Radar Data Assimilation Using the High Resolution Ensemble Kalman Filter

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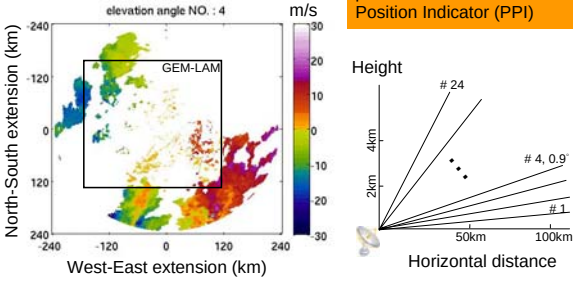
Introduction

- We examine the benefit of the Ensemble Kalman Filter (EnKF) for radar data assimilation in order to improve convective scale weather forecast.
- We use Canadian GEM-Limited Area Model (GEM-LAM) at 1 km horizontal resolution covering the Montréal region.
- We assimilate only radial winds that are real radar observations from McGill Radar Observatory.
- Methodologies include batching procedure, data thinning and quality control.
- Observation operator includes U, V W wind components and terminal velocity.
- The impact of sequential radar data assimilation on analysis and short-term forecasts is studied in one case.

Radar observations

Radial wind for 2010 July 22 0000 UTC

Radar observations are on polar coordinate or Plan Position Indicator (PPI)

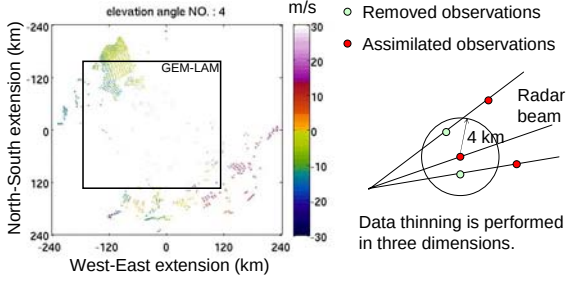


- Radial winds are assimilated (Reflectivities are assimilated implicitly).
- The radial resolution of raw radar data is 1km; angular resolution is 1°.

Data thinning for radial wind

Data thinning is required because: 1. the error structure of radial wind observation is unknown; 2. the batching procedure is valid for uncorrelated observation errors.

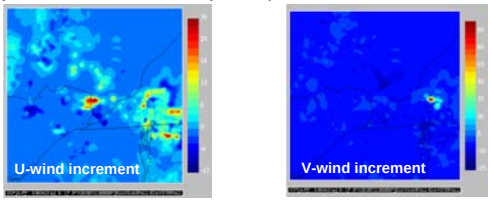
4 km data thinning result



Data thinning is performed in three dimensions.

Problem of no data thinning

If data thinning is not applied and all radial wind information is used, the analysis increment of one analysis step is not realistic.



- Data thinning reduces the number of observations significantly.

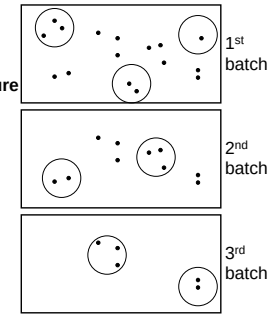
For current case study: 2010 July 22, 0000 UTC

Radial wind (VR)	Total number of observations	Percentage
All data	~15000	100%
4 km Data thinning	~1500	~10%

Details of EnKF algorithms

Batching procedure

Example of batching procedure



- The GEM-LAM EnKF uses the same localization and batching procedures as in the Meteorological Service of Canada's global EnKF system (Houtekamer et al., 2009).
- Batching procedure separates observations into different batches. The innovations among different batches are uncorrelated.
- The localization technique removes the noise on small error correlations caused by limited ensemble size.

Quality control

The observations will NOT be assimilated when the following condition applies.

$$|y - HX_f| > 2\sqrt{\sigma_o^2 + \sigma_f^2}$$

where y is the observation, X_f is the forecast, H is the observation operator, σ_o and σ_f are the standard deviations of observation error and forecast error in observation space respectively. Quality control prevents the model from being shocked by EnKF system.

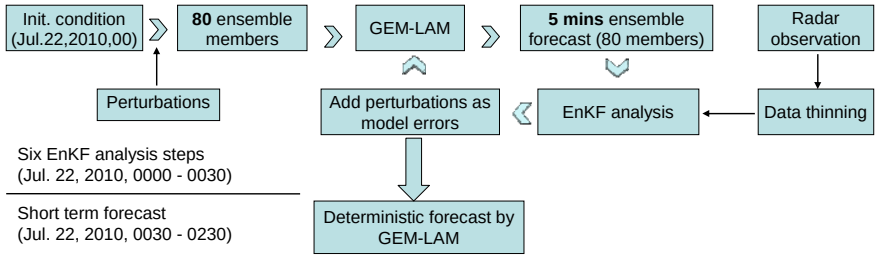
Observation operator

$$V_r = (U\sin\varphi + V\cos\varphi)\cos\alpha + (W + V_T)\sin\alpha$$

where V_r is radial wind, U, V, W are the three components of wind, V_T is the terminal velocity, φ and α are azimuth angle and elevation angle respectively.

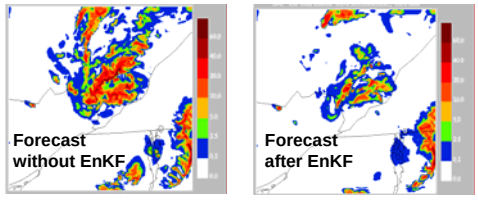
The terminal velocity is calculated from observations of reflectivity.

Case study

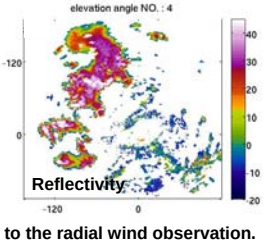


Impact of EnKF data assimilation on short term forecast

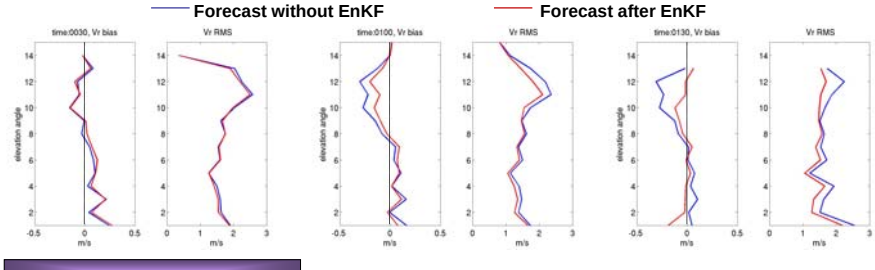
Model output at 0130 UTC: Surface precipitation



Radar observation at 0130 UTC



Average and RMS of the forecast in observation space, compared to the radial wind observation.



Conclusion

A convective scale EnKF was built to assimilate radial wind observations into Environment Canada's GEM-LAM 1 km model. Data thinning is applied on real radar observations. The batching procedure and localization help to assimilate a large number of observations. The observation operator includes the vertical wind component and the terminal velocity.

From the current case study, EnKF data assimilation removes a portion of false precipitation. The forecast after the EnKF data assimilation is closer to radar observations based on objective scores. EnKF data assimilation helps the forecast maintain a smaller rms error during the forecast time.

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