Global ensemble data assimilation on the unstructured mesh

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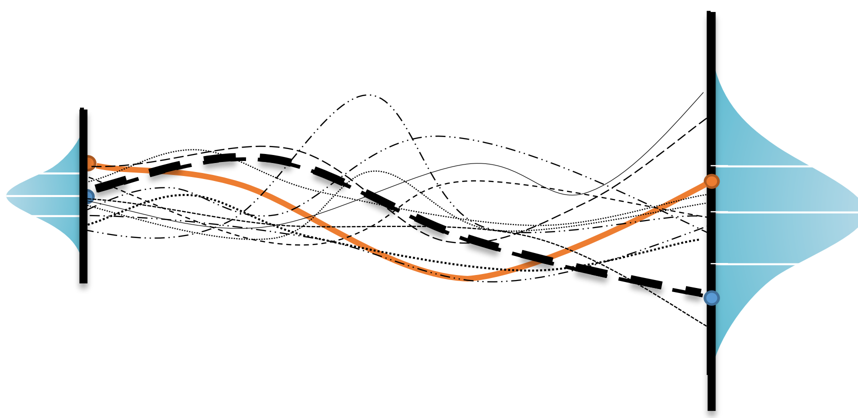
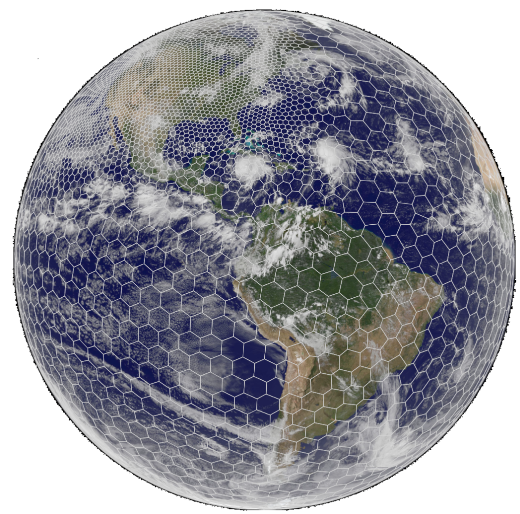
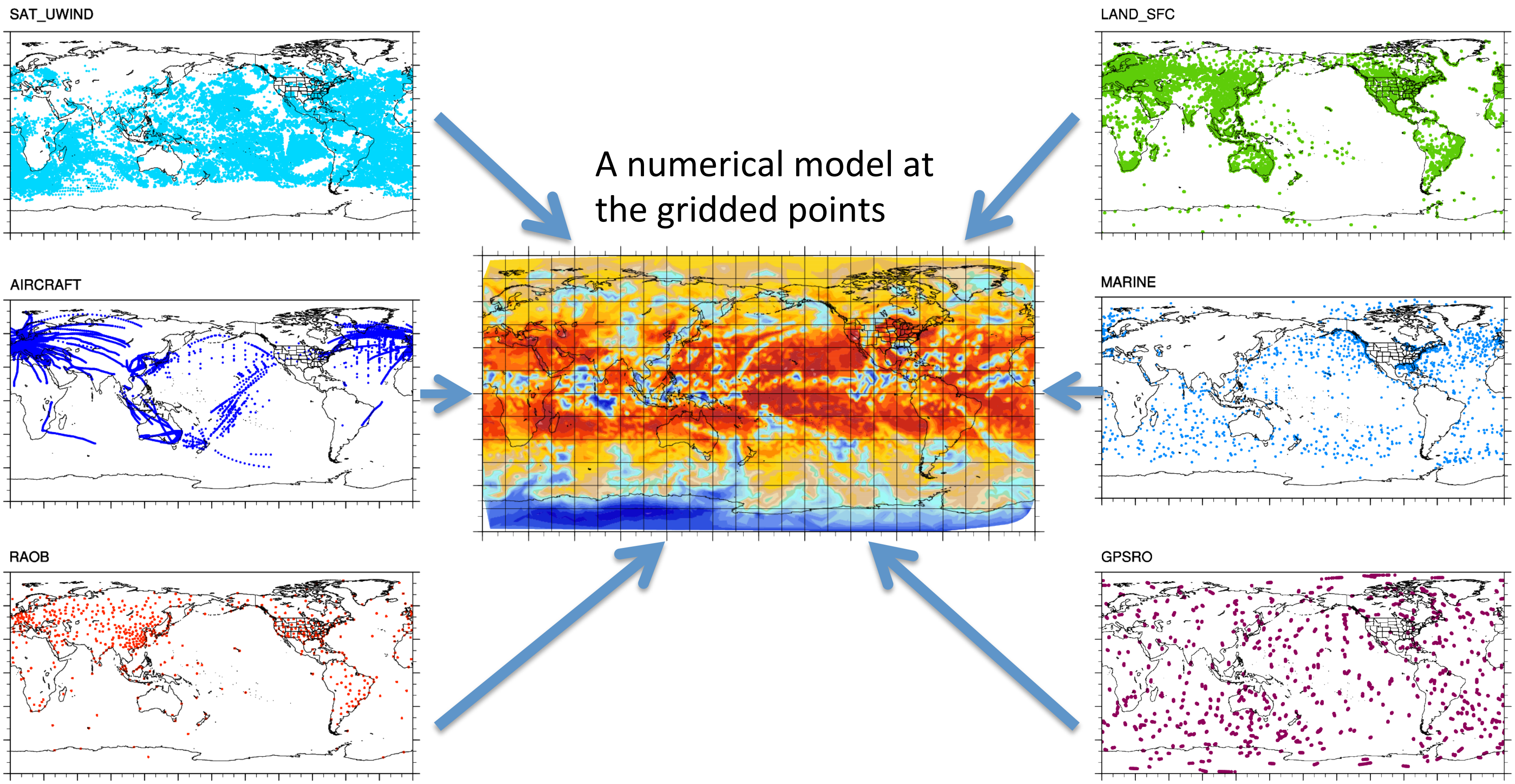




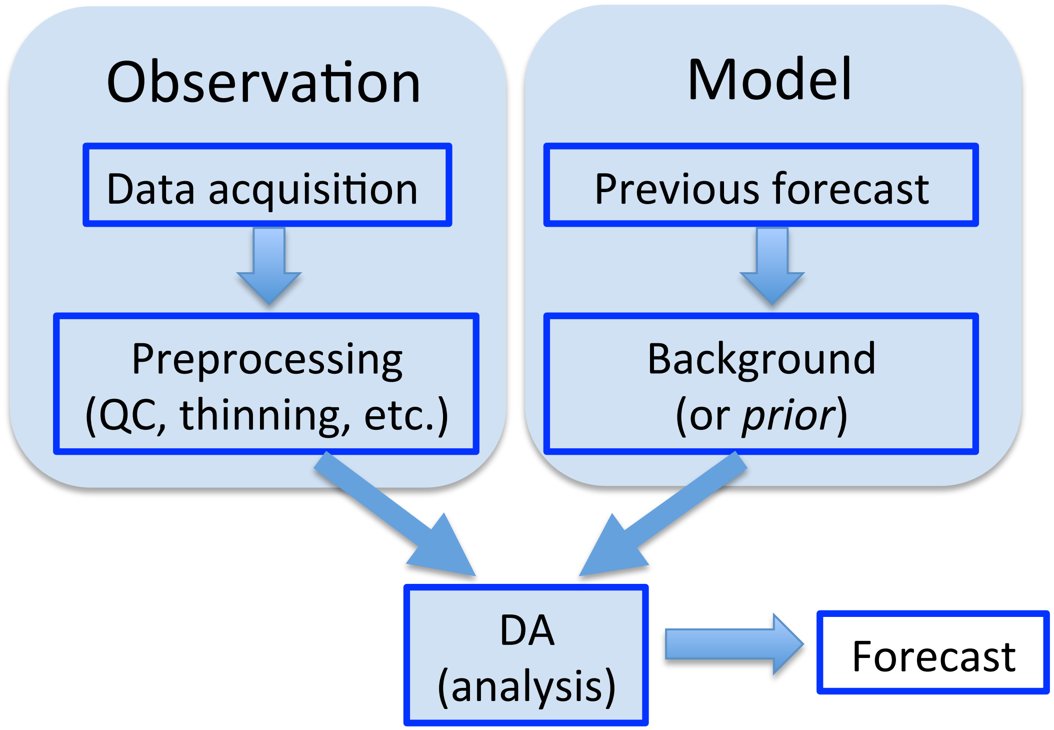
Data assimilation (DA)

Observations unevenly distributed in space and time



- High dimensional problem: $N_x \sim O(10^6 - 10^8)$ for model states x
- Not enough observations to define the state x uniquely
- Highly underdetermined system (an ill-posed problem): $N_x >> N_y$

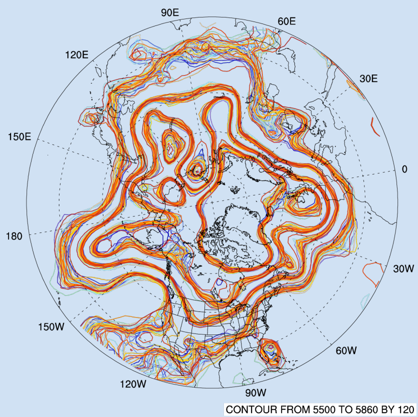
The Data Assimilation Process



- Both observations and a numerical model contain errors. How can we combine the two (properly weighting the errors) to yield the best possible estimate of the fluid motions?
- How can we propagate the observed information through the system?
- How can we update unobserved model states from an observed variable?

The ingredients for a challenging problem

AN IMPERFECT MODEL



Systematic biases

Unresolved processes

A SUBOPTIMAL DA METHOD

$$\widehat{\mathbf{x}}_{k+1|k} = \mathbf{M}_k \widehat{\mathbf{x}}_{k|k}$$
$$\mathbf{P}_{k+1|k} = \mathbf{M}_k \mathbf{P}_{k|k} \mathbf{M}_k^T + \mathbf{Q}_k.$$

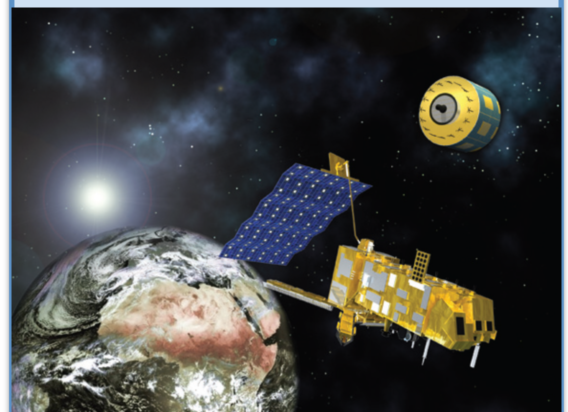
$$\widehat{\mathbf{x}}_{k|k} = \widehat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{y}_k - \mathbf{H}_k \widehat{\mathbf{x}}_{k|k-1})$$
$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}^T + \mathbf{R}_k)^{-1}$$
$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1}.$$

Linear/Gaussian assumption violated

Misspecified error characteristics

Undersampling

OBSERVATIONS



Sparse

Inhomogeneous

Instrument/ retrieval error

Bayesian data assimilation

unknown forecast

$$x^{true} = x^b + \varepsilon^b; \quad x^t, x^b, \varepsilon^b \in \mathbb{R}^n$$

$$with \;\; covariance \;\; \mathrm{E}\left[\varepsilon^b (\varepsilon^b)^T\right] = P^b$$

$$x_{t+1} = Mx_t + \eta_t, \quad \left\langle \eta_t \eta_t^{\,T} \right\rangle = Q$$

Observations at discrete times

$$y_k = h(x_k, t_k) + \varepsilon_k^o \quad where\; k = 0, 1, 2, ... \quad and \quad t_{k+1} > t_k$$

Complete history of observations

$$Y_\tau = \{y_k; t_k \le \tau\}$$

Assume Gaussian errors in both model states and observations

$$\varepsilon_k^o \to N(0, R); \quad \varepsilon^b \to N(0, P^b)$$

Bayesian data assimilation (cont'd)

A DA system properly combines information from disparate sources – prior distribution, observation likelihood, and the relationship between the two.

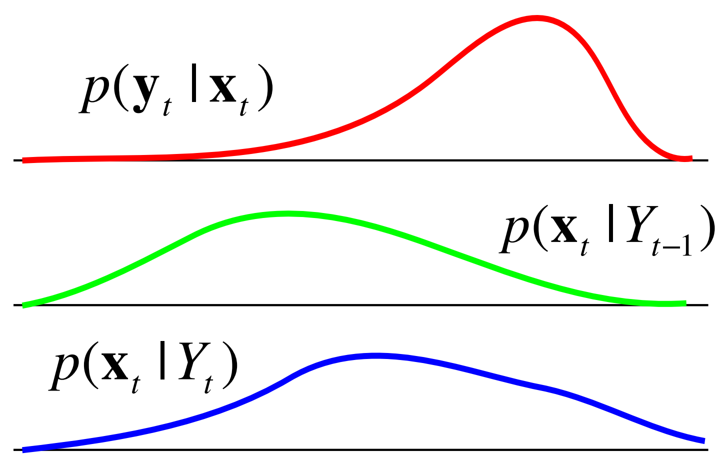
➔ Analysis: A solution to Bayesian relationship for conditional probabilities, which maximizes the posterior probability distribution

➔ Uncertainty (error): a measure of its variability

<u>Goal</u>: Find probability distribution for state ($\mathbf{x}_t$) at time t

$$p(\mathbf{x}_t \mid Y_t) \propto p(\mathbf{y}_t \mid \mathbf{x}_t)\, p(\mathbf{x}_t \mid Y_{t-1})$$

"Posterior" "Prior"



Kalman filter formulation

Simplifications:

1. Linearization of model around non-linear control trajectory
2. Error distributions assumed Gaussian

a: analysis, b: background (forecast)

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

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

$$\mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^b$$

$$\mathbf{P}_{t+1}^b = \mathbf{M}\mathbf{P}^a\mathbf{M}^T + \mathbf{Q}$$

$$\mathbf{x}_{t+1}^b = \mathbf{M}\mathbf{x}^a$$

- Covariance propagation step P_t^a -> P_{t+1}^b too expensive
- Still need tangent linear/adjoint models for evolving covariances, linear error growth assumption questionable.

Kalman filter formulation

- Optimal for a linear forecast model, Gaussian prior and observation error distributions, and Gaussian observation likelihood

a: analysis, b: background (forecast)

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

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

$$\mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^b$$

$$\mathbf{P}^b_{t+1} = \mathbf{M}\mathbf{P}^a\mathbf{M}^T + \mathbf{Q}$$

$$\mathbf{x}^b_{t+1} = \mathbf{M}\mathbf{x}^a$$

<u>Ensemble Kalman filter</u>

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

$$\mathbf{P}^b = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{x}_i^b - \overline{\mathbf{x}_i^b})(\mathbf{x}_i^b - \overline{\mathbf{x}_i^b})^T$$

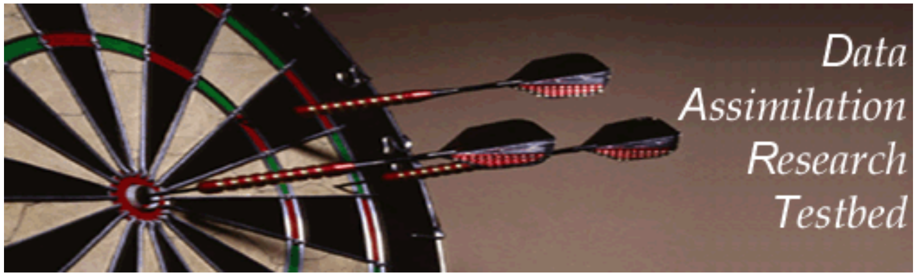
$$\mathbf{P}^b\mathbf{H}^T = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{x}_i^b - \overline{\mathbf{x}_i^b})(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})^T$$

$$\mathbf{H}\mathbf{P}^b\mathbf{H}^T \equiv \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})^T$$

$$\mathbf{x}_i^b(t+1) = M(\mathbf{x}_i^a) + q_i$$

- Covariance propagation step P_t^a -> P_{t+1}^b too expensive
- Still need tangent linear/adjoint models for evolving covariances, linear error growth assumption questionable.

- Huge P^b is never explicitly formed.
- Model integration using a fully nonlinear model



A community facility for ensemble data assimilation developed and maintained by the Data Assimilation Research Section (DAReS) at NCAR

www.image.ucar.edu/DAReS/DART/index.php

Welcome to the IMPROVED **D**ata **A**ssimilation **R**esearch **T**estbed - DART Manhattan.

DART has been reformulated to better support the ensemble data assimilation needs of researchers who are interested in native netCDF support, less filesystem I/O, better computational performance, good scaling for large processor counts, and support for the memory requirements of very large models. Manhattan has support for many of our larger models (**WRF, POP, CAM, CICE, CLM, ROMS, MPAS_ATM,** ...) with many more being added as time permits. The hallmarks of DART; tutorials, examples, extensive documentation, introductory materials, and performance diagnostics are maintained in an easier-to-grasp organization:

1. assimilation_code (programs and support modules)
2. build_templates (hardware/compiler options)
3. diagnostics
4. documentation
5. developer_tests
6. models
7. observations (observation converters and forward operators)

How an Ensemble Filter Works

Theory: Impact of observation on each state variable can be handled sequentially.

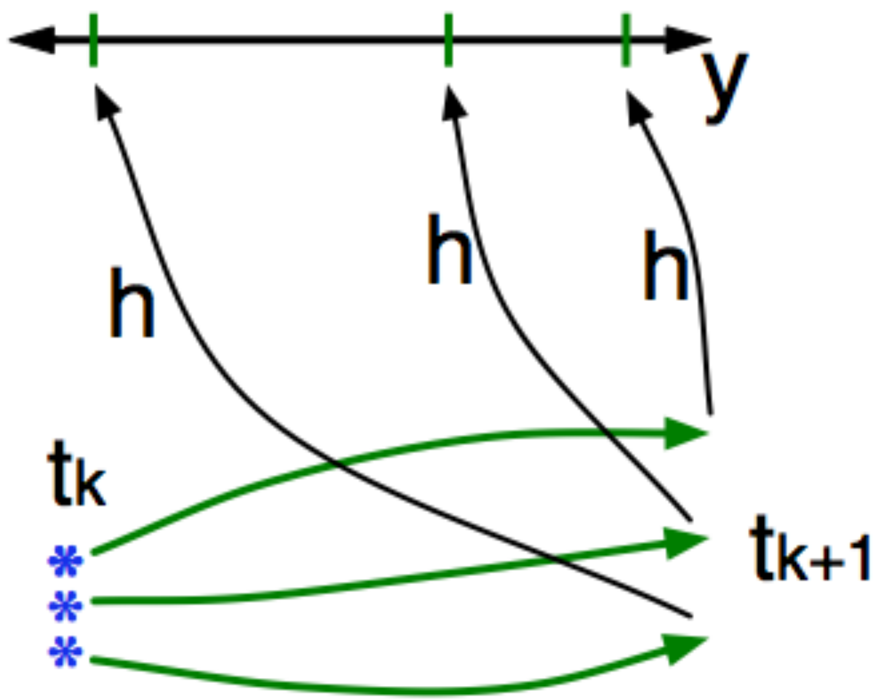
1. Use model to advance ensemble (3 members here) to time at which next observation becomes available.

Ensemble state estimate, $x(t_k)$, after using previous observation (analysis)

Ensemble state at time of next observation (prior)

Ensemble Filter For Large Geophysical Models

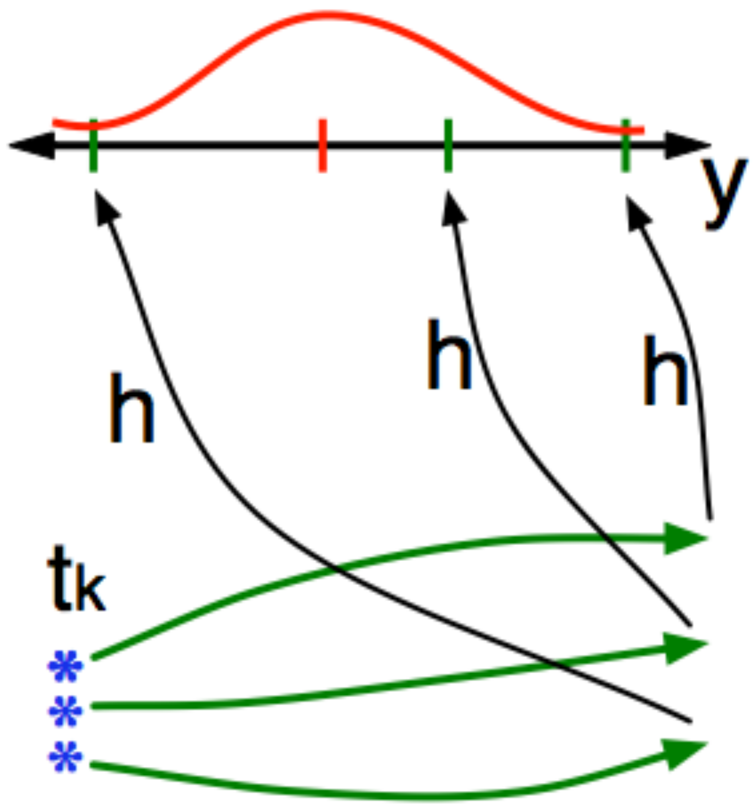
2. Get prior ensemble sample of observation, y = h(x), by applying forward operator **h** to each ensemble member.



Theory: observations from instruments with uncorrelated errors can be done sequentially.

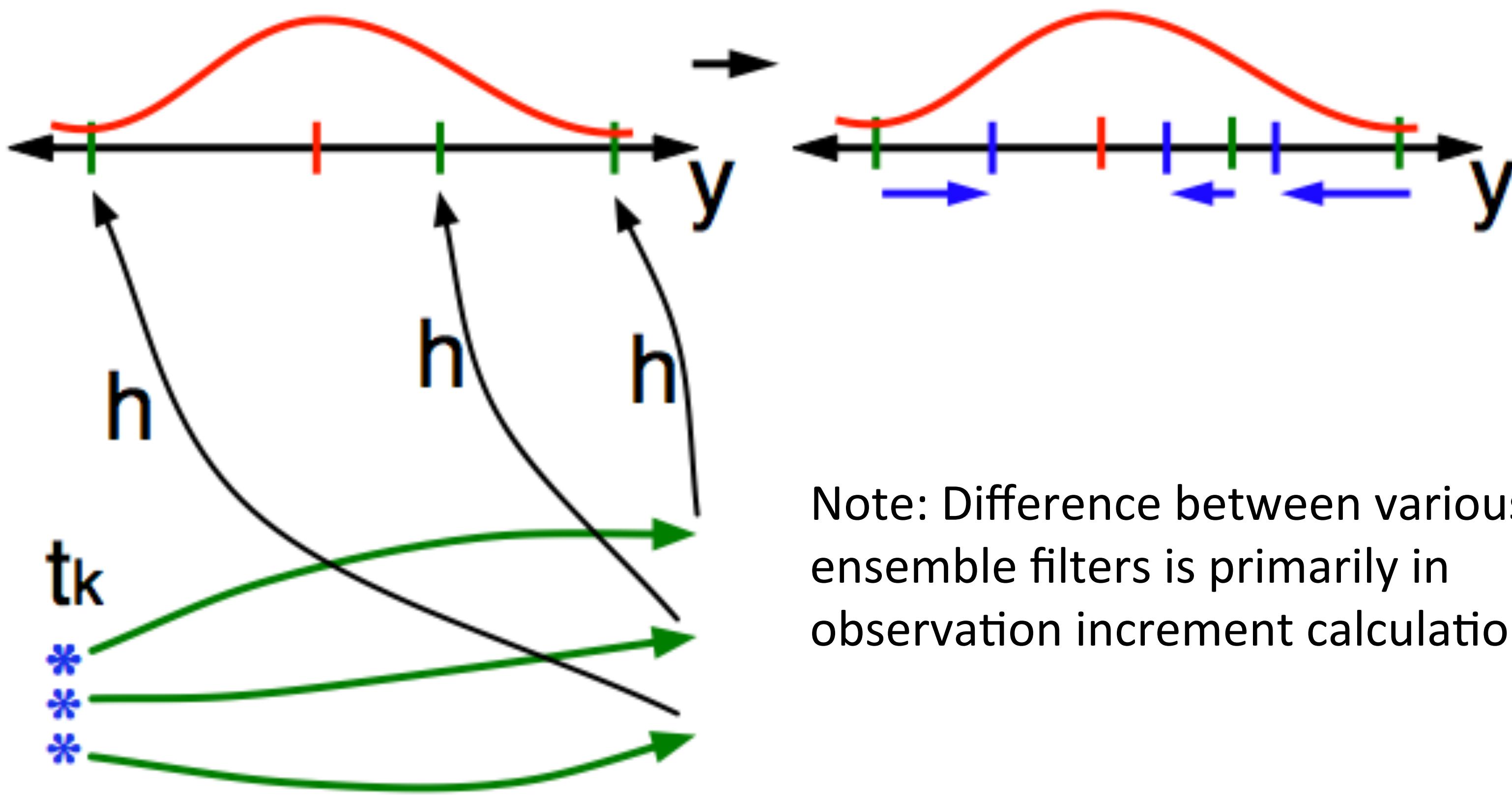
Ensemble Filter For Large Geophysical Models

3. Get observed value and observational error distribution from observing system.



Ensemble Filter For Large Geophysical Models

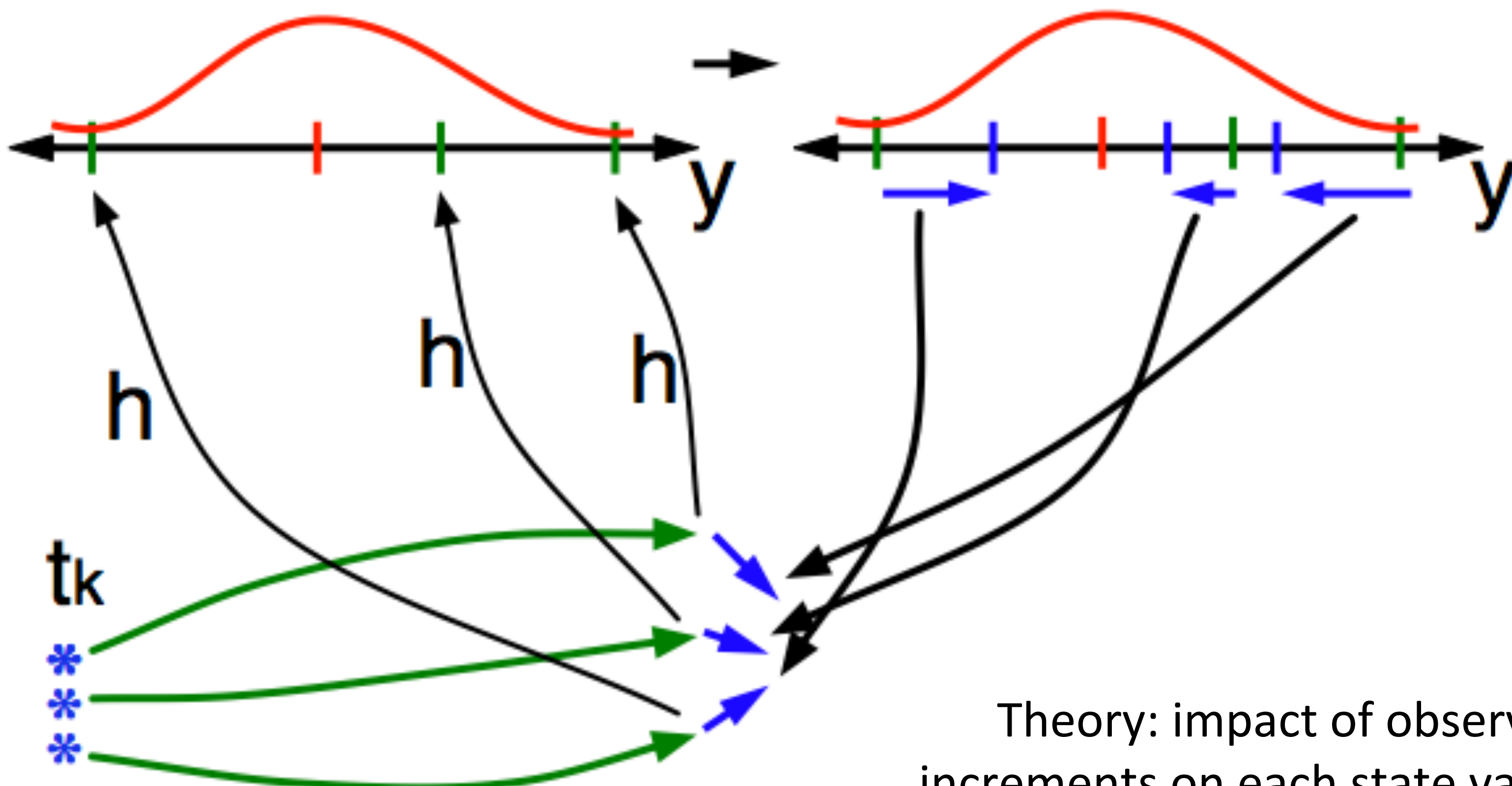
4. Compute the increments for the prior observation ensemble (this is a scalar problem for uncorrelated observation errors).



Note: Difference between various ensemble filters is primarily in observation increment calculation.

Ensemble Filter For Large Geophysical Models

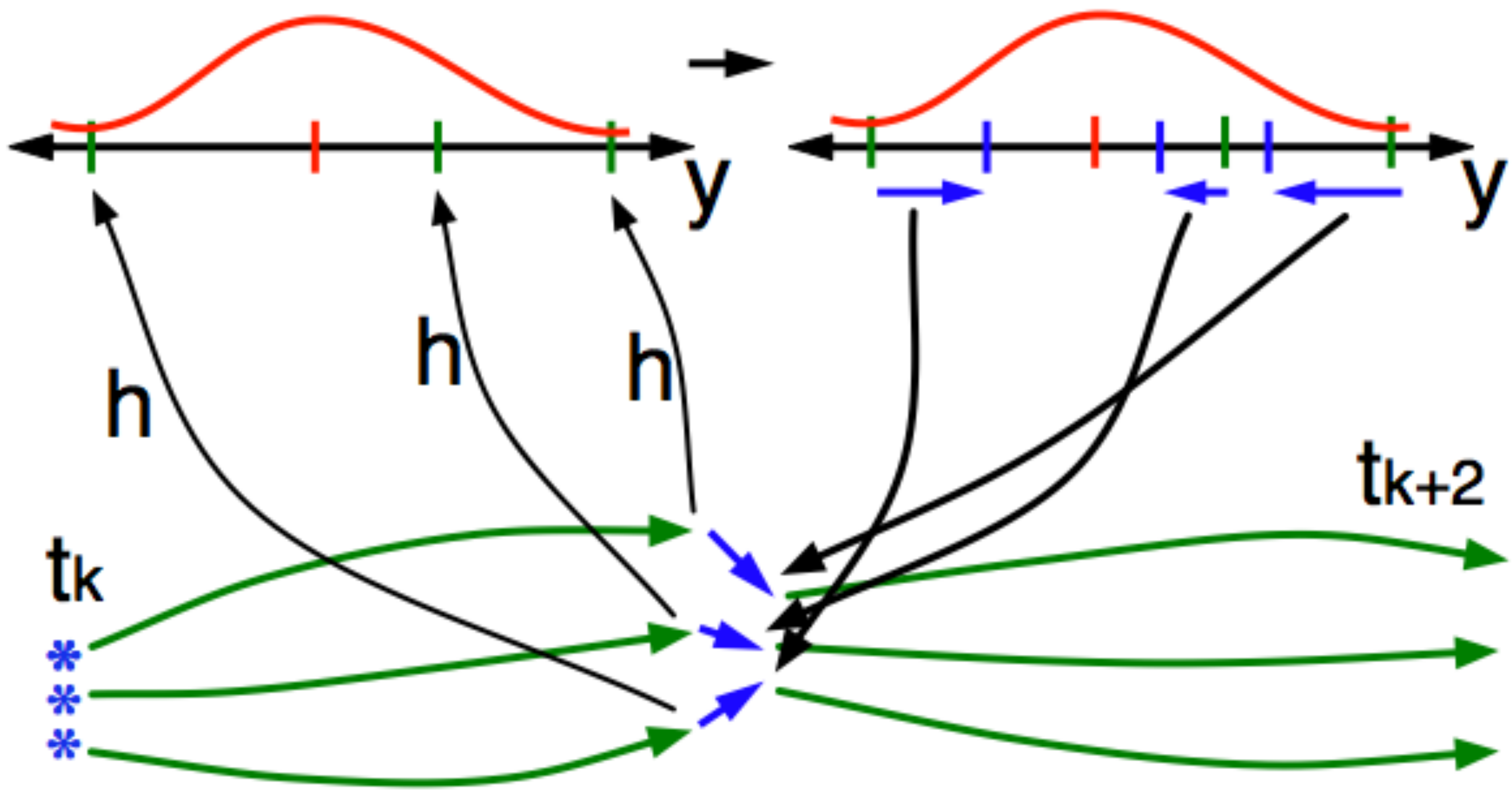
5. Use ensemble samples of **y** and each state variable to linearly regress observation increments onto state variable increments.



Theory: impact of observation increments on each state variable can be handled independently

Ensemble Filter For Large Geophysical Models

6. When all ensemble members for each state variable are updated, there is a new analysis. Integrate to time of next observation …



Issues in ensemble data assimilation

1. Sampling error <- localization and inflation

   : This is a unique problem in ensemble DA.

2. Non-Gaussianity and non-linearity in prior distribution and observation likelihood

3. Observation error specification

   : instrument error + forward operator error + representative error

4. Model uncertainty in the numerical modeling system

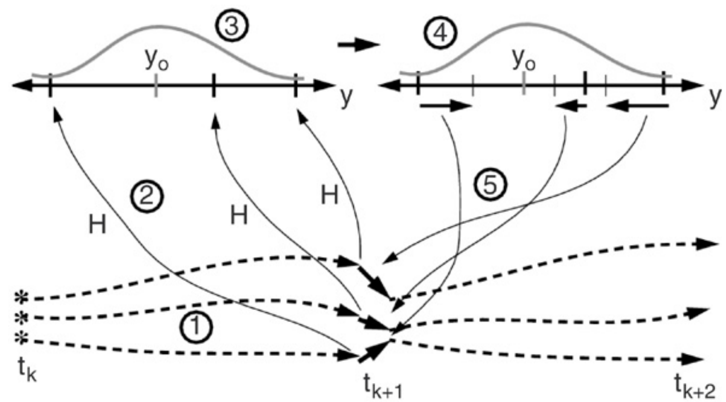


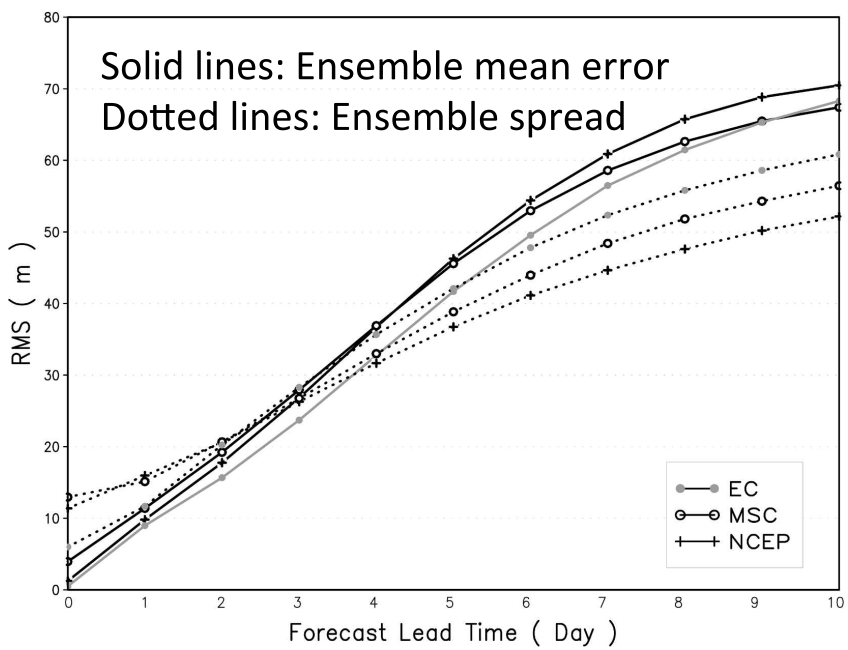
Fig. 1. Schematic representation of the implementation of the ensemble filter used here with possible error sources marked by numbers 1 through 5.

Anderson (2007)

Model uncertainty in the ensemble prediction system

- Typically underdispersive

500hPa geopotential height over the Northern Hemisphere (May-Jul 2002)



Buizza et al. 2005

Ensemble mean error grows faster than ensemble spread

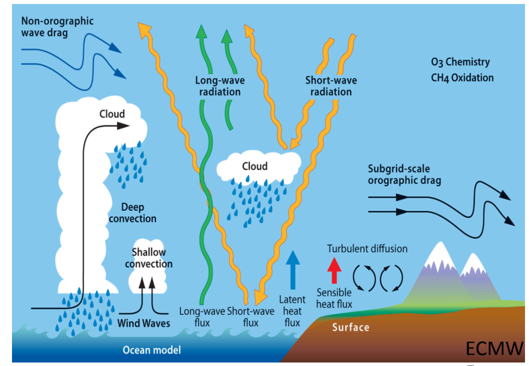
- Ensemble forecast is overconfident
- Underdispersion is a form of model error

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.

What are the sources of model uncertainties?

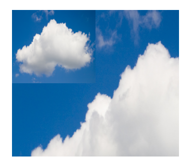
- ❑ Approximations and assumptions in the construction of a numerical model of the physics laws
  - ○ Land-surface parameterization
  - ○ Boundary-layer parameterization
  - ○ Convective parameterization
  - ○ Microphysical parameterization
  - ○ Short- and long-wave radiation schemes



ECMWF

- ❑ 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 <u>not</u> discuss about that here.

How can we account for model uncertainties?

- ❑ The uncertainty should be represented at its source
- ❑ Multi-model, multi-physics, and multi-parameter ensemble
- ❑ Stochastic parameterizations
  - Use deterministic parameterization schemes, but stochastically perturb mean states.
  - SKEBS (Stochastic Kinetic Energy Backscatter Scheme; Shutts 2005), SPPT (Stochastically perturbed parameterization tendencies; Buizza et al. 1999), SPP (Stochastic parameter perturbation; Jankov 2017), etc.

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

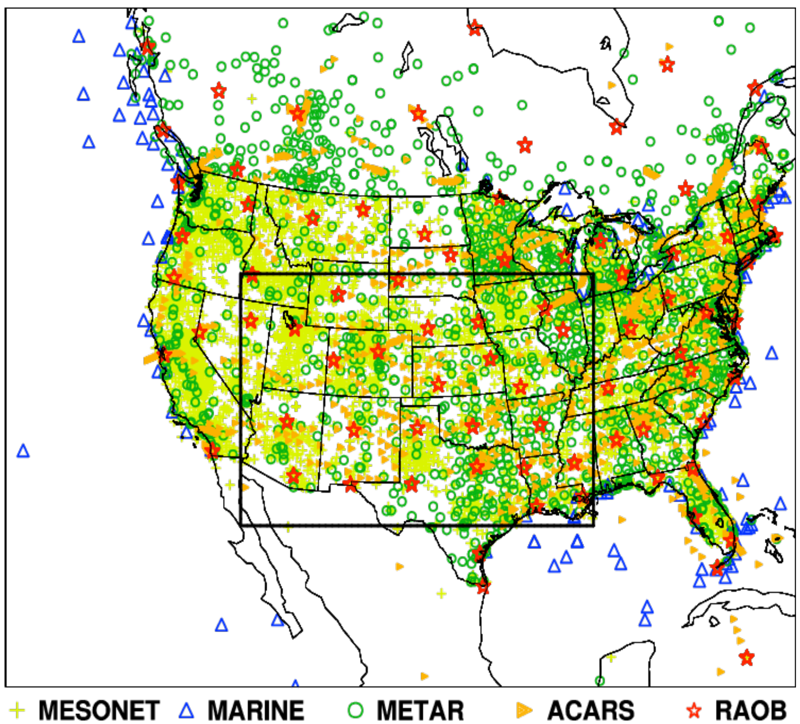
$$e_j(d,T) = e_j(d,0) + \int_0^T [\underbrace{A(e_j,t)} + \underbrace{P(e_j,t)} + \underbrace{\delta P_j(e_j,t)}]dt$$

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

WRF THE WEATHER RESEARCH & FORECASTING MODEL

Data Assimilation Research Testbed

Model error representation in the cycled analysis system



- Ensemble analysis/forecast cycling using WRFV3.3/DART
- 45/15-km in a two-way nesting, 41 levels up to 50 hPa
- One-month period of June 2008 at 3-h intervals
- EAKF assimilation w/ covariance localization radius of 600/8-km (H/V)

Soyoung Ha, Judith Berner and Chris Snyder: A comparison of model error representations in mesoscale ensemble data assimilation (*Mon. Wea. Rev. 2015*)

Cycling experiments w/ model error techniques

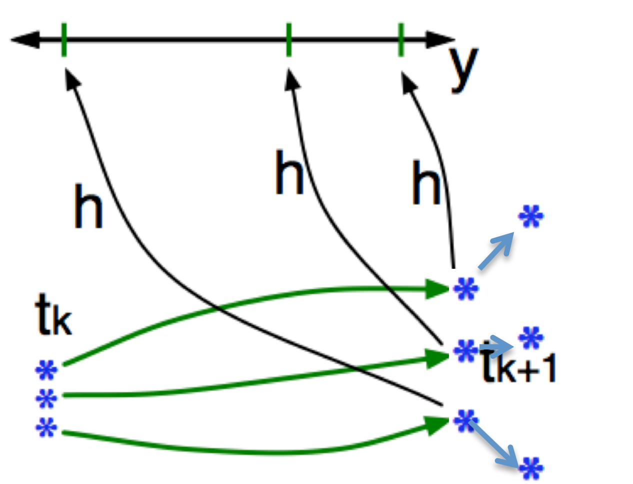
- CNTL w/ adaptive inflation only
- SKEB: CNTL + SKEBS
- PHYS: CNTL+ multi-physics

TABLE 2. Physics combinations for the PHYS ensemble.

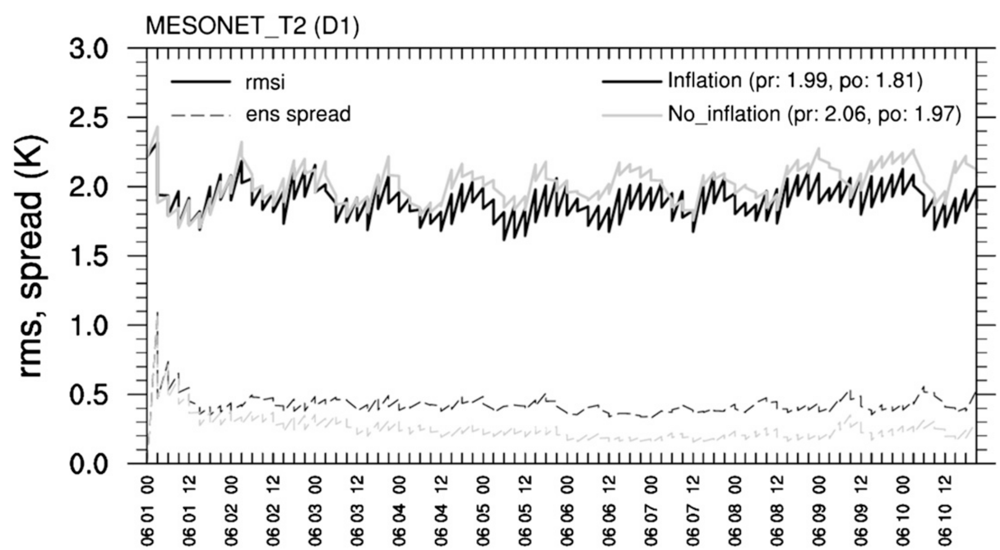
Physics suite	Surface	Microphysics	PBL	Cumulus	LW	SW
1	Thermal	Kessler	YSU	KF	RRTM	Dudhia
2	Thermal	WSM6	MYJ	KF	RRTM	CAM
3	Noah	Kessler	MYJ	BM	CAM	Dudhia
4	Noah	Lin	MYJ	Grell	CAM	CAM
5	Noah	WSM5	YSU	KF	RRTM	Dudhia
6	Noah	WSM5	MYJ	Grell	RRTM	Dudhia
7	RUC	Lin	YSU	BM	CAM	Dudhia
8	RUC	Eta	MYJ	KF	RRTM	Dudhia
9	RUC	Eta	YSU	BM	RRTM	CAM
10	RUC	Thompson	MYJ	Grell	CAM	CAM

Model error representation: Adaptive inflation

- A spatially and temporally varying covariance inflation estimated using a Bayesian algorithm to deal with various sources of error such as sampling error and model error at the analysis step (Anderson 2009)
- Large inflation is needed to account for model error in regions where dense observations reduce ensemble spread the most.



Inflate prior



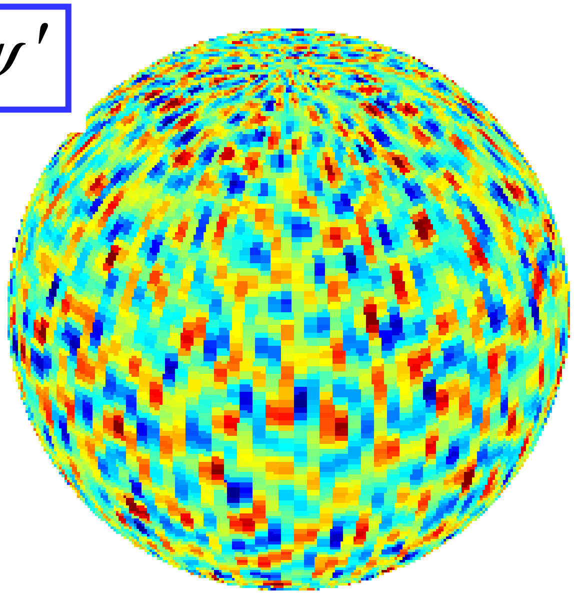
Ha et al. (MWR 2015)

Model error representation: Stochastic kinetic energy backscatter scheme (SKEBS)

Rationale: A fraction of the dissipated energy is scattered upscale and acts as streamfunction forcing for the resolved-scale flow.

$$\Delta \psi^* \propto \sqrt{D}\psi'$$

ψ'



Spectral Markov chain: temporal and spatial correlations prescribed

<u>Characteristics</u>

- Stochastic (additive noise)
- Spatial and temporal correlations
- Control over wavenumber forcing allows scale selection
- Flow-dependent (weighting with dissipation rates)
- Injects energy in the regions of large dissipation, which corresponds to the regions of large model error

Model error representation: SKEBS (cont'd)

- To represent unresolved upscale energy transfer, stochastic, small-amplitude perturbations are added to the rotational component of horizontal wind and potential temperature tendency equations at each time step.

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

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

- A random pattern is created in spectral space and each wavenumber separately evolves as a first-order autoregressive process

$$\psi'_{k,l}(t+\Delta t) = (1-\alpha)\psi'_{k,l}(t) + g_{k,l}\sqrt{\alpha}\epsilon_{k,l}(t).$$

- A simplified version with constant dissipation rate can be considered as additive noise with spatial and temporal correlations.

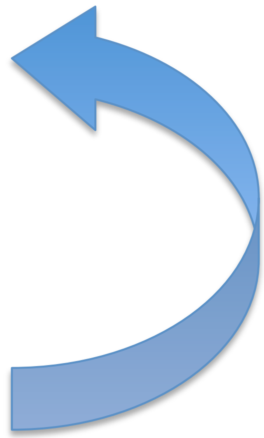
Model error representation in the EnKF cycling

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

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

$$\mathbf{P}^b\mathbf{H}^T = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{x}_i^b - \overline{\mathbf{x}_i^b})(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})^T$$

$$\mathbf{H}\mathbf{P}^b\mathbf{H}^T \equiv \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})(\mathbf{H}\mathbf{x}_i^b - \overline{\mathbf{H}\mathbf{x}_i^b})^T$$



$$x_i^b(t+1) = \underline{M}(x_i^a) + Q_i, \quad i = 1, \ldots, N$$

A fully nonlinear model

Model error

$$x_{i,j}^{\inf} = \sqrt{\lambda}(x_{i,j} - \overline{x}_j) + \overline{x}_j, \quad i = 1, \ldots, N; \;\; j = 1, \ldots, S$$

Inflation factor

Model error representation in the EnKF cycling

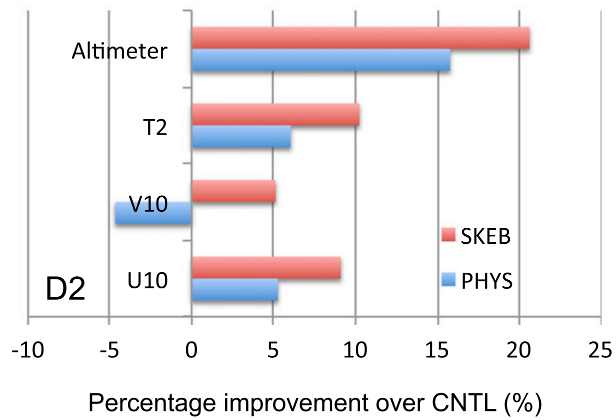


FIG. 7. The improvement (%) of forecast error in SKEB and PHYS over the one in CNTL for both domains (top) 1 and (bottom) 2 in various surface fields. The rms innovations are computed against mesonet observations and averaged over the month-long cycles. Positive means an improvement relative to CNTL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

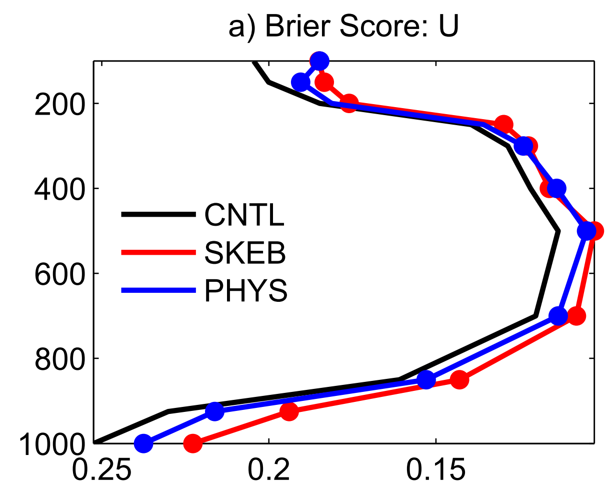


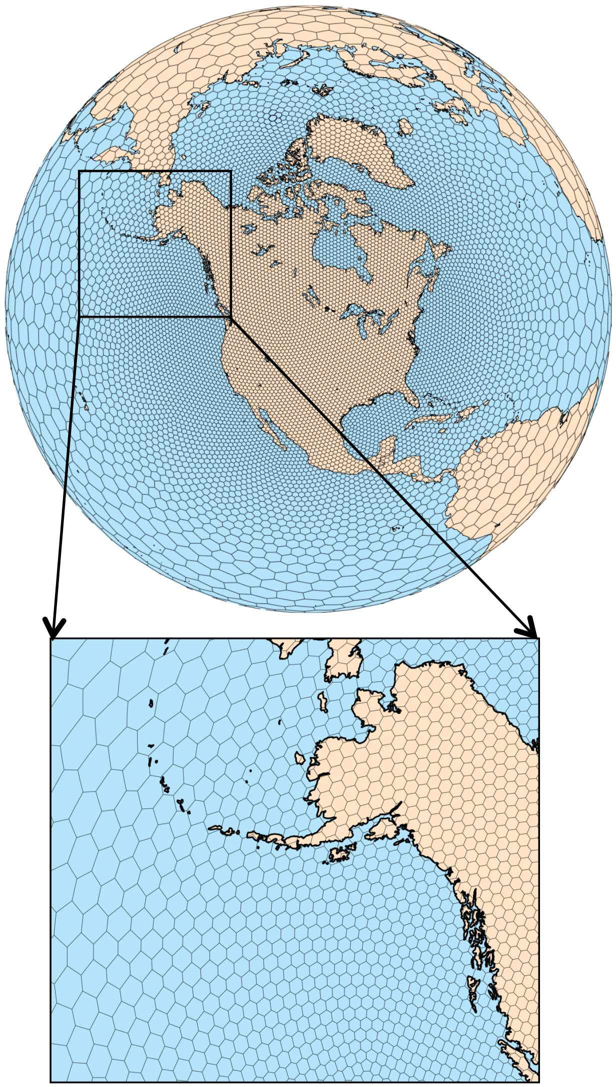
FIG. 11. Brier scores of the 3-h ensemble forecast in (a) u wind bin1: $f > \mu_o + \sigma_o$

In the cycling DA, representing model uncertainties (in PHYS and SKEB) improves ensemble forecasts deterministically and probabilistically, verified against independent observations.

Summary about Ensemble DA

- An estimate of analysis and forecast uncertainty is provided
- Flow-dependent background error covariance
  - determines how to spread out an observed information in the model space based on "errors of the day"
  - Sampling errors due to the limited ensemble size <-> localization and/or inflation
  - Makes it easy to exploit new types of observations by sampling the covariance among variables directly from the ensemble.
- However, ensemble sample error covariance is subject to model error that can eventually degrade the quality of the ensemble analysis/forecast.

MPAS
Model for Prediction Across Scales



Based on unstructured centroidal Voronoi (hexagonal) meshes using C-grid staggering and selective grid refinement.

Jointly developed, primarily by NCAR and LANL/DOE for weather, regional climate, and climate applications

A multi-core system

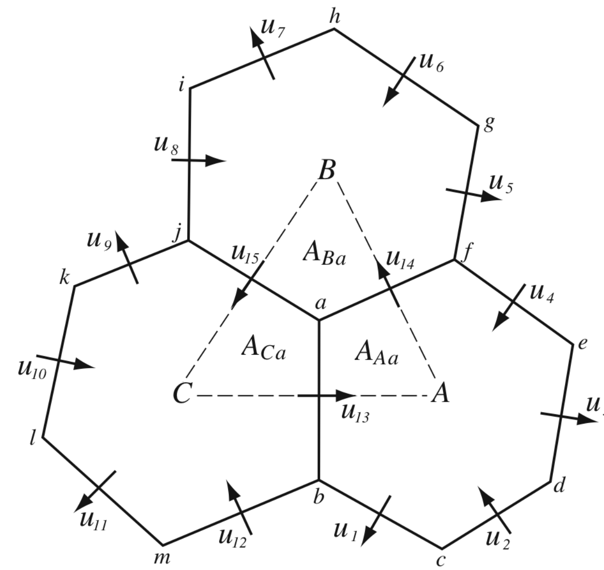
- MPAS-Atmosphere: model development led by Bill Skamarock in MMM/NCAR - mainly for applications in high-resolution numerical weather prediction (NWP) and regional climate
- MPAS-Ocean/Ice: model development led by Todd Ringler in Los Alamos National Laboratory (LANL) – for climate research and applications

Current version: 5.1 http://mpas-dev.github.io/

Courtesy of Bill Skamarock for MPAS-A slides

MPAS
Model for Prediction Across Scales

MPAS-Atmosphere



Unstructured spherical Centroidal Voronoi meshes

- Mostly *hexagons*, some pentagons and 7-sided cells.
- Cell centers are at cell center-of-mass (centroidal).
- Cell edges bisect lines connecting cell centers; perpendicular.
- Uniform resolution – traditional icosahedral mesh.

C-grid staggering

- Solve for normal velocities on cell edges.
- Zonal and meridional winds are reconstructed at cell centers.

Solvers

- Fully compressible nonhydrostatic equations

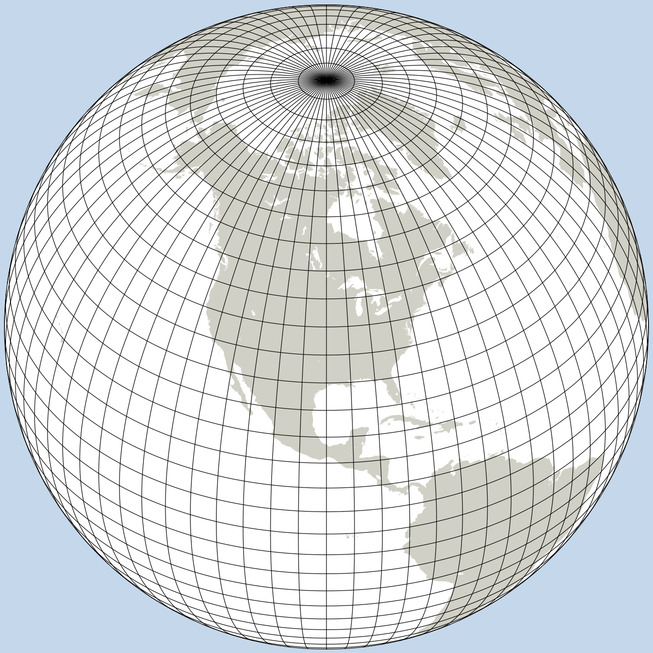
Physics parameterization schemes

- 2-3 suites of physics parameterization (adopted from WRF) + contributed physics (by users)
- Scale-awareness in development (for different behaviors across variable meshes)

MPAS
Model for Prediction Across Scales

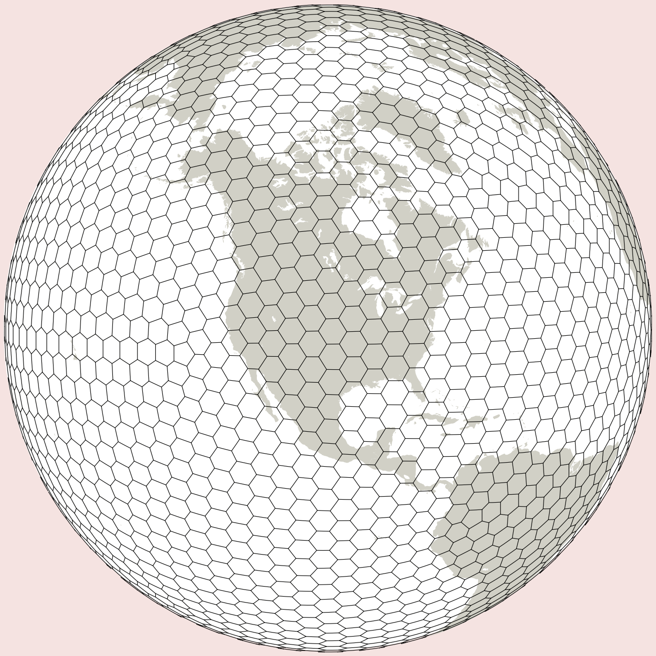
Why MPAS?

Significant differences between WRF and MPAS



WRF
Lat-Lon global grid

- Anisotropic grid cells
- Polar filtering required
- Poor scaling on massively parallel computers

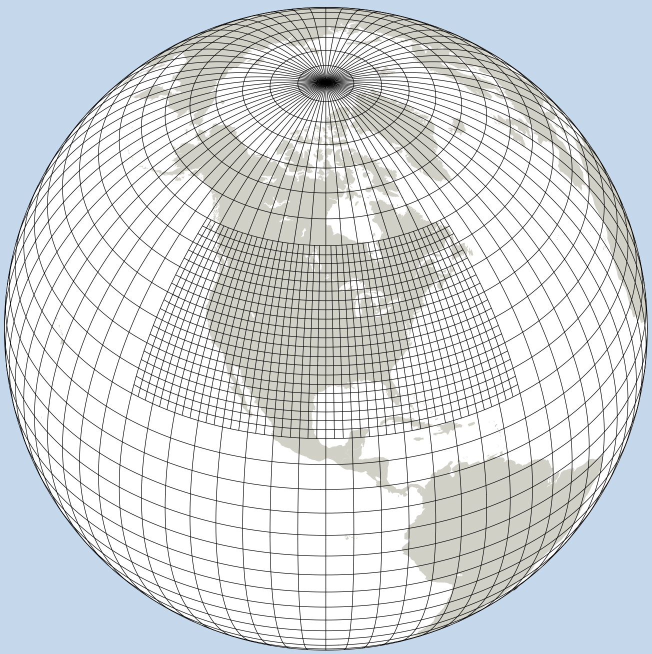


MPAS
Unstructured Voronoi (hexagonal) grid

- Good scaling on massively parallel computers
- No pole problems

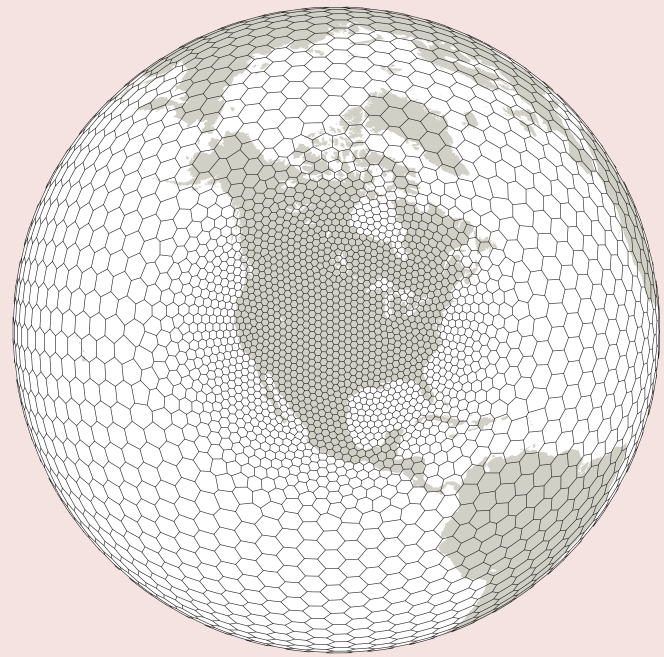
MPAS
Model for Prediction Across Scales

Why MPAS?
Significant differences between WRF and MPAS



WRF
Grid refinement through domain nesting

- Flow distortions at nest boundaries

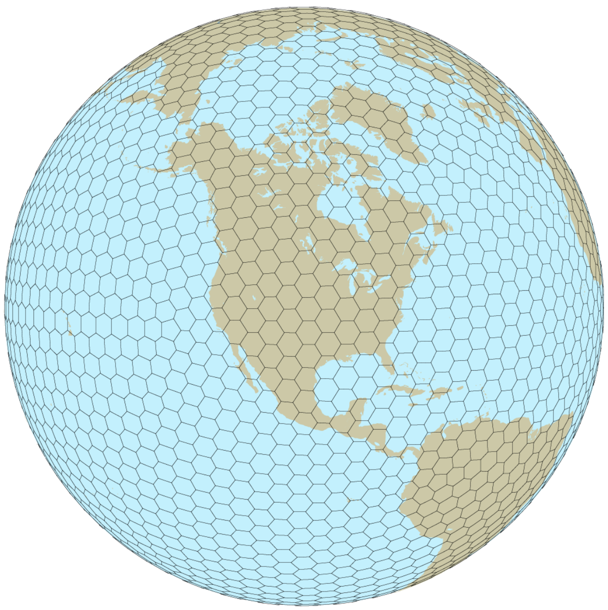


MPAS
Smooth grid refinement on a conformal mesh

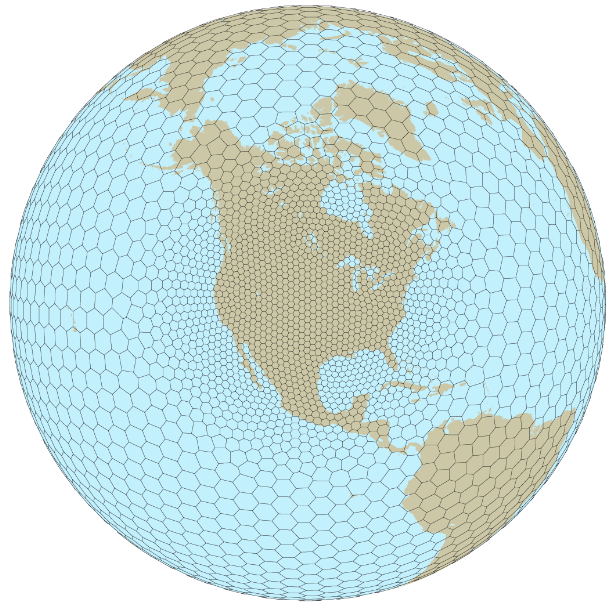
- Increased accuracy and flexibility for variable resolution applications
- No abrupt mesh transitions.

MPAS
Model for Prediction Across Scales

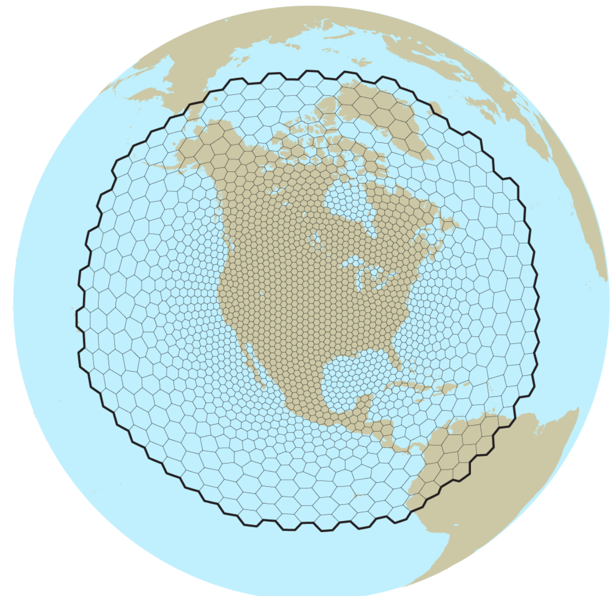
Global Meshes and Local Refinement



Global uniform mesh



Global variable-resolution mesh



Regional mesh

The regional forecast can be driven from other model forecasts, or from previous MPAS forecasts.

If the regional mesh boundary matches the global mesh, no spatial interpolation is required to drive the regional forecast.

MPAS
Model for Prediction Across Scales

MPAS-A Model Summary

- MPAS-Atmosphere has the flexibility to run globally on uniform or variable-resolution meshes.
- MPAS-Atmosphere produces forecast similar to the Advanced Research WRF (ARW) at large scales and at cloud scales.
- Variable-resolution meshes show the benefit of high-resolution simulations. *Scale-aware physics* are underway.
- Coupling: Porting MPAS dynamical cores to the Community Atmosphere Model (CAM) in the Community Earth Systems Model (CESM) to provide coupling between MPAS-A and MPAS-O components and coupling to the CAM physics and other components of the CESM system.

MPAS/DART: Observation operators

- Built on the unstructured grid mesh (using a dual mesh of a Voronoi tessellation)
- Barycentric interpolation in the triangle for scalar variables
- As a prognostic wind variable is normal velocity on the edge, there are various options to assimilate wind observations.

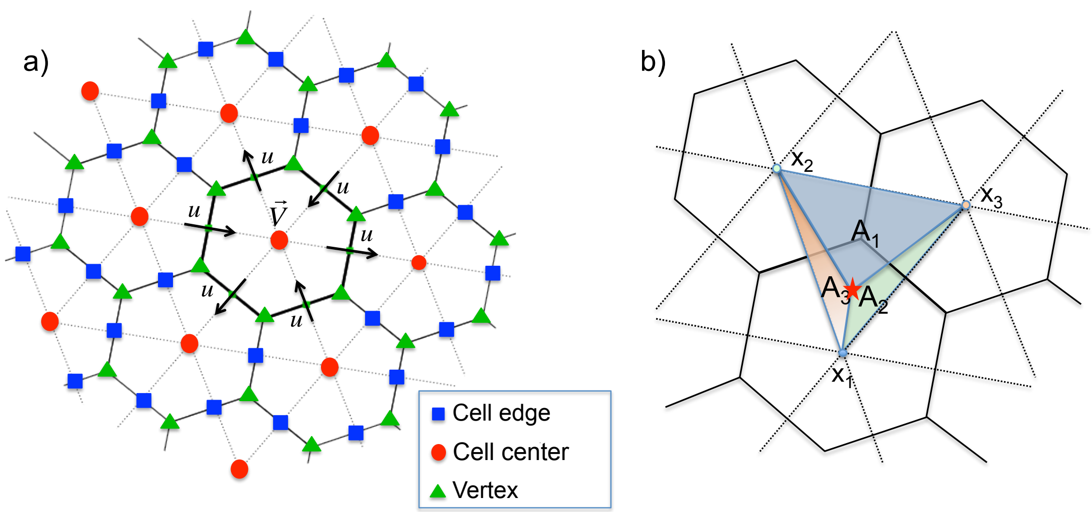
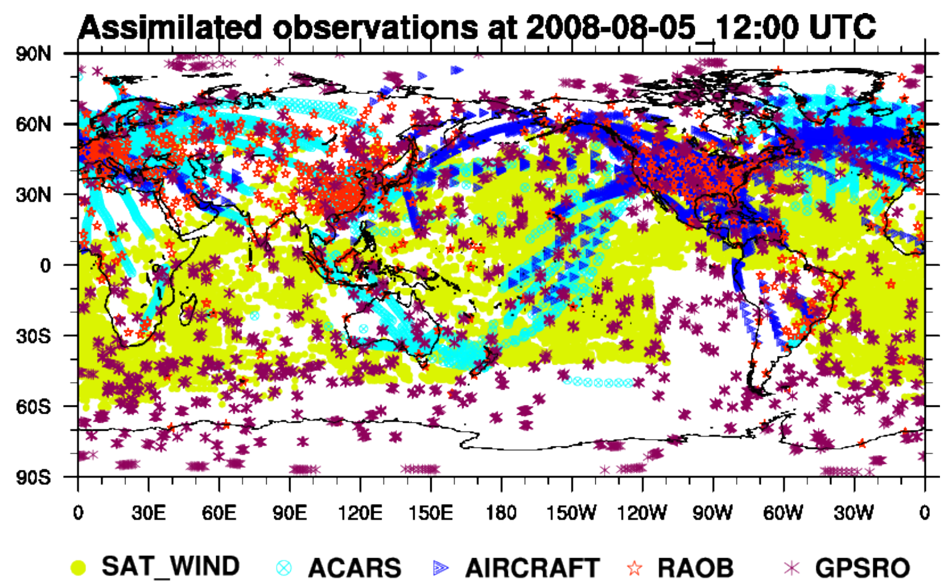
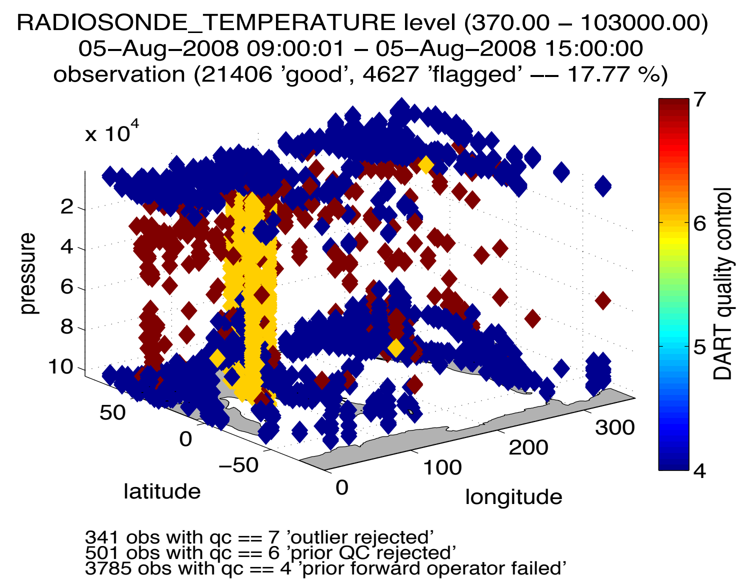


FIG. 1. Depiction of the horizontal MPAS grids that are constructed using an unstructured centroidal Voronoi tessellation. Primary cells are shown as hexagons in solid lines while the dual of the hexagonal mesh is marked as dotted triangles. As illustrated in a), all scalar fields and reconstructed zonal and meridional winds are defined at the primary cell centers (red dots) and normal velocity (u) is defined at cell edges (blue square). In MPAS/DART, vertices (green triangle) are used to search the triangle in the dual mesh that encloses an arbitrary observation point. b) depicts a barycentric interpolation to an observation point (red star) within the triangle.

Assimilation of real observations in MPAS/DART

- Model configuration: 80-member ensemble at ~2-degree uniform mesh, 41 vertical levels w/ the model top at 30-km
- Conventional observations (NCEP PrepBUFR) + GPS RO
- Ensemble filter data assimilation design: localization (1200H/4V), adaptive inflation in prior state, 6-hrly cycling for one month of August 2008.
- WRF-Physics: WSM6 microphysics, YSU PBL, NOAH LSM, Tiedtke cumulus parameterization, CAM SW/LW radiation schemes

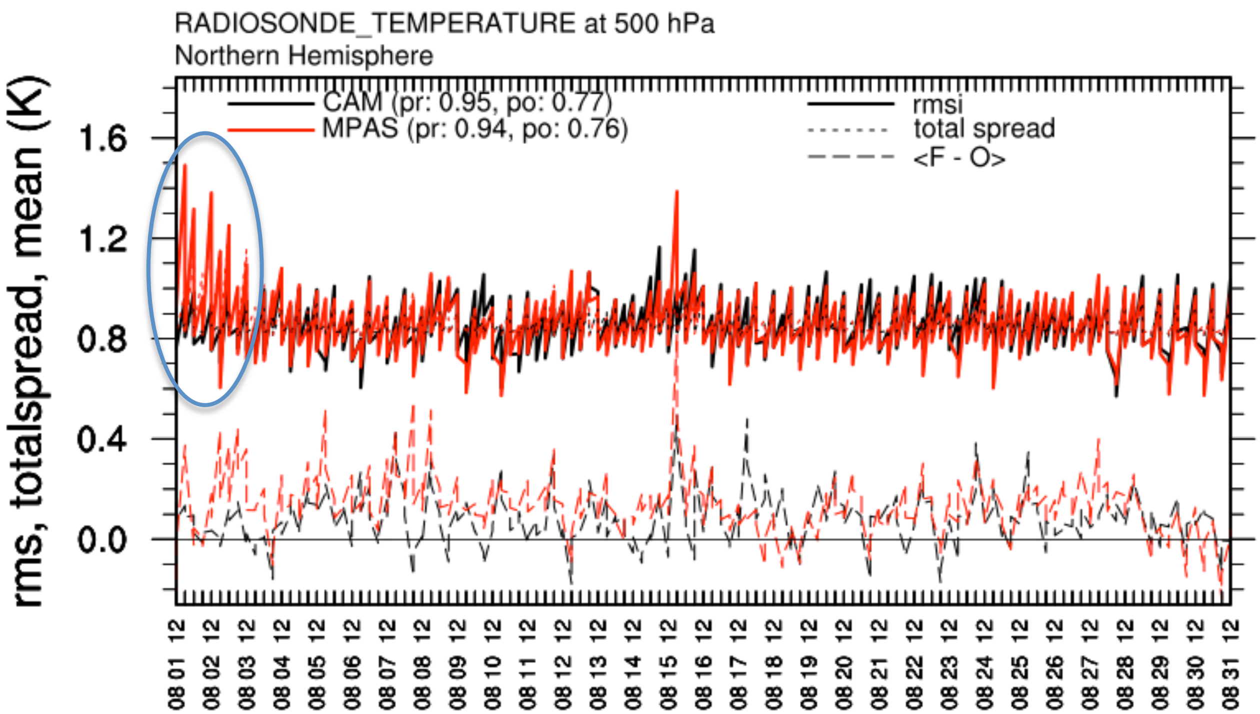




Comparison w/ CAM/DART

- CAM/DART run by Kevin Reader (IMAGe/NCAR)
- CCSM4.0 on ~2-degree resolution w/ the model top at 3 mb
- Assimilating same observations
- Very similar filter configuration
- Climate data assimilation cycling for ~10 yrs starting from 2000
- Verification for the same month of August 2008 in the observation space

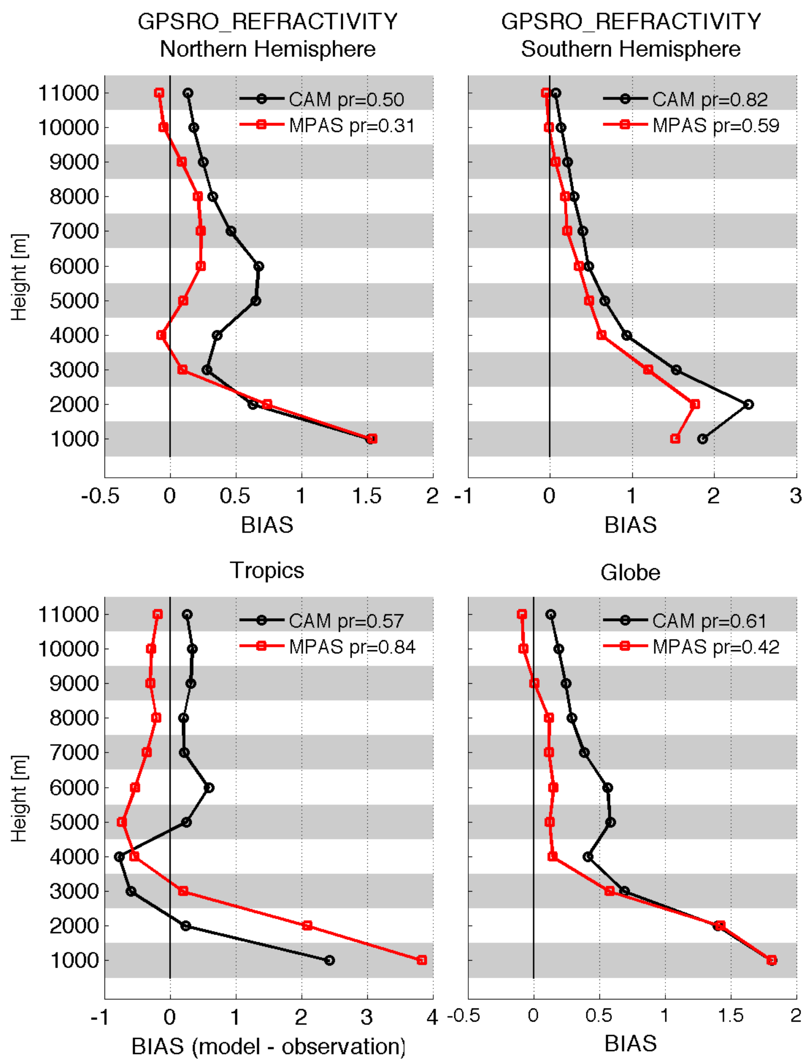
Sounding verification: Comparison w/ CAM/DART



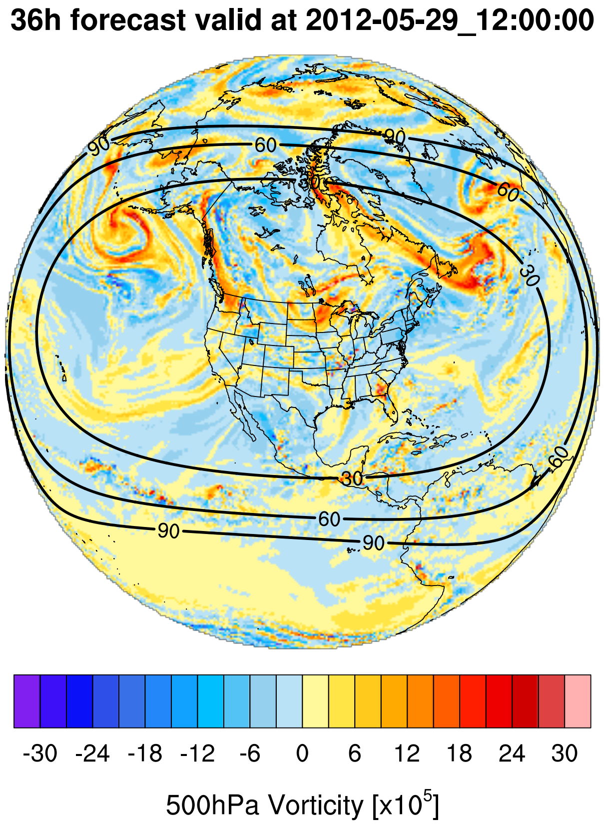
- MPAS/DART looks pretty reliable after a spinup for the first couple of days.
- CAM/DART and MPAS/DART are broadly comparable and reliable.

GPSRO_REFRACTIVITY verification: 6-h forecast (prior)

BIAS



Variable-resolution DA with MPAS/DART

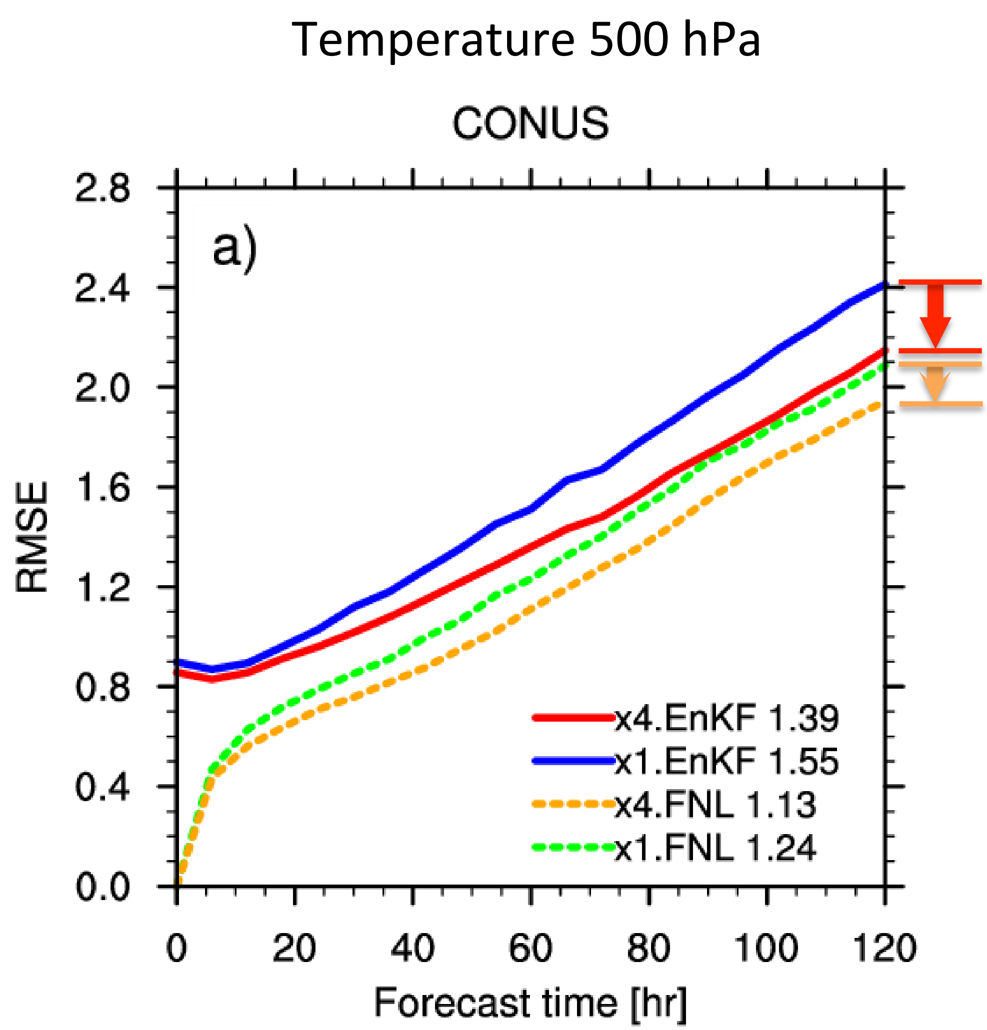


Grid resolution in 120-30 km mesh (named "x4"), contouring every 30 km.

- MPAS V4 and DART-Lanai
- A variable-resolution mesh (120-30 km) is used in both analysis and forecast during the cycling DA.
- Compare the variable-resolution (x4) to a coarse uniform (x1) mesh w/ 120-km resolution; Assimilating the same observations using the very similar analysis and model configurations.

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

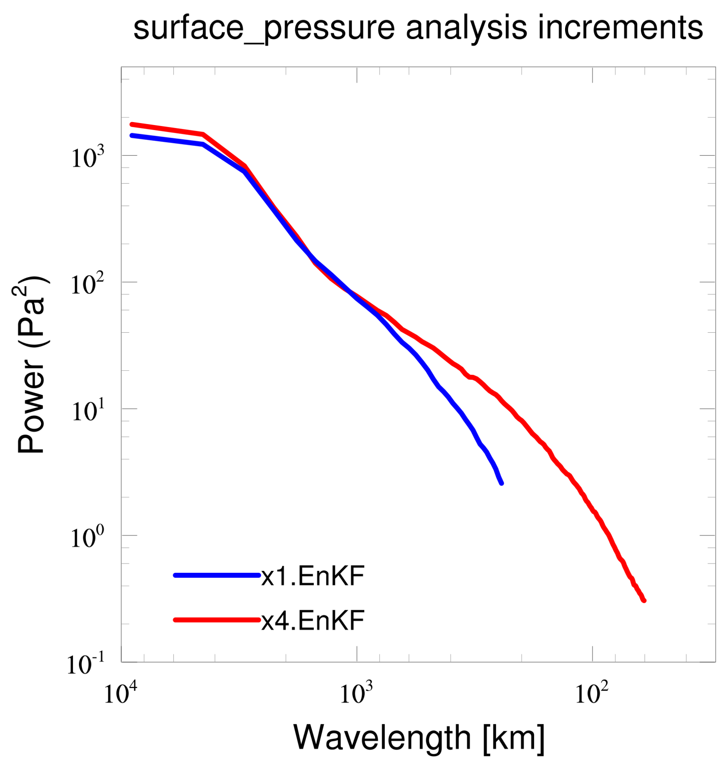
Variable-resolution DA with MPAS/DART



5-day MPAS forecast 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 forecast are well shown in the cold-start run (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)

Variable-resolution DA with MPAS/DART

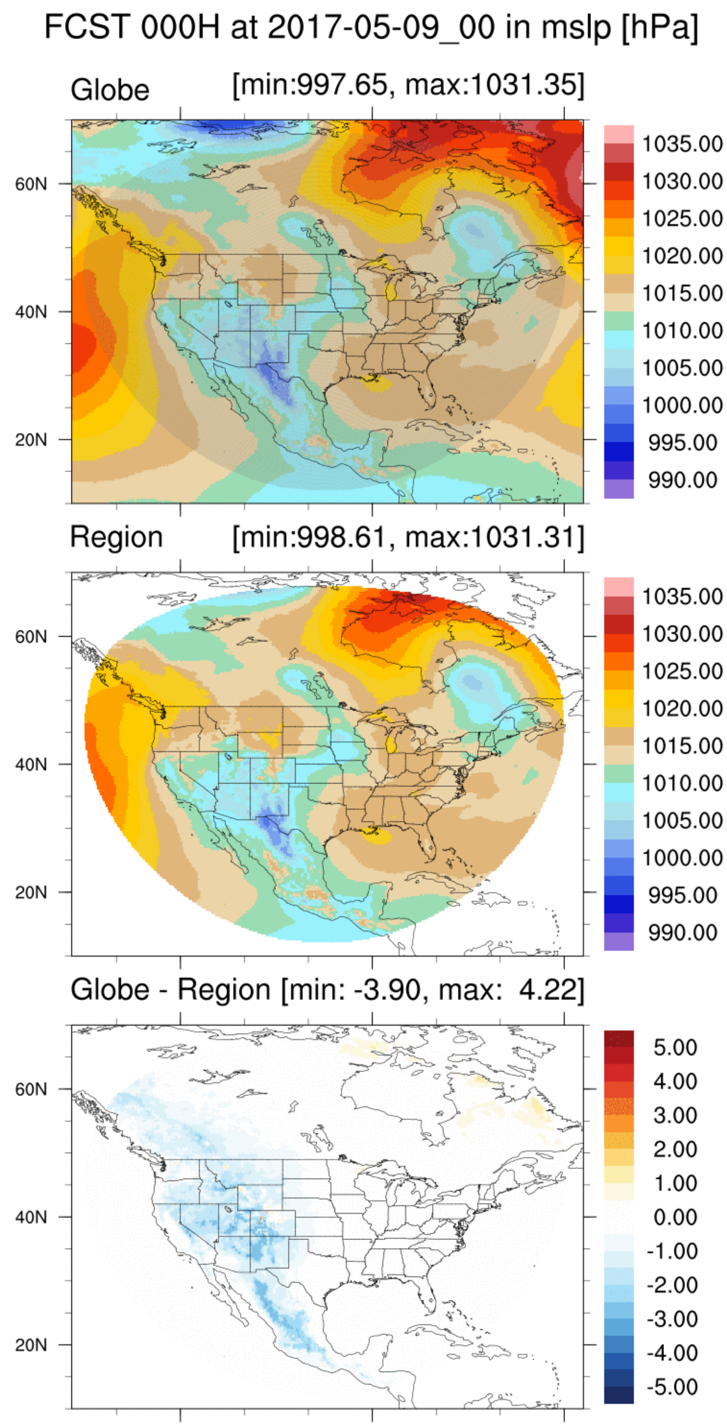


Power Spectra of ensemble analysis increments in surface pressure over the CONUS domain:

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

Summary for MPAS/DART

- ❑ The MPAS/DART interface is available with full capabilities.
- ❑ The analysis/forecast cycling was successfully tested assimilating real observations for different period of time.
- ❑ MPAS/DART on the quasi-uniform mesh is reliable and broadly comparable to CAM/DART.
- ❑ The EnKF analysis on the variable mesh further improves MPAS forecasts, showing the benefit of higher resolution grids.
- ❑ MPAS/DART is available in CESM for coupled models.



Regional-mode MPAS is underway.

- Model versions are slightly different between global and regional MPAS.
- No artifacts along the lateral boundaries for inflow/outflow.