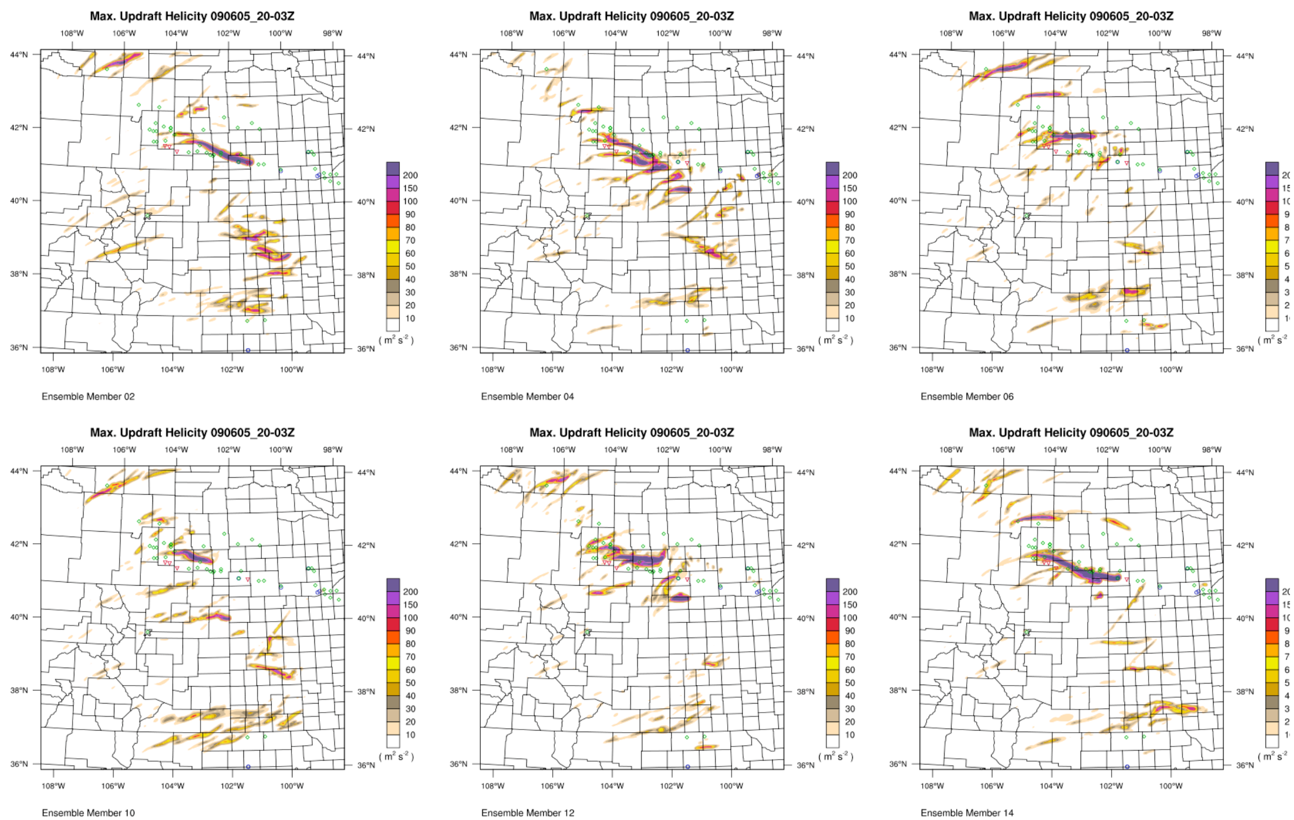
Recent Experience with Ensemble Data Assimilation in WRF/DART



Chris Snyder (NCAR)

NCAR is supported by the National Science Foundation

Recent Experience with Ensemble Data Assimilation in WRF/DART

DART = Data Assimilation Research Testbed

Recent Experience with Ensemble Data Assimilation in WRF/DART

Assimilation of radar obs:

David Dowell, Wiebke Deierling

Tropical cyclone results:

Ryan Torn (SUNY Albany), Steven Cavallo

Assimilation of surface obs:

Soyoung Ha, Glen Romine (w/ partial support of AFWA)

DART development:

Jeff Anderson, Nancy Collins, Glen Romine, Tim Hoar

Plus: Altug Aksoy (CIMAS) Alain Caya (Environment Canada), Yongsheng Chen (York U), Josh Hacker (NPS), Hui Liu, Bill Skamarock

The Ensemble Kalman Filter (EnKF)

EnKF combines data assimilation and ensemble forecasting

- Analysis step produces ensemble of analyses, given new obserations
- Analysis step employs cov(obs, state), estimated from short-range ensemble (schematic explanation can be found after concluding slide)
- In forecast step, make ensemble of short-range forecasts from ensemble of analyses

Attractions for mesoscale applications

- Few assumptions about covariances, so applicable to range of scales/phenomena
- Flexible to details of model, such as complex microphysical schemes
- Ease of implementation and parallelization; no adjoints

For applications here, use 50-100 members

Data Assimilation Research Testbed (DART)

Provides general, model-independent algorithms for ensemble filtering

Numerous DART-compliant models

- ARW, CAM, NOGAPS, …

Parallel analysis scheme that scales well to 100's of processors

See http://www.image.ucar.edu/DAReS/DART/

WRF/DART

Interfaces for WRF in DART

- WRF variables on model grid ↔ DART state vector
- Distance between any two elements of state vector

Suite of observation operators

- Includes Doppler radar and various GPS; no radiances

Scripts for advancing WRF under DART control

Capable of assimilation on multiple, nested domains simultaneously

Radar Assimilation for Convective Storms

WRF configured as idealized cloud model

- No terrain, no PBL, open lateral boundaries
- O(1 km) horizontal resolution, O(200 km X 200 km) domains
- Larger scales represented only via specified environmental sounding, e.g., from nearby radiosonde

Assimilate radial velocity, reflectivity from Doppler radar(s)

- Analyses every 2 min; each elevation angle assimilated separately
- Automated velocity unfolding within EnKF

Radar Assimilation for Convective Storms (cont.)

Successful assimilation in > 10 cases to date

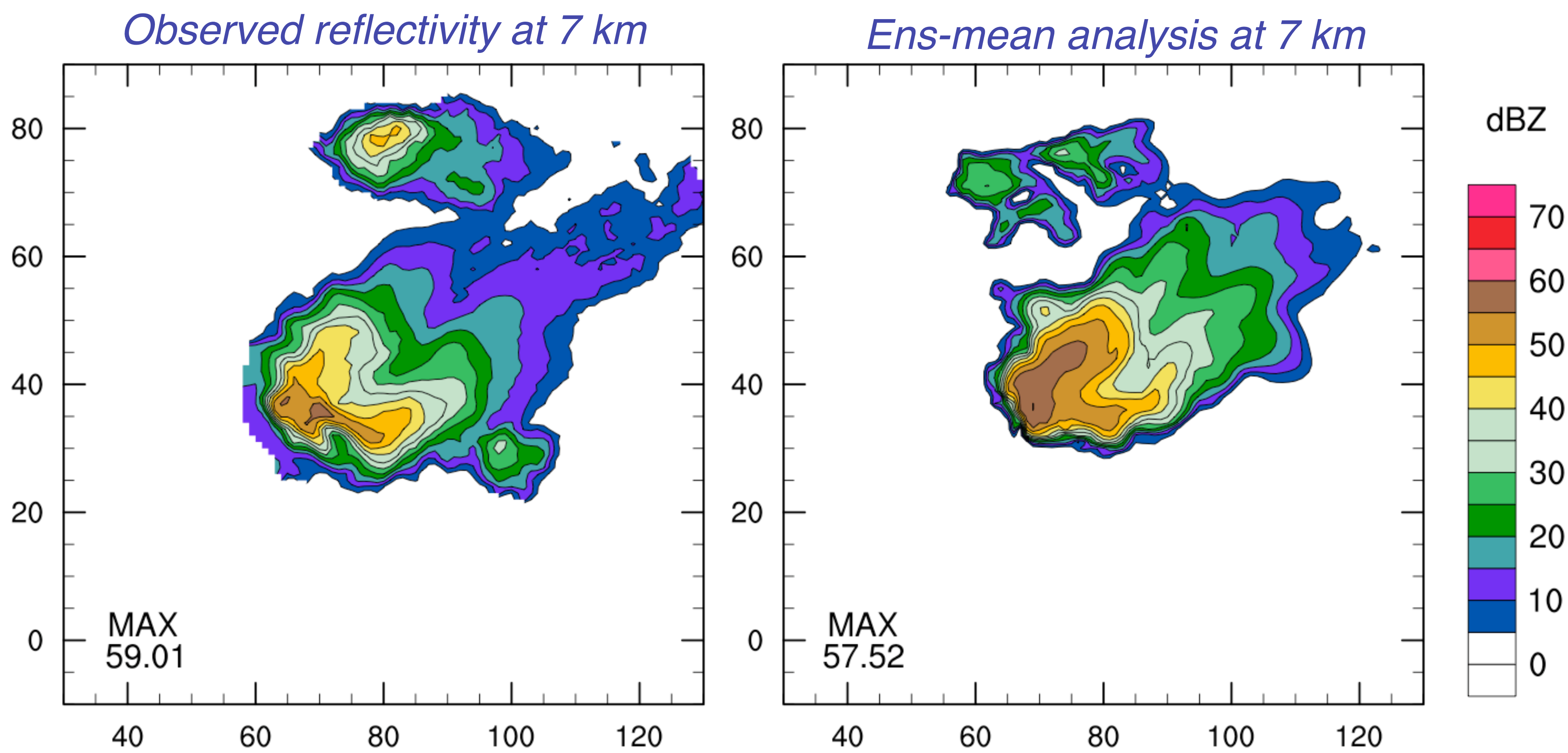
- Rms fit of background forecast to obs ~ 5 m/s, 8 dBZ

Useful today for radar analysis, as replacement for traditional retriveval techniques.

Radar Assimilation for Convective Storms (cont.)

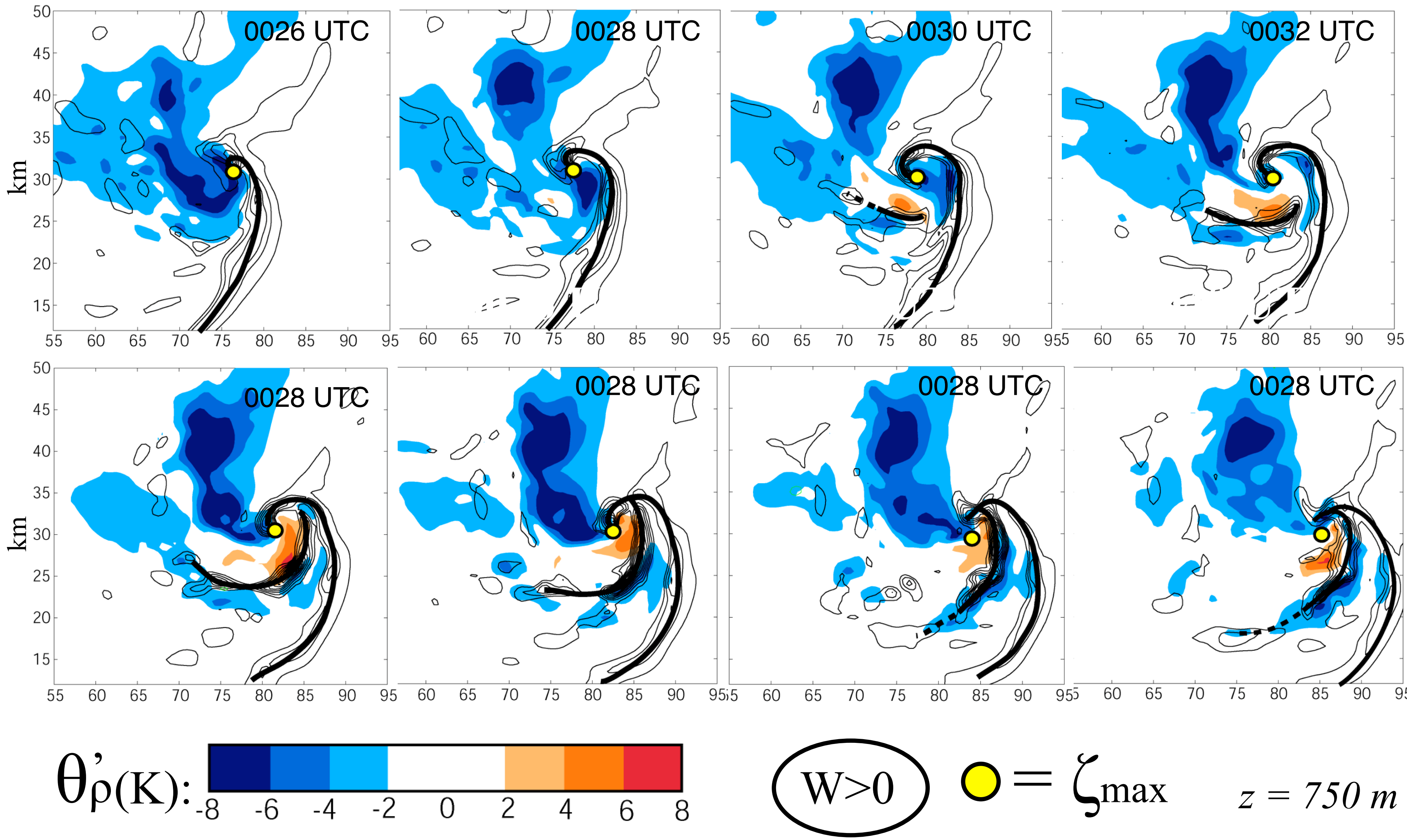
One example: 5 July 2000 supercell (STEPS)

- Assimilate only radial velocity; reflectivity is independent observation.



Courtesy W. Deierling and D. Dowell

Analyses from DOW v_r obs, courtesy of Jim Marquis (Penn St)



Real-Time Analyses for Tropical Cyclones

Analyses from WRF/DART provided ICs for NCAR's high-res TC forecasts during 2009 season

Produced 36-km analyses every 6 h

- Assimilate conventional obs + satellite winds + vortex position, intensity
- **NO** bogussing of any kind; no satellite radiances

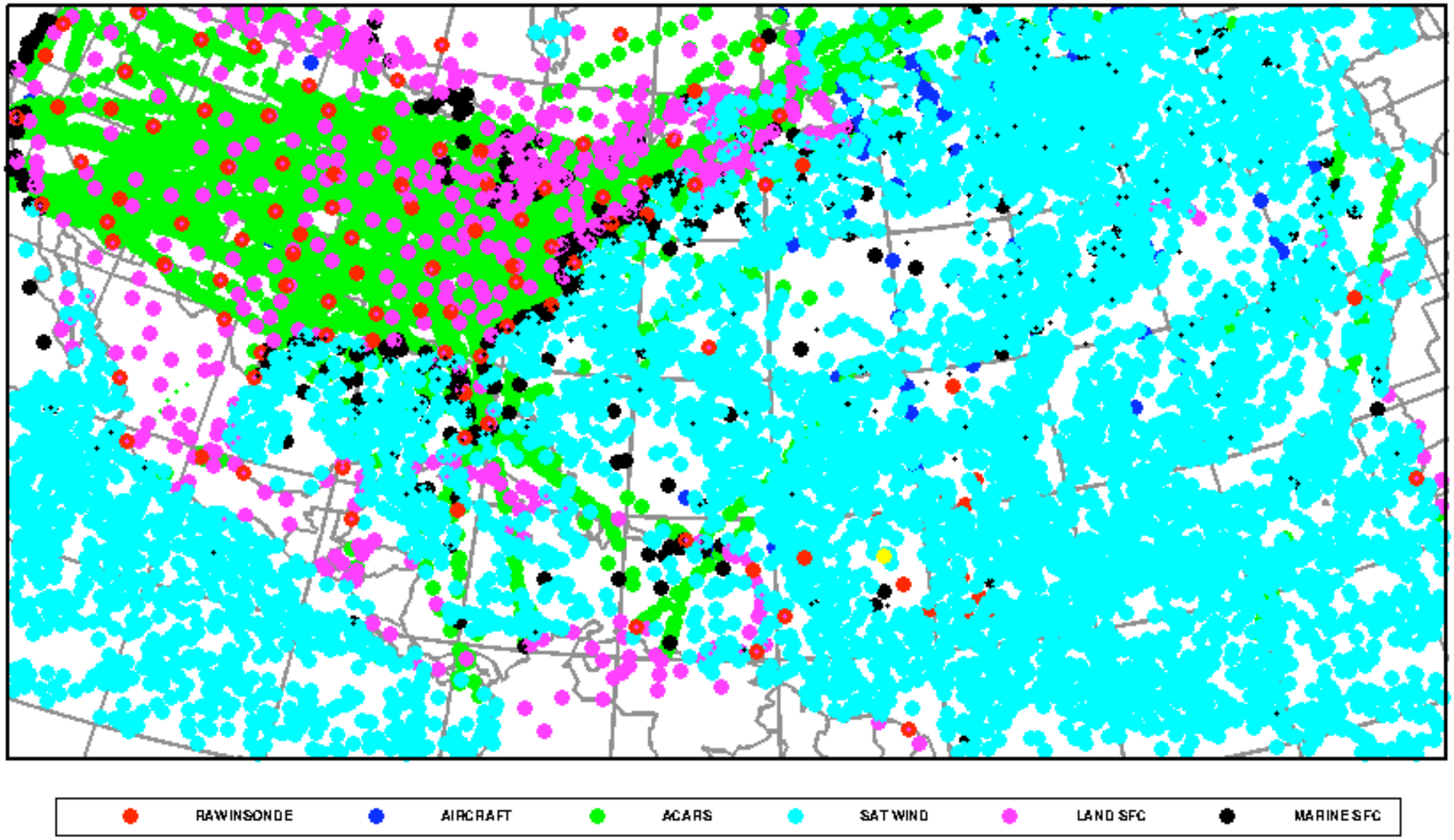
WRF configuration

- "hurricane" physics + KF convection
- 36 km, with stationary 12-km nest centered on each TC/TS/TD

System cycled continuously for ~ 4 months

- Large drift in stratosphere owing to radiation bias, now fixed. See:
  Cavallo, S. M., J. Dudhia and C. Snyder, 2010: An improved upper boundary condition for longwave radiative flux in the stratosphere to correct model biases. *Mon. Wea. Rev.*, submitted.

Real-Time Analyses for Tropical Cyclones (cont.)

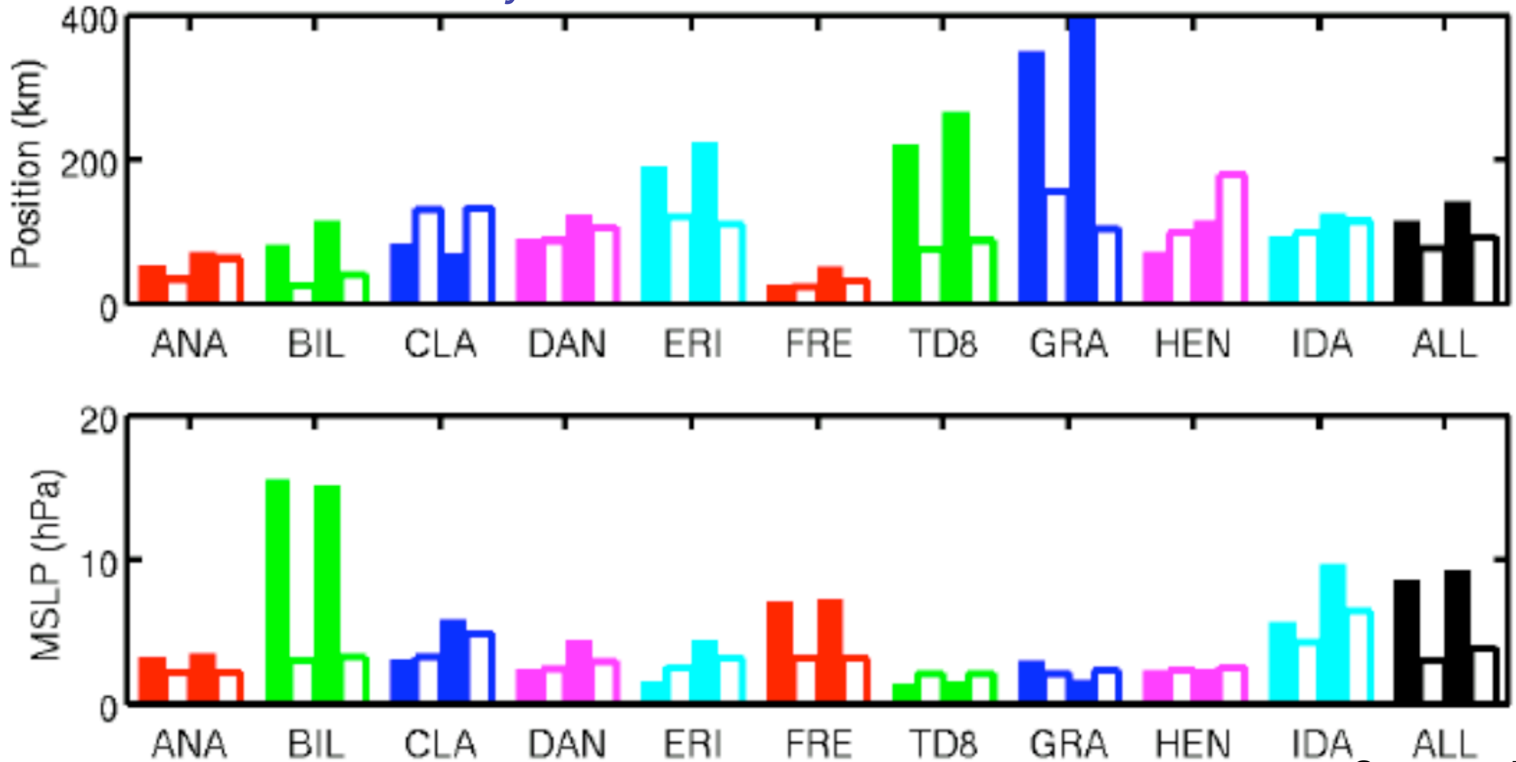


Real-Time Analyses for Tropical Cyclones (cont.)

Analyses captured all 2009 storms, from depressions to hurricanes.

- No need to bogus
- No spurious storms, despite not assimilating radiances

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

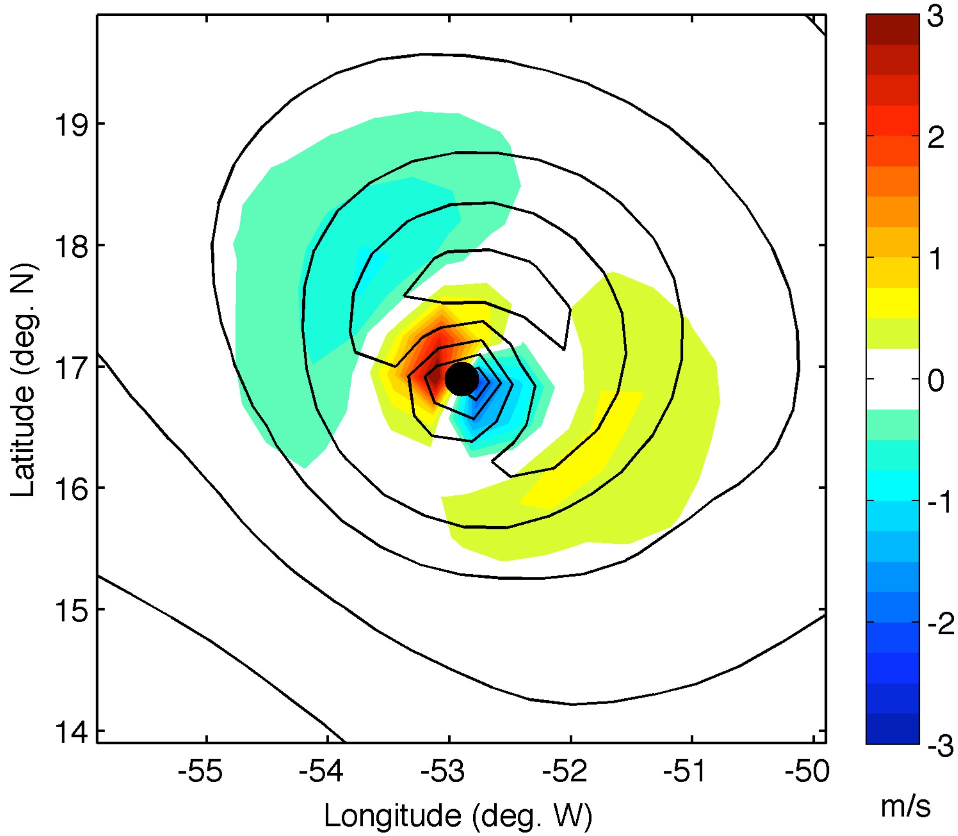


Courtesy R. Torn

Real-Time Analyses for Tropical Cyclones (cont.)

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)

Courtesy S. Cavallo

Toward Short-Range Forecasts of Convection

WRF/DART already works well for analysis of isolated convection on limited domain.

Wish to handle larger convective systems, multiple radars **and** make forecasts at 0-6 h.

- Need “full” ARW: terrain, PBL and other parameterizations, LBCs/nesting
- Need larger domains + good analyses of mesoscale environment
- Need to assimilate obs from multiple Doppler radars

VORTEX2 Retrospective Analyses and Forecast

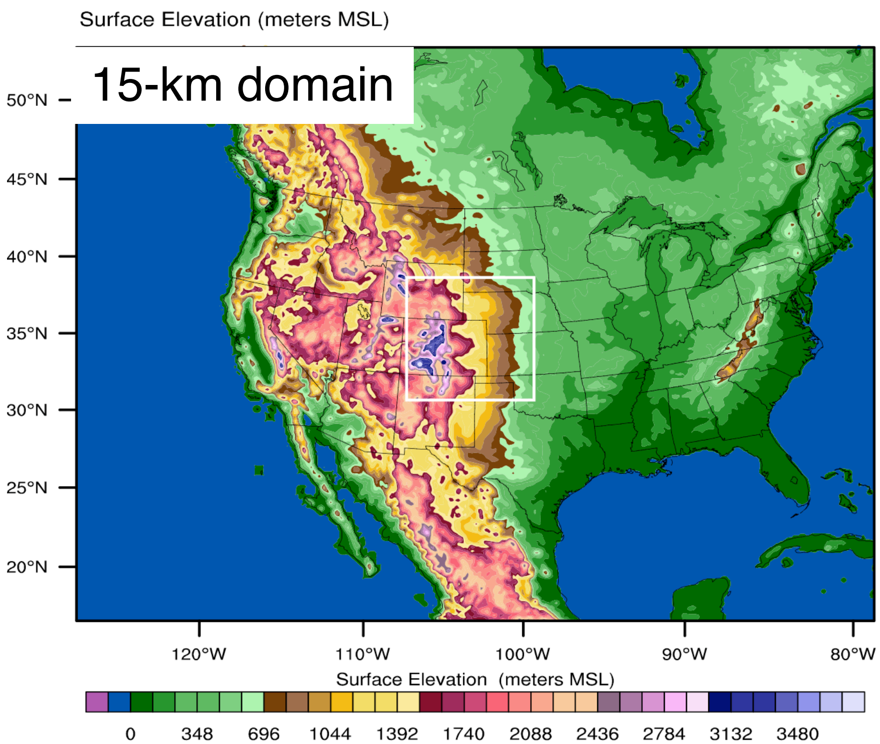
4-17 June 2009, covering most interesting VORTEX2 period

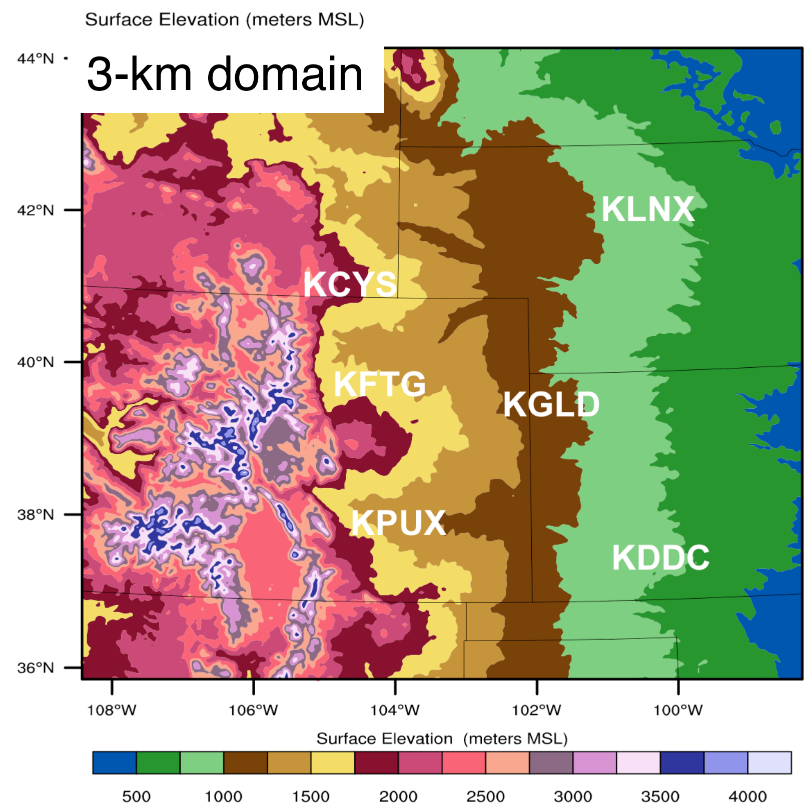
15-km domain provides “mesoanalysis”

- Full-physics ARW, KF convective scheme
- Assimilation of conventional obs, 6-h cycling

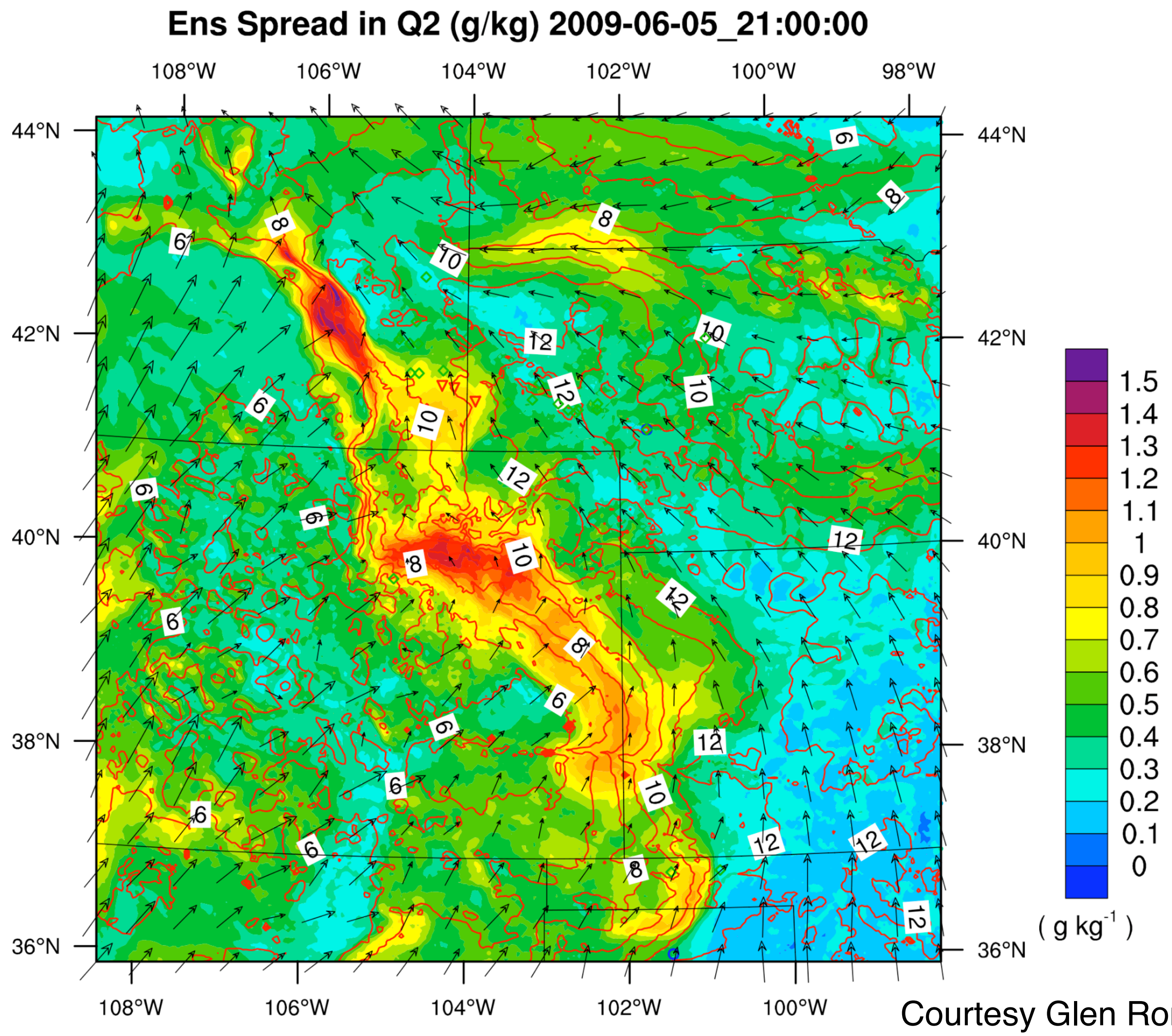
3-km domain uses no convective scheme

- Still to come: assimilation of radar obs with very freqent cycling [O(minutes)]



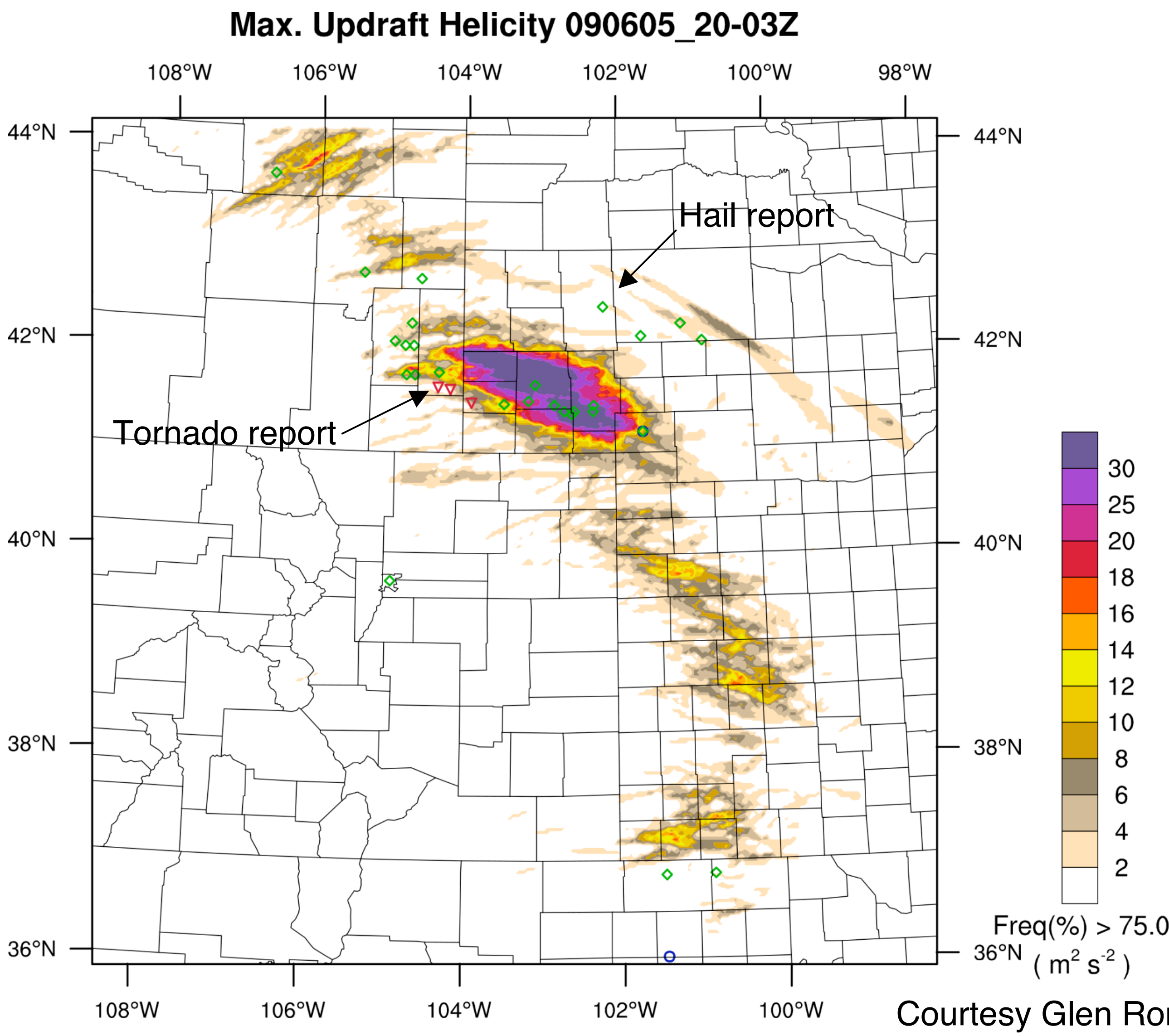


6-h forecast of surface specific humidity (contours: ensemble mean)



Courtesy Glen Romine

6-h forecast, probability (%) of max helicity > 75 m^2/s^2



Courtesy Glen Romine

Summary and Closing Thoughts

WRF/DART now a reliable research tool

- Applicable to range of scales and phenomena
- Applicable both for NWP and "science"
- Good results and stable performance with limited observation sets; e.g., no bogussing and no radiances for TC applications

Analyses with range of scales are frontier

- E.g. convection/clouds + mesoscale

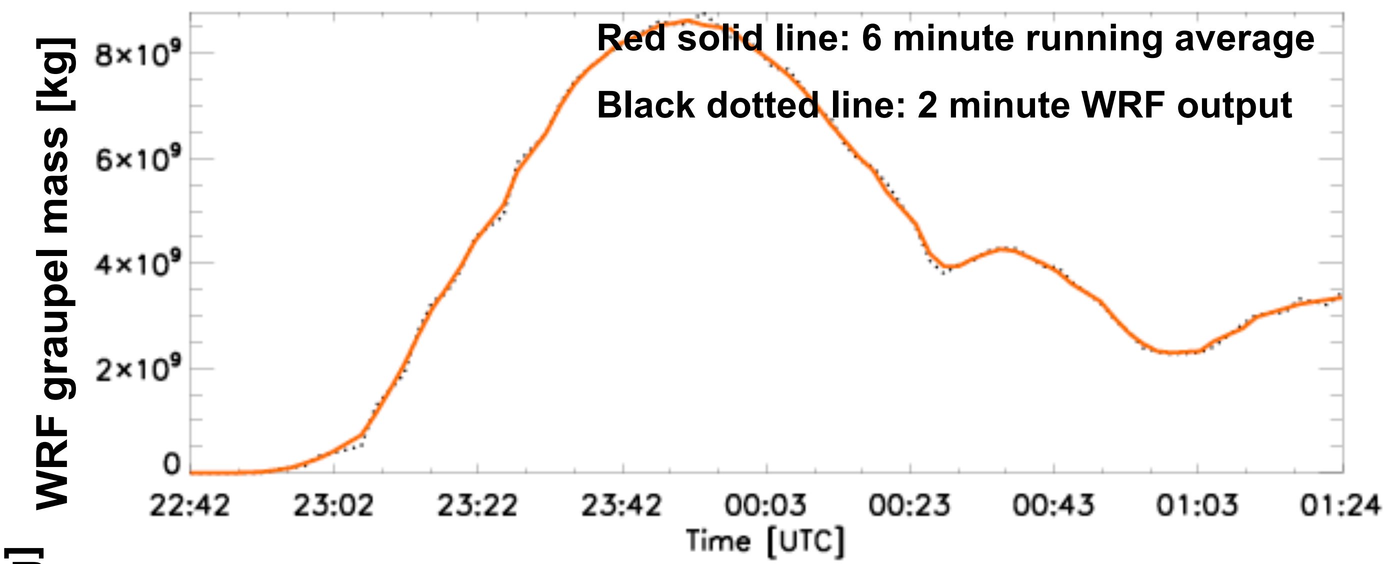
Cycling data assimilation for model evaluation

- Model errors $\rightarrow$ significant (dramatic!) analysis errors when cycling for long periods
- Eliminates some sources of bias, such as from external analysis

A good forecast model is crucial

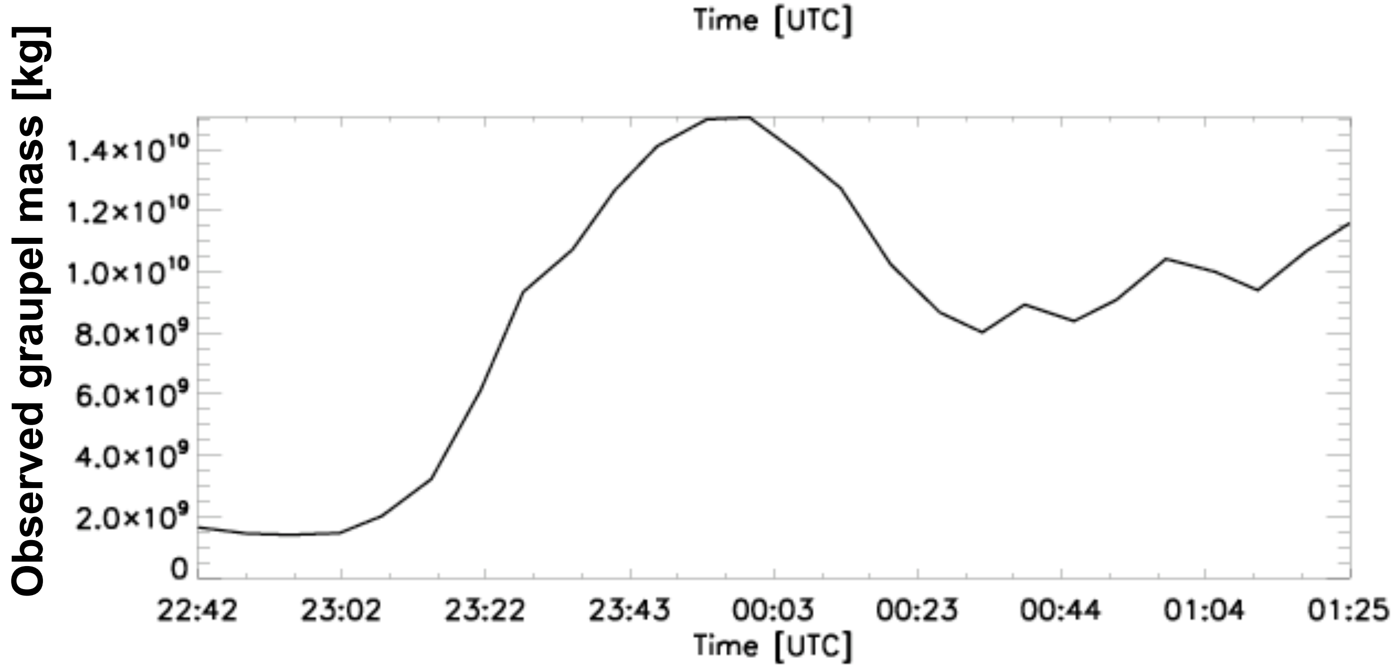
- EnKF uses model solutions in estimating covariances; biased or unphysical solutions will be reflected in analysis increments

5 July 2000 STEPS supercell



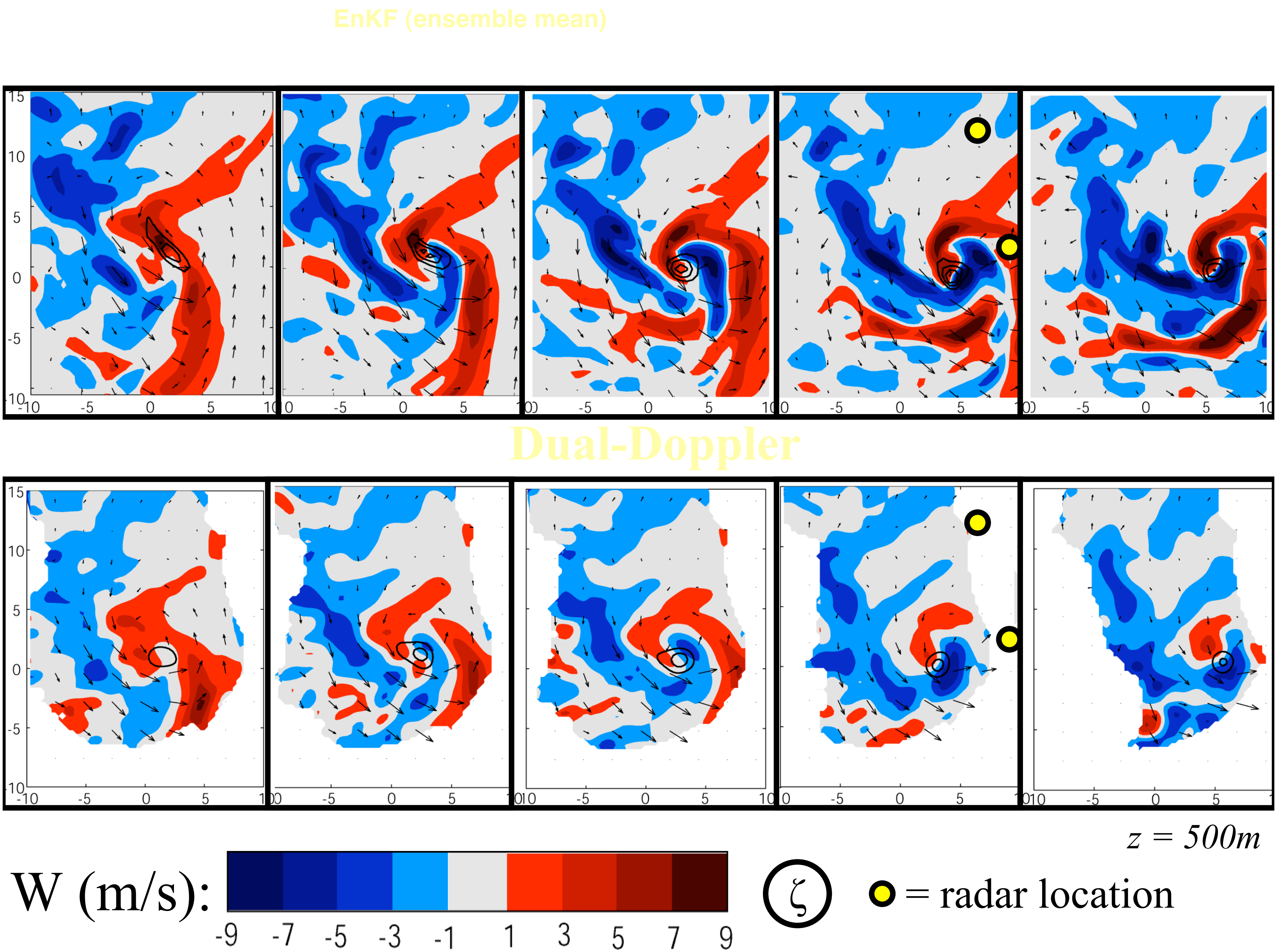
WRF graupel mass

r = 0.87



Observed graupel mass

Note: graupel+hail trend similar


EnKF (ensemble mean)
Dual-Doppler
z = 500m
W (m/s):
-9 -7 -5 -3 -1 1 3 5 7 9
ζ
= radar location

How the EnKF works

Suppose we wish to assimilate an observation of v_r
Consider how assimilation affects a model variable, say w.

Begin with:

– ensemble of short-range forecasts (of model variables)
– Observed value of v_r

How the EnKF works (cont.)

1. Compute v_r for each ensemble member

How the EnKF works (cont.)

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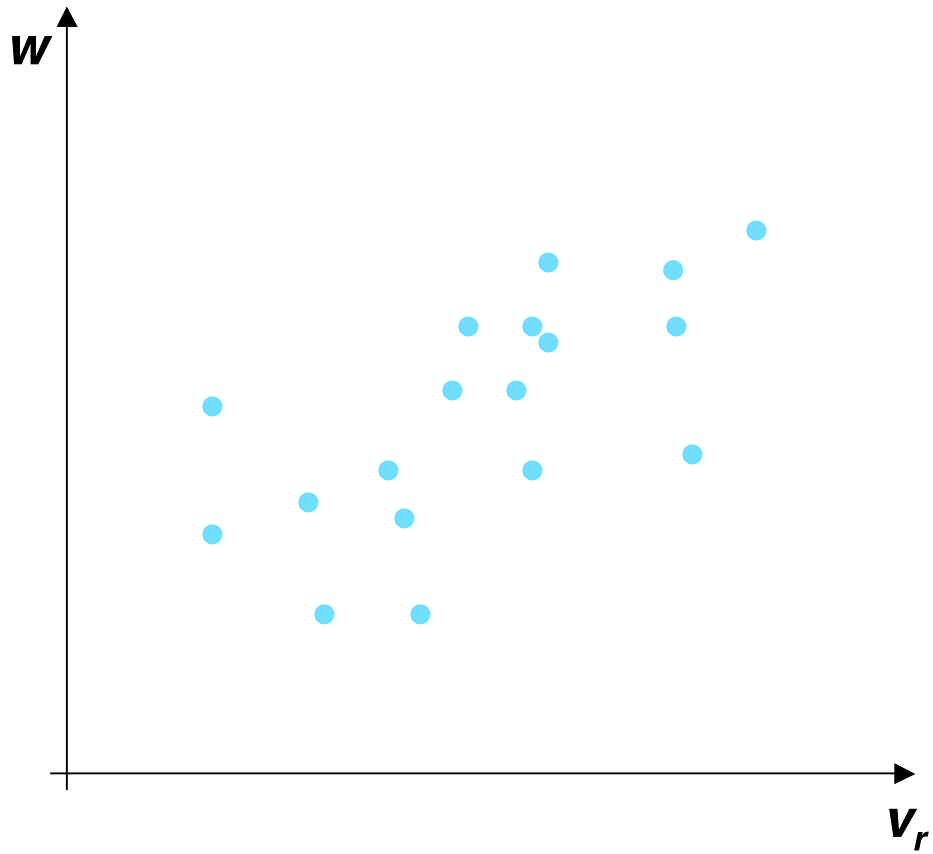

How the EnKF works (cont.)

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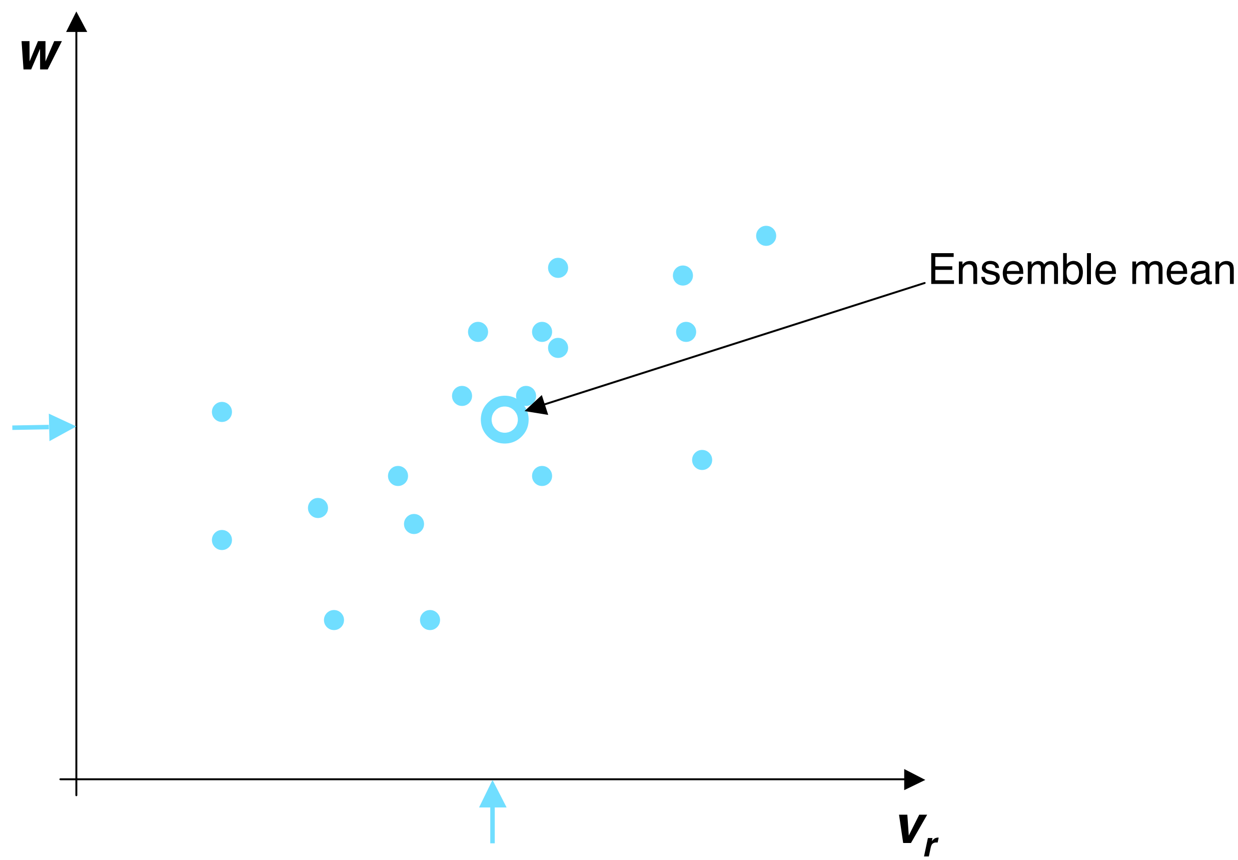
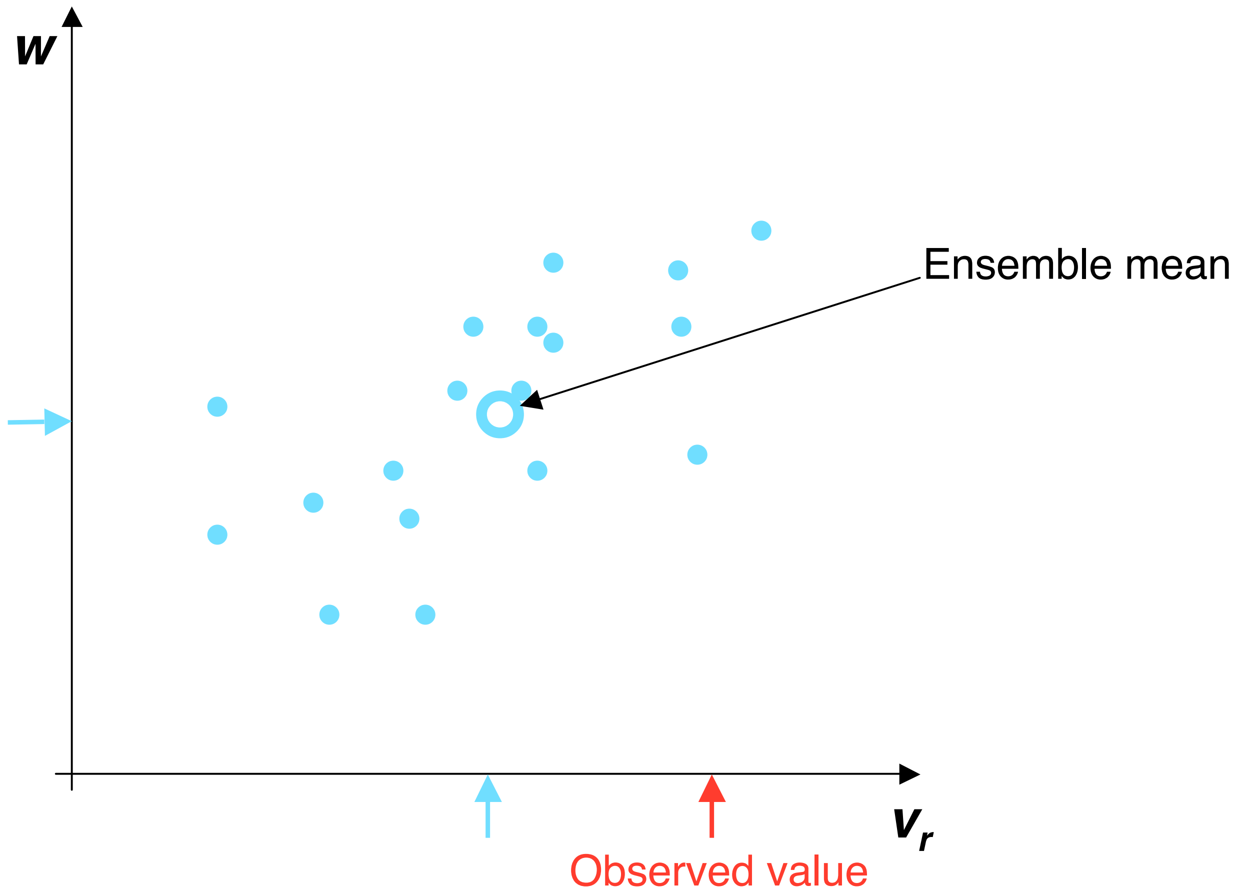


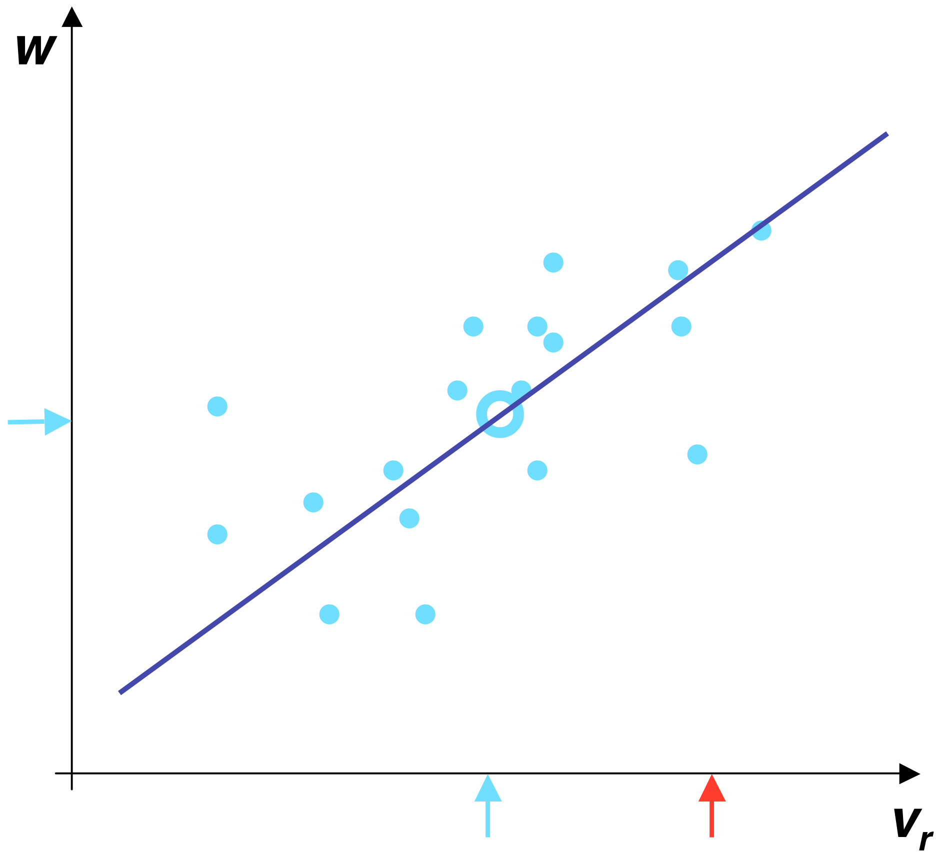
How the EnKF works (cont.)

1. Compute v_r for each ensemble member



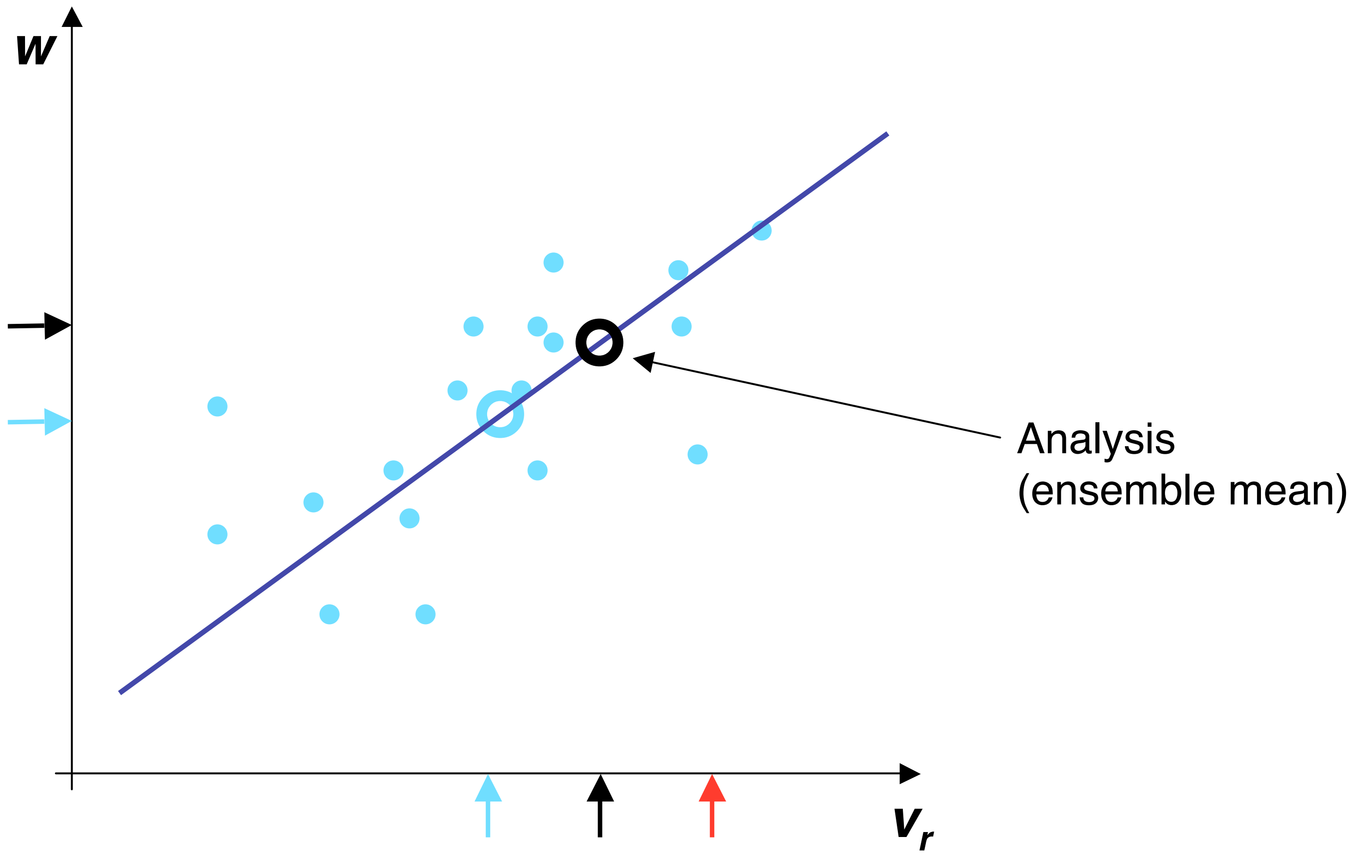
How the EnKF works (cont.)

2. Compute best-fit line that relates v_r and w



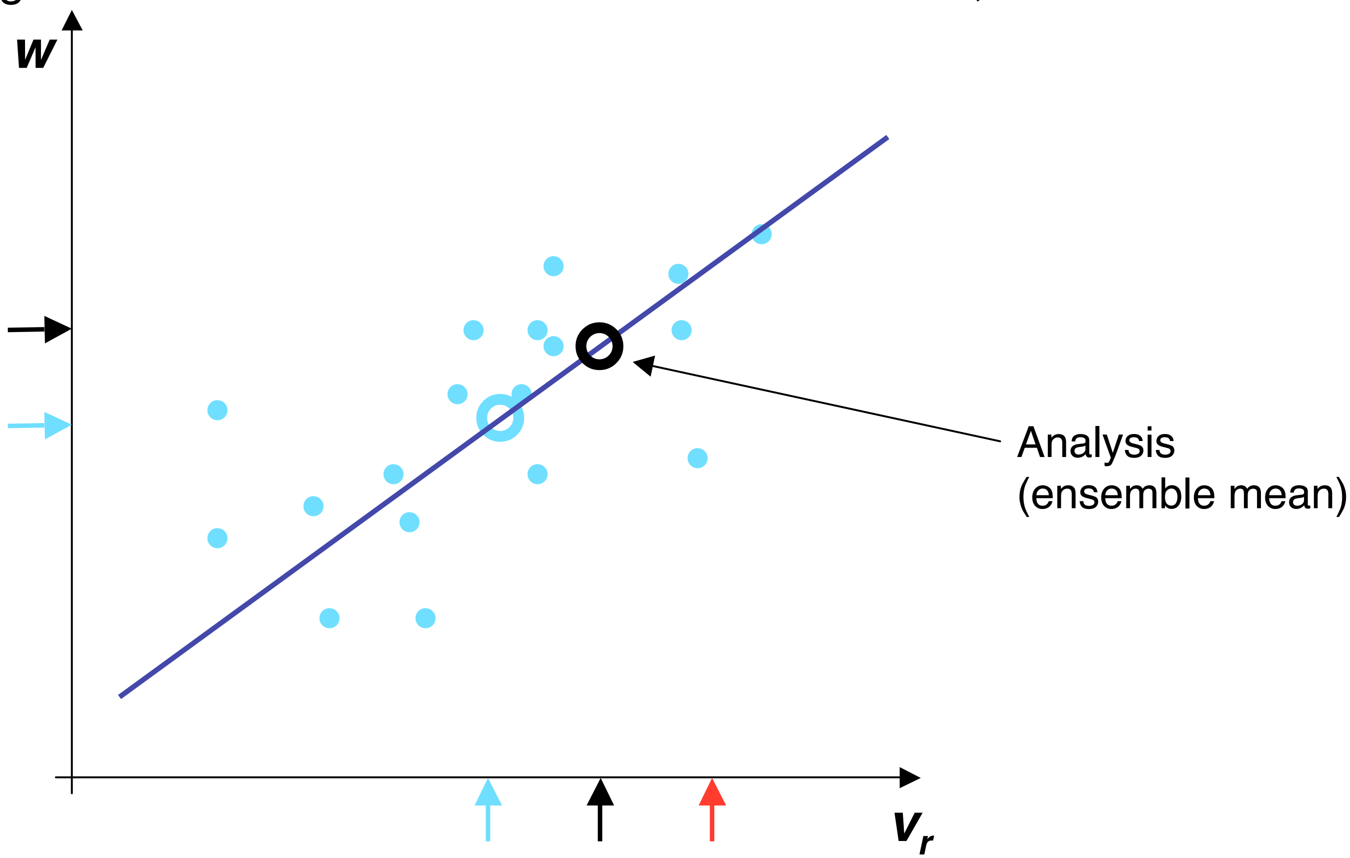
How the EnKF works (cont.)

3. Analysis moves toward observed value of v_r and along best-fit line



How the EnKF works (cont.)

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



How the EnKF works (cont.)

4. Update deviation of each ensemble member about the mean as well.

Yields initial conditions for ensemble forecast to time of next observation.