METHODS FOR DEALING WITH MODEL ERROR IN ENSEMBLE PREDICTION

Carolyn Reynolds, Naval Research Lab

Outline

1) Sources of error in forecasts
2) Dealing with model error: Post-processing
3) Dealing with model error: Ensemble design
    - Multi-model ensembles
    - Multi-parameterization/Multi-parameter ensembles
    - Stochastic parameterizations
4) Quick tour of operational centers
5) Dealing with model error: Ensemble DA

SOURCES OF ERROR IN FORECASTS

1) Analysis errors
   - Imperfect DA
   - Imperfect/sparse obs
   - Imperfect model
2) Boundary condition errors
   - Lateral boundary conditions
   - Lower boundary conditions (coupled model uncertainty, e.g., land surface, waves, ocean, ice, etc.)
3) Model errors
   - Limited resolution
   - Dynamic core
   - Parameterization of physical processes

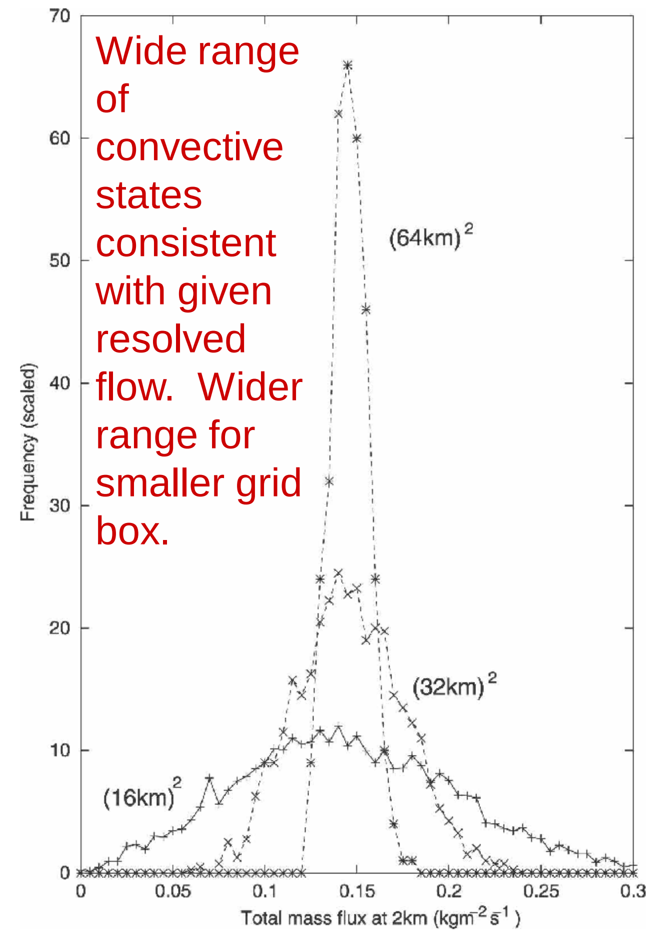


FIG. 1. Frequency plot of total convective mass flux per unit area (at a height of 2 km) obtained from a CRM simulation (Cohen and Craig 2006) of radiative–convective equilibrium. The total mass flux is computed for different-sized areas and binned into intervals of 0.01 kg m^{-2} s^{-1}. Data are taken from the established equilibrium state only using 340 times over 2 days. The vertical axis is scaled to account for the larger number of suitable areas that become available as the unit-averaging area is reduced in size.

A stochastic parameterization for deep convection based on equilibrium statistics

R. S. Plant and G. C. Craig., *JAS*, 65 (2008), 87-105

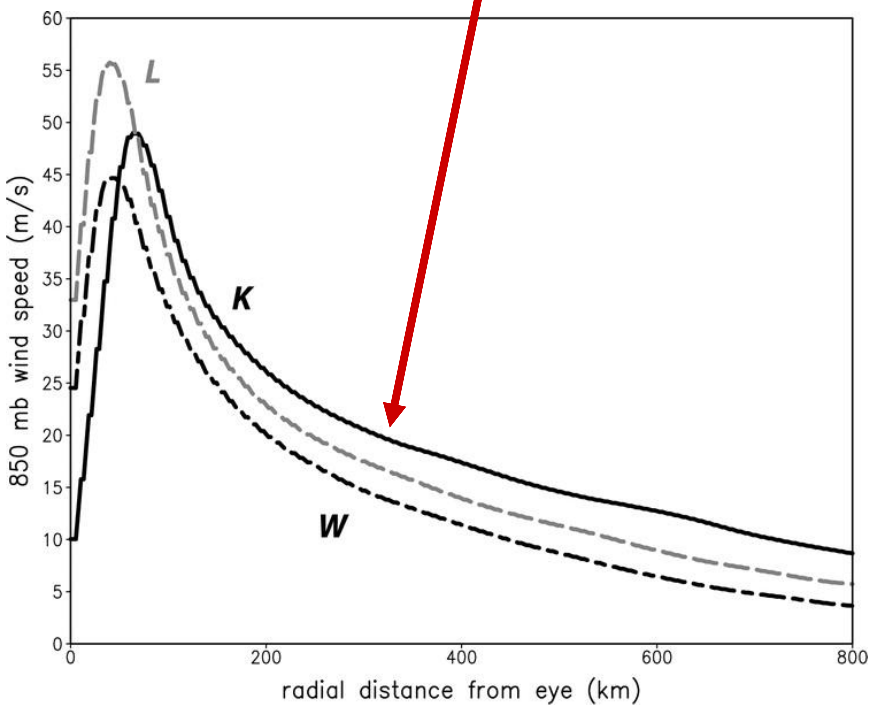
SOURCES OF ERROR IN FORECASTS

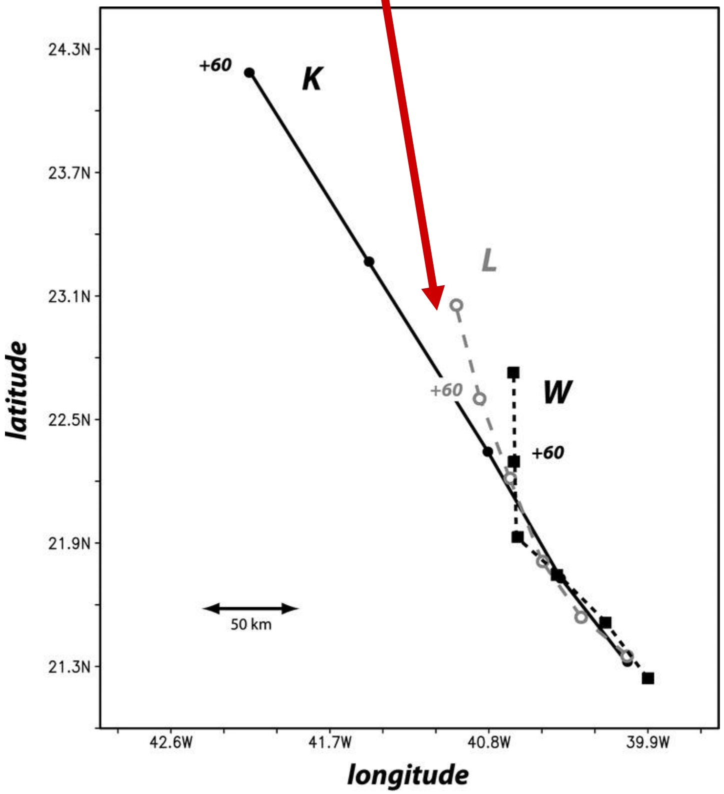
Cloud Microphysics Impact on Hurricane Track as Revealed in Idealized Experiments

Robert G. Fovell, Kristen L. Corbosiero, Hung-Chi Kuo

Journal of the Atmospheric Sciences, Volume 66, Issue 6 (June 2009) pp. 1764-1778

Microphysical assumptions (fall speeds) strongly influence radial temperature gradients, which influence ***winds at outer radius***, influencing beta gyre and ***storm motion***





DEALING WITH MODEL ERROR: POST-PROCESSING

Reforecasts: An Important Dataset for Improving Weather Predictions

Thomas M. Hamill, Jeffrey S. Whitaker, and Steven L. Mullen

Bulletin of the American Meteorological Society, Volume 87, Issue 1 (January 2006) pp. 33–46

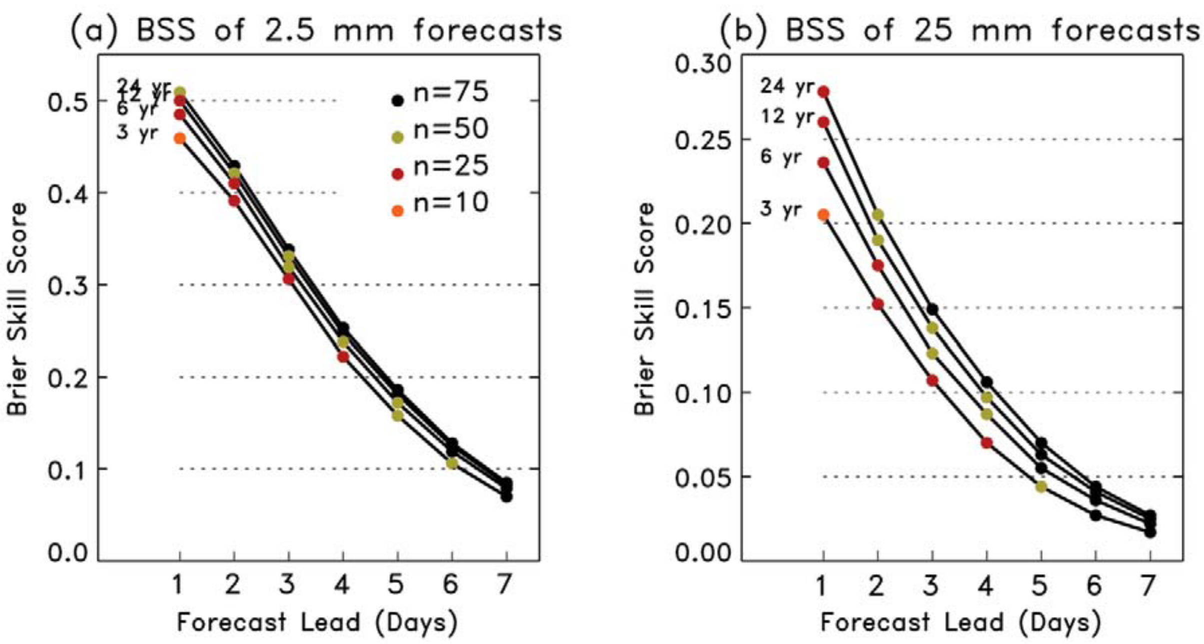


FIG. 7. Brier skill scores of the analog reforecast technique for various lengths of the training dataset. Probabilistic forecasts were calculated for ensembles of sizes 10, 25, 50, and 75; the skill of the ensemble size that was most skillful is the only one plotted. The color of the dot denotes the size of the most skillful ensemble.

- Diagnosis and correction of model error from past forecasts increases forecast skill.
- Extreme events benefit more from longer archive
- More on post-processing in overview talk by Z. Toth

MULTI-MODEL ENSEMBLES

Tropical Cyclone Track Forecasts Using an Ensemble of Dynamical Models

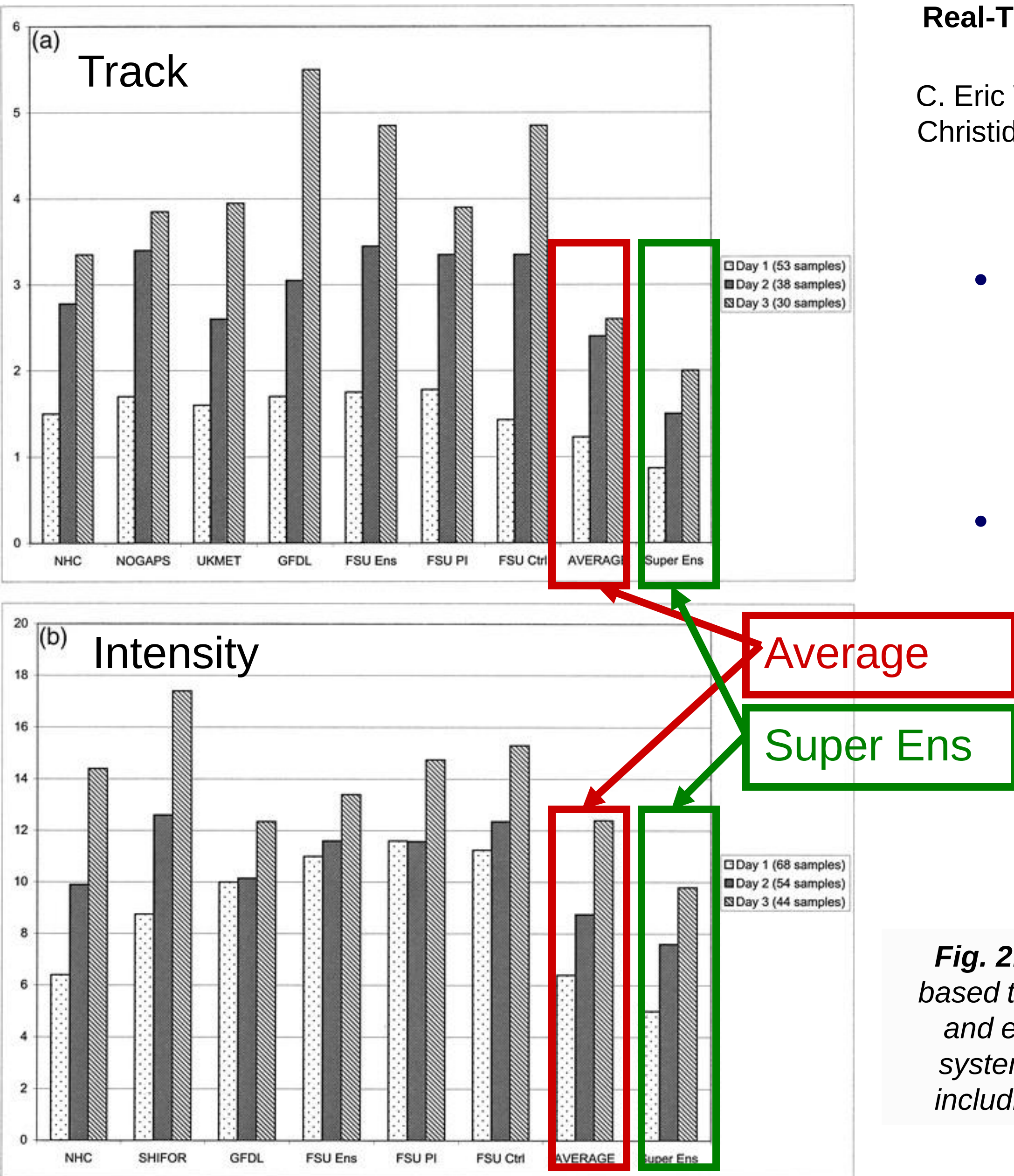
J. S. Goerss, Monthly Weather Review, Volume 128, (2000) pp. 1187-1193

Simple ensemble average (***consensus***) may be more accurate, on average, than the forecasts of the individual models

	N	GFDL	NOGAPS	UKMO	ENSM	CLIPER
24 h	280	142	152	152	120	187
48 h	221	246	255	244	194	389
72 h	166	364	383	348	266	607

Table 2. *Homogeneous comparison of the GFDL model, NOGAPS, UKMO, the ensemble average (ENSM), and CLIPER TC position errors (km) for a sample of (N) forecasts of tropical storms and hurricanes during the 1995–96 Atlantic hurricane seasons.*

MULTI-MODEL ENSEMBLES AND POSTPROCESSING



Real-Time Multimodel Superensemble Forecasts of Atlantic Tropical Systems of 1999

C. Eric Williford, T. N. Krishnamurti, R. C. Torres, S. Cocke, Z. Christidis, and T. S. Vijaya Kumar, *MWR*, **131**, 2003, 1878–1894

- Model biases of position and intensity errors of past forecasts summarized via simple linear multiple regression.
- Errors for superensemble are generally less than those of all the participating models during 1-5 day real-time forecasts.

Fig. 2. *(a) The 1998 Atlantic tropical system cross-validation-based track errors, hours 12–72, including FSU superensemble and ensemble mean forecasts; (b) the 1998 Atlantic tropical system cross-validation-based intensity errors, hours 12–72, including FSU superensemble and ensemble mean forecasts*

MULTI-PARAMETERIZATIONS vs INITIAL PERTURBATIONS

Using Initial Condition and Model Physics Perturbations in Short-Range Ensemble Simulations of Mesoscale Convective Systems

D. J. Stensrud, J. –W. Bao, and T. T. Warner, MWR, 128, (2000) 2077–2107

Two ensembles

1) Different model physics parameterizations

2) Different initial conditions (Monte Carlo)

Findings:

- Model physics ensemble more skillful when large-scale forcing for upward motion is week.
- Initial condition ensemble more skillful when large scale forcing for upward motion is strong.

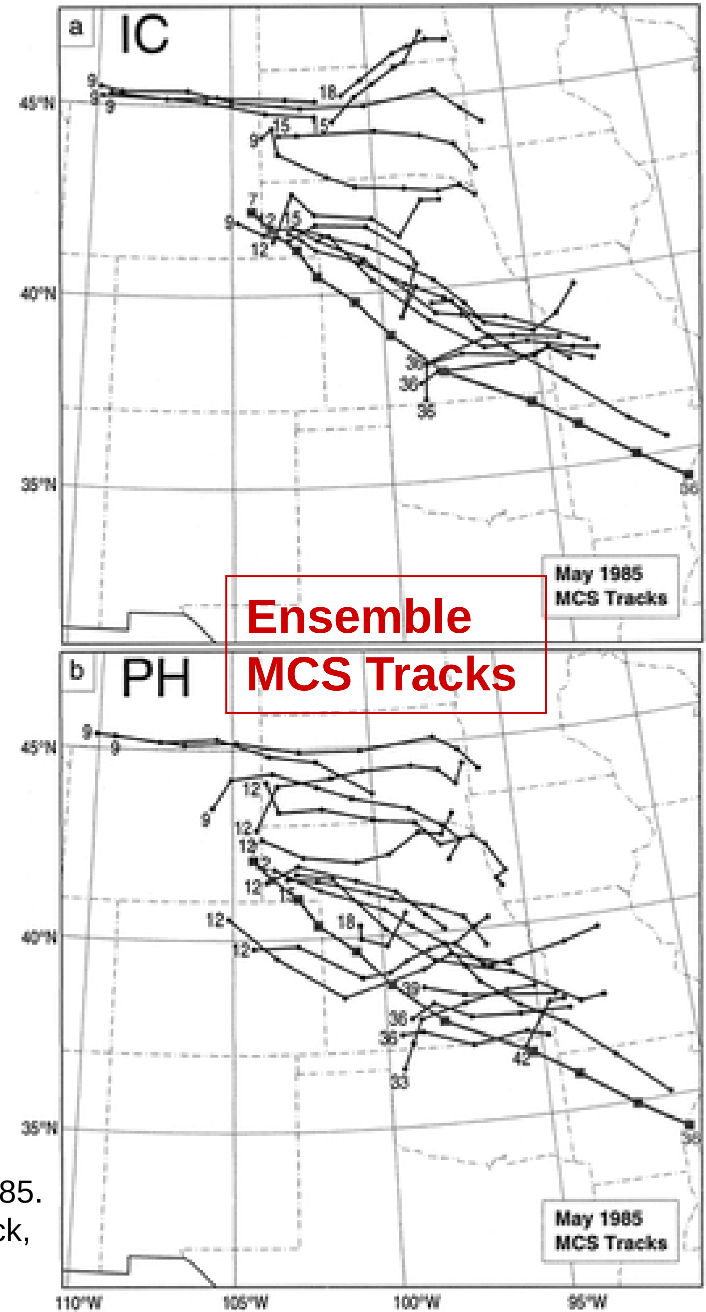


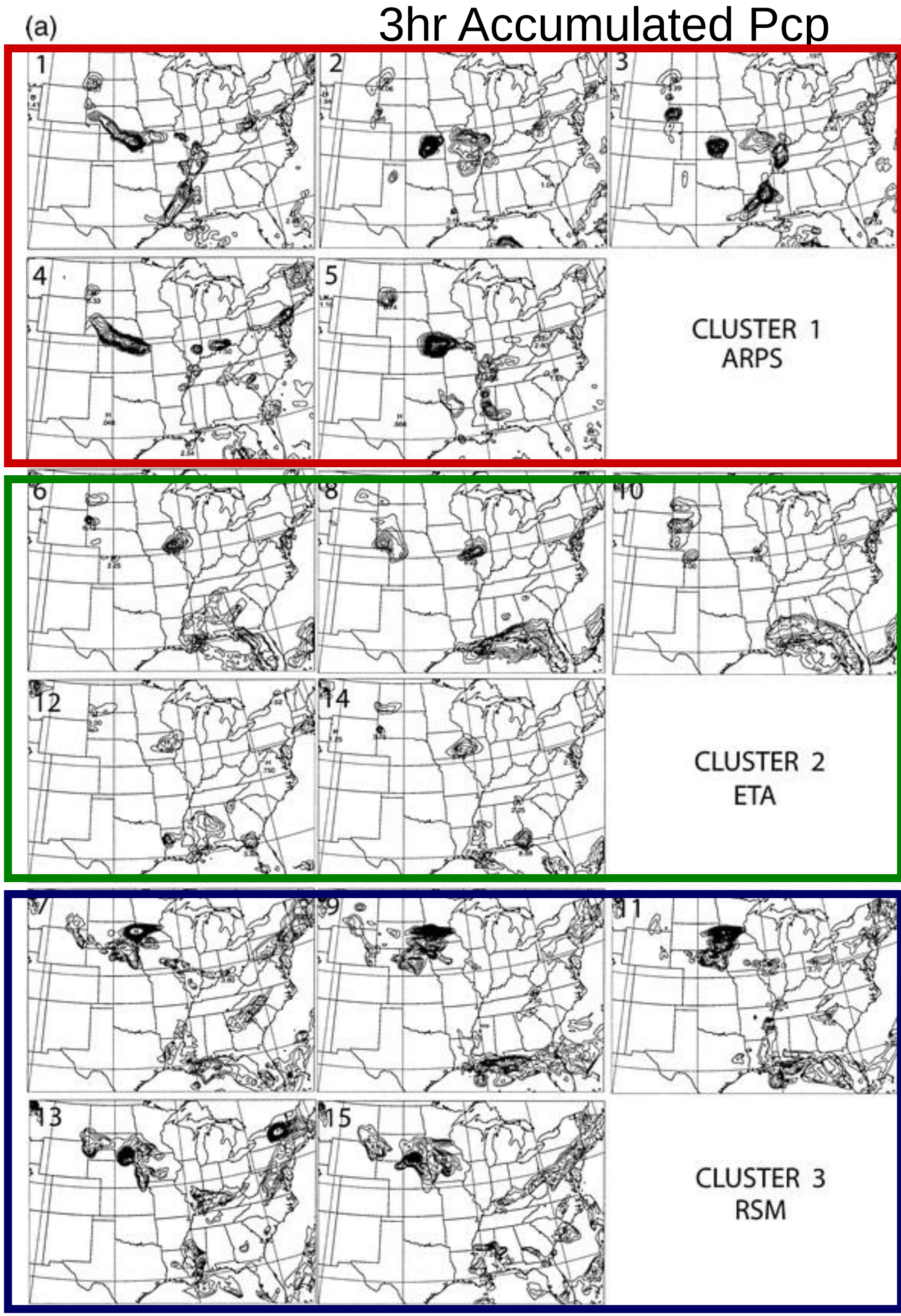
Fig. 12. Tracks of the simulated MCSs from the (a) initial-condition and (b) physics ensembles during the 48-h period beginning 1200 UTC 27 May 1985. Tracks subjectively determined from 3-h model output. Observed MCS track, derived from radar data, shown in gray.

MULTI-MODEL ENSEMBLES

Cluster Analysis of Multimodel Ensemble Data from SAMEX
A. Alhamed, S. Lakshmivarahan, and D. J. Stensrud
MWR, 130, (2002) pp. 226–256

- Cluster analysis: Forecasts cluster largely by model, occurs within first few hours and persists.

- Using totally different models fruitful approach; however, these do not produce a smooth distribution.



The 3-h accumulated precipitation (mm) valid at 30 h from all 25 ensemble members grouped subjectively into four clusters. Numbers in the upper-left-hand corner indicate the ensemble member as defined in Table 1. Isolines every 1 mm

MULTI-MODEL ENSEMBLES

On the ability of global Ensemble Prediction Systems to predict tropical cyclone track probabilities
S. J. Majumdar and P. M. Finocchio, MWR, early online release

Clustering of forecasts also seen in Hurricane track ensemble forecasts.

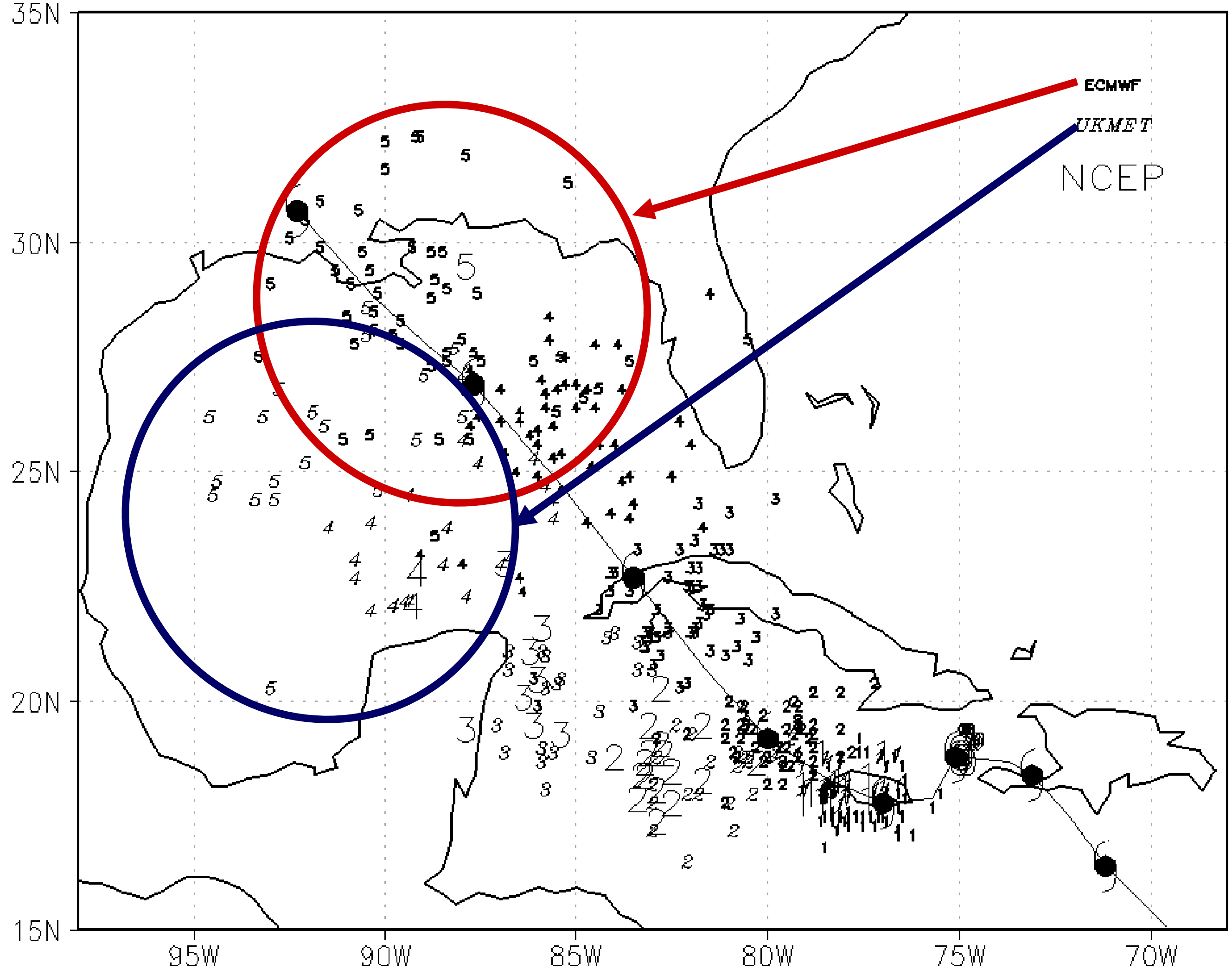


FIGURE 5. 5-day ECMWF, UKMET and NCEP ensemble forecasts for Hurricane Gustav, initialized at 00 UTC 28 August 2008. Each center's forecast is represented by a different font style, with the length of forecast depicted by the integer value.

STOCHASTIC PERTURBATIONS

Stochastic representation of model uncertainties in the ECMWF ensemble prediction system
QJRMS,125, October 1999 Part B, 2887-2908, R. Buizza, M. Miller, T. N. Palmer

- Simulate model random errors associated with physical parameterizations by multiplying total parameterized tendencies by random number between 0.5 and 1.5
- Increases spread of ensemble
- Improves skill of probabilistic prediction of weather parameters such as precipitation

$x = (\lambda, \phi, \sigma)$ (identified by its latitude, longitude and vertical hybrid coordinate), the perturbed parametrized tendency (of each state vector component) is defined as

$$\mathbf{P}'_j(\mathbf{e}_j;\, t) \equiv \langle r_j(\lambda, \phi;\, t)\rangle_{D,T}\, \mathbf{P}_j(\mathbf{e}_j;\, t), \tag{6}$$

where $\langle \ldots \rangle_{D,T}$ means that the same random number r_j has been used for all grid points inside a $D \times D$ degree box and over T time steps. Random numbers have been sampled uniformly from three different intervals for so-called high-, medium- and low-amplitude stochastic forcing configurations:

- Recent refinements made to stochastic perturbations (Palmer et al 2009)

STOCHASTIC PERTURBATIONS: IMPACT ON TC INTENSITY

Ensemble prediction of tropical cyclones using targeted diabatic singular vectors
QJRMS, 127, January 2001 Part B, 709-731, K. Puri, J. Barkmeijer, T. N. Palmer

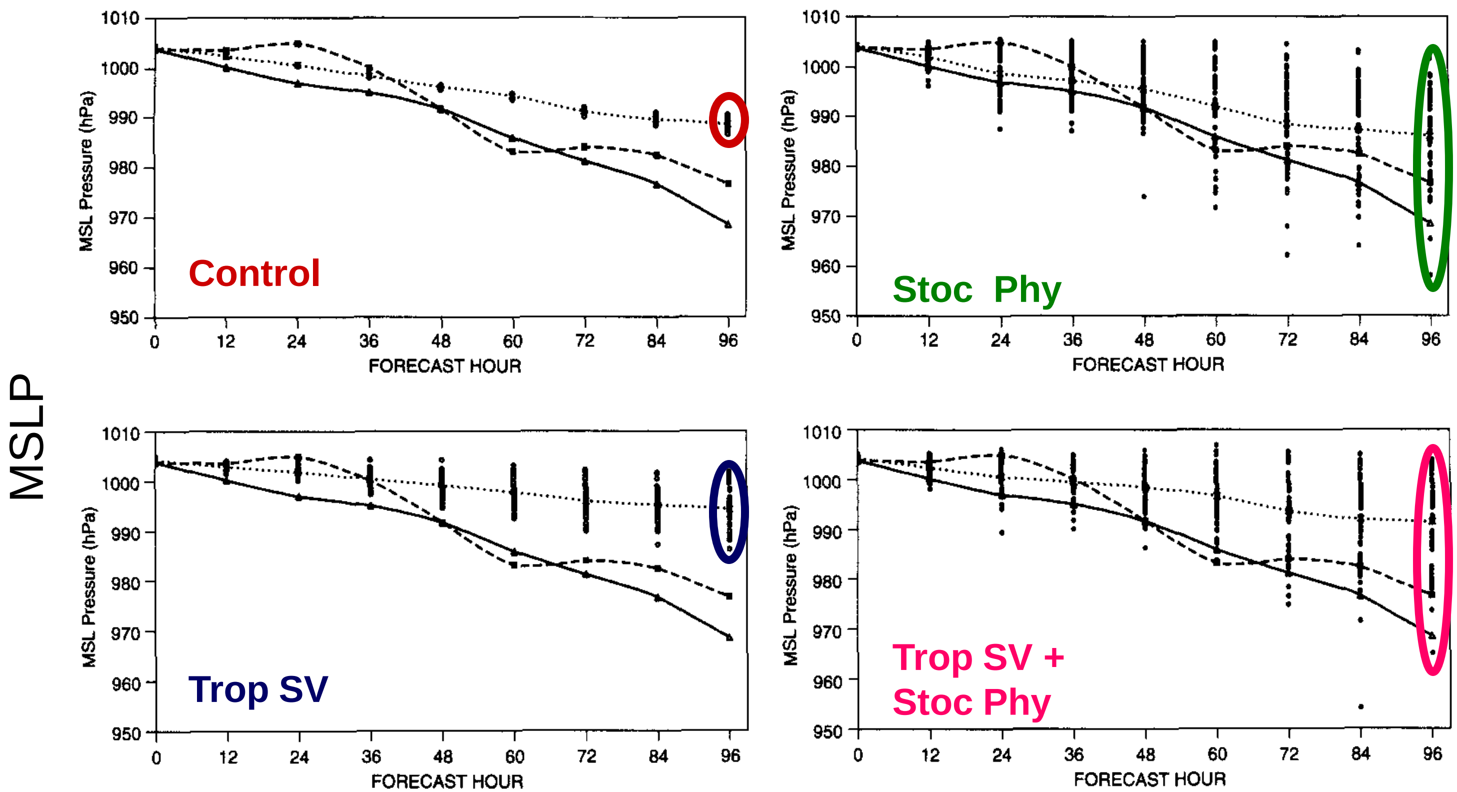


Figure 4(c). As in Fig. 3(b) but for TC Zeb and ensemble prediction system run with no stochastic physics (top left), with stochastic physics (top right), tropical singular vectors (SVs) (bottom left) and tropical SVs + stochastic physics (bottom right).

- Significant spread in tracks from moist-SV based initial perturbations.
- Inclusion of stochastic physics leads to larger spread in the central pressures.
- Higher model resolution (TL255) also lead to significantly increased pressure spread.

STOCHASTIC KINETIC ENERGY BACKSCATTER (SKEB)

A Spectral Stochastic Kinetic Energy Backscatter Scheme and Its Impact on Flow-Dependent Predictability in the ECMWF Ensemble Prediction System

J. Berner, G. J. Shutts, M. Leutbecher, and T. N. Palmer, JAS, **66**, (2009) pp. 603–626

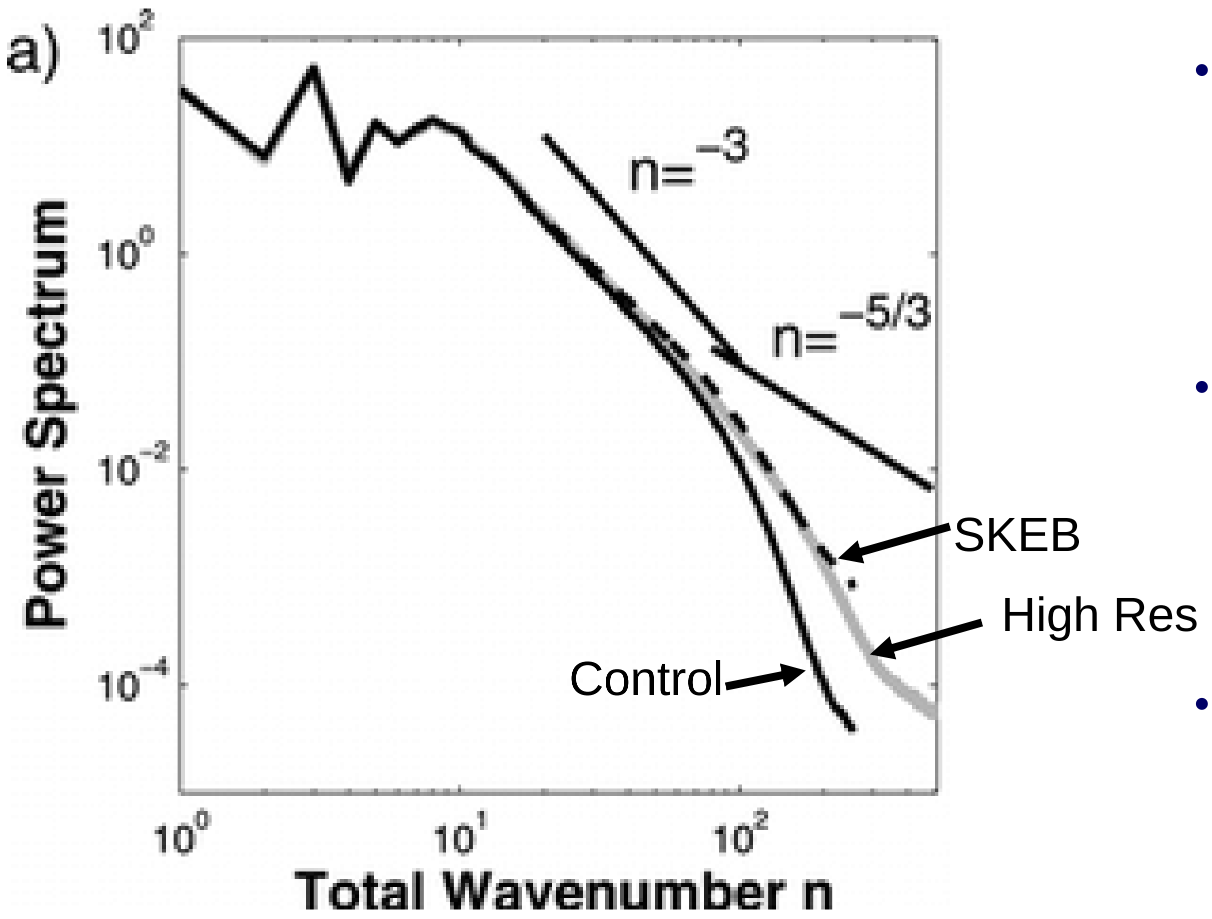


Fig. 6. Kinetic energy spectra for the (a) rotational component of the flow for TL511 analysis (gray solid), forecasts with the operational ensemble configuration (OPER; black solid), and the ensemble system with stochastic backscatter (SSBS-FULLDISS; black dashed). Lines denote power-law behavior with slopes of −3 and −5/3.

- Spectral SKEB used to simulate upscale-propagating errors caused by unresolved subgidscale processes.
- SEKB gives better spread-error relationship, more realistic KE spectra, improved rainfall forecasts, better probabilistic skill.
- Improvements most pronounced in tropics.

Operational Centers: Model Error in Ensemble Design

	Current
ECMWF	Stochastic perturbations, SKEB (planned)
Meteo Service Canada Global	Multi-parameterizations, Stochastic pert., SKEB. Physical parameterizations that incorporate model uncertainty (planned)
Meteo Service Canada Mesoscale	Stochastic parameter perturbations
NCEP: GFS	Stochastic perturbations
NCEP: SREF	Multi-model, multi-parameterizations. Stochastic convection (planned)
NRL Global	SKEB and Diurnal SST variations (planned).
NRL mesoscale	Parameter variations in atmospheric component (planned)
UKMO	Random Parameters, SKEB2. Soil moisture and other surface perturbations planned.
JMA	Stochastic perturbations (planned)
Meteo-France SREP	Multi-parameterization
COSMO-DE EPS (DWD)	Parameter variations (planned)
COSMO-LEPS (Italy)	Multi-parameterizations; perturbations in turbulence scheme

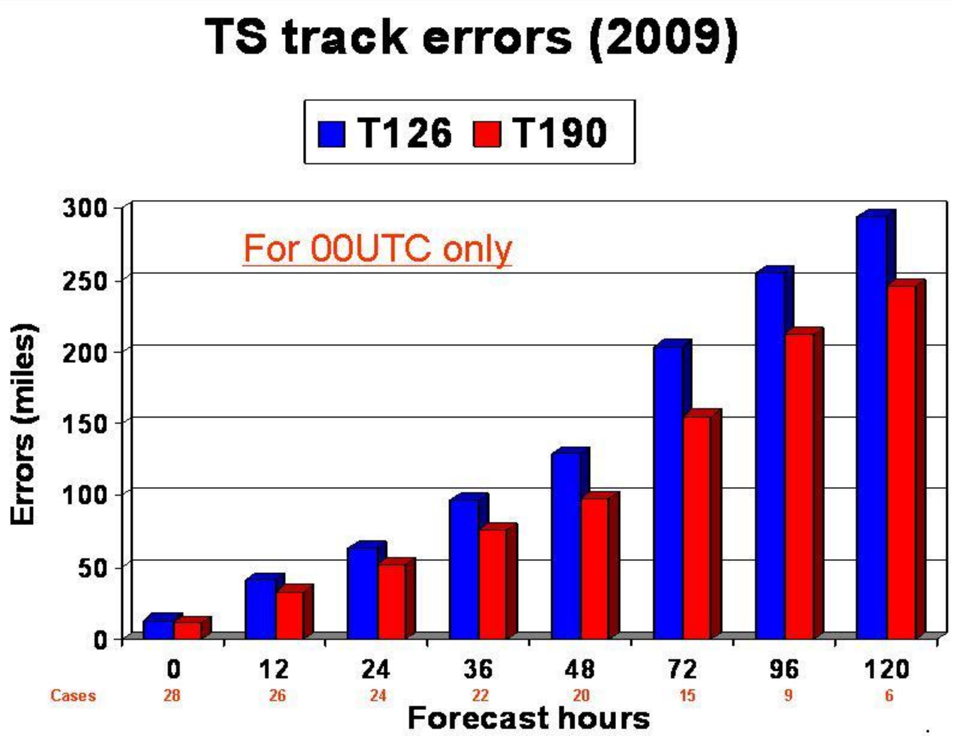
NCEP GEFS:

Achievement for HFIP Project from Ensemble Team

Yuejian Zhu, 23 March 2010

- There was a major implementation for GEFS (Global Ensemble Forecast System) in February 23rd 2010. This upgrade mainly includes:
- Increasing horizontal resolution to 70km from 90km
- Using 8th order horizontal diffusion instead of 4th order, all resolutions
- Adding stochastic perturbation scheme to account for random model errors

Summary of the important cases of Bill, Jimena, Rick and Ida



ACCOUNTING FOR MODEL ERROR IN ENSEMBLE DA

Model Error Representation in an Operational Ensemble Kalman Filter
P. L. Houtekamer, H. L. Mitchell, and X. Deng, MWR,137, (2009) pp. 2126–2143

Tested in Meteorological Service Canada Ensemble Kalman Filter

(i) Addative isotropic model error perturbations

(ii) Different versions of the model for different ensemble members

(iii) Stochastic perturbations to physical tendencies

(iv) Stochastic kinetic energy backscatter

Findings:

(i) Had largest impact. (ii) had small but clearly positive impact. (iii) and (iv) did not lead to further improvements. (i) and (ii) used in operations.

ACCOUNTING FOR MODEL ERROR IN ENSEMBLE DA

Ensemble Data Assimilation with the NCEP Global Forecast System

J. S. Whitaker, T. M. Hamill, X. Wei, Y. Song, and Z. Toth, MWR, 136, (2008) pp. 463–482

Tested in NCEP GFS Ensemble DA system (not in forecasts)

(i) additive Inflation (scaled random differences between adjacent 6-h analyses from the NCEP-NCAR reanalysis to each ensemble member)

(ii) Multiplicative Inflation (after Anderson and Anderson 1999, inflates ensemble perturbations by factor > 1.0)

(iii) Relaxation to prior (Zhang et al 2004), relaxes analysis perturbations back toward the prior perturbations independently at each analysis point. Only modified where observations have an effect on the analysis.

Each method applied to posterior ensemble, after computation of analysis increment and before running the forecasts.

Findings:

(i) Slightly better than (ii) or (iii)

Discussion Points

A well-designed ensemble should account for model error in some way.

- •What are the model errors/uncertainties that have biggest impact on TC forecasts?
- •How do we determine the characteristics of these model errors?

Inclusion of model uncertainty can be costly (computationally and effort-wise). When is it worthwhile?

- •Metric is key (e.g., some forms of uncertainty impact ensemble dispersion, not ensemble mean).

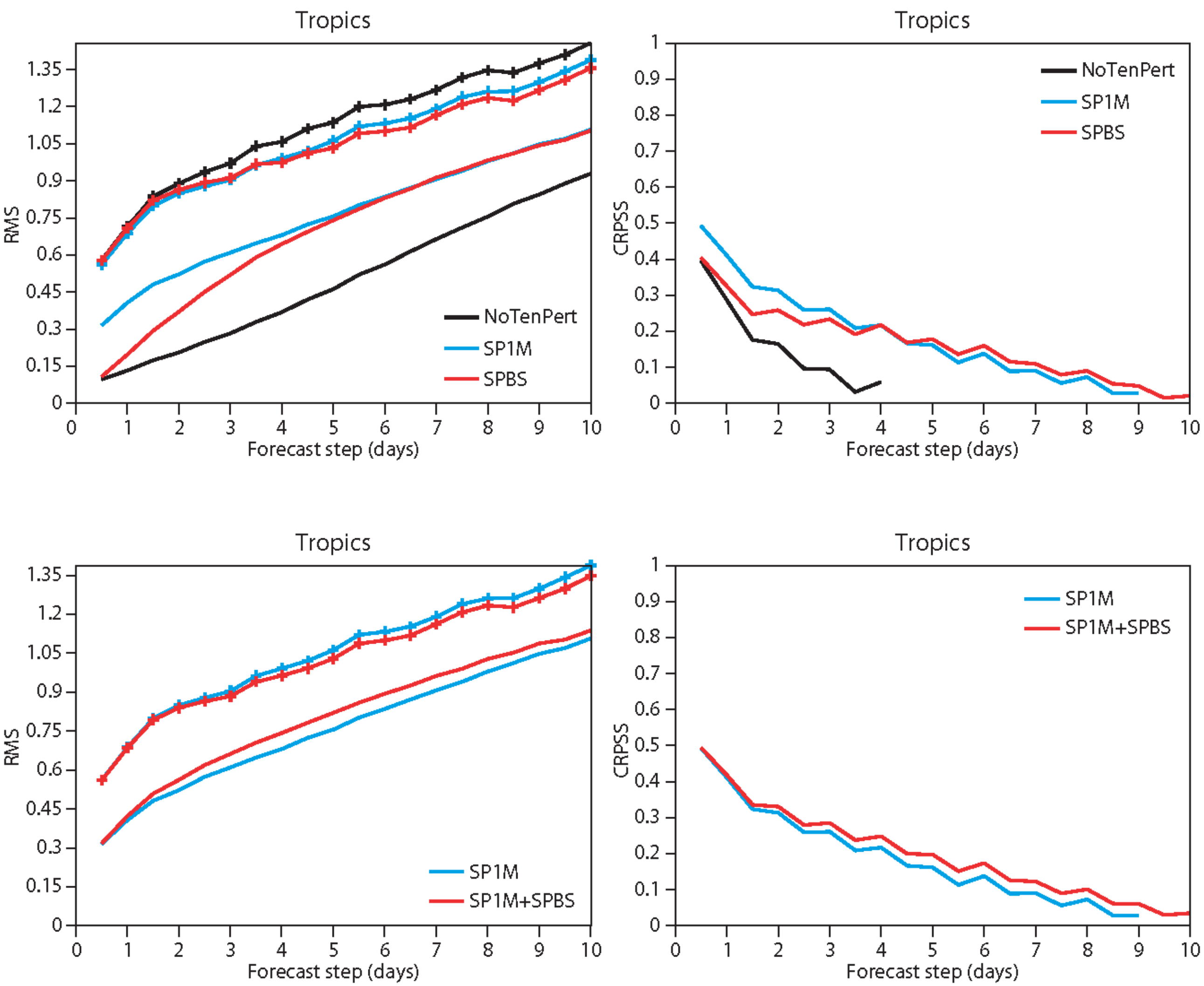
EXTRA SLIDES

ECMWF

Stochastic Parameterizations and Model Uncertainty

Palmer, T. N., R. BUizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. J. Shutts, M. Steinheimer, A. Weisheimer

ECMWF Tech Memo 598, 8 October 2009



- Current system: Stochastic Perturbations to Parameterization tendencies (Buizza et al. 1999). Concerned with aspects of uncertainty in existing parameterization schemes (e.g., grid-box sampling)
- Testing SKEB (Shutts 2005). Concerned with physical process missing in conventional parameterization schemes. Aspects of structural uncertainty in conventional parameterization

Meteorological Service of Canada

Towards Random Sampling of Model Error in the Canadian Ensemble Prediction System
Charron, M., G. Pellerin, L. Spacek, P. L Houtekamer, N. Gagnon, H. L. Mitchell, and L. Michelin
Monthly Weather Review (early online release)

•Current system has

- •Multi-Parameterizations (Kuo, RAS, KF for deep convection): Biggest impact on mid-trop temp.
  - •Challenge to maintain, artificial multi-modality, but stochastic forcing alone less skillful
- •Stochastic perturbations (Buizza et al 1999): Dispersion of upper-air dynamic fields and 500-hPa Z bias degraded when stochastic perturbations removed.
- •SKEB (Shutts 2005): Forcing of rotational components more effective than forcing divergent components. Has an impact on model biases. Mostly improves the reliability of the forecasts through ensemble dispersion.

•Recently went from two dynamical cores to one (GEM), as SEF considerably less skillful

•Eventually move to physical parameterizations that incorporate probability and random realizations

NCEP GEFS:

A Stochastic Parameterization Scheme within NCEP Global Ensemble Forecast System.

D. Hou, Z. Toth, and Y. Zhu,

Extended Abstract, AMS Annual Meeting, Atlanta, GA, 2006

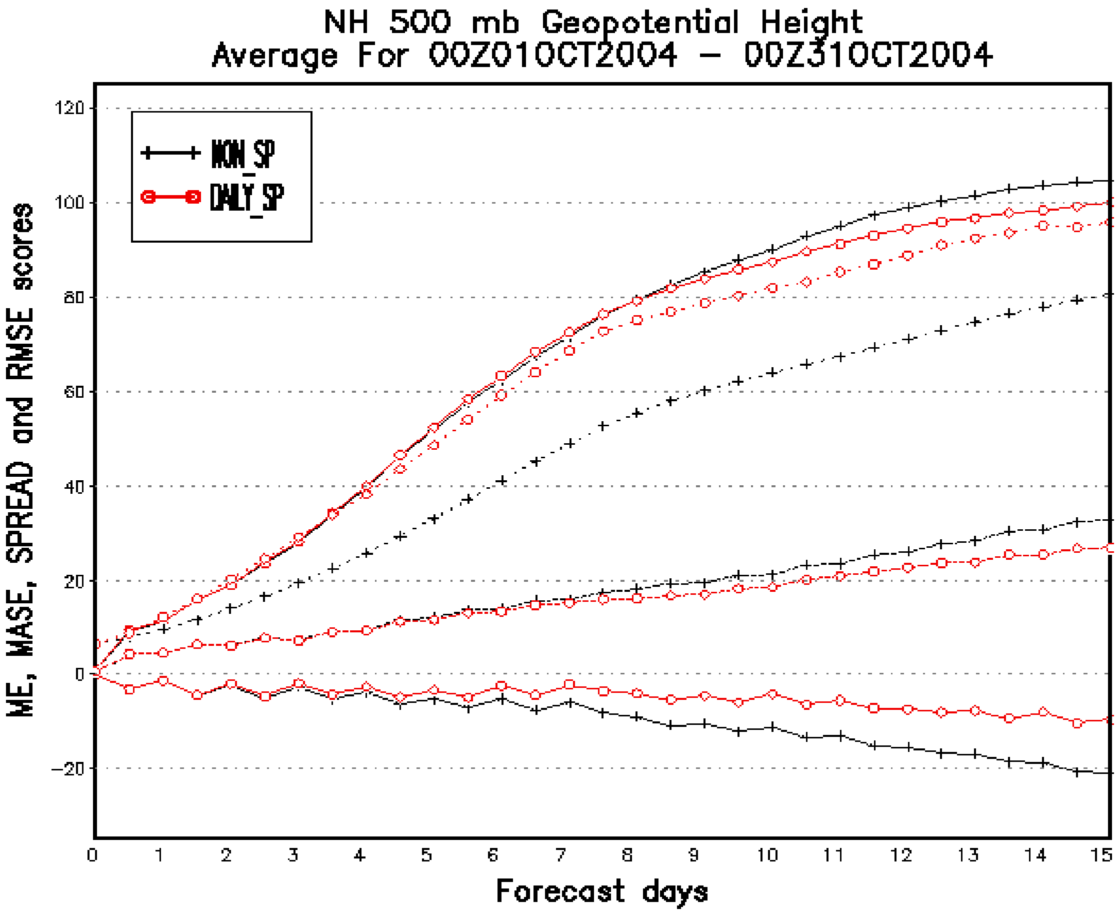


Fig.4 Ensemble spread, ME, MASE and RMSE of 500hPa height ensemble mean forecast, averaged for October, 2004, as functions of forecast lead time. The red and black lines are for the ensemble with and without SP, respectively.

Stochastic Forcing

linked to total conventional forcing (including grid scale and subgrid scale parameterizations)

sampled from differences in conventional tendency between ensemble members and control forecast. Scheme applied every 6 hours.

Increased spread, lower RMS error, lower average error, decreased bias.

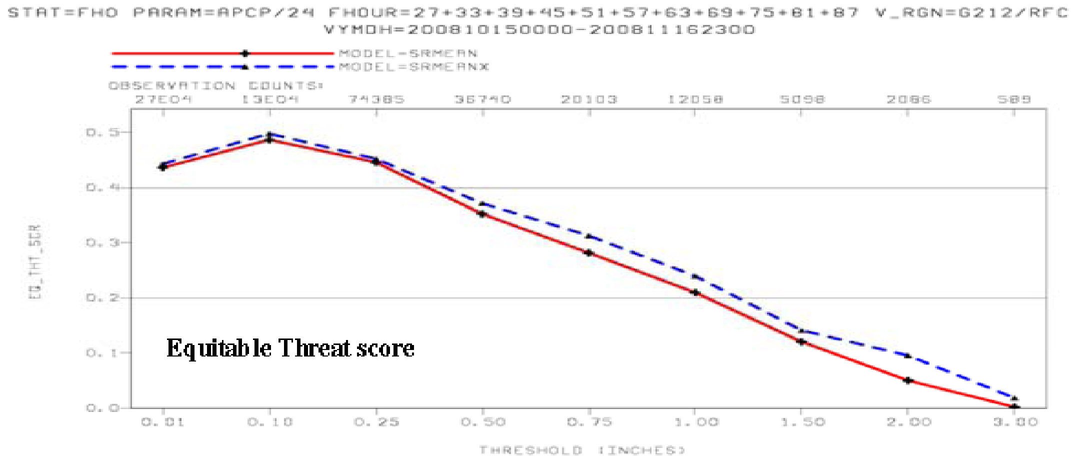
NCEP SREF:

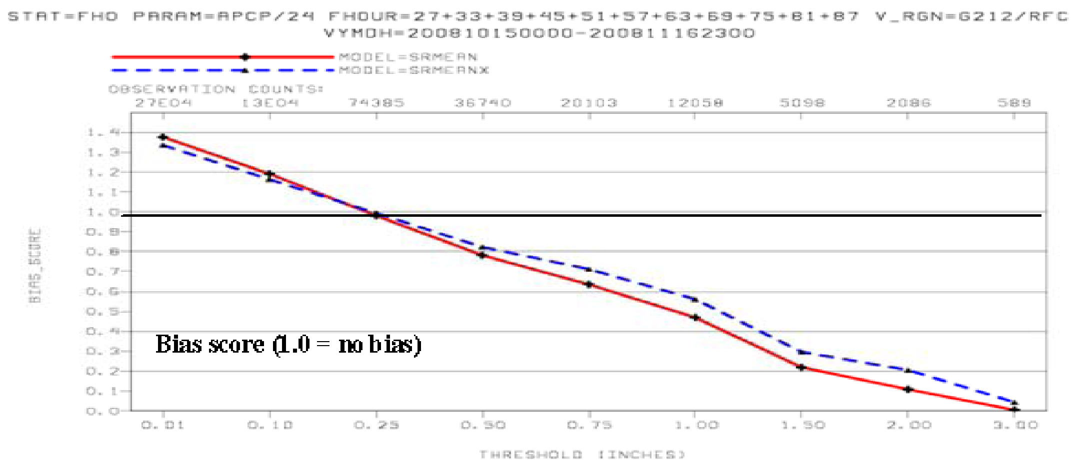
NCEP SREF System Upgrade in 2009

J. Du, G. DiMego, Z. Toth, D. Jovic, B. Zhoa, J. Zhu, H.-Y. Chuang, J. Wang, H. Juang, E. Rogers, and Y. Lin

19th conf. on NWP, 23rd Conf on WAF, 1-5 June 2009, Omaha NE.

Fig. 7: Equitable Threat score (ETS) and Bias score of 24h-accumulated precipitation forecasts of ensemble mean over CONUS, averaged over the period of Oct. 15 – Nov. 16, 2008. New SREF is in dash line and old SREF in solid line. Both ETS and Bias score improved, smaller bias and larger ETS for all thresholds especially heavier precipitation, for the new SREF (against Stage-II precip analysis)

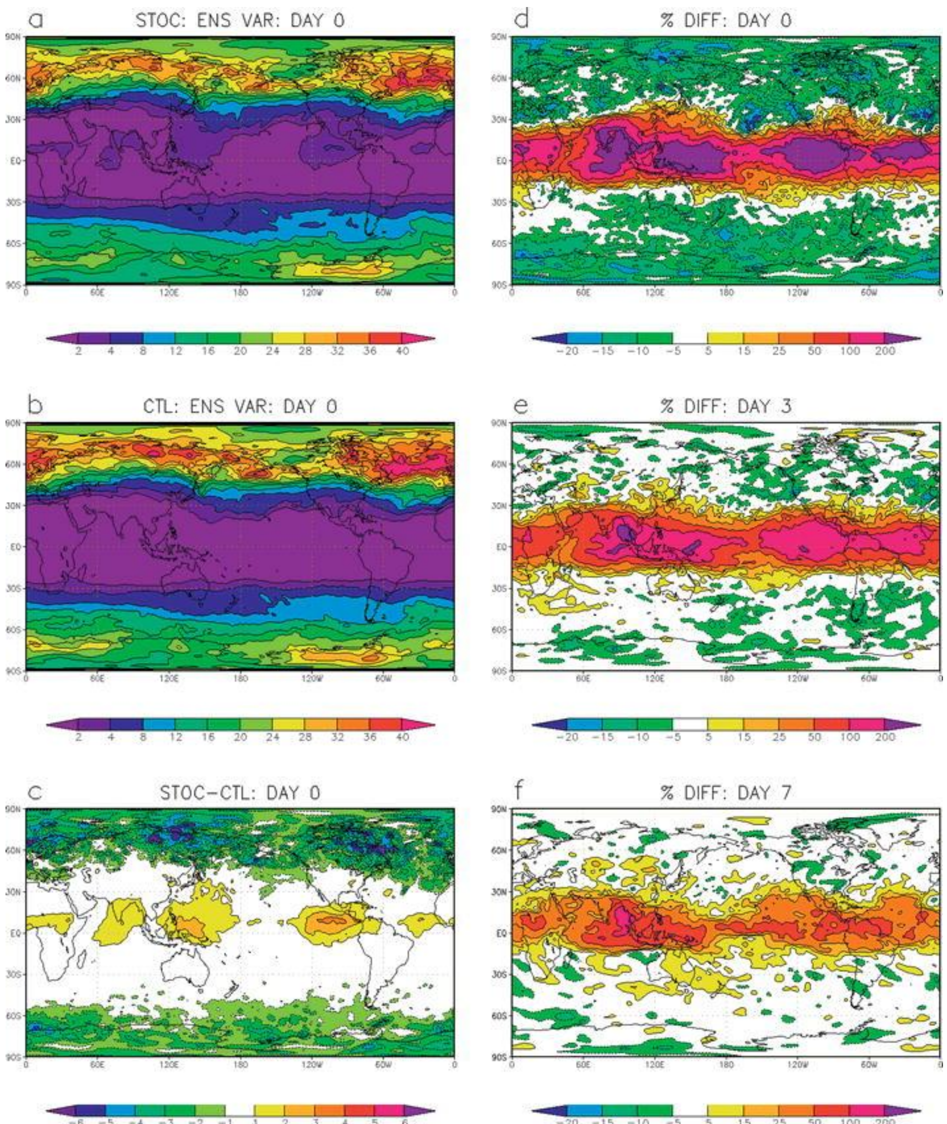




- Current SREF: Multi-model and multi-physics approach, 21 members, 32Km, 72hr
- Multi-model (Eta, RSM, NMM, ARW). Multi parameterizations (ET:BM and KF, RSM: SAS and Ferrier MP and RAS Zhao MP).
- Future: stochastic parameterized physics, one single unified modeling framework (NOAA Environmental Modeling System), surface variable perturbations.

NRL/FNMOC

Impact of Stochastic Convection on the Ensemble Transform
*C. A. Reynolds, J. Teixeira, and J. G. McLay, MWR,*136, (2008) pp. 4517–4526



- No accounting for model error in current operational system.
- Under testing:
    - Stochastic Perturbations (convection, SKEB)
    - Diurnal SST variations
    - Parameter Variations
- Model changes will have both direct and indirect impact on ensembles produced using a cycling scheme.

UKMO

The MOGREPS Short-range Ensemble Prediction System

N. E. Bowler, A. Arribas, K. R. Mylne, K. B. Robertson and S. E. Beare

QJRMS 2008, v134, 703-722.

Stochastic Physics in MOGREPS and plans for perturbations of surface fields.

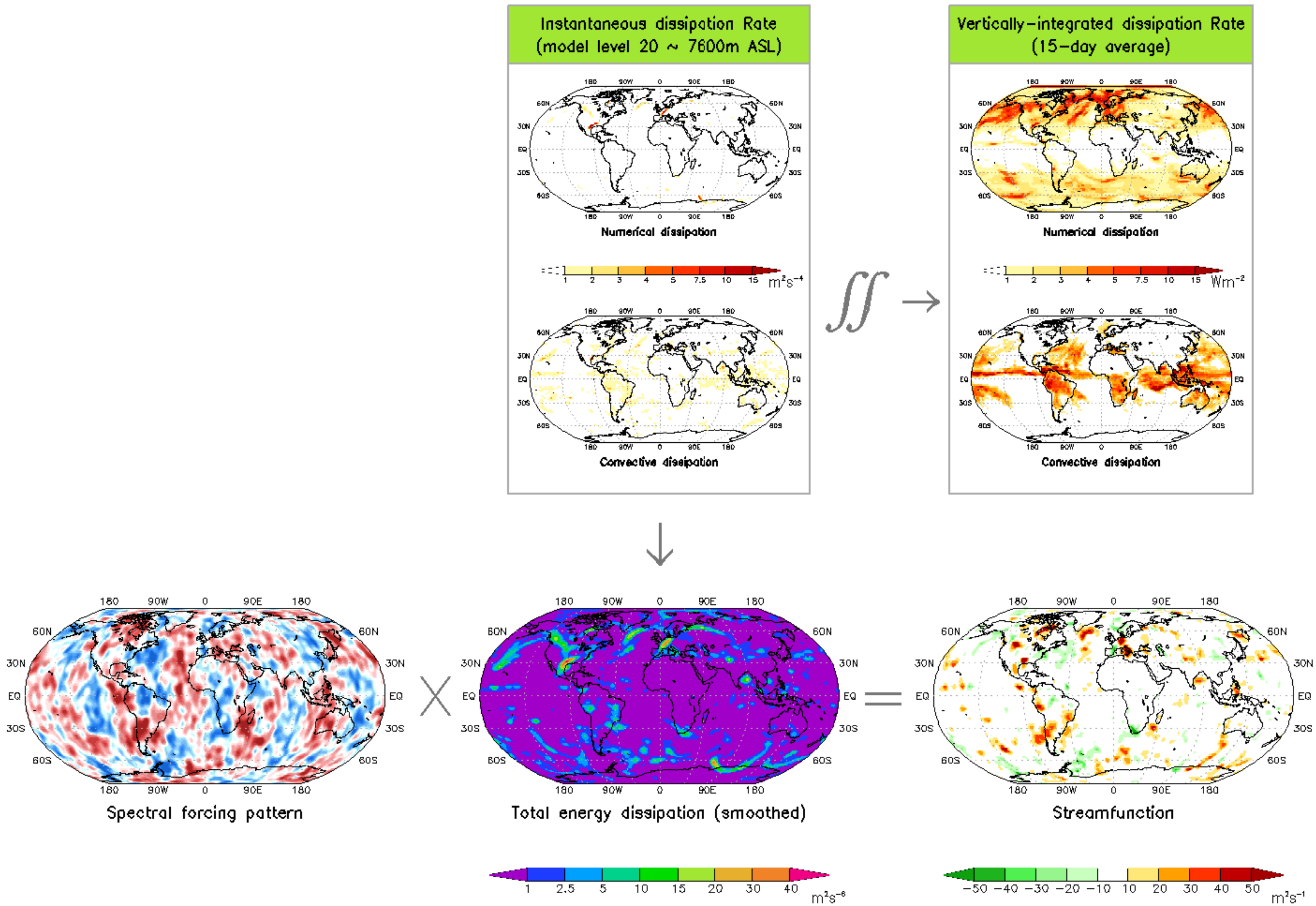
Warren Tennant, 31st EWGLAM Workshop 28 Sep 1 Oct 2009

- Random Parameters
  - Random parameters $P_t = u + r(P_{t-1} - u) + e$
  - P_t is parameter value, u is mean value, r is auto correlation of P, e is stochastic shock term
  - Eight parameters from four different physical parameterizations included (lsp, conv. BL, and GWD)
- SKEB2
- No longer using stochastic convection vorticity scheme
- Testing impact of surface perturbations (SST, soil moisture)

UKMO: SKEB2

Stochastic Physics in MOGREPS and plans for perturbations of surface fields.

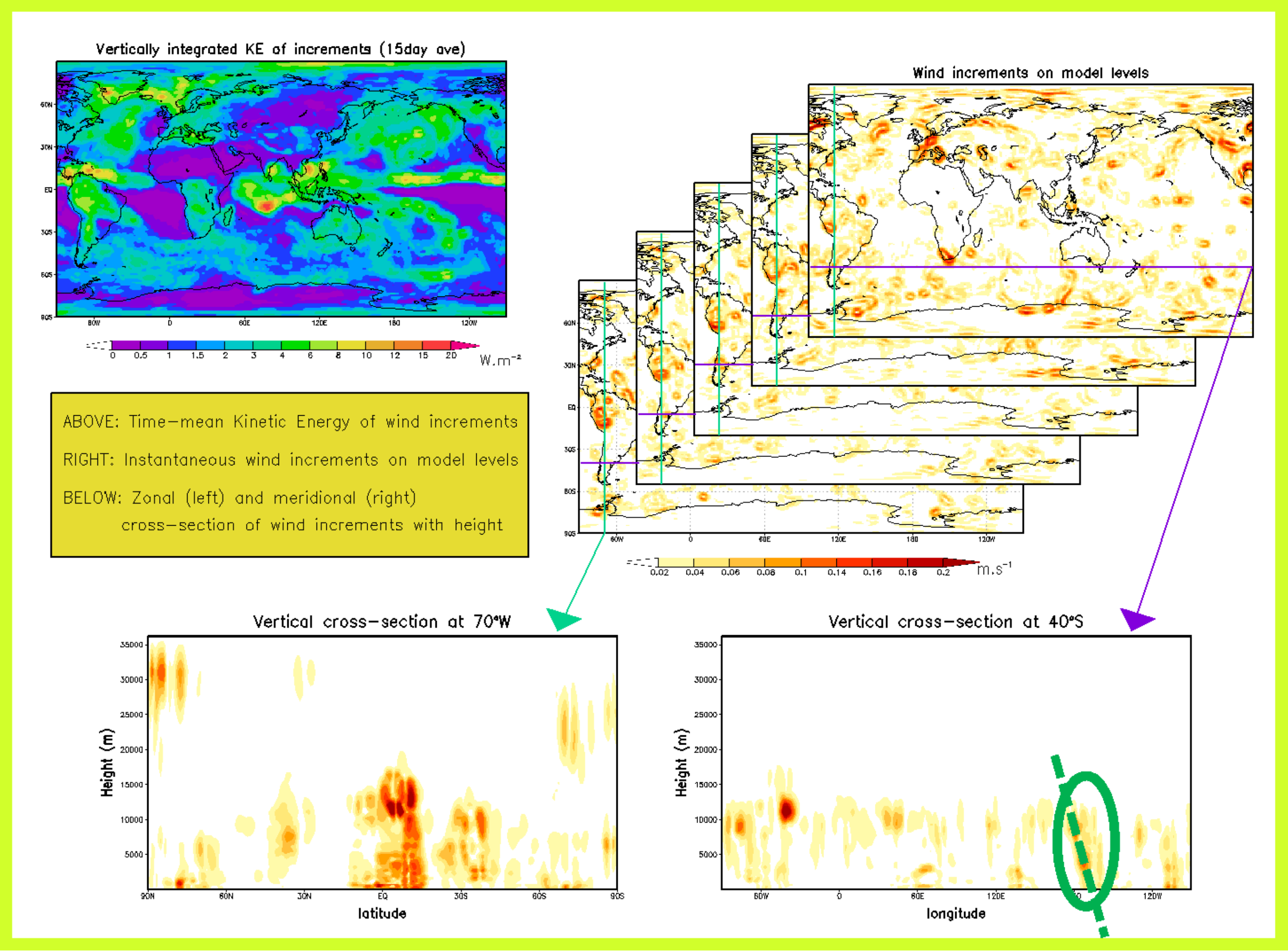
Warren Tennant, 31st EWGLAM Workshop 28 Sep 1 Oct 2009



UKMO: SKEB2

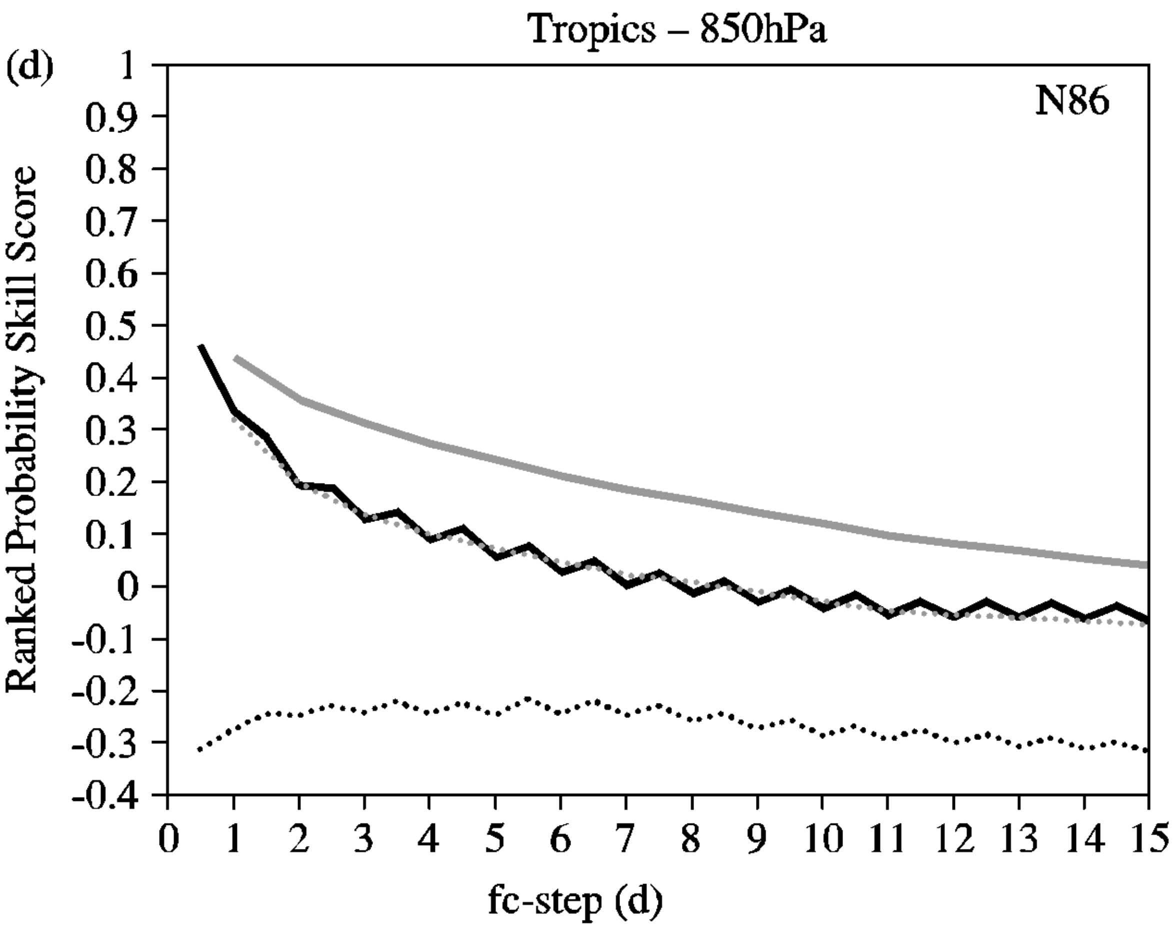
Stochastic Physics in MOGREPS and plans for perturbations of surface fields.

Warren Tennant, 31st EWGLAM Workshop 28 Sep 1 Oct 2009



MULTI-MODEL ENSEMBLE of ENSEMBLES

TIGGE: Preliminary results on comparing and combining ensembles
Quarterly Journal of the Royal Meteorological Society
Volume 134, Issue 637, Date: October 2008 Part B, Pages: 2029-2050
Young-Youn Park, Roberto Buizza, Martin Leutbecher



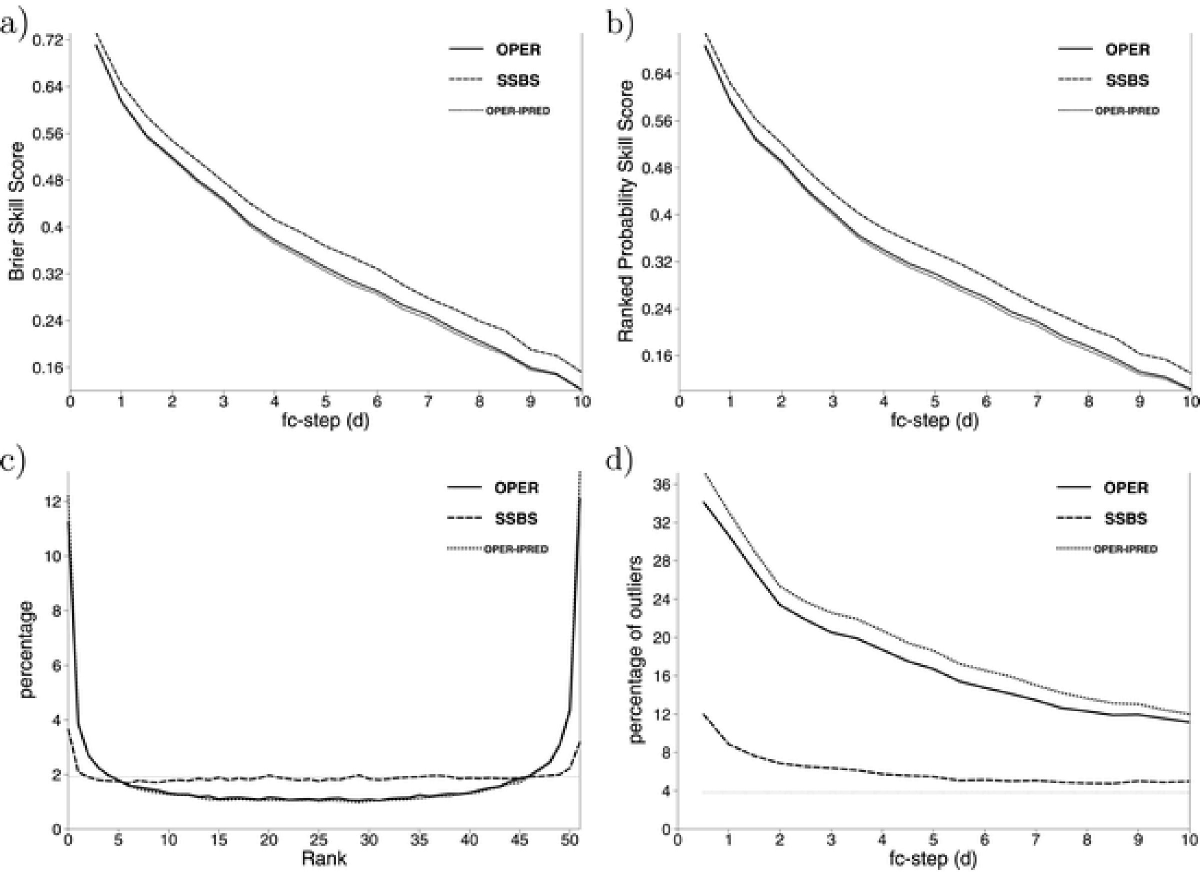
- Differences between skill of best ensemble system and combined ensemble generated considering up to four different ensemble systems. Difference is very small in areas where ECMWF ensemble system has a well tuned ensemble spread, equivalent to less than 6 hours predictability in the medium range.
- Larger and mode detectable in areas where EC system has too low ensemble spread (e.g., tropics).

STOCHASTIC KINETIC ENERGY BACKSCATTER

A Spectral Stochastic Kinetic Energy Backscatter Scheme and Its Impact on Flow-Dependent Predictability in the ECMWF Ensemble Prediction System

J. Berner, G. J. Shutts, M. Leutbecher, and T. N. Palmer,

Journal of the Atmospheric Sciences
Volume 66, Issue 3 (March 2009) pp. 603–626



- Spectral stochastic kinetic energy backscatter used to simulate upscale-propagating errors caused by unresolved subgidscale processes.
- ECMWF ensemble shows better spread-error relationship, more realistic KE spectra, better representation of forecast error growth, improved flow-dependent predictability, improved rainfall forecasts, better probabilistic skill.
- Improvements most pronounced in tropics.

Stochastic Parameterizations

Short-Range Ensemble Forecasts of Precipitation during the Southwest Monsoon

D. R. Bright and S. L. Mullen, Wea. Forecasting, 17 (2002) pp. 1080-1100

- MM5 Ensembles with Multi-parameterizations and stochastic perturbations to KF cumulus and PBL.
- Choice of cumulus parameterization effects predicted precip much more than PBL scheme or stochastic physics.

Influence of a stochastic moist convective parameterization on tropical climate variability.

Lin, J. W-B. and J. D. Neelin, Geophys. Res. Lett., 27 (2000) pp. 3691-3694

- Simple stochastic convective parameterization that includes a random contribution to the convective available potential energy in deep convection (BM) scheme. Impacts tropical intraseasonal variability.
- Sensitive to noise amplitude and autocorrelation time. (in intermediate complexity model, quasi-equilibrium tropical circulation model

ACCOUNTING FOR MODEL ERROR IN ENSEMBLE FORECASTS

Toward Improved Convection-Allowing Ensembles: Model Physics Sensitivities and Optimizing Probabilistic Guidance with Small Ensemble Membership

Craig S. Schwartz and co-authors, Weather and Forecasting ,25, (2010) pp. 263–280

- 10-member 4km ensemble forecasts over US using WRF-ARW for 2007 NOAA hazardous weather test bed spring experiment.
- Ensemble forecasts reveal WRF-ARW sensitivity to microphysics and PBL schemes.
- A neighborhood approach is described and shown to considerably enhance skill of probabilistic precip forecasts when combined with traditional ensemble probability field techniques.

ECMWF

Stochastic Parameterizations and Model Uncertainty

Palmer, T. N., R. BUizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. J. Shutts, M. Steinheimer, A. Weisheimer

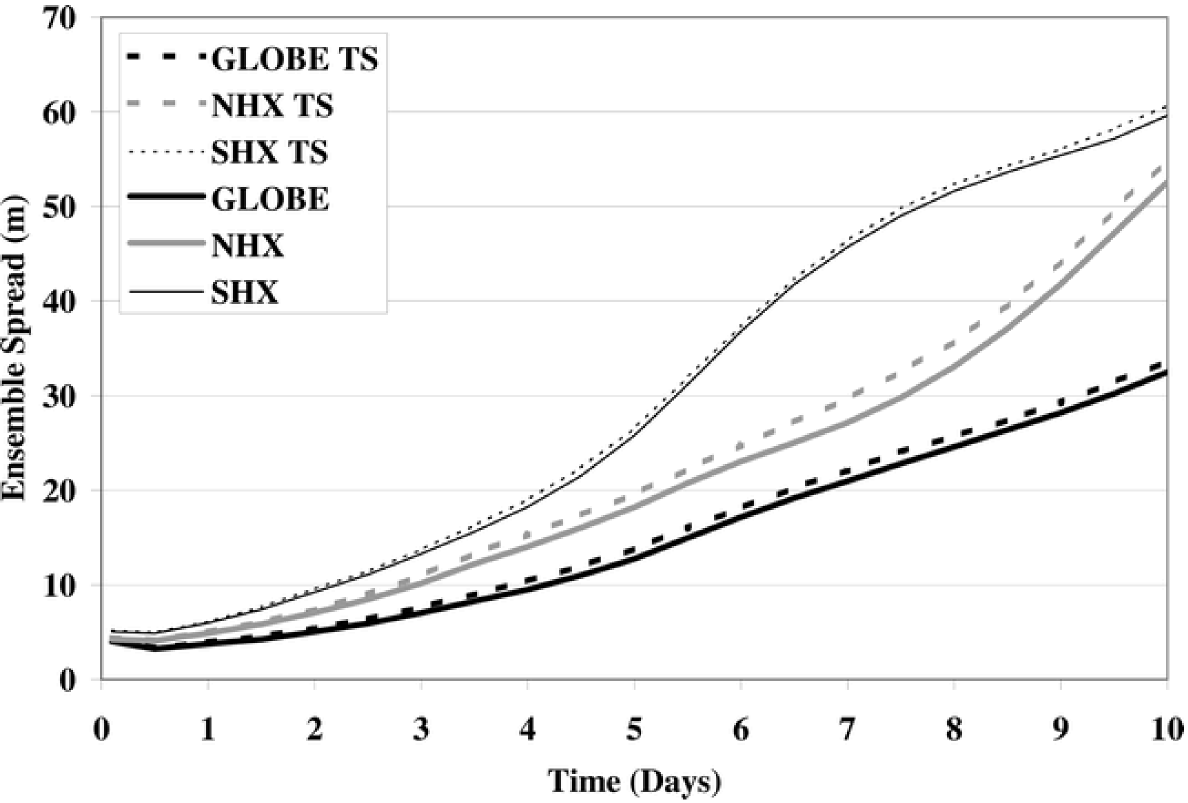
ECMWF Tech Memo 598, 8 October 2009

- Current system: Stochastic Perturbations to Parameterization tendencies (Buizza et al. 1999). Concerned with aspects of uncertainty in existing parameterization schemes (e.g., grid-box sampling)
  - Recently revised: Old version, different random numbers for u,v, T, and q, 10x10 boxes, constant for 4 hours. Uniform distribution range
  - Same random number for u,v, T and q. Gaussian distribution, spectral pattern generator, AR1 process, reduced perturbations near surface.
- Testing SKEB (Shutts 2005). Concerned with physical process missing in conventional parameterization schemes. Aspects of structural uncertainty in conventional parameterization

TIME-STEP SENSITIVITY

Time Step Sensitivity of Nonlinear Atmospheric Models: Numerical Convergence, Truncation Error Growth, and Ensemble Design

J. Teixeira, C. A. Reynolds, and K. Judd, JAS, 64, (2007) pp. 175–189



- Decoupling of solutions due to different time steps follows a logarithmic rule (function of time step) similar in three models of varying complexity.
- Suggests different time steps may be simple way of introducing important component of model error in ensemble design.