Model error treatment in ensemble predictions

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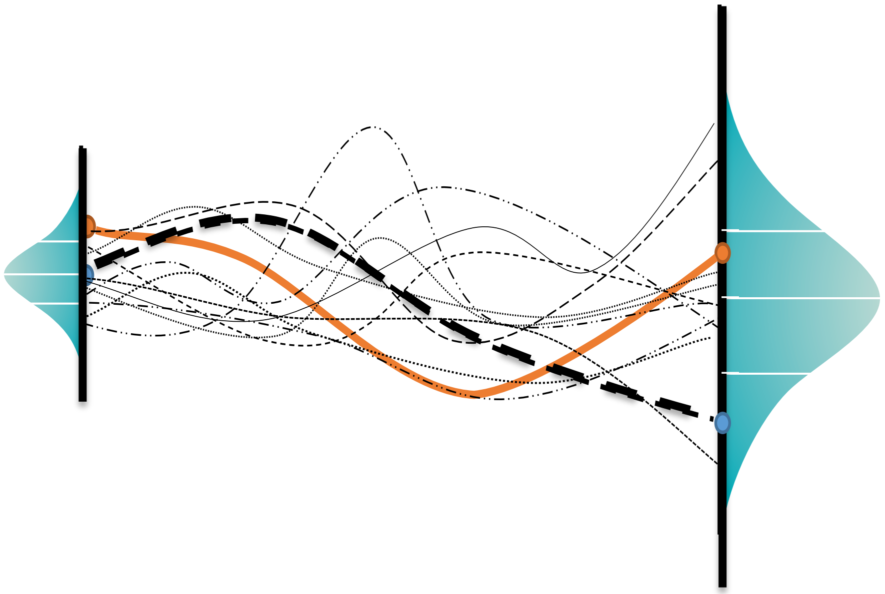
(With contributions from Judith Berner)



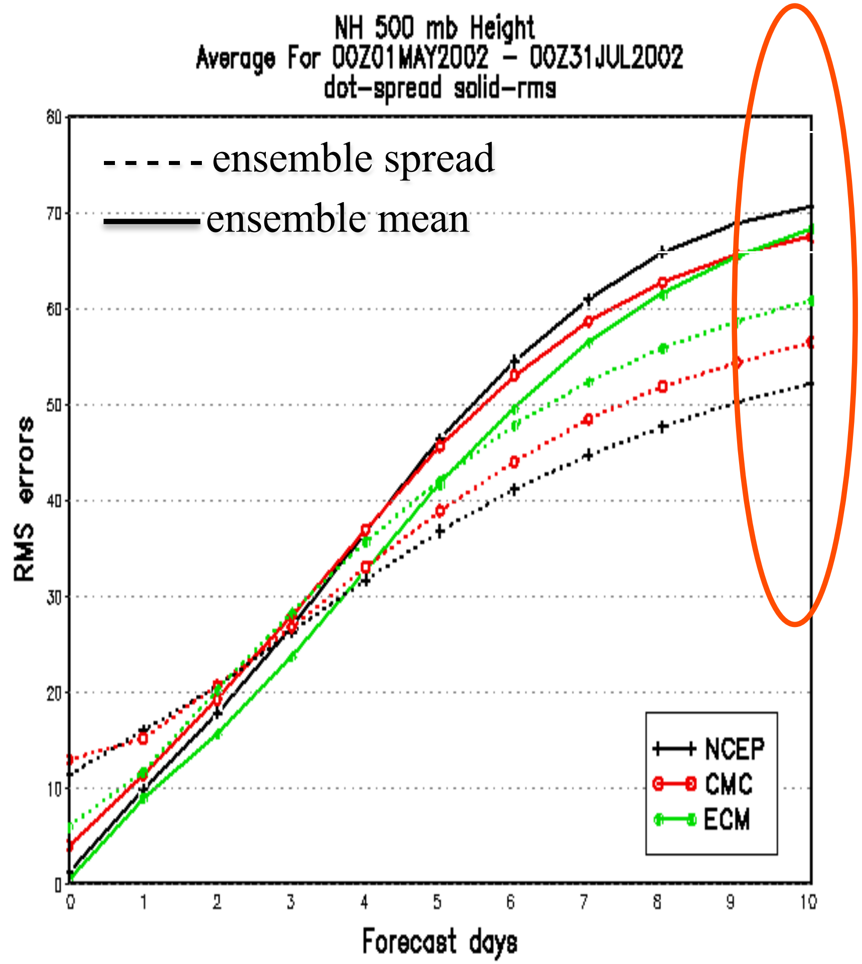
Ensemble Tutorial at WRF User's workshop

July 1, 2016

Questions

1. Should we care about model uncertainties?
2. What are the sources of model uncertainties?
3. How can we account for such uncertainties?
4. How much can we improve ensemble forecasting by representing model uncertainties?

1. Should we care about model uncertainties?



Buizza et al. (2004)

Ensemble mean error grows faster than ensemble spread

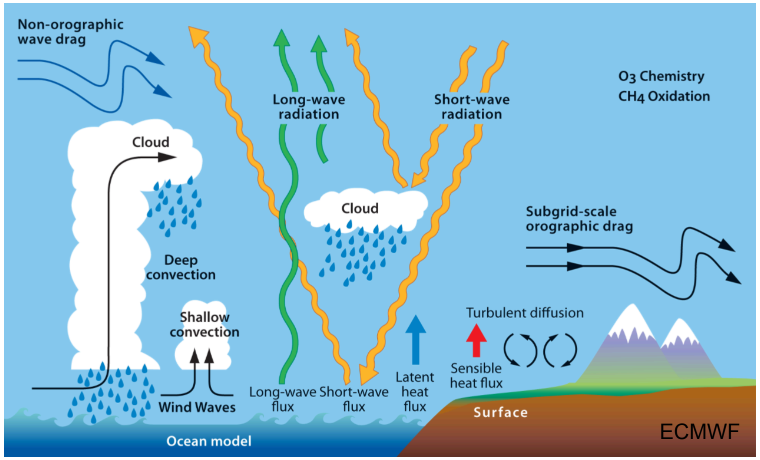
- Ensemble forecast is overconfident
- Underdispersion is a form of model error

Forecast error = initial error + model error (+ boundary error)

If we want to improve the accuracy and reliability of our ensemble system, we should simulate model uncertainties.

2. What are the sources of model uncertainties?

- ❑ Approximations and assumptions in the construction of a numerical model of the physics laws
  - Land-surface parameterization
  - Boundary-layer parameterization
  - Convective parameterization
  - Microphysical parameterization
  - Short- and long-wave radiation schemes



- ❑ Insufficient grid spacing; sub-grid scale uncertainties

- ❑ Systematic model error (e.g., bias) is a critical factor in both ensemble analyses and forecasts, but we do not discuss about that here.

3. How can we account for model uncertainties?

- A multi-model ensemble
- A multi-physics ensemble
- A multi-parameter ensemble
- Stochastic parameterizations
- Various combinations of all those
- Stochastic parameter perturbations (SPP)

Each ensemble forecast is given by the time integration of perturbed equations

$$e_j(d,T) = e_j(d,0) + \int_0^T [\underline{A(e_j,t)} + \underline{P(e_j,t)} + \underline{\delta P_j(e_j,t)}]dt$$

$$\delta P_j(\lambda,\varphi,p) = \underbrace{r_j(\lambda,\varphi)P_j(\lambda,\varphi,p)}_{\textbf{SPPT}} + \underbrace{F_\Psi(\lambda,\varphi,p)}_{\textbf{SKEB}}$$

3. a. A multi-model approach

- Solves different dynamical equations

The International Grand Global Ensemble (TIGGE)
http://tigge.ecmwf.int

Table 1. TIGGE project partners.

Center	Country	Acronym
Bureau of Meteorology	Australia	BoM
China Meteorological Administration	China	CMA
Canadian Meteorological Centre	Canada	CMC
Centro de Previsão de Tempo e Estudos Climáticos	Brazil	CTPEC
European Centre for Medium-Range Weather Forecasts	Europe	ECMWF
Japan Meteorological Agency	Japan	JMA
Korea Meteorological Administration	Korea	KMA
Météo-France	France	MF
Met Office	United Kingdom	UKMO
National Center for Atmospheric Research	United States	NCAR
National Centers for Environmental Prediction	United States	NCEP
National Climatic Data Center	United States	NCDC

Swinbank et al. (BAMS 2016)

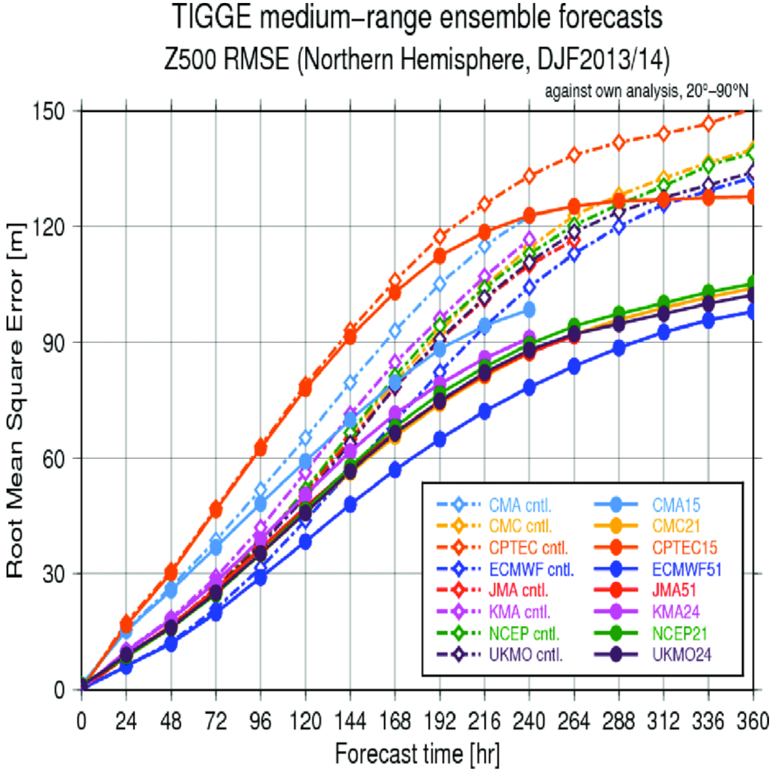


Fig. 1. Comparison of the skill of Northern Hemisphere 500-hPa forecasts from systems contributing to TIGGE for Dec 2013 through Feb 2014. Each forecast is verified against its own analysis. Solid lines show the RMS error of the ensemble mean, and dashed lines show the control member of each ensemble. Refer to Table 1 for forecast center abbreviations. The number following the center name indicates the number of ensemble members used.

3. b. A multi-physics approach

- Different physics parameterization schemes with different assumptions and parameters
- Each ensemble member uses different physics combinations, predicting a trajectory on a different attractor
- Easy to construct the ensemble; WRF provides dozens of different options for each physics parameterization scheme
- But members are not exchangeable and have different error distributions.
- Hard to interpret the role of each parameterization scheme and ensemble covariances
- Greater development and maintenance costs

b. A multi-physics approach (example)

Tellus SERIES A DYNAMIC METEOROLOGY AND OCEANOGRAPHY
PUBLISHED BY THE INTERNATIONAL METEOROLOGICAL INSTITUTE IN STOCKHOLM

Tellus (2011), 63A, 625–641

TELLUS

The U.S. Air Force Weather Agency's mesoscale ensemble: scientific description and performance results

By J. P. HACKER[1*], S.-Y. HA[2], C. SNYDER[2], J. BERNER[2], F. A. ECKEL[3], E. KUCHERA[4], M. POCERNICH[2], S. RUGG[4], J. SCHRAMM[2] and X. WANG[5], [1]*Naval Postgraduate School, Monterey, CA, USA;* [2]*National Center for Atmospheric Research, Boulder, CO, USA;* [3]*National Weather Service Office of Science and Technology, Silver Spring, MD, USA;* [4]*Air Force Weather Agency, Bellevue, NE, USA;* [5]*University of Oklahoma, Norman, OK, USA*

(Manuscript received 14 April 2010; in final form 1 December 2010)

ABSTRACT

This work evaluates several techniques to account for mesoscale initial-condition (IC) and model uncertainty in a short-range ensemble prediction system based on the Weather Research and Forecast (WRF) model. A scientific description and verification of several candidate methods for implementation in the U.S. Air Force Weather Agency mesoscale ensemble is presented. Model perturbation methods tested include multiple parametrization suites, land-surface property perturbations, perturbations to parameters within physics schemes and stochastic 'backscatter' stream-function perturbations. IC perturbations considered include perturbed observations in 10 independent WRF-3DVar cycles and the ensemble-transform Kalman filter (ETKF). A hybrid of ETKF (for IC perturbations) and WRF-3DVar (to update the ensemble mean) is also tested. Results show that all of the model and IC perturbation methods examined are more skilful than direct dynamical downscaling of the global ensemble. IC perturbations are most helpful during the first 12 h of the forecasts. Physical parametrization diversity appears critical for boundary-layer forecasts. In an effort to reduce system complexity by reducing the number of suites of physical parametrizations, a smaller set of parametrization suites was combined with perturbed parameters and stochastic backscatter, resulting in the most skilful and statistically consistent ensemble predictions.

- WRF ARW V3.1
- Test period: Nov-Dec 2008
- Tested over CONUS at 45/15km one-way nested domain
- 10-member ensemble with various ensemble methods
- A control ensemble uses a downscaled global ensemble (10 members out of 21-member GEFS)
- Observation-space verification on domain 1

b. A multi-physics approach (example)

Table 2. Configuration of multiphysics ensemble.

Member	Land Surface	PBL	Microphysics	Cumulus	Long-wave	Short-wave
1	Thermal	YSU	Kessler	KF	RRTM	Dudhia
2	RUC	MYJ	Eta	KF	RRTM	Dudhia
3	Thermal	MYJ	WSM6	KF	RRTM	CAM
4	Noah	MYJ	Kessler	BM	CAM	Dudhia
5	Noah	MYJ	Lin	Grell	CAM	CAM
6	Noah	YSU	WSM5	KF	RRTM	Dudhia
7	Noah	MYJ	WSM5	Grell	RRTM	Dudhia
8	RUC	YSU	Lin	BM	CAM	Dudhia
9	RUC	YSU	Eta	BM	RRTM	CAM
10	RUC	MYJ	Thompson	Grell	CAM	CAM

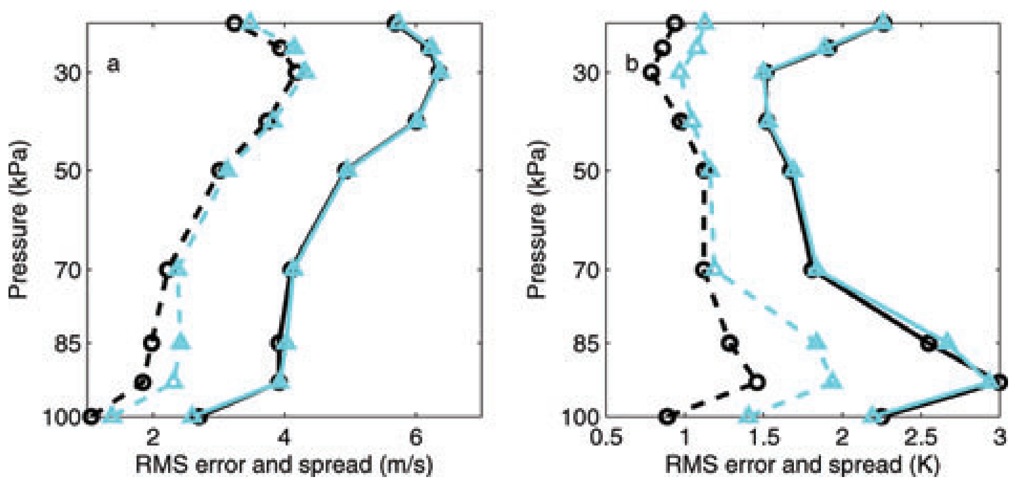
Ensemble mean error

$$\left[\frac{1}{N-1}\sum_{n=1}^{N}\left(o_n-\overline{f_n}\right)^2\right]^{1/2}$$

$$\approx\left[\frac{1}{N-1}\sum_{n=1}^{N}\left(\sigma_{f,n}^2+\sigma_{o,n}^2\right)\right]^{1/2}$$

Total spread

(N: total number of observations)



Verification against sounding obs

Fig. 4. Root-mean-square ensemble-mean error (RMSE; solid curves) and total spread (dashed curves) of *Cntl* (circle) and *Phys* (triangle). Shown are (a) zonal wind component and (b) temperature for 62 forecasts at 48-h lead time during November 2008–January 2009 over the continental United States.

3. c. A multi-parameter approach

- Perturbs parameters within a single physics suite
- No need to develop and maintain multiple physics schemes
- Relatively costly to develop and maintain (given that the model is frequently updated)
- Which parameters (and how much) should we perturb in a realistic mesoscale ensemble prediction system? => Needs an expert's opinion on the choice of parameters and the range of their uncertainties in each parameterization scheme
- Hard to find a strong linear parameter-state relationship

3. c. A multi-parameter approach (example)

Multi-parameter ensemble using WRF (Hacker et al., Tellus 2011b)

- 10-member ensemble at 45-km resolution over the CONUS
- Same IC and LBCs for the 10 members
- Only varying parameters in the control physics parameterization
- Subgrid-cloud radius in cumulus; Entrainment rate in the convective PBL; intercept parameter for rain-drop size distribution in WSM5; scattering parameter in SW

Table 1. Parameters or variables chosen for the perturbation experiments, with descriptions of the initial distributions assigned

Scheme	Parameter	Units	Min	Mean	Max	Distribution
KF	ΔR	m	-300	0	300	$\beta(6, 6)$
YSU	A_R	None	0.1	0.15	0.3	$\beta(2, 6)$
WSM5	N_0	m^{-4}	2×10^6	8×10^6	2×10^9	$\beta(1.5, 6)$
Dudhia	α_{CA}	$m^2\ kg^{-1}$	2×10^{-6}	1×10^{-5}	2×10^{-5}	$\beta(4.8, 6)$

c. A multi-parameter approach (cont'd)

- Perturbations in each parameter generally produced similar magnitude responses, but with different response time scale.
- Lacking of a priori knowledge on the broad effect of each parameter in various physics scheme, it is not easy for a multi-parameter approach to produce large ensemble spread which can lead to reliable and improved mesoscale forecasts, although previous studies proved that it is superior to a downscaled ensemble.

3. d. Stochastic parameterizations (SPPT)

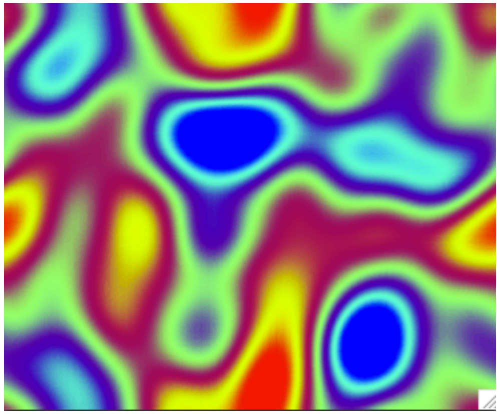
- Stochastically Perturbed Parametrization Tendency scheme (SPPT; Buizza et al. 1999, Palmer et al. 2009, Berner et al. 2014)

  Rational: As grid resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale states should be sampled.

$$\left.\frac{\partial X}{\partial t}\right|_{total} = \left.\frac{\partial X}{\partial t}\right|_{dynamics} + (\mathrm{r}+1)\left.\frac{\partial X}{\partial t}\right|_{physics}$$

Local tendency for variable X — Dynamical tendencies => Resolved scales — Physical tendencies => Unresolved scales

- To represent uncertainty associated with parameterizations, perturb accumulated tendencies from physics parameterizations (in u, v, t, and q_v)



3. d. Stochastic parameterizations (SKEB)

- Stochastic Kinetic Energy Backscatter scheme (SKEB; Shutts 2005, Berner et al. 2011, 2015)

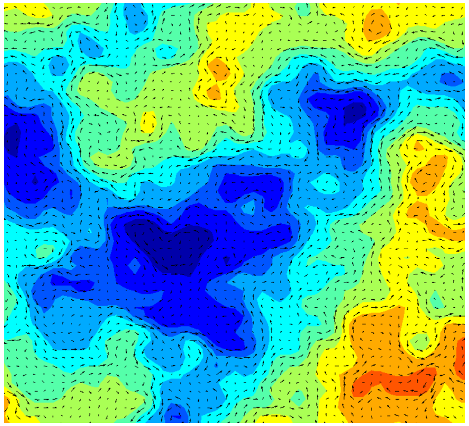
Rational: A fraction of the subgrid-scale energy is scattered upscale and acts as random streamfunction and temperature forcing for the resolved-scale flow. Here a simplified version with constant dissipation rate can be considered as additive noise with spatial and temporal correlations.

$$\left.\frac{\partial X}{\partial t}\right|_{total} = \left.\frac{\partial X}{\partial t}\right|_{dynamics} + \left.\frac{\partial X}{\partial t}\right|_{physics} + \left.\frac{\partial X}{\partial t}\right|_{stoch}$$

Local tendency for variable X	Dynamical tendencies => Resolved scales	Physical tendencies => Unresolved scales	Stochastic perturbation tendencies => Unresolved scales

- Represent unresolved upscale energy transfer

Stochastic Forcing Pattern →



3. d. Stochastic parameterizations (cont'd)

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

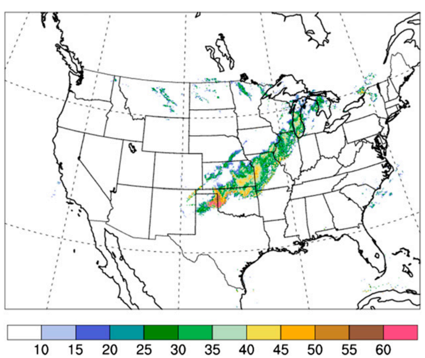


FIG. 3. A radar reflectivity image valid at 0000 UTC 9 Jun 2008.

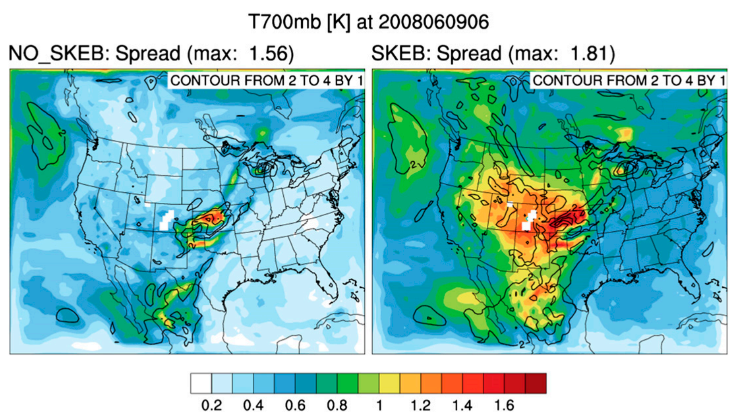


FIG. 4. The 12-h forecast ensemble spread with ("SKEB") and without ("NO_SKEB") the stochastic forcing valid at 0600 UTC 9 Jun 2008. The spread (as standard deviation) of horizontal wind speed at 700 hPa larger than 2 m s^{-1} is contoured every 1 m s^{-1}, while the one of temperature at 700 hPa greater than 0.2 K is colored.

Ha et al. (MWR 2015)

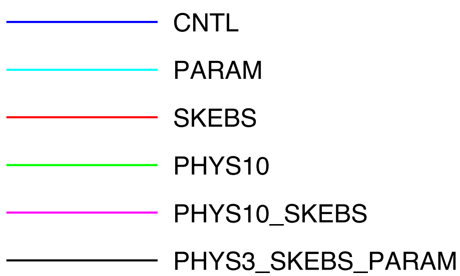
3. d. Stochastic physics parameterizations (cont'd)

<u>Release status in WRF</u>

- SKEBS and the option for a random (or stochastic) pattern generation are released
- SPPT is not officially released, but can be switched on starting WRFV3.8.
- SPP (Stochastically perturbed parameters) will be released in Spring 2017 (beta-testers welcome)

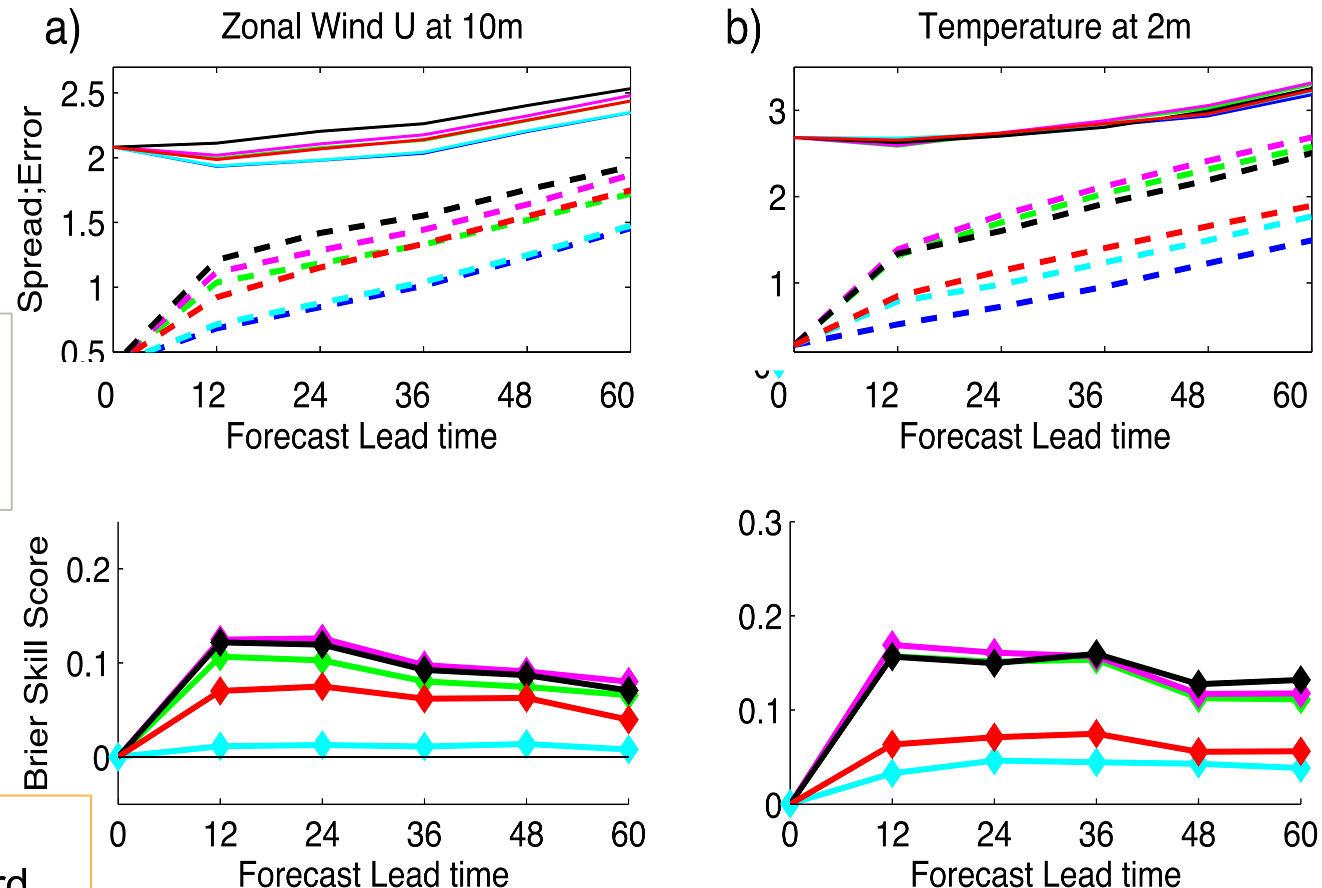
```
&stoch
rand_perturb      = 1,   1,   1,
skebs             = 1,   1,   1,
sppt              = 1,   1,   1,
spp               = 1,   1,   1,  /
```

4. How much can we improve ensemble forecasting?



Solid lines: rms error of ensemble mean

Dashed: spread



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

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

Berner et al. (MWR 2015)

4. How much can we improve ensemble forecasting? (cont'd)

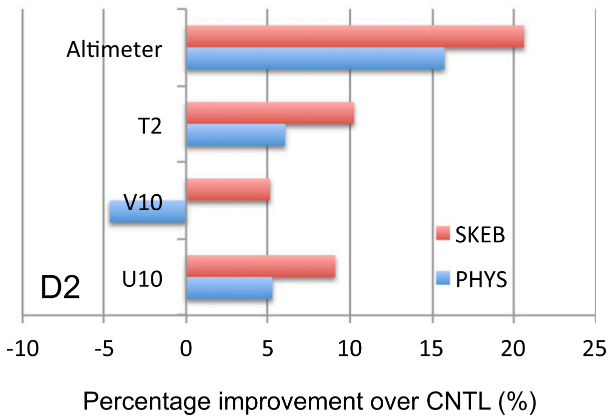


FIG. 7. The improvement (%) of forecast error in SKEB and PHYS over the one in CNTL for both domains (top) 1 and (bottom) 2 in various surface fields. The rms innovations are computed against mesonet observations and averaged over the month-long cycles. Positive means an improvement relative to CNTL in the 3-h ensemble mean forecast.

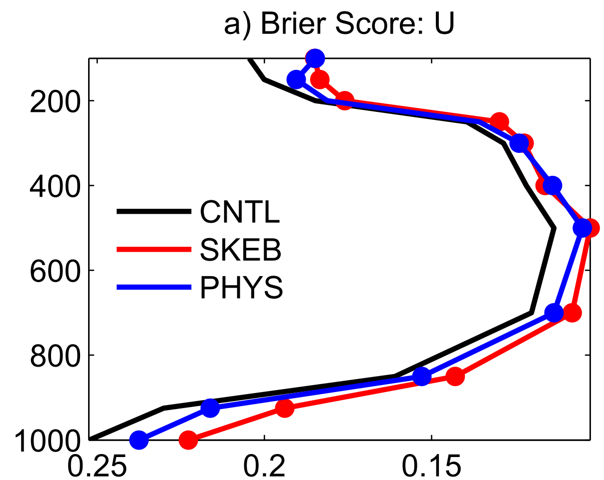


FIG. 11. Brier scores of the 3-h ensemble forecast in (a) u wind bin1: $f > \mu_o + \sigma_o$.

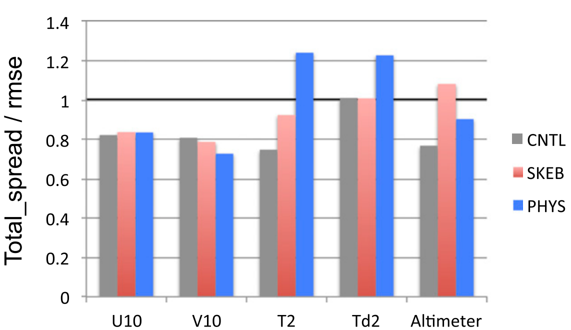


FIG. 9. The ratio of total spread to rms errors of 3-h ensemble mean forecasts in each experiment for different surface variables over domain 2, verified against mesonet (unassimilated) observations.

- In the mesoscale cycling DA, representing model-error uncertainties (in PHYS and SKEB) improves ensemble forecasts deterministically and probabilistically (verified against independent observations).
- SKEB moderately increases the spread, improving the forecast most.

Ha et al. (MWR 2015)

4. How much can we improve ensemble forecasting?

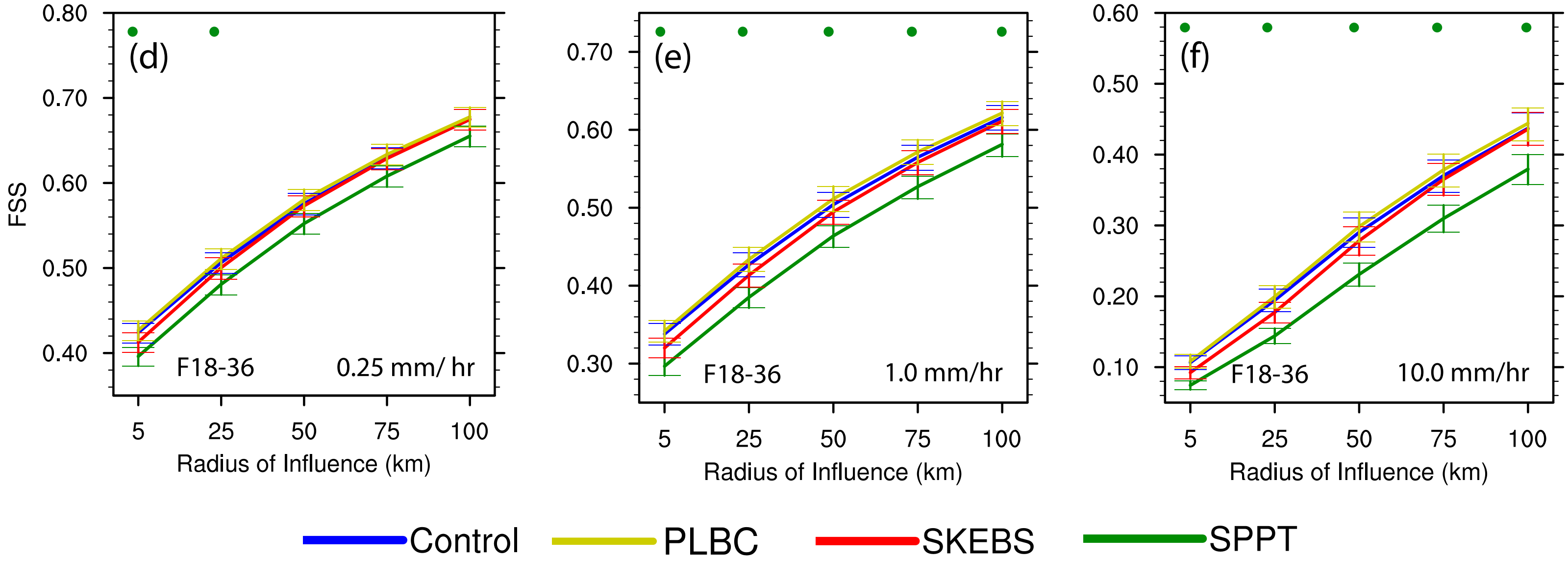


FIG. 13. Fractions skill score as a function of radius of influence for probabilistic forecasts for the (a)–(c) early (forecast hours 1–12) and (d)–(f) late (forecast hours 18–36) periods from the control (blue), PLBC (mustard), SKEBS (red), and SPPT (green) averaged over ensemble forecasts initialized from 25 May to 25 Jun 2012, for rain-rate thresholds of (a),(d) 0.25; (b),(e) 1.0; and (c),(f) 10.0 mm h^{-1}. Error bars indicate the bounds of the 90% confidence intervals. Where the control curve is not seen, it is behind the PLBC curve. Colored markers indicate where ensemble forecast configurations have statistically significant differences from the control ensemble forecast.

Romine et al. (MWR 2014)

Key points

- ✓ There is model uncertainty in weather and climate prediction; It is essential to represent the model uncertainty.
- ✓ Easy to increase ensemble spread; Hard to reduce errors (maintaining a robust ensemble system).
- ✓ In a reliable ensemble system, total spread matches the ensemble mean error.
- ✓ In NWP, we can use observations to determine model uncertainty (although a proper observation error characterization can be challenging due to the representativeness error).

Thank you!

Buizza, R., M. Milleer, and T. N. Palmer, 1999: Stochastic representation of model uncertainties in the ECMWF ensemble prediction system. Quart. J. Roy. Meteor. Soc., **125**, 2887–2908.

Shutts, G. J., 2005: A kinetic energy backscatter algorithm for use in ensemble prediction systems. Quart. J. Roy. Meteor. Soc., **131**, 3079–3102.

Palmer, T., R. Buizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. Shutts, M. Steinheimer, and A. Weisheimer, 2009: Stochastic parameterization and model uncertainty. Tech. Rep. ECMWF RD Tech. Memo. 598, 42 pp.

Berner, J, S.-Y. Ha, J. P. Hacker, A. Fournier, C. Snyder 2011:“Model uncertainty in a mesoscale ensemble prediction system: Stochastic versus multi-physics representations”, *Mon. Wea. Rev.*, **139**, 1972-1995.

Hacker, J.P., S.-Y. Ha, C.M. Snyder, J. Berner, F.A. Eckel, E. Kuchera, M. Pocernich, S. Rugg, J. Schramm, and X. Wang, 2011: The U.S. Air Force Weather Agency's mesoscale ensemble: Scientific description and performance results. Tellus, **63A**, 625-641.

Hacker, J.P., C. Snyder, S.-Y. Ha and M. Pocernich, 2011: Linear and non-linear response to parameter variations in a mesoscale model. Tellus, **63A**, 429-444.

Romine, G., J. Berner, K. Fossell, C. Snyder, J. L. Anderson and M. L. Weisman, 2014: Representing forecast error in a convection-permitting ensemble system, *Mon. Wea. Rev.*, **142** , 4519—4541.

Berner, J, K. Fossell, S.-Y. Ha, J. P. Hacker, C. Snyder 2015: “Increasing the skill of probailistics forecasts: Underatanding performance improvements from model-error representations, *Mon. Wea. Rev*., **139**, 1972-1995.

Ha S.-Y., J. Berner, C. Snyder, 2015: “Model-Error representation in ensemble data assimilation”, *Mon. Wea. Rev.*, **143**, 3893-3911.

Backup slides

Namelist parameters

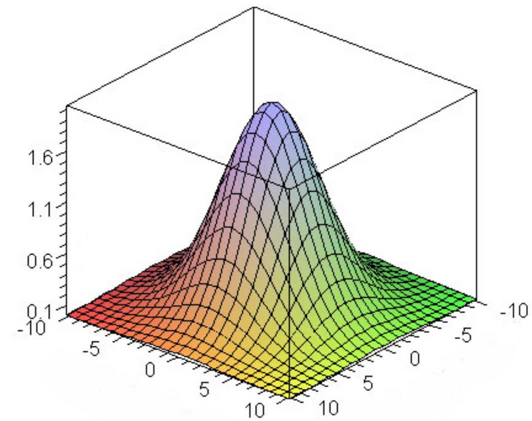
Generally the following characteristics of the stochastic pattern can be tuned:

- the spatial lengthscale
- temporal decorrelation time
- pattern amplitude
- random seed (to generate different random number stream)
- threshold value (to cut off values beyond a threshold)

```
&stoch
 rand_perturb             = 1,   0,   0
 gridpt_stddev_rand_pert   = 0.3, 0.3, 0.3
 stddev_cutoff_rand_pert   = 3.0, 3.0, 3.0
 lengthscale_rand_pert     = 50000.0, 50000.0, 50000.0
 timescale_rand_pert       = 21600.0, 21600.0, 21600.0
```

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)

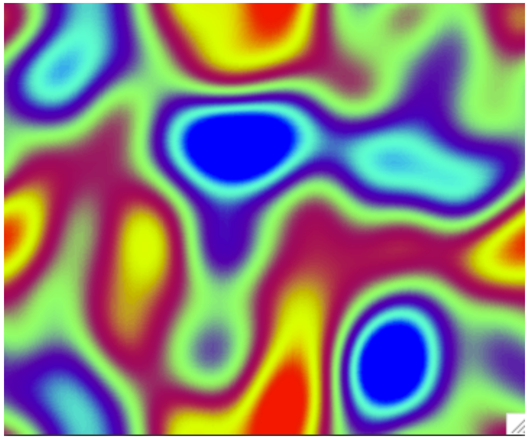


$$\frac{\partial X}{\partial t} = D_X + (r+1)P_X$$

Local tendency for variable X

Dynamical tendencies => Resolved scales

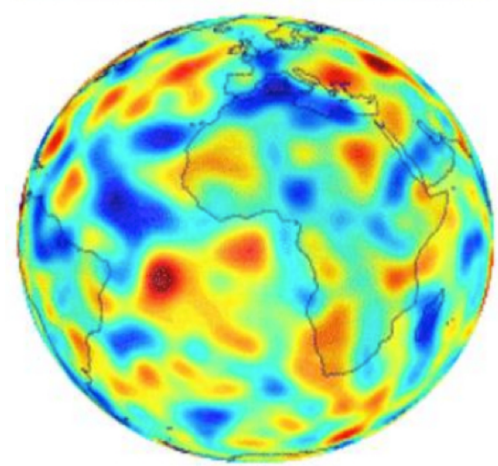
Physical tendencies => Unresolved scales



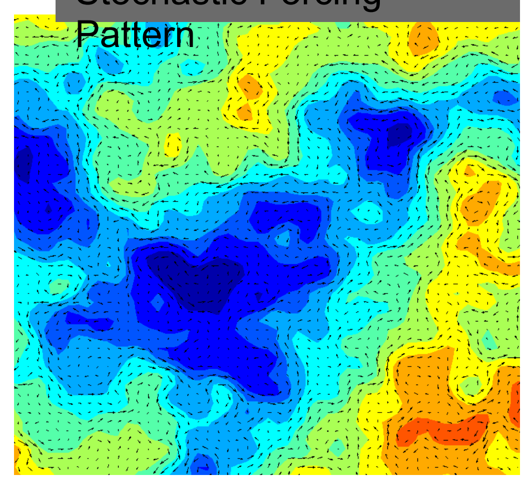
- ✧ Perturbs accumulated U,V,T,Q tendencies from physical parameterizations packages
- ✧ Same pattern for all tendencies to minimize introduction of imbalances

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



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

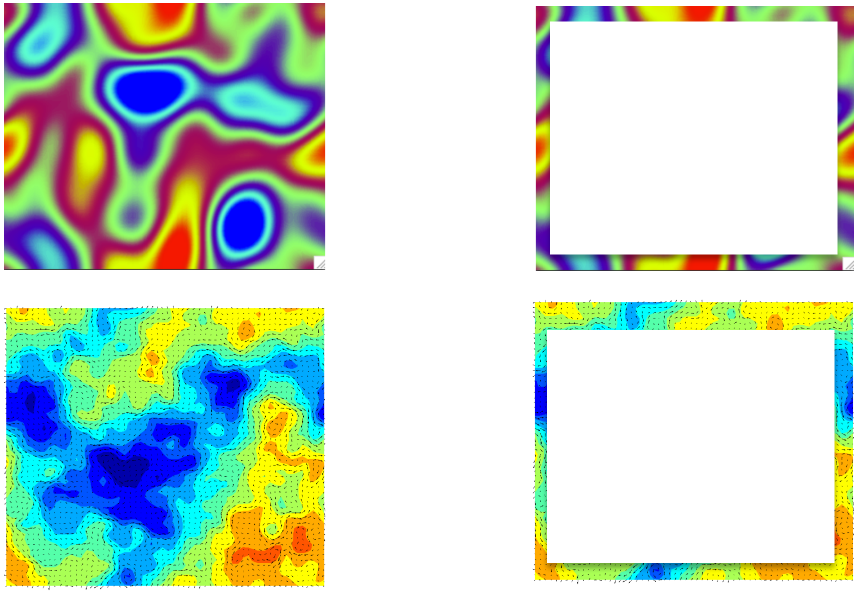
Local tendency for variable X =U,V,T

Dynamical tendencies => Resolved scales

Physical tendencies => Unresolved scales

Additive stochastic perturbation tendencies => Unresolved scales

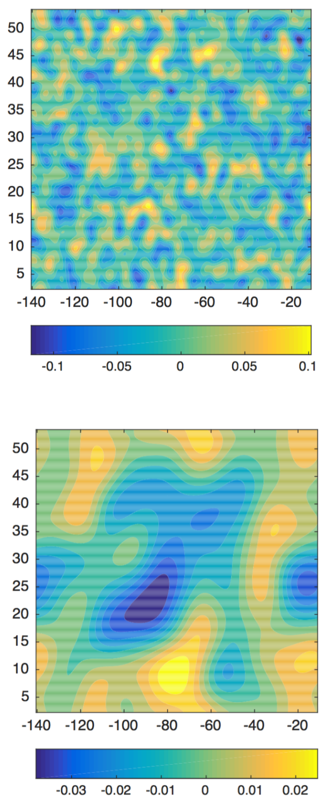
WRF3.7:Random Fields

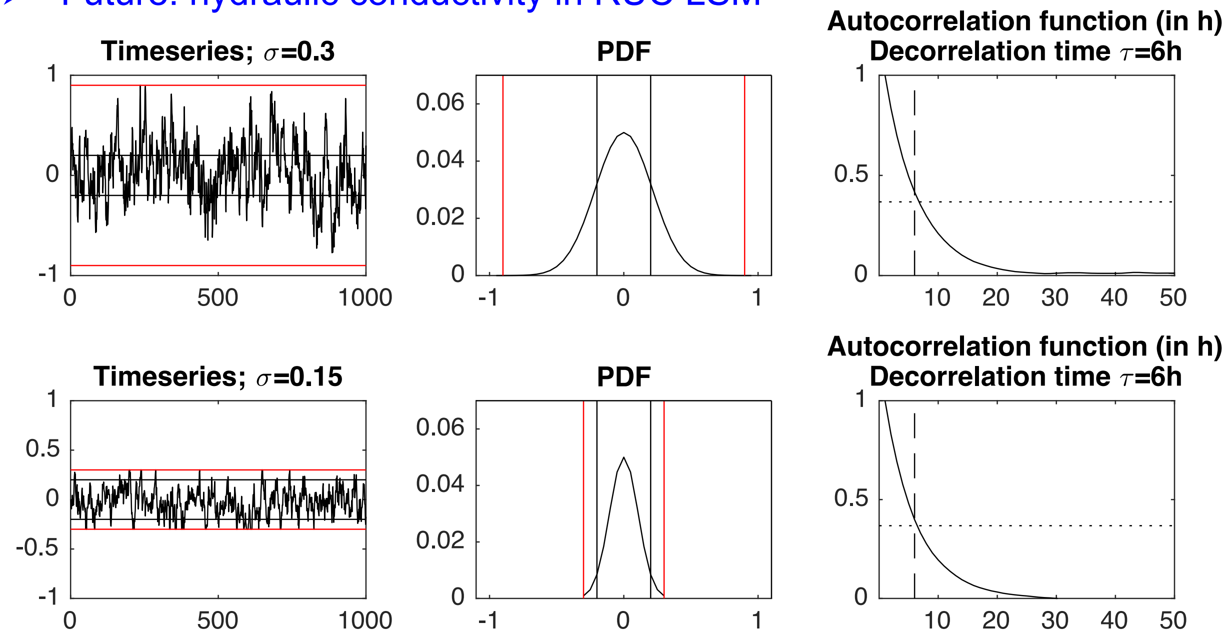


- Random pattern can be used to perturb user specific fields, e.g., lower boundary conditions or parameters (does nothing, unless user specifies interface)
- SKEBS or SPPT pattern can now also be used to perturb the lateral boundaries
  - Either in conjunction with interior SKEBS perturbations or just as lateral boundary perturbation

Stochastic parameter perturbations (SPP)

Stochastic pattern perturbs parameters
- closure tendencies in GF convection scheme
- Turbulent mixing length, subgrid cloud fraction, thermal and moisture roughness lengths in MYNN PBL
- Future: hydraulic conductivity in RUC LSM





Jankov et al., et al 2016