

P11 Utilizing Ensemble Sensitivity for Data Denial Experiments on the 4 April 2012 Dallas, Texas Dryline-Initiated Convective Outbreak Using West Texas Mesonet Observations with WRF-DART Data Assimilation Aaron Hill, Chris Weiss, Brian Ancell, Atmospheric Science Group, Texas Tech University

Ensemble Sensitivity

- Utilizing statistics of ensemble forecasts to provide information of how forecasts and errors will change as the initial conditions change (Torn and Hakim 2008)
- Linear relationship between a forecast metric and initial conditions

$$\frac{\partial J}{\partial x} = \frac{\operatorname{cov}\operatorname{ar}(J, x)}{\operatorname{var}(x)}$$

- Defined as the covariance between the metric J and initial condition x divided by the variance of x, or simply the linear regression between J and x.
- Utilizing this relationship, further information can be gathered to determine what impacts additional observations can have upon the forecast metric, forecast error, and where to obtain those observations.
- Ensemble sensitivity techniques have proven valuable in assessing forecast sensitivity to initial conditions on synoptic scales (Torn and Hakim 2008, Ancell and Hakim 2007, Torn 2010). Little has been investigated on the mesoscale
- This study aims to apply sensitivity and observation targeting techniques to a convective case to determine whether assimilating adaptive observations can reduce forecast error and if such error can be accurately predicted on small scales.



Figure 1: Scatters of forecast metrics (a) max dBZ (dBZ), (b) max vertical velocity (m s⁻¹), and (c) average 2-meter temperature (K) at forecast hour 24 against initial condition 2-meter temperature at model initialization

Observation Targeting

• Locations are determined where, if additional observations are assimilated from that location, forecast error of the chosen metric will be reduced (variance reduced)

var(ob) + var(x)

- Change in variance is the squared covariance between J and x normalized by the sum of the variance in x and an assumed observation variance (full derivation can be found from Ancell and Hakim 2007).
- It would be beneficial to determine where observations should be taken to reduce forecast error when forecasts have high impact to society, deploy those observations in real-time, and assimilate them into regional numerical weather models (e.g., TTU-WRF EnKF).



Figure 3: West Texas Mesonet stations

Model Setup



- WRF Model 36/12/4km nested domains
- GFS Boundary Conditions
- Thompson Microphysics
- RRTM Longwave
- Dudhia Shortwave
- Kain Fritsch Convective - No parameterization on fine-scale grid
- NOAH Land Surface
- Yonsei Boundary Layer

Table 1: Observations Used

	Т	U wind	V wind	Q	RH	Td	Alt	Р
Radiosonde	Х	X	X	X	X	Х	X (surf)	
Satellite		X	X					
ACARS	Х	X	X	X	X	Х		
METAR	Х	X	X	X	X	Х	X	Х
Marine	Х	X	X	X	X	Х	X	
Land_Surface	Х	X	X	X	X	Х	Х	
West Texas Mesonet	X							

Methodology/Experimental Setup

- 2-meter temperature initial condition variable at forecast initialization
- Three forecast metrics: max dBZ, Max vertical velocity, average 2-meter temperature. Calculated within response region, depicted in Figure 4 as a black box within the domain
- West Texas Mesonet stations chosen as a proxy for adaptive observations
- Targeted stations chosen that had highest expected variance reduction
- Initial condition observation at targeted station assimilated into subsequent forecasts. Process repeated for 5 observations

Case Study Overview





Figure 4: Ensemble mean of forecast metrics (a) max dBZ (contours, dBZ), (b) max vertical velocty (colored, m s⁻¹), and (c) average 2meter temperature (contours, K). Ensemble spread of max dBZ and average 2-meter temperature are colored in (a) and (c). Forecast metric region shown with rectangular box.

- (http://www.spc.noaa.gov/climo/reports/120403_rpts.html)
- A dryline propagated eastward during the daytime hours and converged upon a stationary outflow boundary around the Dallas/Fort Worth metroplex Ensemble-mean of reflectivity failed to reproduce the convection and accurately predict convective initiation



Dryline and outflow-initiated convective event over North-Central Texas with 22 tornado reports



- Expected variance reduction did not match variance change seen
- In some cases, variance increased when additional observations were assimilated, which should not happen according to theory
- Non-linearity between initial condition and forecast metric could play a role, since ensemble sensitivity and observation targeting assume a linear relationship. This may not be the case with convective metrics such as reflectivity and vertical velocity





Figure 6: Expected (red) and actual (blue) variance of the forecast metrics (a) max dBZ (dBZ²), (b) max vertical velocity (m² s⁻²), and (c) average 2-meter temperature (K²) as additional observations are assimilated.

- Design a set of experiments to determine how non-linearity, bi-modal distributions, and other response functions can influence variance reduction
- Develop a different sensitivity value that takes into account different "regimes" of a forecast metric, such as when convection occurs and when it doesn't. Apply a new targeting technique to this sensitivity calculation

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- Figure 5: Observation targeting for three forecast metrics (a) max dBZ (dBZ²/C), (b) max vertical velocity (m² s⁻²/C), and (c) average 2-meter temperature (C²/C), and corresponding ensemble sensitivity fields (d,e,f)
 - Forecast metrics may not be normally distributed, as needed for correct sensitivity analysis

Future Work

References

- Ancell, B., and G. J. Hakim, 2007: Comparing adjoint- and ensemble-sensitivity analysis with applications to observation targeting. Mon. Wea. Rev., 135, 4117-4134.
- Torn, Ryan D., 2010. Ensemble-based sensitivity analysis applied to African easterly waves.
- Torn, R. D., and G. J. Hakim, 2008: Ensemble-based sensitivity analysis. *Mon. Wea. Rev.*, **136**,

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