Comparing Representations of Model Error for Assimilation of Surface Observations

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1. Introduction

Historically, surface observations have been central to analyzing and understanding mesoscale motions and their dynamics. The potential information from these observations has yet to be fully realized for numerical weather prediction, however. Assimilation of surface observations often yields limited or even negative effects on short-range forecast skill. There are two main difficulties associated with assimilation of surface observations: 1) The strong vertical correlations among variables within the planetary boundary layer (PBL), and the strong variation of these with the state of the flow and the time of day, and 2) the many deficiencies of numerical models and their parameterized physics in the PBL and the land surface. (Representativeness of the observations is, in our view, a secondary problem except in complex terrain.)

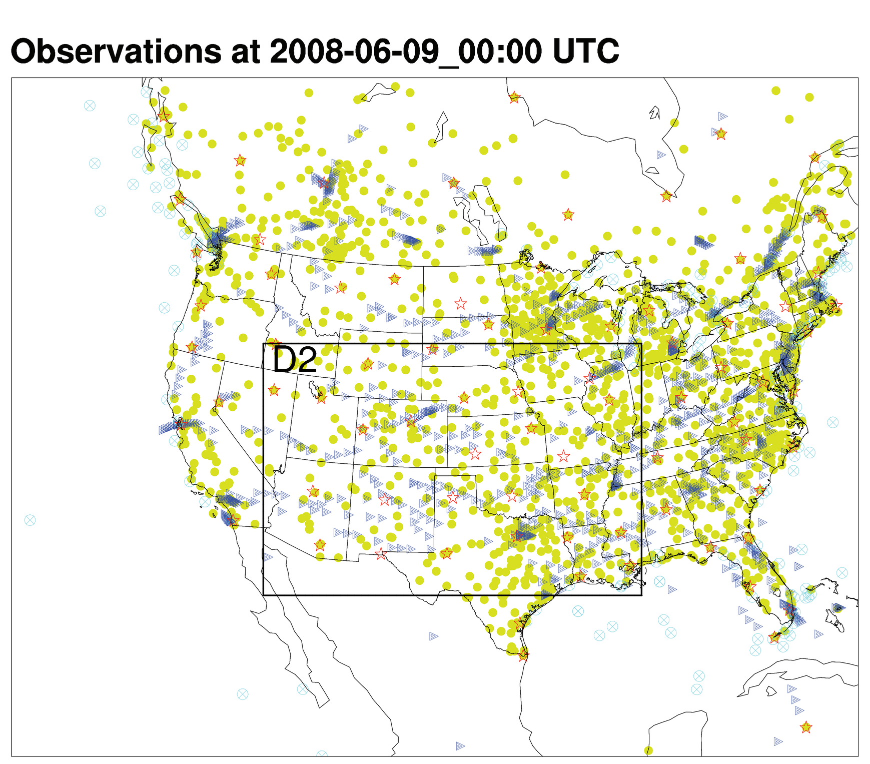
Ensemble Kalman filters (EnKFs) appear to address (1) (Hacker and Snyder 2005, Hacker and Rostkier-Edelstein 2007, Stensrud et al. 2007, Ancell et al.2011), yet in doing so are potentially even more strongly affected by (2), since the vertical and cross-variable covariances that help with (1) depend on precisely those aspects of the model that are prone to error. While improving the model is crucial and will likely yield the largest benefits in the long term, it is also important to account in the EnKF for the presence of model error, either explicitly in the forecast step or implicitly in the analysis itself. Here we show results that support the effectiveness of the EnKF for assimilation of surface observations, despite errors in the model's parameterizations, and we examine two techniques to represent model error in the forecast step.

2. WRF/DART experiments

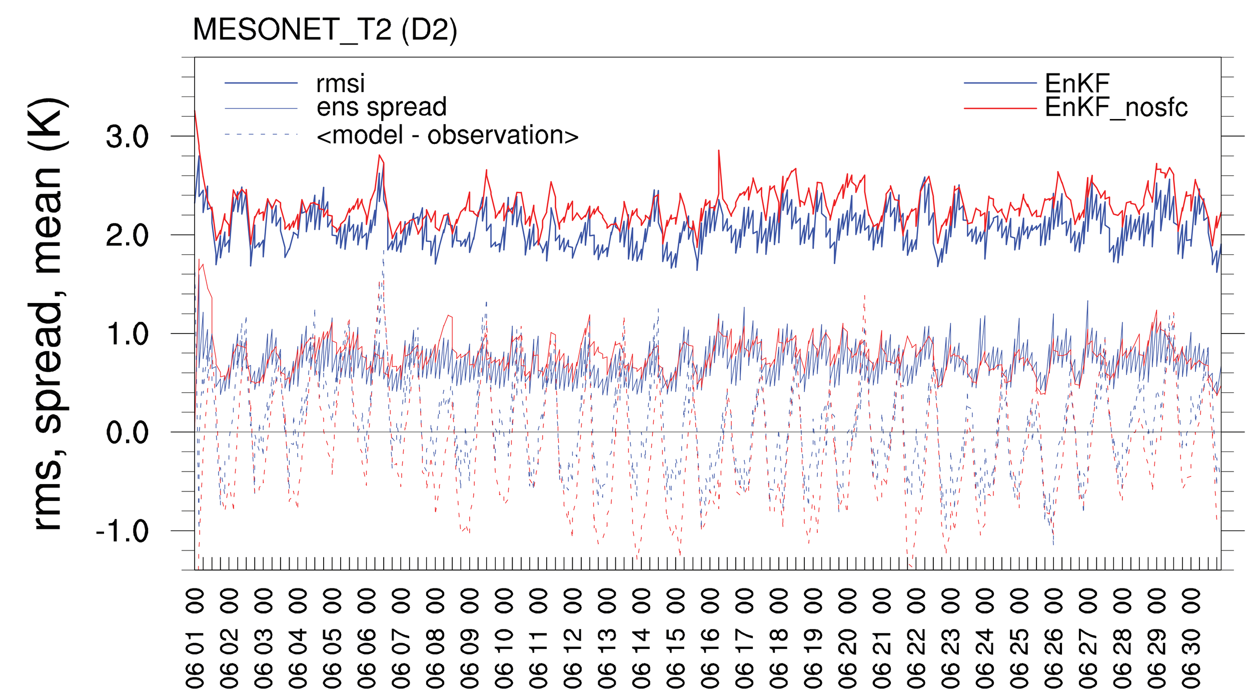
Data Assimilation Research Testbed (DART): Model-independent, parallel ensemble DA algorithms. See http://www.image.ucar.edu/DAReS/DART/

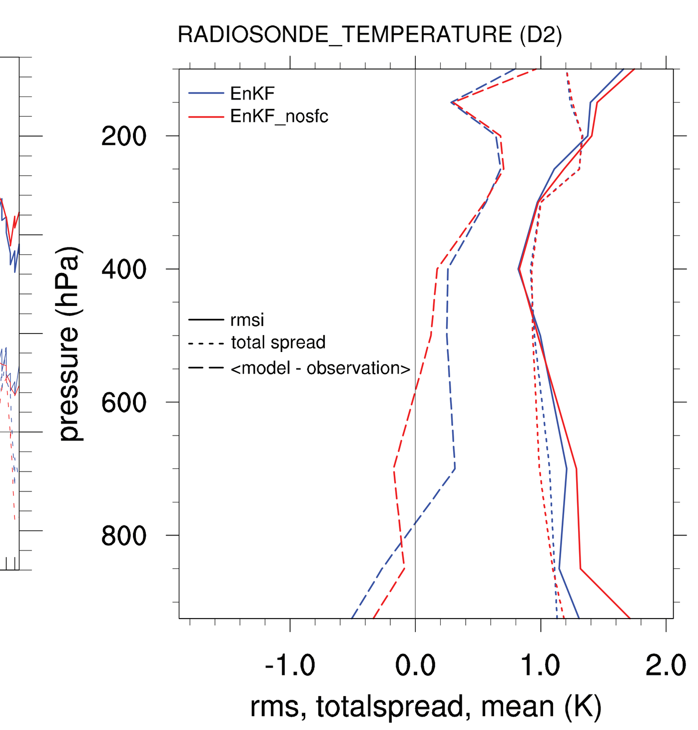
Weather Research and Forecasting model (WRF): nonhydrostatic Advanced Research (ARW) core; multiple physics scheme available. See http://www.mmm.ucar.edu/wrf/users

Details of experiments: System cycled for 1-30 June 2008, assimilating conventional obs every 3 h, including METAR observations of 10-m u and v and 2-m T and T_d. Both 45- and 15-km domains are updated simultaneously. Mesonet surface observations withheld and used to evaluate quality of analyses and forecasts. Use 50 members, localization radius ~ 600 km/8 km in horizontal/vertical, and adaptive inflation (Anderson 2009).



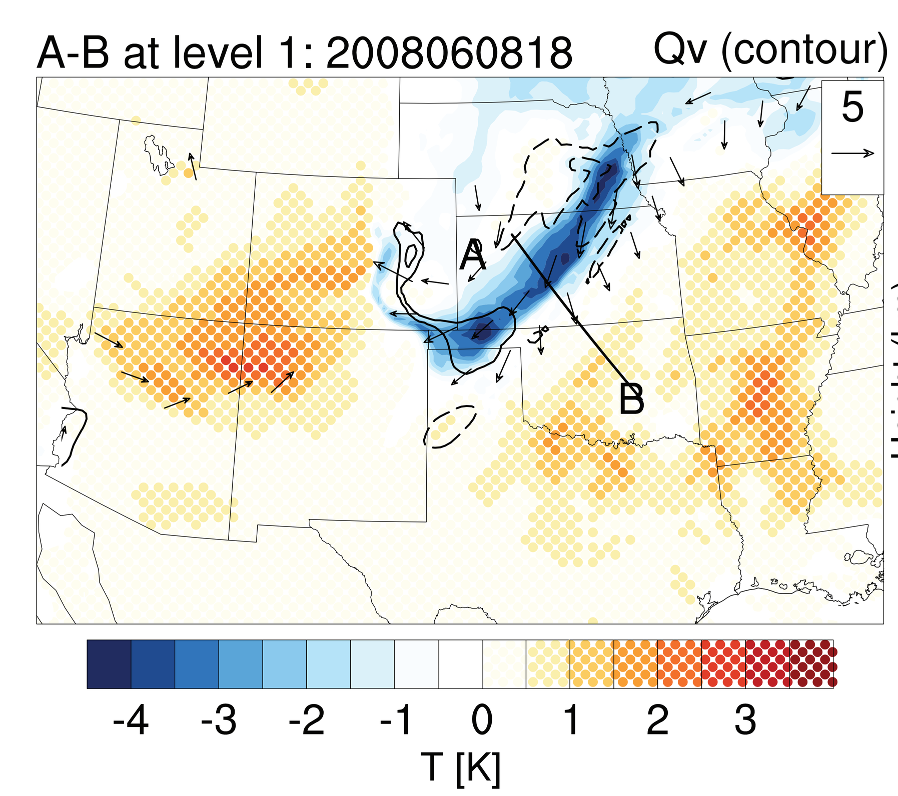
3. Influence of surface observations

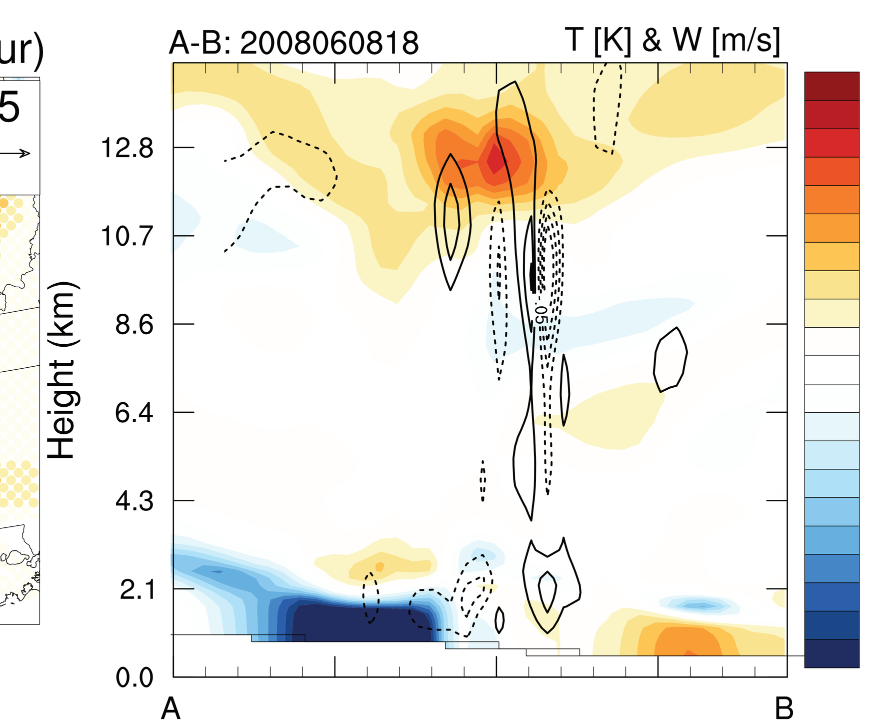




Above left: Statistics of analysis and 3-h forecast differences from MESONET 2-m T observations for experiments with (black lines) and without (gray) METAR observations. Time series are shown for the rms value over D01 (solid lines), the ensemble spread (short dashed) and the bias (long dashed).

Above right: Statistics of 3-h forecast differences from radiosonde T observations for experiments with (black lines) and without (gray) METAR observations. Shown are the rms difference averaged over the experimental period (solid), the "total" spread (i.e. square root of sum of ensemble variance and observation-error variance; short dashed) and bias (long dashed).





Analysis increment at 18Z 06 June from the experiment including METAR observations. This increment arises largely from the METAR observations; for the experiment without METAR, the temperature increment at this time is < 0.5K at levels below 4 km. The panel at right shows the increment at the lowest model level for temperature (shaded), water vapor (contours) and horizontal wind (vectors) on D02. The left panel shows a vertical section of increments for temperature (shaded) and vertical velocity (contoured) at the location indicated in the right panel.

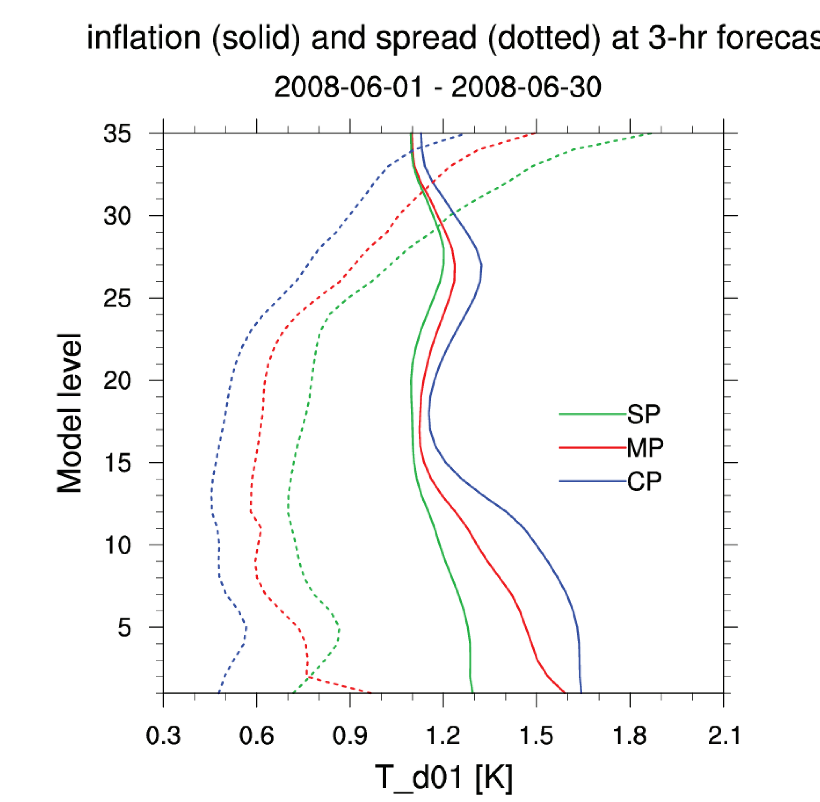
4. Two representations of model error

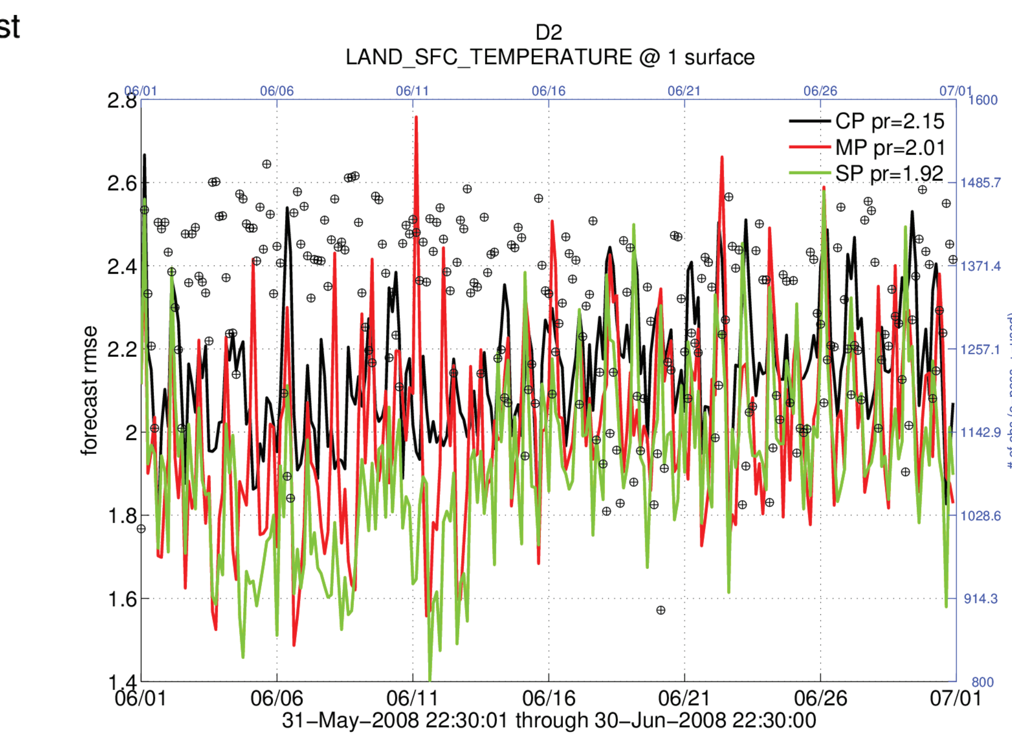
Consider two approaches that explicitly represent model error in EnKF forecast step:

Multi-physics (MP): Employ 10 suites of physics--5 member using each suite

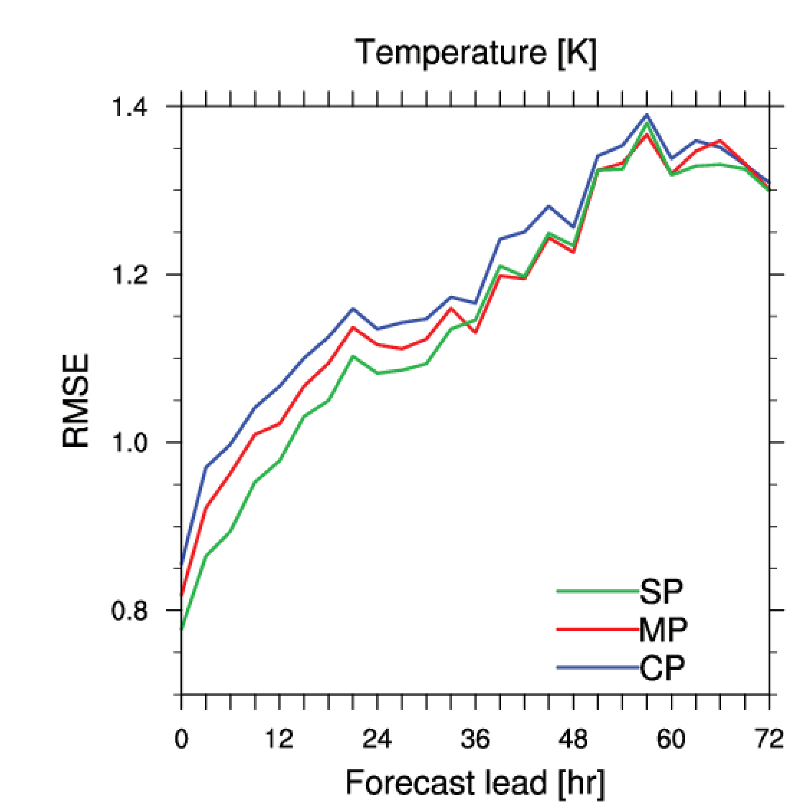
Stochastic backscatter (SP): Forecasts use backscatter scheme of Berner et al. (2011), in which adds spatially correlated, random noise to the wind and temperature fields at each time step.

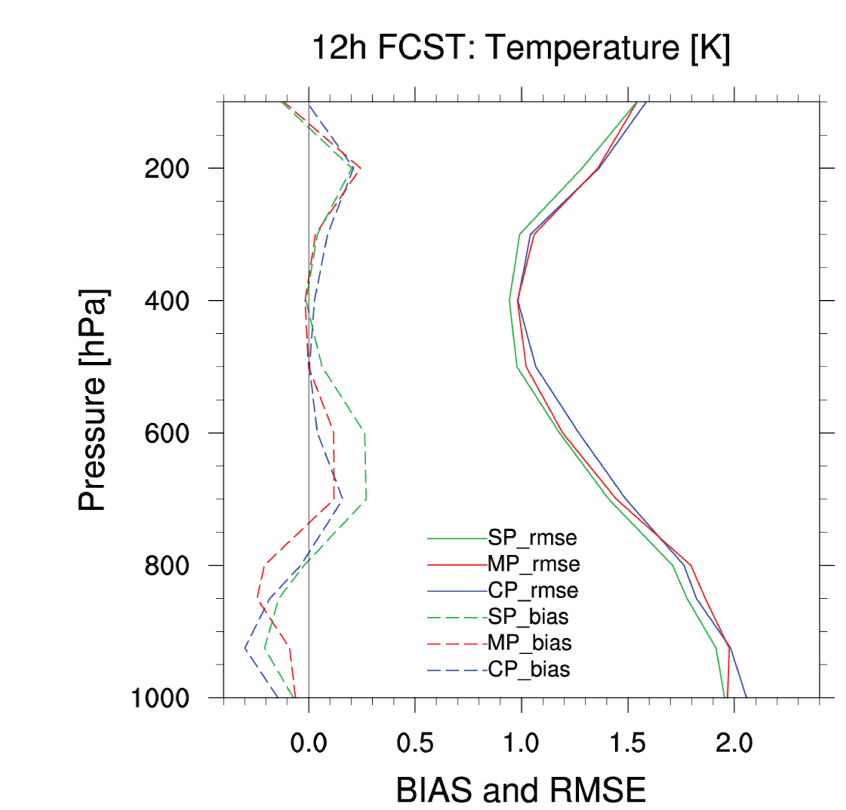
In addition, the adaptive inflation can be thought of as also, in part, accounting for model error, as it compensates for the net effect of all factors leading to an underdispersive ensemble. Experiment with only adaptive inflation is denoted by CP.





Above left: Vertical profiles of horizontal- and time-averaged inflation factor (solid lines) and ensemble spread (dashed) for experiments CP (blue), MP (red) and SP (green).
Above right: Time series of rms 3-h forecast differences from MESONET 2-m T observations for CP (black), MP (red), SP (green).





RMS differences relative to the RUC analysis for forecasts of 500-hPa T as a function of lead time (left) and for 12-h forecasts as a function of vertical level (right). Three experiments are shown: CP (blue), MP (red), SP (green). Forecasts are from ensemble-mean analysis.

4. Conclusions

EnKF assimilates surface observations effectively: Fits of short-range forecasts to observations, both near surface and aloft, are improved with assimilation of METAR. Analysis fits to independent MESONET observations are also improved. Analysis increments from surface observations exhibit clear influences of important physical features, such as surface fronts and the PBL.

Stochastic backscatter performs well as a model-error representation: Forecast fits to observations, comparison of longer forecasts to RUC analyses and analysis fits to independent observations are all improved consistently by the use of backscatter relative to both multi-physics and only adaptive inflation. Improvements are, however, moderatess; all three approaches are broadly comparable.

Model bias in PBL appears to be a limiting factor: Not really shown here; nevertheless, bias in surface quantities is often much larger than improvements obtained from assimilating surface observations. Thus, an expedient treatment of model error, together with focused efforts to diagnose and correct model deficiencies, may yield the greatest benefits. Consideration of land-surface model and surface-layer treatment will also be important.