Assimilation of HIWRAP Doppler velocity data during HS3: An example from Hurricane Karl (2010)

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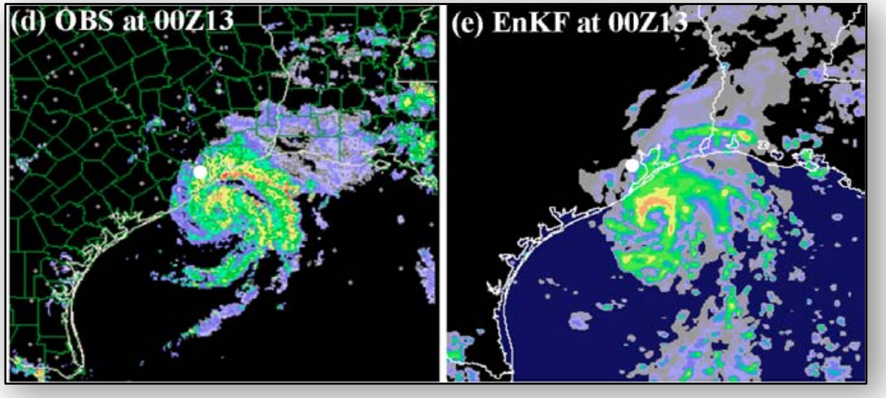
Why assimilate HIWRAP Vr?

- HIWRAP is a new Doppler radar onboard NASAs Global Hawk
  - 26-h flight time; 330-kt cruise speed at; 19-km altitude
  - Flights will allow for better observations of nearby storms and distant storms
- Assimilating Doppler velocities (e.g., 88-D and P-3) leads to better analyses and forecasts

Global Hawk at NASA's Dryden hangar



(Left) Observed reflectivity and (right) EnKF-analyzed reflectivity of Hurricane Humberto

Background: Ensemble Kalman filter

Least squares approach for *scalar* data assimilation (e.g., temperature)

$$T_a = \frac{\sigma_o^2}{\sigma_f^2+\sigma_o^2} T_f + \frac{\sigma_f^2}{\sigma_f^2+\sigma_o^2} T_o$$

Rearrange to

$$T_a = T_f + \frac{\sigma_f^2}{\sigma_f^2+\sigma_o^2} \left(T_o - T_f\right)$$

T_a = analysis

T_f = forecast

σ_f^2 = forecast error variance

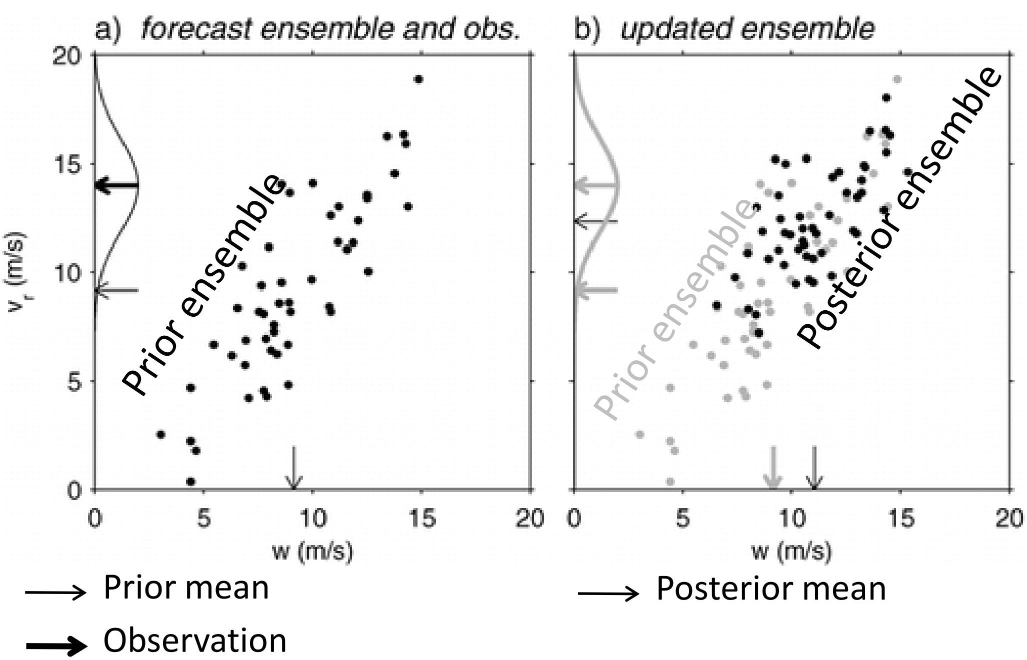
T_o = observation

σ_o^2 = observation error variance

Background: Ensemble Kalman filter

Example for model state

$$x_a = x_f + \frac{P_{fxy}}{P_{fyy} + R} (y_o - y_f)$$



Source: Snyder and Zhang (2003)

x_a = analysis (posterior)

x_f = forecast (prior) provided by ensemble

y_f = ensemble mean forecast estimate of y

P_f = error covariance from ensemble

y_o = observation

R = observation error variance

Objectives

1. Generate a 48-h ensemble without data assimilation

2. Select ‘truth’ realizations for simulated data experiments

3. Assimilate simulated HIWRAP observations with an ensemble Kalman filter (EnKF)

4. Assess quality of analyses and forecasts

WRF-EnKF system

- EnKF from Zhang et al. (2009)
- WRF-ARW V3.1.1, 27/9/3 km
- 30-member ensemble + 1 ‘truth’ member, IC/BCs from WRF-VAR + GFS
- Initialized at 00 UTC 16 September, integrated 12 h to generate mesoscale covariance
- YSU PBL, WSM-6 mp

Model domains

Selecting 'truth' realizations

Realizations selected to test EnKF performance in face of:

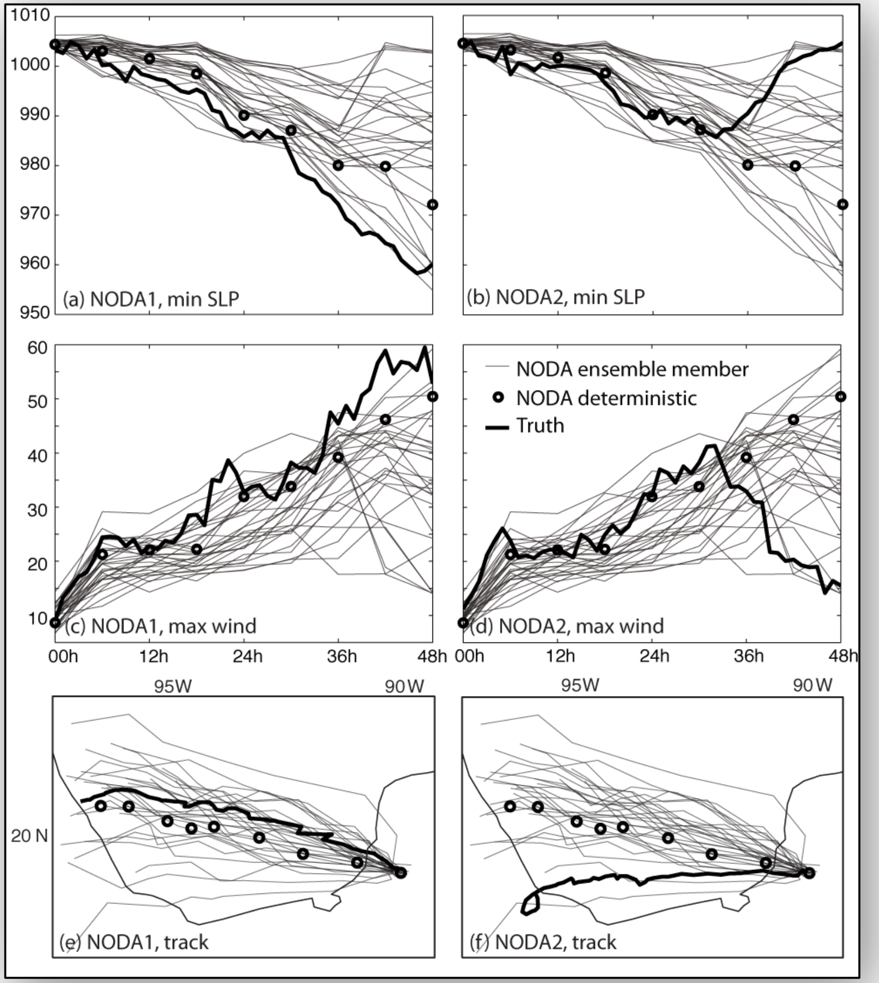
- Small error of the prior

  How much improvement does the EnKF offer when the forecast is already pretty good? (NODA1)

- Large error of the prior

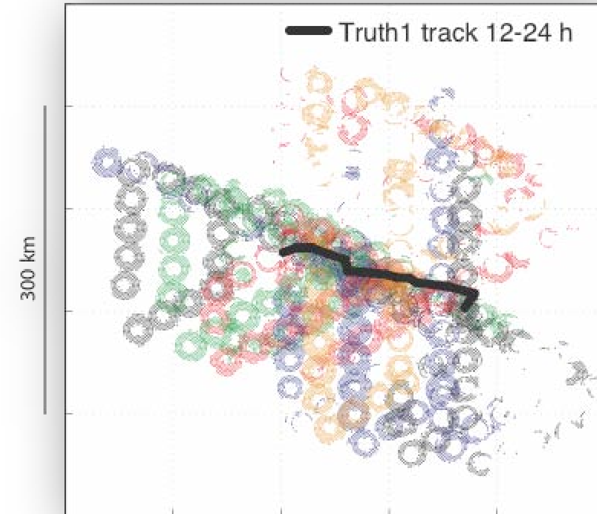
  How well can the EnKF correct when the truth is unlike most of the prior? (NODA2)

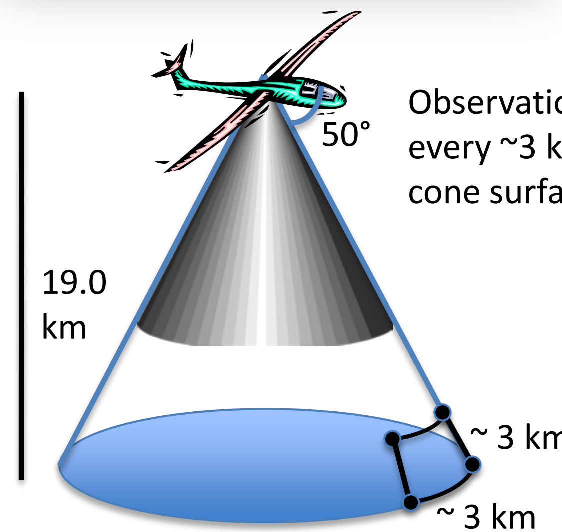
'Truth' realizations and NODA forecasts



‘Truth’ simulation flight tracks

- Instantaneous scans every ~28 km; observation cones slightly overlap at surface
- Data grouped into 1-h flight segments from same output time; ~1900 obs/hr
- Add 3 m/s random error, only assimilate when attenuated dBZ > 10

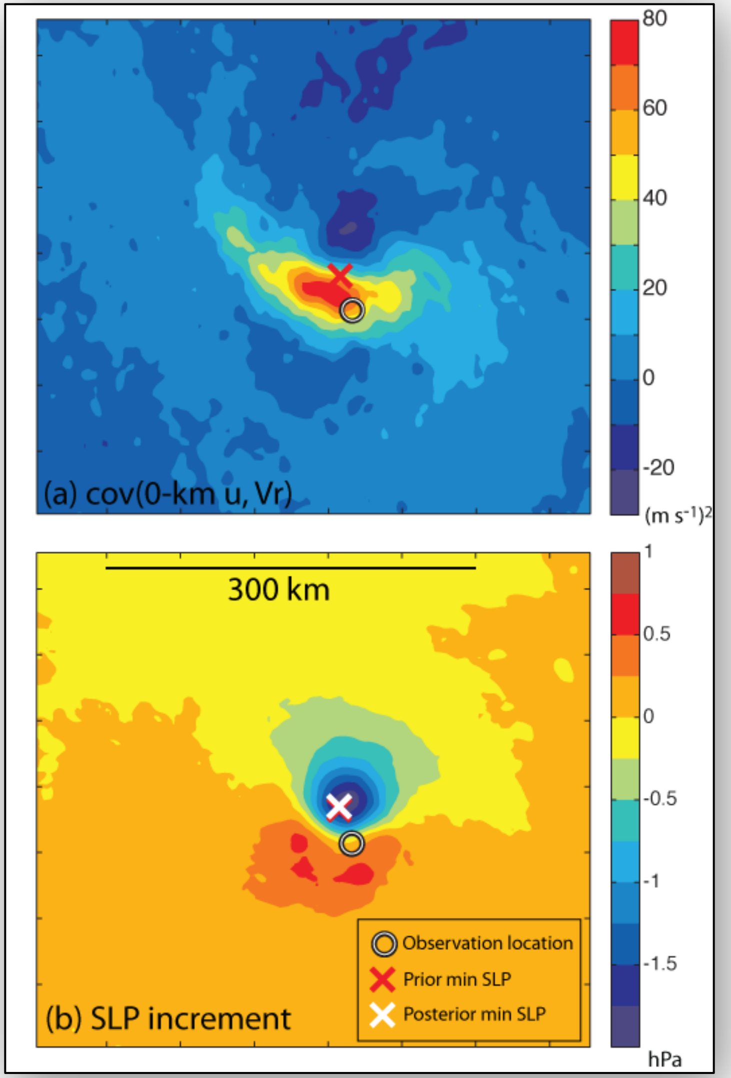




Assimilating one observation

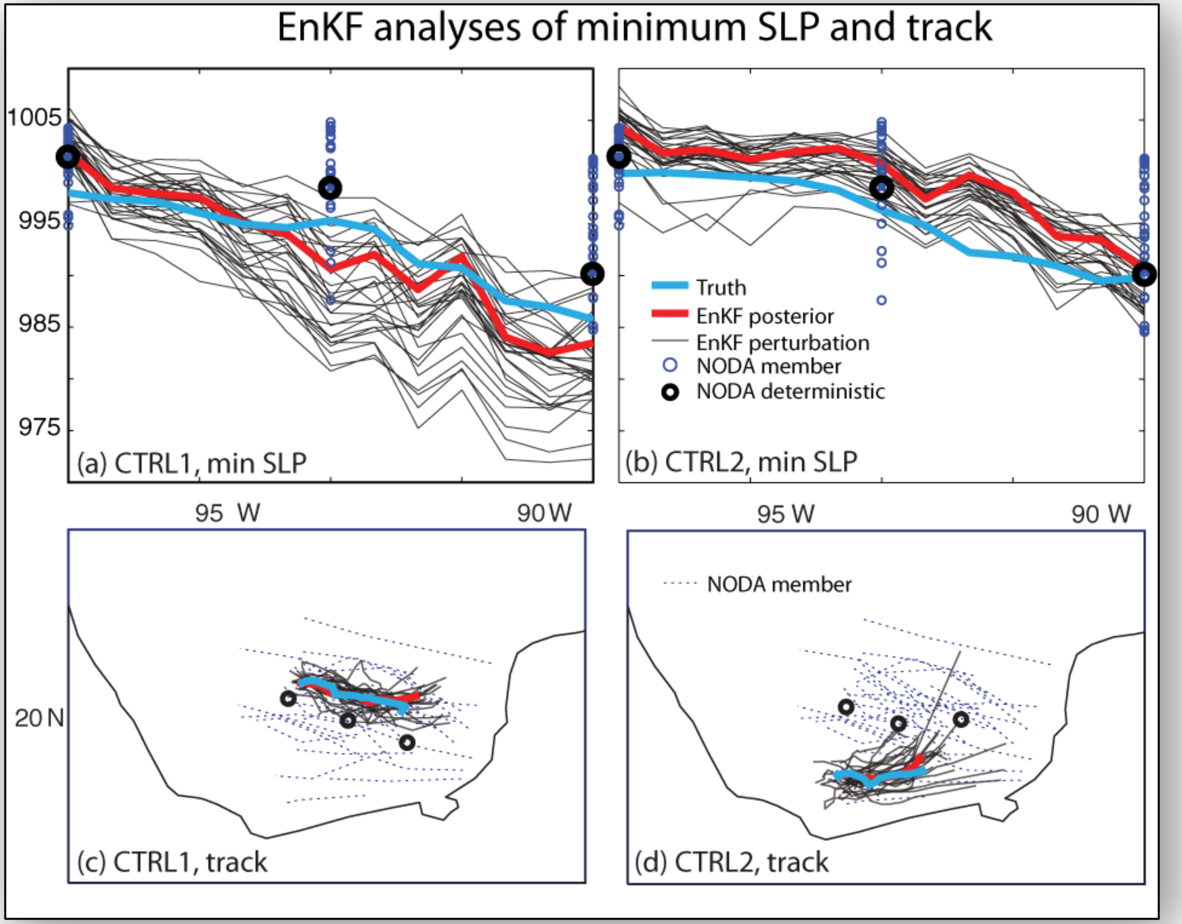
- Observation details:
  - Time: 19 h
  - Height: 3 km
  - Azimuth: 0 (East)
  - Observed Vr: +12.16 m/s
  - Forecast Vr: +6.0 m/s

- Forecast error covariance spreads observation impact to surface, helping to spin up vortex and lower SLP



Results: CTRL analyses evolution

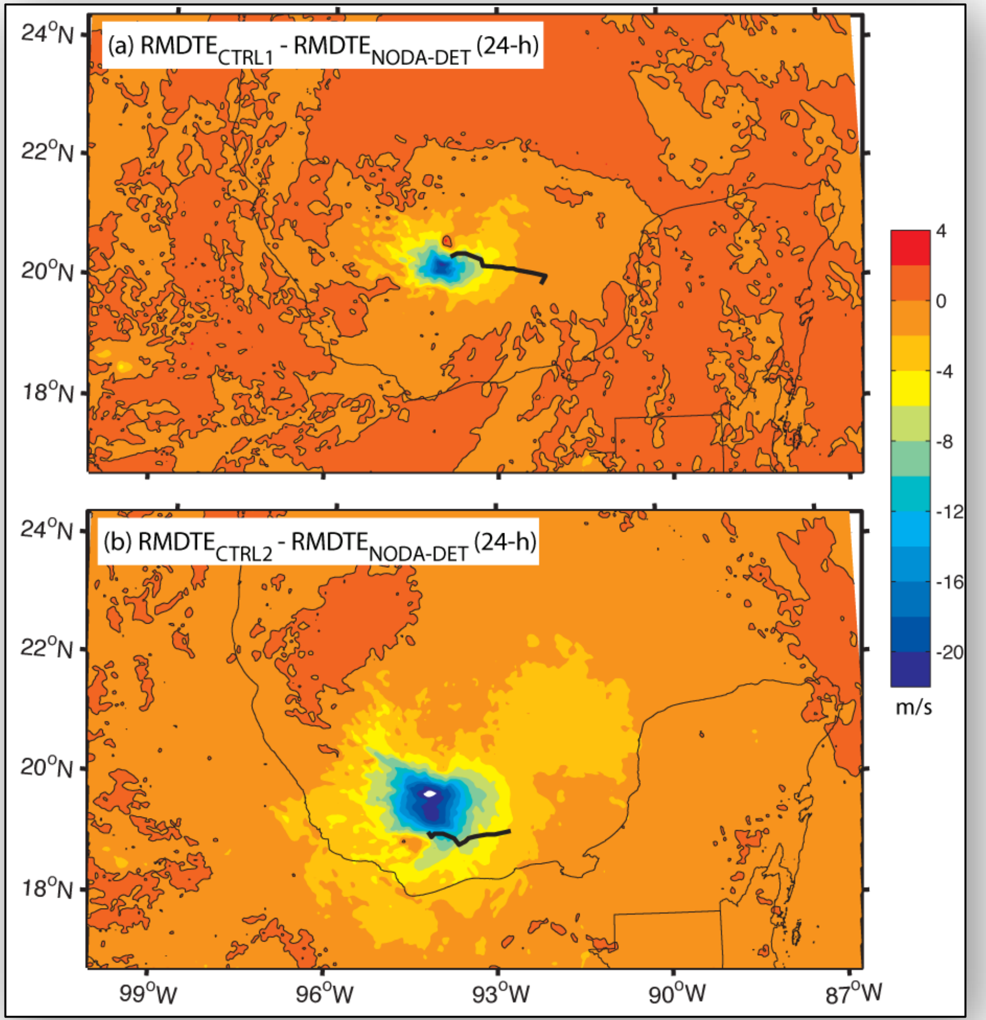
- CTRL1: small corrections to location and min SLP
- CTRL2: large correction to location, SLP takes longer correct



Results: Analysis error reduction

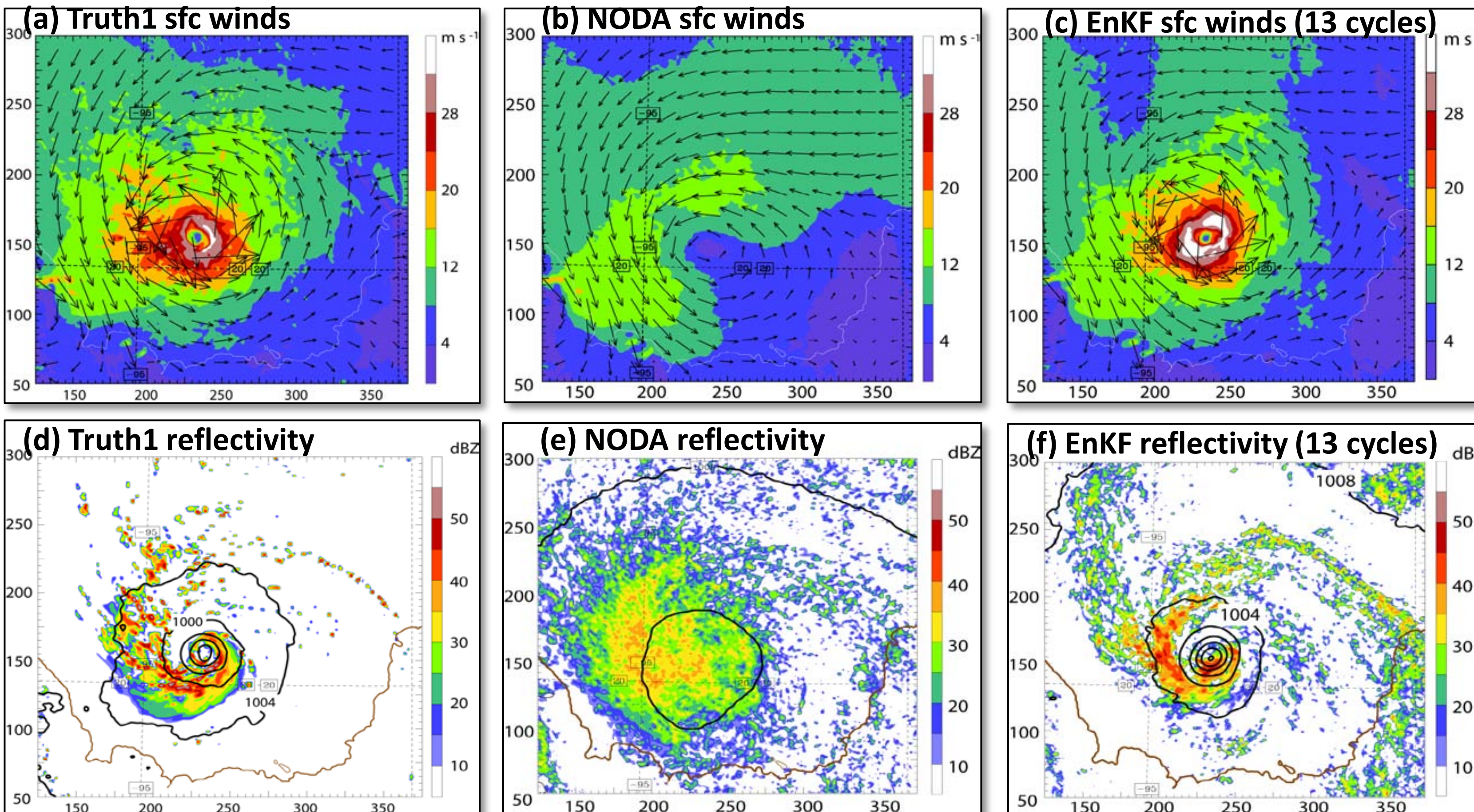
- EnKF reduce RM-DTE > 80% after 13 cycles in both cases [DTE = 0.5 (u\`u\` + v\`v\` + Cp/Tr T\`T\`), prime is difference from truth]

- CTRL2 has larger and more widespread error reduction than CTRL1



Comparison of RM-DTE differences

Results: CTRL1 after 13 cycles

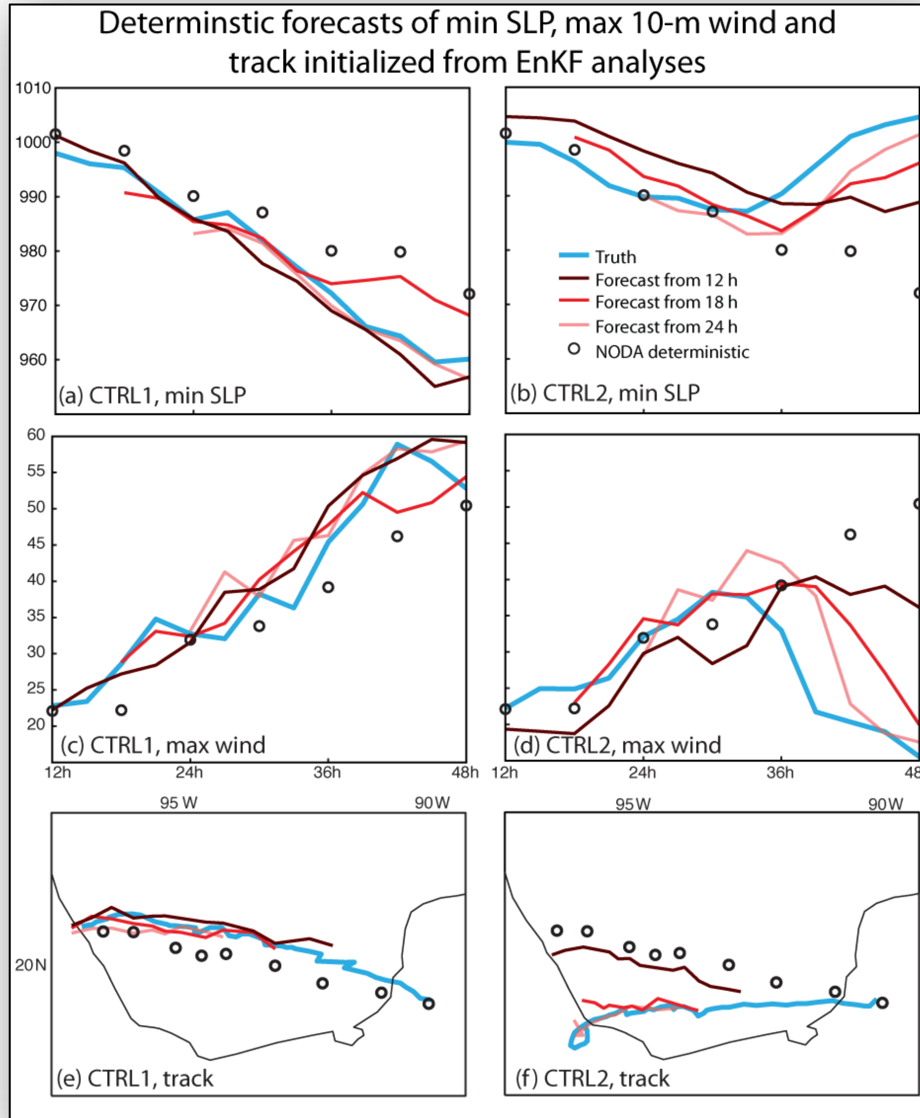


Comparison of TRUTH1, NODA ensemble mean and CTRL1 EnKF analysis at 24 h, after 13 h of assimilation

Results: Deterministic forecasts

- Forecast error is reduced relative to NODA in both cases, particularly from 36-48 h

- NODA2 needs more time to produce better analyses (i.e., that produce 'good' forecasts)



Summary

- HIWRAP data appears to be useful for EnKF analyses and subsequent forecasts of a hurricane
- Analysis error reduced >80% after 13 cycles with stronger error reduction for a poor first guess
- Notable improvements in forecast strength and position after just one assimilation cycle
- A longer assimilation window appears to benefit forecast more, particularly when the first guess is poor; this particularly highlights the benefit of the long Global Hawk on-station time

Results: Ensemble fcst SLP

- Significant ensemble forecast differences result from changing 1 cycle of random observation error
- 12 h of cycling again more beneficial than 6 h
- Variable-leg pattern does not result in better forecasts

Deterministic forecasts of min SLP: a comparison of No DA and DA experiments and sensitivity to one cycle of different observation error