



# Stochastic Physics in FV3GFS

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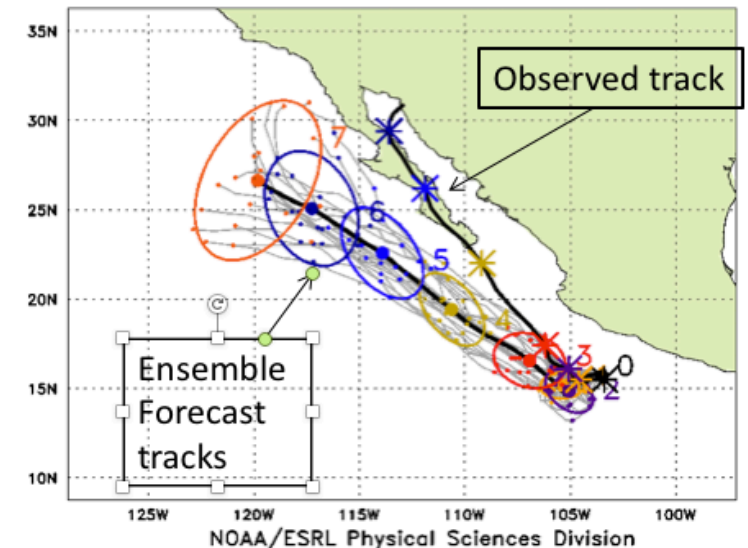
Boulder, CO

# Why is there a need for stochastic physics?

## In medium range NWP

- Even if the model is initialized with perfect initial conditions, there will be errors in the forecast due to model error.
- There are many sources of errors in the model:
  - Discretion in space and time of a continuous fluid
  - Errors in the physical parametrizations
  - Missing physics
- These errors manifest themselves as an overconfident forecast in an ensemble prediction system.
- Stochastic physics adds random perturbations to represent the uncertainty associated with unresolved processes.

Hurricane Odile: Initialized Sept. 11, 2014 at 00Z  
GEFS operational ensemble



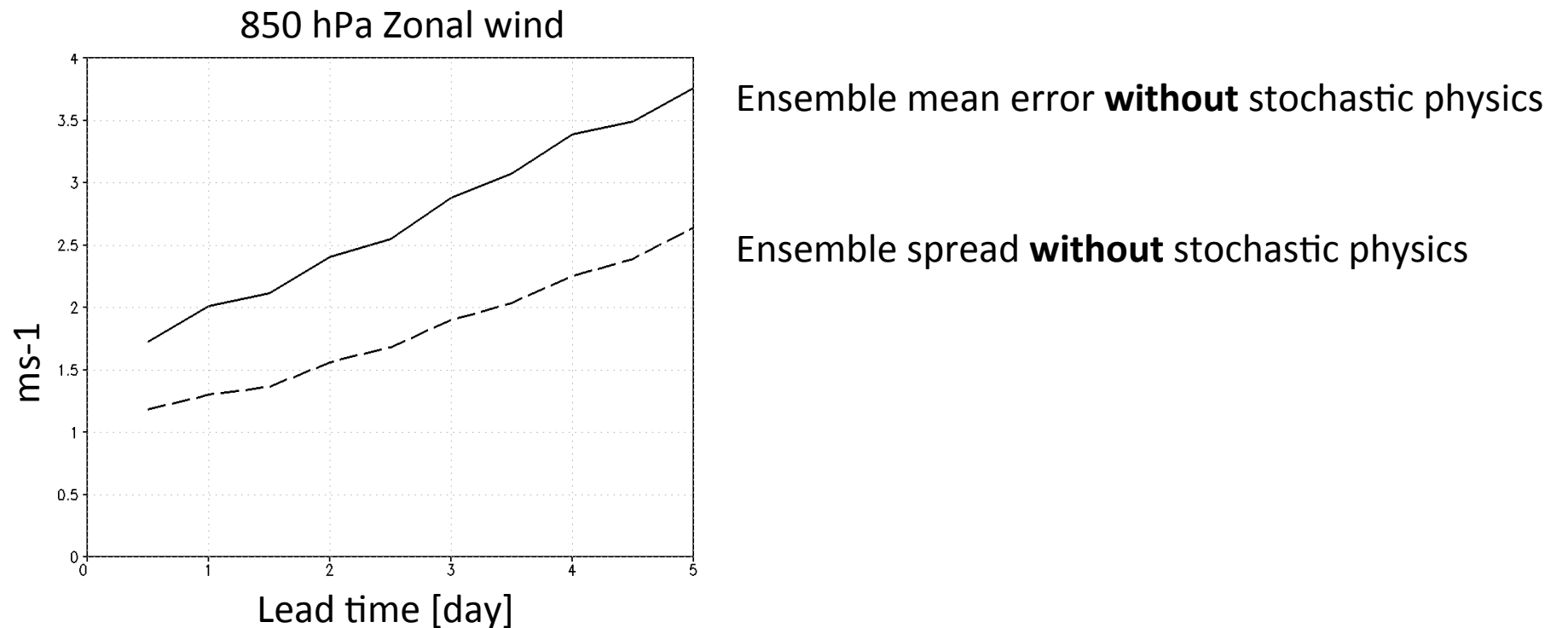
GFS ensemble was confident that the hurricane would stay off shore.

## In ensemble Data assimilation

- Model error results in a first guess forecast that is deficient in spread. This lack of spread would result in the EnKF analysis giving too much weight to the model, and not draw close enough to the observations.
- During the 9-hour forecast, the ensemble spread would actually decrease since the noise added that the analysis time would not project onto the growing modes.
- At the time, multiplicative and additive noise was applied to the analysis ensemble to make up for the lack of spread. But this initial spread actually decrease during the first few hours of the first guess.

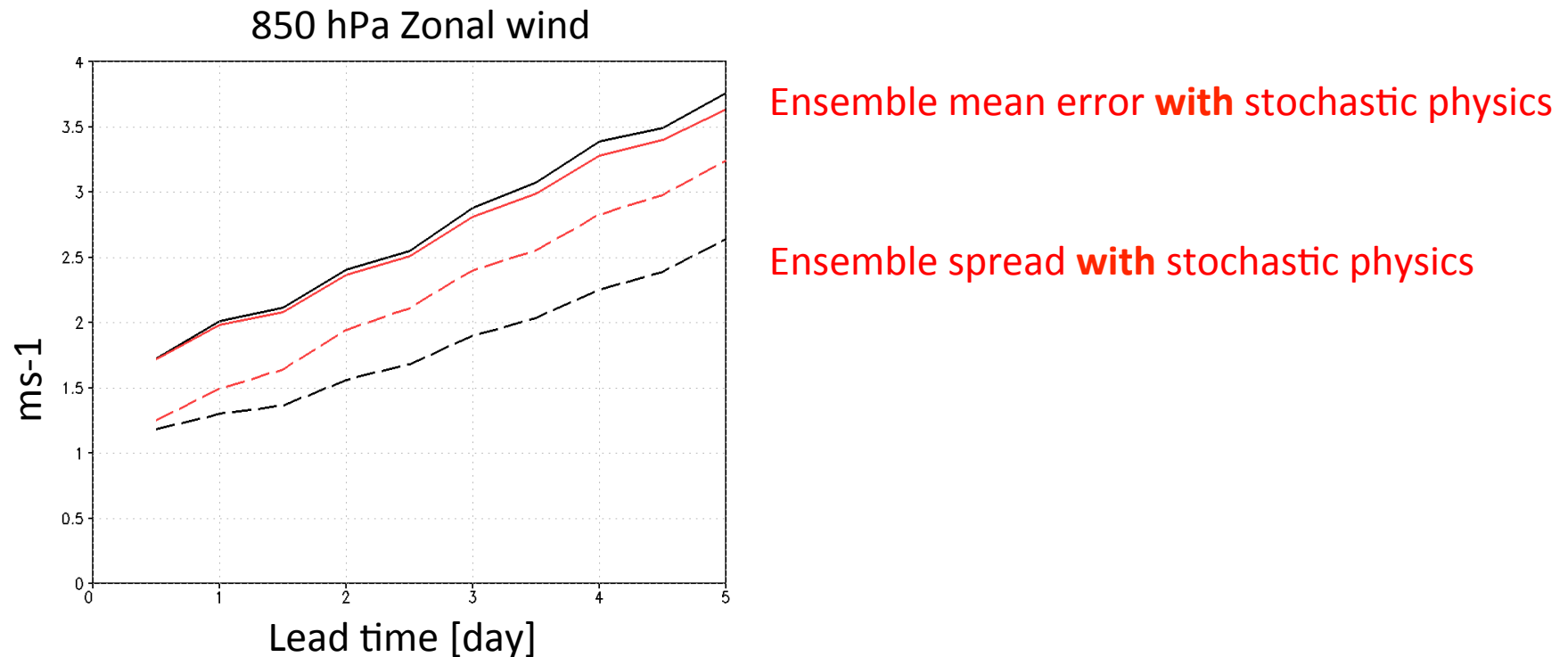
# Benefit of stochastic physics

- Increase in ensemble spread, which makes the forecasts more reliable.
- A bonus result is a decrease in the Ensemble mean RMS error!



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# What is implemented?

- **SKEB: Stochastic Kinetic Energy Backscatter** (Berner *et al.*, 2009)
  - Add wind perturbations to model state. Perturbations are random in space/time, but amplitude is determined by a smoothed dissipation estimate provided by the dynamical core.
  - **Addresses errors in the dynamics - more active in the mid-latitudes**
- **SPPT: Stochastically Perturbed Physics Tendencies** (Palmer *et al.*, 2009 )
  - Multiply the physics tendencies by a random number  $O [0,2]$  before updated the model state.

$$X_p = (1 + r\mu)X_c$$

- **Addresses error in the physics parameterizations – most active in boundary layer and convective regions**

# What is implemented?

- **SHUM:** Specific HUMidity perturbations (inspired by Tompkins and Berner, 2008 )
  - Multiply the low-level specific humidity by a small random number each time-step.

$$q_{perturbed} = (1 + r\mu)q$$

- **Attempts to address missing physics - most active in convective regions**
- **Land surface perturbations** (Gehne et al. 2018 Submitted):
  - Allow for land surface parameters such as Albedo, Soil Hydraulic Conductivity, LAI, roughness lengths to vary in space.
  - **Addresses error in the land model**

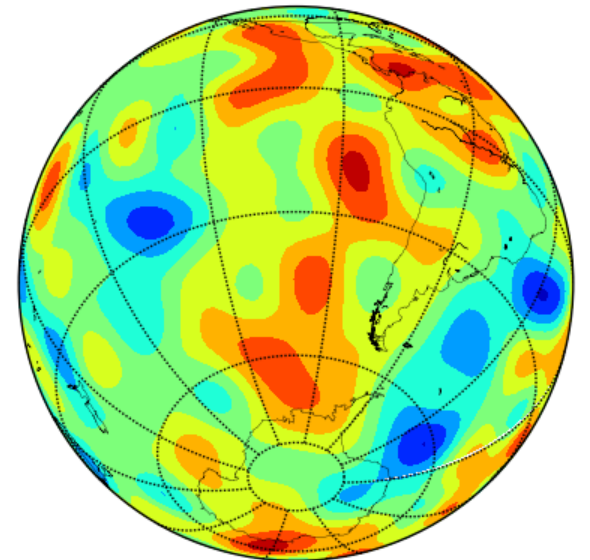
# Special handling for stochastic physics

- Traditional physics operates on columns, and does not know about the surrounding neighbors.
- Stochastic physics requires that the random numbers used are correlated in space and time.
  - Time is easy, space is more complicated on the cubed-sphere grid.
- The random pattern generator is outside of the physics and dynamics.
- Currently uses spherical harmonics and spectral transforms transplanted from the GSM.



# Creating random patterns correlated in space and time

- We aim for random patterns to have a spatial decorrelation scale on the order of 500 km and a 6-hour time-scale.
- The spectral resolution of the random patterns is independent of the "C" resolution of the model, but due to the parallelization of the spherical harmonics, there is a minimum spectral resolution for a given number of mpi tasks.



# Step-by-step

1. An AR(1) time-series is generated for each spherical harmonic:

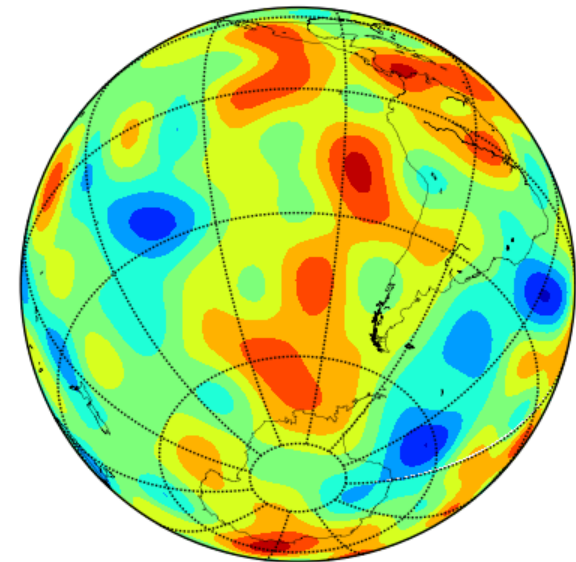
$$r_{lmn}(t) = \phi r_{lmn}(t - \Delta t) + \sigma_{ln} \sqrt{(1 - \phi^2)} \eta_{lmn}(t)$$

$r_{lmn}$  spherical harmonic for zonal wave number  $m$  and total wavenumber  $n$

$\sigma_{ln}$  standard deviation of the time-series. Is a function of  $n$ , decorrelation length scale, and desired amplitude of the pattern

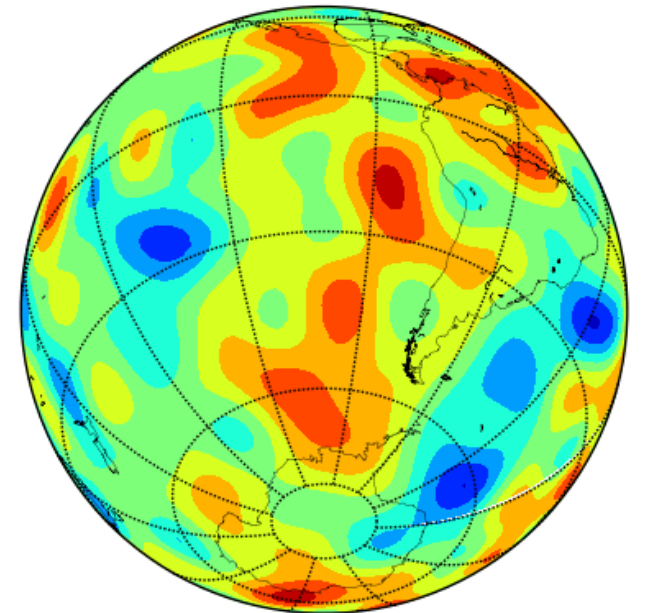
$\phi$  temporal decorrelation

$\eta_{lmn}$  random gaussian number  $E(0,1)$

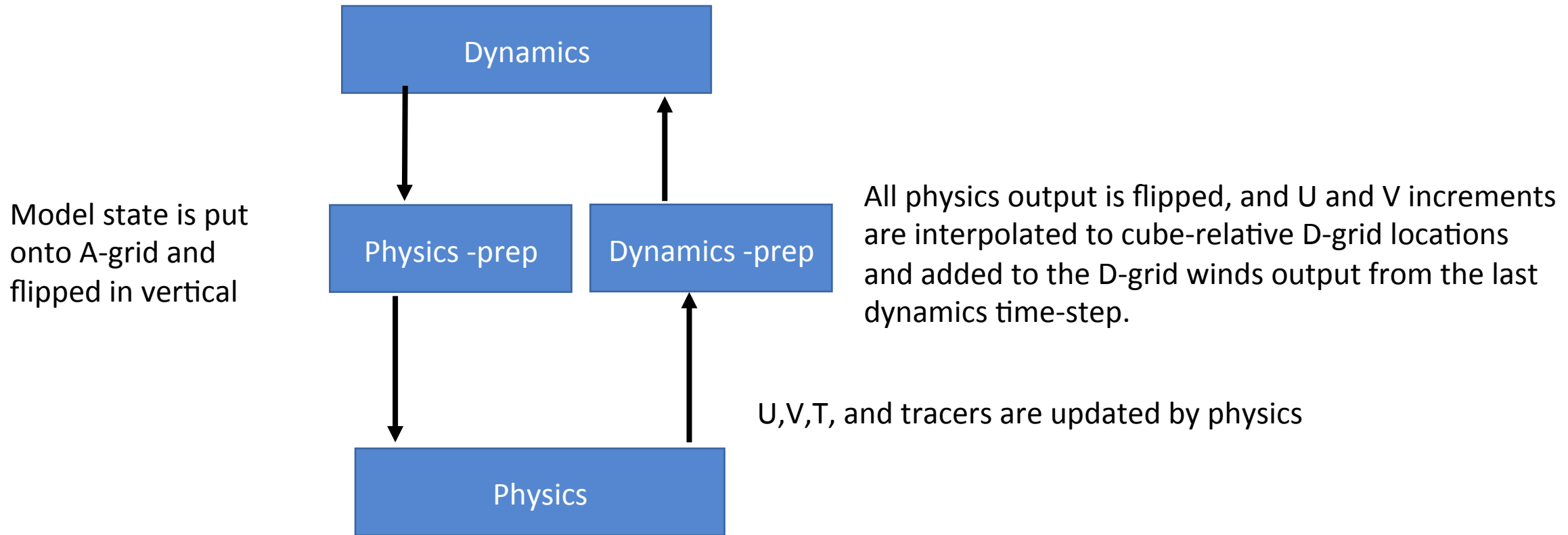


# Step-by-step

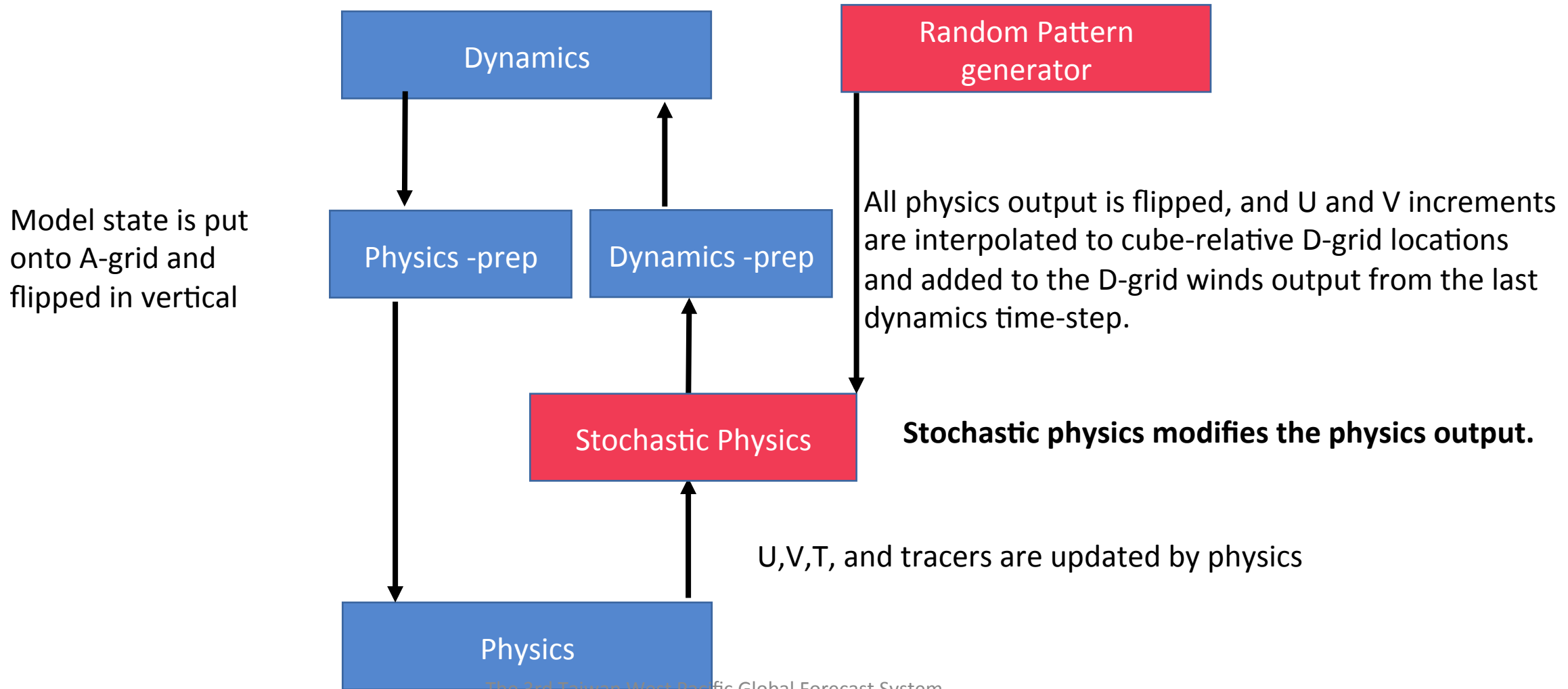
2. A Legendre-Fourier transform converts the spherical harmonics to a random pattern on a gaussian grid.
3. Each mpi task gathers the entire global gaussian grid to interpolate to its piece of the cubed-sphere (inefficient)



# Schematic without stochastic physics



# Schematic with stochastic physics



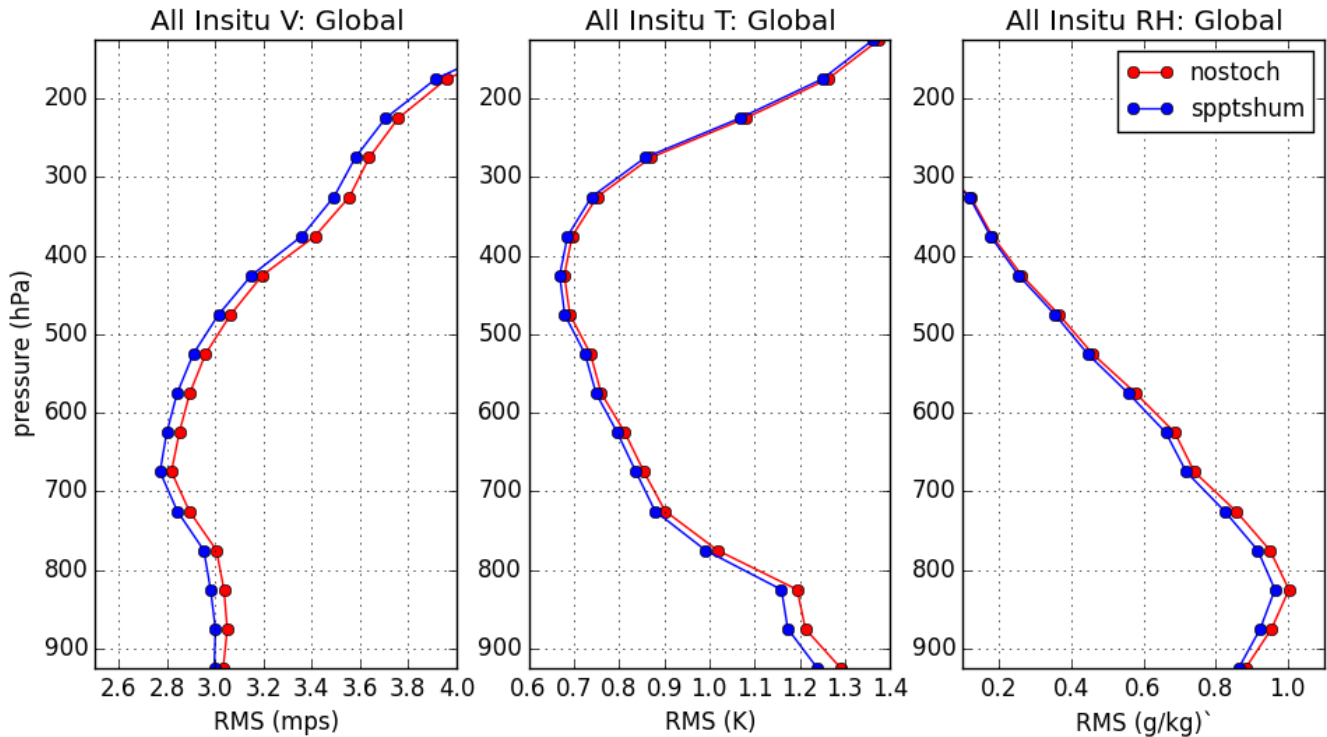
# Results from FV3GFS with cycled Data assimilation

- Hybrid 4D Ensemble-Var run at C192 (~52 KM)
- 80-member ensemble
- 20-days of cycling for January 2016.

# Control vs SPPT/SHUM

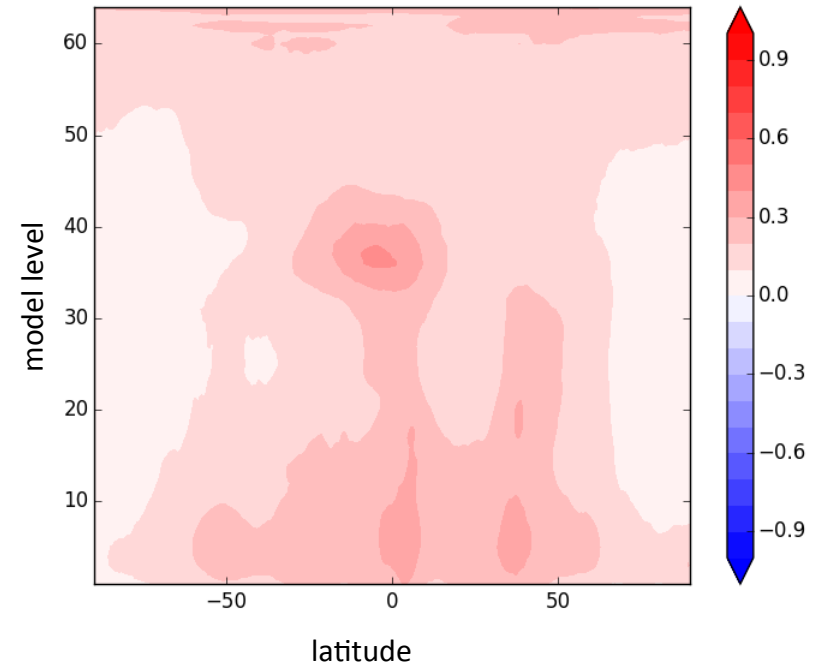
(left innovation stats, right spread difference)

RMS O-F (2016010500-2016012500)



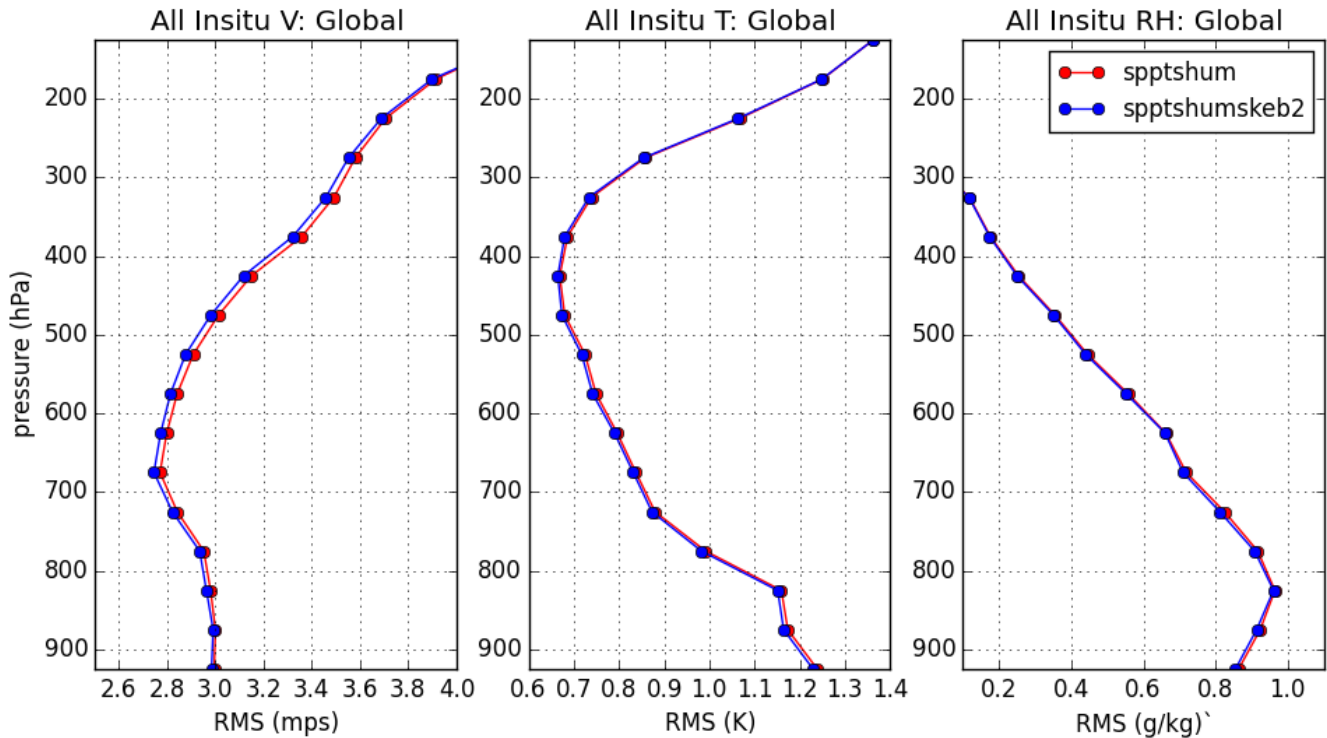
Large positive impact of adding SPPT/SHUM

Wind spread difference  
SPPT+SHUM - nostoch

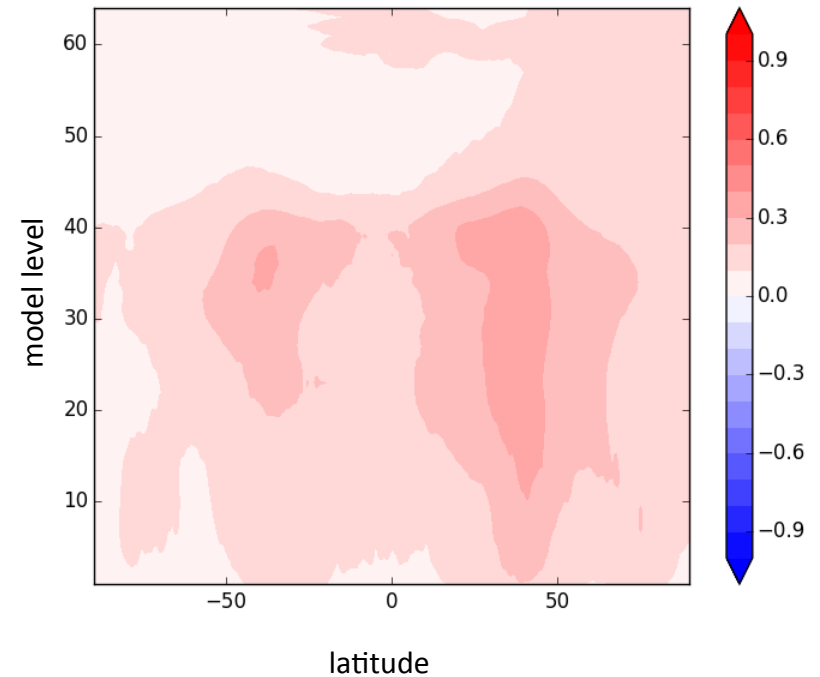


# SPPT/SHUM vs SPPT/SHUM/SKEB (left innov stats, right spread difference)

RMS O-F (2016010500-2016012500)



Wind spread difference  
SPPT+SHUM+SKEB – SPPT+SHUM



Small positive impact on wind stats adding SKEB to SPPT/SHUM



# Medium range forecasts

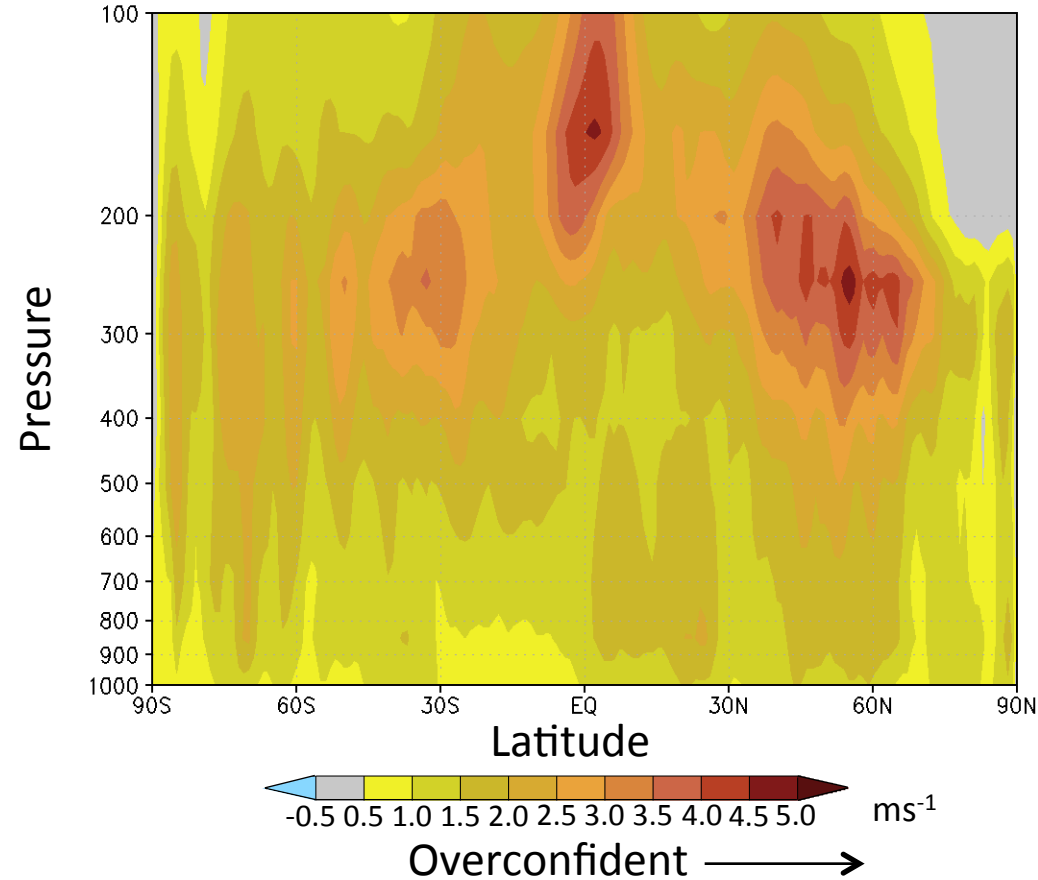
- 20-member ensemble at C192
- Initialized with spectral GFS initial conditions for 7 cases in August 2014.
- 5-day forecasts verified against ECMWF operational analysis

# 5-day forecast Zonal Wind RMS error – Spread

zonal average from 1 month of forecasts: August 2014

**RMS error:** ensemble mean error with respect to verifying analyses

**Spread:** standard deviation among ensemble members

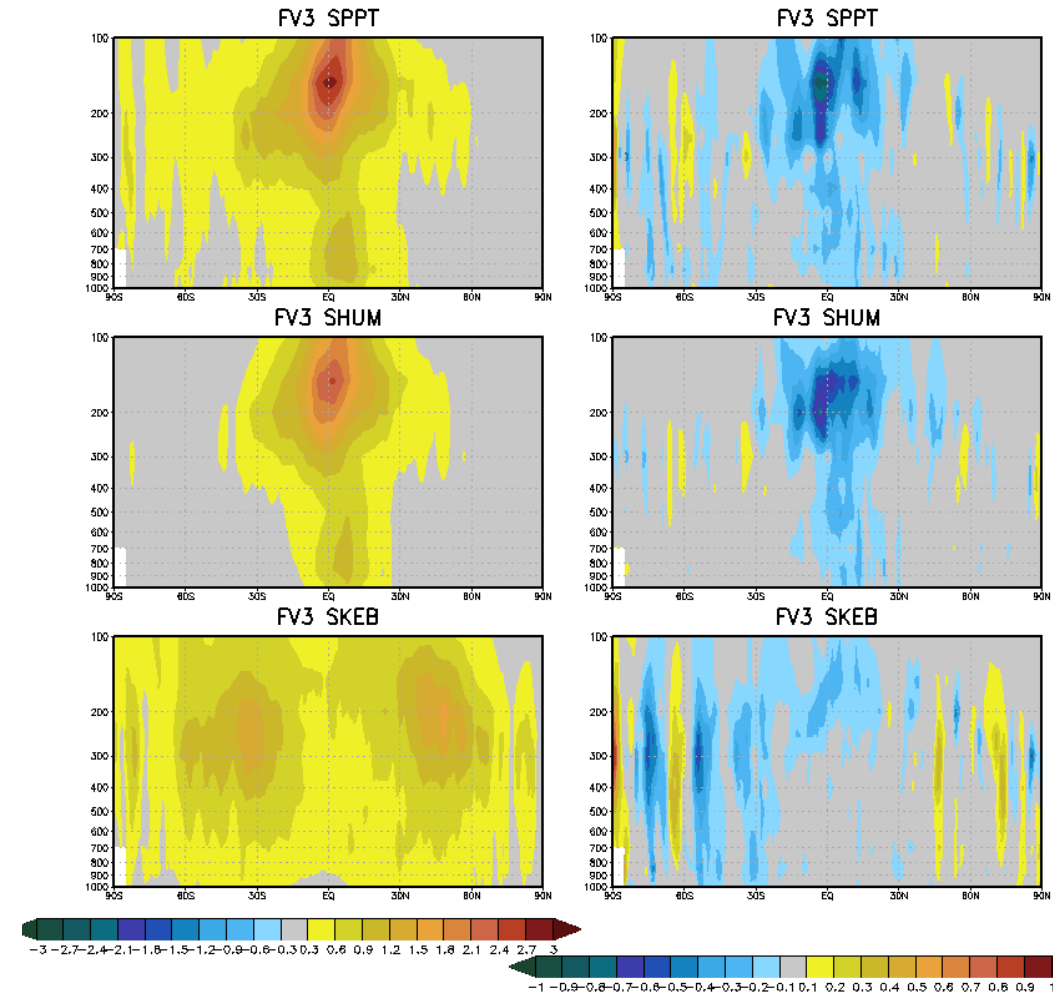


GFS ensemble, no treatment for model error “baseline”

# Impact of stochastic physics at day-5

Zonal Wind Error and Spread

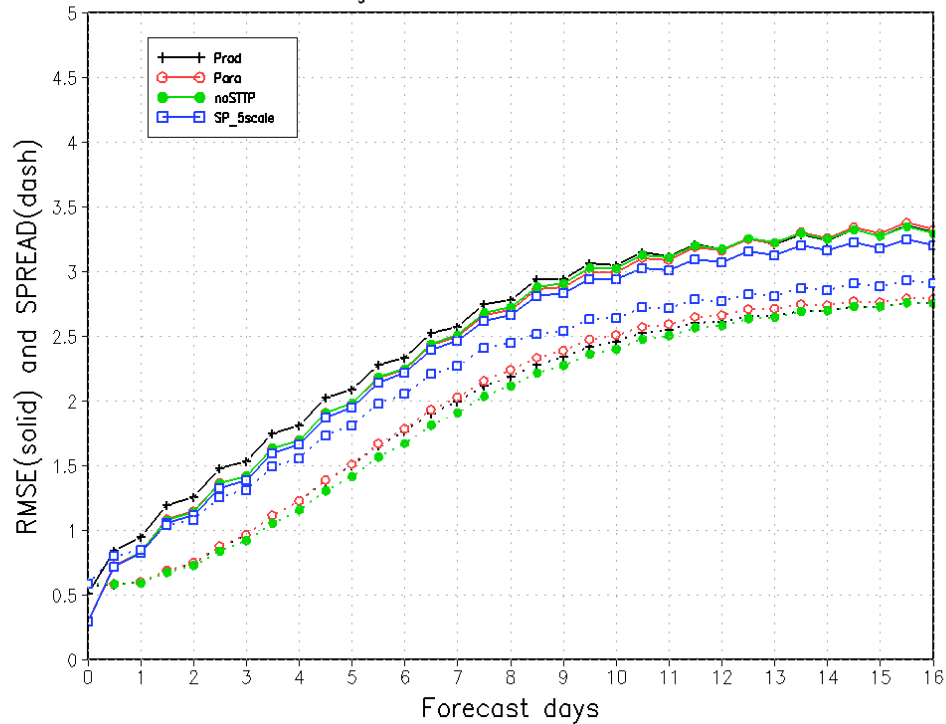
- The three stochastic parameterizations all result in an increase in spread, and a slight reduction in ensemble mean error.



# Surface quantities are still under-spread

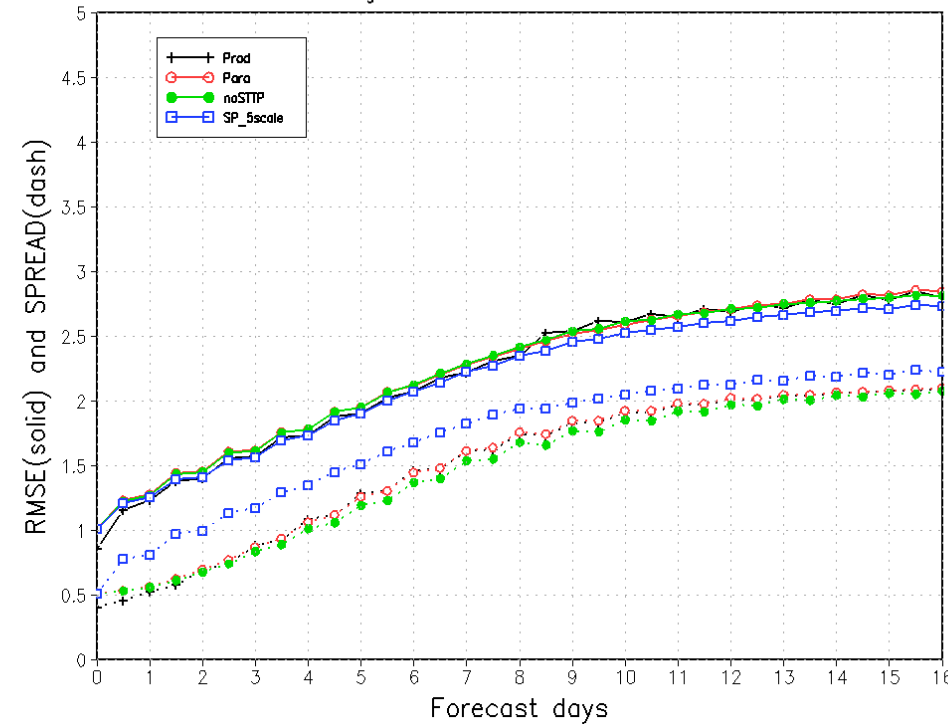
T850

Northern Hemisphere 850hPa Temp.  
Ensemble Mean RMSE and Ensemble SPREAD  
Average For 20130601 - 20130731



T2M

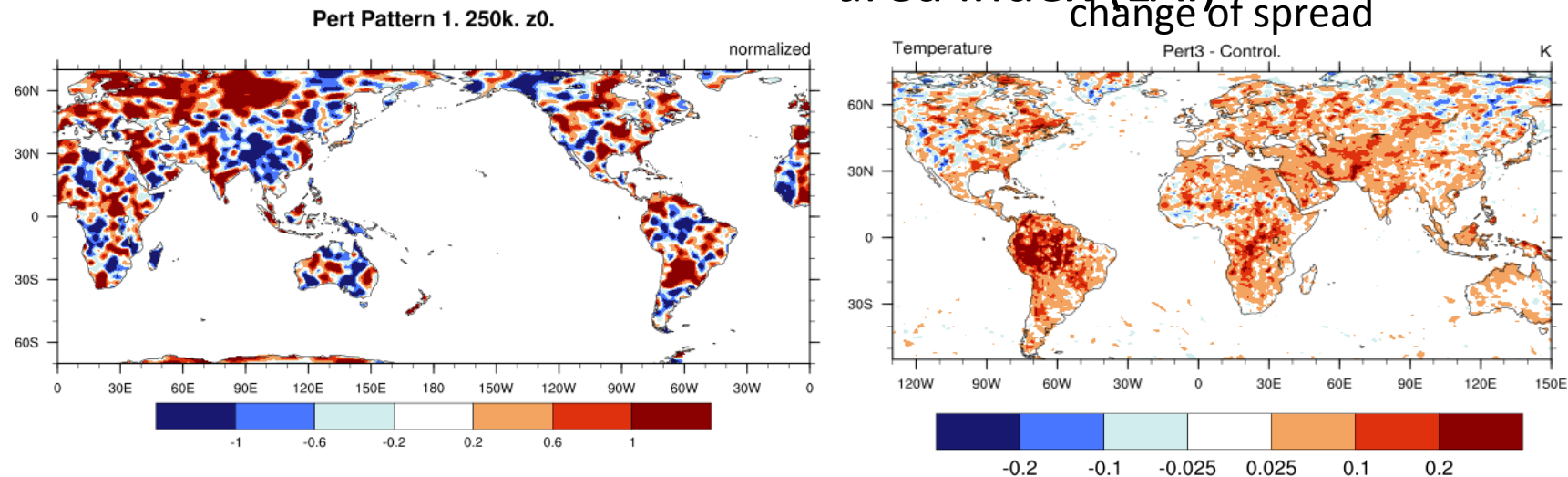
Northern Hemisphere 2 Meter Temp.  
Ensemble Mean RMSE and Ensemble SPREAD  
Average For 20130601 - 20130731



Still a large gap between error and spread

# Surface Perturbations

- There are errors associated with the lower boundary conditions
  - Errors associated with land surface model and initial conditions (not addressed here)
- Methods
  - Perturb surface momentum roughness length (Z0), thermal roughness length (zt) and soil hydraulic conductivity (SHC) and leaf area index (LAI)

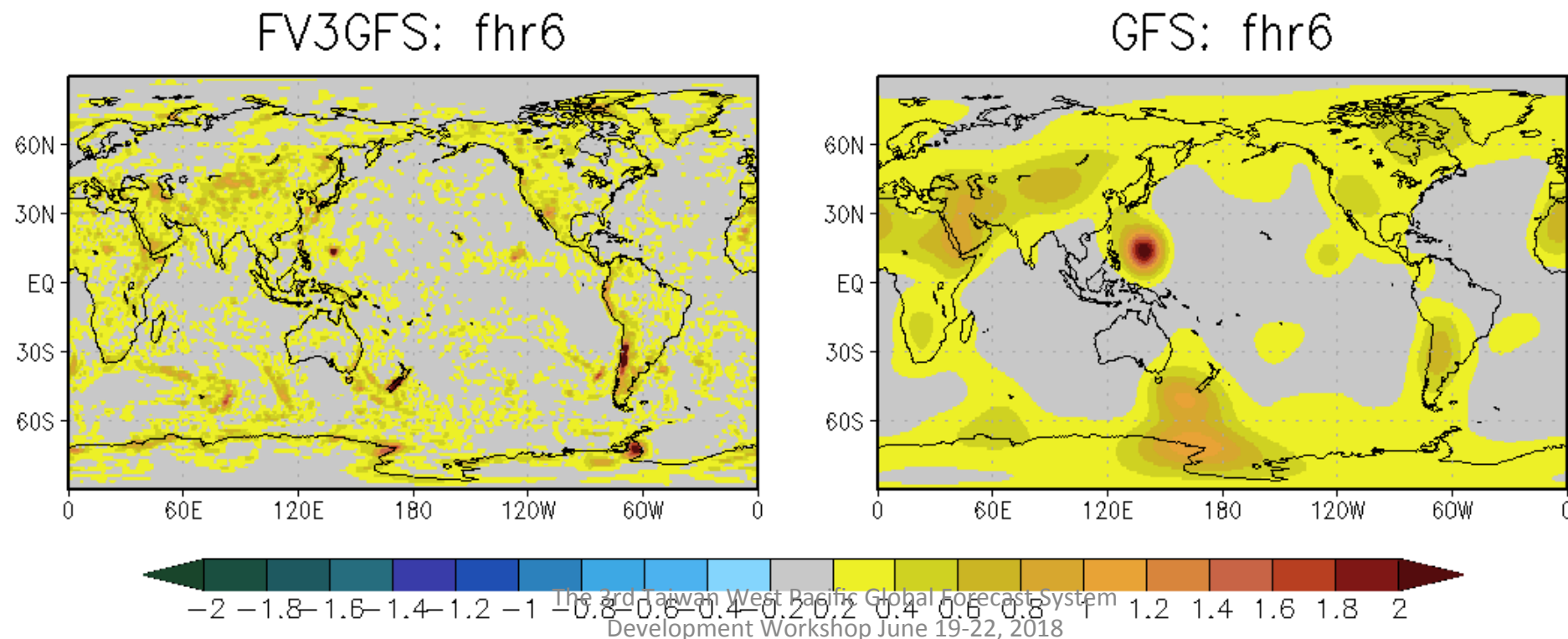


# Differences compared to spectral GFS

- SKEB is formulated differently in FV3GFS compared to the spectral version of the model
- Spectral GFS used the vorticity gradient as an the dissipation estimate and the dissipation was smoothed spectrally
- FV3GFS directly provides the numerical dissipation associated with diffusion. This dissipation term is smooth on the model's cubed sphere grid.

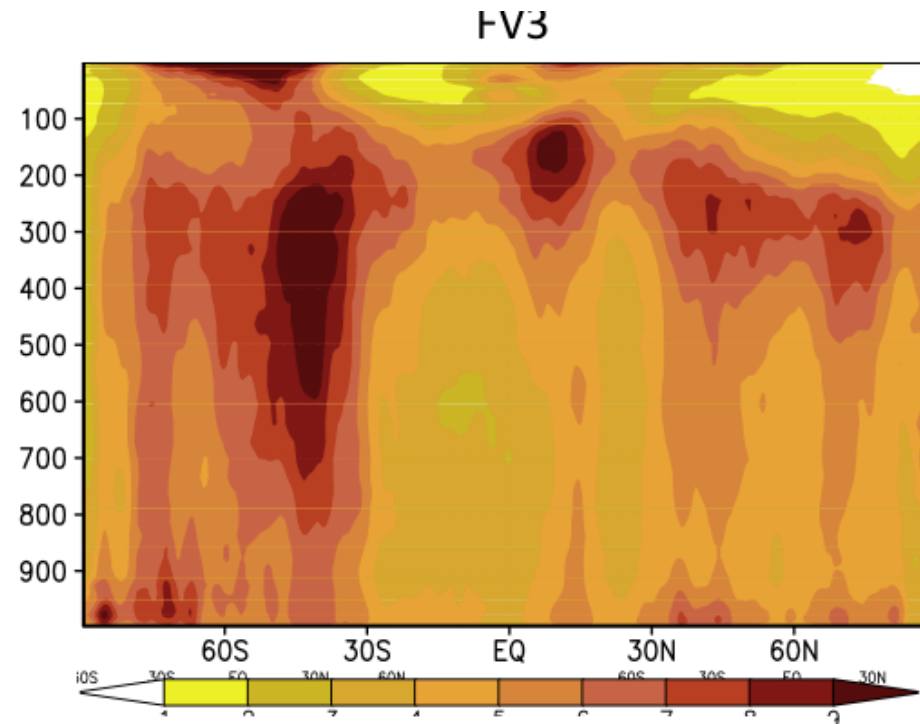
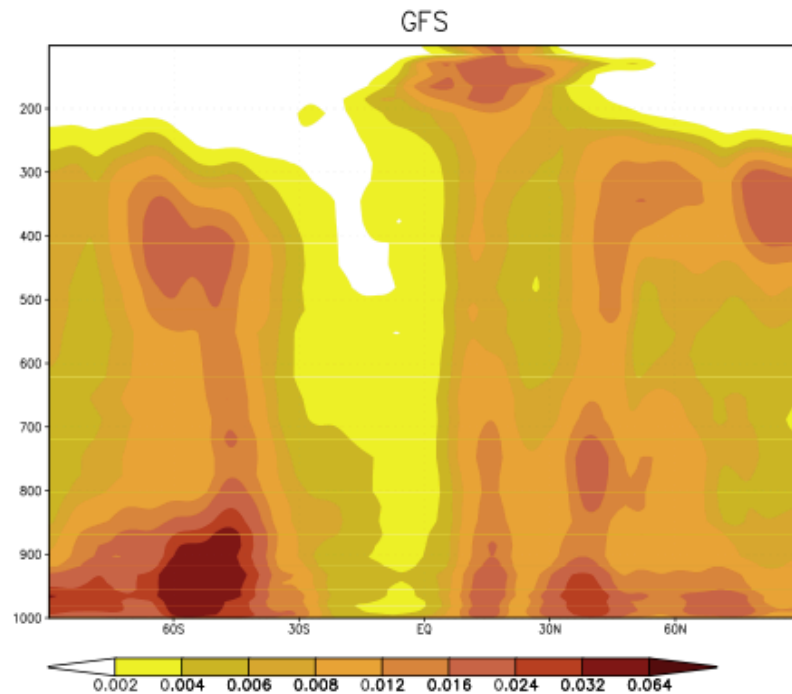
# New dissipation estimate in SKEB (maps at 850hPA)

- Much less horizontal smoothing is applied in FV3 (12 passes of laplacian smoother).
- GSM used T12 spectral filter.
- Generation of vertical correlations in random patterns in FV3 modified, computational cost reduced.



# New dissipation estimate in SKEB

- GSM used spectrally smoothed vorticity gradient.
- FV3 directly calculates the loss of kinetic energy at each time-step due to momentum diffusion.
- Estimates are different near tropopause, especially in the tropics.





# Summary

- The current stochastic physics schemes that are operational in the GDAS first guess ensemble are available in FV3GFS.
- In addition, new land surface perturbations are also available.
- Overall, the overall effect from the stochastic physics in the new model is consistent with the spectral GFS.
- Caution: Although SPPT has been developed with a potential coupled model in mind, mass and energy conservation have not been rigorously tested (e.g. surface fluxes may not be consistent with heating of atmosphere).

## Thank you

# References

- Berner, J., G. Shutts, M. Leutbecher, and T. Palmer, 2009: A spectral stochastic kinetic energy backscatter scheme and its impact on flow- dependent predictability in the ECMWF ensemble prediction system. *J. Atmos. Sci.*, **66**, 603–626, doi:10.1175/2008JAS2677.1.
- Gehne, M., T. Hamill, G. Bates, P. Pegion, W. Kolczynski 2018: Land-surface parameter and state perturbations in the Global Ensemble Forecast System. *Mon. Wea. Rev.* Submitted
- Palmer, T. N., R. Buizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. J. Shutts, M. Steinheimer, and A. Weisheimer, 2009: Stochastic parametrization and model uncertainty. *ECMWF Tech. Memo.* **598**, 42 pp
- Tompkins, A. M., and J. Berner, 2008: A stochastic convective approach to account for model uncertainty due to unresolved humidity variability. *J. Geophys. Res.*, **113**, D18101, doi:10.1029/2007JD009284.