Real-time Ensemble Prediction and Data Assimilation of Tropical Cyclones with COAMPS-TC®

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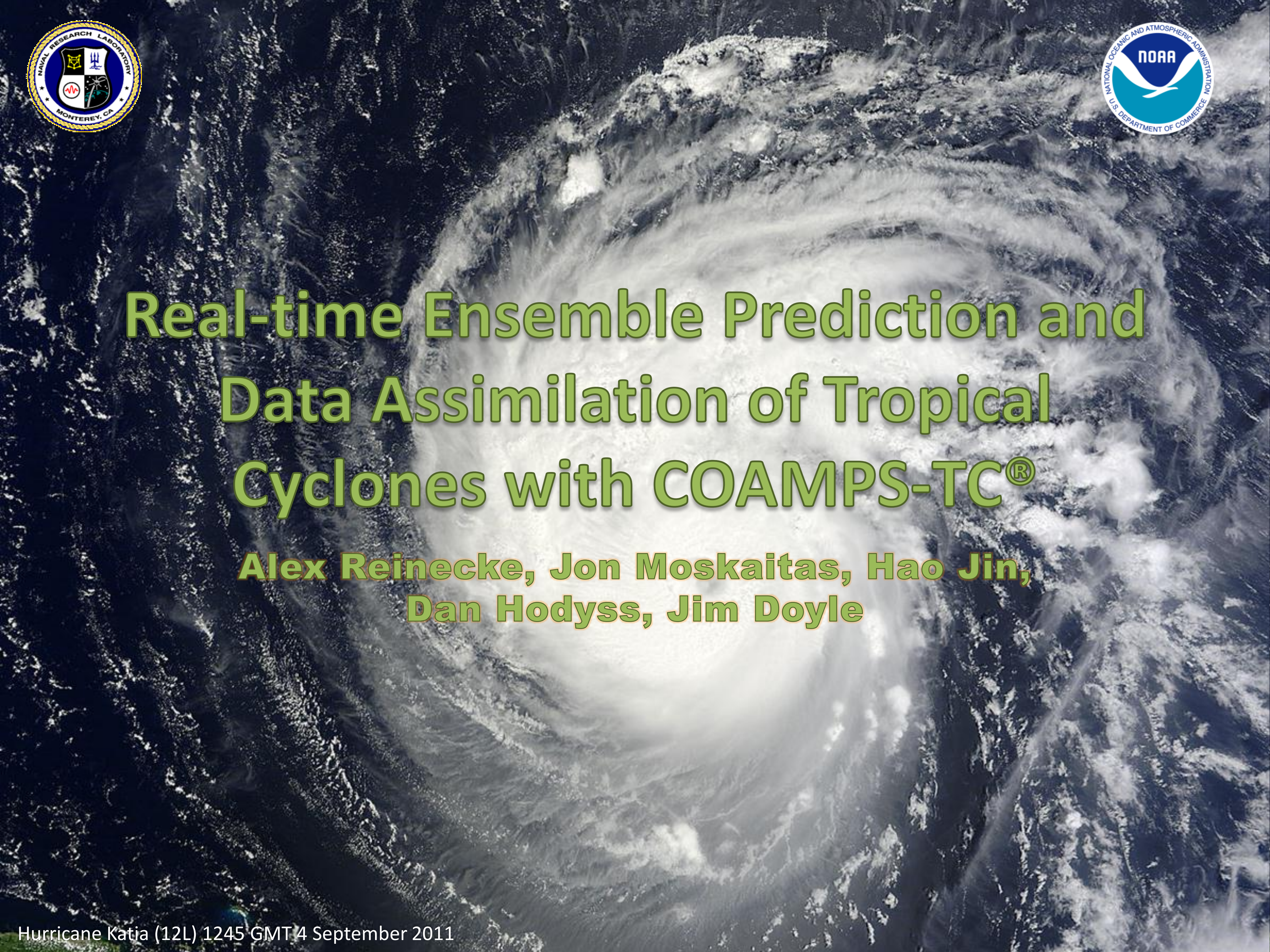


Hurricane Katia (12L) 1245 GMT 4 September 2011

A successful demonstration of the COAMPS-TC ensemble DA and forecasting system

Provided real-time ensemble forecast for 15 named storms

- 257 80-member data assimilation cycles
- 140 10-member forecasts
- Forecast for the Atlantic, Eastern-Pacific, and Western-Pacific Basins from 01 August to 30 September, 2011

Real time delivery of data:

- Web output for visualization
- Tracks to ATCF and NCAR DTC for statistics (and forecasters use?)

Identification of several areas needing improvement

- Archive of data for future analyses and experiments

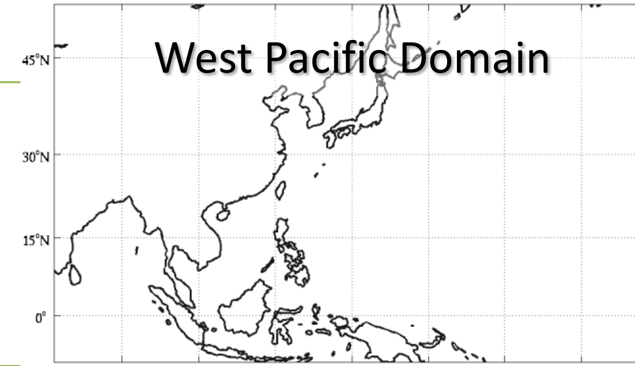
Demonstrated real-time capability of the DART system

- Scalability and efficiency fully demonstrated

Real Time COAMPS-TC Data Assimilation Ensemble

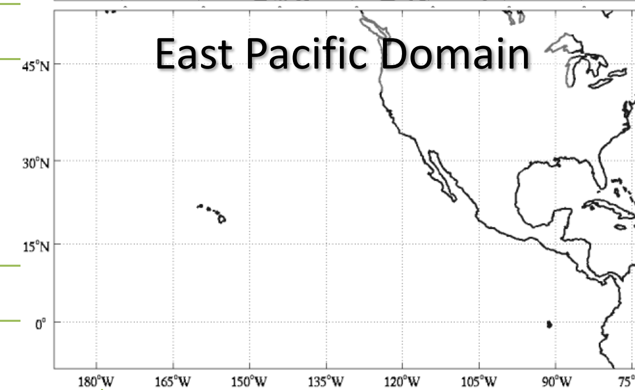
Serial EnKF (DART)

- Two-way interactive DA – highest resolution nest defines the innovation
- Observations: Surface/ship stations, cloud-track winds, aircraft data, dropsondes, radiosondes, synthetic tropical cyclone observations, storm position.
- Distance based localization, multiplicative based adaptive inflation.



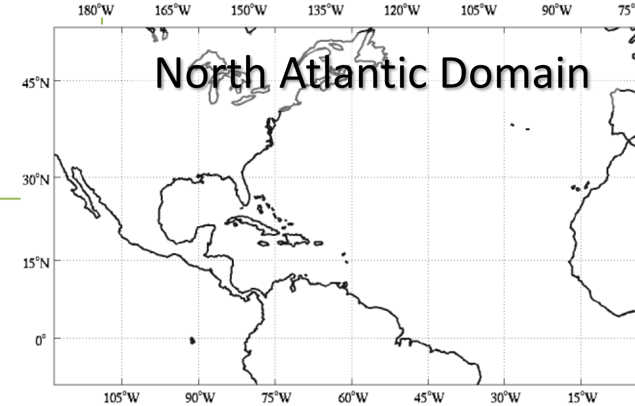
80-member ensemble for Data Assimilation

- 6-hr update cycle
- GFS-EnKF fields interpolated to COAMPS grid for the initial ensemble
- GFS-EnKF lateral boundary conditions.



DA and forecast for Atlantic, EastPac, and WestPac basins

- Fixed 45-km mesh for each basin
- Imbedded 15- and 5-km moving nests
- Only one set of high resolution nests per basin
- For each storm mesh is initialized with GFS-EnKF fields



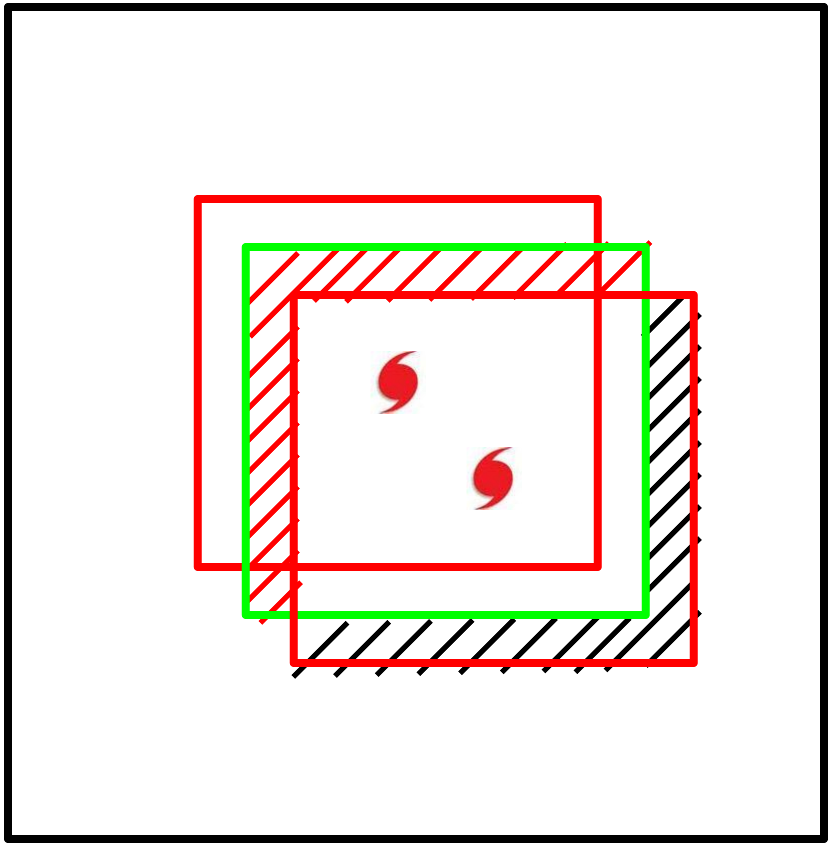
Moving Nests

A challenge for regional ensemble data assimilation systems.

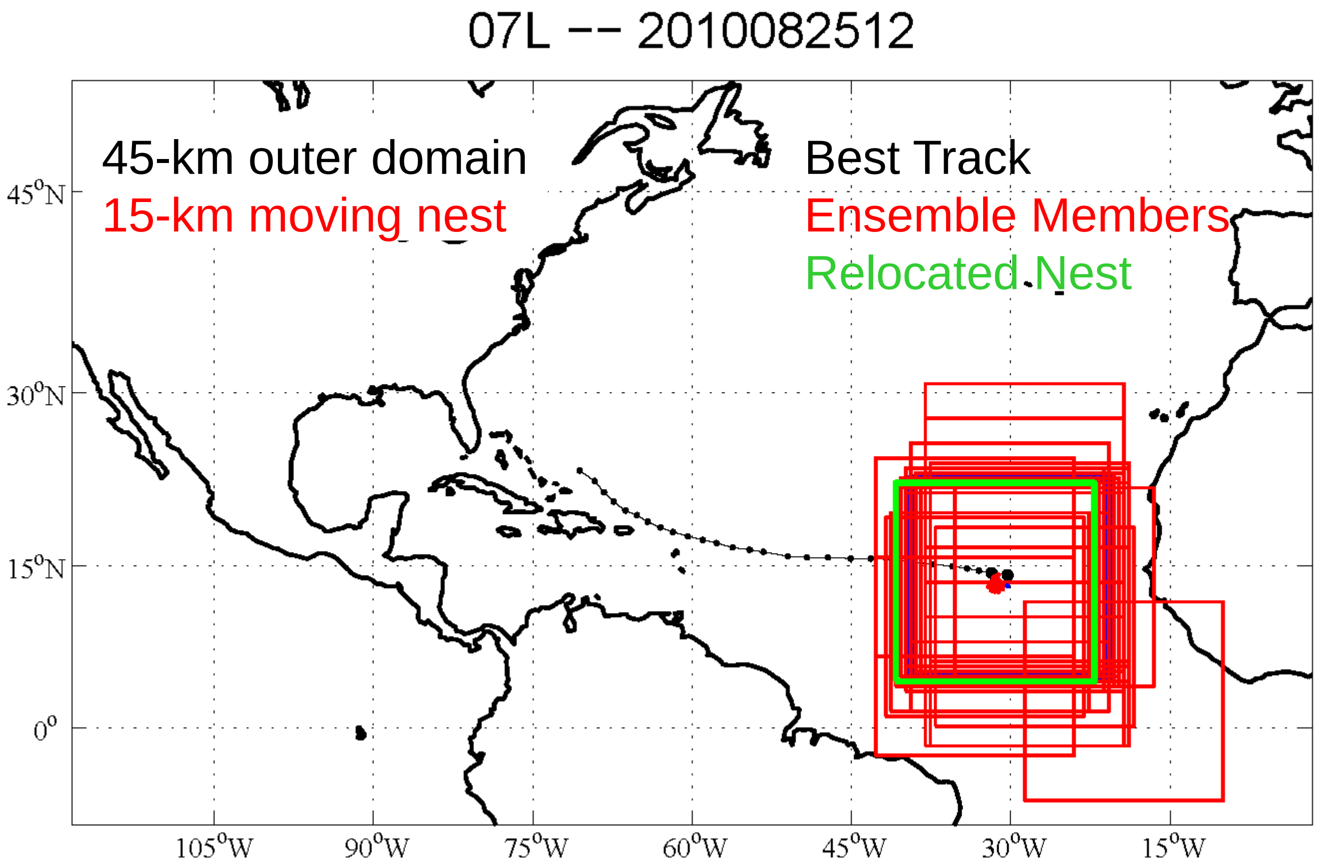
- Each member will move independently
- Ensemble prior nest location not constrained to be collocated

Compute prior mean nest location and define a new nest there

- Relocate nest of each member to the mean nest location
- Interpolate fields where mean and member nest do not overlap
- Directly insert fields in overlap region



Ensemble of Moving Nests



- For initial ensemble nests move in an inconsistent manner
- As ensemble spins-up, nests location nearly converged
- Algorithm is robust and can handle members missing nest

COAMPS-TC Forecast Ensemble

10-members (option to run 20-members)

- 120-h lead time twice daily (00 and 12 UTC)
- GFS-EnKF lateral boundary conditions
- Only group to run real-time forecasts from a cycling ensemble DA system (?)

Perturbations

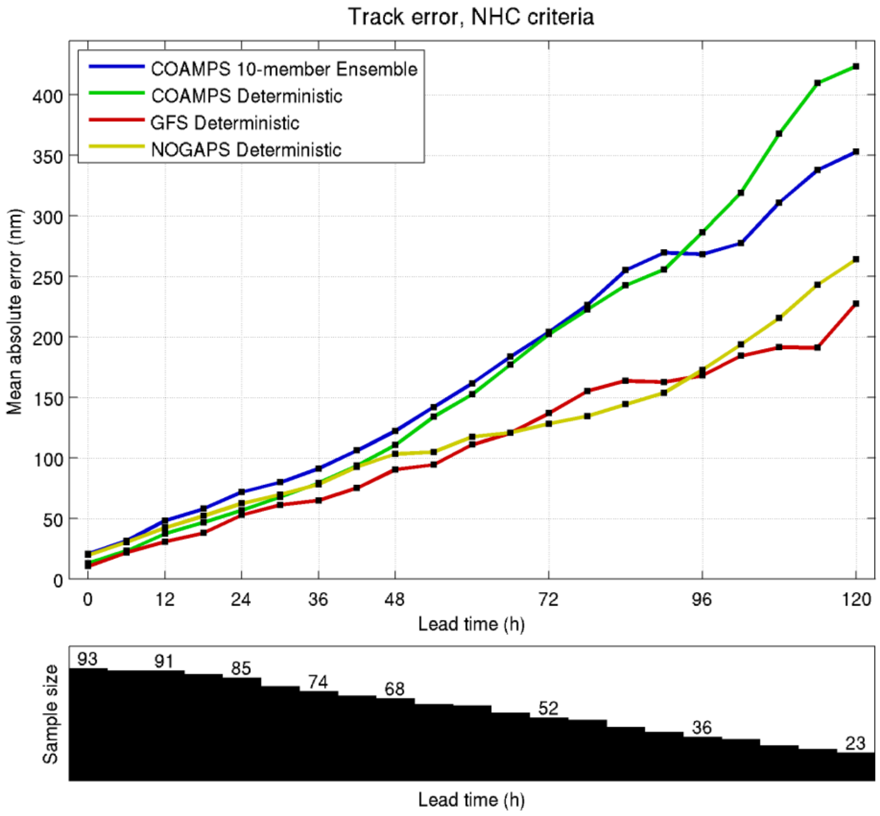
- IC perturbations from member 1-10 of the DA ensemble
- No perturbations to model dynamics or parameterizations

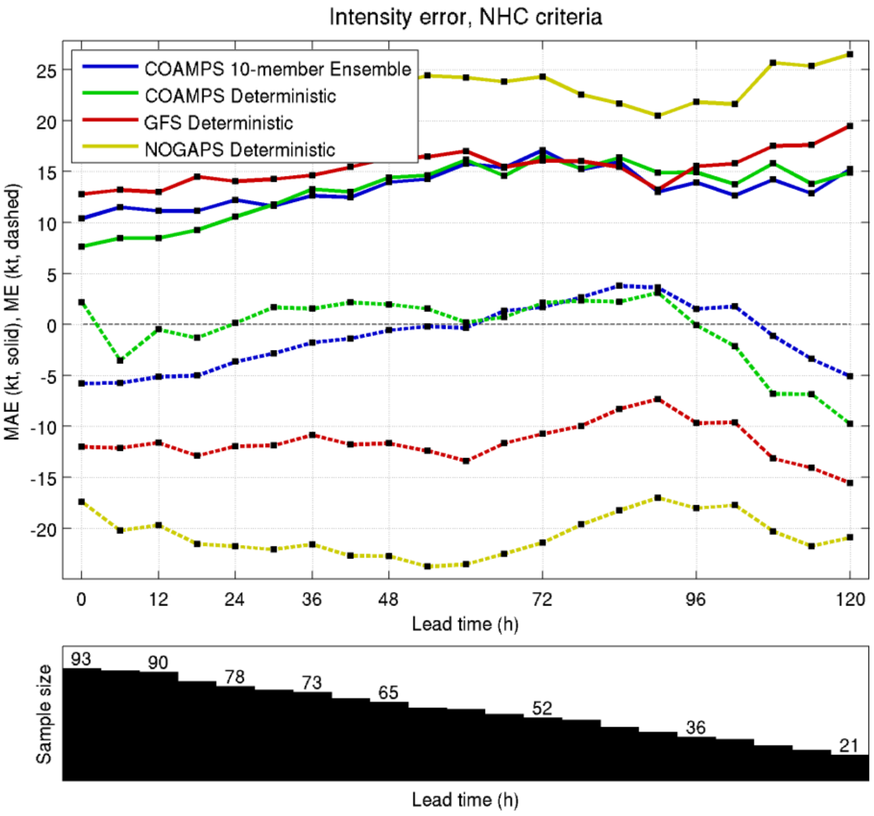
Graphics output to web

- Summary plots for intensity, size, and track
- 15 and 5 km mesh graphics computed in storm relative coordinate

Track and Intensity Errors

Homogeneous Comparison -- 2011

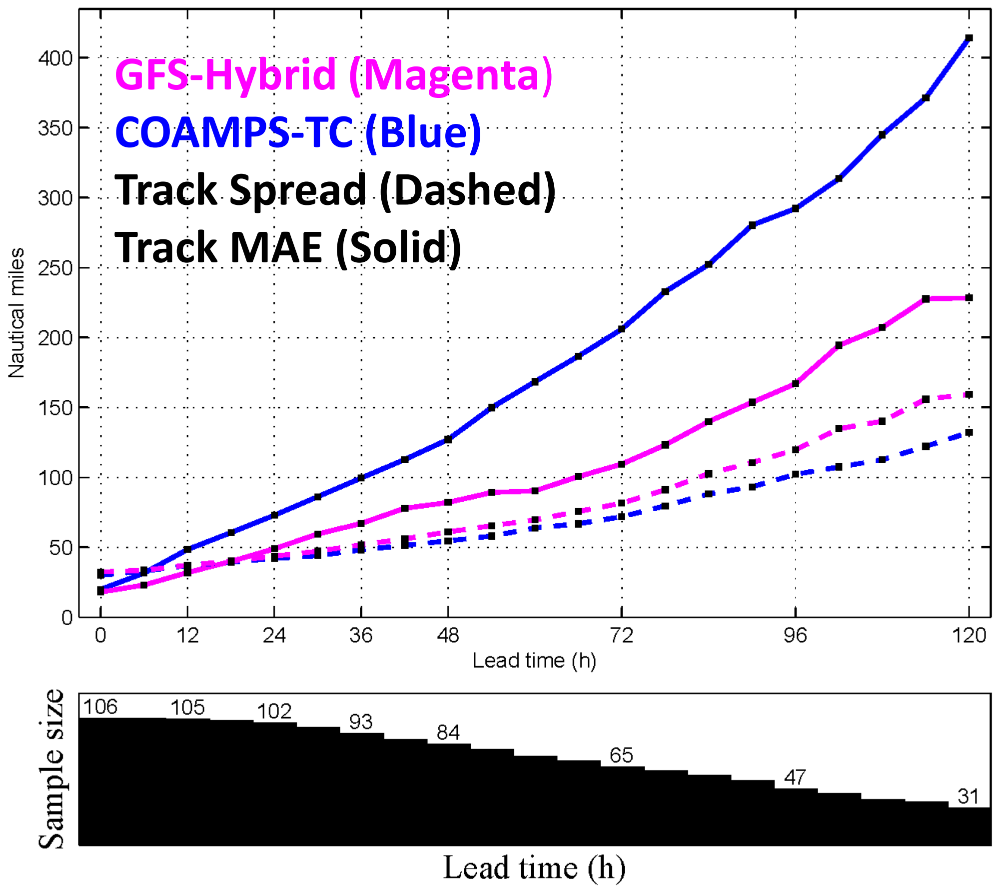




- COAMPS (det. & ens.) track forecast worse than global models, intensity is better.
- Ensemble system track forecast are better than deterministic system beyond 72 hours.
- Low wind speed bias for ensemble system from 0 to 48 hours.

Track Spread-Skill Relationship

Homogeneous comparison to GFS-Hybrid

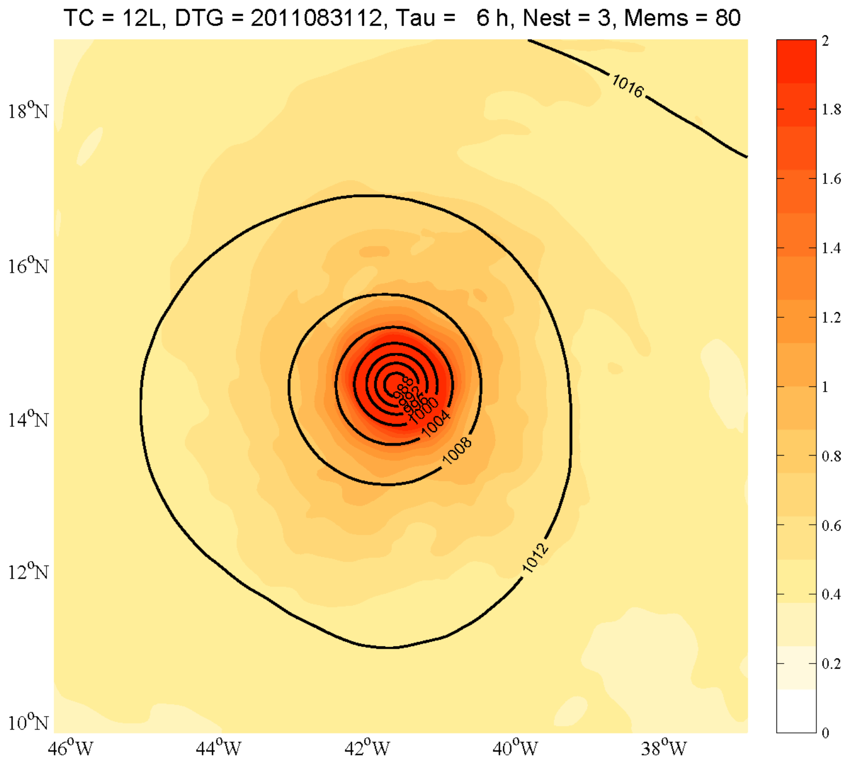


- Track spread is comparable to HFIP GFS-Hybrid system
- Large track errors are similar to deterministic COAMPS-TC system
- On average spread-skill good at analysis time

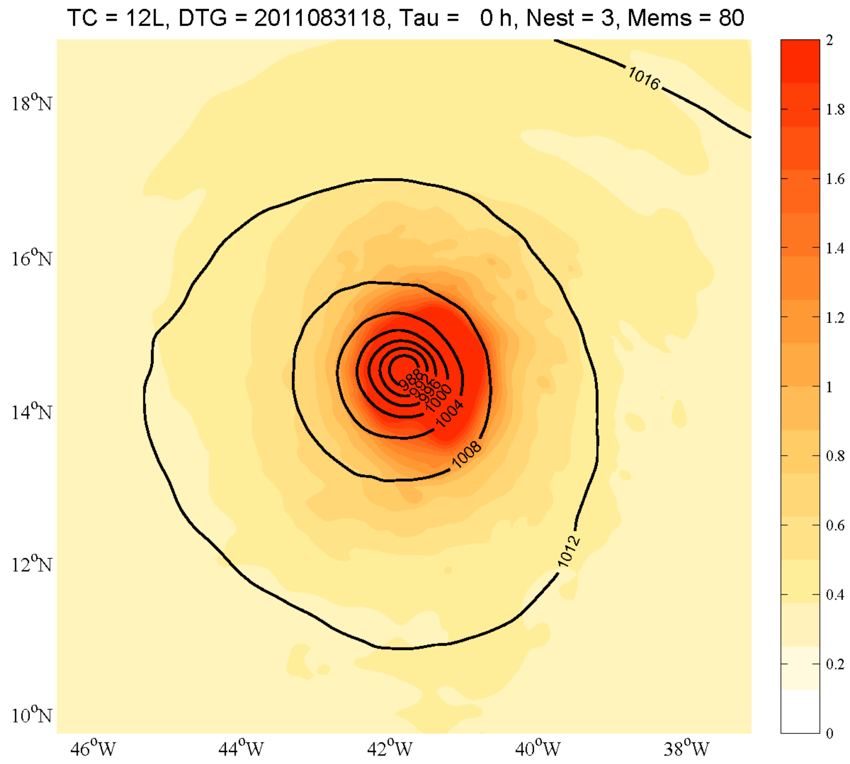
SLP Analyses

Assimilating u/v synthetic data

Background SLP mean & standard deviation

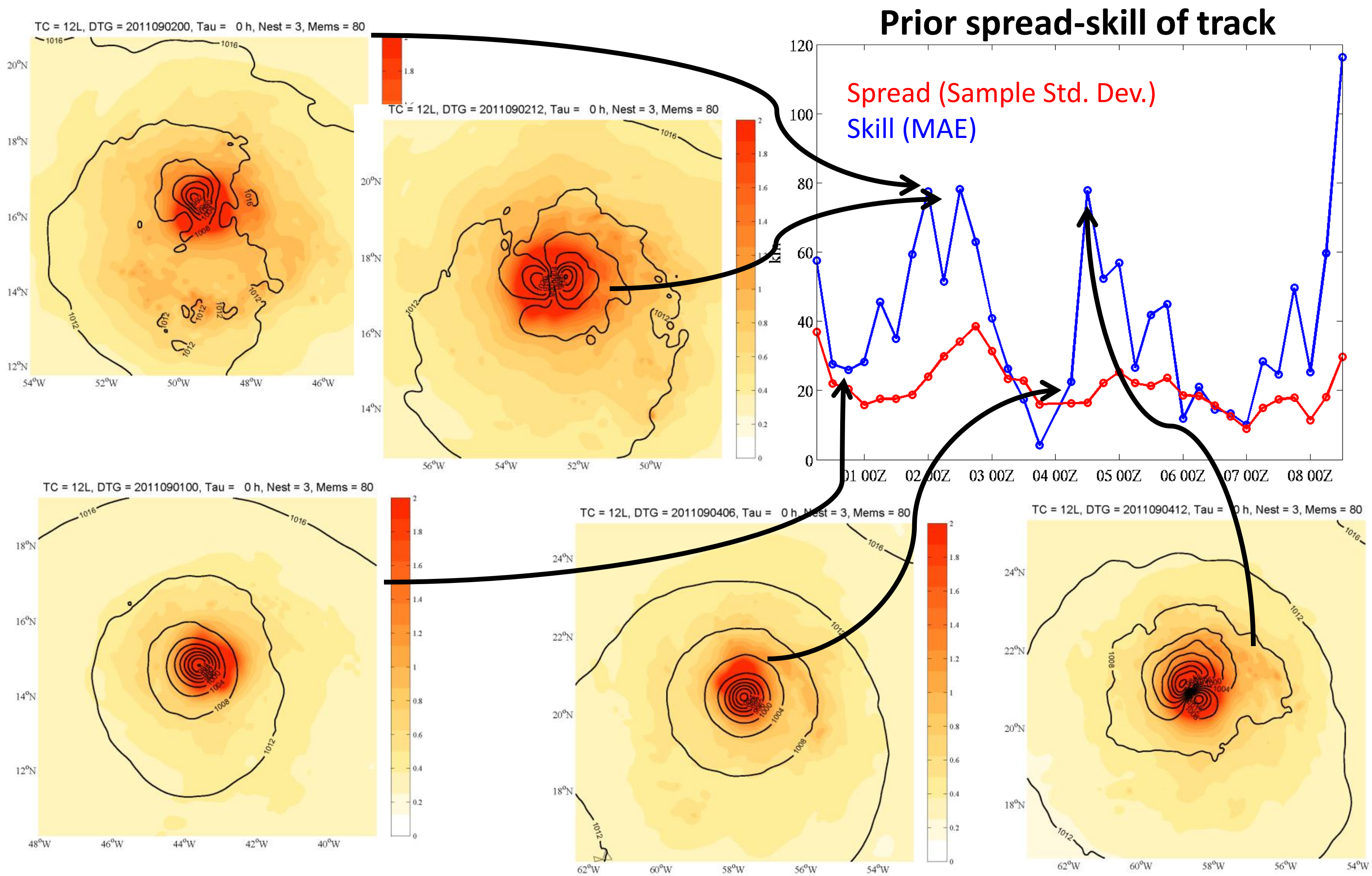


Analysis SLP mean & standard deviation



- Poor quality analysis at several assimilation times
- Leads to low bias in the forecast intensity

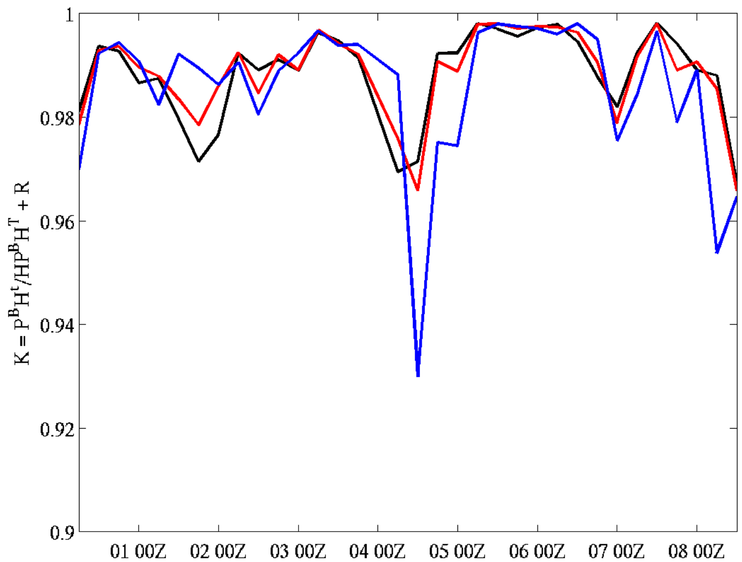
Track errors and assimilation quality

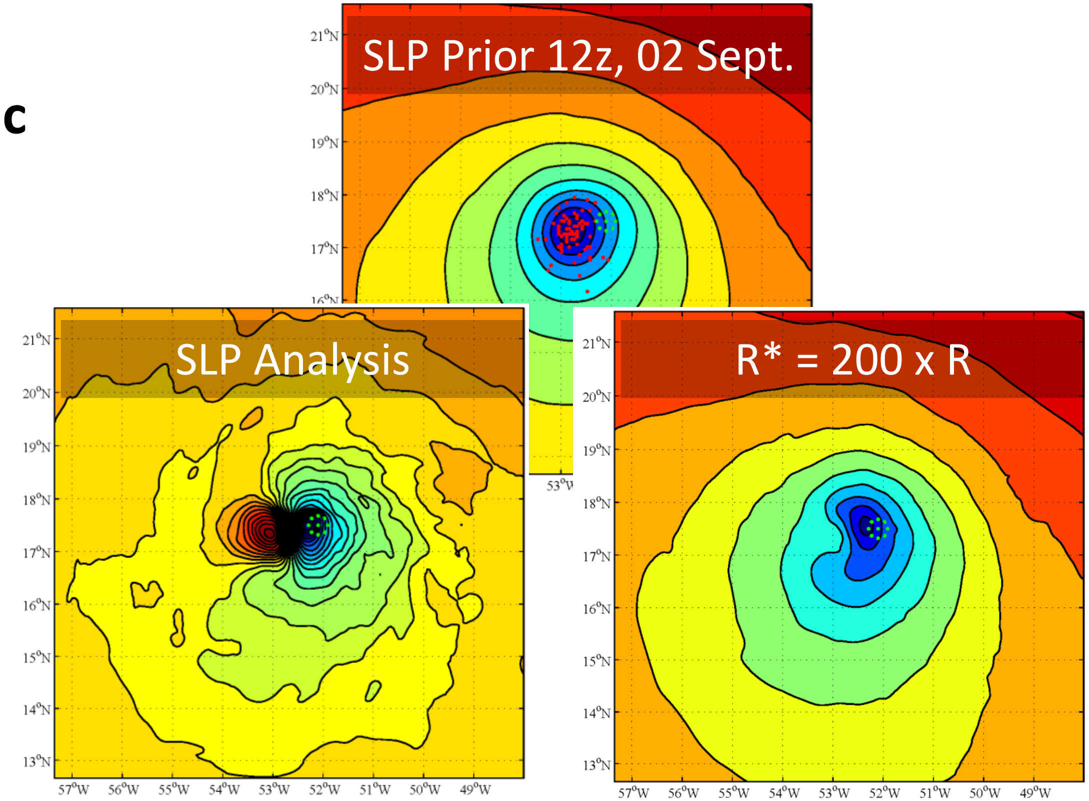


- Well behaved analysis when the prior track error is small
- Poor quality analysis when the prior track error is large

Storm scale assimilation

Kalman gain at several synthetic U-wind obs.



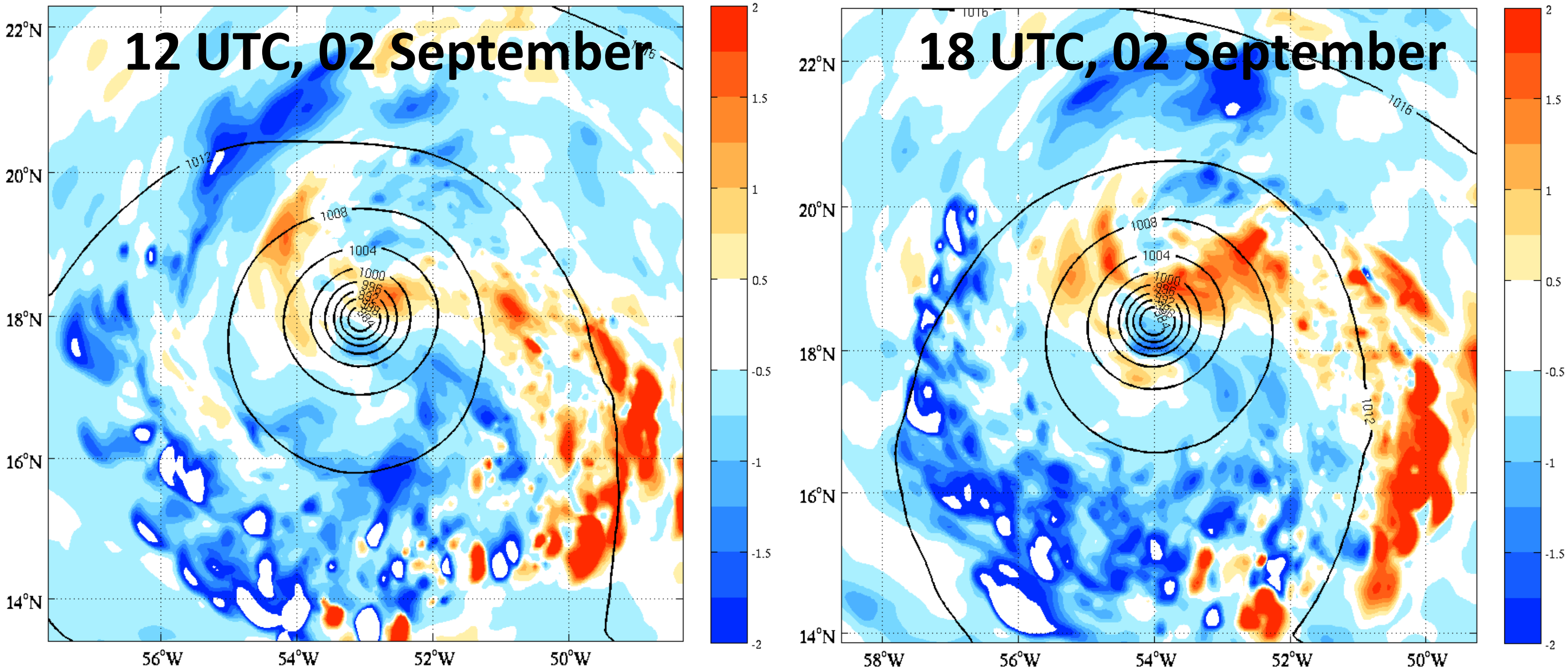


Large ensemble variability due to sharp gradients and **poor characterization of observation error** leads to over fitting observations

Not fundamentally linked to synthetic observations, happens in cases without synthetics where there are many observations (e.g. Irene)

Non-Gaussian Prior Distributions

Prior skewness of 10-m zonal wind
Katia (12L) -- 12 UTC, 02 September 2011

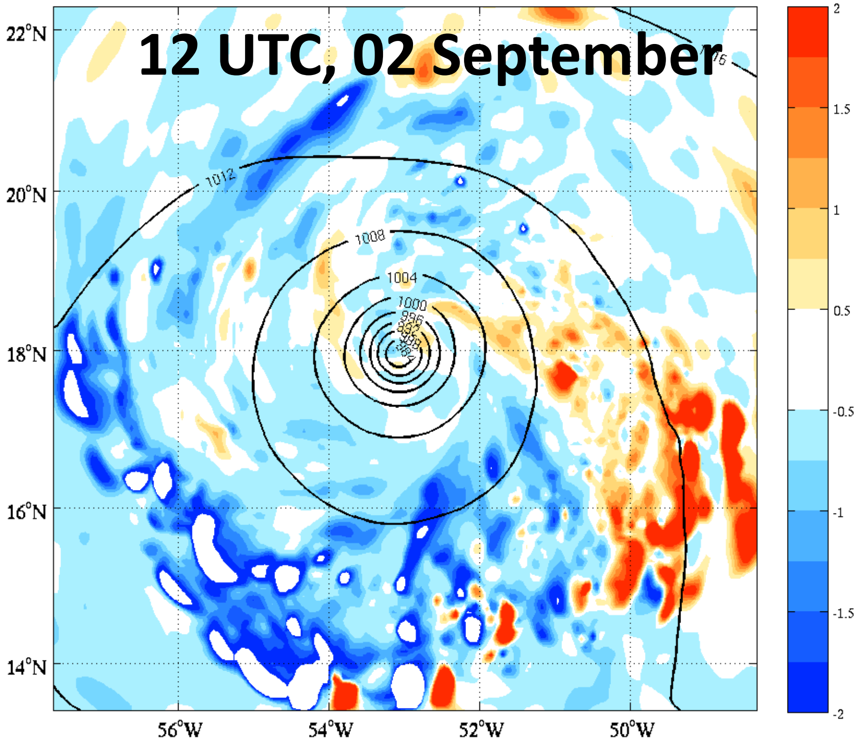


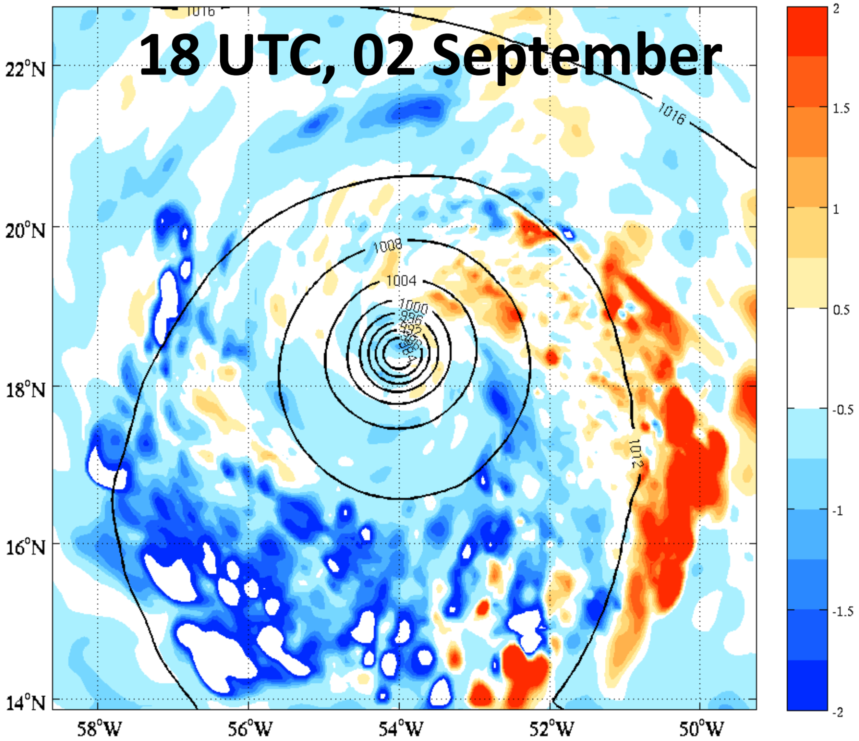
EnKF, variational methods, and hybrid methods do not and **cannot** account for non-gaussian distributions

Storm Relocation Distribution

Prior skewness of 10-m zonal wind

Katia (12L)

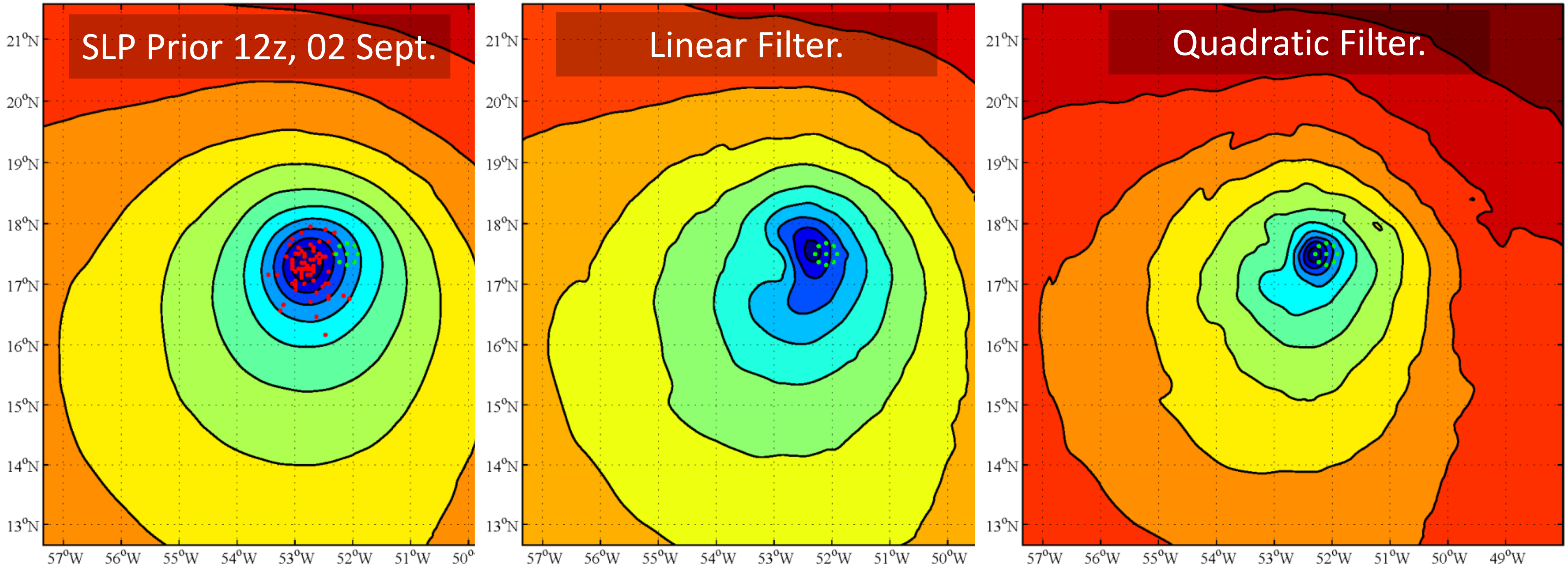




Even with a storm relative data assimilation system, non-Gaussian structures dominate the prior distribution

Explicitly account for 3rd moments

Quadratic Filter



$$\bar{x}_a = \underbrace{\bar{x}_f + Kv}_{Kalman\ Filter} + \underbrace{Q\left[v^2 - \alpha_0 + \alpha_1 v\right]}_{New\ Term}$$

α_0 – Correction to 0th order term

α_1 – Higher-order correction to the Kalman gain

Quadratic filter more capable than Kalman filter at recovering the observation set

Hodyss, D, 2011: Ensemble State Estimation for Nonlinear Systems Using Polynomial Expansions in the Innovation

Summary

Significant issues need to be addressed before an effective storm-scale assimilation system can be realized.

Observation error (representativeness error) generally unknown within tropical cyclones.

- Artificially low errors lead to the DA system to over fit the obs.
- Ad-hoc inflation of the observation error is not a desirable solution

Non-Gaussian prior distributions within the ensemble present a major obstacle to the correct assimilation of storm-scale data

- Relocation of the TC to a common point helps, but significant 3^{rd} moments still present.
- Need to explicitly deal with 3^{rd} moments.
- Testing of quadratic filter that explicitly accounts for 3^{rd} moment underway in the COAMPS-DART framework.

Questions/Comments?