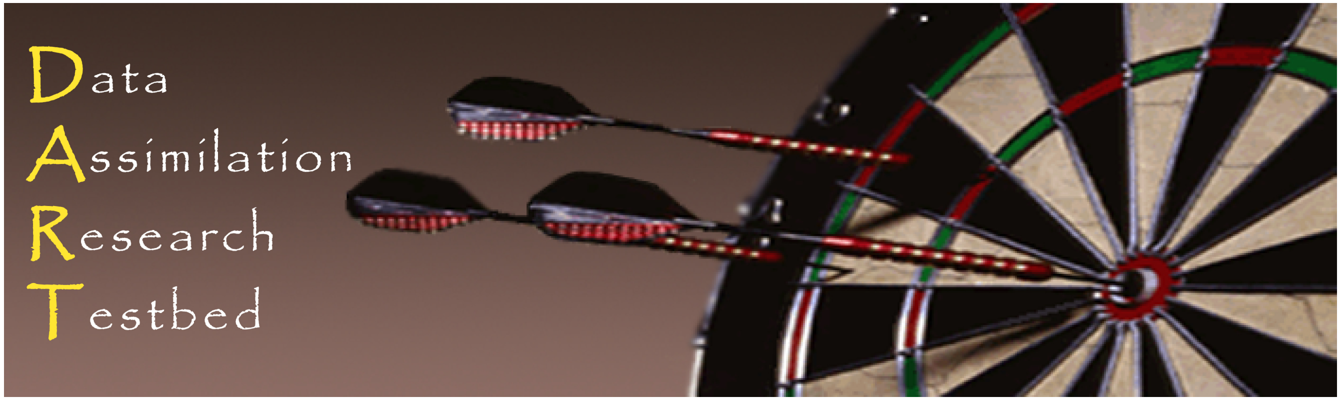
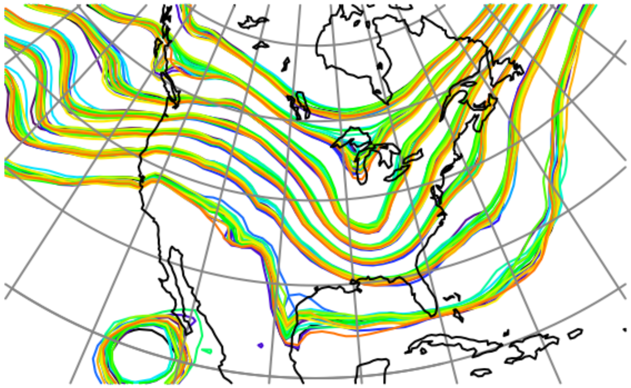


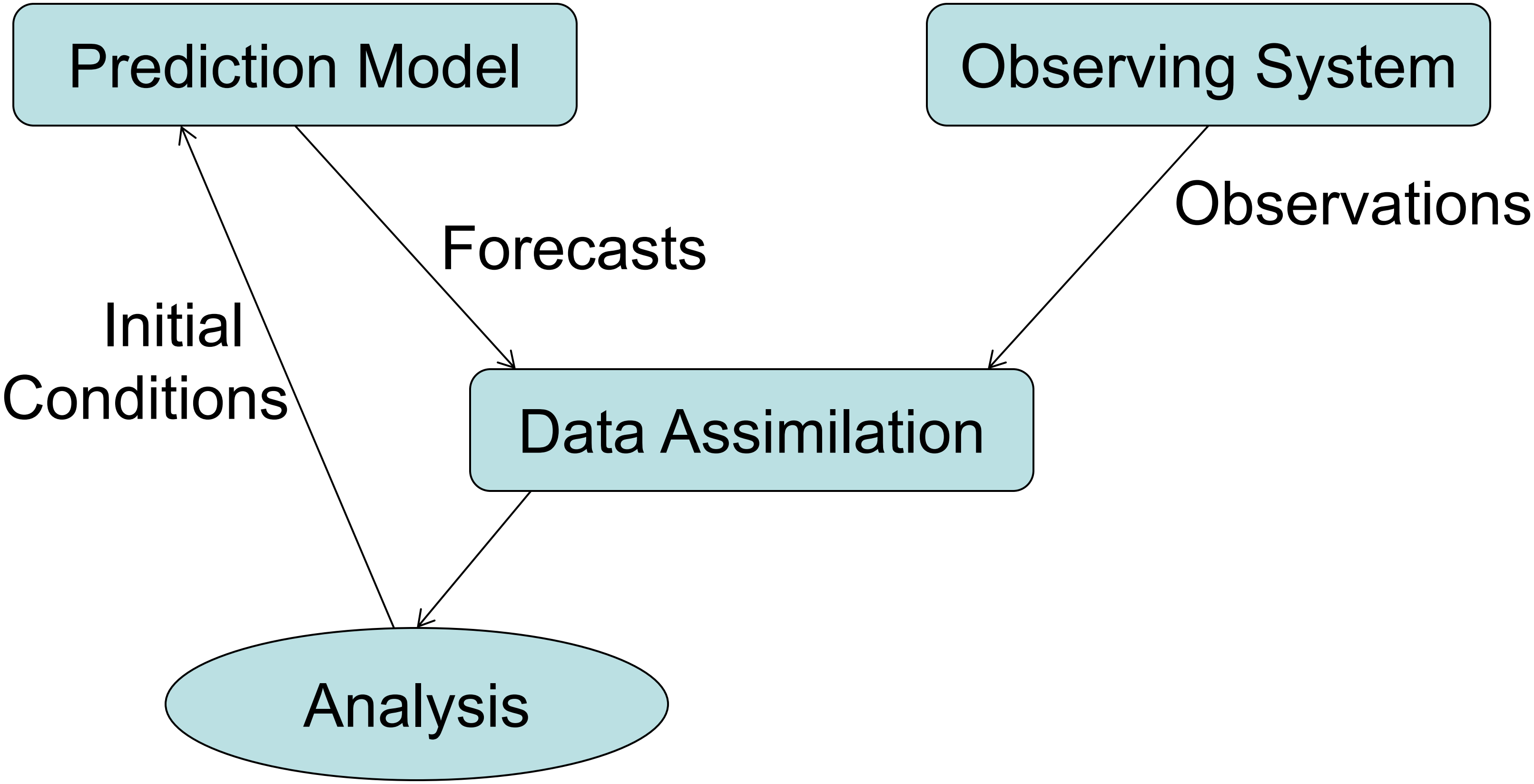
Practical Implementations of the Ensemble Kalman Filter

Jeff Anderson representing the NCAR Data Assimilation Research Section



NCAR | National Center for
UCAR | Atmospheric Research

Building a Forecast System



Prediction Model

Observing System

Forecasts

Observations

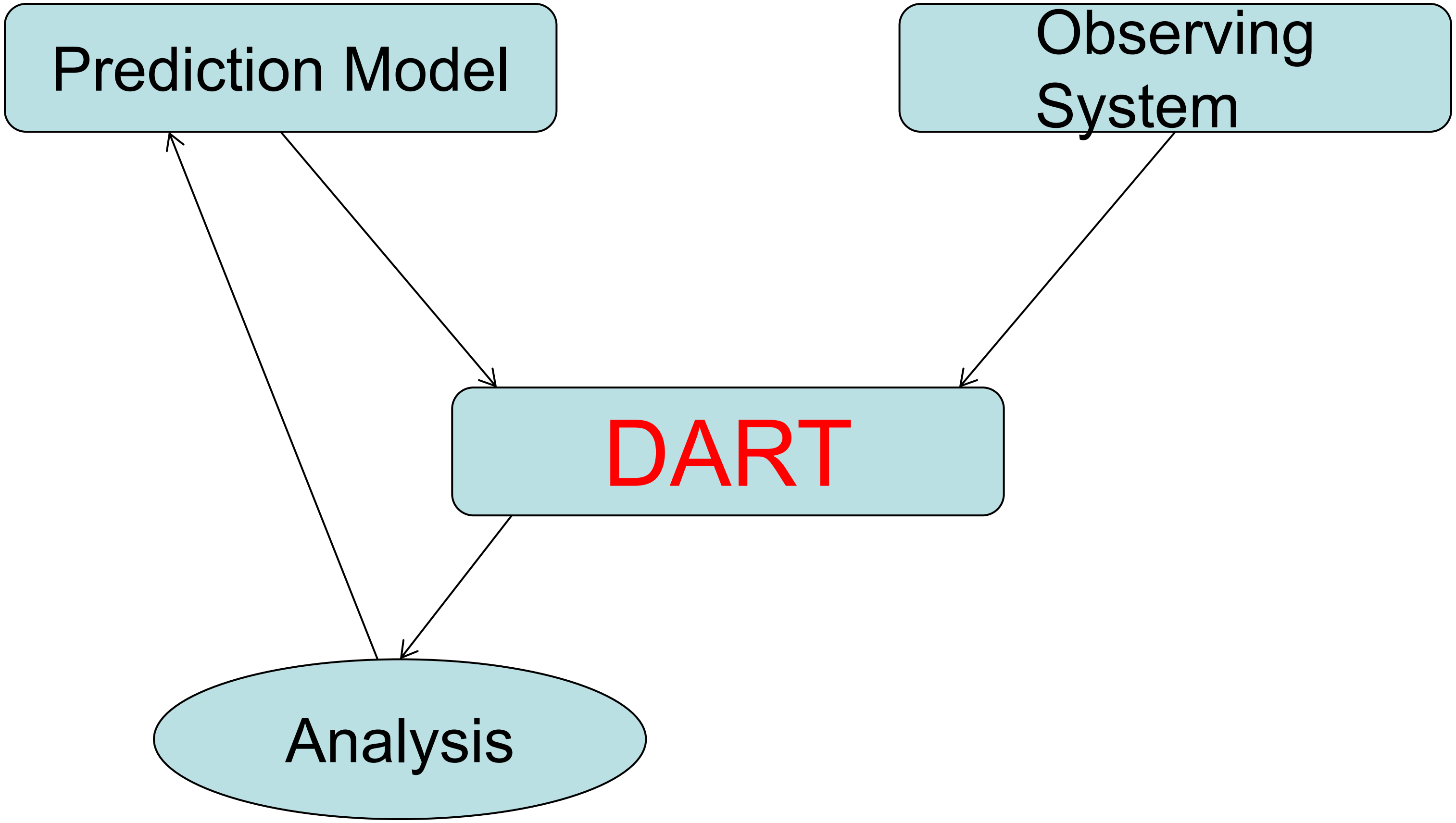
Initial Conditions

Data Assimilation

Analysis

The Data Assimilation Research Testbed (DART)

DART provides data assimilation ‘glue’ to build state-of-the-art ensemble forecast systems for even the largest models.



Prediction Model

Observing System

DART

Analysis

DART Goals

Provide State-of-the-Art Data Assimilation capability to:

- Prediction research scientists,
- Model developers,
- Observation system developers,

Who may not have any assimilation expertise.

DART Design Constraints

- Models small to huge.
- Few or many observations.
- Tiny to huge computational resources.
- Entry cost must be low.
- Competitive with existing methods for weather prediction:

  Scientific quality of results,
  Total computational effort.

Methods: Kalman Filter

Product of d-dimensional normals (gaussians) with means μ_1 and μ_2 and covariance matrics Σ_1 and Σ_1 is normal.

$$N(\mu_1, \Sigma_1) N(\mu_2, \Sigma_2) = cN(\mu, \Sigma) \qquad (11)$$

Covariance: $$\Sigma = (\Sigma_1^{-1} + \Sigma_2^{-1})^{-1} \qquad (12)$$

Mean: $$\mu = \Sigma(\Sigma_1^{-1}\mu_1 + \Sigma_2^{-1}\mu_2) \qquad (13)$$

Weight: $$c = \frac{1}{(2\pi)^{d/2}|\Sigma_1+\Sigma_2|^{1/2}} \exp\left\{-\frac{1}{2}[(\mu_2 - \mu_1)^T (\Sigma_1 + \Sigma_2)^{-1} (\mu_2 - \mu_1)]\right\}$$

We’ll ignore the weight since we immediately normalize products to be PDFs.

Methods: Kalman Filter

Recall our earlier assimilation update equation.

$$P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_k}\right) = \frac{P(\mathbf{y}_k|\mathbf{x})P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_{k-1}}\right)}{Normalization} \tag{10}$$

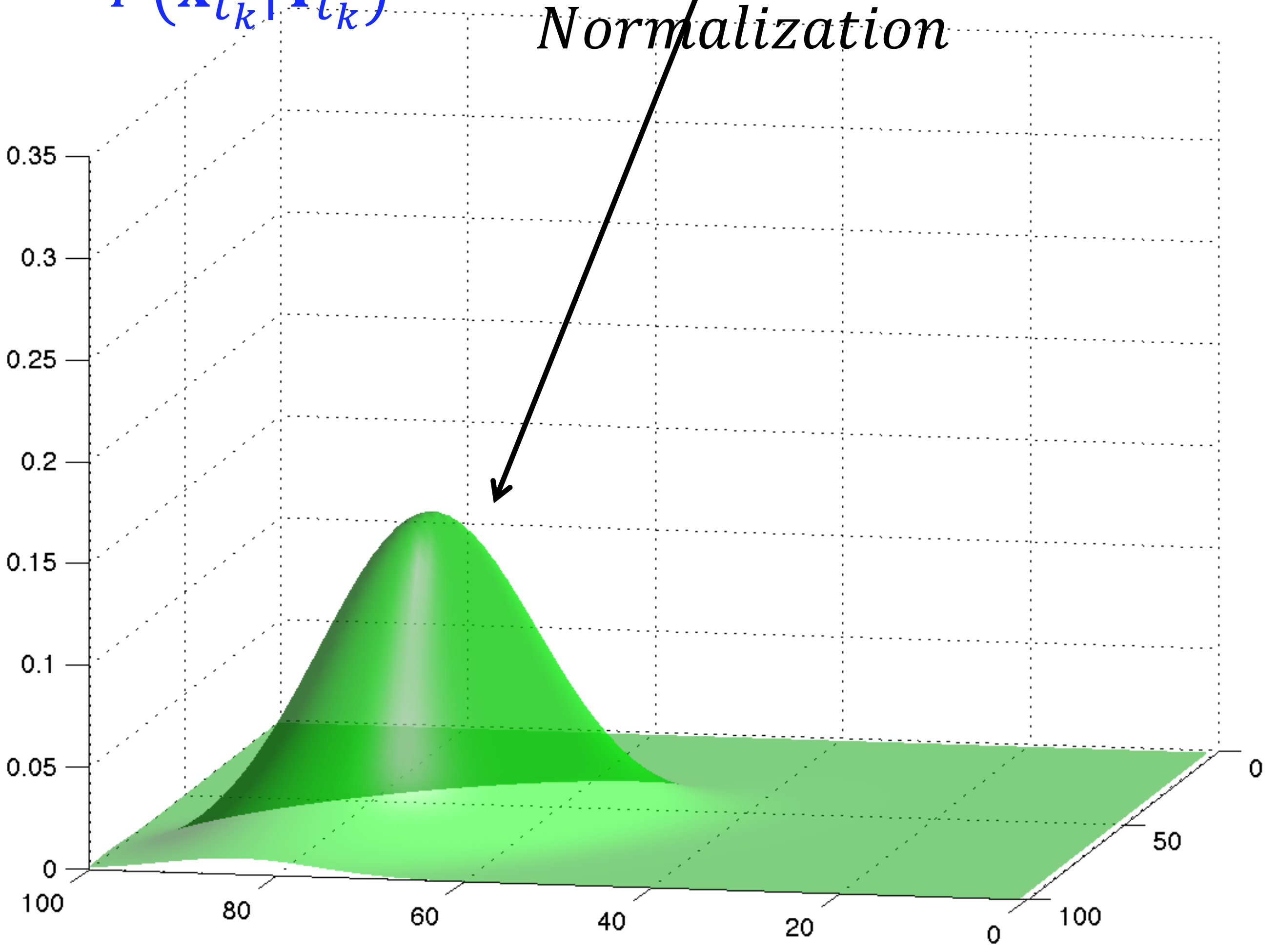
Numerator is just product of two gaussians.

Denominator just normalizes posterior to be a PDF.

Methods: Kalman Filter

Prior is gaussian, comes from forecast model.

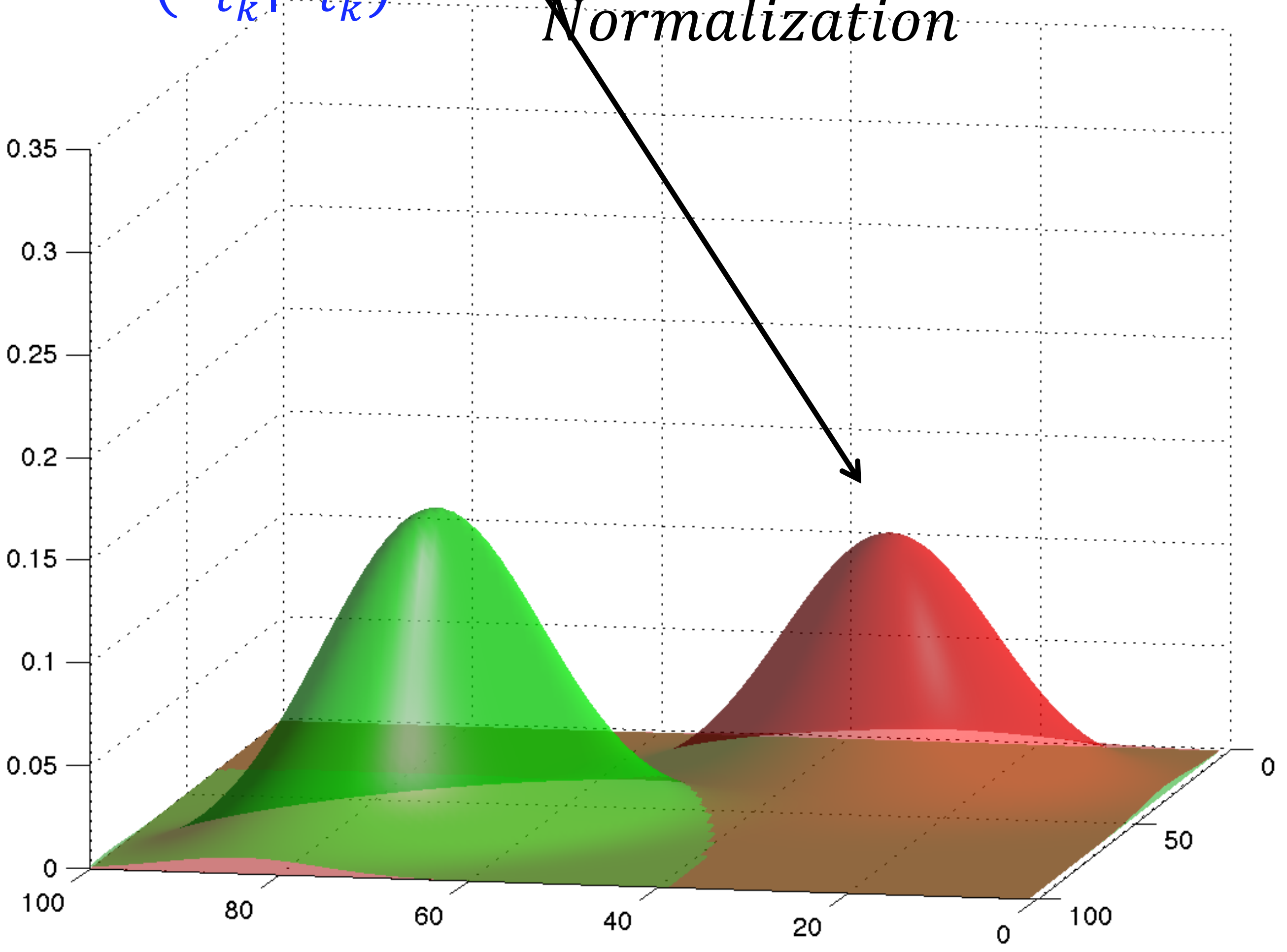
$$P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_k}\right) = \frac{P(\mathbf{y}_k|\mathbf{x})P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_{k-1}}\right)}{Normalization} \quad (10)$$



Methods: Kalman Filter

Likelihood is gaussian, mean measured, covariance from designer.

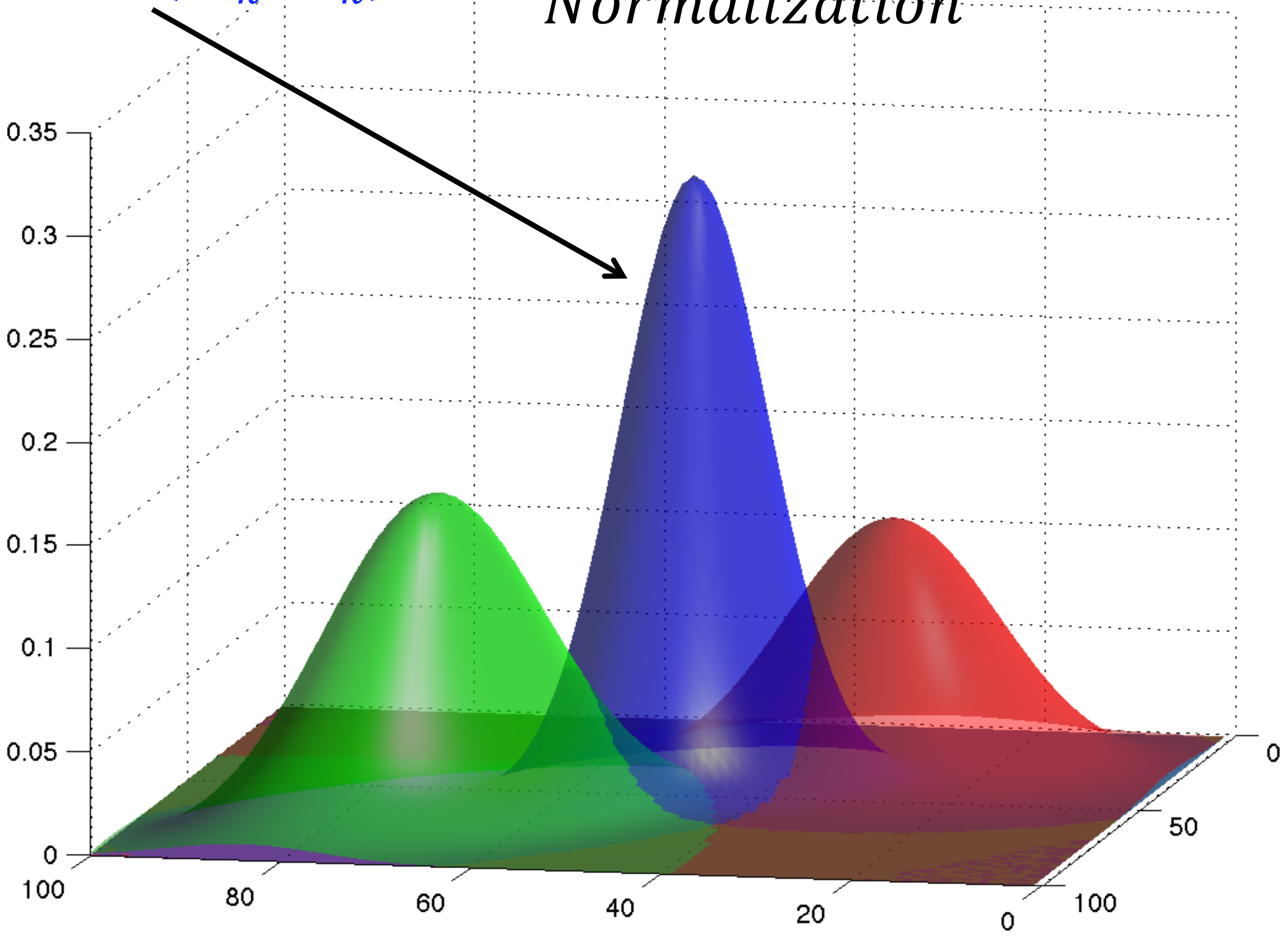
$$P\left(\mathbf{x}_{t_k} | \mathbf{Y}_{t_k}\right) = \frac{P(\mathbf{y}_k | \mathbf{x}) P\left(\mathbf{x}_{t_k} | \mathbf{Y}_{t_{k-1}}\right)}{Normalization} \quad (10)$$



Methods: Kalman Filter

Posterior is gaussian, from (11).

$$P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_k}\right) = \frac{P(\mathbf{y}_k|\mathbf{x})P\left(\mathbf{x}_{t_k}|\mathbf{Y}_{t_{k-1}}\right)}{Normalization} \qquad (10)$$

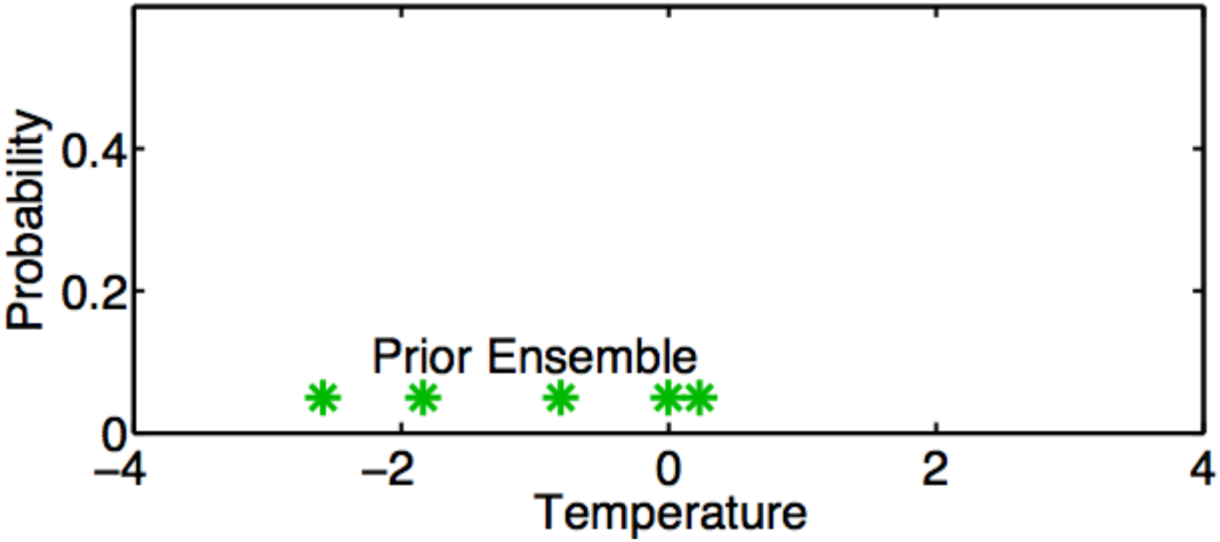


A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
    - Localization
    - Inflation
5. Parameter estimation.
6. Some sample applications.

A One-Dimensional Ensemble Kalman Filter

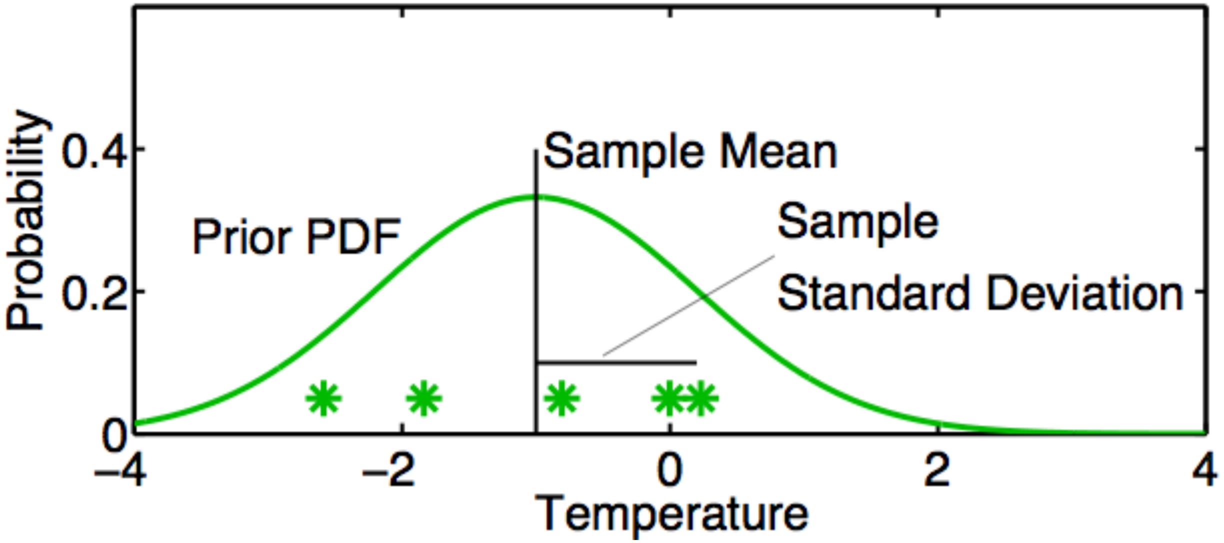
Represent a prior pdf by a sample (ensemble) of N values:



Example: Predict temperature on the Nanjing campus.

A One-Dimensional Ensemble Kalman Filter

Represent a prior pdf by a sample (ensemble) of N values:



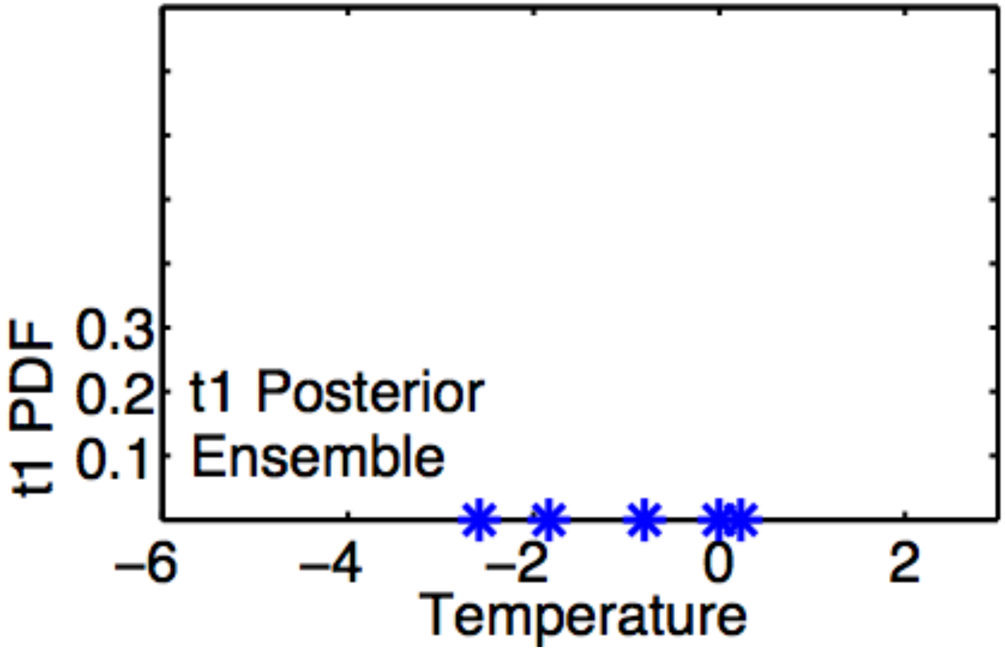
Use sample mean $\overline{T} = \sum_{n=1}^{N} T_n / N$

and sample standard deviation $\sigma_T = \sqrt{\sum_{n=1}^{N} (T_n - \overline{T})^2 / (N-1)}$

to determine a corresponding continuous distribution $Normal(\overline{T}, \sigma_T)$

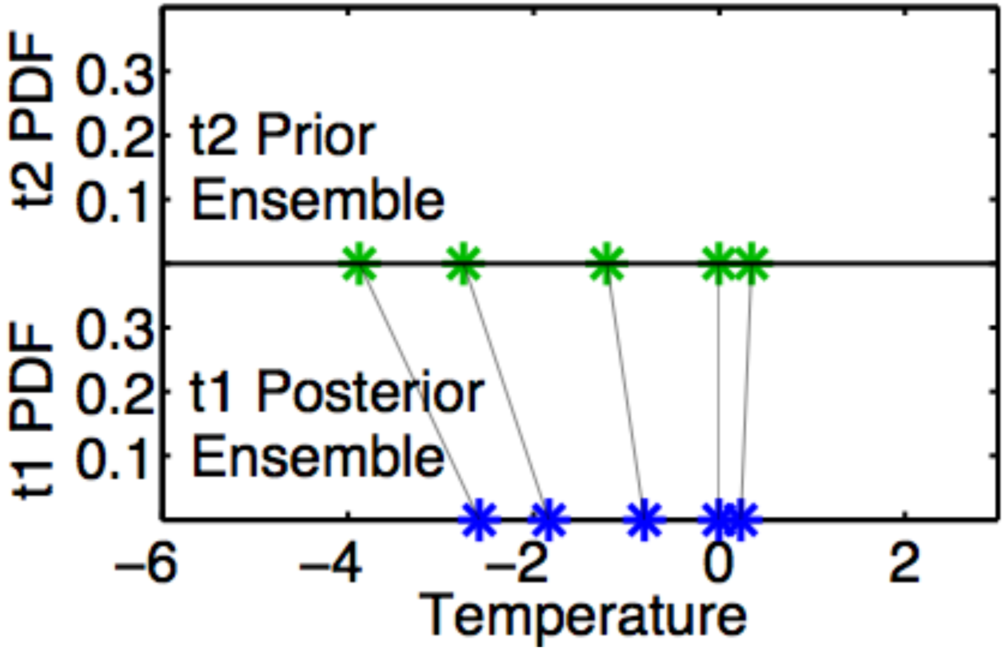
A One-Dimensional Ensemble Kalman Filter: Model Advance

If posterior ensemble at time t_1 is $T_{1,n}$, $n = 1, \ldots, N$



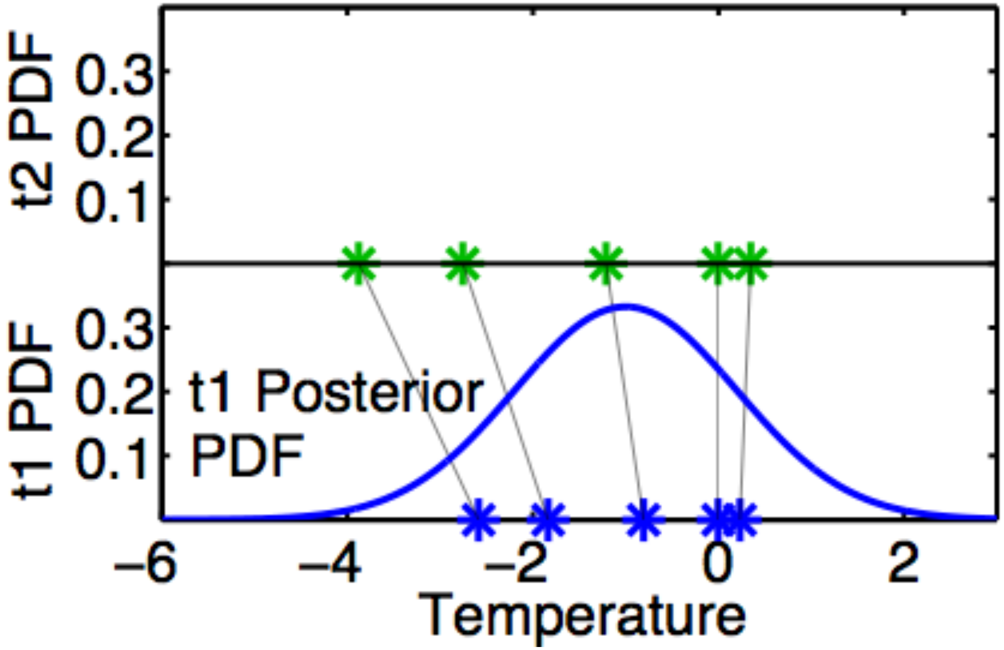
A One-Dimensional Ensemble Kalman Filter: Model Advance

If posterior ensemble at time t_1 is $T_{1,n}$, $n = 1, \ldots, N$,
advance each member to time t_2 with model, $T_{2,n} = L(T_{1,n})$ $n = 1, \ldots, N$.



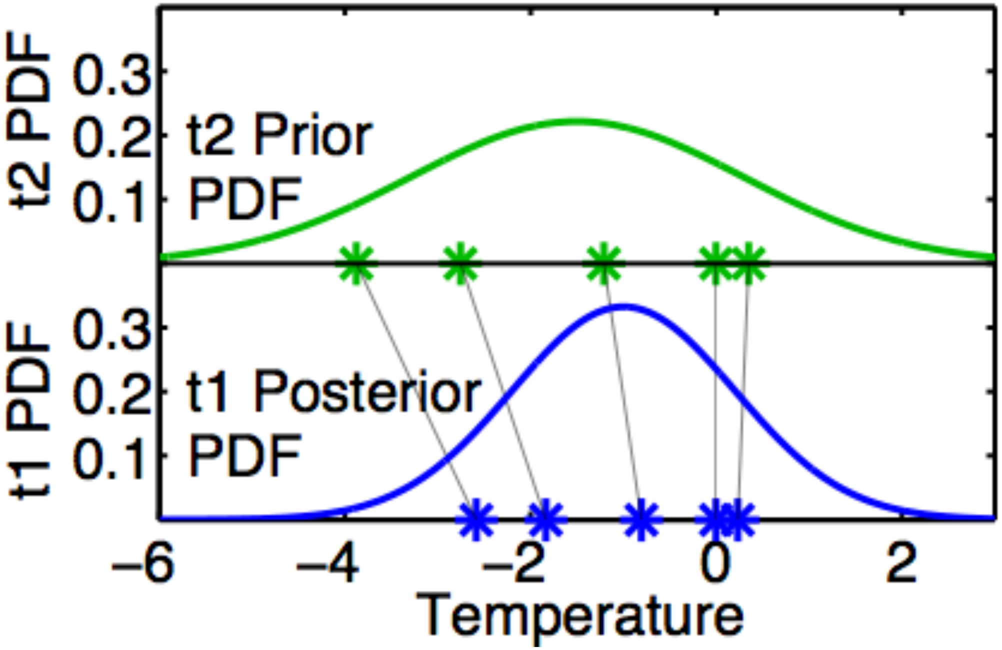
A One-Dimensional Ensemble Kalman Filter: Model Advance

Same as advancing continuous pdf at time t_1 …

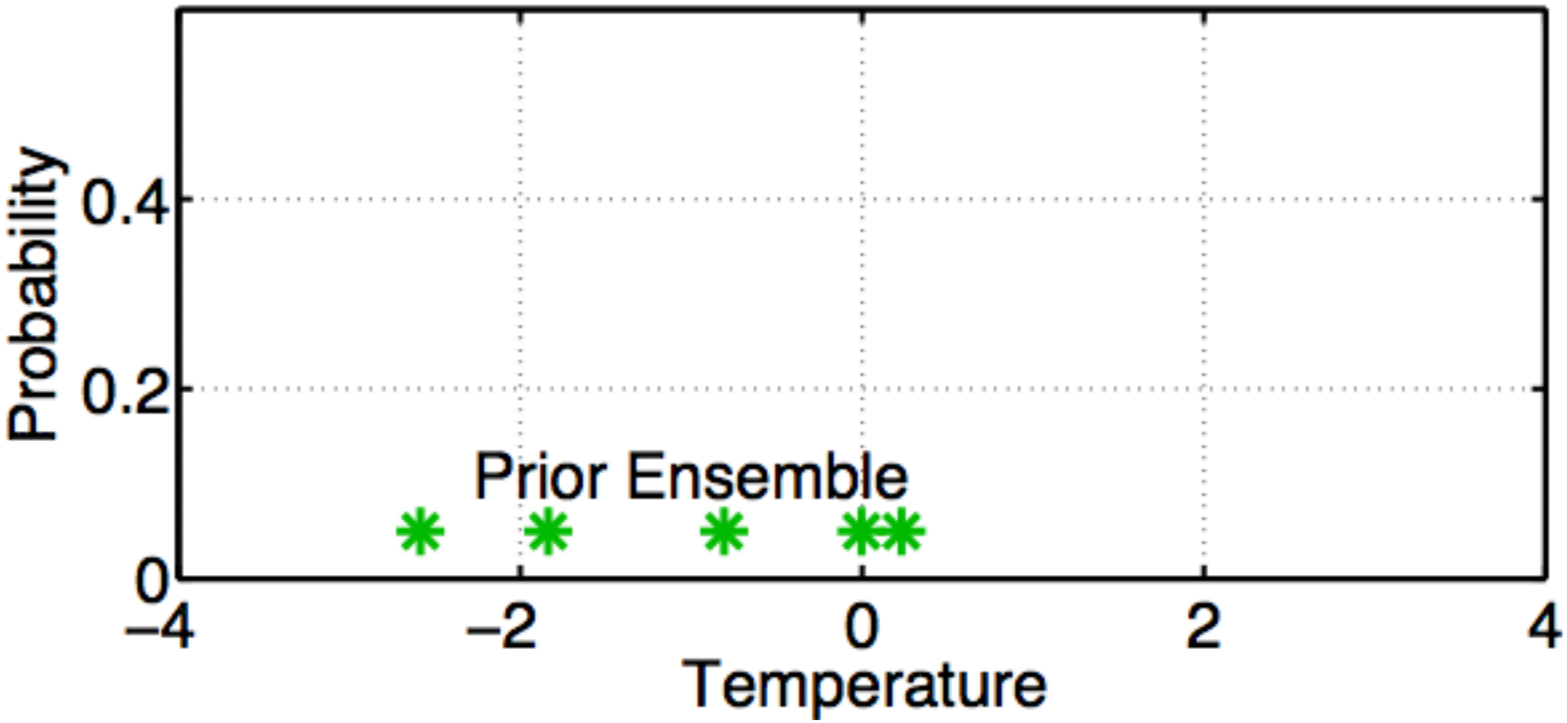


A One-Dimensional Ensemble Kalman Filter: Model Advance

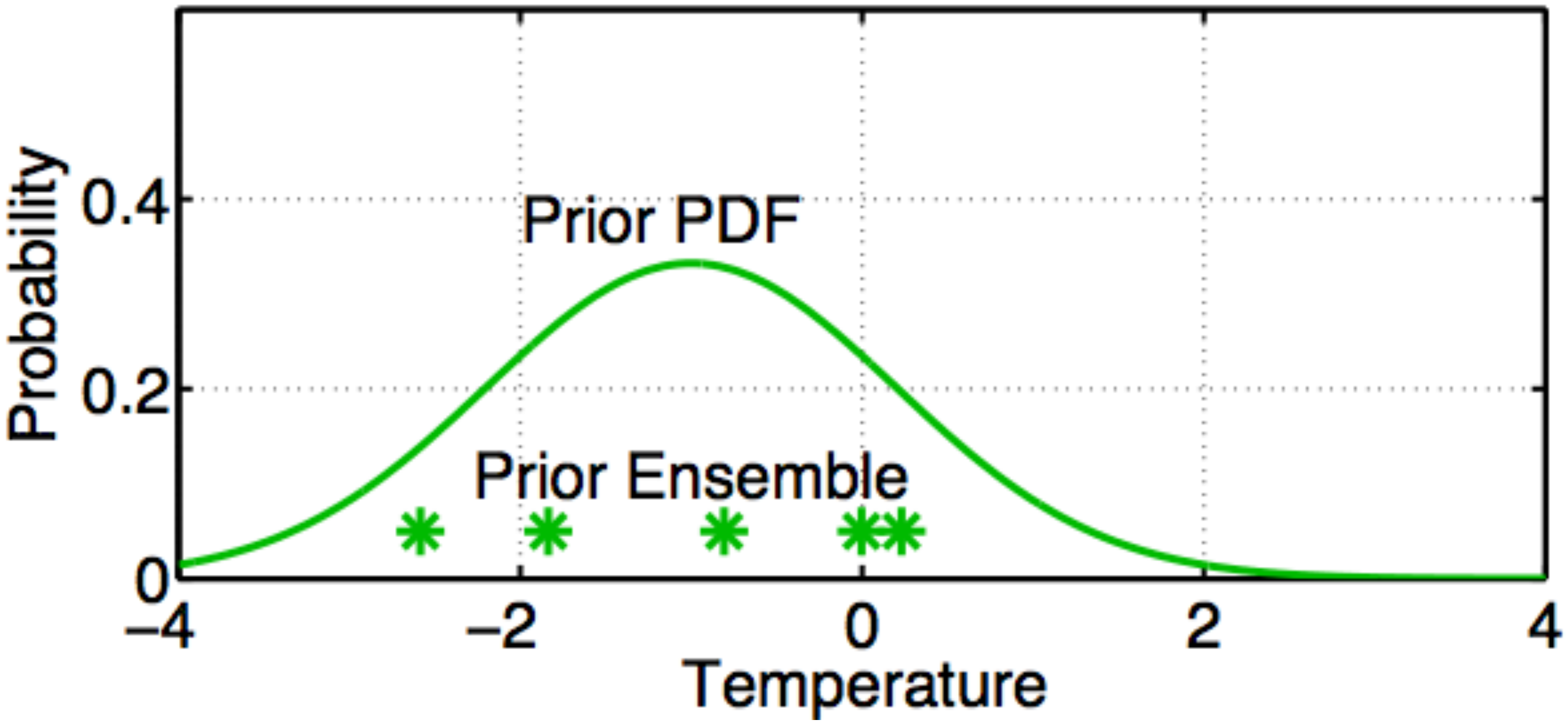
Same as advancing continuous pdf at time t_1 to time t_2 with model L.



One-Dimensional Ensemble Kalman Filter: Assimilating an Observation

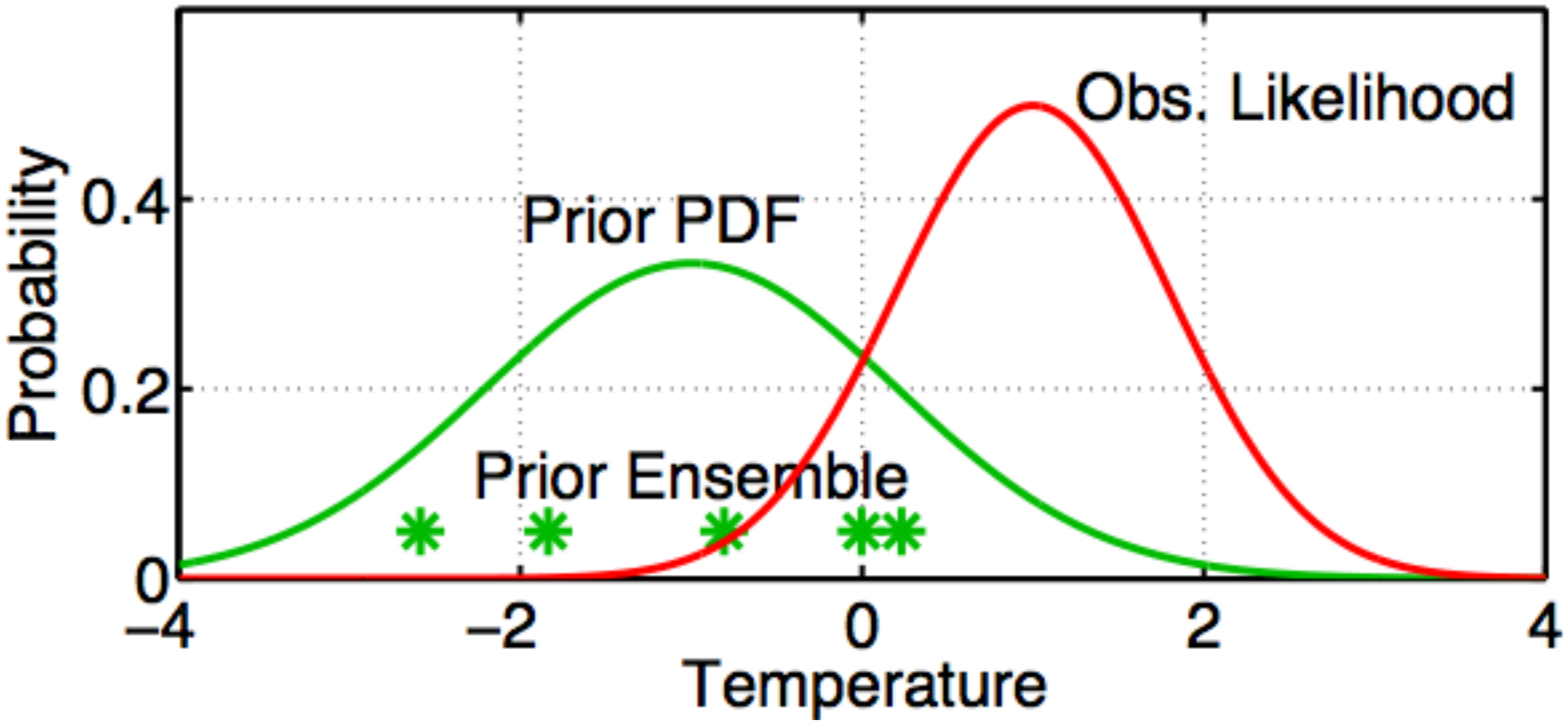


One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



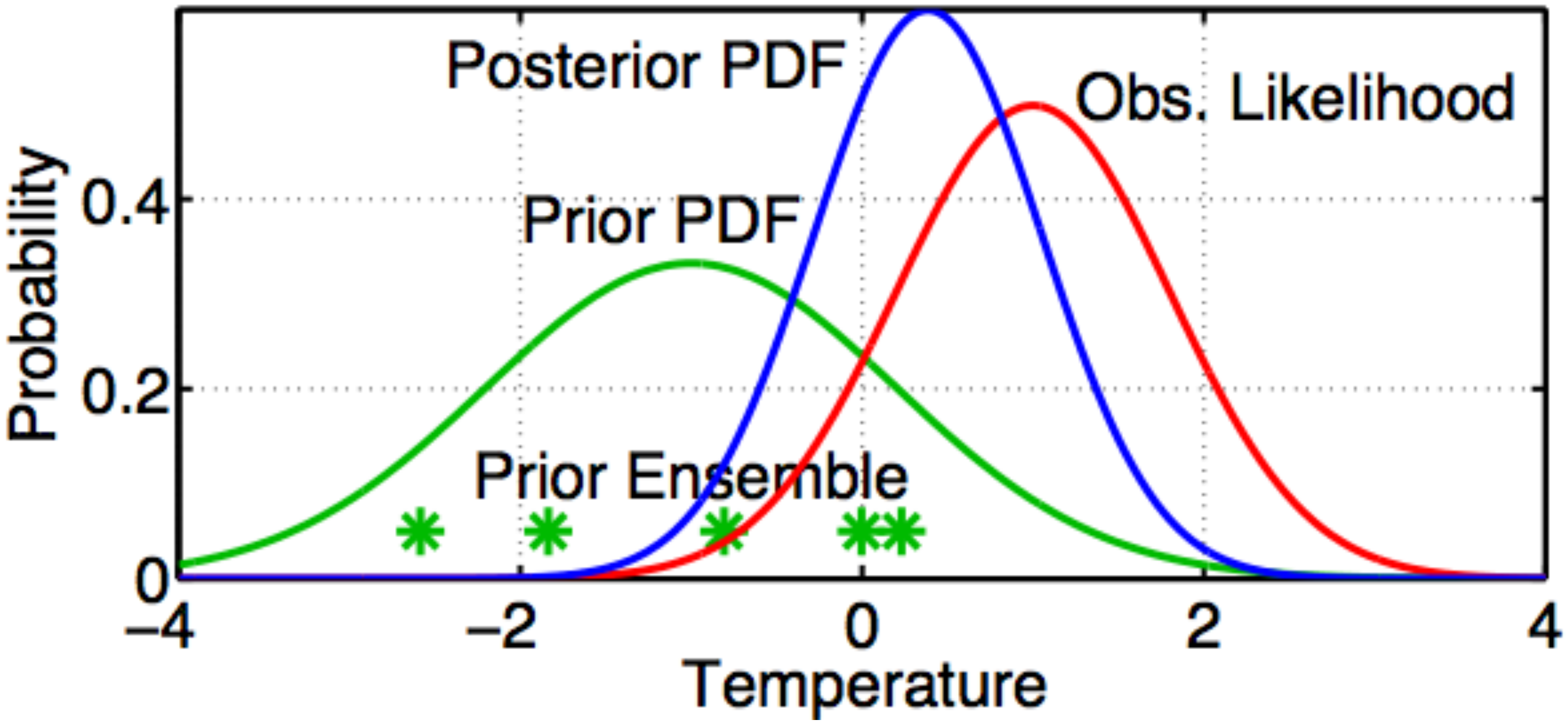
Fit a Gaussian to the sample.

One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



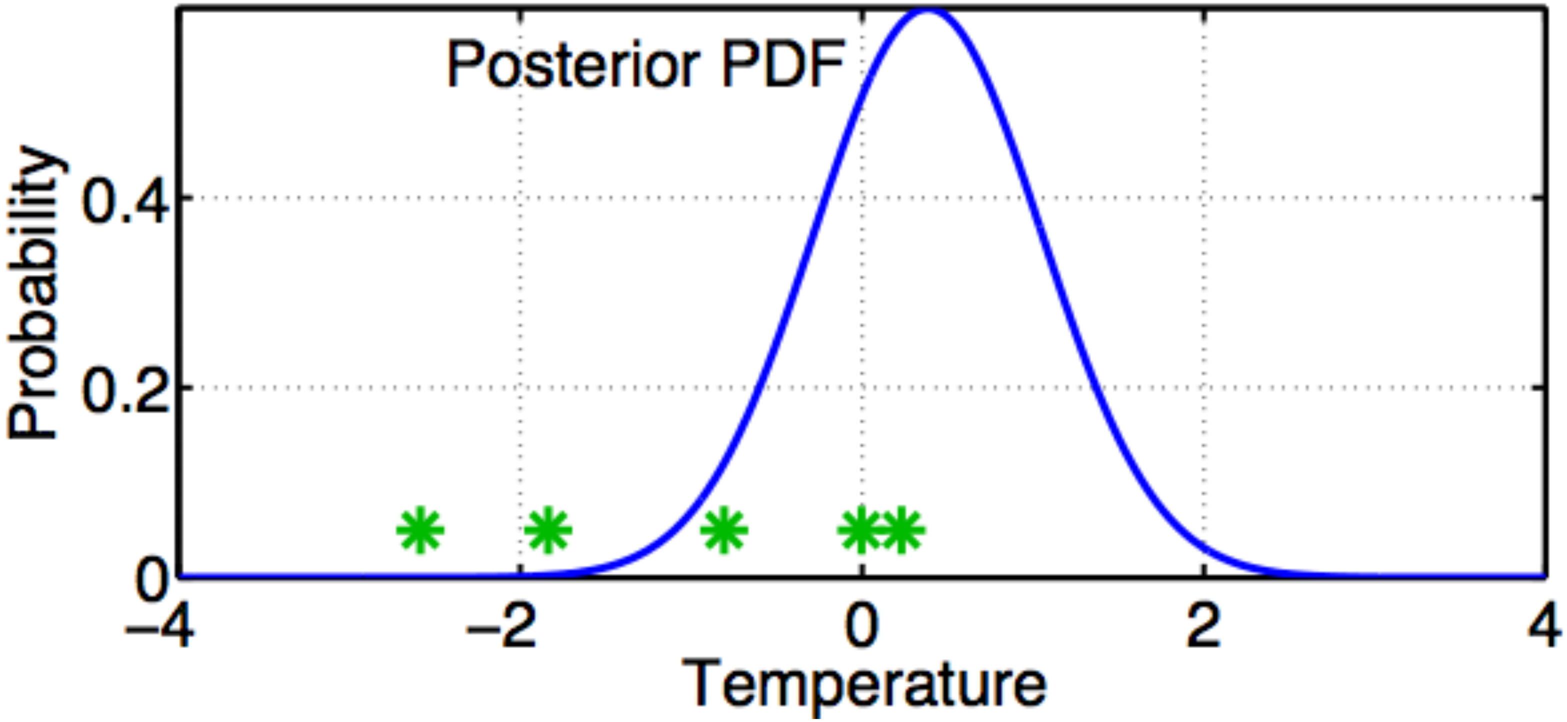
Get the observation likelihood.

One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



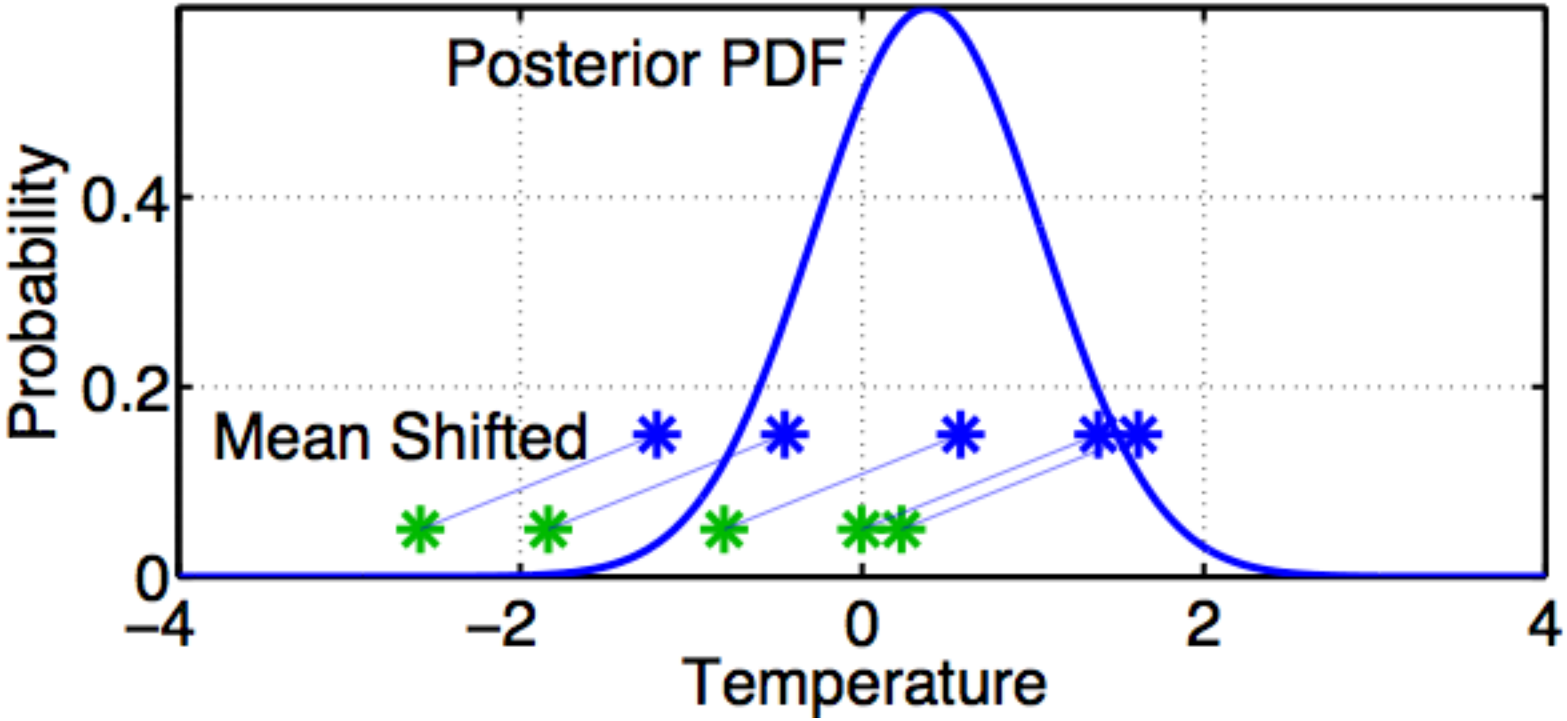
Compute the continuous posterior PDF.

One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



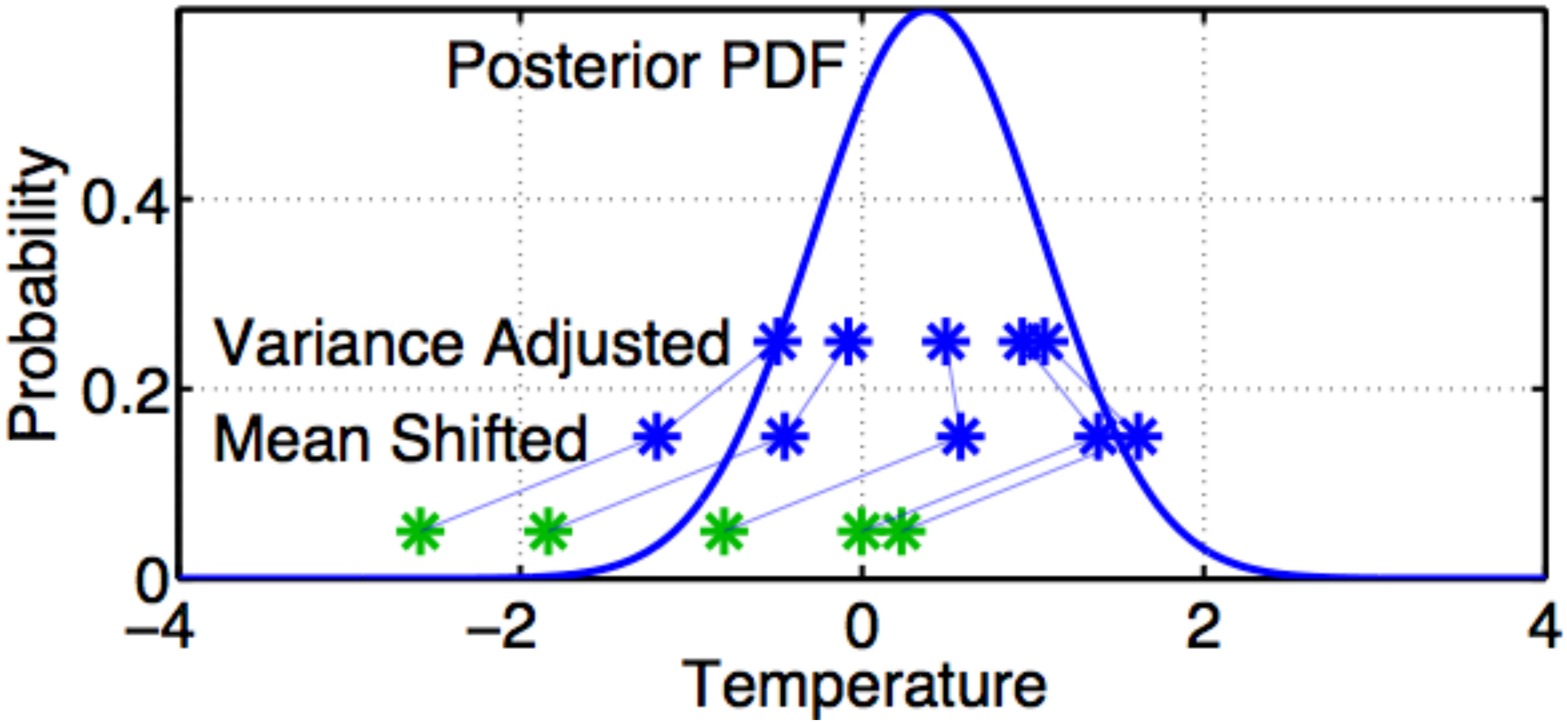
Use a deterministic algorithm to ‘adjust’ the ensemble.

One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



First, ‘shift’ the ensemble to have the exact mean of the posterior.

One-Dimensional Ensemble Kalman Filter: Assimilating an Observation



First, ‘shift’ the ensemble to have the exact mean of the posterior.

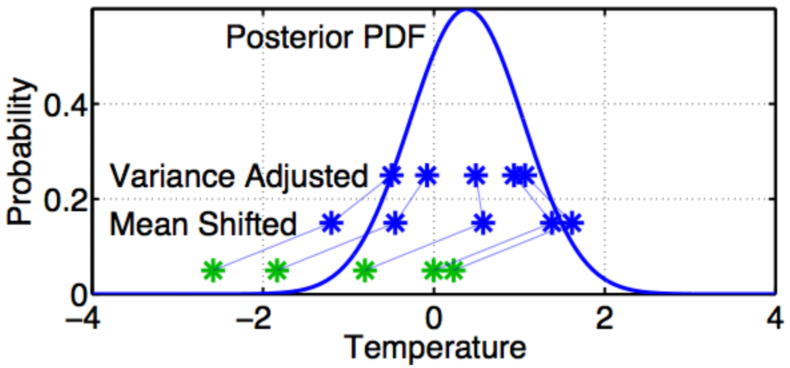
Second, linearly contract to have the exact variance of the posterior.

Sample statistics are identical to Kalman filter.

A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
    - Localization
    - Inflation
5. Parameter estimation.
6. Some sample applications.

One observed, one unobserved variable.



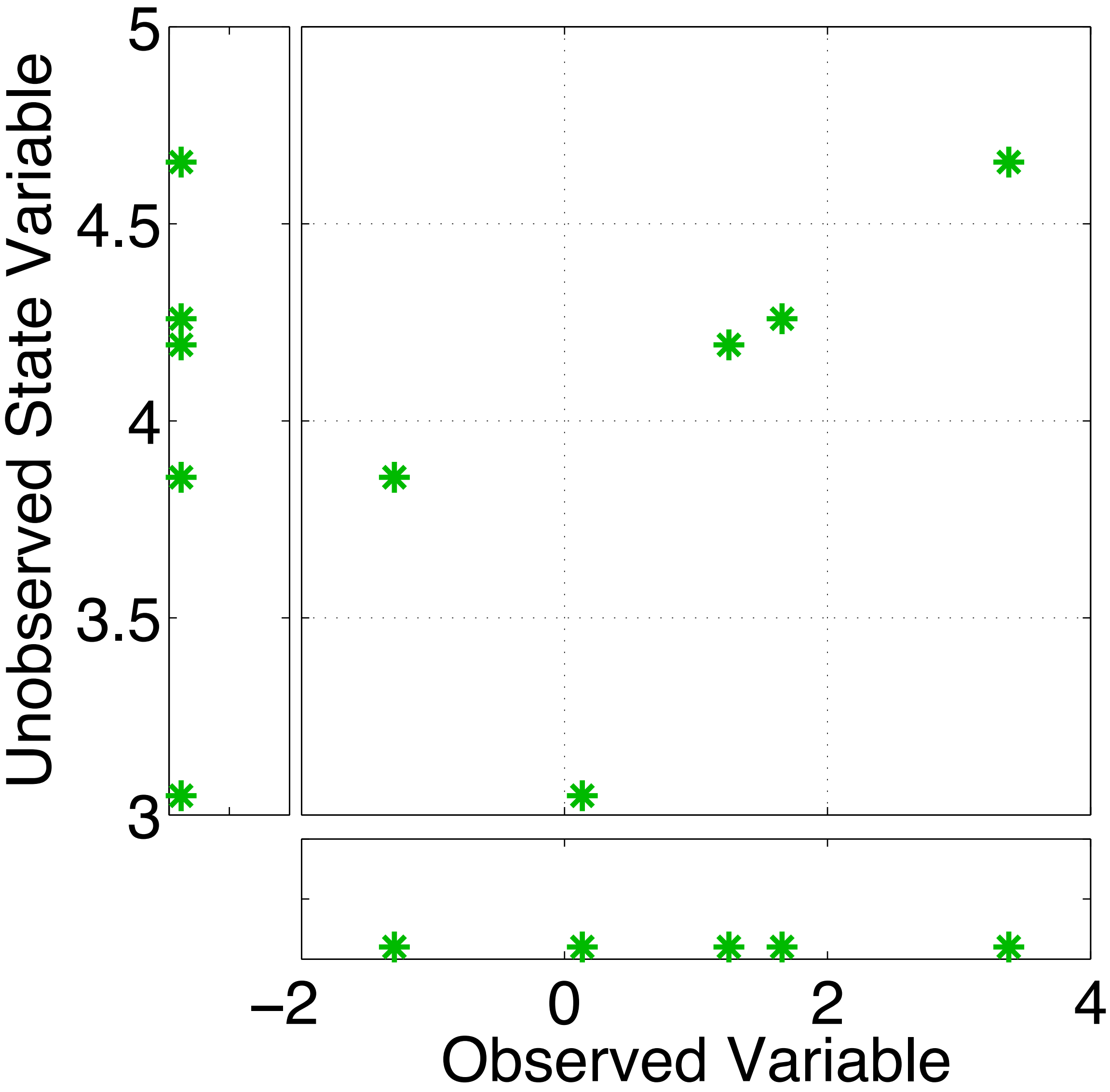
So far, we have a known likelihood for a single variable.

Now, suppose the model state has an additional variable,

temperature at Shanghai.

How should ensemble members update the additional variable?

One observed, one unobserved variable.

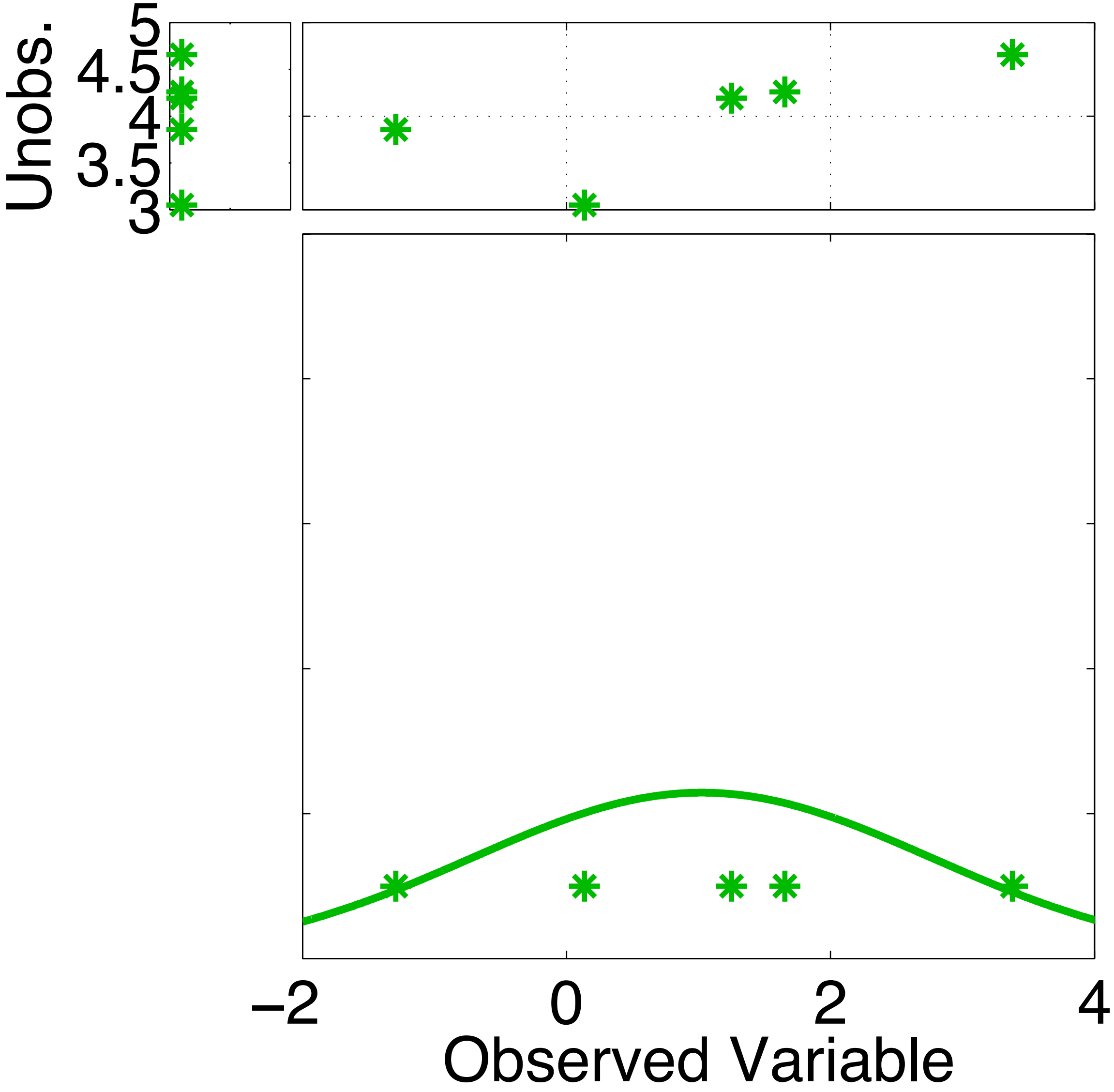


Assume that all we know is the prior joint distribution.

One variable is observed.

What should happen to the unobserved variable?

One observed, one unobserved variable.

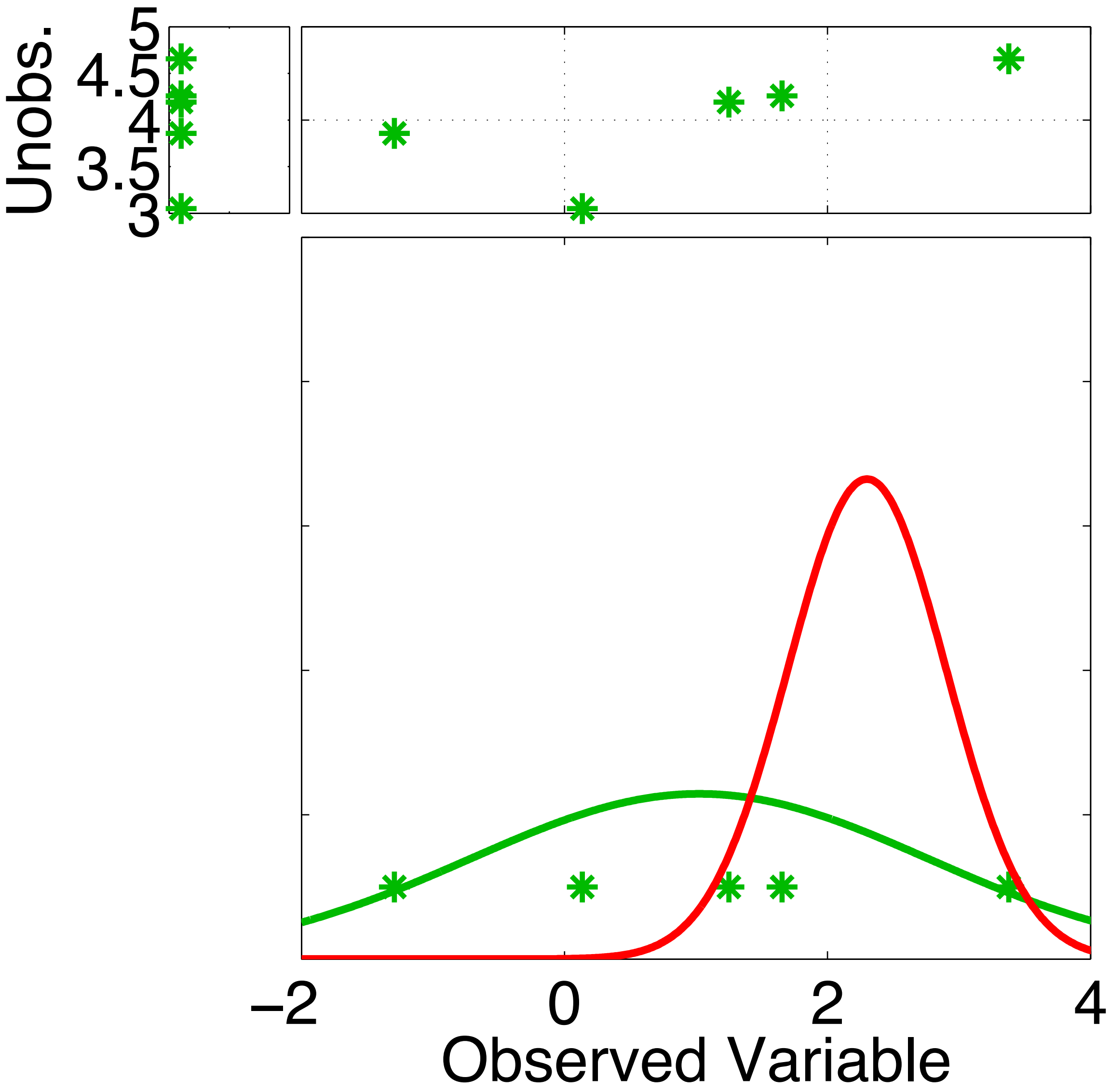


Assume that all we know is the prior joint distribution.

One variable is observed.

Update observed variable with ensemble Kalman filter.

One observed, one unobserved variable.

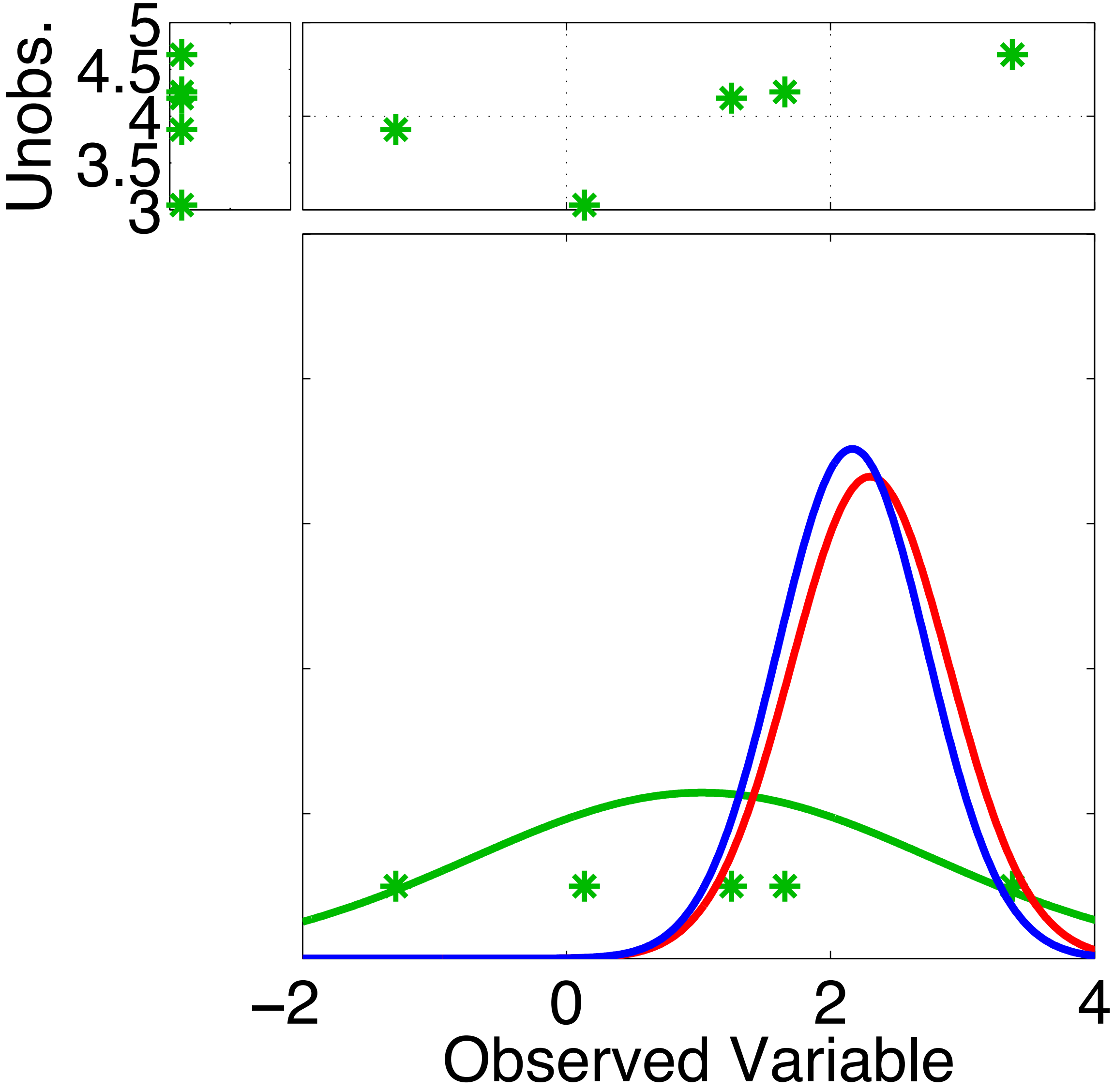


Assume that all we know is the prior joint distribution.

One variable is observed.

Update observed variable with ensemble Kalman filter.

One observed, one unobserved variable.

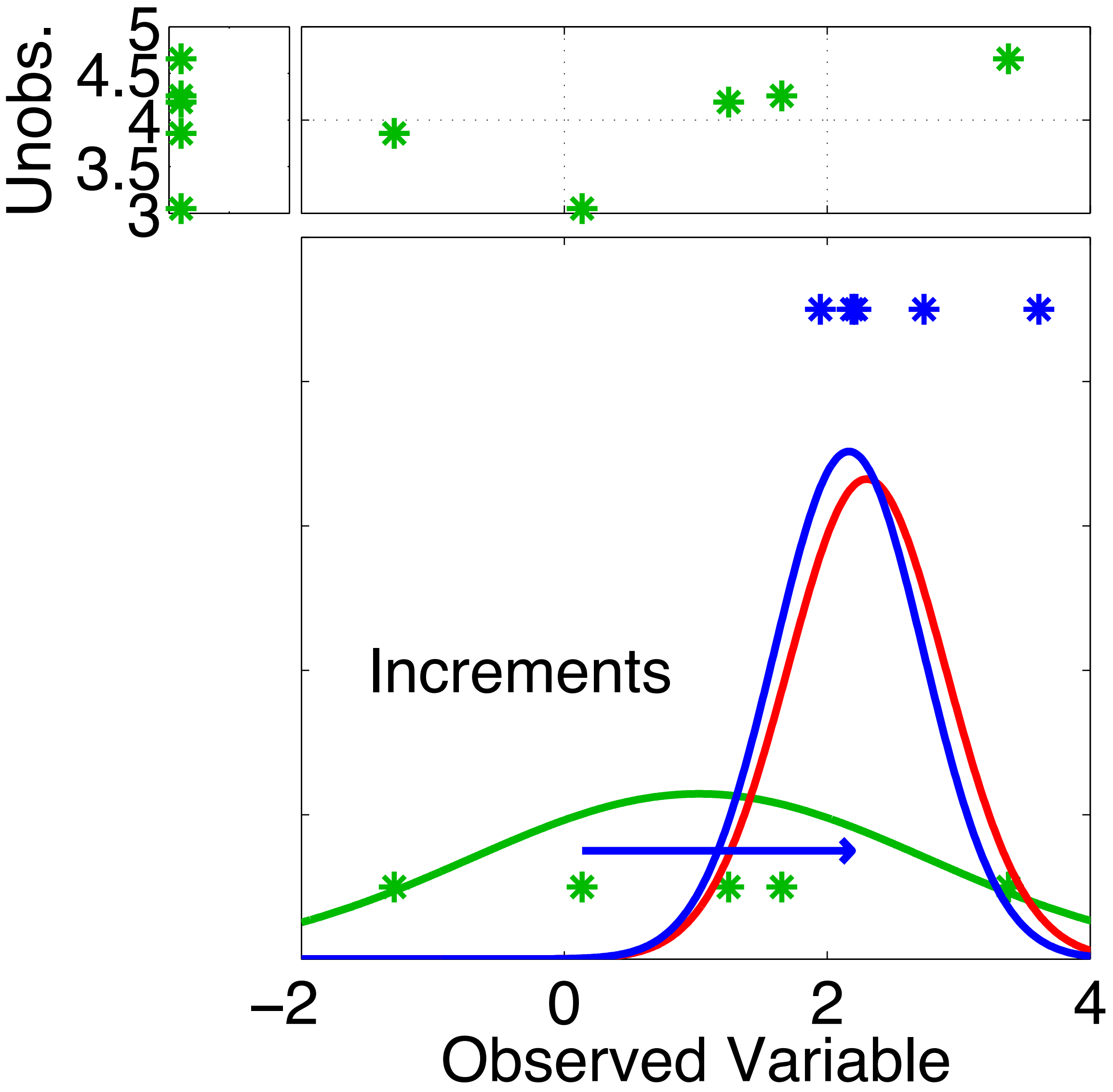


Assume that all we know is the prior joint distribution.

One variable is observed.

Update observed variable with ensemble Kalman filter.

One observed, one unobserved variable.

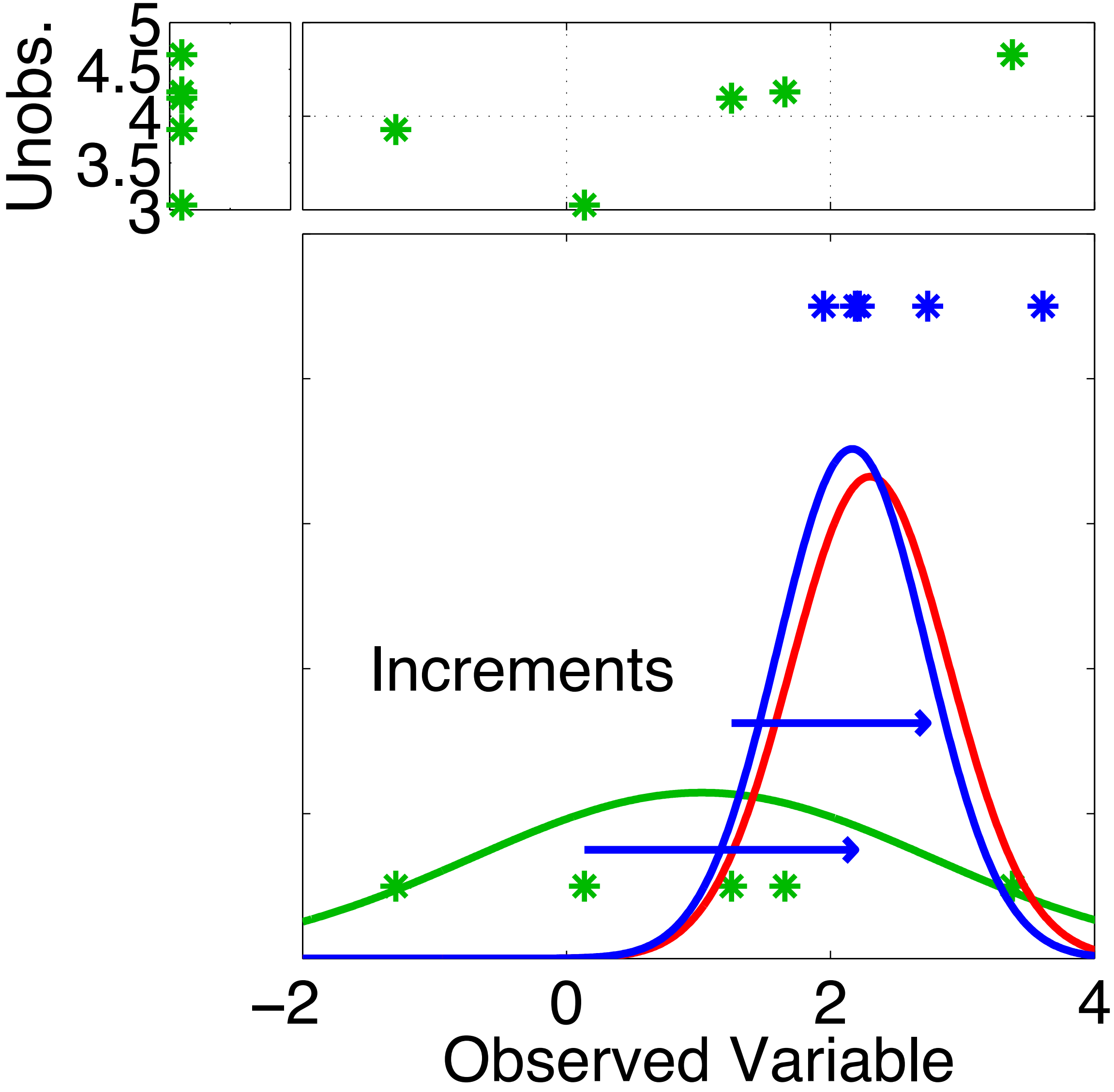


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute increments for prior ensemble members of observed variable.

One observed, one unobserved variable.

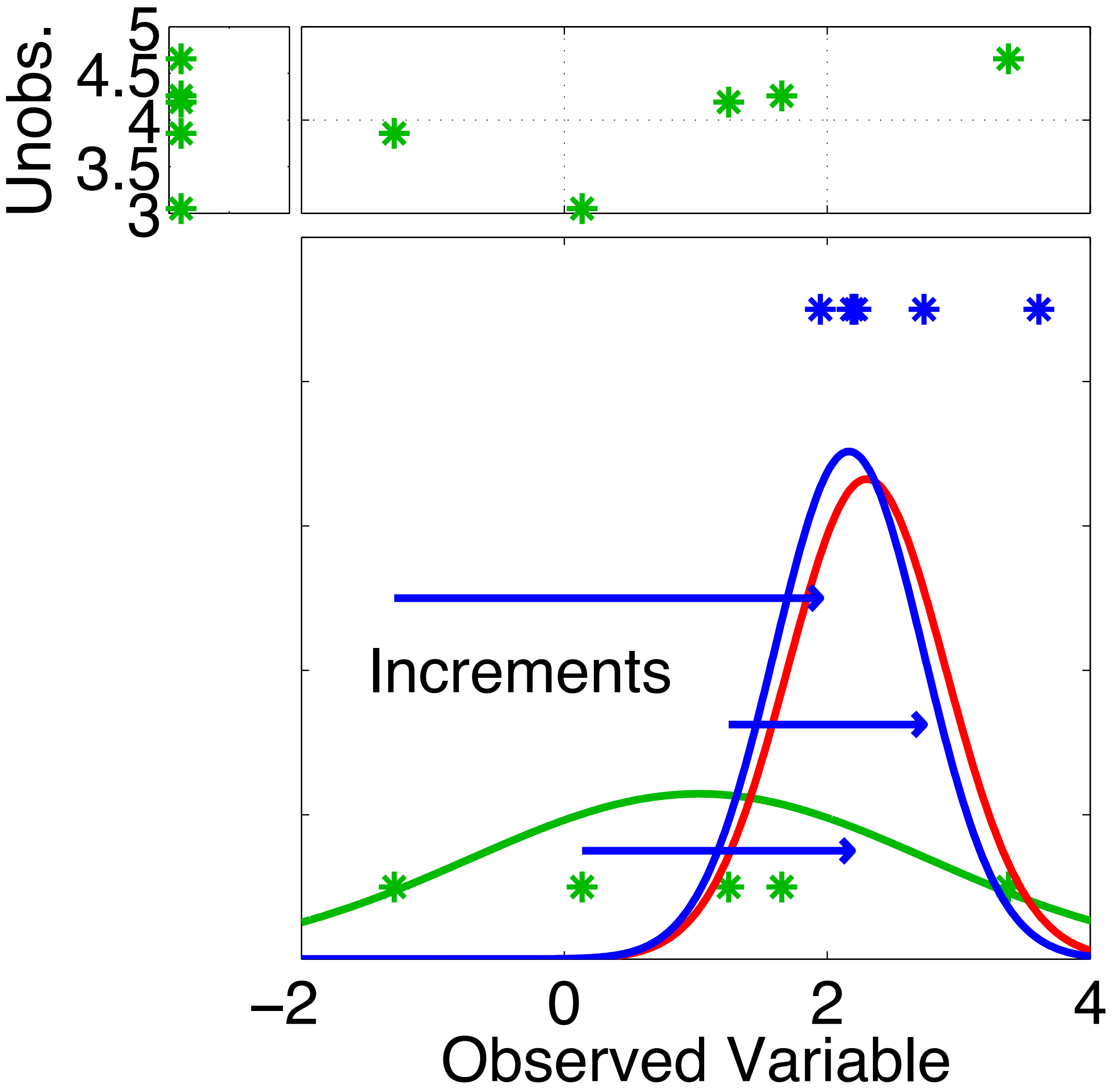


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute increments for prior ensemble members of observed variable.

One observed, one unobserved variable.

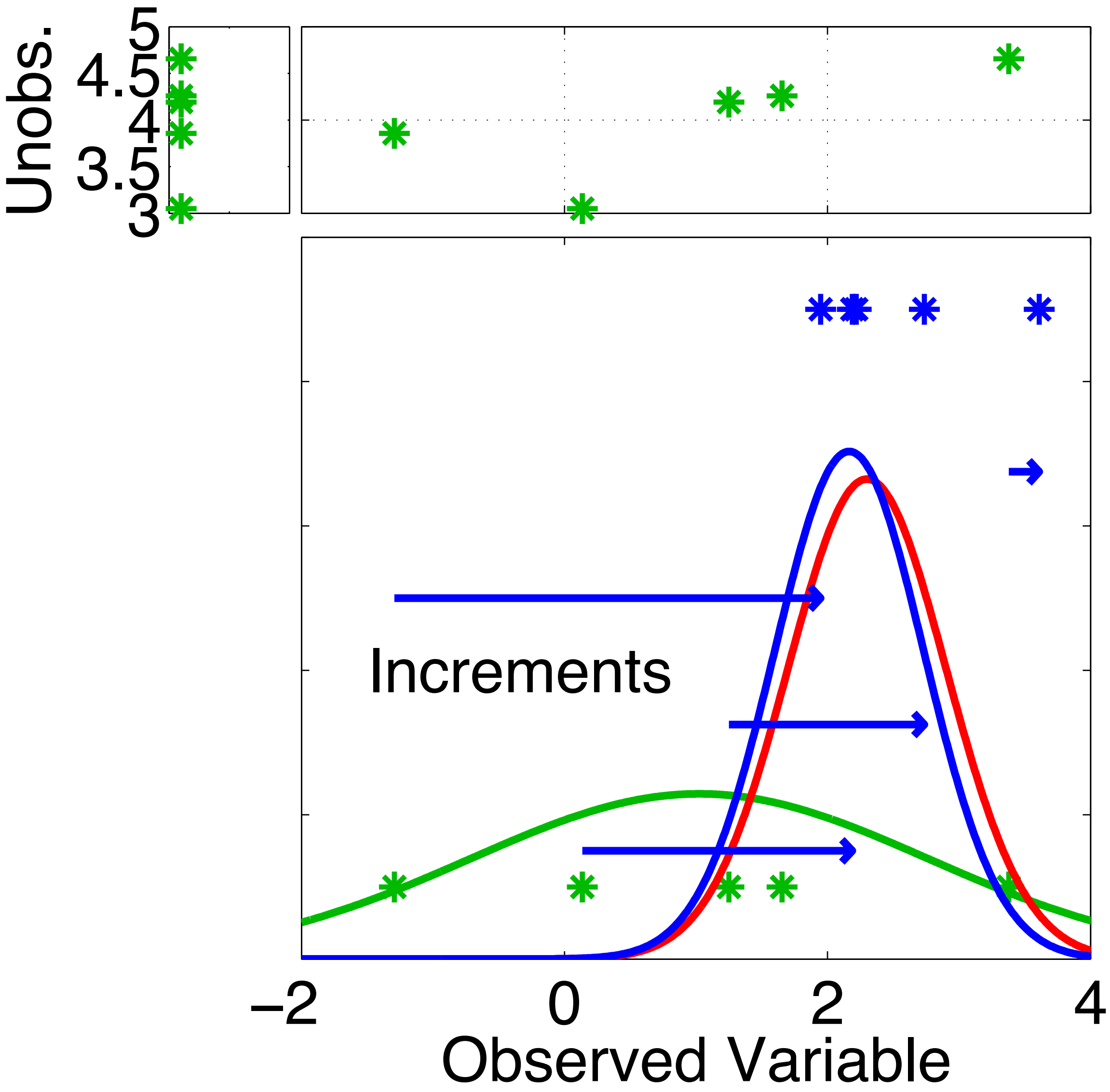


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute increments for prior ensemble members of observed variable.

One observed, one unobserved variable.

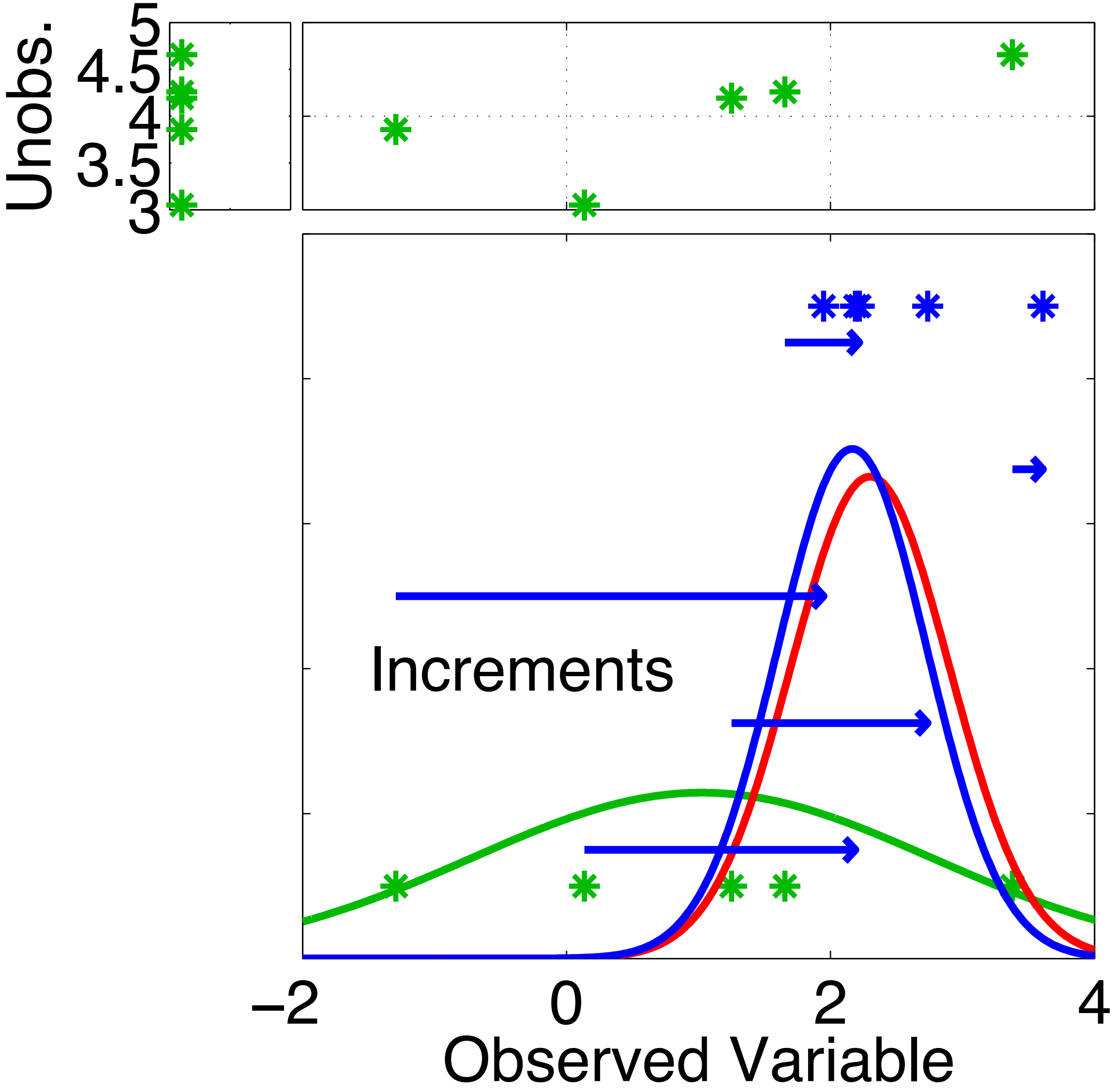


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute increments for prior ensemble members of observed variable.

One observed, one unobserved variable.

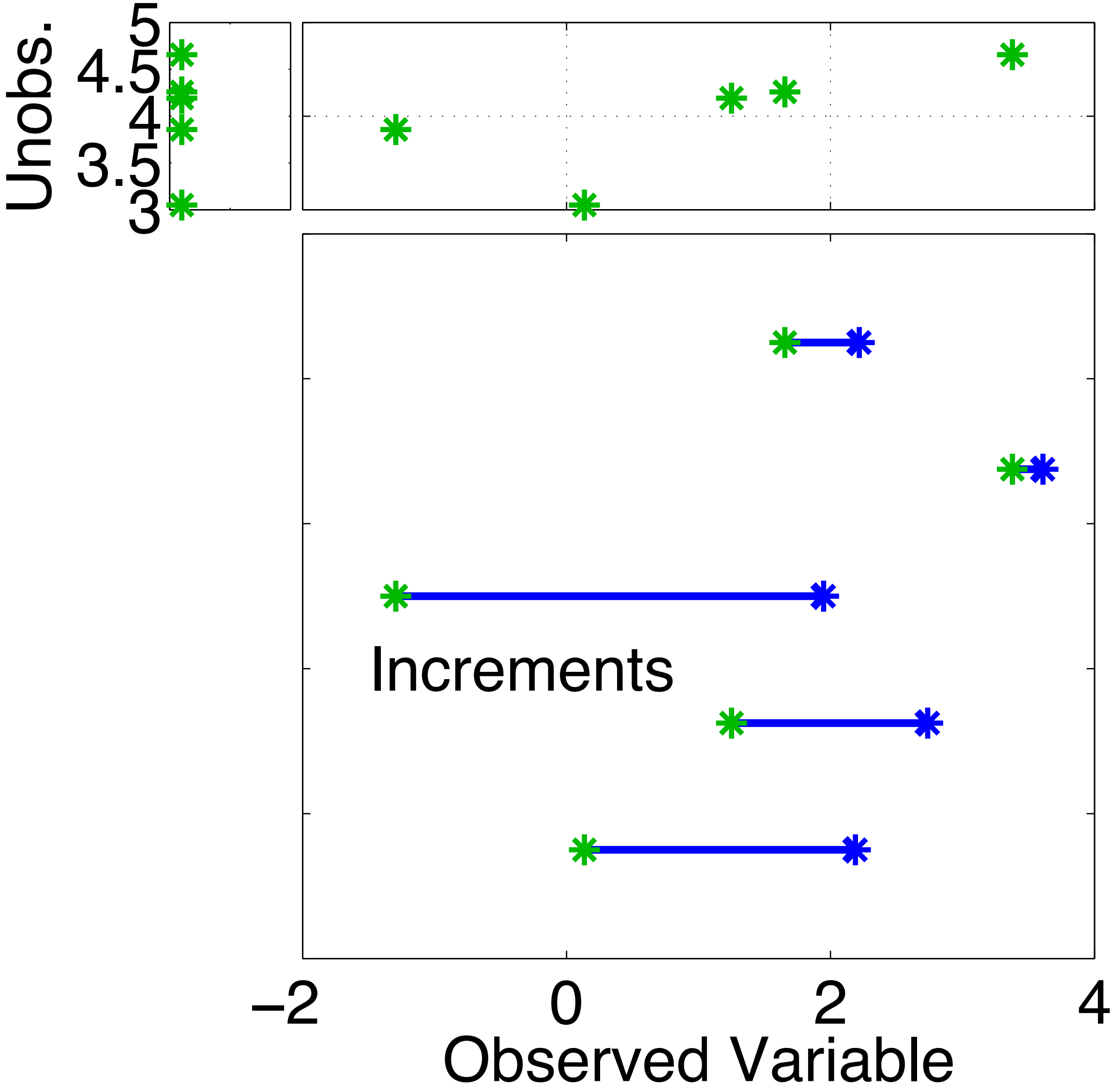


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute increments for prior ensemble members of observed variable.

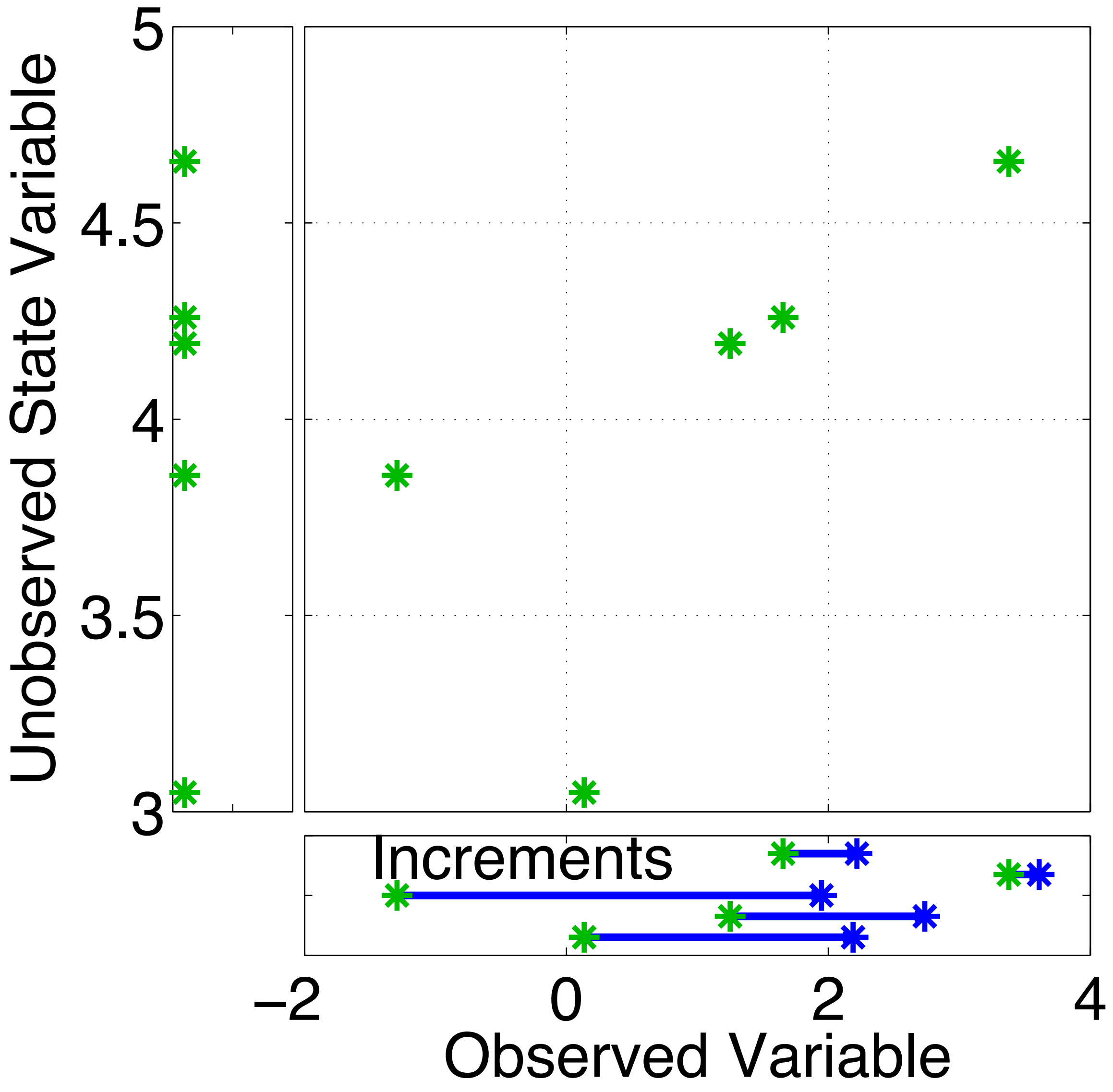
One observed, one unobserved variable.



Using only increments guarantees that if observation had no impact on observed variable, the unobserved variable is unchanged.

Highly desirable!

One observed, one unobserved variable.



Assume that all we know is the prior joint distribution.

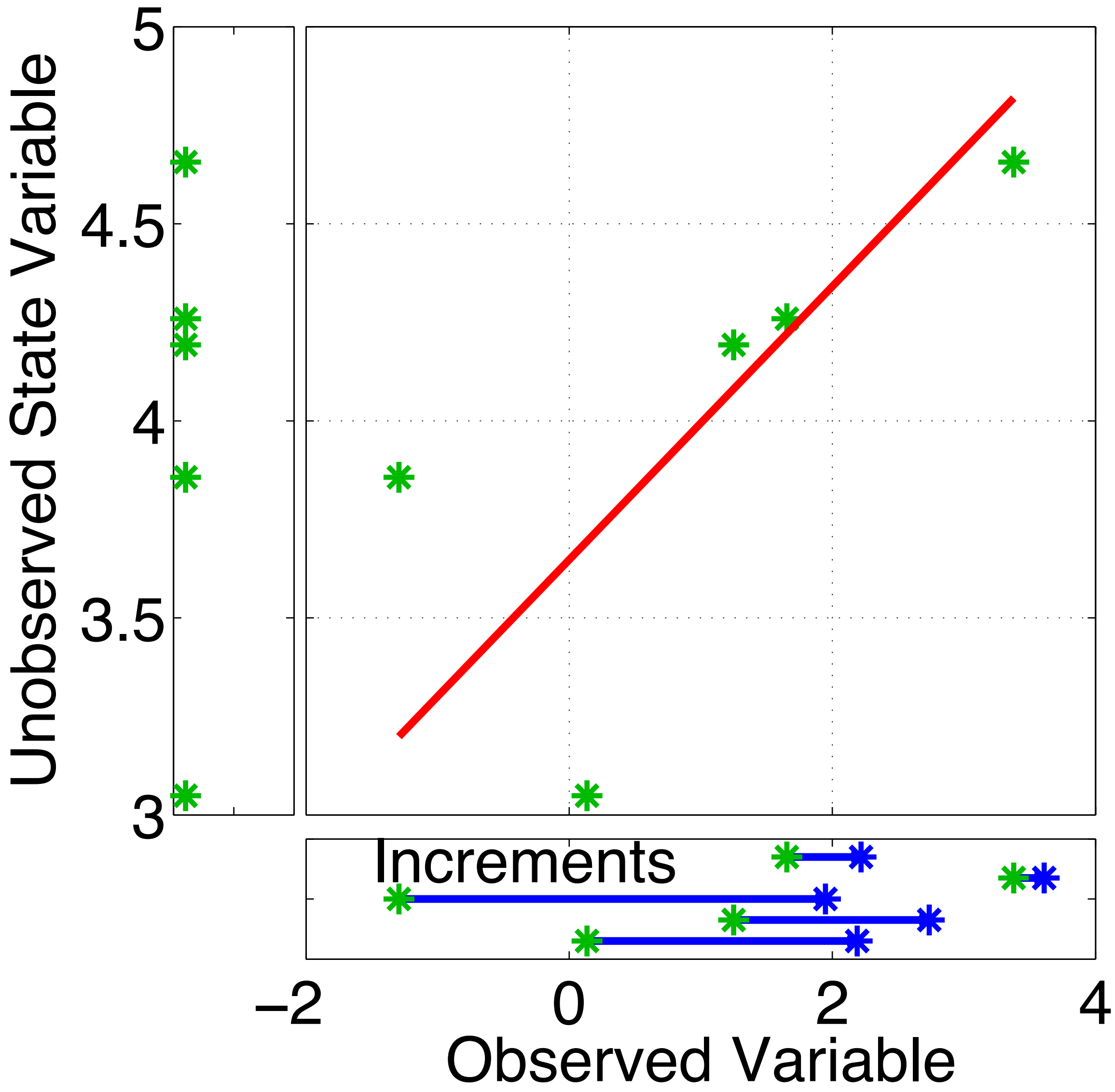
How should the unobserved variable be impacted?

1st choice: least squares

Equivalent to linear regression.

Same as assuming binormal prior.

One observed, one unobserved variable.



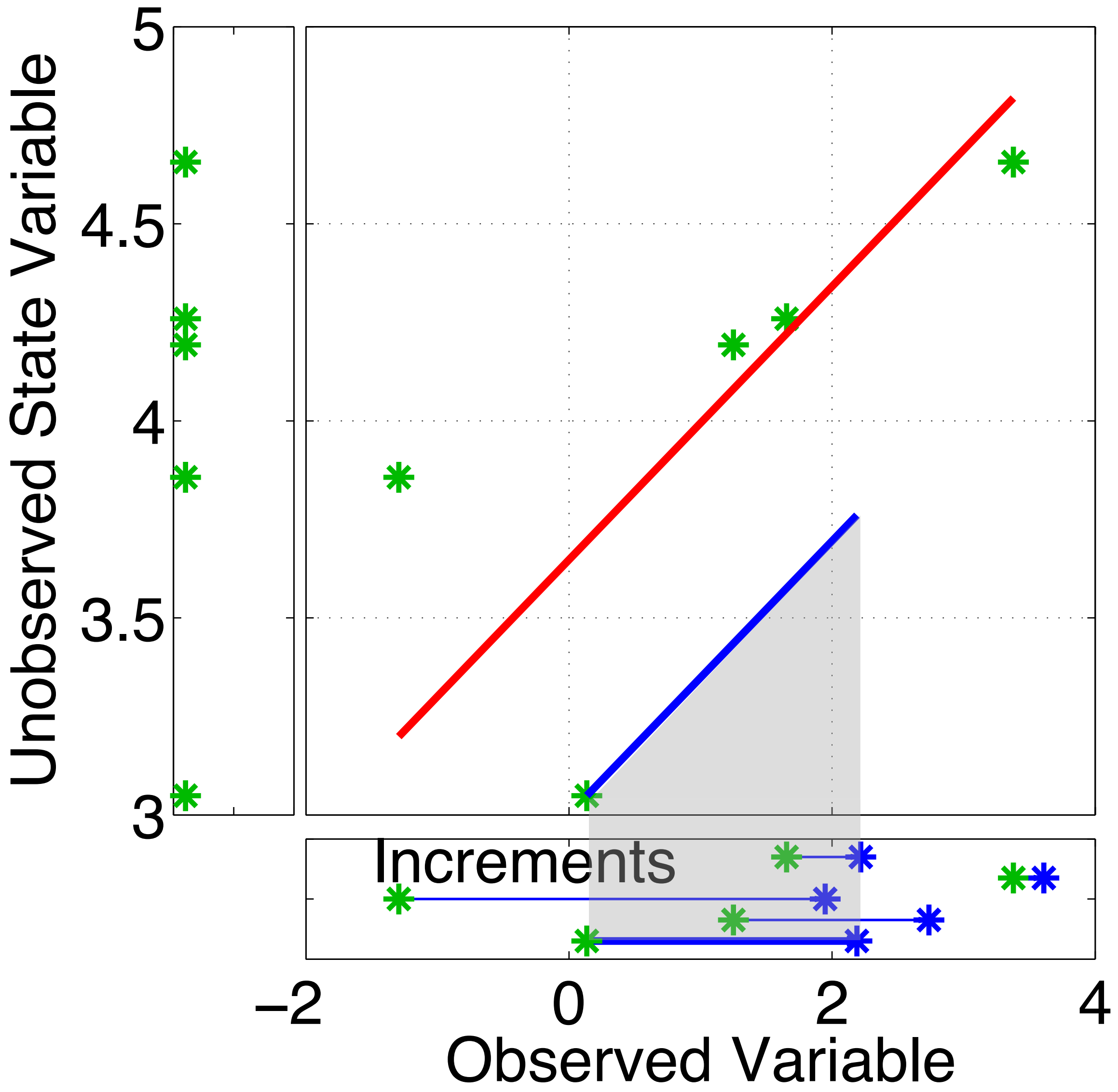
Have joint prior distribution of two variables.

How should the unobserved variable be impacted?

1^{st} choice: least squares

Begin by finding least squares fit.

One observed, one unobserved variable.

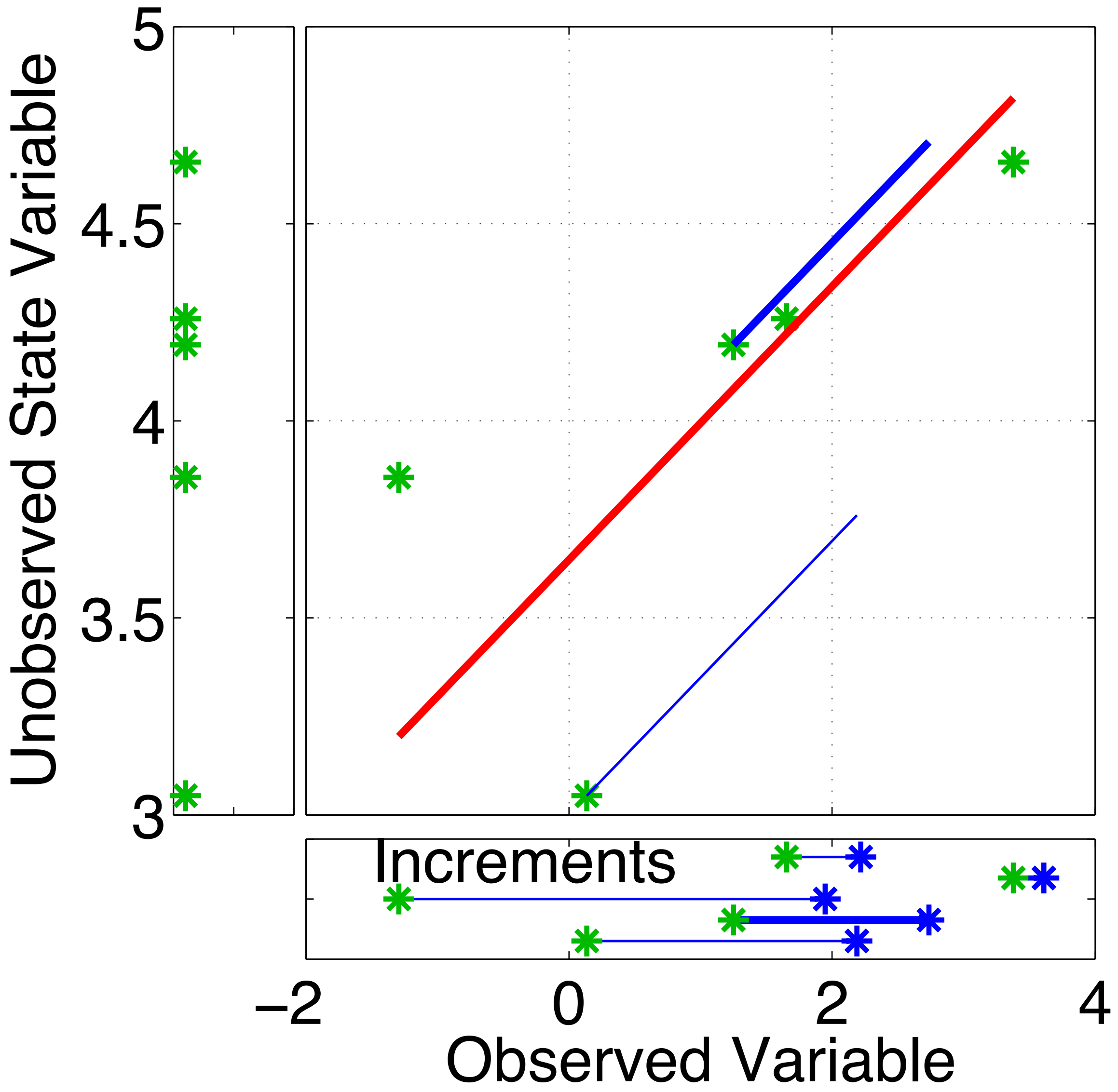


Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Equivalent to first finding image of increment in joint space.

One observed, one unobserved variable.

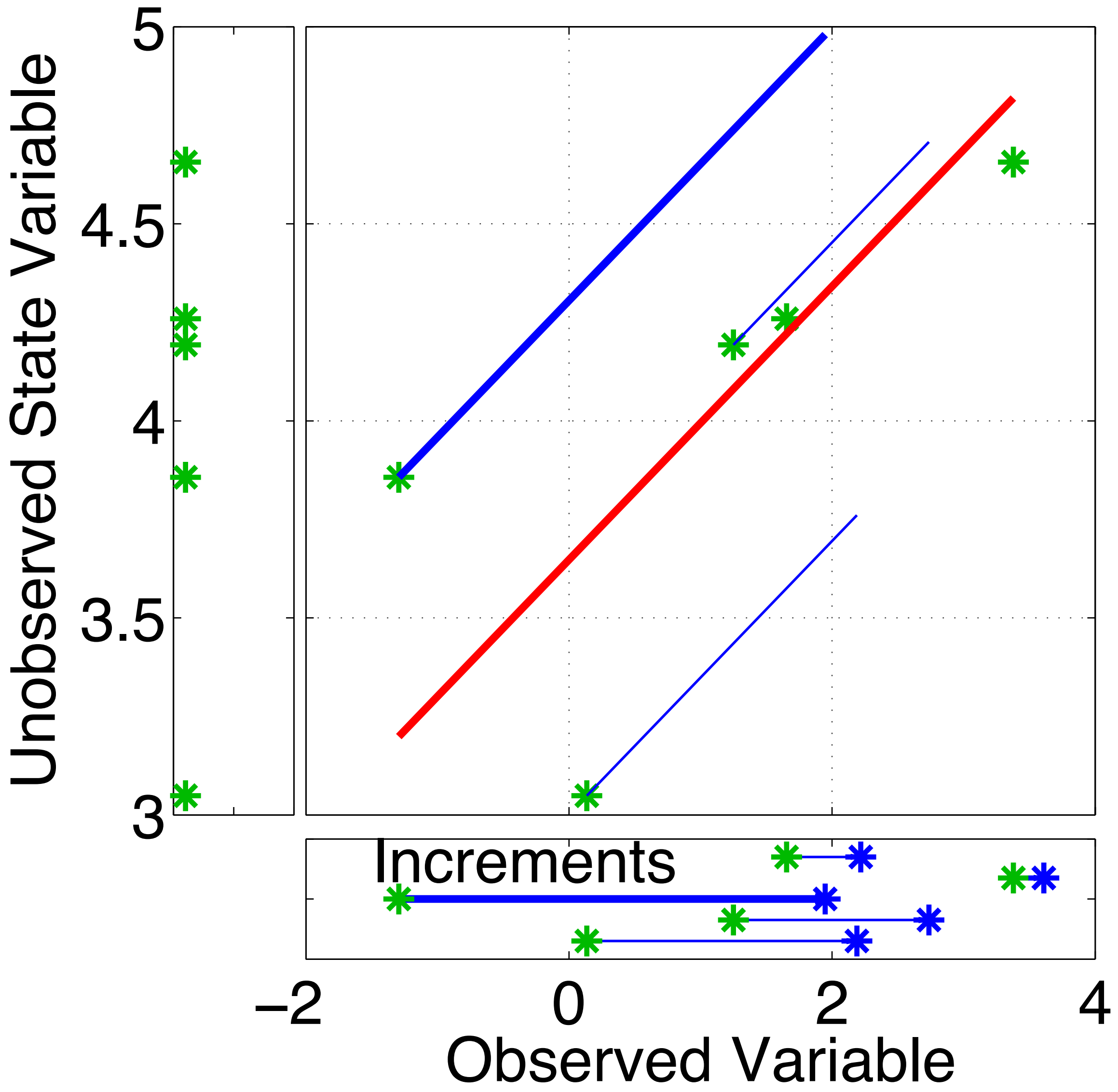


Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Equivalent to first finding image of increment in joint space.

One observed, one unobserved variable.

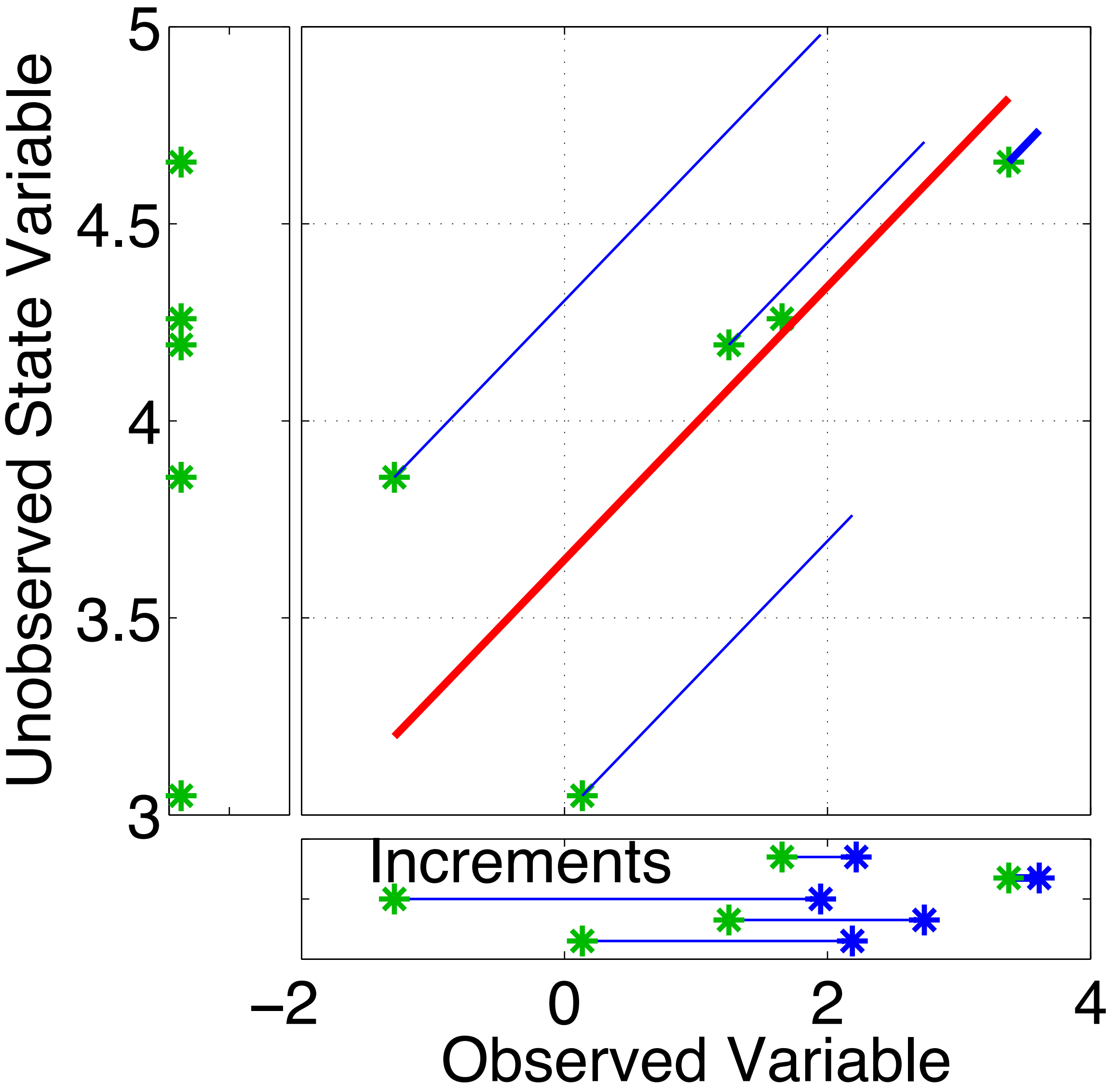


Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Equivalent to first finding image of increment in joint space.

One observed, one unobserved variable.

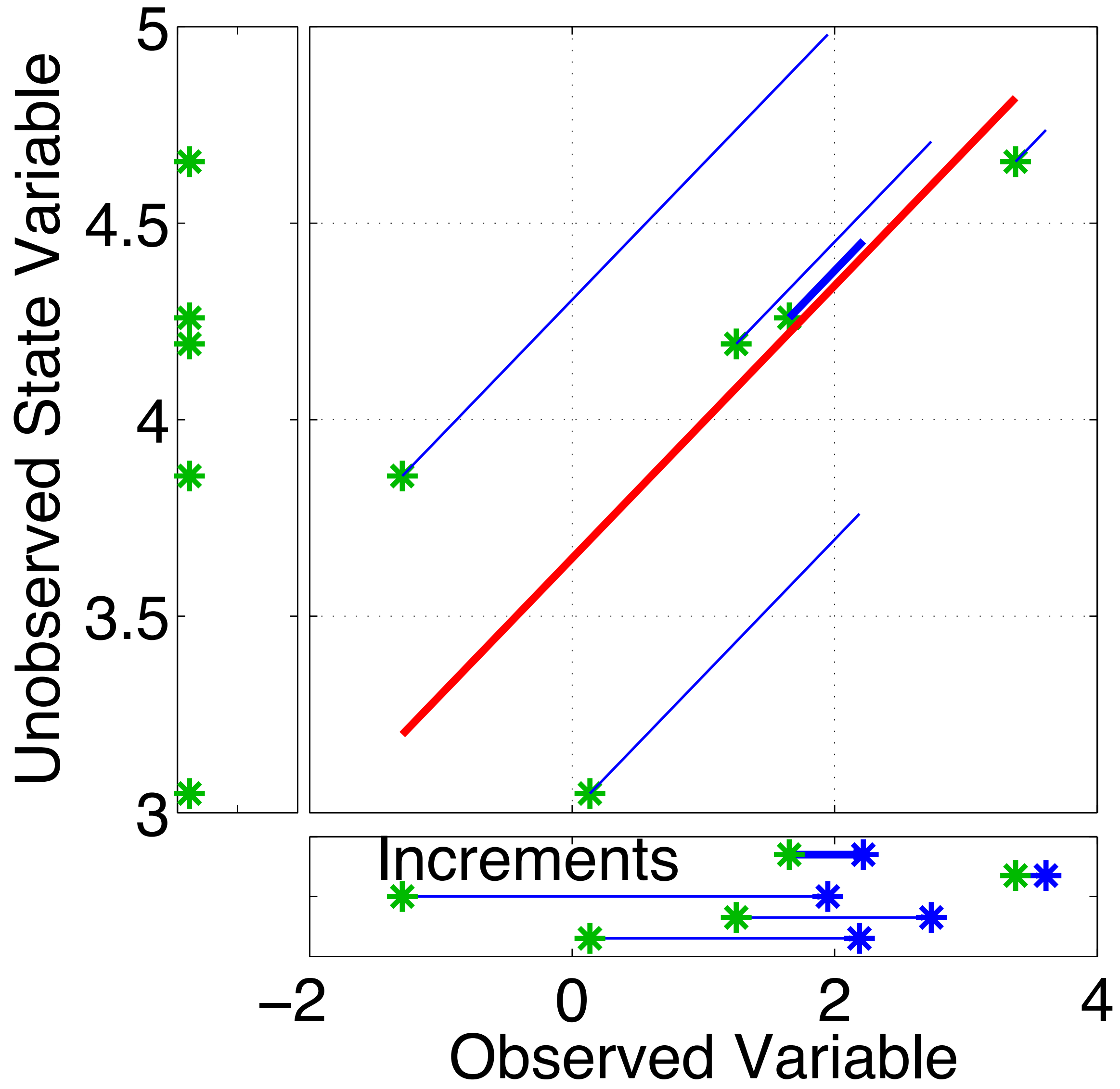


Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Equivalent to first finding image of increment in joint space.

One observed, one unobserved variable.

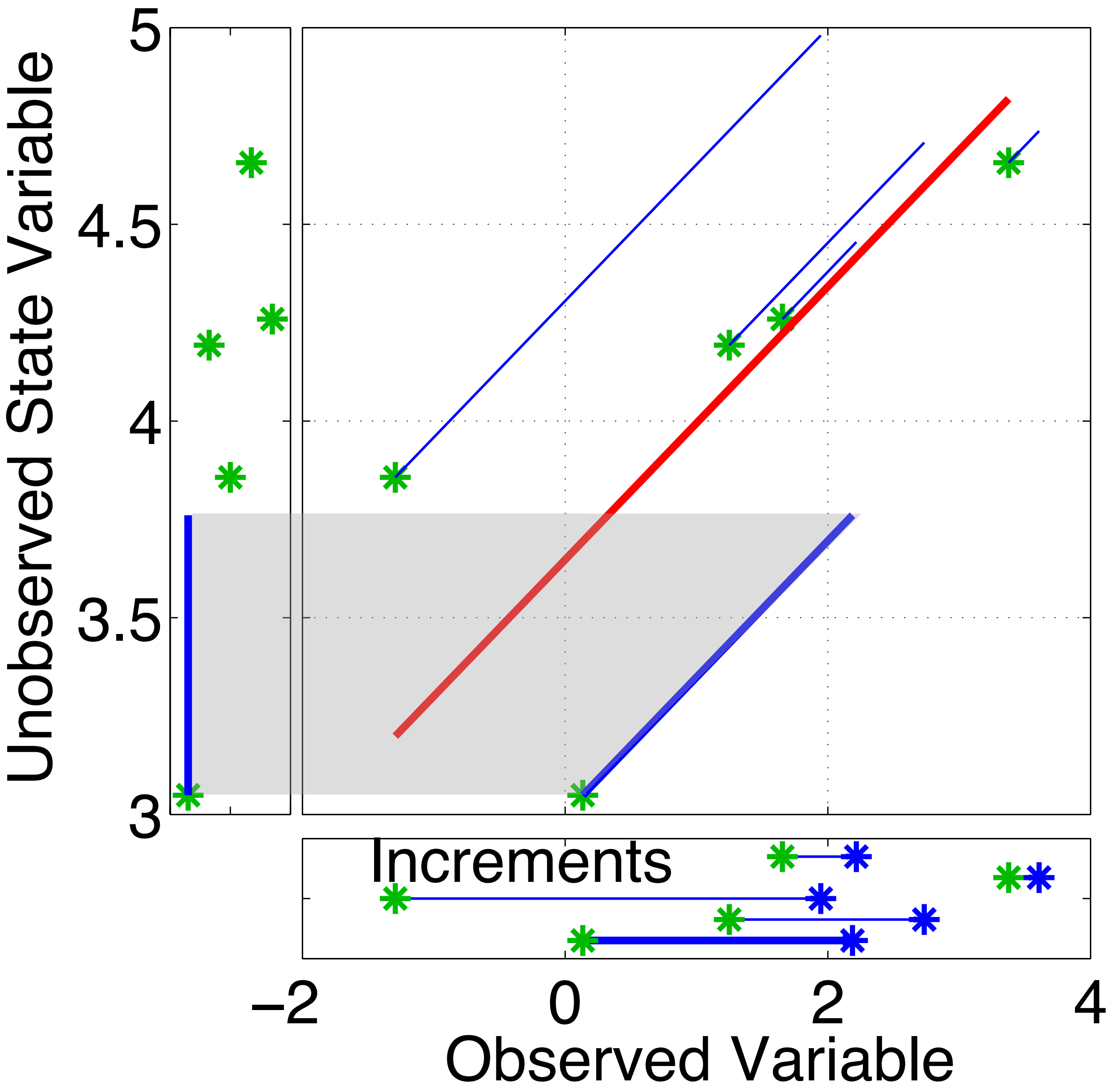


Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Equivalent to first finding image of increment in joint space.

One observed, one unobserved variable.

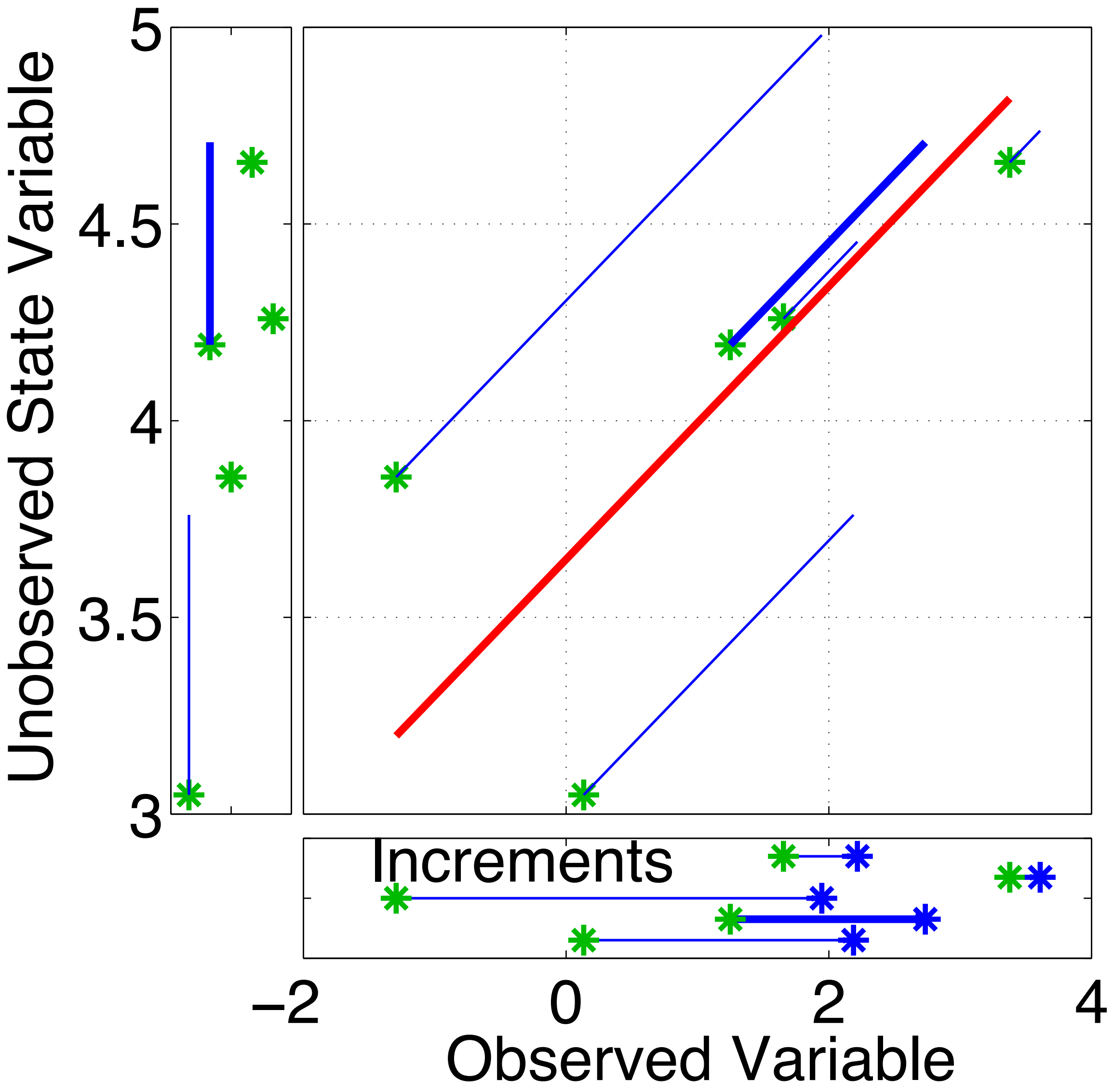


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

One observed, one unobserved variable.

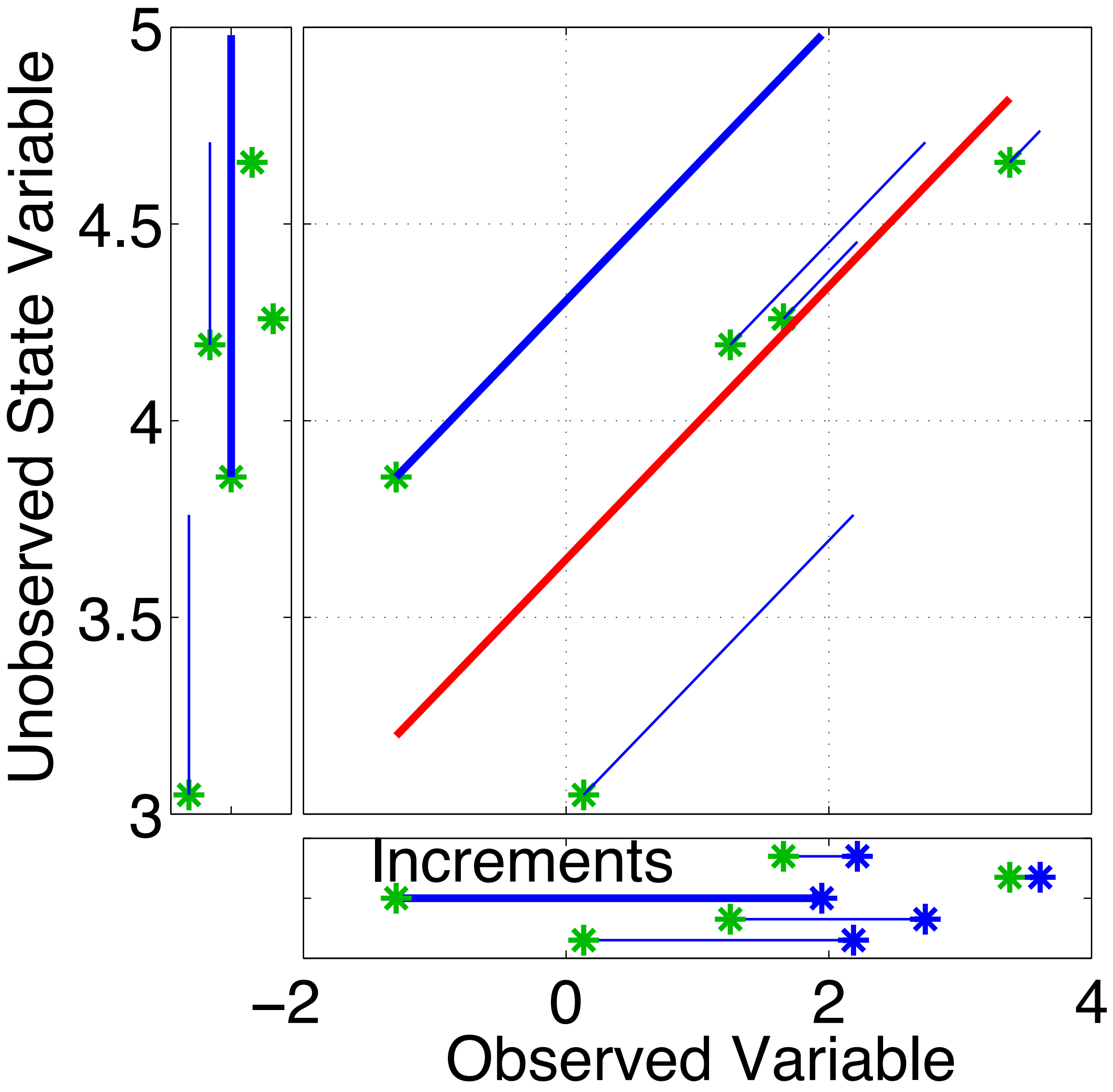


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

One observed, one unobserved variable.

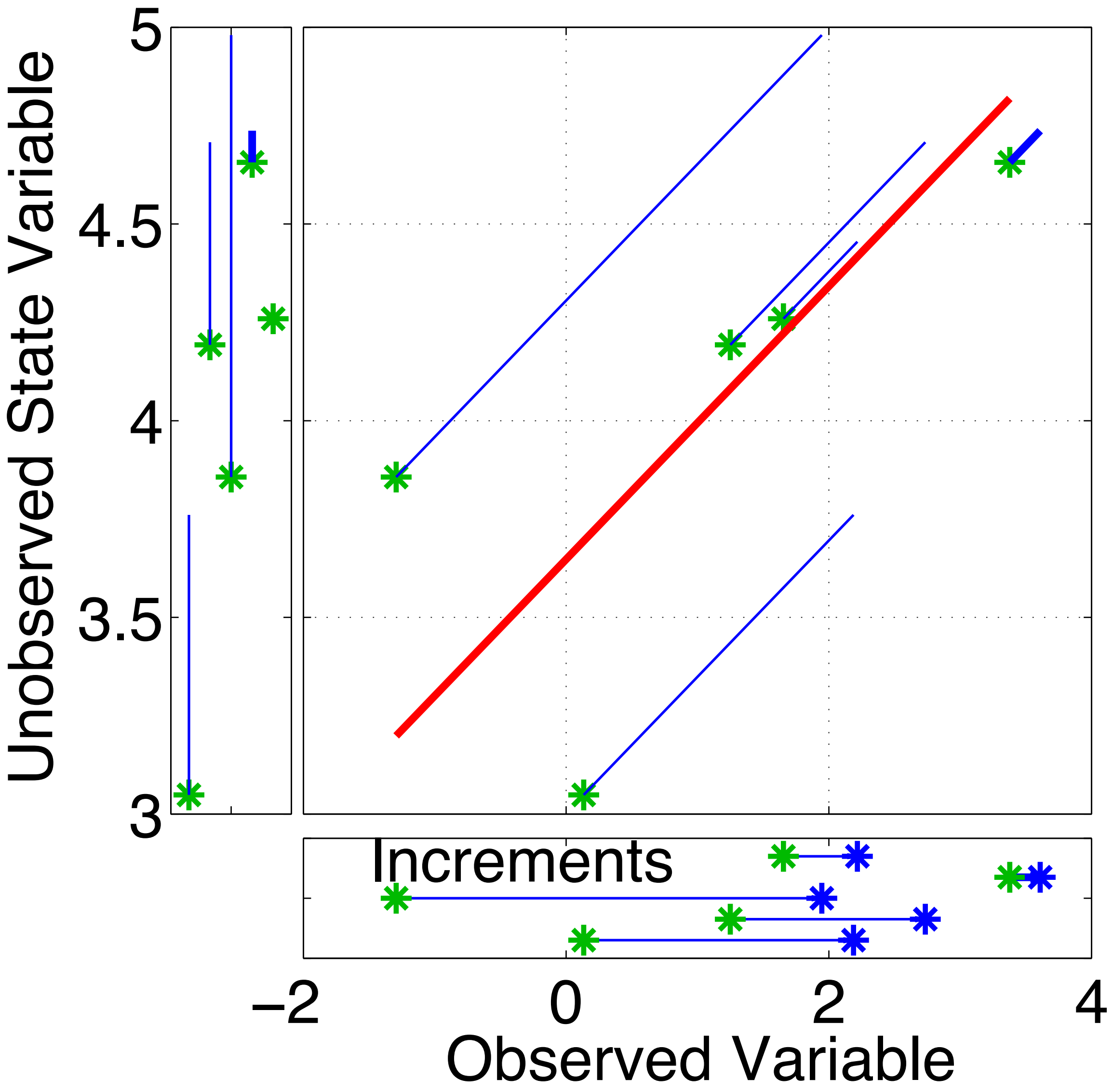


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

One observed, one unobserved variable.

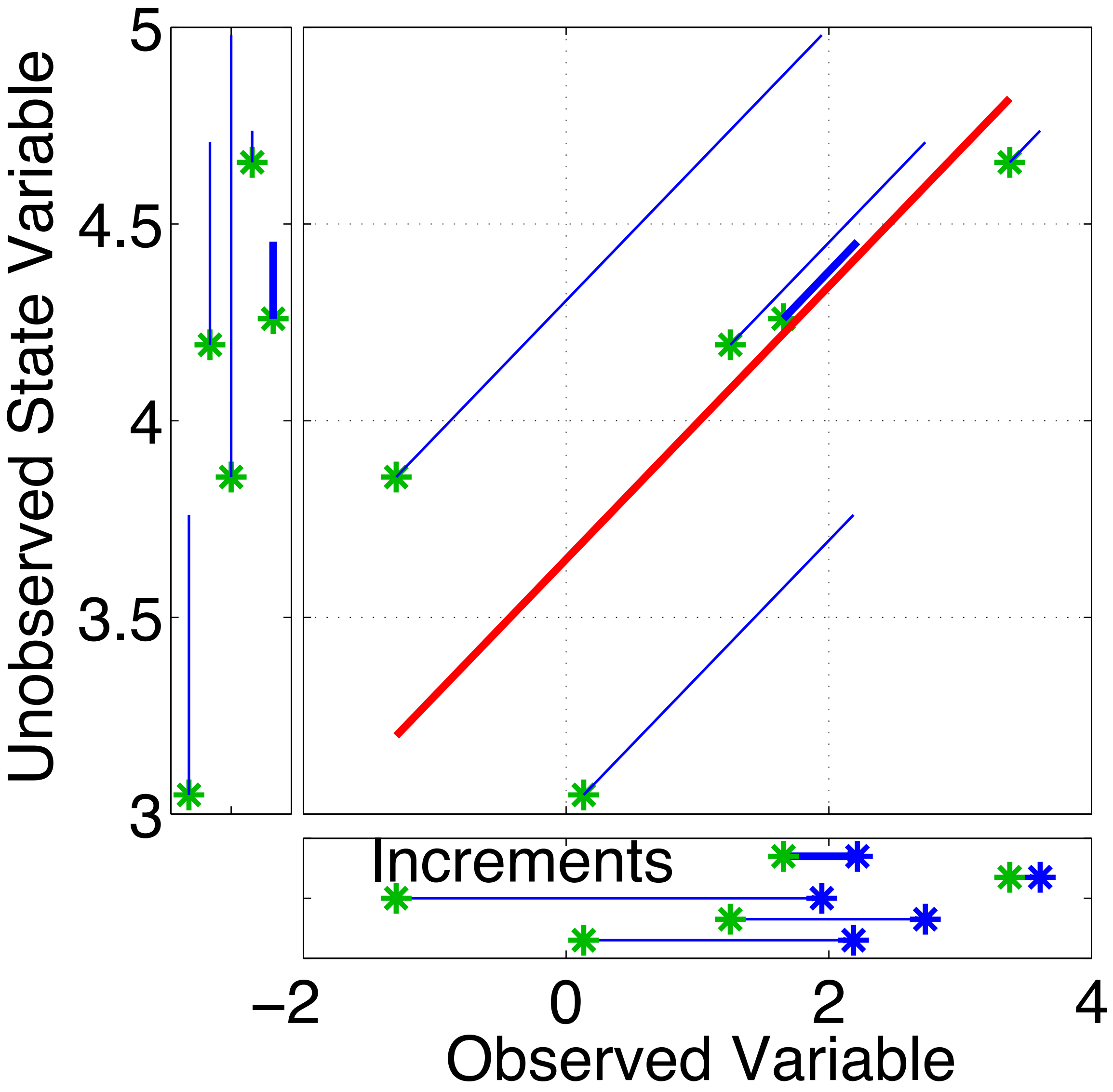


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

One observed, one unobserved variable.

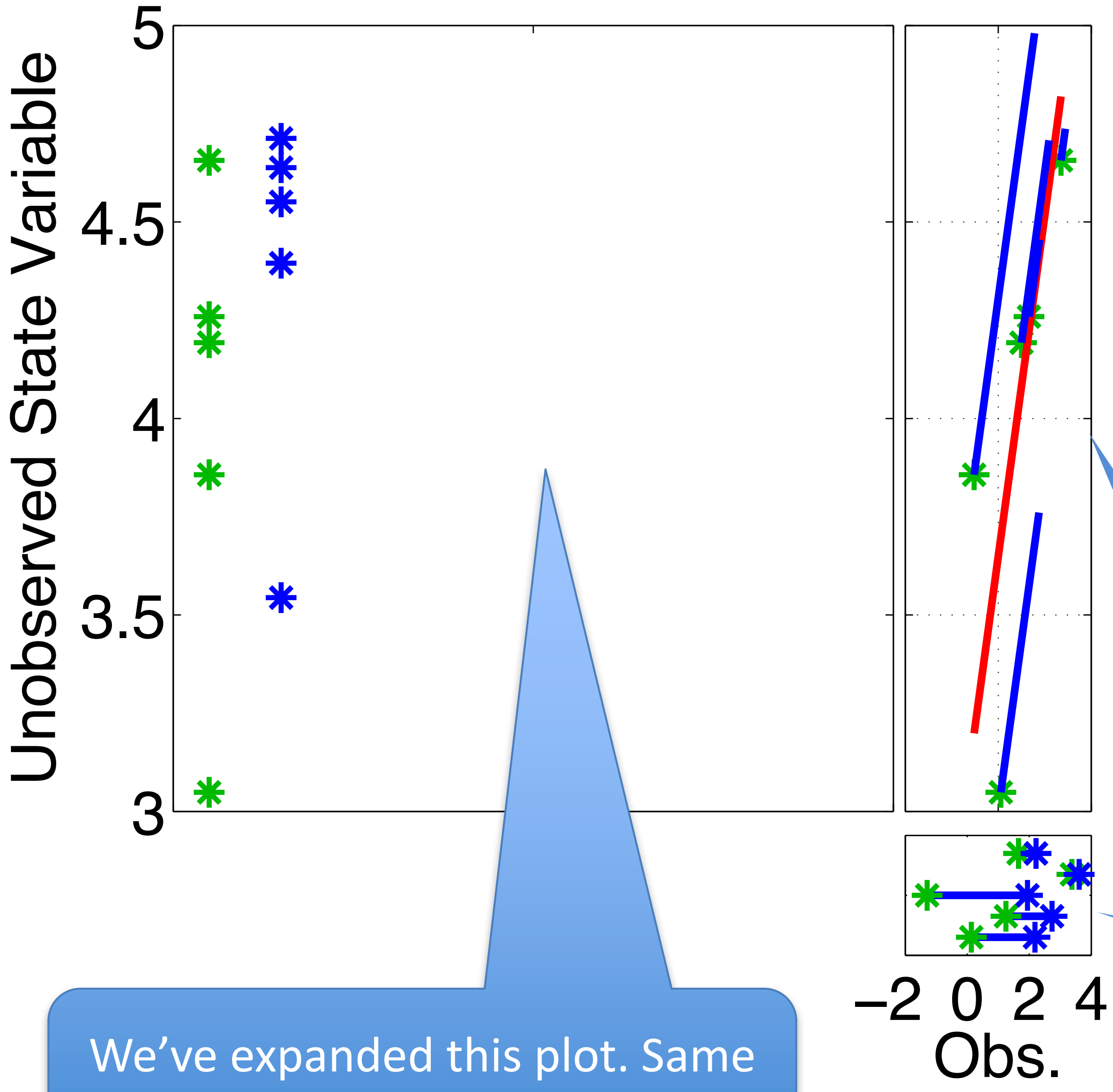


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

One observed, one unobserved variable.

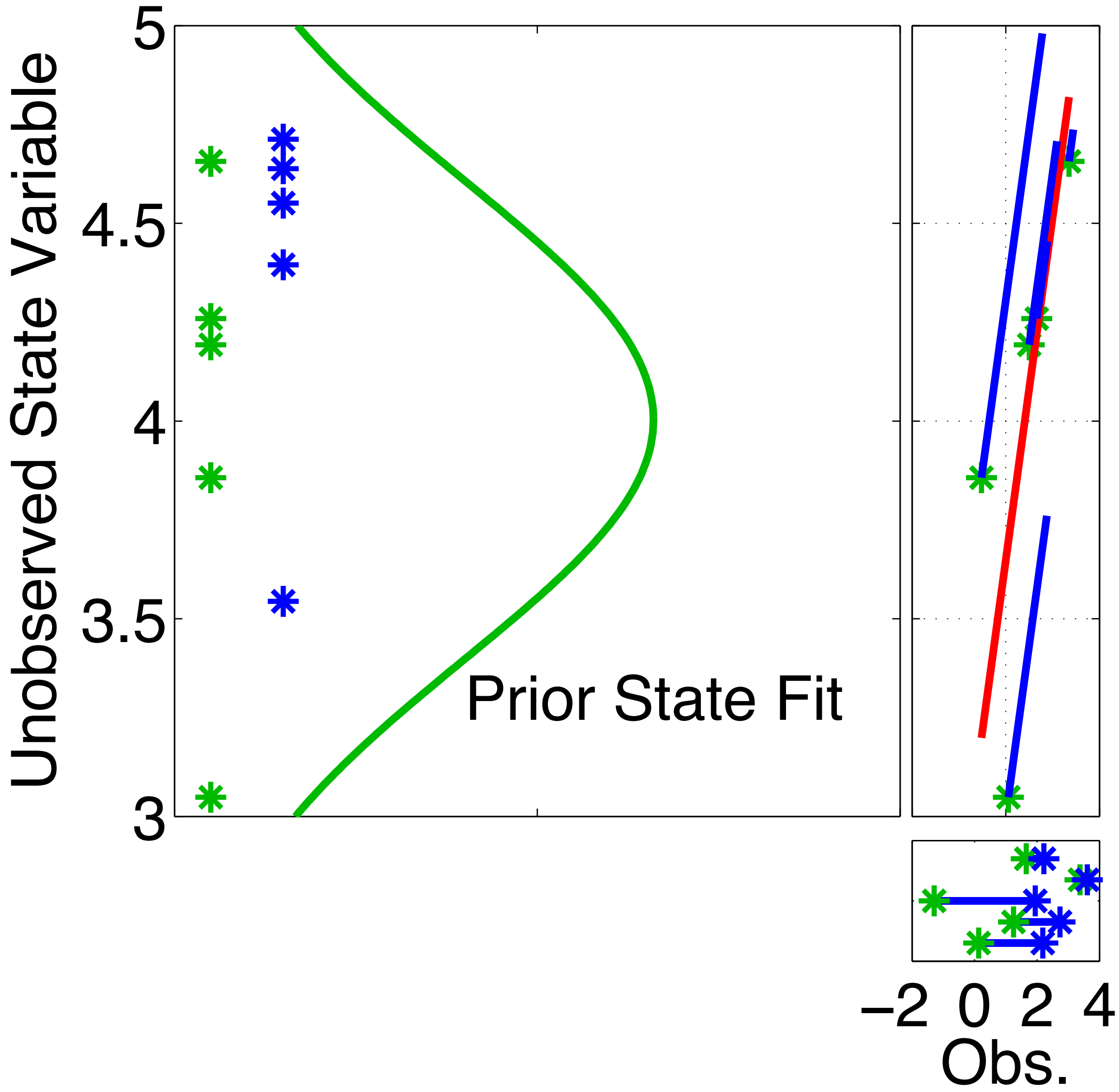


Now have an updated (posterior) ensemble for the unobserved variable.

We've expanded this plot. Same information as previous slides.

Compressed these two.

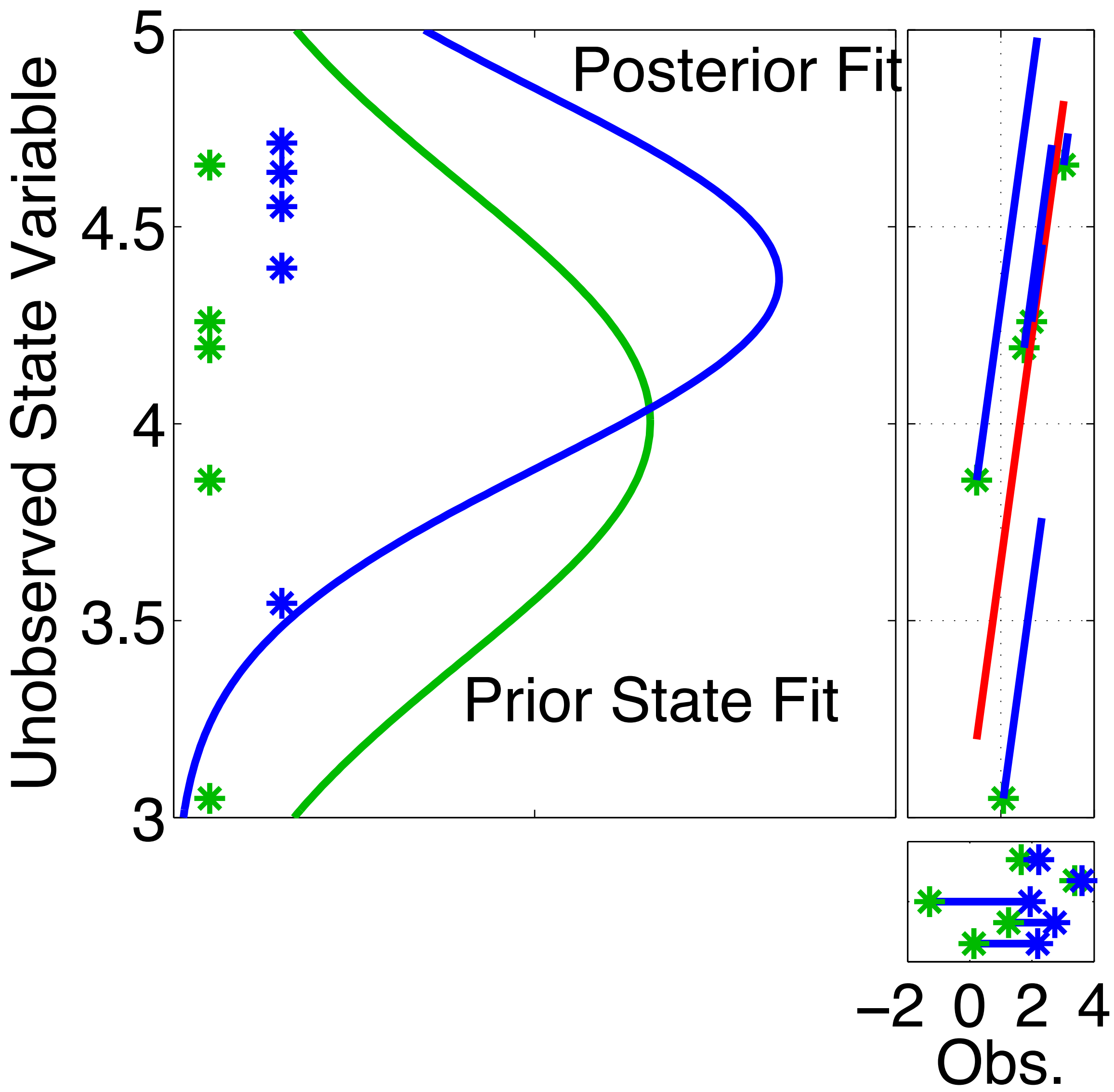
One observed, one unobserved variable.



Now have an updated (posterior) ensemble for the unobserved variable.

Fitting Gaussians shows that mean and variance have changed.

One observed, one unobserved variable.



Now have an updated (posterior) ensemble for the unobserved variable.

Fitting Gaussians shows that mean and variance have changed.

Other features of the prior distribution may also have changed.

A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
    - Localization
    - Inflation
5. Parameter estimation.
6. Some sample applications.

Ensemble Kalman Filter: A full implementation.

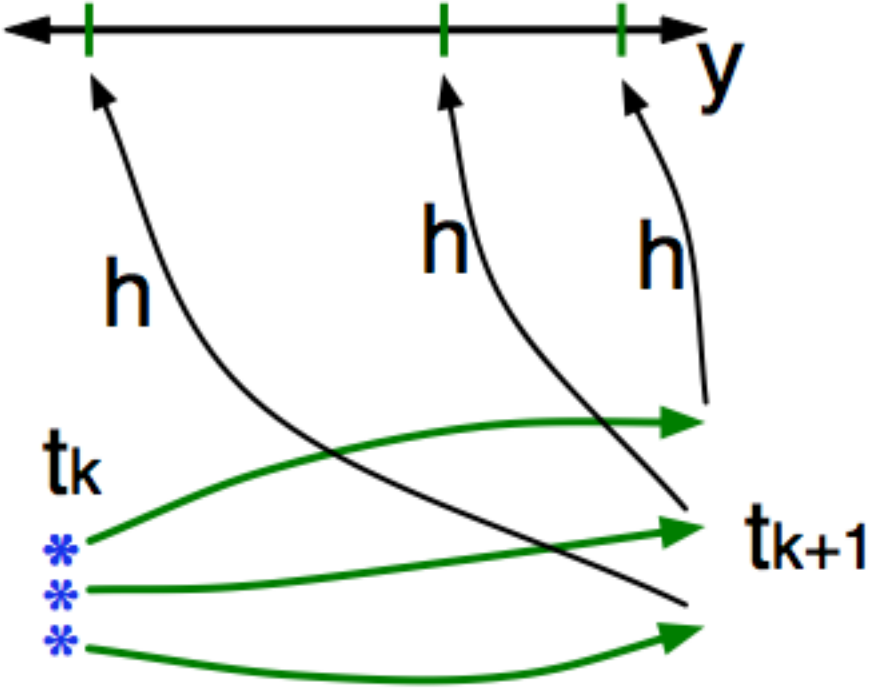
1. Use model to advance ensemble (3 members here) to time at which next observation becomes available.

Ensemble state estimate after using previous observation (analysis)

Ensemble state at time of next observation (prior)

Ensemble Kalman Filter: A full implementation.

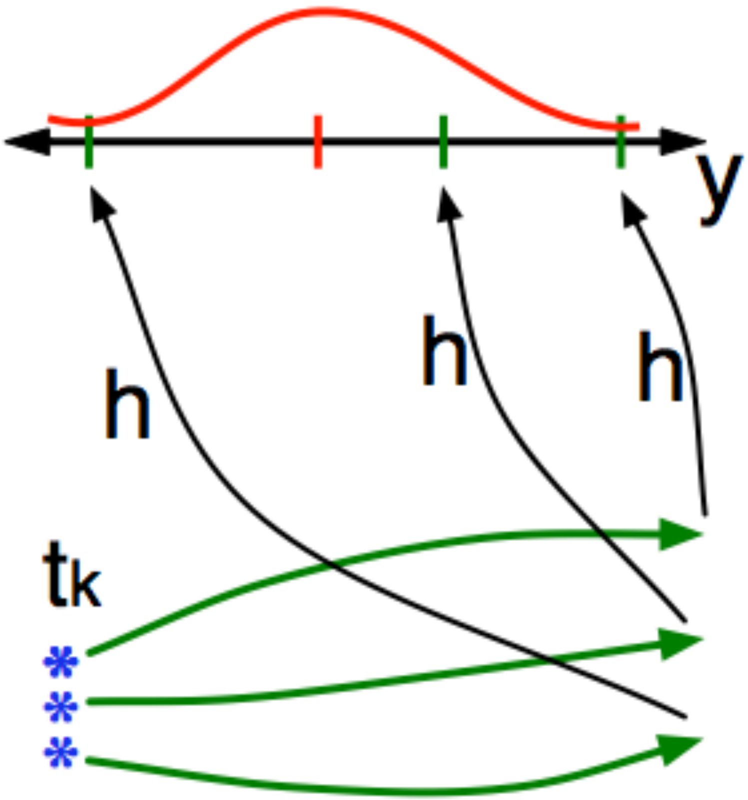
2. Get prior ensemble sample of observation, $y = h(x)$, by applying forward operator *h* to each ensemble member.



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

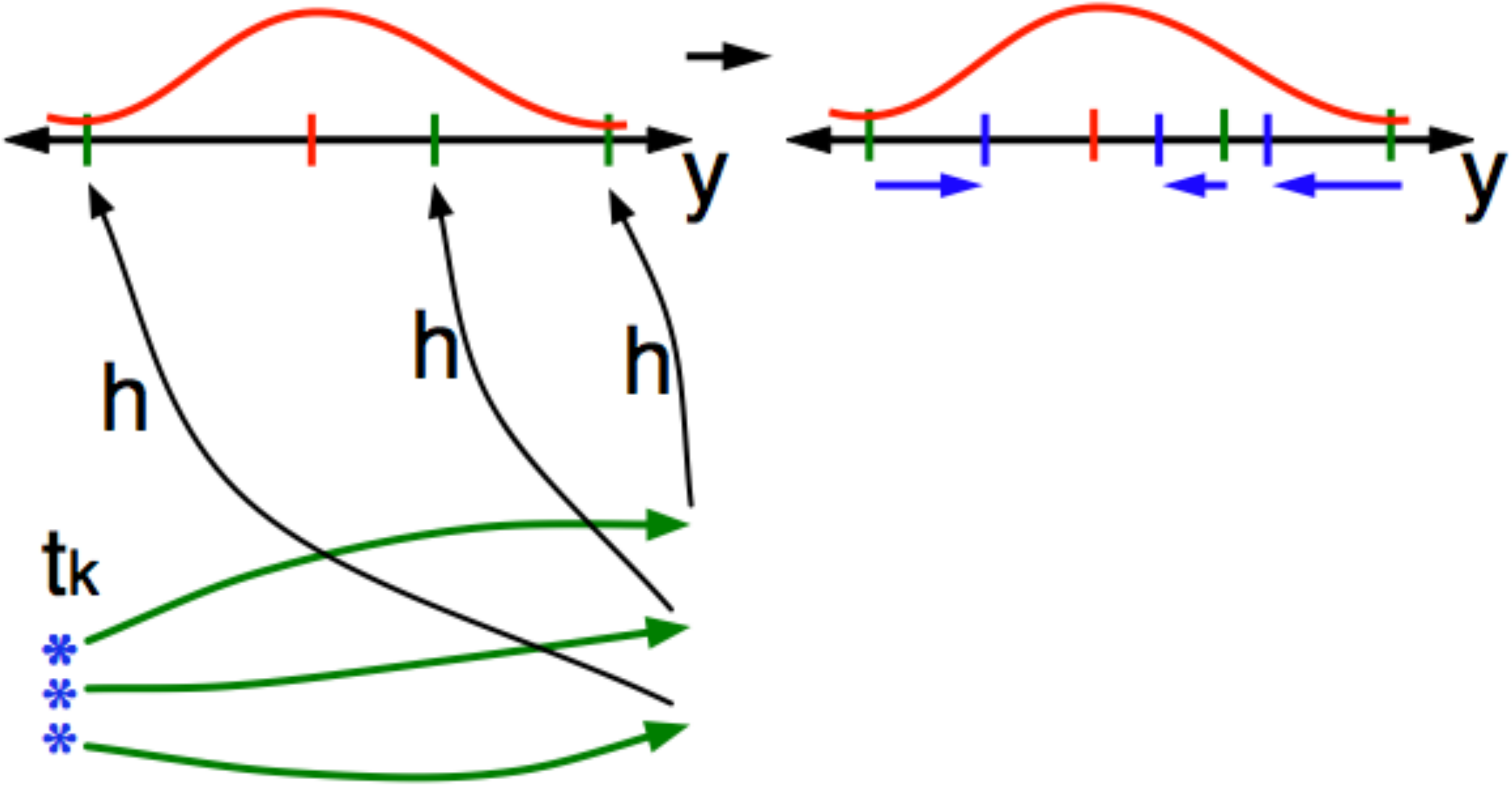
Ensemble Kalman Filter: A full implementation.

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



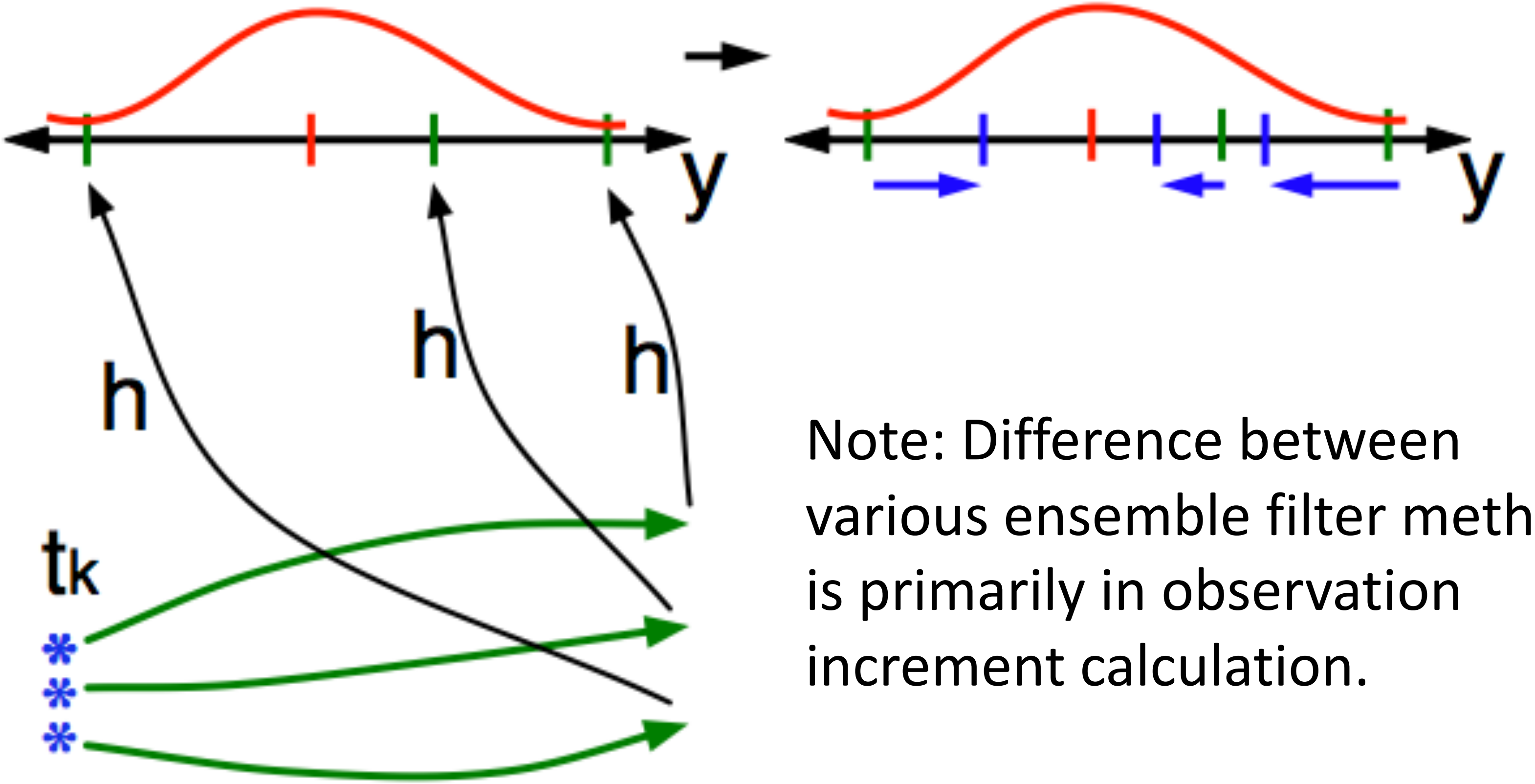
Ensemble Kalman Filter: A full implementation.

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



Ensemble Kalman Filter: A full implementation.

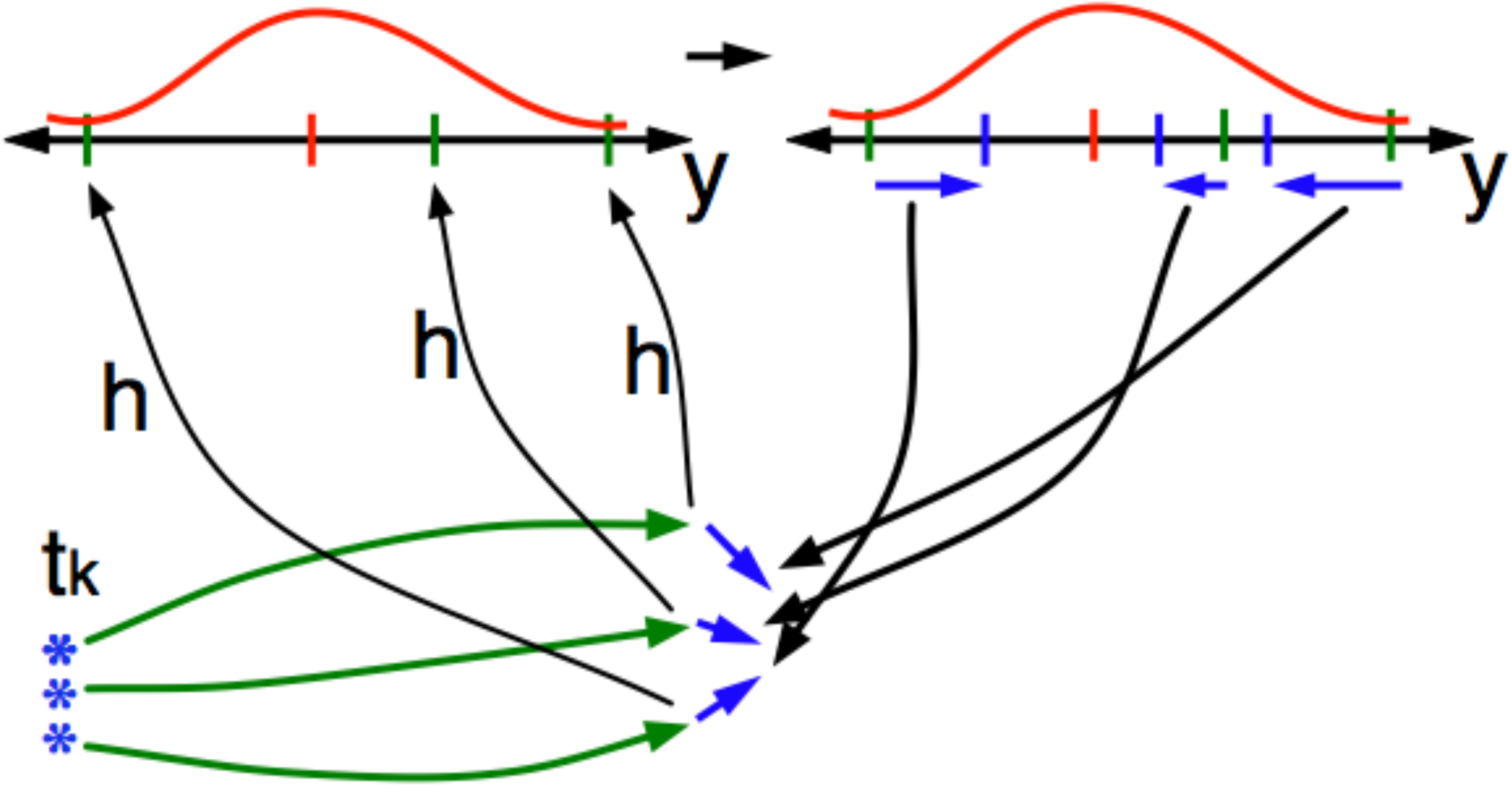
4. Find the increments for the prior observation ensemble (this is a scalar problem for uncorrelated observation errors).



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

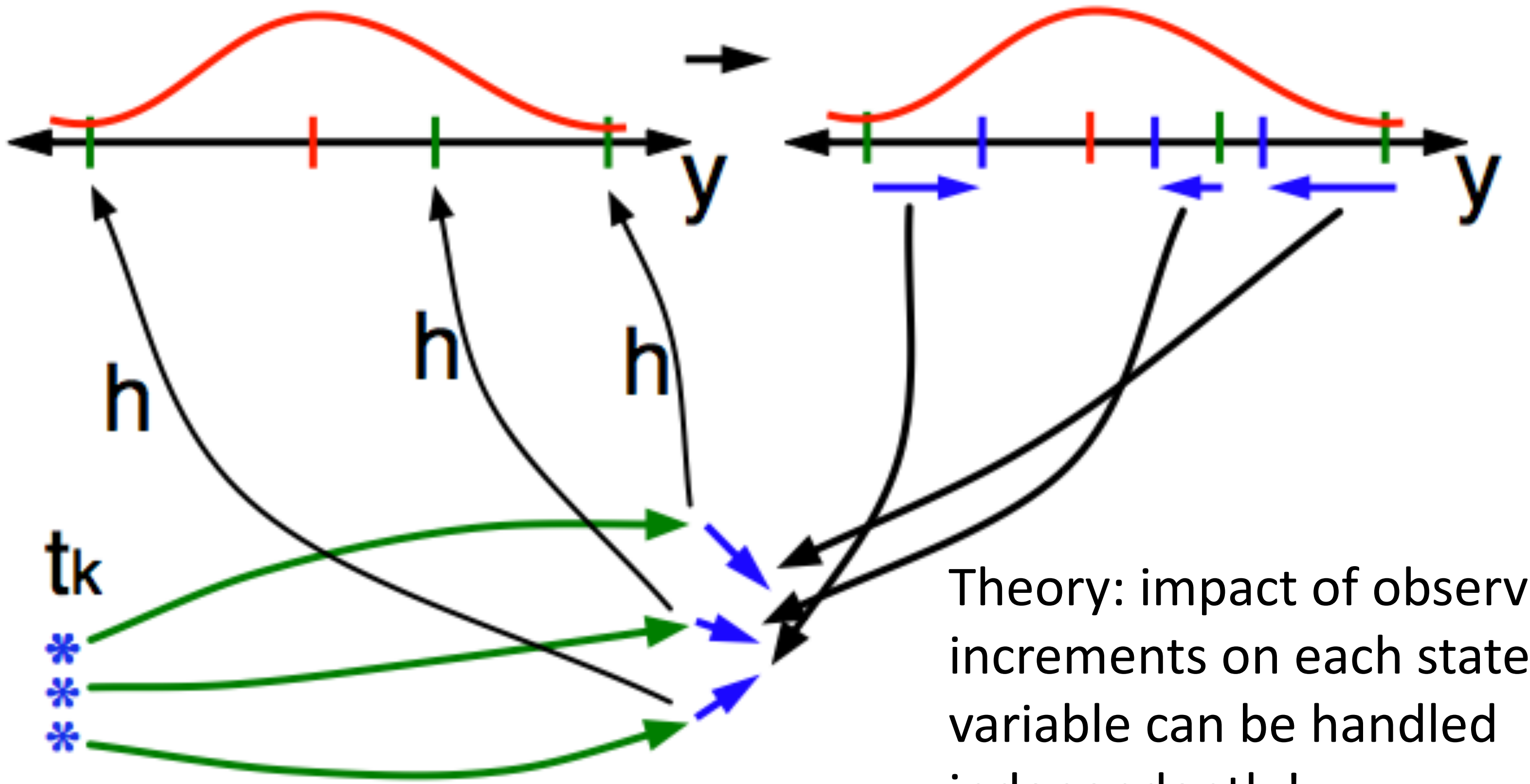
Ensemble Kalman Filter: A full implementation.

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



Ensemble Kalman Filter: A full implementation.

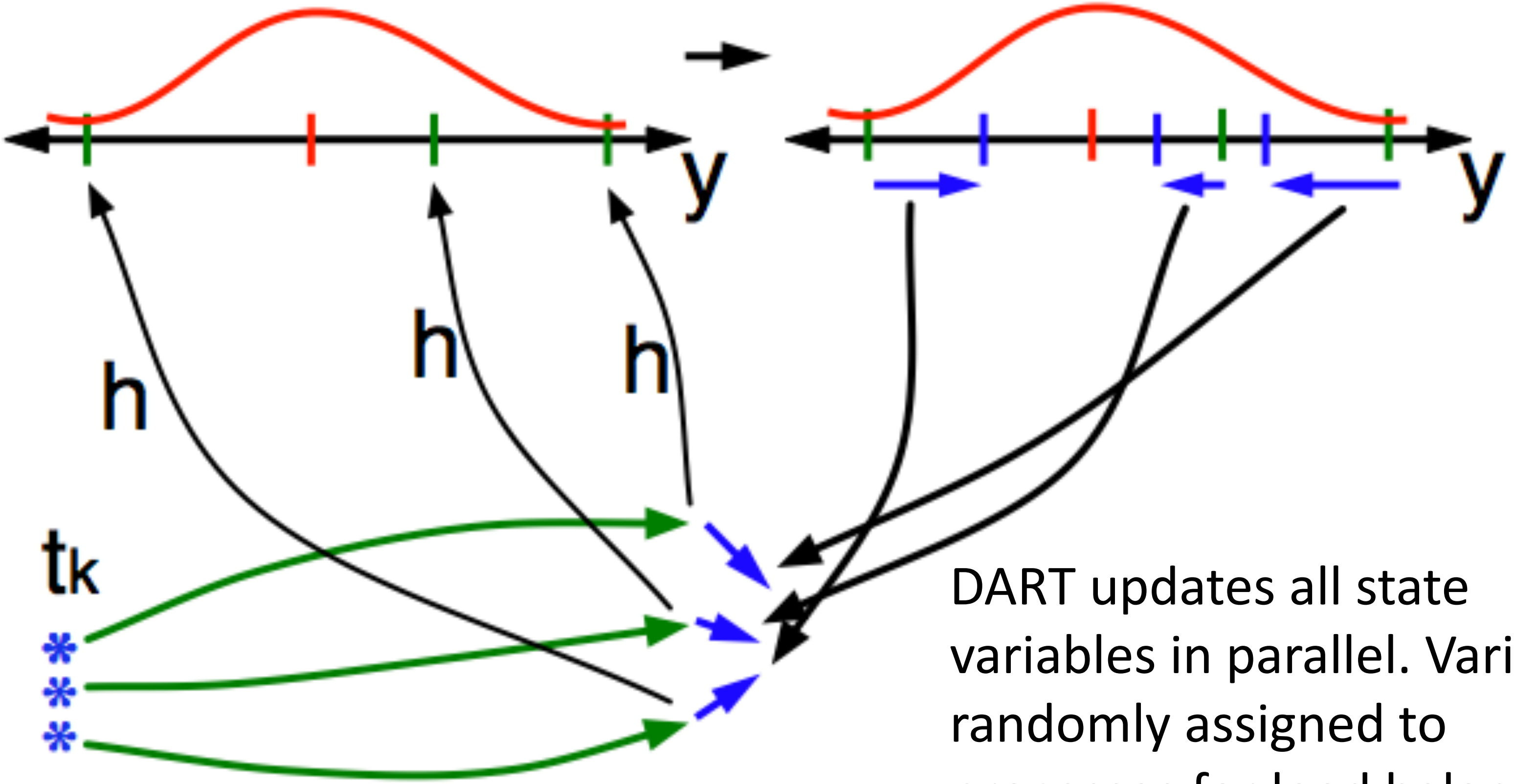
5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments.



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

Ensemble Kalman Filter: A full implementation.

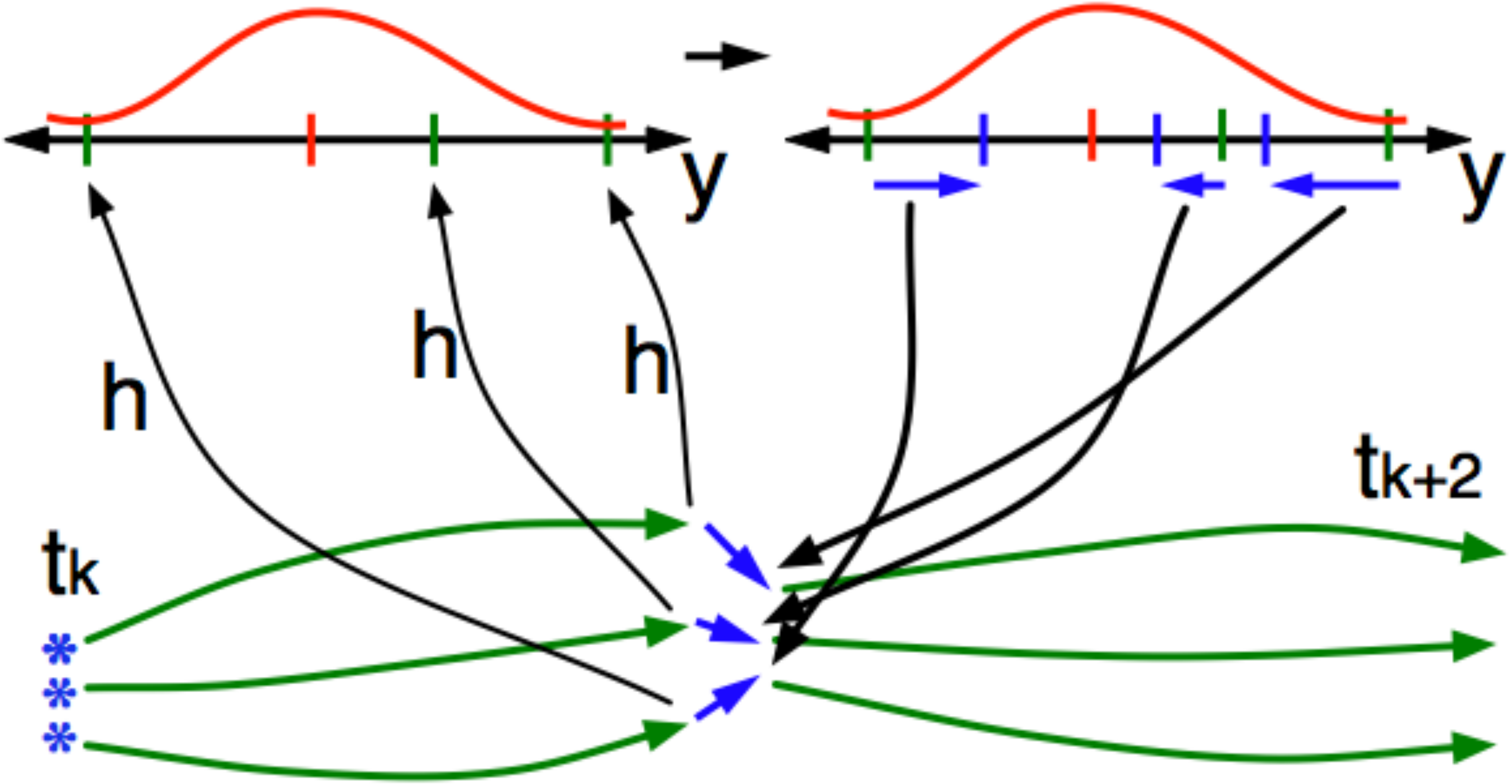
5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments.



DART updates all state variables in parallel. Variables randomly assigned to processes for load balancing.

Ensemble Kalman Filter: A full implementation.

6. When all ensemble members for each state variable are updated, integrate to time of next observation …



Ensemble Kalman Filter: A full implementation.

For linear, gaussian problem:

If, ensemble size $N > N_{crit}$

Mean and covariance are identical to Kalman Filter,

Else

Diverges.

Ncrit: Number of positive singular values in SVD of covariance matrix.

Ensemble Kalman Filter: A full implementation.

- (Ensemble) KF optimal for linear model, gaussian likelihood, perfect model.
- In KF, only mean and covariance have meaning.

- Ensemble allows computation of many other statistics.
- What do they mean? Not entirely clear.

- What do they mean when there are all sorts of error?
  Even less clear.

- Must Calibrate and Validate results.

A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
   - Localization
   - Inflation
5. Parameter estimation.
6. Some sample applications.

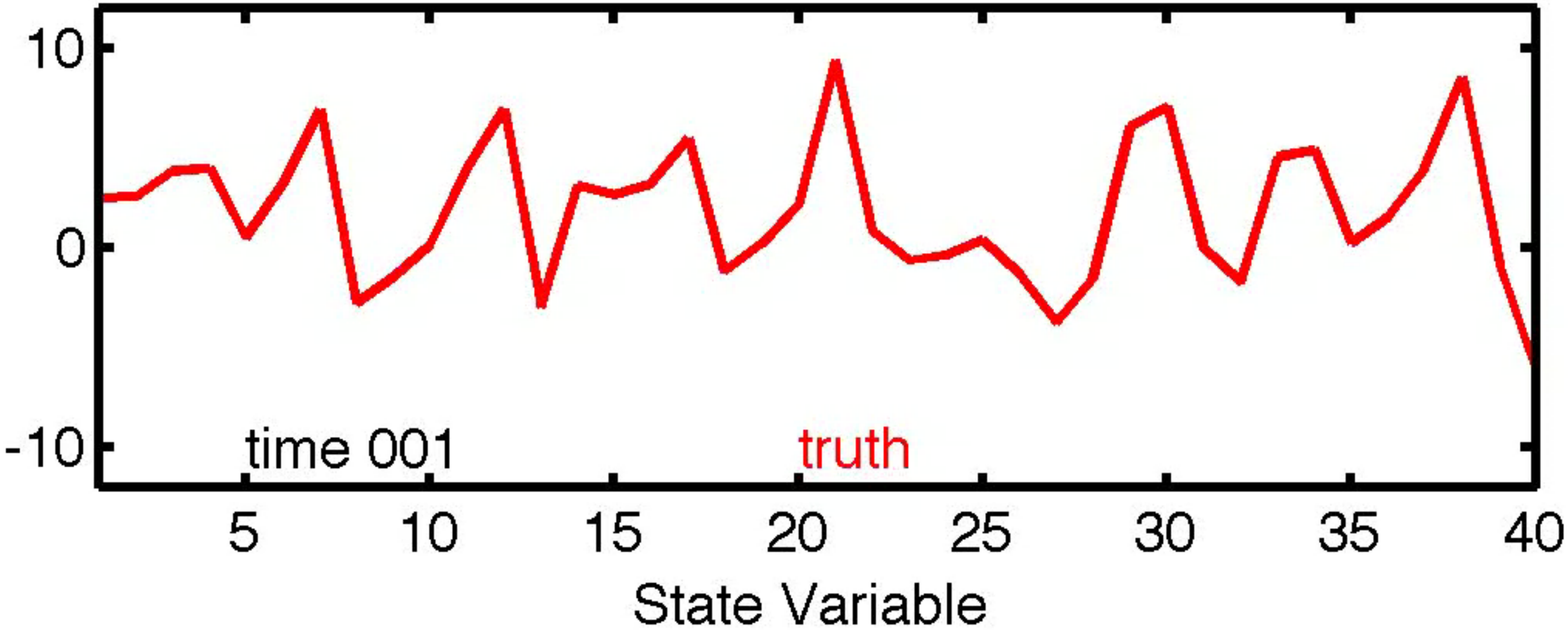
Making it work:

Lorenz-96 low-order model example.

40 state variables: X_1, X_2,..., X_{40}.

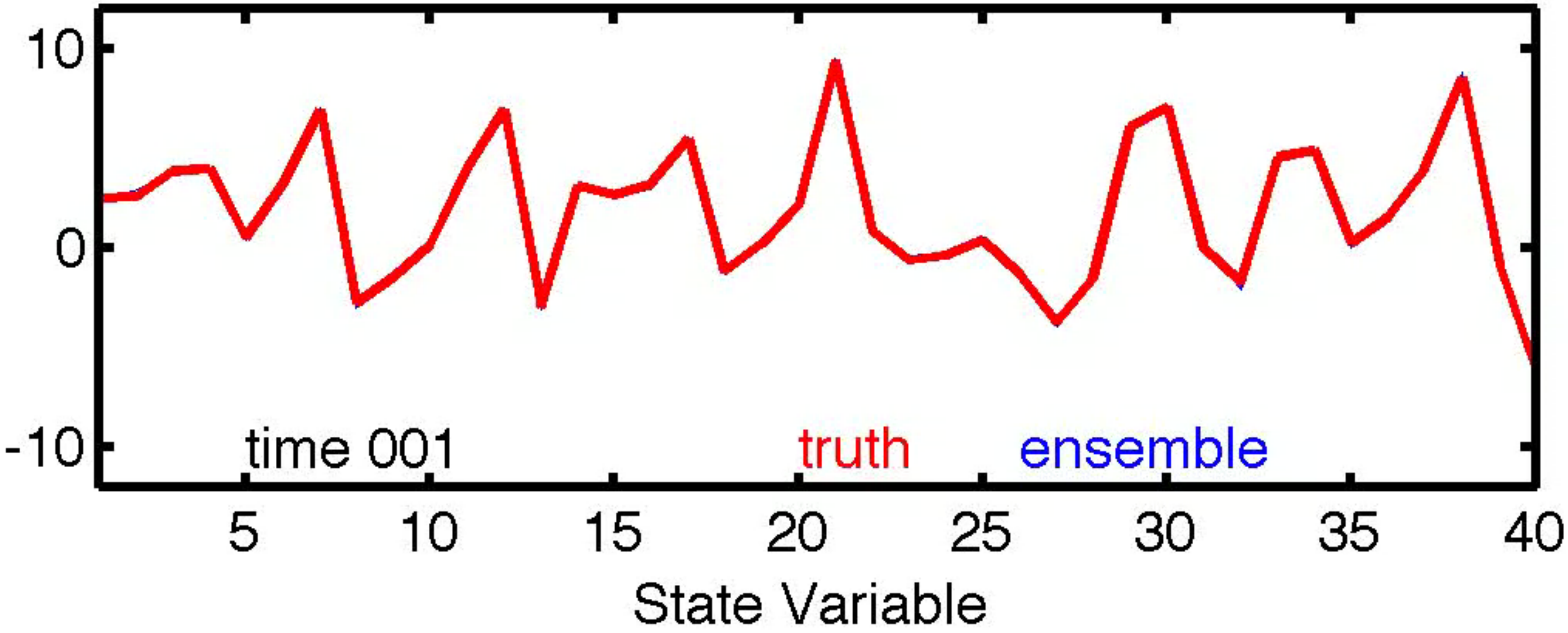
$dX_i / dt = (X_{i+1} - X_{i-2})X_{i-1} - X_i + F$.

Acts ‘something’ like weather around a latitude band.



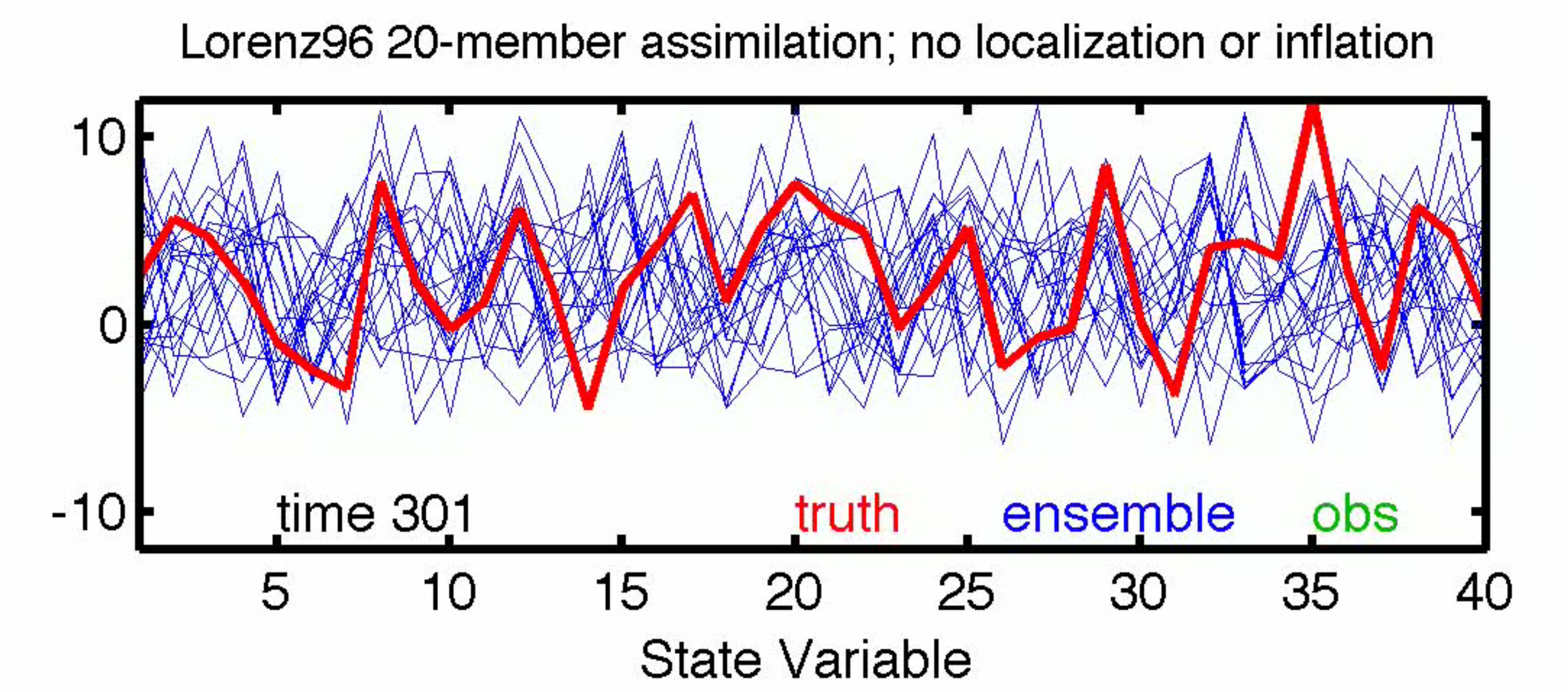
Making it work:

Lorenz-96 is sensitive to small perturbations.
Introduce 20 ‘ensemble’ state estimates.
Each is perturbed for each of the 40-variables at time 0.
Refer to unperturbed control integration as ‘truth’.



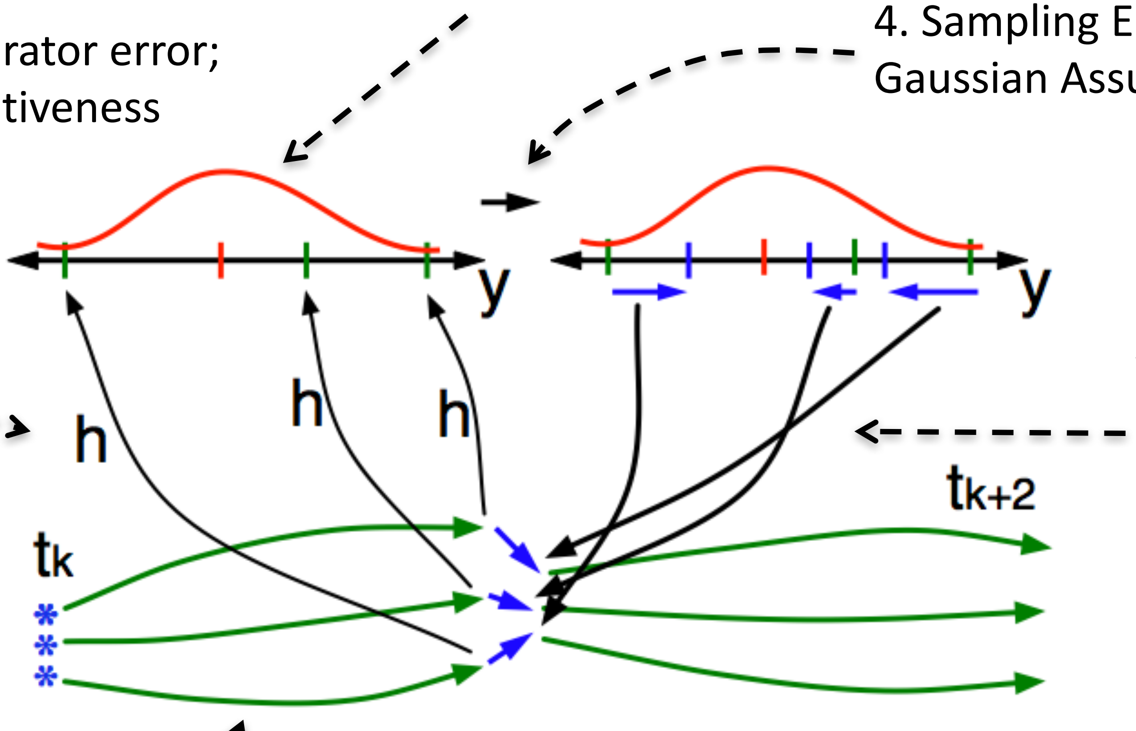
Making it work:

Assimilate ‘observations’ from 40 random locations.
Interpolate truth to station location.
Simulate observational error:
Add random draw from N(0, 16) to each.
Start from ‘climatological’ 20-member ensemble.



Making it work:

Some error sources in ensemble filters.



3. Observation error

2. Obs. operator error;
Representativeness

4. Sampling Error;
Gaussian Assumption

5. Sampling Error;
Assuming Linear
Statistical Relation

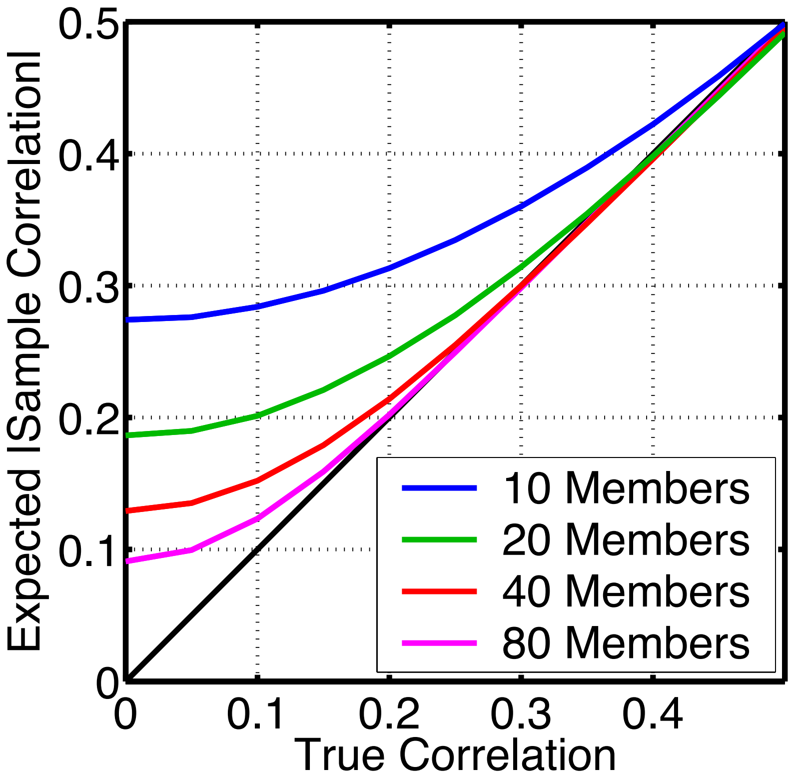
1. Model error

A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
    - Localization
    - Inflation
5. Parameter estimation.
6. Some sample applications.

Making it work: Localization

Sampling Error: Observations Impact Unrelated State Variables



Plot shows expected absolute value of sample correlation vs. true correlation.

Unrelated obs. reduce spread, increase error.

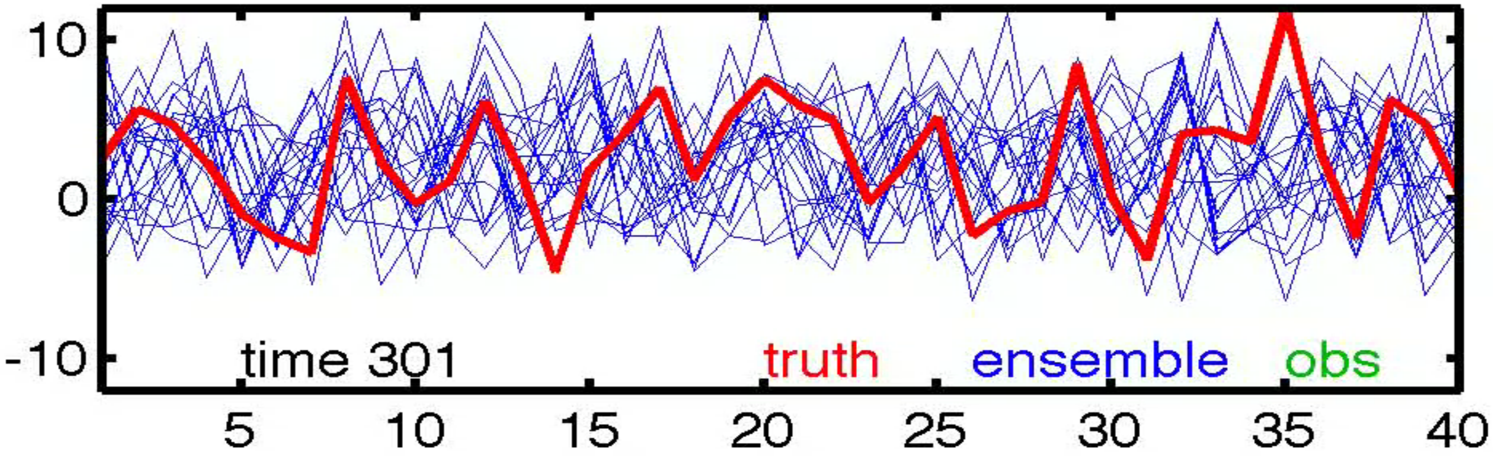
Attack with localization.

Reduce impact of observation on weakly correlated state variables.

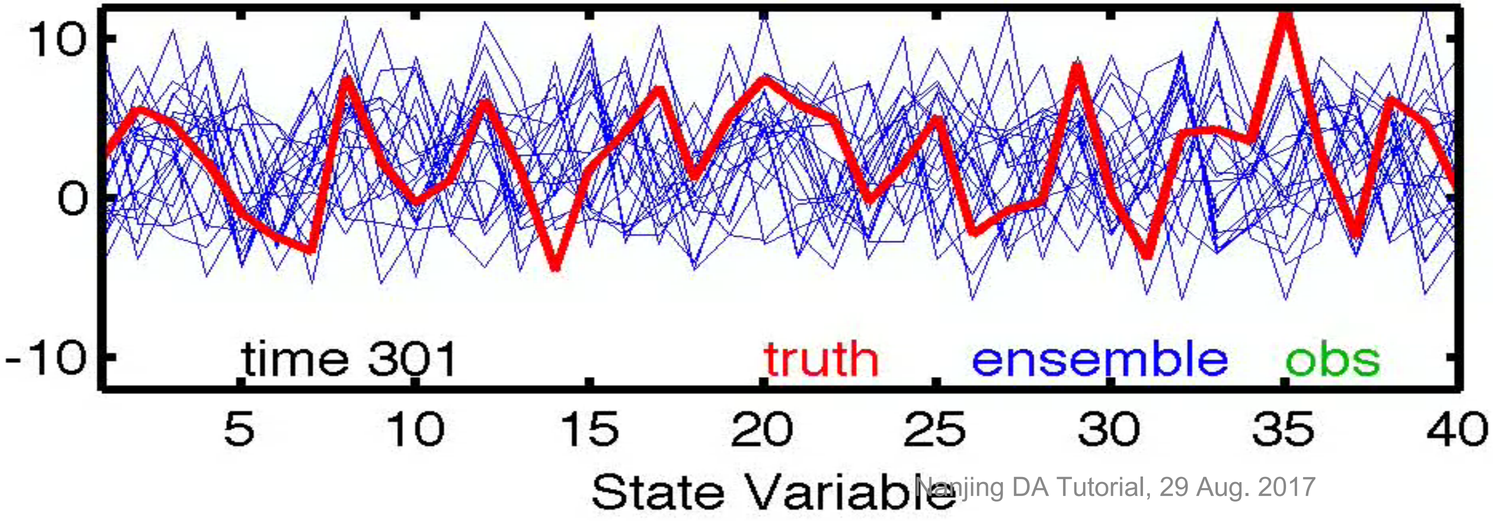
Let weight go to zero for many ‘unrelated’ variables to save on computing.

Making it work: Localization

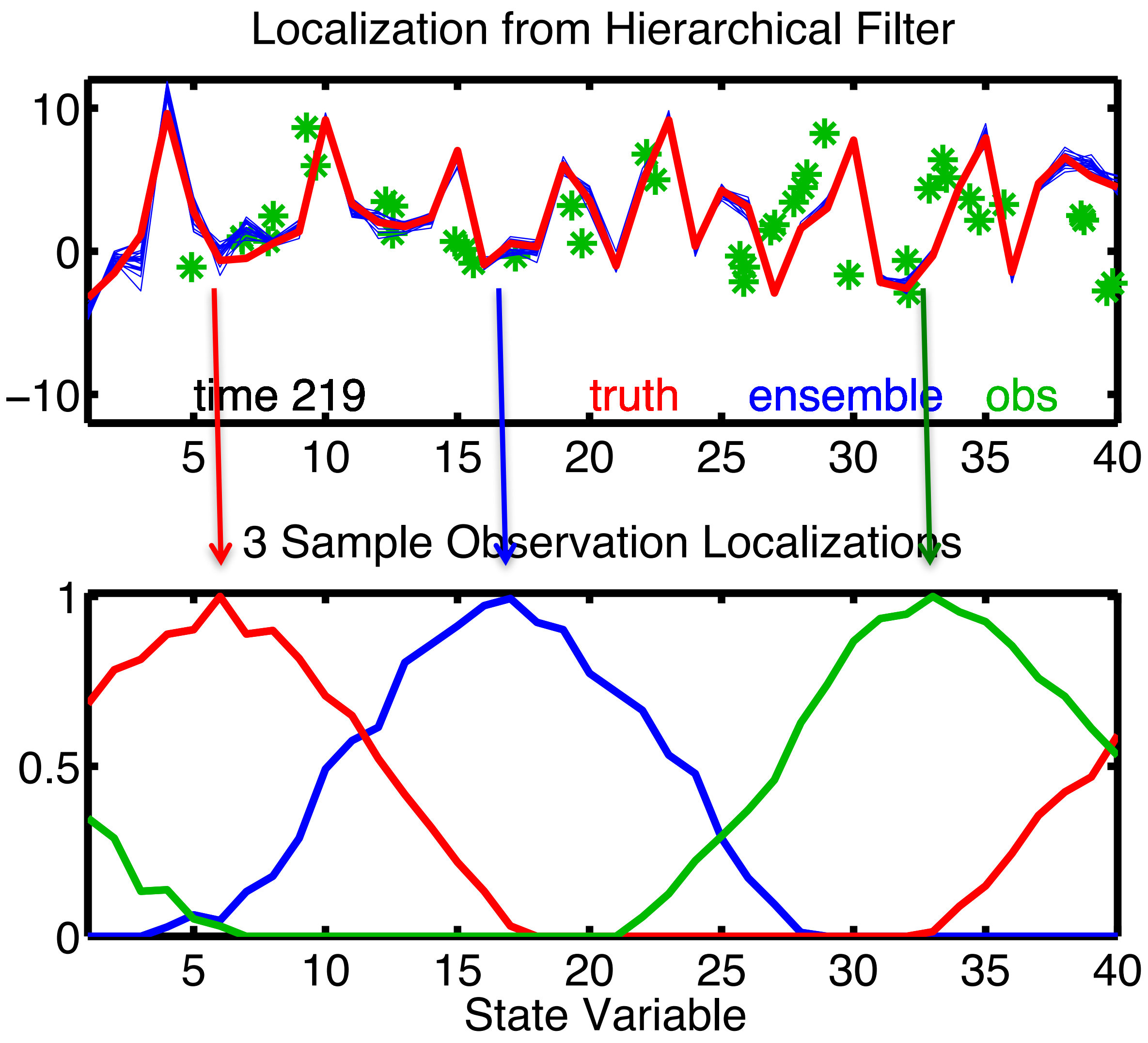
Localization from Hierarchical Filter



No Localization



Making it work: Localization

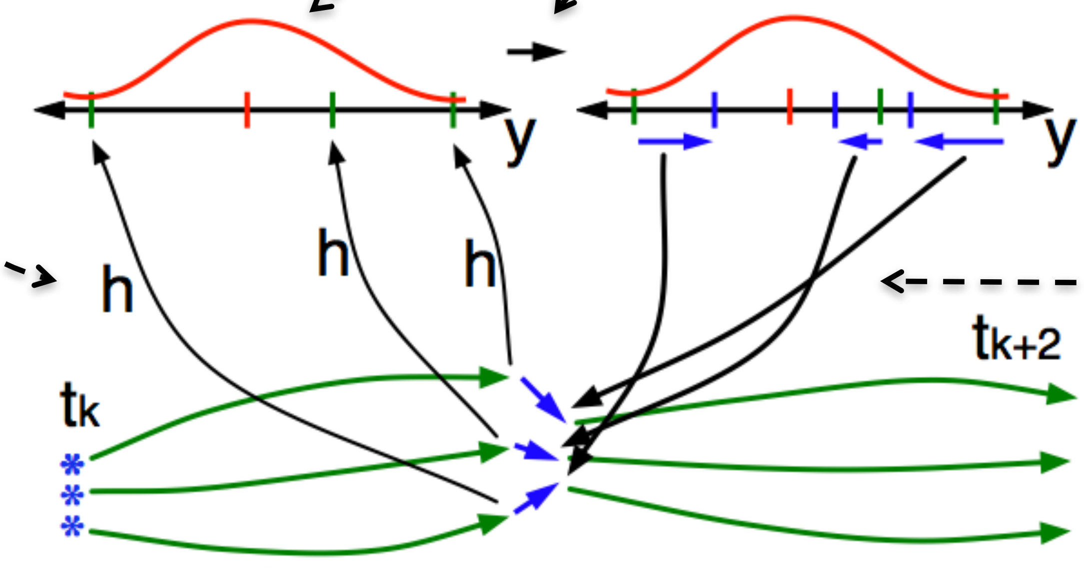


A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
    - Localization
    - Inflation
5. Parameter estimation.
6. Some sample applications.

Making it work: Inflation

Some error sources in ensemble filters.



3. Observation error

2. Obs. operator error;
Representativeness

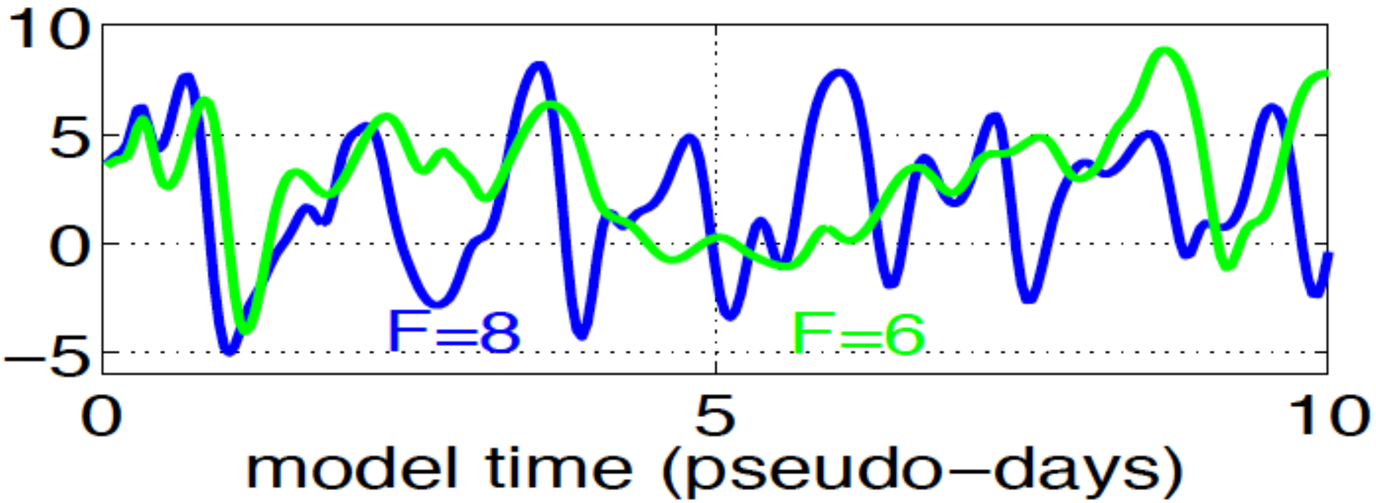
4. Sampling Error;
Gaussian Assumption

5. Sampling Error;
Assuming Linear
Statistical Relation

1. Model error

Making it work: Inflation

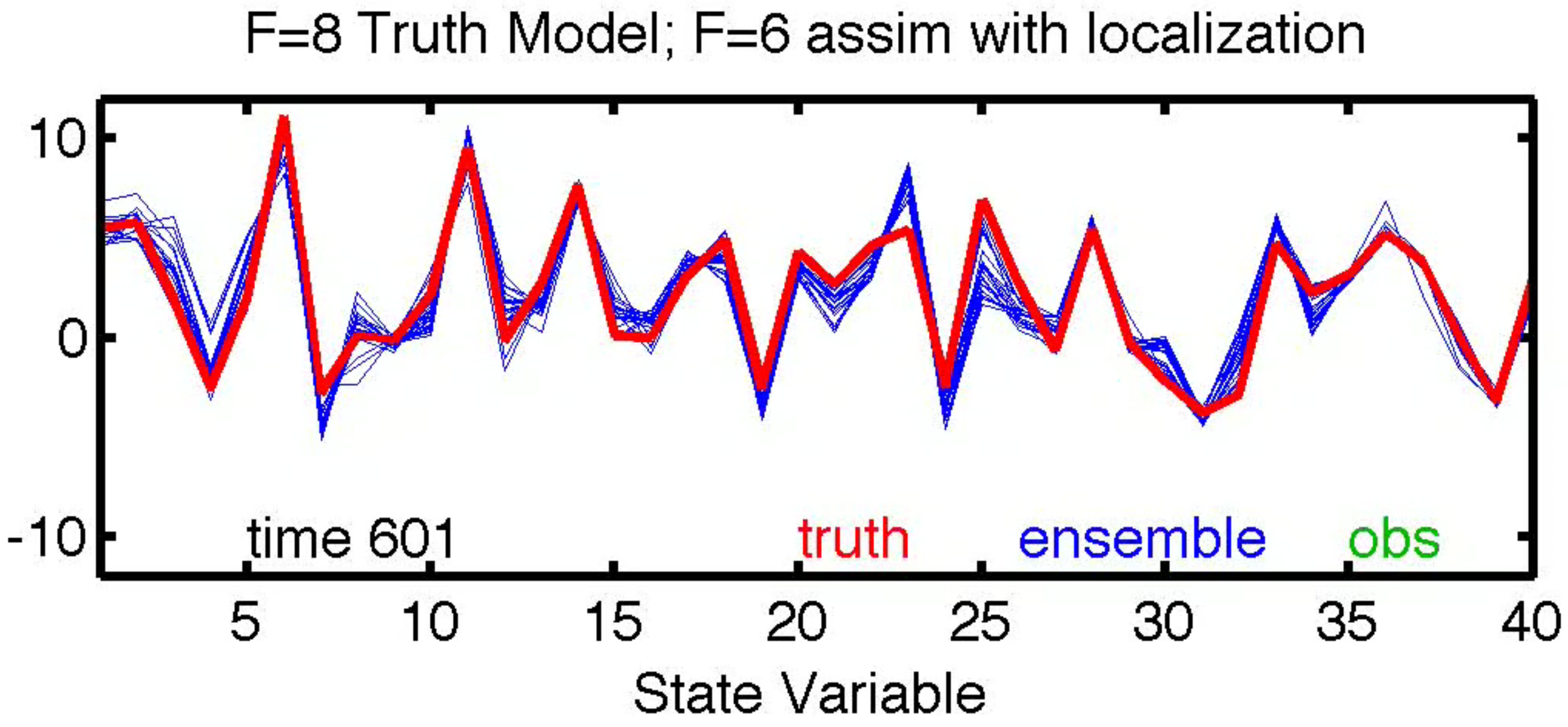
Assimilating with simulated model error.
$dXi / dt = (Xi+1 - Xi-2)Xi-1 - Xi + F.$
For truth, use F = 8.
In assimilating model, use F = 6.



Time evolution for first state variable shown.
Assimilating model quickly diverges from ‘true’ model.

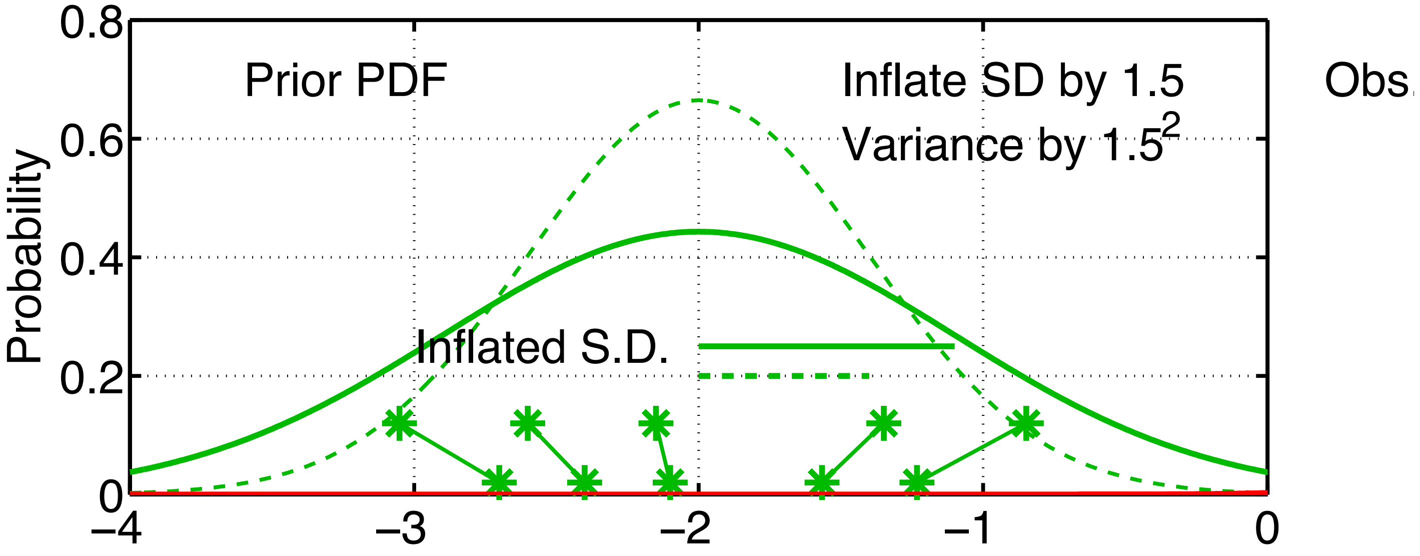
Making it work: Inflation

Assimilating with simulated model error.
dXi / dt = (Xi+1 - Xi-2)Xi-1 - Xi + F.
For truth, use F = 8.
In assimilating model, use F = 6.



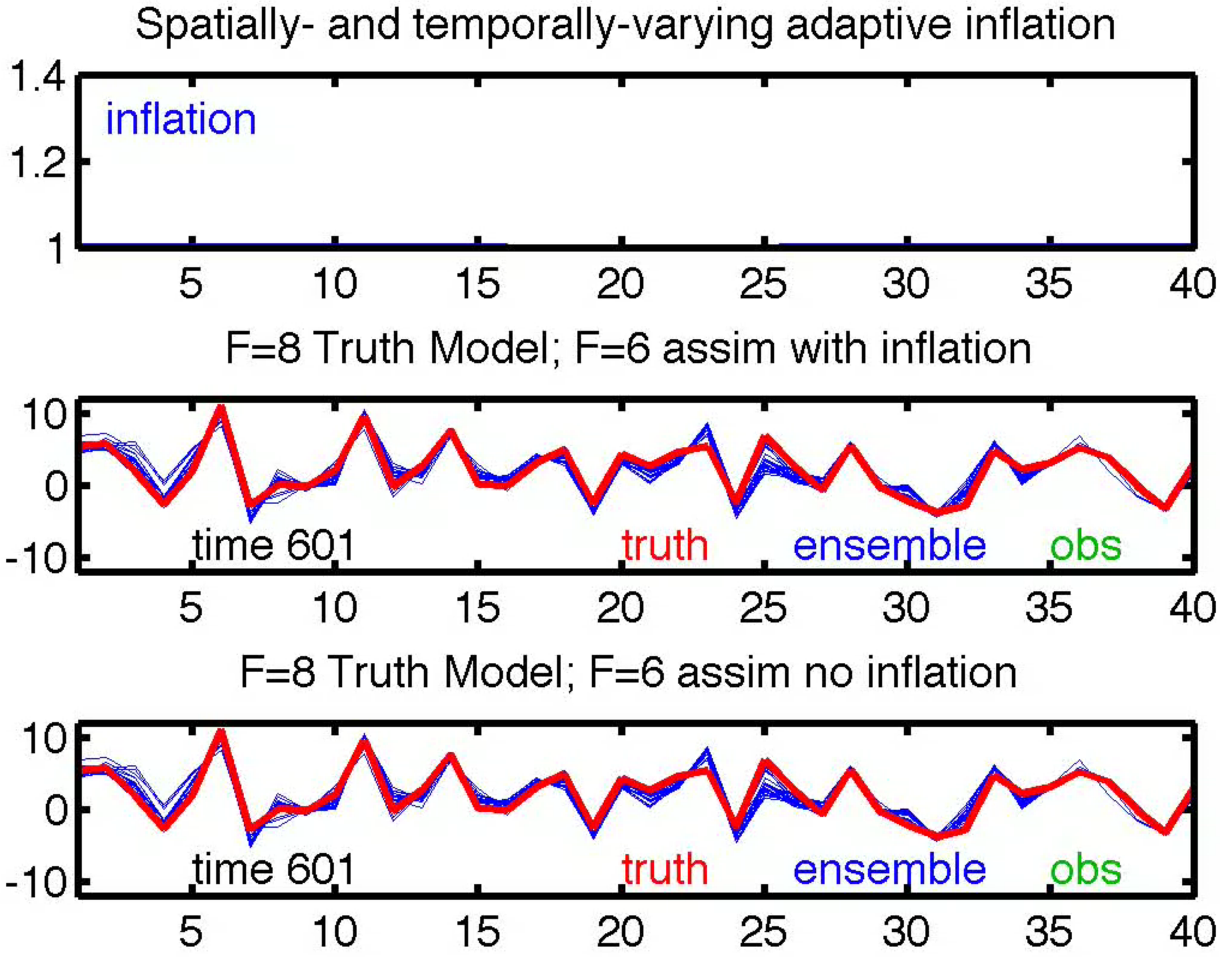
Making it work: Inflation

Reduce confidence in prior to deal with model error.
Use inflation.
Simply increase prior ensemble variance for each state variable.
Adaptive algorithms use observations to guide this.



Making it work: Inflation

Inflation is a function of state variable and time.
Automatically selected by adaptive inflation algorithm.



A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
   - Localization
   - Inflation
5. Parameter estimation.
6. Some sample applications.

Parameter Estimation

A time-varying state-vector $\mathbf{x}_t$,

Times t_k with observations: $k = 1, 2, \dots;$ $t_{k+1} > t_k \geq t_0$,

Observations at t_k related to $\mathbf{x}_{t_k}$; $\mathbf{y}_k = h_k(\mathbf{x}_{t_k}) + \nu_k$, (1)

Observation error is zero mean, normal, $\nu_k = N(0, \mathbf{R}_k)$, (2)

A forecast model m for the state-vector; $\mathbf{x}_{t_{k+1}} = m_{k:k+1}(\mathbf{x}_{t_k})$ (3)

Parameter Estimation

A time-varying state-vector $\mathbf{x}_t$,

Times t_k with observations: $k = 1, 2, \ldots;$ $t_{k+1} > t_k \geq t_0$,

Observations at t_k related to $\mathbf{x}_{t_k}$; $\mathbf{y}_k = h_k(\mathbf{x}_{t_k}) + \nu_k$, (1)

Observation error is zero mean, normal, $\nu_k = N(0, \mathbf{R}_k)$, (2)

A forecast model m for the state-vector; $\mathbf{x}_{t_{k+1}} = m_{k:k+1}(\mathbf{x}_{t_k}; \boldsymbol{\alpha})$ (3a)

With model parameter vector $\boldsymbol{\alpha}$.

Parameter Estimation

A time-varying state-vector $\mathbf{x}_t$,

Times t_k with observations: $k = 1, 2, \ldots;$ $t_{k+1} > t_k \geq t_0,$

Observations at t_k related to $\mathbf{x}_{t_k}$; $\mathbf{y}_k = h_k\left(\mathbf{x}_{t_k}\right) + \nu_k,$ (1)

Observation error is zero mean, normal, $\nu_k = N(0, \mathbf{R}_k),$ (2)

A forecast model m for the state-vector; $\mathbf{x}_{t_{k+1}} = m_{k:k+1}\left(\mathbf{x}_{t_k}; \boldsymbol{\alpha}\right)$ (3a)

With model parameter vector $\boldsymbol{\alpha}$.

Parameters could be tuning for parameterizations, external forcing,…

Example: Sources for chemical tracers in atmosphere.

Parameter Estimation

A forecast model m for the state-vector; $\mathbf{x}_{t_{k+1}} = m_{k:k+1}\left(\mathbf{x}_{t_k}; \boldsymbol{\alpha}\right)$ (3a)

One solution: State augmentation.

Define augmented state vector $\mathbf{x}^+ = (\mathbf{x}, \boldsymbol{\alpha})$

Prediction model becomes (just a change in notation):

$$\mathbf{x}^+_{t_{k+1}} = m_{k:k+1}\left(\mathbf{x}^+_{t_k}\right)$$

Parameter Estimation

State augmentation challenges:

In general, no time prediction model for parameters.

- If we had a prediction model, they would just have been state.
- Kalman filter prior covariance comes from prediction model.

Parameter Estimation

State augmentation challenges:

In general, no time prediction model for parameters.

- If we had a prediction model, they would just have been state.
- Kalman filter prior covariance comes from prediction model.

Prior ensembles for parameters must be specified.

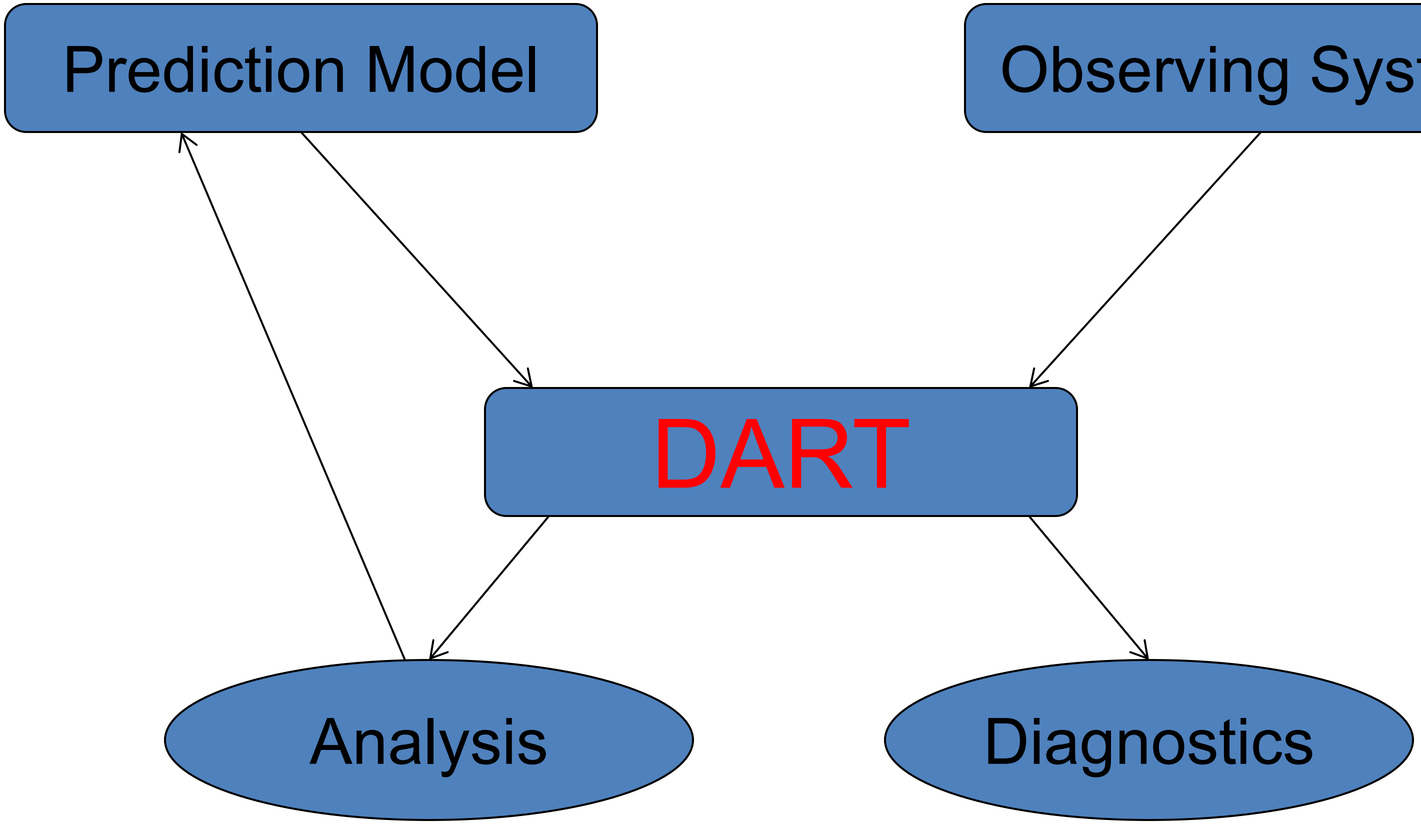
- Prior sample covariance controls impact of observations on parameters.
- If prior covariance is not well-known, estimating parameters can be challenging.

A Fast, Simple, Sequential Ensemble Kalman Filter

1. A one-dimensional ensemble Kalman filter.
2. One observed, one unobserved variable.
3. Ensemble Kalman Filter: A full implementation.
4. Making it work:
   - Localization
   - Inflation
5. Parameter estimation.
6. Some sample applications.

The Data Assimilation Research Testbed (DART)

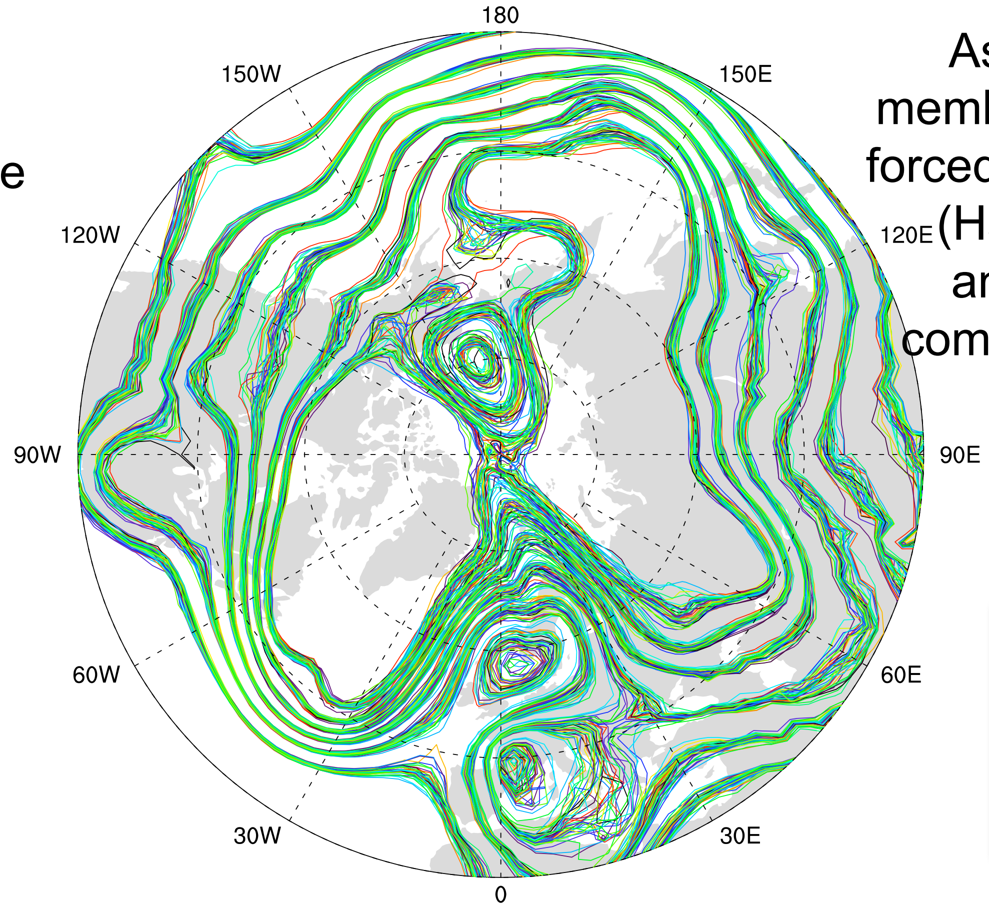
DART provides data assimilation ‘glue’ to build ensemble forecast systems for the atmosphere, ocean, land, …



DART Science and Collaborators (1)

Science: A global atmospheric ensemble reanalysis.
Collaborators: Model Developers at NCAR

O(1 million) atmospheric obs are assimilated every day.



500 hPa GPH
Feb 17 2003

Assimilation uses 80 members of 2° FV CAM forced by a single ocean (Hadley+ NCEP-OI2) and produces a very competitive reanalysis.

1998-2010
4x daily
is available.

DART Science and Collaborators (2)

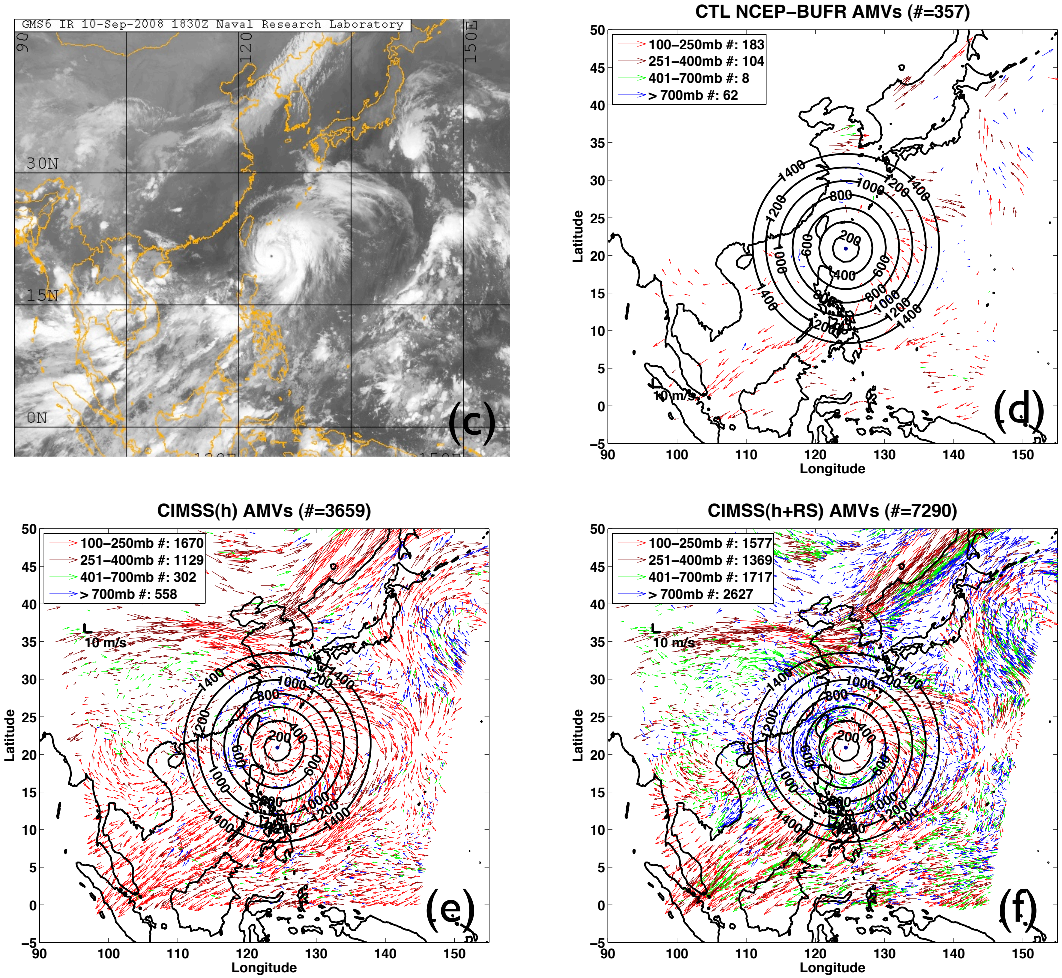
Science: *Do new satellite observations of cloud motion improve hurricane forecasts?*

Atmospheric motion vectors from CIMMS at University of Wisconsin.

Collaborator: Ting-Chi Wu,
Graduate Student,
University of Miami.

DART Science and Collaborators (2)

Tropical Cyclones and Atmospheric Motion Vectors



Wu et al., 2014, MWR, **142**, 49–71.

DART Science and Collaborators (3)

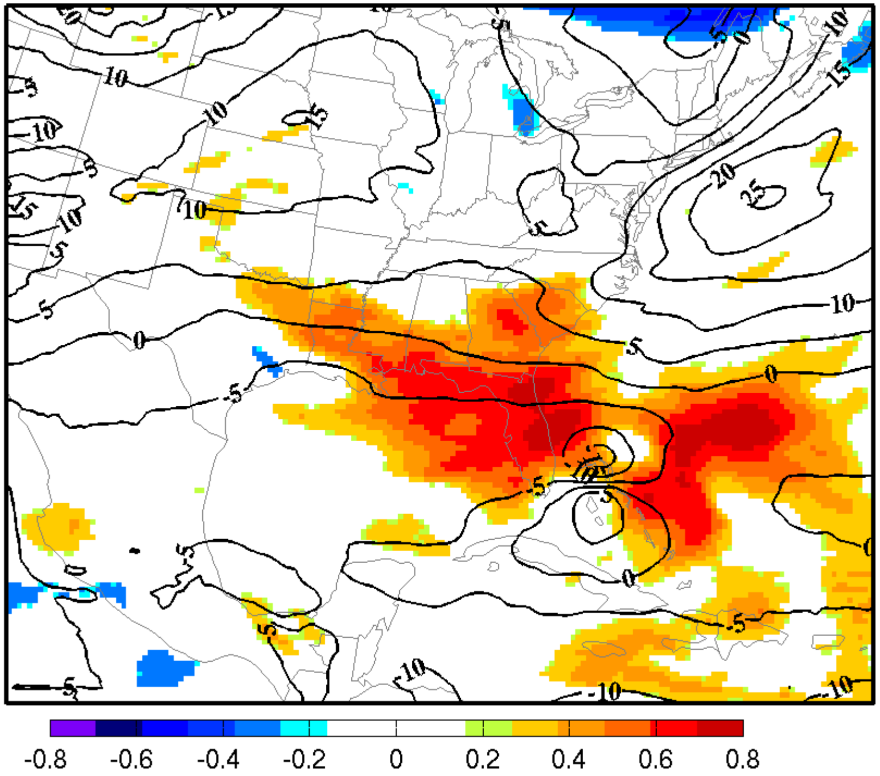
Science: *Where should more observations be taken to improve landfall forecasts?*

Ensemble sensitivity analysis for Katrina.

Collaborator: Ryan Torn, University at Albany.

DART Science and Collaborators (3)

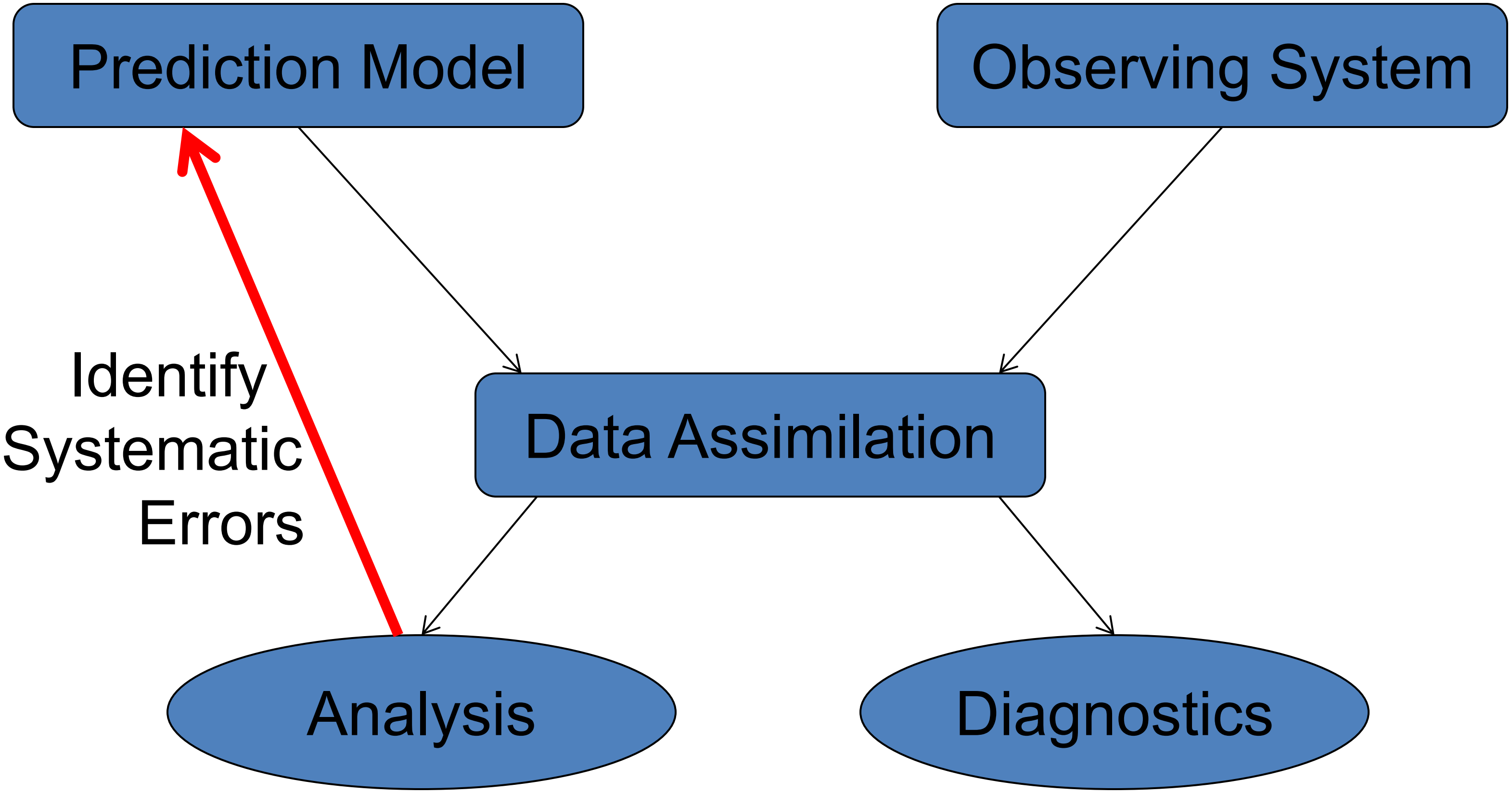
Hurricane Katrina Sensitivity Analysis



Contours are ensemble mean 48h forecast of deep-layer mean wind.

Color shows where observations could help.

Identifying Model Systematic Errors



Prediction Model

Observing System

Data Assimilation

Identify Systematic Errors

Analysis

Diagnostics

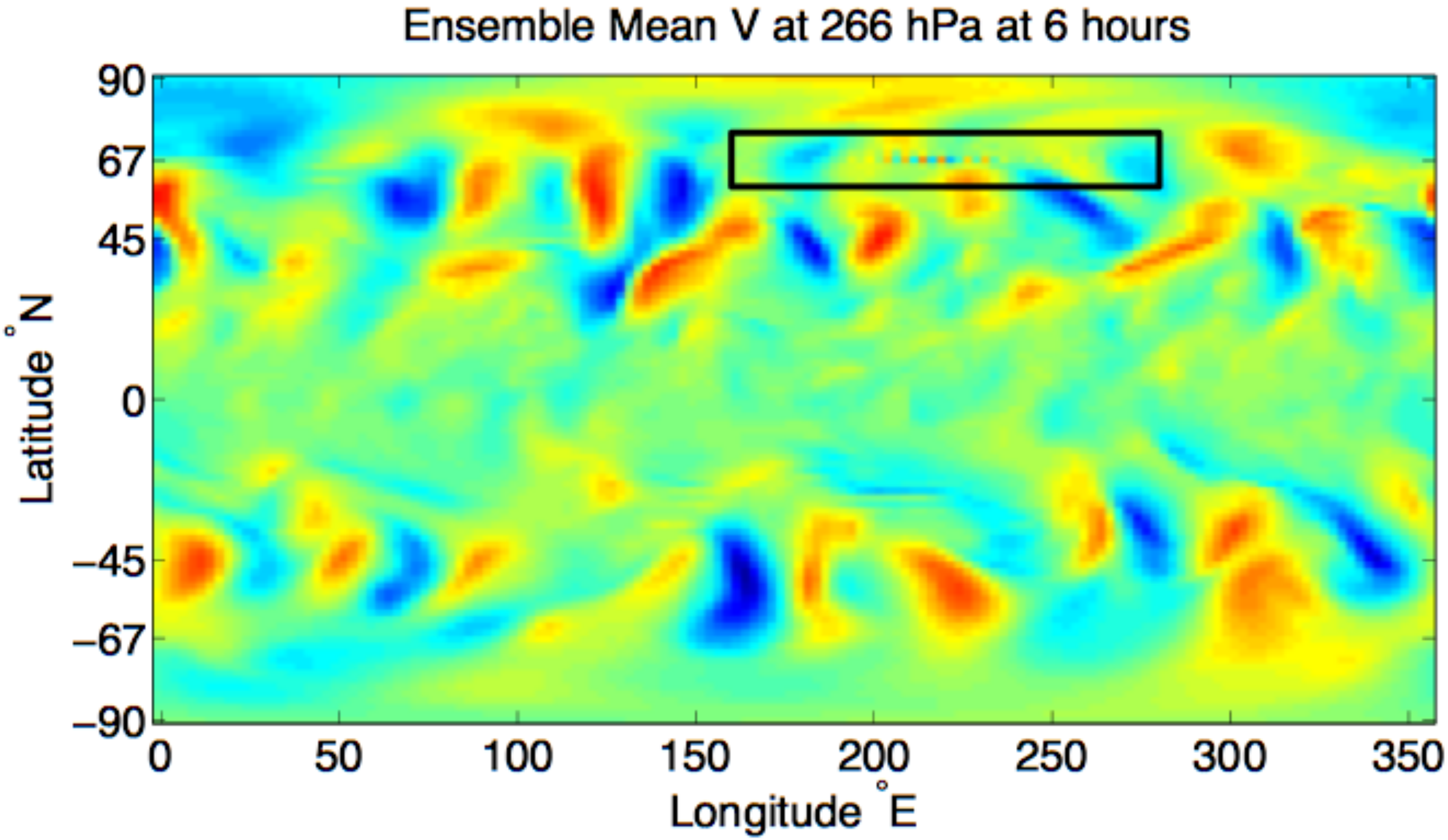
DART Science and Collaborators (4)

Science: Diagnosing and correcting errors in the CAM FV core.

Collaborator: Peter Lauritzen, CGD.

DART Science and Collaborators (4)

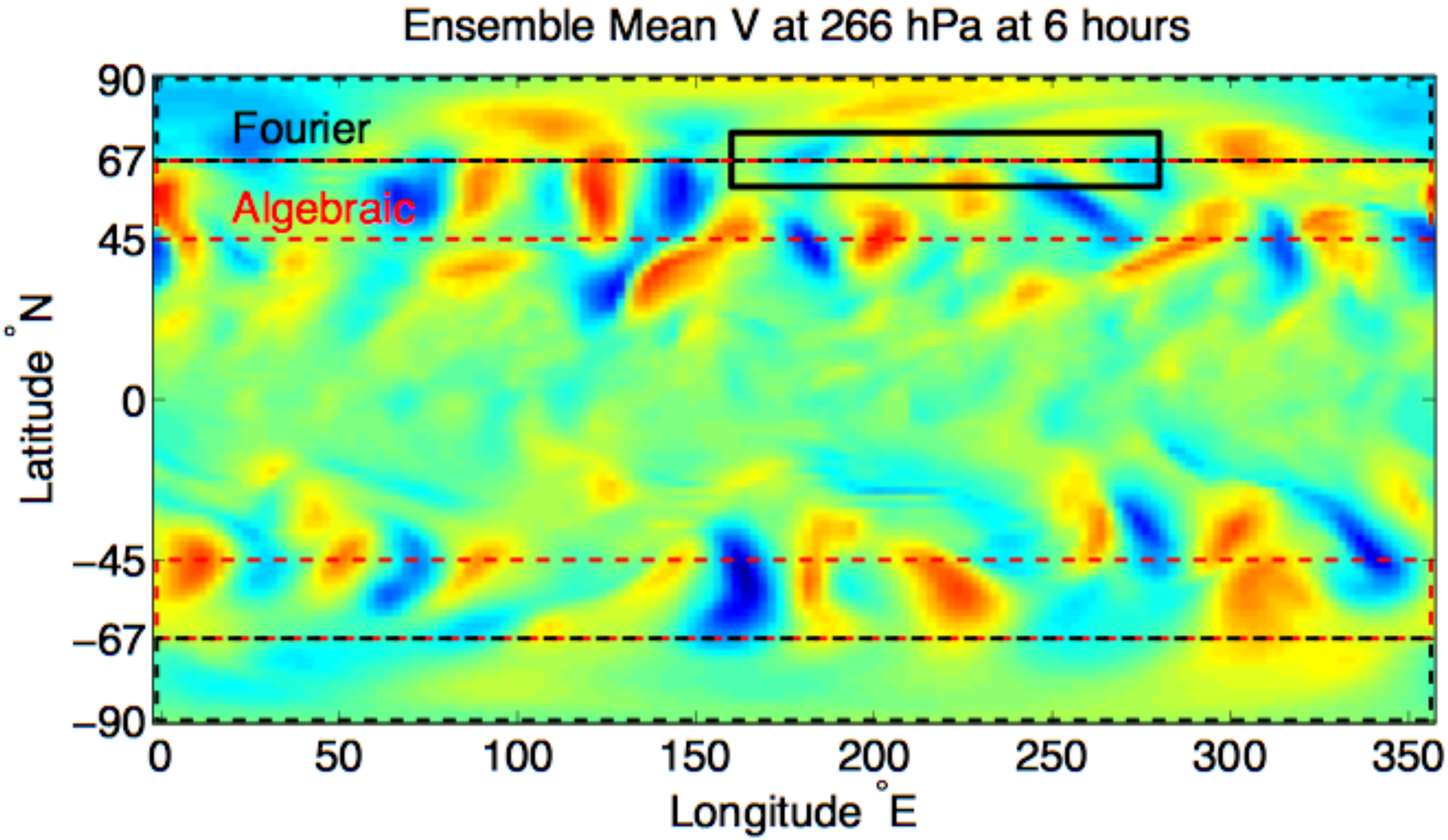
Gridpoint noise detected in CAM/DART analysis



CAM FV core - 80 member mean - 00Z 25 September 2006

DART Science and Collaborators (4)

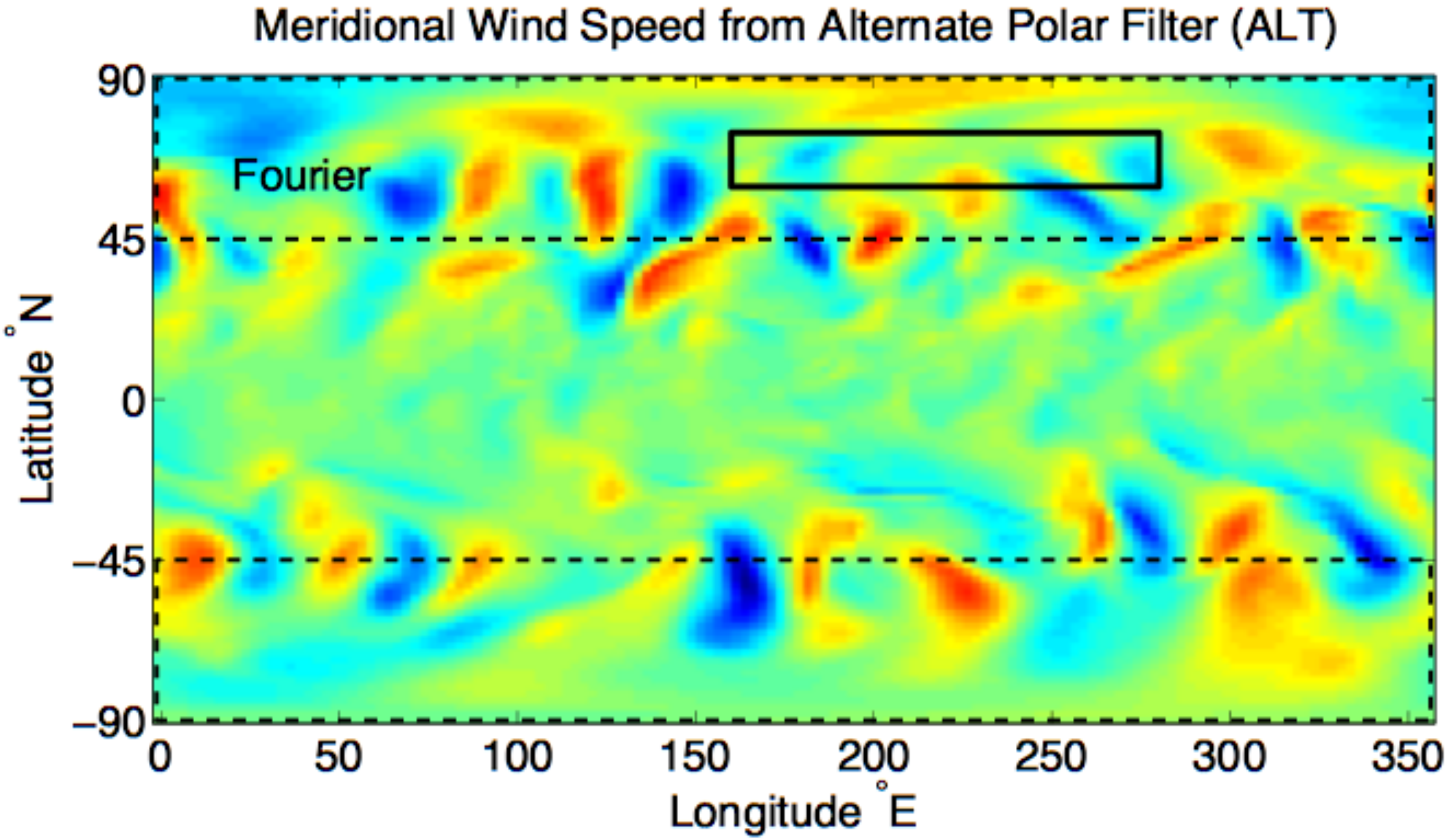
Suspicions turned to the polar filter (DPF)



CAM FV core - 80 member mean - 00Z 25 September 2006

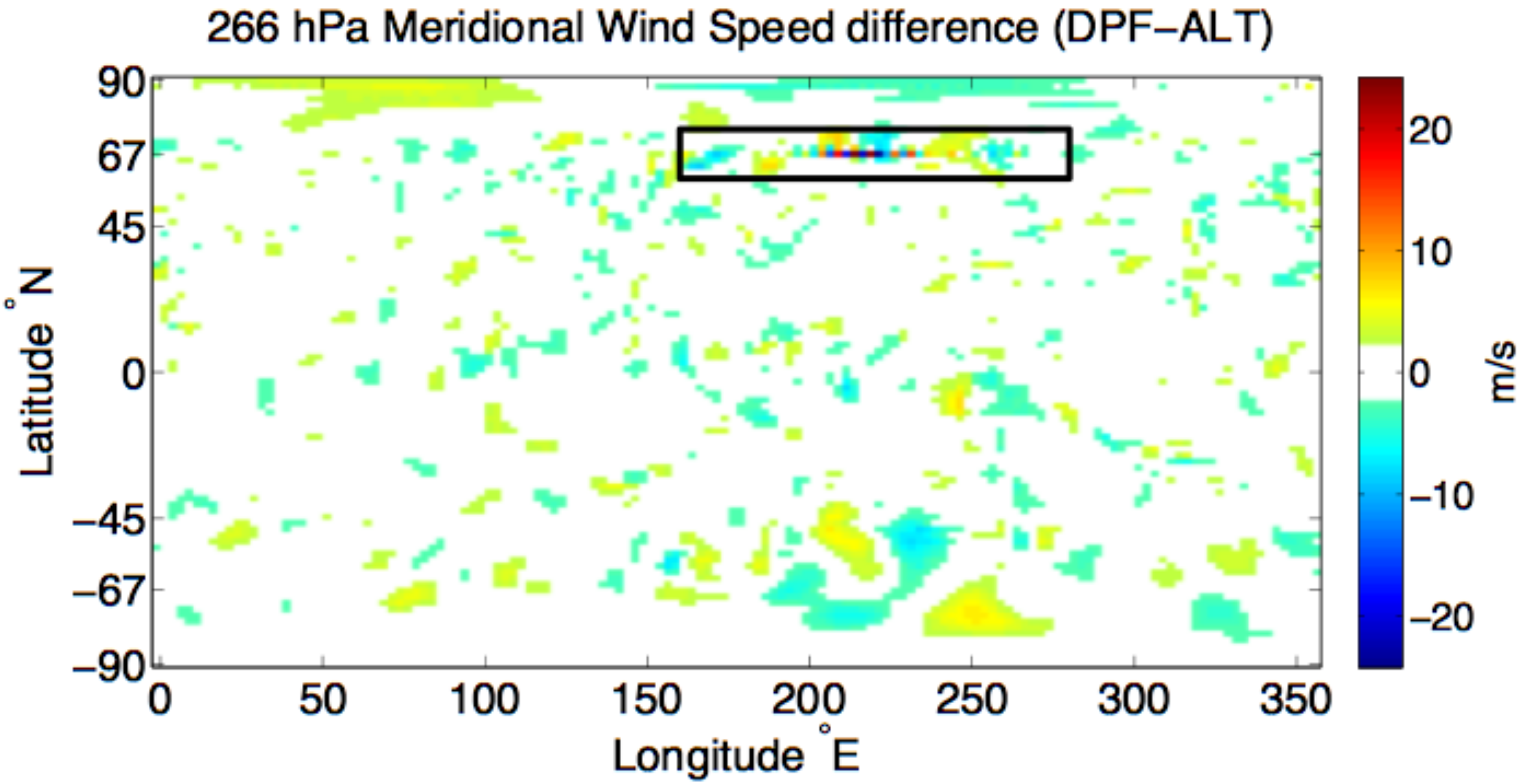
DART Science and Collaborators (4)

Continuous polar filter (alt-pft) eliminated noise.



DART Science and Collaborators (4)

Differences mostly in transition region of default filter.



DART Science and Collaborators (4)

- The use of DART diagnosed a problem that had been unrecognized (or at least undocumented).
- Could have an important effect on any physics in which meridional mixing is important.
- The problem can be seen in ‘free runs’ - it is not a data assimilation artifact.
- Without assimilation, can’t get reproducing occurrences to diagnose.

DART Science and Collaborators (5)

Science: Global Ocean data assimilation.
Collaborators: Alicia Karspeck, Steve Yeager, CGD.

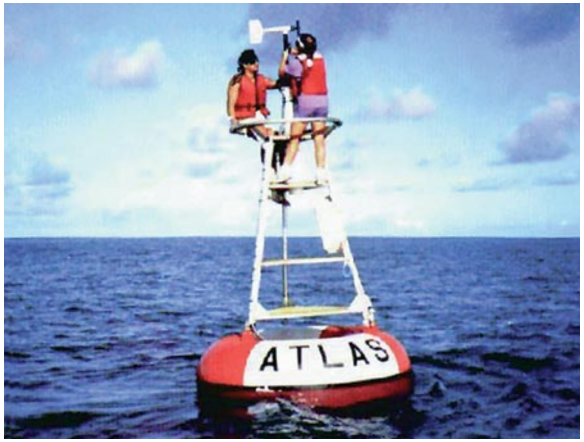
- Climate change over time scales of 1 to several decades has been identified as very important for mitigation and infrastructure planning.
- Need ocean initial conditions for the IPCC decadal prediction program (and maybe a crystal ball, too!).

DART Science and Collaborators (5)

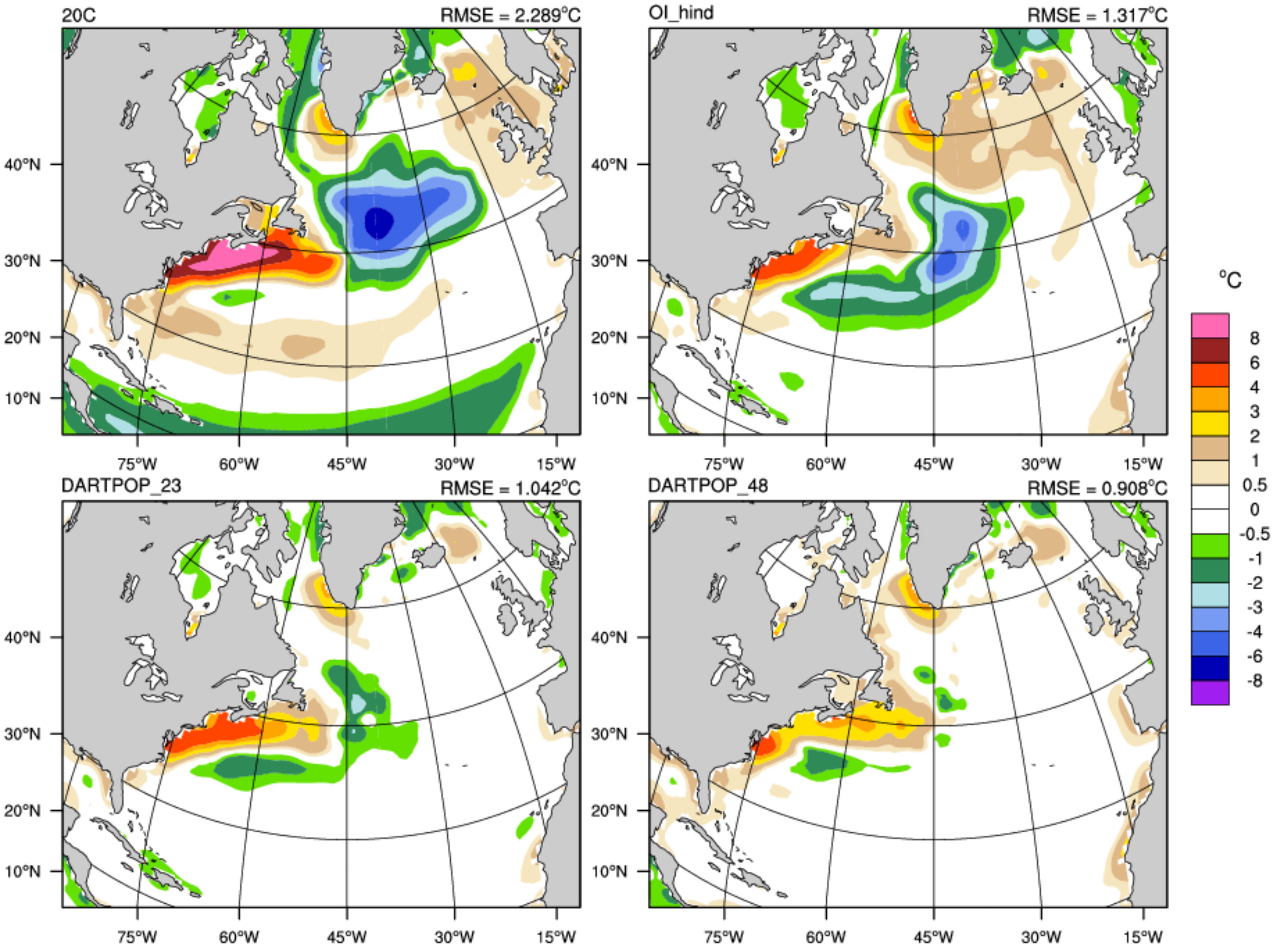
World Ocean Database T, S observation counts.

These counts are for 1998 & 1999 and are representative.

FLOAT_SALINITY	68200
FLOAT_TEMPERATURE	395032
DRIFTER_TEMPERATURE	33963
MOORING_SALINITY	27476
MOORING_TEMPERATURE	623967
BOTTLE_SALINITY	79855
BOTTLE_TEMPERATURE	81488
CTD_SALINITY	328812
CTD_TEMPERATURE	368715
STD_SALINITY	674
STD_TEMPERATURE	677
XCTD_SALINITY	3328
XCTD_TEMPERATURE	5790
MBT_TEMPERATURE	58206
XBT_TEMPERATURE	1093330
APB_TEMPERATURE	580111



Physical Space: 1998/1999 SST Anomaly from HadOI-SST



Coupled Free Run

23 POP 1 DATM

POP forced by observed atmosphere (hindcast)

48 POP 48 CAM

DART Science and Collaborators (6)

Science: Land surface analysis with DART/CLM.
Collaborator: Yongfei Zhang, UT Austin.

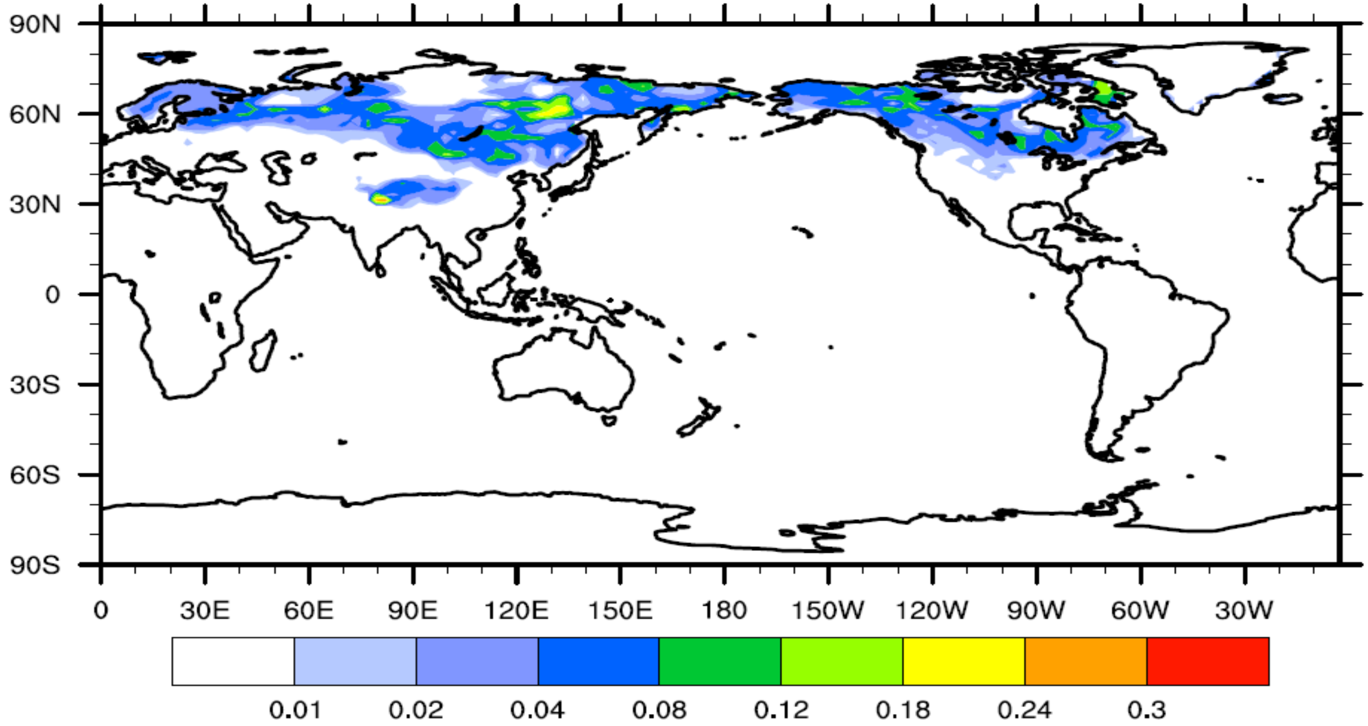
Land surface analysis with DART/CLM:

Estimate snow water equivalent with observations of snow cover fraction from satellites (MODIS).

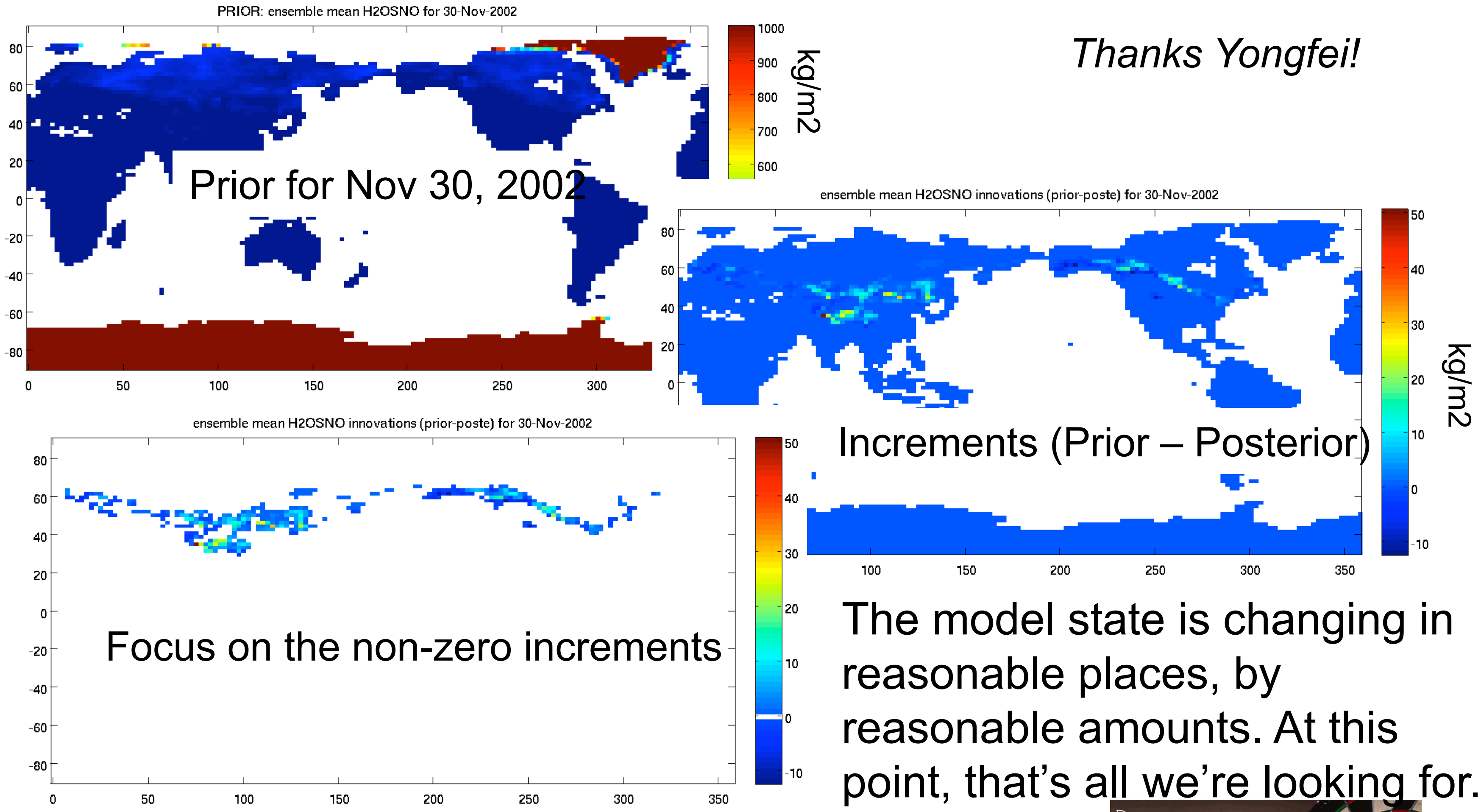
Assimilation of MODIS snow cover fraction

- 80 member ensemble for onset of NH winter
- Assimilate once per day
- Level 3 MODIS product – regridded to a daily 1 degree grid
- Observation error variance is 0.1 (for lack of a better value)
- Observations can impact state variables within 200km
- CLM variable to be updated is the snow water equivalent "`H2OSNO`"

Standard deviation of the snow cover fraction initial conditions for Oct. 2002



An early result: assimilation of MODIS *snowcover fraction* on total *snow water equivalent* in CLM.



Prior for Nov 30, 2002

Thanks Yongfei!

Increments (Prior – Posterior)

Focus on the non-zero increments

The model state is changing in reasonable places, by reasonable amounts. At this point, that's all we're looking for.

Data
Assimilation
Research
Testbed

DART Science and Collaborators (7)

Science: Regional Atmospheric Chemistry.
Collaborator: Arthur Mizzi, NCAR/ACD.

WRF/Chem Chemical Weather Forecast System

- **WRF-Chem** – Weather Research and Forecasting Model (WRF) with online chemistry.
- **Meteorological Observations** – NOAA PREPBUFR conventional observations.
- **Chemistry Observations** – MOPITT CO retrieval profiles (also IASI CO retrievals – results not shown).

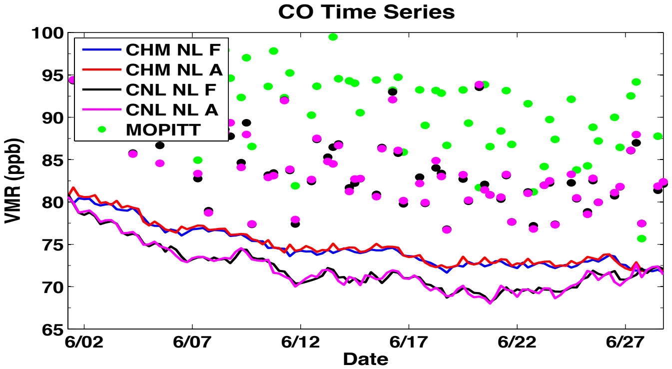
WRF/Chem Chemical Weather Forecast System

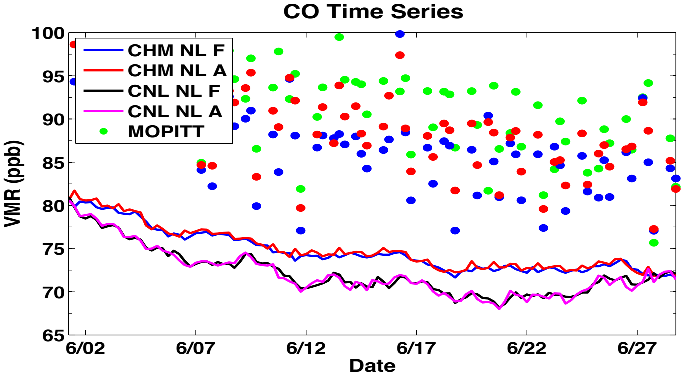
- **WRF/Chem-DART** cycling with conventional meteorological observations and MOPITT CO V5 retrieval profiles.
- Continuous six-hr cycling (00Z, 06Z, 12Z, and 18Z).
- CONUS grid with 101x41x34 grid points and 100 km resolution.
- 20-member ensemble.
- June 1 - 30, 2008 (112 cycles) study period.
- Full state variable/obs interaction.
- Initial and lateral chemical boundary conditions from MOZART-4 simulation.
- Emissions: Biogenic – MEGAN, Anthropogenic – global inventories, and Fire – Fire Inventory from NCAR (FINN).

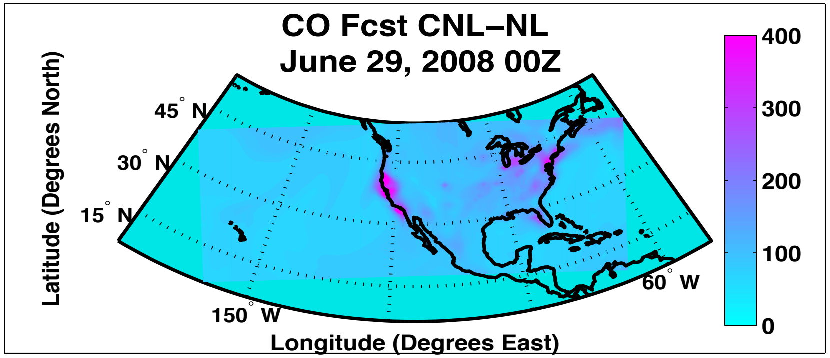
WRF/Chem Chemical Weather Forecast System

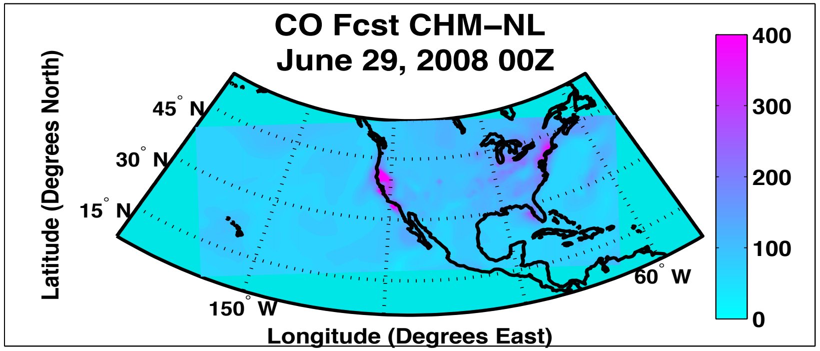
- Two experiments:
  - Exp 1: PREPBUFR conventional obs (**CNTL DA**).
  - Exp 2: MOPITT CO retrieval profiles and PREPBUFR conventional obs (**CHEM DA**).

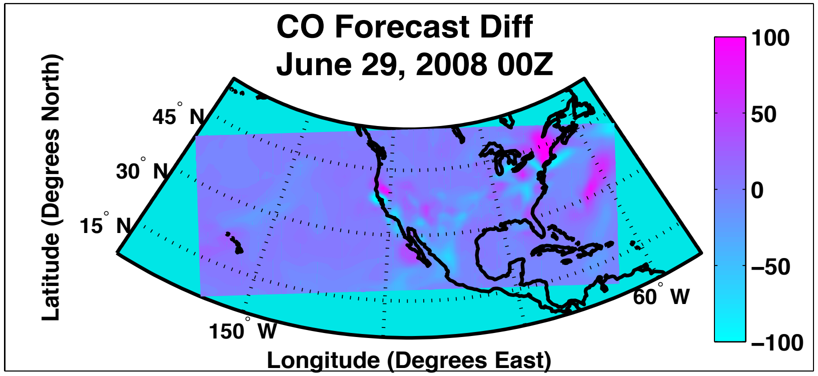
WRF/Chem Chemical Weather Forecast System











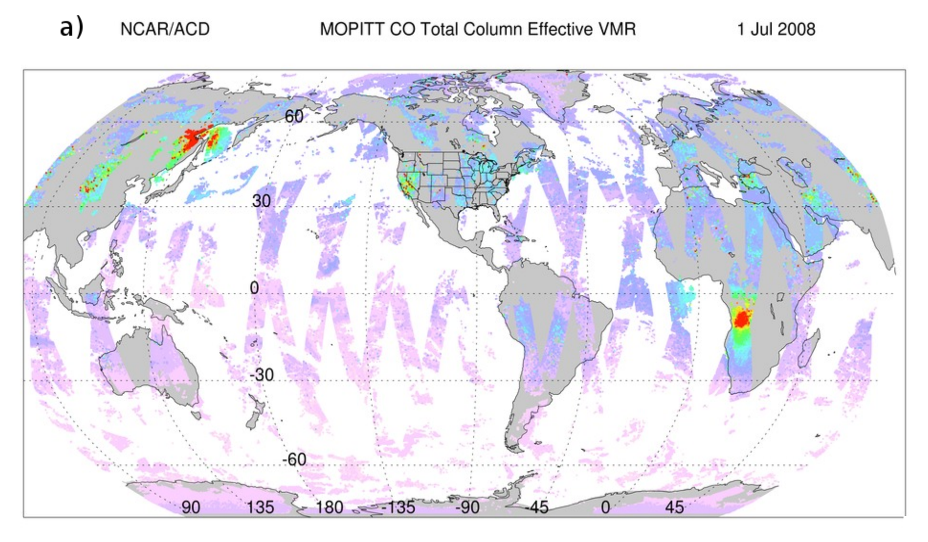
DART Science and Collaborators (8)

Science: Global Atmospheric Chemistry.
Collaborators: Jerome Barre,
Benjamin Gaubert, NCAR/ACD.

Uses global CAM/Chem model, 1 degree.

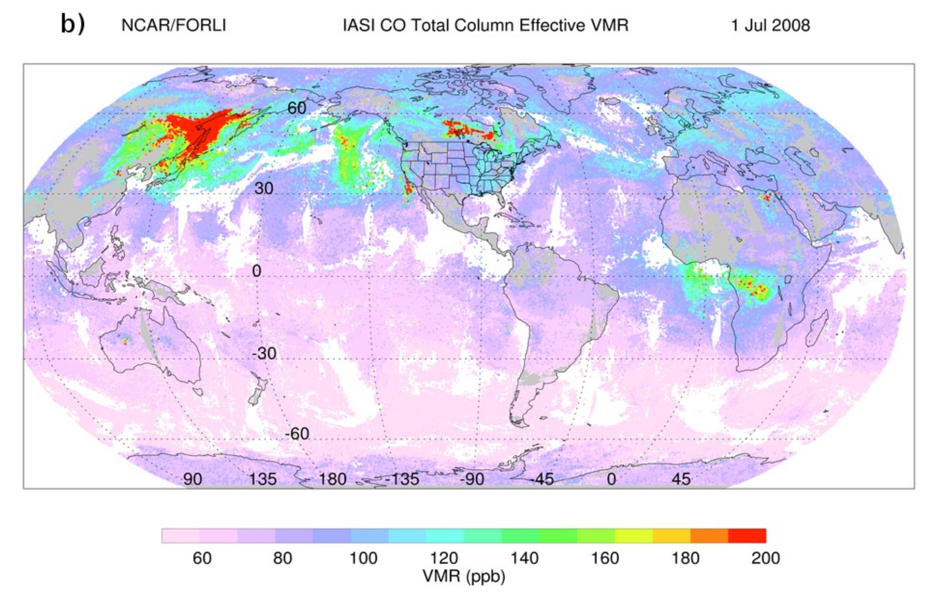
Have full meteorological assimilation capability already.

CAM/Chem Chemical DA System



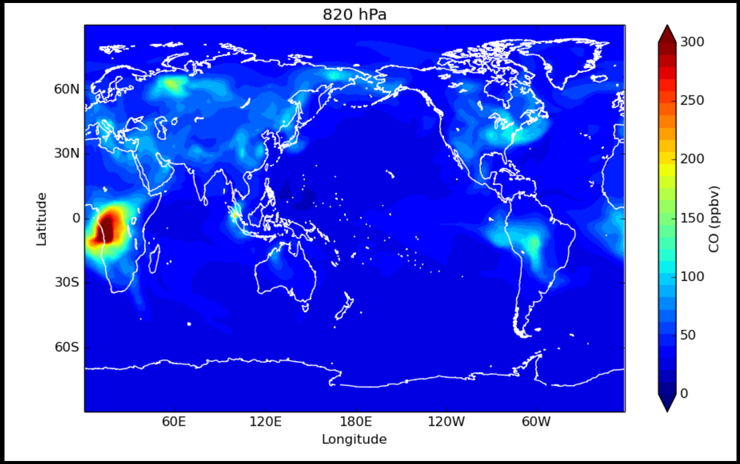
<u>MOPITT CO:</u>
On TERRA satellite
tropospheric profiles
Global coverage in 4 days
Multispectral retrievals
high sensitivity on surface land/day

<u>IASI CO:</u>
On MetOpA satellite
tropospheric profiles
Global coverage in 1 day
Only thermal infrared
Sensitivity on upper PBL &
mid troposphere

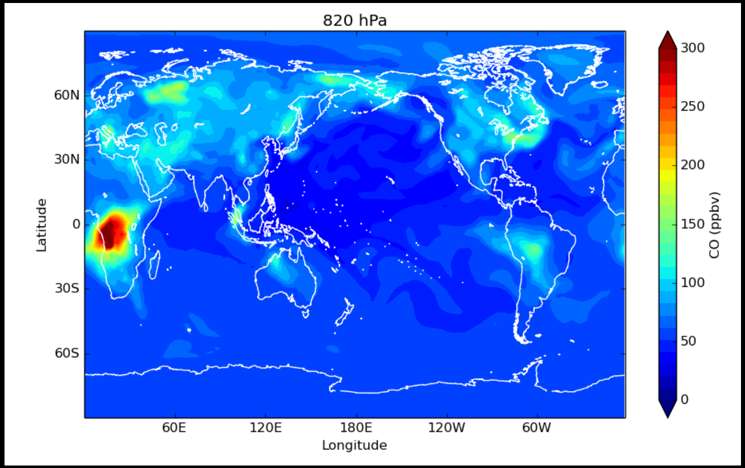


CAM/Chem Chemical DA System

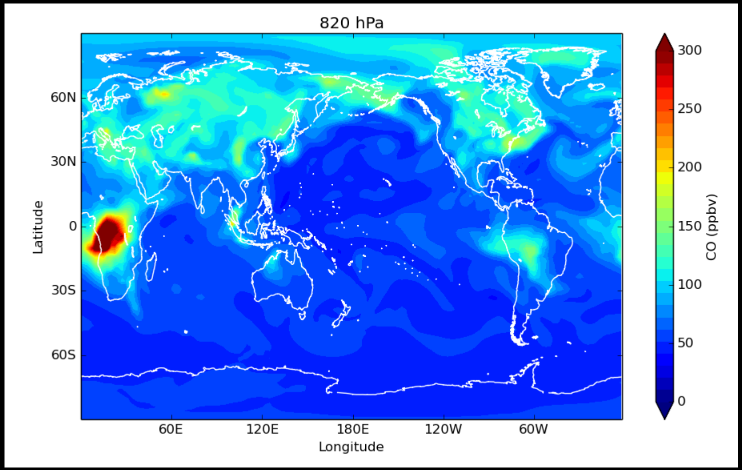
Control run: Met Only assimilated



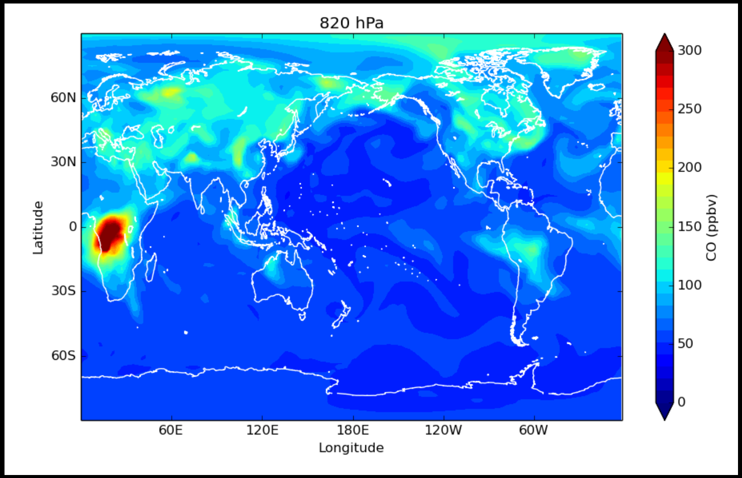
MOPITT run: Met + MOPITT assimilated



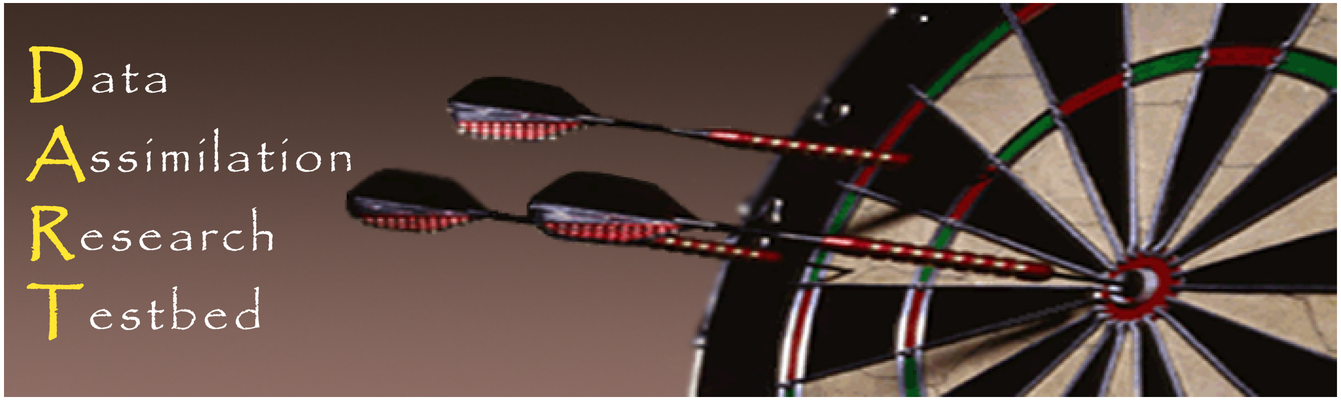
IASI run: Met + IASI assimilated



Combined run: Met + MOP+ IASI assimilated



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