The global Ensemble Kalman filter (EnKF) analysis for the Model for Prediction Across Scales (MPAS) on the variable-resolution meshes

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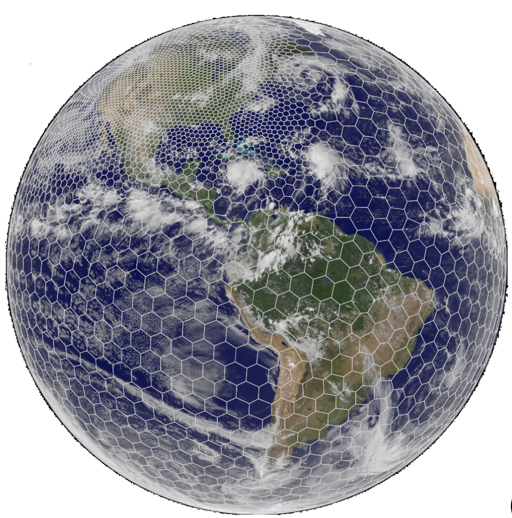
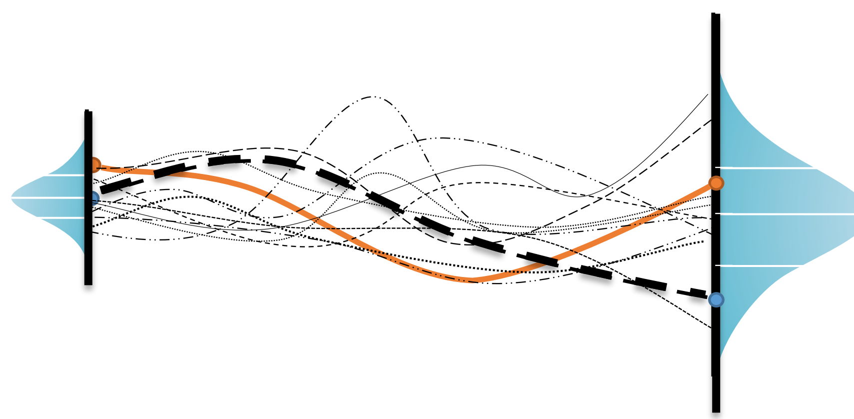




Contributions from Jeff Anderson, Nancy Collins (IMAGe), Joe Klemp, Michael Duda, and Laura Fowler (MMM)

The 18th Annual WRF Users' workshop

MPAS
Model for Prediction Across Scales

Global ensemble analyses

Data Assimilation Research Testbed

- **Forecast model: Model for Prediction Across Scales (MPAS)-Atmosphere**
  - Unstructured meshes on C-staggering, a terrain-following height coordinate
  - Global, nonhydrostatic simulations w/ horizontally variable resolution grids
  - 'mesoscale_reference' and 'convection-permitting' physics suites
  - A cycling capability

    &restart
    config_do_DAcycling = true
    config_do_restart = true
  - Incremental Analysis Updates (IAU) available from V5

    &IAU
    config_IAU_option = 'on'
    config_IAU_window_length_s = 21600.
  - Current release V5.1: http://mpas-dev.github.io/

- **Analysis system: Data Assimilation Research Testbed (DART)**
  - Ensemble Kalman filter (EnKF) analysis
  - Observation operators are built on native MPAS meshes

    => Analysis on variable-resolution meshes
  - Analysis variables in DART ≈ prognostic variables in MPAS
  - The latest release named "Manhattan"
    http://www.image.ucar.edu/DAReS/DART

Challenges in MPAS data assimilation

1. Unstructured meshes

   => Develop a new observation operator **H**

   - Barycentric interpolation using a triangular mesh
   - All locations are considered on the cartesian planes

   => Hard to estimate $\mathbf{P}^b$ (esp., on variable-resolution meshes);

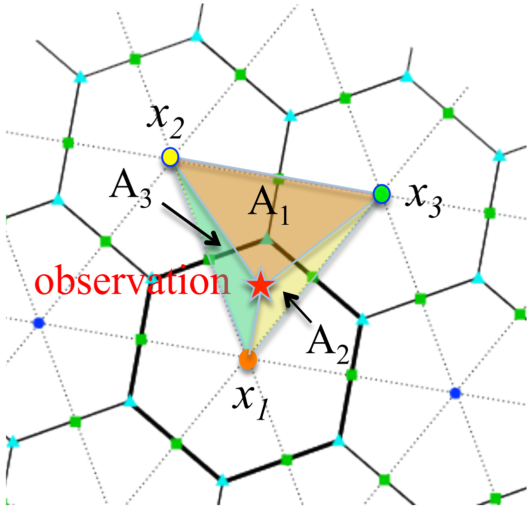
Estimate $\mathbf{P}^b\mathbf{H}^T$ and $\mathbf{H}\mathbf{P}^b\mathbf{H}^T$ from ensemble forecasts on native meshes.

Standard Kalman filter for a linear, unbiased analysis:

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{K}(\mathbf{y}^o - \mathbf{H}(\mathbf{x}^b))$$

$$\mathbf{K} = \mathbf{P}^b\mathbf{H}^T(\mathbf{H}\mathbf{P}^b\mathbf{H}^T + \mathbf{R})^{-1}$$

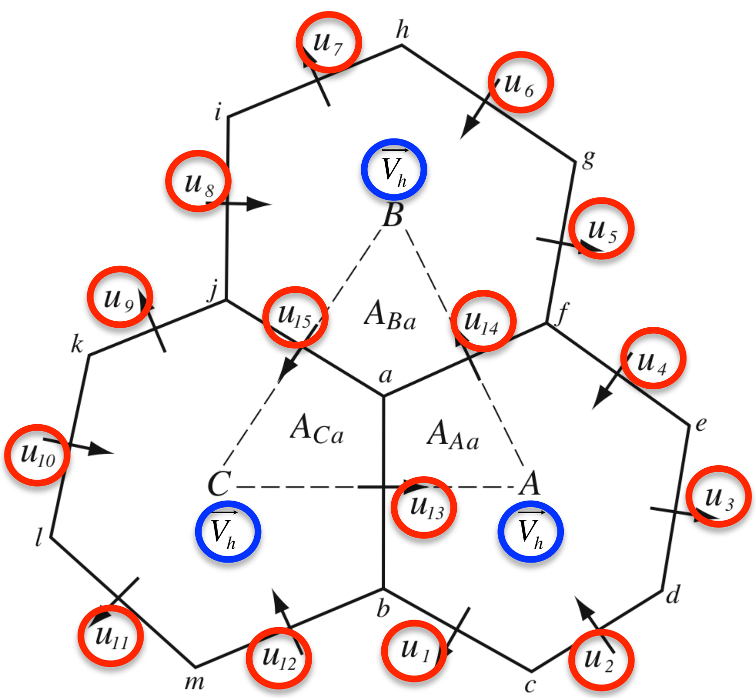
x^a: analysis state; x^b: background (or prior)
y^o: observations; $H(x^b)=y^b$: prior obs
P^b: background error covariance
R: observation error covariance



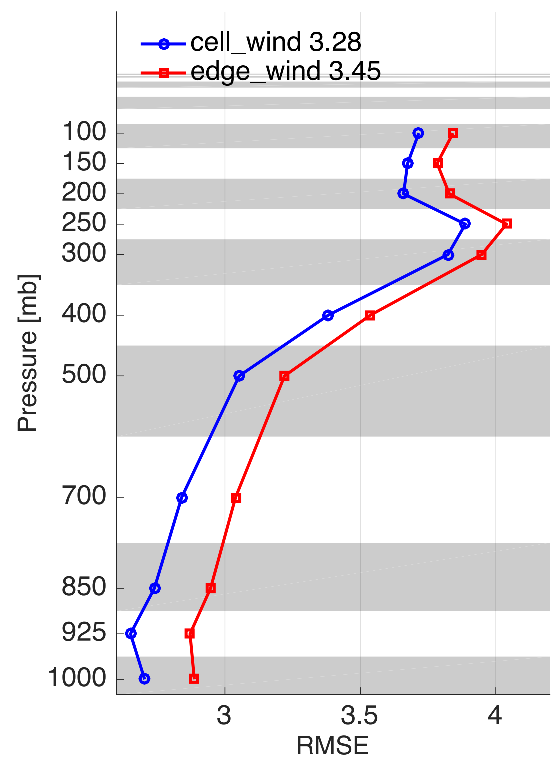
$$y^b_{obs} = (A_1x_1 + A_2x_2 + A_3x_3)/(A_1 + A_2 + A_3)$$

Challenges in MPAS data assimilation

2. Treatment of horizontal wind => new *H* for winds
   - A prognostic wind variable is normal velocity (u) at cell edges
   - Zonal and meridional winds ($\vec{V}_h$) are reconstructed at cell centers using Radial Basis Functions (RBFs); used for physics

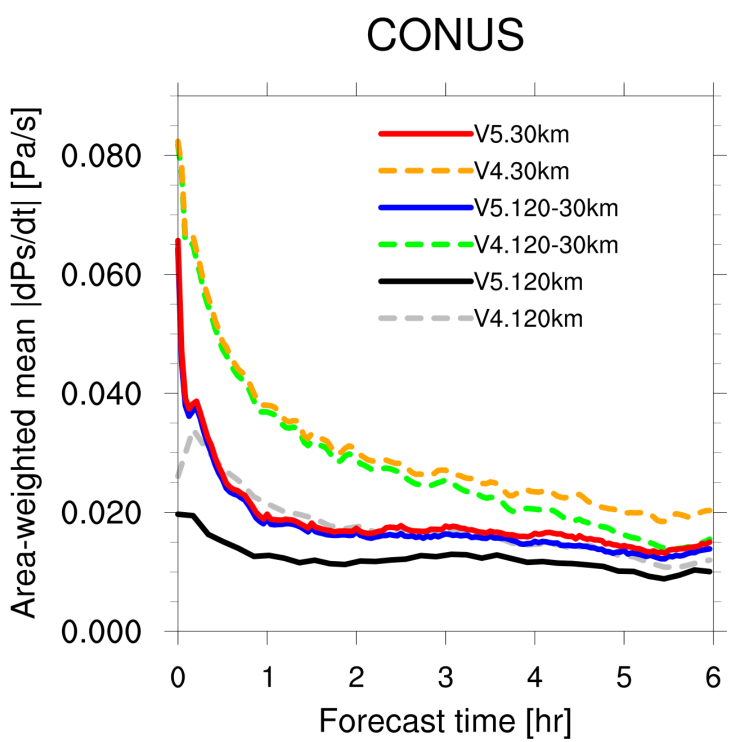


6-h forecast, global RMS error (m/s) against RADIOSONDE_U_WIND, June 2012



Challenges in MPAS data assimilation

3. Noise Control
   - In the global analysis, it is critical to effectively suppress high-frequency oscillations for the numerical stability and the quality of subsequent forecasts.
   - MPAS V5.1 introduces a new, scale-aware 3-D divergence damping for acoustic waves.

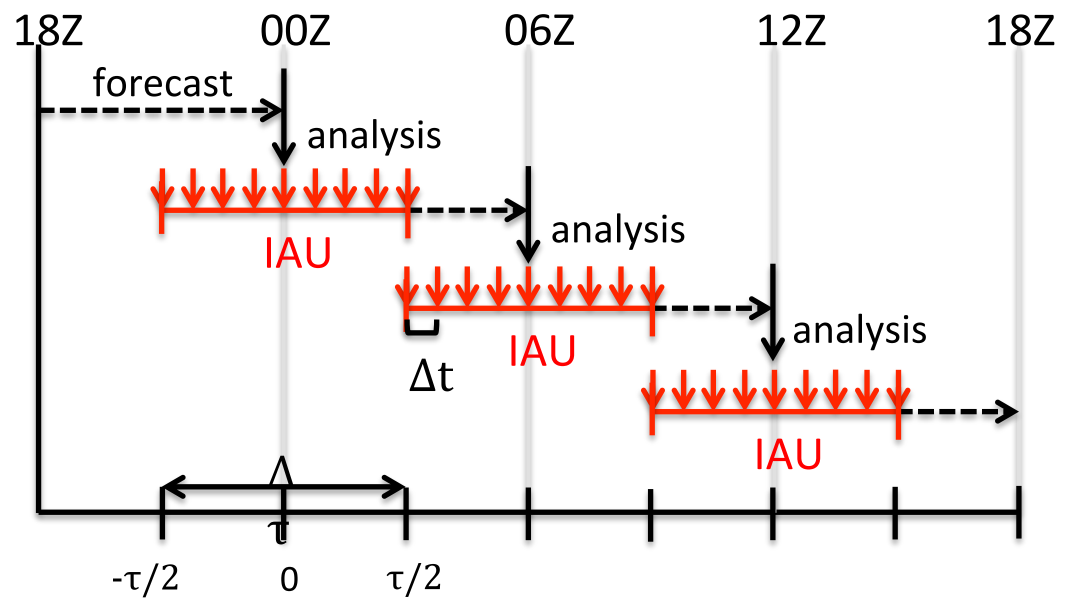


- MPAS forecasts initialized from the NCEP FNL analysis at 2012-06-11_12:00:00 UTC
- Area-weighted global mean surface pressure tendencies at each time step to measure high-frequency noise
- Version 5 reduces the noise from Version 4 in all different meshes

Challenges in MPAS data assimilation

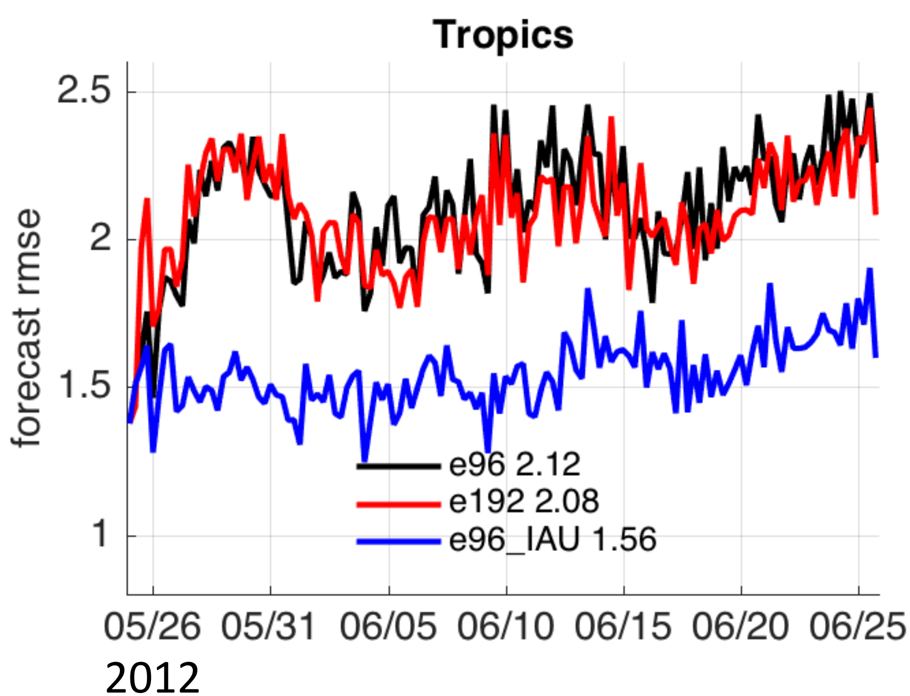
3. Noise Control - IAU

- The analysis quality is often degraded by spurious waves generated from dynamical imbalances arising from analysis increments.
- During cycling, the analysis is usually used as an initial condition for the following forecast. => Sudden localized changes can shock the model.
- The IAU incorporates analysis increments (rather than full fields) into the model tendency in a gradual fashion. (Bloom et al. 1996)



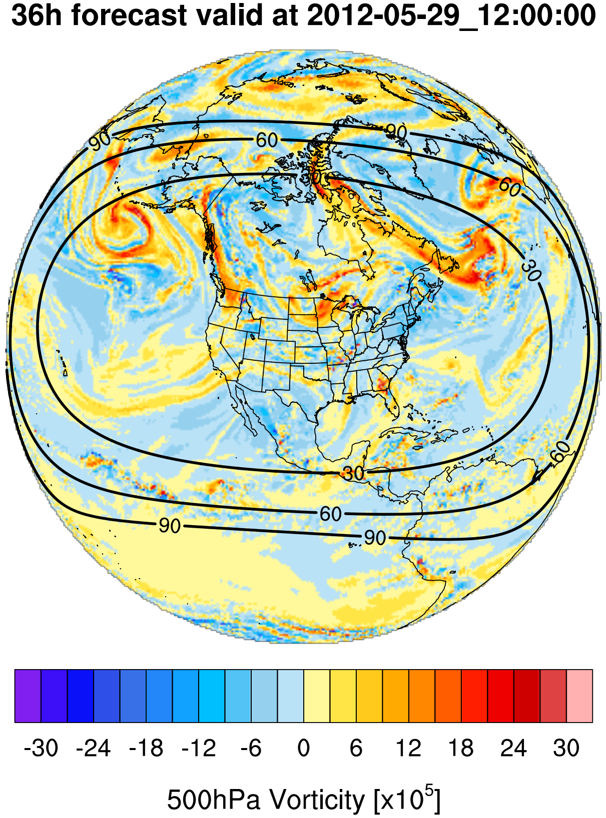
Challenges in MPAS data assimilation

3. Noise Control (cont'd)
   - Cycling w/ a 96-member ensemble ("e96")
   - Cycling w/ a 96-member ensemble and IAU ("e96_IAU")
   - Cycling w/ a 192-member ensemble ("e192")

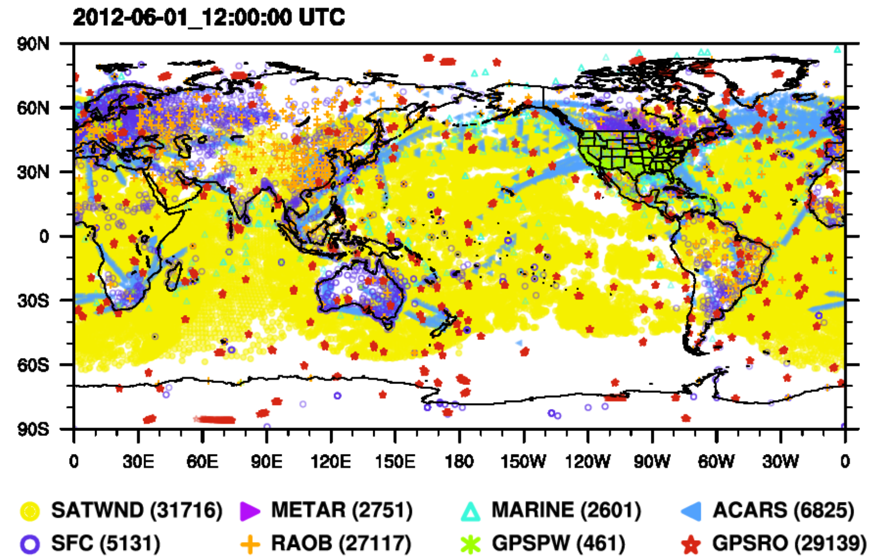


- 6-h ensemble mean forecast rms fit to surface altimeter observations during the cycles
- The IAU improved the EnKF analysis, especially over the tropics.
- The use of IAU was more effective than double the ensemble size.

Variable-resolution DA with MPAS/DART



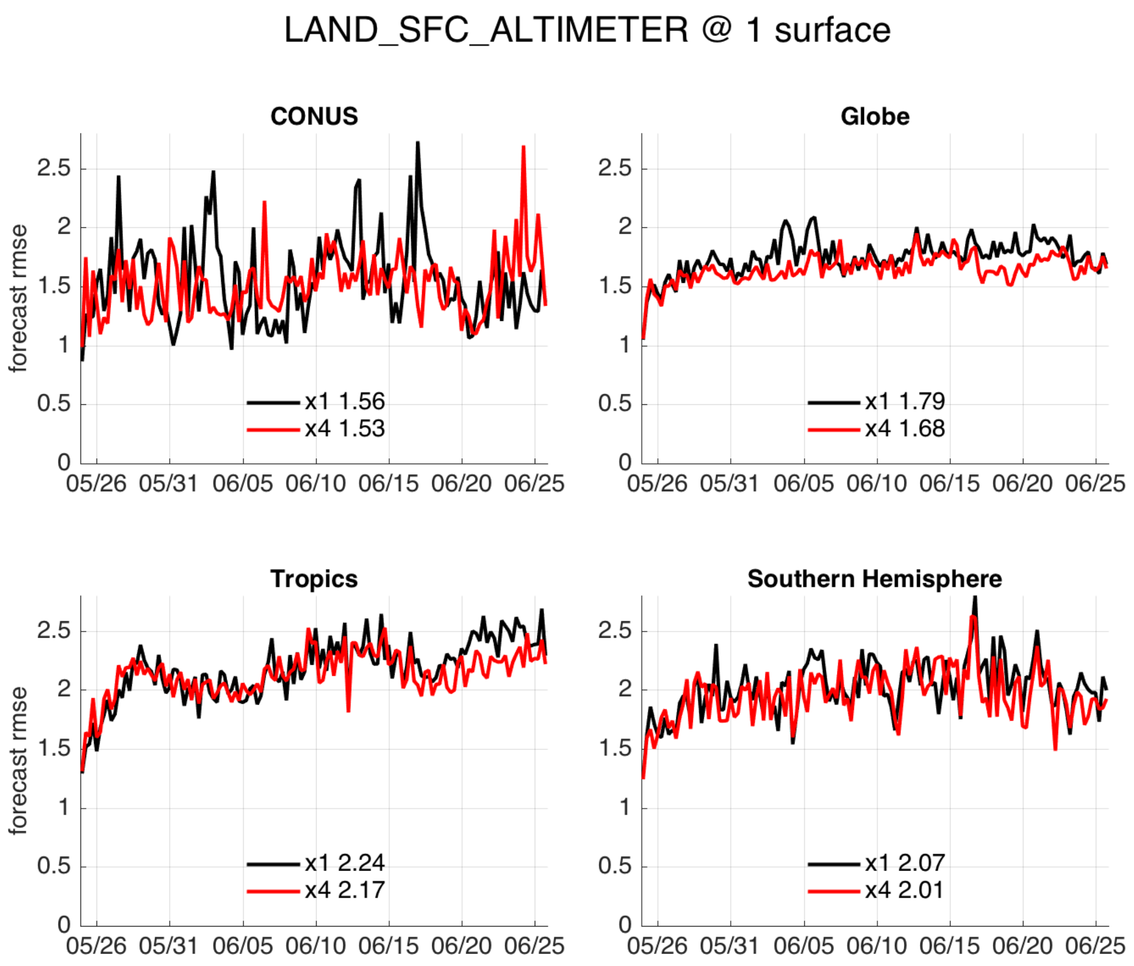
Grid resolution in 120-30 km mesh (named "x4"), contouring every 30 km.



- A 96-member global ensemble
- A variable-resolution mesh (120-30 km) is used in *both* analysis and forecast in the cycling experiment.
- Compare the variable-resolution (x4) to a coarse uniform (x1) mesh w/ 120-km resolution

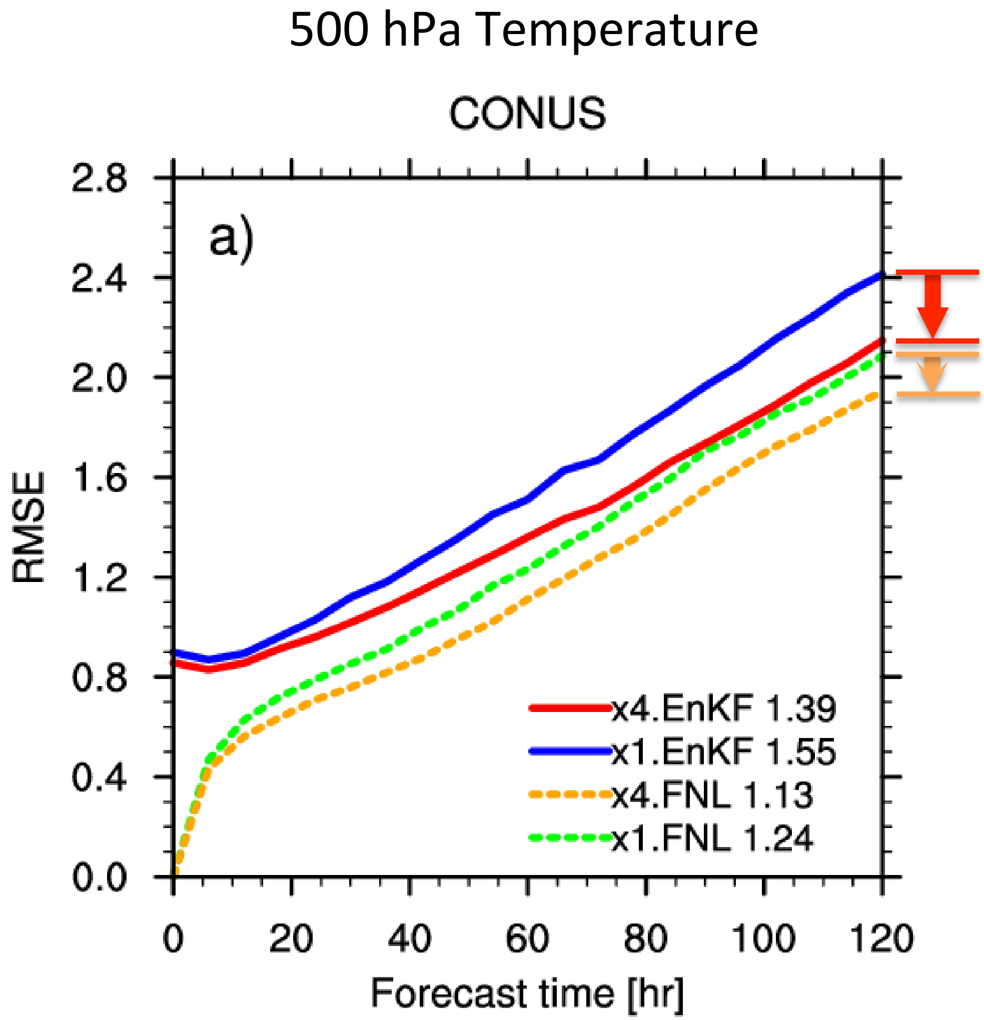
Ha et al. (Submitted to *Mon. Wea. Rev.*)

6-h ensemble mean forecast error



- Both meshes are reliable throughout the cycling period.
- They are mostly comparable to each other in 6-h prior forecast.

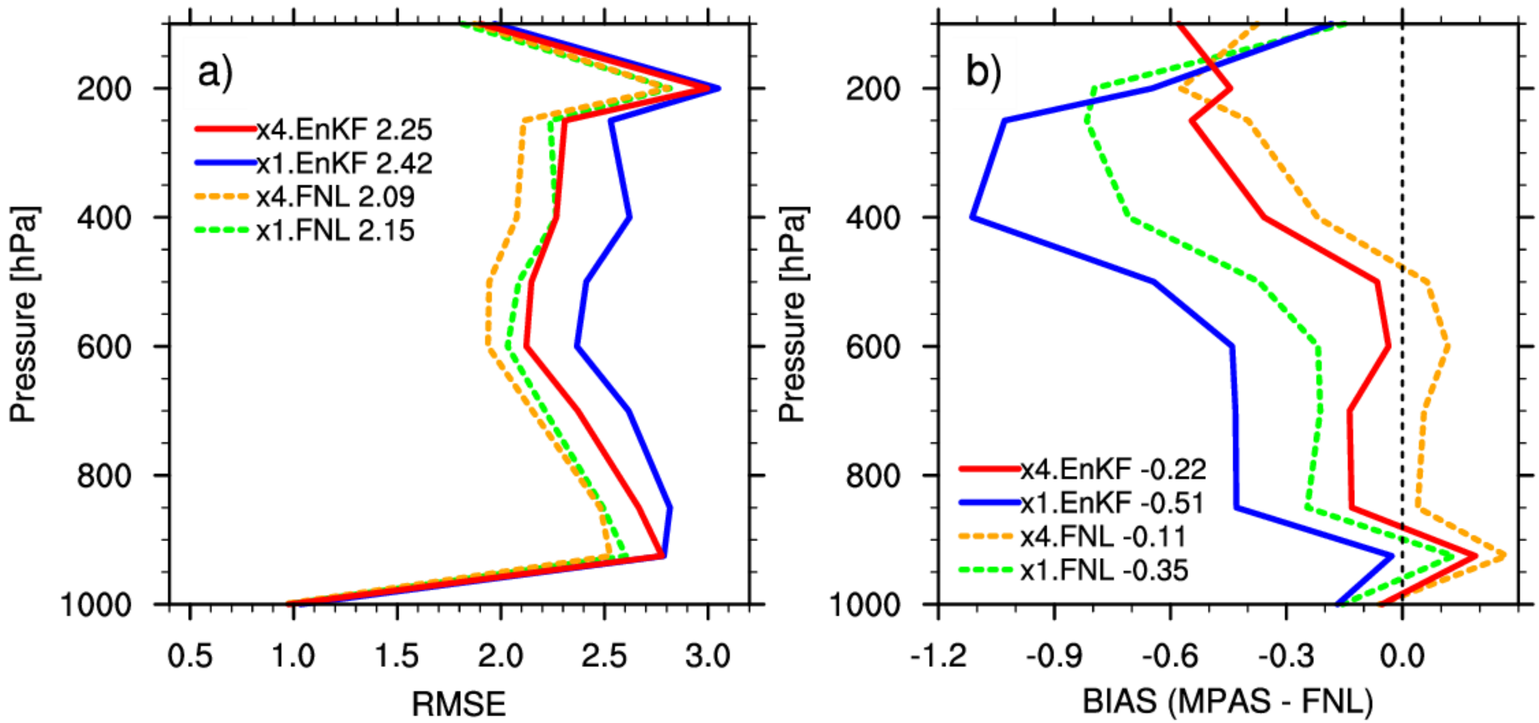
5-day MPAS forecast from the EnKF mean analysis



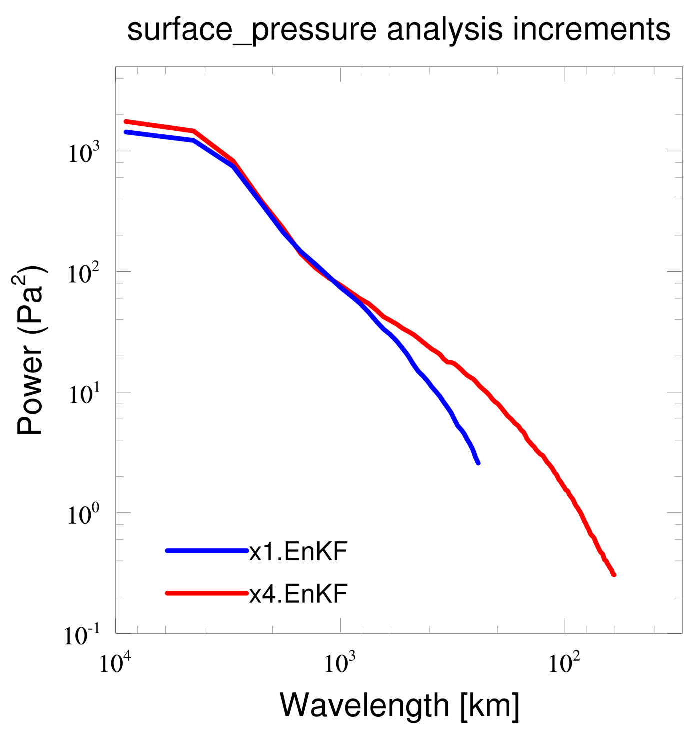
Verification w.r.t. NCEP FNL analysis: The rms error was computed from May 28 to June 25, 2012, twice daily, every other day.

- Benefits of high-resolution model forecasts are well shown in cold-start runs. (orange vs. green)
- The use of variable-mesh in the EnKF analysis improves the benefit nearly as twice as large that in cold-start runs. (red vs. blue)

5-day MPAS forecast from the EnKF mean analysis (cont'd)



Power spectra of ensemble analysis increments (CONUS)

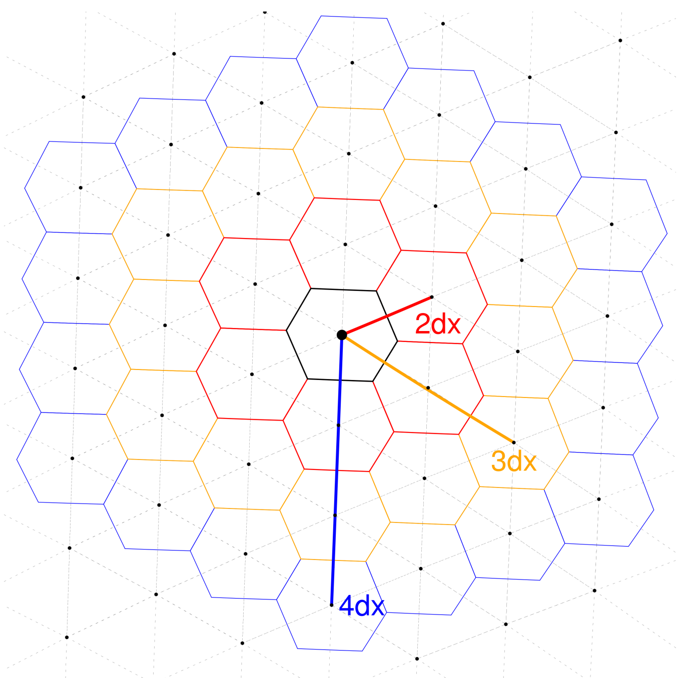


- ➢ Both meshes show almost the same power at synoptic scale
- ➢ Variable mesh (x4) has much more power at mesoscale range (< 1,000 km)

Precipitation forecast

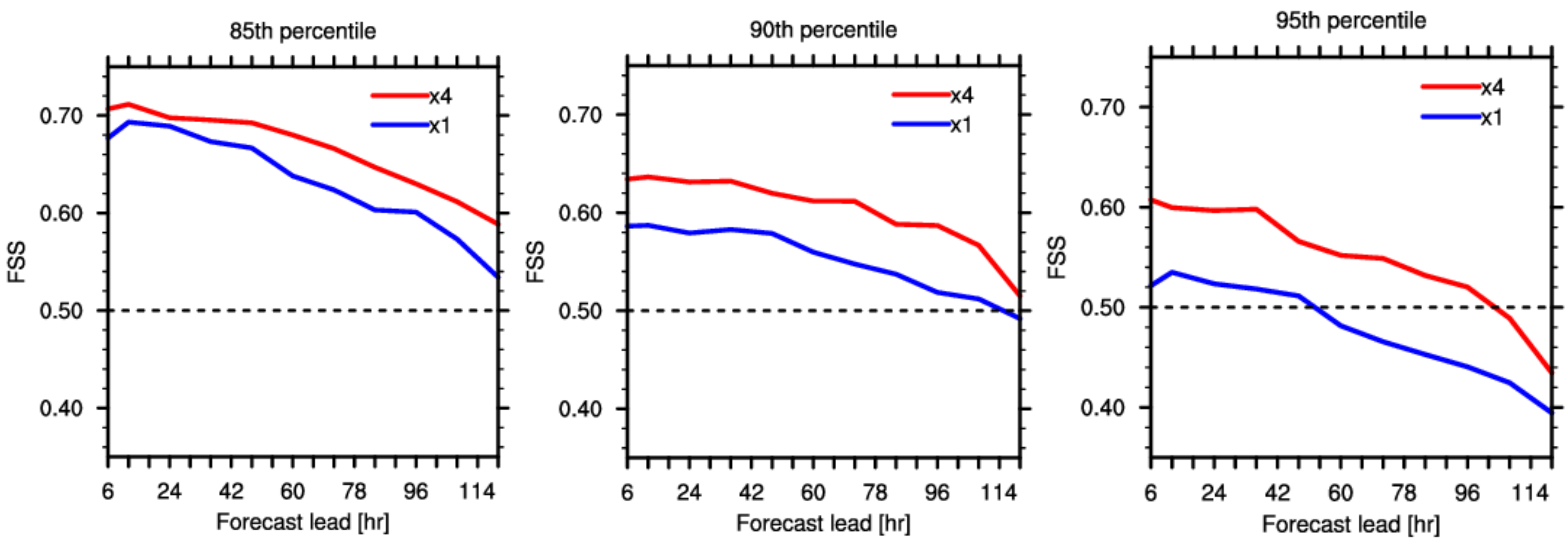
Fractions Skill Scores (FSS) over the MPAS unstructured mesh

- FSS is computed to find the smallest scale over which the model is skillful.
- Both model and observations are projected onto the same verification cells.
- The fraction of occurrences of specified rainfall accumulations is computed over a range of spatial scales (*n*dx).
- Verification area: CONUS (w/ dx = 30km in the variable-resolution mesh)



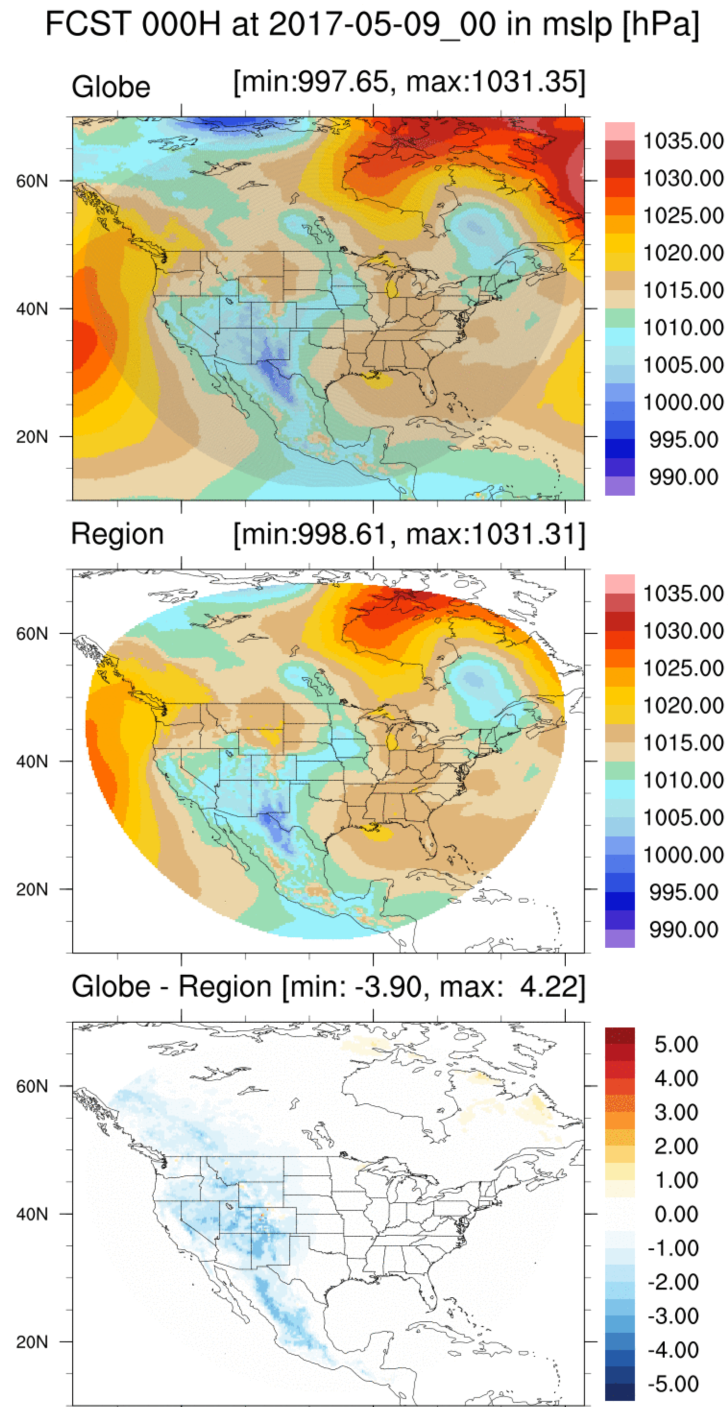
FSS: x1 vs. x4

- Observations: NCEP Stage IV data (in 4-km resolution) projected onto the x4 mesh over the CONUS domain
- 5-day forecasts from the coarse uniform (x1) mesh are also projected onto the x4 mesh.
- FSS is compared within the radius of 600 km (e.g. 5dx for “x1” mesh) for three different percentile thresholds.



Summary

- Both analyses and forecasts are conducted using the *native* MPAS unstructured mesh => applicable to variable-resolution meshes as well as quasi-uniform meshes.
- Assimilating real observations, the global ensemble analysis/ forecast system is reliable throughout a month-long cycling period regardless of the mesh configuration.
- MPAS forecasts on the variable mesh is benefited from high-resolution simulations in the local refinement area.
- The EnKF analysis on the variable mesh further improves MPAS forecasts, suppressing forecast error growth.



Future plan

- Conduct cycled MPAS forecasts initialized with EnKF analyses using regional and global MPAS

- Comparison between WRF and regional-MPAS forecasts using the same LBCs from global-MPAS forecasts in the ensemble cycling context

- High-resolution (O(1km)) cycled forecasts using variable-resolution meshes in the regional MPAS

Recap on Data Assimilation: Kalman Filter Algorithm

- Analysis step

Assuming that observation and background errors are unbiased, normally distributed, and uncorrelated, the Best Linear Unbiased Estimate (BLUE) is analytically defined as

$$\mathbf{x}^{\mathbf{a}} = \mathbf{x}^{\mathbf{b}} + \mathbf{K}(\mathbf{y}^{\mathbf{o}} - \mathbf{H}(\mathbf{x}^{\mathbf{b}}))$$

$$\mathbf{K} = \mathbf{P}^{\mathbf{b}}\mathbf{H}^{\mathbf{T}}(\mathbf{H}\mathbf{P}^{\mathbf{b}}\mathbf{H}^{\mathbf{T}} + \mathbf{R})^{-1}$$

But P^b is too large and the true state is unknown. In an Ensemble Kalman Filter, ensemble-based approximations are made as below.

$$\mathbf{P}^{\mathbf{b}}\mathbf{H}^{\mathbf{T}} \equiv \frac{1}{N_e - 1}\sum_{e=1}^{N_e}(\mathbf{x}_{\mathbf{e}}^{\mathbf{b}} - \overline{\mathbf{x}^{\mathbf{b}}})(\mathbf{H}\mathbf{x}_{\mathbf{e}}^{\mathbf{b}} - \overline{\mathbf{H}\mathbf{x}^{\mathbf{b}}})^{\mathbf{T}}$$

$$\mathbf{H}\mathbf{P}^{\mathbf{b}}\mathbf{H}^{\mathbf{T}} \equiv \frac{1}{N_e - 1}\sum_{e=1}^{N_e}(\mathbf{H}\mathbf{x}_{\mathbf{e}}^{\mathbf{b}} - \overline{\mathbf{H}\mathbf{x}^{\mathbf{b}}})(\mathbf{H}\mathbf{x}_{\mathbf{e}}^{\mathbf{b}} - \overline{\mathbf{H}\mathbf{x}^{\mathbf{b}}})^{\mathbf{T}}$$

$$\textit{where} \quad \overline{\mathbf{x}^{\mathbf{b}}} = \frac{1}{N_e}\sum_{e=1}^{N_e}\mathbf{x}_{\mathbf{e}}^{\mathbf{b}} \quad \textit{and} \quad \overline{\mathbf{H}\mathbf{x}^{\mathbf{b}}} = \frac{1}{N_e}\sum_{e=1}^{N_e}\mathbf{H}\mathbf{x}_{\mathbf{e}}^{\mathbf{b}}$$

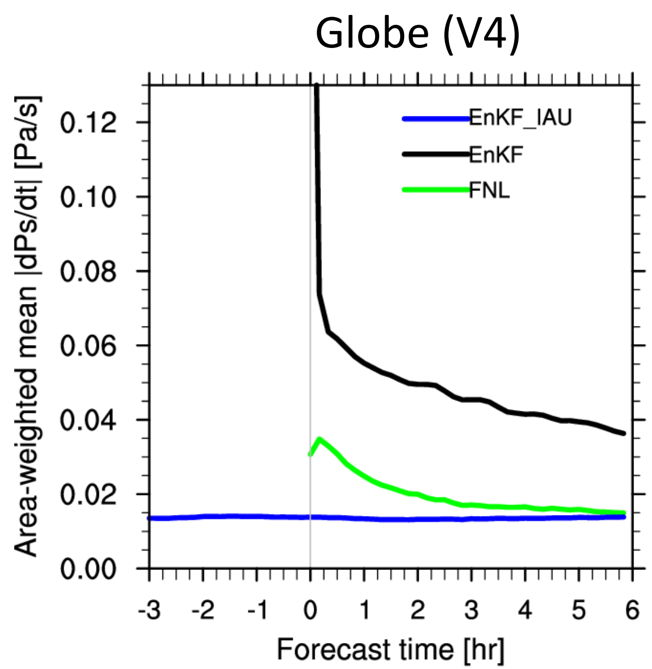
- Forecast step

$$\mathbf{x}^{\mathbf{b}} = \mathbf{M}(\mathbf{x}^{\mathbf{a}}) + \varepsilon^{b}$$

$$\mathbf{P}^{\mathbf{b}} = \mathbf{M}\mathbf{P}^{\mathbf{a}}\mathbf{M}^{\mathbf{T}} + \mathbf{Q}$$

$$\textit{where} \ \ \mathrm{E}(\varepsilon^{b}) = 0 \ \ \textit{and} \ \ \mathbf{Q} = \mathrm{E}[\varepsilon^{b}(\varepsilon^{b})^{T}]$$

IAU



MPAS forecast from different analyses valid at 2012-06-11_12:00:00 UTC (120-km uniform mesh)