



Model-error representation in ensemble systems

WRF user Workshop, Boulder, 2017

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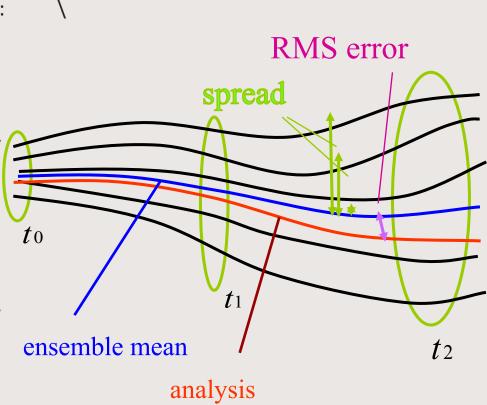
National Center for Atmospheric Research

Outline

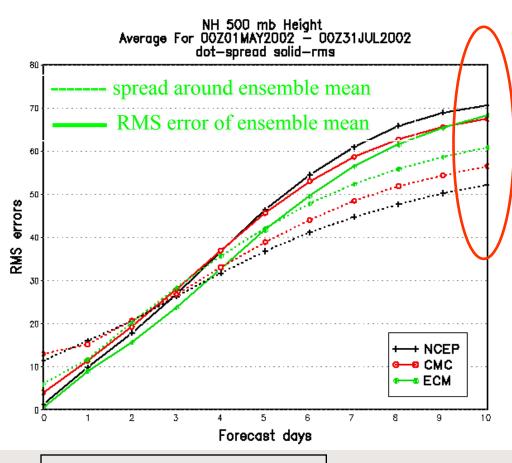
- Model-error in ensemble systems
- Model-error schemes
- Examples in WRF
- Model bias
- Predictability

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



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

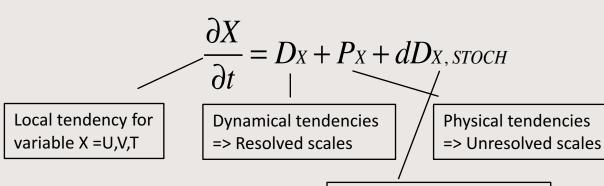
Buizza et al., 2005

Predictability on weather timescales:The problem

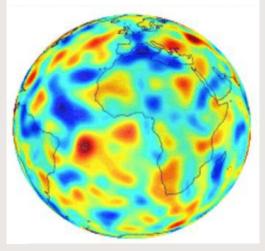
- Best estimates of initial condition uncertainty do not introduce the necessary spread for reliable forecasts on the short-, medium- and seasonal scales.
 - One source of model-error are uncertainties in the physical parameterization schemes.
 - Our best estimate of parameterization uncertainties does not yield sufficient spread.

Stochastic-kinetic energy backscatter scheme (SKEBS)

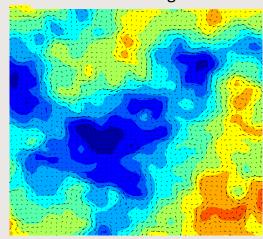
Rationale: A fraction of the subgrid-scale energy is scattered upscale and acts as random streamfunction and temperature forcing for the resolved-scale flow (Shutts 2005, Berner et. al 08,09,11,15). Here simplified version with constant dissipation rate: can be considered as additive noise with spatial and temporal correlations.



Additive stochastic perturbation tendencies => Unresolved scales

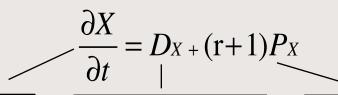


Stochastic Forcing Pattern



Stochastically perturbed tendency scheme (SPPT)

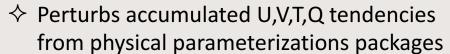
Rationale: Especially as resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale state should be sampled (Buizza et al. 1999, Palmer et al. 2009, Berner et al. 2015)



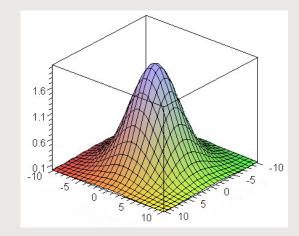
Local tendency for variable X

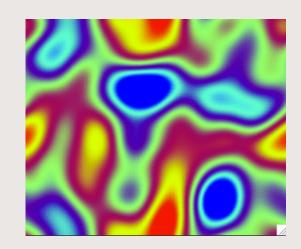
Dynamical tendencies => Resolved scales

Physical tendencies => Unresolved scales



♦ Same pattern for all tendencies to minimize introduction of imbalances





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).

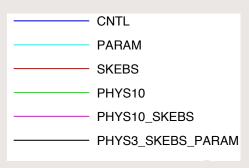
Experiment setup

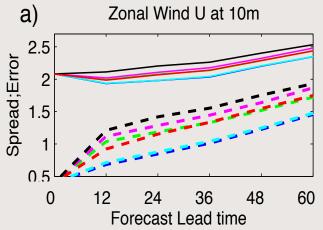
- Weather Research and Forecast Model WRFV3.1.1 (or WRFV3.3.1)
- 45km horizontal resolution and 41 vertical levels
- 10-member ensemble, integrated for 60h (short-range forecast)
- ❖ 15 dates in Nov-Dec 2009, 00Z and 12Z, amounting to 30 cycles
- Limited area model: Contiguous United States (CONUS)
- Boundary and initial conditions are taken from GEFS
- Verification against observations (soundings and METAR)

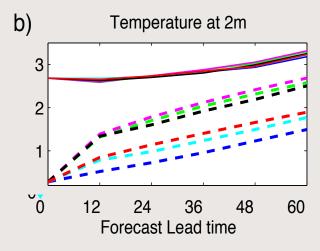
Summary of experiments

Experiment	Model-error representation	Color	Reference	
CNTL	Control Physics	blue	Hacker et al. (2011b)	
SKEBS	Stochastic kinetic-energy	red	Berner et al. (2011)	
	backscatter scheme			
PARAM	Multi-parameter	cyan	Hacker et al. (2011a)	
SPPT	Stochastically perturbed	orange	Palmer et al. (2009)	
	physics tendencies			
PHYS4	Limited multi-physics (4 packages)	light green	Hacker et al. (2011b)	
PHYS10	Multi-physics (10 packages)	dark green	Hacker et al. (2011b)	
			Berner et al. (2011)	
PHYS10_SKEBS	Multi-physics (10 packages) +	magenta	Berner et al. (2011)	
	+ SKEBS			
PHYS4_SKEBS_PARAM	Limited multi-physics +	black	Hacker et al. (2011b)	
	(4 packages) + PARAM + SKEBS			

Spread and error near the surface





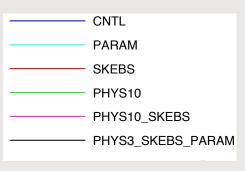


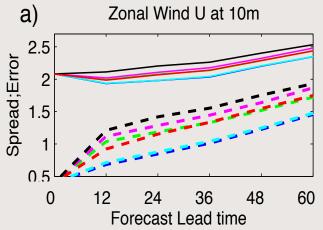
Solid lines: rms error of ensemble mean

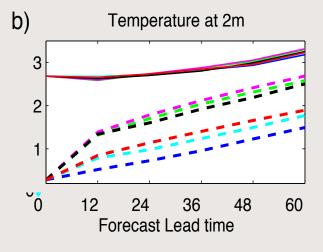
Dashed: spread

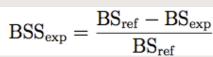
- Ensemble is underdispersive (= not enough spread)
 - Unreliable and over-confident
 - Depending on cost-loss ration potentially large socio-economic impact (e.g. should roads be salted)

Brierscore skill score near the surface





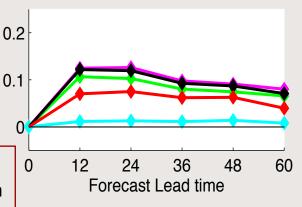


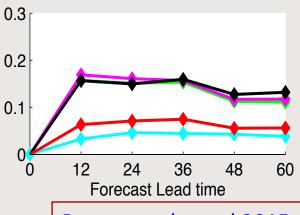


Brier skill measures probabilistic skill in regard to a reference (here CNTL).

Verified event: $\mu < x < \mu + \sigma$

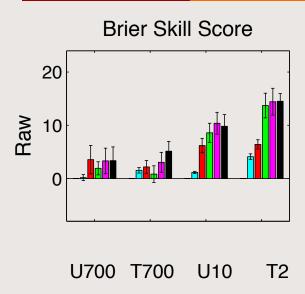
3rier Skill Score

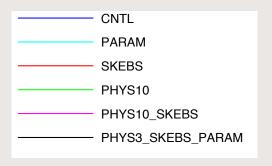




Berner et al., et al 2015

Skill improvement from model-error schemes





- Average over all forecast lead times
- Variables are U700, T700, U10, T2

Berner et al., et al 2015

Spread/Error over Taiwan

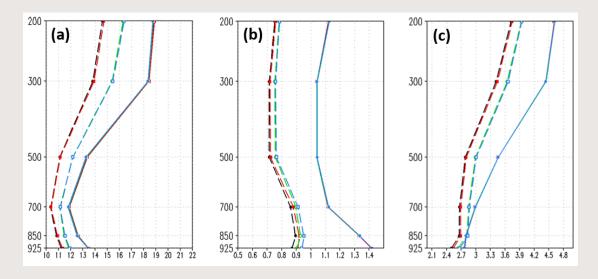


FIG. 2 Spread (dashed) and RMSE (solid) of four ensemble systems over the East Asia domain for (a) geopotential height, (b) temperature and (c) zonal wind. The different experiments are denoted by line colors: MP (black), SPPT+MP (red), SKEB+MP (green), and SKEB+SPPT+MP (blue).

Li et al., 2017, submitted

A priori vs a posteriori

Model uncertainty added a posteriori:

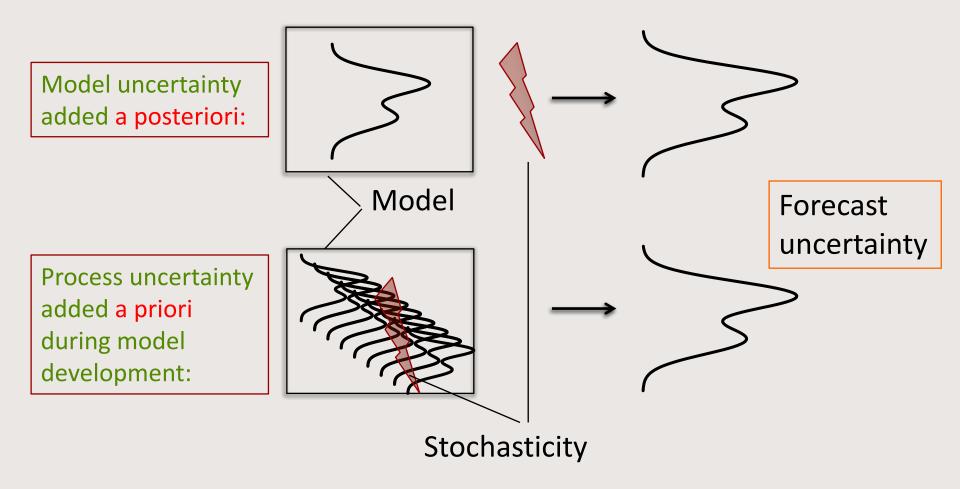
Model

Fore unce

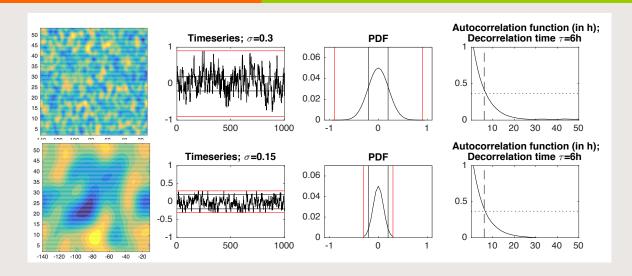
Forecast uncertainty

Stochasticity

A priori vs a posteriori



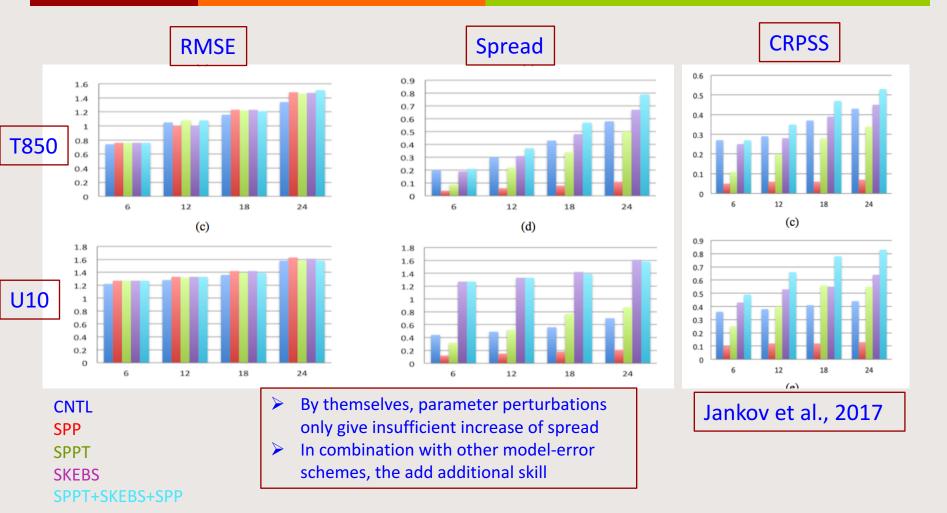
Stochastic parameter perturbations (SPP)



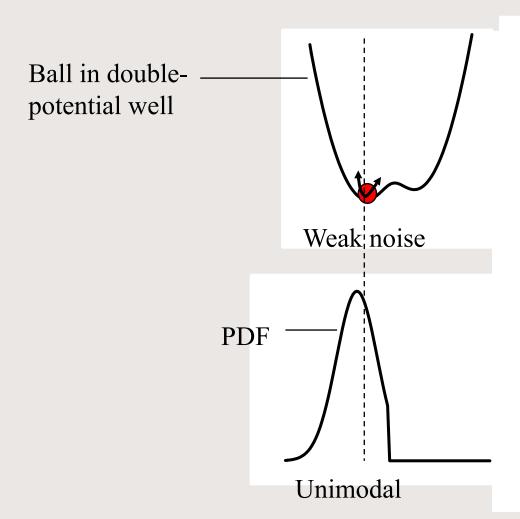
- Stochastically perturbs parameters in convection and PBL scheme
 - Grell convection scheme: Closure tendencies
 - MYNN PBL: Turbulent mixing length, subgrid cloud fraction, thermal and moisture roughness lengths (perturbations correlated and anti-correlated informed by expert knowledge)
- Results from RAP ensemble system @15km, currently tested in 3km

Jankov et al., 2017

Stochastically Perturbed Parameter Scheme (SPP)



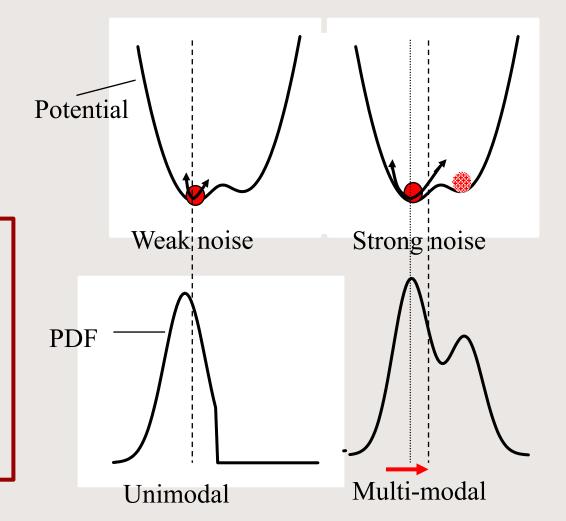
Potential of stochastic parameterizations to reduce model error



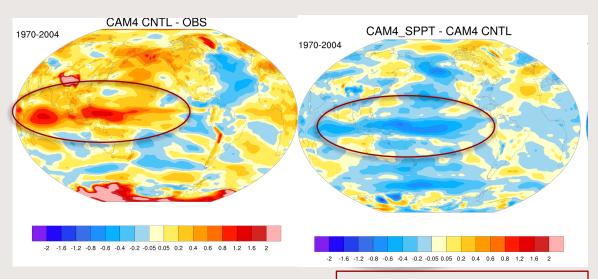
Potential of stochastic parameterizations to reduce model error

Stochastic parameterizations can change the mean and variance of a PDF

- Impacts variability
- Impacts mean bias

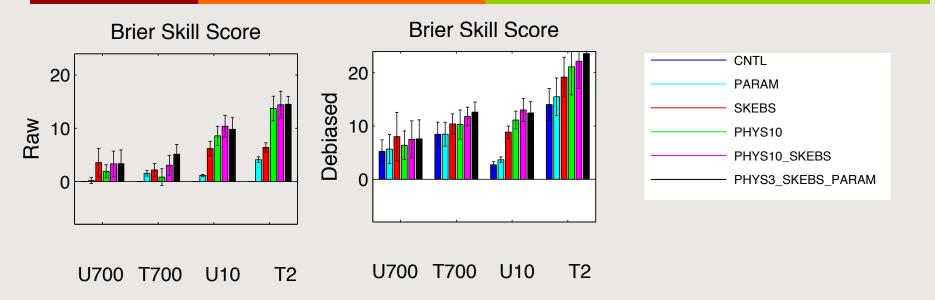


Bias in U850 variability



Christensen et al. 2017

Skill improvement from debiasing



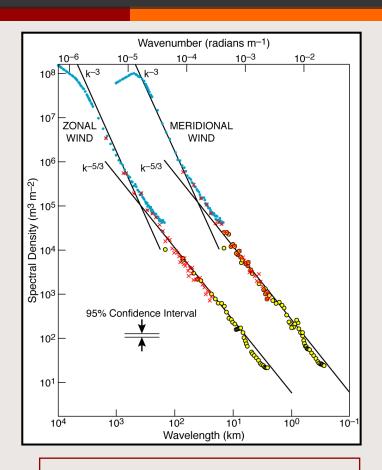
- Skill improvement from debiasing larger than from introducing a model-error scheme
- Ensembles with model-error schemes better than CNTL, even if ensembles are debiased
- Model-error schemes can represent certain aspects of structural model error

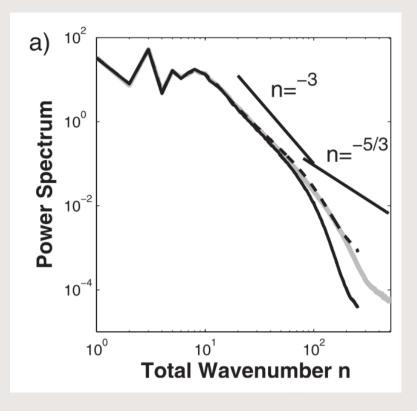
Berner et al., et al 2015

Predictability on weather timescales: the problem

- There are other sources of model-error, e.g. the absence of a -5/3 slope in the kinetic energy spectra. These result in in leading to incorrect dispersion between any two ensemble members (incorrect error-growth characteristic).
- As long as the model has insufficient error-growth, it will be insufficient to represent model uncertainty where it occurs.

Kinetic-energy spectra





Nastrom and Gage, 1985

Limited vs unlimited predictability in Lorenz 1969

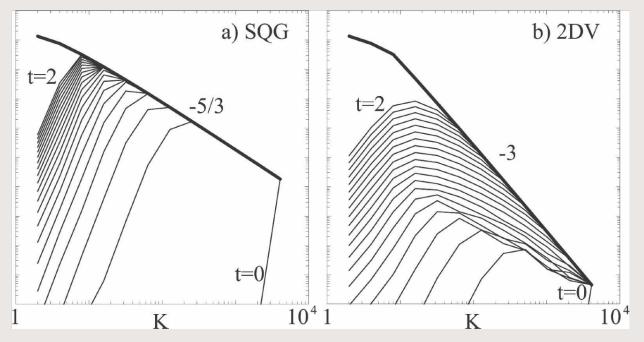
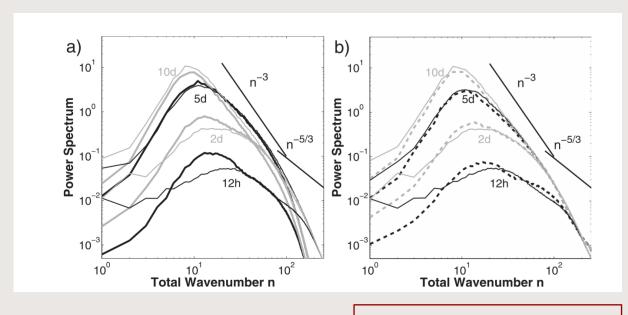


FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K, t)$ for t = 0, 2 in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a -5/3 slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

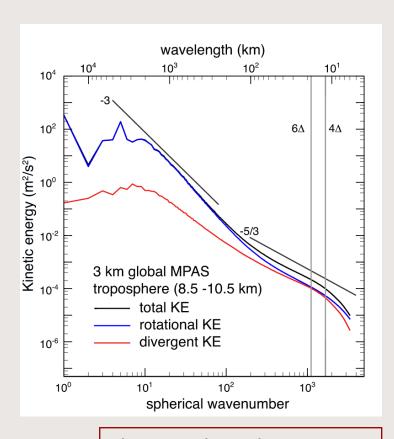
see also: Tribbia and Baumhefner 2004

Forecast error spectra



Berner et al. 2009

Kinetic-energy spectra



Skamarock et al. 2014

Bulletin of the American Society, March

STOCHASTIC PARAMETERIZATION

Toward a New View of Weather and Climate Models

Judith Berner, Ulrich Achatz, Lauriane Batté, Lisa Bengtsson, Alvaro de la Cámara, Hannah M. Christensen, Matteo Colangeli, Danielle R. B. Coleman, Daan Crommelin, Stamen I. Dolaptchiev, Christian L. E. Franzke, Petra Friederichs, Peter Imkeller, Heikki Järvinen, Stephan Juricke, Vassili Kitsios, François Lott, Valerio Lucarini, Salil Mahajan, Timothy N. Palmer, Cécile Penland, Mirjana Sakradzija, Jin-Song von Storch, Antje Weisheimer, Michael Weniger, Paul D. Williams, and Jun-Ichi Yano

Stochastic parameterizations—empirically derived or based on rigorous mathematical and statistical concepts—have great potential to increase the predictive capability of next-generation weather and climate models.

Thank you!