Using Observations to Estimate Climate Model Parameters

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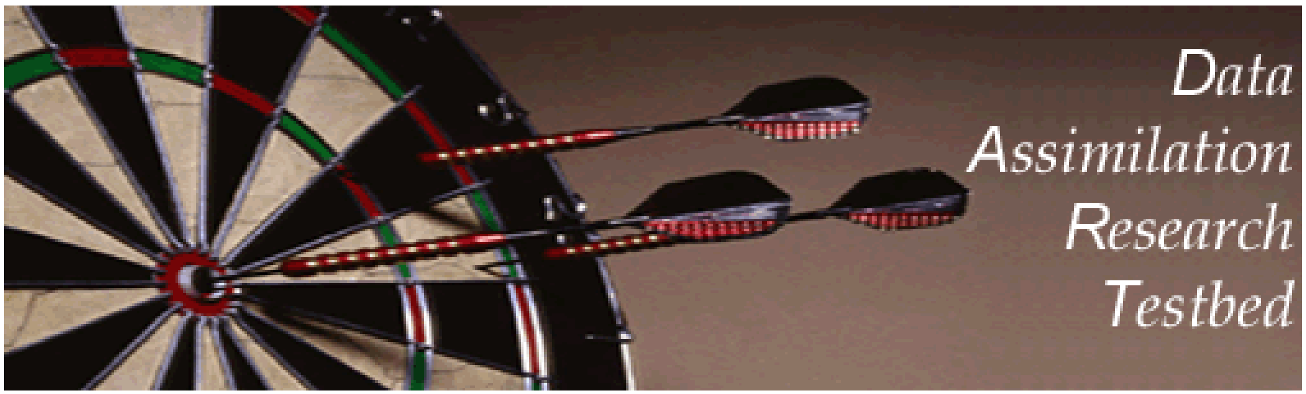
NCAR Data Assimilation Research Section (DAReS)



MSRI Symposium on Climate Change

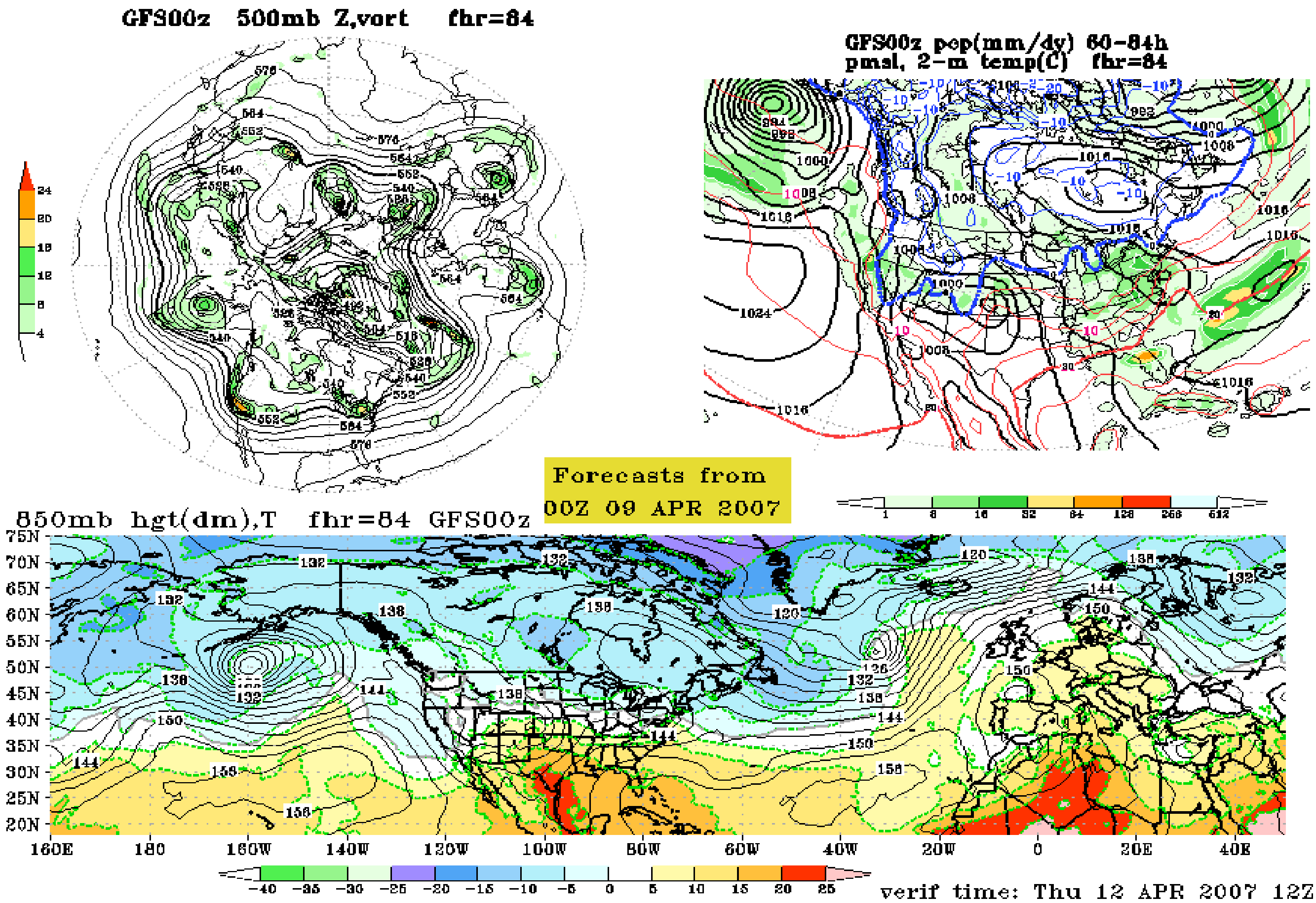
Global Climate Models <u>are</u> Global Weather Prediction Models

1. Some models are used for both purposes.

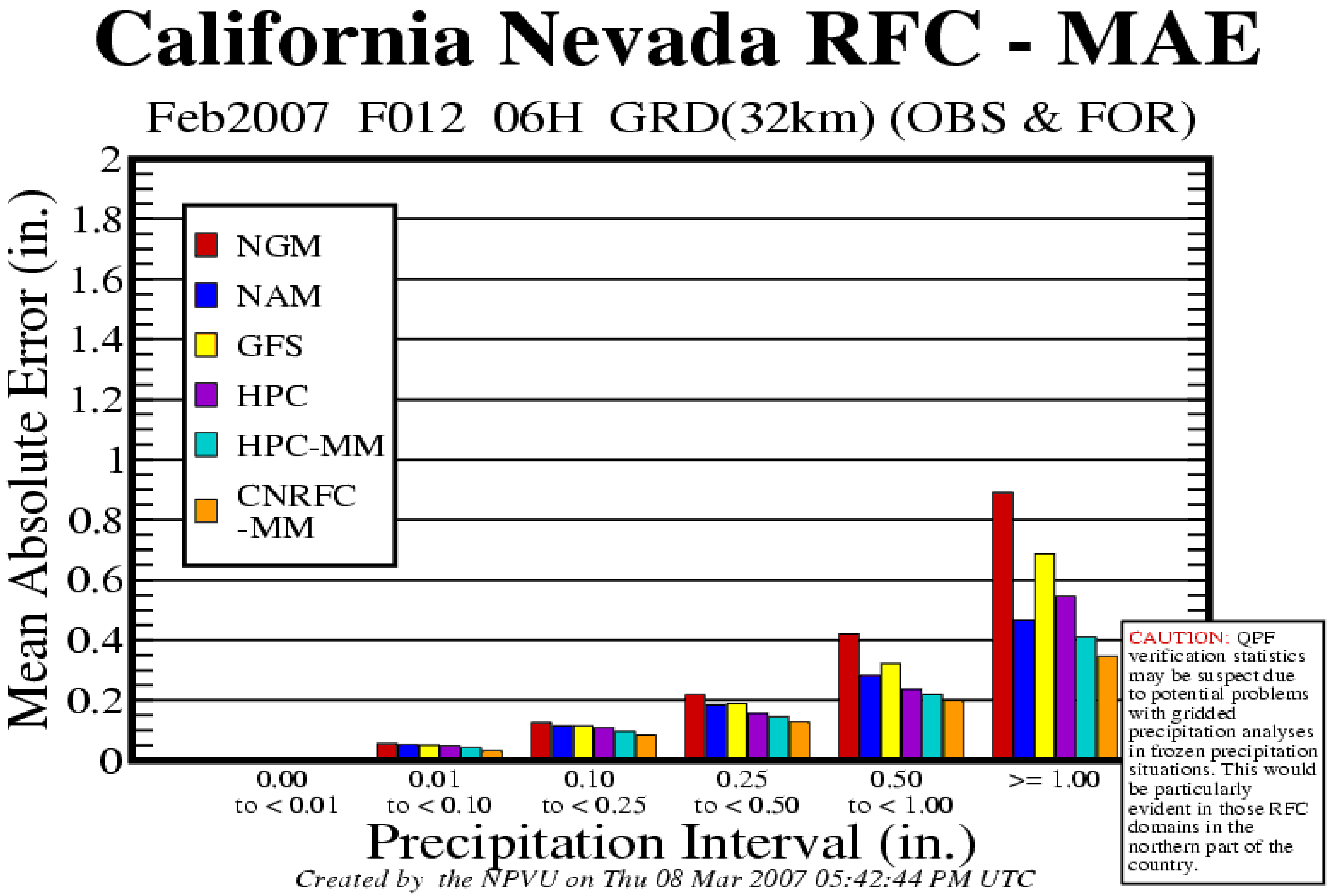
2. Others have been developed independently.

3. <u>Should a good climate model be a good weather prediction model?</u>

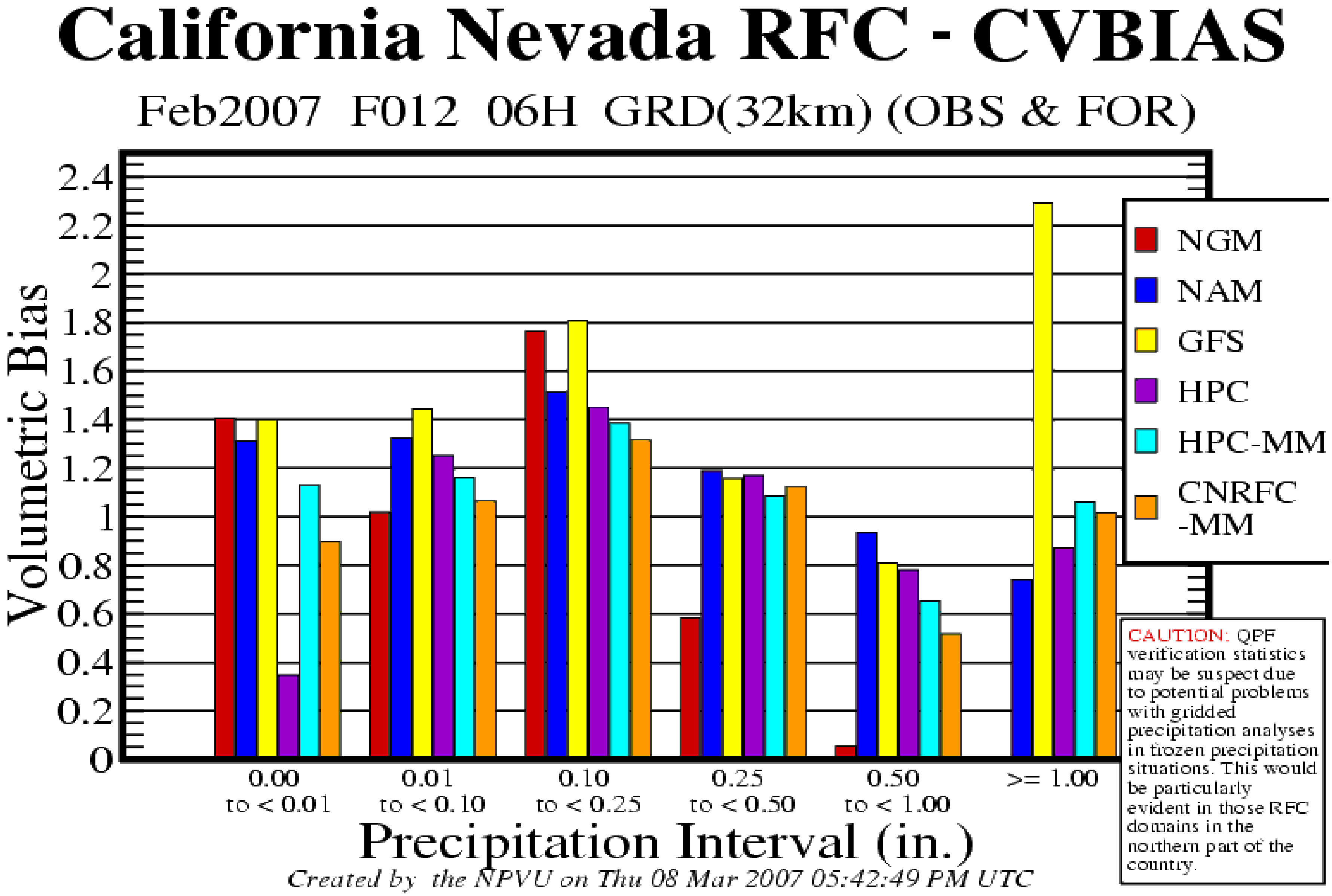
4. And vice versa?



NWP models are great at predicting mid-tropospheric heights.



Not so good at surface temperature, precip., freezing precip., wind...



Have LARGE biases, too. NWS forecasters make a living off this.

Biases are corrected for by statistics and forecasters (and users).

Challenges:

1. Correct bias in a perturbed (unknown) climate.
2. Correct for small spatial scales.
3. Correct for precipitation.
4. Correct for frozen precipitation.

Climate Model Bias Challenges

The smaller the scale,

the nearer the surface,

the more moisture is involved,

the more the climate has changed,

the closer to the freezing point,

the harder things get.

Need to test and improve climate models' weather prediction skill.

At least there are some observations available.

Do this via (ensemble) data assimilation.

The Geophysical Data Assimilation Problem:

Given: 1. A physical system (atmosphere, ocean, climate system...)

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2. Observations of the physical system

Often sparse and irregular in time and space.
Instruments have error of which we have a (poor) estimate.
Observations may be of quantities not found in model.
Many observations may have very low information content.

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3. A model of the physical system

Usually approximates time evolution.
Truncated representation of ‘continuous’ physical system.
Often quasi-regular discretization in space and/or time.
Generally characterized by ‘large’ systematic errors.
Often ergodic with some sort of ‘attractor’.

Assimilation increases information about all three pieces:

1. Get an improved estimate of state of physical system.

Initial conditions for forecasts.
Includes time evolution and 'balances'.
High quality analyses (re-analyses).

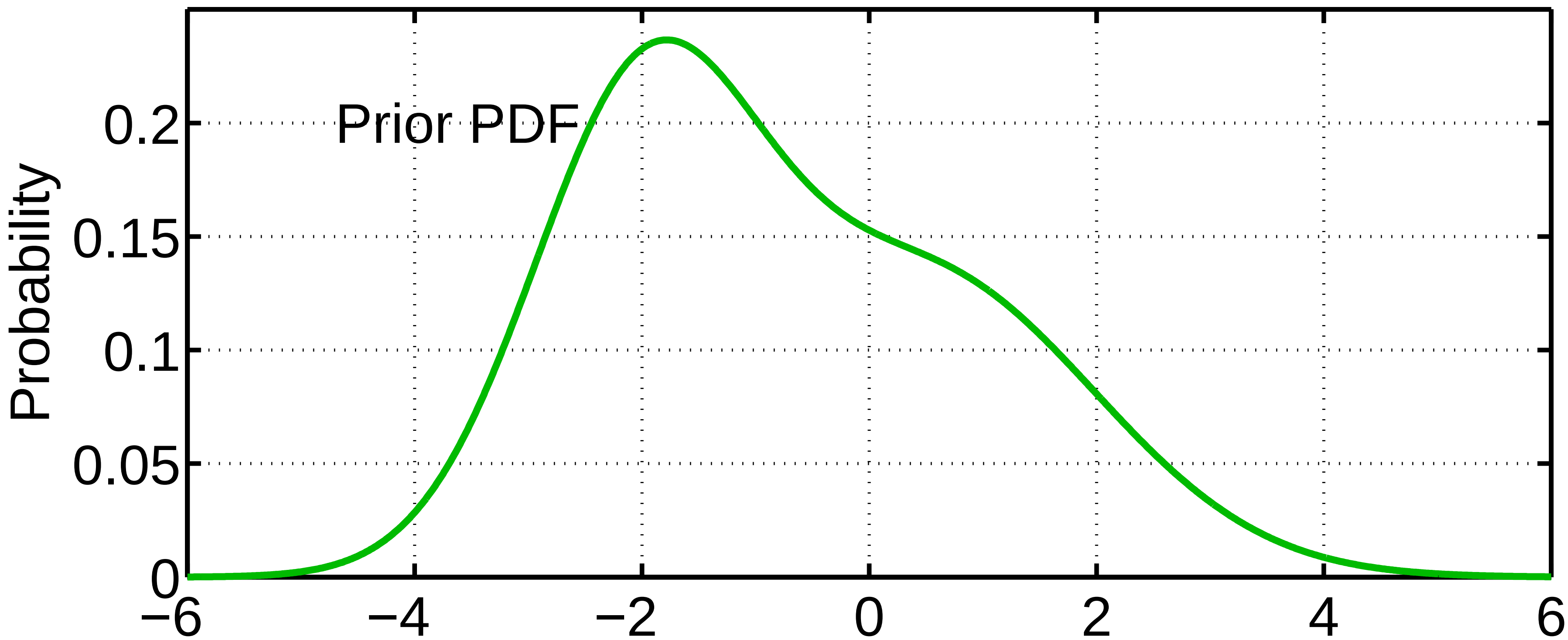
2. Get better estimates of observing system error characteristics.

Estimate value of existing or planned observations.
Design observing systems that provide increased information.

3. Improve model of physical system.

Evaluate model systematic errors.
Forward and backward sensitivity analysis (adjoint and linear tangent replacement).
Select appropriate values for model parameters.

Bayes rule: $p(A|BC) = \dfrac{p(B|AC)p(A|C)}{p(B|C)} = \dfrac{p(B|AC)p(A|C)}{\int p(B|x)p(x|C)dx}$



A: Prior estimate based on all previous information, C.

B: An additional observation.

$p(A|BC)$: Posterior (updated estimate) based on C and B.

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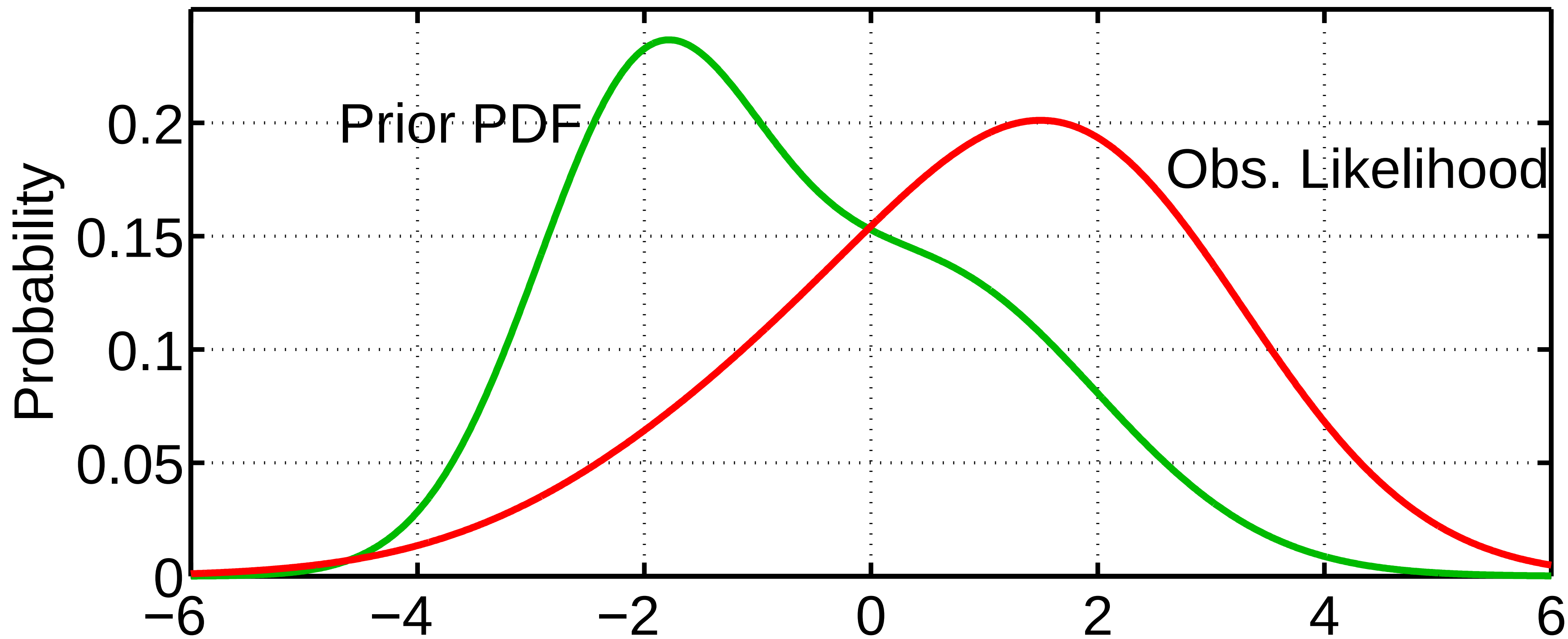

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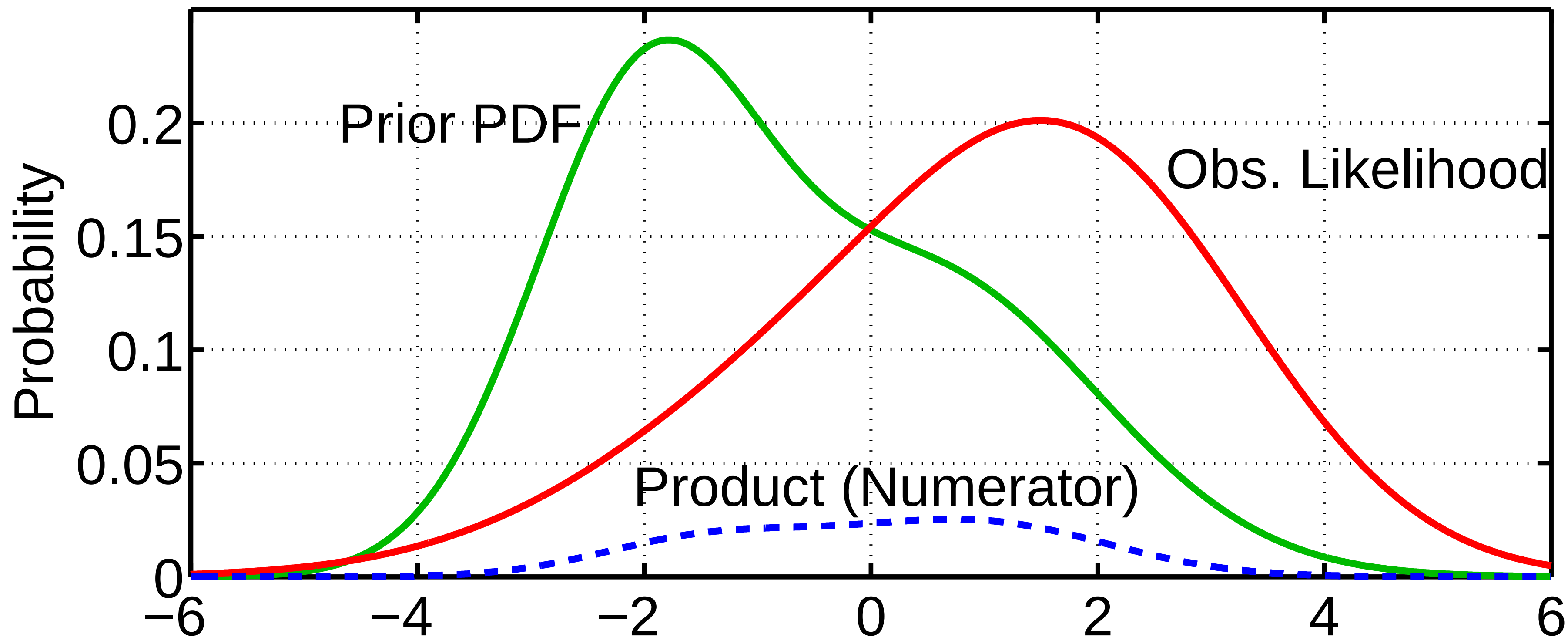

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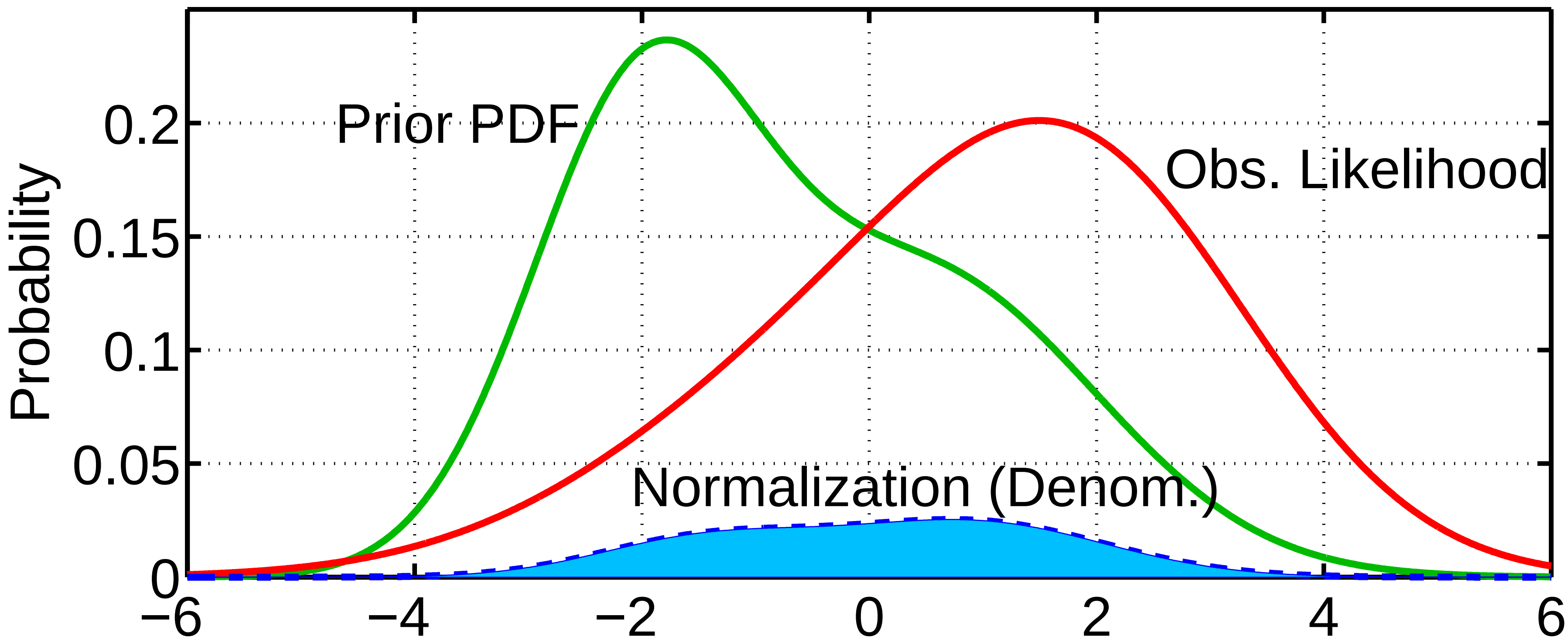

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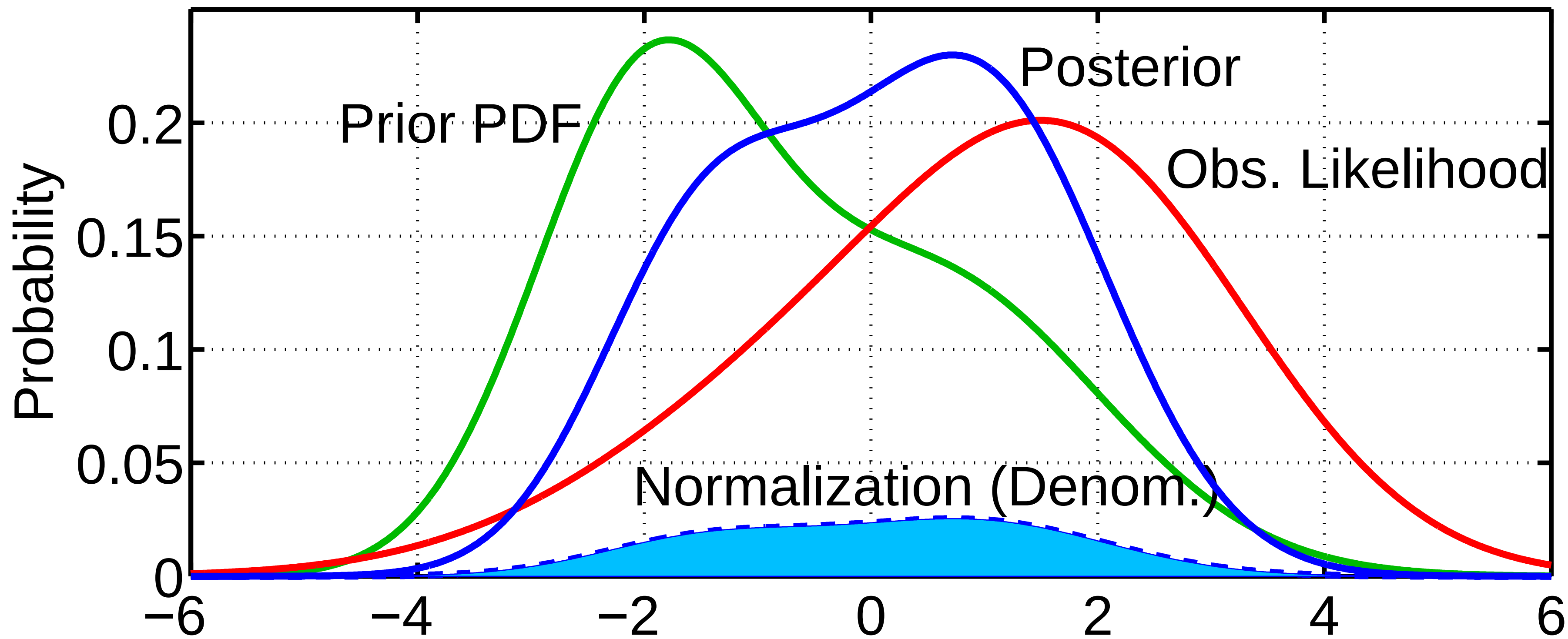

A: Prior estimate based on all previous information, C.

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Consistent Color Scheme Throughout Tutorial

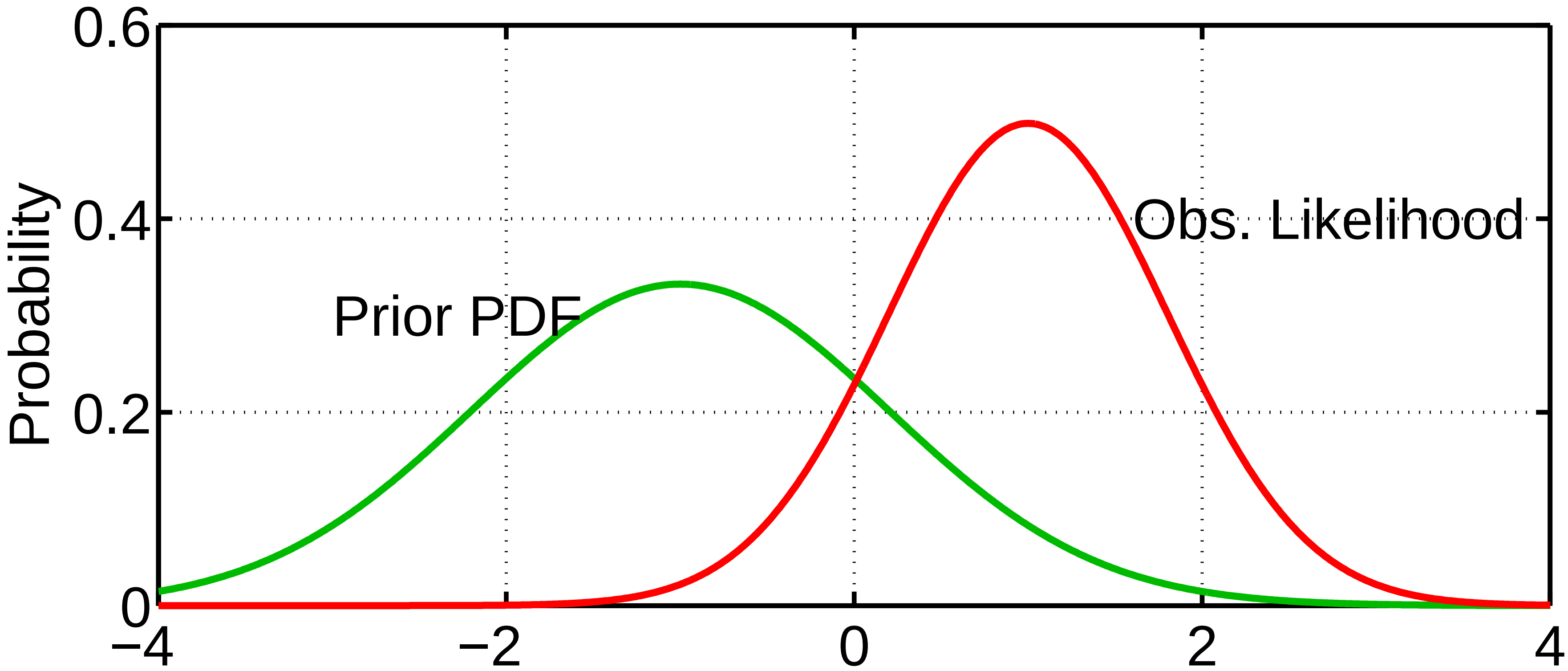
Green = Prior

Red = Observation

Blue = Posterior

Bayes rule: $p(A|BC) = \dfrac{p(B|AC)p(A|C)}{p(B|C)} = \dfrac{p(B|AC)p(A|C)}{\int p(B|x)p(x|C)dx}$

This product is closed for Gaussian distributions.



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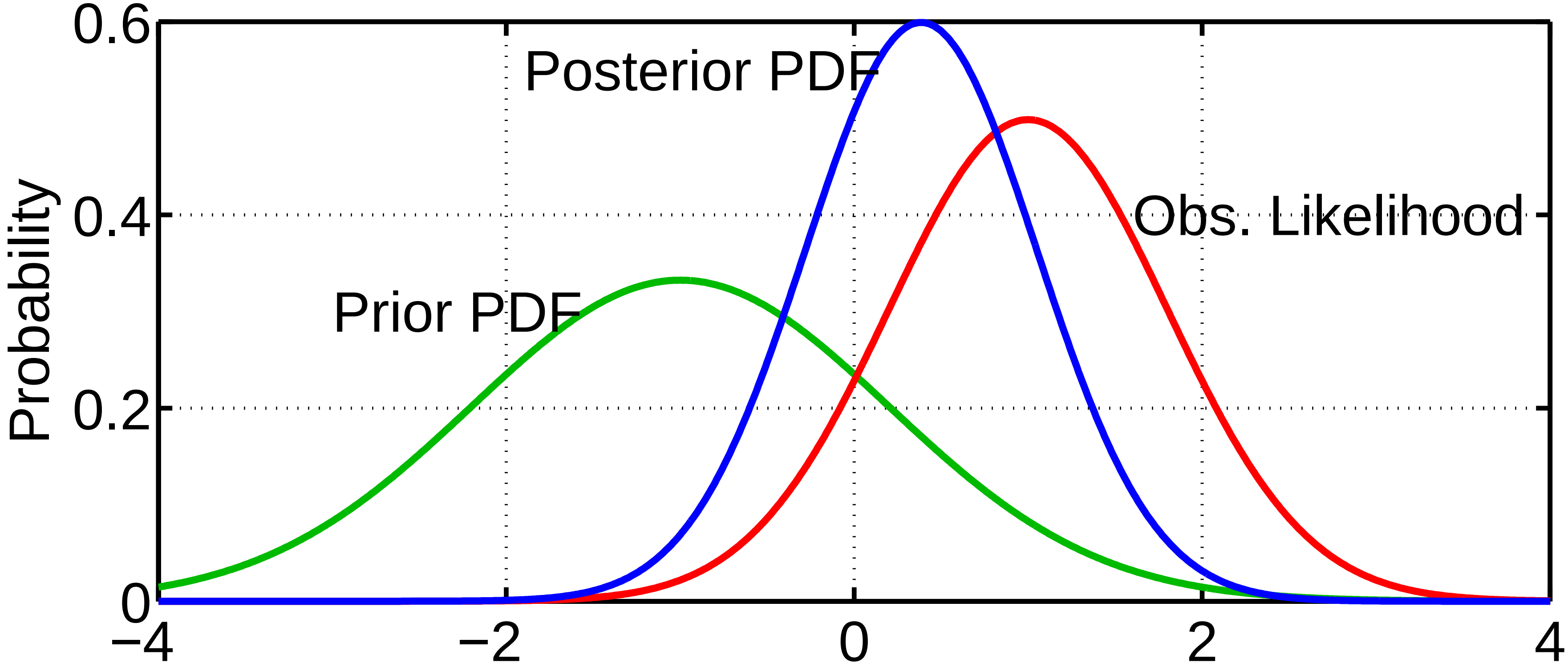

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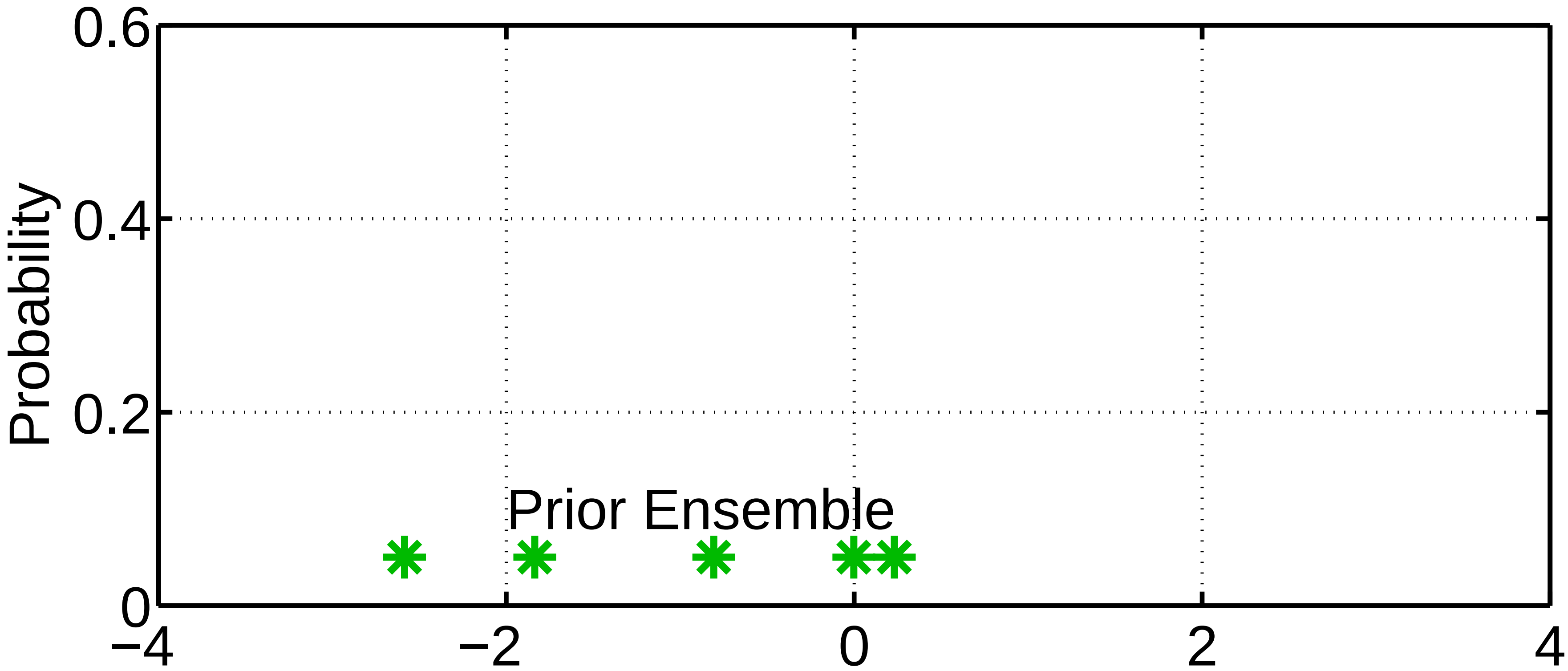
Ensemble filters: Prior is available as finite sample.

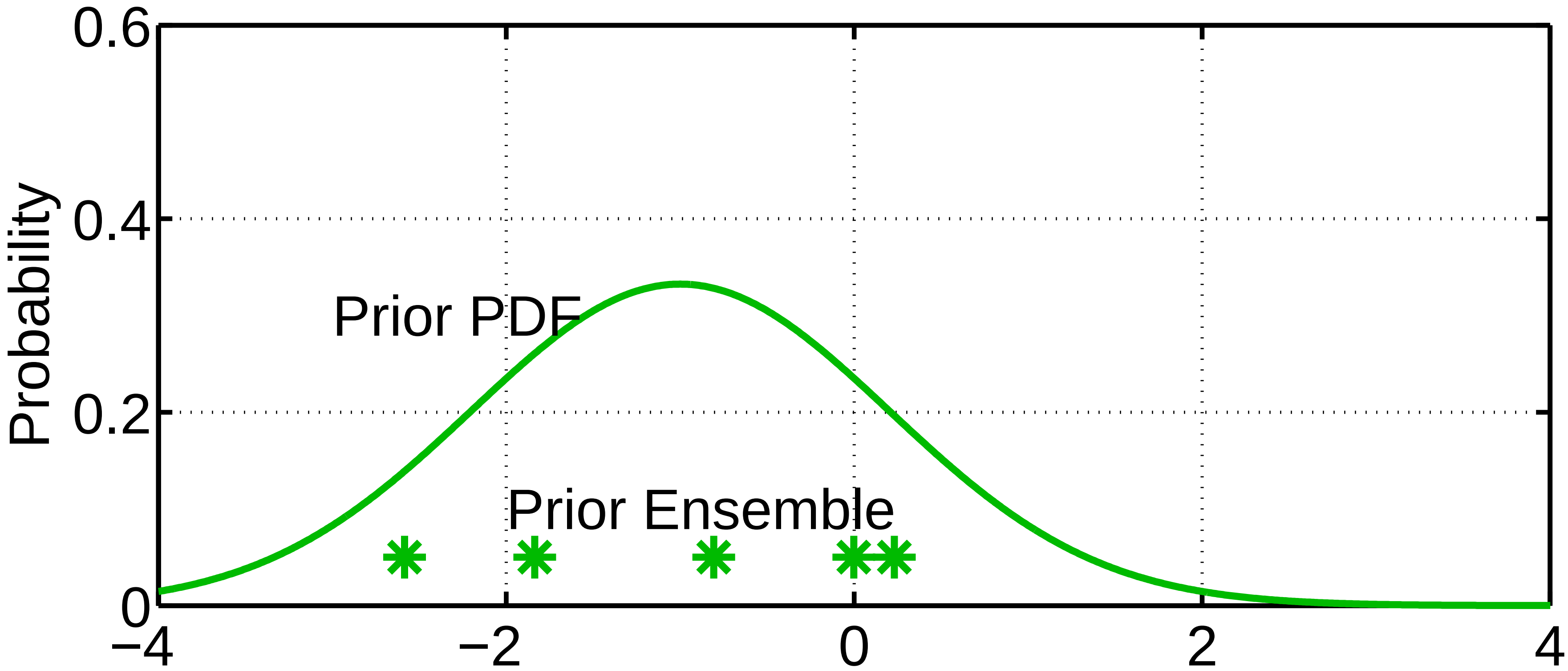


Don’t know much about properties of this sample.

May naively assume it is random draw from ‘truth’.

Bayes rule: $p(A|BC) = \frac{p(B|AC)p(A|C)}{p(B|C)} = \frac{p(B|AC)p(A|C)}{\int p(B|x)p(x|C)dx}$

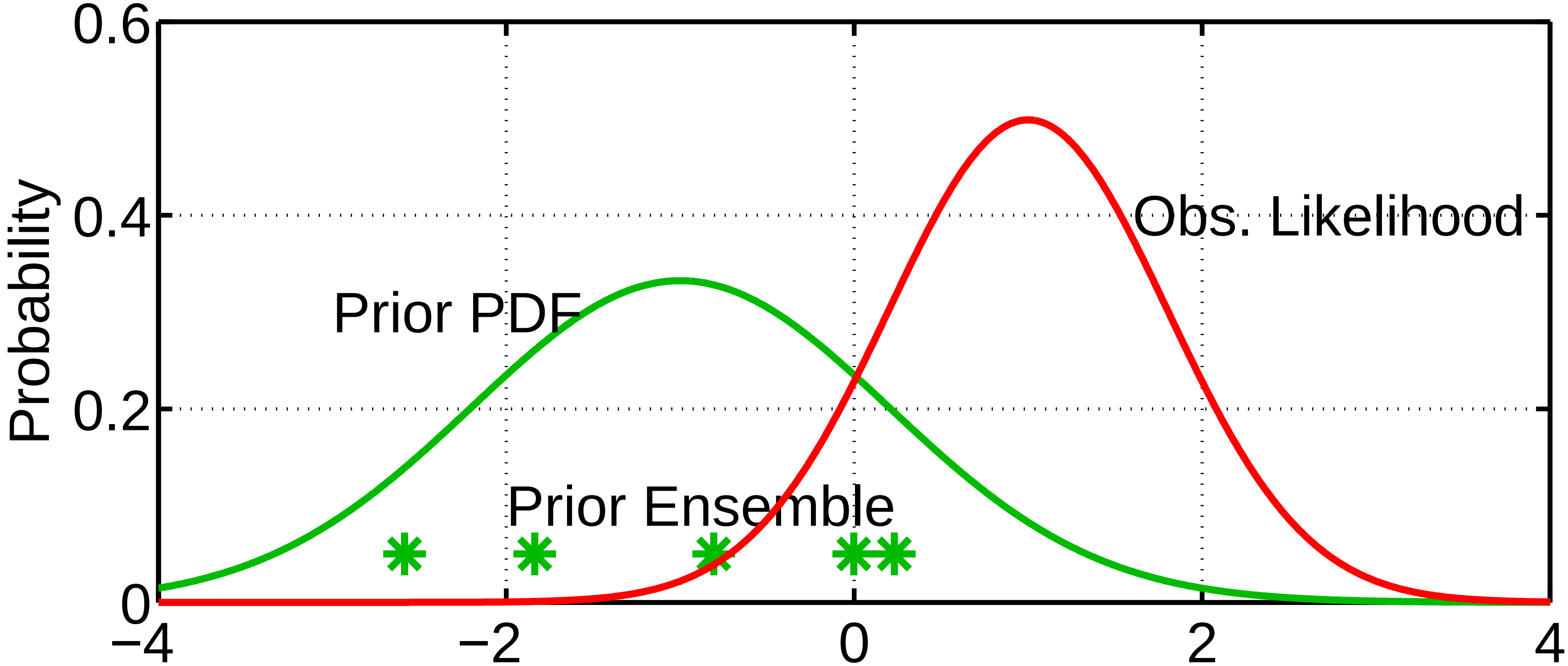
How can we take product of sample with continuous likelihood?



Fit a Gaussian distribution to sample.

Bayes rule: $p(A|BC) = \dfrac{p(B|AC)p(A|C)}{p(B|C)} = \dfrac{p(B|AC)p(A|C)}{\int p(B|x)p(x|C)dx}$

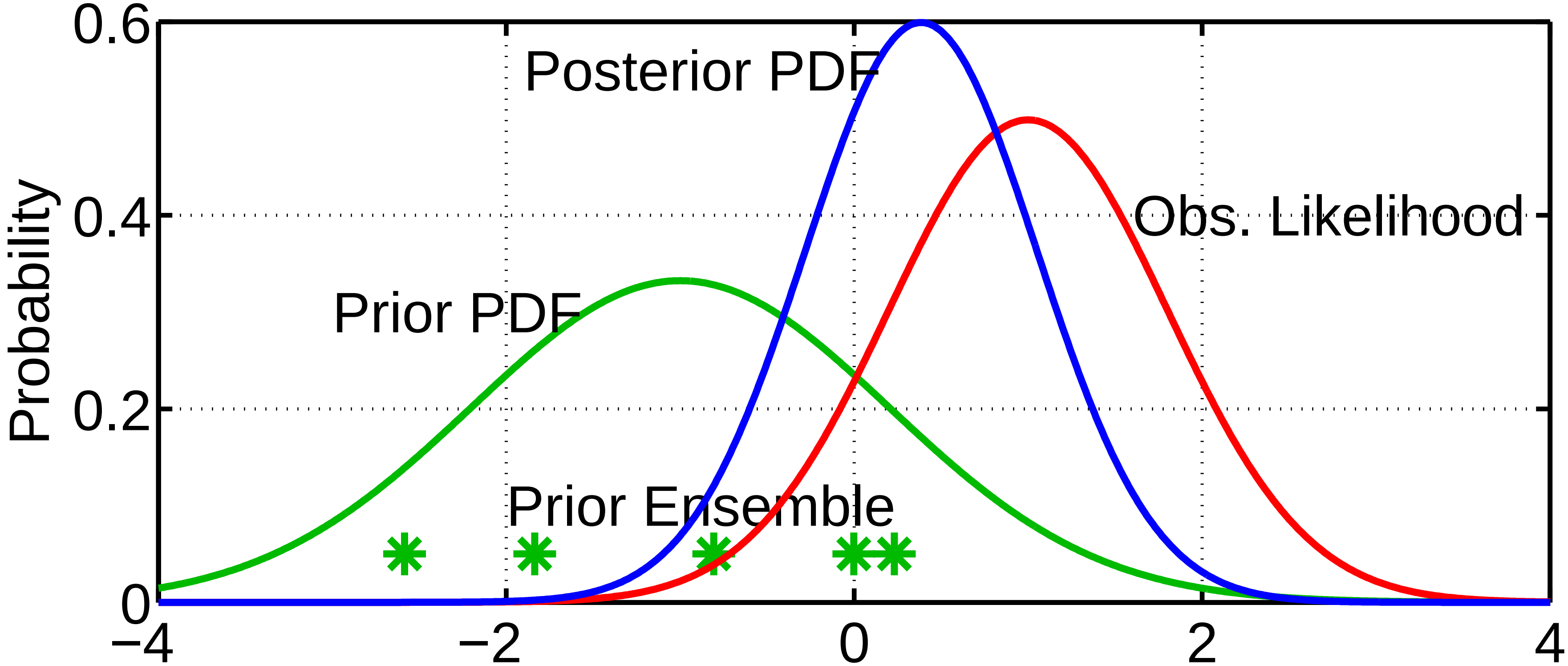
Observation likelihood usually continuous (nearly always Gaussian).



If Obs. Likelihood isn’t Gaussian, can generalize methods below.
For instance, can fit set of Gaussian kernels to obs. likelihood.

Bayes rule: $p(A|BC) = \frac{p(B|AC)p(A|C)}{p(B|C)} = \frac{p(B|AC)p(A|C)}{\int p(B|x)p(x|C)dx}$

Product of prior Gaussian fit and Obs. likelihood is Gaussian.

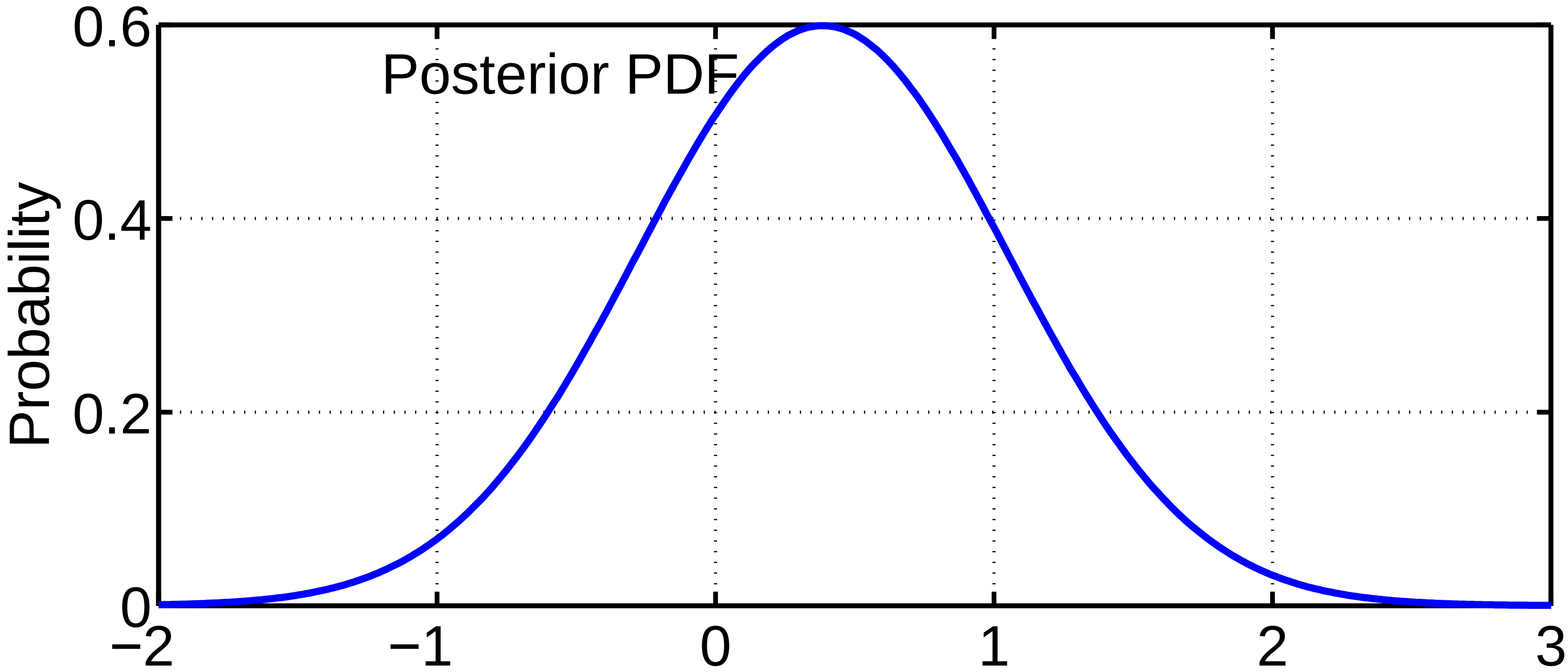


Computing continuous posterior is simple.

BUT, need to have a SAMPLE of this PDF.

Sampling Posterior PDF:

There are many ways to do this.

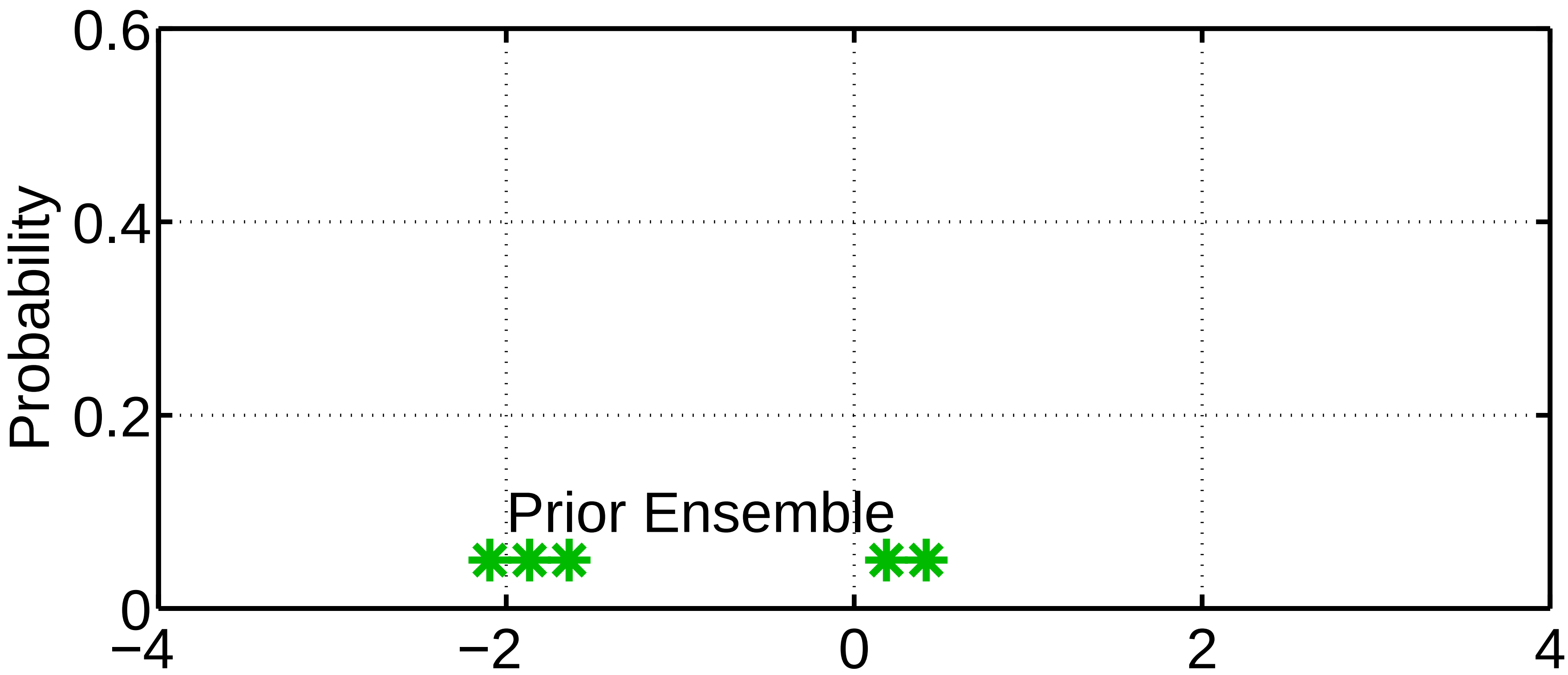


Exact properties of different methods may be unclear.

Trial and error still best way to see how they perform.

Will interact with properties of prediction models, etc.

Ensemble Adjustment (Kalman) Filter:



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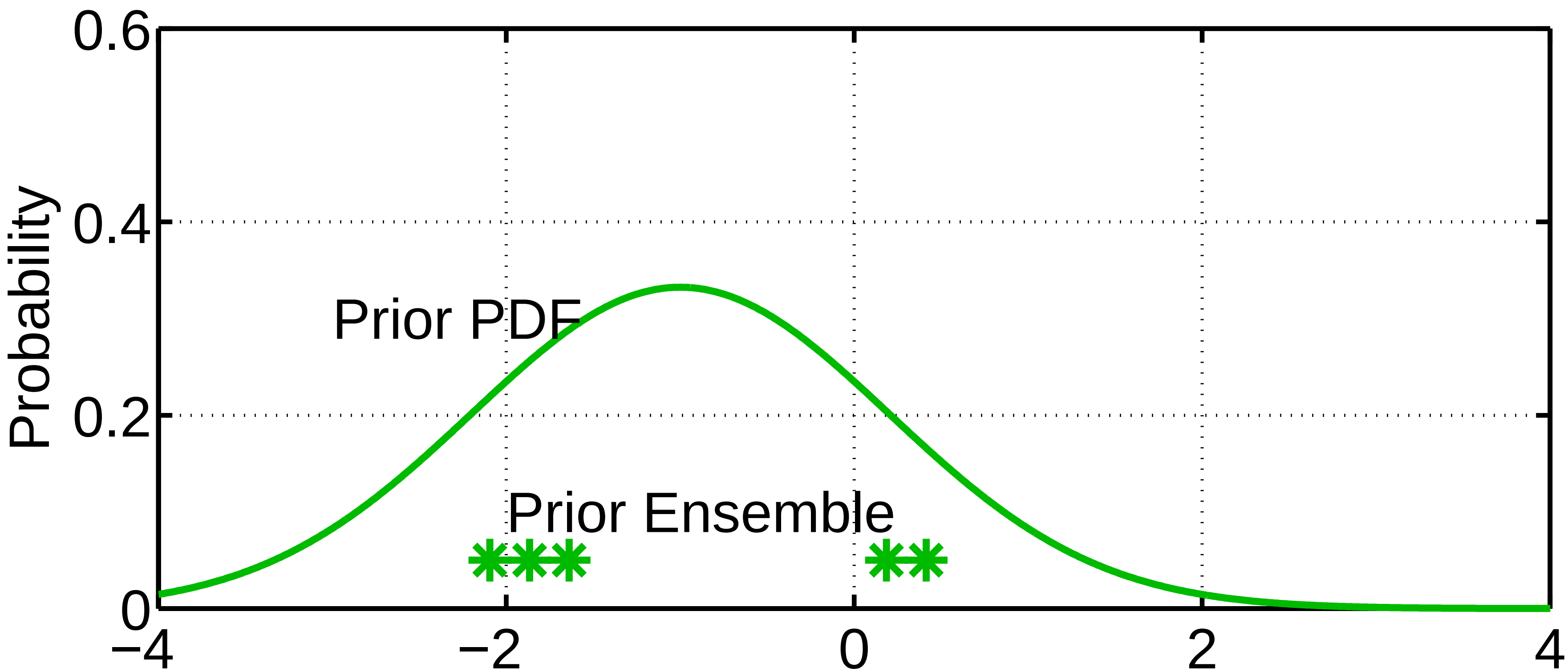
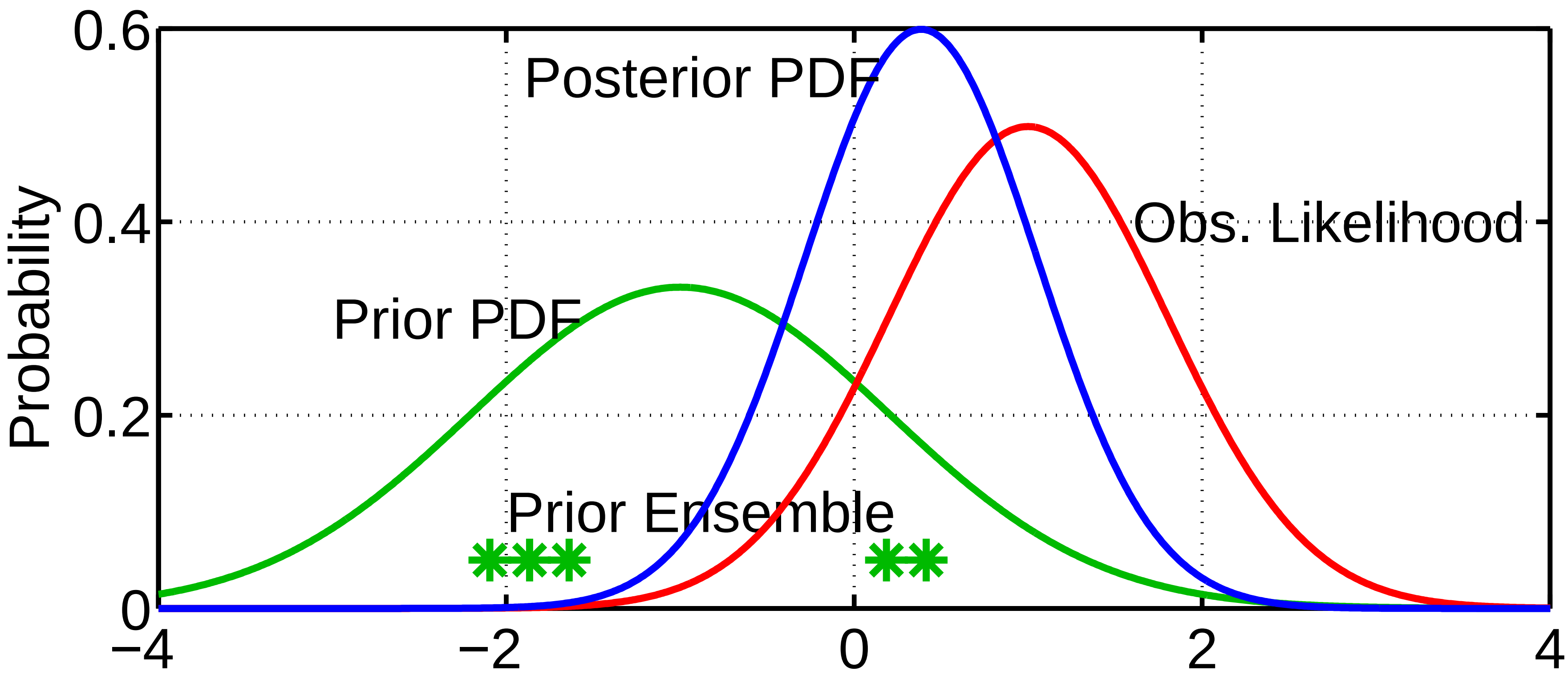


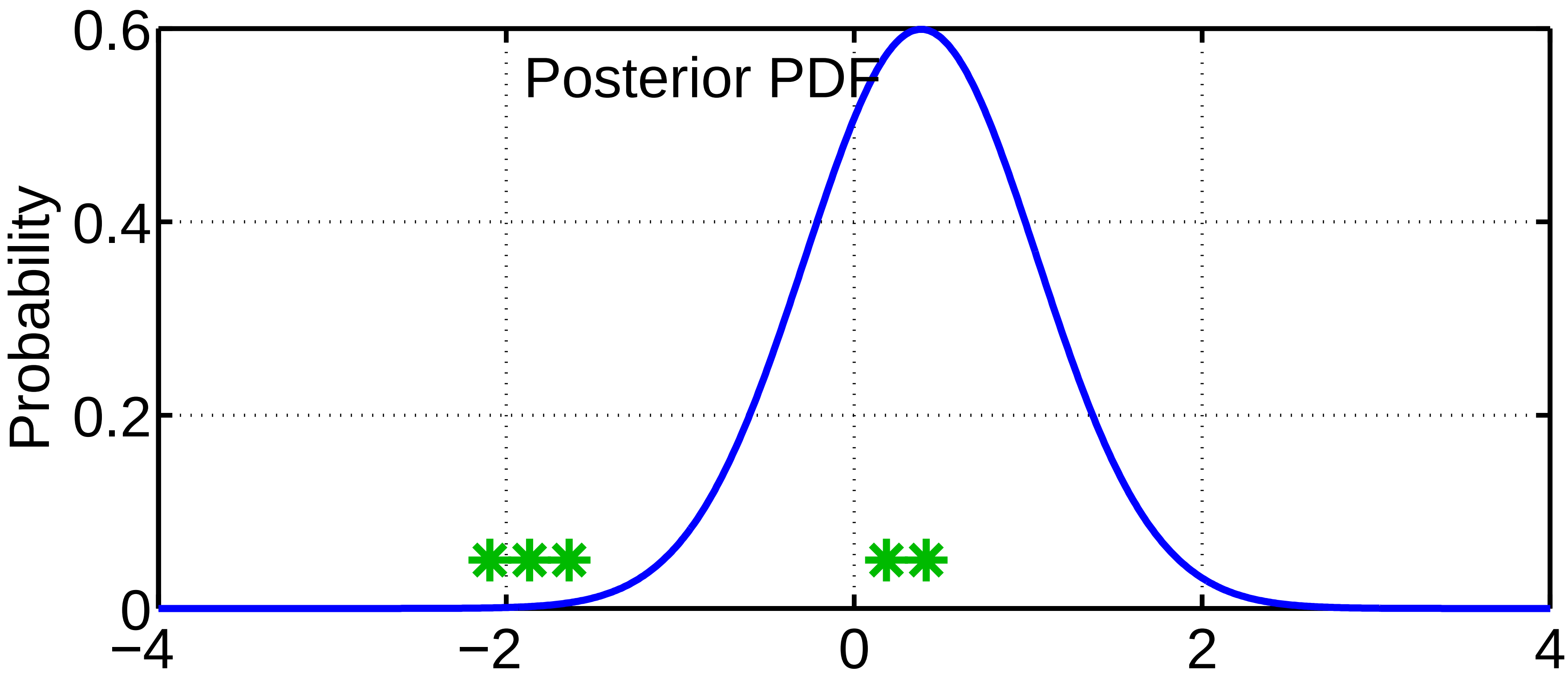
Again, fit a Gaussian to sample.

Ensemble Adjustment Kalman Filter:



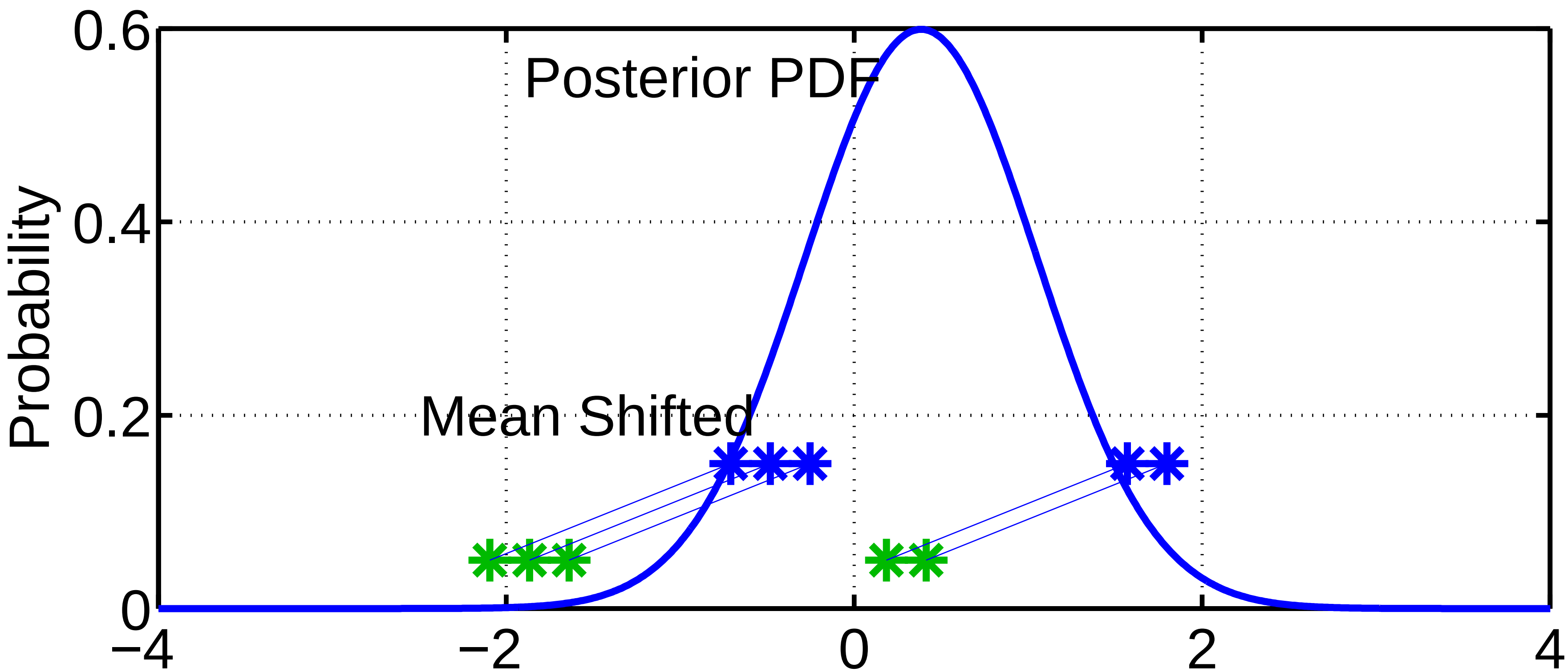
Compute posterior PDF.

Ensemble Adjustment (Kalman) Filter:



Use deterministic algorithm to 'adjust' ensemble.

Ensemble Adjustment (Kalman) Filter:



Use deterministic algorithm to ‘adjust’ ensemble.

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

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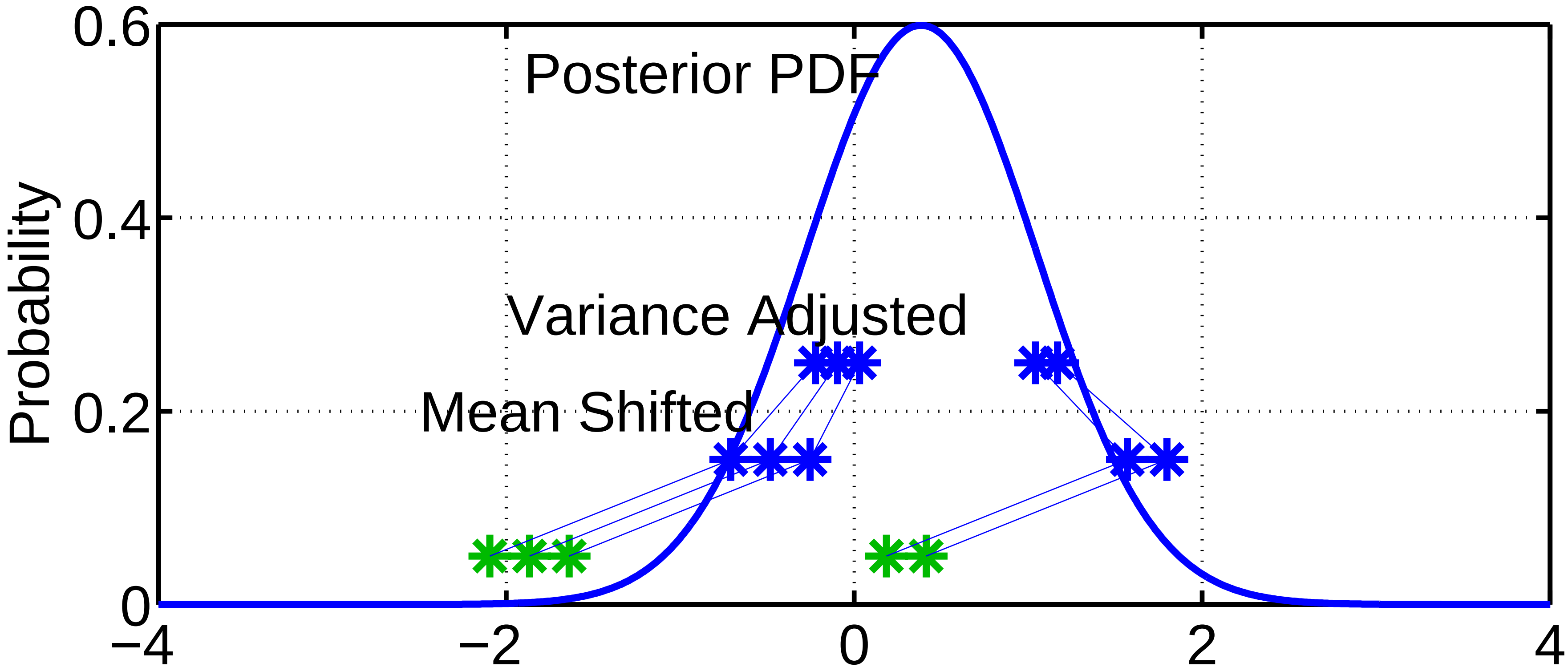


Use deterministic algorithm to 'adjust' ensemble.

First, 'shift' ensemble to have exact mean of posterior.

Second, use linear contraction to have exact variance of posterior.

Phase 2: Single observed variable, single unobserved variable

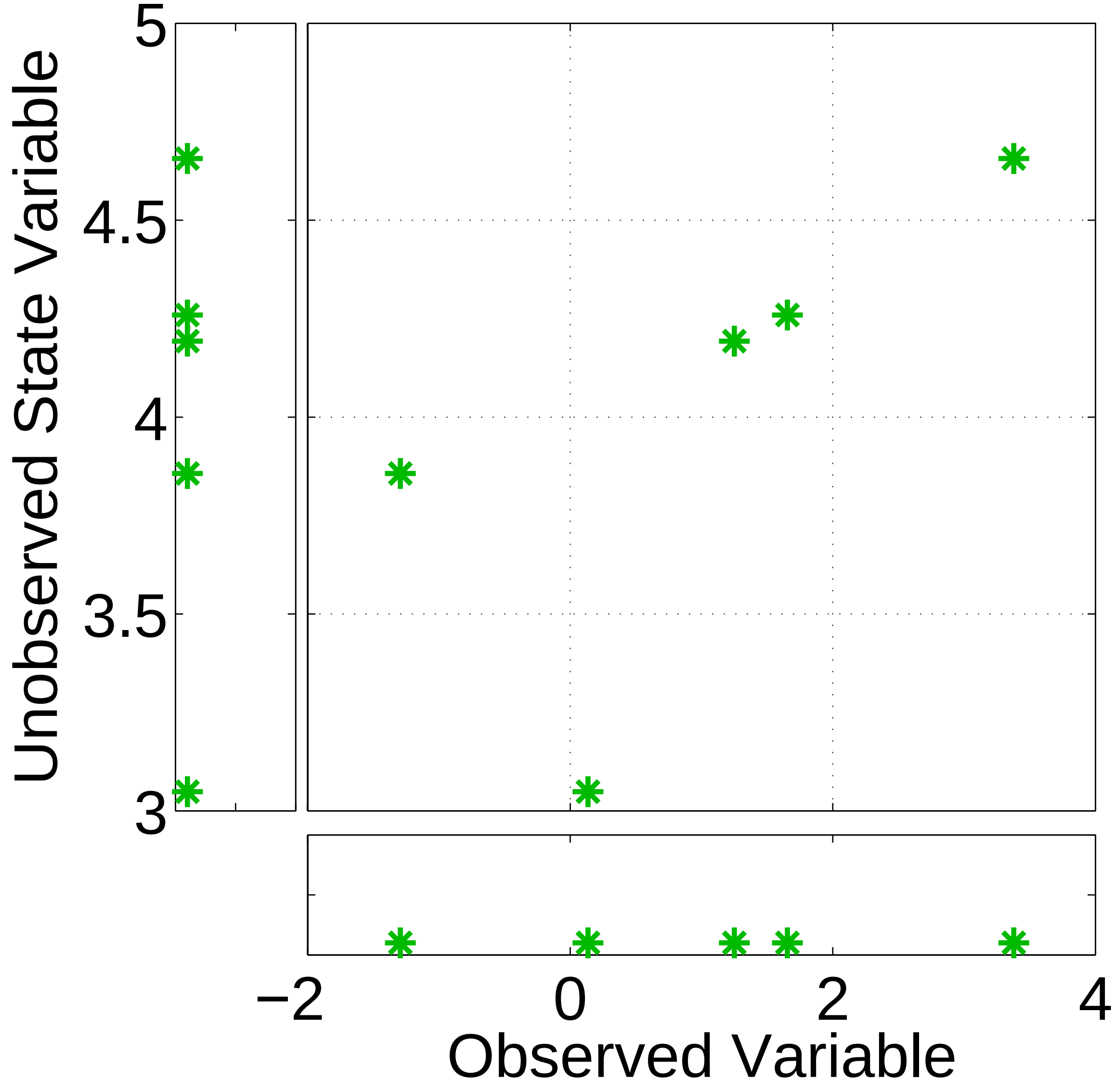
So far, have known observation likelihood for single variable.

Now, suppose prior has an additional variable.

Will examine how ensemble methods update additional variable.

Basic method generalizes to any number of additional variables.

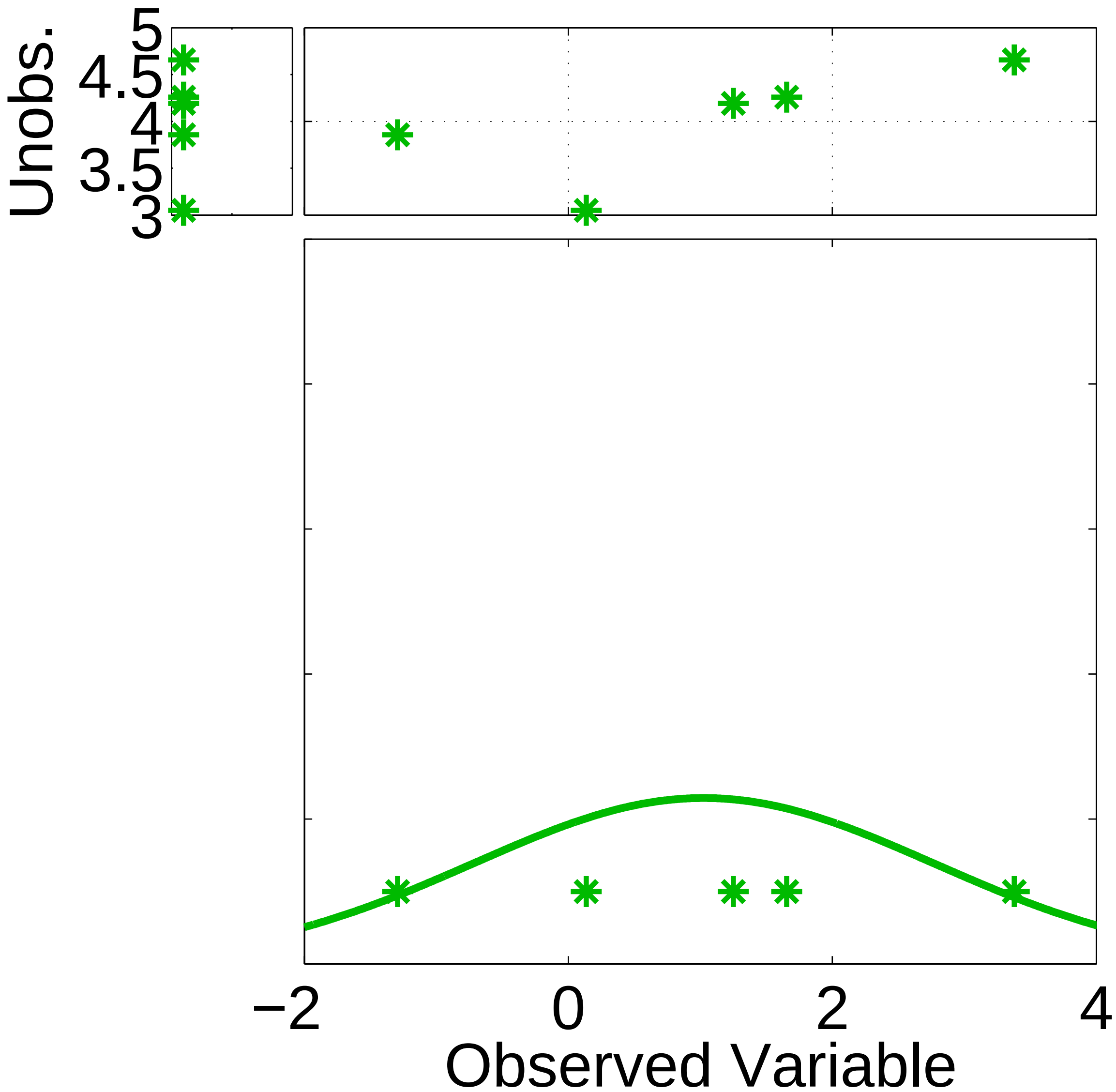
Ensemble filters: Updating additional prior state variables



Assume that all we know is prior joint distribution.

One variable is observed (SFO temperature).
What should happen to unobserved variable (S. CA. Gridpoint wind)?

Ensemble filters: Updating additional prior state variables



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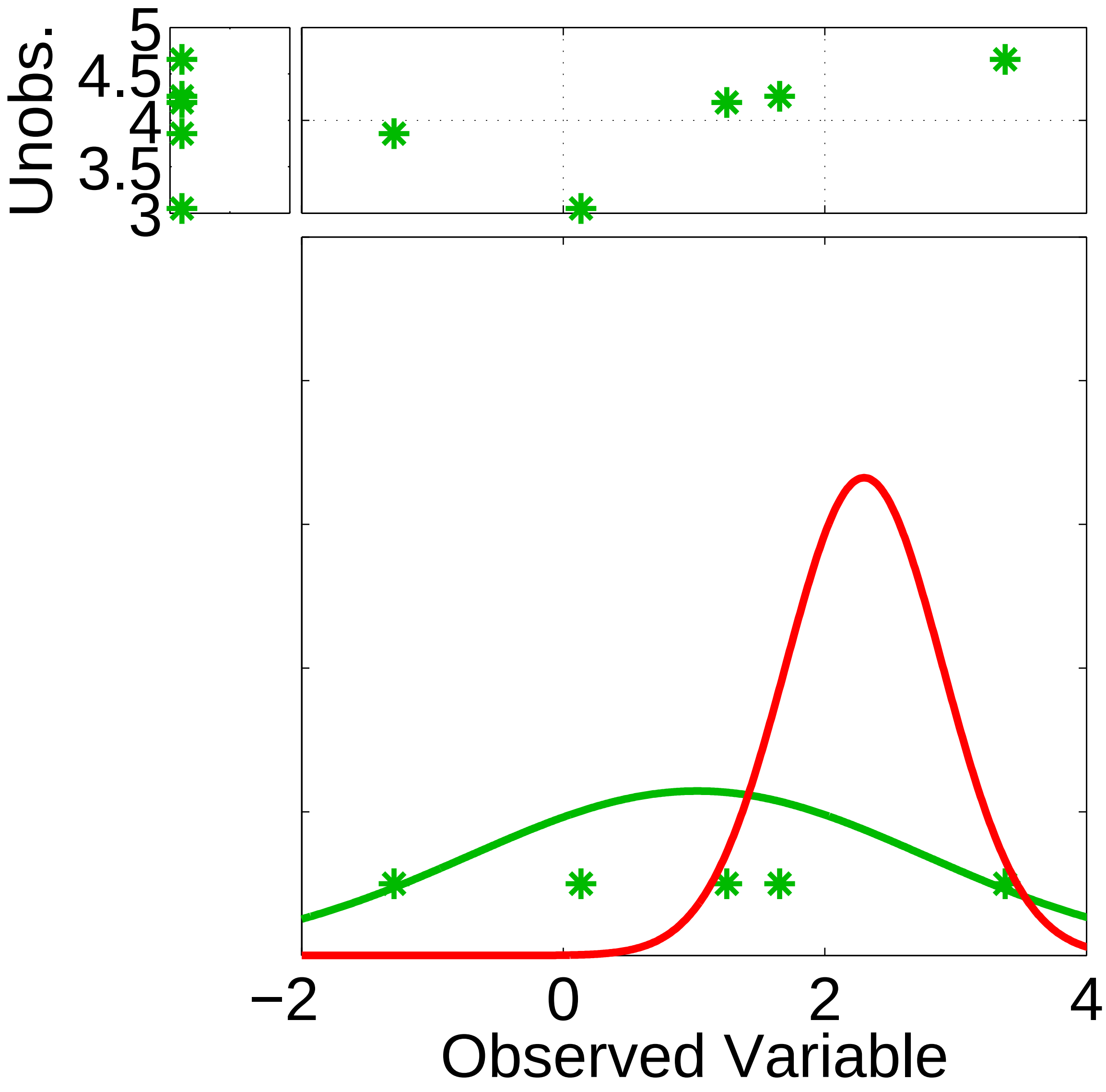
One variable is observed.

Update observed variable with ensemble adjustment filter.

Ensemble filters: Updating additional prior state variables



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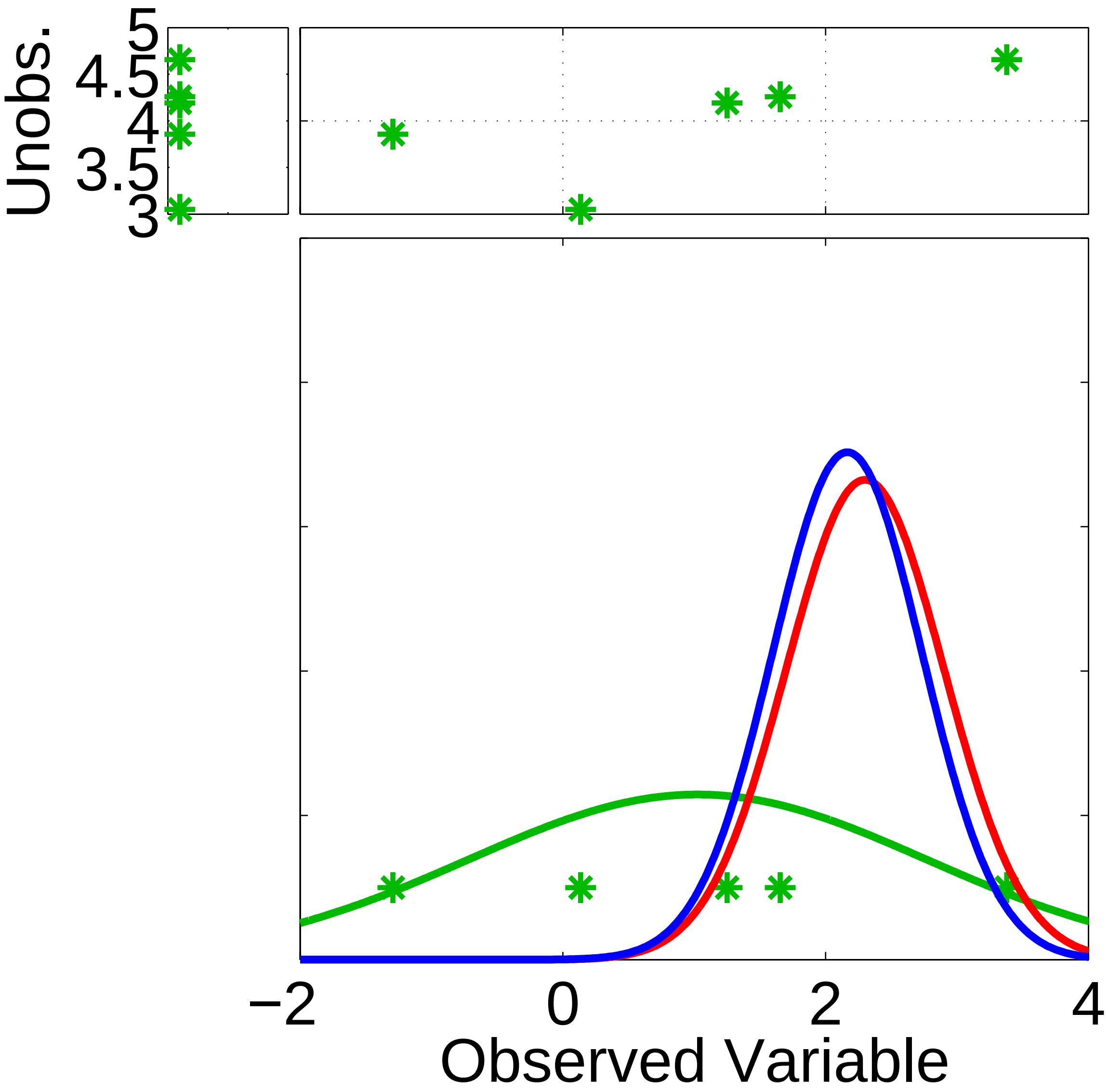

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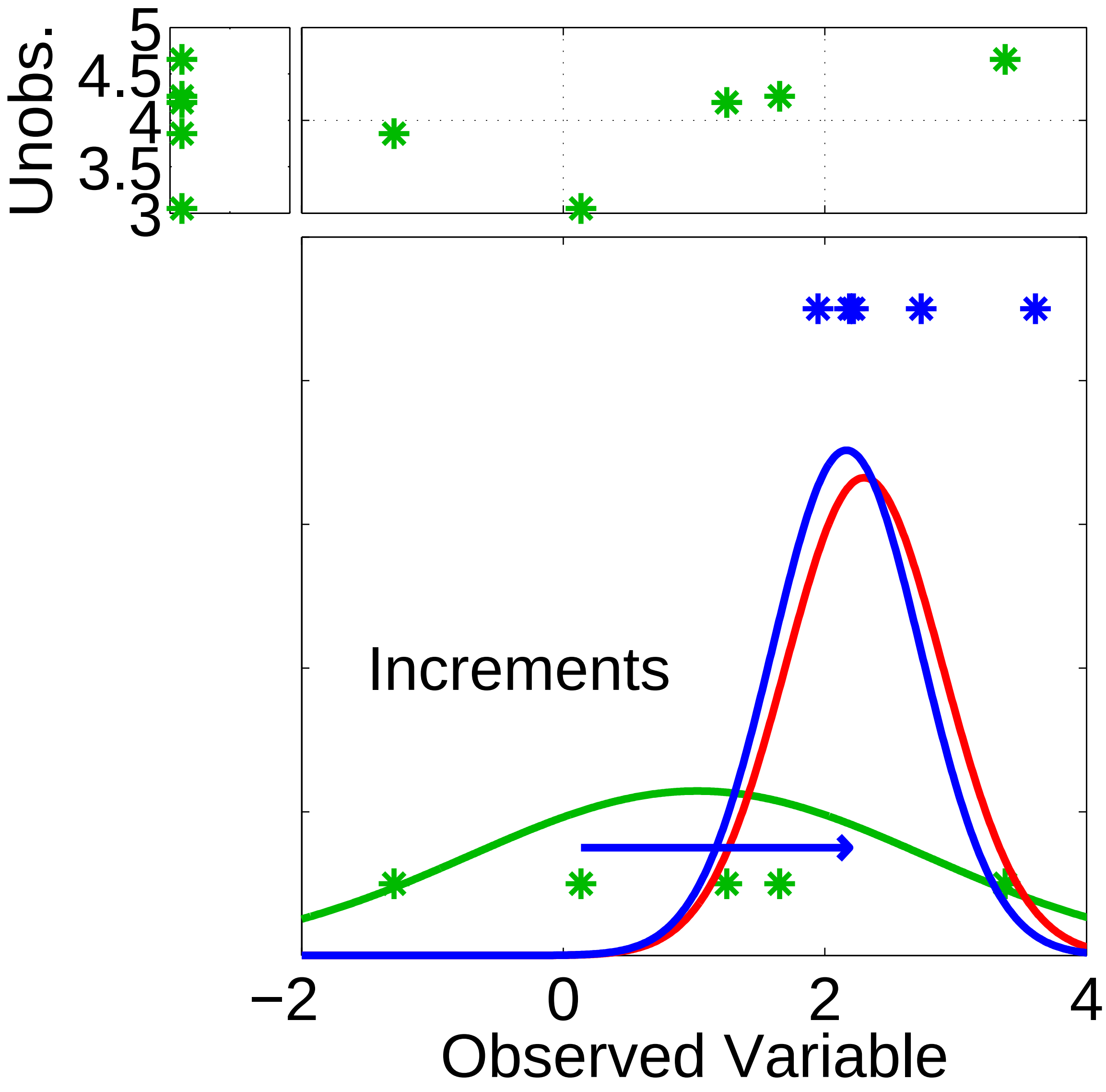

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One variable is observed.

Compute increments for prior ensemble members of observed variable.

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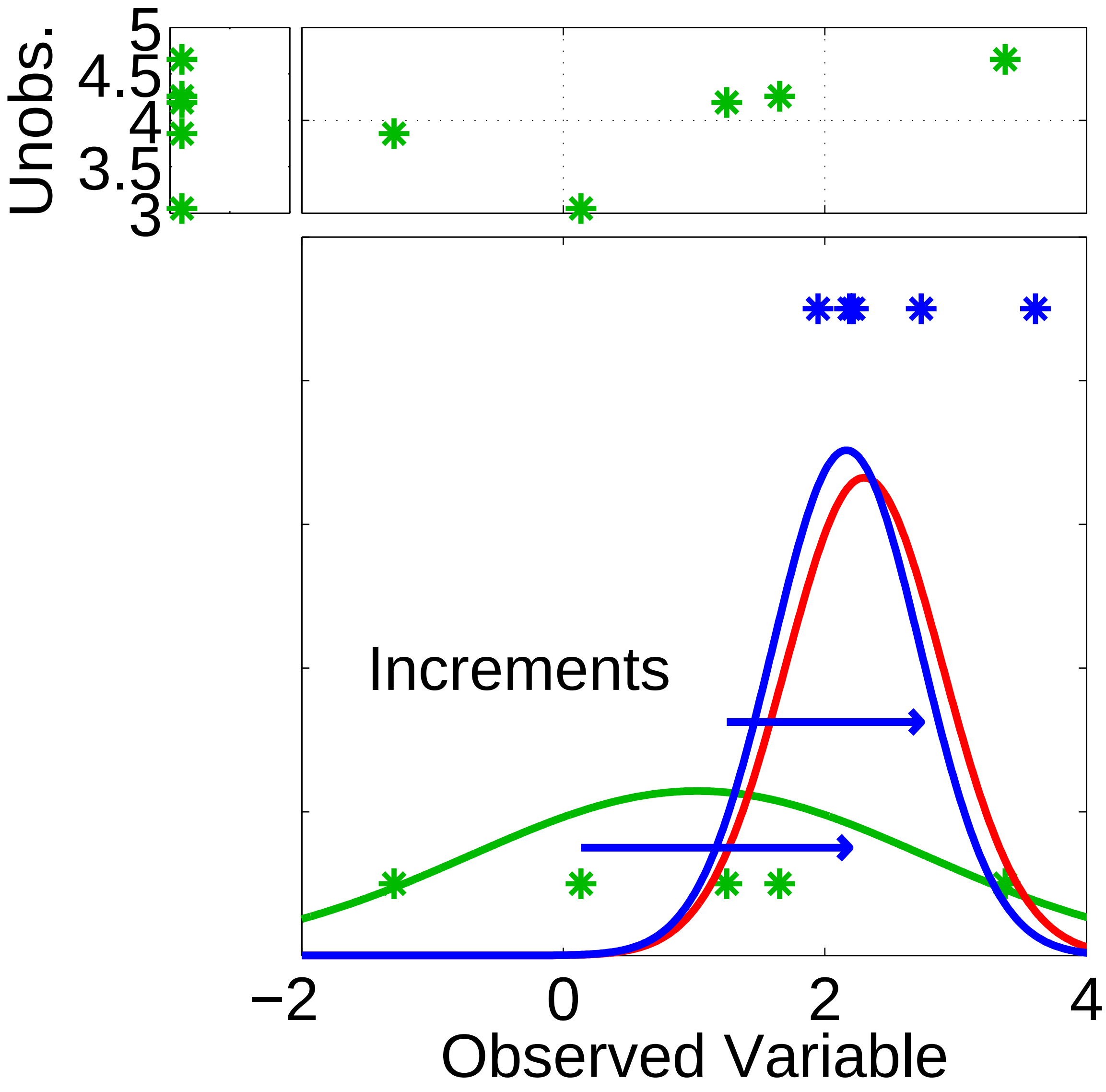

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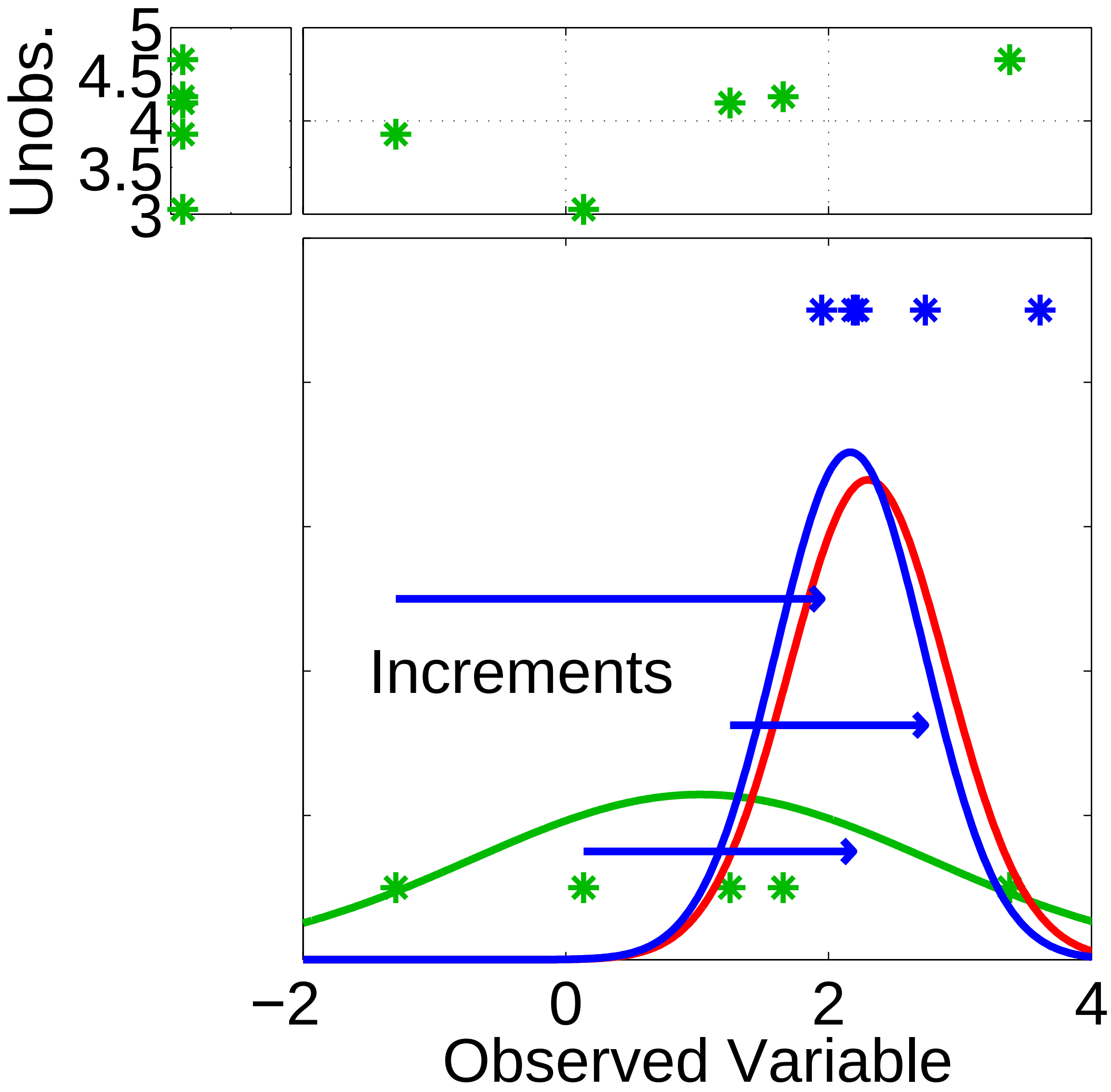

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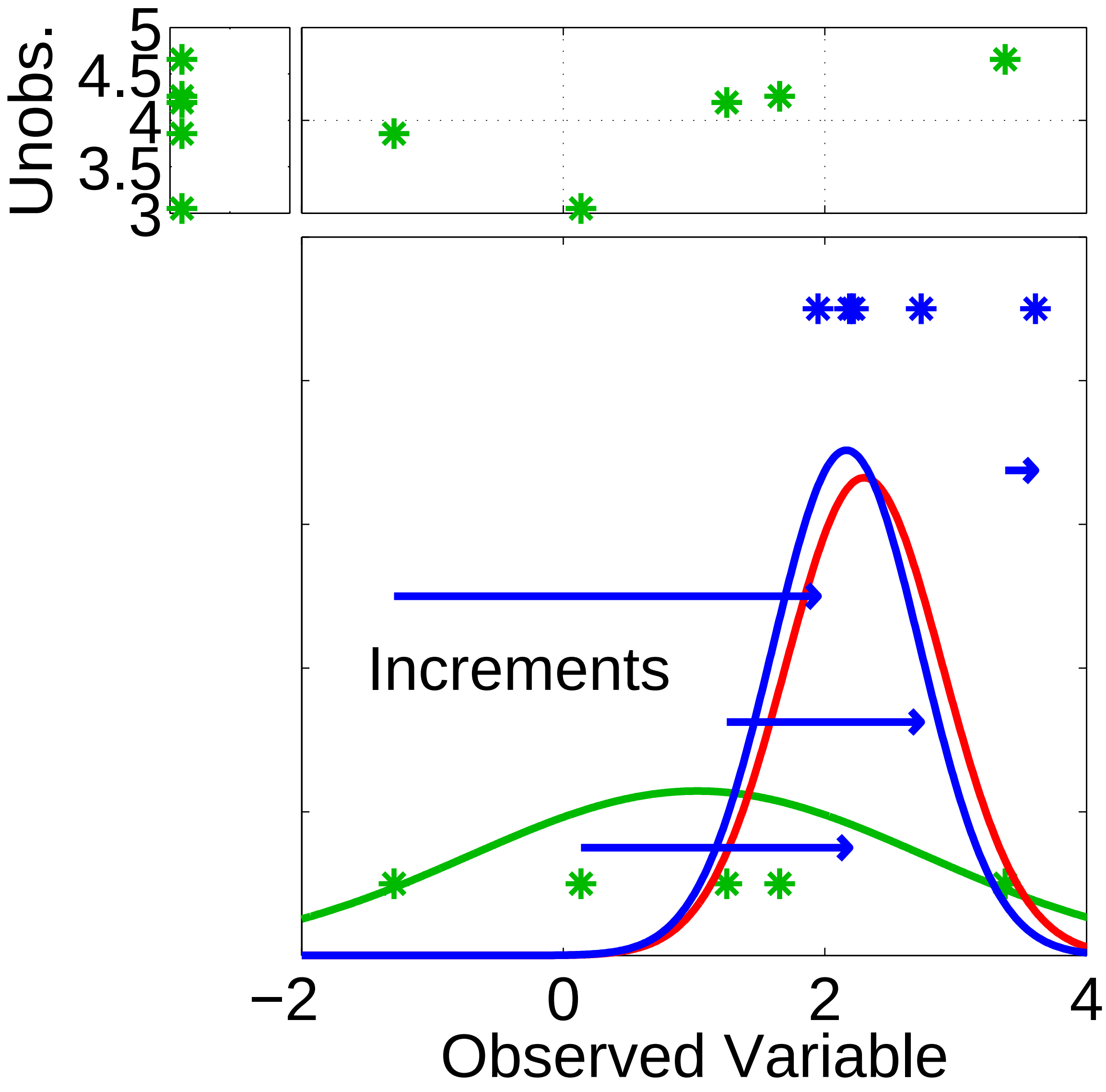

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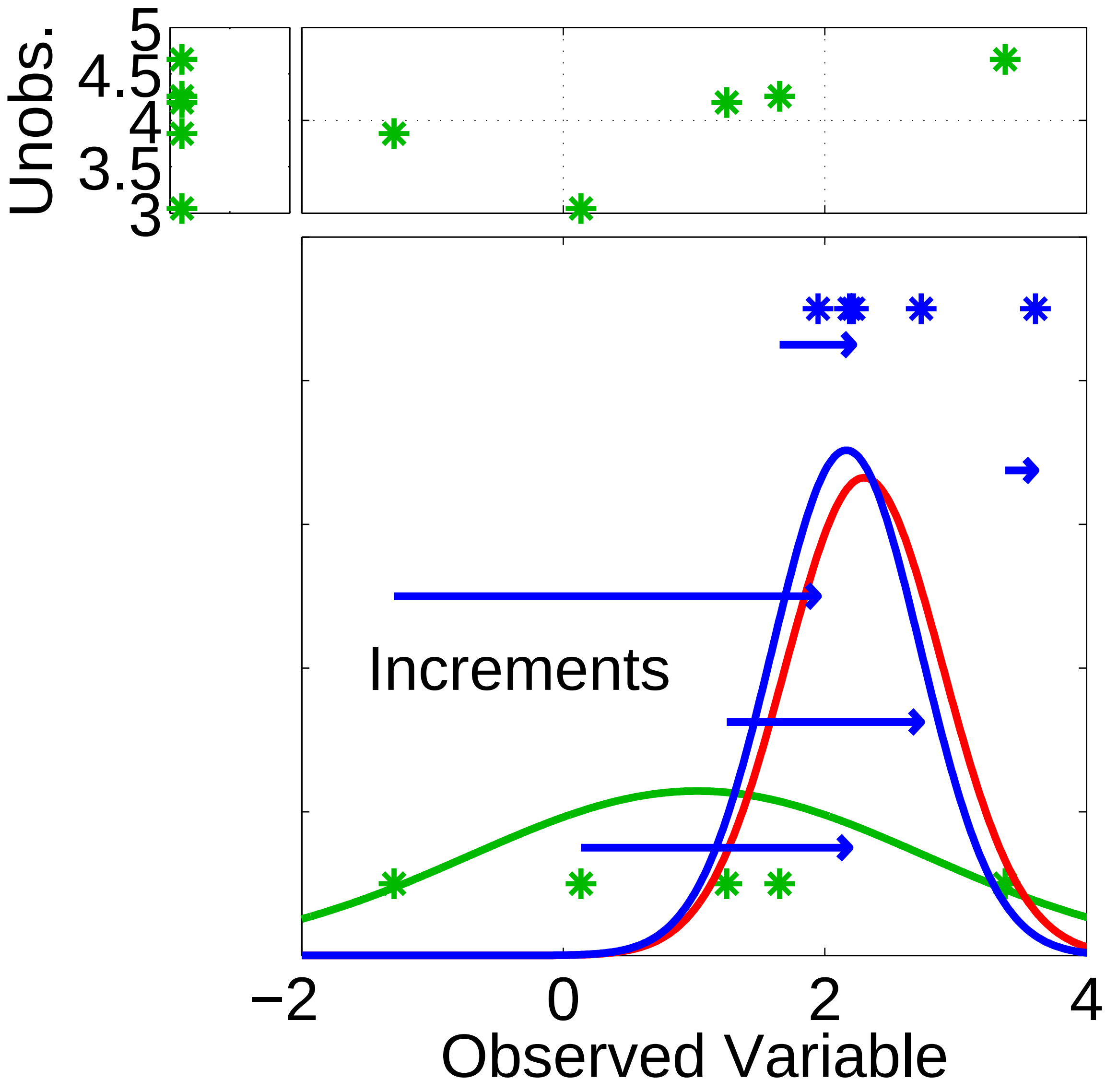

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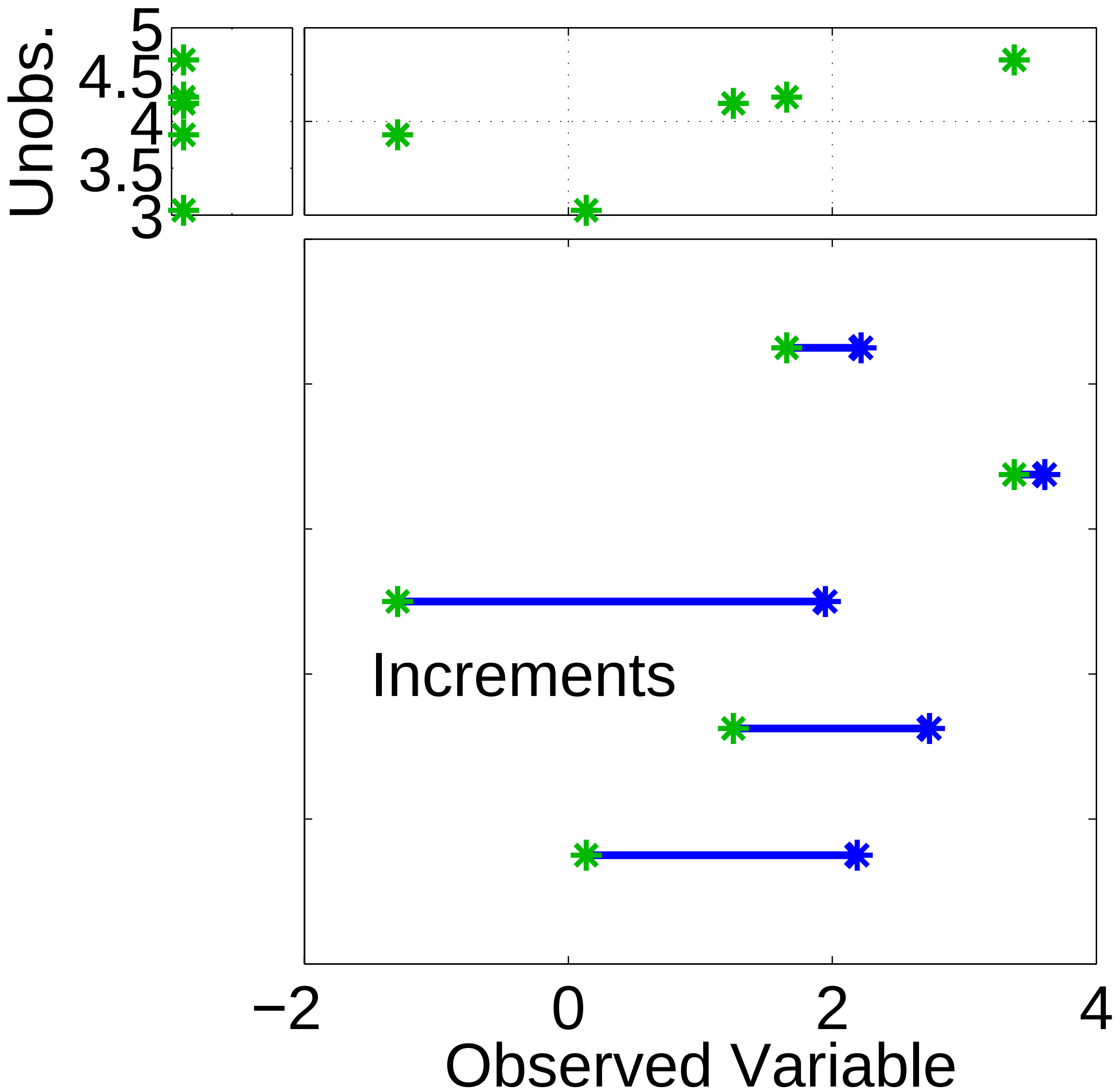
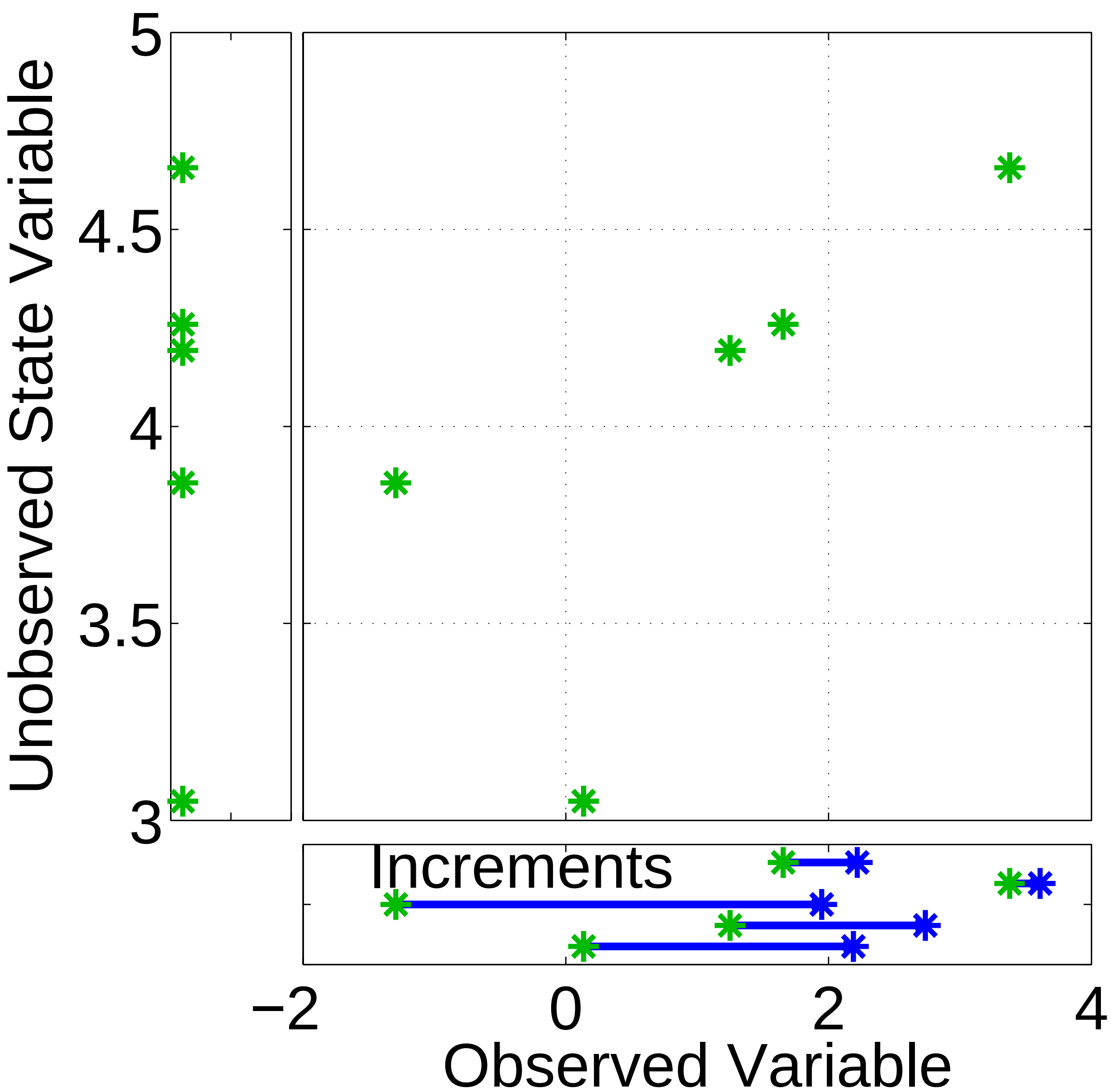


Assume that all we know is prior joint distribution.

One variable is observed.

Using only increments guarantees that if observation had no impact on observed variable, unobserved variable is unchanged (highly desirable).

Ensemble filters: Updating additional prior state variables



Assume that all we know is prior joint distribution.

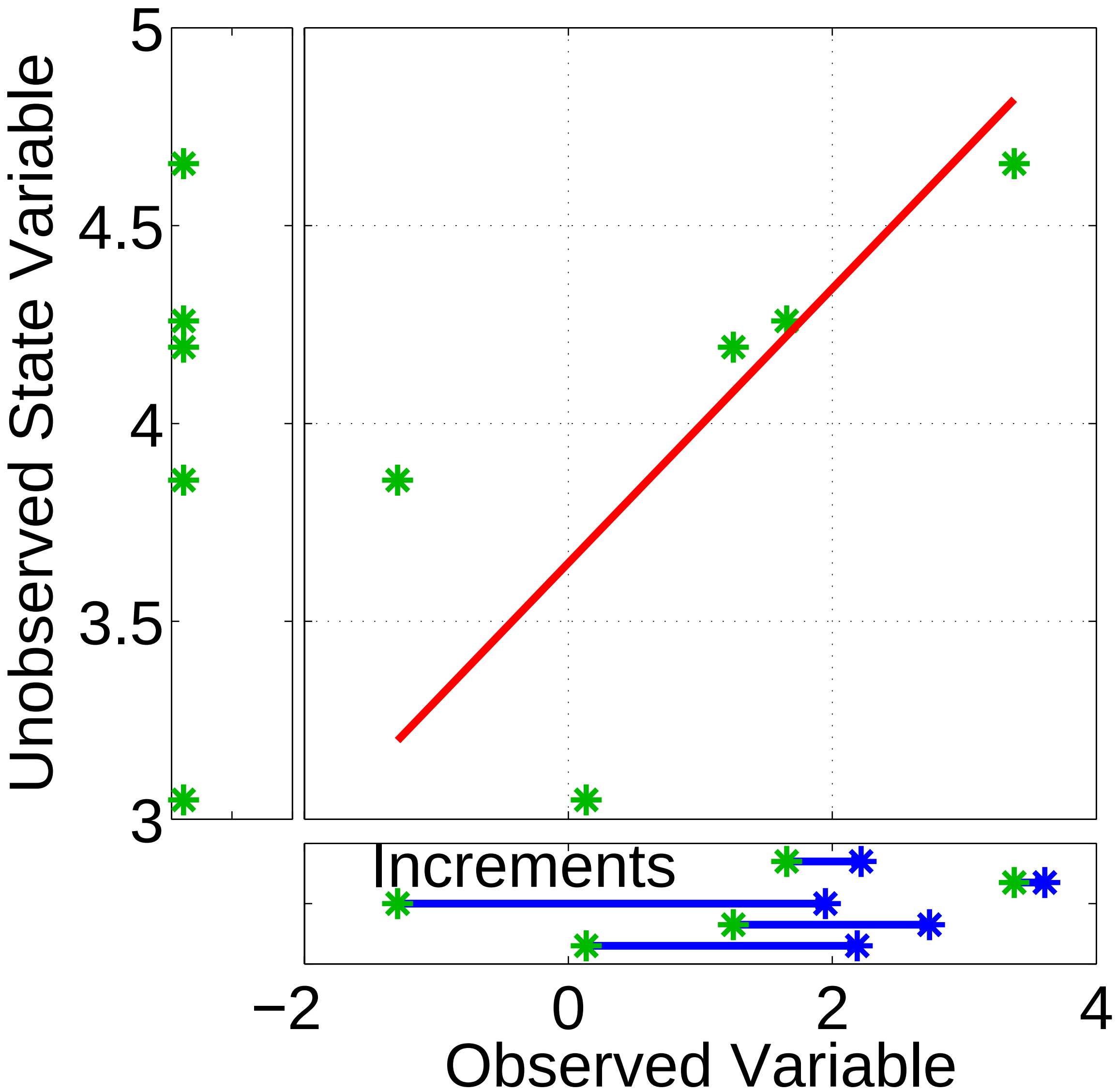
How should the unobserved variable be impacted?

First choice: least squares

Equivalent to linear regression.

Same as assuming binormal prior.

Ensemble filters: Updating additional prior state variables



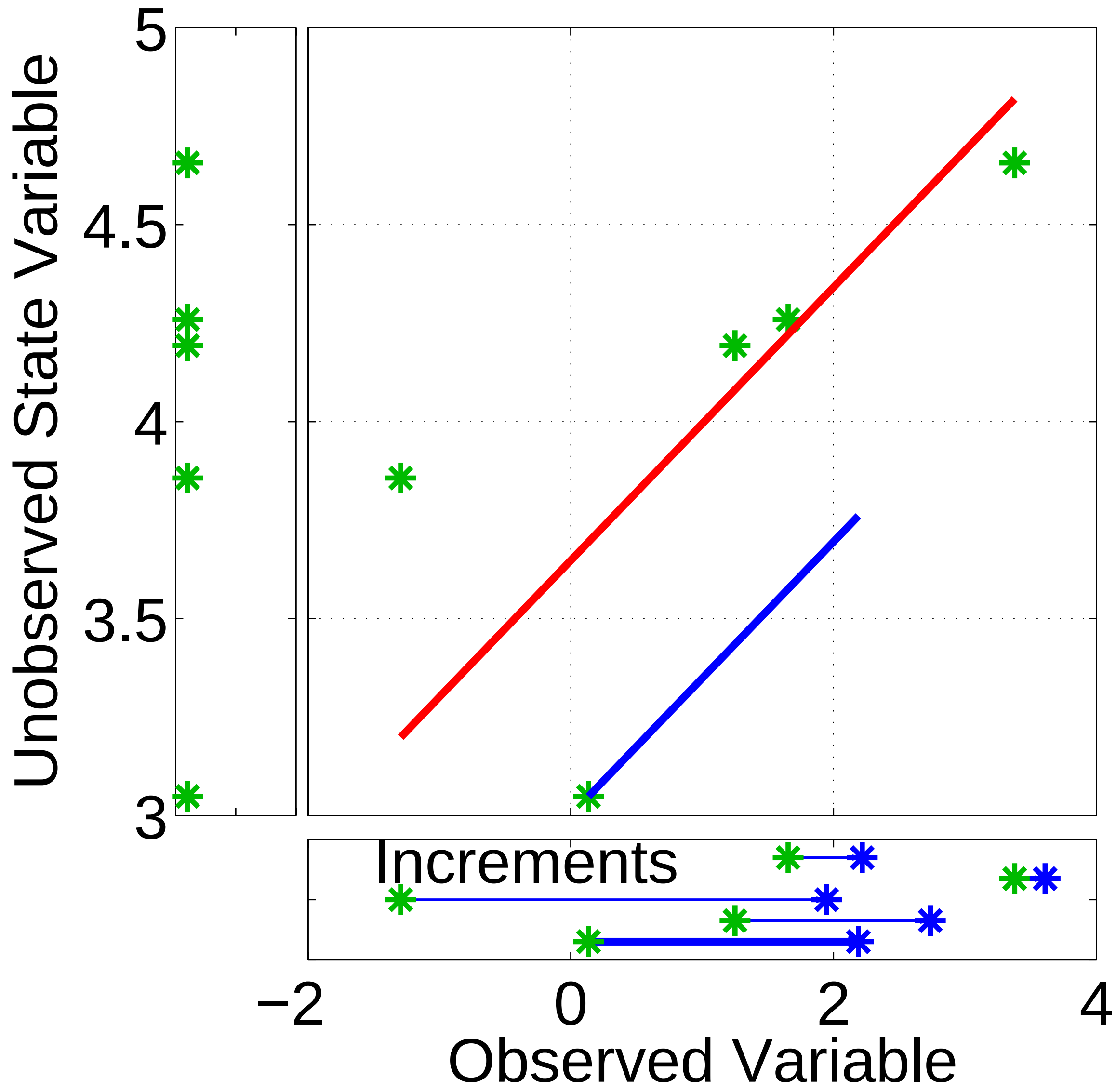
Have joint prior distribution of two variables.

How should the unobserved variable be impacted?

First choice: least squares

Begin by finding least squares fit.

Ensemble filters: Updating additional prior state variables

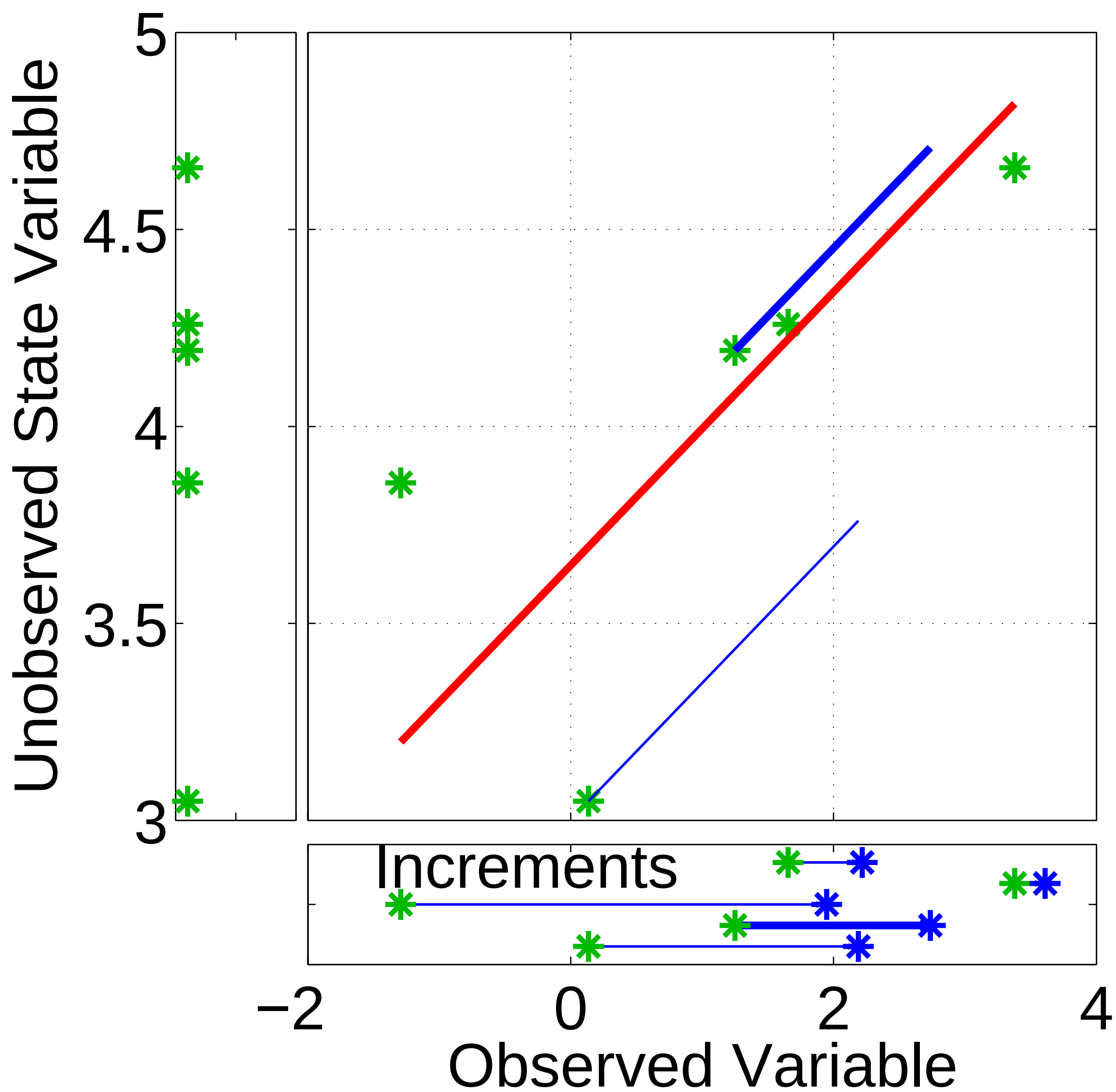


Have joint prior distribution of two variables.

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

Equivalent to first finding image of increment in joint space.

Ensemble filters: Updating additional prior state variables



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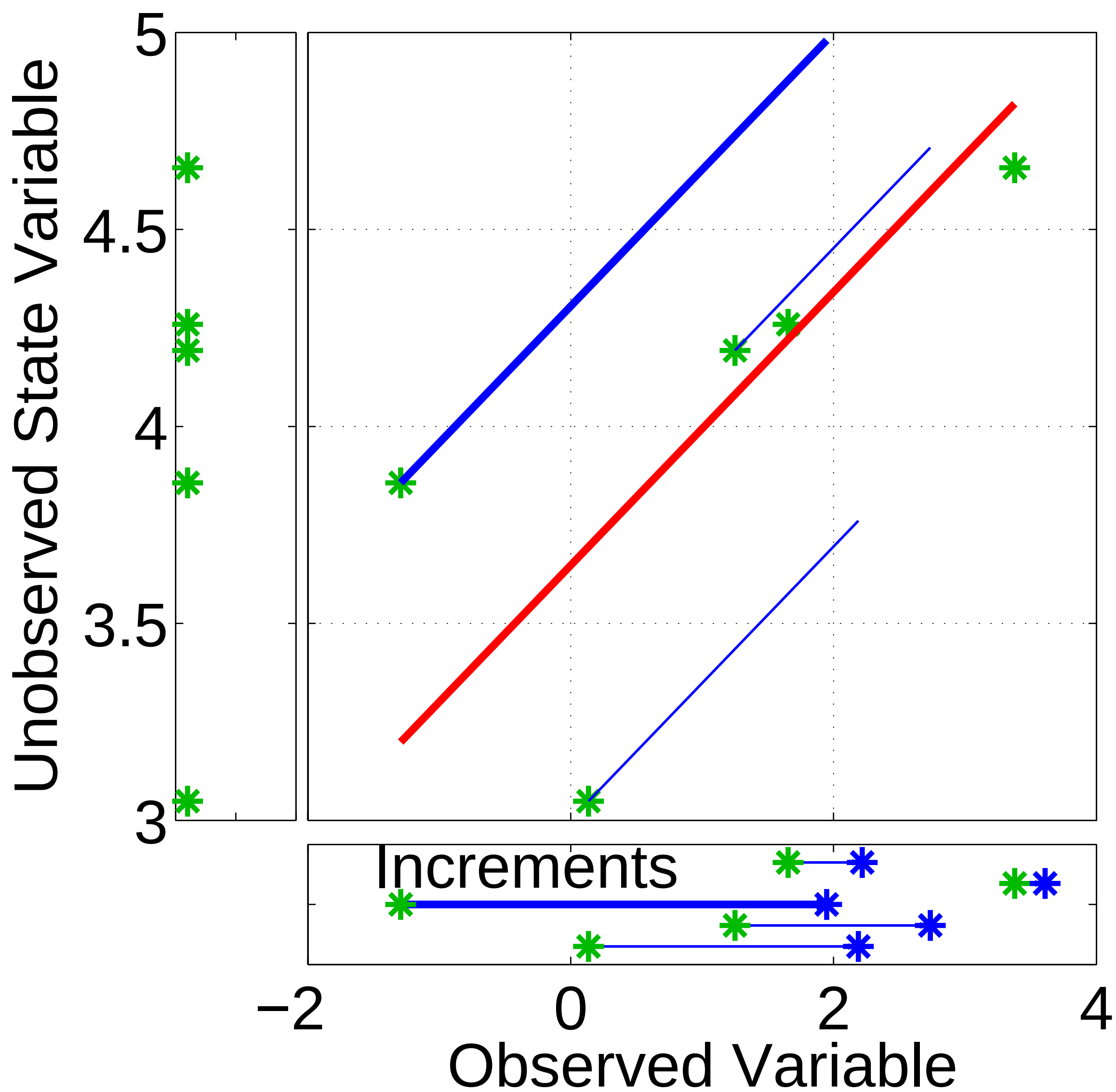

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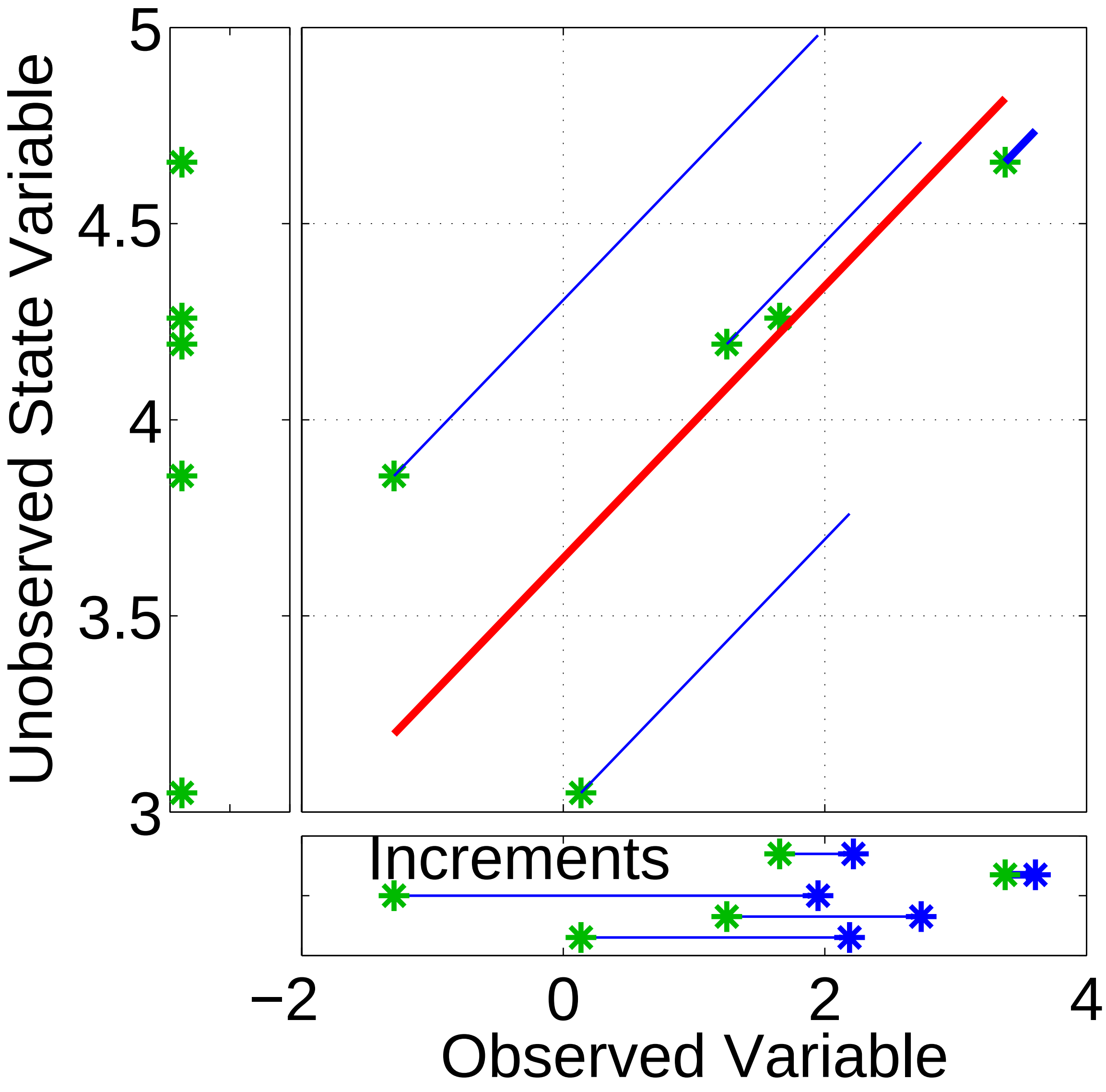

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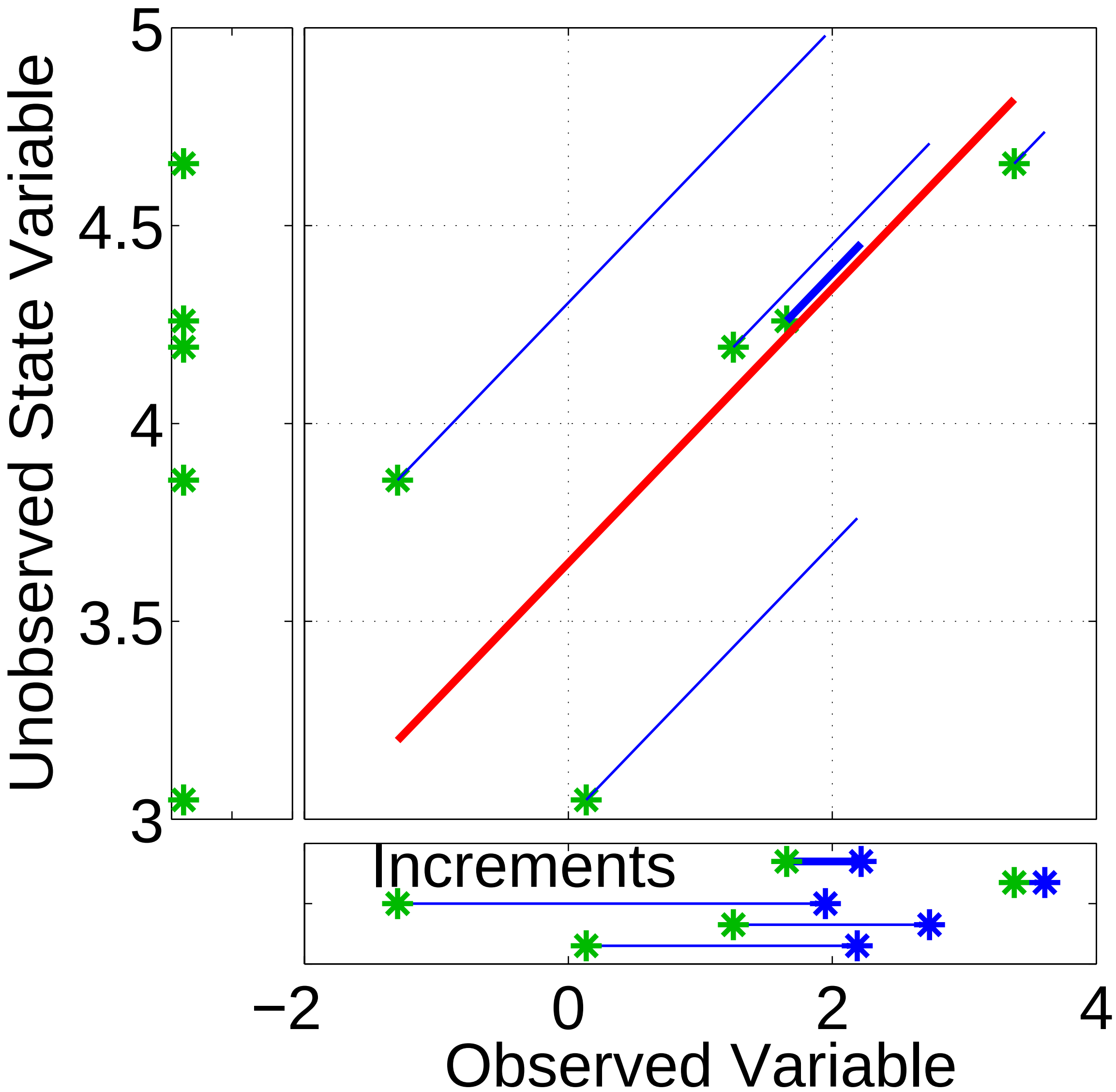

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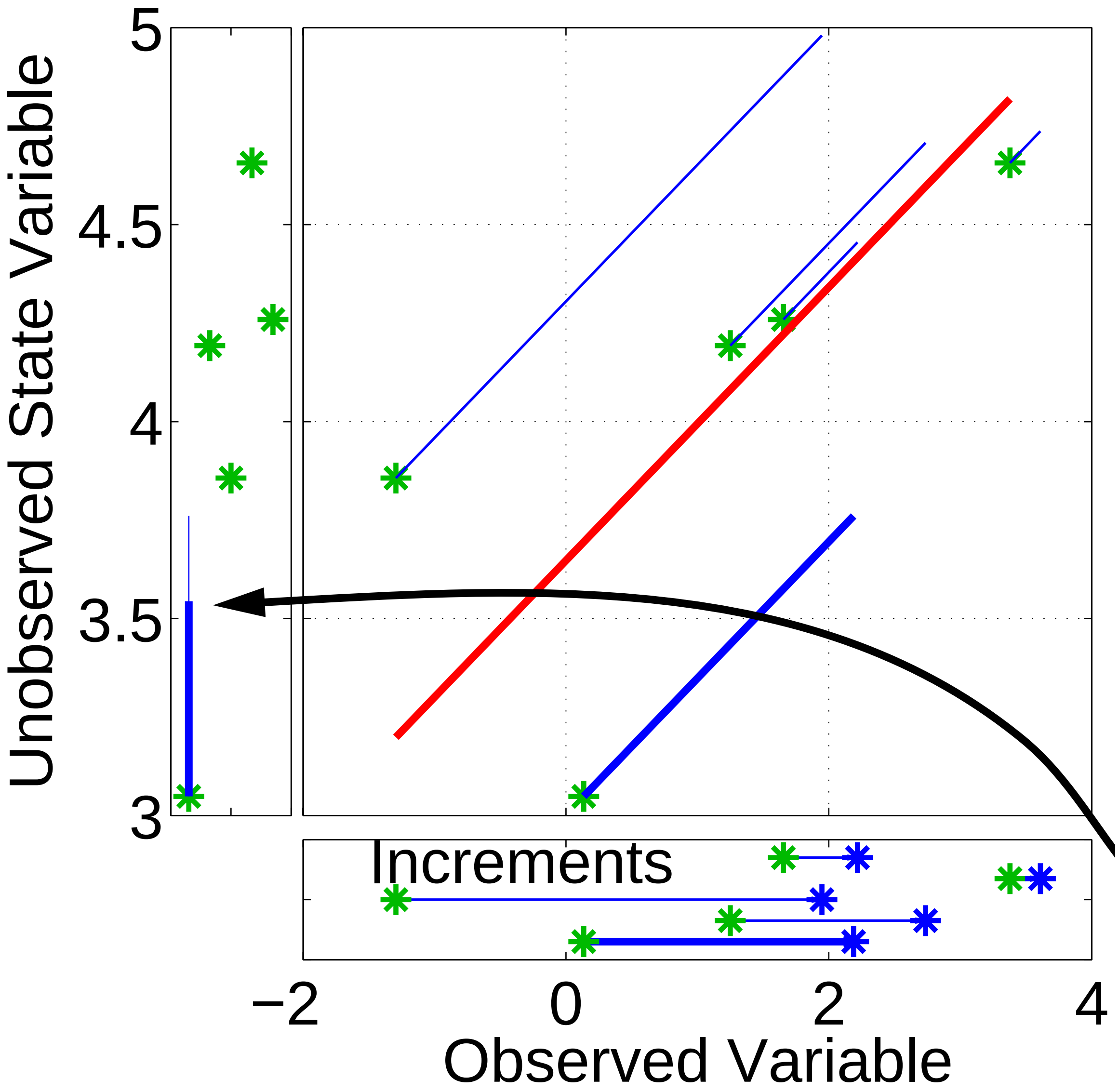


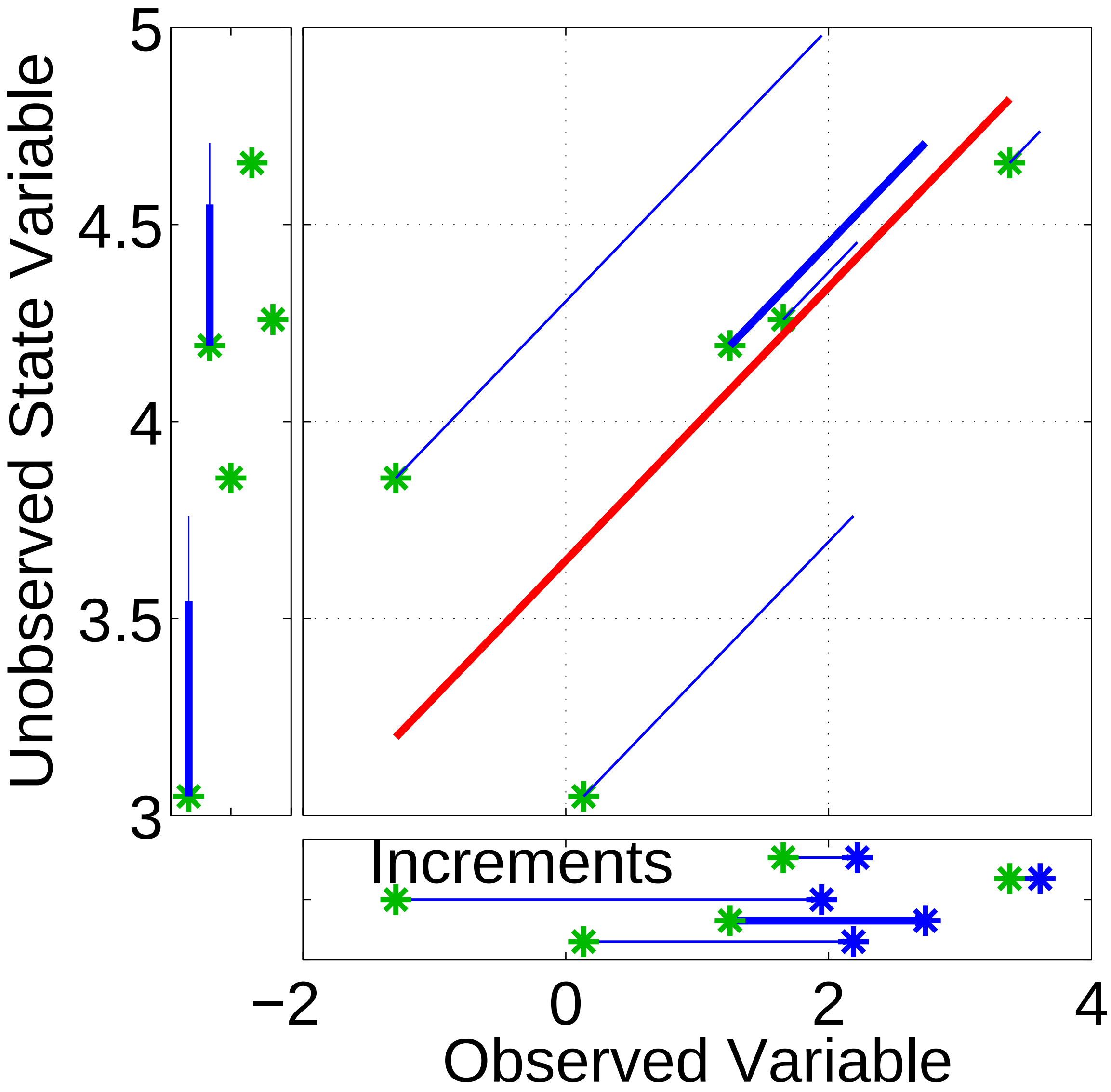
Have joint prior distribution of two variables.

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

Then projecting from joint space onto unobserved priors.

Finally, multiply by prior sample correlation.

Ensemble filters: Updating additional prior state variables



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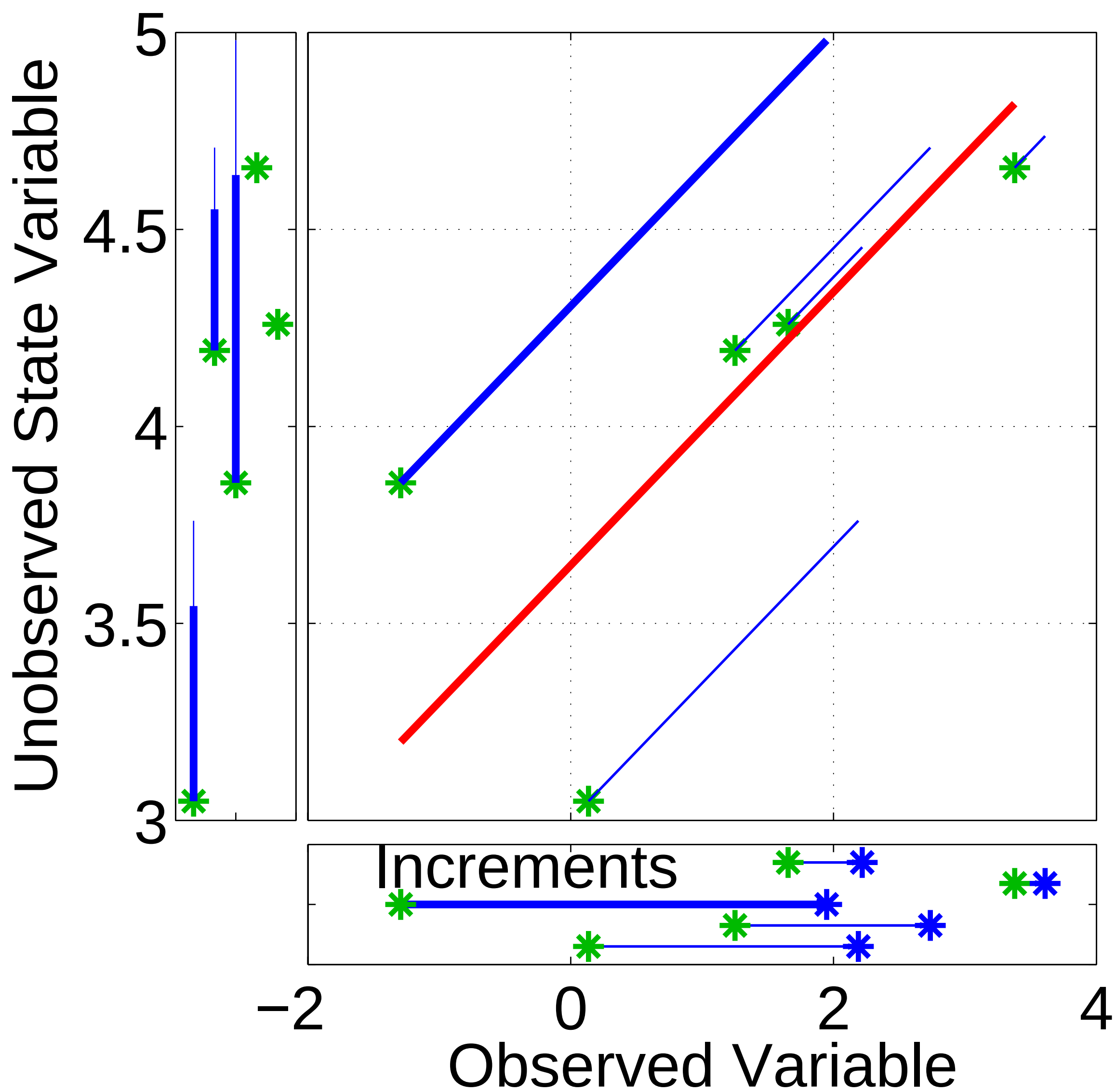

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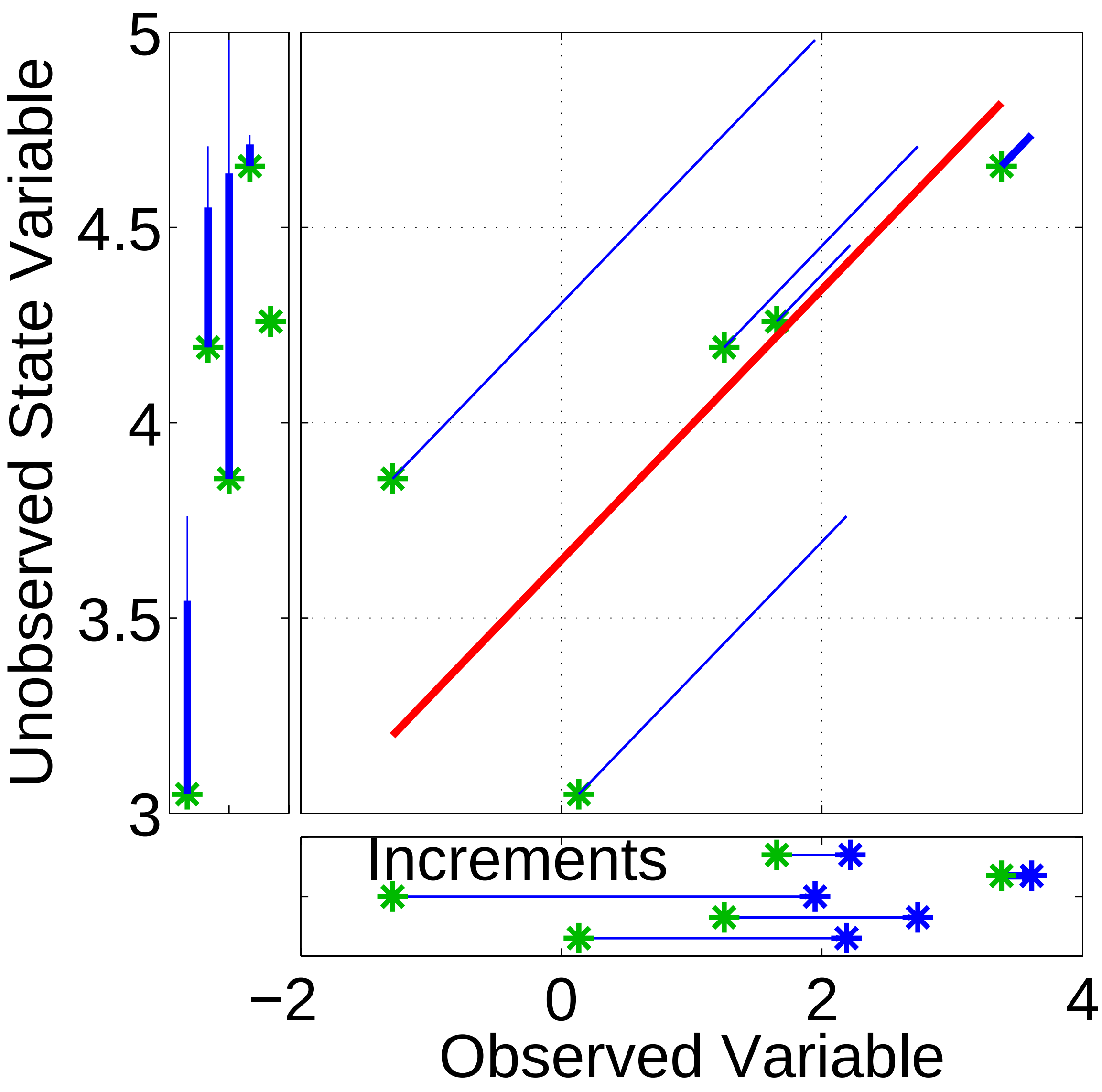

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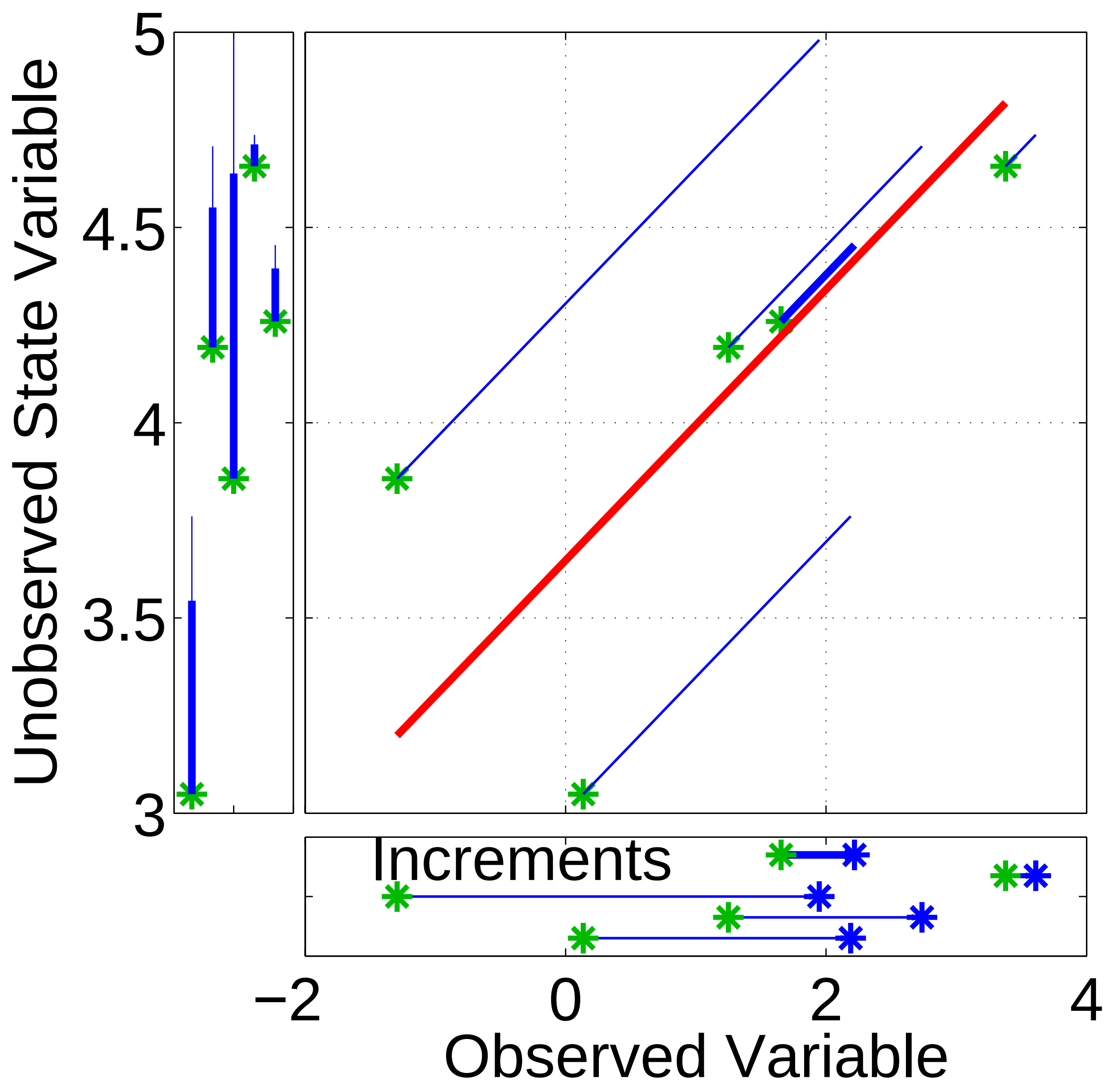

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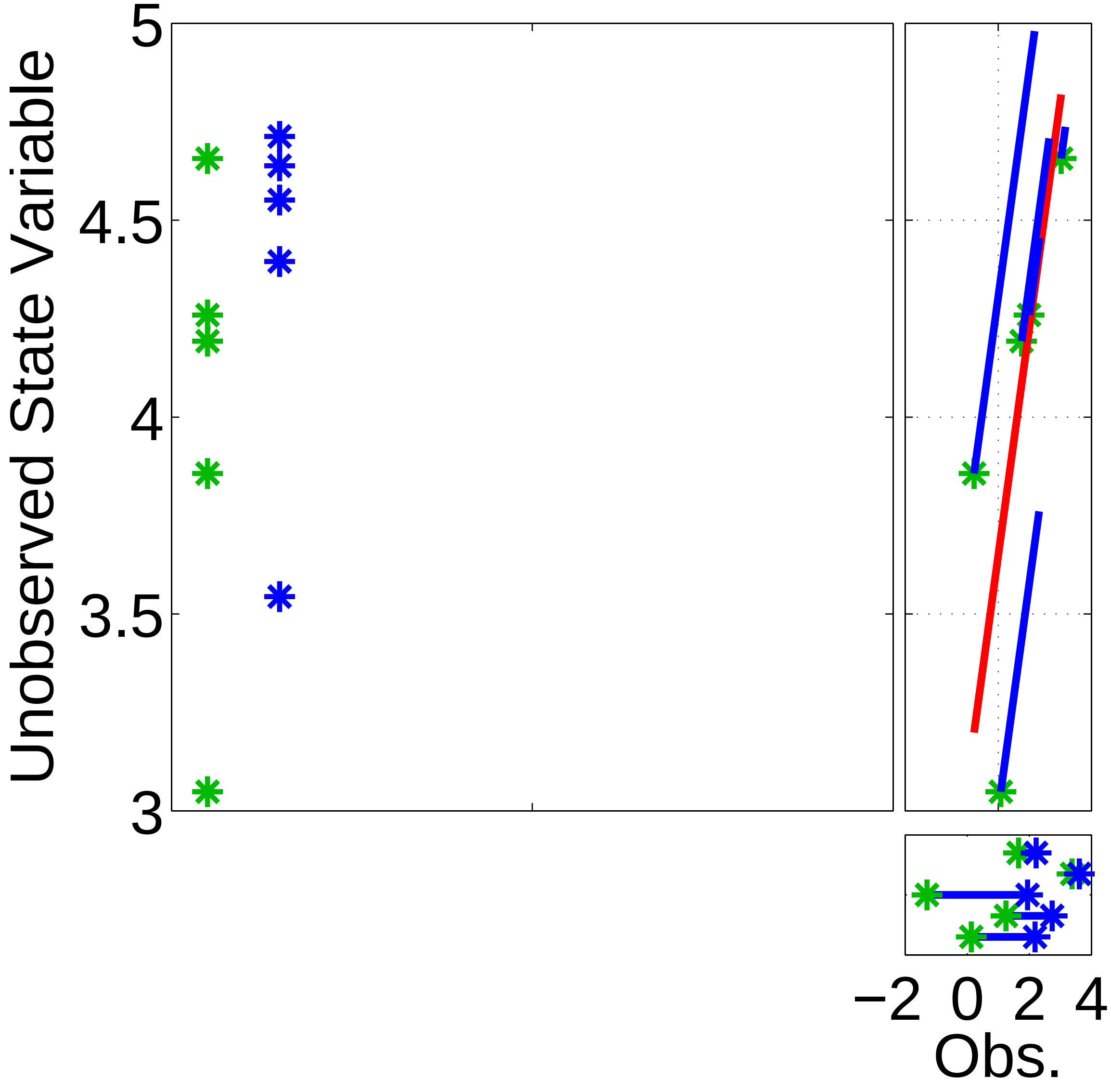

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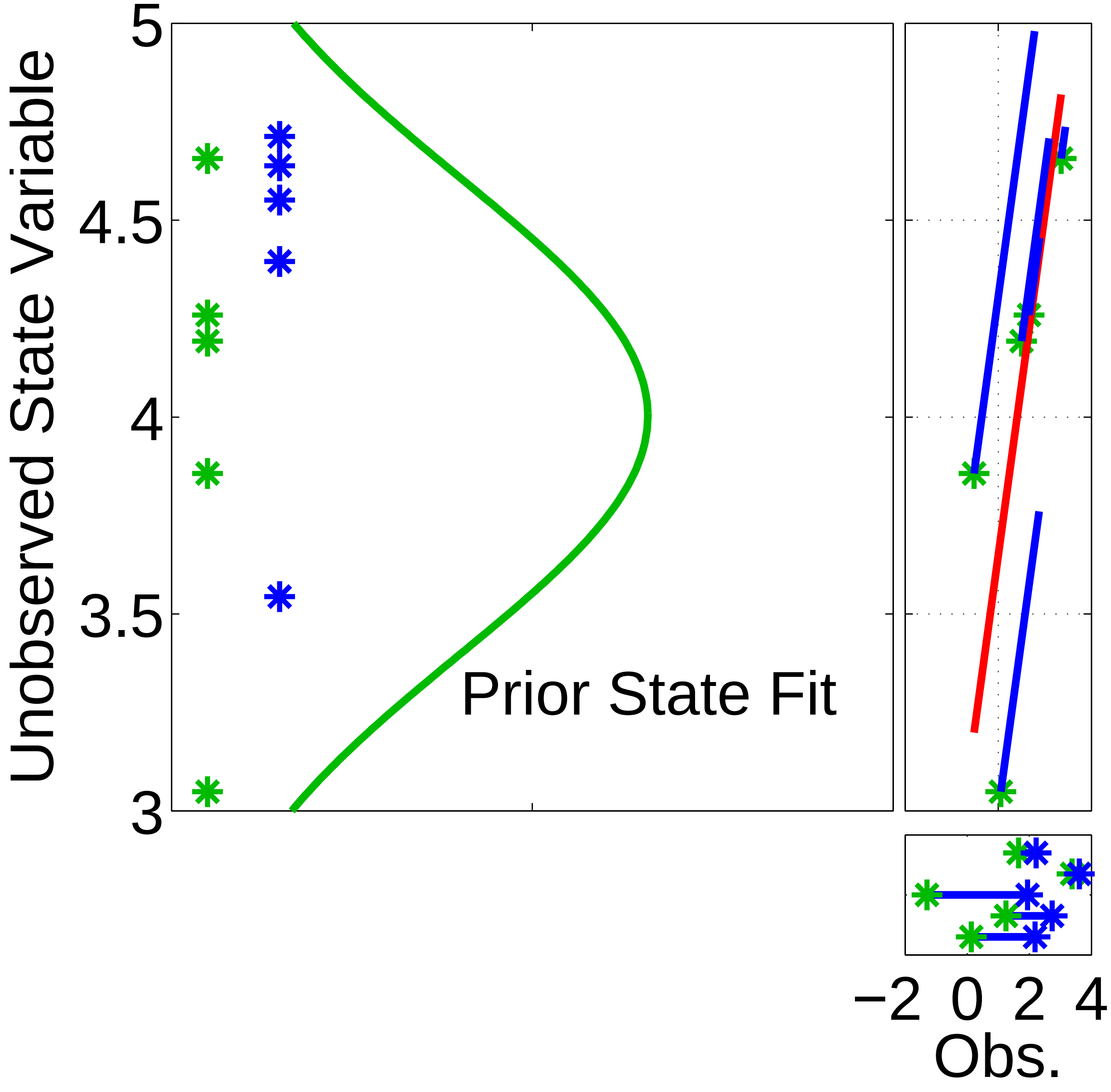

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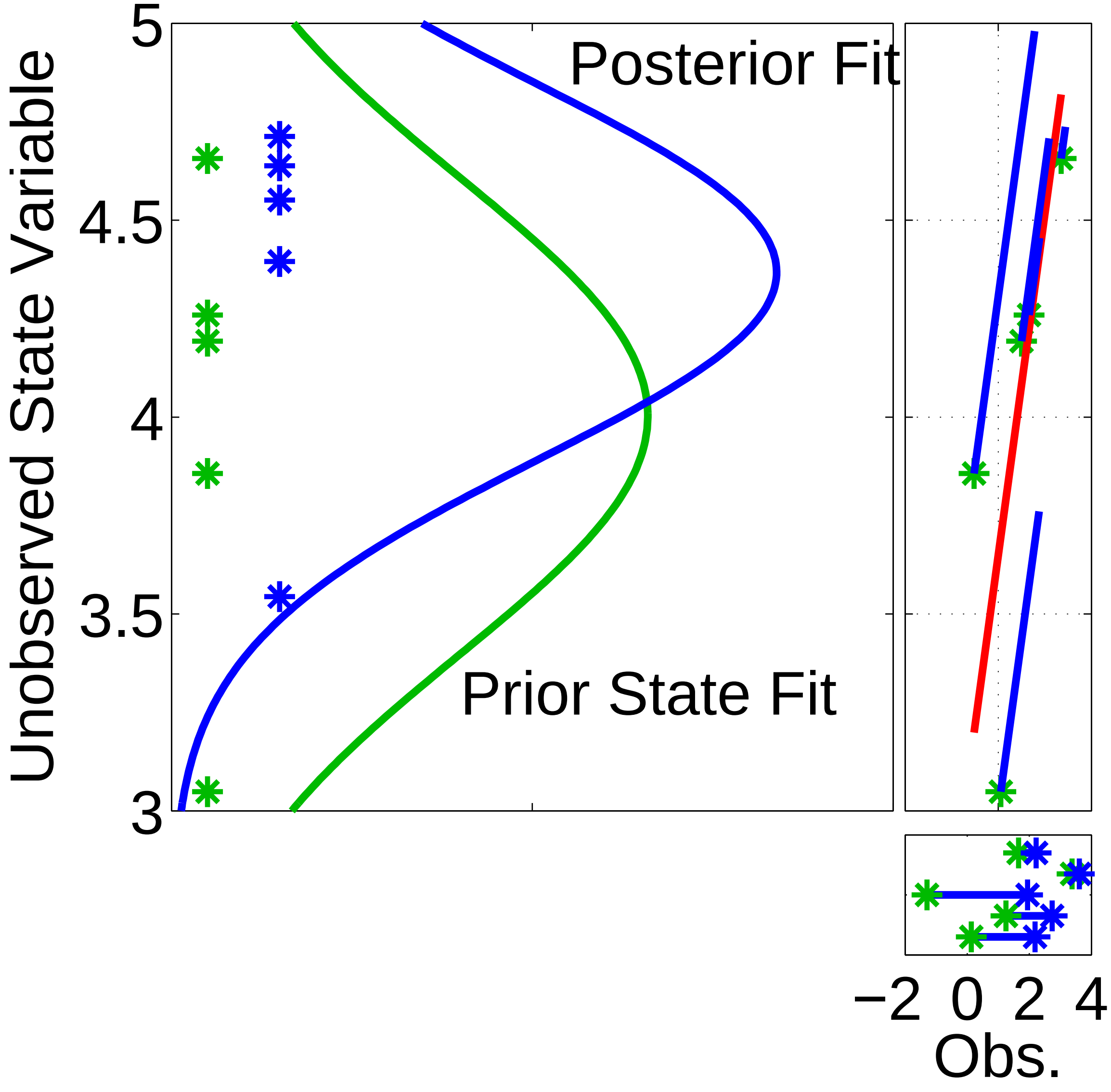
Fitting Gaussians shows that mean and variance have changed.

Ensemble filters: Updating additional prior state variables



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

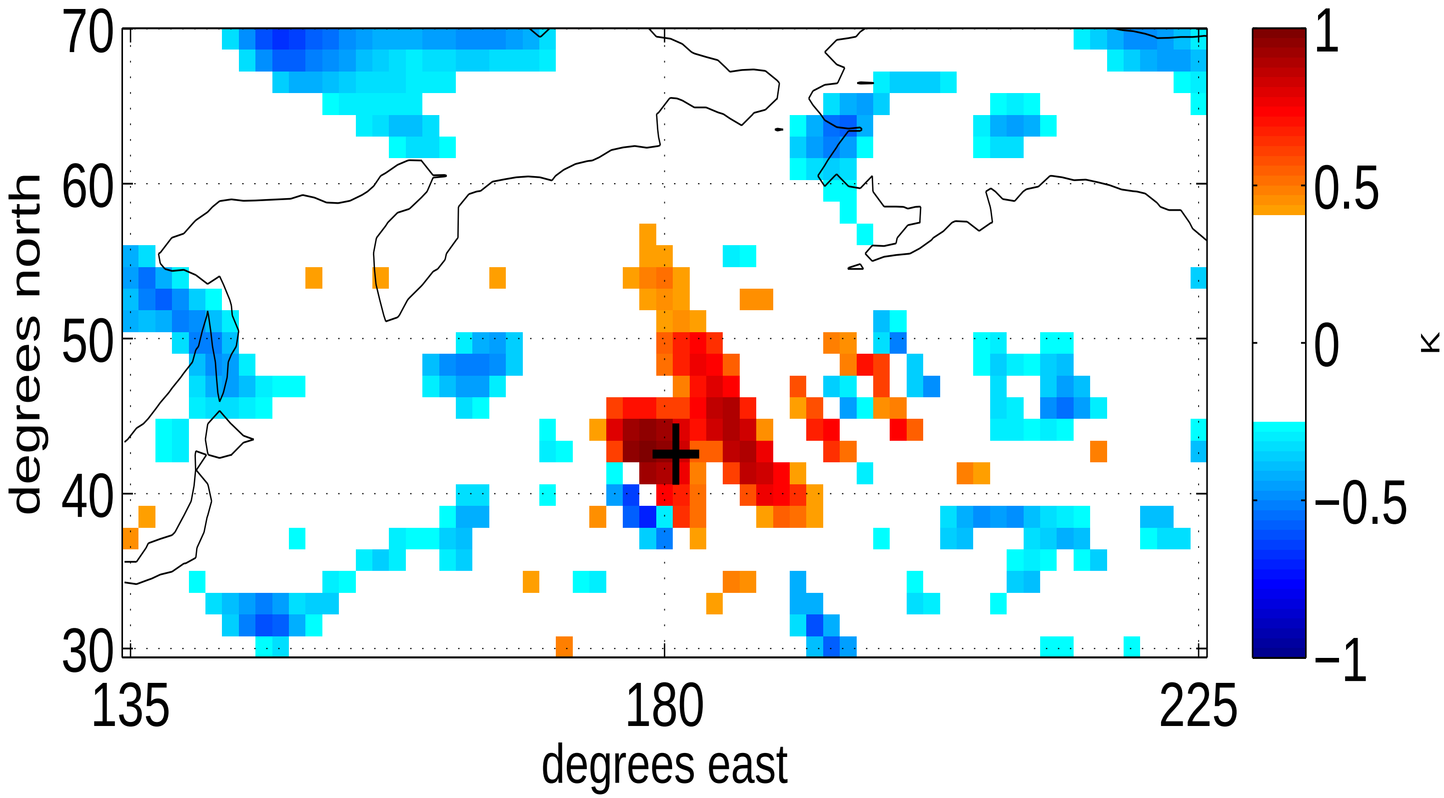
Fitting Gaussians shows that mean and variance have changed.

Other features of the prior distribution may also have changed.

If unobserved variable is part of model state...

This can work fine.

Have time-varying model-generated sample covariance.



Example: Correlation of east-west wind at point with temperature.

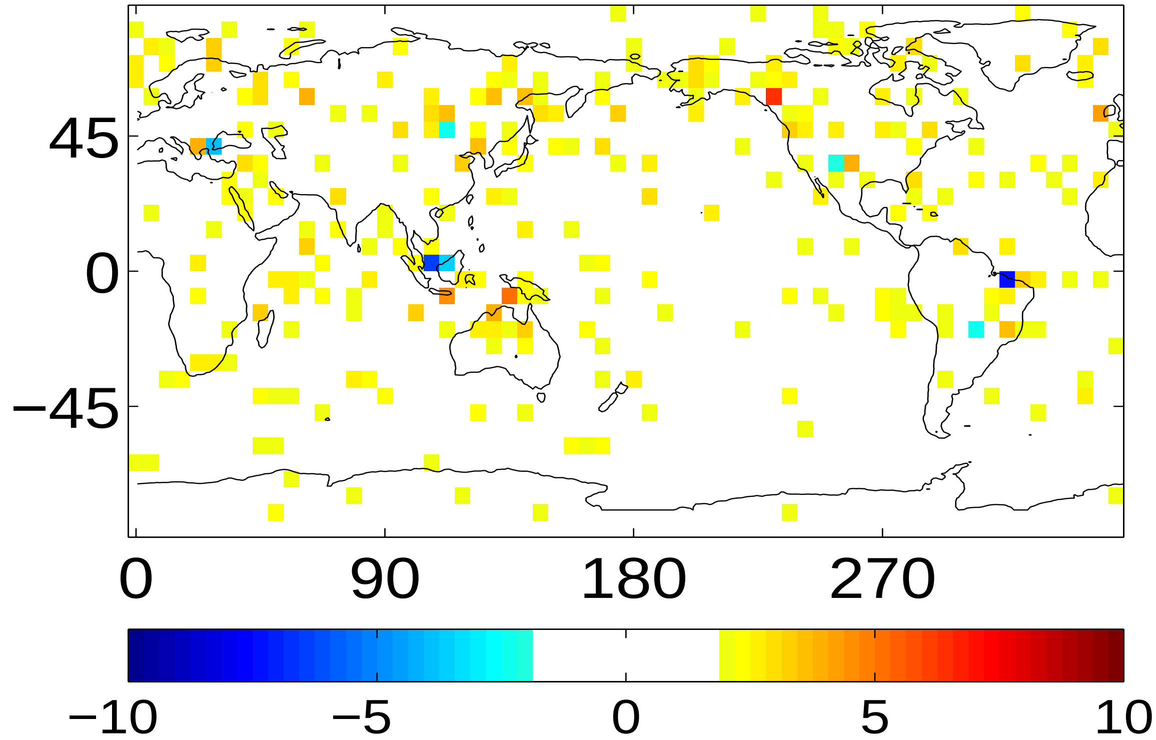
Can make a model parameter the unobserved quantity.

Use observations to ‘tune’ model parameters.

Climate models have MANY real-valued parameters.

Generally adjusted via physical intuition, trial and error, or...

Climate Model Parameter Estimation via Ensemble Data Assimilation.



T21 CAM assimilation of gravity wave drag efficiency parameter.

Oceanic values are noise (should be 0).

0< efficiency< ~4 suggested by modelers.

Positive values over NH land expected.
Problem: large negative values over tropical land near convection.
May reduce wind bias in tropical troposphere, but for ‘Wrong Reason’.

Assimilation tries to use free parameter to fix ALL model problems

Parameter ‘Assimilation’ Challenges for math/stats folks!

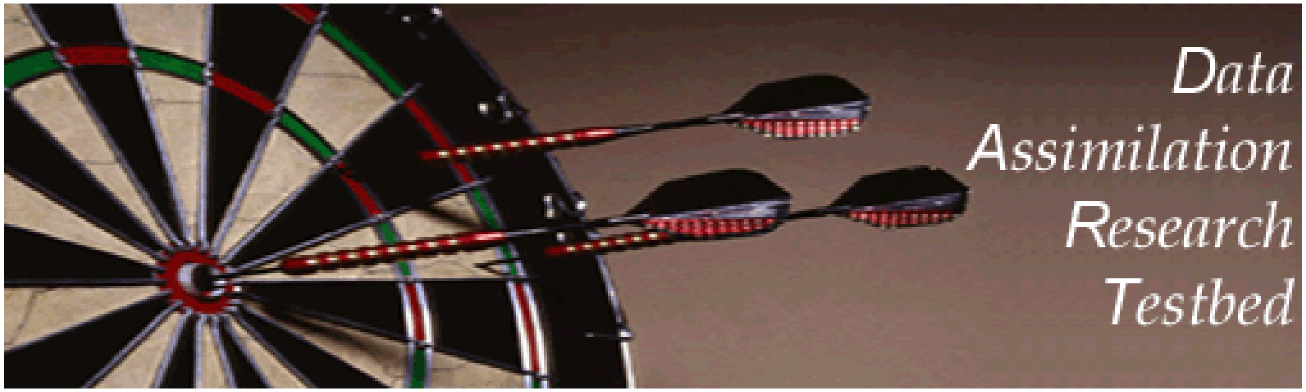
1. Distribution for parameters is only changed by observations:
    a. Variance will disappear.
    b. Initial correlation ‘spatial’ structure remains.
    c. Can add some ‘system noise’, but how?

2. How should the initial covariance structure be picked?
    a. Randomly at each gridpoint (noisy!)?
    b. Globally (smooth)?

3. What about just using covariance from a model variable (say winds)?
    a. This works for adaptively adjusting assimilation system params.
    b. For gravity wave drag example, which model variable to use?

4. What if signal is weak or non-linear (time to give up and go home)?

Data Assimilation Research Testbed (DART)



Software to do everything here (and more) is in DART.

Requires F90 compiler, Matlab.

Available from www.image.ucar.edu/DAReS/DART.

Phase 4: Quick look at real atmospheric applications...

Results from CAM Assimilation: January, 2003

Model:

CAM 3.1 T85L26

U,V, T, Q and PS state variables impacted by observations.

Land model (CLM 2.0) not impacted by observations.

Climatological SSTs.

Assimilation / Prediction Experiments:

80 member ensemble divided into 4 equal groups.

Adaptive error correction algorithm.

Initialized from a climatological distribution (huge spread).

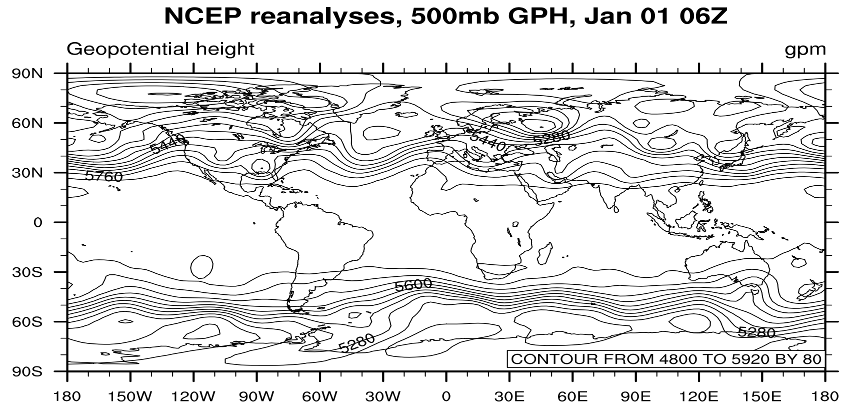
Uses most observations used in reanalysis

(Radiosondes, ACARS, Sat. Winds..., no surface obs. or retrievals).

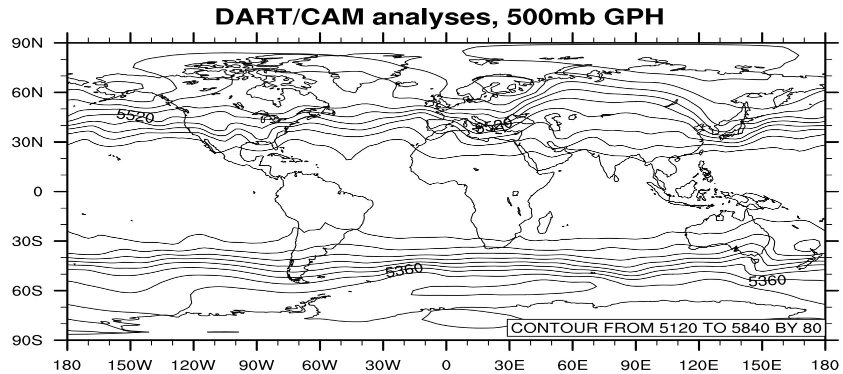
Assimilated every 6 hours; +/- 1.5 hour window for obs.

After 6 hours.

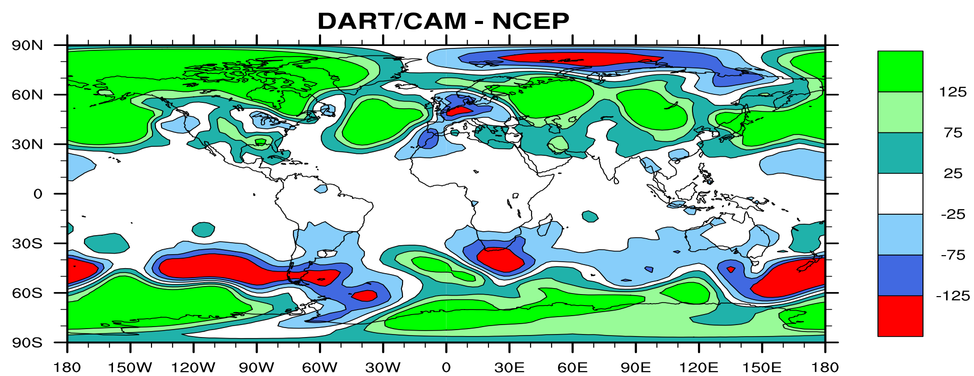
NCEP



DART/CAM

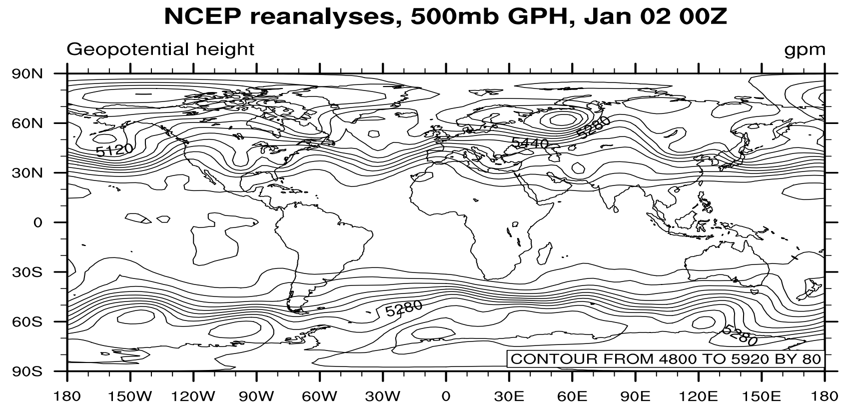


Difference.

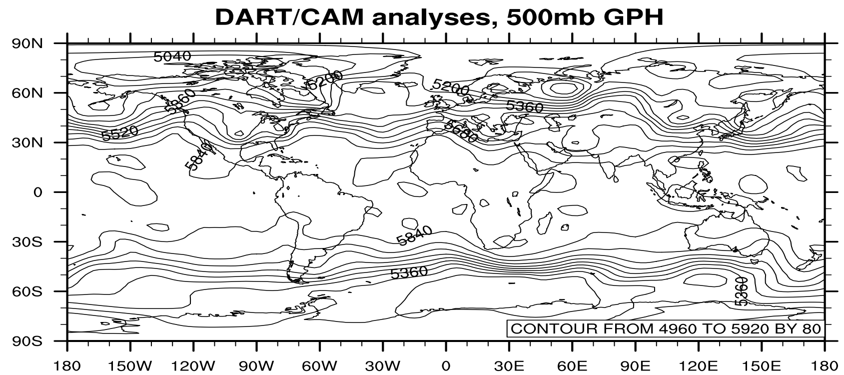


After 1 day.

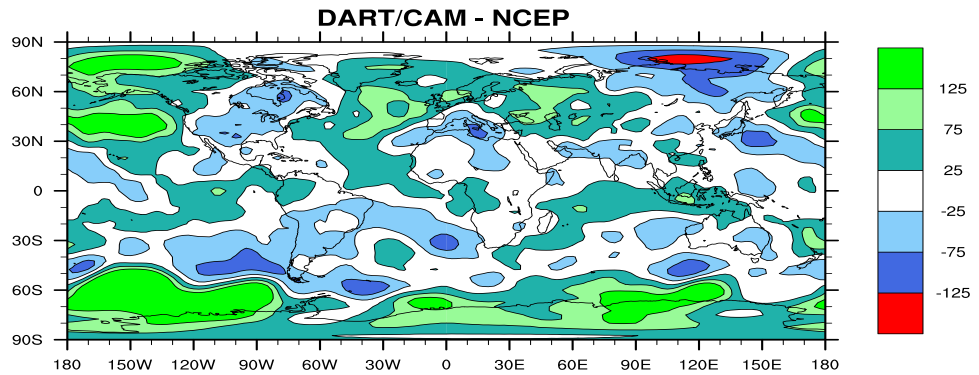
NCEP



DART/CAM



Difference.

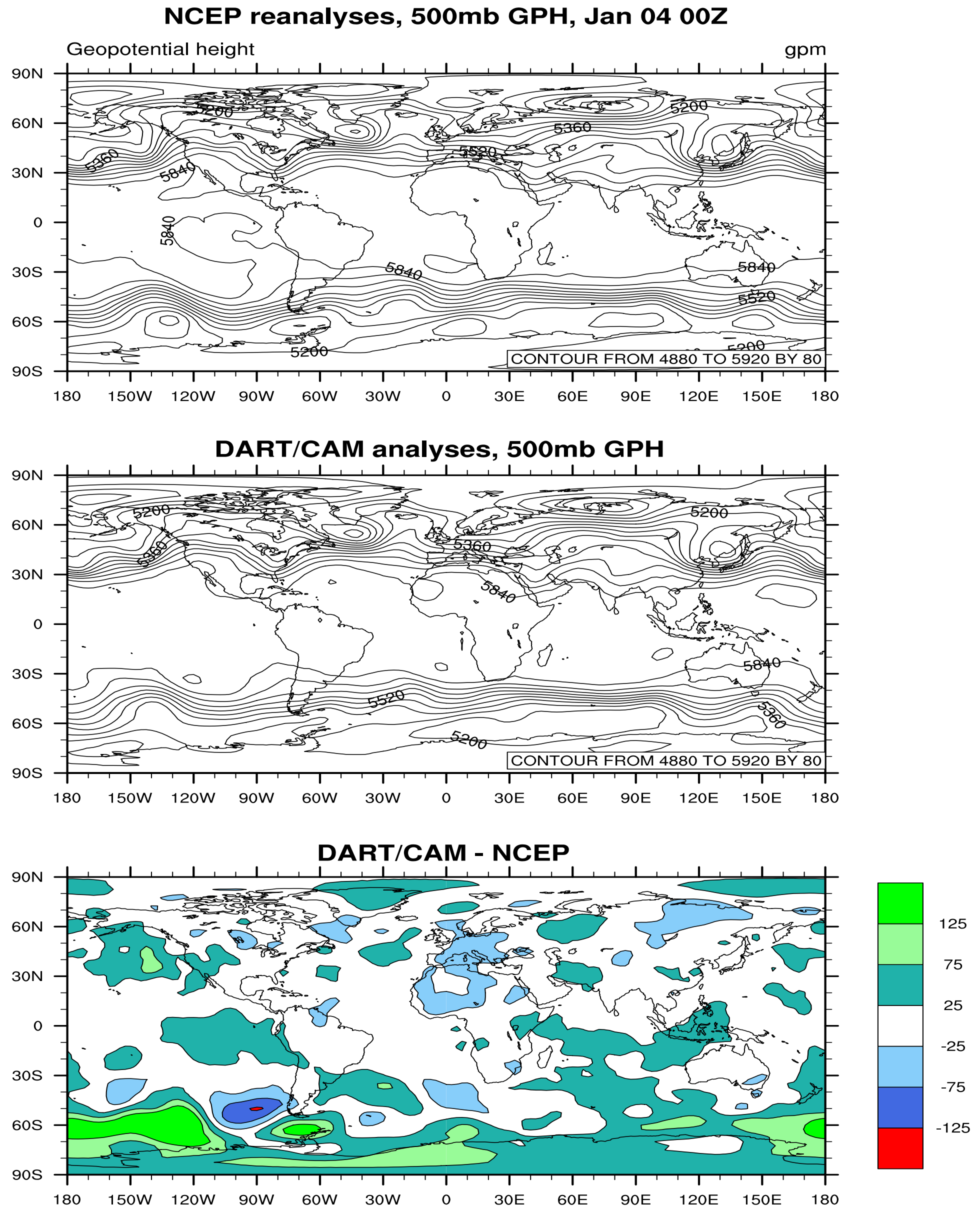


After 3 days.

NCEP

DART/CAM

Difference.

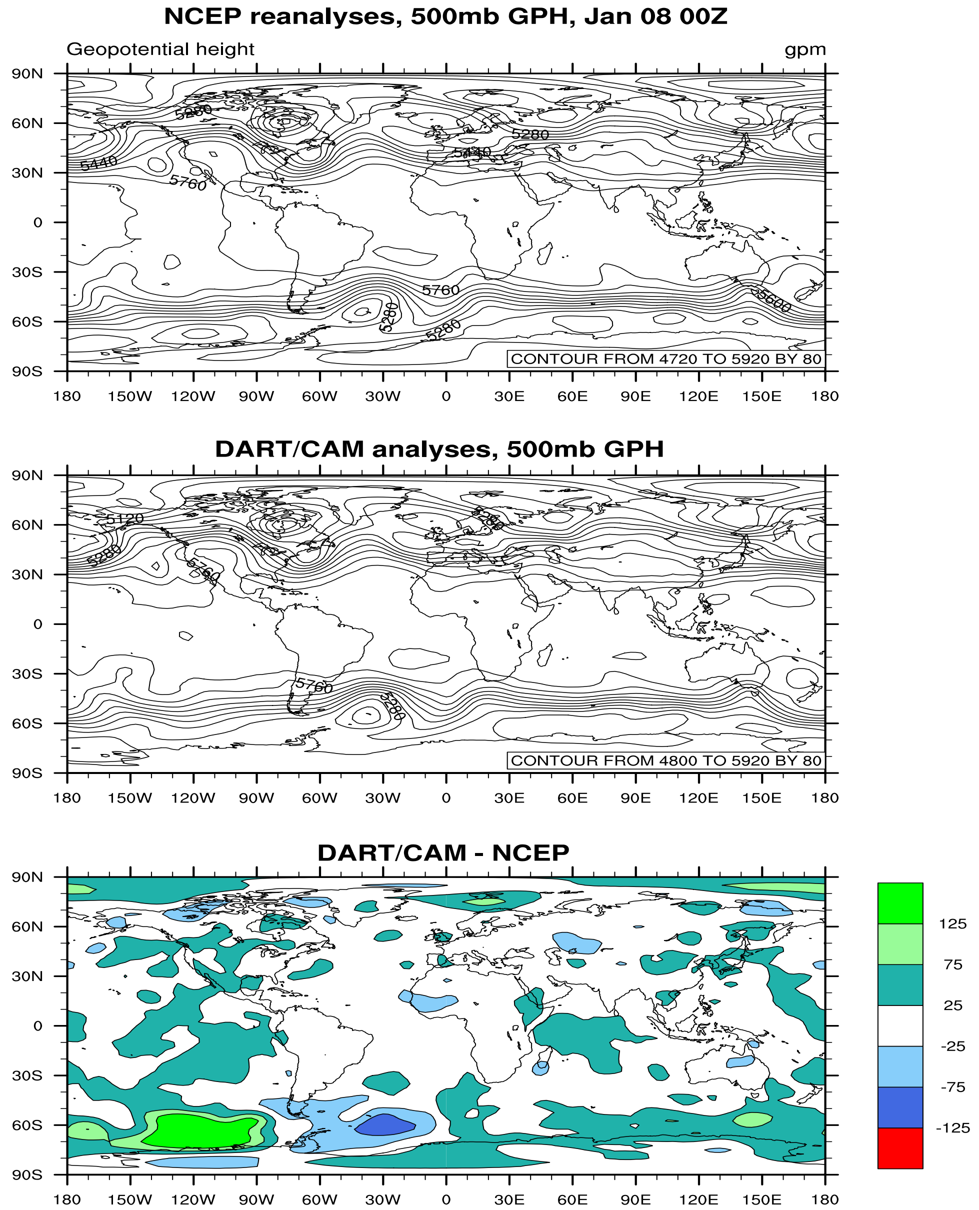


After 7 days.

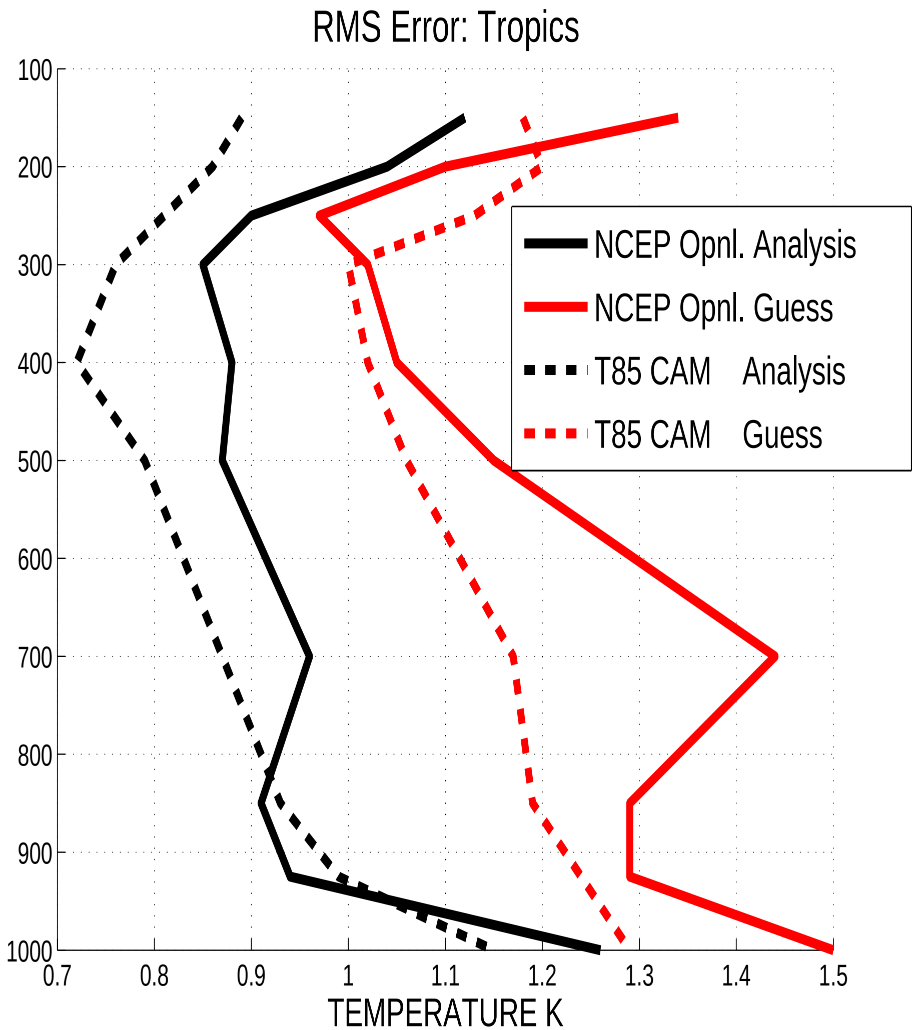
NCEP

DART/CAM

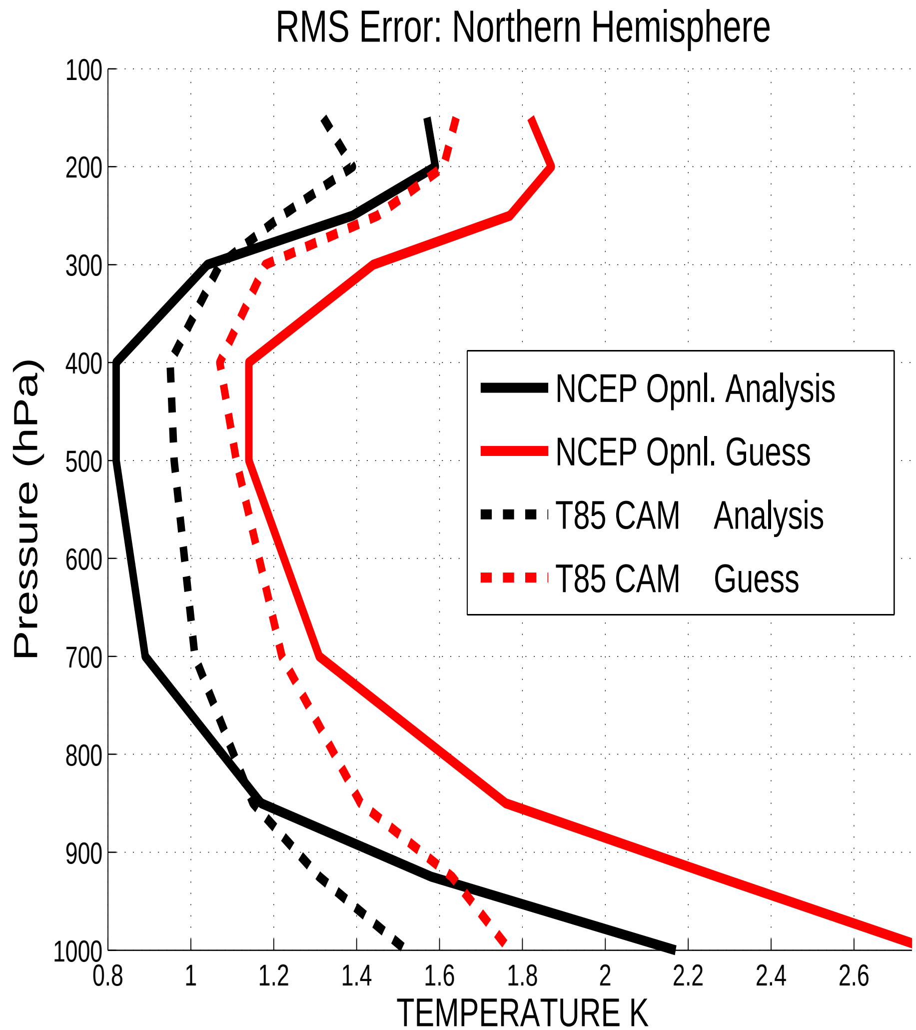
Difference.



6-Hour Forecast and Analysis Observation Space Temperature RMS

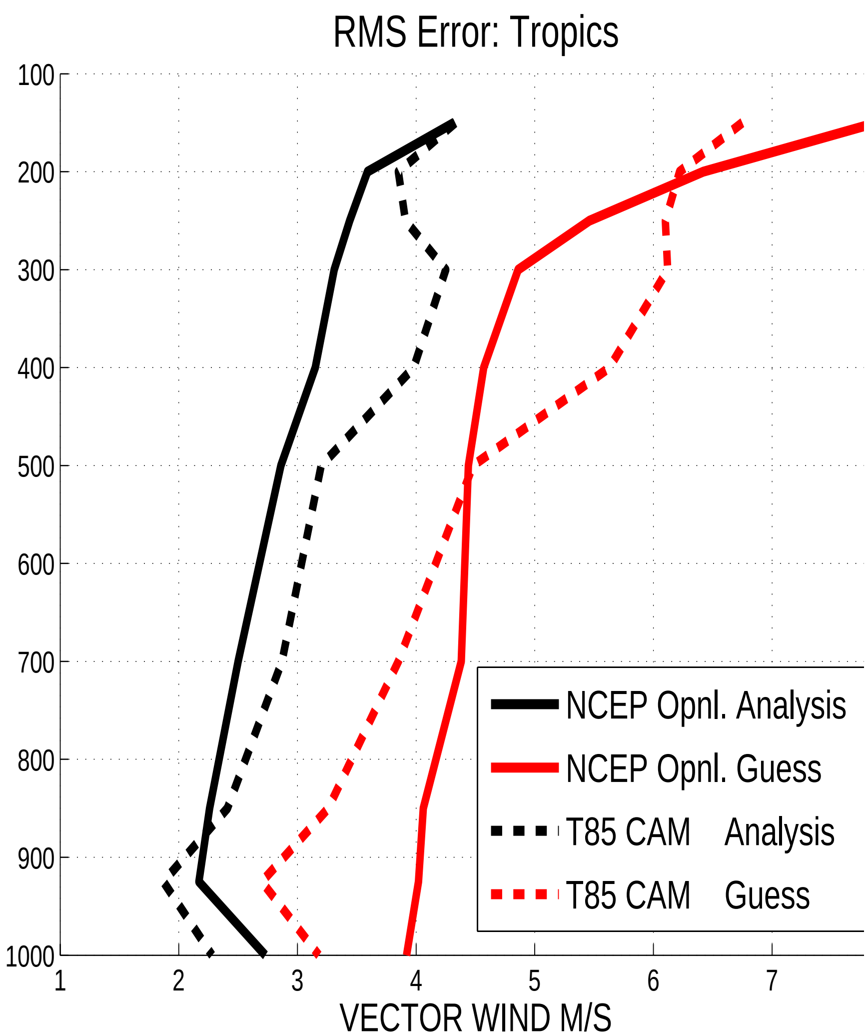


Tropics

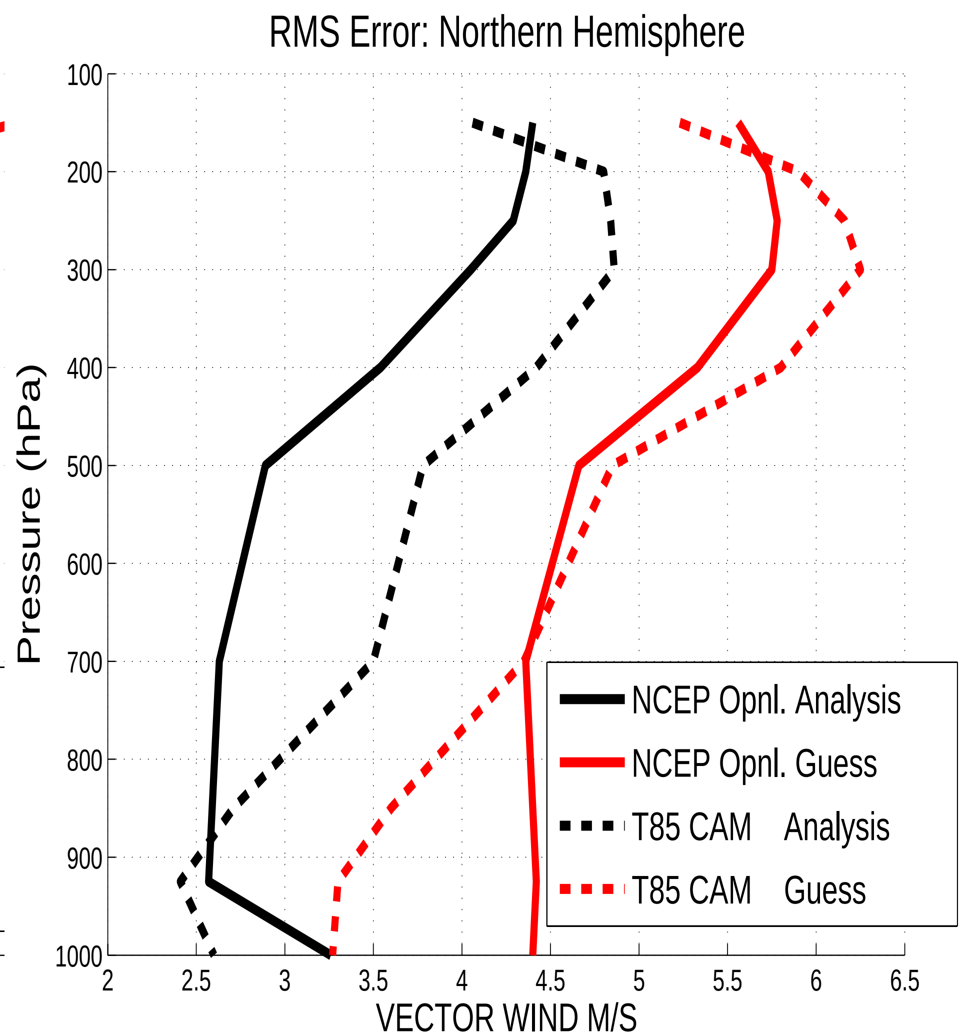


Northern Hemisphere

6-Hour Forecast and Analysis Observation Space Wind RMS



Tropics



Northern Hemisphere