J5.8 ESTIMATES OF BOUNDARY LAYER PROFILES BY MEANS OF ENSEMBLE-FILTER ASSIMILATION OF NEAR SURFACE OBSERVATIONS IN A PARAMETERIZED PBL

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1. Introduction

Surface (shelter and anemometer-height) observations are frequently under-utilized in data assimilation systems because of several difficulties. First, transient strong coupling with the Earth's surface and the free atmosphere produce intermittent, anisotropic, and nonstationary correlations of the observations with the model background state. Second, the error growth estimated with models providing the background state is largely unknown, highly variable, and likely not well-represented in current mesoscale models. Third, dynamic balances often exploited in large-scale data assimilation are inappropriate for PBL observations of temperature (T), component winds (U, V), and mixing ratio (Q). Finally, irreversible processes such as turbulent mixing are difficult to construct for variational data assimilation systems requiring a model adjoint.

Ensemble filters are, theoretically, a path to overcoming many of these difficulties, but this approach to PBL assimilation is just beginning. The ensemble provides a means of estimating flow-dependent background error statistics, including the full error covariance, and formally handling model deficiencies. Adjoints are not necessary and construction of ensemble data assimilation systems is much simpler than the more complex variational schemes. Hacker and Snyder (2005) showed in perfect-model observation-system simulation experiments (OSSEs) that ensemble assimilation could prove fruitful for specifying overlying PBL profiles from surface observations. They also showed that semi-physical land-surface parameters could be effectively estimated in the ensemble-filtering framework.

Here we take the step from observation-system simulation experiments (OSSEs) to observation-system experiments (OSEs) by assimilating real observations. A column over the Atmospheric Radiation Measurement (ARM) program Southern Great Plains Central Facility near Lamont, OK, is selected for analysis because of the robust data for both assimilation and verification. The lack of complex topography in that region also reduces the likelihood that the climatology will be determined by mesoscale features, and should be random above the PBL.

The column model contains soil, surface-layer, and PBL parameterization schemes that are the same as those in the Weather Research and Forecast (WRF) mesoscale model. This results in a response to observations that is similar to what can be expected in the WRF. It also facilitates efficient research on errors in those schemes.

The utility of surface observations for determining the PBL is quantified by verifying the retrieved profiles against rawinsonde observations. Useful skill is assessed by comparing against climatology and also WRF forecasts. Comparison against climatology shows the full effect of assimilating surface observations with the ensemble filter, because the only additional sources of information are a background climatological distribution and the column model. Comparison against the WRF forecasts is useful to demonstrate what additional information might be available to a forecaster who had access to retrieved profiles such as this. Future work will combine background information from the most-recent WRF forecast and the assimilation of surface observations in the column model, providing a more optimal and practically useful retrieval.

The next section describes the model, the observation

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and verification data, and the assimilation system. Section 3 presents verification and comparison against climatology and the WRF forecasts, and section 4 summarizes the key findings of this work.

2. Experiment description

This section summarizes some aspects of the column model used in this study, the experiment data, and the experiment design.

2.1 The 1D column model

A column model containing a suite of physical parameterization schemes is suitable for the experiments described here. We are interested in only vertical structures and relationships within and near the PBL, and a column model allows experimentation at a fraction of the cost associated with a 3D mesoscale model. Large ensembles are feasible, enabling convergence of results and experimentation with sensitivity to ensemble size.

Our model can be thought of as a simpler cousin to the Weather Research and Forecast (WRF) mesoscale model (Skamarock et al. 2005). It contains the same suite of physical parameterizations for subgrid processes associated with the soil, surface layer, and PBL. For these experiments, we chose the Mellor-Yamada-Janjić (MYJ) PBL scheme (Janjić 2001) and the Noah land-surface model (LSM) for the soil (Ek et al. 2003). The vertical grid is defined as 33 vertically stretched atmospheric levels, with the first layer extending to approximately 40 m above the surface and a top at approximately 4800 m. Further details of the column model are given in Pagowski (2004), Pagowski et al. (2005) and in Appendix A of Hacker et al. (2006).

Initial conditions, large-scale forcing, and surface radiation are imposed by randomly sampling two forecasts from a (warm) season of WRF real-time forecasts at a column located over Oklahoma, then combining them with a uniform random coefficient between zero and one ($\mathcal{U}[0,1]$). WRF 36-h forecasts from the Bow Echo and Mesoscale Convective Vortex Experiment (BAMEX) observation period spanning 03 May through 14 July 2003 constitute the sample. Forecasts were launched at 00 UTC every day, on a $\Delta x = 4$ km grid. More details on the sampling approach are available in Hacker and Snyder (2005). This approach permits construction of a large ensemble, containing slow time scales, with forecast error that is saturated with respect to a conditional climatology. Although the distribution of large-scale forcing is narrowed with this approach, the small-scale effects on the column are isolated and ensembles larger than the WRF sample are available.

2.2 Assimilation and verification data

The Southern Great Plains Central Facility of the ARM program is well-instrumented, providing observations for both assimilation and verification of the column analyses. Observations for assimilation are 30-minute averages of temperature and water vapor mixing ratio at $z = 2$ m (T_2, Q_2), and winds at $z = 10$ m (U_{10}, V_{10}), include quality-control flags and estimates of uncertainty. Rawinsonde observations valid every 6 h are used for verification. Measurements of flux at the land interface and soil profiles are used to evaluate the model configuration as well as the consistency of model diagnostic shelter and anemometer-height states with model representations of the soil and fluxes. Archived WRF forecasts from the BAMEX period are used for the background ensemble climatology, as described above, and also to provide a performance baseline.

2.3 Experiment design

Assimilation experiments are run for each day in the BAMEX period. The cycling is begun at 12 UTC, 12 h after the WRF initialization. Observations are assimilated hourly for the subsequent 24 h period. The observation errors are assumed to be uncorrelated with variances 0.08 K^2, 1.1 m^2 s^{-2}, and 7.7×10^{-8} kg^2 kg^{-2}, for T_2, (U_{10}, V_{10}), and Q_2 respectively. These values are the 30-minute average variances of the assimilated variables averaged over the period of the assimilation experiments. The observations are assimilated via the ensemble adjustment Kalman filter, implemented with a sequential least-squares algorithm, as described in Anderson (2003). Vertical covariance localization is accomplished using a fifth-order piecewise polynomial (Gaspari and Cohn 1999). We do not present the ensemble-filter algorithm in detail here, but the interested reader can refer to the growing body of literature (e.g. Evensen 1994; Burgers et al. 1998; Houtekamer and Mitchell 1998). In summary, the technique provides a direct estimate for background error covariances for solution to the linear statistical-analysis equation. Computationally, the assimilation algorithm scales with the number of observations, and the majority of the cost is in the ensemble of model integrations. For typical atmospheric data assimilation problems, the cost is roughly equivalent to four-dimensional variational assimilation (4DVAR), where the cost is in a 4D minimization algorithm. Ensemble filters provide the added benefit of an ensemble of analyses that can be used for probabilistic prediction. In these experiments, ensembles with $N = 100$ members are used, and 24 hours of integration/assimilation takes a few minutes on a desktop computer.

Here we present a straightforward verification, based on comparison of analyzed PBL profiles and observed rawinsonde profiles. The analysis procedure is at a considerable disadvantage because the only "information" provided to it, besides a climatology, is the surface observations themselves. A climatology is constructed by running the column model, forced by the WRF climatology, over the same periods as the assimilation experiments. The depth of the profile in the column that shows less error than the climatological mean quantifies the information content in those surface observations. The depth of the profile in the column that shows less error than a 3D WRF forecast is a stricter test. It suggests the benefit of local observations in reducing error independent of time-dependent 3D dynamics.

3. Skill compared to climatology and WRF forecasts

In this section we present the verification of the analyzed PBL, the climatological mean and the 3D WRF forecast profiles against rawinsondes profiles. Figures 1 and 2 show the mean average error (MAE) of the component winds (U, V), potential temperature (θ), and mixing ratio (Q) over the period of the assimilation experiments as a function of height AGL, valid at 00 UTC (19 LT) and 18 UTC (13 LT) respectively.

The analyzed PBL profiles show a reduction in the MAE relative to the climatological mean profiles, which on the whole, becomes less significant with height and is roughly bounded by climatology. In addition, improvement is observed as compared to the 3D WRF forecasts in the lower hundreds of meters. Figs. 3 and 4 show the percentage of MAE reduction in the analyzed PBL profiles relative to the climatological mean and the 3D WRF forecast profiles as a function of height AGL valid at 00 UTC (17 LT) and 18 UTC (13 LT) respectively. While the MAE reduction curves look similar for the two hours shown, some differences are distinguishable.

The benefit of the information content in the assimilated observations, shown by the MAE reduction relative to the climatological mean, depends on the analyzed variable and the hour. The greatest impact for all variables is observed at 19 LT (Fig. 3). The maximum MAE reduction is obtained for θ, 80 to 85% up to 900 m AGL. θ shows also the maximum vertical extent of MAE reduction. The highest vertical extent of MAE reduction for all variables is obtained at 13 LT (Fig. 4). The differences obtained between the curves at 17 LT and 13 LT and between the different variables reflect the transient coupling between the surface and the atmosphere, the different coupling between the surface and the atmosphere for the different variables, the effect of the length of the assimilation period and the information content in the climatological profiles as a function of the diurnal cycle. The results shown are insufficient to isolate the effect of the different factors. Still, the strongest impact in the lowest few hundred meters at 19 LT may suggest the effect of the longer assimilation period (12 hours of assimilation) as compared to 13 LT (6 hours of assimilation).

The MAE reduction relative to the 3D WRF forecasts shows a time and variable dependence too. The most significant MAE reduction, 60% for θ up to 700 m is observed at 19 LT and the maximum vertical extent is obtained at 19 LT too (for Q up to 1400 m). The better skill of the 3D WRF forecast profiles above roughly the lower kilometer suggest the need to drive the column model with profiles that contain information richer than climatology.

4. Summary

- This work investigates the usefulness of assimilating surface observations via an ensemble filter in a parameterized PBL driven by climatological profiles. The effectiveness of the assimilation of the surface observations was tested by verification of the analyzed PBL, climatological mean and WRF forecasts profiles against rawinsonde profiles.

- The analyzed PBL profiles show a significant reduction in the error (e.g.,up to 85% in the lower 900 m for the potential temperature) relative to the climatological-mean profile that extends up to 2-3 km AGL. This reflects the information content of the surface observations assimilated with the ensemble filter. Comparison against WRF forecast profiles (at a horizontal resolution of 4 km) show an error reduction of 30 to 60% in the lower 700 m and a positive effect up to 1400 m. This shows the advantage of local observations regardless of time-dependent 3D dynamics.

- Ongoing work focuses on improving the retrieved profiles by providing enhanced initial and forcing information to the 1D column model using most recent WRF forecast or observed profiles. In addition, the usefulness of the method as a short term (6-12 hours) forecast tool is being assessed.

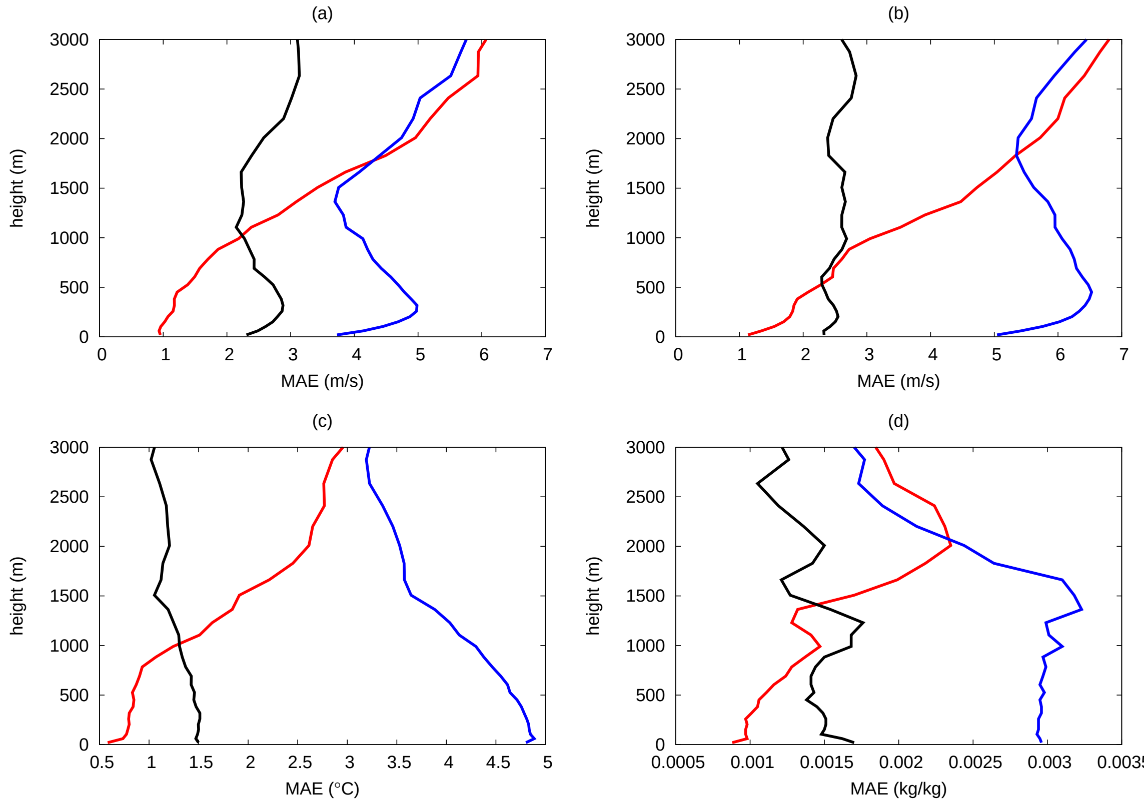

Figure 1: Mean absolute error (MAE) as a function of height AGL in the analyzed PBL (red curve), climatology (blue curve) and 3D WRF forecast profiles (black curve) for (a) U, (b) V, (c) T and (d) Q. Results are valid at 00 UTC. See text for further details.

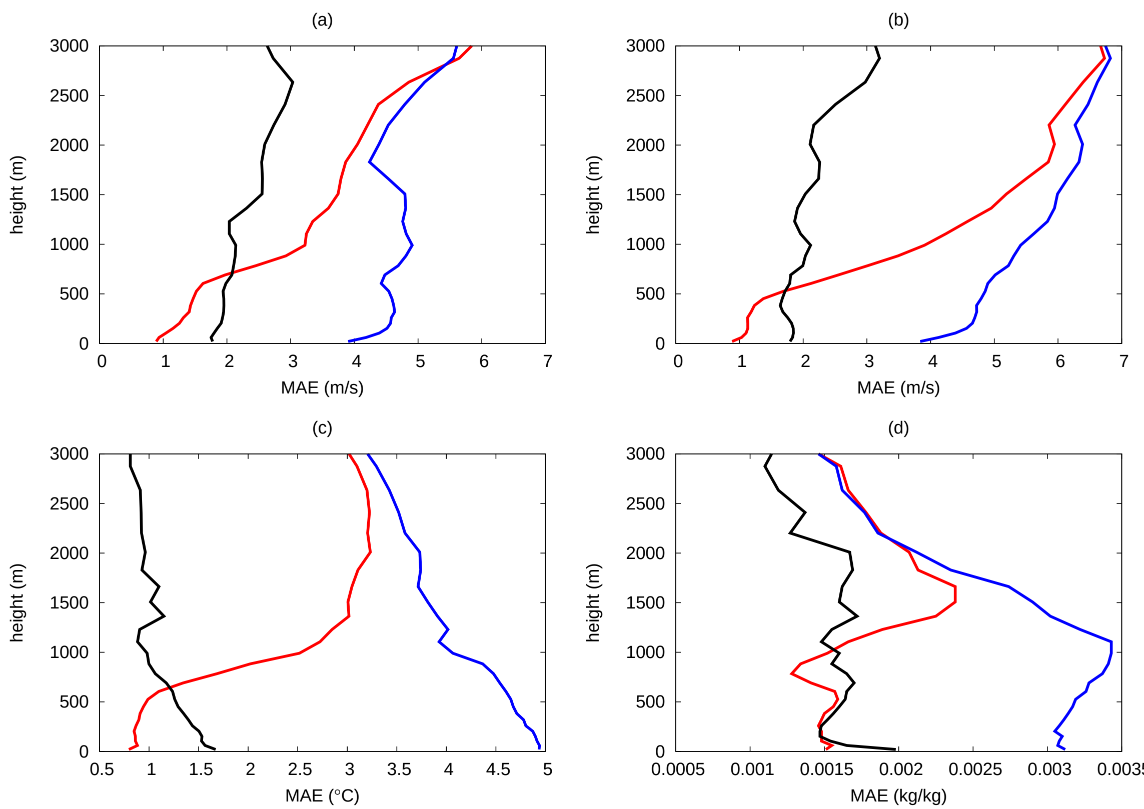

Figure 2: Same as Fig. 1 but valid at 18 UTC.

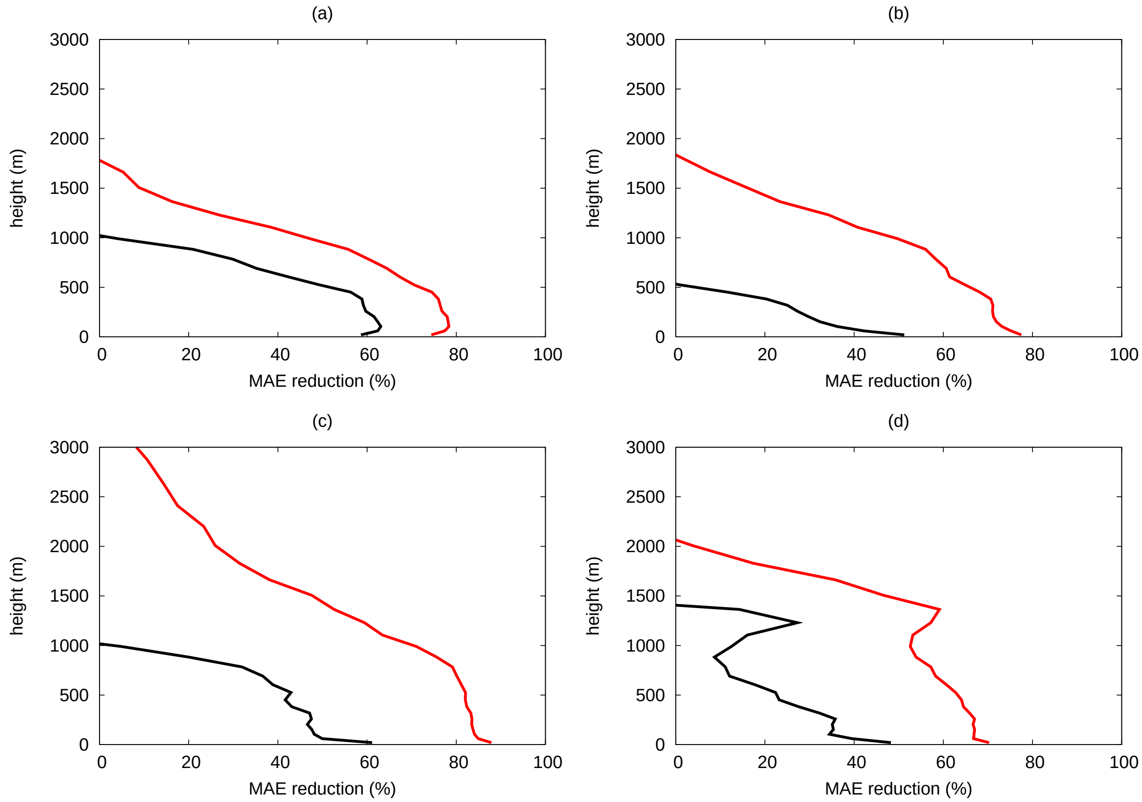

Figure 3: Percentage of MAE reduction in the analyzed PBL as a function of height AGL relative to climatology (red curve) and 3D WRF forecast profiles (black curve) for (a) U, (b) V, (c) T and (d) Q. Results are valid at 00 UTC.

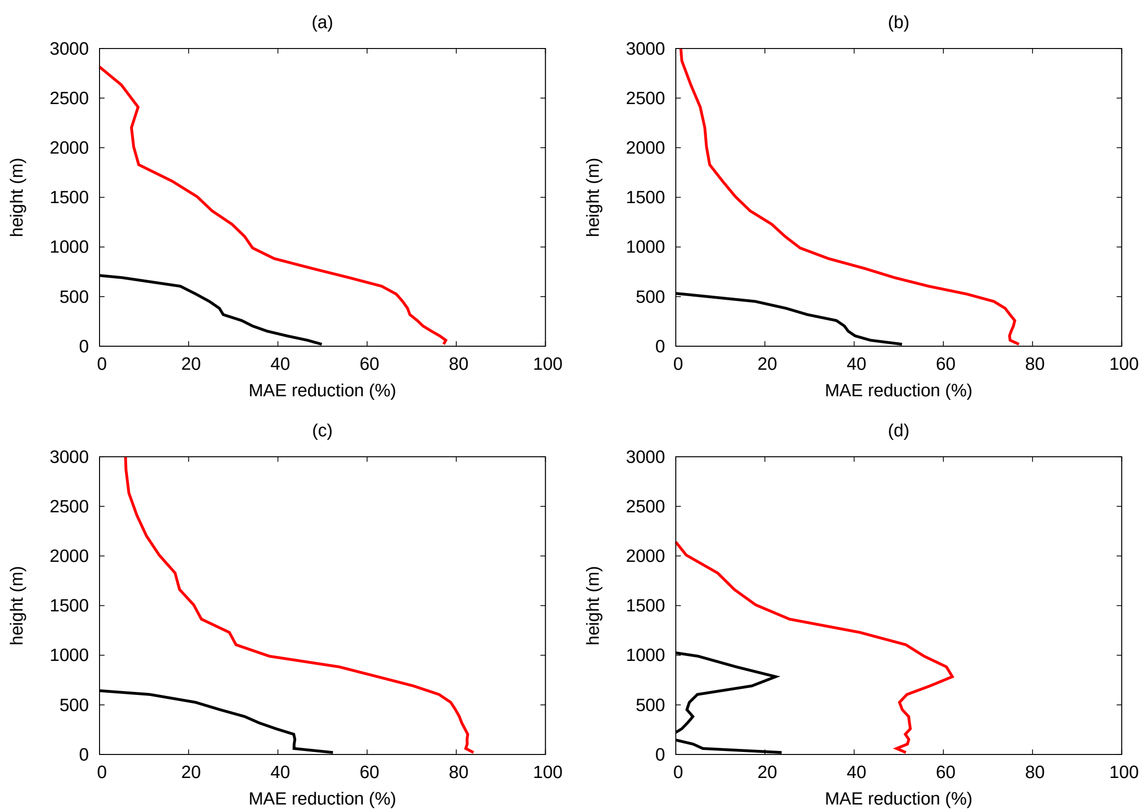

Figure 4: Same as Fig. 3 but valid at 18 UTC.

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