COMPARISON OF RTMA AND ENSEMBLE KALMAN FILTER SURFACE ANALYSES

Extended Abstract

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1. Introduction

Two high-resolution surface analysis techniques are currently being used at the National Weather Service (NWS): the Real Time Mesoscale Analysis (RTMA) and Match Observations All (MOA) systems. The RTMA is a two-dimensional variational data assimilation technique that utilizes the Rapid Update Cycle (RUC) model 1-hr forecast as a first guess, and is run at 5-km grid spacing. Observational information is spread spatially in the RTMA using climatological covariances obtained by the Numerical Modeling Center (NMC) method involving North American Model (NAM) forecasts. The MOA system is run at 2.5-km grid spacing and uses real-time forecasts from the University of Washington Weather Research and Forecasting (WRF) modeling system as a first guess, and spreads observational information spatially with weighting functions. The surface analyses from both systems are very important in providing forecaster awareness of the current meteorological conditions, and also serve as “truth” for other models to be verified against in the NWS National Digital Forecast Database (NDFD).

A variety of studies (e.g. Whitaker et al. 2004, Hacker and Rostkier-Edelstein 2007, Meng and Zhang 2008) have shown improved analyses and forecasts using an ensemble Kalman filter (EnKF) over those of a three-dimensional variational data assimilation system, presumably due to the flow-dependent covariances used during data assimilation. These studies suggest surface analyses produced with an EnKF, created using flow-dependent covariances, may be more accurate than those produced without flow dependence such as those from the RTMA and MOA systems. The goal of this project is to compare surface temperature and wind analyses from the RTMA, MOA, and EnKF to determine which produces the best surface analyses.

2. Methodology

This initial portion of the project focuses on an objective comparison of surface analyses from the RTMA and the EnKF. We compare RTMA and EnKF surface wind and temperature analyses over a historical period of 2 months (October/November 2009 – 173 assimilation cycles). The RTMA system is based on the Gridpoint Statistical Interpolation (GSI) three-dimensional variational data assimilation system developed by the Environmental Modeling Center at the National Centers for Environmental Prediction (Kleist et al. 2009), and is used to produce surface analyses in these experiments that represent those of the RTMA. An EnKF based on the University of Washington EnKF system (Torn and Hakim 2008) is also be used to produce surface analyses. Figure 1 shows the modeling domain used in these experiments. The EnKF in this study is an 80-member ensemble and is run on a 6-hour update cycle, and assimilates surface, aircraft, cloud-track wind, and radiosonde data. Since the GSI system produces analysis increments on model sigma levels and not at the surface, surface analysis increments are produced in both the EnKF and the GSI by multiplying the lowest sigma level analysis increments by EnKF analysis error covariances between the lowest model sigma level and the surface.

In order to fairly compare the two data assimilation systems, both use an identical first guess field, observations, and observation errors. Each member of the 36-km EnKF system is downscaled to the 12-km grid after assimilation, and 6-hr forecasts are produced using the lateral boundary conditions from the 36-km runs. Biases are removed from each 12-km forecast using the technique of Ancell et al. (2011), and the subsequent mean 6-hr forecast serves as the first-guess field for both the EnKF and GSI analysis procedure. Roughly 1000 surface wind and temperature observations are assimilated, and about 1000 independent observations are used for verification each assimilation cycle for both the EnKF and GSI. In this way, these experiments test only the differences among background error covariances used during data assimilation.

3. Initial Results

Figure 2 shows the analysis increment made to the surface temperature field by both the EnKF and the GSI for a single assimilation cycle at 0000 UTC October 10, 2009. Qualitatively, analysis increments from both systems appear in the same general location with similar magnitudes. The EnKF, however, appears to contain smaller-scale structure in these increments, and seems to focus the increments along terrain and coastal features such as the Cascade mountain range in central Washington, the high terrain of northern California, and near Vancouver Island northwest of Washington. Figure 3 depicts another example showing the zonal wind analysis increment made by both systems at 0600 UTC October 23, 2009. Figure 3 focuses on the region of Vancouver Island and western Washington, and again shows EnKF analysis increments there that better correspond to the terrain and coastal features.

Figure 4 depicts the RMS errors with respect to unassimilated observations for both the EnKF and GSI surface analyses over all 173 assimilation cycles. Averaged over all cycles, RMS temperature errors are 2.24^{o}C for the GSI and 1.82^{o}C for the EnKF, and RMS wind errors are 2.11 m/s for the GSI and 2.02 m/s for the EnKF. This results in a 4% improvement in surface wind analyses, and a 19% improvement in surface temperature analyses by the EnKF. One important goal of this work is to determine whether this improvement of the EnKF exists over specific regions dominated by certain terrain features, such as coastlines, high terrain, or strongly-sloped terrain. Surface RMS wind errors were calculated over two initial sub-regions: western Washington lowlands (Washington State west of the Cascade Mountain range with elevation less than 300 m) and high terrain (any part of the domain with an elevation higher than 1000 m). For the western Washington lowlands, the improvement of the EnKF increased to 16%, although for high terrain the GSI exhibited a 4% improvement over that of the EnKF.

4. Summary and Future Work

Surface wind and temperature analyses from the GSI 3DVAR and an EnKF data assimilation system were compared over a domain in the Pacific Northwest for a two-month period in this study. Both systems used the same first guess field, the same observations, and the same observation errors. Surface analyses produced with an EnKF showed an improvement over those produced with the GSI when RMS errors were averaged over the whole domain. These improvements in the wind field became larger when considering only the lowlands of western Washington, but the GSI showed an improvement when considering only high terrain. Determining the relative performance of both systems in all types of terrain features, such as coastlines and strongly-sloping terrain, is a major goal in the near future.

We also plan on conducting a set of additional experiments evaluating surface analyses from the actual RTMA. Only GSI surface analyses have been considered here, but the RTMA modifies background error covariances based on the degree of terrain slope. Thus, RTMA surface analyses may show an improvement over those of the GSI. Furthermore, we plan on testing whether the improvements of the EnKF found here at 12-km grid spacing extend to a domain configuration at 4-km grid spacing, more closely resembling the operational RTMA system (5-km grid spacing).

References

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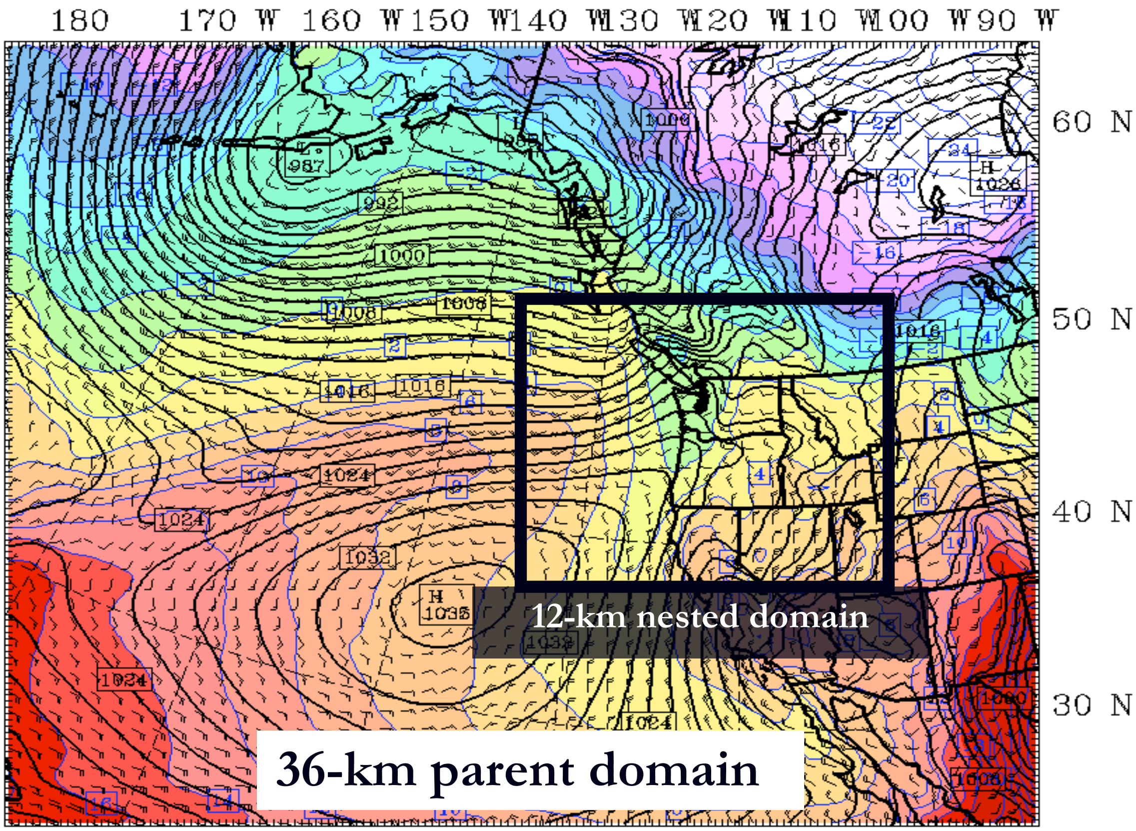

Figure 1 – The 36-km parent and 12-km nested domain configuration used in this study.

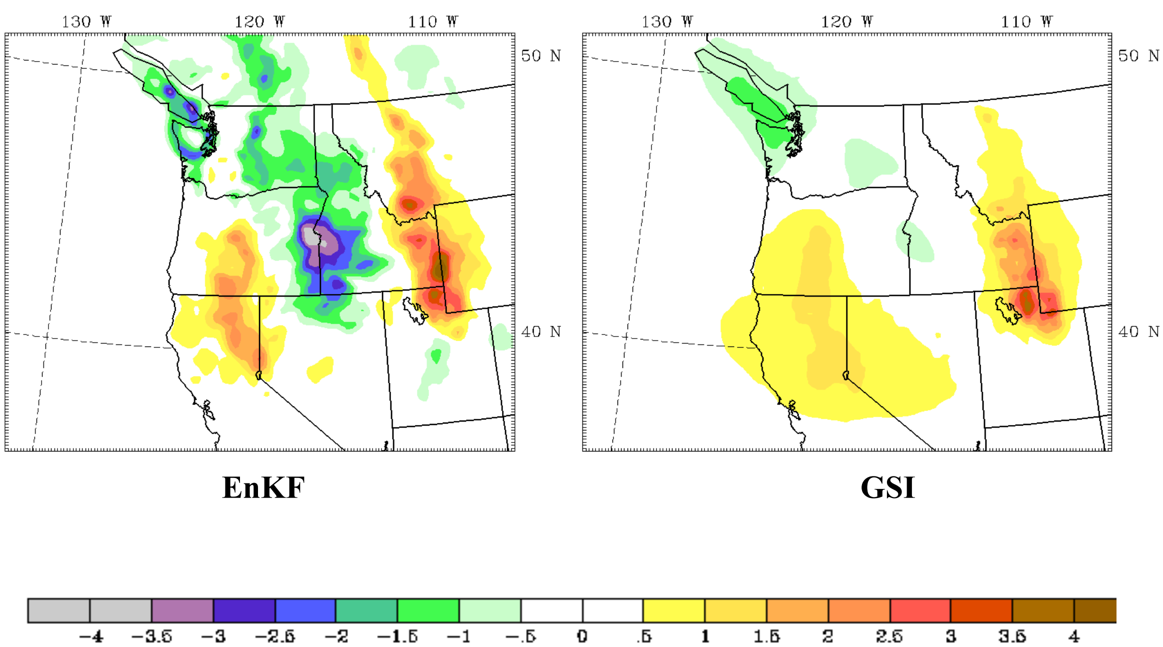

Figure 2 – Surface temperature analysis increments (shaded, units are ^{o}F) made by both the EnKF and GSI at 0000 UTC October 30, 2009.

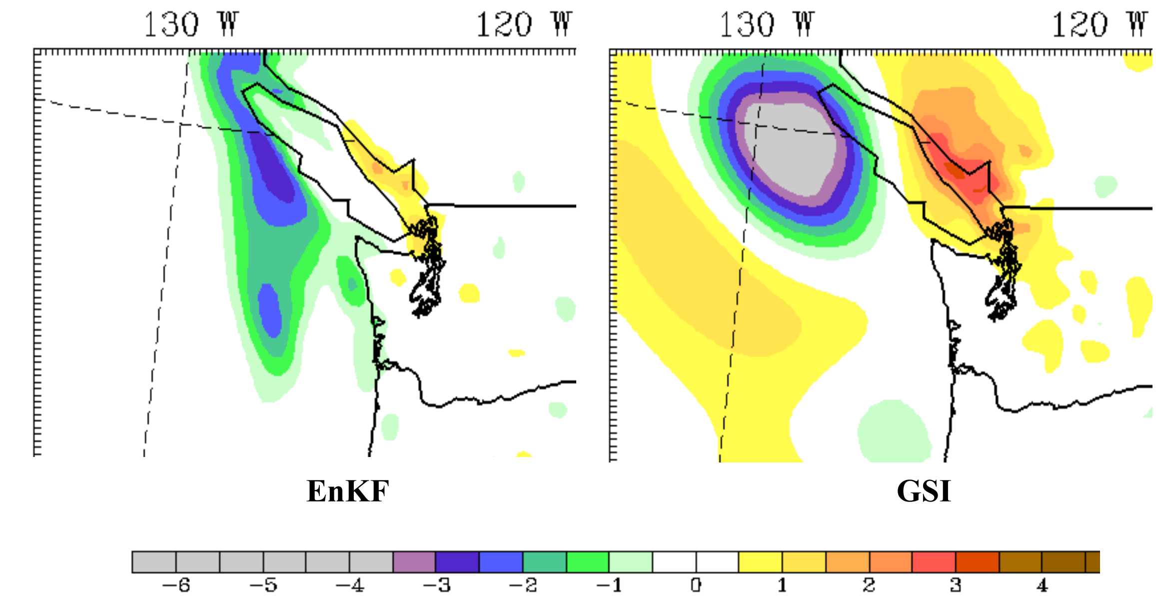

Figure 3 – Surface zonal wind analysis increments (shaded, units are m/s) made by both the EnKF and GSI at 0600 UTC October 23, 2009.

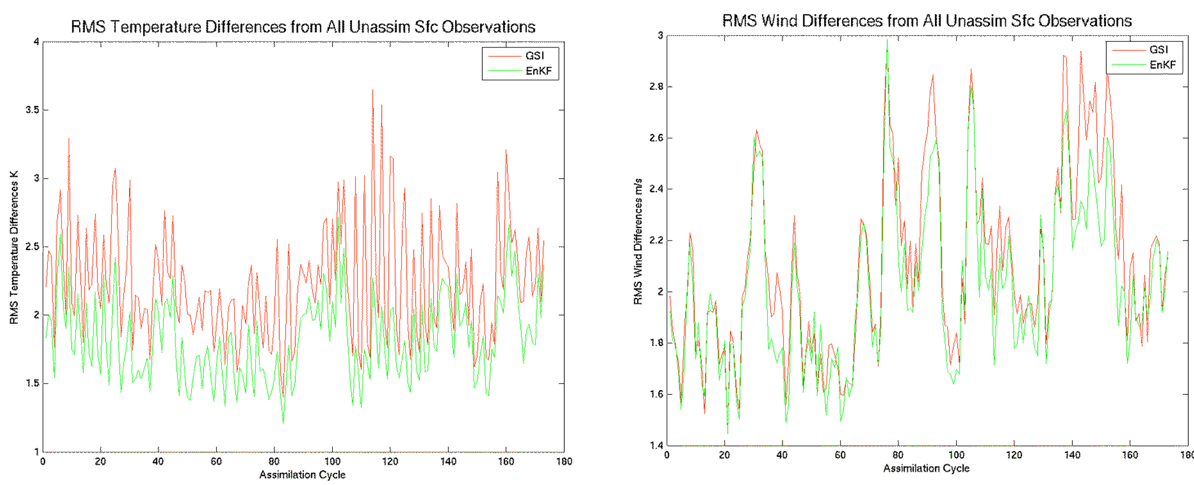

Figure 4 – Surface RMS temperature and wind analysis errors over all assimilation cycles for both the EnKF and GSI.