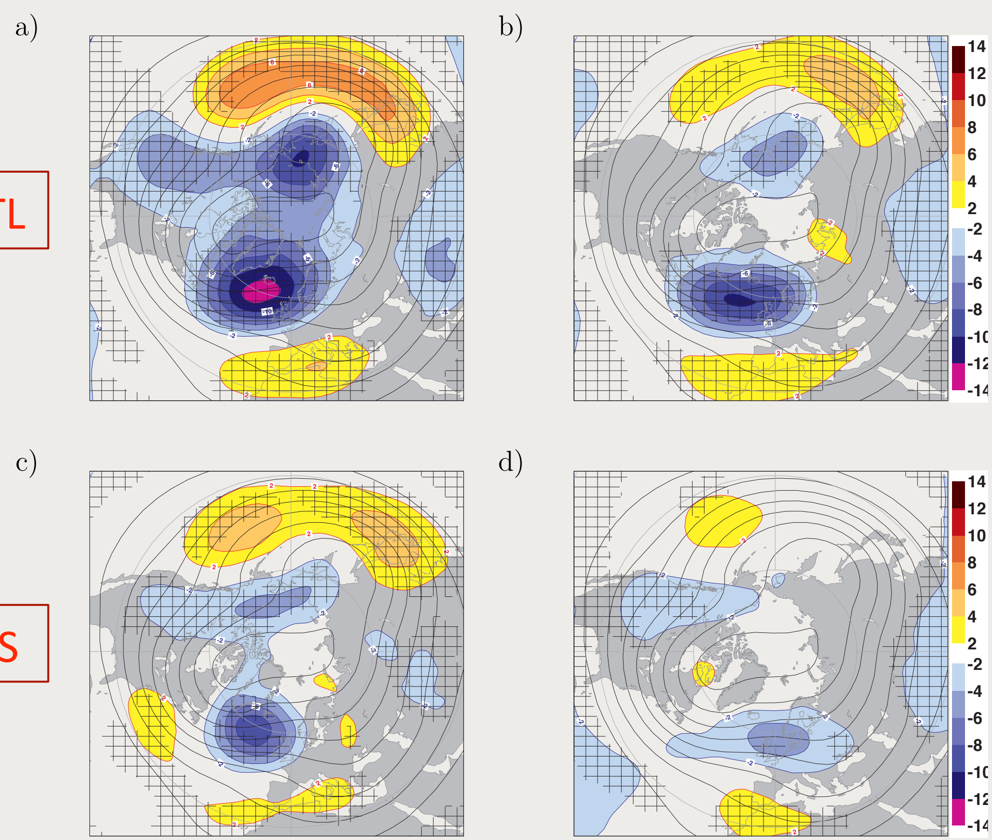
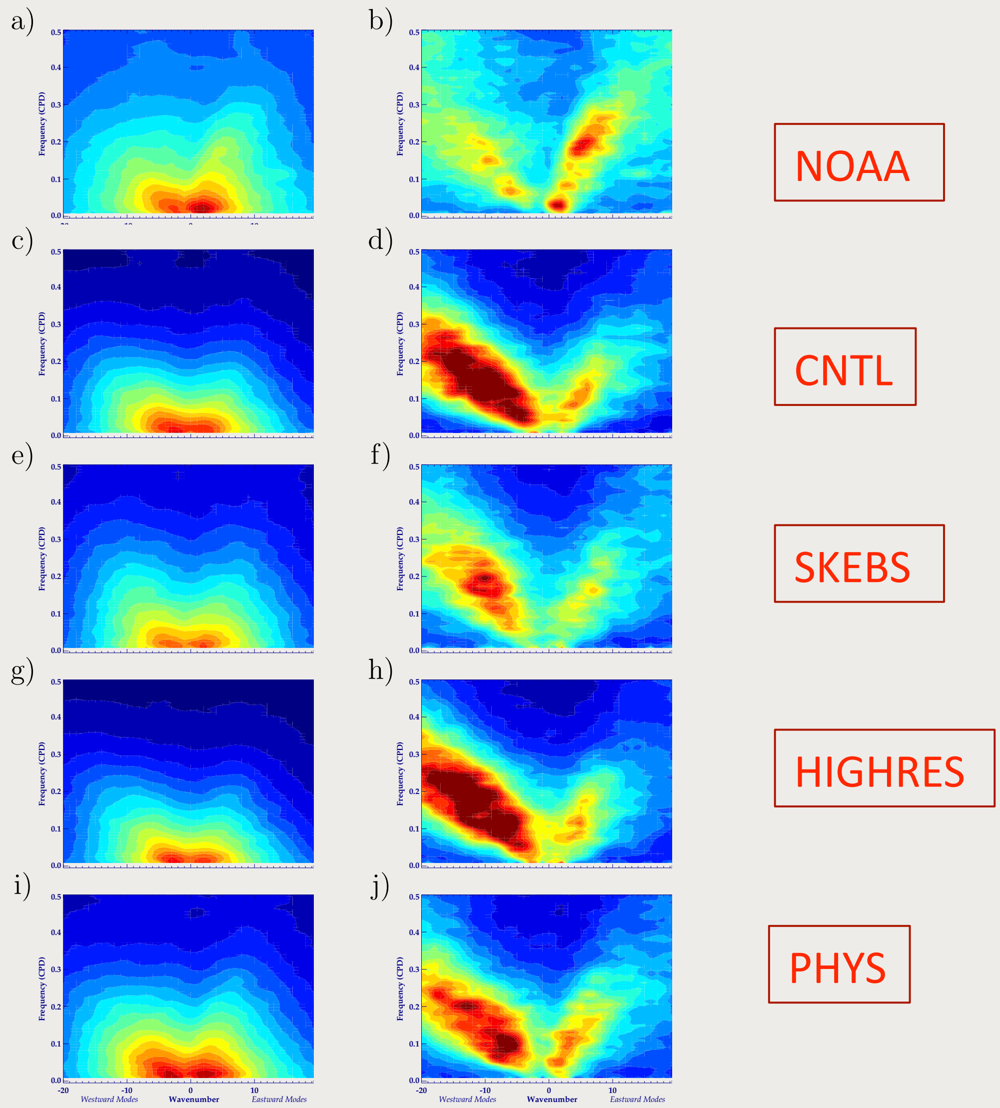


Berner et al. 2011

Frequency-Wavenumber spectra of OLR in IFS



Berner et al. 2012

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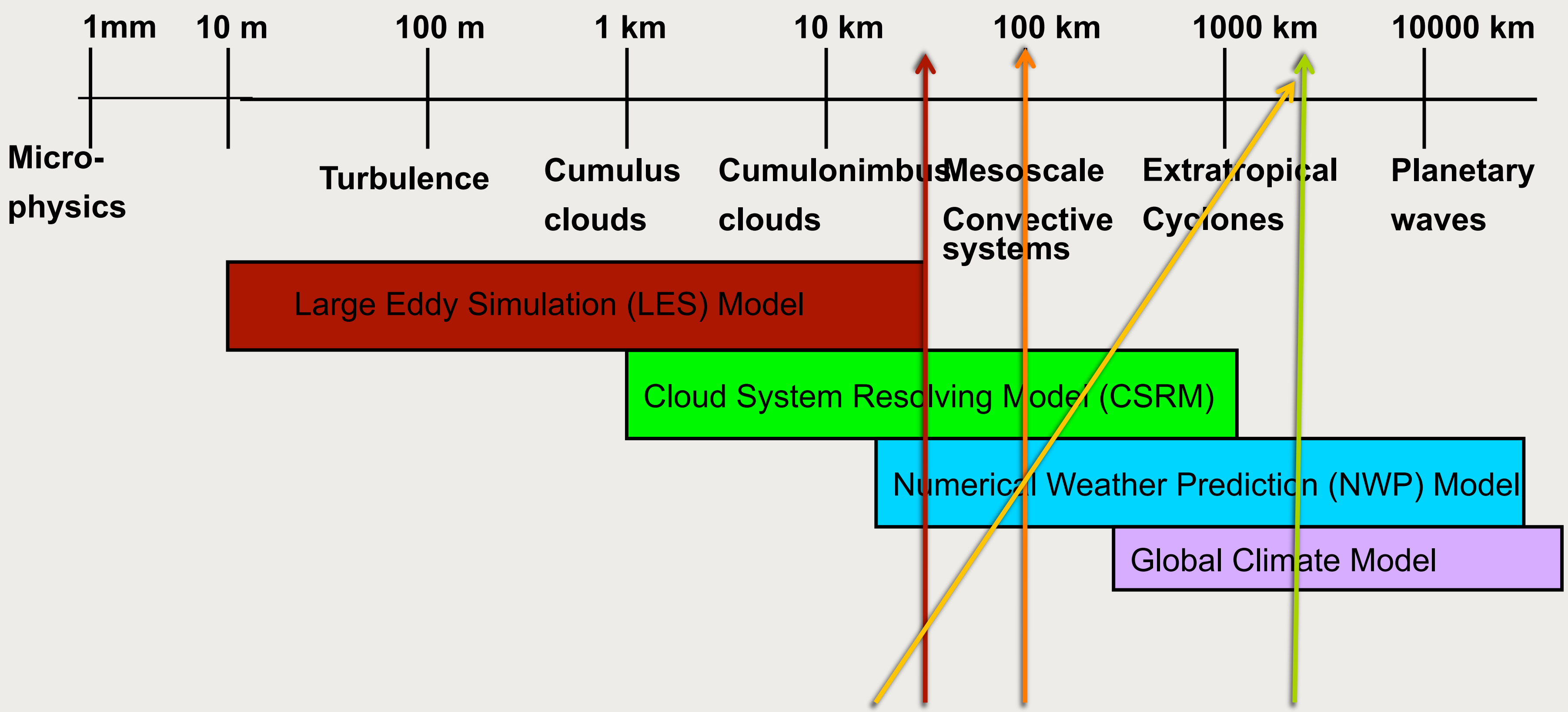
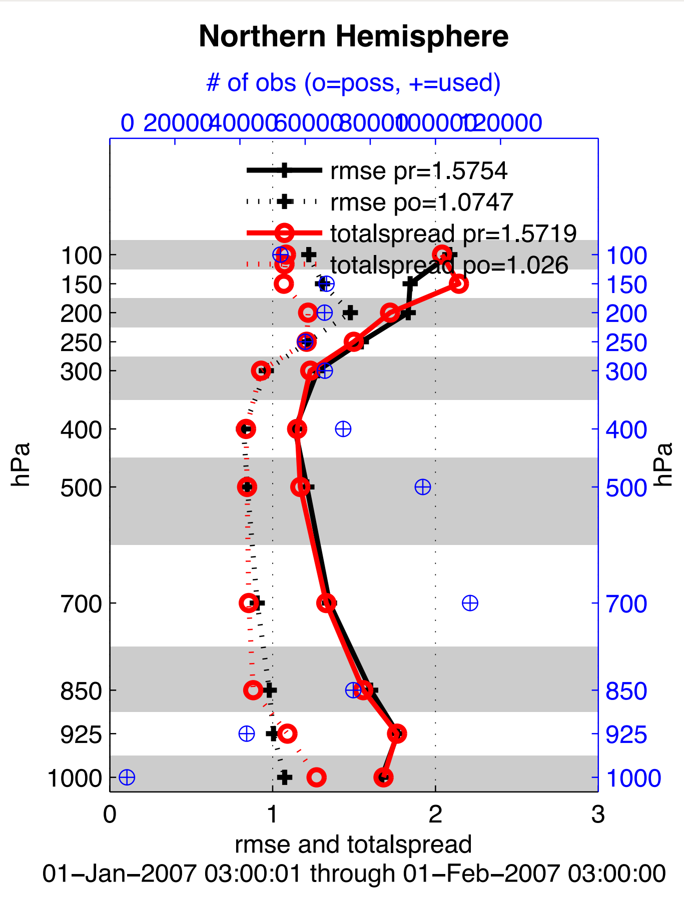


Confronting climate models with data: Spread/Error Relationship of T

SKEBS



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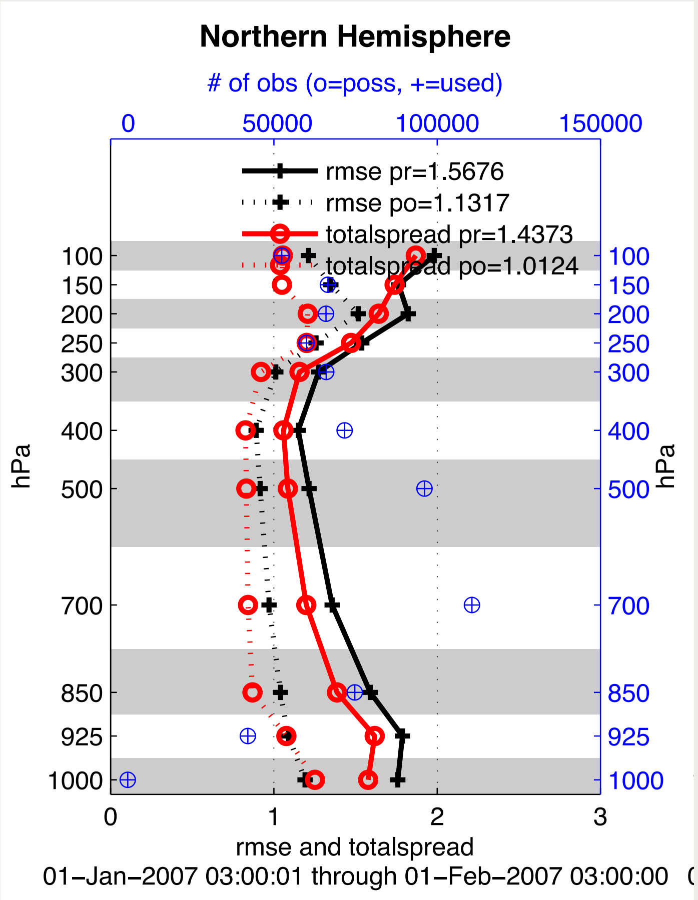
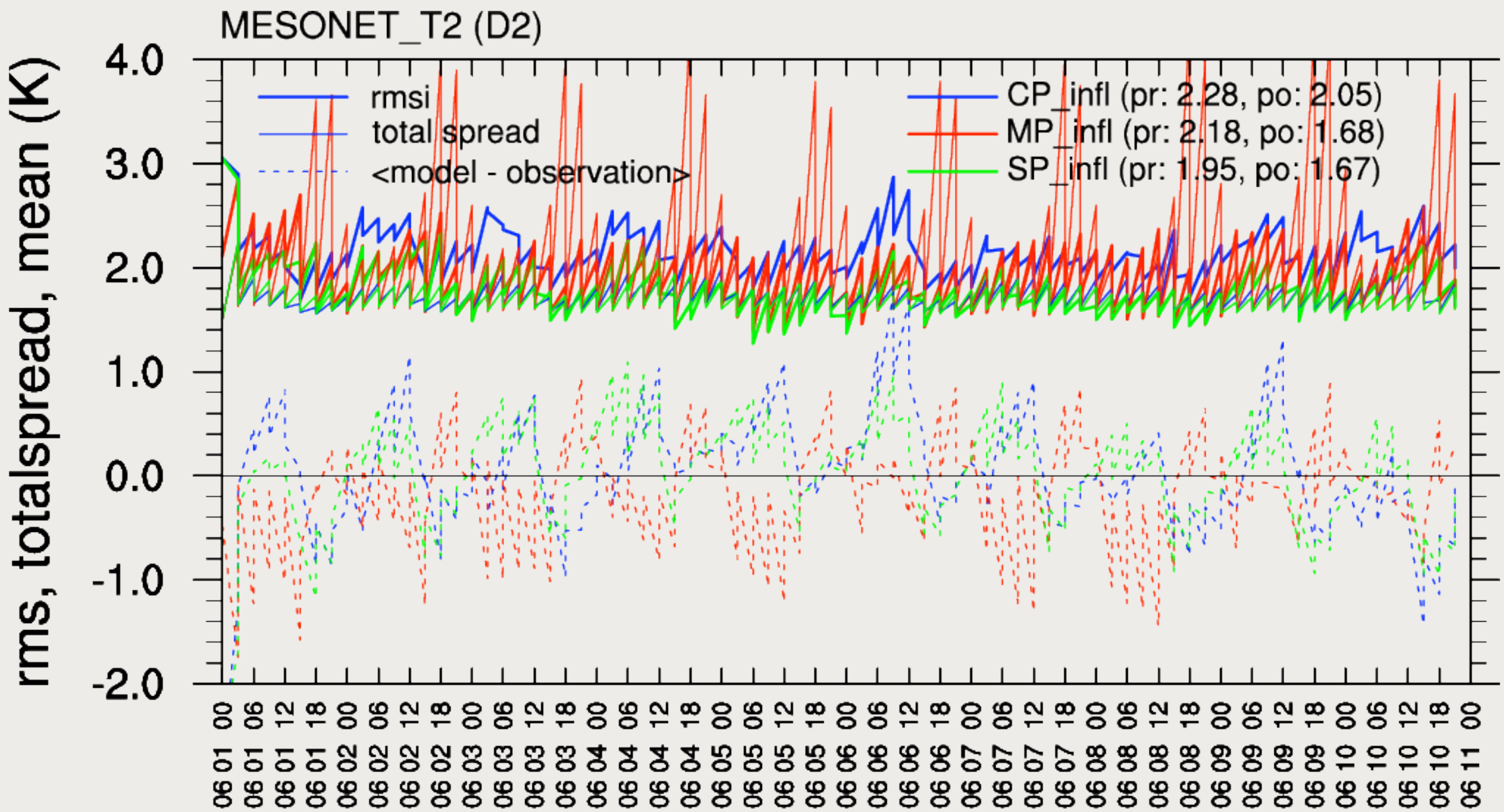


WRF-DART:RMS innovations of T_2



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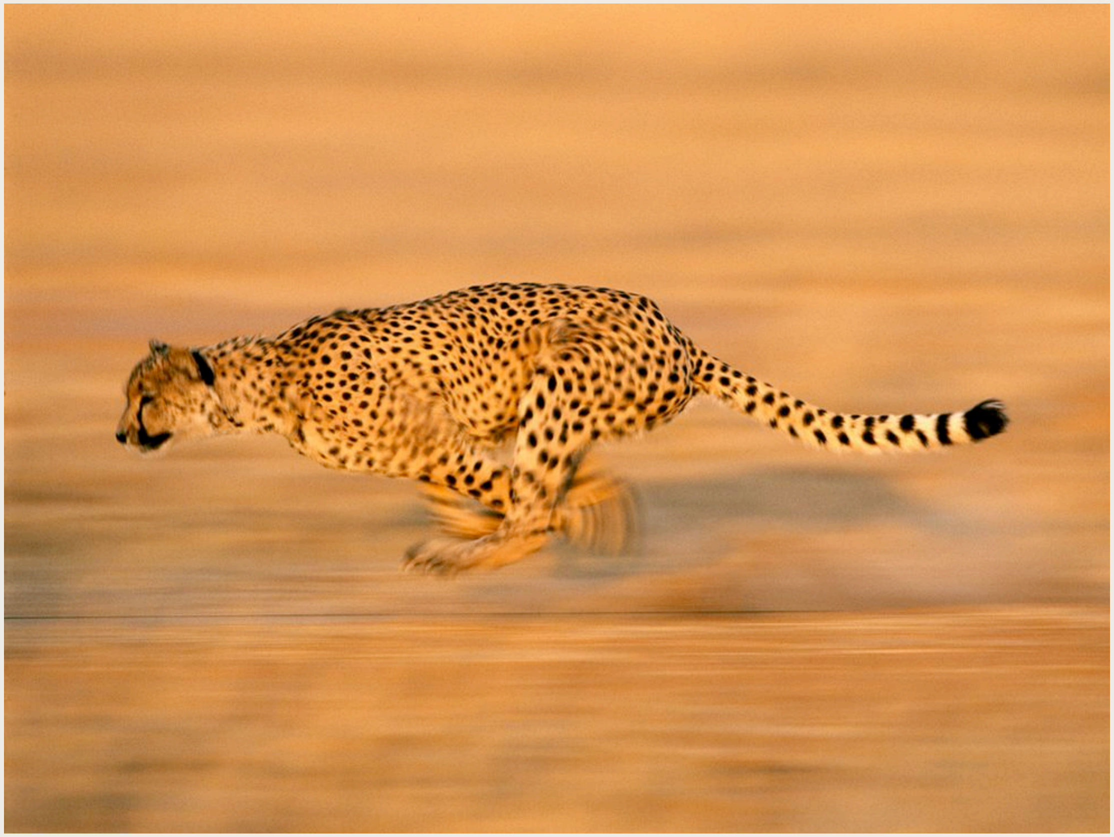
Run!!!



Does accuracy still matter?

- “If we want ensemble systems that represent uncertainty, why should we solve the dynamical equations with high accuracy?”
- Especially when people like me come along and spend their lives putting random numbers in the equations
- G. Shutts, T. Allen, J. Berner, 2008: “Vorticity confinement”
- T. N. Palmer, 2012: “Stochastic processors”
- Problem: Is the error bounded?

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.
- Stochastic parameterizations are starting to become a alternative to other model-error representations

Extras

How to design an ensemble system:

Multi-models

- Each member has different invariant distribution/ climatology
- Pro: Samples Bias
- Con: Not a distribution

Stochastic parameterizations

- All members have the same underlying distribution
- As the core models improve all members improve at the same time