Uncertainty Prediction Across the Scales:

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Acknowledgements: So-young Ha, Dani Bundy, Chris Snyder, Jeff Anderson, Tim Palmer, Thomas Jung, Kevin Raedar, Joe Tribbia

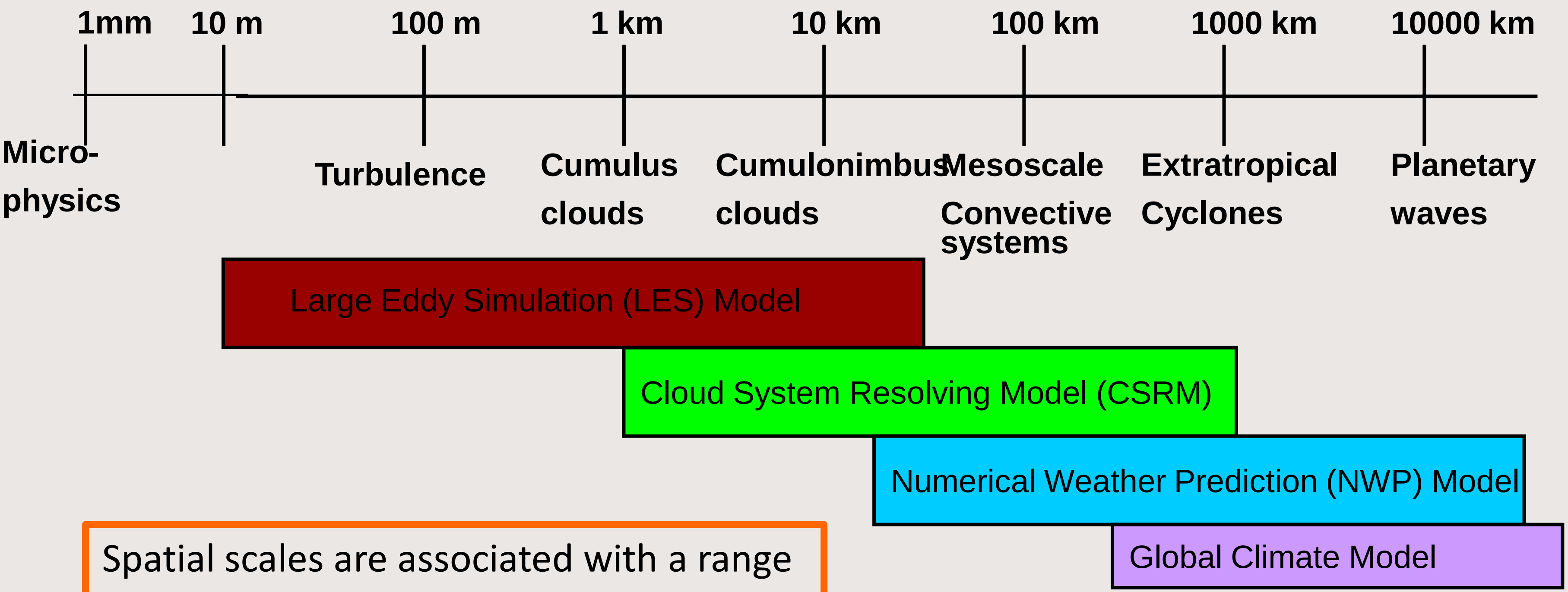
Key points

- 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
- IMO: Stochastic parameterizations are starting to become a (superior?) alternative to other model-error representations

Overview

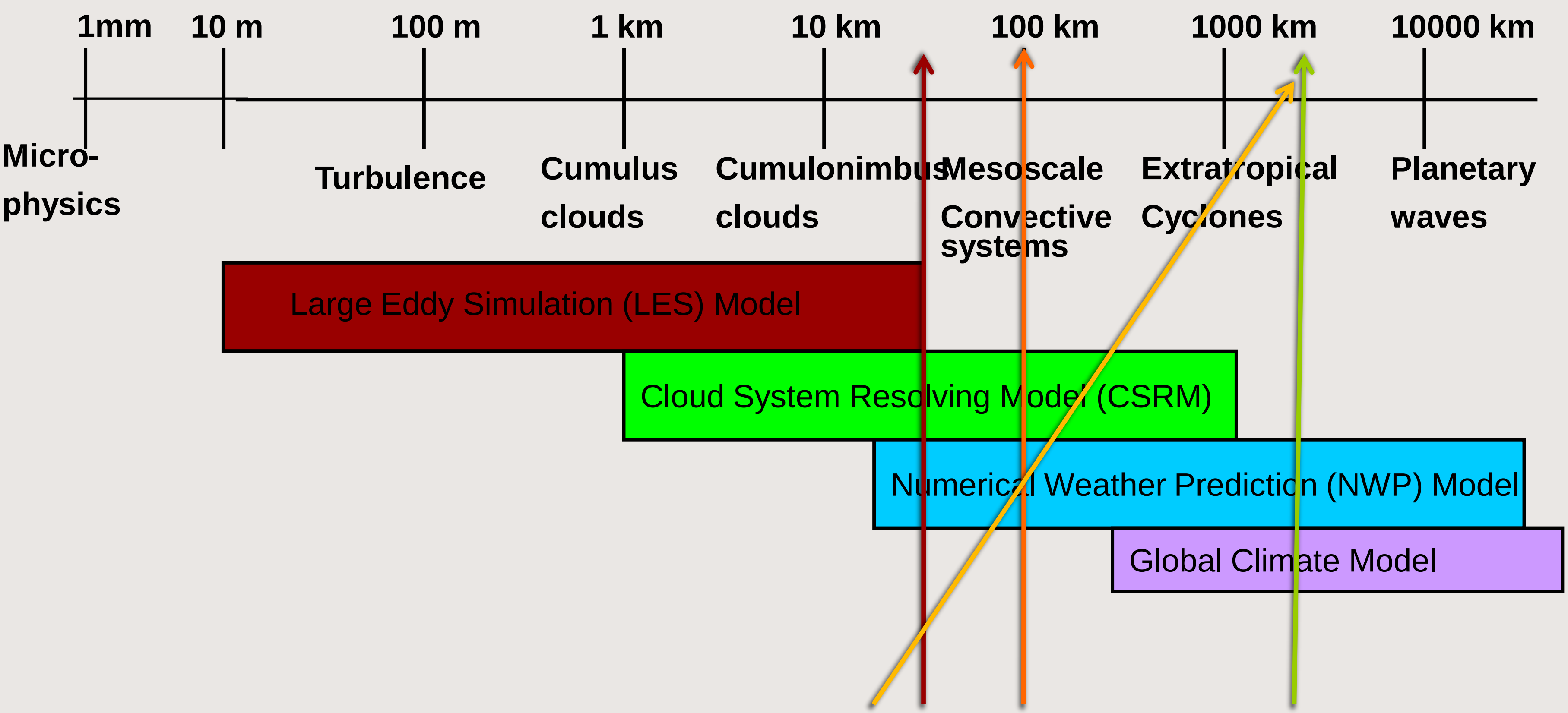
- Why should we use Model Error Representations (MER) for weather and climate predictions?
- Model Error Representations in short-range forecasts (Stochastic Parameterizations, Multi-physics)
- Impact of MER on systematic model errors and seasonal predictions
- Use of MER in Ensemble Data Analysis

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

The "spectral gap" argument (Stull 1960)

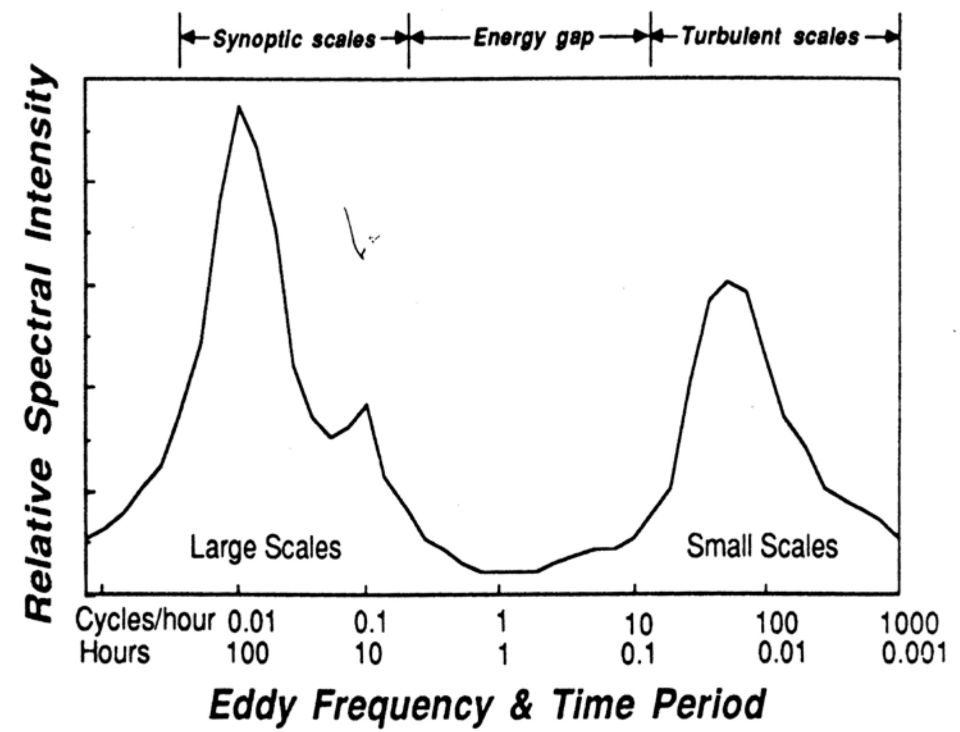
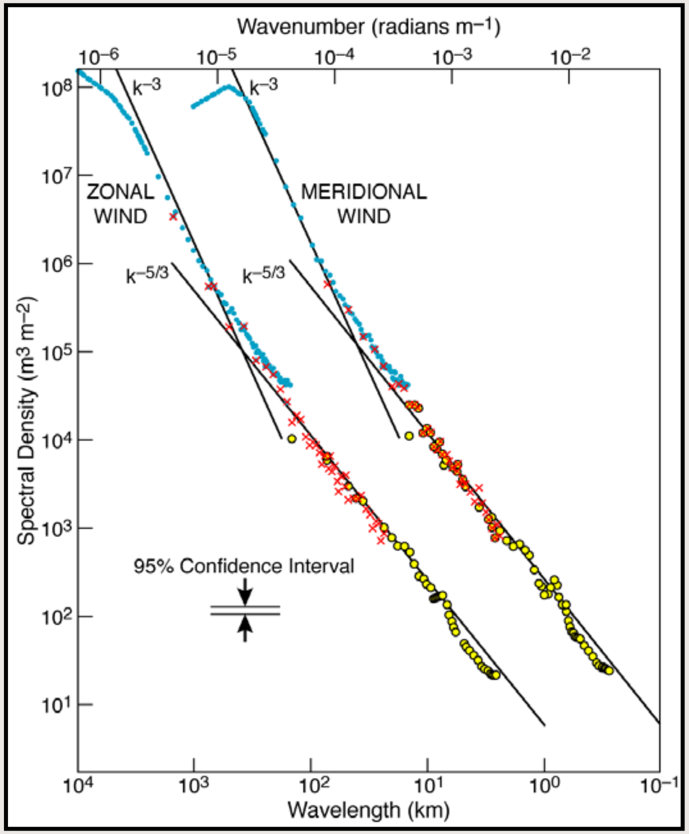


Fig. 2.2 Schematic spectrum of wind speed near the ground estimated from a study of Van der Hoven (1957).

Kinetic energy spectra



Nastrom and Gage, 1985

Limited vs unlimited predictability in Lorenz 1969

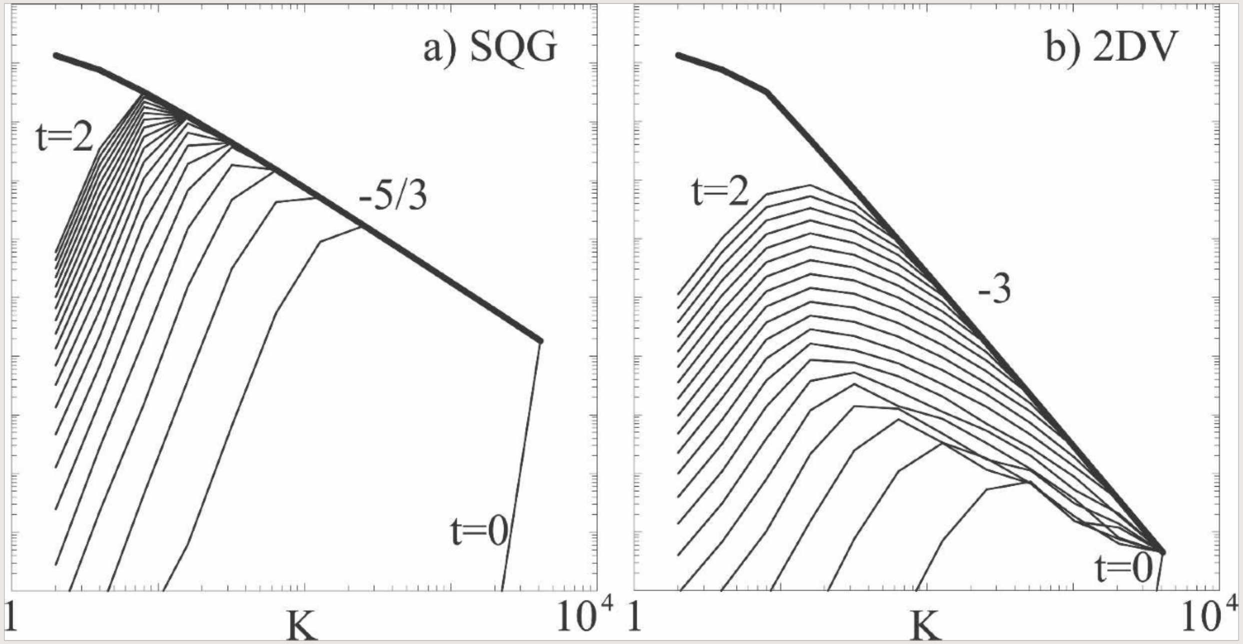


FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K,t)$ for $t = 0, 2$ in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a $-5/3$ slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

see also: Tribbia and Baumhefner 2004

The "Spectral Gap" (Stull, 1960)

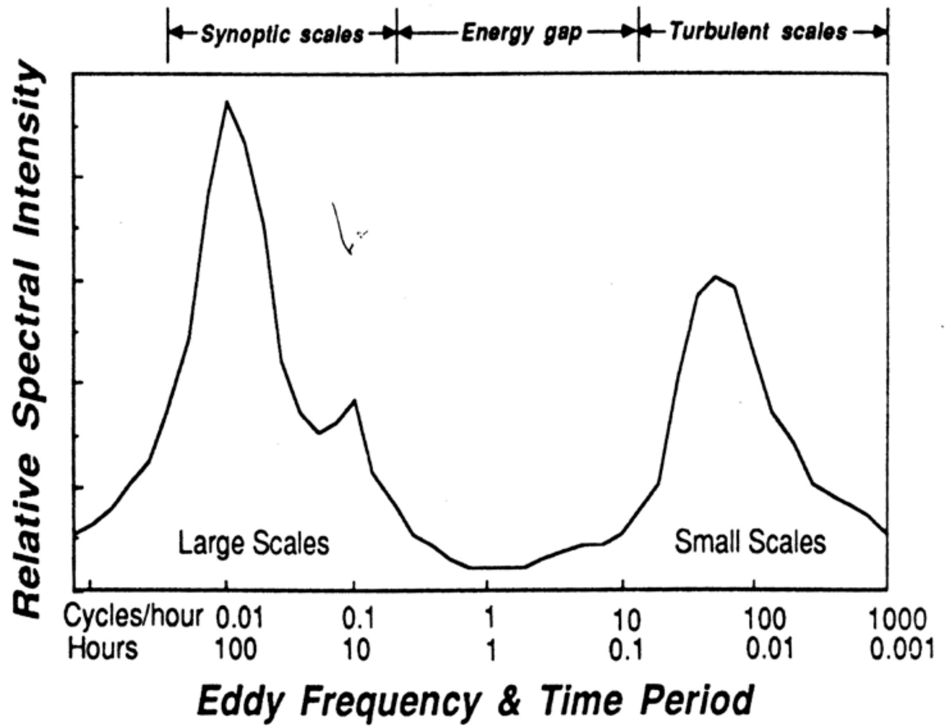
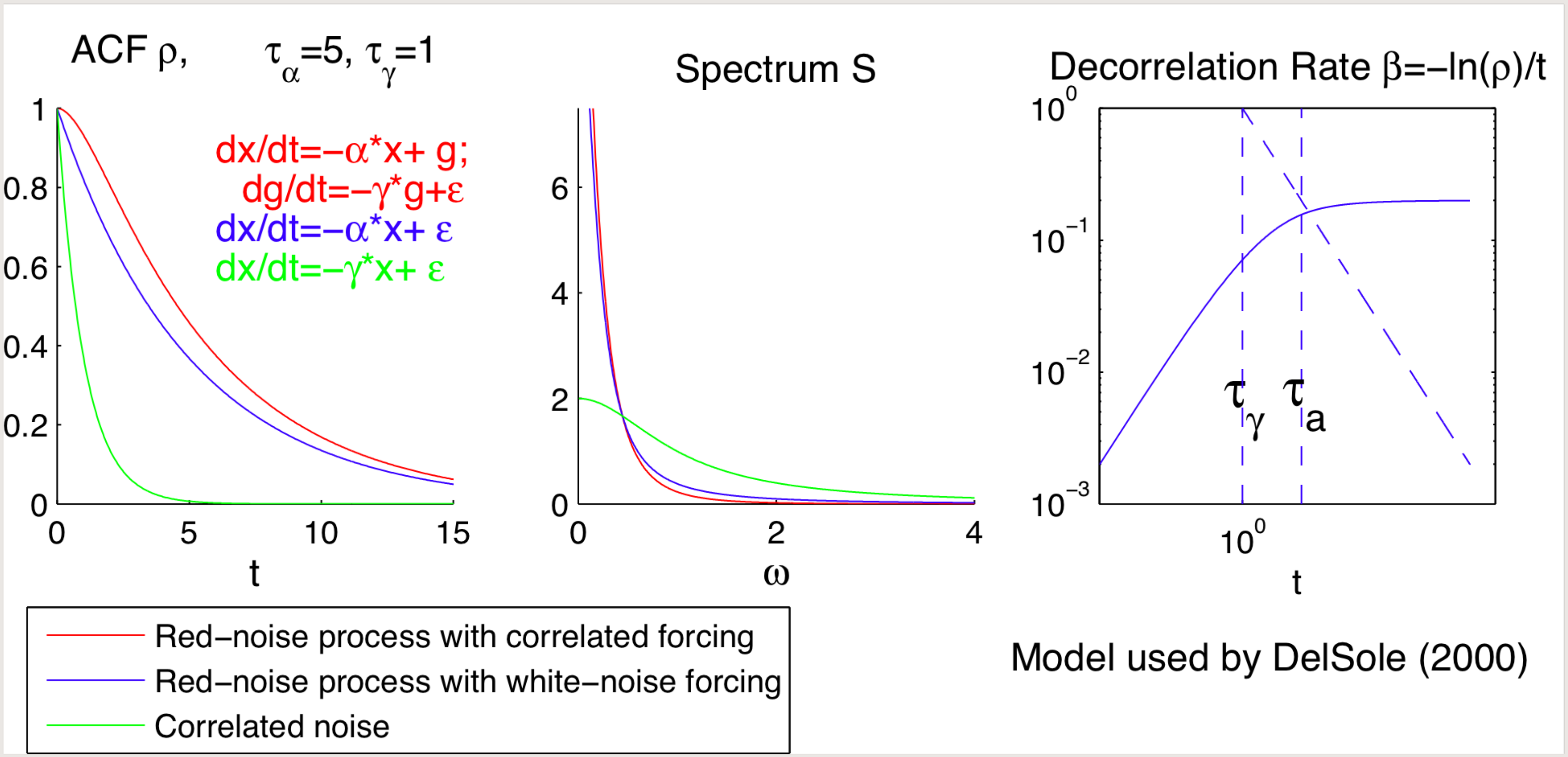


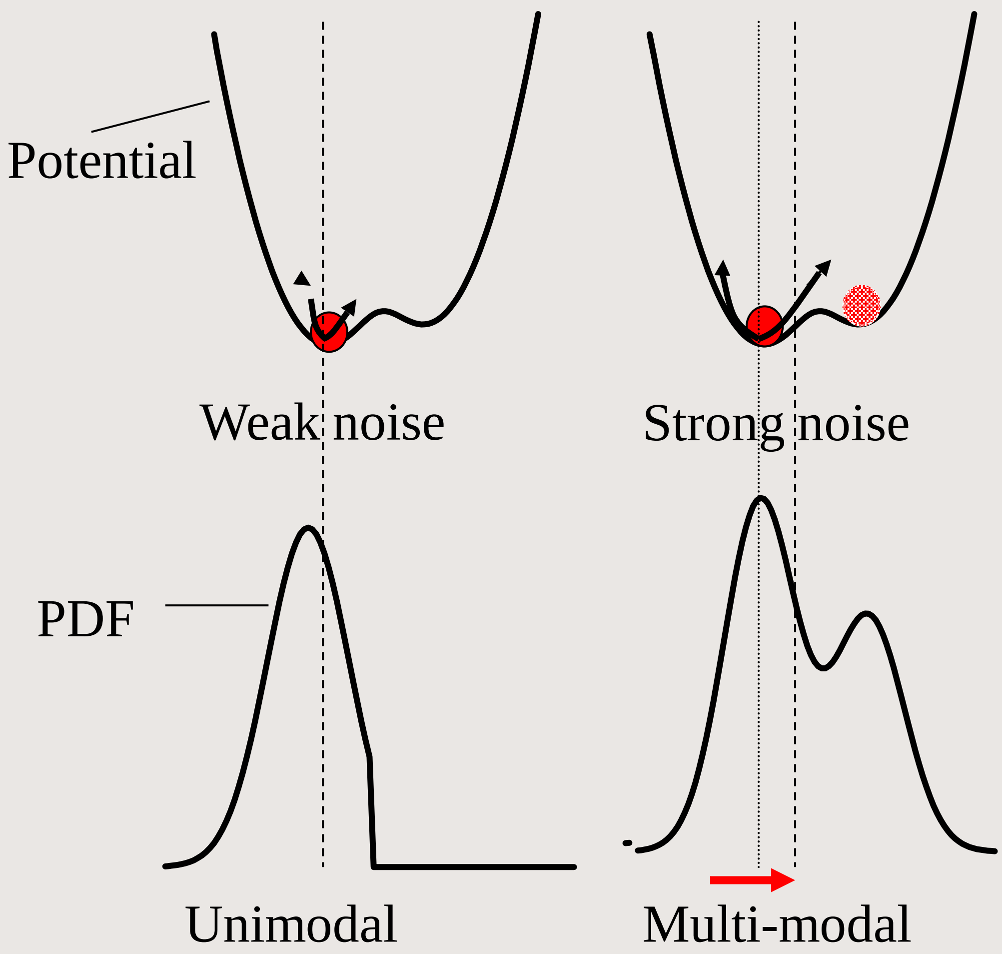
Fig. 2.2 Schematic spectrum of wind speed near the ground estimated from a study of Van der Hoven (1957).

Spectral gap not necessary for stochastic parameterizations



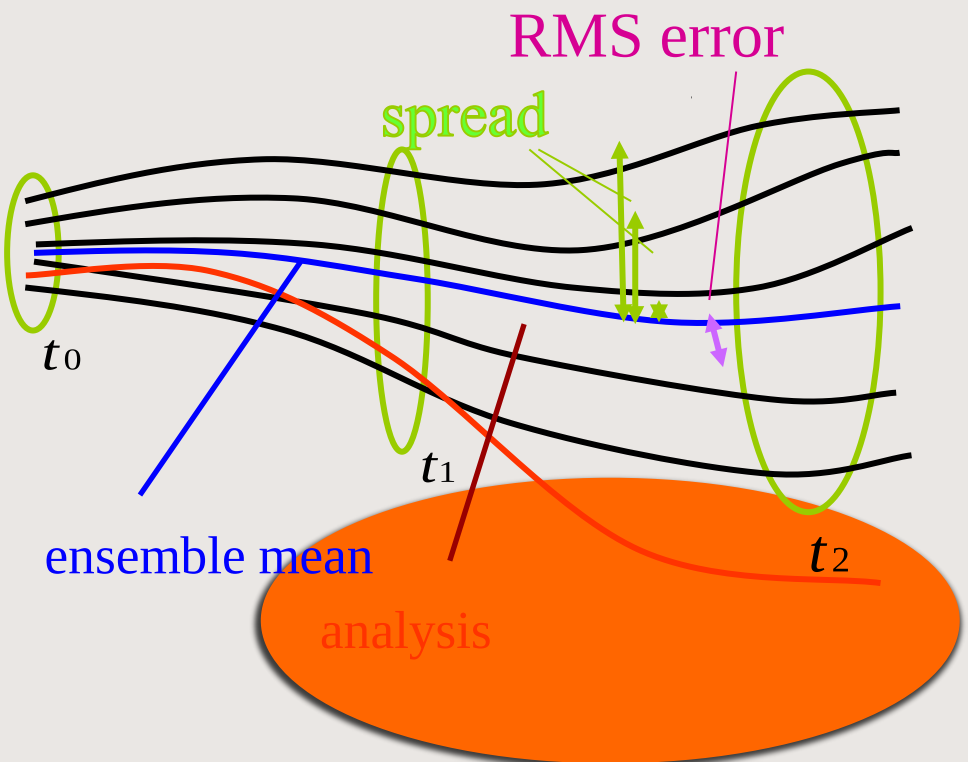
Potential to reduce model error

- 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)

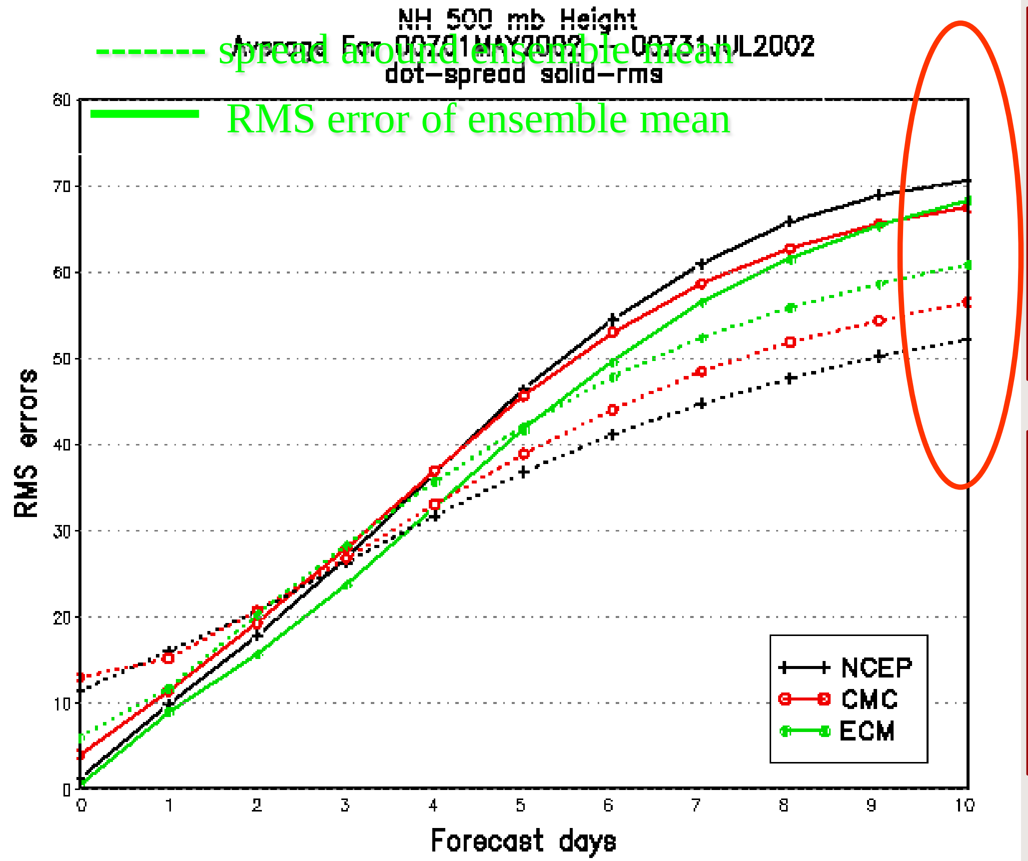


Why model uncertainty representations

- Represent/sample subgrid-scale fluctuations
- Represent structural model error



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***

Representing model error in ensemble systems

- 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)
- The multi-parameter approach: each ensemble member uses the control physics, but the parameters are varied from one ensemble member to the next
- Stochastic parameterizations: each ensemble member is perturbed by a stochastic forcing term that represents the statistical fluctuations in the subgrid-scale fluxes (stochastic diabatic tendencies) as well as altogether unrepresented interactions between the resolved an unresolved scale (stochastic kinetic energy backscatter)

Recent attempts at remedying model error in NWP

Using conventional parameterizations

- Stochastic parameterizations (Buizza et al. 1999, Lin and Neelin 2000, Palmer et al 2009)
- Multi-parameterization approaches (Houtekamer 1996, Berner et. al. 2010)
- Multi-parameter approaches (e.g. Murphy et al. 2004, Stainforth et al. 2004)
- Multi-Models (e.g. DEMETER, ENSEMBLES, TIGGE, Krishnamurti et al. 1999)

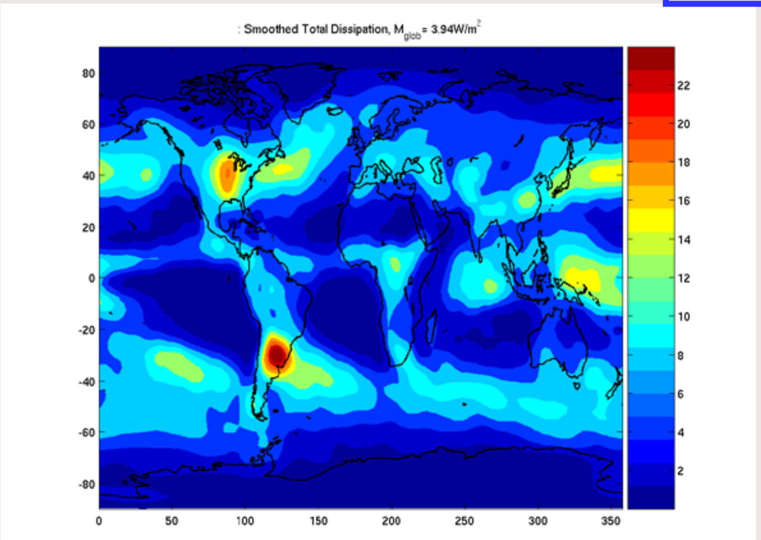
Outside conventional parameterizations

- Cloud-resolving convective parameterization (CRCP) (Grabowski and Smolarkiewicz 1999, Khairoutdinov and Randall 2001)
- Nonlocal parameterization., e.g., cellular automata pattern generator (Palmer, 1997, 2001, Bengtsson-Sedlar et al. 2011)
- Stochastic kinetic energy backscatter in NWP (Shutts, 2005, Berner et al. 2008,2009,2011,Charron et al. 2010, Tennenant et. al 2010)

Stochastic kinetic-energy backscatter scheme

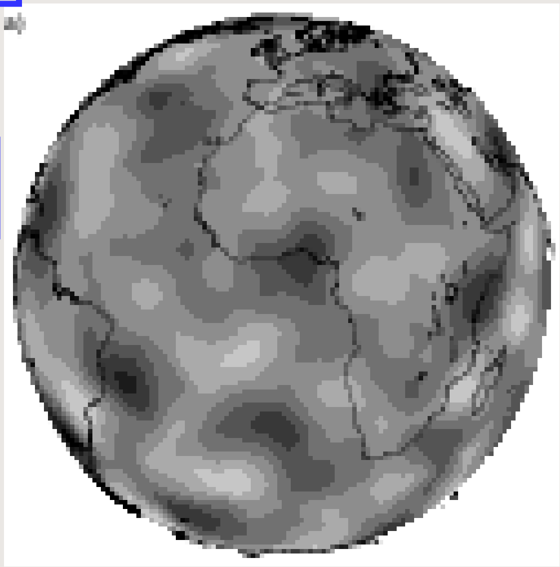
Rationale: A fraction of the dissipated energy is scattered upscale and acts as streamfunction forcing for the resolved-scale flow

$$\boxed{\Delta\psi^* \propto \sqrt{D}\psi'}$$



Total Dissipation rate from numerical dissipation, convection, gravity/mountain wave drag.

$$\boxed{\psi'}$$



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 $g_n = t \quad n^p$

so that prescribed kinetic energy dE is injected into the flow

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

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

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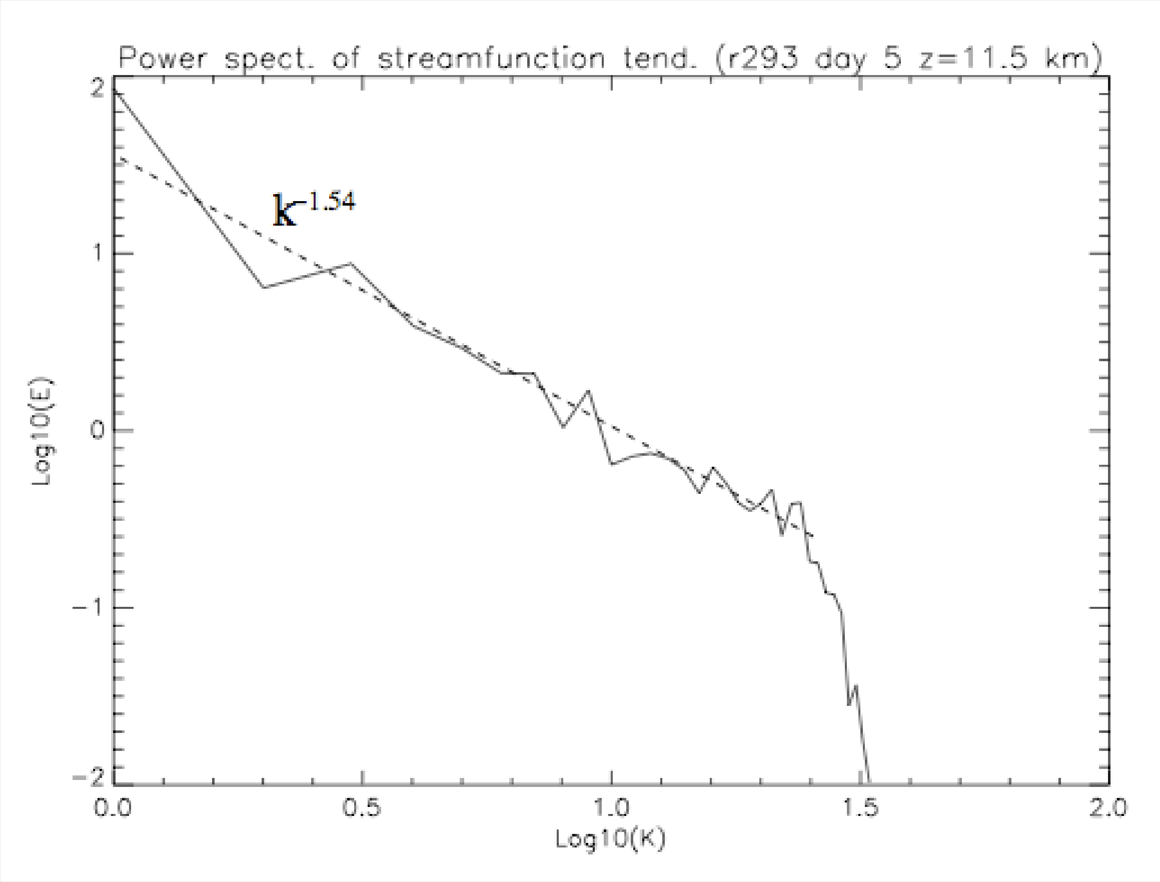
Forcing streamfunction spectra by coarse-graining CRMs



-> Glenn's talk

Hierarchical Parameterization Strategy

- High-resolution model informs output of lower resolution model
- Stochastic kinetic energy backscatter provide such a framework
- … But there are others, e.g. Cloud-resolving convective parameterization

Stochastic kinetic energy backscatter schemes …

- … in LES
  - Mason and Thompson, 1992, Weinbrecht and Mason, 2008, …
- … in simplified models
  - Frederiksen and Keupert, 2004
- … in NWP
  - IFS EPS, ECMWF: Shutts 2005; Berner et al. 2008, 2009; Palmer et al. 2009
  - MOGREPS, MetOffice: Bowler et al 2008,2009; Tennant et al. 2010
  - Canadian Ensemble system: Li et al. 2008, Charron et al. 2010
  - AWFA mesoscale ensemble system, NCAR: Berner et al. 2011

Model uncertainty in short-range weather forecasts of WRF

- WRF-Weather Research and Forecast Model
- Mesoscale Ensemble Prediction System (MEPS)
- A simplified (constant dissipation) SKEBS- scheme was released this spring with WRF3.3
- Acknowledgements: So-young Ha, Chris Snyder, Josh Hacker, Aime Fournier

Experimental Setup

- Weather Research and Forecast Model
- 15 dates between Nov 2008 and Dec 2009, 00Z and 12Z, 30 cycles or cases
- 40km horizontal resolution and 41 vertical levels
- Limited area model: Continuous United States (CONUS)
- Initial and boundary conditions from GFS (downscaled from NCEPs Global Forecast System)
- Ensemble CNTL: 10 member ensemble with control physics
- Ensemble PHYS: 10 member ensemble with multi-physics scheme
- Ensemble STOCH: 10 member ensemble with backscatter scheme
- Ensemble PHYS_STOCH: STOCH+PHYS

Multi-Physics combinations

Member	Land Surface	Microphysics	PBL	Cumulus	Longwave	Shortwave
1	Thermal	Kessler	YSU	KF	RRTM	Dudhia
2	Thermal	WSM6	MYJ	KF	RRTM	CAM
3	Noah	Kessler	MYJ	BM	CAM	Dudhia
4	Noah	Lin	MYJ	Grell	CAM	CAM
5	Noah	WSM6	YSU	KF	RRTM	Dudhia
6	Noah	WSM6	MYJ	Grell	RRTM	Dudhia
7	RUC	Lin	YSU	BM	CAM	Dudhia
8	RUC	Eta	MYJ	KF	RRTM	Dudhia
9	RUC	Eta	YSU	BM	RRTM	CAM
10	RUC	Thompson	MYJ	Grell	CAM	CAM

TABLE 2. Configuration of the multi-physics ensemble. Abbreviations are: BM – Betts-Miller; CAM – Community Atmosphere Model; KF – Kain-Fritsch; MYJ – Mellor-Yamada-Janjic; RRTM – Rapid Radiative Transfer Model; RUC – Rapid Update Cycle; WSM6 – WRF Single-Moment Six-class; YSU – Yonsei University. For details on the physical parameterization packages and references see Skamarock et al. (2008).

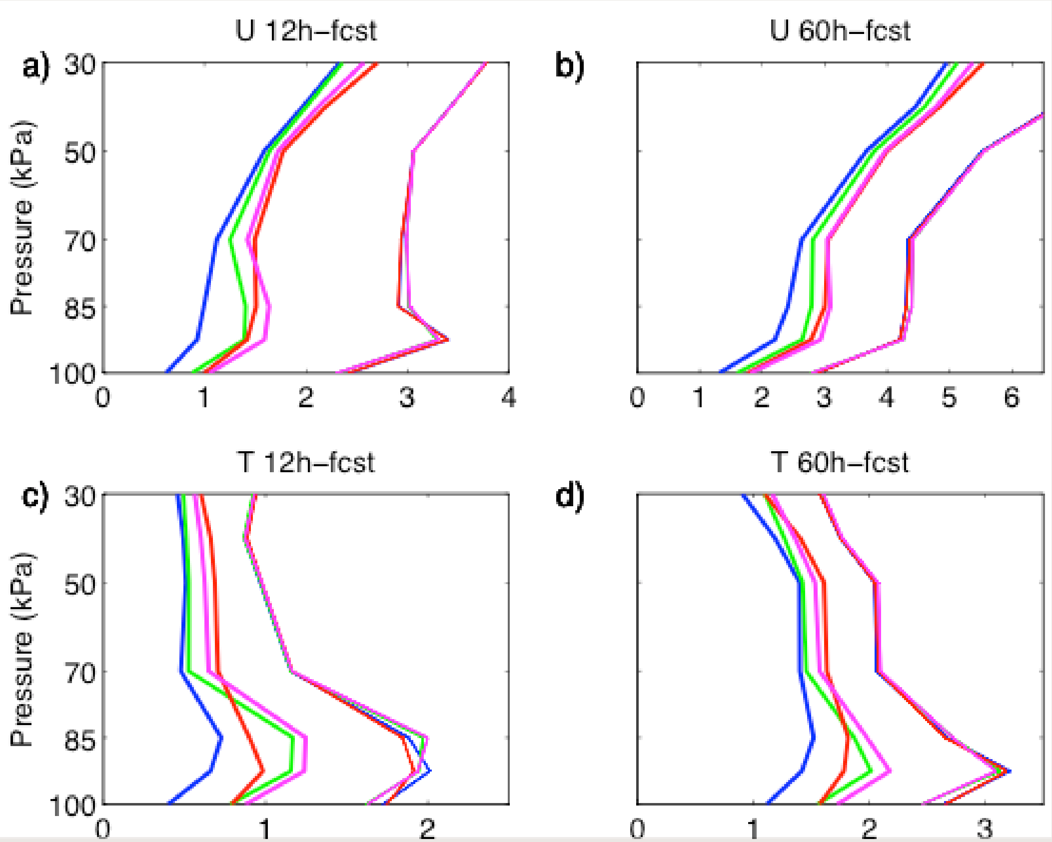
Note:

- One of the first studies to compare multi-physics and stochastic parameterization within the SAME ensemble prediction system
- Multi-physics schemes are very tedious to maintain (Charron et al., 2010, So-young Ha (pers. Communication), but WRF has at advantage of having different parameterization schemes as part of the release.

Verification against Observations

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

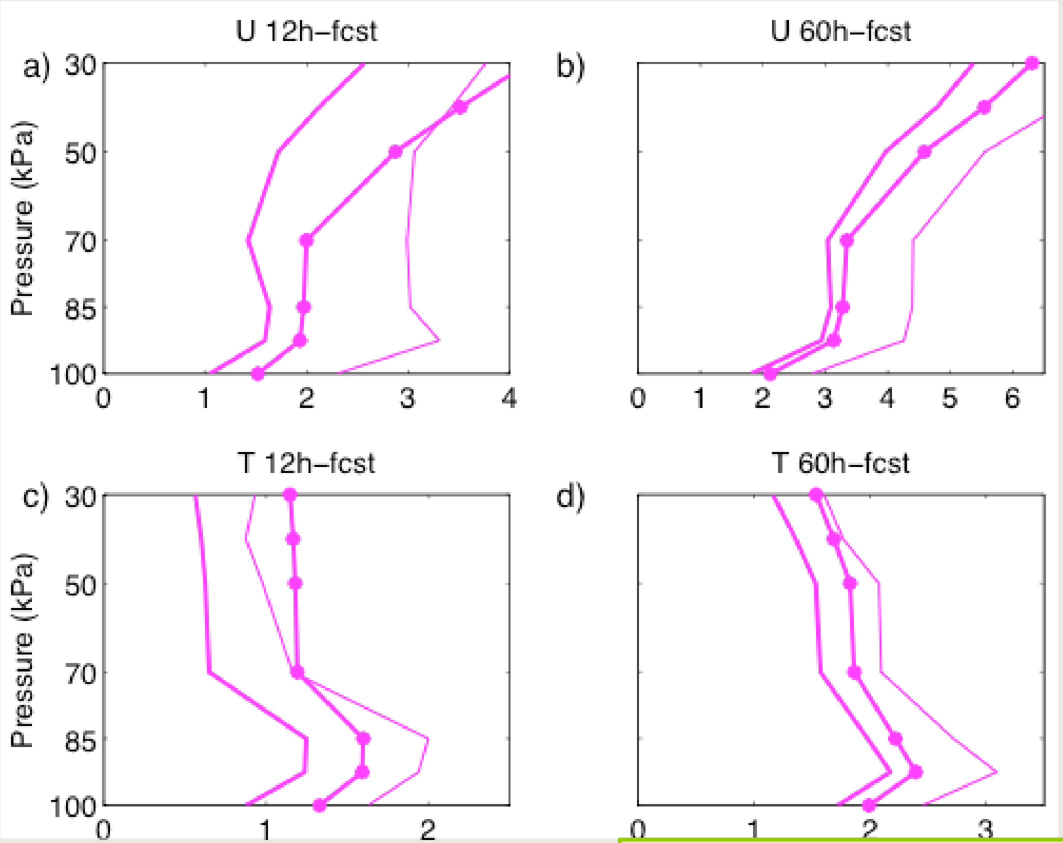
CNTL	
STOCH	
PHYS	
PHYS_STOCH	



Berner et al. 2011

Dependence on observation error

PHYS_STOCH
PHYS_STOCH
With obs error



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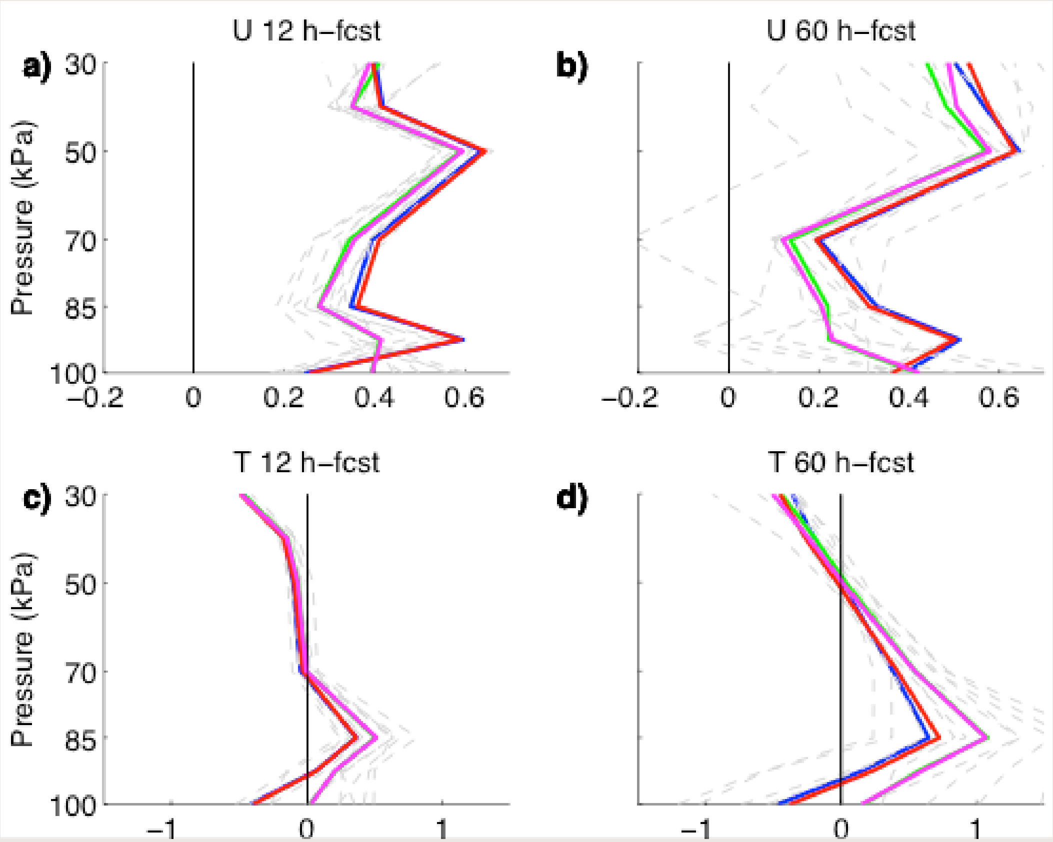
Mean Bias

CNTL
STOCH
PHYS
PHYS_STOCH



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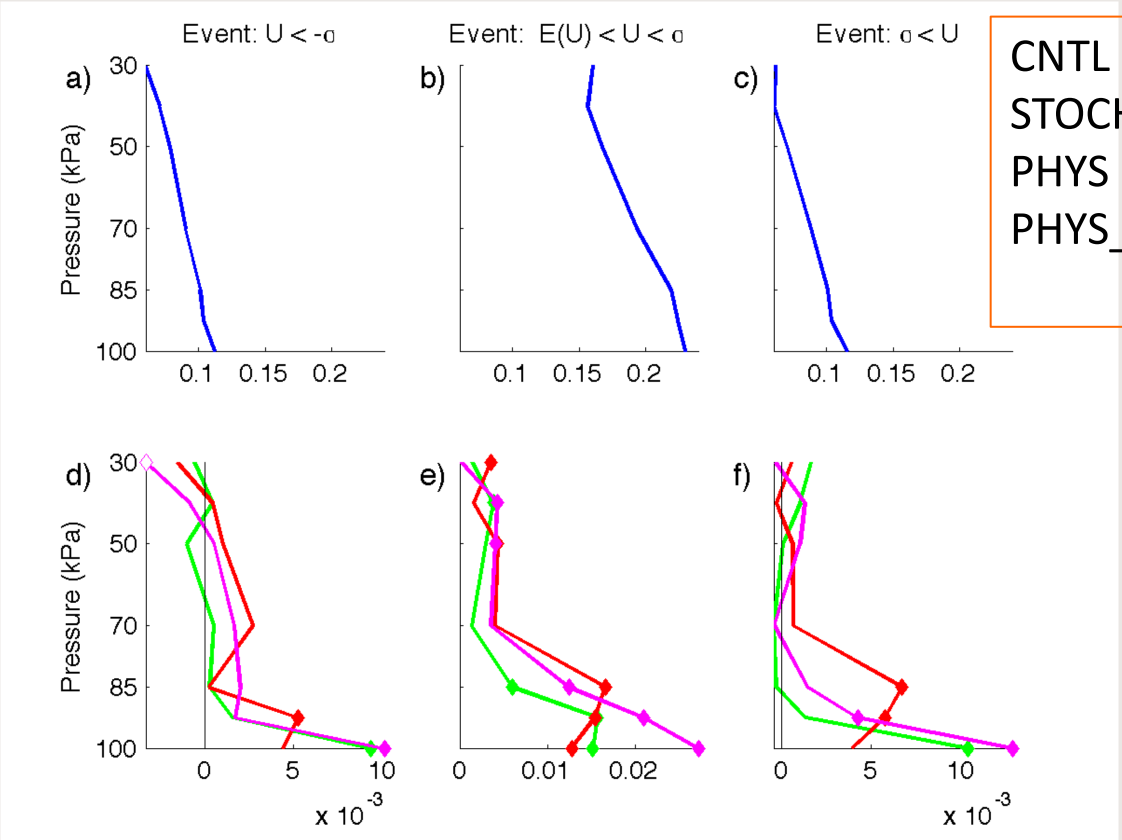
Brier Score Profiles: U

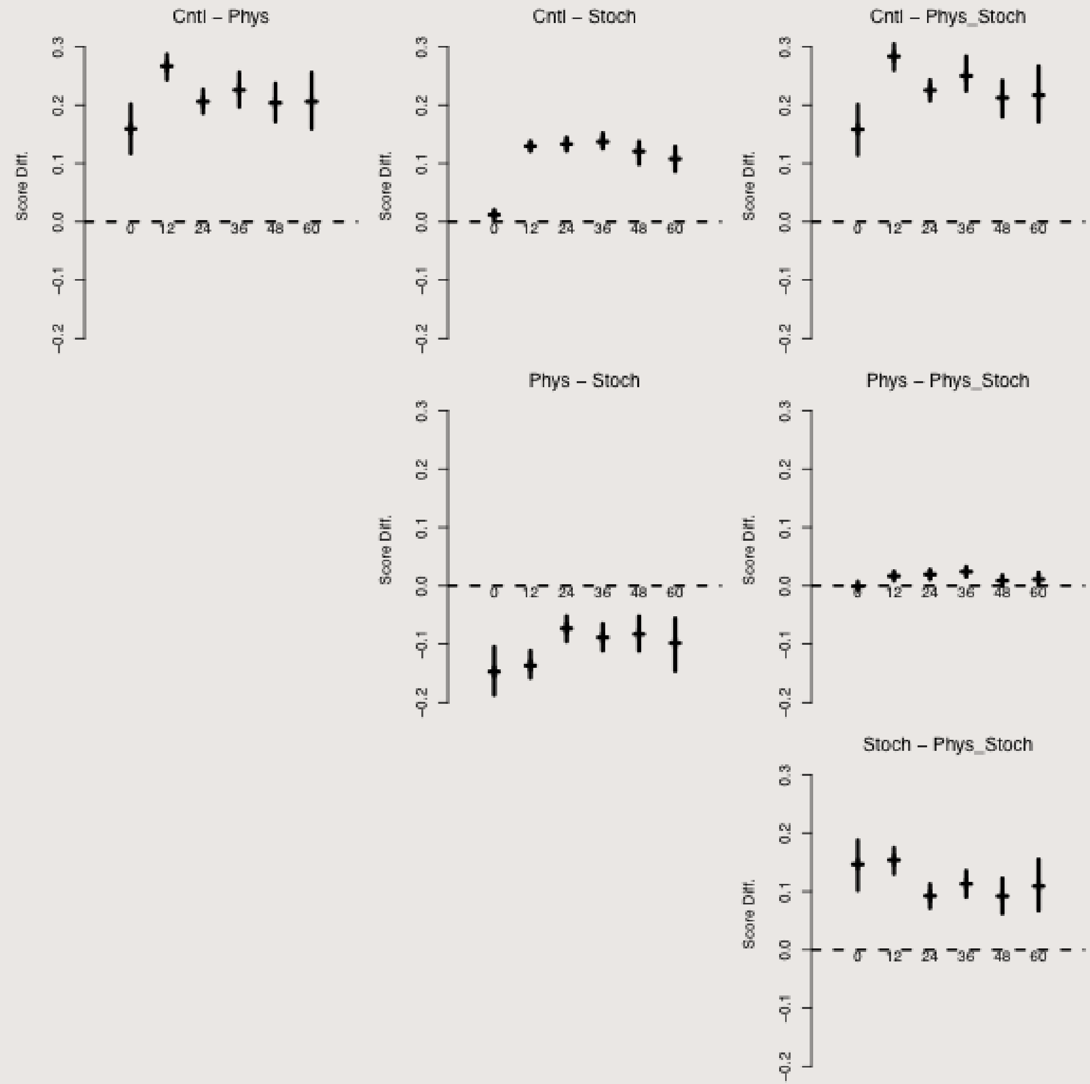
Score profile for CNTL



CNTL
STOCH
PHYS
PHYS_STOCH

Score difference with CNTL. Positive differences mean improvement over CNTL. Diamonds denote significance at 95% confidence level.

Berner et al. 2011



Pairwise comparison: T at 2m

Berner et al. 2011

Summary of pairwise comparison

Statistics over different forecast times, variables and vertical levels

	PHYS better		PHYS worse		STOCH better		STOCH worse		PHYS_STOCH better		PHYS_STOCH worse	
CNTL	82	**(39)**	18	**(2)**	93	**(57)**	7	**(1)**	87	**(54)**	13	**(3)**
PHYS					63	**(14)**	37	**(5)**	79	**(31)**	21	**(3)**
STOCH									58	**(14)**	42	**(8)**

TABLE 3. Pairwise comparison of the percentage of outcomes, where model A (columns) performs better or worse than model B (rows) as measured by the Brier score when verified against observations. The outcomes comprise the forecast lead times 12 h and 60 h, four verification events (see text) and seven vertical levels for the variables zonal wind u, meridional wind v and temperature T, totaling 168 outcomes. The bold numbers in parentheses denote statistically significant outcomes at the 95% confidence level. The mean monthly bias was removed from each ensemble member prior to the verification.

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Conclusions

- Including a model-error representation leads to ensemble systems that produce significantly better probabilistic forecasts than a control physics ensemble that uses the same physics schemes for all ensemble members.
- Overall, the stochastic kinetic-energy backscatter scheme outperforms the ensemble system utilizing multiple combinations of different physics-schemes. This is especially the case for u and v in the free atmosphere.
- However, for T at the surface the multi-physics ensemble produces better probabilistic forecasts, especially when verified against observations (currently being improved)

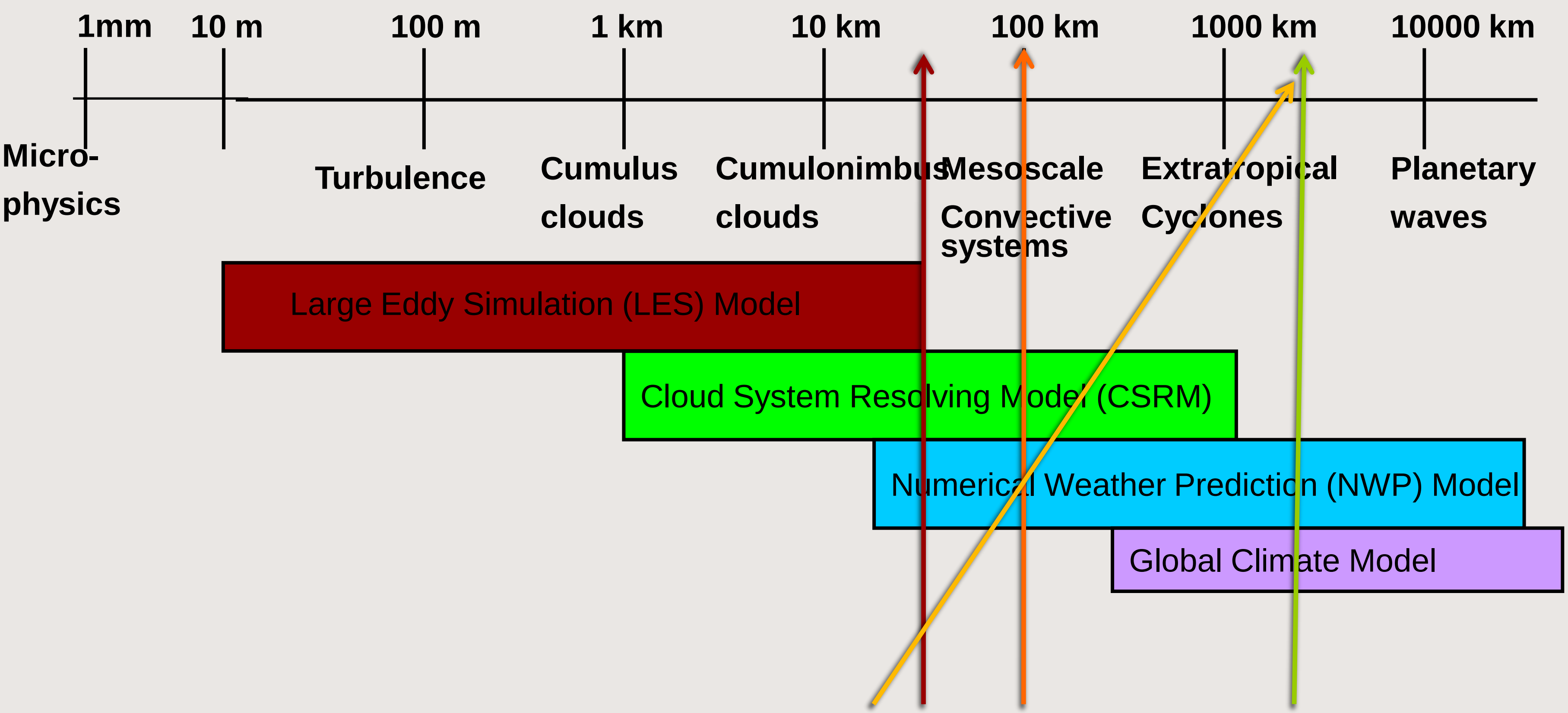
Conclusions

- The best performing ensemble system is obtained by combining the multi-physics scheme with the stochastic kinetic-energy backscatter scheme. The superiority of the combined scheme is most evident at the surface and in the boundary layer.
- Consistent with other studies (Palmer et al. (2009), Charron et al. (2010) and Hacker et al. (2011):Combining multiple stochastic parameterizations or stochastic parameterization with multiple physics-suites resulted in the most skillful ensemble prediction system.

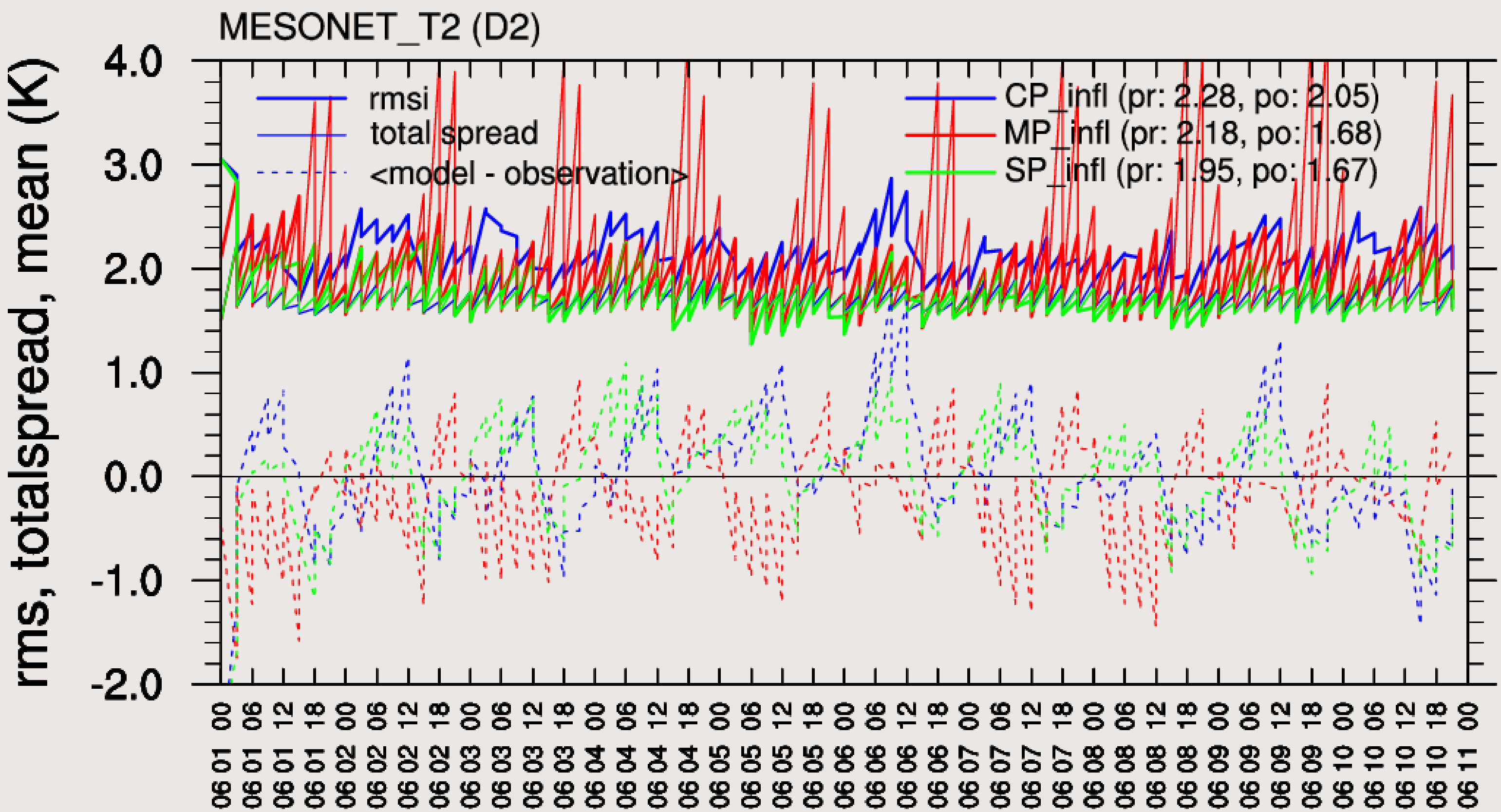
Uncertainty in state estimation using WRF-DART

- Create an ensemble of analyses that is representative of analysis error => initial conditions
- DART- Data Assimilation Research Testbed based on Ensemble Kalman Filter (EnKF)
- Ensemble analysis is under-dispersive, e.g. due to sampling error => inflation factor => can model uncertainty scheme make inflation redundant?
- 2 Domains nested with feedbacks: outer 45km, inner 15km
- Collaborators: So-young Ha, Chris Snyder

Multiple scales of motion

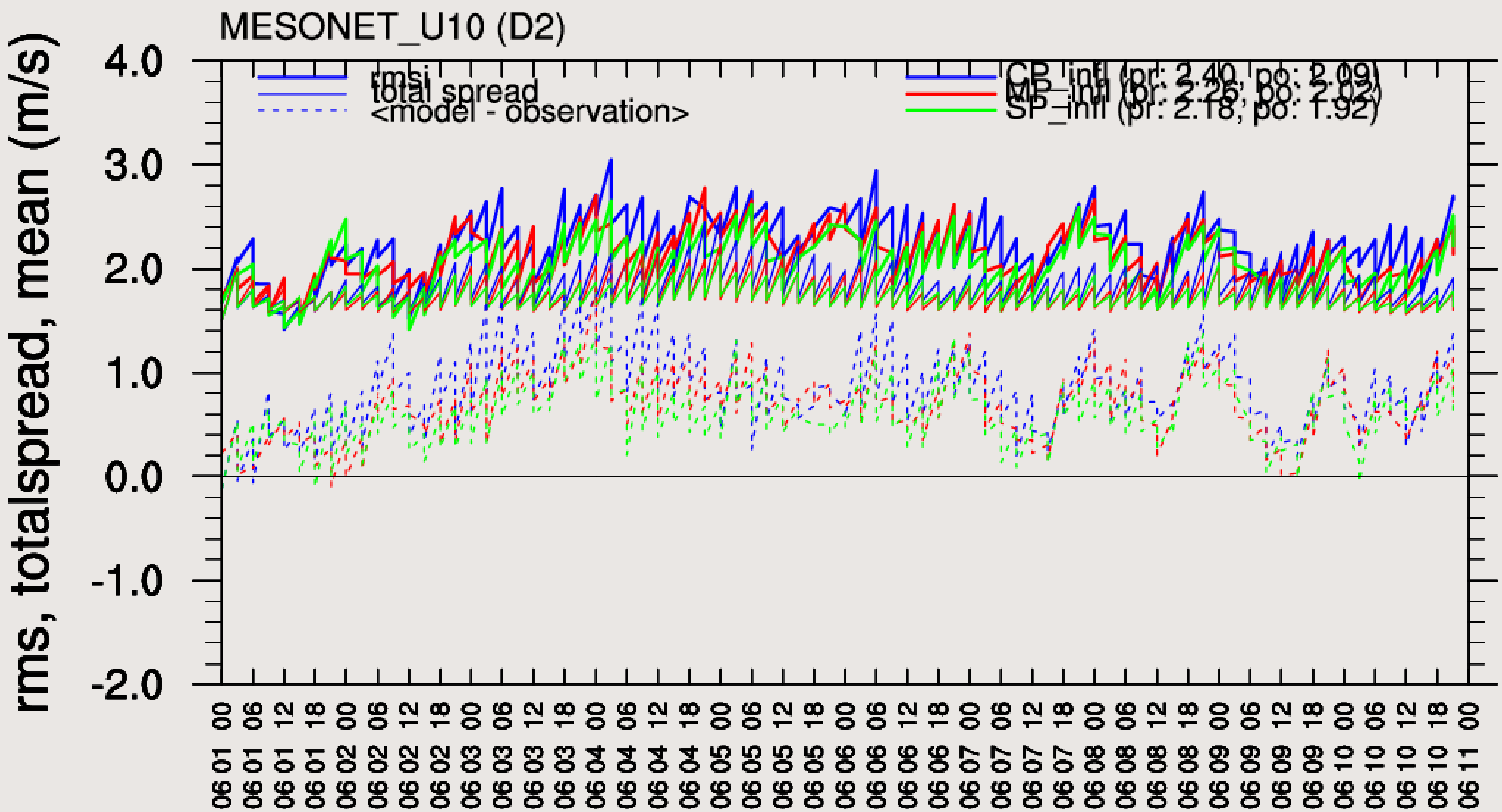


RMS innovations of T2



CNTL
PHYS
STOCH

TMS innovations U10

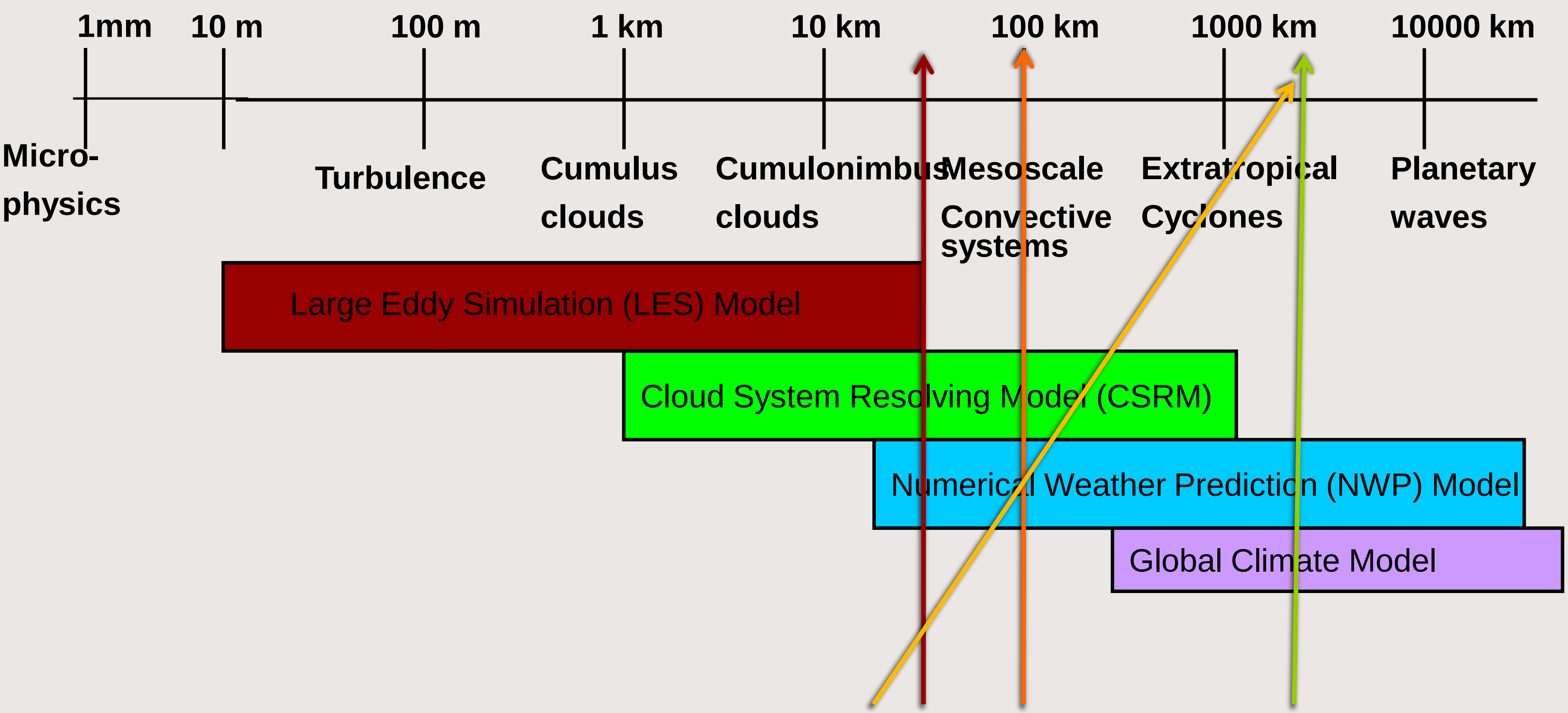


CNTL
PHYS
STOCH

Preliminary Results

- STOCH has smallest RMS innovations for both U and T
- Adaptive inflation factor is reduced when used in adaptive mode
- STOCH can replace the adaptive inflation (results almost as good as those shown)
- But: Sampling error is fundamental different from model error represented by SKEBS, so maybe both should be retained
- Or: Combined model and sampling error into a single term

Multiple scales of motion



Impact on Systematic Error Model Error

- Low res control (LOWRES): IFS CY31R2 T95L91
- HIGHRES: T511L91
- STOCH: Stochastic kinetic energy backscatter
- PHYS: Improved physics packages: IFS CY36
- 15 (40) years: 1990-2005, forced by observed SSTs
- 5 month integrations started Nov1; 1st month discarded
- Compared against (re-)analyses

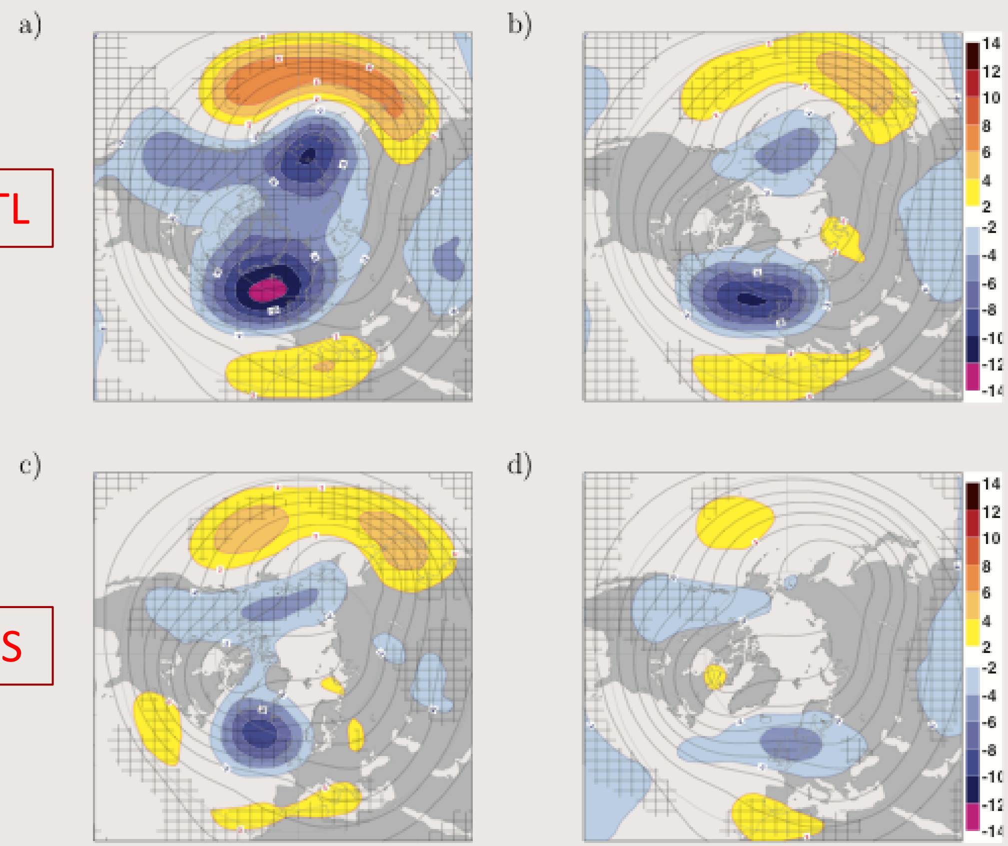
Bias of z500 in IFS

CNTL

SKEBS

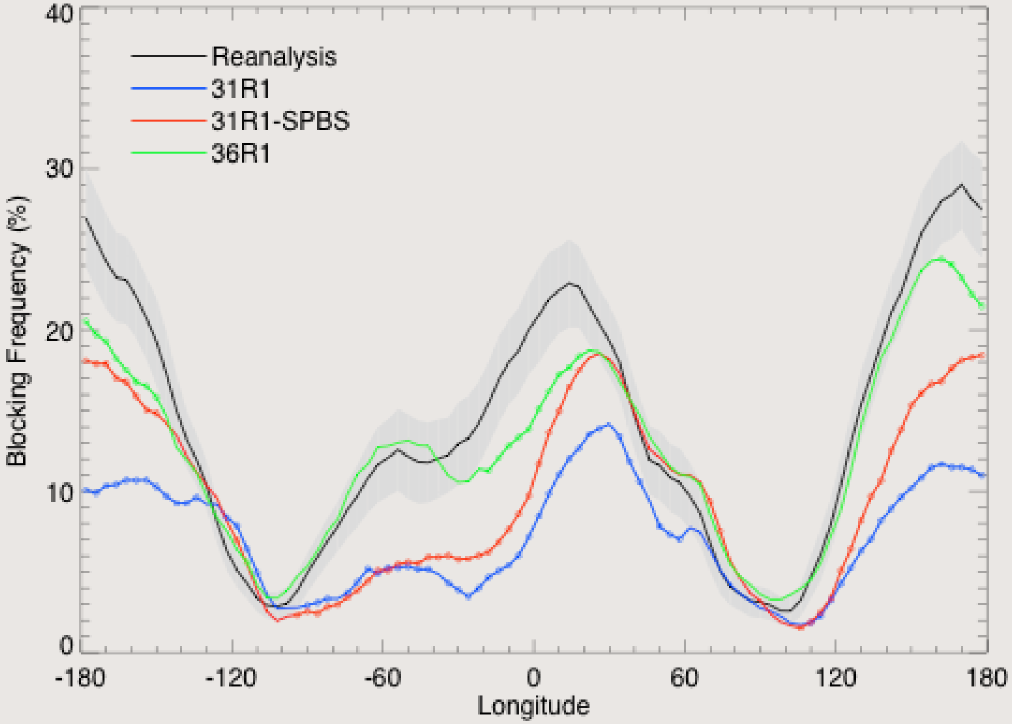
HIGHRES

PHYS



Berner et al. 2011, J. Clim, submitted

Blocking 1962-2005



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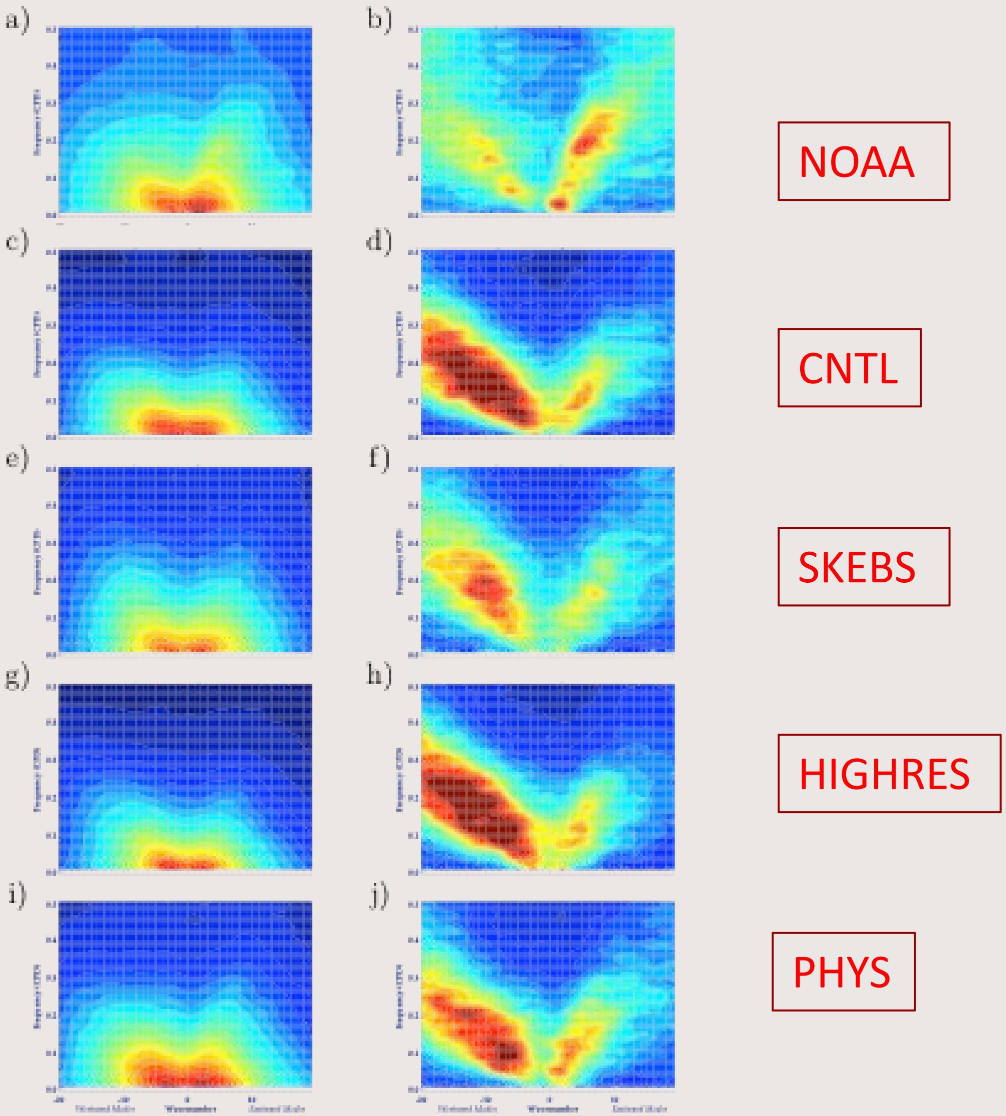

Frequency-Wavenumber spectra of OLR in IFS

Berner et al. 2011, J. Clim, submitted

Conclusions

- Increasing horizontal resolution, improving the physics packages and including a stochastic parameterization all improve certain aspects of model error, e.g. z500 bias
- Others aspects, e.g. tropical waves were positively influenced by STOCH and PHYS, but not HIGHRES
- => Unresolved scales may play an important role, but results also give raise to a cautionary note
- => Stochastic parameterizations should be included ab initio in physics-parameterization development

Future work

- Understand differences between multi-physics and stochastic representation physically and/or structurally
- Impact on extreme events on decadal timescales
- Implement SKEBS in CAM and assess impact on climate variability

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 (superior?) alternative to other model-error representations

Thank you!

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