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 NASA's 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

(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

\[
T_a = T_f + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_o^2} (T_o - T_f)
\]

- \(T_a = \text{analysis}\)
- \(T_f = \text{forecast}\)
- \(\sigma_f^2 = \text{forecast error variance}\)
- \(T_o = \text{observation}\)
- \(\sigma_o^2 = \text{observation error variance}\)
Background: Ensemble Kalman filter

Example for model state

\[
x_a = \underbrace{x_f}_{\text{forecast (prior)}} + \frac{P_{fxy}}{P_{fyy}+R} (y_o - y_f)
\]

- \(x_a\) = 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

Source: Snyder and Zhang (2003)
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
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’ 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 \[DTE = 0.5 (u'\cdot u' + v'\cdot v' + C_p/T)\], 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