Uncertainty Prediction Across the Scales:

Judith Berner (CGD/MMM)
Acknowledgements: So-young Ha, Dani Bundy, Chris Snyder, Jeff Anderson, Tim Palmer, Thomas Jung, Kevin Raedar, Joe Tribbia
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

- Microphysics
- Turbulence
- Cumulus clouds
- Cumulonimbus clouds
- Convective systems
- Extrapolar Cyclones
- Planetary waves

Models:
- Large Eddy Simulation (LES) Model
- Cloud System Resolving Model (CSRM)
- Numerical Weather Prediction (NWP) Model
- Global Climate Model
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

\( \tau_\alpha = 5, \tau_\gamma = 1 \)

\[
\begin{align*}
    \frac{dx}{dt} &= -\alpha x + g; \\
    \frac{dg}{dt} &= -\gamma g + \varepsilon \\
    \frac{dx}{dt} &= -\alpha x + \varepsilon \\
    \frac{dx}{dt} &= -\gamma x + \varepsilon
\end{align*}
\]

Model used by DelSole (2000)
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

- RMS error
- Spread
- Ensemble mean
- Analysis

$\text{Represent/sample subgrid-scale fluctuations}$

$\text{Represent structural model error}$
Underdispersiveness of ensemble systems

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

Buizza et al., 2004
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 and unresolved scale (stochastic kinetic energy backscatter).
Recent attempts at remedying model error in NWP

Using conventional parameterizations

- 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)
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

\[ \Delta \psi^* \propto \sqrt{D\psi'} \]

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

Spectral Markov chain: temporal and spatial correlations prescribed
Assume a streamfunction perturbation in spherical harmonics representation

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

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

\[ \psi_{n,m}^{m}(t+1) = (1 - \alpha)\psi_{n,m}^{m}(t) + g_{n}\sqrt{\alpha}\epsilon(t) \]

Find the wavenumber dependent noise amplitudes

so that prescribed kinetic energy \( dE \) is injected into the flow

\[ b_{i} = \left( \frac{4\pi a^{2}\alpha}{\sigma_{z}\Gamma} dE' \right)^{1/2} \]

with \( \Gamma = \sum_{n=n_{1}}^{n_{2}} n(n+1)(2n+1)n^{2p} \)
Assume a streamfunction perturbation in *spherical harmonics* representation

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Forcing streamfunction spectra by coarse-graining CRMs

\[ k^{-1.54} \]

-> 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
  - 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

<table>
<thead>
<tr>
<th>Member</th>
<th>Land Surface</th>
<th>Microphysics</th>
<th>PBL</th>
<th>Cumulus</th>
<th>Longwave</th>
<th>Shortwave</th>
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<td>YSU</td>
<td>KF</td>
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**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).
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

Berner et al. 2011
Mean Bias

CNTL
STOCH
PHYS
PHYS_STOCH

Berner et al. 2011
Brier Score Profiles: U

Score profile for CNTL

Score difference with CNTL. Positive differences mean improvement over CNTL. Diamonds denote significance at 95% confidence level.
Pairwise comparison: T at 2m

Berner et al. 2011
### Summary of pairwise comparison

Statistics over different forecast times, variables and vertical levels

<table>
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<tr>
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**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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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).
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

- Micro-physics
- Turbulence
- Cumulus clouds
- Mesoscale convective systems
- Extratropical cyclones
- Planetary waves

- 1mm
- 10 m
- 100 m
- 1 km
- 10 km
- 100 km
- 1000 km
- 10000 km

- Large Eddy Simulation (LES) Model
- Cloud System Resolving Model (CSRM)
- Numerical Weather Prediction (NWP) Model
- Global Climate Model
RMS innovations of $T_2$

**Diagram: MESONET T2 (D2)**

- **rmsi**
- **total spread**
- **<model - observation>**

Lines represent:
- CP_infl (pr: 2.28, po: 2.05)
- MP_infl (pr: 2.18, po: 1.68)
- SP_infl (pr: 1.95, po: 1.67)

Legend:
- CNTL
- PHYS
- STOCH
TMS innovations U10

MESONET_U10 (D2)

rms, totalspread, mean (m/s)

CNTL

PHYS

STOCH

<model - observation>
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

- Micropysics
- Turbulence
- Cumulus clouds
- Cumulonimbus clouds
- Mesoscale convective systems
- Extratropical cyclones
- Planetary waves

Modeling approaches:
- Large Eddy Simulation (LES) Model
- Cloud System Resolving Model (CSRM)
- Numerical Weather Prediction (NWP) Model
- Global Climate Model
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

Berner et al. 2011, J. Clim, submitted
Blocking 1962-2005

Berner et al. 2011, J. Clim, submitted
Frequency-Wavenumber spectra of OLR in IFS

Berner et al. 2011, J. Clim, submitted
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
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!


