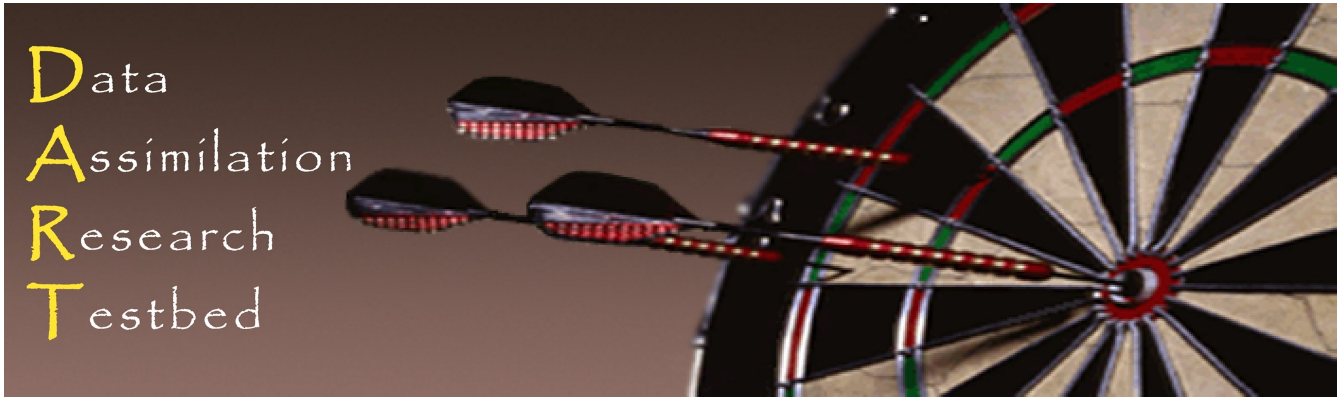
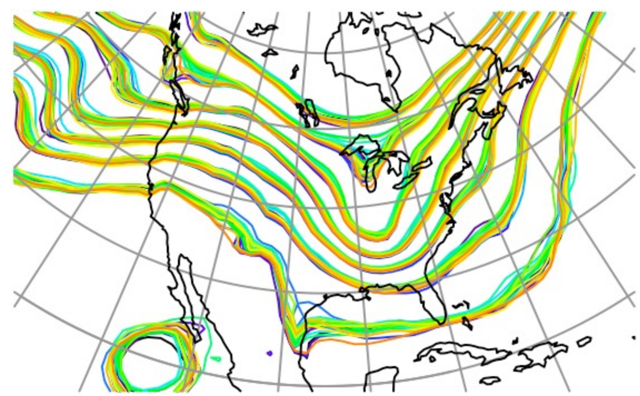


Using the Data Assimilation Research Testbed for Geospace Applications: Successes and Challenges in Ensemble Assimilation for Strongly-Forced Systems

Jeff Anderson, NCAR/DAReS



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A General Description of the Forecast Problem

A FORECAST MODEL; (stochastic) Difference Equation:

$$dx_t = f(x_t, t) + G(x_t, t)\, d\beta_t, \qquad t \geq 0$$

FORWARD OPERATORS: Relates model to observations:

$$y_k = h(x_k, t_k) + v_k; \qquad k = 1, 2, \ldots; \qquad t_{k+1} > t_k \geq t_0$$

Complete history of observations is:

$$Y_\tau = \{ y_l ; t_l \leq \tau \}$$

Goal: Find probability distribution for state:

$p(x, t \mid Y_t)$ Analysis $\qquad$ $p(x, t^+ \mid Y_t)$ Forecast

A General Description of the Forecast Problem

DATA ASSIMILATION: Observations impact model:

Prior (model forecast)

Likelihood (Obs. Error)

$$p\left(x, t_k \mid Y_{t_k}\right) = \frac{p\left(y_k \mid x\right) p\left(x, t_k \mid Y_{t_{k-1}}\right)}{\int p(y_k \mid \xi) p(\xi, t_k \mid Y_{t_{k-1}}) d\xi} \tag{10}$$

Posterior (analysis).

Denominator just normalization.

Solving the Forecast Problem: The Kalman Filter

Assumes:

linear model

Gaussian noise

$$dx_t = f(x_t, t) + G(x_t, t)\, d\beta_t, \qquad t \geq 0$$

Gaussian state

linear forward operator,

$$y_k = h(x_k, t_k) + v_k; \qquad k = 1, 2, \ldots; \qquad t_{k+1} > t_k \geq t_0$$

Gaussian observation error

Kalman Filter: Product of Two Gaussians

Product of d-dimensional normals with means μ_1 and μ_2 and covariance matrices Σ_1 and Σ_2 is normal.

$$N(\mu_1, \Sigma_1) N(\mu_2, \Sigma_2) = c N(\mu, \Sigma)$$

Covariance: $$\Sigma = (\Sigma_1^{-1} + \Sigma_2^{-1})^{-1}$$

Mean: $$\mu = \Sigma(\Sigma_1^{-1}\mu_1 + \Sigma_2^{-1}\mu_2)$$

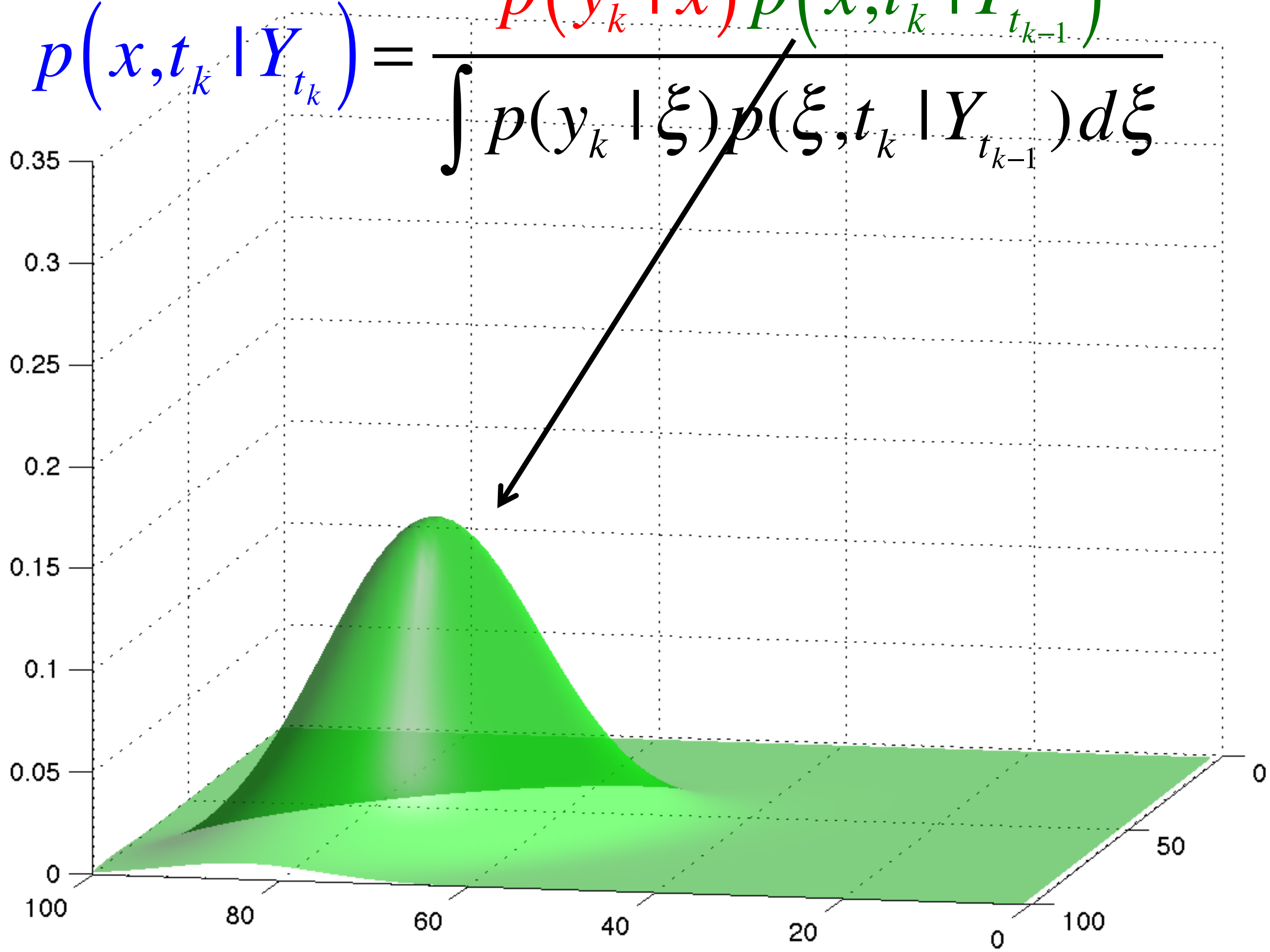
The Kalman Filter

$$p\left(x, t_k \mid Y_{t_k}\right) = \frac{p\left(y_k \mid x\right) p\left(x, t_k \mid Y_{t_{k-1}}\right)}{\int p(y_k \mid \xi) p(\xi, t_k \mid Y_{t_{k-1}}) d\xi}$$

Numerator is just product of two gaussians.

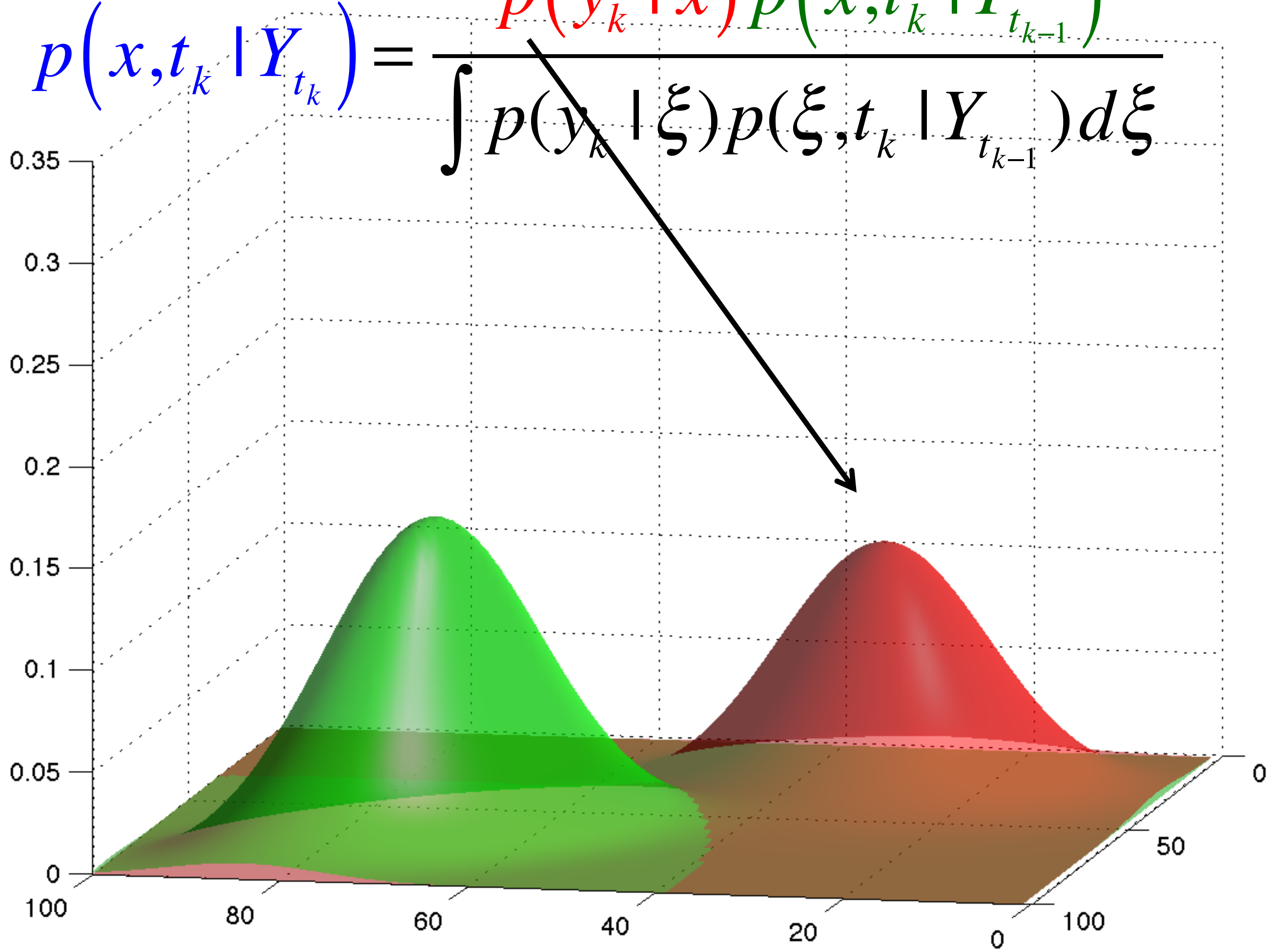
Denominator just normalizes posterior to be a PDF.

$$p\left(x,t_k \mid Y_{t_k}\right) = \frac{p\left(y_k \mid x\right) p\left(x,t_k \mid Y_{t_{k-1}}\right)}{\int p(y_k \mid \xi)\, p(\xi,t_k \mid Y_{t_{k-1}})\, d\xi}$$



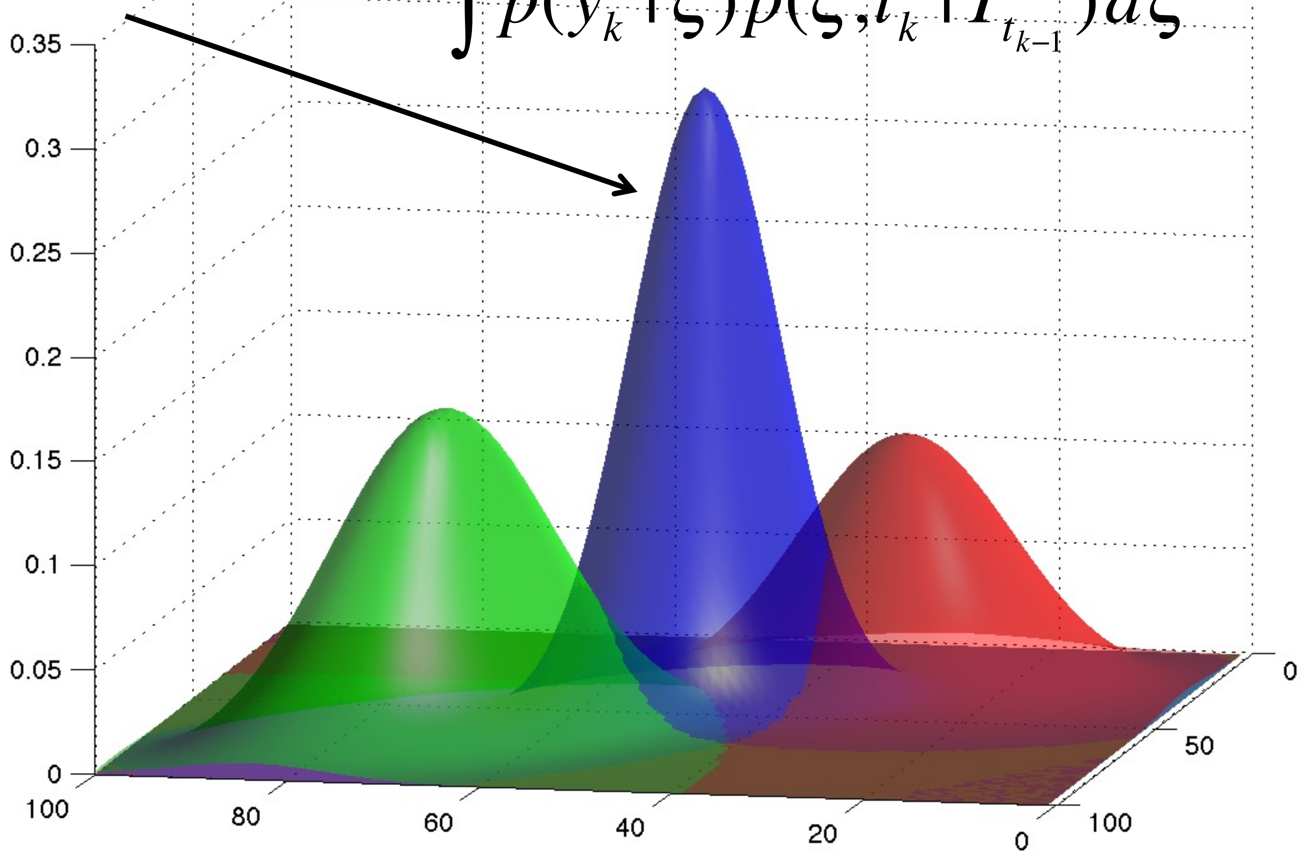
The Kalman Filter

$$p\left(x,t_k \mid Y_{t_k}\right) = \frac{p\left(y_k \mid x\right) p\left(x,t_k \mid Y_{t_{k-1}}\right)}{\int p(y_k \mid \xi) p(\xi,t_k \mid Y_{t_{k-1}}) d\xi}$$



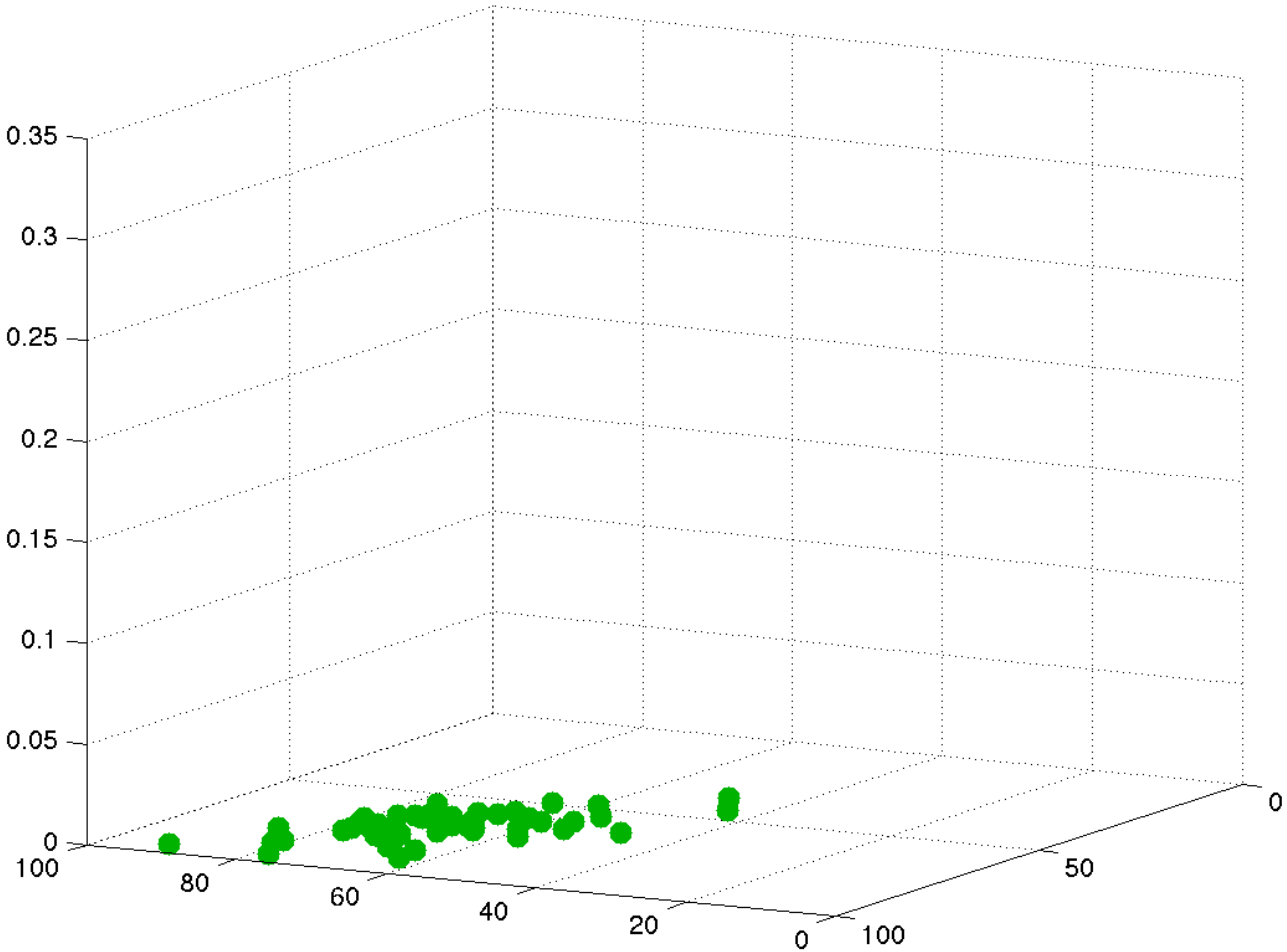
The Kalman Filter

$$p\left(x,t_k \mid Y_{t_k}\right) = \frac{p\left(y_k \mid x\right) p\left(x,t_k \mid Y_{t_{k-1}}\right)}{\int p(y_k \mid \xi) p(\xi,t_k \mid Y_{t_{k-1}}) d\xi}$$



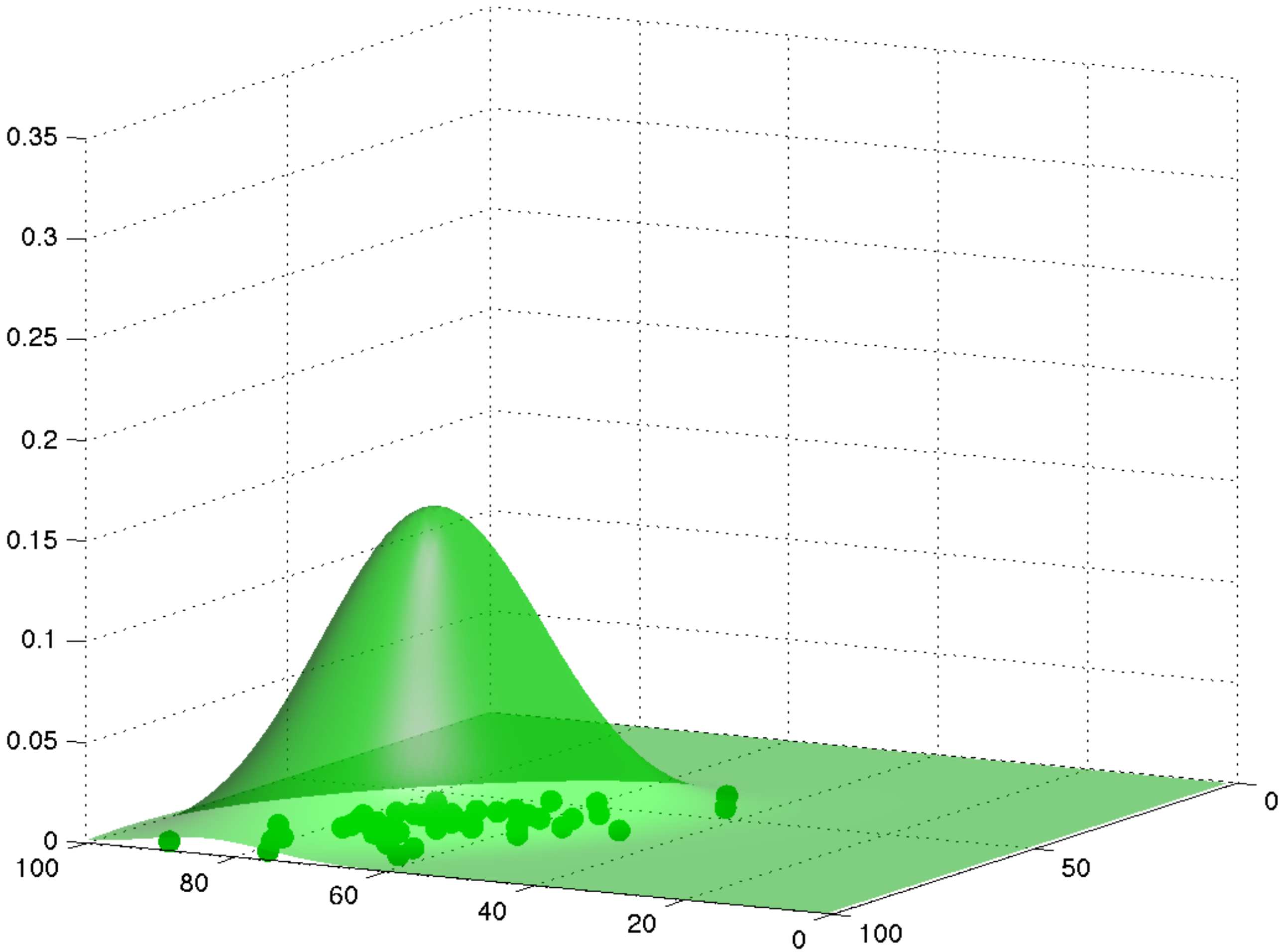
The Ensemble Kalman Filter

1. Start with ensemble of forecasts.



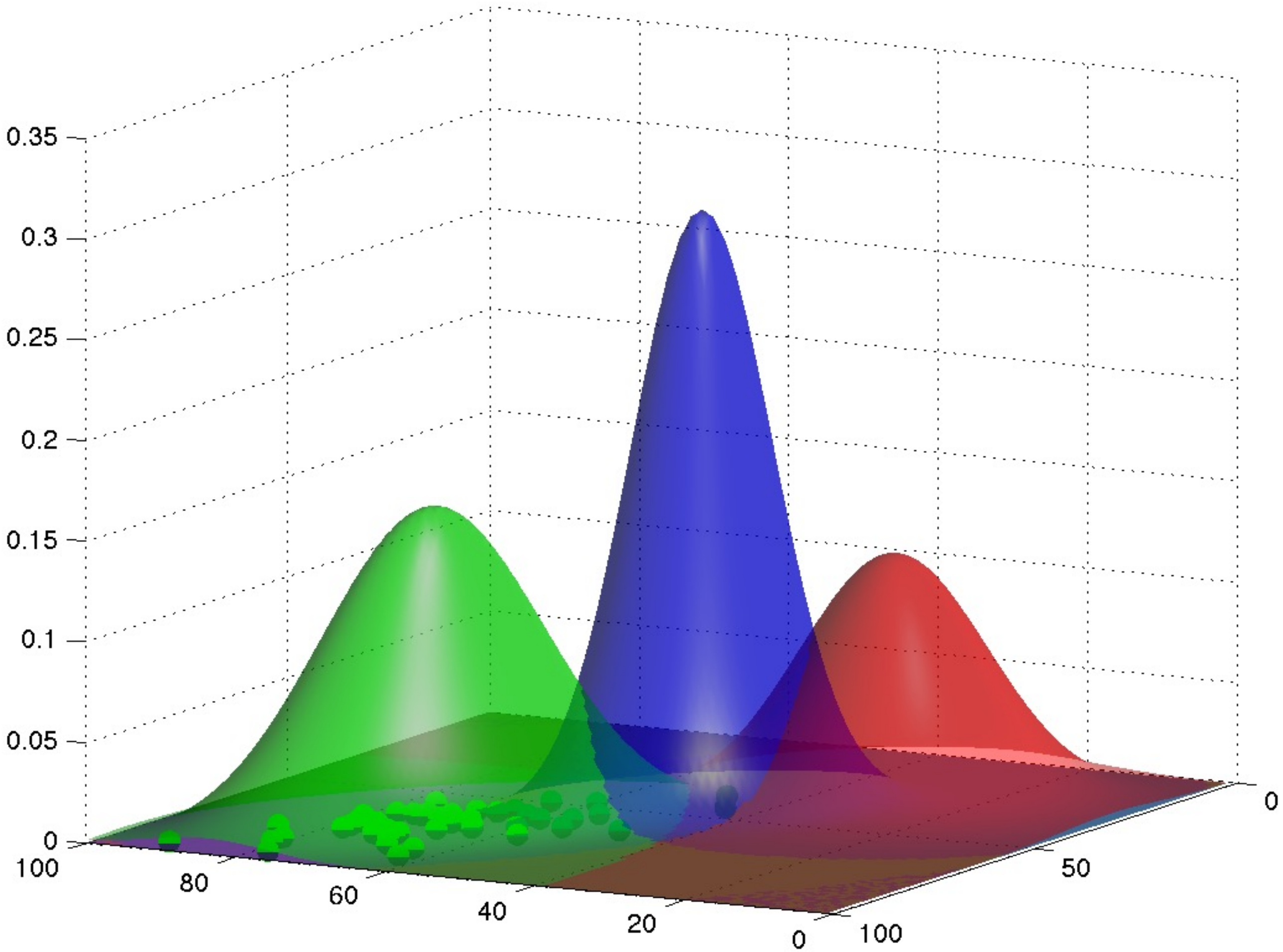
The Ensemble Kalman Filter

2. Fit a normal to ensemble.



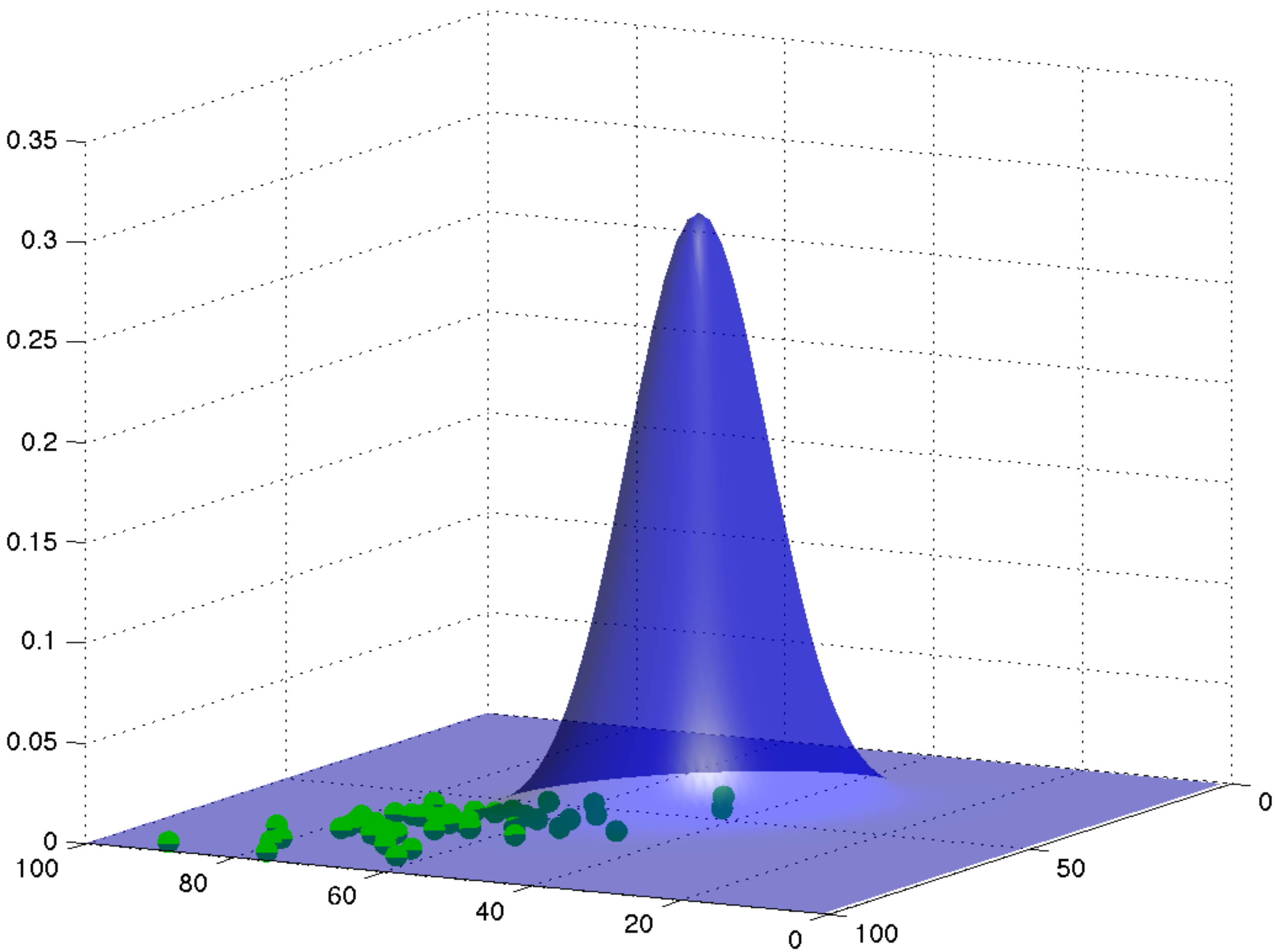
The Ensemble Kalman Filter

3. Do standard Kalman filter.



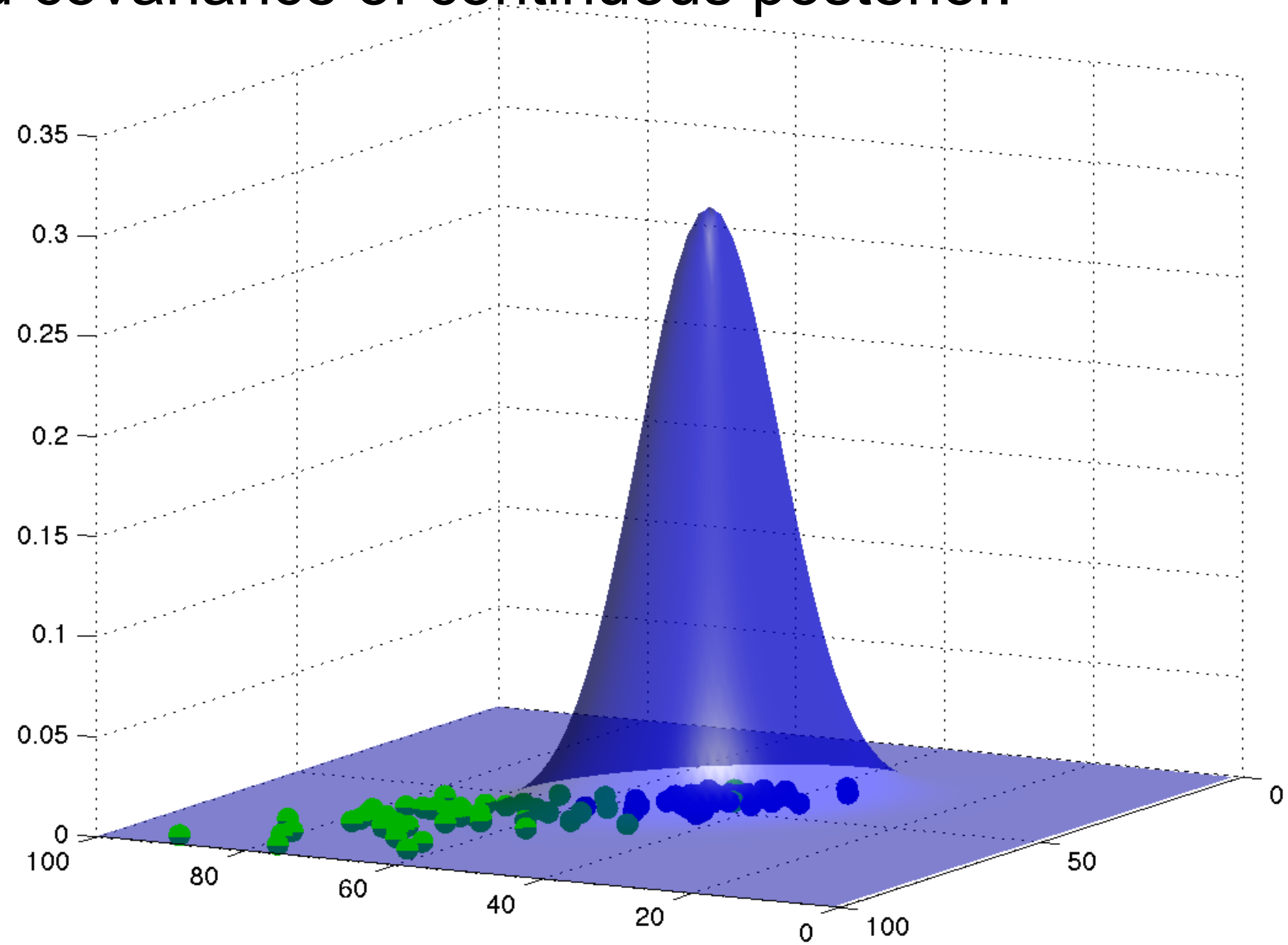
The Ensemble Kalman Filter

Have continuous posterior; need an ensemble.



The Ensemble Kalman Filter

4. Can create an ensemble with exact sample mean and covariance of continuous posterior.



Example Geospace Applications with DART

1. Assimilation of RO Data for Mass Density Estimation
   PIs: Tomoko Matsuo, Chih-Ting Hsu, Nick Dietrich
   Model: TIEGCM

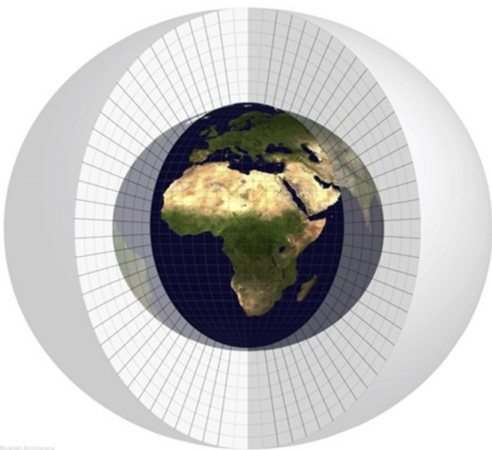
2. Assimilation of Ground- and Space-Based Ionosphere Obs.
   PIs: Nick Pedatella et al.
   Model: WACCM-X

3. Observing Tsunamis via the Ionosphere
   PIs: Panagiotis, Xing Meng, Attila Komjathy
   Model: WP-GITM

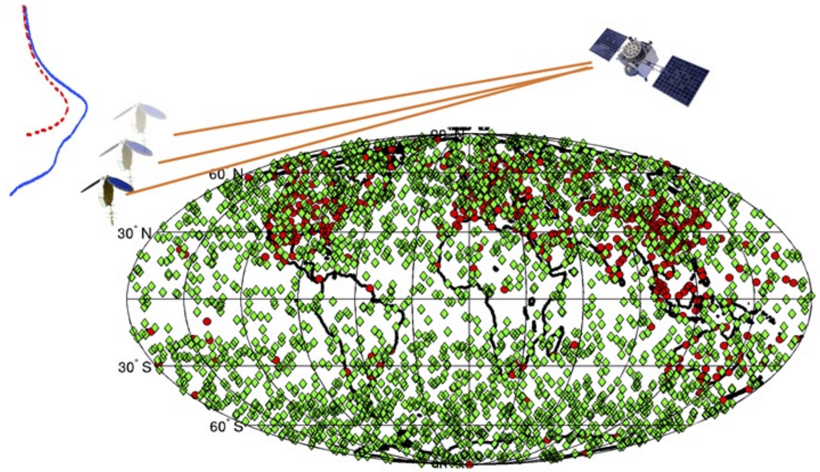
4. Estimating the Solar Meridional Circulation Speed
   PIs: Mausumi Dikpati and Dhrubaditya Mitra

Assimilation of RO Data for Mass Density Estimation

NCAR TIEGCM



COSMIC RO Observations



CHAMP Mass Density

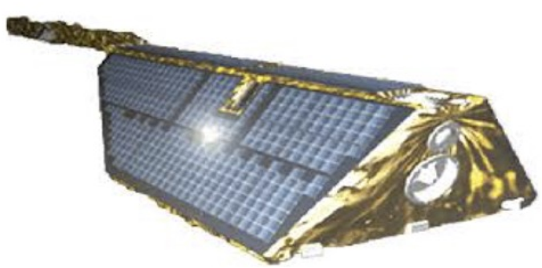
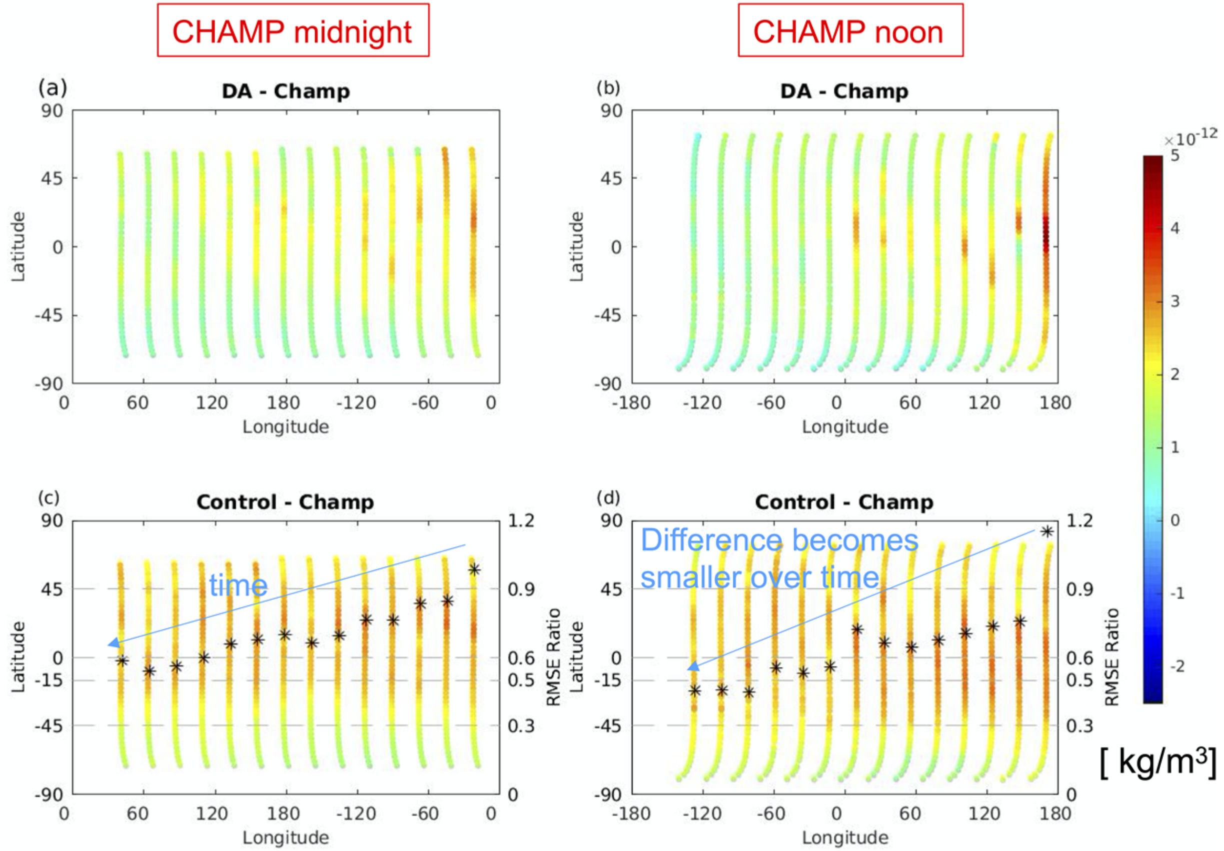


Image Courtesy: UCAR, GFDL & GFZ

Assimilation of RO Data For Mass Density Estimation

Observed vs. Estimated Neutral Mass Density

***OSE:** ~2500 profiles/day; June 23 2008; 60 min assimilation cycle; 90 members*



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Assimilation of Ground and Space-Based Ionosphere Observations in WACCMX+DART

Nick Pedatella[1,2], Jeff Anderson[3], Koichi Chen[4], Kevin Raeder[3], Jing Liu[5], Hanli Liu[1], and Charles Lin[4]

[1]High Altitude Observatory, National Center for Atmospheric Research
[2]COSMIC Program Office, University Corp. for Atmospheric Research
[3]Computational and Information Systems Laboratory, National Center for Atmospheric Research
[4]National Cheng Kung University, Taiwan
[5]Sandong University, China

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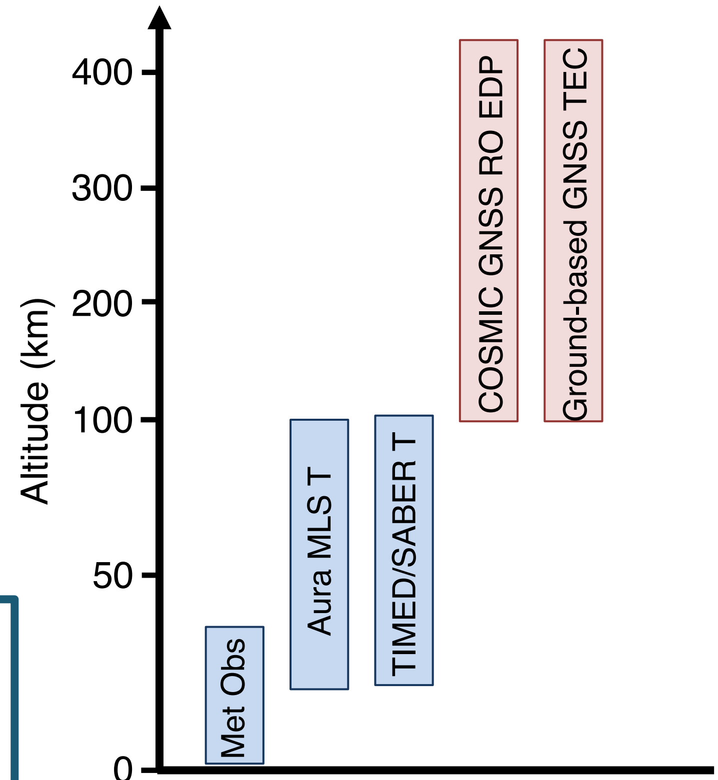
This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

Observations Assimilated in WACCM(X)+DART

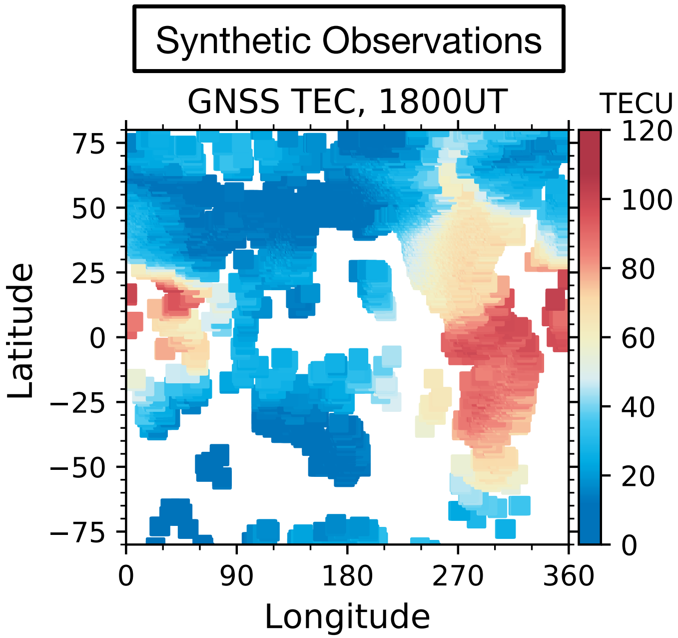
Conventional Lower Atmosphere Observations:
- Aircraft temperature and wind
- Radiosonde temperature and wind
- Satellite drift winds
- COSMIC GPS RO refractivity

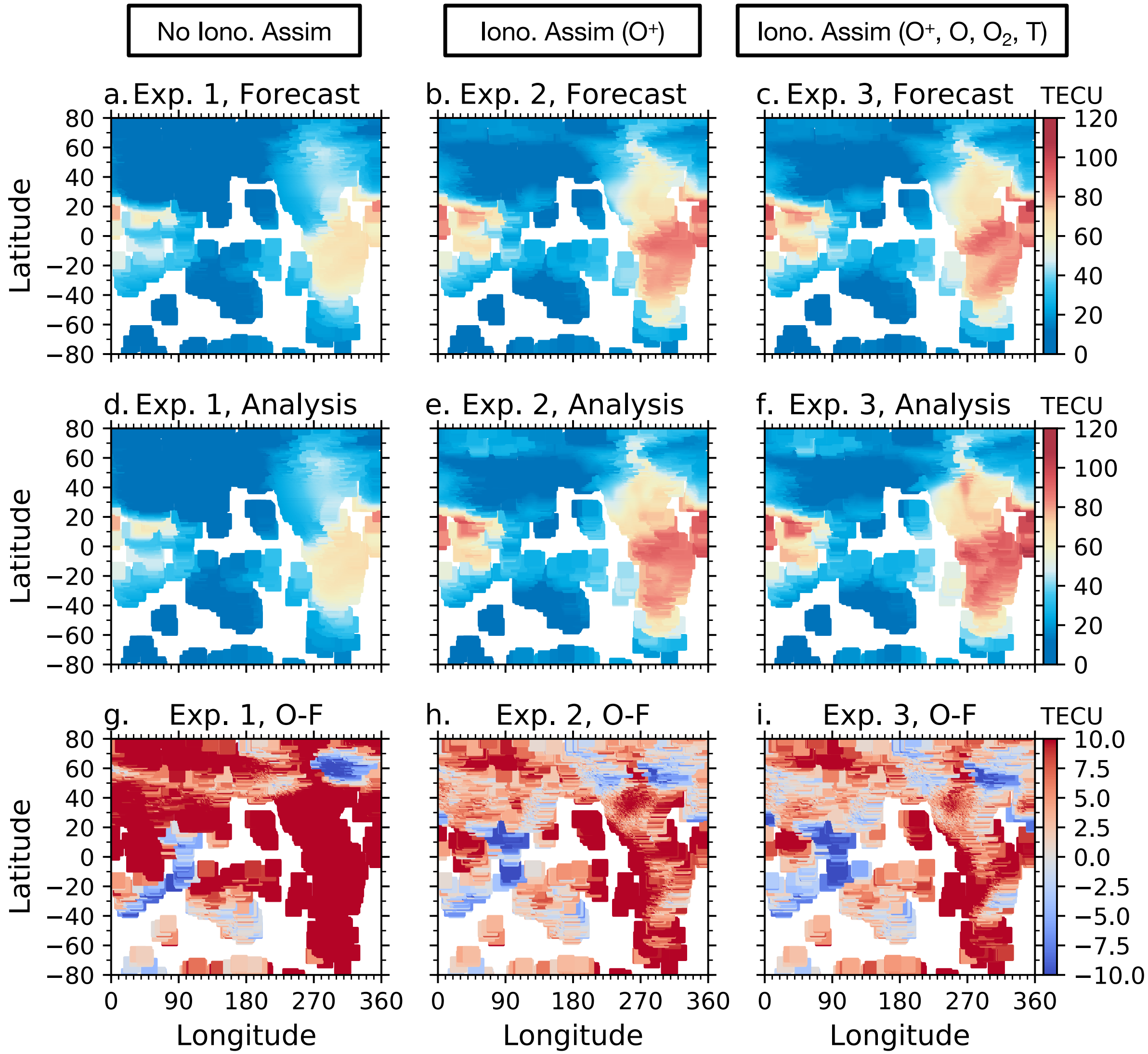
Sparse Middle/Upper Atmosphere Observations:
- TIMED/SABER Temperature (100 - 5×10^{-4} hPa)
- Aura MLS Temperature (260 - 1×10^{-3} hPa)

Ionosphere Observations
- COSMIC GNSS RO electron density profiles
- Ground-based GNSS total electron content (TEC)



Assimilation of ionosphere observations is effective in removing the bias that exists in WACCMX+DART relative to the truth simulation





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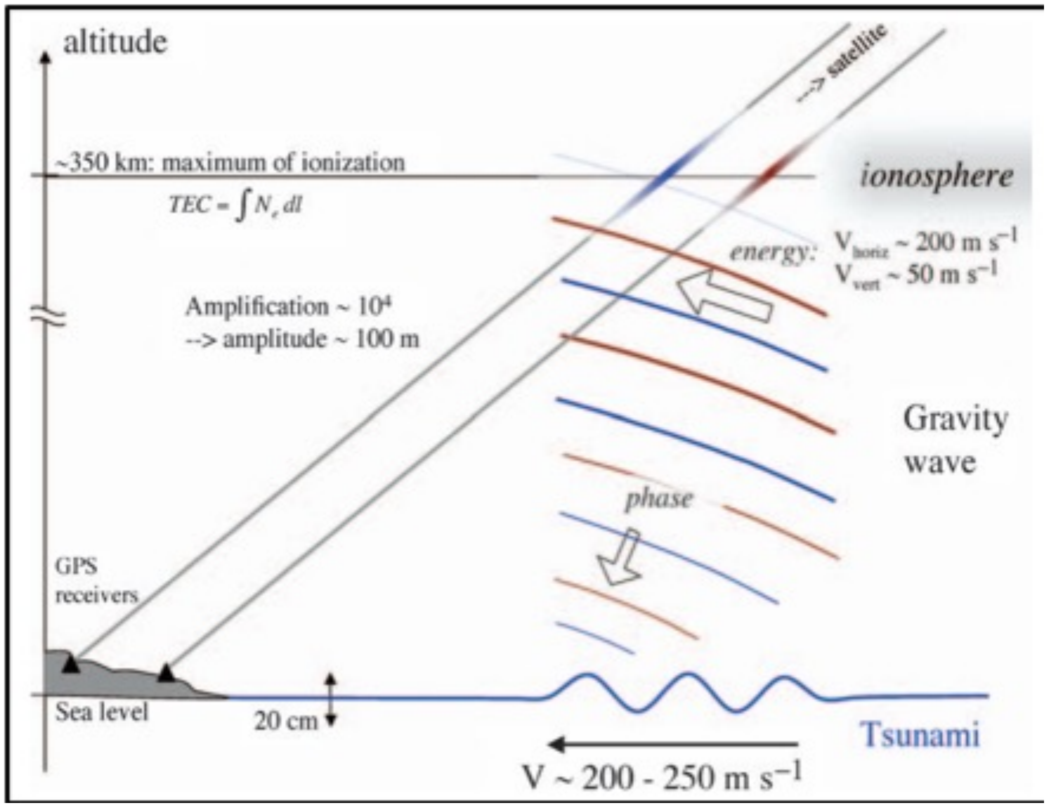
Observing Tsunamis via the Ionopshere

Tsunamis make very small changes to sea surface height in open ocean.
But, waves amplify in the atmosphere, 100m plus amplitude in ionosphere.
Changes Total Electron Content (TEC) of Ionosphere.
GPS signals are slowed by electrons.
Delays at ground stations can detect tsunami impacts in ionosphere (no way)!

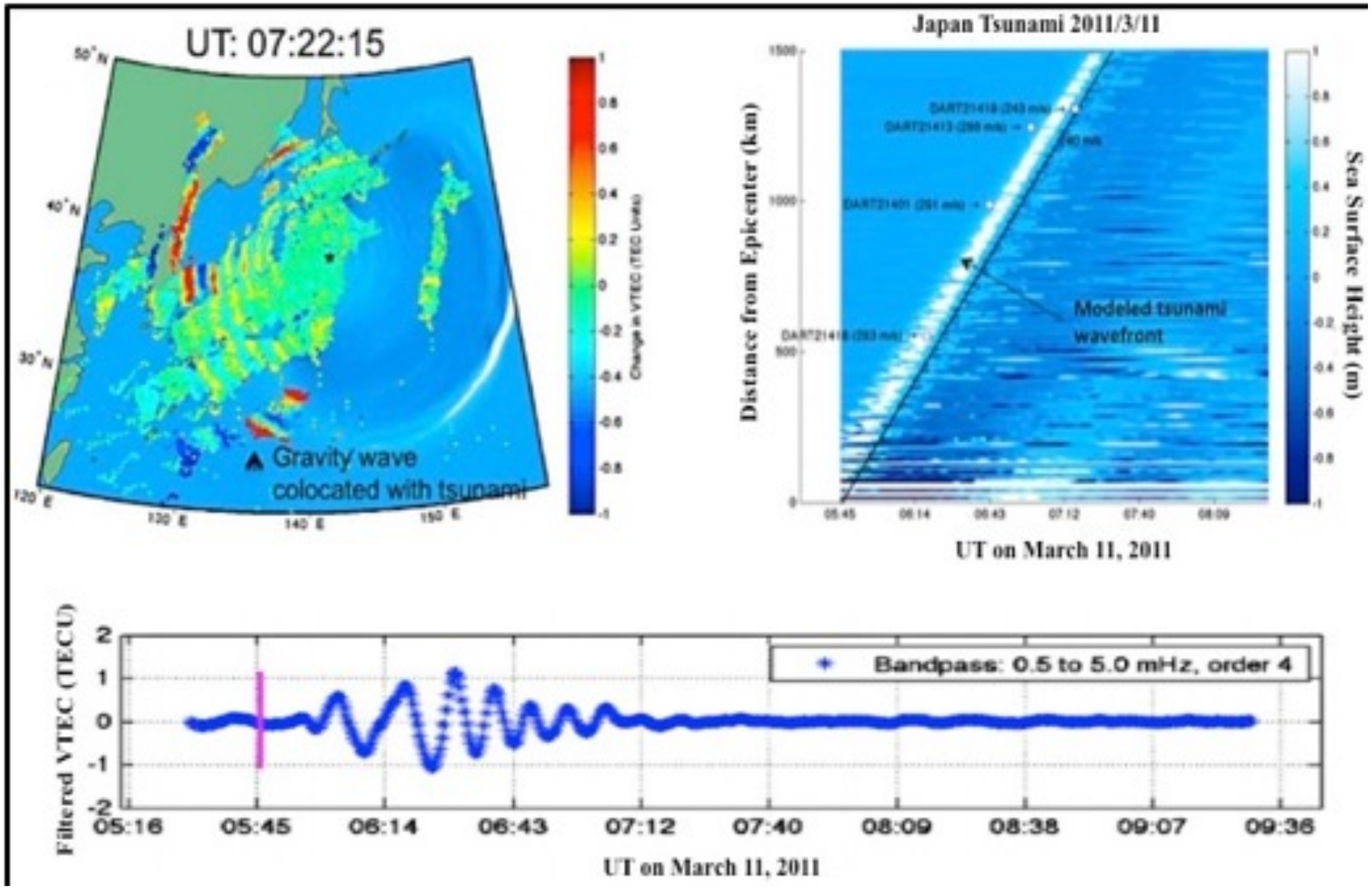


Anderson: LMAG 2020

Observing Tsunamis via the Ionopshere

Tohoku example: Gravity waves in ionosphere over tsunami waves in ocean.

Use DART to find tsunami amplitude by assimilating GPS observations of TEC.



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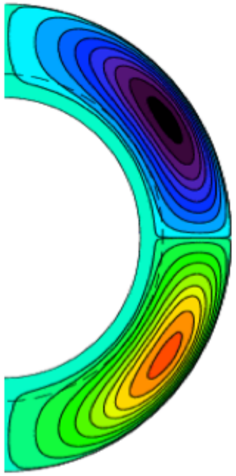
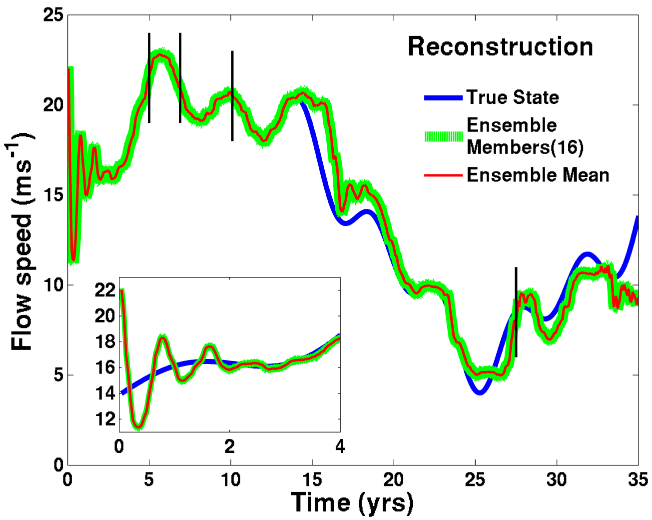
What can DART DA do for earth system applications?

Reconstruction of the Sun's meridional circulation speed using EnKF-DART

Solar meridional circulation plays a crucial role in spot-producing magnetic fields' dynamics, but its spatio-temporal pattern is not fully known





- DART has been demonstrated to be a powerful tool for reconstructing time-varying meridional flow-speed (see, e.g., Dikpati, Anderson & Mitra, 2014, 2016a, 2016b)
- Reconstruction (red curve) is reasonably good with 16 ensemble members, and gets much improved with decrease in observational error and increase in number of observations and ensemble size.
- For an initial guess far-off from truth, reconstructed state asymptotically converges toward the truth (blue curve)

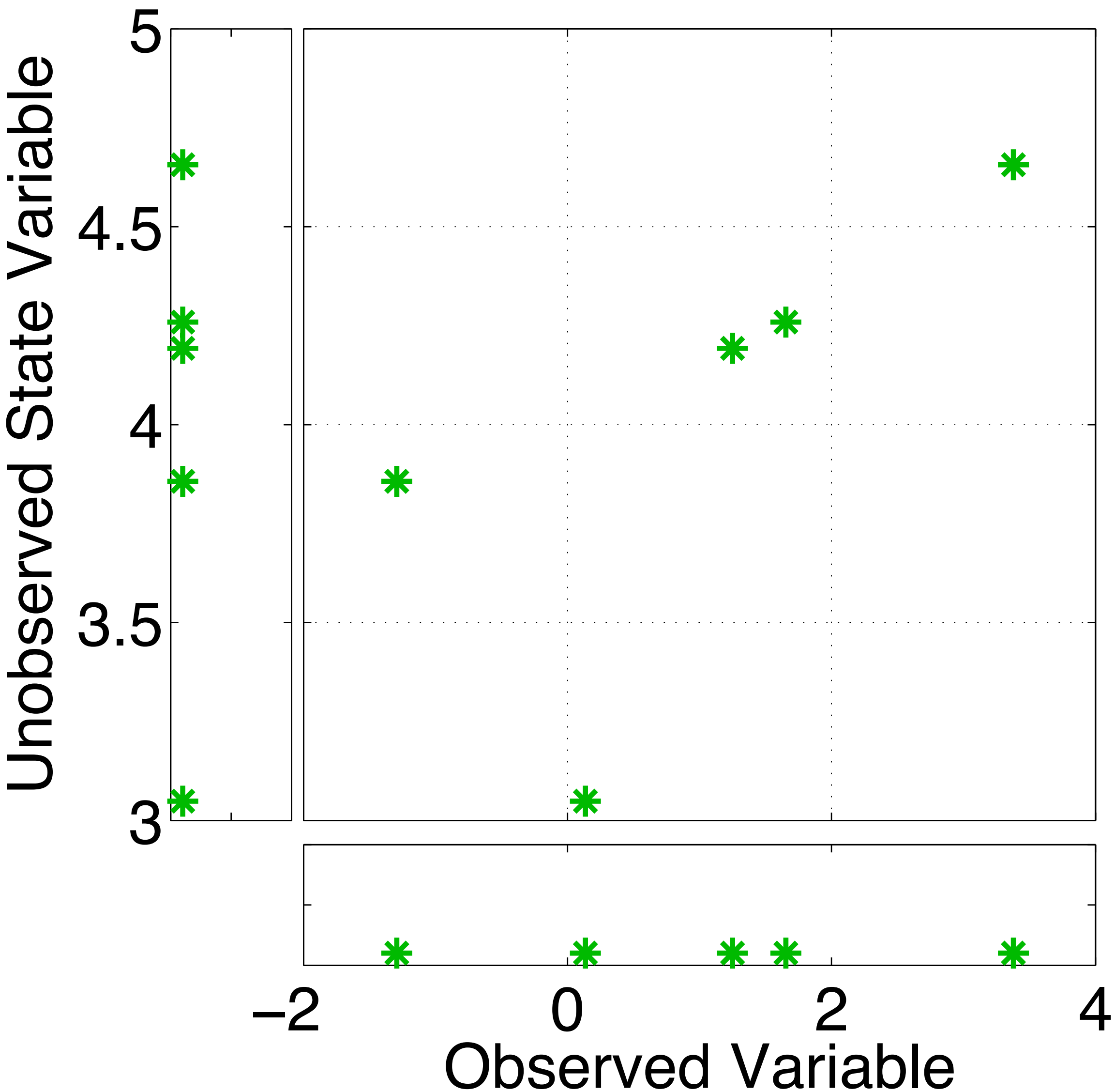
Simple Implementation of Ensemble Filter (EnKF)

Ensemble Filters can also be implemented as 2 simple steps:

1. Compute forward operator for a single observed quantity and use a 1D ensemble filter to compute increments.
   - ➢ Compares model estimate to actual observation.

2. Regress these increments onto each model state variable.
   - ➢ Computes impact of observation on state variables.

EnKF: Use regression to update state variable with obs.

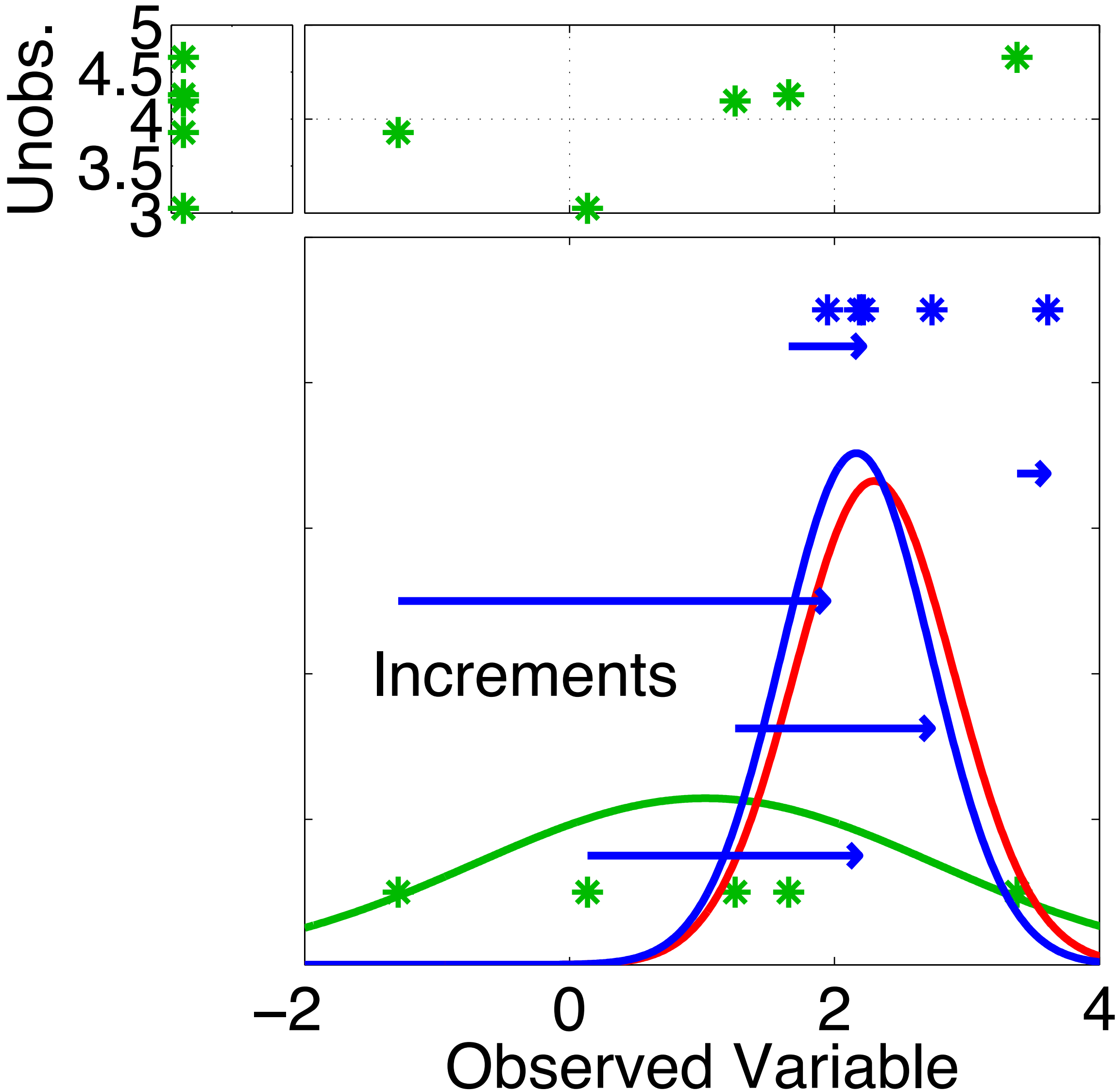


Assume that all we know is the prior joint distribution.

One variable is observed.

What should happen to the unobserved variable?

EnKF: Use regression to update state variable with obs.

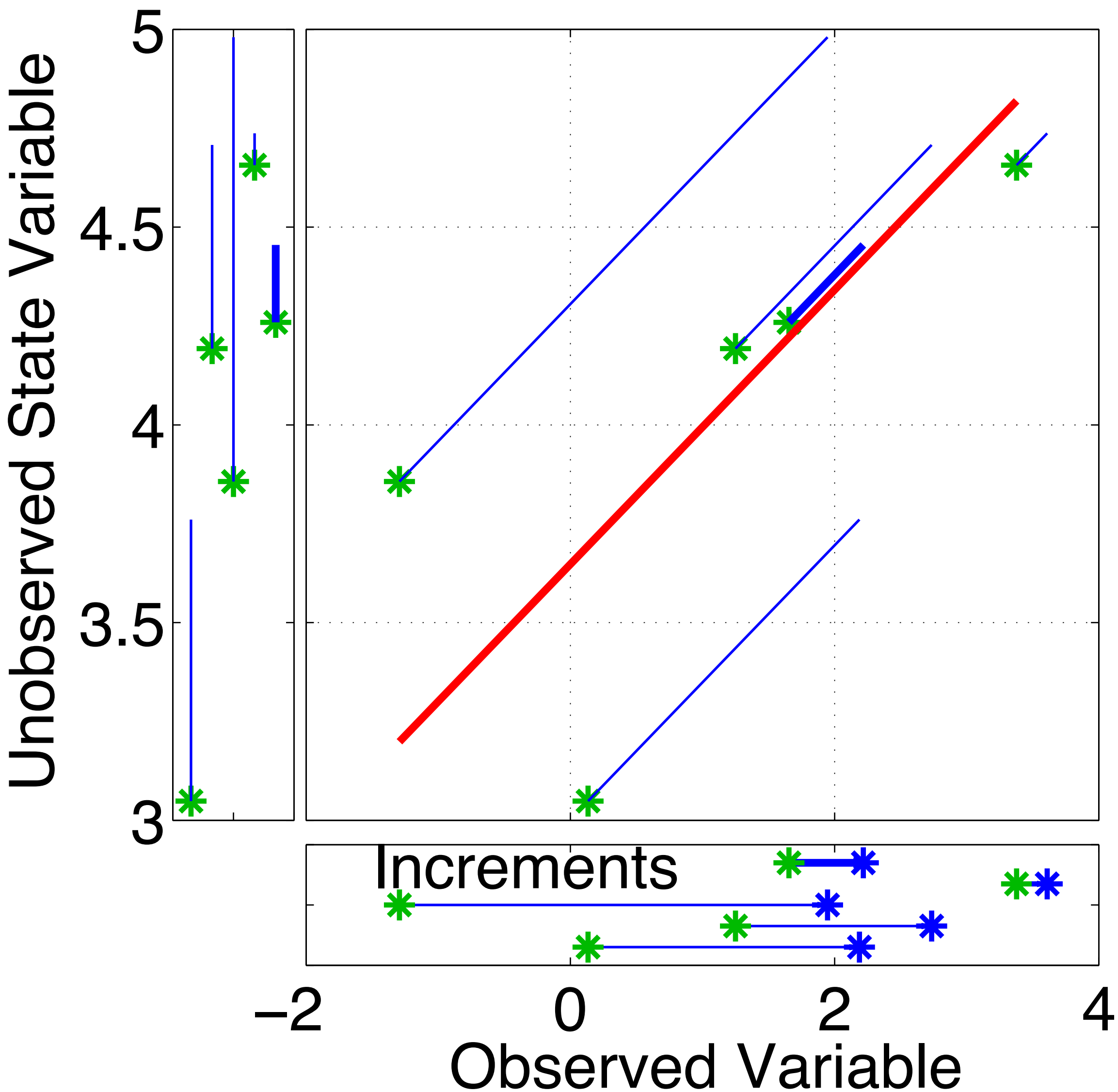


Assume that all we know is the prior joint distribution.

One variable is observed.

Update the observed variable with 1D ensemble filter.

EnKF: Use regression to update state variable with obs.



Have joint prior distribution of two variables.

Regress the observation increments onto each model state variable independently.

Major Challenges for Geospace DA

1. Quality of Model Prior Estimates of Observations.

- Strongly forced means important things aren't in the model.
- Models may have many other challenges.
- Hard to get good priors.
- Machine Learning methods can be applied to improve forecast priors.

2. Model bivariate statistics for model impact have errors.

- Have vast numbers of ensemble bivariate distributions.
- Basic ensemble DA just does regression for each.
- Can mine these to get better estimates of impact of particular types of observations on particular state variables.

Conclusions

1. Ensemble DA already widely applied for geospace.

2. Challenges due to model/obs quality need to be addressed.

3. Enhancing ensemble DA with machine learning is a path forward.

Learn more about DART at:

www.image.ucar.edu/DAReS/DART

dart@ucar.edu

Anderson, J., Hoar, T., Raeder, K., Liu, H., Collins, N., Torn, R., Arellano, A., 2009: *The Data Assimilation Research Testbed: A community facility.* BAMS, **90**, 1283—1296, doi: 10.1175/2009BAMS2618.1