# Impact of Model Uncertainty on Hurricane Ensembles

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## Outline

- Sources of error in forecasts
- Operational center ensemble design overview
- Stochastic forcing
- Surface Perturbations (SST, Soil moisture)
- Parameter variations and parameter estimation
- Discussion

# 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

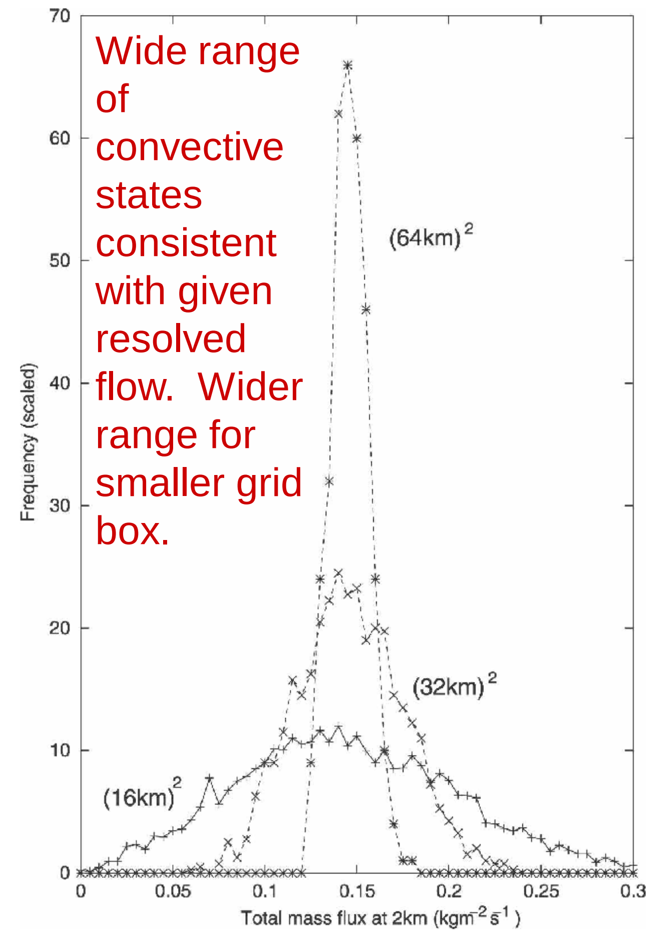


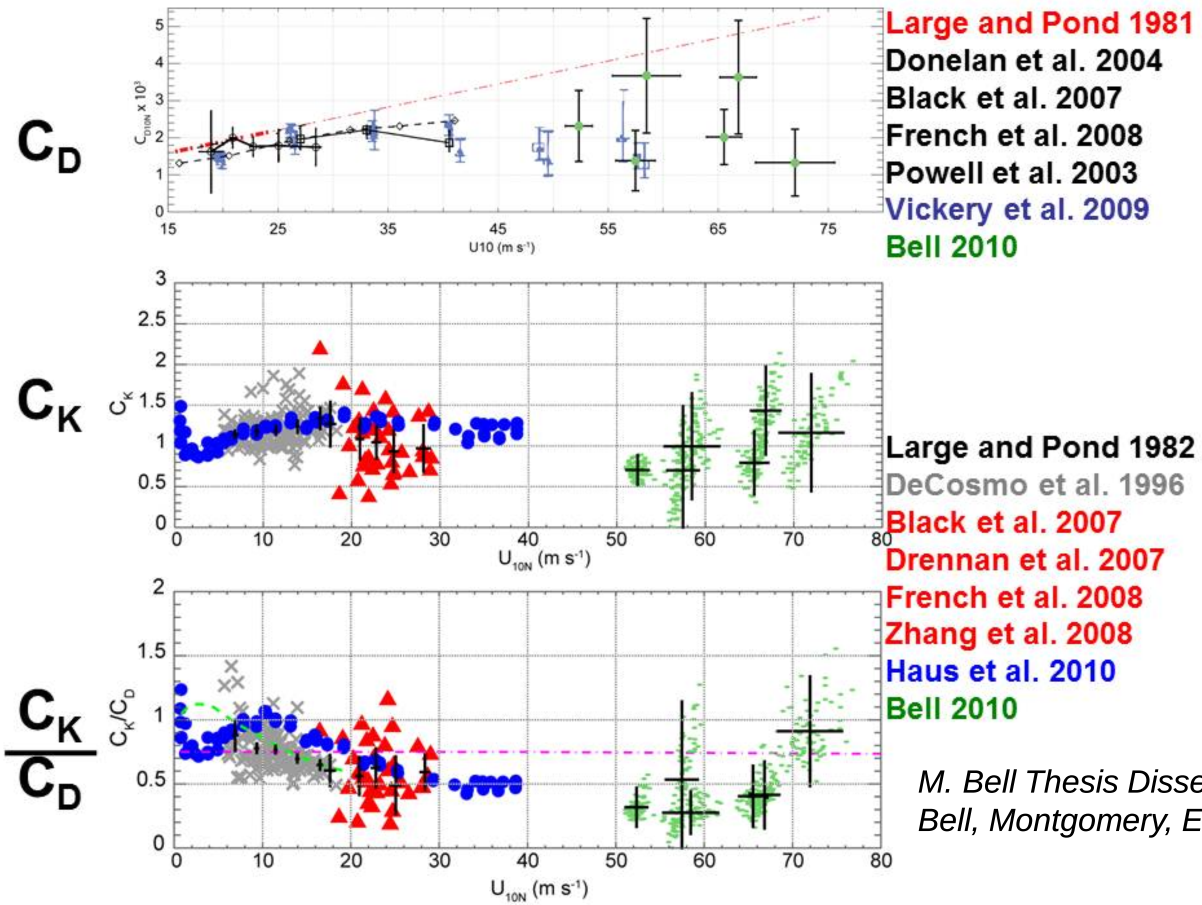

FIG. 1. Frequency plot of total convective mass flux per unit area (at a height of 2 km) obtained from a CRM simulation (Cohen and Craig 2006) of radiative–convective equilibrium. The total mass flux is computed for different-sized areas and binned into intervals of 0.01 kg $m^{-2}$ $s^{-1}$. Data are 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

## Momentum and Enthalpy at High Winds




*M. Bell Thesis Dissertation (2010)*
*Bell, Montgomery, Emanuel (2012)*

**Substantial range in observations (and estimates) for $C_D$, $C_K$, and ratio $C_K/C_D$ for given 10-m wind speed.**

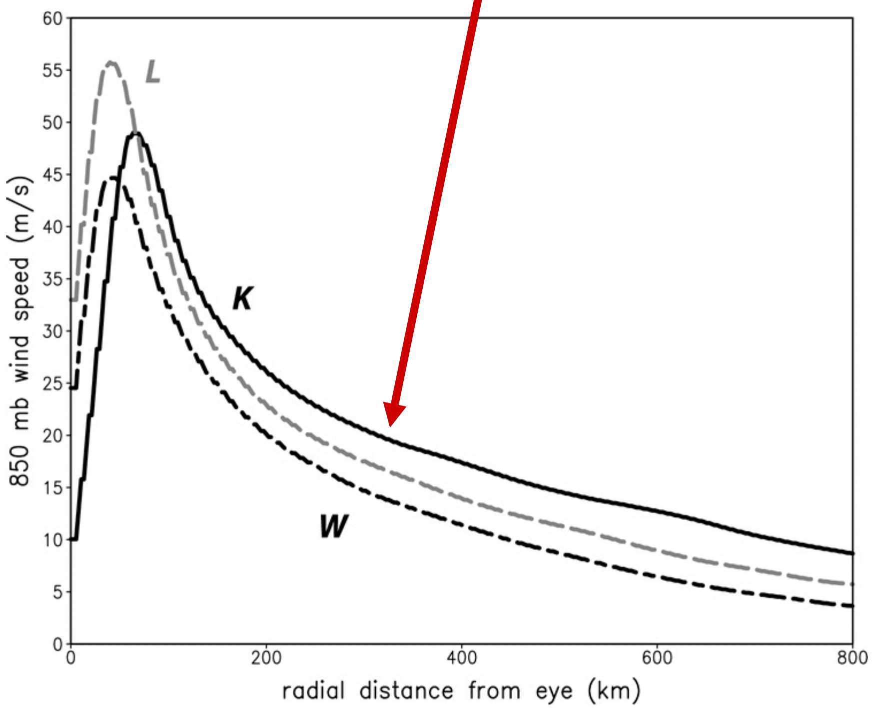
# SOURCES OF ERROR IN FORECASTS

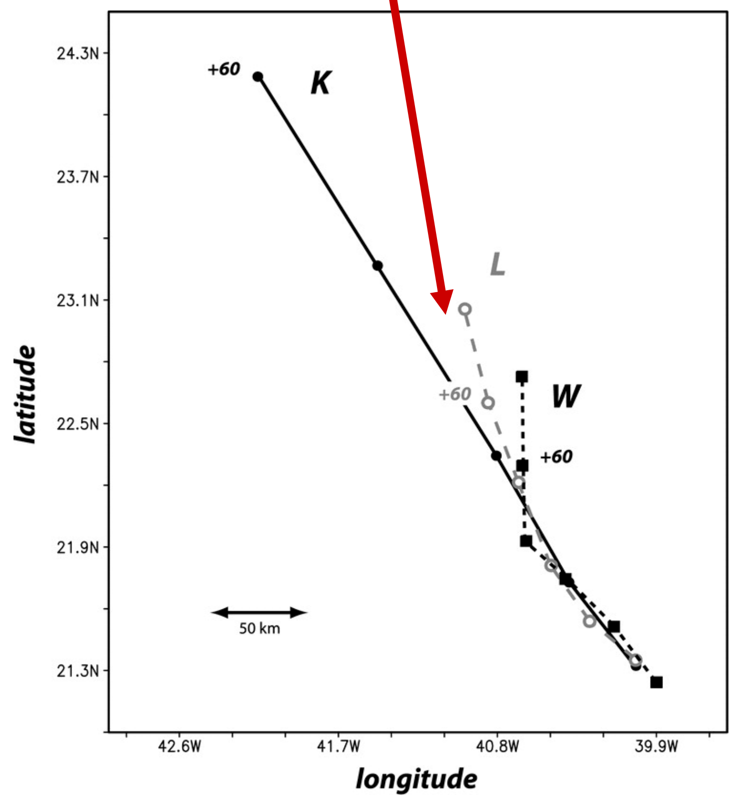
**Cloud Microphysics Impact on Hurricane Track as Revealed in Idealized Experiments**

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

*JAS,* 66, 1764-1778.

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

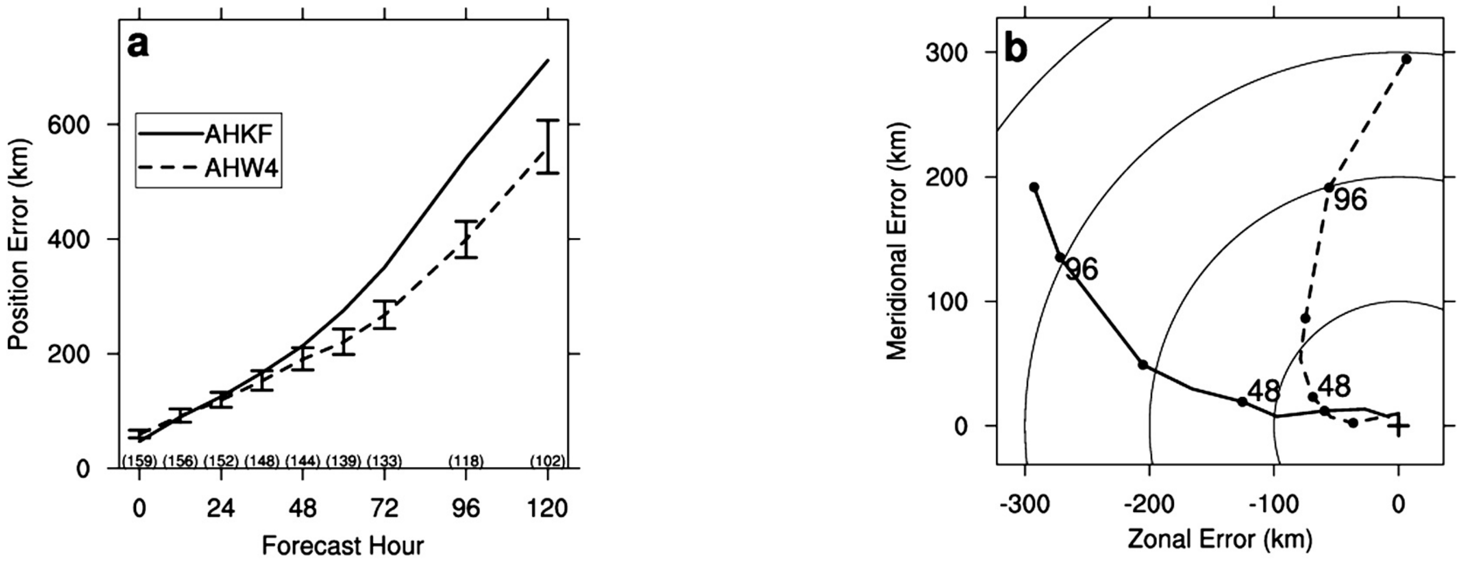


# Shallow Convection influence on AHW TC Track

Ryan D. Torn and Christopher A. Davis, 2012: **The Influence of Shallow Convection on Tropical Cyclone Track Forecasts.** *MWR.*, **140**, 2188–2197.

**Structural errors in the processes that determine the tropical temperature profile, such as shallow convection, can lead to biases in TC position.**




Mean absolute error in (left) TC track in AHW forecasts that use the Kain–Fritsch (AHKF; solid) and Tiedtke (AHW4; dashed) cumulus convection on the outer two domains as a function of forecast hour, (right) The position bias as a function of forecast hour.

# MULTI-MODEL ENSEMBLES

**On the ability of global Ensemble Prediction Systems to predict tropical cyclone track probabilities**

S. J. Majumdar and P. M. Finocchio, 2014, *MWR,* 95, 1741-1751.

**Multi-model ensembles often outperform single model ensembles. However, issues persist, e.g. clustering of forecast track by model.**

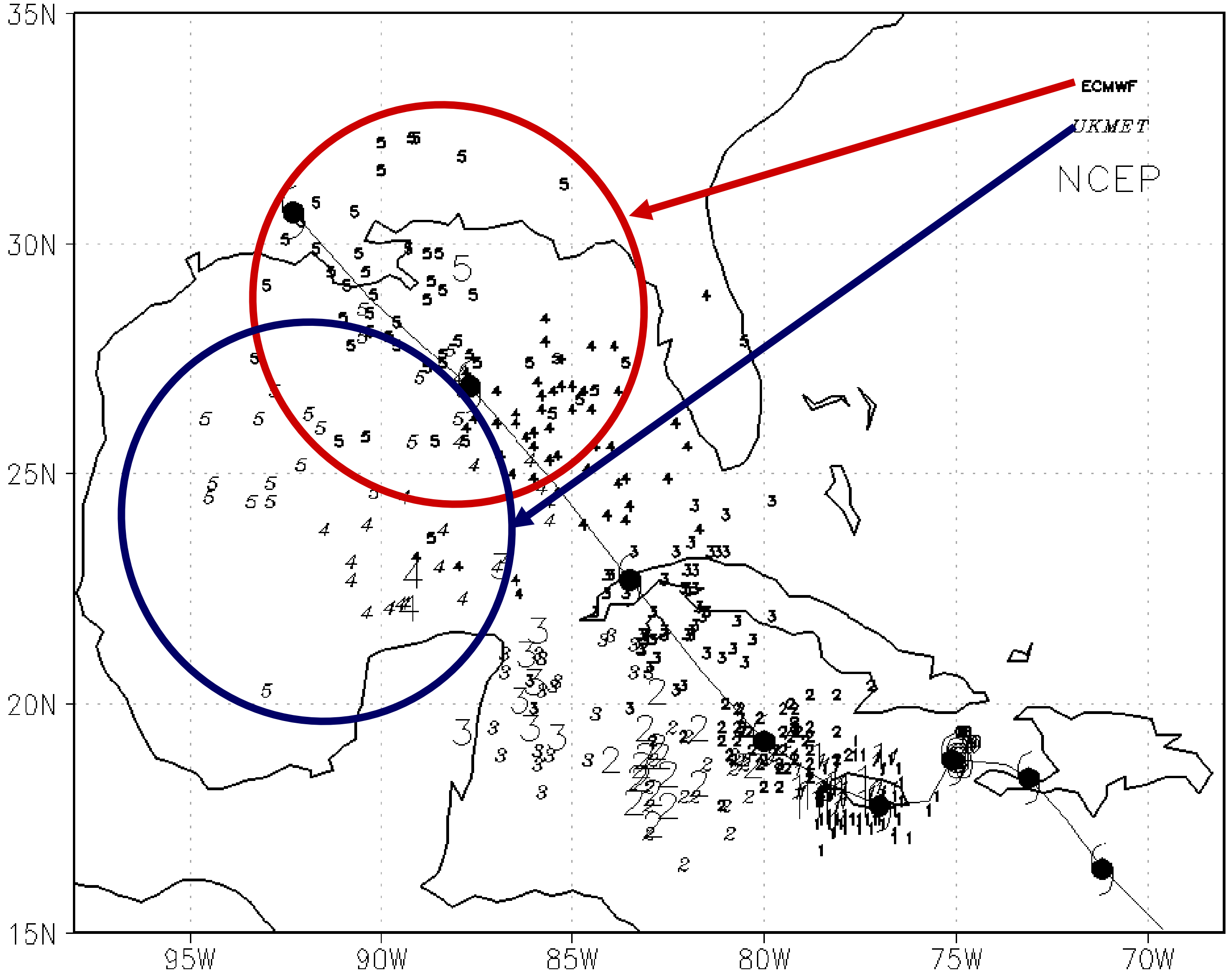



FIGURE 5. 5-day ECMWF, UKMET and NCEP ensemble forecasts for Hurricane Gustav, initialized at 00 UTC 28 August 2008. Each center's forecast is represented by a different font style, with the length of forecast depicted by the integer value.

# Most Ensemble Prediction System include some method to account for model uncertainty

## Operational regional EPS

| Center | Resolutions | FC Range | Members | Initial perturbation, DA | Model Uncertainty | B.C. | Note |
|---|---|---|---|---|---|---|---|
| Met Office (UK) | 2.2kmL70 | 36h | 11+1<br>18/24 (p) | Interpolated from global EPS<br>Convective ensemble DA (p) | SPPT (p) | | UM |
| Meteo France (France) | 2.5km | 42h | 11+1 | Rescaled and centered from global EPS<br>EDA or B-based random noise (r) | SPPT | correlated random perturbations of SST, soil moisture/humidity, snow, physiographies | AROME Pre-operation |
| DWD (German) | 2.8km | 27h | 20<br>40 (r) | IFS, GMS, GME, GSM<br>Ensemble DA based on LETKF (r) | Pert. Parameters<br>SPPT (r) | IFS, GMS, GME, GSM<br>Add COSMO-LEPS (p)<br>Global ICON EPS (r) | COSMO |
| HMC (Russia) | 2.2km | 48h | 10 | COSMO-S14-EPS | N<br>SPPT (p) | COSMO-S14-EPS | COSMO |
| JMA (Japan) | 5kmL48 | 39h | 10+1<br>20+1 (p) | SV(Total energy norm)<br>Hybrid DA (r) | N<br>Pert. tendency (r) | JMA global EPS<br>Perturbed SST (r) | JMA-NHM Test-operation |
| NRL/FNMOC (US) | 27/9/3km | 120h | 10+1 | Perturbed synoptic scales<br>Perturbed Rankine Vortex | N | GEFS/NAVGEM with synoptic perturbations | COAMPS-TC |
| NRL/FNMOC (US) | 45/15/5km | 72h | 20+1 | ETKF | Parameter variations | NAVGEM ensembles | COAMPS |
| CMC (Canada) | 15km | 72h | 20+1 | Interpolated from global EPS | Stochastic pert. of physics | Global EPS | GEM |
| KMA (Korea) | 3kmL70 | 45h | 23+1 | Downscale from Global EPS<br>LETKF | RP | Global EPS | UM |

- **HWRF accounts for model uncertainty through stochastic convective trigger in SAS and stochastic boundary layer height perturbations in PBL.**
- **GFDL accounts for model uncertainty through surface physics modifications.**

# Growing Interest in Accounting for Model Uncertainty

*Strategic Goals for NWP Centres: Minimising RMS error or maximising forecast reliability, T. Palmer, U. Oxford, WWOSC, August 2014*

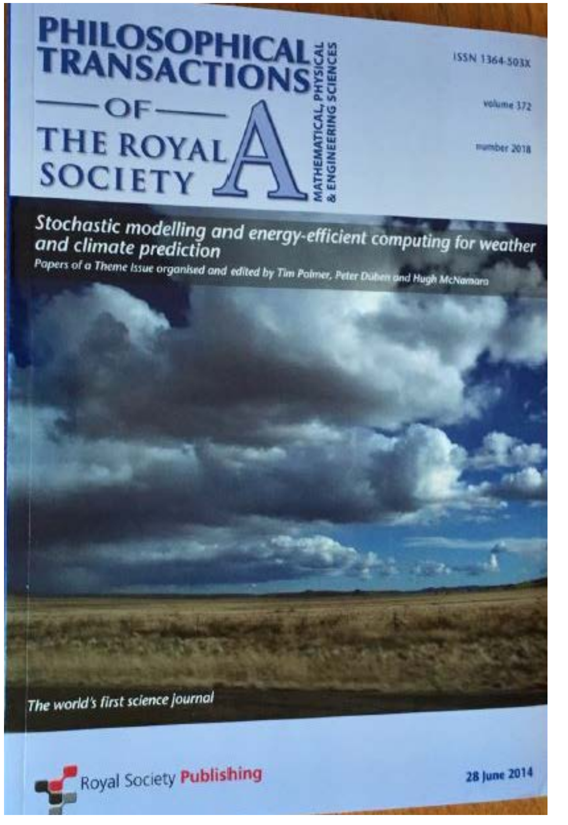
## Conclusions

Palmer T.N., 2012: Towards the probabilistic earth-system simulator: a vision for the future of weather and climate prediction. Quart J R Met Soc, 138, 841-861 ( Royal Met Soc Presidential Address)

Stochastic parametrisation improves probabilistic scores and can reduce systematic errors. It does not (necessarily) reduce the rms error of deterministic forecasts.

Primary headline metrics should measure the usefulness of weather forecasts for real-world decision making. RMS error/ACC of Z500 does not measure this; CRPSS does.

If RMS Error and Anomaly Correlation Coefficient remain the primary headline metrics to evaluate an NWP Centre's performance, the development of parametrisations with (e.g.stochastic) representations of their own uncertainty will not be given first priority by model development teams.




**Recommendations from EUMETNET Joint PHY-EPS Workshop 2013:**

- **Introduce stochasticity only where appropriate (maintain physical meaning).**
- **Sensitivity studies and process studies, in addition to predictability studies, are necessary to understand impacts.**
- **Parameter perturbations useful diagnostic to understand spatio-temporal characteristics of uncertainty.**

# *Parameterization of Moist Processes for Next-Generation Weather Prediction*

## *NOAA Center for Weather & Climate Prediction, College Park, Maryland, January 27-29, 2015*

**It is natural to expect that model uncertainty could be estimated directly by parameterizations and expressed by, for example, drawing the parameterization tendency from a distribution of expected outcomes.**

**However, the parameterization community is not yet ready to provide estimates of state-dependent parameterization error to replace current ad-hoc estimates of model error to increase ensemble spread….**

**Nonetheless, ad hoc perturbations to physical tendencies remain the most effective solution for maintaining the dispersion of ensembles through the duration of a forecast.**

# STOCHASTIC PERTURBATIONS: IMPACT ON TCs

Lang, S. T. K., M. Leutbecher, and S. C. Jones, 2012: **Impact of perturbation methods in the ECMWF ensemble prediction system on tropical cyclone forecasts.** *QJRMS*, 138., 2030-2046.

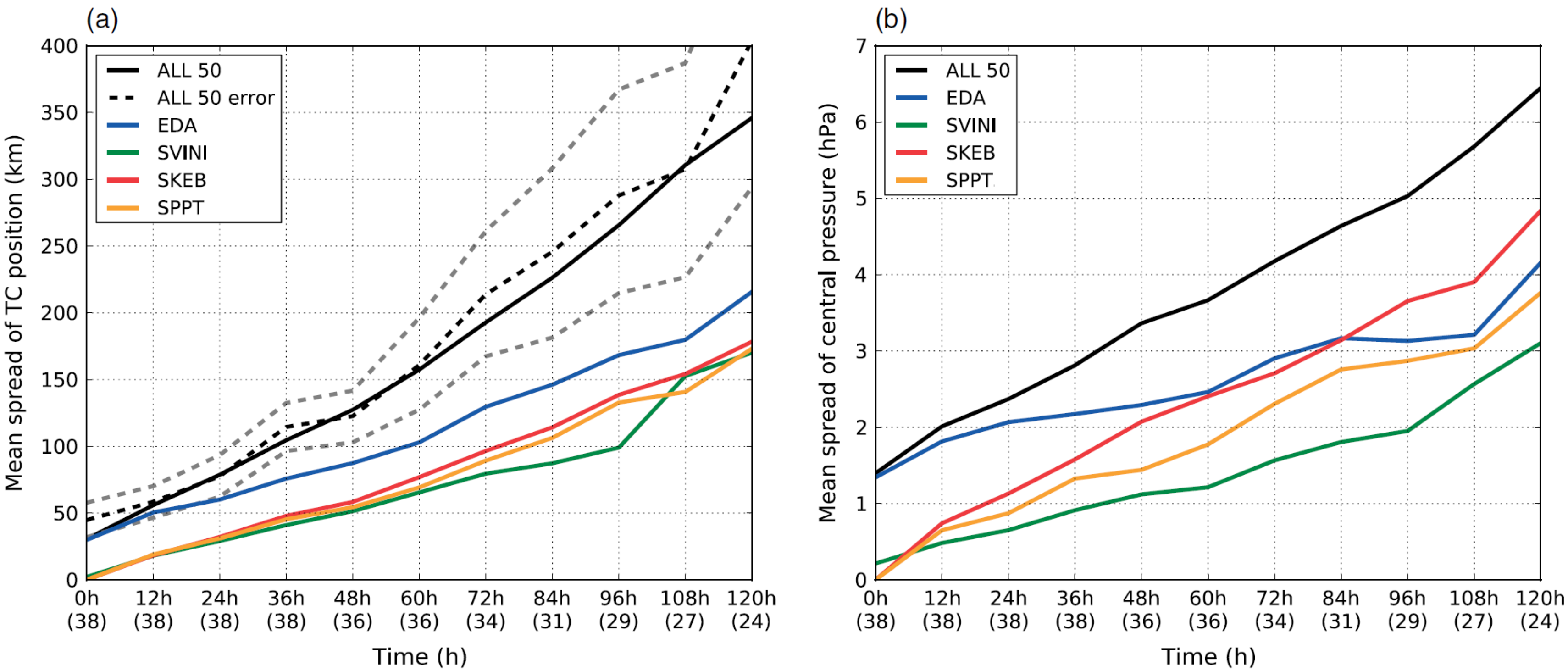



**Figure 13.** Mean ensemble spread of (a) TC track and (b) central pressure of the different ensembles. The dashed black line indicates the mean track error of the ALL50 ensemble-mean. The dashed grey lines indicate the 95% confidence interval for the difference between mean error and mean spread of the ALL50 ensemble. Hence if the black line lies within the range indicated by the grey dashed lines, we consider the differences not to be statistically significant. The numbers in parentheses indicate how many forecasts were considered for the respective lead time.

**EDA has largest impact on TC track spread.**
**SKEB has biggest impact on central pressure spread at later times.**

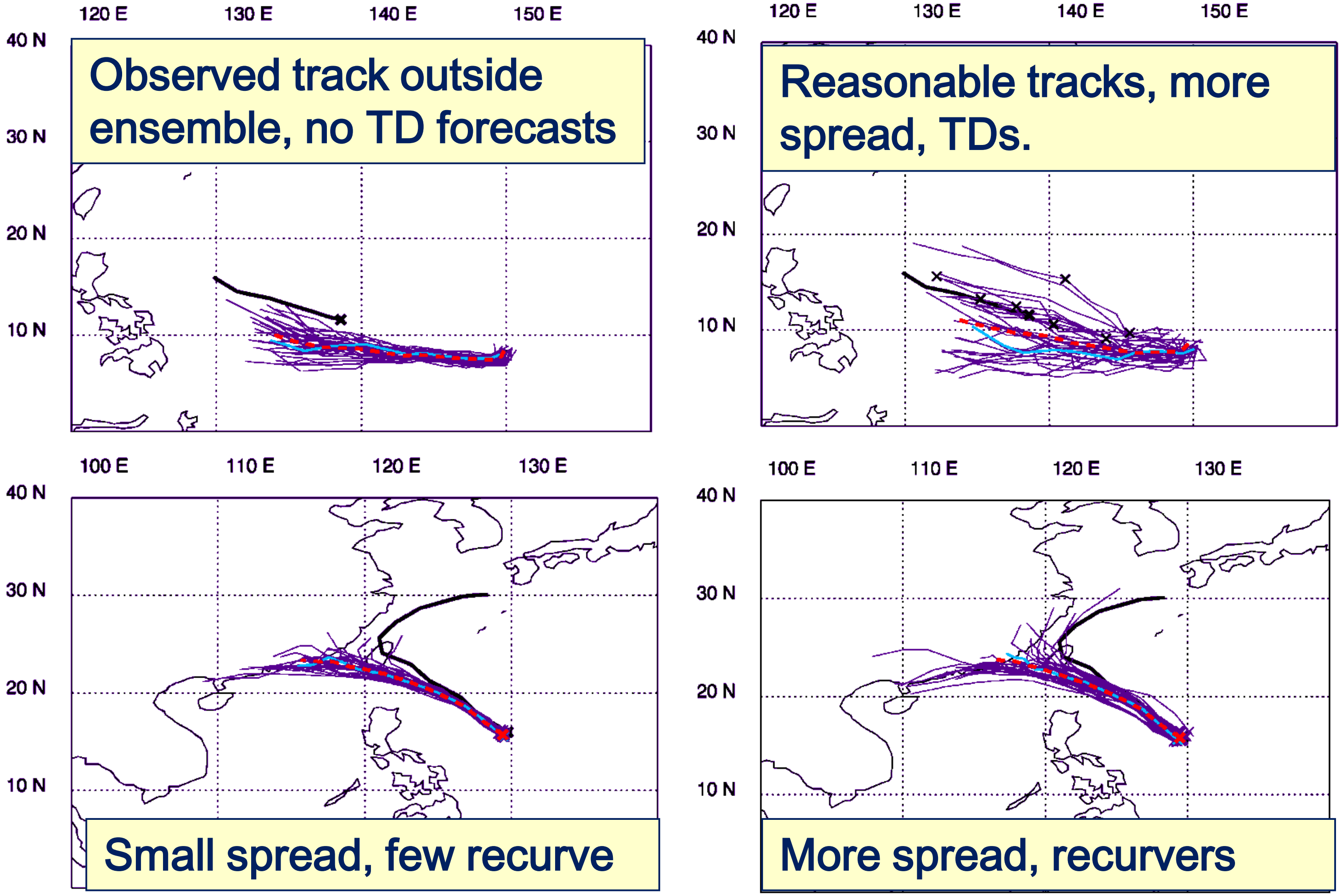
# Stochastic Convection: Impact on TC Genesis and Track

Snyder, A., Z. Pu and C. A. Reynolds, 2011: **Impact of stochastic convection on ensemble forecasts of tropical cyclone development.** *MWR*, 139, 620-626.

## No Model Uncertainty

## Stochastic Forcing

## TC Jangmi Sept. 2008



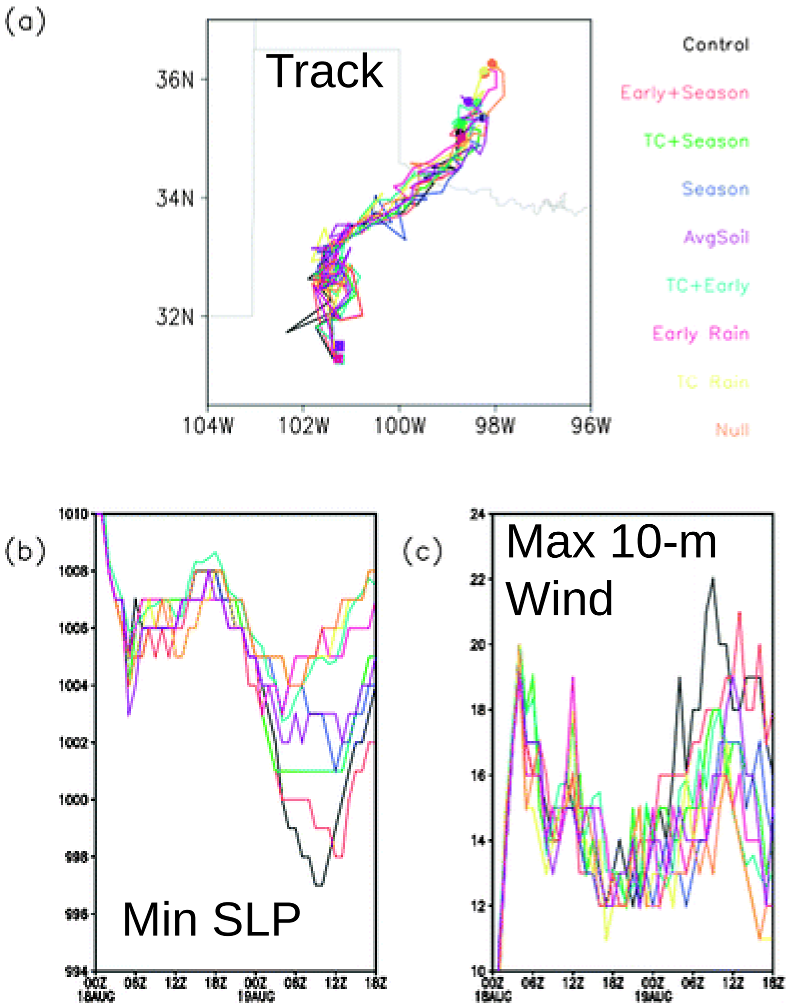

**21 Sept. 66h before Tropical Depression**

**26 Sept. 54h after TD**

**Inclusion of sub-grid scale processes improves probabilistic prediction of TCs. Stochastic forcing improves prediction of TC genesis.**

# Sensitivity of TC Erin to Soil Moisture

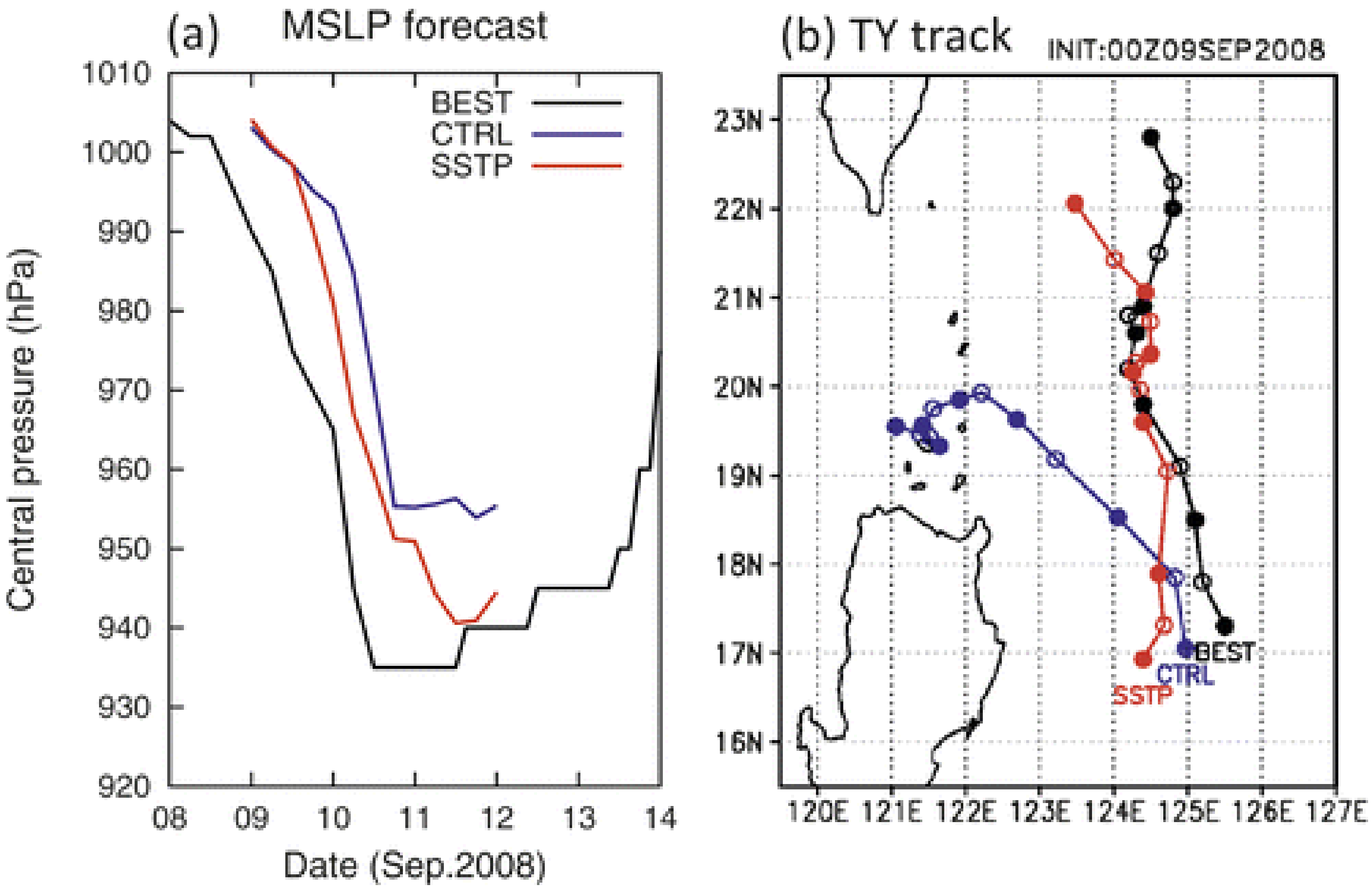
Clark Evans, Russ S. Schumacher, and Thomas J. Galarneau Jr., 2011: **Sensitivity in the Overland Reintensification of Tropical Cyclone Erin (2007) to Near-Surface Soil Moisture Characteristics**. *MWR*, **139**, 3848–3870.




**WRF-ARW simulations of TC Erin redevelopment over land exhibit substantial intensity sensitivity to soil moisture.**

# Sensitivity of TC Sinlaku LETKF to SST Perturbations

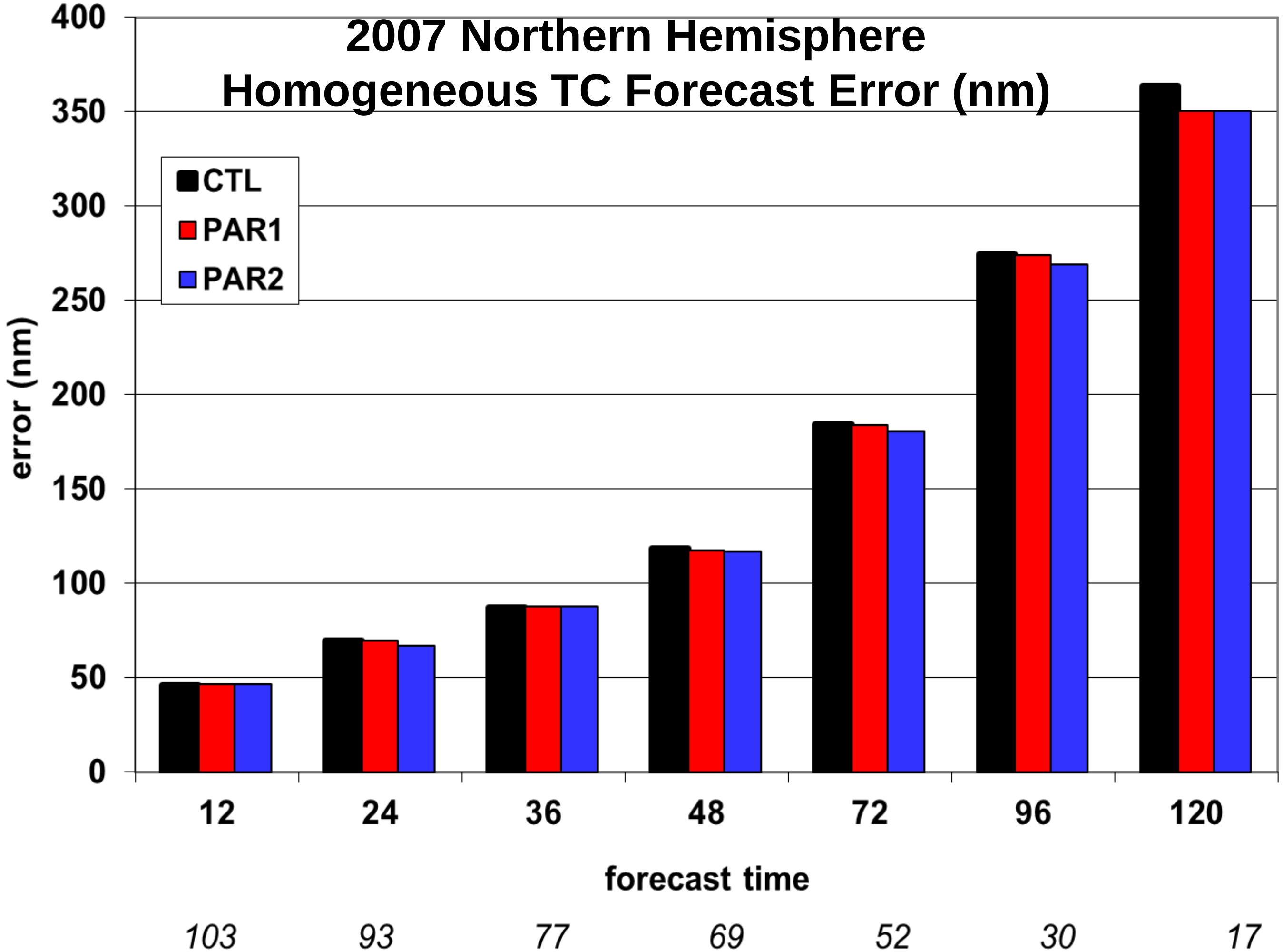
Masaru Kunii and Takemasa Miyoshi, 2012: **Including Uncertainties of Sea Surface Temperature in an Ensemble Kalman Filter: A Case Study of Typhoon Sinlaku (2008).** *Wea. Forecasting*, **27**, 1586–1597.




**SST perturbations within EnKF generally improve analyses and their subsequent forecasts within the WRF system.**
**Suggests importance of coupled Air-Ocean DA and forecasts.**

# Parameter Variations: Impact on TC Tracks

Reynolds, C. A., J. A. Ridout, and J. G. McLay, 2011: **Examination of parameter variations in the U. S. Navy Global Ensemble.** *Tellus*, **63A**, 841-857.




**Small but significant improvements to TC track forecasts with inclusion of parameter variations in convection and PBL schemes.**

# Summary and Discussion Points

There are substantial uncertainties in many of the model processes and forcing that impact TC track and intensity (e.g., lateral and surface boundary forcing, parameterizations, parameter values).

A well-designed ensemble should account for these model uncertainties.

- Different methods can be complementary, but they are not necessarily independent.
- How do we determine the characteristics of these model uncertainties?

  (e.g., parameter estimation methods; Rios-Berrios et al. 2014)

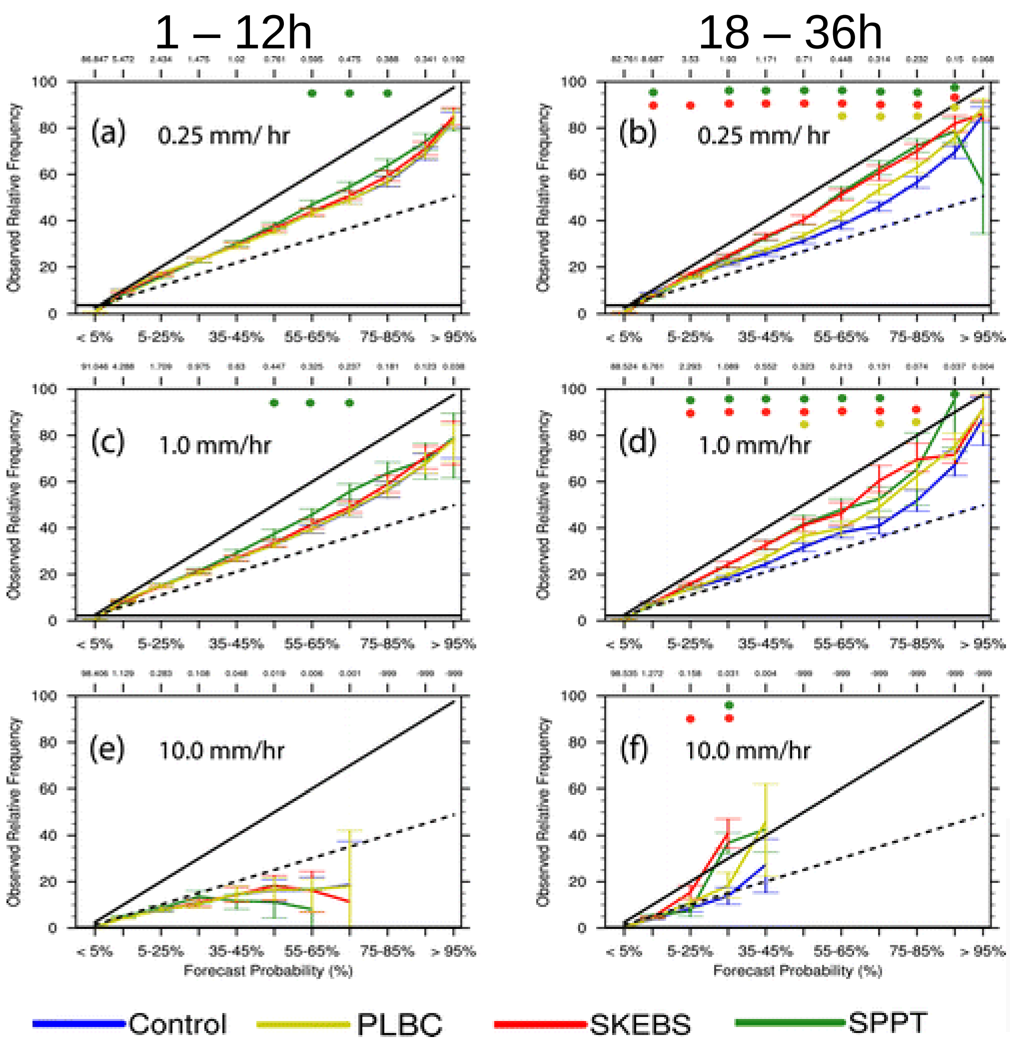
Improvements in both deterministic and probabilistic verification are obtained through inclusion of model uncertainty in ensemble design (e.g., multi-model ensembles, parameter variations, stochastic forcing, lateral and surface boundary forcing).

- 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

# Model Uncertainty in Convection Permitting EFSs

G. S. Romine, C.S. Schwartz, J.Berner, K.R. Fossell, C.Snyder, J.L. Anderson, and M. L. Weisman, 2014: **Representing Forecast Error in a Convection-Permitting Ensemble System**. *MWR.*, **142**, 4519–4541.



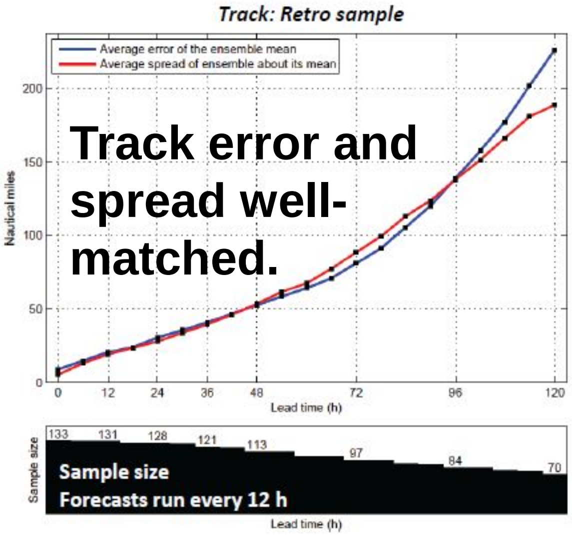

**Rain-rate reliability improves with addition of perturbed lateral boundary conditions, SKEBS and SPPT.**

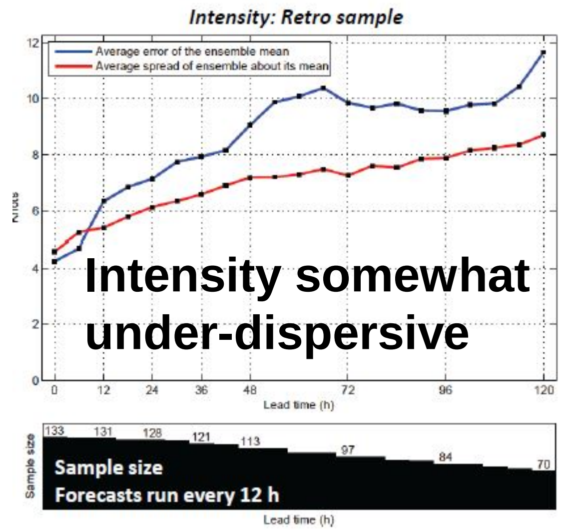
**Deterministic ensemble member forecast skill decreases when forecast perturbations are added, while ensemble mean forecasts remain similarly skillful to the control.**

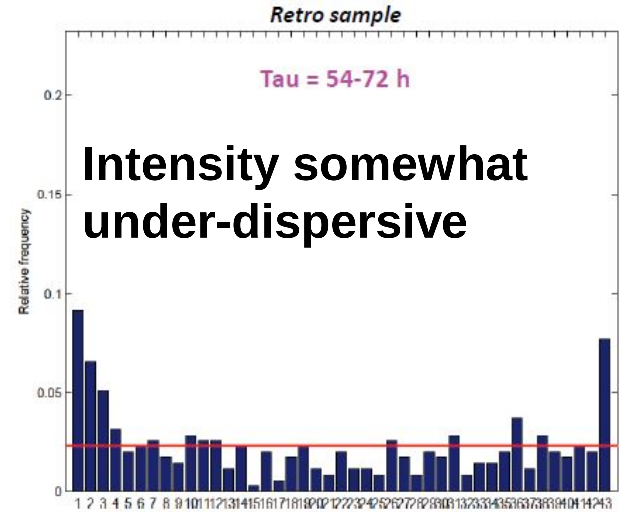
Attributes diagrams for ensemble forecasts initialized from 25 May to 25 Jun 2012. Perfect reliability (diagonal line), observed frequency (solid black line from observed relative frequency axis), "no skill" relative to climatology (dashed line).

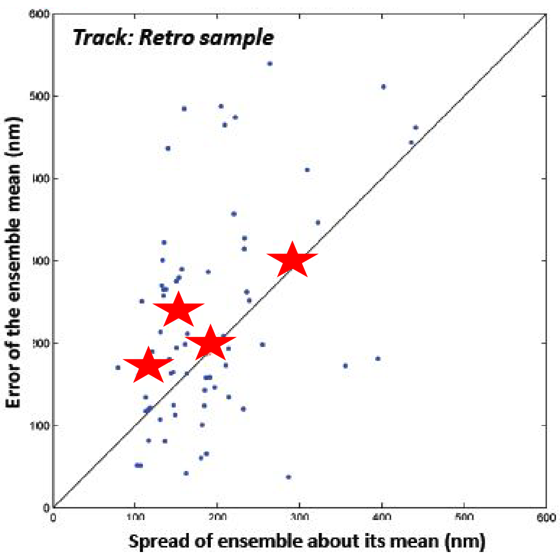
# NOAA HFIP Multi-Model Ensemble

**HWRF EPS (27/9/3 km, 42 levels) – 21 members**
**GFDL EPS (55/18/6 km, 42 levels) – 10 members**
**COAMPS-TC EPS (27/9/3 km, 40 levels) – 11 members**

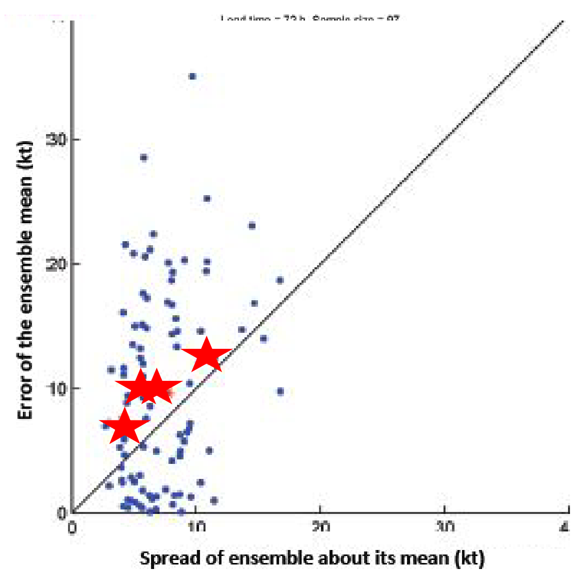



**Larger 120-h track error (left) and larger 72-h intensity error (right) associated with larger ensemble spread, on average**



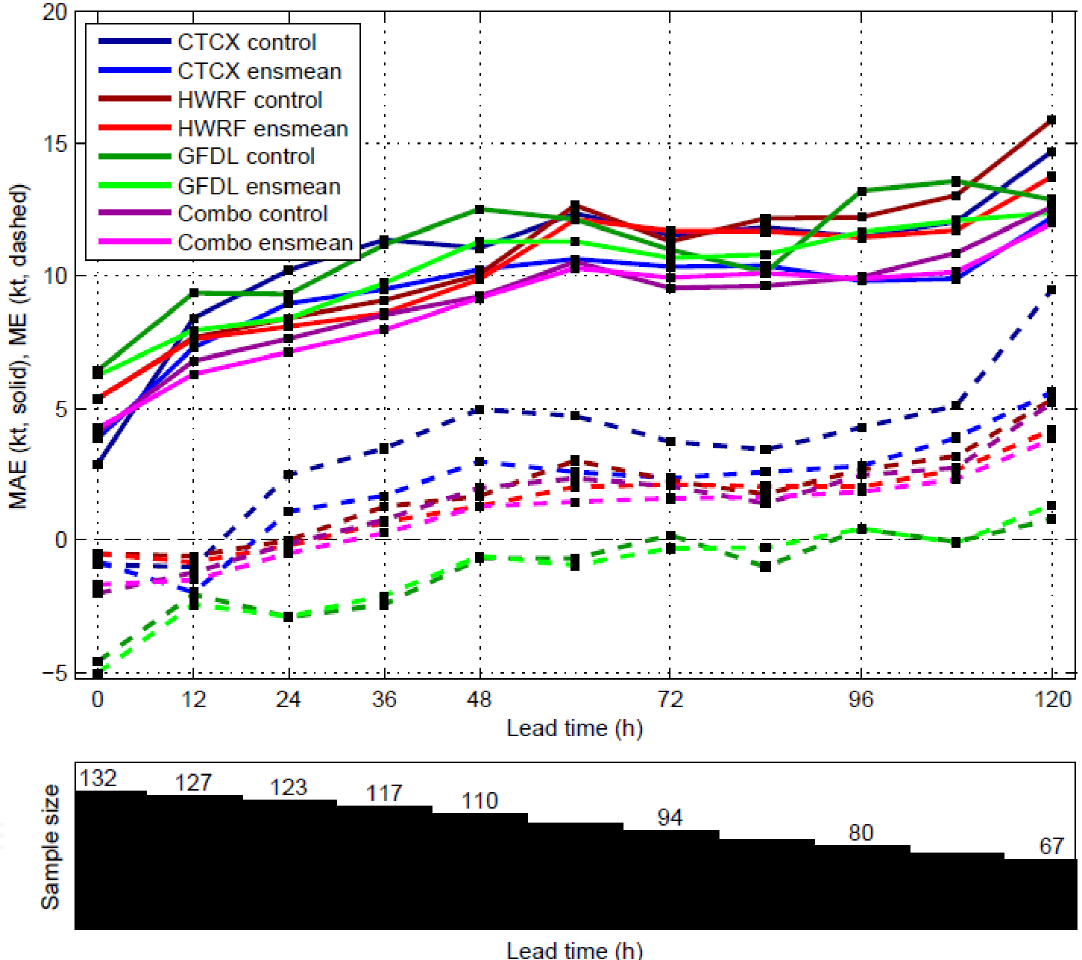

*NRL Analysis*

# NOAA HFIP Multi-model Ensemble

## NOAA Hurricane Forecast Improvement Program multi-model

**HWRF EPS (27/9/3 km, 42 levels) – 21 members**
**GFDL EPS (55/18/6 km, 42 levels) – 10 members**
**COAMPS-TC EPS (27/9/3 km, 40 levels) – 11 members**

*Solid: Mean absolute error   Dashed: Mean error*




**For individual model, ensemble mean has improved accuracy relative to the control**

**Combined ensemble mean has accuracy similar to consensus of three control members**

**In this 2011-2013 retro sample, combo control and ensemble mean outperform component models**

**Control forecasts:**
COAMPS-TC: C00C
HWRF: HW00
GFDL: GP00
Combo : Consensus of C00C, HW00, and GP00

**Ensemble mean requirements**:
COAMPS-TC: 9 of 11 members
HWRF: 17 of 21 members
GFDL: 8 of 10 members
Combo: 34 of 42 members

# MULTI-MODEL ENSEMBLES

**Tropical Cyclone Track Forecasts Using an Ensemble of Dynamical Models**

J. S. Goerss, *MWR*, 128, (2000) 1187-1193

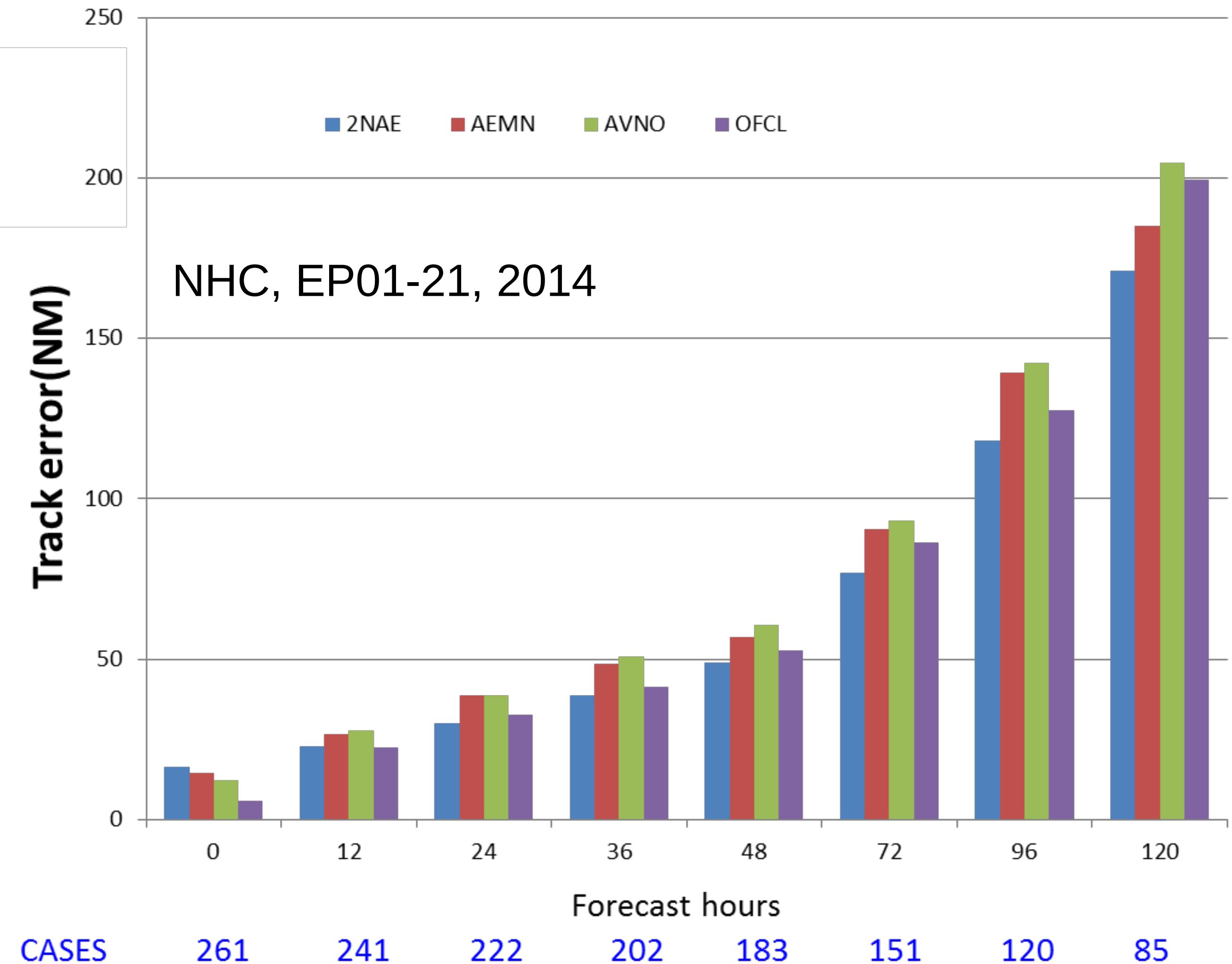
Simple ensemble average (***consensus***) may be more accurate, on average, than the forecasts of the individual models.

| | $N$ | 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

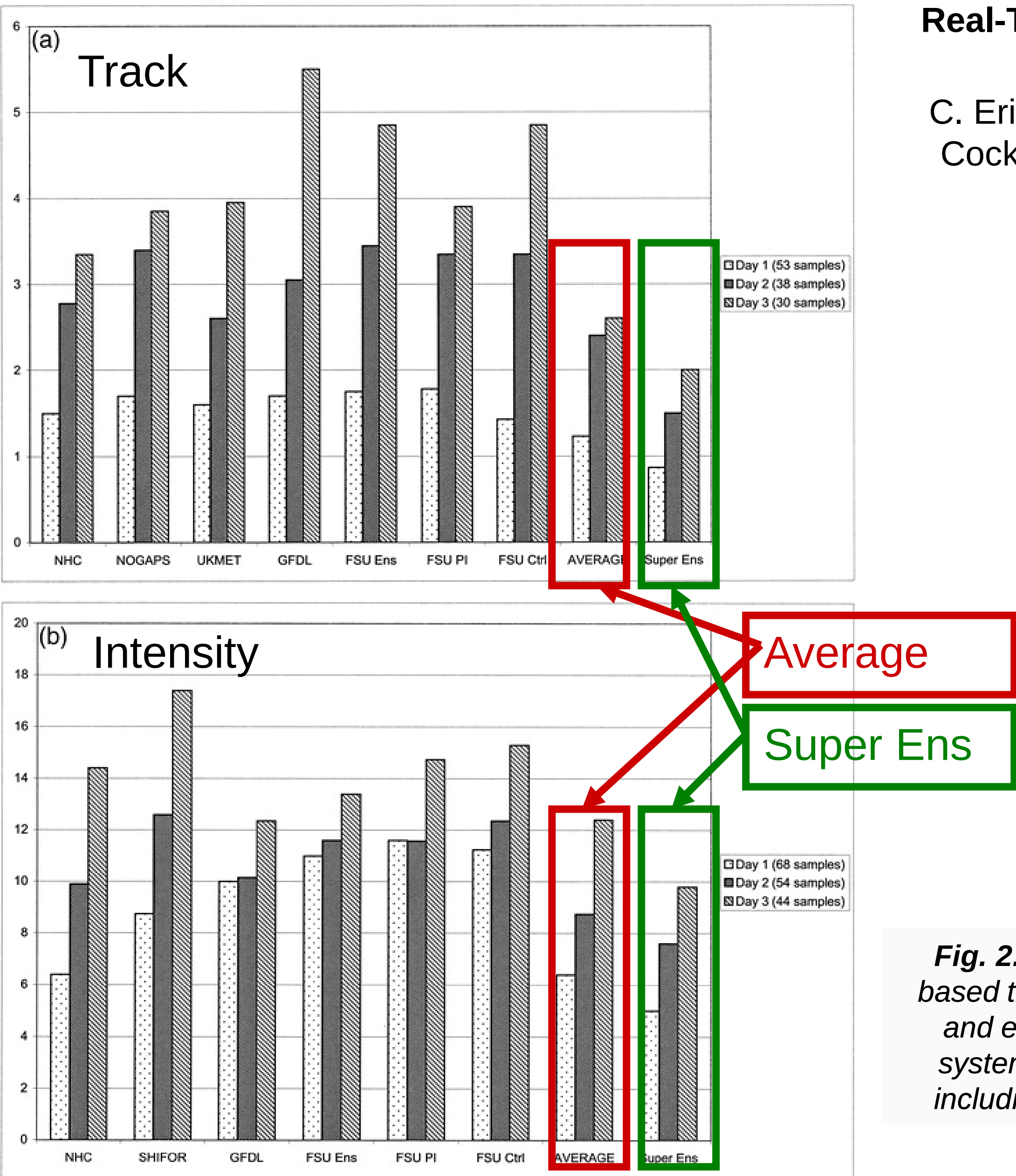
**2014 NUOPC TC Track Verification from Jiayi Peng and the EMC Ensemble Tem**




**Multi-model ensemble (2NAE) superior to either the GFS determinisitc (AVNO) or GFS ensemble (AEMN).**

**However, multi-model ensembles do not necessarily out-perform best single-model ensemble if there are substantial differences in single-model ensemble skill.**

# 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.**

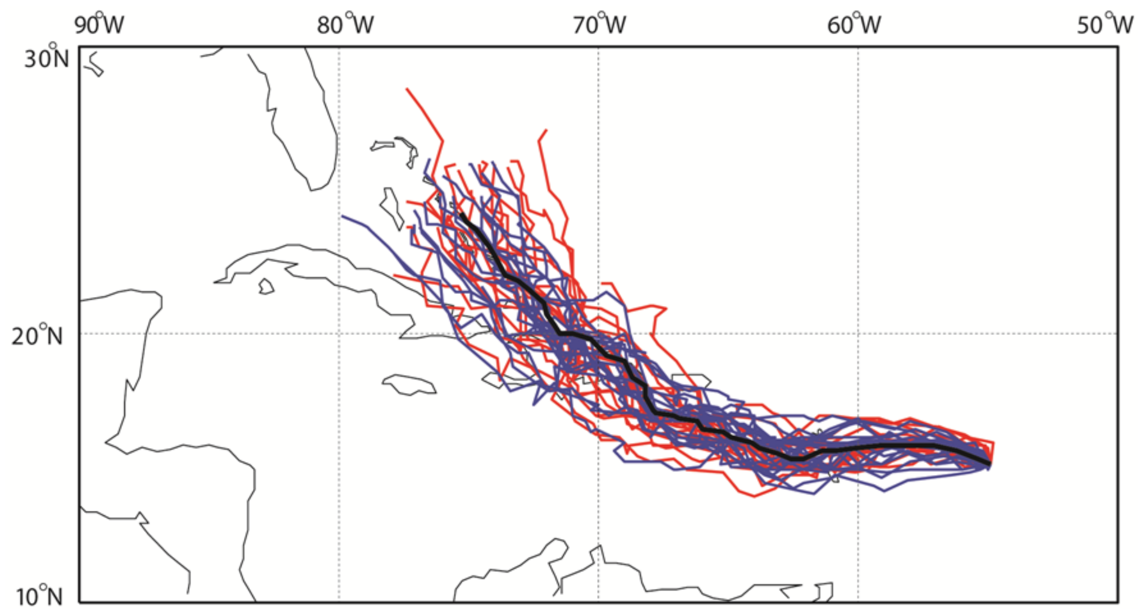
**Errors for superensemble are generally less than those of all the participating models during 1-5 day real-time forecasts.**

***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*

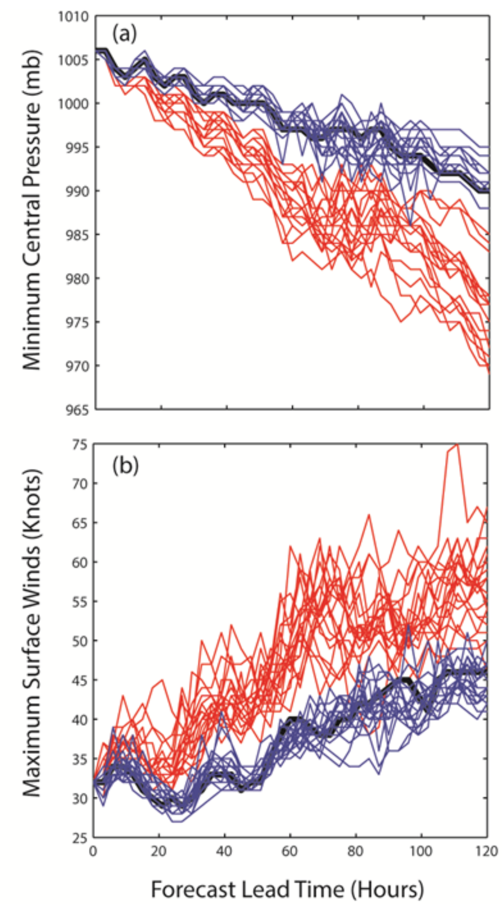
# Inducing TCs to undergo Brownian Motion

Daniel Hodyss, Justin G. McLay, Jon Moskaitis, and Efren A. Serra, 2014: **Inducing Tropical Cyclones to Undergo Brownian Motion: A Comparison between Itô and Stratonovich in a Numerical Weather Prediction Model**. *MWR*, 142, 1982–1996.

## Hurricane Isaac (2012)




**Red - Itô  Blue - Stratonovich  Black - Control**

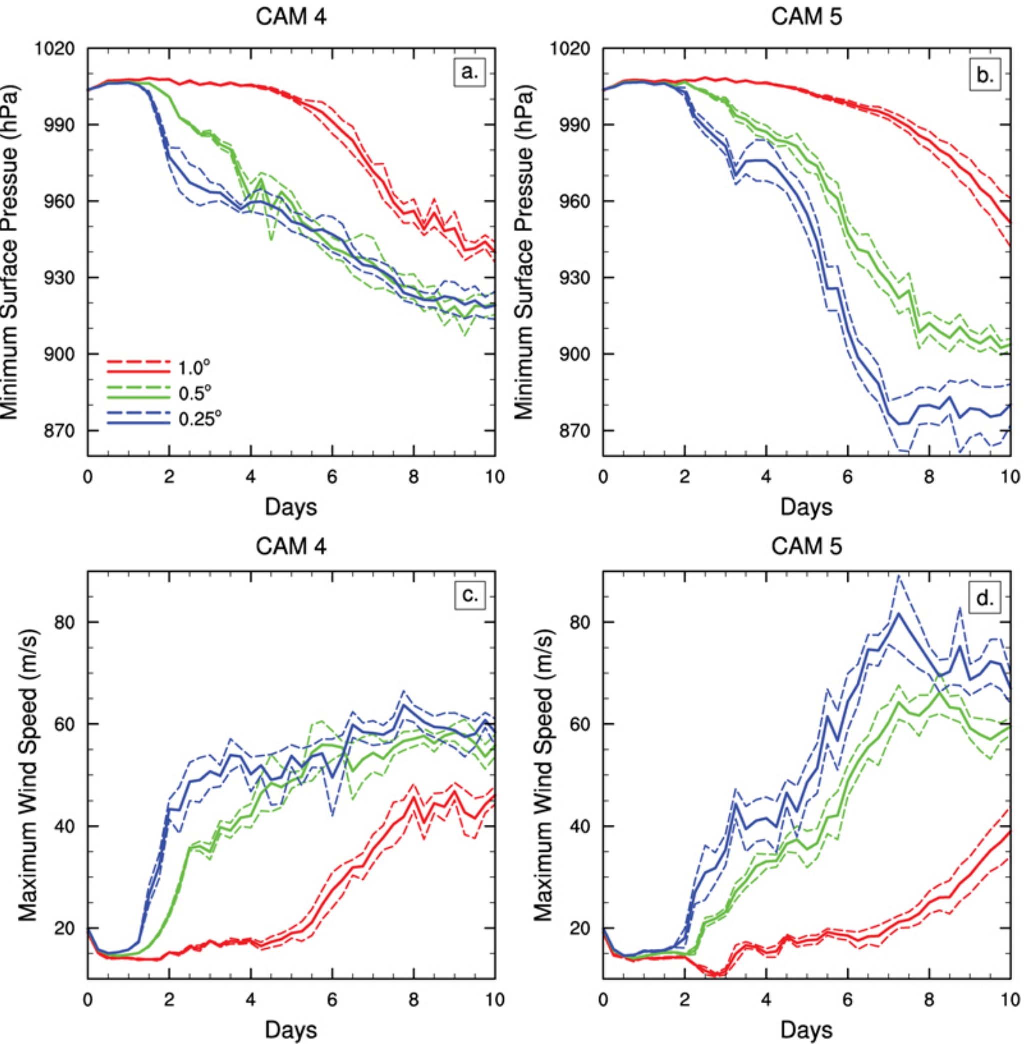



**Ensemble TC distribution can be inflated using a stochastic phase speed parameterization. The stochastic parameterization must be implemented properly (blue) to get the correct solution.**

**The intensity of the TCs are too strong from the Itô algorithm.**

# Aqua-planet CAM4 and CAM5 TC Sensitivity to Resolution

Reed and Jablonowski, 2011: **Assessing the Uncertainty in Tropical Cyclone Simulations in NCAR's Community Atmosphere Model**. *JAMES* V3.




**No systematic difference in the ensemble simulations when comparing the initial-data and parameter uncertainties.**

**The majority of the uncertainty depends on two main factors: the horizontal resolution and the version of CAM.**

Time evolution of the (top) minimum surface pressure and (bottom) maximum wind speed at 100 m of the control case at the horizontal resolutions of 1.0° (red), 0.5° (green) and 0.25° (blue) with CAM 4 and CAM 5. Solid line represents control case and dashed lines represent that the variance as determined by the ensemble RMSD.

# 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

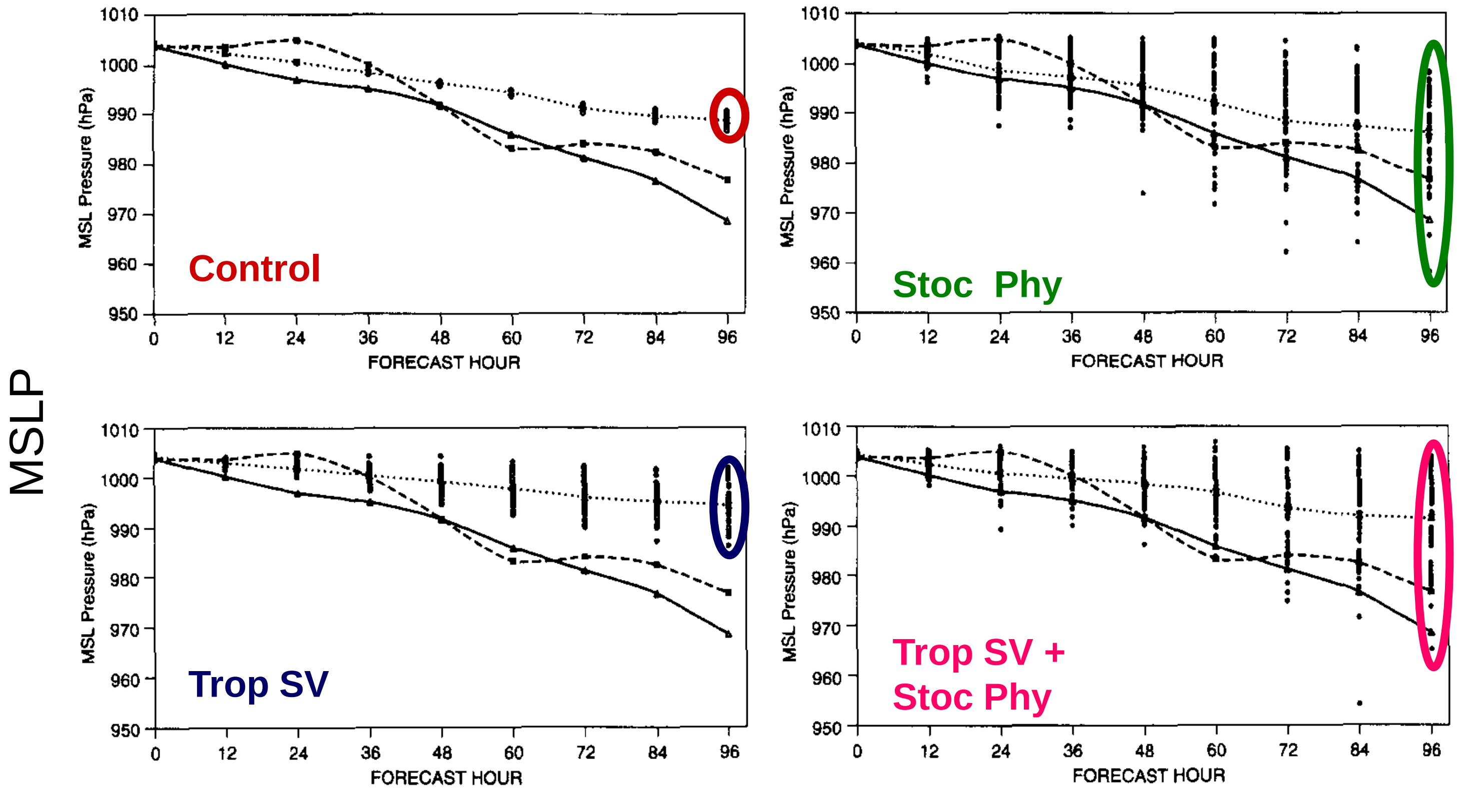



Figure 4(c). As in Fig. 3(b) but for TC Zeb and ensemble prediction system run with no stochastic physics (top left), with stochastic physics (top right), tropical singular vectors (SVs) (bottom left) and tropical SVs + stochastic physics (bottom right).

- 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 PERTURBATIONS: IMPACT ON TCs

Lang, S. T. K., M. Leutbecher, and S. C. Jones, 2012: **Impact of perturbation methods in the ECMWF ensemble prediction system on tropical cyclone forecasts.** *QJRMS*., 138., 2030-2046.

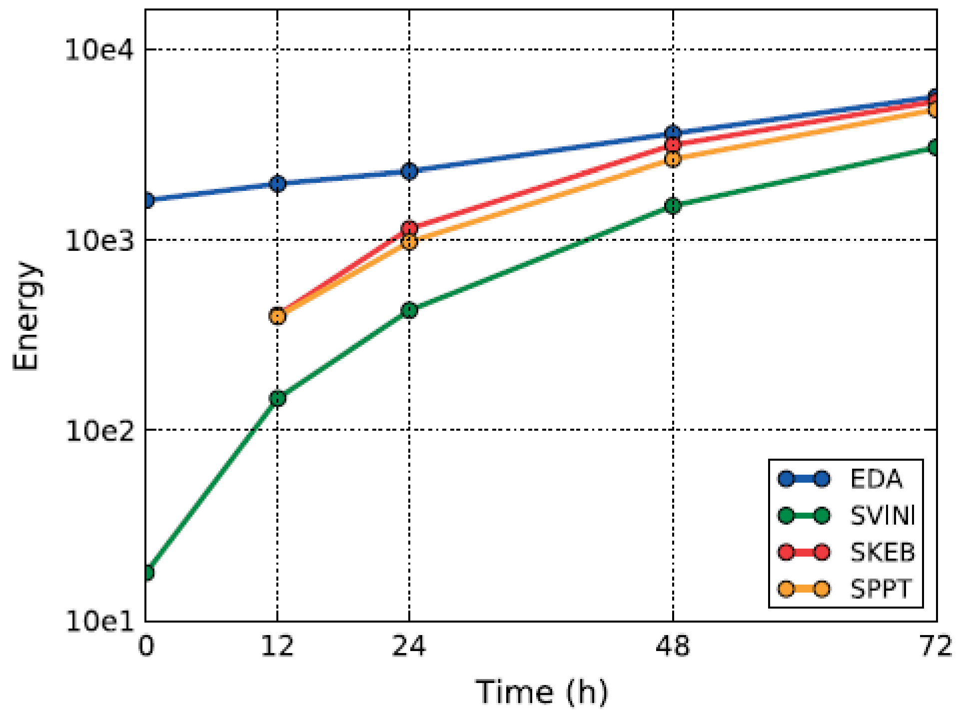
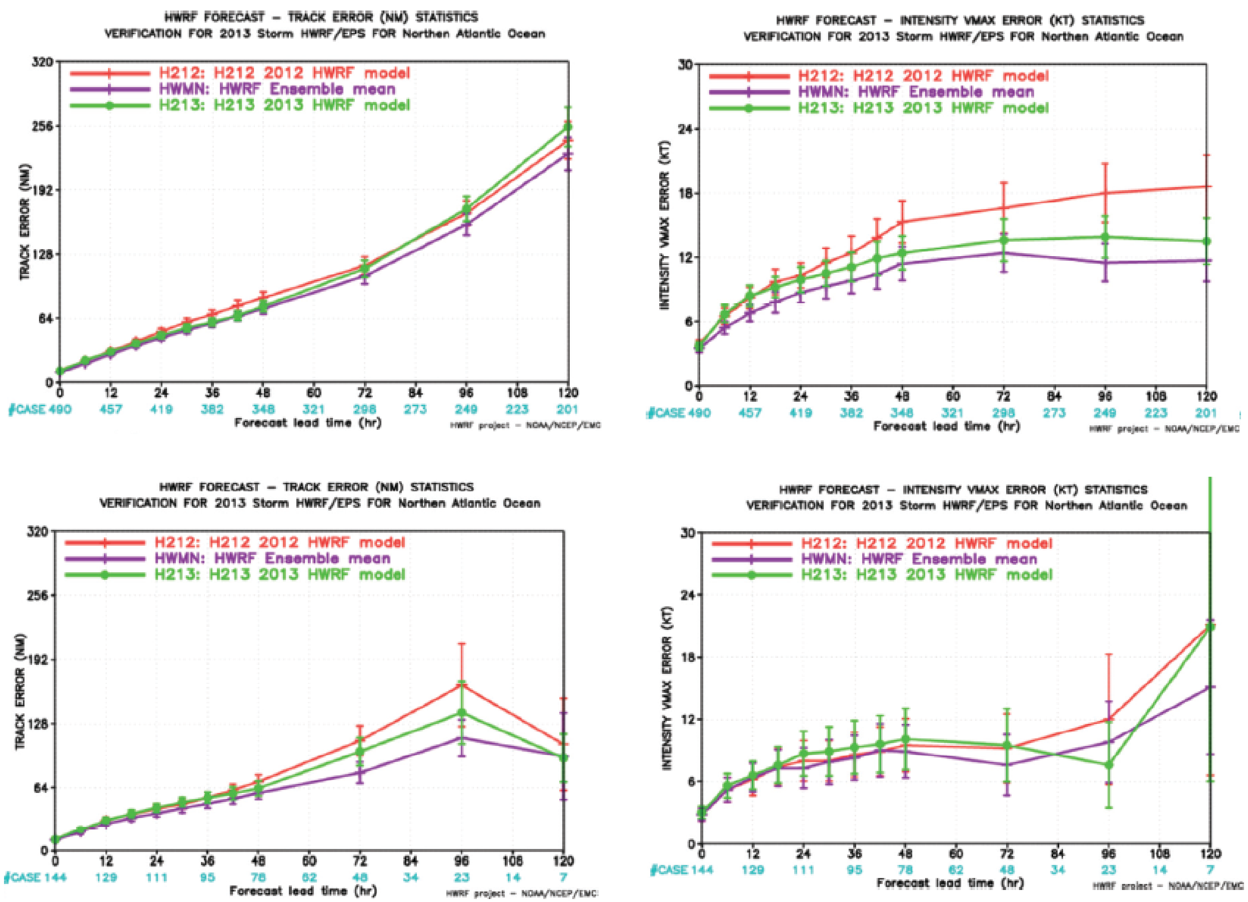



**Figure 1.** Mean perturbation total energy (integrated and area-weighted) within a 20° × 20° box centred on the forecast positions of the TCs. The scaling of the *y*-axis is logarithmic.

**Different perturbation methods have very different impacts on TC track and minimum SLP at early times, but converge after a few days.**

# HWRF Ensembles: Stochastic Convection Trigger Function

Z. Zhang, V. Tallapragada, C. Kieu, S. Trahan, and W. Wang, 2014: **HWRF based ensemble prediction system using perturbations from GEFS and stochastic convective trigger function.** *Tropical Cyclone Research and Review*, 3, 145-161.




**HWRF ensemble mean with stochastic convective trigger function and GEFS perturbations outperforms deterministic HWRF.**

FIG. 2. Comparison of the statistics of the mean track errors (nautical miles) and the mean intensity errors (kts) during the 2011-2012 hurricane seasons between HWRF EPS (purple, HWMN) and its deterministic models H212 (red, 2012 operational HWRF) and H213 (green, 2013 operational HWRF) for the Atlantic basin (top panels: track at left, intensity at right) and Eastern Pacific basin (bottom panels: track at left, intensity at right). The vertical bars in the plots indicate 95% confidence levels. The number below the x-axis denote the number of cases (cycles) verified at each forecast lead time.

# Most Ensemble Prediction System include some method to account for model uncertainty

## Operational global (weather) EPS

Black: current, Red: recent upgrade, green: planned or research

| Center | Resolutions | FC Range | Members | Initial perturbation, DA | Model Uncertainty | B.C. |
|---|---|---|---|---|---|---|
| ECMWF (Europe) | TL639L91<br>TL319L91<br>18/36km (p) | 10d<br>+5d | 51 | SV(Total energy norm) + EnDA | SKEB and Stochastic physics<br>update of backscatter scheme | coupling to ocean model, EDA-based land-surface pert. in ENS ICs |
| Met Office (UK) | 33kmL70<br>21km (p) | 7d | 11+1<br>18/24 (p) | ETKF<br>En-4D-EnVar (p), 4D-EnVar (p) | Random Parameters (RP2) and SKEB2. | N<br>Coupling to ocean (p) |
| Meteo France (France) | TL538(C2.4)L65 | 4d | 35 | SV (Total Energy Norm)+ EnDA | different packages, randomly used | N |
| HMC (Russia) | T169L31<br>25-30km (p) | 10d | 12+1+1 | Breeding<br>EnVar DA (r) | N<br>SPPT (p) | ? |
| NCEP (USA) | T254L42<br>T190L42<br>$T_L$573/382L64 (p) | 8d<br>+8d<br>35d (p) | 45 | Ensemble Transform with Rescaling | stochastic pert. to account for random model errors<br>SKEB, SPPT, SHUM (p) | N<br>Stochastic pert. of land, couple with ocean (p) |
| NRL/FNMOC (USA) | T159L42<br>T359L60 (p) | 16d | 20 | local ET<br>Hybrid 4D-Var (r) | N<br>SKEB-mc (p) | N<br>SST initial pert. (p) ocean, ice, wave coupling (r) |
| CMC (Canada) | 0.6° L40 | 16d | 20 | Ensemble KF | stochastic pert. of physical tendencies and SKEB<br>further pert. to the physics | new method to evolve SST and sea-ice |
| CPTEC/INPE (Brazil) | T126 L28 | 15d | 15 | EOF-based perturbation | N | N |
| BoM (Australia) | ~60kmL70 | 10d | 24 | ETKF | Random Parameters (RP2) and SKEB2. | N |
| JMA (Japan) | TL479 L60<br>TL479L100 (p) | 11d<br>18d (p) | 27 | SV(Total energy norm)<br>Reduce tropical initial pert. (p) | Stochastic perturbation of physics tendency | N<br>Rev, SST and sea ice (p) |
| CMA (China) | T213 L31 | 10d | 15 | bred vector method | N | N |
| KMA (Korea) | ~40kmL70<br>32km (p) | 12d | 24<br>44 | ETKF<br>Hybrid Ensemble 4D-Var | Random Parameters (RP2) and SKEB2. | N |

**Ishida and Reynolds WGNE ensemble report, March 2015**

# *Parameterization of Moist Processes for Next-Generation Weather Prediction*

## *NOAA Center for Weather & Climate Prediction, College Park, Maryland, January 27-29, 2015*

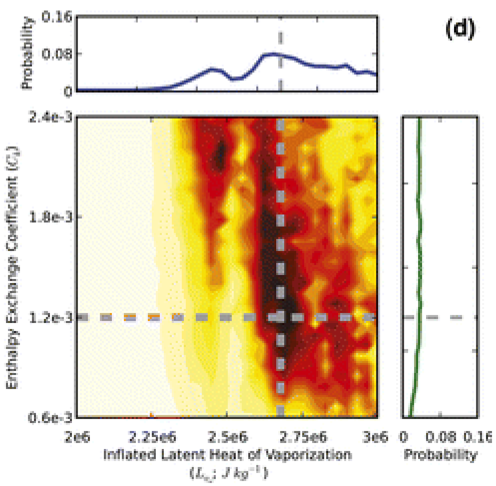
Probability distributions are useful in two distinct contexts: 1) for representing variability at scales below or approaching the model resolution, and 2) to describe uncertainty and improve spread-skill relationships in probabilistic ensemble forecasts. **It is natural to expect that model uncertainty could be estimated directly by parameterizations and expressed by, for example, drawing the parameterization tendency from a distribution of expected outcomes.**

**However, the parameterization community is not yet ready to provide estimates of state-dependent parameterization error to replace current ad-hoc estimates of model error to increase ensemble spread.** Data assimilation, sensitivity assessment, and parameter estimation are the most useful current approaches for developing understanding of the response of model output to changes in parameters, how this response maps onto the resolved scales, and how the local and grid scale response changes with environment, flow, etc. Nonetheless, **ad hoc perturbations to physical tendencies remain the most effective solution for maintaining the dispersion of ensembles through the duration of a forecast.**

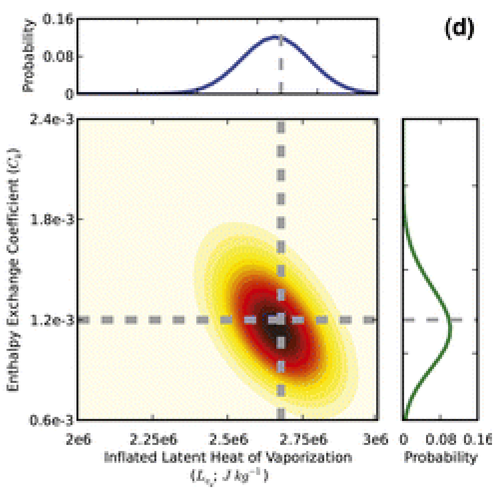
# Axisymmetric Simplified Pseudoadiabatic Entropy Conserving Hurricane (ASPECH) model.

Rosimar Rios-Berrios, Tomislava Vukicevic, and Brian Tang, 2014**: Adopting Model Uncertainties for Tropical Cyclone Intensity Prediction**. *MWR*, **142**, 72–78.

Posterior Joint PDF estimates of enthalpy exchange coefficient and latent heat of vaporization:




Poor results based on Vmax only




Good results based on radial, tangential, and vertical wind within 150-km radius, surface to 18-km.

**Results support need to use an ensemble of model parameterizations for TC intensity prediction.**

**Results also indicate that the ensemble should be based on the optimal estimation in order to include realistic ranges and mutually dependent parameter perturbations between different processes.**