Future Directions in Ensemble DA for Hurricane Prediction Applications

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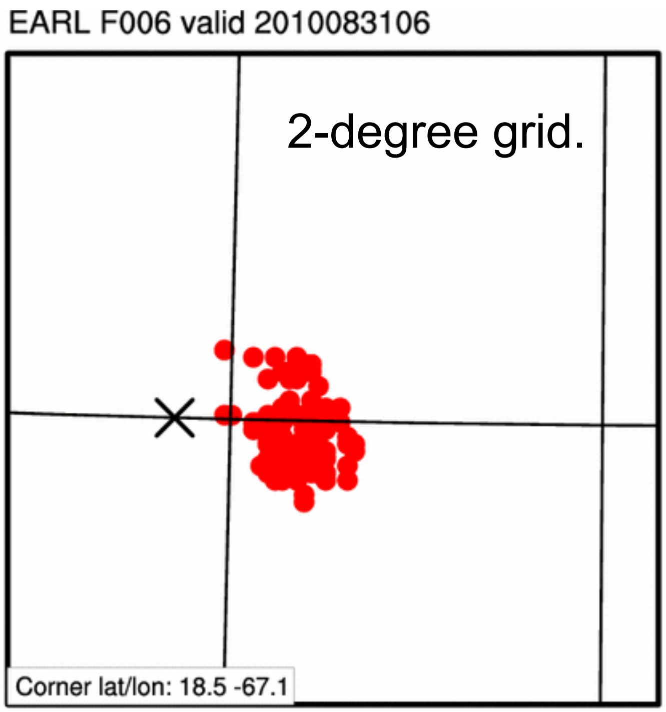
NCAR

Ensemble Assimilation for Tropical Storms

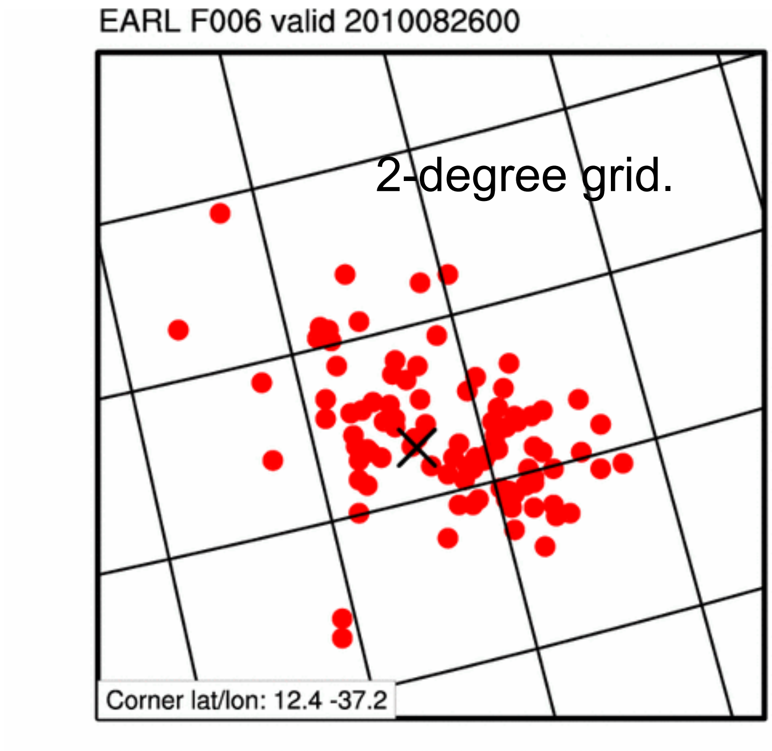


Position of 96 prior ensemble members for mature hurricane.

- Storms close enough that strong winds overlap
  (but eyewall winds may overlap eye from another ensemble).

- Prior sample for winds at a gridpoint are approximately gaussian?

Ensemble Assimilation for Tropical Storms



Position of 96 prior ensemble members for weak developing TS.

- Ensemble storms may not overlap at all.
- Prior sample for winds at a gridpoint are NOT gaussian.

Basic Ensemble Kalman Filters Assume…

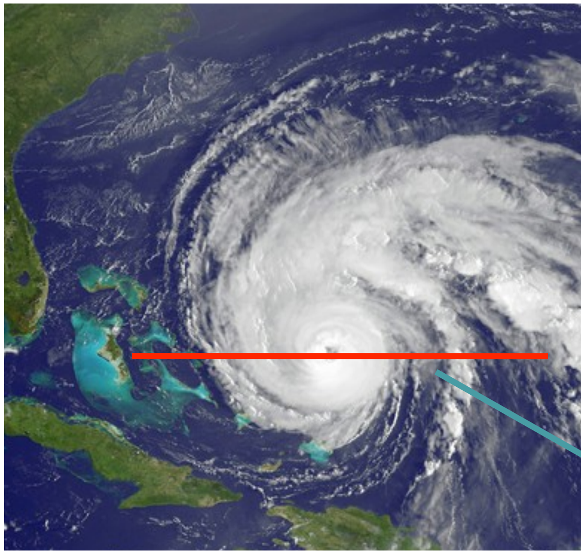
- Ensemble Winds at point should be gaussian.

- Least squares is reasonable for relation between observation and state variable.
  (Same as saying linear regression is useful).

Priors with discrete structures like a TS clearly violate these assumptions, but…

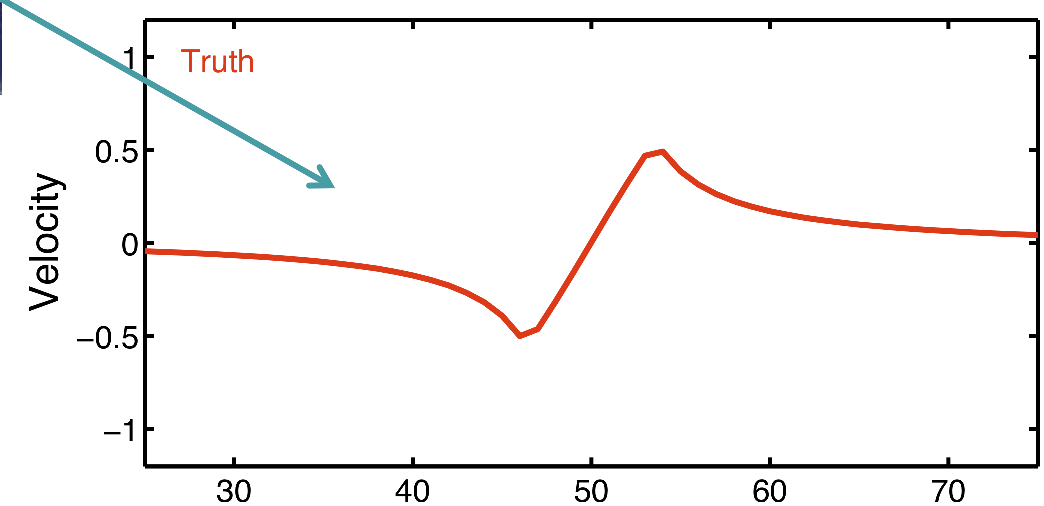
How serious are these problems?

Thought Experiment: 1D Hurricane Vortex Assimilation



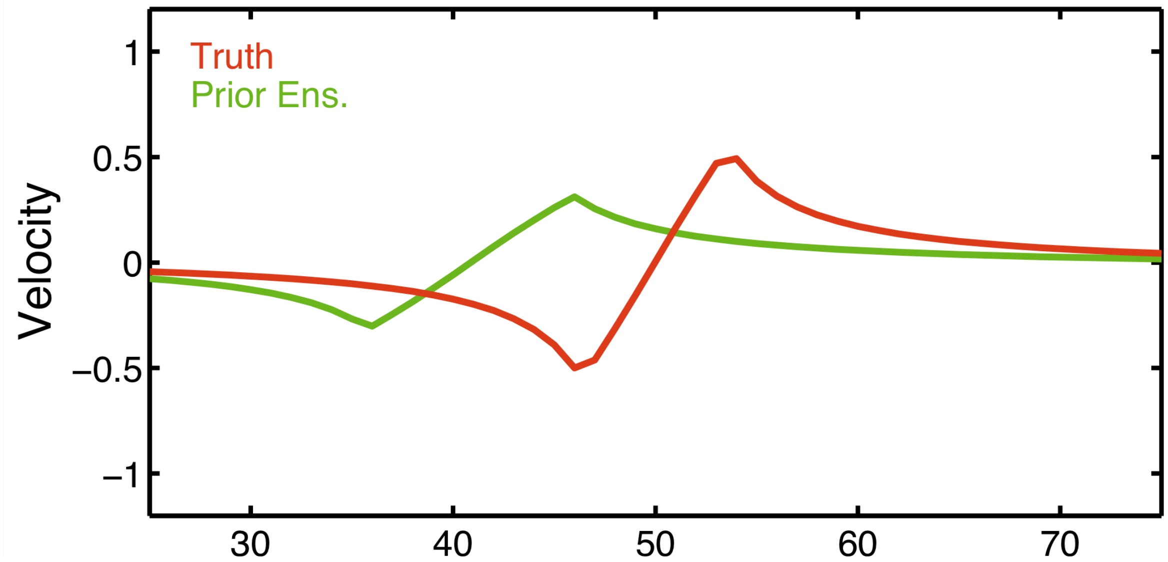
Model of meridional wind across vortex.

'Truth' is Rankine vortex.



Meridional wind cross section.

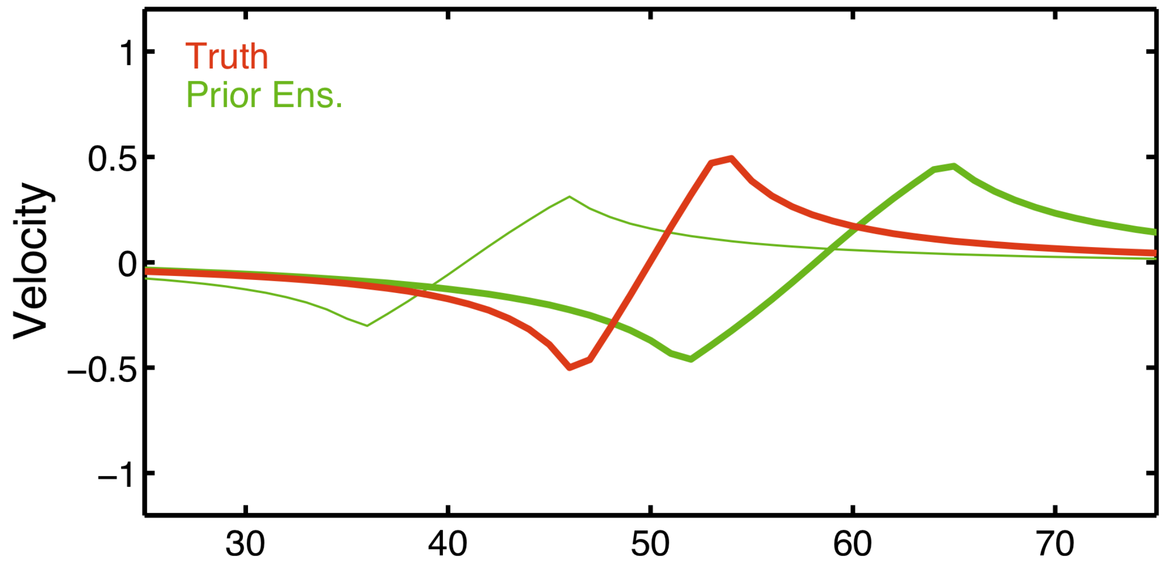
1D Vortex Assimilation: Generate Prior Ensemble



Select prior ensemble members:

- Position drawn from unbiased normal;
- Amplitude drawn from unbiased normal;
- Vortex width unchanged here.

1D Vortex Assimilation: Generate Prior Ensemble



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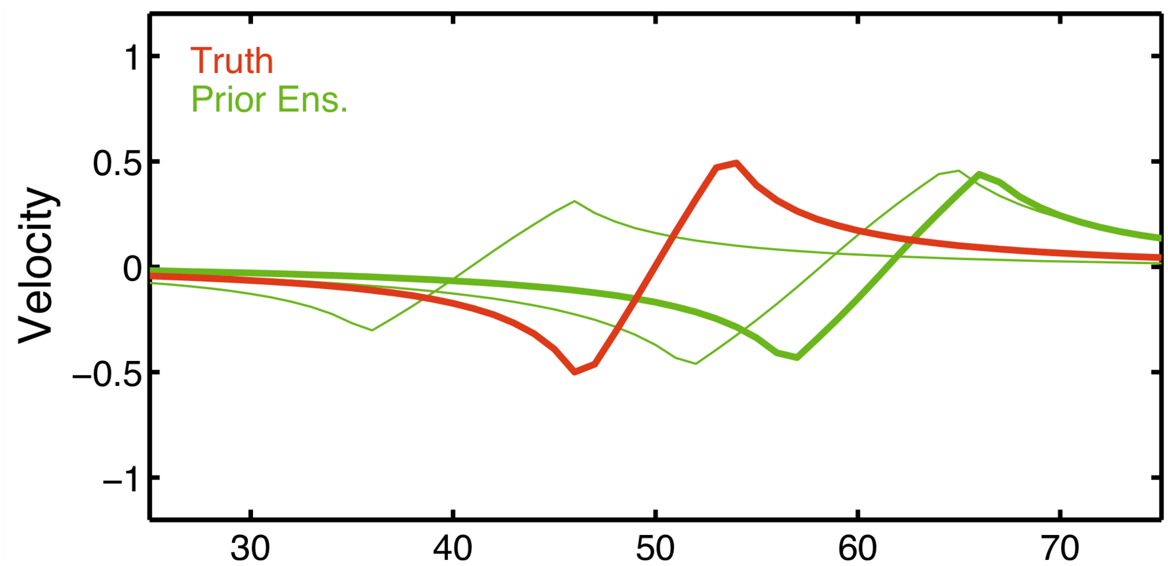

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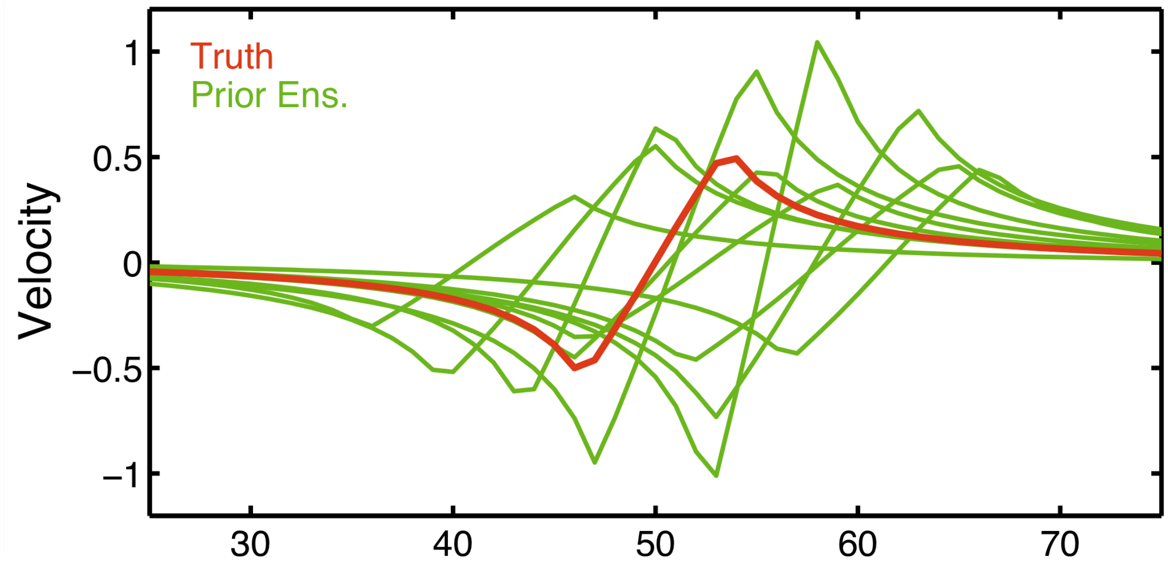
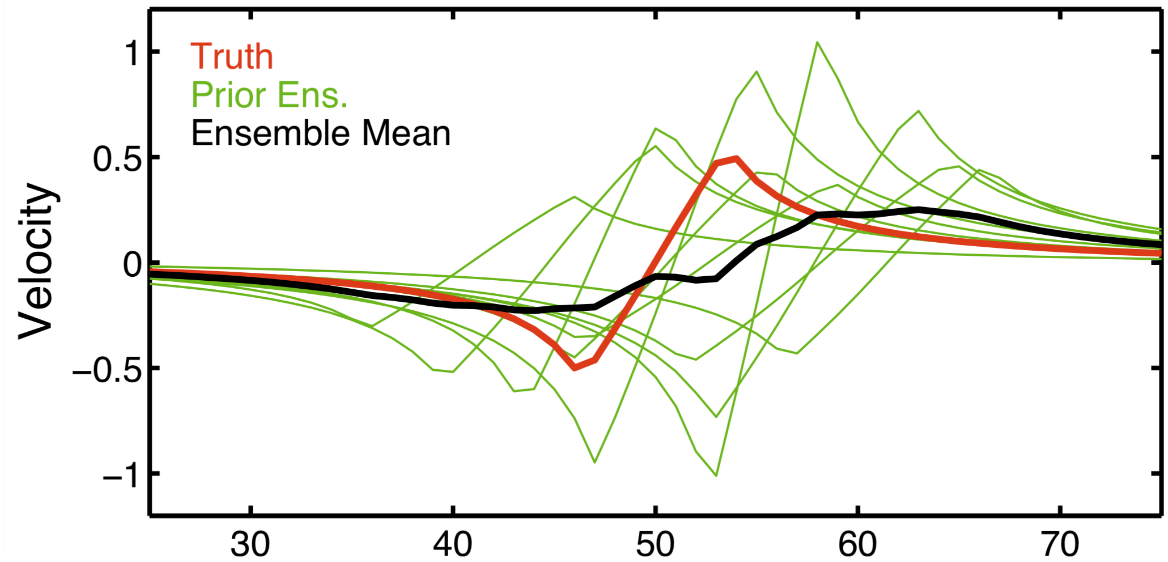


Select prior ensemble members:

- Variation in position big compared to vortex size;
- All priors have a vortex (not always so for real cases);
- Strength is unbiased (unlikely for real cases).

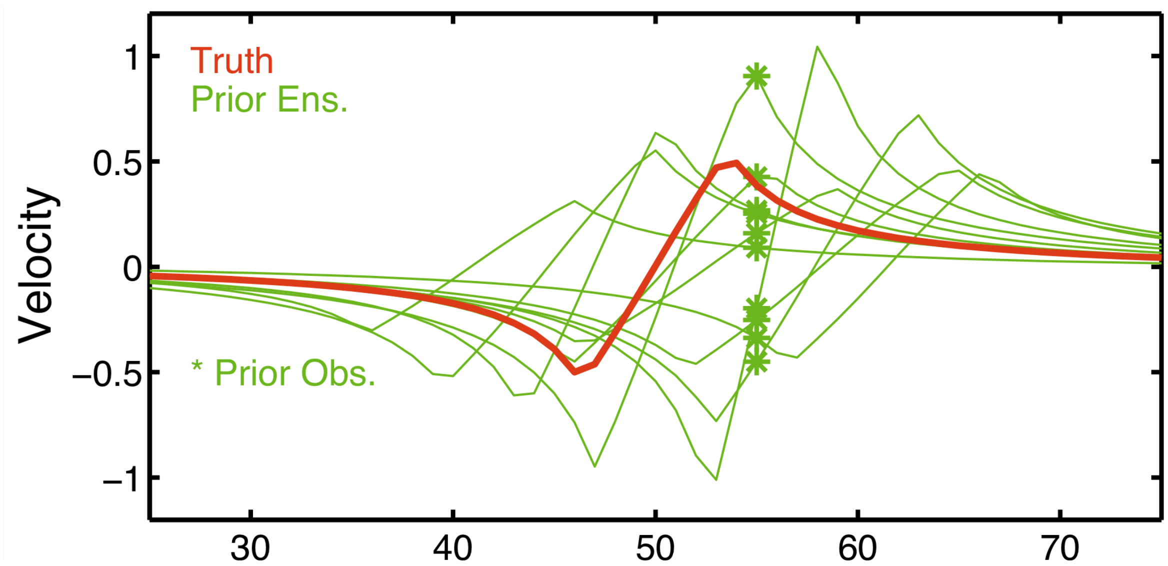
1D Vortex Assimilation: Prior Ensemble Mean



Prior ensemble mean:

- Has limited amplitude, poor phase;
- A feature-based mean might be more natural;
- Suggests gaussian assumption is suspect.

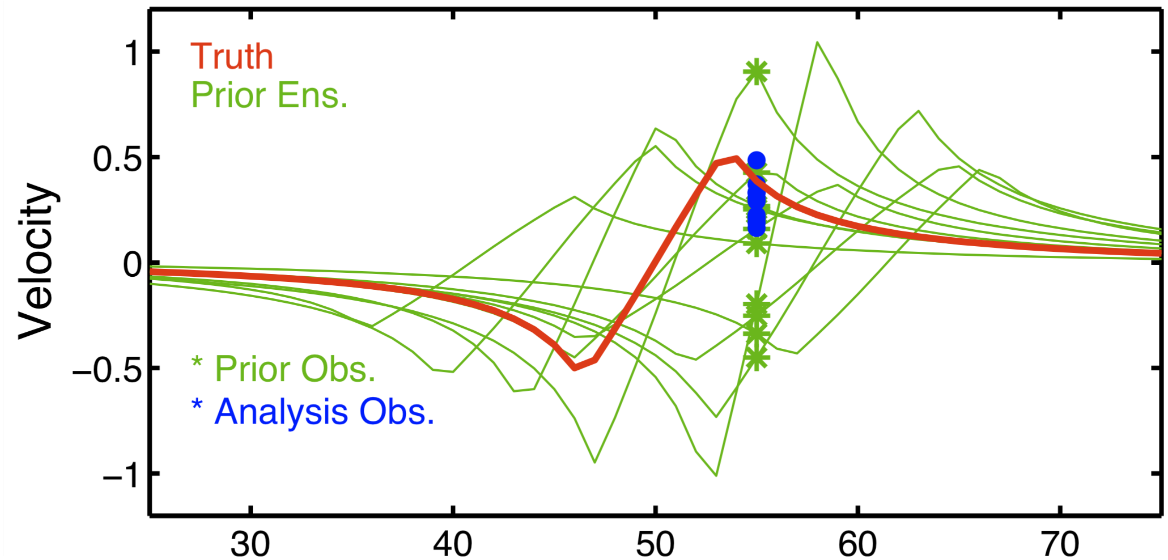
1D Vortex Assimilation: Impact of a wind observation



Observe wind at 'longitude' 55:

- Located near peak true winds;
- Prior distribution biased weak;
- Prior doesn't look very gaussian (more later).

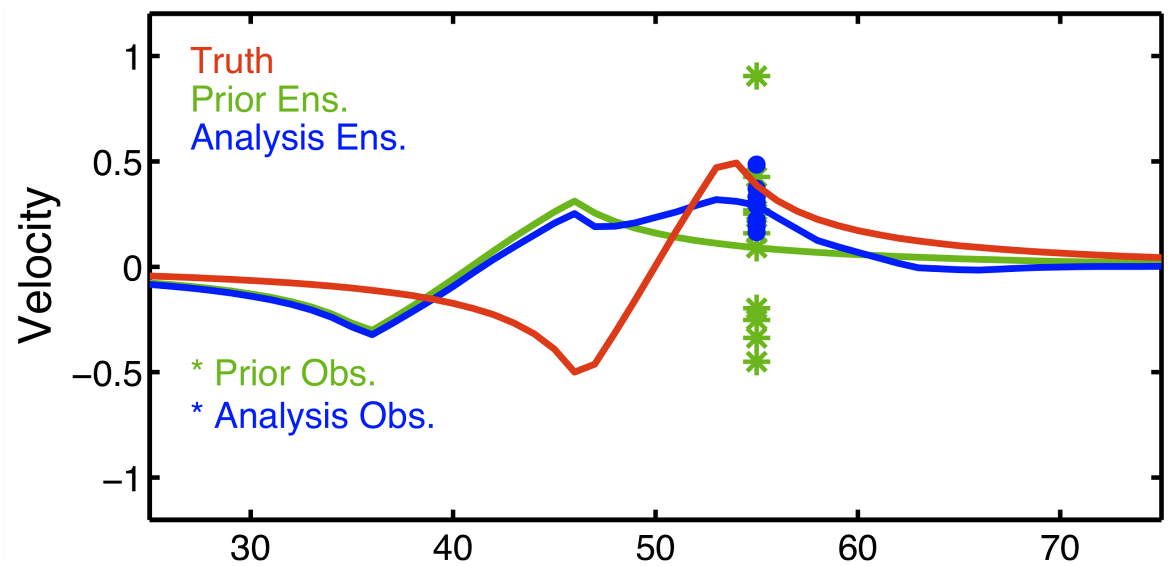
Step 1: Analysis for observed quantity (wind at 55)



Analysis (posterior) distribution:

- Is closer to true wind;
- Has less spread as expected.

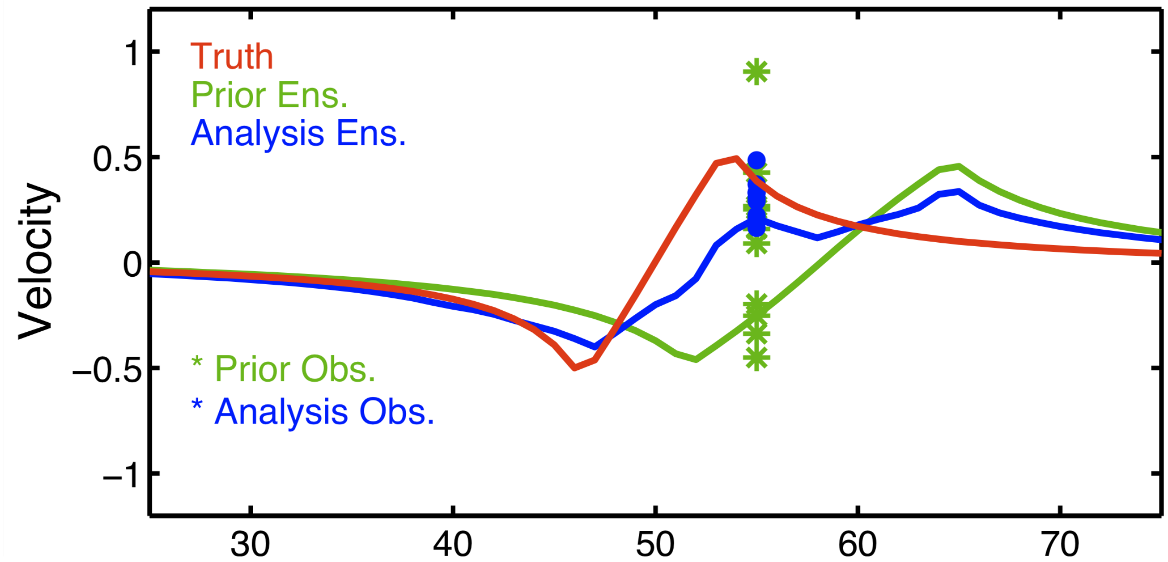
Step 2: Regress observed increments onto gridpoints



Analysis for selected ensemble member (1):

- Is closer to true wind in most locations;
- Has lots of un-Rankine like structure;
- Might not be what we expected.

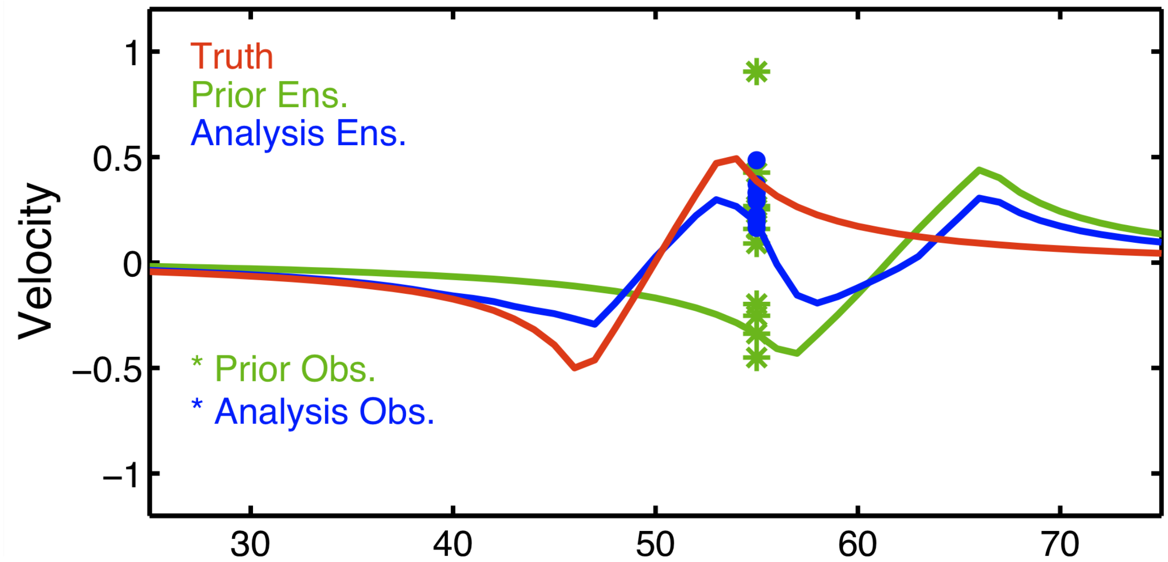
Step 2: Regress observed increments onto gridpoints



Analysis for selected ensemble member (2):

- Is closer to true wind in most locations;
- Has lots of un-Rankine like structure;
- Might not be what we expected.

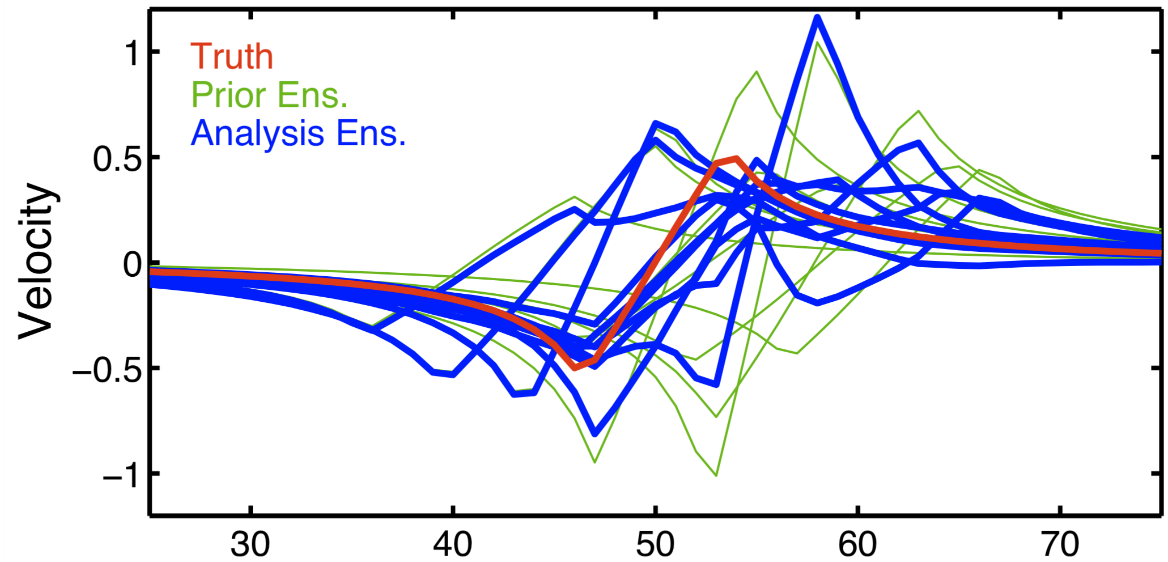
Step 2: Regress observed increments onto gridpoints



Analysis for selected ensemble member (3):

- Is closer to true wind in most locations;
- Has lots of un-Rankine like structure;
- Might not be what we expected.

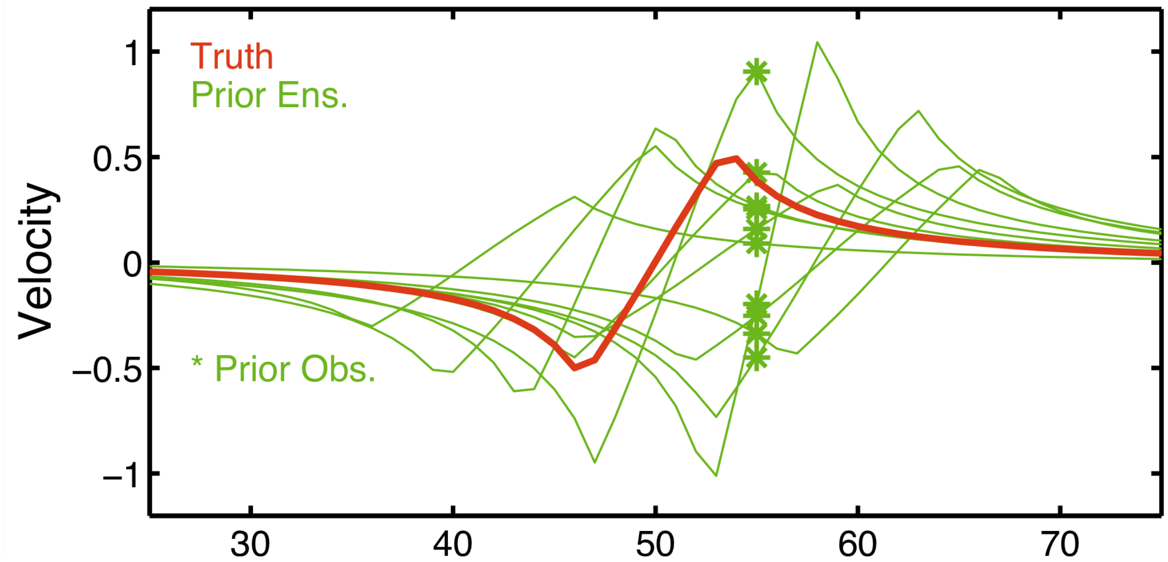
Step 2: Regress observed increments onto gridpoints



Analysis for all ensemble members:

- Has increased wind away from vortex;
- Not clear where analysis position is;
- Is significantly noisier than prior.

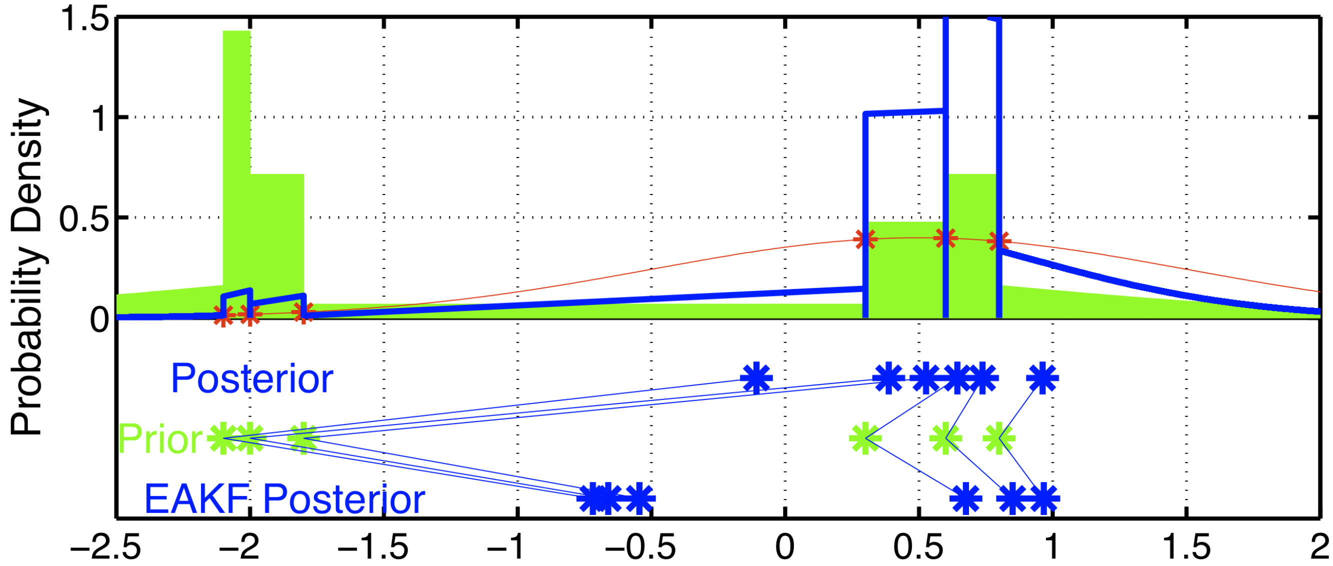
Challenge 1: Non-gaussian observation prior distribution



If wind gradients are large compared to position uncertainty:

- The prior observed distribution is non-gaussian;
- Few priors have strong winds;
- In this example, few have very weak winds;
- Essentially bimodal; worse for large ensembles.

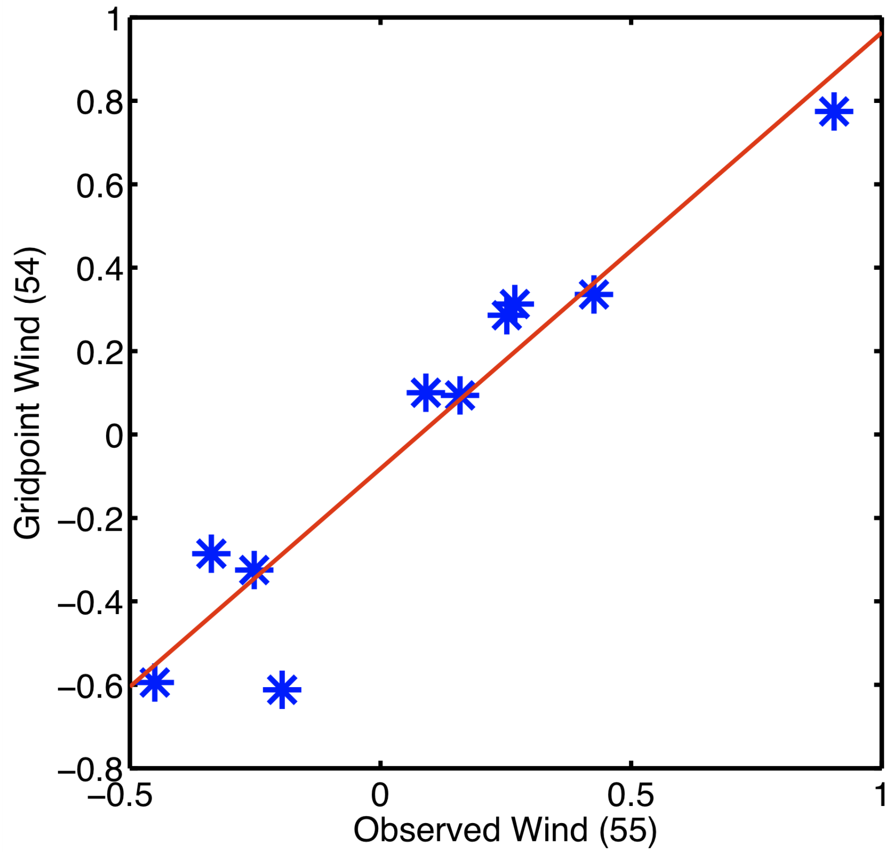
Possbile solution: Non-gaussian ensemble filters



Ensemble Kalman filter vs. non-gaussian filter:

- Strongly bimodal prior ensemble (green asterisks);
- Non-gaussian: all members in observed mode (top blue asterisks)
- Kalman filter: 3 members in no-mans land (bottom blue asterisks);
- In our case, this would weaken vortex.

Challenge 2: Non-linear joint prior distributions

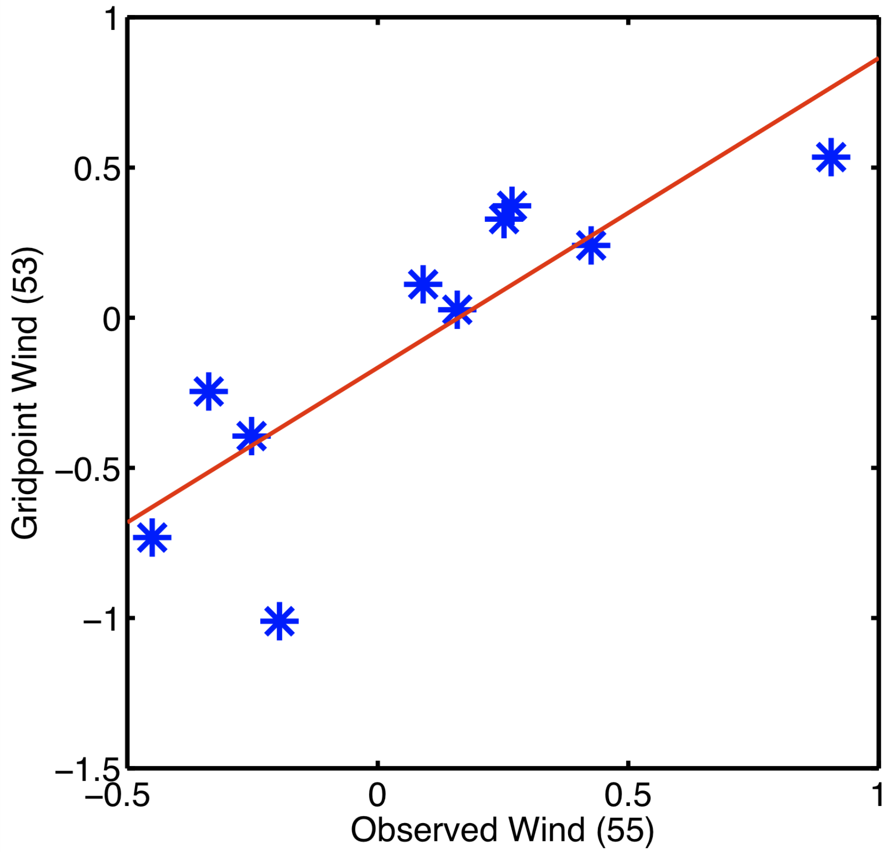


Second step of filter regresses observed increments onto gridpoints.

Uses prior joint distribution.

For close gridpoints linear fit is okay.

Challenge 2: Non-linear joint prior distributions

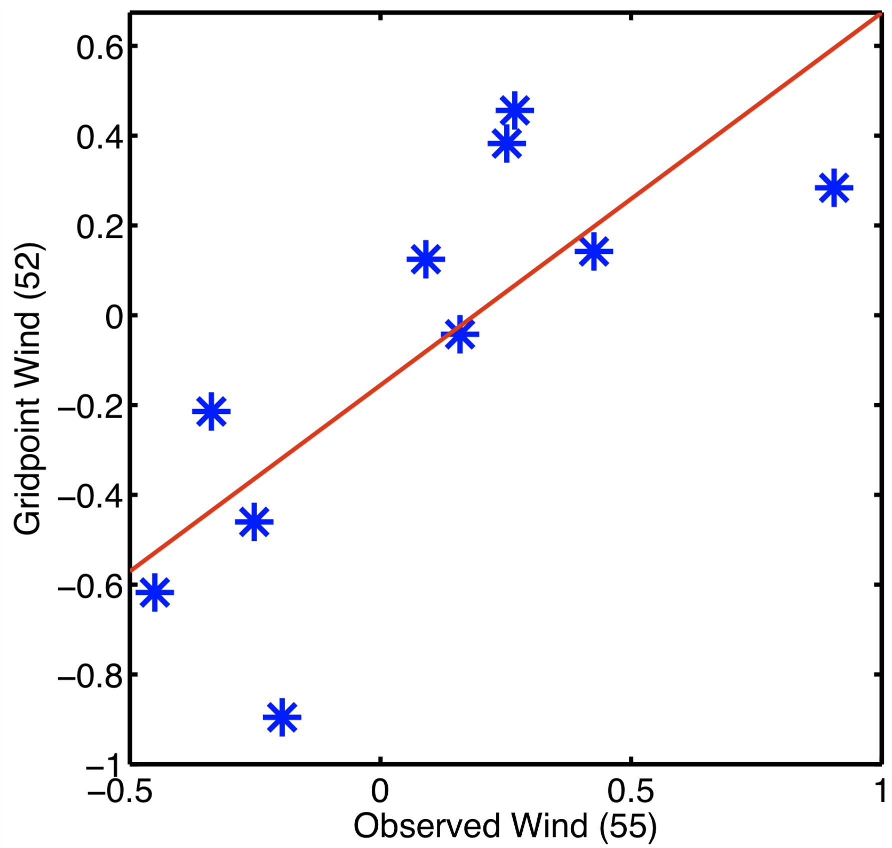


Second step of filter regresses observed increments onto gridpoints.

Uses prior joint distribution.

For more distant gridpoints linear fit degrades.

Challenge 2: Non-linear joint prior distributions



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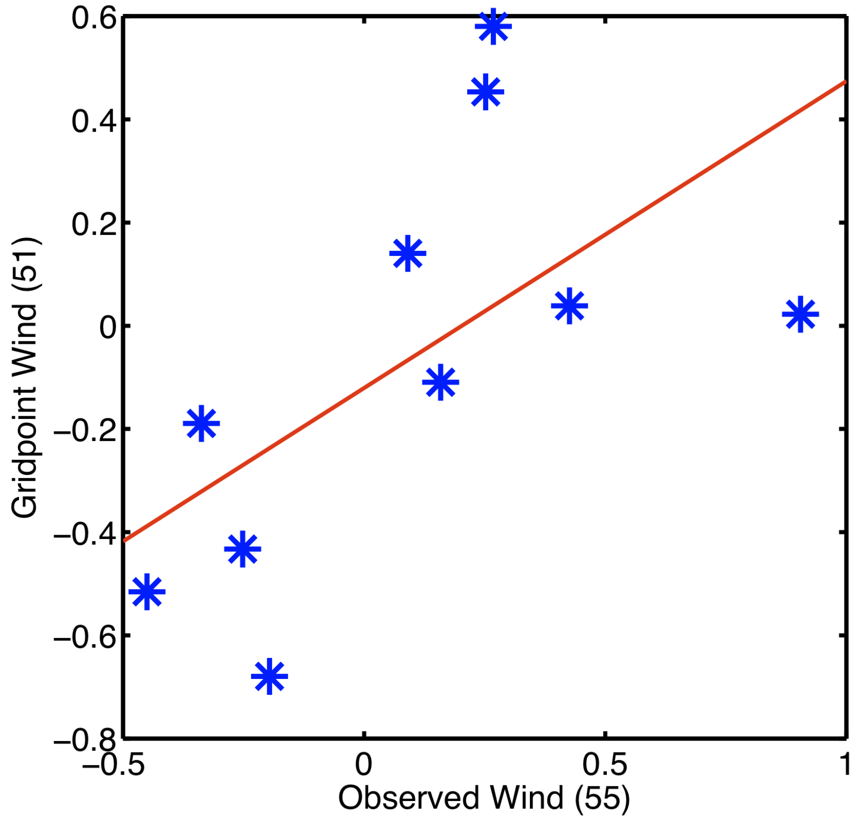

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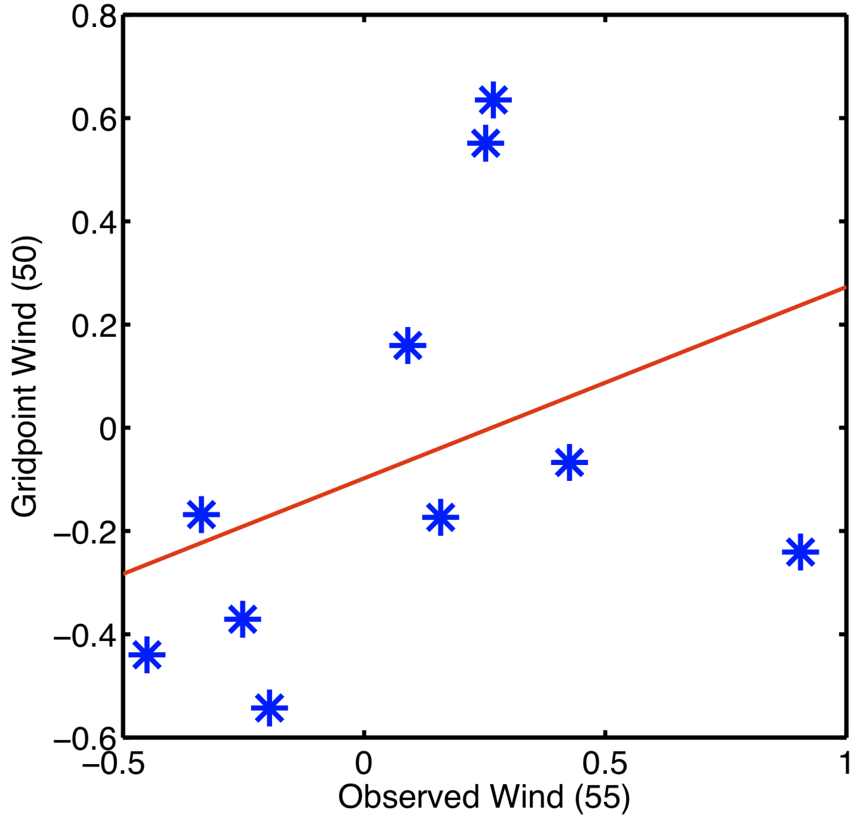

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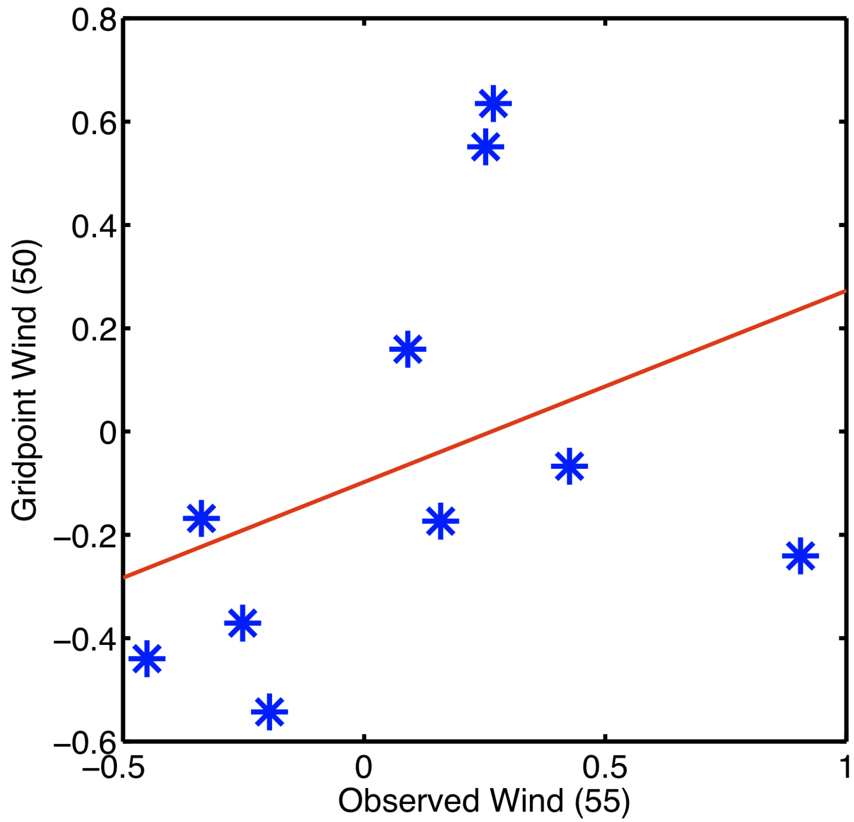


Part of this is just gaussian noise; not a serious problem

Part is non-linear relation between observation and gridpoint. This is a huge challenge.

Partial Solution: Improved localization

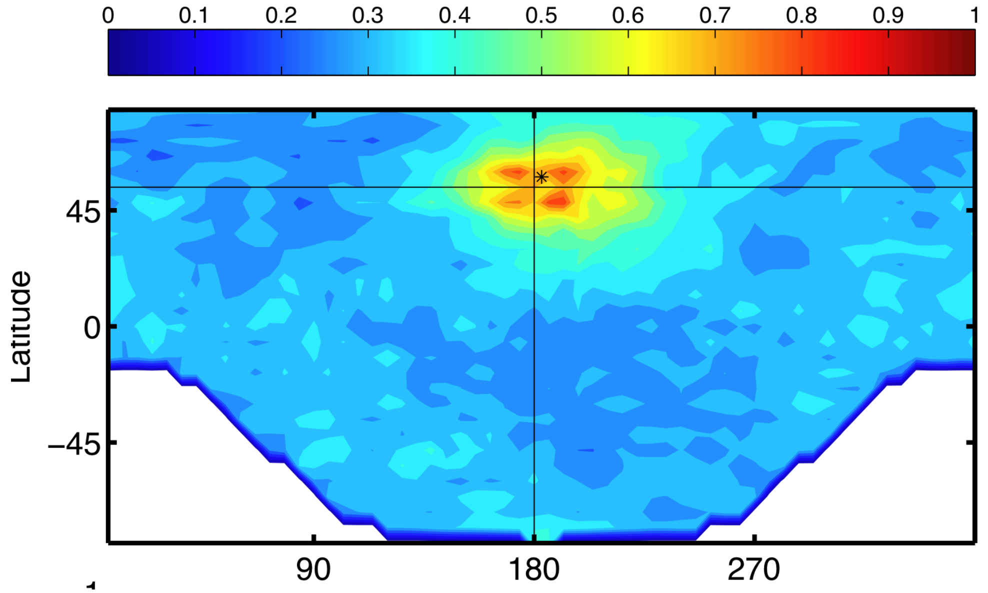
Localization limits impact of observation on gridpoint.

Often just a function of horizontal distance; distant observations don't do much.

Clearly insufficient near vortex.

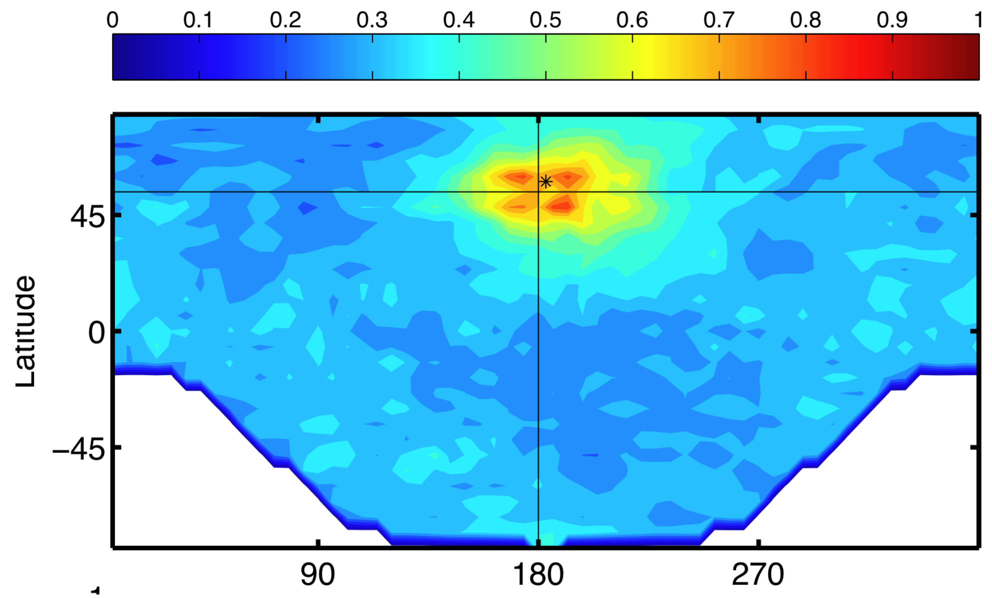
Need spatially inhomogeneous localization.

Partial Solution: Improved localization



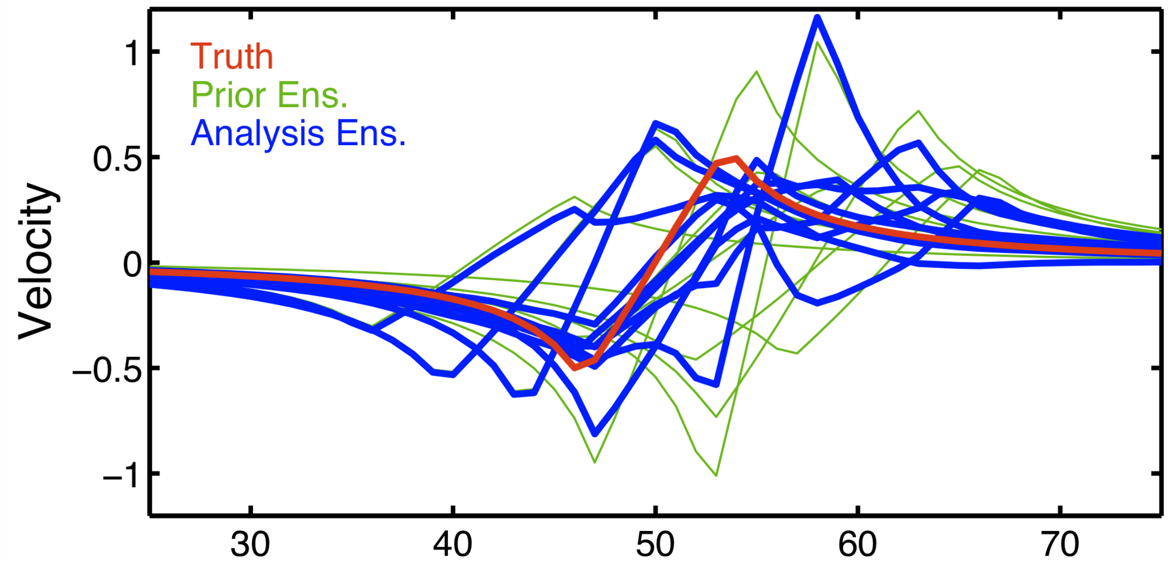
- ➢Adaptive localization tools being developed.
- ➢Example here shows localization for v wind observation on u wind state variables in GCM.
- ➢Local structure around TS will be more complex.

Partial Solution: Improved localization



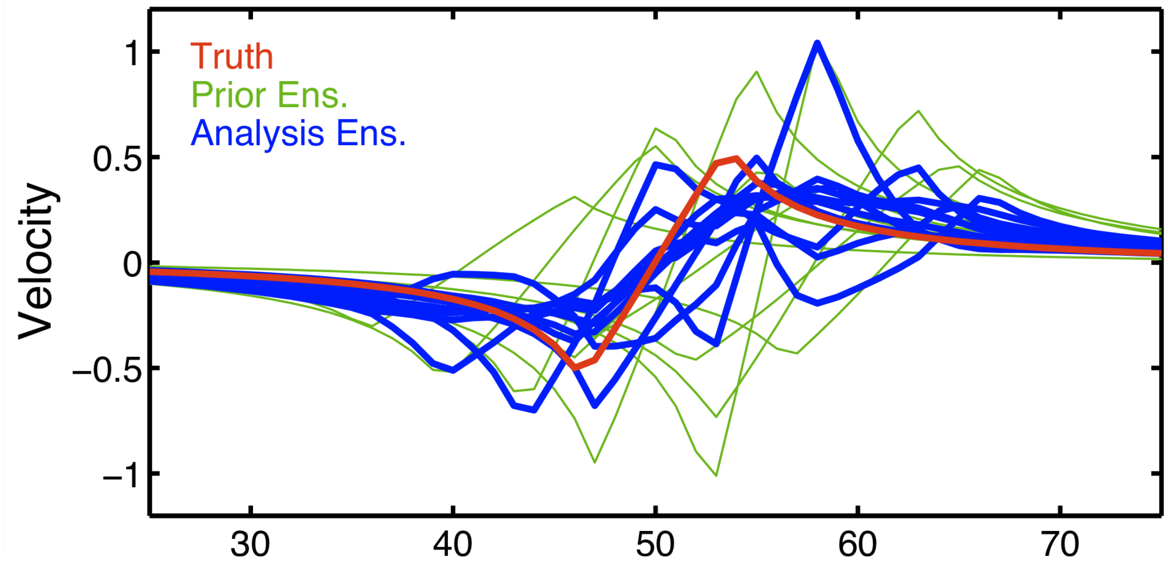
- ➢Adaptive localization works for sampling error.
- ➢Dealing with non-linear priors requires more research.
- ➢Might need non-linear regression (HARD).

Assimilation of vortex specific observations



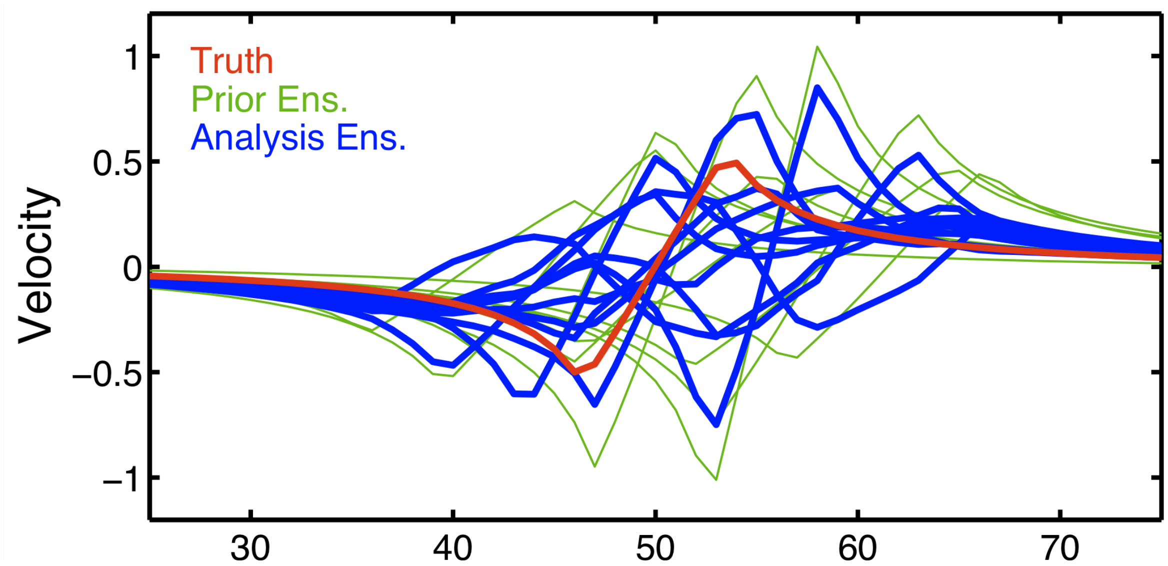
This is the original analysis after one wind observation.

Assimilation of vortex specific observations



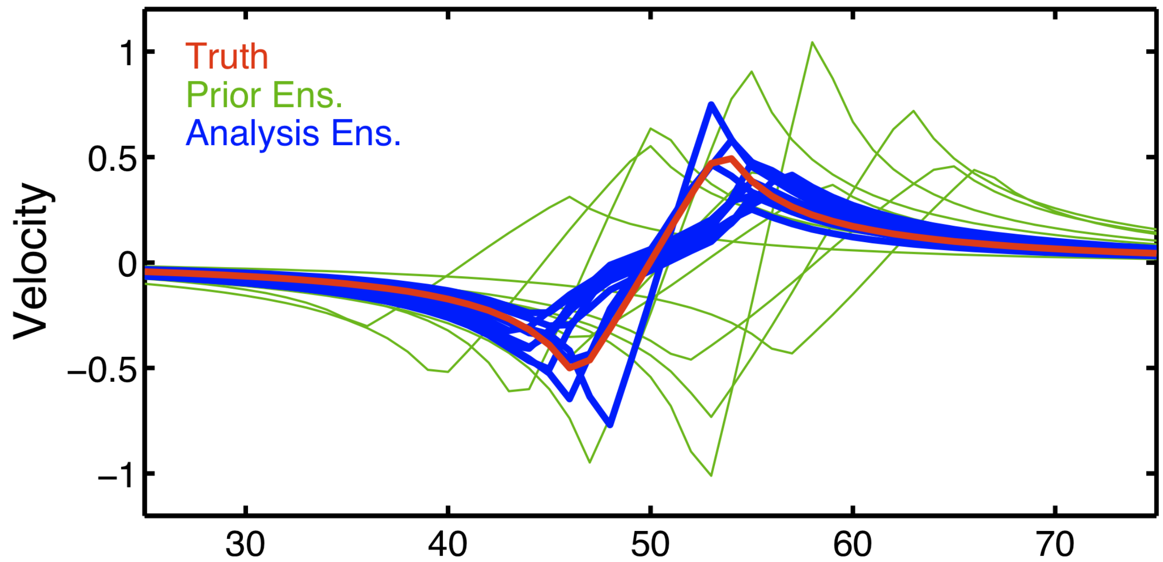
Also assimilating an observation of the vortex position improves the analysis.
The position prior is generally nicely gaussian.

Assimilation of vortex specific observations



Instead of assimilating wind, one can assimilate wind as a function of distance from center.
This reduces non-gaussianity but can increase non-linearity.

Invertible transformation of state before assimilation



Transform state to position and wind relative to center.
Assimilate observation of wind and position.
Transform back.

Invertible transformation of state before assimilation

- Transforming to position and wind relative to center works very well here, but this is by construction.
- Removing vortex from background is tricky (witness GFDL and bogusing).
- Less vortex specific transformations may prove useful.
- Applying transformations to make prior more linear near strong gradients is a research topic.

Some other promising approaches

- ➢Extending particle filters (handle arbitrary priors) to large problems.

- ➢Hybrid use of variational and ensemble methods (this is too much work for me).

Summary

1. Strong gradients and discrete structures in TS ensemble assimilation is a special challenge.
2. Leads to non-gaussian, non-linear prior ensembles.
3. Non-gaussian observation methods are available.
4. More sophisticated localization needed.
5. More research needed on state transformation.
6. Short-term goal: good use of observations in core.

Caveat 1: This is my highly-biased viewpoint.

Caveat 2: Good models with frequent observations fixes everything.