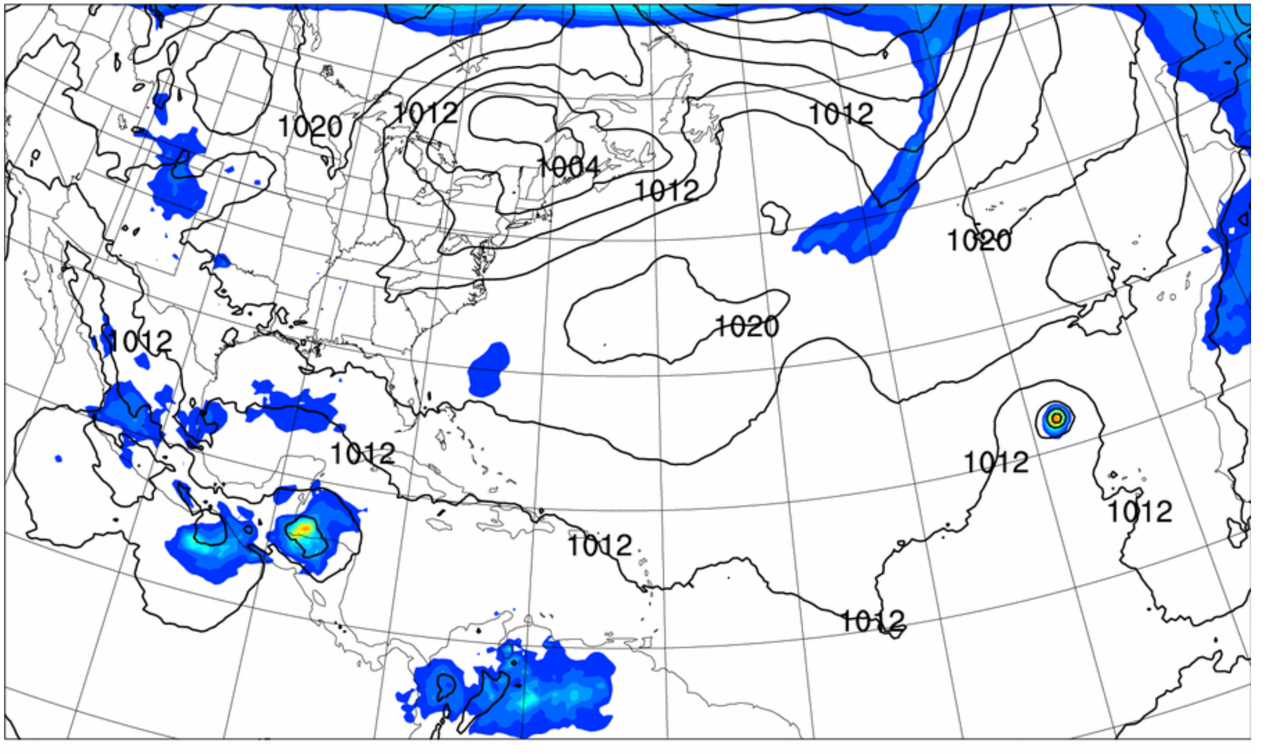
Mesoscale Data Assimilation for Tropical Cyclone Prediction



Chris Snyder, NCAR

NCAR is supported by the National Science Foundation

Mesoscale Data Assimilation for Tropical Cyclone Prediction

Real-time results at end of talk:

courtesy Ryan Torn (SUNY Albany) and Steven Cavallo (NCAR)

Initial conditions for TC prediction

Difficult and still only partially solved

Need accurate estimate/analysis of both environment and TC itself

Initial conditions for TC prediction (cont.)

Observations relevant for environment

- "Conventional" observations, esp. aircraft
- Satellite radiances
- Cloud-track winds
- Special dropsondes

Observations relevant for vortex

- Sat images & recon flights distilled to advisory position, intensity, RMW
- Other: cloud-track winds, scatterometer, special dropsondes, Doppler radar

Observations are limited and intermittent

- Certainly do not resolve all aspects of vortex structure or evolution

Initial conditions for TC prediction (cont.)

Ad hoc techniques are frequently used and often effective

Bogussing

- Based on assumed vortex structure
- Direct insertion of bogus vortex or assimilation of simulated/bogus obs

Vortex removal and relocation

- Extract vortex from model forecast through spatial filtering or vorticity inversion
- Insert vortex in correct position

Initial conditions for TC prediction (cont.)

E.g., GFDL technique:

1. Remove vortex from GFS analysis
2. Spin up axisymmetric vortex from axisymmetric version of GFDL model forced by radial profile of low-level tangential wind
3. Estimate vortex asymmetry by spatial filtering of previous 12-h forecast
4. Insert vortex + asymmetry into GFS analysis.

Initial conditions for hurricane prediction (cont.)

Data assimilation (DA)

- Assimilate observations relevant to TCs like any other observation
- Rely on assimilation scheme to produce vortex in correct location and with realistic structure

Not a trivial or solved problem

- Good results to date (e.g. ECMWF, WRF/DART) and strong potential for continued improvements
- Can avoid separate prediction system for TCs; reduces costs of development and maintenance

(Brief) Background on DA

Wish to estimate atmospheric state, using information from obs and from a previous forecast.

DA provides estimate as function of obs and forecast.

- State estimate = analysis = ICs for next forecast

Optimal DA gives estimate with smaller expected error than either obs or forecast

Background on DA (cont.)

Thus, DA requires knowledge of or assumptions about:

- Observation-error statistics
- Error statistics for forecast used in assimilation

Optimal DA for linear, Gaussian system:

$$x^a = x^f + K (y - y^f),$$

where:

x^a = estimate of state

x^f = forecast of state

y = observation

y^f = forecast of observation

K = "gain" = $\mathrm{cov}(x^f, y^f)\,(\mathrm{var}(y^f) + r)^{-1}$

Background on DA (cont.)

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y = observation

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$$\boxed{K = \text{“gain”} = \mathrm{cov}(x^f, y^f)\ (\ \mathrm{var}(y^f) + r\ )^{-1}}$$

Determines spatial structure of analysis increment

Background on DA (cont.)

Simplest DA schemes make strong assumptions about cov(x,y)

- No time dependence
- Spatially isotropic and homogeneous; i.e. depends only on distance between x and y
- No dependence on atmospheric state; e.g. independent of presence or absence of hurricane

More sophisticated schemes relax these assumptions and explicitly incorporate information from model dynamics

- Four-dimensional variational DA (4DVar)
- Ensemble Kalman filter (EnKF)

How the EnKF Works

Suppose we wish to assimilate an observation, y
Consider how assimilation affects a model variable, x.

EnKF estimates required covariance from ensemble of forecasts

Begin with:

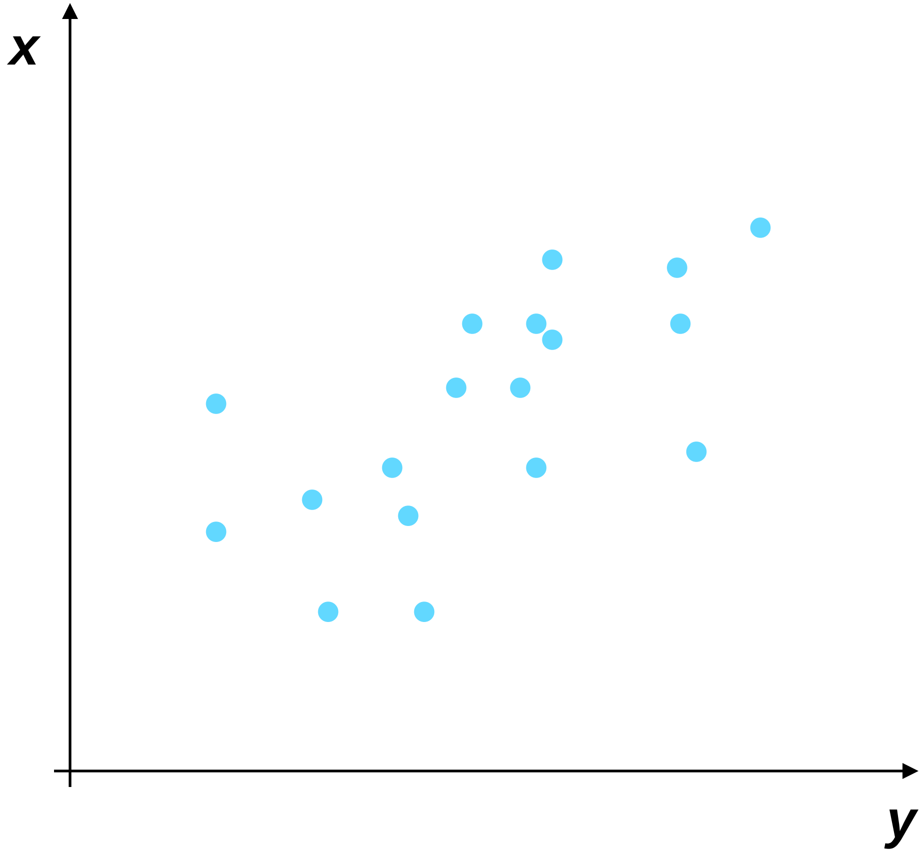
- ensemble of short-range forecasts for x
- Observed value of y

How the EnKF Works (cont.)

1. Compute y for each ensemble member

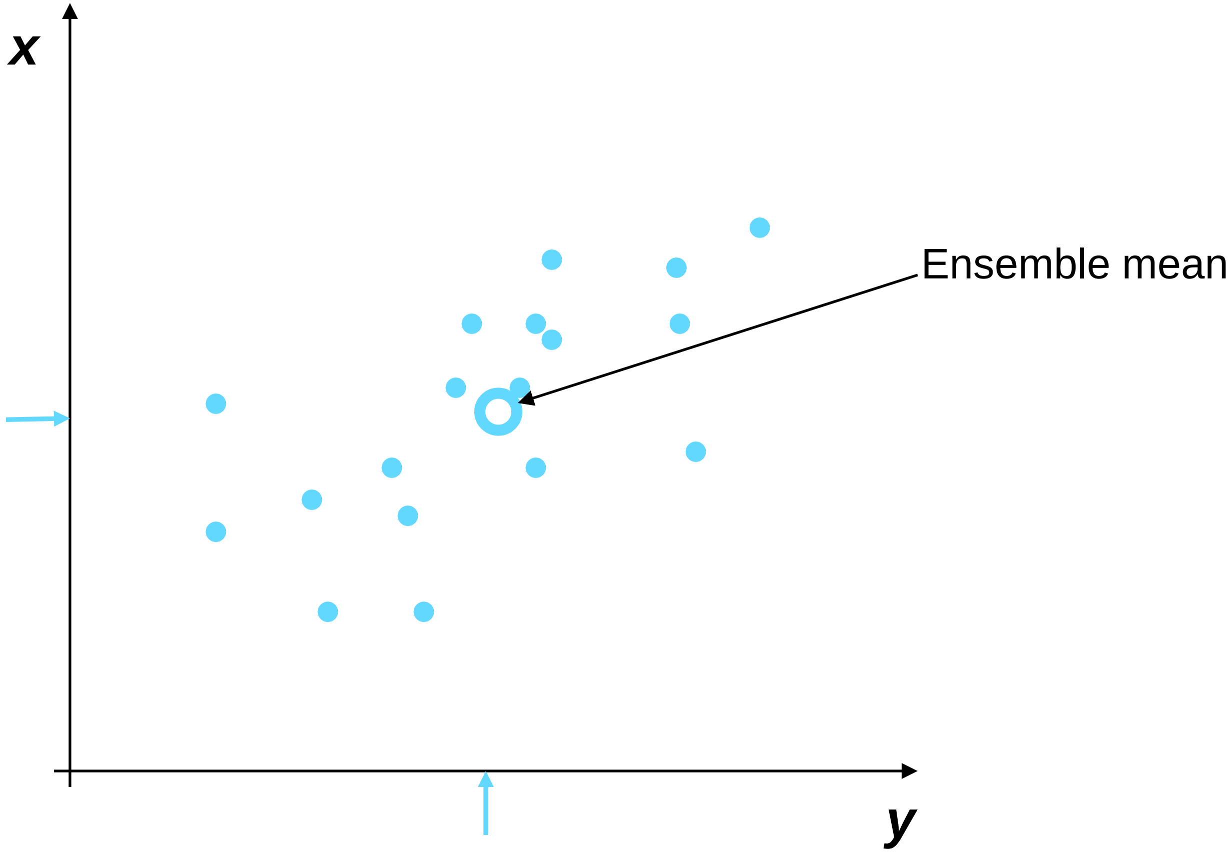
How the EnKF Works (cont.)

1. Compute *y* for each ensemble member



How the EnKF Works (cont.)

1. Compute *y* for each ensemble member



How the EnKF Works (cont.)

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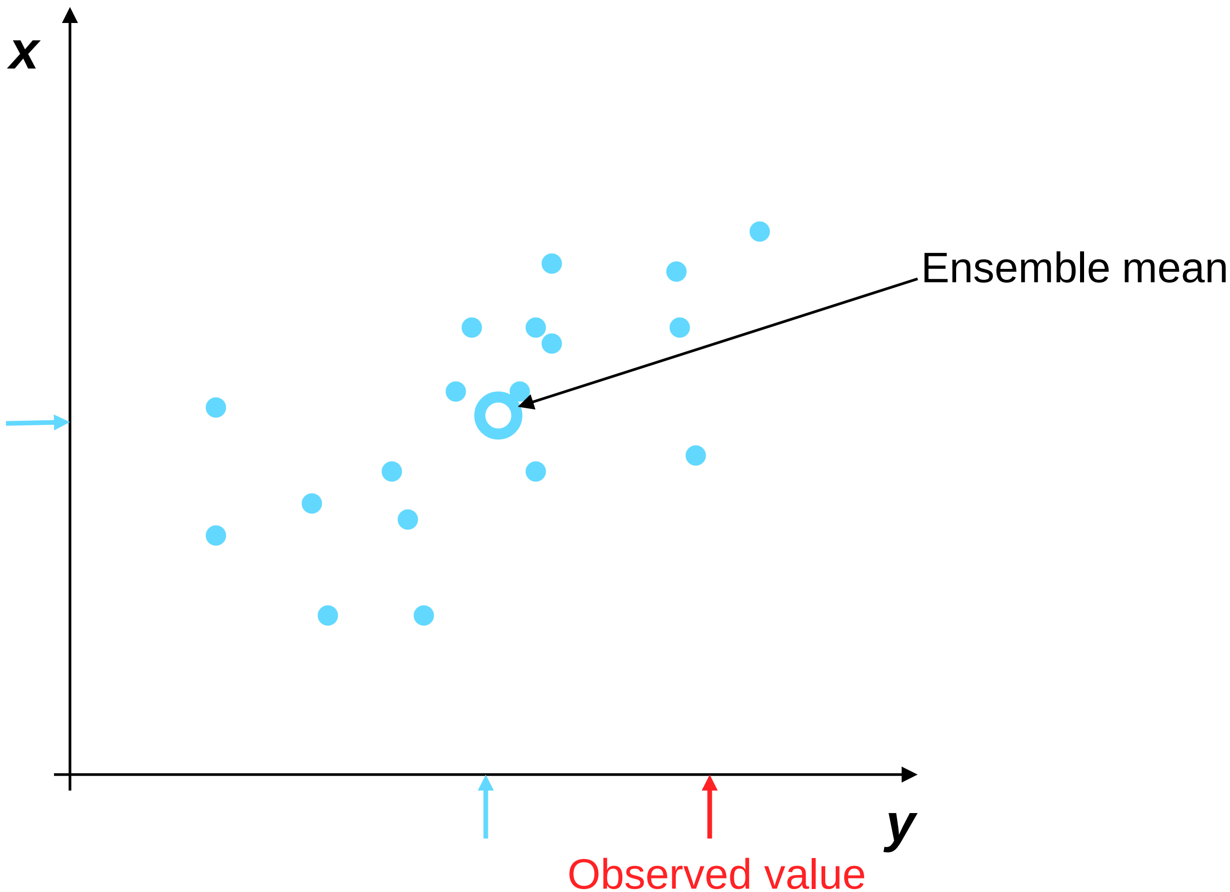
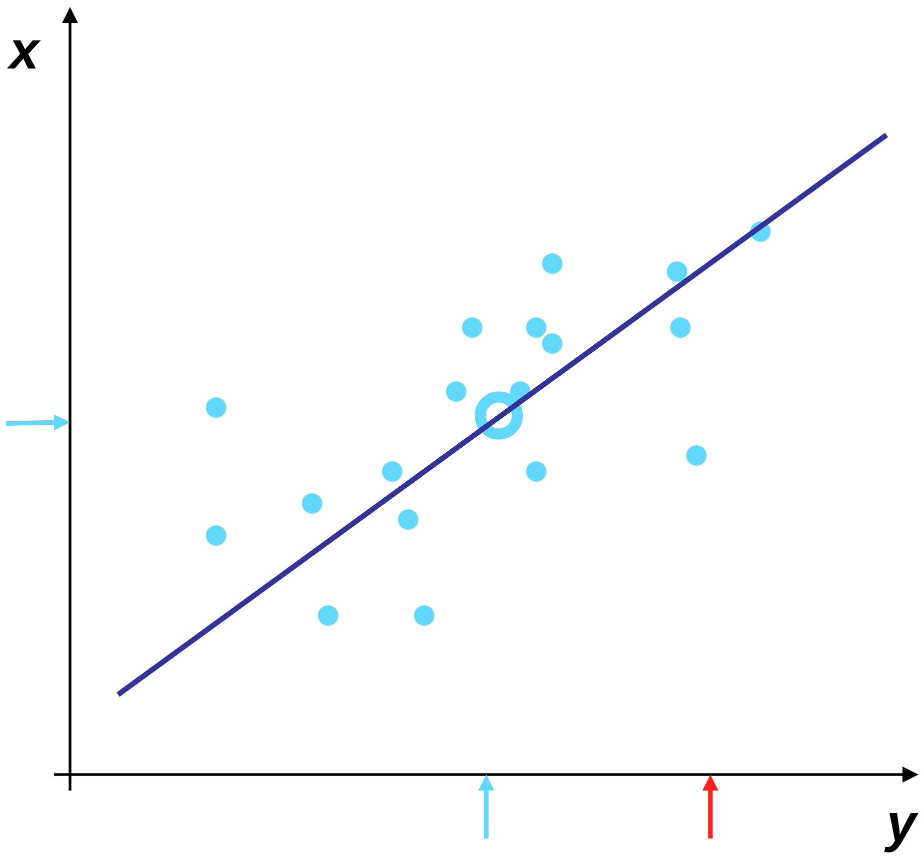


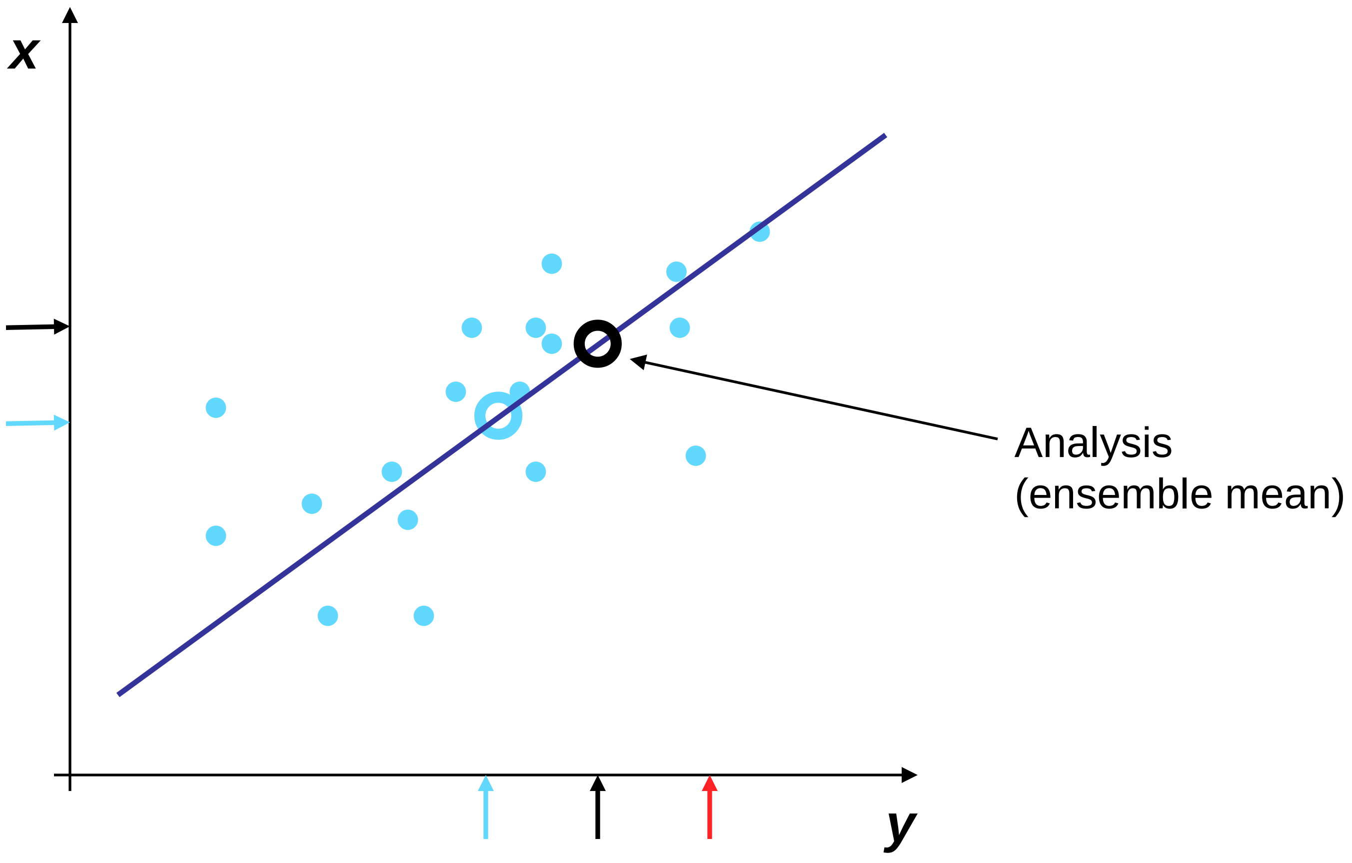
How the EnKF Works (cont.)

2. Compute best-fit line that relates *y* and *x*



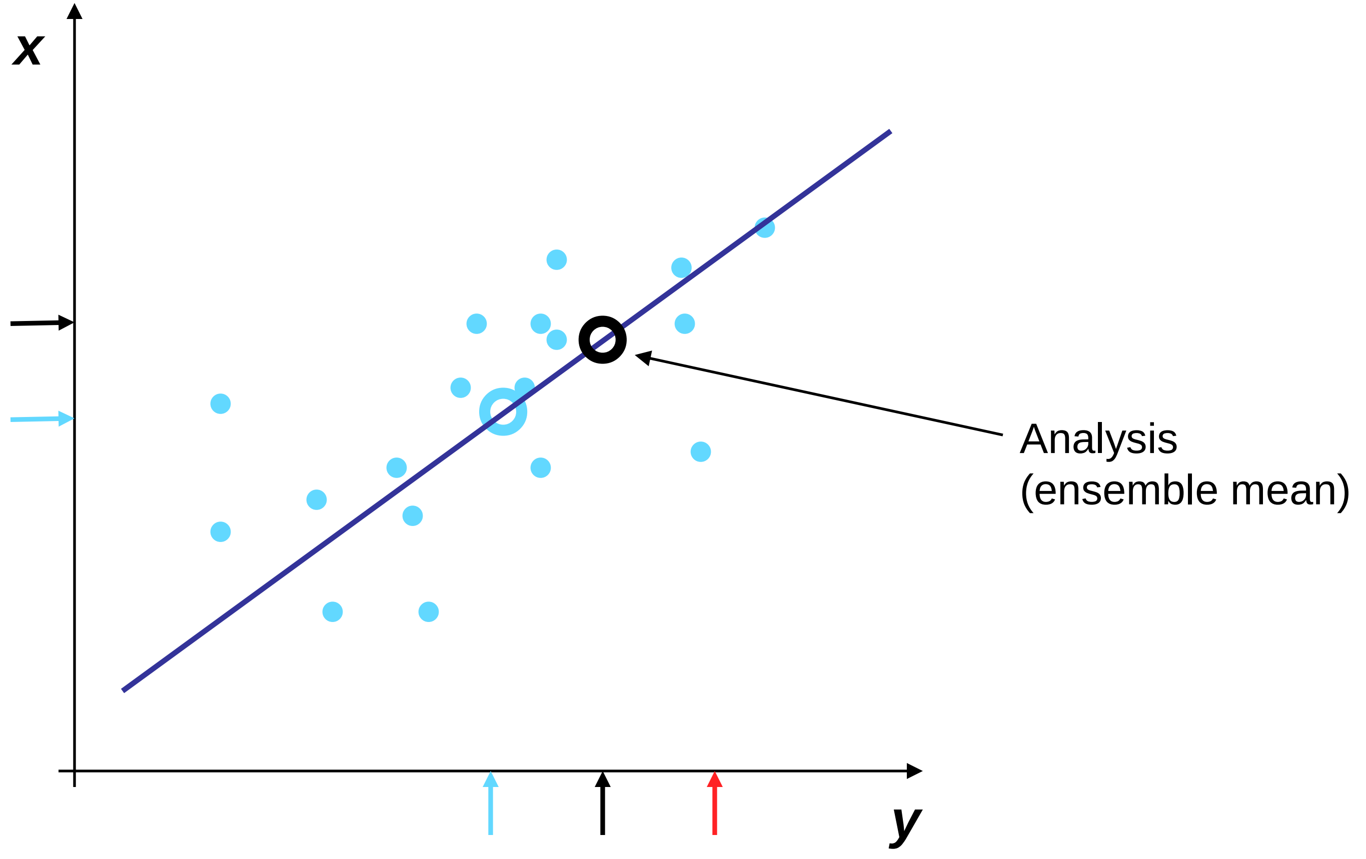
How the EnKF Works (cont.)

3. Analysis moves toward observed *y* and along best-fit line



How the EnKF Works (cont.)

3. Analysis moves toward observed value of *y* and along best-fit line … have gained information about unobserved variable, *x*



How the EnKF Works (cont.)

4. Update deviation of each ensemble member about the mean as well, consistent with covariance update of Kalman filter

Yields initial conditions for ensemble forecast to time of next observation. “Ensemble of analyses”

How the EnKF Works (cont.)

Forecast step:

- Ensemble forecast, using full nonlinear forecast model, to next obs time
- Need to account for uncertainty in lateral and surface BCs and in model

Analysis step (one version):

- Compute "simulated observation" $\mathbf{y}^f = H(\mathbf{x}) + \varepsilon$ for each member
- Compute analysis for each member according to Kalman-filter equations based on sample covariances

Behavior with Incomplete Observations

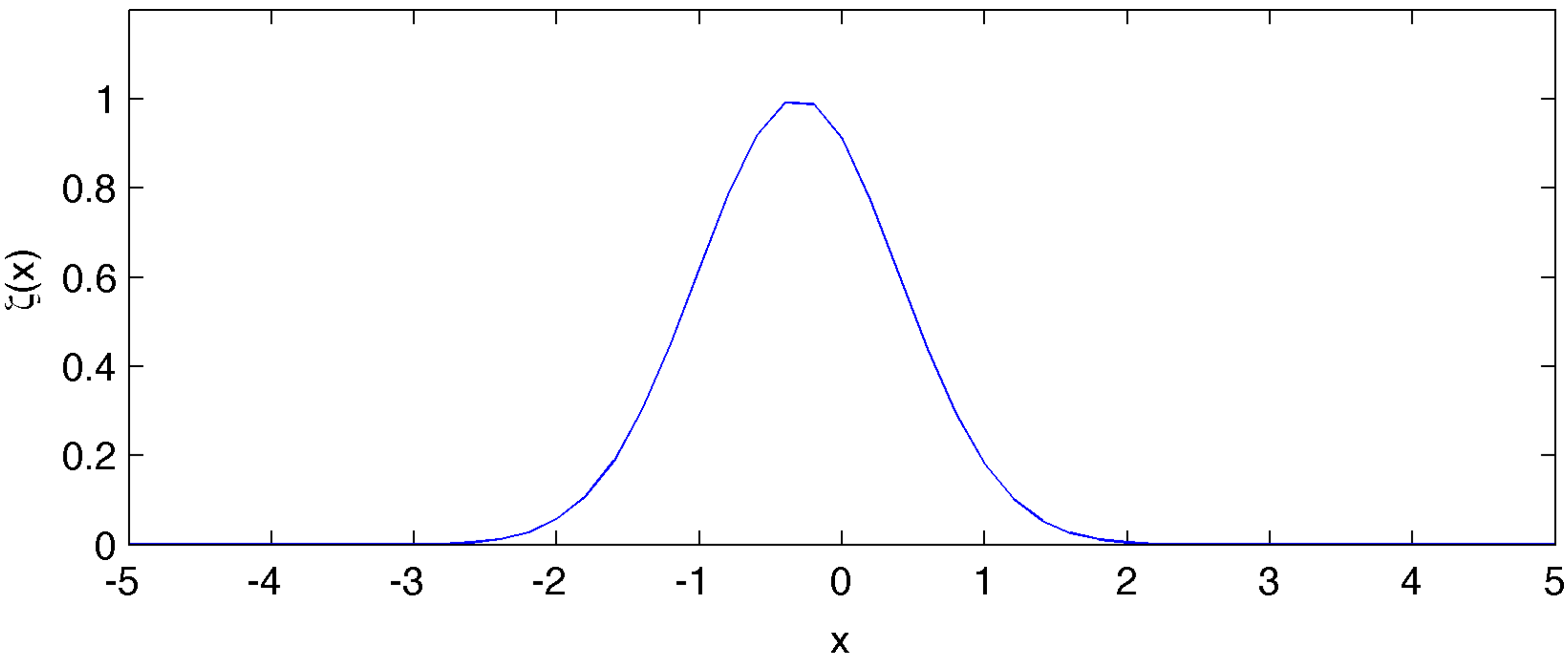
Differences between DA schemes esp. apparent when observations are incomplete

- Contrast 3DVar and EnKF

Behavior with Incomplete Observations (cont.)

1D example:

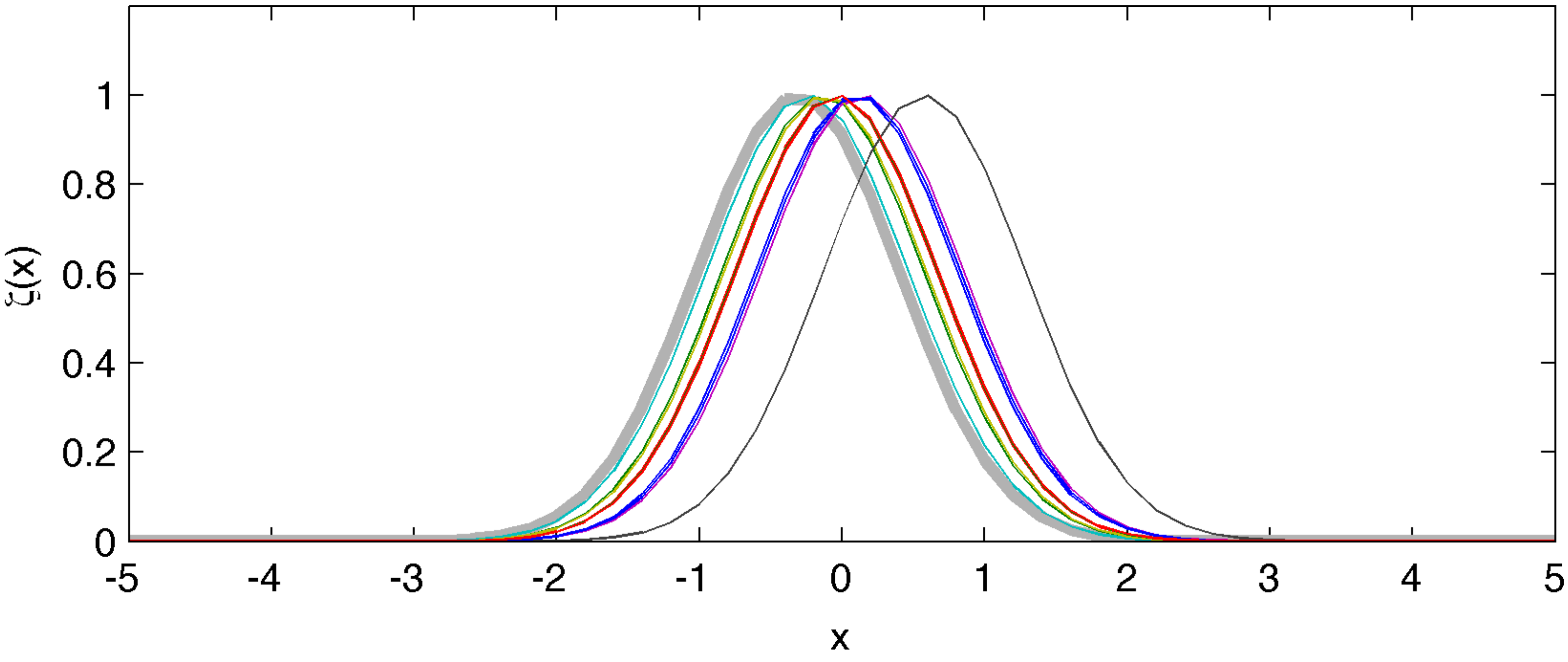
- Vorticity is function of single spatial coordinate, $\zeta = \zeta(x)$
- "Vortex" = isolated maximum in ζ



Behavior with Incomplete Observations (cont.)

Suppose that:

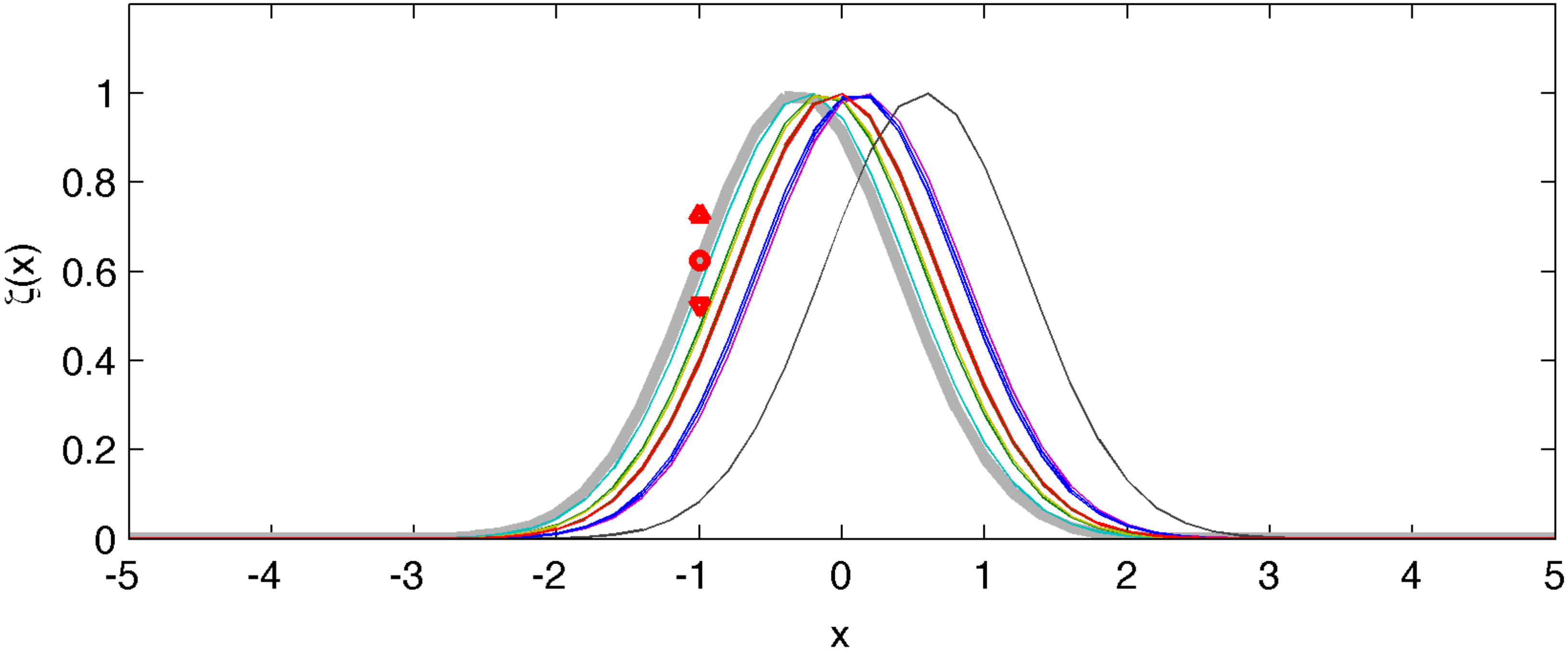
1. Forecast captures structure/amplitude of vortex but position is incorrect



Behavior with Incomplete Observations (cont.)

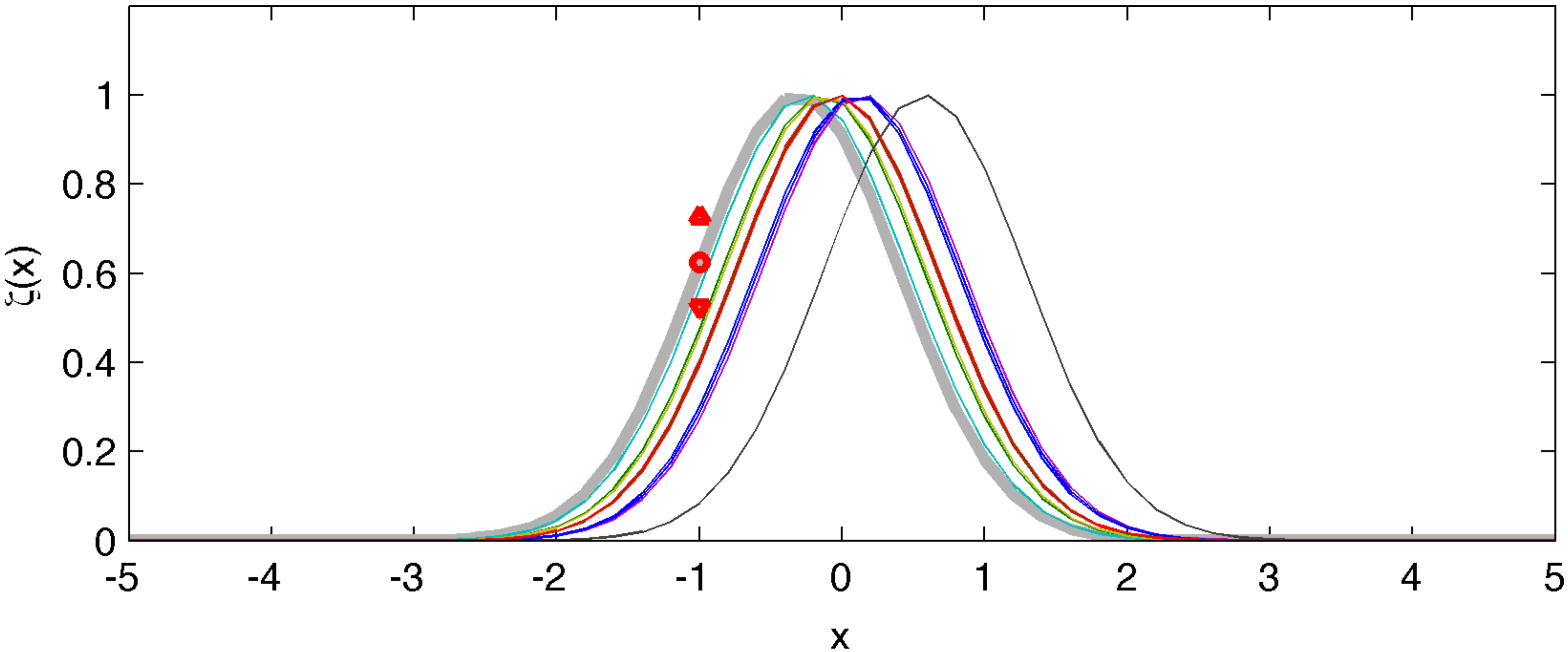
Suppose that:

1. Forecast captures structure/amplitude of vortex but position is incorrect
2. We are given a single observation of ζ at x = -1



Behavior with Incomplete Observations (cont.)

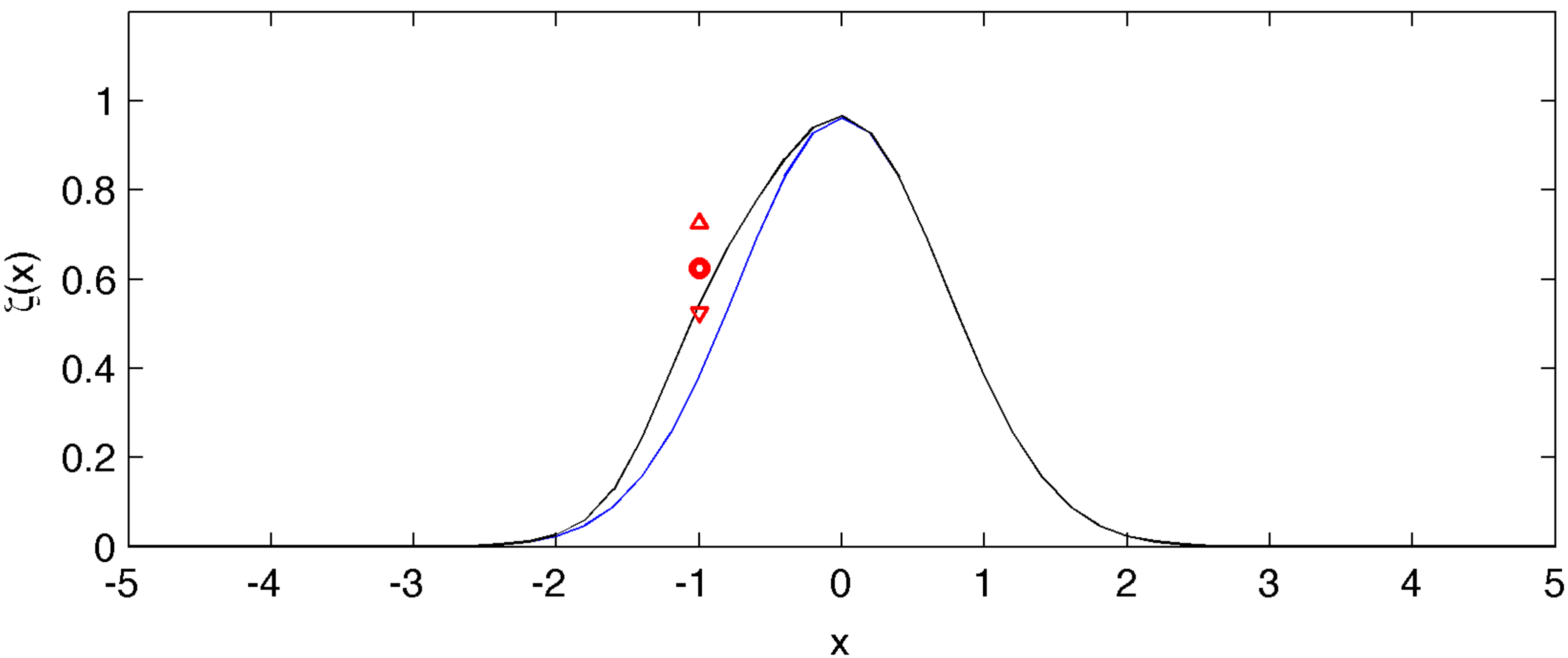
Recall cov(state, obs) determines spatial structure of increment.



Behavior with Incomplete Observations (cont.)

3DVar

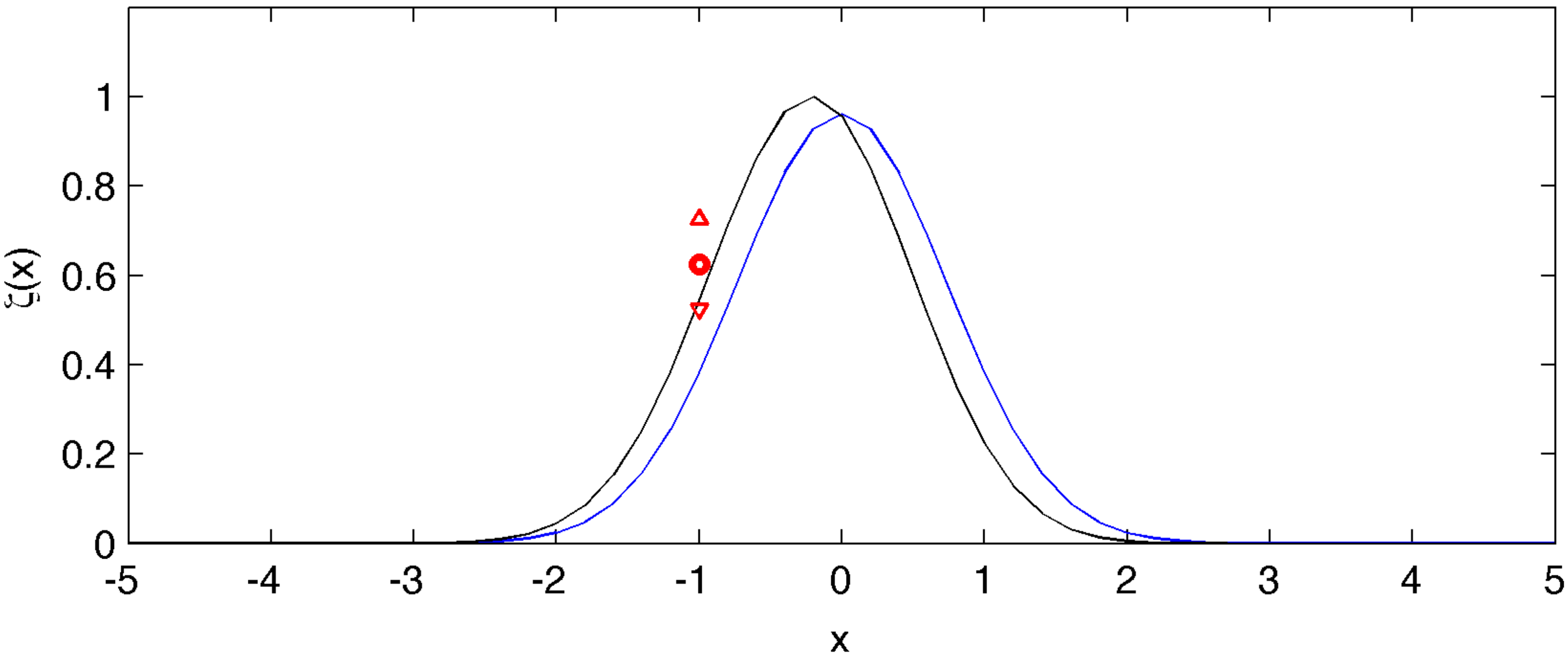
- cov(state, obs) is homogeneous and independent of vortex location
- Assimilation of single observation adds “bump” to forecast vortex
- Is this helpful? Fits observation but degrades vortex structure



Behavior with Incomplete Observations (cont.)

EnKF

- cov(state, obs) inhomogeneous; depends on forecast location of vortex
- Assimilation of single observation shifts forecast vortex coherently



Real-Time Analyses for Tropical Cyclones

Analyses from WRF/DART EnKF provided ICs for NCAR’s high-res TC forecasts during 2009, 2010 seasons

Produced 36-km analyses every 6 h

- Assimilate conventional obs + satellite winds + vortex position, intensity
- No radiances
- **NO** bogussing, assimilation of synthetic obs, relocation, etc
- No obs assimilated near vortex core (except position, intensity)

Other details

- 96 members
- GFS 6-h forecasts + spatially correlated noise for lateral boundary conditions

WRF/DART

"Hurricane" version of WRF/ARW is forecast model

Data Assimilation Research Testbed (DART)

- Provides EnKF algorithm(s)
- General framework, used for several other models
- See http://www.image.ucar.edu/DAReS/DART/

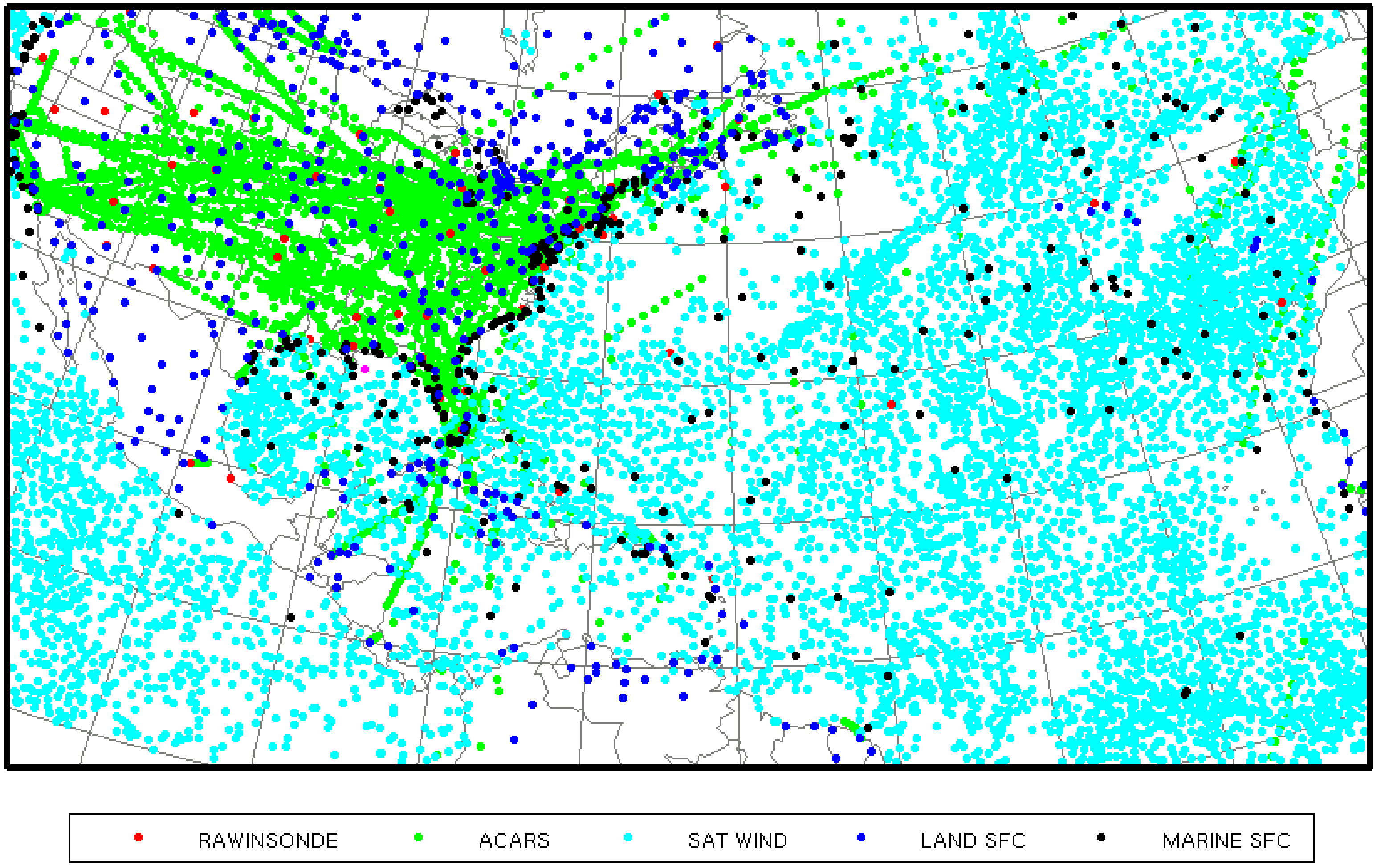
Suite of observation operators

- Includes Doppler radar and various GPS; no radiances

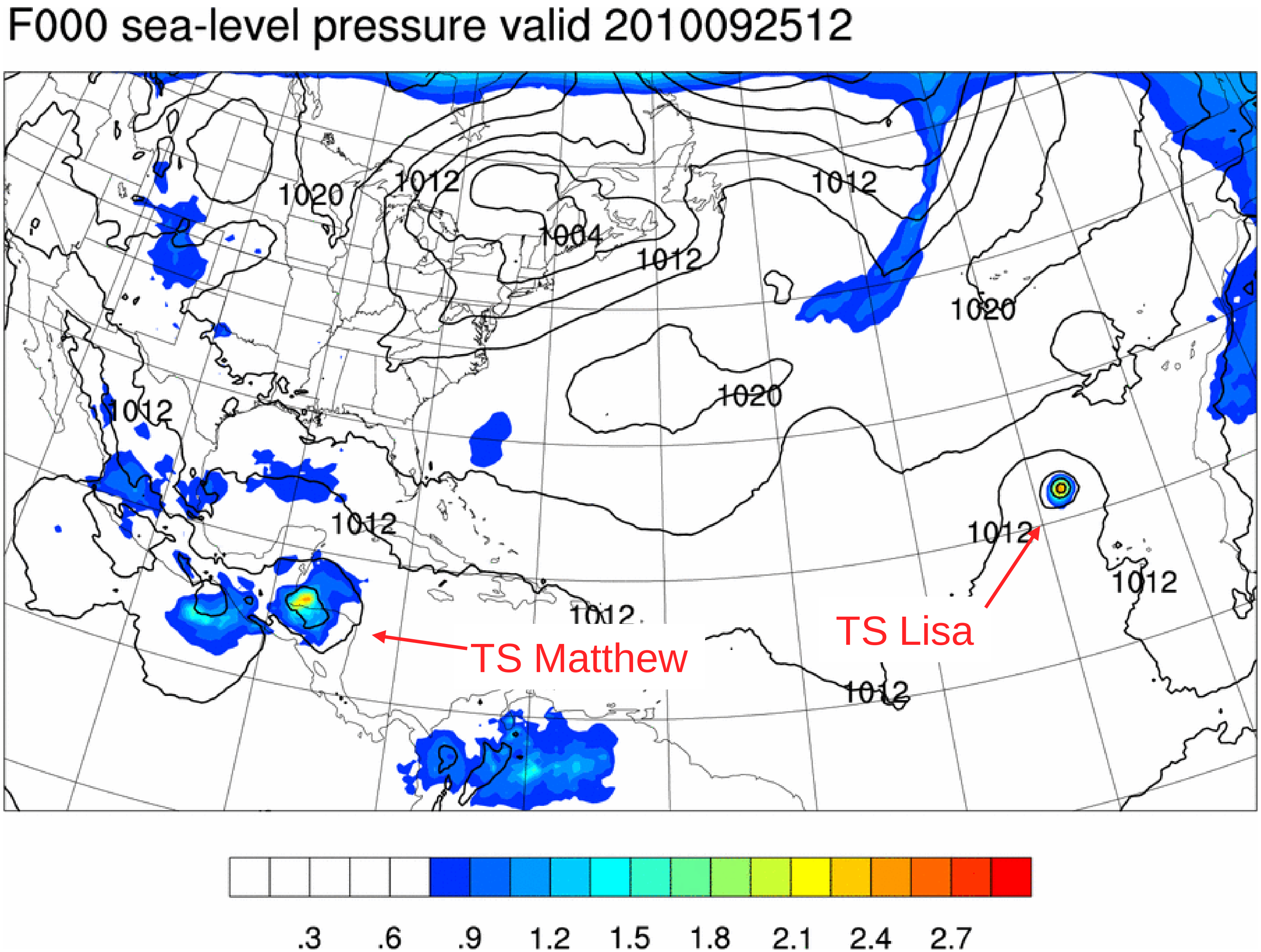
Capable of assimilation on multiple, nested domains simultaneously

Real-Time Analyses for Tropical Cyclones (cont.)

– Observations at 00Z 10 Nov 2009 and domain



Real-Time Analyses for Tropical Cyclones (cont.)



www.atmos.albany.edu/facstaff/torn/atlenkf/

Real-Time Analyses for Tropical Cyclones (cont.)

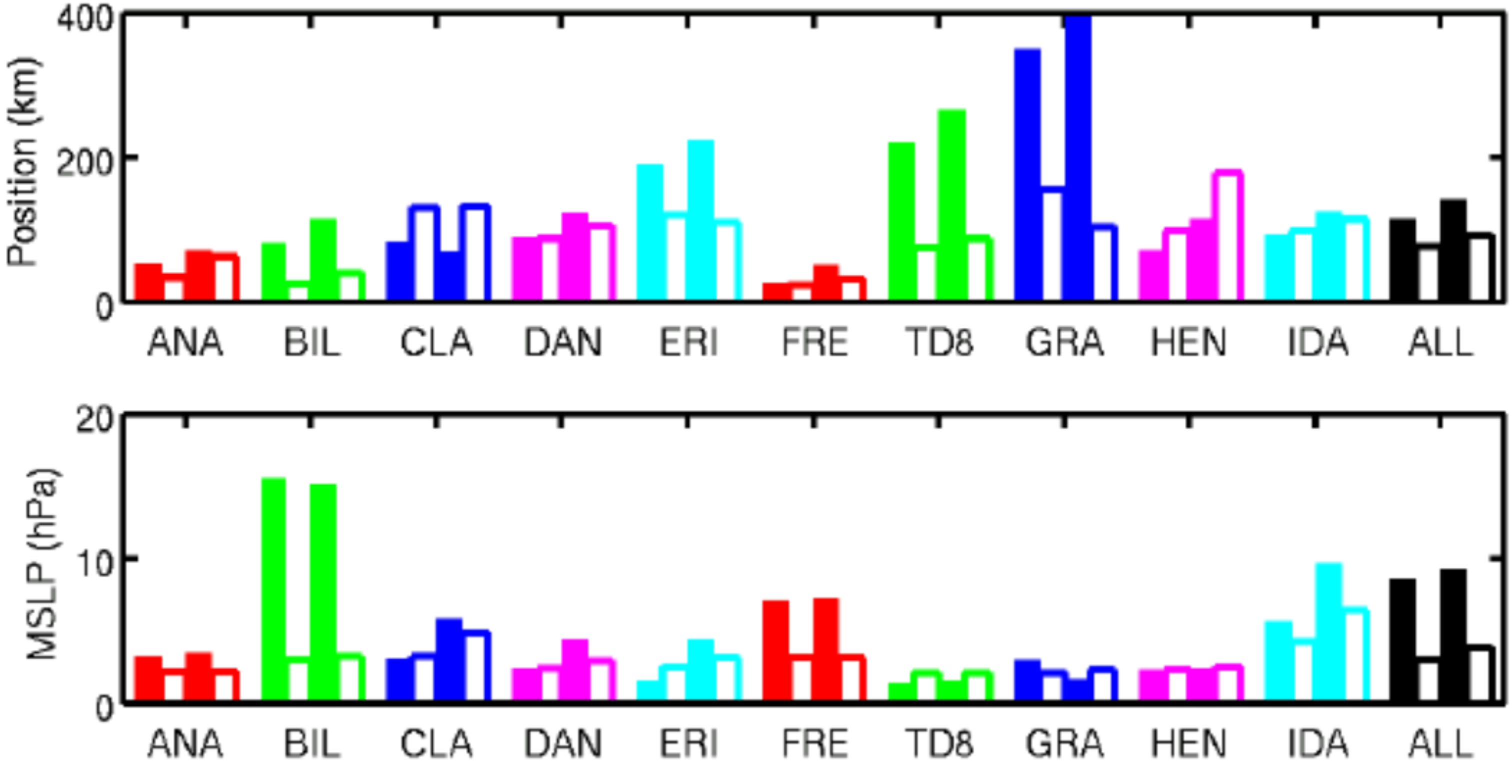
System cycled continuously for ~ 4 months in 2009, 2010.

Analyses captured all 2009, 2010 storms, from TD through TC

- No intervention in position or structure of storms, except from EnKF
- No spurious storms, despite not assimilating radiances

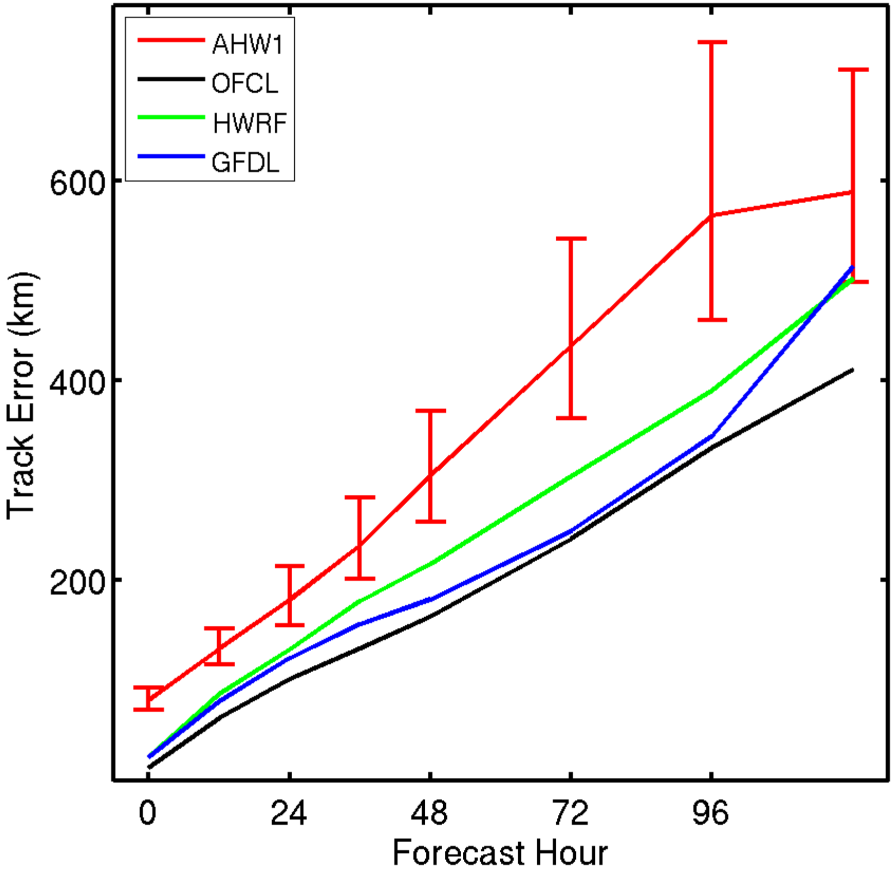
Real-Time Analyses for Tropical Cyclones (cont.)

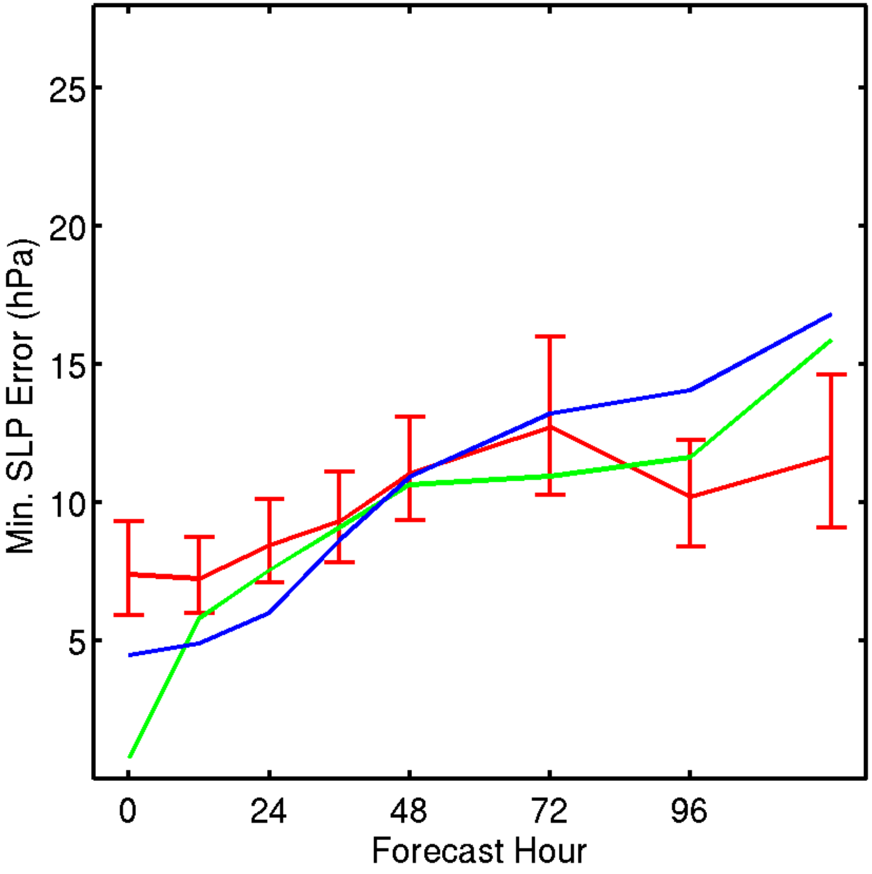
RMS fits of analysis and 6-h forecast to best-track estimates, 2009



Real-Time Analyses for Tropical Cyclones (cont.)

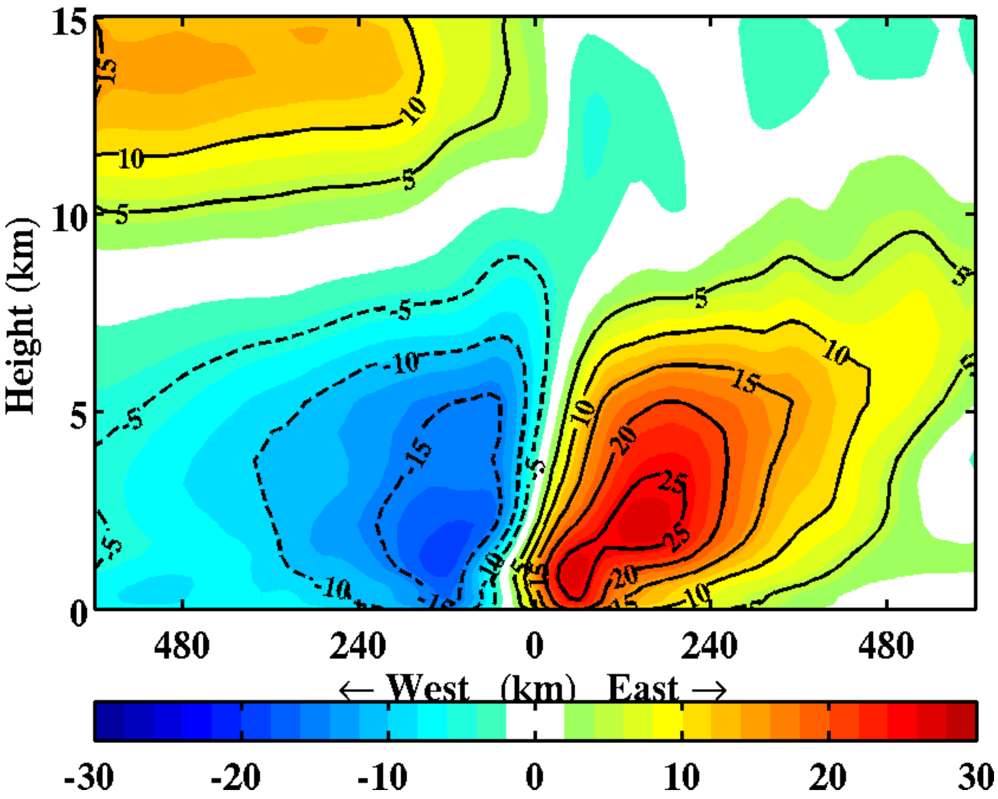
MAE for track and SLP relative to best-track estimates, 2010





Tropical Storm Erika

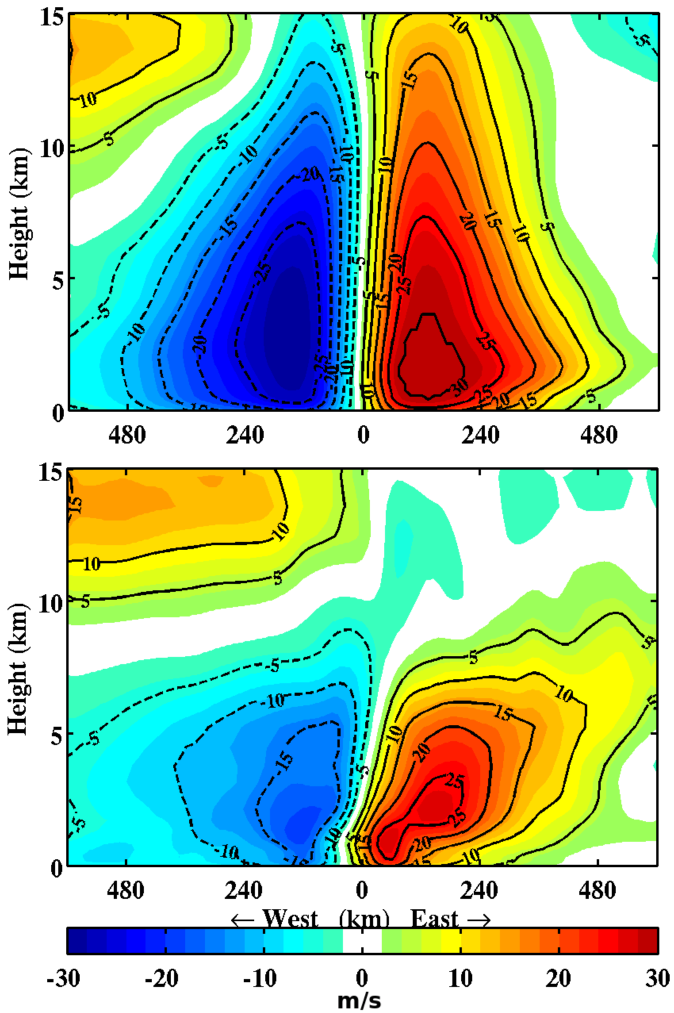
Analyses indicate tilted vortex, consistent with sheared env.



Zonal cross section of v
00Z 2 Sep 2009

Tropical Storm Erika (cont.)

To test importance of storm structure, forecasts from HWRF IC

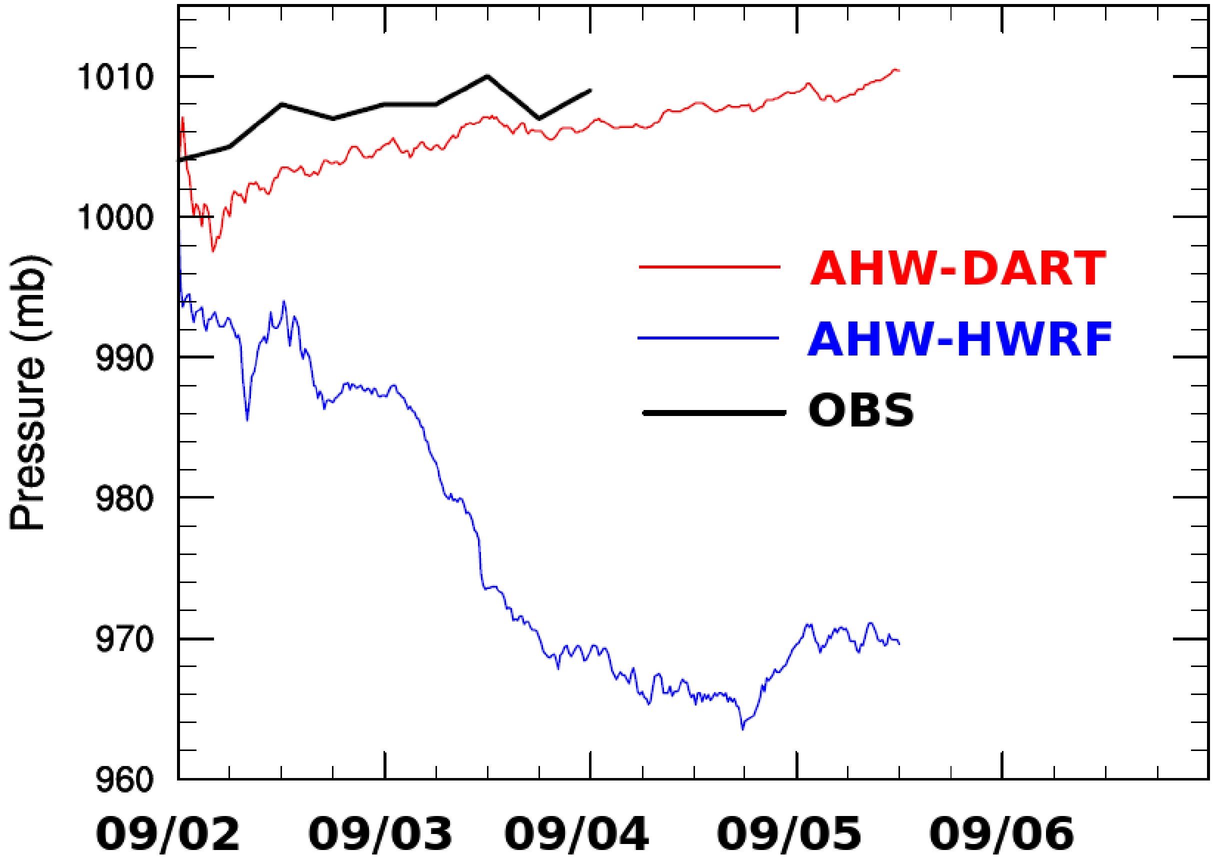


HWRF zonal cross section
(uses bogus/simulated observations)

EnKF zonal cross section

Tropical Storm Erika (cont.)

Tilt appears to be crucial to intensity forecast. (Track still poor.)

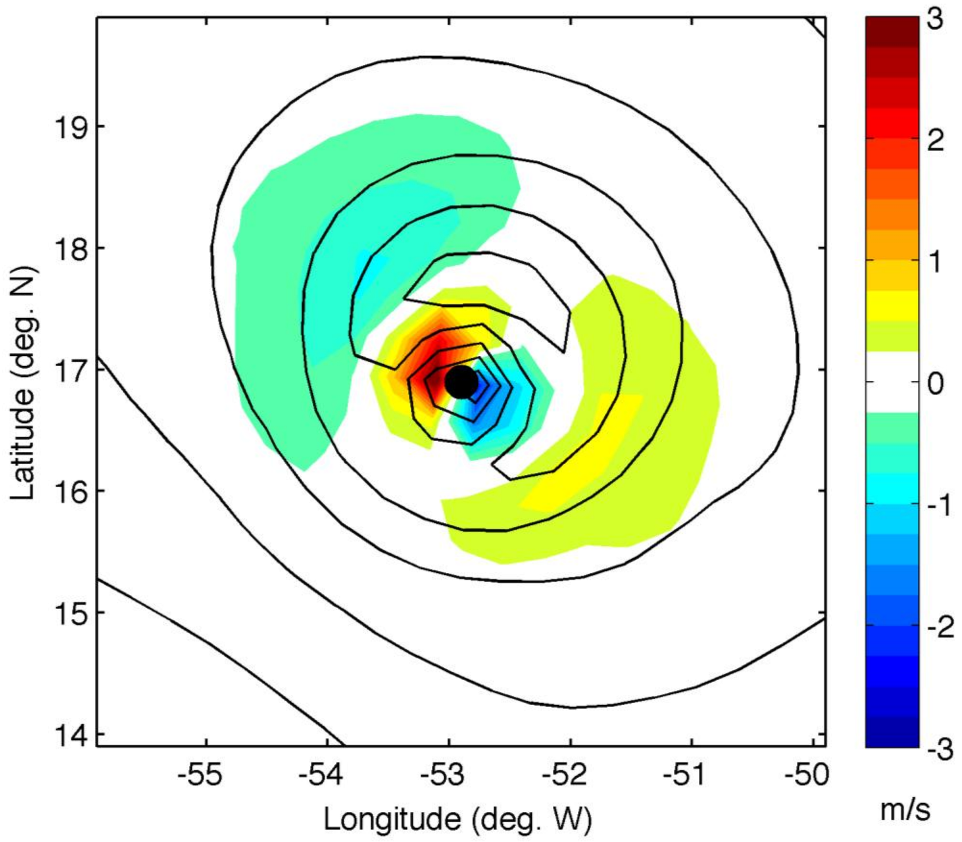


Courtesy S. Cavallo & W. Wang

Importance of Forecast Covariances

Analysis increment from position observation

- Reflects cov(wind speed, vortex position), which in turn reflects vortex structure
- Shifts vortex coherently and consistently in all model fields



Hurricane Bill, 00Z 19 Aug 2009

Wind speed @ 1st level

contours: ens.-mean, 6-h forecast

colors: increment given obs of vortex position (analysis - forecast)

Key Points

Credible TC analyses and forecasts possible purely through DA

- Conventional obs + EnKF from WRF/DART here
- Full suite of obs (including radiances) + 4DVar at ECMWF produces even better results

In TCs, crucial for DA to include "flow dependent" covariances via model dynamics

Observations of environment provide significant control of vortex characteristics

The Kalman Filter (KF)

Assume

- $\mathbf{x}^t \sim N(\overline{\mathbf{x}}^f, \mathbf{P}^f)$; Gaussian forecast errors
- $\epsilon \sim N(\mathbf{0}, \mathbf{R})$; Gaussian observation errors

KF analysis implements Bayes rule for Gaussians

- analysis equations:

$$\overline{\mathbf{x}}^a = \overline{\mathbf{x}}^f + \mathbf{K}(\mathbf{y} - \mathbf{H}\overline{\mathbf{x}}^f) \quad ; \quad \mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^f,$$

- Kalman gain

$$\mathbf{K} = \mathbf{P}^f\mathbf{H}^T(\mathbf{H}\mathbf{P}^f\mathbf{H}^T + \mathbf{R})^{-1}$$

Computationally difficult unless problem is small

- $\mathbf{P}^f$, $\mathbf{P}^a$ are $N_x \times N_x$, w/ $N_x = \dim \mathbf{x}$

EnKF Algorithm (cont.)

EnKF pseudo-code:

Forecasts:
for each member
    $x^f = M(x^a)$
end

At each analysis time:
for each (scalar) observation y in $\mathbf{y}$
    for each member
        $y^f = H(\mathbf{x}) + \varepsilon$
    end
    for each element x of $\mathbf{x}$
        for each member
            $x^a = x^f + k\,(y - y^f)$, with $k = \mathrm{cov}(x, y^f) / \mathrm{var}(y^f)$
        end
    end
end

Return to forecasts

Real-Time Analyses for Tropical Cyclones (cont.)

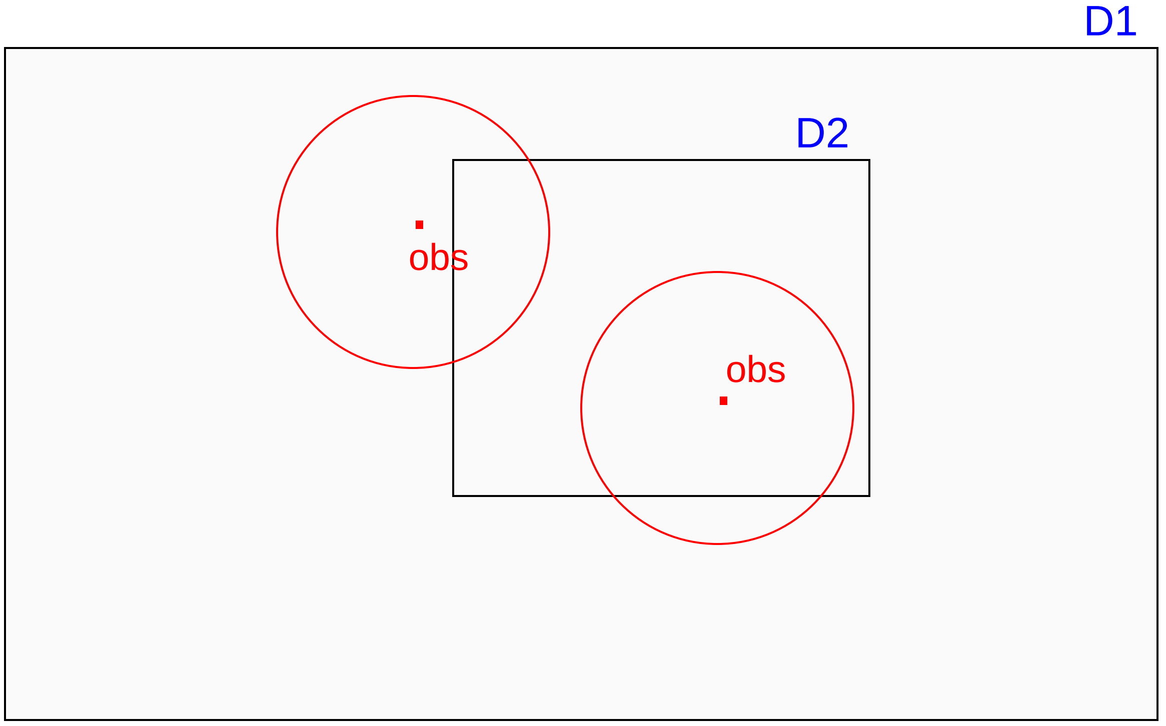
EnKF details

- 96 members
- 2000-km covariance localization; reduced where obs are dense
- Adaptive inflation (Anderson 2006)
- Ensemble of lateral BCs = GFS + N(0, **B)** perturbations, with **B** from WRF variational system

2010 Modifications for Real-Time System

Include 12-km nests in both forecasts, analyses

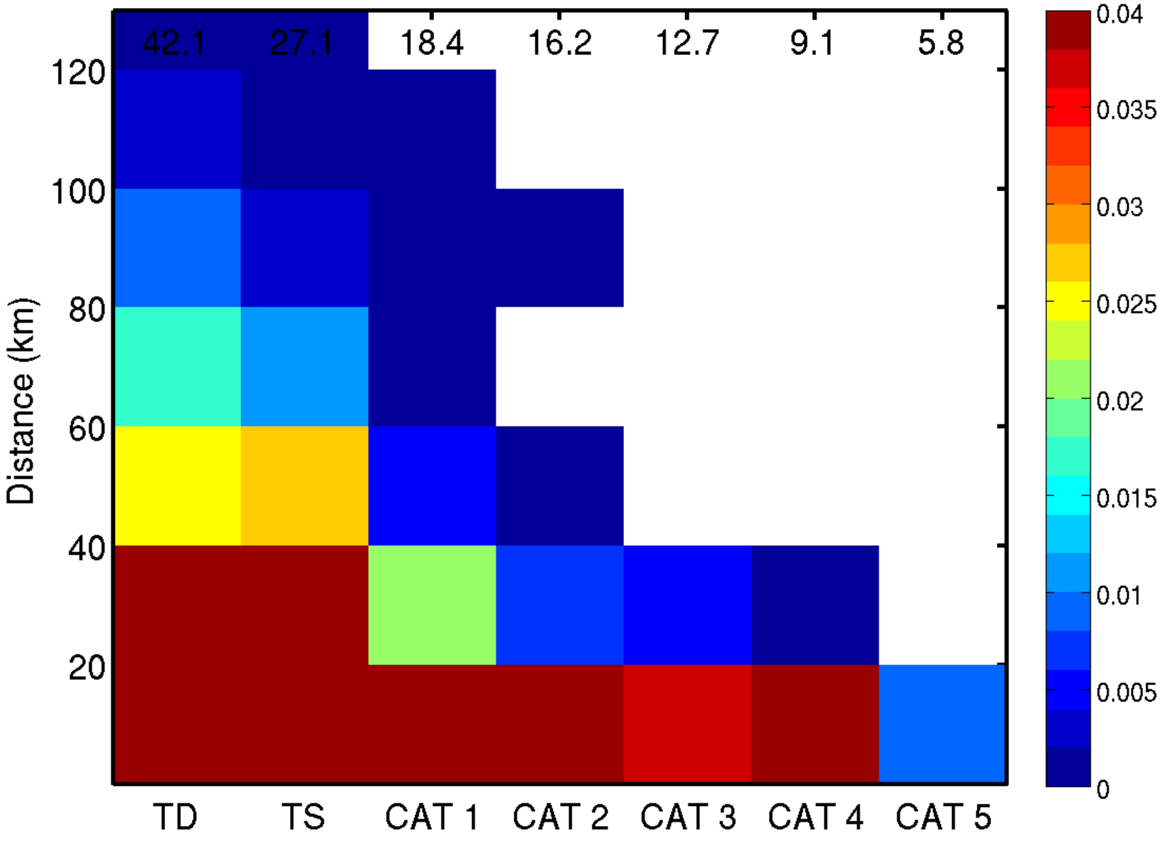
- Nest initialized whenever tropical depression is declared
- Analysis performed simultaneously on coarse grid and nest



2010 Mods (cont.)

Improved operator for vortex position, improved obs errors

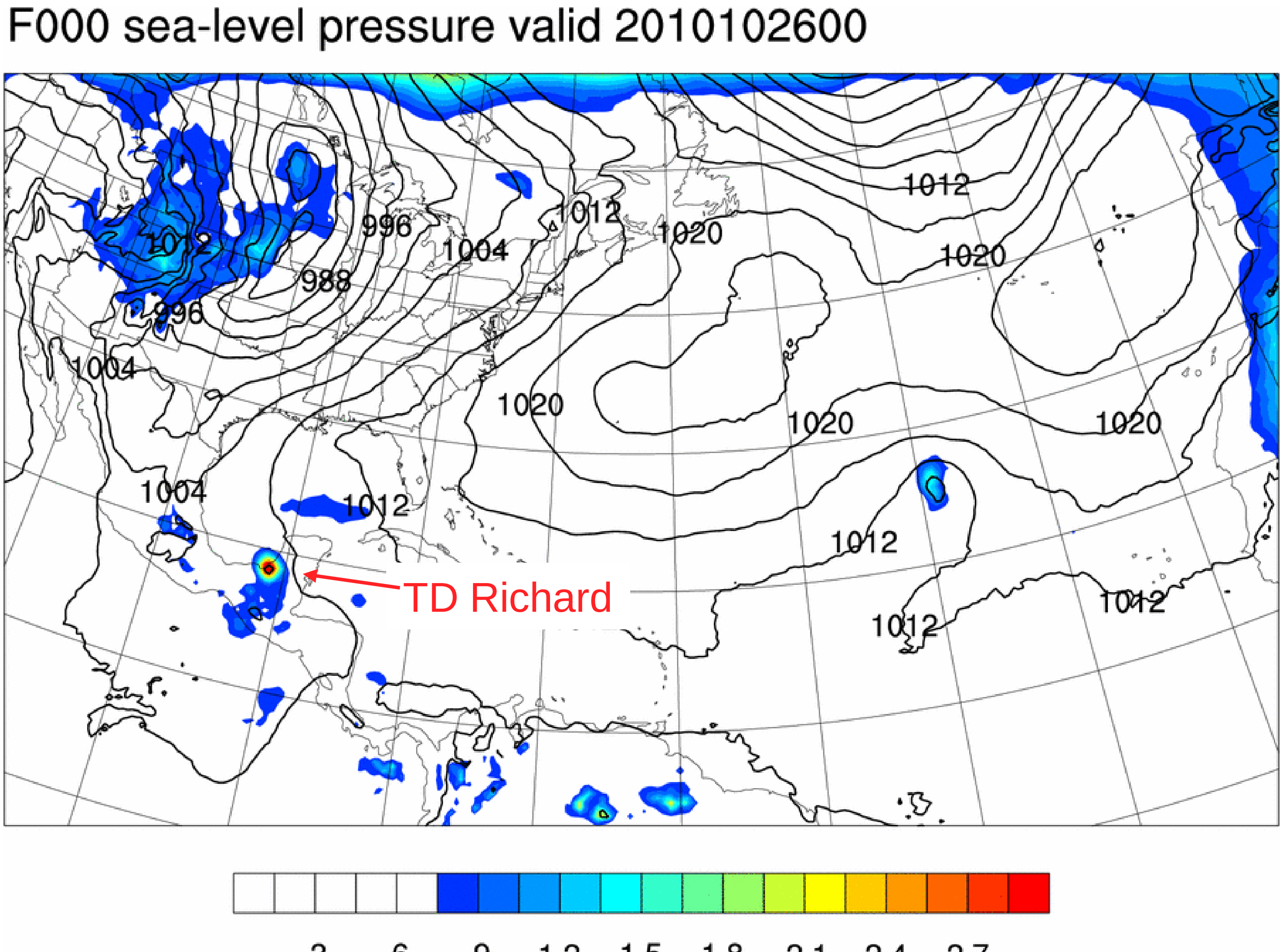
- Vortex position based on circulation at 850 hPa (vs. SLP previously)
- Obs errors estimated from advisory-best track diffs; vary from TD to TC



Histogram, rms differences for position

Courtesy R. Torn

Real-Time Analyses for Tropical Cyclones (cont.)

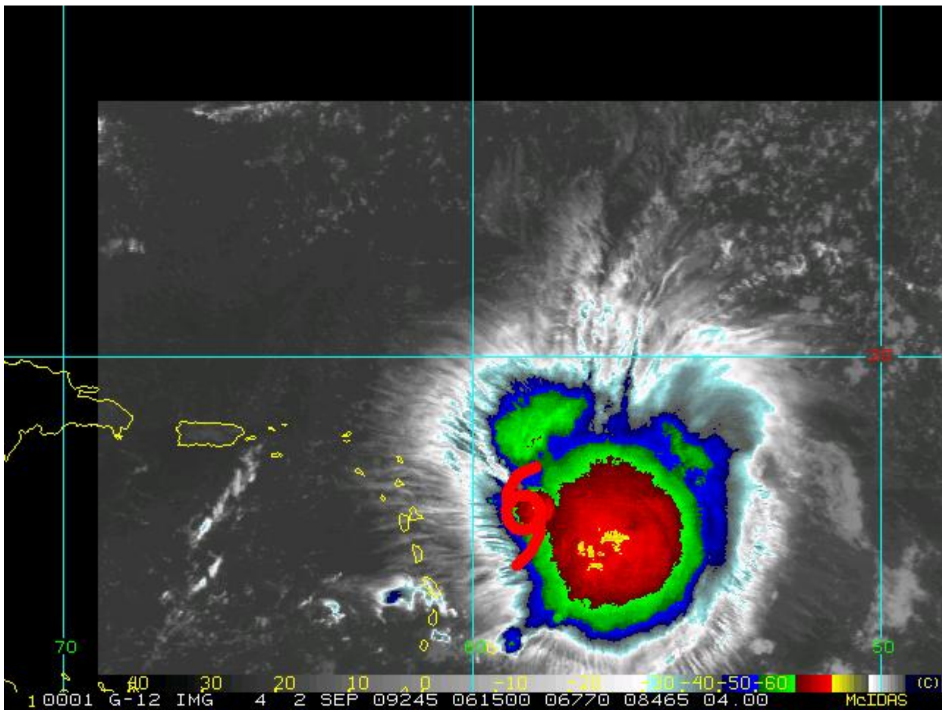


www.atmos.albany.edu/facstaff/torn/atlenkf/

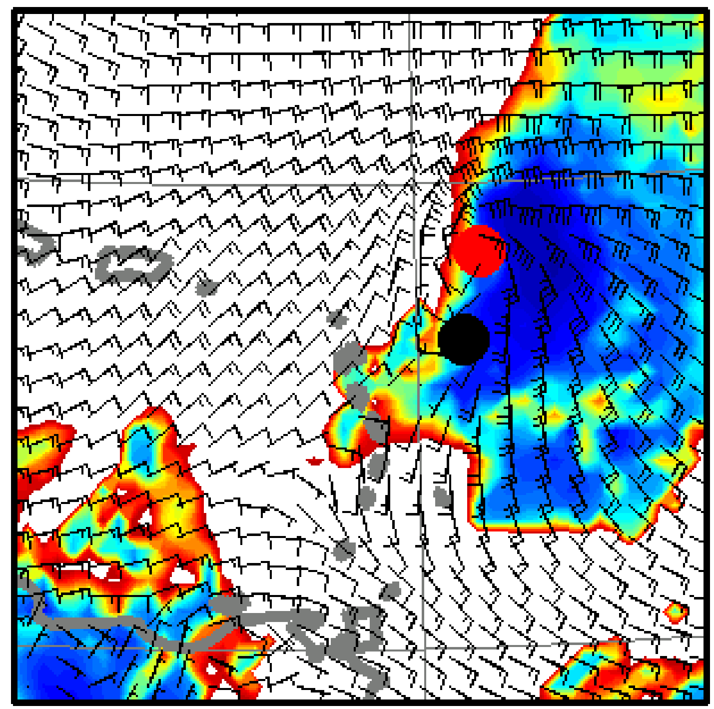
Tropical Storm Erika (cont.)

Deep convection E of center in both obs and analysis

Satellite IR



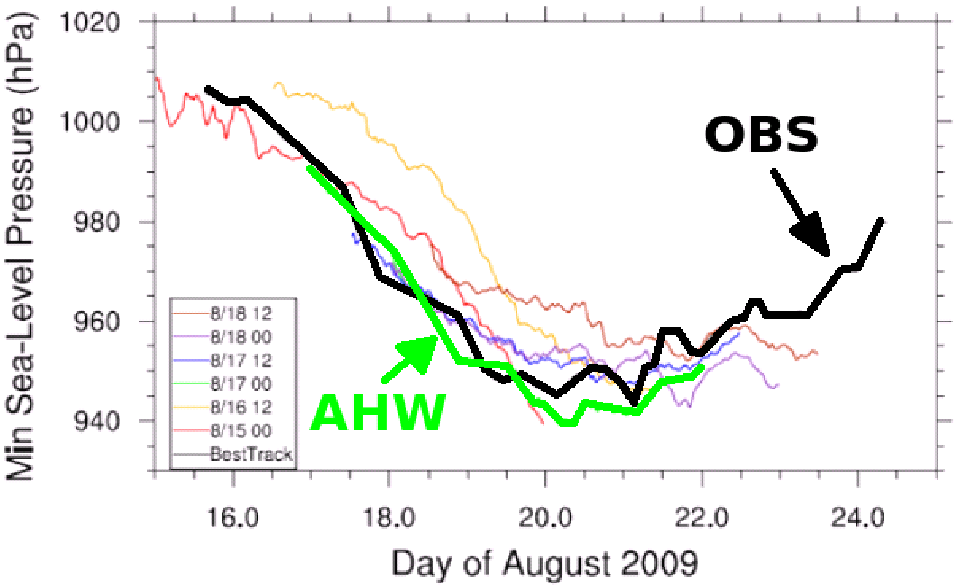
Cloud-top T, surface ***v***

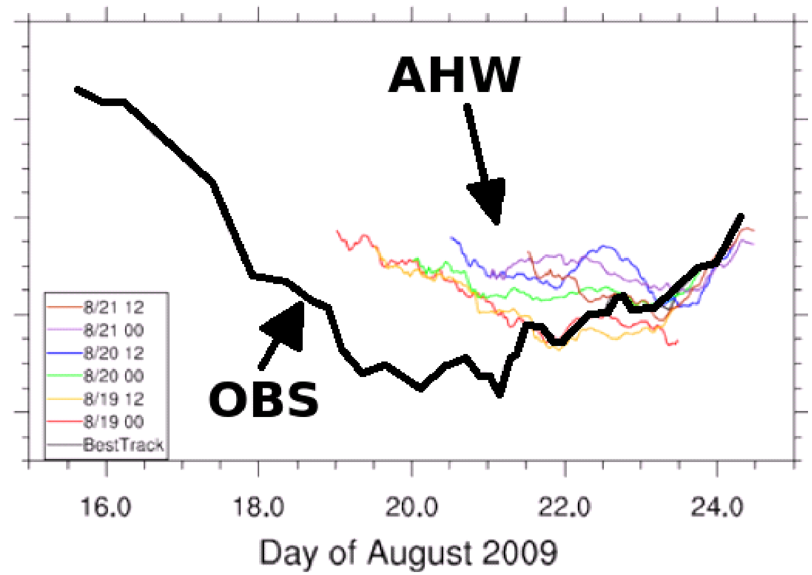


Courtesy S. Cavallo

Hurricane Bill

Poor analyses, forecasts of intensity at *mature* stage

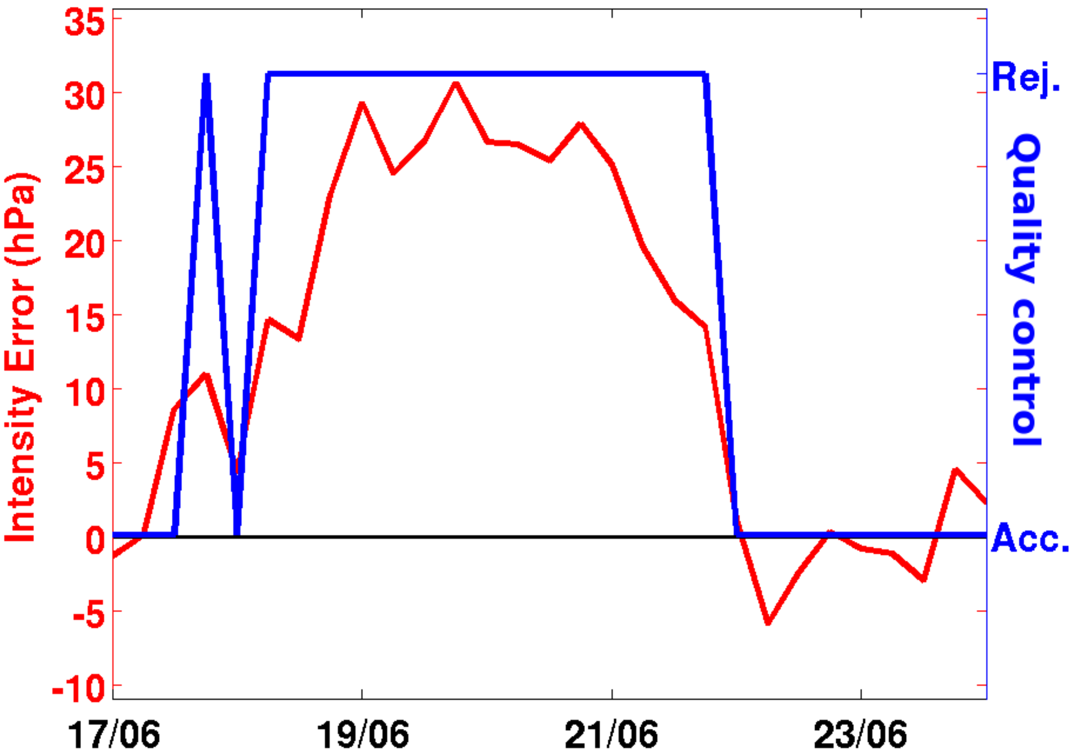




Courtesy S. Cavallo, W. Wang

Hurricane Bill (cont.)

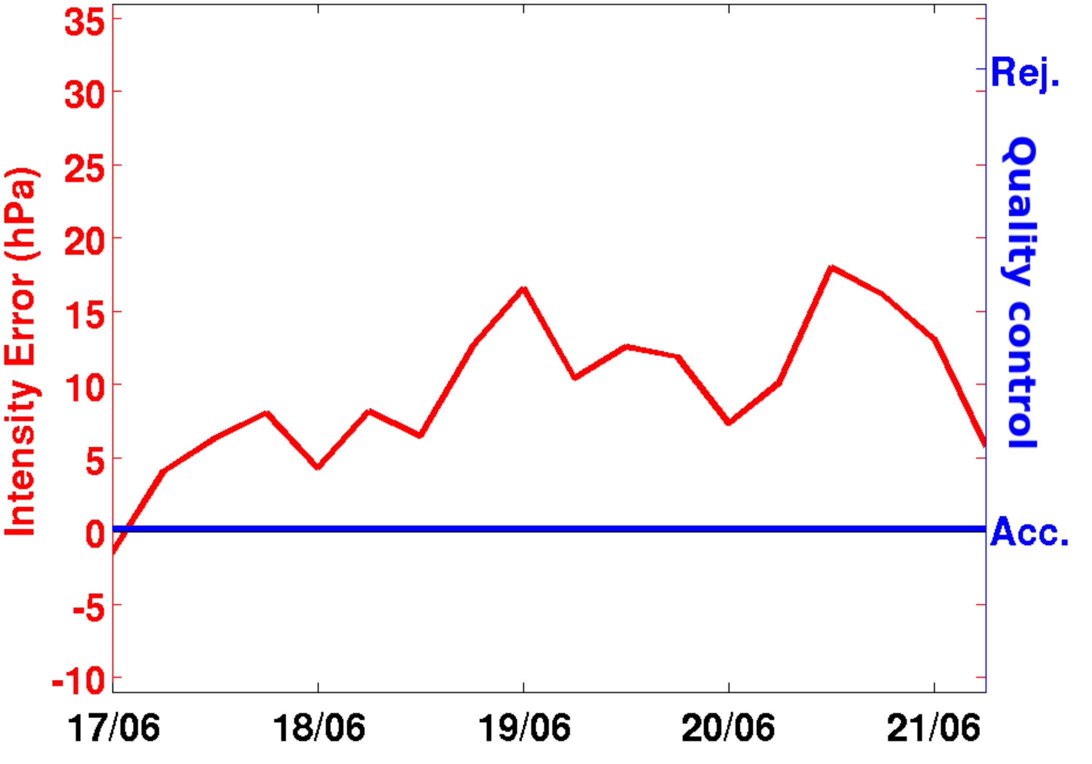
Vortex-intensity observations rejected.



Courtesy S. Cavallo

Hurricane Bill (cont.)

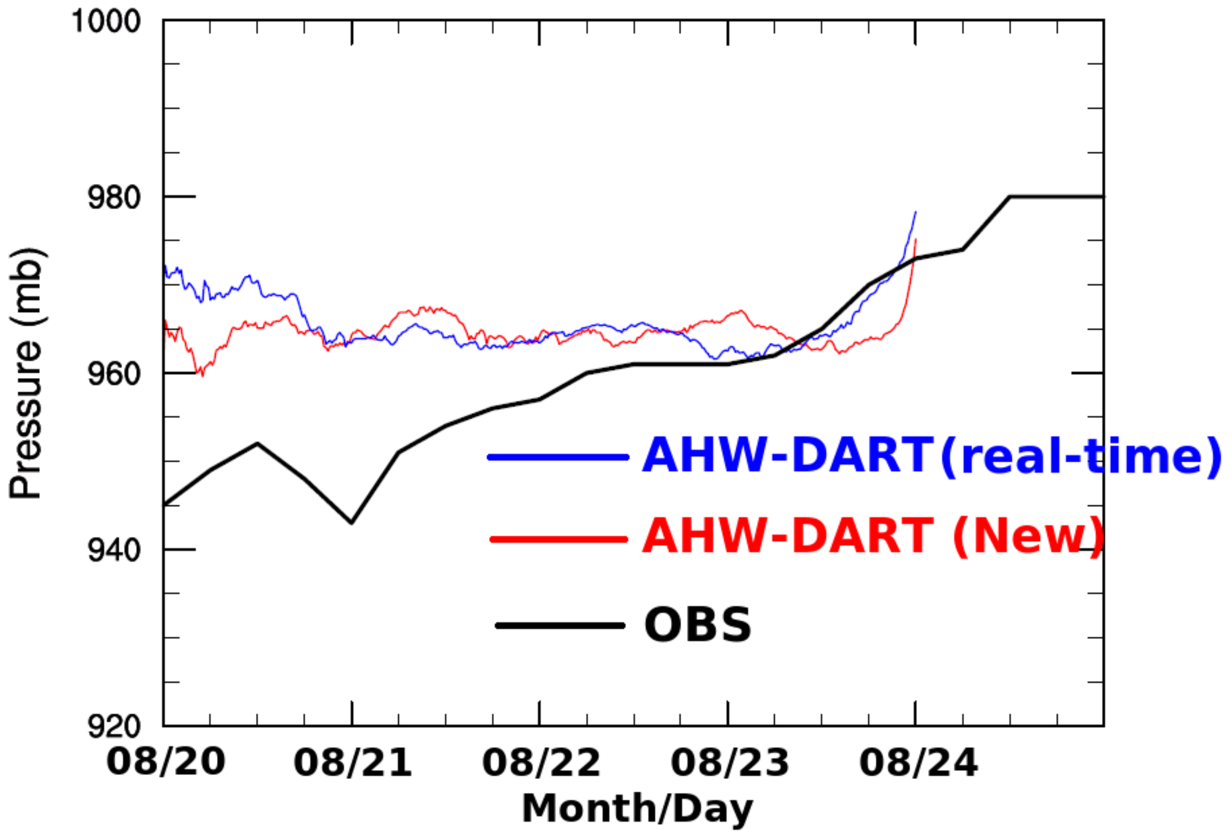
Removing QC, so intensity obs assimilated, improves analysis



Courtesy S. Cavallo

Hurricane Bill (cont.)

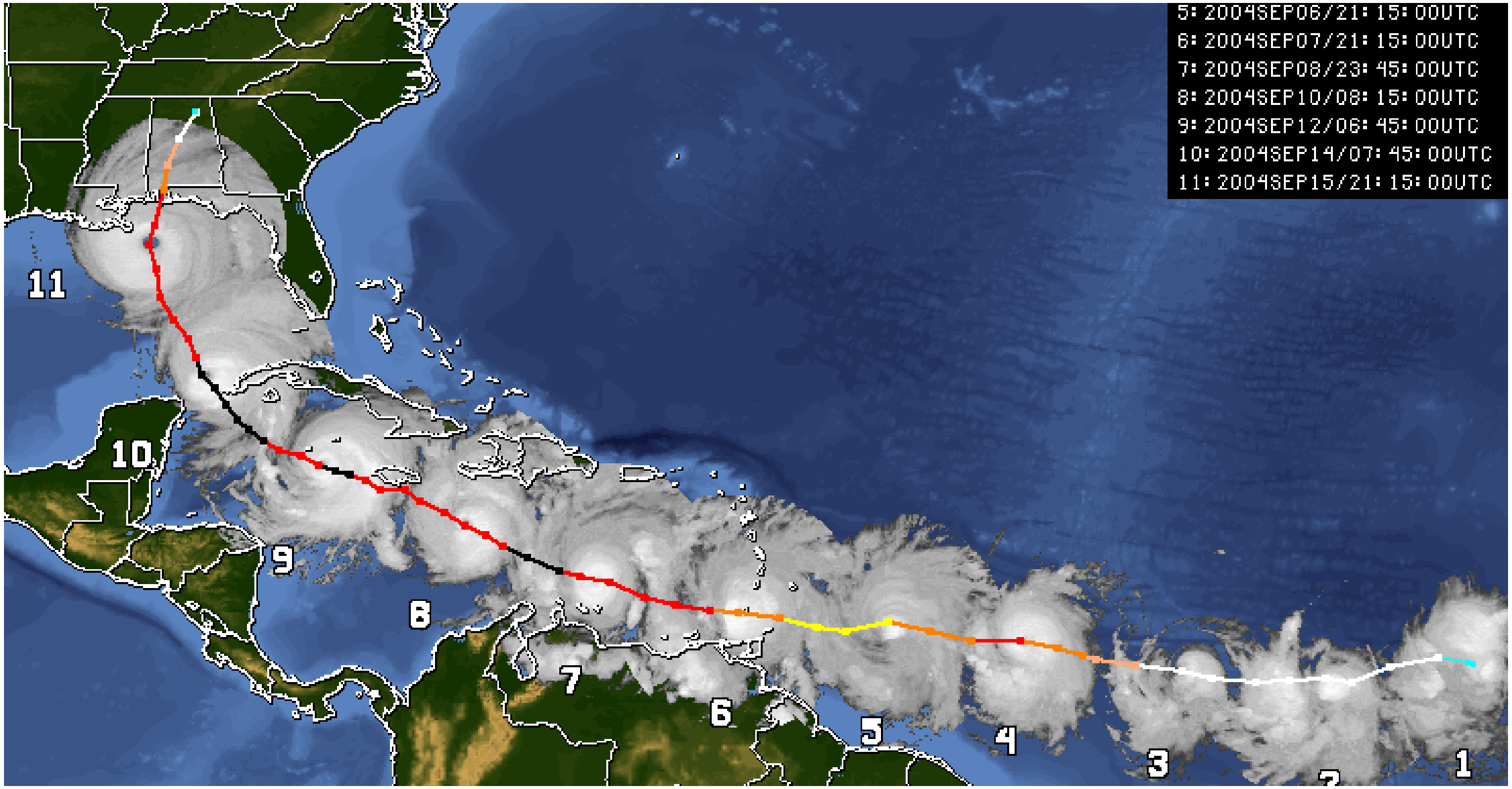
… but has only short-term effect on the forecast.



Courtesy S. Cavallo

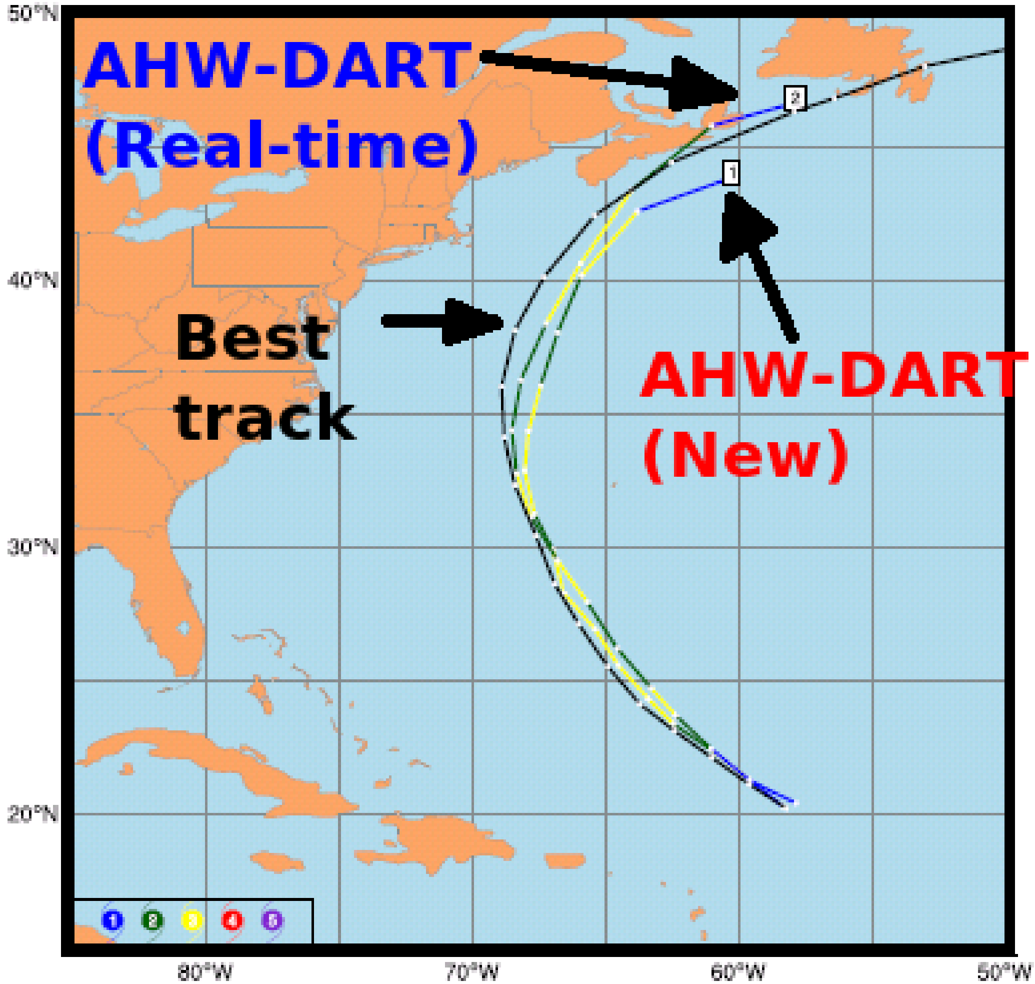
Assimilation of Hurricane Position

- Even moderate position errors problematic for assimilation
- Geostationary obs of position almost continuous in time
- Wish to avoid vortex "bogussing" and "relocation" by direct assimilation of position observations

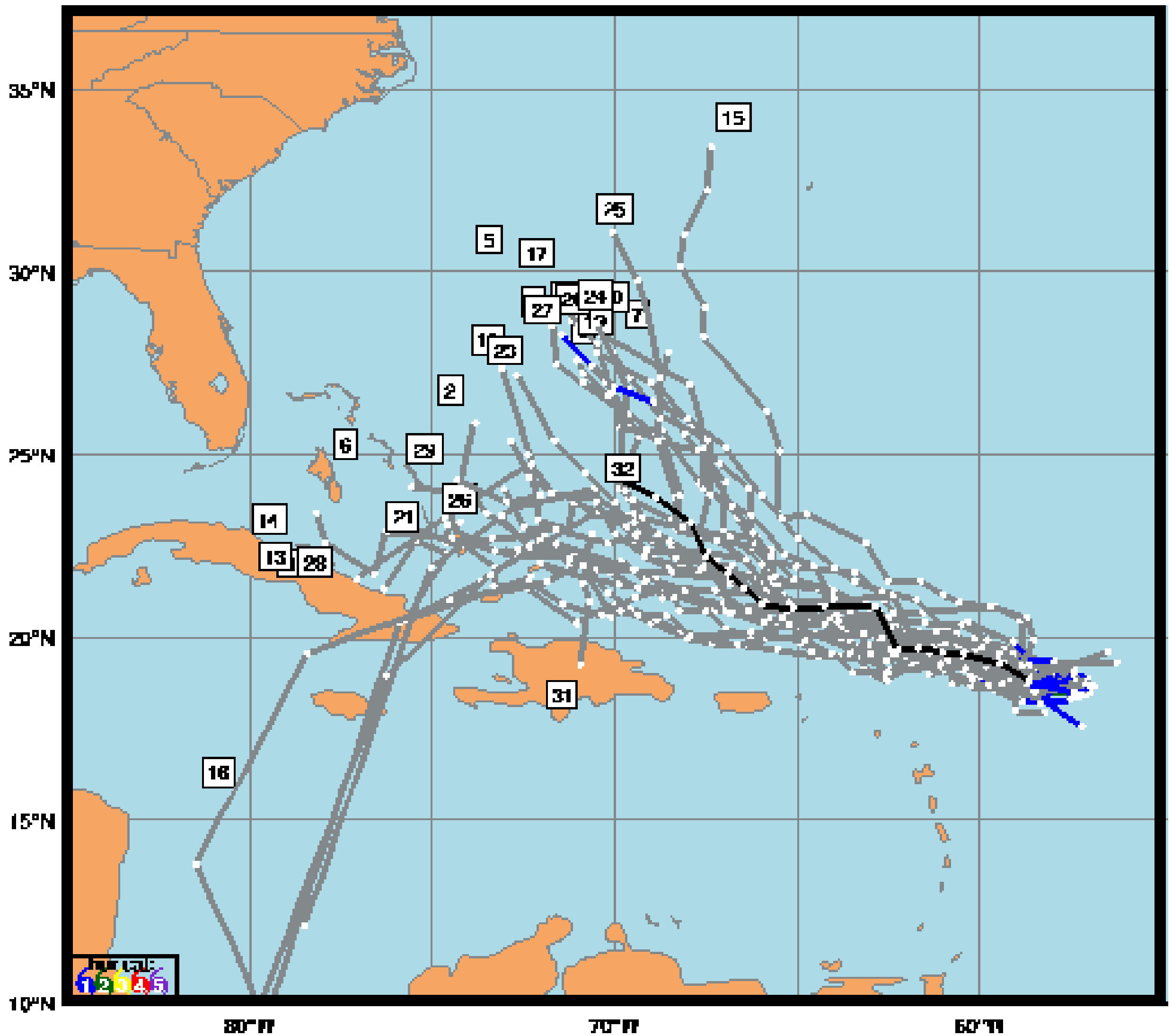


http://cimss.ssec.wisc.edu/tropic/archive/montage/atlantic/2004/IVAN-track.gif

Real-Time Analyses for Tropical Cyclones (cont.)



Tropical Storm Erika



Cavallo